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Ministry of Higher Education and Scientific Research
University of Babylon
College of Information Technology
Software Department



"Chaotic Parameters Estimation Based on Meta-heuristic Methods:Speech Descrambling Case Study"

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By

Duaa Abdul Rida Raheem Mohammed

Supervised by

Prof. Dr. Nidaa A. Abbas Hassan

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Signature:

Supervisor Name: **Prof. Dr. Nidaa A. Abbas Hassan**

Date: / / 2022

The Head of the Department Certification

In view of the available recommendations, I forward the thesis entitled “**Chaotic Parameters Estimation Based on Meta-heuristic Methods: Speech Descrambling Case Study**” for debate by the examination committee.

Signature:

Assis. Prof. Dr. Ahmed Saleem Abbass

Head of Software Department

Date: / / 2022

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Name: Dr.Sattar B.Sadkan
Title: **Professor**
Date: / / **2022**
(**Chairman**)

Signature:
Name:Dr. Rana Jumaa Surayh
Title: **Assistant Professor**
Date: / / **2022**
(**Member**)

Signature:
Name: Dr. Haydar Kadhim Zghair
Title: **Lecture**
Date: / / **2022**
(**Member**)

Signature:
Name: **Dr.Nidaa A.Abbas**
Title: **Professor.**
Date: / / **2022**
(**Supervisor**)

Approved by the Dean of the College of information technology,
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Signature:
Name: **Dr. Hussain Ateya Al-Khalidi**
Title: **Professor.**
Date: / / **2022**
(**Dean of Collage of Information Technology**)

Dedication

To those who pursue their goals and never give up....

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Abstract

A chaotic system is a dynamic and deterministic nonlinear system. Its performance is non-periodic, and dependent on the initial conditions and system parameters and chaotic systems are necessary for speech scrambling applications because of their characteristics. In this thesis, meta-heuristic algorithms are used to estimate the parameters of a chaotic system. It is characterized by good durability and ease implementation.

This thesis used an estimate of the chaotic maps parameters, including estimation of the parameter (r) in a logistic map and estimation of the parameters(k and Ω) in a circle map, and an estimate of the parameter using the meta-heuristic algorithms, including particle swarm optimization (PSO) and quantum particle swarm optimization (QPSO). The minimum mean square error (MSE) and sum square error(SSE) are used as fitness functions for PSO and QPSO algorithms. The simulation results show that the QPSO algorithm is better than the PSO algorithm for the estimated parameter of the logistic map (r), but the PSO algorithm is better(if the value (r) has two values after the separator (ex. $r=3.66$)). The PSO algorithm is better than the QPSO algorithm in estimating the two parameters (k and Ω) for a circle map. The signal-to-noise ratio (SNR) and correlation coefficients (CC) were used to measure quality speech signals

Declaration Associated with this Thesis

Some of the works presented in this thesis have been published or accepted as below.

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List of Abbreviations

Abbreviation	Meaning
PSO	Particle Swarm Optimization
QPSO	Quantum Particle Swarm Optimization
MSE	Mean Square Error
SSE	Sum Square Error
BSA	Bird Swarm Algorithm
DE	Differential Evolution
C.EPSO	Chaotic Ensemble Particle Swarm Optimization
EPSO	Ensemble Particle Swarm Optimization
PMSM	Permanent Magnet Synchronous Motor
IPSO	Improved Particle Swarm Optimizatio
GFPA	Global Flower Pollination Algorithm
FPA	Flower Pollination Algorithm
BSA	Backtracking Search Optimization Algorithm
API	Pachycondyla Apicalis
ABC	Artificial Bee Colonies
CS	Cuckoo Search
1D	One Domination
MSM-PCOA	Master-Slave Model- Parallel Chaos Optimization Algorithm
PSO-ACO	Particle Swarm Optimization-Ant Colony Optimization
DPSO	Dual Particle Swarm Optimization

FWA	Fireworks Algorithm
QPPSO	Quantum Parallel Particle Swarm Optimization
HABC	Hybrid Artificial Bee Colony
CM	Circle Map
LM	Logistic Map
GA	Genetic Algorithm
3D	Three Domination
Pbest	Best Position
Gbest	Global Best Position
Fc	High Frequency
Fs	Sample Rate
Hz	Hertz
ADC	Analog to Digital
DAC	Digital to Analog
PR	Pseudorandom Permutations
TSP	Time Segment Permutation
PRNG	Pseudo Random Number Generators
FFT	Fast Fourier Transform
DCT	Discrete Cosine Transform
2D	Two Domination
MDCT	Modified Discrete Cosine Transform
TX	Transmitter
RX	Receiver
CC	Correlation Coefficients
SNR	Signal-to-Noise Ratio

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Chapter One

Introduction

*Chapter One**Introduction***1.1 Background**

With the rapid development of wireless communication, data transmission security has become a more vital problem. Communication systems are considered trusted as long as progresses a high level of security to protect data from snoopers and attackers. Usually, users share the main information among themselves. Therefore, the means of transmission must be provided for the security, confidentiality, reliability, and integrity of the exchanged data, when it is transmitted through the public channel (untrusted channel), which is not secure. For this purpose, wireless security methods have been developed to protect communications from eavesdroppers and attackers[1].The coding schemes suggest several algorithms to protect multimedia data such as speech signals, images, and video clips [2].

The chaotic theory contains differential equations with one or more dimensions. Chaos theory has the essential features that it is nonlinear, unstable constrained dynamic performance, shows sensitive dependence on initial conditions and system parameters, and includes infinitely unstable periodic motions[3]. These properties that cause chaos theory have become extremely important for cryptographic applications. Because the mixing and randomness of chaos are similar to the confusion and diffusion effects in cryptography, the chaotic encryption method shows more potential than traditional methods [4]. In previous decades, many scientists focused on controlling and synchronizing a chaotic system applied to a wide field of information security [5]. Chaotic signals have been used as highly secret, unpredictable, and often unbreakable cipher keys. Several strategies operate on the supposition that chaotic systems are previously known. It is challenging to define parameters in the real world due to the complexity of

chaotic systems [6]. Besides, not all dynamic parameters are known despite physical information for these systems [7].

Scrambling speech is a technique used to convert original speech into incomprehensible speech. It is difficult to decrypt without a key; It is used to avoid attackers and eavesdropping. It also plays an essential role in securing speech when transmitted over insecure channels [8].

The scrambling method can be classified as analog and digital scrambling. Analog scrambling is one of the more common encoding methods used in speech communication [9]. In analog scrambling algorithms, speech signals are converted into their discrete form, digitally processed with digital signal processing tools, and then converted back into their analog form. Digital scrambling is a speech signal that is digitally transmitted, processed, and received. The digital speech encoder contains a digitizer for converting analog to digital speech and back, an encoder, and a compressor [10]. Scrambling is performed by permuting the elements of speech in the time domain and the frequency domain and combining the time domain and the frequency [9].

The study of the problem of estimating parameters has a long history. According to Kirchho {the privacy of the method does not rely on the cipher system or algorithm, it relies just upon the key). Thus, estimation of the parameter is a warning to chaotic coding due to the ability to precisely parameter estimation (system parameters and initial values). In this system, the chaotic system's parameters estimation is proposed using meta-heuristic methods. The meta-heuristic algorithm is a unity of the most popular techniques for effectively estimating chaotic system parameters. It is characterized by good durability and ease of implementation, such as genetic algorithm (GA), particle swarm optimization (PSO) algorithm, hybrid PSO algorithm, variant PSO algorithm, flower pollination algorithm, teaching-learning-based algorithm, bird swarm algorithm (BSA), differential

evolution (DE) algorithm and its hybrid algorithm. However, all of these algorithms need to get the initial values from the original system. Changing parameters estimation into an optimization problem and the earlier knowledge of parameter estimation just gets some pseudorandom sequences created by chaos systems as the samples [4][5]. If it can estimate the initial values and system parameters, it will decrypt the secret key of the chaotic map. Accordingly, it is necessary to identify the type of chaotic map that can withstand an attack to estimate parameters. Also, the number of parameters estimated has an important impact on the estimation outcomes. The higher the number of parameters, the more difficult it becomes to estimate parameters [4].

The particle swarm optimization algorithm (PSO) starts with collecting random solutions in the search space and is scanning for an ideal solution by transforming potential solutions across generations [11]. Through the PSO, the perfect solution will be obtained. The quantum particle swarm optimization (QPSO) algorithm is a probabilistic algorithm. It requires fewer parameters than PSO, is easier to implement, and needs no particle velocity vectors [11]. The optimal solution is obtained using two algorithms by detecting the lowest error rate (fitness function) using the minimum mean square error (MSE) and the sum of square error (SSE). In this thesis, estimations of the parameters for the chaotic maps will be used for speech descrambling as a case study, which will be explained in detail in Chapter Two.

1.2. Related Works

D. Yousri, M. B. Eteiba, A. F. Zobaa, and D. Allam, 2021[12], novel variants for the Ensemble Particle Swarm Optimizer (EPSO) are proposed for parameter estimation where ten chaos maps are combined to improve EPSO production by adaptively tuning its key parameters. The comparison

among proposed variables and the beforehand published algorithm demonstrates the efficiency of the improved technique, and the results emerge that the Chaotic Ensemble Particle Swarm variants with the Gauss/mouse map are the most suitable alternatives for parameters estimation of equal order and variable-order fractional PMSM models, and the algorithm results in less error, high convergence speed, and short performance time. This may result in faster-unwanted performance control and better damage protection.

P. Yue-xi, S. Ke-hui, H. Shao-bo, 2020 [4], proposed a dynamics analysis of the cryptography for chaotic maps estimating parameters by a meta-heuristic algorithm using improved particle swarm optimization (IPSO) algorithm.

Y. Peng, K. Sun, S. He, D. Peng, 2019 [13], the optimized particle swarm optimization algorithm for parameter determination is proposed. Numerical simulations of the Cat Map, fractional-order form, and Hénon map, as well as the fractional-order standard iterated map with hidden attractors, are shown. Determining the most appropriate sample size is discussed, taking into account parameter determination with noise interference. The experimental results showed that the proposed algorithm has better results than other algorithms and is suitable even with random noise interference.

Y. Chen, d. Pi, Bi Wang, 2019[14], an enhanced global flower pollination algorithm (GFPA) is proposed for parameter identification of chaotic and hyper-chaotic systems. an enhanced global flower pollination algorithm (GFPA) is proposed for parameter identification of chaotic and hyper-chaotic systems . Through the analysis algorithm, the proposed new algorithm can guarantee the convergence of the algorithm without increasing the time complexity, but GFPA does not always ensure the optimal value of the theory in implement of the algorithm in the future, Finally, they identify and validation the system of the Lorenz, Rössler, Chen and the system of the

Rössler hyper-chaotic, Chen hyper-chaotic. GFPA is practical and efficient to more accurately assess unknown parameters of a chaotic system without growing the time complexity of hyper-chaotic and chaotic systems.

M. A. Ahandani¹, A. R. Ghiasi¹, and H. Kharrati, 2018[15], proposed two easy and efficient estimation methods to discover unknown parameters of the chaotic system. Certain techniques are adapted to improve the production of a lately suggested evolutionary method named the BSA (backtracking search optimization) algorithm. The feature of the suggested method in parameter determination of ten typical chaotic methods has been verified. Work experiments and non-parametric tests of the outcomes obtained explain that both the suggested concepts for improving the production of the original BSA are efficient and powerful. Better execution of the suggested methods is based on objective mean methods.

F. Maamri, S. Bououden, M. Chadli, and Boulkaibet, 2018,[16], The proposed Pachycondyla Apicalis meta-heuristic algorithm (API) was applied to determine the parameters of the electrical chaotic process controller to confirm the stabilization of the oscillatory nonlinear duffing solution. The simulation results indicate that the API algorithm can effectively identify the unknown parameters for given chaotic systems with high accuracy and low deviations.

D. Zhenghao, LU Zhongrong, and L. Jike, 2018[17], they proposed the Hybrid Artificial Bee Colony algorithm is a combination of two algorithms which are Artificial Bee Colonies (ABC) with the Cuckoo Search Strategy (CS) that used an estimation of the parameters for chaotic methods (Lorenz system and a hyper-chaotic system). Numerical simulations illustrate the suggested algorithm as a strong tool for an estimation of the parameters with high precision and low deviations. It is not sensitive to artificial measurement noise even using limited input data.

Y. Peng, K. Sun, S. He, and Xi Yang, 2018 [5], proposed a way to improve the estimation of parameters whose initial values are unknown using a novel algorithm named chaotic particle behavior optimization algorithm. The results of the algorithm were reasonable compared to other algorithms.

A. S. Sheludko, 2018 [18], proposed, parameter estimation of a one-dimensional (1D) chaotic system using two steps: the first step is to preprocess the measurements by the guaranteed method, and the result of the guaranteed method is the period estimation for unknown parameters (parameter and initial state of the chaotic map), the second step is to reduce cost function utilizing particle swarm optimization (PSO). The pre-calculate period estimation determines the set of possible values for the cost method. The proposed estimation technique is useful in the case of a small number of available measurements.

X. Yuan, T. Zhang, X. Dai, L Wu, 2016 [19], they proposed a master-slave model (MSM) based parallel chaos optimization algorithm (PCOA) (denoted as MSM-PCOA) for parameter identification problems. MSM-PCOA is implemented to define two complex systems: a two-way inductive power transmission system and chaotic methods. Simulation results and comparisons with other optimization methods explain that MSM-PCOA has the best performance for identification parameters .

J.A.Lazzús, M. Rivera, C. H. López-Caraballo, 2016 [20], proposed a new hybrid swarm intelligence algorithm for estimating chaotic system parameters. The proposed hybrid algorithm is Particle Swarm Optimization (PSO) with Ant Colony Optimization (ACO) (PSO-ACO) applied to estimate parameters on multidimensional Lorenz systems. The statistical results of the Lorenz system in the proposed algorithm, in comparison with another algorithm, showed that the PSO-ACO algorithm is an important tool for estimating parameters with great precision and fewer deviations.

Y. Jiang, F. C. M. Lau, S. Wang, and C. K. Tse, 2016 [21], they proposed a Dual Particle Swarm Optimization (DPSO) algorithm to determine the parameters of chaotic systems. Validation of the efficiency of the suggested DPSO algorithm by estimating the parameters of the Lorenz system. The simulation results showed that the suggested algorithm is always superior to the classical PSO algorithm.

H. Li, P. Bai, J. Xue, and J. Zhu, H. Zhang, 2015 [22], suggesting an algorithm for parameter estimation for the chaotic method with three completely unknown parameters (Rossler and Lorenz chaotic system) is the Fireworks Algorithm (FWA) which is used for parameter estimation that showed good computational performance, accuracy, and better power for parameter estimation.

Yu H., Feng G., Yongling L., and Yufeng L, 2015 [23], they proposed Quantum Parallel Particle Swarm Optimization (QPPSO) algorithm to an estimation of the parameters of the fractal-order chaotic Lorenz and Rossler systems. Numerical simulation based on several typical fractional-order systems and comparisons with some typical existing algorithms show the effectiveness and efficiency of the proposed algorithm.

W. Hu, Y. Yu, and S. Zhang, 2015 [24], they proposed Hybrid Artificial Bee Colony (HABC) algorithm to identify chaotic systems of uncertain fractal order. Fractional ordered economic chaotic systems and Rössler systems are selected for performance testing. The results of the experiments explain that the proposed method to determine the uncertain fractal-order chaotic methods is a successful and promising approach with higher computation precision and quicker convergence velocity.

Table 1.1 Summary of Algorithms Estimating Parameters for Chaos Map.

Number of the reference	Chaotic map used	Methods used to estimate of parameters and fitness function
[12]	Chebyshev, Circle, Gauss/mouse, Iterative, Logistic, Piecewise, Sine, Singer, Sinusoidal, Tent.	C.EPSO(Chaotic Ensemble Particle Swarm Optimization). Mean Square Error(MSE) as fitness function
[4]	2D-Logistic Map , 2D-LASM , Logistic-Logistic (L-L) map , 2D-SLMM , Chebyshev map (2D) and 2DLICM	Improved Particle Swarm Optimization(IPSO). Mean Square Error(MSE) as fitness function
[13]	Hénon map, Cat map, Fractional-order Hénon map, Fractional-order Cat map	Computed with ABC, BSA, DE, APSO, PSO Algorithms, and IPSO . IPSO is best performance for parameter identification. Mean Square Error(MSE) as fitness function
[14]	Lorenz, Rössler, Chen and Rössler hyper-chaotic, Chen hyper-chaotic .	Global Flower Pollination Algorithm (GFPA). Mean Square Error(MSE) as fitness function.
[15]	Lorenz,Chen, Rossler, Arneodo, Duffing, Genesio-Tesi, financial, Lu, Chuas, Henon .	Used SBSA (Shuffled Backtracking Search Optimization Algorithm)as optimization method, SSE(Sum Square Error) as fitness function
[18]	Logistic map	GA is applied to reduce possible values of the unknown variables, and PSO is used to solve the minimization problem for cost function. LSM (least square method) as fitness function.
[17]	Lorenz system and a hyper chaotic system,	Improved Artificial Bee Colony (ABC) algorithm Compared with PSO , EP , DE ,and GA PSO-ACO. Improved Artificial Bee Colony (ABC) algorithm Is better than other algorithm. Mean Squared Error (MSE) as fitness function
[5]	Fractional-order simplified Lorenz hyper chaotic system and fractional-order Chen hyper chaotic system	Chaos Behaved Particle Swarm Optimization (CBPSO) algorithm. Mean Square Error (MSE) as fitness function
[16]	Determine the control parameters of the electrical chaotic system.	Pachycondyla Picalis Meta-Heuristic (API) algorithm. Mean Square Error (MSE) as fitness function
[20]	Lorenz system	Particle Swarm Optimization with Ant Colony Optimization (PSO-ACO). Mean Square Error(MSE) as fitness function
[19]	One-dimensional maps: Chebyshev map , Circle map ,Cubic map Gauss map , ICMIC	Master-Slave Model (MSM) based Parallel Chaos Optimization Algorithm (PCOA) (denoted as MSM-PCOA).

	map, Logistic map ,Sinusoidal map , Tent map	Mean Absolute Error (MAE)Or Mean Square Error(MSE) as fitness function
[21]	Lorenz system.	Dual-Particle Swarm Optimization (DPSO) .
[24]	Fractional ordered Economic chaotic systems and Rössler systems	HABC(Hybrid Artificial Bee Colony)algorithm as optimization method , used identification of uncertain fractal order for Economic chaotic systems and Rössler systems. And used SSE(Sum Square Error) as fitness function
[22]	Lorenz Chaotic System, Rossler Chaotic System	Fireworks Algorithm(FWA),and MSE (Mean Square Error) as fitness function.
[23]	Fractional-order Chen system, fractional order Lorenz system, fractional-order Rössler system, and fractional-order Lü system	Quantum parallel particle swarm Optimization (QPPSO), Mean Absolute Error or Mean Square Error as fitness function

1.3 Problem Statement

This thesis deals with the problem of estimating the parameters of the chaotic system, it is one of the threat techniques of the chaotic encryption .

1.4 The Aim of Thesis

1- Estimate parameters of a chaotic map (one parameter of the logistic map and two parameters of the circle map) where we used the meta-heuristic algorithm in estimating parameters are particle swarm optimization (PSO) algorithm and quantum particle swarm optimization (QPSO) algorithm.

2- This thesis tries to estimate the parameters of the chaotic maps and used them in the speech descrambling process. It used the chaotic map as pseudo-random number generators (PRNG) to generate random keystream bits.

1.5 The Thesis Challenges

The main contributions of the thesis are the estimation of the parameters of the chaotic system (one parameter for logistic map and two parameters for circle map) based on the meta-heuristic algorithm and the used of estimated parameters as a key to decoding the speech signal that is used as a case study in this thesis.

1.6 Thesis Outline

This thesis is organized as in the following:

- ✓ **Chapter One:** This chapter involves an introduction, presents a literature survey for estimating parameters based on a meta-heuristic algorithm, thesis contributions, and the objectives of the thesis.
- ✓ **Chapter Two:** This chapter includes the basic idea of chaos theory, the basic idea of a meta-heuristic algorithm, speech scrambling system technologies on a chaotic system, and different measures to test the proposed system.
- ✓ **Chapter Three:** Focuses on the proposed system design in detail and the algorithms used in the system.
- ✓ **Chapter Four:** Represents the results of the system which are discussed in detail.
- ✓ **Chapter Five:** Lists and discusses the conclusions and the suggested future works.

Chapter Two

Theoretical Background

*Chapter Two**Theoretical Background***2.1 Overview**

This chapter introduces the basic idea of chaos theory and the types of chaos maps used in this thesis. It presents the main characteristics of chaos maps, estimating the parameters of a chaotic map, and meta-heuristic algorithms, and shows the principle of estimating the parameters of a chaotic system by meta-heuristic algorithms. Also, an illustration of speech scrambling techniques is explained, which include: sample amplitude, time domain, frequency domain, hybrid (time and frequency), orthogonal (transformation). Finally, the presentation of various scales (objective test) to evaluate the proposed system is illustrated.

2.2. Chaos Theory

Chaos is a pseudo-random process that is provided in a dynamic and non-linear system. Naturally, it behaves as a long-term aperiodic in deterministic systems (meaning not to repeat itself at any time), is non-convergent, and is sensitive to the initial condition [25]. Chaos is one of the potential behaviors connected with the development of a non-linear physical system and happens for special values of system parameters [26].

Since the 1970s, chaos theory has been used in several different types of research fields, like engineering, biology, physics, and mathematics [27]. Mathematicians refer to chaos as randomness resulting from deterministic systems. In mathematics, a complex system such as Earth's weather system is studied, which helps entirely to understand chaos theory, the behavior of boiling water, etc. . But since the 1990s, many researchers have noted a close relationship between chaos and cryptography. Chaos-based communication security has been studied by many researchers although

there are some problems when using chaos theory with encryption. It can be assumed that chaos is one of the most difficult nonlinear problems[1].

The chaos theory has nonlinear features; it also has the behavior of unstable dynamics and is sensitive to initial conditions that include infinite unstable cyclic movements. The field was pioneered by Lorenz (1963), who was studying turbulent flow dynamics in liquids [7].

2.3 Types of Chaotic Maps

The chaotic map is a discrete-time chaotic system, and the chaotic sample is generated from the difference equalization set, i.e.

$$Y_m = K (Y_{m-1}) \quad (2.1)$$

Where Y_m stands for status vector and $k(.)$ means the iterative method chaotic map [28].

Multiple chaotic maps are used in cryptography. This part describes some of the kinds of chaos maps used in chaos-based cryptography.

2.3.1 Circle Map (CM)

A circle map is a one-dimensional map and the related maps on the circle. A circle map is a nonlinear repeating map described by:

$$\theta_{n+1} = (\theta_n + \Omega - \frac{K}{2\pi} \sin(2\pi\theta_n)) \bmod 1 \quad (2.2)$$

Where θ_n is the initial condition, Ω is the constant angular advance of the sinusoidal oscillator, and k is the coupling strength, k is a value between $(0, 1)$. The initial values used in the thesis are $\Omega = 0.5$, $\theta_n = 0.5$, $k = 0.712$ in the speech descrambling process[29].

2.3.2 Logistic Map (LM)

The one-dimensional logistic map was discovered by Pierre Verholst in 1845. It is a well-known map applied in non-linear systems, equation (2.3) expresses the logistic map mathematically as follows [33]:-

$$X_{(m+1)} = r X_m (1 - X_m) \quad (2.3)$$

Where ' r ' is a parameter that is within a period (0, 4), when 'r' follows the interval $[3.57 < r \leq 4]$ the logistic map becomes chaotic, X_m is the initial condition and within a period (0, 1). Any small change in either the initial conditions ' X_0 ' or the parameter ' r ' leads to the production of different sequences of actual values that are random and irregular[26].

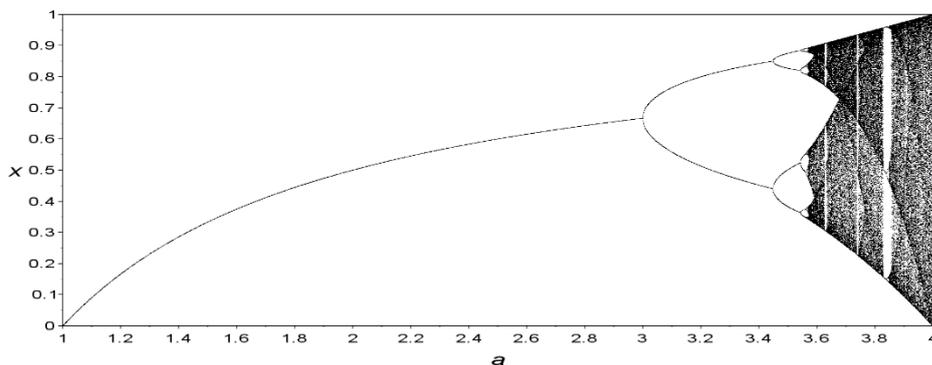


Figure 2.1: Diagram showing the Shape of the Logistic.

For example, the logistic map contains the parameter equal to the values ($r = 2.5$, $r=3.2$, $r = 3.5$, and $r = 3.8$) and the initial condition ($X_0=0.6$). If we implement the logistic equation, the output of this map is four various sequences as shown in figure (2.2), which shows the use of four values for (r), the initial parameters, and one initial condition $X_0=0.6$, random distribution of values occurs, the closer a value initial parameter is to a value of four, the more random the function becomes.

Figure (2.2) shows the sensitivity of the logistic map to the initial parameter. Figure shows (2.2.a) when $r = 2.5$, $X_0 = 0.6$ is a constant shape and there is no randomness. Figure shows (2.2.b) when $r = 3.2$, $X_0 = 0.6$, periodic form and without any randomness. Figure shows (2.2.c) when $r = 3.5$, $X_0 = 0.6$, a bit of randomness and periodicity. Figure shows (2.2.d) when $r = 3.8$, $X_0 = 0.6$, a larger random and a chaotic system appears in series.

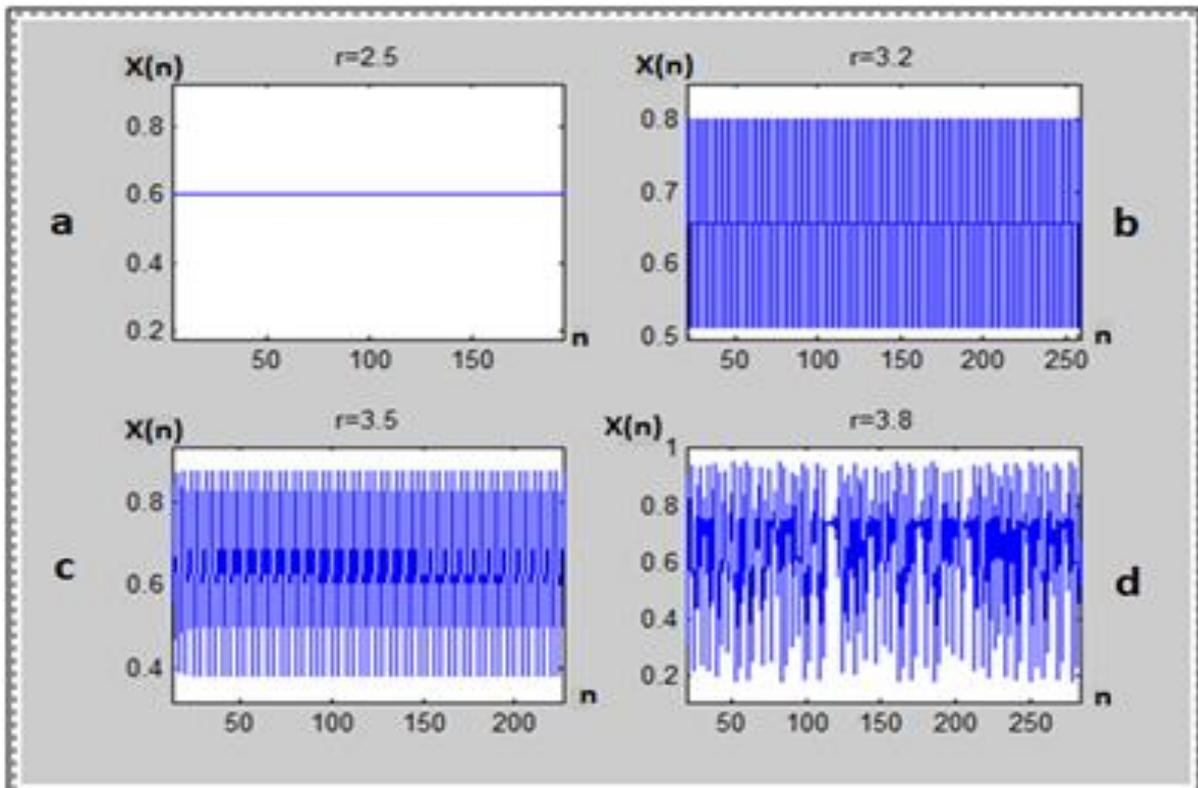


Figure 2.2: Logistic Map showing Sensitivity to the Initial Parameter.

(a) Constant shape, $r = 2.5$ (b) Periodic form and without any randomness, $r = 3.2$, (c) A bit of randomness and periodicity, $r = 3.5$ (d) Chaotic system appears in series, $r = 3.8$.

2.4 The Main Properties of Chaos Maps

Chaos system has properties that include [30, 31]:

1. **Nonlinearity:** In a linear system, chaos cannot occur. Nonlinearity is very important in the occurrence of chaos. In a chaotic system, its irregular performance is the cause of its non-linearity in the system.
2. **Deterministic system:** It means improbable. A chaotic system contains one or more mathematical equations. These equations include non-random input parameters. In other words, these are deterministic, not probabilistic parameters.
3. **A chaotic system depends on its sensitivity to initial conditions and parameters:** a small change in the initial state of the system or a disturbance in the current path of the chaotic map leads to completely different behavior in the future. The chaotic system also depends on any small change in the parameters of the chaotic map will greatly affect the dynamics of the system.
4. **Chaotic ergodic systems.** Ergodicity is an essential feature of the chaotic system. This means that the system shows similar behavior over time, across the space of all states of the system, regardless of the number of states, or the map path in which the states of the system move.
5. **The irregularity** refers to the persistence of irregularity in the chaotic work of the maps, and the hidden arrangement involves a large number of unexpected periodic models. This forms the basis of chaotic maps, which means that the order-in-disorder.
6. **Long-term non-periodic behavior:** means that the trajectories are not resting on fixed points or periodic or semi-periodic orbits such as $t \rightarrow \infty$ [7].

2.5 Chaos Theory Based on Information Security

In the previous years, there has been great interest in examining the behavior of chaotic systems. Chaos theory is a new field that is

emerged in the field of cryptography, and the reason for this use in the field of cryptography is due to its characteristics and advantages. It has many characteristics that are sensitive to initial conditions, the broadband spectrum is continuous, and ergodicity. The term ergodic originated from the Greeks and consists of two words. Ergon (meaning work) and odos (meaning path). Boltzmann discovered the chaotic theory. It was used to express a dynamic system. It has many definitions found in many fields; the common definition to define this theory is long-term behavioral studies of advanced systems in time. Which are closely related to the main components (diffusion and confusion) that should be present in a good coding system and will be explained in detail later [1][32].

Several researchers have pointed out a relationship between cryptographic chaos and cryptographic chaos analysis. In actual application, chaos and noise are two types of normal, irregular behavior. Therefore, it is possible to use them in encryption. But there is a big and fundamental difference between noise and chaos theory, which has a deterministic property. Accordingly, a comprehensive understanding of the initial parameters and conditions of a chaotic system leads to the return of data to its original form after it is encrypted. The concept of using chaos theory with cryptography goes back to Shannon [33]. Although he did not use the term chaos explicitly, he did point out that well-mixed conversions in a good umbilical system can be constructed based on the stretching and folding mechanism [34].

The main purpose of any encryption system is to convert plaintext into ciphertext via a secure algorithm. The encryption method uses two processes, confusion and diffusion:-

1. Diffusion is the effect of the plaintext or key bits on the ciphertext as much as possible and also statistical relationships of the plaintext and ciphertext are hidden. This makes cipher analysis more difficult, because

of chaos methods being sensitive to initial conditions, the property of diffusion is established or guaranteed.

2. Confusion means hiding any association between plaintext, ciphertext, and the key. Good confusion will make relationship statistics so complex that even robust encryption tools cannot be achieved [1] [34].

In cryptographic techniques, confusion and diffusion are features of the secure encryption process discovered by Claude Shannon in the 1940s a mathematical theory of cryptography. These features, when present, serve to thwart the usage of statistics and another cryptanalysis technique. These concepts are also necessary for designing powerful pseudo-random hash functions. Figures (2.3, 2.4) display the methods of confusion and diffusion [28][35].

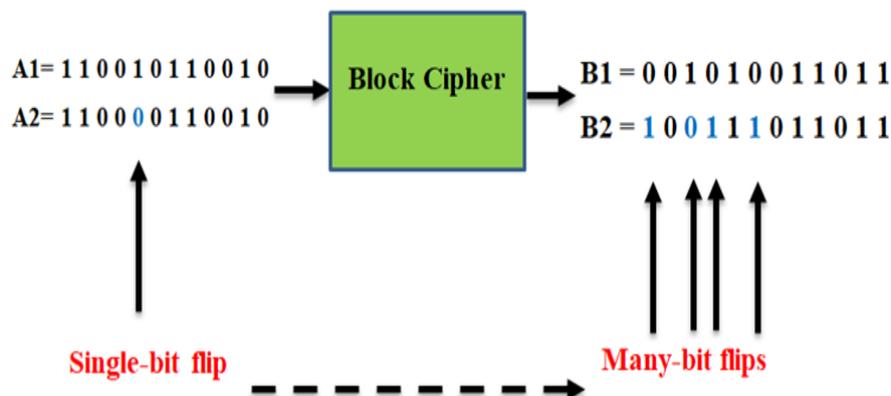


Figure 2.3 Impact of the Diffusion Method.

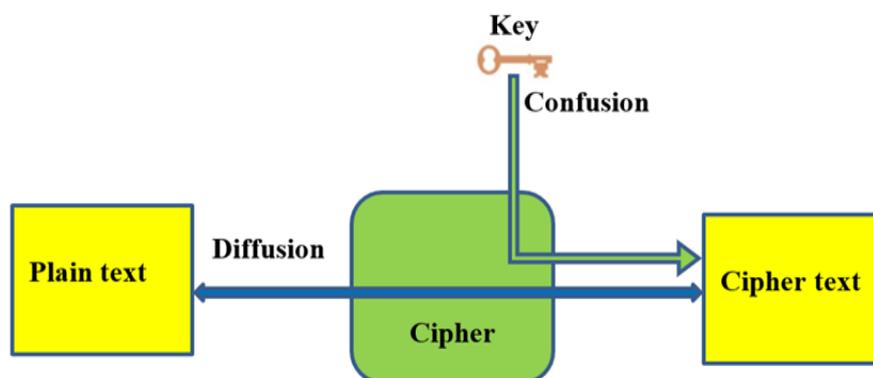


Figure 2.4: The Relation between Confusion and Diffusion.

2.6 Performance of Cryptosystems

Two common terms found in crypto society: “It is very easy to design a secure but very slow cipher” another term is “It is very easy to create a secure but very large cipher” . Thus, the three main principles for assessing new cryptographic systems are the level of security, efficiency, and easy implementation. Encryption algorithms are usually divided into two types: symmetric (private key) and asymmetric (public key) as shown in figure (2.5)[36].

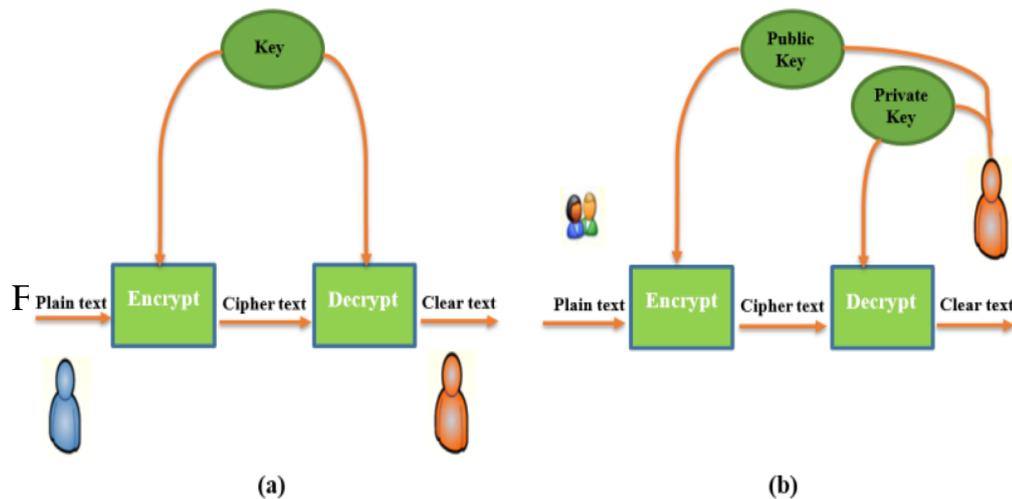


Figure 2.5: Block Diagram (a) symmetric encryption process (private key)

(b) asymmetric encryption process (public key).

Symmetric encryption systems use a similar key to both encryption and decryption operations and are very fast at handling large amounts of high-speed data. Asymmetric encryption systems use a different key for encryption and decryption operations. There is usually a pair of keys, one known to everyone and the other hidden which is a private key. This is considered slow algorithms because it involves very large and very expensive computations [36].

The chaotic system diagram is divided into two stages which are the the chaos-confusion and diffusion method. The diffusion process uses the initial value of the chaotic map as the diffusion key, the confusion process uses the parameters of the chaotic map as the confusion-key, and both the diffusion and confusion diagram are reproduced multiple times to reinforce the safeness of the system[28][37].

The goal of using any cryptosystem is to transform plain-text into cipher-text using a secure algorithm. Generally, this is achieved by the diffusion and confusion processes being iterative many times in any cryptosystem, as the displayed scheme in figure (2.6). It can be defined mathematically:

$$A = DF^{\alpha}(CF^{\beta}(B, K_1), K_2) \quad (2.4)$$

Where A and B represent ciphertext and plaintext sequentially, CF and DF represent the confusion and diffusion methods, K_1 and K_2 represent the confusion key and the diffusion key, and β and α represented rounds number of encryption process for confusion and diffusion, respectively.. Eq. (2.4) specifies the strength of the cryptosystem; the most sensitive functions (CF and DF) of their keys (KC and KD), and the larger the key space, the more secure. The key space to a system is expressed as:

$$KS = (S_1^{\beta} S_2)^{\alpha} \quad (2.5)$$

Where KS is a key space, S_1 and S_2 are the diffusion key space and confusion key space, and the key spaces are defined for the initial conditions, diffusion, and confusion procedure parameters.

In eq. (2.5) the more power (β and α), the more keyspace, so does the security of the system is more. But also the encoding and decoding time (EDT) increases. So, a balance must be found between security and velocity while evolving new cryptographic systems [28][37].

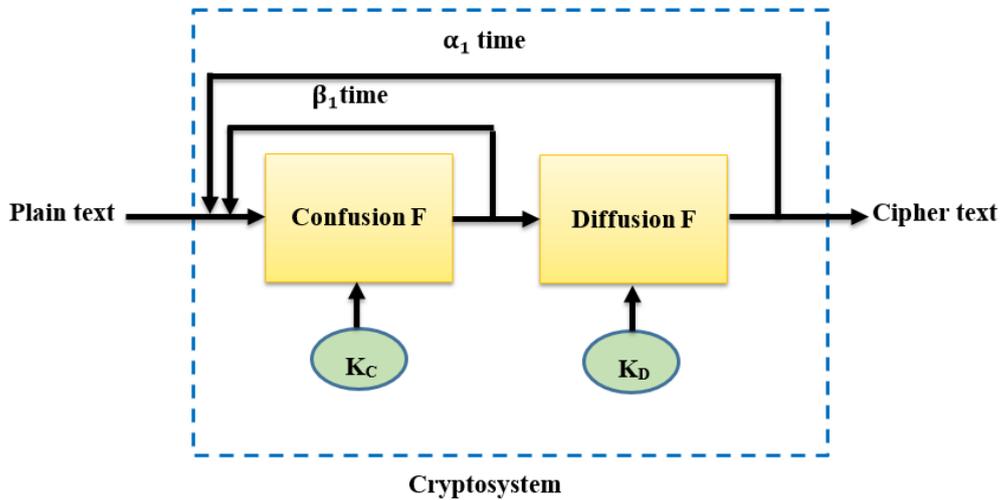


Figure 2.6: Generic Diagram of a Chaotic System.

2.7 Comparison between Characteristics of Chaotic Map and Cryptography Algorithms

Since the 1990s, several researchers have seen a relation between the chaotic map and the cryptography algorithm. Several of the characteristics of chaotic systems are the same as in cryptosystems traditional [1][36].

Table 2.1: Contains a List of Similar and Different Characteristics between Chaotic Map and Cryptographic Algorithms [36].

Chaotic Map	Cryptography	Description
Ergodicity property	Confusion property	The output has the same distribution for any input
Sensitivity to parameters and	Diffusion with a simple modification	A small change in the input can lead to completely different behavior in the

initial conditions	of secret key and plain text	future.
Mixing feature	Diffusion involves a tiny change in a single block of the plain text that changes the entire text.	A small difference in a local region can create a big difference in the entire region
Deterministic dynamics system	Deterministic pseudo-randomness.	The deterministic operation creates a behavior similar to random (pseudo-random).
Construction complexity	Complexity algorithm	The simple operation has a great degree of complexity.
Iterations	Rounds	Chaotic map iterations scatter the initial area on the whole phase area. Encryption algorithm cipher rounds give good diffusion /confusion properties.
Parameters	Key	The initial parameters and conditions are as keys in encryption algorithms.

2.8 Estimating the Parameters of a Chaotic Map

Chaos theory is a popular theory in the study of nonlinear systems. Recently, there has been great interest in nonlinear systems to describe many aspects of dynamic and complex systems. In this context, a chaotic system with partial differential equations has performed a fundamental role in describing these phenomena. Although the information is available about the physical characteristics of several chaotic systems, not all dynamic parameters are generally known, in such cases, the parameters must be estimated [14][20].

The estimation of the parameters for chaotic systems is one of the main problems in the area of non-linear sciences (such as control theory and

signal processing), which has attracted more importance in many research areas and that parameter estimation can be mainly modeled as a multidimensional optimization problem after determining a suitable fitness function. So far, various types of classical systems have been developed to deal with the parameter estimation problem. The structure of the system model in this problem has been predetermined, and optimization systems must improve the fitness function which is the difference between the estimated and real values of the system under equivalent inputs. Through this modeling, a variety of optimization functions can be used to extract unknown parameters. This problem has become the subject of several types of research over the previous two decades. It is not easy to estimate the original parameters of the chaotic system due to the unsteady dynamics of the chaotic system. At the same time, it is hard for traditional mathematical functions to determine the real parameters to perform global optimization, the reason is that there are so many local-optima in the fitness function landscape [14][20].

The meta-heuristic algorithm is one of the most popular methods of effectively estimating chaotic system parameters. It is characterized by good durability and ease of implementation, such as genetic algorithm (GA), particle swarm optimization algorithm (PSO), PSO hybrid algorithm, etc. However, all of these systems want to get the original system's initial values. It changes parameter estimation to an optimization problem, and prior knowledge for estimating parameters only takes some pseudo-random sequences resulting from chaotic systems as samples [5][6].

There are many research studies on estimating the parameters of the chaotic system, and these studies may stimulate consideration of a new problem if the estimation of the system parameters and the initial values of the chaotic system can be carried out. The type of chaotic map that can withstand the parameter estimation attack must be checked. Also, the

number of estimated parameters has a significant impact on the estimation outcomes [4].

2.9 The Meta-heuristics Algorithms

In general, meta-heuristic techniques are used to solve optimization problems. The term meta-heuristic consists of two terms meta and heuristic. Meta refers to beyond or a high-level methodology, while heuristic refers to the art of finding new ways by trial and error to solve a problem. A meta-heuristic is a heuristic algorithm that does not depend on the type of the problem [38]. All meta-heuristic algorithms use some randomness and local search. It should be noted that there is no agreed definition of meta-heuristics in the researches. All random algorithms with randomization and local search are named meta-heuristic algorithms. Randomization is a good step to move from a local search to a global search. Accordingly, each meta-heuristic algorithm is designed to suit global optimization. Meta-heuristic is an effective algorithm for producing acceptable solutions by trial and error to a complex problem in a reasonable practical time. The complexities of the problem cause the inability to search for every possible solution or group of solutions, the purpose of which is to find a good and appropriate solution within an acceptable time range. There is no guarantee that the best solution will be found, and we may not even know if the algorithm will work and why if it does, although we may know the initial elements that can help in the work. The concept is to have an efficient but practical algorithm that works most of the time and is able to produce high-quality solutions. Among the quality solutions found, some are expected to be almost perfect, although there is often no guarantee of such improvement.

Meta-heuristics are the actions that guide the search process. The purpose of meta-heuristics is to efficiently explore and exploit the search

space and use learning methods to structure information to get optimal solutions or near [43].

There are two basic features of meta-heuristic [40]:-

- **Intensification (Exploitation)** is the ability to explore the vicinity of a potential solution and plays an essential role in optimizing the possible solution while searching and exploiting the areas near the potential solution to find the optimal solution.
- **Diversification (Exploration)** is the ability to explore the entire research space. On the other hand, diversification is quite necessary to avoid being entrapped by the local optimum solution.

In other concepts, intensification is a local search, and diversification is a global search. These two elements must be in balance to achieve high achievements [40].

2.9.1 Particle Swarm Optimization (PSO)

The particle swarm optimization algorithm is one of the meta-heuristic algorithms that depend on the idea of swarm intelligence working with complex computational problems found in engineering [41]. Kennedy and Eberhart 1995 developed the PSO after the study of social behavior (i.e., collective behavior) of fish schooling or birds flocking [2].

The idea of the PSO algorithm is that a flock of birds searches for food in a limited space, where the food is randomly located in that area, and the birds do not know where the food is. The best solution is for the birds to spread randomly in the entire area, with the birds telling each other about the locations of the food every time. The best solution represents good information. The birds start a searching look at random, and with each return, the items come close to the most accurate and optimal solution (the area filled with food) and the food resource is the

most optimistic solution during the round. The optimal solution in the PSO algorithm can be found through the cooperation of individuals with each other [41][42].

In the PSO algorithm, a swarm of collectively moving particles is evaluated by the objective function. Each particle has fitness values that are evaluated by objective function or fitness function to be improved. These particles are related to the locations and velocities that direct the particles' motion [41].

The particle swarm optimization algorithm begins with a random group of individuals called a swarm of particles, and then these particles search for an optimal level by updating their locations and velocities. Every j particle contains 3D (three dimension) vectors that are the position vector y_j (the particle's current location), the velocity vector V_j , and $pbest_j$ (the individual particle location that is best remembered), which is represented as $y_j = (y_1, y_2, y_3, \dots, y_n)$, $V_j = (V_1, V_2, V_3, \dots, V_n)$, and $pbest_j = (pbest_1, pbest_2, pbest_3, \dots, pbest_n)$ respectively. The current location y_j can be thought of as a collection of coordinates that point to a point in space. The current location is calculated as a solution to an objective function in every period of the algorithm.

The particle location describes possible optimization solutions. Particles are generated arbitrarily in the search space. In each iteration, the particle consists of two parts: a deterministic part and a random part. This means that each particle is moved to its best position ($pbest$) called a local search operation indicating the ability to apply prior knowledge to find a better solution, and the current best global position ($gbest$) in its history, and is considered the best value achieved so far, by any particle in all population; at the same time called global search operation, it has a target that moves randomly. The two operations are contradicted each other, and the inertia weight (w) is the key to balancing them. So, the w

must be set reasonably to achieve better performance. To a particle with position y_j and velocity V_j , calculate the change in velocity in the current time step [43][44][45]:-

$$V_j(k+1) = w * V_j(k) + C_1 * \text{rand1} * (p\text{Best} - y_j(k)) + C_2 * \text{rand2} * (g\text{Best} - y_j(k)) \quad (2.6)$$

Where :

k is the current repetition.

$V_j(k+1)$: velocity of the particle at repetition $(k+1)$.

$V_j(k)$: particle velocity at repetition (k) .

Learning factors (C_1 and C_2) are weights of the stochastic acceleration terms that pull each particle toward pbest and gbest (or nbest). In several states, C_1 and C_2 are valued at 2.0, including the region centered in pbest and gbest.

$\text{rand1}()$, $\text{rand2}()$: Rand is random number between $(0, 1)$ and changed at every iteration.

gbest: It's the gbest swarm location (best solution found in the entire swarm).

pbest: It is the pbest location of the particle (the best solution found for the current particle).

We will compute particles to their new location:

$$y_j(k+1) = y_j(k) + V_j(k+1) \quad (2.7)$$

Where :

$y_j(k+1)$: is the particle's location at iteration $(k+1)$.

$y_j(k)$: is the particle's location at iteration (k) .

Each particle repeatedly across a search space towards the best fitness location obtained over time by the same particle (local best) and the best particle among neighbors (global best) [46].

In the PSO algorithm, inertia weight(w) is used to control the power of particles. In 1998 the idea of linearly decreasing inertia weight with increasing iterations has been proposed . Eq. (2.8) shows how to compute updated w :-

$$w = w_{\max} - \frac{k}{N} * (w_{\max} - w_{\min}) \quad (2.8)$$

Where N is maximum iteration, w_{\max} and w_{\min} indicate the maximum and minimum values of inertia weight and are preferred to be 0.9 and 0.4, respectively.

In this thesis, some parameters that are constant particle swarm optimization (PSO) algorithm are used, for example acceleration constants, maximum inertia weight (w_{\max}), minimum inertia weight (w_{\min}), number of swarm particles (j) and maximum iteration (N). The Flow chart included in the PSO is shown in figure (2.7).

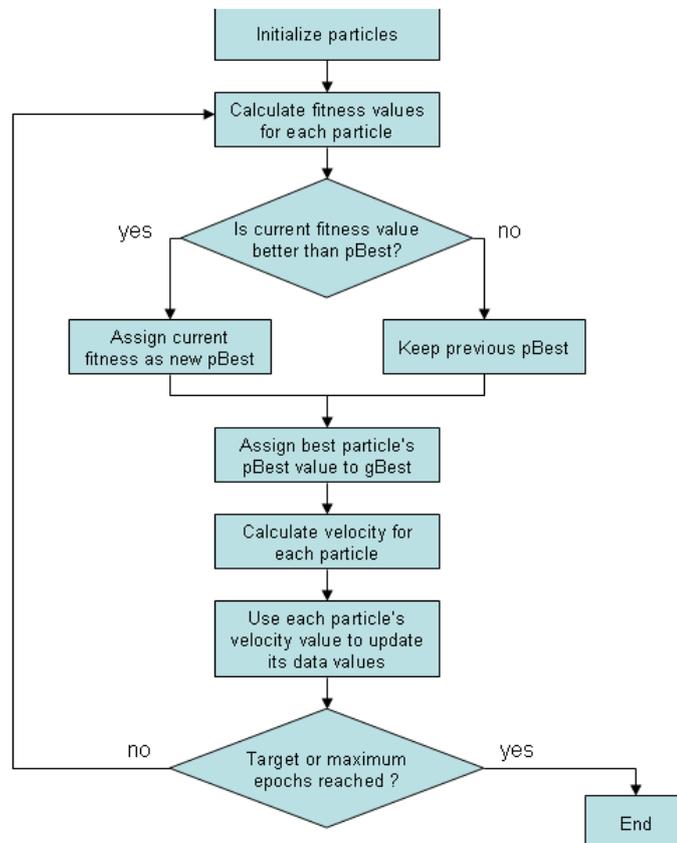


Figure 2.7: The PSO Algorithm.

2.9.2 Quantum Particle Swarm Optimization (QPSO)

Since the 1995s, many improvements to the performance of PSO have been made by experts and scientists. But, Vanden Bergh showed that particle swarm optimization (PSO) is a non-global optimization algorithm. Sun *et al.* showed that the quantitative approach was combined with the particle swarm optimization (PSO) algorithm to create the quantitative particle swarm optimization (QPSO) algorithm. This algorithm assures that the globally optimal solution is found in the search space. The empirical outcomes shown on the different measurement employment showed that the suggested algorithm can develop the standard PSO algorithm. QPSO's global convergence ensures that the global optimal solution is determined in the event of infinite search repetitions. Therefore, this condition becomes unworkable in the working problems because any optimization function will only allow a restricted number of repetitions to seek an optimal solution. QPSO is also likely to fall into optimal or slow local convergence [47].

QPSO is similar to the PSO algorithm, but they have different evolution equations [48]. QPSO does not need the velocity parameters; it just needs a small number of parameters and is more straightforward to perform than PSO; therefore, it solves many optimization problems. The QPSO algorithm prepares the particle's current locations and the best personal locations. Thus, the location of the particle swarm can be changed using the equation:-

$$Y_{ij}(k + 1) = X_{ij}(k) \pm \beta * |n_j(k) - Y_{ij}(k)| * \ln(1/r) \quad (2.9)$$

Where β has indicated that the contraction expansion factor is the control balance between exploration and algorithm exploitation, and if it

has a large value, it will compress the particle towards global exploration, while if the smaller value is towards adjusting the current search region [49], the fixed value is used too, $Y_{i,j}(k)$ is the current location of the particle swarm, $X_{i,j}$ is the local vector that focuses on the particle, r is a random value distributed uniformly between (0,1), and n represents (mean the best location) which can be set as the mean of a particle's personal best location (pbest), meaning that every particle will be impressed by the information of all particles. Where we can calculate the mean of the best location:-

$$n(k) = (n_1(k), n_2(k), \dots, n_m(k))$$

$$n(k) = \left(\frac{1}{N} \sum_{i=1}^N X_{i,1}(k), \frac{1}{N} \sum_{i=1}^N X_{i,2}(k), \dots, \frac{1}{N} \sum_{i=1}^N X_{i,n}(k) \right) \quad (2.10)$$

Where X_i is the pbest location of i -particle and N is population size.

In the QPSO algorithm, every particle uses the weighted average position of the individual optimal historic location and the optimal ensemble date location as a performance. This calculation can be inferred from the results of the particle motion path. Although this type of computation is easy, it has two obvious drawbacks:

1) Regardless of its learning experience, every particle location depends on the optimal historic location of the collection. This drives a speedy decrease in the variety of great collections which decreases the ability of the algorithm to resolve complex symbol multiplication optimization problems.

(2) The potential area of the distribution of every particle gradually decreases as the algorithm evolves. Particles are confined to a rectangle with the points pbest (k) and gbest, $X_{i,j}$ gradually approaching. Finally, the algorithm couldn't skip the optimal local plane in the definitive phase [47][50].

Determining the vector local focus of the particle $X_{i,j}(k)$ is computed from the equation following:

$$X_{i,j}(k) = u * pbest(k) + (1-u) * gbest \quad (2.11)$$

$$u = \text{rand}(0, 1)$$

Where $pbest$ is the best local location and $gbest$ is the current best global location [47]. The flow chart of the QPSO algorithm is shown in figure (2.8).

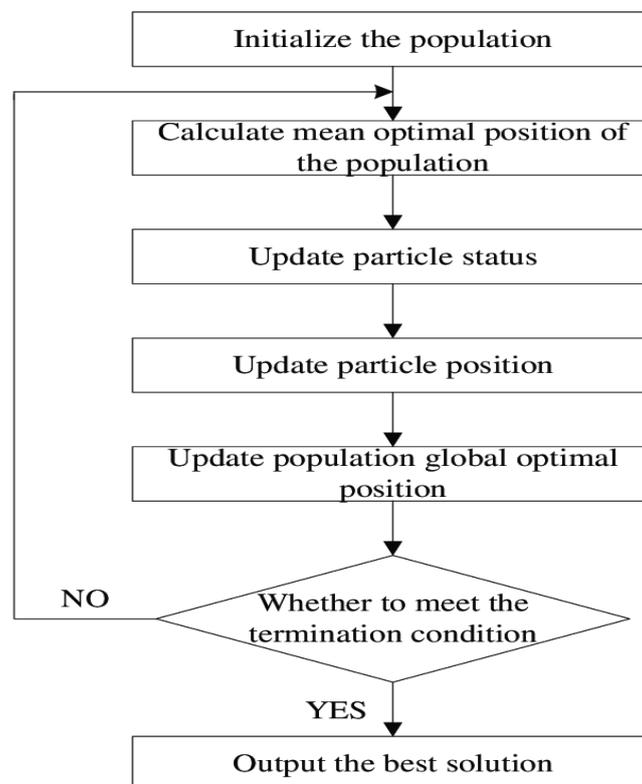


Figure 2.8: QPSO Algorithm.

2.9.3 Fitness Function

The fitness function in optimizing methods is to find the method that must be minimized or maximized to determine the best solution to a specific problem from a possible set of weak solutions. If the optimization problem is minimization then it is termed the cost method, or if the optimization problem is the maximization of the objective

method, then the same function can additionally be called the fitness function. The fitness function assessment describes the quality of every search space solution. We can order (or arrange) all search space solutions according to the fitness function. The objective function moves the search to solutions suitable for the research space [39].

2.10 The Principle of Estimating the Parameters of a Chaotic System by the Meta-heuristic Algorithms

The hypothetical structure of a parameter estimation system for a chaotic system with an unknown system parameter is shown in the figure (2.9).

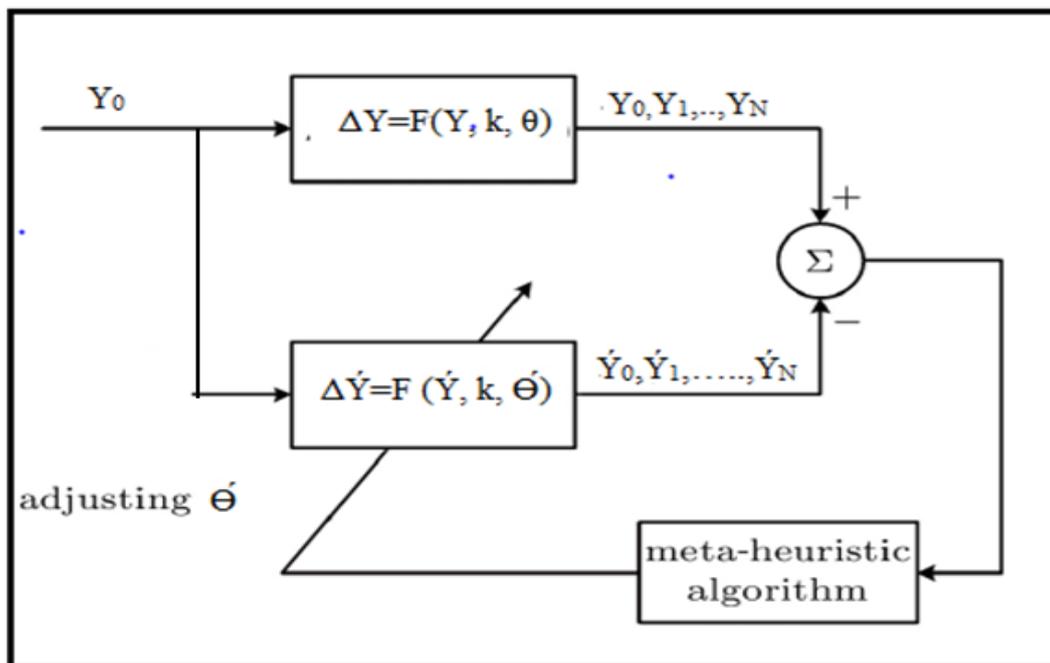


Figure 2.9: The Structure of Parameter Estimation System for a Chaotic System[4]

An original chaotic map is represented as follows:

$$\Delta Y = F(Y, k, \theta) \quad (2.12)$$

Where $Y = (Y_0, Y_1, \dots, Y_N)^k \in \mathbb{R}^N$ is the N-dimensional element vector of the initial system ($1 \leq N \leq k$), k is the iteration number of a chaotic system, θ denotes the original system parameter.

The estimated system is represented as follows:

$$\Delta \hat{Y} = F(\hat{Y}, k, \hat{\theta}) \quad (2.13)$$

Where $\hat{Y} = (\hat{Y}_0, \hat{Y}_1, \hat{Y}_N)^k \in \mathbb{R}^N$ is the N-dimensional element vector of the estimated system, $\hat{\theta}$ is the estimated parameter for the system. Y_0 is used as input value in both original and estimated systems.

The problem of parameter estimation can be expressed (by suitable searching) using fitness functions. The fitness functions that are used in the thesis are minimizing mean squared error (MSE) and sum square error (SSE) between the estimated and real values for several given samples.

We can define MSE as follows:

$$MSE = \text{Min}(1/N \sum_{Z=1}^N (Y_Z - \hat{Y}_Z)^2) \quad (2.14)$$

Where N indicates the range of data used for parameter estimation, MSE is mean square error, Y_Z and \hat{Y}_Z ($Z= 1, 2, \dots, N$) show state at the Z-the time of original and estimated systems [39].

We can define SSE as follows:

$$SSE = \sum_{K=1}^N \|Y_K - \hat{Y}_K\|^2 \quad (2.15)$$

Where N indicates the range of data used for parameter estimation, Y_K and \hat{Y}_K ($K= 1, 2, \dots, N$) shows a state at the K-the time of original and estimated values, and describes $\|\cdot\|$ Euclidean norm[67]. Euclidean norm ($\|\cdot\|$) or known 2-norm is the square root for the sum of square two samples [51]. It is defined by:

$$\|\cdot\| = \sqrt{\sum_{K=1}^N (Y_K - \hat{Y}_K)^2} \quad (2.16)$$

In this thesis, the parameter estimation technique of chaotic systems (logistic map and circle map) is a one-dimensional optimization problem; using the optimization functions, we can determine the system parameter (r) that is found in the logistic map equation, and determine the k and Ω that is found in the circle map equation, and the goal of the optimization method is to reduce MSE and SSE. Figure (2.9) shows parameter estimation for the chaotic system of the optimization meaning, and because of the unstable dynamic chaotic system, it is not easy to obtain the parameter of the system.

2.11 Speech Signal

Speech is registered through a wired microphone using an audio card associated with a computer, or intelligible speech is registered by computer speakers for a canal, the talker can be a woman or a man of various ages, and the audio is registered as an analog signal transformed through the audio card into digital that is sampled as a string of digits that is saved to a computer. The recorded sound of a secure communication scheme is successfully prepared, the quantification and sampling rate must be set up in the right manner. [31].

The sampling rate is the sampling process that occurs when a speech signal is converted from an analog signal to a digital signal to describe an audio sample. When increasing the sample rate per second, the quality and accuracy of stored sound will increase and vice versa as presented in figure (2.10).

There is a problem in determining the number of bits that describe the sound during a given period. To prevent this problem, the Nyquist

theorem is used, so that the sampling rate per second is at the smallest twice the maximum frequency of the analog signal, if the highest frequency (f_c) and sampling rate (f_s), in other words, $f_s \geq 2f_c$. So a sampling rate of 8000 Hz is enough to represent human speech in the (40 - 3200) Hz ranges. In this thesis, the sample rate (8000) Hz is used [28][31].

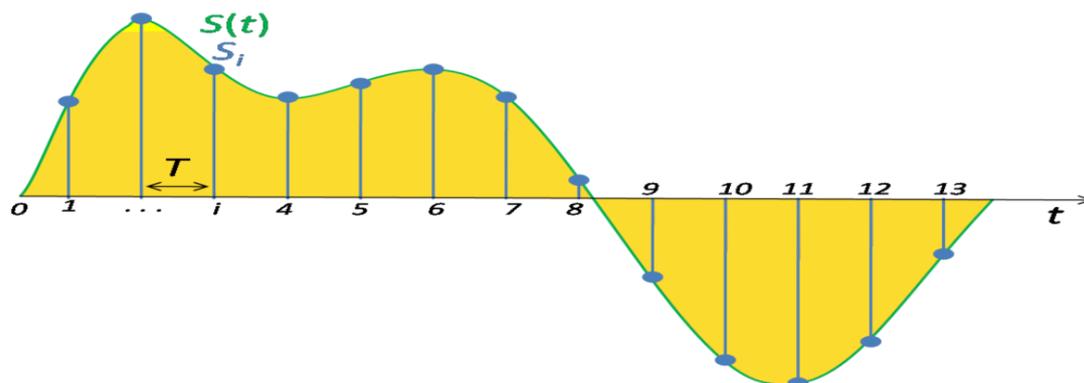


Figure 2.10: Sampling of Analog Signal.

Sample quantization describes the number of bits assigned to each sample in the speaker sample. In general, one of the more important variables when converting a speech signal into a digital format is to maintain audio accuracy. When the number of bits used to describe the sample is increased, the signal will be near the original sound, and this affects the file size, as shown in figure (2.11), which will be increased to accommodate the converted signal. This thesis uses the sample quantization of 16 bits to describe speech samples, and thus sample values range from $(0-2^{16})$. Usually a limited set of values. The use of 16 bit is due to not causing loss of speech data when a system is binary or return to normal description. If the sample portions are increased such as using (32 bits per sample), the quality of the speech signal increases at the same time that the processing time also increases [28][31].

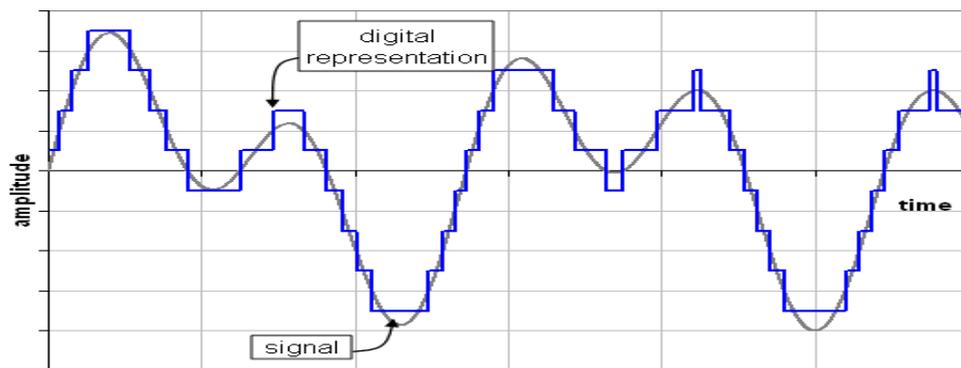


Figure 2.11: Description of the Signal Quantization.

2.12 Speech Scrambling Techniques

Speech scrambling systems are used to combine original speech into incomprehensible signals to avoid eavesdropping, [52]. The speech scrambling algorithm converts intelligible speech into unintelligible speech so that it is difficult to decipher it without knowing the key. Most traditional scrambling techniques include residual intelligibility in the scrambled signal, so it will be easy to guess. Typically, a speech scrambling algorithm functions as a transactional role of a segment of speech in the time domain, frequency, temporal frequency domain, or permutation in the order of the speech blocks' transform coefficient for each speech block. Given the low residual clarity, time-frequency algorithms are algorithms of great use [19].

Scrambling methods can be classified as analog and digital scrambling [1][7].

▪ Analog Scrambling

The incoming and outgoing signals are analog, while each processing is digitally realized. There is no necessity for modem and pressure. The speech signal is transmitted through a set of steps, involve: digitization, coding operation can apply any algorithm, conversion to an analog signal, transmission to another side (receiver), and back-processing to retrieve the speech signal and convert it to analog. Figure (2.12) shows the

principal steps of analog scrambling. Analog audio encryption is defined as speech scrambling. This process works on the same analog audio samples.

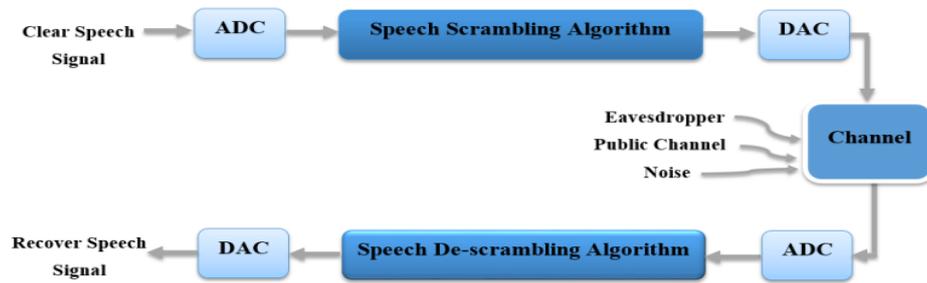


Figure 2.12: Analog Scrambling.

▪ **Digital Scrambling**

The speech signal travels through a set of stages, which includes digitization and compression to obtain a stream of bits at an appropriate bit rate, the process of encoding utilizing any algorithm, and sending into the receiver side via digital forms, means that the signal in and out of the streams is digital. This method is the speech feature of the disabled digital encoder operation. Figure (2.13) shows the principal steps of digital scrambling.



Figure 2.13: Digital Scrambling.

In general, digital provides lower residual clarity and higher resistance to attacks than analog , and digital provides lower quality compared to analog method type [56].

2.13 Techniques Speech Scrambling

Many techniques have been applied in a method of speech scrambling, which involves:

1. Sample Amplitude Technique Speech Scrambling.
2. Time Domain Technique Speech Scrambling.
3. Frequency Domain Technique Speech Scrambling.
4. Hybrid (Time and Frequency) Techniques Speech Scrambling.
5. Orthogonal (Transform) Techniques Speech Scrambling.

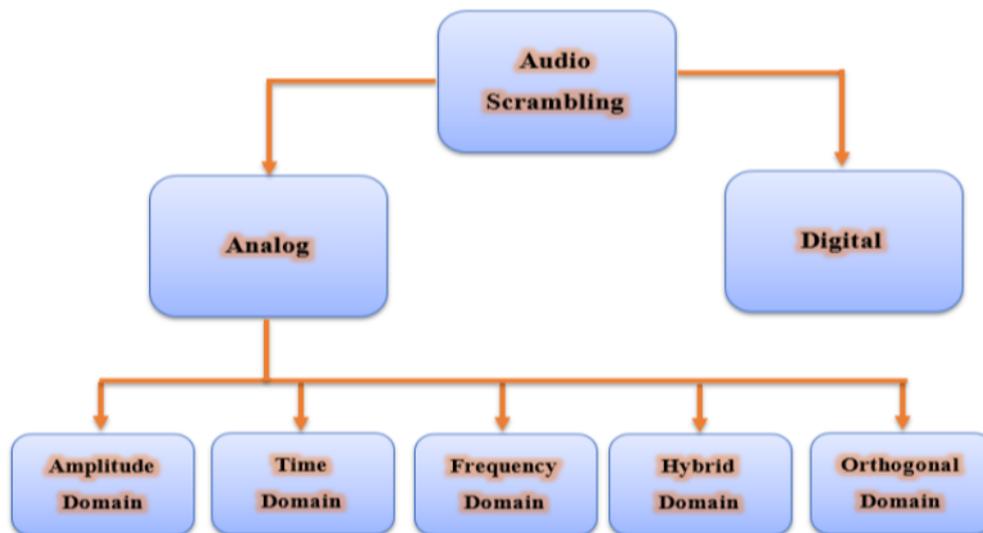


Figure 2.14 : Classification of the Analog Audio Scrambling Algorithms.

1. Sample Amplitude Technique Speech Scrambling.

These techniques show that primary signal amplitude samples are used in the scrambling method. This technique typically interchanges or permutes speech samples, linear addition of pseudorandom noise amplitude, and nonlinear computational additions [53]. There are two kinds of permutations shift register produces pseudorandom permutations (PR) and uniform permutations. Some kinds of scramblers include in addition to sampling the amplitude of masking signals, and these masking

signals may be either binary pseudorandom permutations (PR) or a series of computations [54].

2. Time Domain Technique Speech Scrambling.

It is one of the main techniques used in speech scrambling. It is used with analog signs, in these scrambling techniques, the speech sign in the time domain technique is broken into frames so that every frame is divided into a segment, after which the segments are shuffled by the permutation key, i.e. time segment permutation (TSP), that produces the generator that generates pseudo-random numbers (PRNG), as presented in figure (2.15). This is a technique that cannot produce sufficient security against cryptanalysis because the amount of permutations is not large enough to produce a sufficient amount of various permutations and limitations in device and time processing [1][35][53].

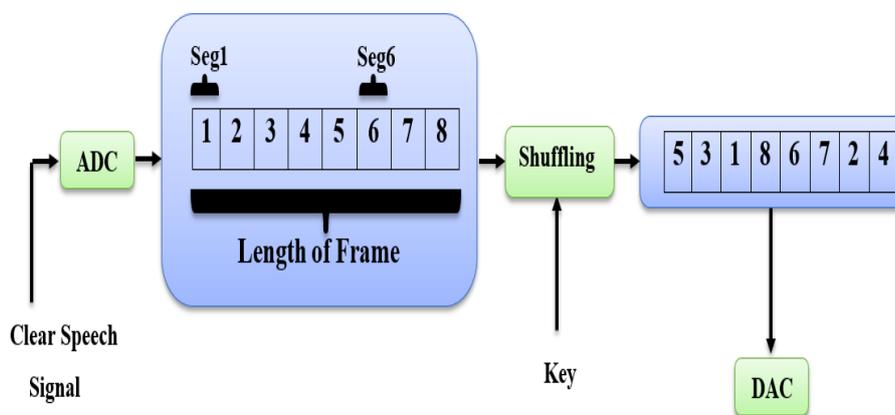


Figure 2.15: Permutation Frames in the Time Domain.

3. Frequency Domain Technique Speech Scrambling

The spectrum of the speech signal is divided into several sub-bands in this type of scrambling and then the position of these sub-bands is permuted. The initial bandwidth is guaranteed unchanged. The first initial algorithms in this technique were based on the Fast Fourier Transform (FFT) technique, where the framing of FFT coefficients is allowed. Discrete cosine transform (DCT) techniques for cosine

transform principal component analysis, wavelet transform, etc. This is a technique that cannot produce sufficient security toward cryptanalysis because the quantity of permutations is not large sufficient to produce a sufficient quantity of various permutations and limitations in time processing and devices [35][56]. This technique is displayed in figure (2.16).

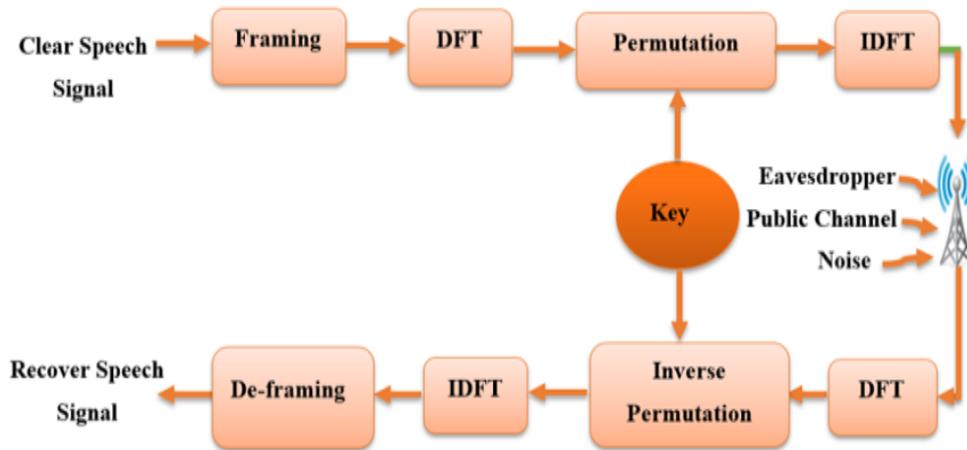


Figure 2.16 : Frequency Domain Technique Speech Scrambling.

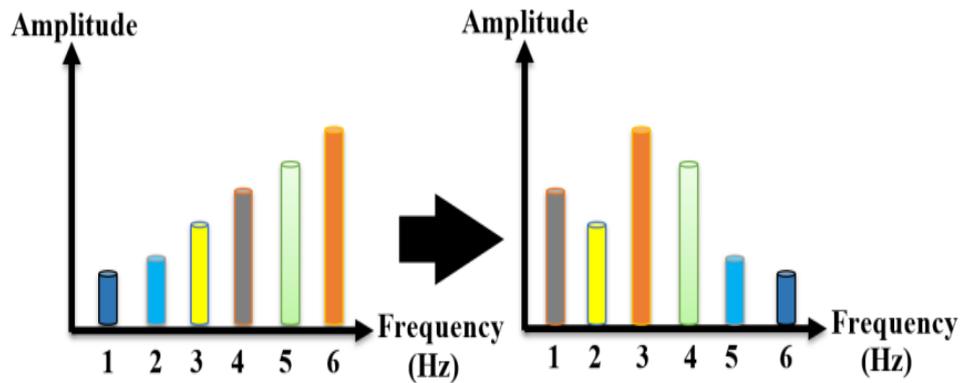


Figure 2.17: Permutation in the Frequency Domain.

4. Hybrid (Time and Frequency) Techniques Speech Scrambling.

A hybrid (two-dimensional) scrambler based on two technologies: time and frequency domain speech scrambling. The two-dimensional scrambling runs in the time and frequency domains. The basic purpose is

to break the speech frame into regular N sub-band and the resulting sub-band divisions into N blocks [53]. The time and frequency segments are then switched and the resulting scrambling frame is assembled. This type of technology is characterized by a high degree of residual clarity and security [56] but is difficult in terms of regulating the amount of distortion in the encoded signal because this is a technology that goes through two distinct phases in two different areas. The first directly affects the speech signal and indirectly affects the speech signal produced by the first transform [28].

5. Orthogonal (Transform) Techniques Speech Scrambling

These techniques of analog scramblers are based on actions performed on the audio sample linear transformation coefficients [27]. The conversion types offered are Wavelet Transform(WT), Discrete Cosine Transform(DCT), Fast Fourier Transform(FFT), Circular Transform, Modified Discrete Cosine Transform (MDCT) [57], this process is shown in figure (2.18).

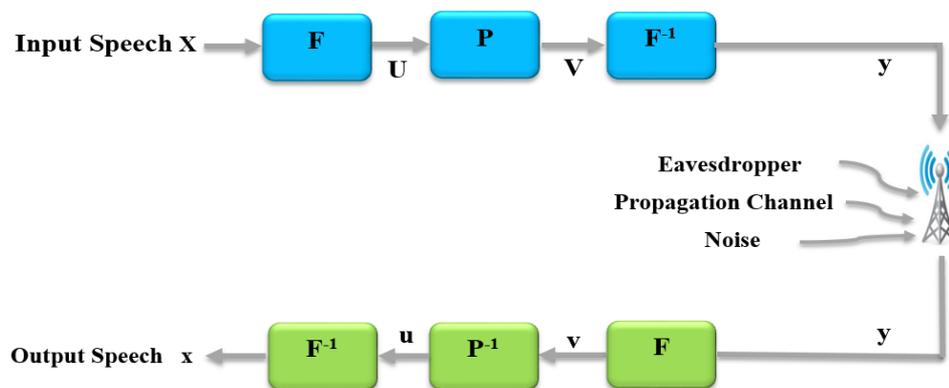


Figure 2.18: Orthogonal (Transform) Techniques Speech Scrambling.

An analog scrambling process can be described using matrix algebra. Suppose that 'X' denotes a transformation matrix with size $M * M$, 'M' length of the frames, and 'F' denote a vector of the sample. The following equations show the scrambling process:

$$U = F X \quad (2.17)$$

Where 'U' is the audio signal 'X' .

To produce the speech scrambled matrix (V), the vector-matrix (P) permutation $M * M$ is merged with the sound vector (U).

$$V = P U \quad (2.18)$$

The inverse conversion F^{-1} is used in scrambling speech (V) to produce a scrambling audio signal Y [58].

$$Y = F^{-1} V \quad (2.19)$$

2.14 Secure Speech Communication

There are several goals for the user to hide the meaning of the transmitted speech. Secure speech communication refers to masked speech communication. In general, secure speech communication, as shown in figure (2.19), discusses three parts for secure speech communication:

1. The first section: a transmitter (Tx) creates low-resolution encrypted speech.
2. The second section: the receiver (Rx) can retrieve the encoded speech nearby to the original speech signal.
3. A third section is an eavesdropping machine that attacks the communication operation in many techniques [59].

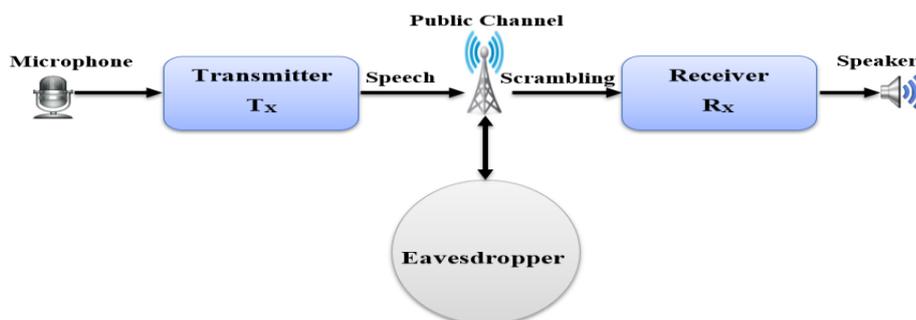


Figure 2.19: Diagram of Secure Speech Communication.

2.15 Evaluation Measurements

There are two type of test which used in this thesis. Subjective tests for example listeners and objective tests for example correlation coefficients (CC) and signal-to-noise ratio (SNR) . It uses for evaluating the performance system security, as follows:

2.15.1 Subjective Test

- **Listeners**

This type of test needs a large number of trained and untrained humans to hear and assess the scrambled speech. This test has three levels of intelligibility. If residual intelligibility is (0%), then perfect intelligibility. If residual intelligibility is between (1% and 10%), then low intelligibility. If residual intelligibility is between (11% and 30%) then medium intelligibility. If residual intelligibility is between (31% and 50%), then high intelligibility. The disadvantages of this test require more time and a large number of people to hear the slurred speech[1].

2.15.2 Objective Tests

2.15.2.1 Correlation Coefficient (CC)

It is a useful measure for assessing the quality of a speech coding system. It is a correlation between two different samples, it is either between original and scrambling speech or between original and recoverd speech. It is calculated as follows:

$$r_{ab} = \frac{\text{Cov}(a,b)}{\sqrt{V(a)V(b)}} \quad (2.20)$$

Where $\text{Cov}(a,b)$ is the covariance between original speech and scrambling speech or between original speech and recoverd speech. $V(a)$

and $V(b)$ are the variances between signals a and b , respectively. In mathematical calculations, it separates mathematical formulation and applied as follows [60]:-

$$E(a) = \frac{1}{T_s} \sum_{i=1}^{T_s} a_i \quad (2.21)$$

$$V(a) = \frac{1}{T_s} \sum_{i=1}^{T_s} (a_i - E(a_i))^2 \quad (2.22)$$

$$\text{cov}(a, b) = \frac{1}{T} \sum_{i=1}^{T_s} (a_i - E(a_i))(b_i - E(b_i)) \quad (2.23)$$

Where a_i is a sample of i th samples of the original speech, b_i is a sample of i th (recovered samples or scrambled speech), and i speech number samples are described. $E(a_i)$ and $E(b_i)$ are mean of samples $(a_1, a_2, a_3, \dots, a_n)$, and $(b_1, b_2, b_3, \dots, b_n)$ respectively.

The correlation coefficient is the correlation between two samples and the range values (1, -1). If $CC = 0$, it means there is no correlation between the original speech and the scrambling, and the attackers will not be able to set the secret key. If the value is close to zero, then scrambling in speech is good. Therefore, there will be more security with less clarity. If $CC = -1$, it means both samples go in a separate direction, and if $CC = +1$, it means both samples go in an equal direction. Therefore, we get high accuracy with low residual security.

2.15.2.2 Signal to Noise Ratio (SNR or S/N)

SNR is the power rate between indicative to information and noise (undesired signal). SNR is presented by:

$$\text{SNR} = P_{\text{signal}} / P_{\text{noise}} \quad (2.24)$$

Where P_{signal} describes signal strength and P_{noise} describes noise strength [61].

An SNR was used to measure the sound quality to evaluate the recovered speech that was returned based on the estimation of the parameters. We can calculate it from the following equation:-

$$\text{SNR} = 10 \log_{10} \frac{\sum_{i=1}^N I^2(i)}{\sum_{i=1}^N (I(i) - D(i))^2} \quad (2.25)$$

$D(i)$ is either scrambling speech values or recovered speech values, and $I(i)$ is the original speech's values. If the signal-to-noise ratio (SNR) is low, then the residual intelligibility of speech scrambling is low, and therefore the security of the system is increased. If the SNR is high, the recovered speech signal is good [23].

2.16 IEEE 754 Converter

It is the process of converting the real values generated by the chaotic map into binary values using a converter (called IEEE 754). Because this converter converts every real value to (64-bit). In the binary system, the value is divided into three sections, and this value is the result of the IEEE754 converter: the sign section, the exponent section, and the fractional section. Figure (2.20) displays these sections.

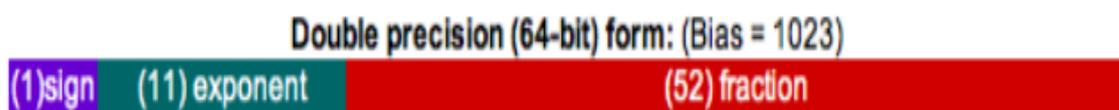


Figure 2.20: Binary Value Divisions using IEEE 754 Converter.

Example: Implementation of IEEE 754

Let's say we want to put the value (-5.75) in IEEE 754 formula .

1. The first step, calculate the sign of the number. If the number is positive, then the sign of the bit 0; if the number is negative, then the sign of the bit 1.

- -5.75 is negative, the sign bit = 1.

The rectangular window is used for different purposes including easy and fast to implement because each window is processed separately from its adjacent window which reduces processing time[1].

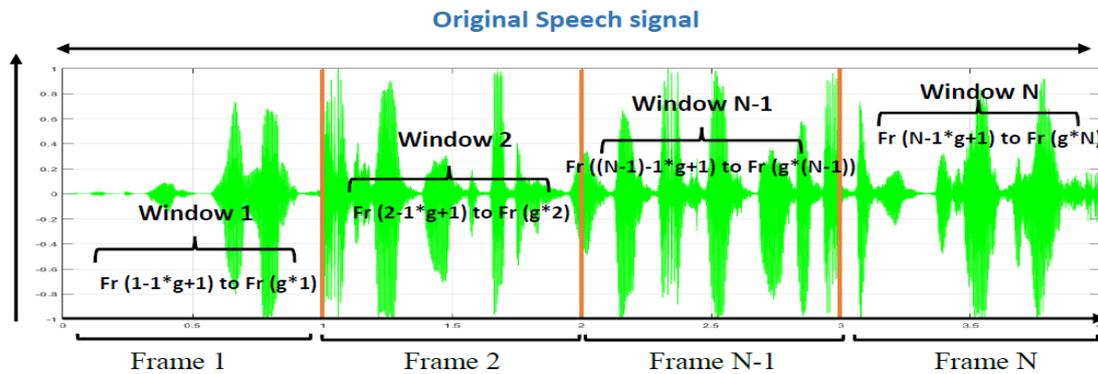


Figure 2.21: Show Splitting the Speech Signal in the Time Domain.

2.18 Mathematical Simulation of Meta-heuristic Algorithms

Calculate the success rate of the algorithms (PSO and QPSO) in the process of estimating the parameters of the chaotic map (logistic map and circle map) through the following equation: -

$$\text{success rate} = \frac{\text{successful estimated times}}{100} * 100 \quad 2.27$$

Chapter Three

The Proposed System

Chapter Three

The Proposed System

3.1 Introduction

This chapter introduces a system for estimating chaotic parameters based on meta-heuristic algorithms: speech descrambling case study. It includes the use of estimated parameters of chaotic maps as pseudo-random number generators (PRNG) for speech signal descrambling.

The main objective of the proposed system is to estimate the parameters of the chaotic map (logistic map and circle map) using meta-heuristic algorithms PSO and QPSO algorithms.

This chapter explains the proposed system, as well as the operational stages of the proposed system using clarified algorithms.

3.2 The Proposed System

The proposed system has through four stages: the first stage is the speech scrambling, the second stage is the estimation of the parameters for the chaotic map, the third stage is the descrambling of the speech signal using the estimated parameters of the chaos map, and the fourth stage is the measures that are used to calculate the quality of the recovered speech.

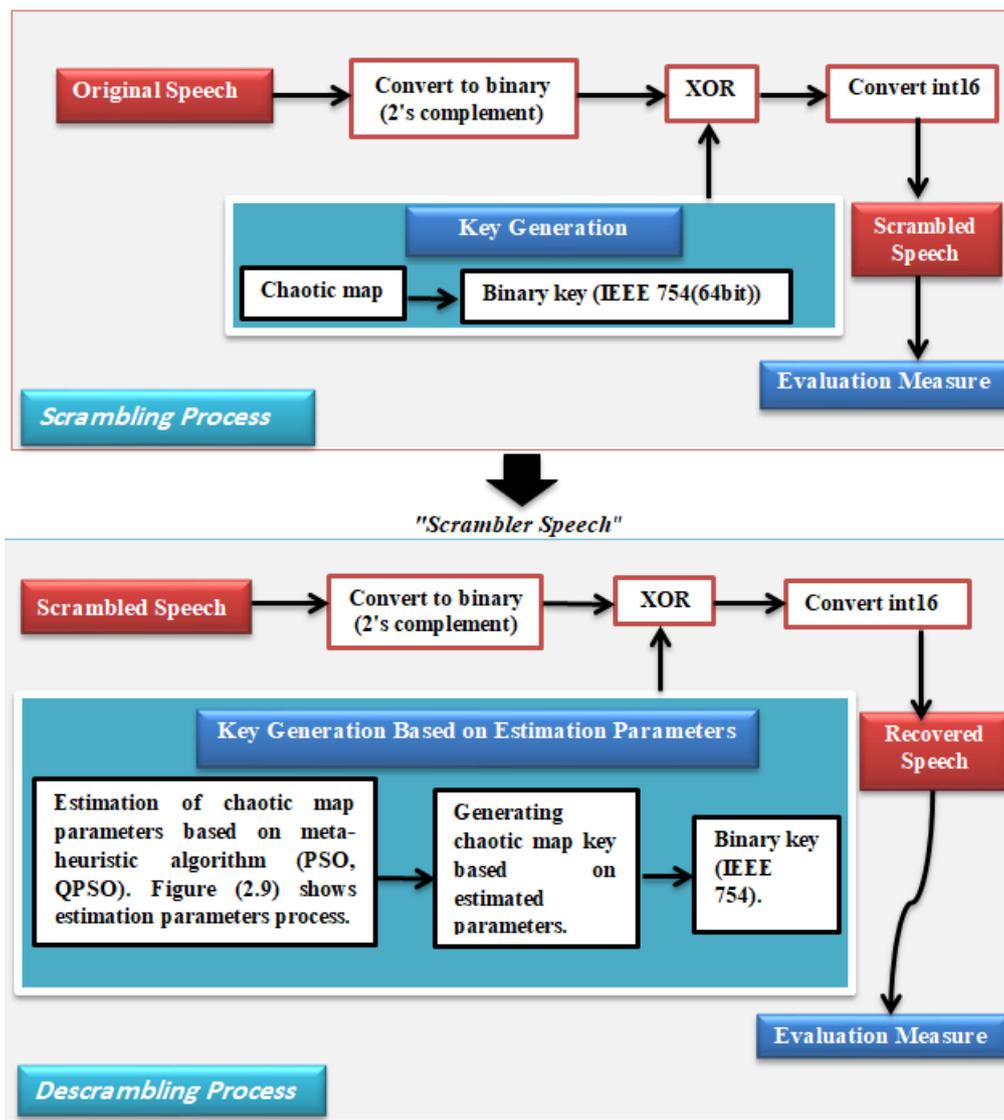


Figure 3.1: The Block Diagram of the Proposed System.

3.2.1 Initialization Speech Signal

The first step to starting and configuring speech for the system is to read the speech.

Algorithm (3.1) Read Speech.

Input: audio file

Output: The original speech data 'dataspeech [W]' is a one- dimension array, data type int16 , where W =wav file size .

Begin :

1. try

```

// try to read from file
2. File Myfile //path audio file
3. If (Myfile.exists())
4.   Read the audio file and convert it into byte data and save it in dataspeech[]
   array.
5.   End If
6. End try
7. catch (IOException e)
8.   If there is an error in the path of an audio file, a message will be printed saying
   that the file cannot be read.
9. End catch
10. catch (UnsupportedAudioFileException e)
11.   If an audio file is not supported, a message will be printed saying that the file is
   not supported.
12. End catch
Return dataspeech
End algorithm

```

3.2.2 Speech Scrambling Based on Chaotic Maps Stage

At this stage, the speech scrambler depends on the chaotic maps that are used as a secret key created in the scrambling process. These chaotic maps generate sequences of real numbers and use these sequences as keys after converting them to a binary system. It is used for scrambling speech. Speech scrambling occurs in the time domain and then the distorted speech is transmitted to the other side (the receiver). There are many steps at this point that will be explained later.

Algorithm (3.2) Speech Scrambling

Input : The original speech data 'dataspeech[W]' array is one-dimensional, where W = wav file size .

Output : 'scr.data[]' is a one-dimension array.

Begin:

<ol style="list-style-type: none"> 1. Enter parameter SFrame. // representing frame length 2. no. frame = floor (W / SFrame). // number frame for speech. 3. Enter the initial parameters of the keys ('x' map). 4. Enter the parameter S = 0, E = SFrame. // representing S=start, E=end, and using this parameter to divide the speech. 5. For i = 1 to no.frame 6. Speech is segmented by rectangle window and stored in dFrameByte[i] array. 7. For j=1 to SFrame 8. Converting every value of dframeByte[j] to binary with 16 bits using two's Complements method and is saved in dFrameBin [j]. 9. End For j 10. Create the key utilizing (x map) and keep it to keymap[i] (real values) then convert to the binary system by utilizing IEEE 754(64bit) converter and save it in KeyBin[i]. 11. For k=1 to SFrame 12. BinaryFrame[k] = dFrameBin[k] \oplus KeyBin[k] . 13. Convert BinaryFrame [k] to int16 and keep it in scr.data[k]. 14. End For k 15. Receive scr. data[k] by Receiver. // this separate part 16. End For i
End algorithm

Algorithm (3.2) shows all the operations that are performed on the sender side, sending the scrambling speech signal to the other side (receiver). This algorithm includes operations as followed: Split the original speech signal into frames, generate key (in this thesis will use two chaotic maps Logistic and circle maps as example), convert the secret key into a binary system using (IEEE 754(64 bit)) converter , convert the data frames to binary using (two's complements), scrambling process is performed using a nonlinear method (XOR operator) between the original speech (every frame of the original speech) and the secrecy key, convert the result of the

previous stage to an integer type (16bits), Finally, the speech scrambling is saved in a .wav file for the test.

3.2.2.1 Split Speech Signal

Figure (2.21) and algorithm (3.3) explain the process of splitting a speech signal into frames. Speech signals are divided into windows or frames using a rectangular window, each frame consists of a number of samples, and the frames are equal in size according to the frame size.

Algorithm (3.3) Split Speech Signal.

Input: The original speech data array 'dataspeech[W]' is a one dimensional array, with data-type '16int', SFrame, enter the parameter (S , E). //Where W = .wav file size, SFrame= length of the frame , S=start ,E=end

Output : dF[] is one dimension array.

Begin:

1. N= 0
2. For K = S to E
3. N = N +1
4. dF(N) = dataspeech (K)
5. End For K
6. S = S + SFrame
7. E = S + SFrame
8. Return dF, S, E

End algorithm

3.2.2.2 Generating Scrambled Keys

In this step, a key is generated using one of the chaotic maps (either logistic map or circle map) scrambling with the original speech signal. Each key agrees with a frame in the speech signal. The key is converted into a binary system, after which it is prepared for scrambling operation.

Algorithms (3.4,3.5) show key generation algorithms using logistic and circle maps, respectively.

Algorithm (3.4) Key Generation by Logistic Map.

Input : system parameter (r), initial value (initVlog), frame length (A).

Output : $\text{LogBin}[A][16]$ is two- dimension array .// $A = \text{frame length}$.

Begin

1. $\text{LSequence} = \text{ceil}(A / 4)$
2. $\text{KLog}[0] = \text{initVlog}$
3. Convert $\text{KLog}[0]$ array into binary system using 'IEEE 754' and save as a row in $\text{LogBin}[0]$.
4. For $J = 1$ to LSequence
5. $\text{KLog}[J] = r * \text{KLog}[J-1] * (1 - \text{KLog}[J-1])$
6. Convert $\text{KLog}[J]$ into binary system using 'IEEE 754 converter' and save as a row in $\text{LogBin}[J]$.
7. End For J
8. LogBin is divided into rows and columns (rows = frame length ,columns =16) using algorithm (3.9).
9. Return LogBin

End algorithm

Algorithm (3.5) Key Generation by Circle Map.

Input: (Ω) is the constant angular advance of the sinusoidal oscillator, (K) is the coupling strength, initial value (initVcir), frame length (A).

Output: $\text{CIRBin}[A][16]$ is a two- dimension array .// Where $A = \text{frame length}$.

Begin

1. $\text{LSequence} = \text{ceil}(A / 4)$
2. $\text{KC}[0] = \text{initVcir}$
3. Convert $\text{KC}[0]$ into binary system using 'IEEE 754' and save as a row in $\text{CIRBin}[0]$.
4. For $J = 1$ to LSequence
5. $\text{KC}[J] = (\text{KC}[J - 1] + \Omega - \frac{K}{2\pi} \sin(2\pi \text{KC}[J - 1])) \bmod 1$
6. Convert $\text{KC}[J]$ into the binary system using 'IEEE 754 converter' and save as a

```

    row in CIRBin [J].
7. End forJ
8. CIRBin is divided into rows and columns (rows = frame length, columns =16)
   using algorithm(3.9).
9. Return CIRBin
End algorithm

```

3.2.2.3 IEEE 754 Converter

At this step, the real values produced via the chaotic map will be converted to binary values using a converter IEEE 754(64bit). Algorithm (3.9) displays the IEEE 754(64bit) Converter algorithm.

Algorithm (3.6) IEEE 754 (64 bit)Converter.

Input: number (num) is the data type float

Output : float2Bin[64] is a one dimension array. // The array represents a binary system for the entered number.

Begin:

1. If num > 0 then // sign bit
2. float2Bin [0] = 0
3. Else
4. float2Bin [0] = 1
5. num = num × -1
6. End If
7. R = real (num)
8. F = Fractional(num)
9. The real part (R) is converted to binary formula and stored in RP.
10. The fractional part (F) is converted to binary formula and stored in FP.
11. Combined RP and FP as a binary formal, Add (merge size – 52) zeros and keep it in float2Bin[.]
12. The shift point between real and fractional to access the last bit 1 is located on the left and save it, calculate the number of shifts, and keep it in parameter (bais).
13. Exp = bais + 1023
14. Convert Exp to binary system and keep it to float2Bin[.] // the exponent bits

15. Return float2Bin
End algorithm

3.2.2.4 Converting Frame of Speech into Binary System

In this step, the original speech signal is converted into a binary system by using a function (two's Complements).

Algorithm (3.7) Convert Integer into Binary Using Two's Complements.

Input : number (num) with data-type (16int)

Output : Bin_Num[16] is a one dimension array.// describes a binary system for the entered number.

Begin :

1. M=16
2. If num > 0 then // if number is positive
3. For j = M to 1
4. If num mod 2 = 0 then
5. Bin_Num[j] = 0
6. Else
7. Bin_Num[j] = 1
8. End If
9. num = num / 2
10. End For j
11. End If
12. If num < 0 then // if number negative
13. num*=-1
14. For j = M to 0
15. If num mod 2 =0 then
16. Bin_Num[j] = 0
17. Else
18. Bin_Num[j] = 1
19. End If
20. num = num / 2
21. End For j

```

22. Bin_Num = Two's-complement(Bin_Num)
23. End If
24. Else //if number=0.
25.   For i = 0 to Bin_Num.length
26.     Bin_Num[i] = 0
27.   End For i
28. End Else
29. Return Bin_Num[.].

```

End Algorithm

Algorithm (3.8)Two's-complement.

Input : Bin_Num[16] is a one dimension array , M=16

Output : one dimension twoComp[16] .

Begin:

```

1. b =[0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1]
2. If Bin_Num[16] = 1 then
3.   c= 0
4.   For j = M to 1
5.     twoComp [j] = (Bin_Num[j]+b[j]+c ) mod 2 // remainder
6.     c = (Bin_Num[j]+b[j]+c) / 2 //quotient
7.   End For j
8. Else
9.   Bin_Num [16] = 1
10.  twoComp = Bin_Num
11. End If
12. Return twoComp[]

```

End Algorithm

Algorithm (3.9) Splitted 64 Bits

Input : Xbin[A][64] is a two dimension array .// Where A= Frame Length /4.

Output : FinalXbin [AA][16]is two dimension array .//Where AA= Frame Length *4.

Begin

```
1. M = 0
2. For i = 0 to A
3.   S = 0, E = 15
4.   For j = 0 to 4
5.     N = 0
6.     For K = S to E
7.       FinalXbin[M][N] = Xbin[i][K]
8.       N=N+1
9.     End For K
10.  S = E+1
11.  E = S+16
12.  M=M+1
13.  End For j
14. End For i
15. Return FinalXbin
End Algorithm
```

Algorithm (3.9) displays the division of the real value into (64 bits), where these values are generated by a chaotic map representing four values in the binary system, each containing its values (16 bits). Figure (3.2) explains this method.

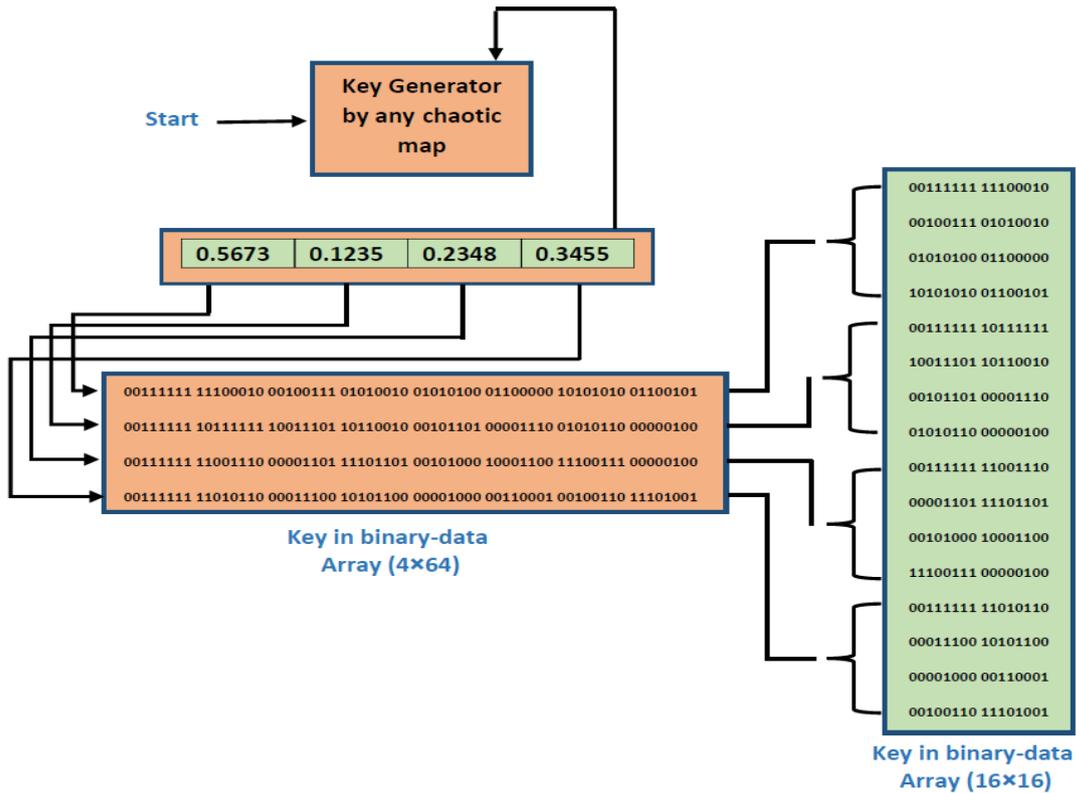


Figure 3.2 : Splitting the Real Value Into 64 Bits.

3.3 Estimating the Parameters of a Chaotic Map

In this part, the parameters of chaotic maps (logistic map and circle map) are estimated using meta-heuristic algorithms. The parameter (system parameter 'r') in the logistic map equation is estimated, but in the circle map, the two parameters (Ω is the constant angular advance of the sinusoidal oscillator, and K is the coupling strength) in the circle map equation are estimated. To estimate the parameters, two algorithms are used, particle swarm optimization (PSO) and quantum particle swarm optimization (QPSO) algorithms. The optimal solution is obtained using two algorithms by detecting the lowest error rate (fitness function) using the minimum mean square error (MSE) and sum of square error (SSE). The estimated parameters are used in the descrambling speech process.

Figure (2.9) shows the structure of the system estimating parameters for a chaotic system. Algorithms (3.10, 3.11) show the meta-heuristic algorithms used in this thesis. Algorithms (3.12, 3.13, 3.14, and 3.15) show fitness functions used with the particle swarm optimization and the quantum particle swarm optimization algorithms.

Algorithm (3.10) Quantum Particle Swarm Optimization.

Input : Maximum number of repetitions (MAXITER) , dimensions of the problem (dim) ,beta(β), population size (pop-size)

Output : best global position (gbest),fitness value .

1. Initialize the position of the particles, set the personal best location of each particle (pbest), determine the fitness values, and get the best global location (gbest).

// The following is the loop of the QPSO's search

2. For k=1 to MAXITER

3. Calculate mean best position (mbest).

4. For i=1 to pop-size //The following is the update of the particle's position

5. For j=1 to dim

6. $u = \text{random};$ // number random among (0, 1)

7. $X_{ij}(k) = u * pbest(k) + (1-u) * gbest$ // determine vector local focus of the particle $X_{ij}(k)$.

8. $r = \text{random}$ // number random between (0, 1)

9. If $r > 0.5$

10. $Y_{ij}(k+1) = X_{ij}(k) + \beta * |mbest(k) - Y_{ij}(k)| * \ln(1/r)$

11. Else

12. $Y_{ij}(k+1) = X_{ij}(k) - \beta * |mbest(k) - Y_{ij}(k)| * \ln(1/r)$

13. End If

14. End For j

15. Evaluate the fitness value of $Y_i(k+1)$, that is, the objective function value $f(Y_i, k+1)$.

16. Update $X_i(k)$ and gbest

16. End For i

17. End For k

18. Return gbest, fitness value

End algorithm

Algorithm (3.11) Particle Swarm Optimization.

Input :Maximum number of repetitions (maxiter) , dimensions of the problem (dim), population size (pop-size), the values of the acceleration coefficients(c1 , c2) , inertia weight (w_{max} and w_{min})

Output : best global position (gbest),fitness value .

Begin :

// initialization population

1. For k=1 to pop-size
2. initialize the position of the particles (y_k), velocity ($v_{:,k}$) randomly.
3. End for k
4. Evaluation of each particle by using a fitness function.
5. For i=0 to pop-size
6. Pbest[i]= fitnessvalue[i]// Determining the personal best position for each particle (pbest).
7. End For i
- //Find a minimum position on pbest[i] represent as gbest .
8. pos = 0
9. gbest = list[0]
10. For i=0 to i< pbest.length
11. If (pbest[i] < gbest)
12. pos = i
13. gbest= pbest[i]
14. End If
15. End For i
- //loop**
16. While (termination condition <= maxiter)
- // update personal best location of each particle (pbest).
17. For i=0 to pop-size
18. If (fitness value[i] < pbest[i])
19. pbest[i] = fitnessvalue[i]
20. End For i

```

//update best global location (gbest) .
21. For i=0 to i<pbest.length
22.   If (pbest[i] < gbest)
23.     gBest = pbest[i]
24.   End For i
25.   update inertia weight (w) by using eq.(2.8).
26.   For i=1 to pop-size
27.     For d=1 to dim
28.       update of the particle's velocity by using eq.(2.6) and update of
         the particle's location by using eq.(2.7).
29.     End For d
30.   End For i
31.   Calculate fitness function to next particle using (minimization fitness function).
32. End while
33. Retune gbest ,fitness value

End algorithm

```

Algorithm (3.12) Mean Square Error of the Logistic Map

Input : system parameter (r), initial value (initVlog), best global position (gbest) . //
 Take a value from a function PSO or QPSO. , N // range of data used for parameter estimation.

Output: MSE

Begin :

1. $Y[0] = \hat{Y}[0] = \text{initVlog}$
2. $\text{rbir} = \text{gbest}$ // best global position return from PSO or QPSO function
3. For J = 1 to N
4. $Y[J] = r * Y[J-1] * (1 - Y[J-1])$ // Original system values
5. $\hat{Y}[J] = (\text{rbir} * \hat{Y}[J-1]) * (1 - \hat{Y}[J-1])$ // Estimated system values
6. End For J
7. Calculate mean square error between original values and estimated values by using eq.(2.14)
8. Return MSE

End algorithm

Algorithm (3.13) Sum Square Error of the Logistic Map

Input : system parameter (r), initial value (initVlog), best global position (gbest)// Take a value from a function PSO or QPSO , N// range of data used for parameter estimation

Output: SSE

Begin :

1. $Y[0]=\hat{Y}[0]=\text{initVlog}$
2. $\text{rbir}=\text{gbest}$ // best global position return from PSO or QPSO function
3. For J = 1 to N
4. $Y[J]=r * Y[J-1] * (1 - Y[J-1])$ // Original system values
5. $\hat{Y}[J]=(\text{rbir} * \hat{Y}[J-1]) * (1 - \hat{Y}[J-1])$ // Estimated system values
6. End For J
7. Calculate sum square error (SSE) between original values and estimated values by using eq.(2.15).
8. Return SSE

End algorithm

Algorithm (3.14) Mean Square Error of the Circle Map

Input : (ω) is the constant angular advance of the sinusoidal oscillator, (K) is the coupling strength, initial value (initv), best global position (gbest1,gbest2)// Take a values from a function PSO or QPSO, N// range of data used for parameter estimation

Output: MSE

Begin :

1. $\text{sum}=0$
2. $X[0]=Y[0]=Z[0]=\text{initv}$
3. $\omega_{\text{est}}=\text{gbest1}, K_{\text{est}}=\text{gbest2}$
4. For J = 1 to N
5. $X[J]=\left(X[J] + \omega - \frac{K}{2\pi} \sin(2\pi X[J])\right) \bmod 1$ //Original system values
6. $Y[J]=\left(Y[J] + \omega_{\text{est}} - \frac{K}{2\pi} \sin(2\pi Y[J])\right) \bmod 1$ //Estimated system values
7. $Z[J]=\left(Z[J] + \omega - \frac{K_{\text{est}}}{2\pi} \sin(2\pi Z[J])\right) \bmod 1$ // Estimated system values.

```

8. End For J
//Calculate the mean square error (MSE)between original values and estimated values
9. For i=0 to N
10. sum=sum+((X[i]-Y[i])^2))+((X[i]-Z[i])^2))
11. End For i
12. MSE=sum/N
13. Return MSE
End algorithm

```

Algorithm (3.15) Sum Square Error of the Circle Map

Input : (Ω) is the constant angular advance of the sinusoidal oscillator, (K) is the coupling strength, initial value (initv), best global position (gbest1,gbest2)// Take a values from a function PSO or QPSO, N// range of data used for parameter estimation

Output: SSE

Begin :

```

1. X[0]=Y[0]= Z[0]= initv
2.  $\Omega_{est} = gbest1, K_{est} = gbest2$ 
3. For J = 1 to N
4.    $X[J] = (X[J] + \Omega - \frac{K}{2\pi} \sin(2\pi X[J])) \bmod 1$  //Original system values
5.    $Y[J] = (Y[J] + \Omega_{est} - \frac{K}{2\pi} \sin(2\pi Y[J])) \bmod 1$  //Estimated system values
6.    $Z[J] = (Z[J] + \Omega - \frac{K_{est}}{2\pi} \sin(2\pi Z[J])) \bmod 1$  // Estimated system values.
7. End For J

```

//Calculate sum square error (SSE)between original values and estimated values

```

8. For i=0 to N
9. sum=sum+((X[i]-Y[i])^2))+((X[i]-Z[i])^2))
10. End For i
11.  $SSE = \sqrt[2]{sum}$ 
12. Return SSE

```

End algorithm

3.4 Speech Descrambling Speech

Algorithm (3.16) shows the speech descrambling algorithm. At this point, the speech scrambling signal is obtained from the sender side frame by frame. Speech is descrambled after the process of estimating the main parameters of the chaotic map is implemented in the scrambling process on the sender side. Apply the same chaotic map method utilized in the scrambling process. After this process, all frames (descrambled frames) are stored in a (.wav) file. The identical header file is used as the original speech signal (number of channel = 1, number of bits per sample = 16 bits, sample rate = 8000 Hz). It describes the restored speech signal.

Algorithm (3.16) Speech Descrambling

Input: *scr.d*[M] is a one dimension array, with the data type int16, the estimated parameters of the chaotic map are entered as initial values to generate the key.

Output : *RData*[M] is one dimension array ,M=file length.

Begin :

1. Enter parameter FL. // representing frame length
2. For i=1 to FL
3. Convert each scramble data frame (src. Data) to a binary system using the two's complement algorithm and store in des. data[i] array.
4. End For i
5. Generate a key based on parameters estimation and convert the key into the binary system using the IEEE 754(64 bit) converter then split 64 bit into 16 bit using (3,9) algorithm, and store it in the 'KeyInBin[]' array.
6. For j=1 to FL
7. $\text{Bin2Xor}[j] = \text{des.data}[j] \oplus \text{KeyInBin}[j]$ // 'XOR' function between des.data and KeyInBin .
8. End For j
9. Convert Bin2xor[] to Byte Frame and keep it in RData array.// saving all frame that come from sender side

10.Return RData.

End algorithm

Chapter Four

Experimental Results and Discussion

*Chapter Four**Experimental Results and Discussion***4.1 introduction**

This chapter presents the results of the proposed system for chaotic parameters estimation based on meta-heuristic algorithms: speech descrambling case study. The estimation of the parameters for the chaotic system is a logistic and circle map, the two meta-heuristic algorithms used are the particle swarm optimization(PSO) and the quantum particle swarm optimization(QPSO) algorithms. The mean square error (MSE) and sum square error (SSE) are fitness functions.

Wave files used in speech descrambling as a case study have different lengths and genders.

The experimental results are implemented on a Lenovo computer, Intel(R) Core(TM) i5-10210U, 4GB of memory, windows10 (64bit), and the programming language is JAVA swing package language.

4.2 Test the Residual Intelligibility of Speech Scrambling

Residual intelligibility (R.I.) is an important parameter used to measure the systems' security. If the residual intelligibility of speech is low, then the speech is not clear (the system becomes too safe).To test the residual intelligibility of speech scrambling, two measures are used (signal-to-noise ratio (SNR), and correlation coefficient (CC)), which are performed between the original speech and the scrambling speech.

The residual intelligibility of scrambling speech was tested for six speech files of different lengths and gender, as well as using the information in the following table (4.1).

Table 4.1: Parameter of the System Speech Scrambling.

Sample rate	8000Hz(8KHz)
Number of bits per sample	16 bit
Frame sample size	1024
Number of channels	1

The audios were taken from the following link: [Open Speech Repository | \(voiptroubleshooter.com\)](http://voiptroubleshooter.com).

Table 4.2: Audio File Information.

Name	Time (second)	Gender
File 1	2	Female
File 2	6	Male
File 3	7	Male
File 4	6	Female
File 5	5	Female
File 6	4	Male

The following tables (4.3, 4.4) show the residual intelligibility of speech scrambling after using the chaotic map (logistic map and circle map) as a key to scrambling.

Table 4.3: Residual intelligibility for Speech Scrambling using the Logistic Map where $r=3.9$.

Speech Files	SNR	CC	Time(sec.)
File 1	-76.53428	0.01639	0.311
File 2	-34.15941	0.01591	0.648
File 3	-70.15809	-0.00454	0.683
File 4	-63.67645	0.00076	0.673

File 5	-63.91305	0.07831	0.361
File 6	-70.23098	-0.03583	0.4

Table 4.4: Residual intelligibility for Speech Scrambling using the Circle Map where $K = 0.712$,
 $\Omega = 0.5$.

Speech Files	SNR	CC	Time(sec.)
File 1	-75.57293	-0.00913	0.198
File 2	-34.15941	0.01591	0.515
File 3	-69.12140	0.05492	0.784
File 4	-62.45572	-0.02953	0.584
File 5	-62.86946	0.06025	0.399
File 6	-69.18893	0.01022	0.339

Tables (4.3, 4.4) show residual intelligibility of speech scrambling for logistic map and circle map. If the value of the correlation coefficient (CC) is close to zero, then the speech scrambler is good, thus more safety with low residual intelligibility. If the signal-to-noise ratio (SNR) is decreased, then the residual intelligibility of speech scrambling is low, and therefore the security of the system is increased.

4.3 Chaotic Map Parameters Estimation Test

The parameters estimation technique is implemented for chaotic maps (logistic map and circle map). In this thesis, the PSO and QPSO algorithms are used to estimate the parameters of the chaotic system, and the minimum MSE and SSE are used as a fitness function with algorithm (PSO/QPSO).

The comparison between PSO and QPSO algorithms that used unknown parameters for this test are (r) in the logistic map and (k, Ω) in the circle map.

A logistic map parameter estimation program is executed using two algorithms, PSO and QPSO many times, and then we chose the best 100 estimated results for the parameter (r).

Table 4.5: Reaches the Best and Worst Values Run 100 Times to Estimate the Parameter Logistic Map where $r=3.5$.

No	PSO/MSE	QPSO/MSE
1.	Best P.Est. $r=3.5$ MSE=0.0	Best P.Est. $r=3.5$ MSE= 0.0
2.	Best P.Est. $r=3.5$ MSE=0.0	Best P.Est. $r=3.5$ MSE= 0.0

5.	Best P.Est. $r=3.5$ MSE=0.0	Best P.Est. $r=3.5$ MSE= 0.0
6.	Best P.Est. $r=3.5$ MSE=0.0	Best P.Est. $r=3.4$ MSE= 0.71673
7.	Best P.Est. $r=3.5$ MSE=0.0	Best P.Est. $r=3.5$ MSE= 0.0

55.	Best P.Est. $r=3.5$ MSE=0.0	Best P.Est. $r=3.5$ MSE= 0.0
56.	Best P.Est. $r=-6972572.0$ MSE=Infinity	Best P.Est. $r=3.5$ MSE= 0.0
57.	Best P.Est. $r=-6035904.9$ MSE=Infinity	Best P.Est. $r=3.5$ MSE= 0.0
58.	Best P.Est. $r=-2477790.1$ MSE=Infinity	Best P.Est. $r=3.5$ MSE= 0.0
59.	Best P.Est. $r=-1600198.2$ MSE=Infinity	Best P.Est. $r=3.5$ MSE= 0.0
60.	Best P.Est. $r=-1327255.4$ MSE=Infinity	Best P.Est. $r=3.5$ MSE= 0.0
61.	Best P.Est. $r=721921.7$ MSE=Infinity	Best P.Est. $r=3.5$ MSE= 0.0
62.	Best P.Est. $r=89034.2$ MSE=Infinity	Best P.Est. $r=3.5$ MSE= 0.0
63.	Best P.Est. $r=3.5$ MSE=0.0	Best P.Est. $r=3.5$ MSE= 0.0

100.	Best P.Est. $r=3.5$ MSE=0.0	Best P.Est. $r=3.5$ MSE= 0.0

Table 4.6: Reaches the Best and Worst Values Run 100 Times to Estimate the Parameter Logistic Map where $r=3.5$.

No	PSO/SSE	QPSO/SSE
1.	Best P.Est. $r=3.5$ SSE= 0.0	Best P.Est. $r=3.5$ SSE= 0.0

20	Best P.Est. $r=3.5$ SSE= 0.0	Best P.Est. $r=3.5$ SSE= 0.0
21	Best P.Est. $r=3.5$ SSE= 0.0	Best P.Est. $r=3.4$ SSE= 0.71673

49	Best P.Est. $r=3.5$ SSE= 0.0	Best P.Est. $r=3.5$ SSE= 0.0
50	Best P.Est. $r=3780692.8$ SSE= Infinity	Best P.Est. $r=3.5$ SSE= 0.0
51	Best P.Est. $r=3639543.5$ SSE= Infinity	Best P.Est. $r=3.5$ SSE= 0.0
52	Best P.Est. $r=415341.9$ SSE= Infinity	Best P.Est. $r=3.5$ SSE= 0.0
53	Best P.Est. $r=-114444.7$ SSE= Infinity	Best P.Est. $r=3.5$ SSE= 0.0
54	Best P.Est. $r=-82556.3$ SSE= Infinity	Best P.Est. $r=3.5$ SSE= 0.0
55	Best P.Est. $r=-319698.4$ SSE= Infinity	Best P.Est. $r=3.5$ SSE= 0.0
56	Best P.Est. $r=-251926.9$ SSE= Infinity	Best P.Est. $r=3.5$ SSE= 0.0
57	Best P.Est. $r=-321744.8$ SSE= Infinity	Best P.Est. $r=3.5$ SSE= 0.0
58	Best P.Est. $r=3.5$ SSE= 0.0	Best P.Est. $r=3.5$ SSE= 0.0

95	Best P.Est. r=3.5 SSE= 0.0	Best P.Est. r=3.5 SSE= 0.0
96	Best P.Est. r=3.5 SSE= 0.0	Best P.Est. r=3.4 SSE= 0.71673
97	Best P.Est. r=3.5 SSE= 0.0	Best P.Est. r=3.5 SSE= 0.0

100	Best P.Est. r=3.5 SSE= 0.0	Best P.Est. r=3.5 SSE= 0.0

Table 4.7: Reaches the Best and Worst Values Run 100 Times to Estimate the Parameter Logistic Map where r=3.9.

No	PSO/MSE	QPSO/MSE
1.	Best P.Est r=3.9 MSE=0.0	Best P.Est. r=3.9 MSE= 0.0

12	Best P.Est r=3.9 MSE=0.0	Best P.Est. r=3.9 MSE= 0.0
13	Best P.Est r=3.9 MSE=0.0	Best P.Est. r=2.5 MSE= 0.08608
14	Best P.Est r=3.9 MSE=0.0	Best P.Est. r=3.9 MSE= 0.0

28	Best P.Est r=3.9 MSE=0.0	Best P.Est. r=3.9 MSE= 0.0
29	Best P.Est r=-1322775.3 MSE=Infinity	Best P.Est. r=3.9 MSE= 0.0
30	Best P.Est r=-1212210.5 MSE=Infinity	Best P.Est. r=3.9 MSE= 0.0
31	Best P.Est r=-1925732.8 MSE=Infinity	Best P.Est. r=3.9 MSE= 0.0
32	Best P.Est r=202492.7 MSE=Infinity	Best P.Est. r=3.9 MSE= 0.0
	Best P.Est r=3.9 MSE=0.0	Best P.Est. r=3.9 MSE= 0.0

43	Best P.Est r=3.9 MSE=0.0	Best P.Est. r=3.9 MSE= 0.0
44	Best P.Est r=3.9 MSE=0.0	Best P.Est. r=2.5 MSE= 0.08608
45	Best P.Est r=3.9 MSE=0.0	Best P.Est. r=3.9 MSE= 0.0

79	Best P.Est r=3.9 MSE=0.0	Best P.Est. r=3.9 MSE= 0.0
80	Best P.Est r=-26091.4 MSE=Infinity	Best P.Est. r=3.9 MSE= 0.0
81	Best P.Est r=3.9 MSE=0.0	Best P.Est. r=3.9 MSE= 0.0

84	Best P.Est r=3.9 MSE=0.0	Best P.Est. r=3.9 MSE= 0.0
85	Best P.Est r=3.03360952E7 MSE=Infinity	Best P.Est. r=3.9 MSE= 0.0
86	Best P.Est r=2.58500963E7 MSE=Infinity	Best P.Est. r=3.9 MSE= 0.0
87	Best P.Est r=-5.10244393E7 MSE=Infinity	Best P.Est. r=3.9 MSE= 0.0
88	Best P.Est r=-1.924944138E8 MSE=Infinity	Best P.Est. r=3.9 MSE= 0.0
89	Best P.Est r=-2.41967731E7 MSE=Infinity	Best P.Est. r=3.9 MSE= 0.0
90	Best P.Est r=-9447410.9 MSE=Infinity	Best P.Est. r=3.9 MSE= 0.0
91	Best P.Est r=-1467272.6 MSE=Infinity	Best P.Est. r=3.9 MSE= 0.0
92	Best P.Est r=-986878.4 MSE=Infinity	Best P.Est. r=3.9 MSE= 0.0
93	Best P.Est r=-6389896.6 MSE=Infinity	Best P.Est. r=3.9 MSE= 0.0
94	Best P.Est r=559223.0 MSE=Infinity	Best P.Est. r=3.9 MSE= 0.0
95	Best P.Est r=3.9 MSE=0.0	Best P.Est. r=3.9 MSE= 0.0

100	Best P.Est r=3.9 MSE=0.0	Best P.Est. r=3.9 MSE= 0.0

Table 4.8: Reaches the Best and Worst Values Run 100 Times to Estimate the Parameter Logistic Map where $r=3.9$.

No	PSO/SSE	QPSO/SSE
1	Best P.Est $r=3.9$ SSE=0.0	Best P.Est. $r=3.9$ SSE= 0.0

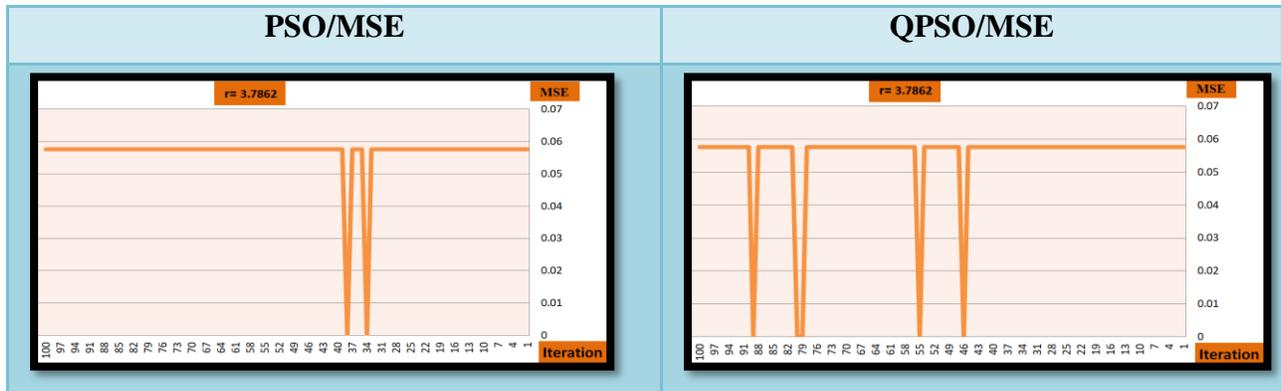
9	Best P.Est $r=3.9$ SSE=0.0	Best P.Est. $r=3.9$ SSE= 0.0
10	Best P.Est $r=3.9$ SSE=0.0	Best P.Est. $r=2.5$ SSE= 4.63898
11	Best P.Est $r=3.9$ SSE=0.0	Best P.Est. $r=3.9$ SSE= 0.0

21	Best P.Est $r=3.9$ SSE=0.0	Best P.Est. $r=3.9$ SSE= 0.0
22	Best P.Est $r=-341964.6$ SSE=Infinity	Best P.Est. $r=3.9$ SSE= 0.0
23	Best P.Est $r=52689.8$ SSE=Infinity	Best P.Est. $r=3.9$ SSE= 0.0
24	Best P.Est $r=3.9$ SSE=0.0	Best P.Est. $r=3.9$ SSE= 0.0

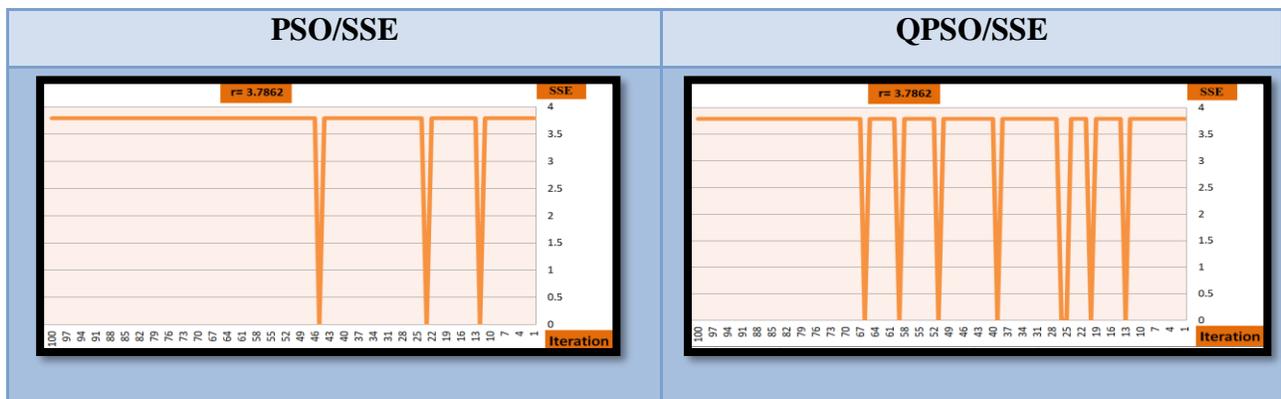
90	Best P.Est $r=3.9$ SSE=0.0	Best P.Est. $r=3.9$ SSE= 0.0
91	Best P.Est $r=8299830.4$ SSE=Infinity	Best P.Est. $r=3.9$ SSE= 0.0
92	Best P.Est $r=2.0536991E7$ SSE=Infinity	Best P.Est. $r=3.9$ SSE= 0.0
93	Best P.Est $r=1.77950045E7$ SSE=Infinity	Best P.Est. $r=3.9$ SSE= 0.0
94	Best P.Est $r=2.54796405E7$ SSE=Infinity	Best P.Est. $r=3.9$ SSE= 0.0
95	Best P.Est $r=5831634.0$ SSE=Infinity	Best P.Est. $r=3.9$ SSE= 0.0
96	Best P.Est $r=1795970.7$ SSE=Infinity	Best P.Est. $r=3.9$ SSE= 0.0
97	Best P.Est $r=972531.8$ SSE=Infinity	Best P.Est. $r=3.9$ SSE= 0.0
98	Best P.Est $r=643826.1$ SSE=Infinity	Best P.Est. $r=3.9$ SSE= 0.0
99	Best P.Est $r=2422843.6$ SSE=Infinity	Best P.Est. $r=3.9$ SSE= 0.0
100	Best P.Est $r=-2864020.1$ SSE=Infinity	Best P.Est. $r=3.9$ SSE= 0.0

Tables (4.5, 4.6, 4.7, and 4.8) show that the QPSO is better than PSO in the process of estimating the logistic parameter (r) if (r) has one or three or more values after the separator. If the MSE/SSE values are equal to zero, then the algorithms PSO and QPSO in estimating the parameter (r) succeed. In other words, the actual value of the parameter (r) has been reached.

Comparison of the estimated parameter (r) obtained by the PSO and QPSO algorithms is done by performing the fitness function. The figures below show the convergence times of the fitness function values for a logistic map that has been done using two algorithms. The numbers in the figures below indicate the MSE or SSE values. If MSE/SSE value is zero, then the algorithm has reached the actual value of the parameter.

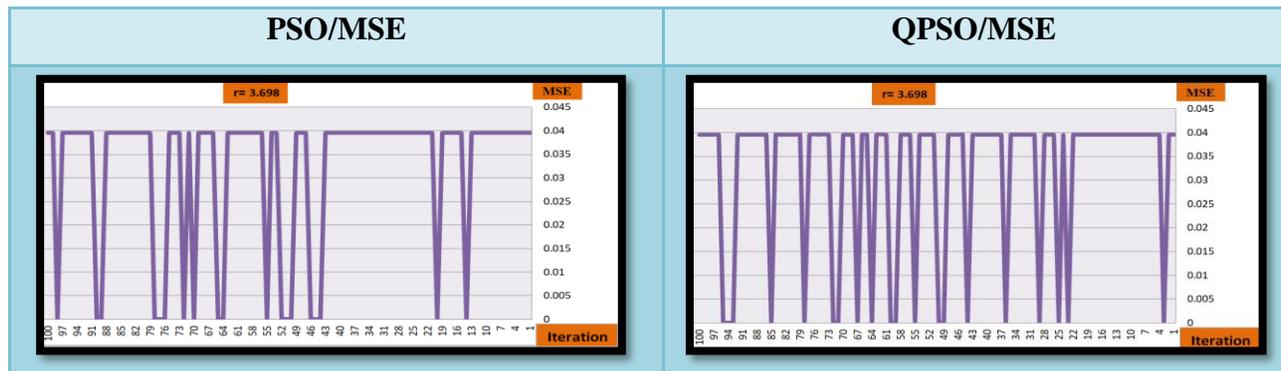


(a) MSE as Fitness Function

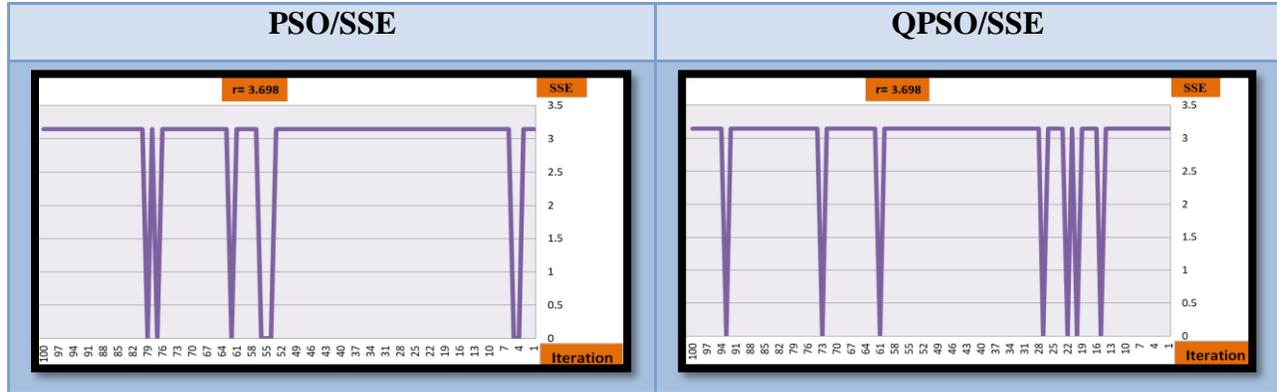


(b) SSE as Fitness Function

Figure 4.1: Reaches the Best and Worst Values Run 100 Times to Estimate the Parameter Logistic Map where $r=3.7862$.

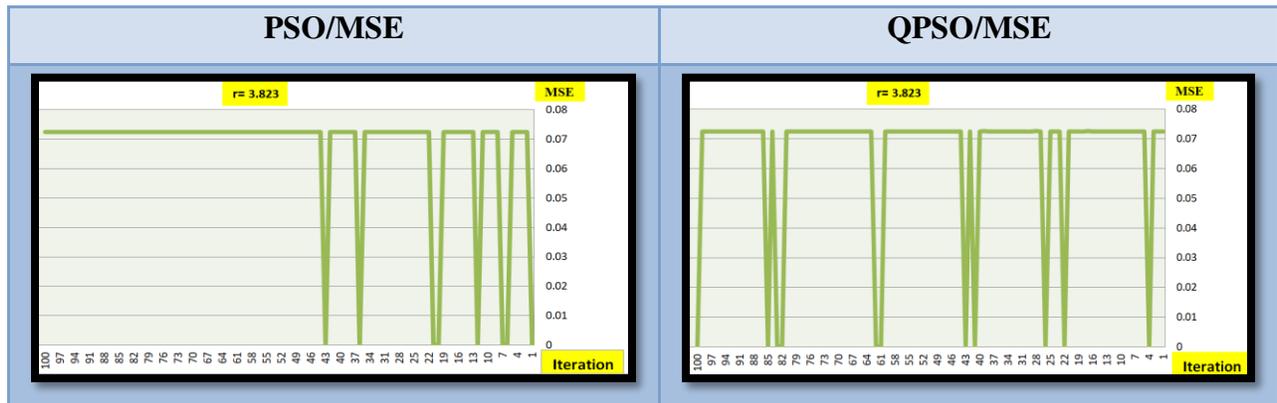


(a) MSE as Fitness Function

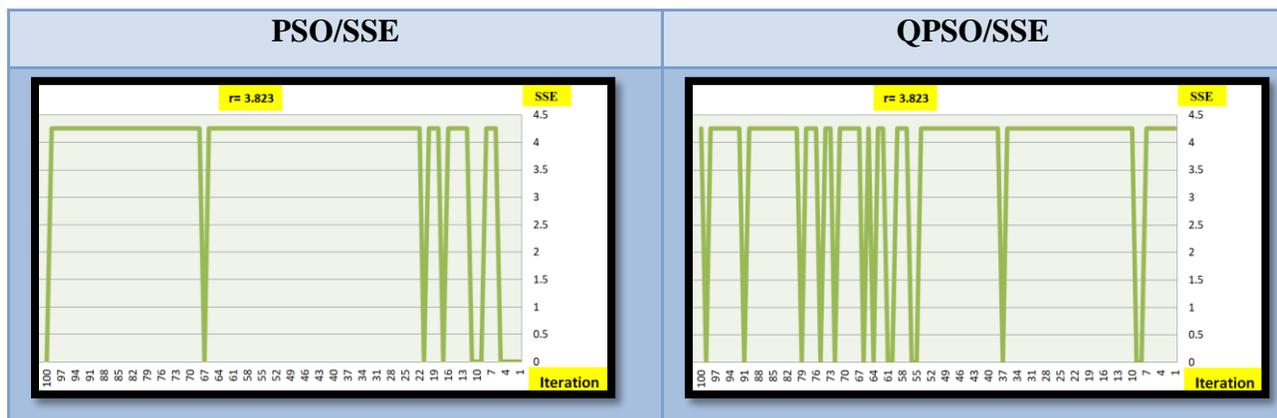


(b) SSE as Fitness Function

Figure 4.2: Reaches the Best and Worst Values Run 100 Times to Estimate the Parameter Logistic Map where $r=3.698$.



(a) MSE as Fitness Function



(b) SSE as Fitness Function

Figure 4.3: Reaches the Best and Worst Values Run 100 Times to Estimate the Parameter Logistic Map where $r=3.823$.

Figures (4.1, 4.2, and 4.3) show that if value (r) is equal to one or three or more from rank after the separator, then the QPSO algorithm is better than the PSO algorithm.

The parameters estimation program of the circle map has been done executed using two algorithms are PSO and QPSO many times, and then we choose the best 100 estimation results of the two parameters are k, Ω , where $k=0.712, \Omega=0.5$.

Table 4.9: Reaches the Best and Worst Values Run 100 Times to Estimate the Parameter Circle Map where $k=0.712, \Omega=0.5$.

No	PSO/MSE
1.	Best $k=0.712$, Best $\Omega=0.5$, MSE=0.0

76.	Best $k=0.712$, Best $\Omega=0.5$, MSE=0.0
77.	Best $k=-0.661$, Best $\Omega=0.5$, MSE=1.83376
78.	Best $k=0.712$, Best $\Omega=0.5$, MSE=0.0

100.	Best $k=0.712$, Best $\Omega=0.5$, MSE=0.0

Table 4.10: Reaches the Best and Worst Values Run 100 Times to Estimate the Parameter Circle Map where $k=0.712, \Omega=0.5$.

No	QPSO/MSE
1.	Best $k=0.699$, Best $\Omega=0.5$, MSE = 0.0662
2.	Best $k=0.704$, Best $\Omega=0.5$, MSE = 0.0310
3.	Best $k=0.703$, Best $\Omega=0.5$, MSE = 0.0374
4.	Best $k=0.711$, Best $\Omega=0.5$, MSE = 0.00079
5.	Best $k=0.715$, Best $\Omega=0.5$, MSE = 0.0135
6.	Best $k=0.721$, Best $\Omega=0.5$, MSE = 0.0997
7.	Best $k=0.697$, Best $\Omega=0.5$, MSE = 0.0821
8.	Best $k=0.712$, Best $\Omega=0.5$, MSE = 0.0
9.	Best $k=0.709$, Best $\Omega=0.5$, MSE = 0.0059
10.	Best $k=0.711$, Best $\Omega=0.5$, MSE = 0.00079
11.	Best $k=0.699$, Best $\Omega=0.5$, MSE = 0.0662
12.	Best $k=0.698$, Best $\Omega=0.5$, MSE = 0.074
13.	Best $k=0.711$, Best $\Omega=0.5$, MSE = 0.00079
14.	Best $k=0.712$, Best $\Omega=0.5$, MSE = 0.0
15.	Best $k=0.711$, Best $\Omega=0.5$, MSE =0.00079
16.	Best $k=0.726$, Best $\Omega=0.5$, MSE = 0.1020
17.	Best $k=0.711$, Best $\Omega=0.5$, MSE = 0.00079
18.	Best $k=0.708$, Best $\Omega=0.5$, MSE = 0.0098
19.	Best $k=0.704$, Best $\Omega=0.5$, MSE = 0.031

20.	Best $k=0.71$, Best $\Omega =0.5$, MSE = 0.0028
21.	Best $k=0.726$, Best $\Omega =0.5$, MSE = 0.102
22.	Best $k=0.703$, Best $\Omega =0.5$, MSE = 0.0374
23.	Best $k=0.712$, Best $\Omega =0.5$, MSE = 0.0
24.	Best $k=0.726$, Best $\Omega =0.5$, MSE = 0.102
25.	Best $k=0.708$, Best $\Omega =0.5$, MSE = 0.0098
26.	Best $k=0.706$, Best $\Omega =0.5$, MSE = 0.0194
27.	Best $k=0.713$, Best $\Omega =0.5$, MSE = 0.001
28.	Best $k=0.712$, Best $\Omega =0.5$, MSE = 0.0
29.	Best $k=0.695$, Best $\Omega =0.5$, MSE = 0.0988
30.	Best $k=0.697$, Best $\Omega =0.5$, MSE = 0.0821
31.	Best $k=0.713$, Best $\Omega =0.5$, MSE = 0.001
32.	Best $k=0.712$, Best $\Omega =0.5$, MSE = 0.0
33.	Best $k=0.723$, Best $\Omega =0.5$, MSE = 0.0998
34.	Best $k=0.711$, Best $\Omega =0.5$, MSE = 0.00079
35.	Best $k=0.71$, Best $\Omega =0.5$, MSE = 0.0028
36.	Best $k=0.696$, Best $\Omega =0.5$, MSE = 0.0903
37.	Best $k=0.711$, Best $\Omega =0.5$, MSE = 0.00079
38.	Best $k=0.71$, Best $\Omega =0.5$, MSE = 0.00287
39.	Best $k=0.714$, Best $\Omega =0.5$, MSE = 0.0047
40.	Best $k=0.698$, Best $\Omega =0.5$, MSE = 0.074
41.	Best $k=0.698$, Best $\Omega =0.5$, MSE = 0.074
42.	Best $k=0.711$, Best $\Omega =0.5$, MSE = 0.00079
43.	Best $k=0.714$, Best $\Omega =0.5$, MSE = 0.0047
44.	Best $k=0.711$, Best $\Omega =0.5$, MSE =0.00079
45.	Best $k=0.724$, Best $\Omega =0.5$, MSE = 0.1003
46.	Best $k=0.704$, Best $\Omega =0.5$, MSE = 0.031
47.	Best $k=0.696$, Best $\Omega =0.5$, MSE = 0.0903
48.	Best $k=0.708$, Best $\Omega =0.5$, MSE = 0.0098
49.	Best $k=0.713$, Best $\Omega =0.5$, MSE = 0.001
50.	Best $k=0.711$, Best $\Omega =0.5$, MSE = 0.00079
51.	Best $k=0.706$, Best $\Omega =0.5$, MSE = 0.0194
52.	Best $k=0.708$, Best $\Omega =0.5$, MSE = 0.0098
53.	Best $k=0.722$, Best $\Omega =0.5$, MSE = 0.0995
54.	Best $k=0.71$, Best $\Omega =0.5$, MSE = 0.00287
55.	Best $k=0.715$, Best $\Omega =0.5$, MSE = 0.0135
56.	Best $k=0.714$, Best $\Omega =0.5$, MSE = 0.0047
57.	Best $k=0.708$, Best $\Omega =0.5$, MSE = 0.0098
58.	Best $k=0.712$, Best $\Omega =0.5$, MSE = 0.0
59.	Best $k=0.698$, Best $\Omega =0.5$, MSE = 0.074
60.	Best $k=0.699$, Best $\Omega =0.5$, MSE = 0.0662
61.	Best $k=0.698$, Best $\Omega =0.5$, MSE = 0.074
62.	Best $k=0.713$, Best $\Omega =0.5$, MSE = 0.001
63.	Best $k=0.703$, Best $\Omega =0.5$, MSE = 0.0374
64.	Best $k=0.723$, Best $\Omega =0.5$, MSE = 0.0998
65.	Best $k=0.711$, Best $\Omega =0.5$, MSE = 0.00079
66.	Best $k=0.714$, Best $\Omega =0.5$, MSE = 0.0047
67.	Best $k=0.708$, Best $\Omega =0.5$, MSE = 0.0098
68.	Best $k=0.696$, Best $\Omega =0.5$, MSE = 0.0 903
69.	Best $k=0.726$, Best $\Omega =0.5$, MSE = 0.102
70.	Best $k=0.726$, Best $\Omega =0.5$, MSE = 0.102

71.	Best $k=0.709$, Best $\Omega =0.5$, MSE = 0.0059
72.	Best $k=0.715$, Best $\Omega =0.5$, MSE = 0.0135
73.	Best $k=0.698$, Best $\Omega =0.5$, MSE = 0.074
74.	Best $k=0.726$, Best $\Omega =0.5$, MSE = 0.102
75.	Best $k=0.712$, Best $\Omega =0.5$, MSE = 0.0
76.	Best $k=0.703$, Best $\Omega =0.5$, MSE = 0.0374
77.	Best $k=0.726$, Best $\Omega =0.5$, MSE = 0.102
78.	Best $k=0.715$, Best $\Omega =0.5$, MSE = 0.0135
79.	Best $k=0.712$, Best $\Omega =0.5$, MSE = 0.0
80.	Best $k=0.71$, Best $\Omega =0.5$, MSE = 0.0028
81.	Best $k=0.709$, Best $\Omega =0.5$, MSE = 0.0059
82.	Best $k=0.71$, Best $\Omega =0.5$, MSE = 0.0028
83.	Best $k=0.708$, Best $\Omega =0.5$, MSE = 0.0098
84.	Best $k=0.722$, Best $\Omega =0.5$, MSE = 0.0995
85.	Best $k=0.723$, Best $\Omega =0.5$, MSE = 0.0998
86.	Best $k=0.712$, Best $\Omega =0.5$, MSE = 0.0
87.	Best $k=0.7$, Best $\Omega =0.5$, MSE = 0.05861
88.	Best $k=0.696$, Best $\Omega =0.5$, MSE = 0.0 9
89.	Best $k=0.71$, Best $\Omega =0.5$, MSE = 0.0028
90.	Best $k=0.708$, Best $\Omega =0.5$, MSE = 0.0098
91.	Best $k=0.711$, Best $\Omega =0.5$, MSE = 0.00079
92.	Best $k=0.708$, Best $\Omega =0.5$, MSE = 0.00983
93.	Best $k=0.699$, Best $\Omega =0.5$, MSE = 0.0662
94.	Best $k=0.715$, Best $\Omega =0.5$, MSE = 0.0135
95.	Best $k=0.708$, Best $\Omega =0.5$, MSE = 0.0098
96.	Best $k=0.709$, Best $\Omega =0.5$, MSE = 0.0059
97.	Best $k=0.726$, Best $\Omega =0.5$, MSE = 0.102
98.	Best $k=0.712$, Best $\Omega =0.5$, MSE = 0.0
99.	Best $k=0.726$, Best $\Omega =0.5$, MSE = 0.102
100.	Best $k=0.726$, Best $\Omega =0.5$, MSE = 0.102

Table 4.11: Reaches the Best and Worst Values Run 100 Times to Estimate the Parameter Circle

Map where $k=0.712$, $\Omega =0.5$.

No	PSO/SSE
1.	Best $k= 0.712$, Best $\Omega= 0.5$, SSE=0.0

76.	Best $k= 0.712$, Best $\Omega= 0.5$, SSE=0.0
68.	Best $k= -0.661$, Best $\Omega= 0.5$, SSE=21.4112
78.	Best $k= 0.712$, Best $\Omega= 0.5$, SSE=0.0

100.	Best $k= 0.712$, Best $\Omega= 0.5$, SSE=0.0

Table 4.12: Reaches the Best and Worst Values Run 100 Times to Estimate the Parameter Circle

Map where $k=0.712$, $\omega=0.5$.

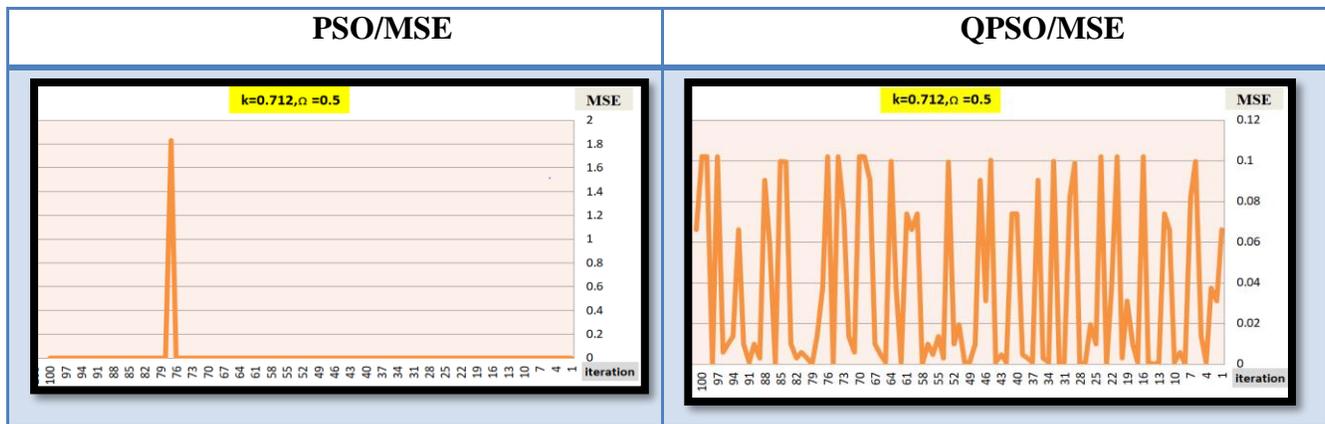
No	QPSO/SSE
1.	Best $k=0.716$, Best $\omega=0.5$, SSE = 0.1941
2.	Best $k=0.725$, Best $\omega=0.5$, SSE = 0.31794
3.	Best $k=0.708$, Best $\omega=0.5$, SSE = 0.0991
4.	Best $k=0.707$, Best $\omega=0.5$, SSE = 0.1198
5.	Best $k=0.696$, Best $\omega=0.5$, SSE = 0.3006
6.	Best $k=0.704$, Best $\omega=0.5$, SSE = 0.1763
7.	Best $k= 0.712$, Best $\omega= 0.5$, SSE=0.0
8.	Best $k=0.705$, Best $\omega=0.5$, SSE = 0.1583
9.	Best $k= 0.712$, Best $\omega= 0.5$, SSE=0.0
10.	Best $k=0.71$, Best $\omega=0.5$, SSE = 0.0536
11.	Best $k=0.714$, Best $\omega=0.5$, SSE = 0.069
12.	Best $k=0.714$, Best $\omega=0.5$, SSE = 0.069
13.	Best $k=0.71$, Best $\omega=0.5$, SSE = 0.0536
14.	Best $k=0.711$, Best $\omega=0.5$, SSE = 0.0281
15.	Best $k=0.716$, Best $\omega=0.5$, SSE = 0.1941
16.	Best $k=0.668$, Best $\omega=0.5$, SSE = 0.5987
17.	Best $k=0.709$, Best $\omega=0.5$, SSE = 0.0771
18.	Best $k=0.666$, Best $\omega=0.5$, SSE = 0.6073
19.	Best $k=0.719$, Best $\omega=0.5$, SSE = 0.322
20.	Best $k=0.697$, Best $\omega=0.5$, SSE = 0.2865
21.	Best $k=0.673$, Best $\omega=0.5$, SSE = 0.5498
22.	Best $k=0.716$, Best $\omega=0.5$, SSE = 0.1941
23.	Best $k=0.687$, Best $\omega=0.5$, SSE = 0.4149
24.	Best $k=0.705$, Best $\omega=0.5$, SSE = 0.1583
25.	Best $k=0.713$, Best $\omega=0.5$, SSE = 0.0317
26.	Best $k=0.709$, Best $\omega=0.5$, SSE = 0.0771
27.	Best $k=0.714$, Best $\omega=0.5$, SSE = 0.069
28.	Best $k=0.715$, Best $\omega=0.5$, SSE = 0.11645
29.	Best $k=0.701$, Best $\omega=0.5$, SSE = 0.2264
30.	Best $k=0.676$, Best $\omega=0.5$, SSE = 0.5247
31.	Best $k=0.705$, Best $\omega=0.5$, SSE = 0.1583
32.	Best $k=0.709$, Best $\omega=0.5$, SSE = 0.0771

33.	Best k= 0.712 , Best Ω= 0.5 , SSE=0.0
34.	Best k=0.707,Best Ω =0.5 , SSE = 0.1198
35.	Best k=0.696,Best Ω =0.5 , SSE = 0.3006
36.	Best k=0.711,Best Ω =0.5 , SSE = 0.0281
37.	Best k=0.706,Best Ω =0.5 , SSE = 0.1395
38.	Best k=0.715,Best Ω =0.5, SSE = 0.1164
39.	Best k=0.72,Best Ω =0.5 , SSE = 0.3172
40.	Best k=0.703,Best Ω =0.5 , SSE = 0.1936
41.	Best k=0.714,Best Ω =0.5 , SSE = 0.069
42.	Best k=0.704,Best Ω =0.5 , SSE = 0.1763
43.	Best k=0.7,Best Ω =0.5 , SSE = 0.2421
44.	Best k=0.711,Best Ω =0.5 , SSE = 0.028
45.	Best k=0.723,Best Ω =0.5 , SSE = 0.3159
46.	Best k=0.701,Best Ω =0.5 , SSE = 0.2264
47.	Best k=0.699,Best Ω =0.5 , SSE = 0.2573
48.	Best k=0.696,Best Ω =0.5 , SSE = 0.3006
49.	Best k=0.71,Best Ω =0.5 , SSE = 0.0536
50.	Best k=0.691,Best Ω =0.5 , SSE = 0.3665
51.	Best k=0.692,Best Ω =0.5 , SSE = 0.3538
52.	Best k=0.704,Best Ω =0.5 , SSE = 0.1763
53.	Best k=0.715,Best Ω =0.5, SSE = 0.1164
54.	Best k=0.708,Best Ω =0.5 , SSE = 0.0991
55.	Best k=0.71,Best Ω =0.5 , SSE = 0.0536
56.	Best k= 0.712 , Best Ω= 0.5 , SSE=0.0
57.	Best k=0.711,Best Ω =0.5 , SSE = 0.0281
58.	Best k=0.709,Best Ω =0.5 , SSE = 0.0771
59.	Best k=0.702,Best Ω =0.5 , SSE = 0.2103
60.	Best k=0.702,Best Ω =0.5 , SSE = 0.2103
61.	Best k=0.711,Best Ω =0.5 , SSE = 0.0281
62.	Best k=0.709,Best Ω =0.5 , SSE = 0.0771
63.	Best k=0.711,Best Ω =0.5 , SSE = 0.0281
64.	Best k=0.699,Best Ω =0.5 , SSE = 0.2573
65.	Best k=0.711,Best Ω =0.5 , SSE = 0.0281
66.	Best k=0.709,Best Ω =0.5 , SSE = 0.0771
67.	Best k=0.686,Best Ω =0.5 , SSE = 0.4265

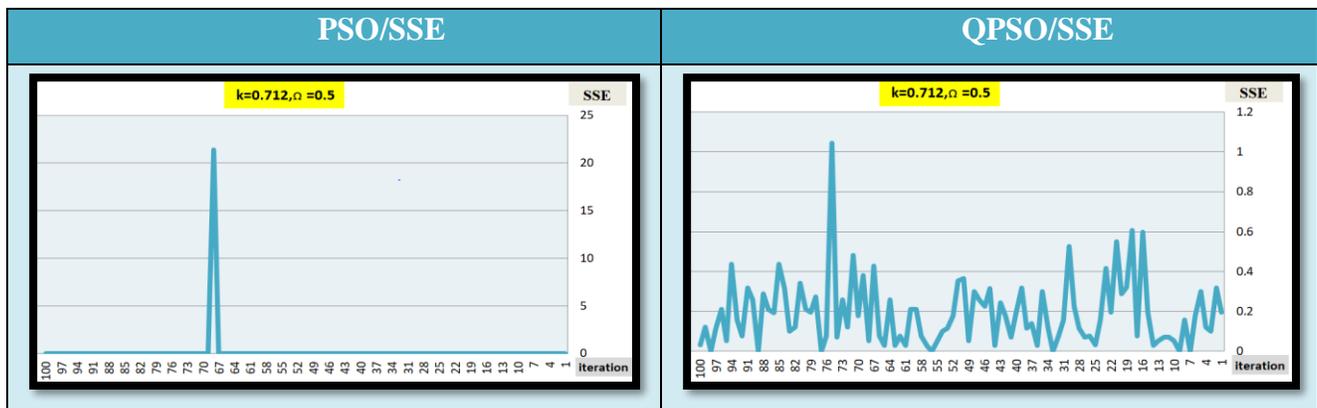
68.	Best $k=0.71$, Best $\Omega=0.5$, SSE = 0.0536
69.	Best $k=0.69$, Best $\Omega=0.5$, SSE = 0.3789
70.	Best $k=0.704$, Best $\Omega=0.5$, SSE = 0.1763
71.	Best $k=0.681$, Best $\Omega=0.5$, SSE = 0.4806
72.	Best $k=0.707$, Best $\Omega=0.5$, SSE = 0.1198
73.	Best $k=0.699$, Best $\Omega=0.5$, SSE = 0.2573
74.	Best $k=0.714$, Best $\Omega=0.5$, SSE = 0.069
75.	Best $k=0.652$, Best $\Omega=0.5$, SSE = 1.0441
76.	Best $k=0.709$, Best $\Omega=0.5$, SSE = 0.0771
77.	Best $k= 0.712$, Best $\Omega= 0.5$, SSE=0.0
78.	Best $k=0.698$, Best $\Omega=0.5$, SSE = 0.2721
79.	Best $k=0.716$, Best $\Omega=0.5$, SSE = 0.1941
80.	Best $k=0.702$, Best $\Omega=0.5$, SSE = 0.2103
81.	Best $k=0.693$, Best $\Omega=0.5$, SSE = 0.3409
82.	Best $k=0.707$, Best $\Omega=0.5$, SSE = 0.1198
83.	Best $k=0.708$, Best $\Omega=0.5$, SSE = 0.0991
84.	Best $k=0.695$, Best $\Omega=0.5$, SSE = 0.3143
85.	Best $k=0.685$, Best $\Omega=0.5$, SSE = 0.4379
86.	Best $k=0.703$, Best $\Omega=0.5$, SSE = 0.1936
87.	Best $k=0.702$, Best $\Omega=0.5$, SSE = 0.2103
88.	Best $k=0.697$, Best $\Omega=0.5$, SSE = 0.2865
89.	Best $k= 0.712$, Best $\Omega= 0.5$, SSE=0.0
90.	Best $k=0.699$, Best $\Omega=0.5$, SSE = 0.2573
91.	Best $k=0.725$, Best $\Omega=0.5$, SSE = 0.3179
92.	Best $k=0.709$, Best $\Omega=0.5$, SSE = 0.0771
93.	Best $k=0.705$, Best $\Omega=0.5$, SSE = 0.1583
94.	Best $k=0.685$, Best $\Omega=0.5$, SSE = 0.4379
95.	Best $k=0.71$, Best $\Omega=0.5$, SSE = 0.0536
96.	Best $k=0.702$, Best $\Omega=0.5$, SSE = 0.2103
97.	Best $k=0.715$, Best $\Omega=0.5$, SSE = 0.1164
98.	Best $k= 0.712$, Best $\Omega= 0.5$, SSE=0.0
99.	Best $k=0.707$, Best $\Omega=0.5$, SSE = 0.1198
100.	Best $k=0.713$, Best $\Omega=0.5$, SSE = 0.0317

The tables (4.9, 4.10, 4.11, and 4.12) show the PSO algorithm is better than the QPSO algorithm in the process of estimating the two parameters (k and Ω) in a circle map.

Comparison of the two parameters of the circle map obtained by the PSO and QPSO algorithms by performing the fitness function. The figure (4.4) shows the convergence times of fitness function values using two algorithms, PSO and QPSO. If MSE/SSE is zero, then the algorithm has reached the actual value of the parameters.



(a) MSE as Fitness Function



(b) SSE as Fitness Function

Figure 4.4: Reaches the Best and Worst Values Run 100 Times to Estimate the Parameter Circle Map where $k=0.712$ and $\Omega=0.5$.

To reduce the randomness of the algorithms (PSO and QPSO) and analyze the security of the chaotic map (logistic map and circle map), the parameter estimation program is executed several times and then we choose the best 100 estimated results for the parameters. Then we calculate the success rate of the algorithms in the process of estimating the values according to equation (2.27). The numbers in the tables indicate the success rate of the PSO and the QPSO algorithm in estimating the parameters.

Table 4.13: Parameter Estimation Results by (PSO /QPSO); MSE Measure is used as Fitness Function.

No	VALUE(r)	PSO	QPSO
1.	5.66	59%	50%
2.	3.76	55%	43%
3.	3.85	84%	40%

Table 4.14: Parameter Estimation Results by (PSO /QPSO); SSE Measure is used as Fitness Function.

No	VALUE(r)	PSO	QPSO
1.	3.66	46%	50%
2.	3.76	75%	52%
3.	3.85	84%	32%

The results tables (4.13, 4.14) show that the logistic map parameter can be estimated accurately. The results in the tables show that the PSO algorithm is better than the QPSO algorithm if "r " is equal to two values after the separator.

Table 4.15: Parameter Estimation Results by (PSO /QPSO); MSE Measure is used as Fitness Function.

No	VALUE(r)	PSO	QPSO
1.	3.5	93%	99%
2.	3.6	66%	100%
3.	3.7	90%	100%
4.	3.8	48%	98%
5.	3.9	85%	98%
6.	4	83%	100%

Table 4.16: Parameter Estimation Results by (PSO /QPSO); SSE Measure is used as Fitness Function.

No	VALUE(r)	PSO	QPSO
1.	3.5	93%	98%
2.	3.6	94%	99%
3.	3.7	87%	98%
4.	3.8	73%	96%
5.	3.9	88%	99%
6.	4	78%	97%

Table 4.17: Parameter Estimation Results by (PSO /QPSO); MSE Measure is used as Fitness Function.

No	VALUE(r)	PSO	QPSO
1.	3.698	19%	20%
2.	3.7862	2%	5%
3.	3.9433	0%	2%
4.	3.8231	3%	5%
5.	3.754	14%	17%
6.	3.823	8%	10%
7.	3.934	5%	8%

Table 4.18: Parameter Estimation Results by (PSO /QPSO); SSE Measure is used as Fitness Function.

No	VALUE(r)	PSO	QPSO
1.	3.698	8%	8%
2.	3.7862	3%	8%
3.	3.9433	0%	2%
4.	3.8231	0%	1%
5.	3.754	24%	8%
6.	3.823	12%	14%
7.	3.935	7%	7%

The results tables (4.15,4.16,4.17,and 4.18) show that the logistic map parameter can be estimated accurately. The results in the tables show that the QPSO algorithm is better than the PSO algorithm if "r " is equal to one or three or more values after the separator. There are few cases in which the PSO is better, for example(r = 3.754) a higher success rate appeared as shown in the table (4.18).

Table 4.19: Parameter Estimation Results by (PSO / QPSO); MSE Measure is used as a Fitness Function.

No	Value	PSO	QPSO
1.	$K = 0.712$	99	10
2.	$\Omega = 0.5$	100	100
3.	$\Omega = 0.5, K = 0.712$	99	10

Table 4.20: Parameter Estimation Results by (PSO / QPSO); SSE Measure is used as a Fitness Function.

No	Value	PSO	QPSO
1.	$K = 0.712$	99	7
2.	$\Omega = 0.5$	100	100
3.	$\Omega = 0.5, K = 0.712$	99	7

*Note: Field No. (3), the two tables above show the success rate of the algorithms in showing (k, Ω) together.

It was concluded from the tables (4.19, 2.20) the PSO algorithm is better than the QPSO algorithm during the execution of the program estimating parameters of the circle map.

The value of the parameter $K = 0.712$, in some executions the PSO algorithm fails in estimating the same value, but the value of the parameter $\Omega = 0.5$ in very few executions the PSO/QPSO algorithms fail in estimating. When two parameters are executed together, the success rate of the PSO algorithm is higher than the QPSO algorithm.

The meta-heuristic algorithms (PSO and QPSO) do not always guarantee the same success rate in executing the program of the estimation for the parameters of the chaotic maps (logistic map and circle map) in the future.

4.4 Test the Quality of Speech Descrambling

In this section, speech descrambling is taken as a case study, and speech descrambling is based on parameter estimation of the chaotic map (logistic map and circle map) using two meta-heuristic algorithms (PSO and QPSO). The two

objective measures are used (signal-to-noise ratio (SNR), correlation coefficient (CC)), which are performed between the original speech and recovered speech.

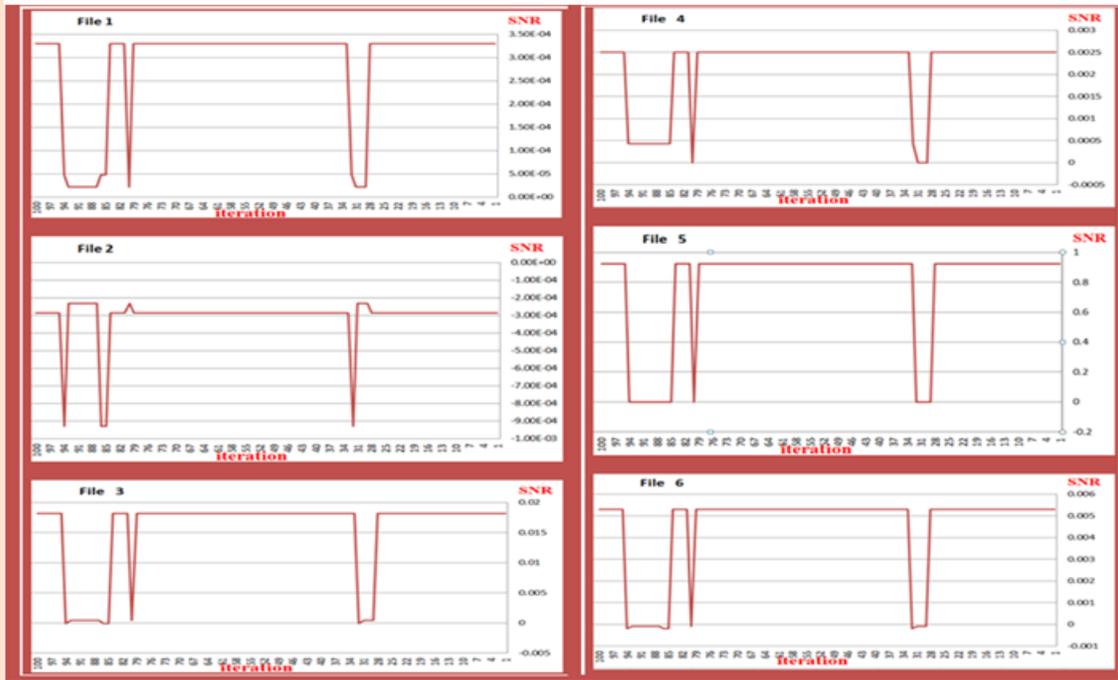
The following figures show the test results of the speech descrambling that was used as a case study for the parameters estimation process of the chaotic map (logistic map and circle map). In the figures below, six audio files of different lengths and genders are used. The information of the audio files is found in the table (4.2).

The parameter estimation program was executed 100 times in order to estimate parameter 'r' (logistic map) where $r=3.9$ based on meta-heuristic algorithms (PSO/QPSO), and (MSE/SSE) as fitness functions with the algorithms PSO and QPSO, then entered the estimated value (r) on the speech descrambling process. The recovered speech signal is measured by SNR and CC.

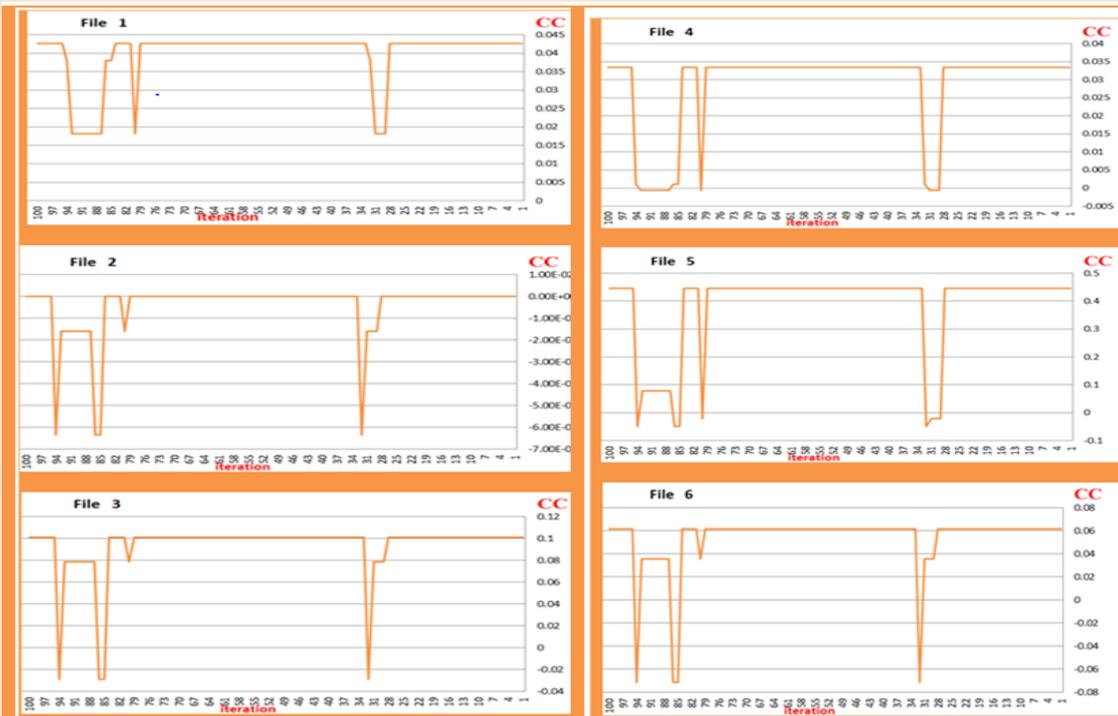
Case study 1:

Figure (4.5) shows the results of speech descrambling signal by using PSO algorithm to estimate the parameter 'r' in the logistic equation. This parameter is used as a key in the speech descrambling process.

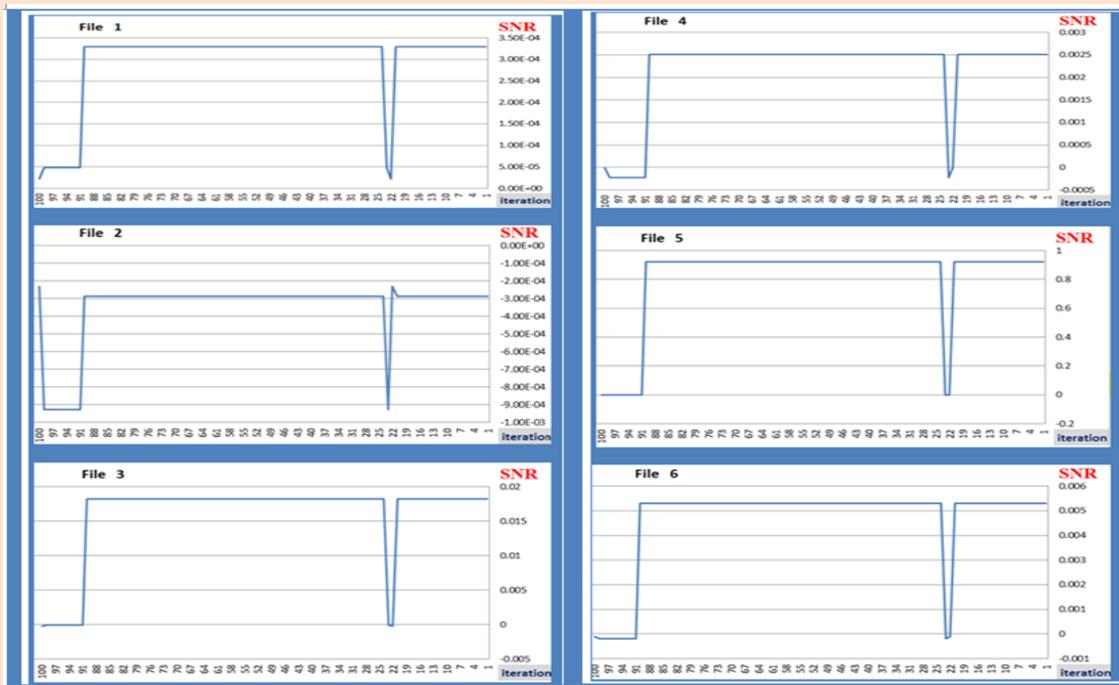
(a) PSO algorithm /MSE as fitness function / SNR measure



(b) PSO algorithm /MSE as fitness function /CC measure



(c) QPSO algorithm / SSE as fitness function / SNR measure



(d) PSO algorithm / SSE as fitness function / CC measure

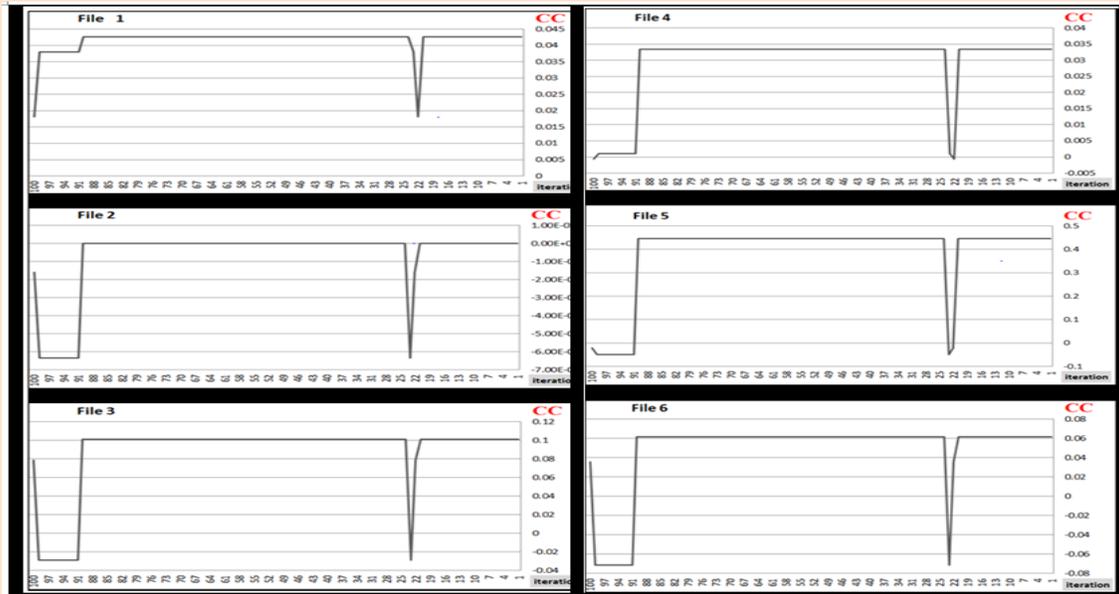
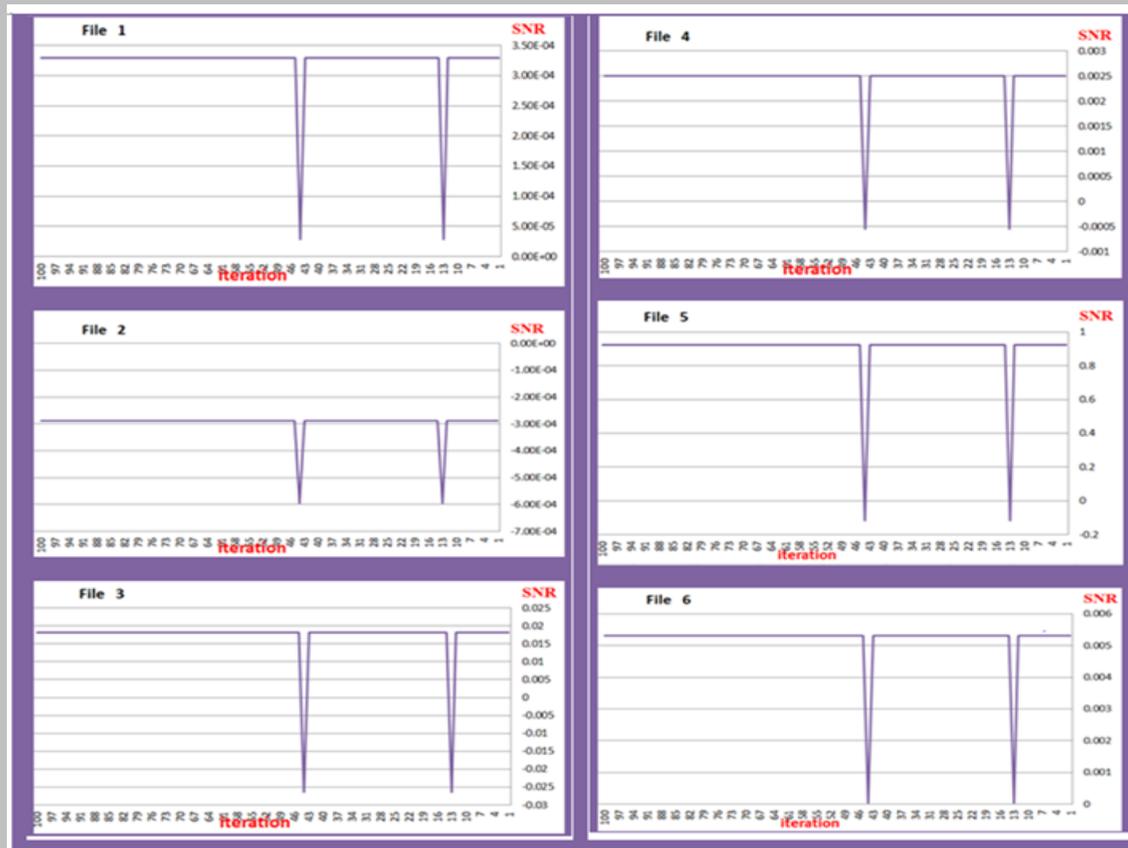


Figure (4.5) Accessing the Best and Worst Values for Test Speech Descrambler Based on Parameter Estimation

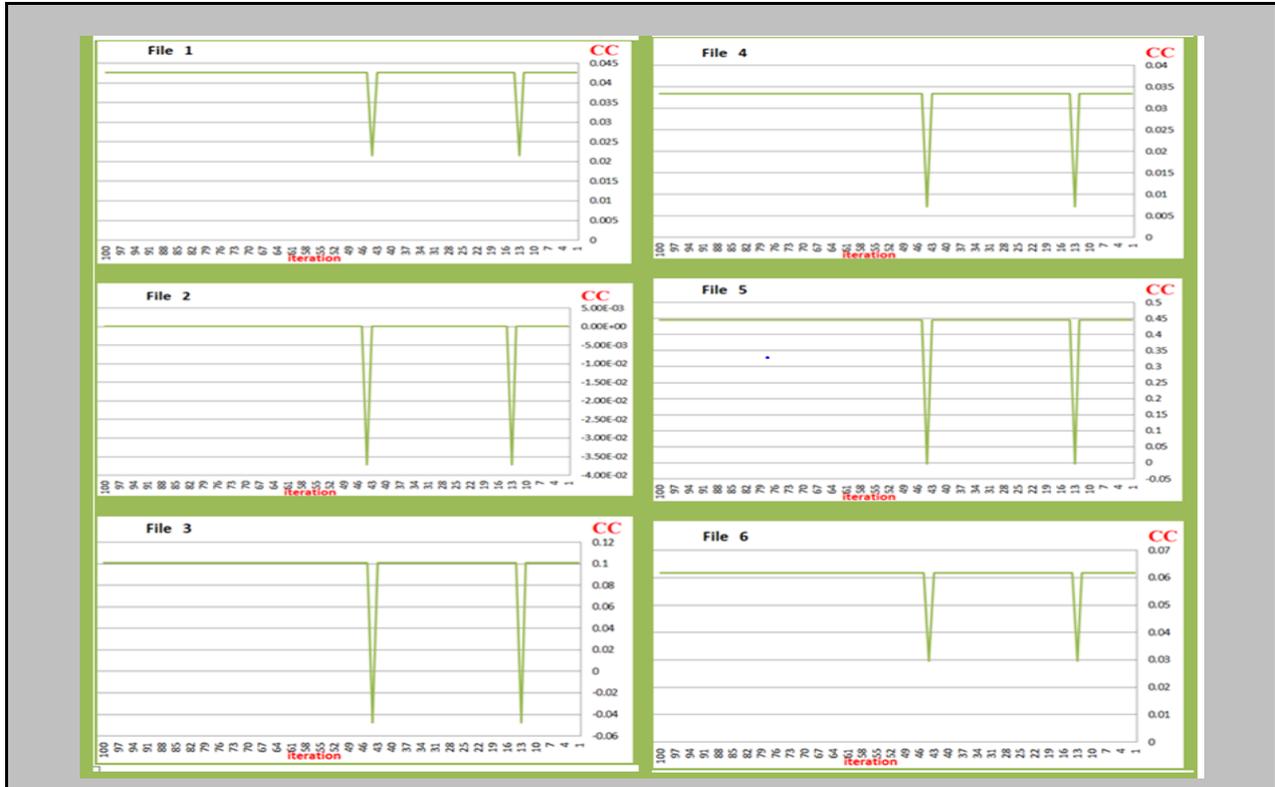
Case study 2:

Figure (4.6) shows the results of speech descrambling signal by using QPSO algorithm to estimate the parameter 'r' in the logistic equation. This parameter is used as a key in the speech descrambling process.

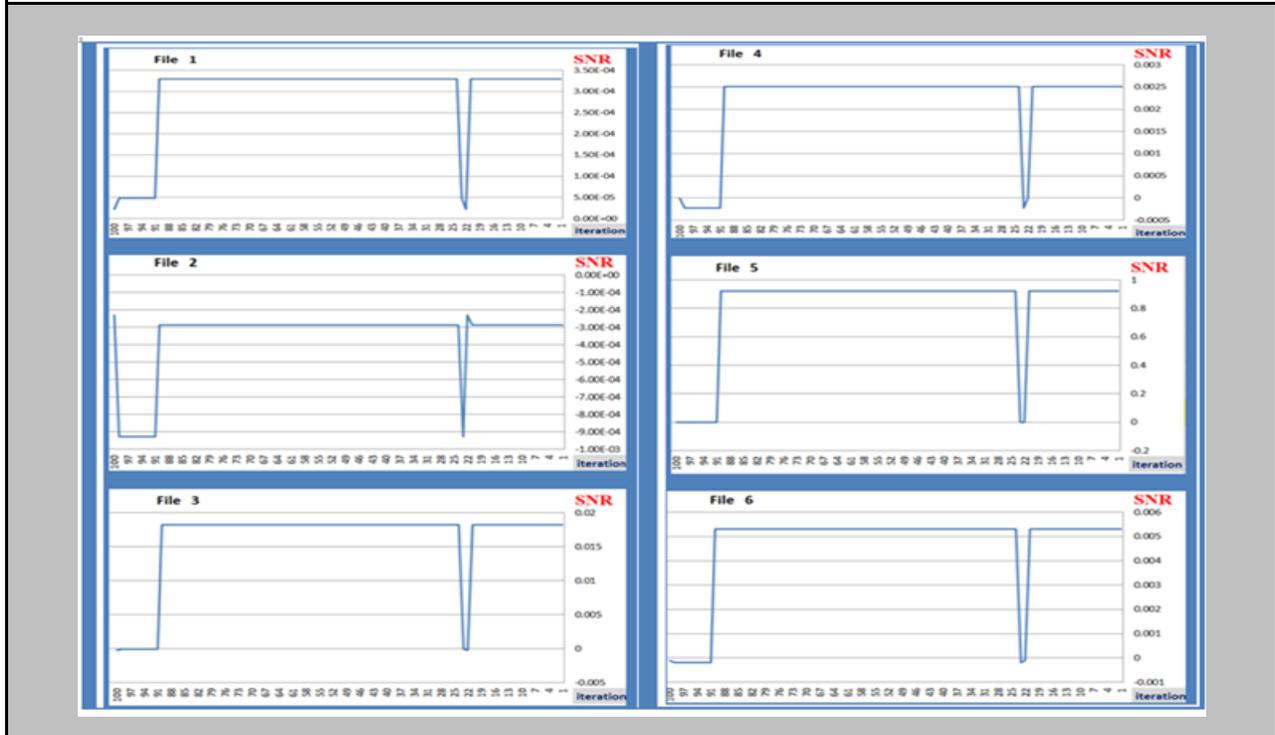
(a) QPSO algorithm /MSE as fitness function /SNR measure



(b) QPSO algorithm /MSE as fitness function /CC measure



(c) QPSO algorithm /SSE as fitness function /SNR measure



(d) QPSO algorithm / SSE as fitness function / CC measure

Figure (4.6) Accessing the Best and Worst Values for Test Speech Descrambler Based on Parameter Estimation.

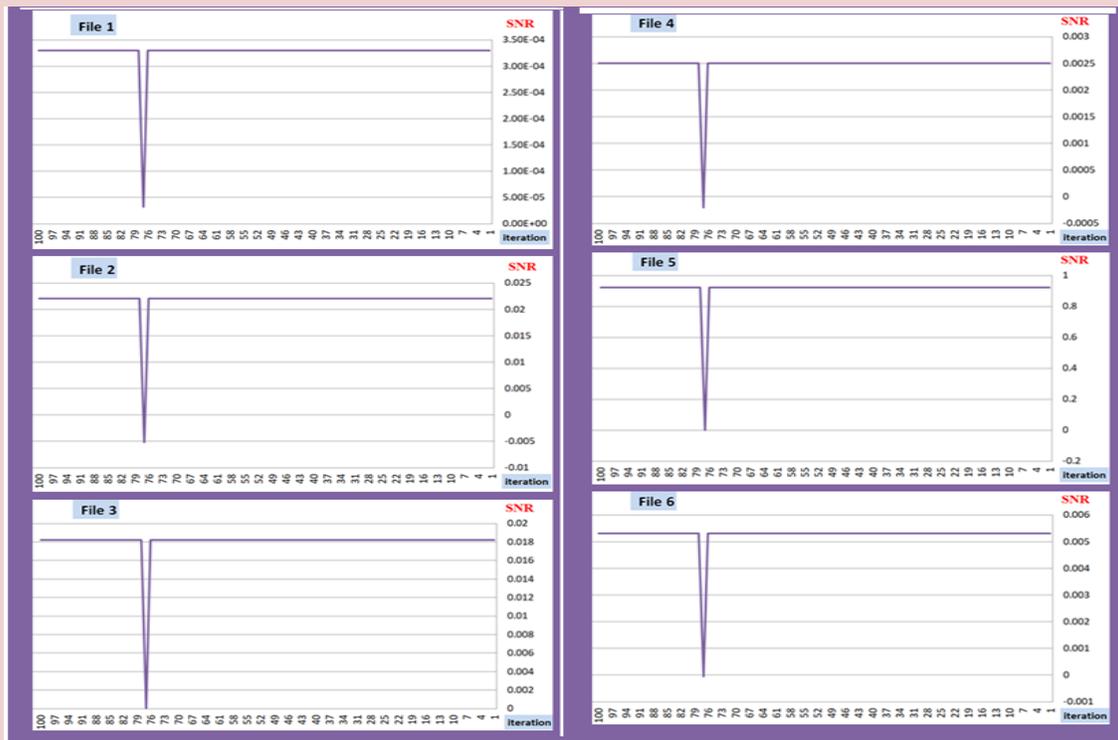
Figures (4.5,4.6) show results of test speech descrambling based on an estimated parameter (r), was used two measures to measure recovered speech are SNR and CC measures when the SNR is high, the recovered speech signal is good, and when $CC = -1$ then both samples (original speech and recovered speech) go in an opposite direction, and if $CC = +1$ then both samples (original speech and recovered speech) goes in an equal direction.

The parameters estimation program was executed 100 times in order to estimate parameters (K, Ω) in a circle map where $K = 0.712$, $\Omega = 0.5$ based on meta-heuristic algorithms (PSO/QPSO), and (MSE/SSE) as fitness functions with the algorithms PSO and QPSO, then entered the estimated values (K, Ω) on the speech descrambling process. The recovered speech signal is measured by SNR and CC.

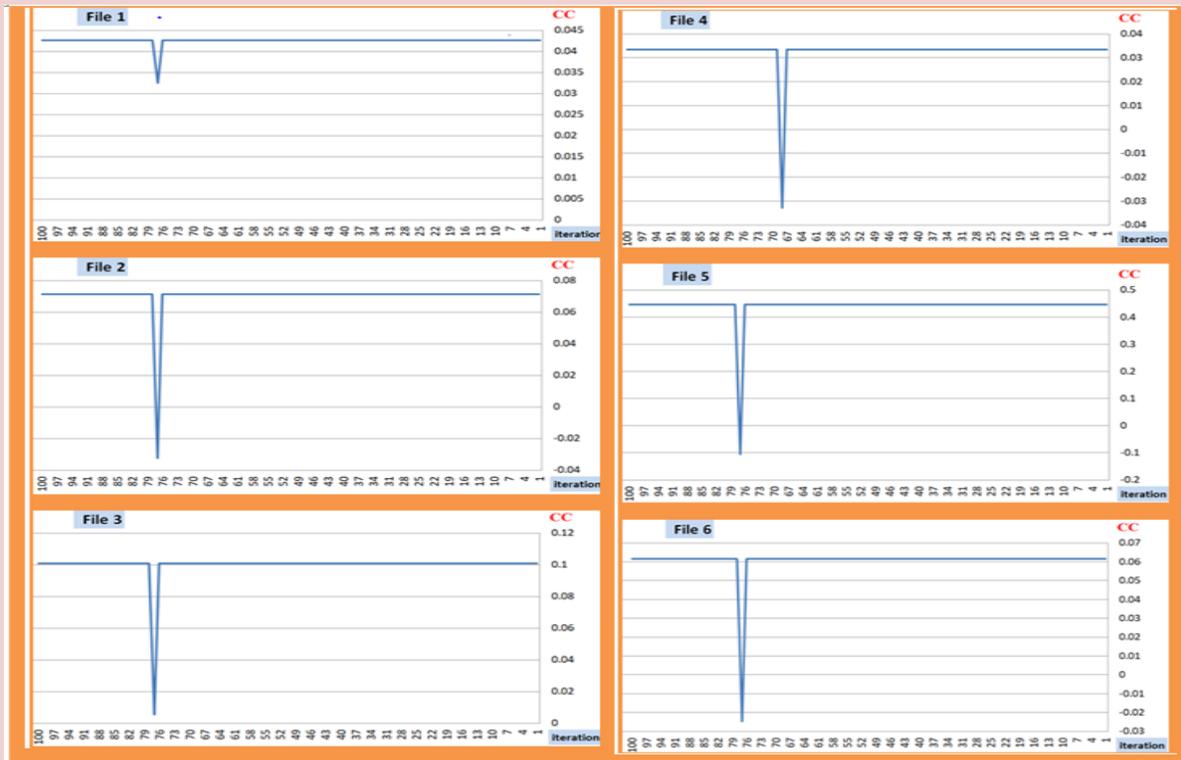
Case study 3

Figure (4.7) shows the results of speech descrambling signal when using the PSO algorithm to estimate the parameters (K, Ω) in the circle equation.

(a) PSO algorithm /MSE as fitness function / SNR measure



(b) PSO algorithm /MSE as fitness function / CC measure



(c) PSO algorithm /SSE as fitness function / SNR measure



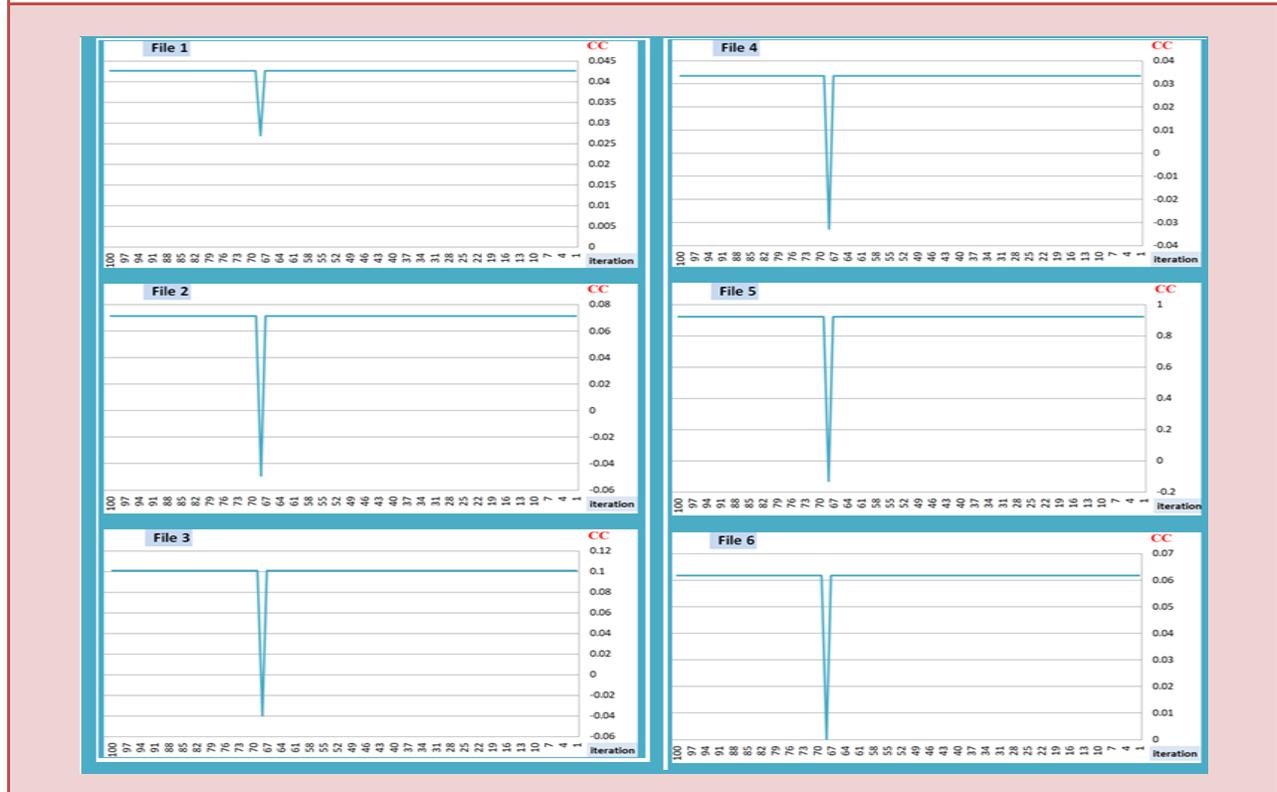
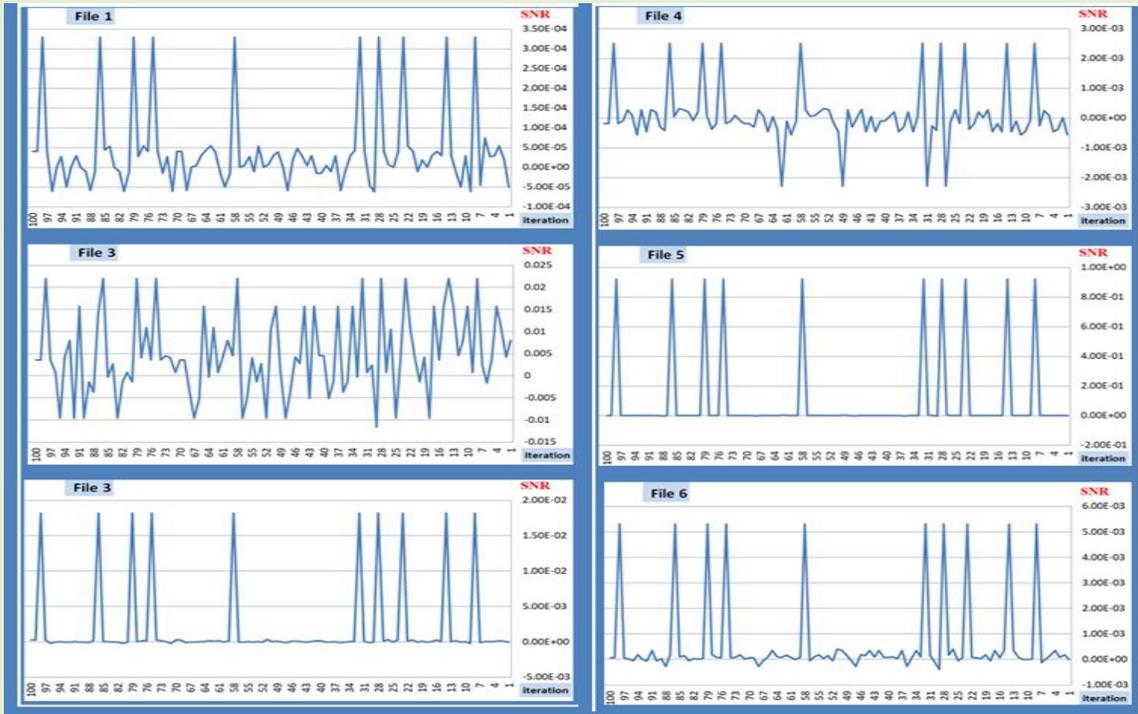
(d) PSO algorithm /SSE as fitness function / CC measure

Figure (4.7) Accessing the Best and Worst Values for Test Speech Descrambler Based on Parameter Estimation

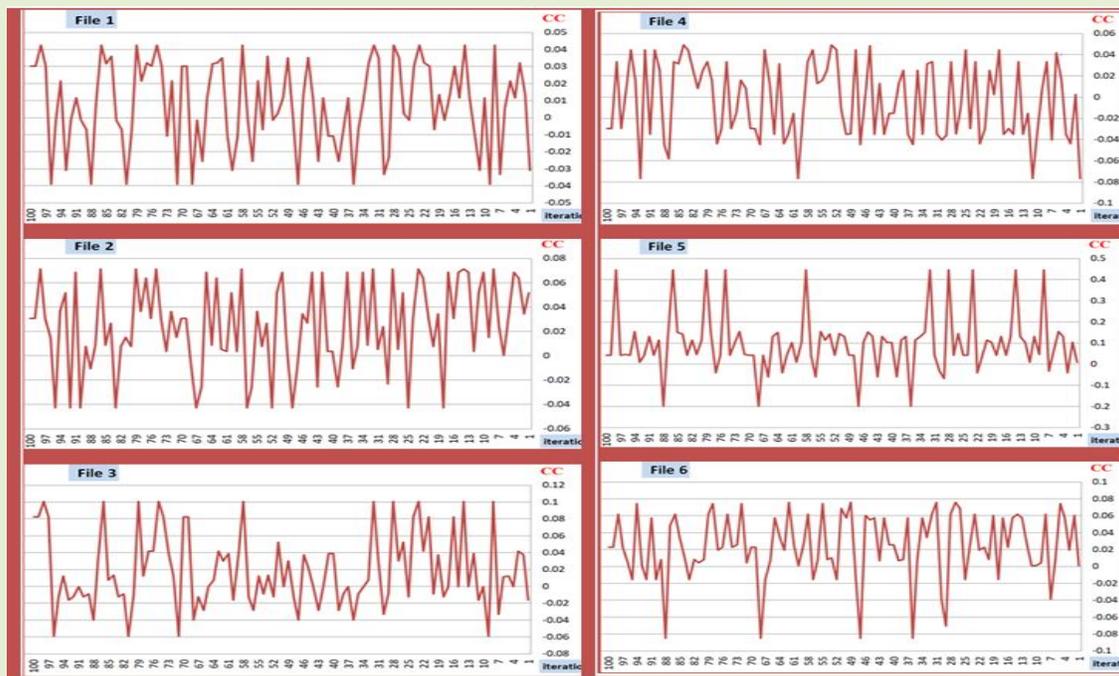
Case study 4:

Figure (4.8) shows the results of speech descrambling signal when using the QPSO algorithm to estimate the parameters (K, Ω) in the circle equation.

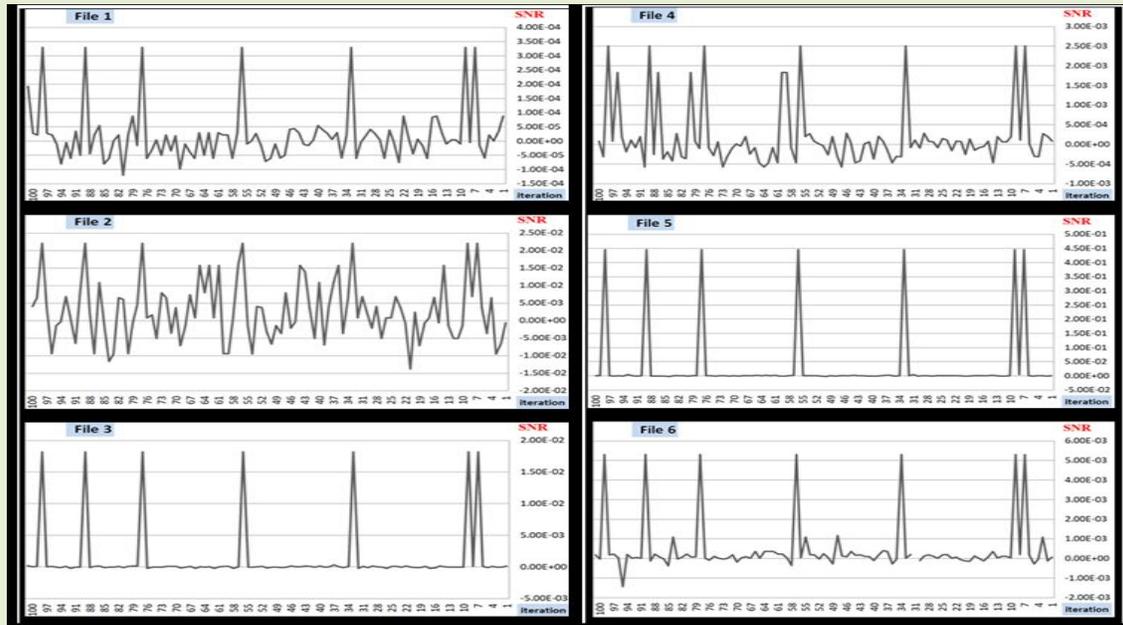
(a) QPSO algorithm /MSE as fitness function / SNR measure



(b) QPSO algorithm /MSE as fitness function / CC measure



(c) QPSO algorithm /SSE as fitness function / SNR measure



(d) QPSO algorithm /SSE as fitness function / SNR measure

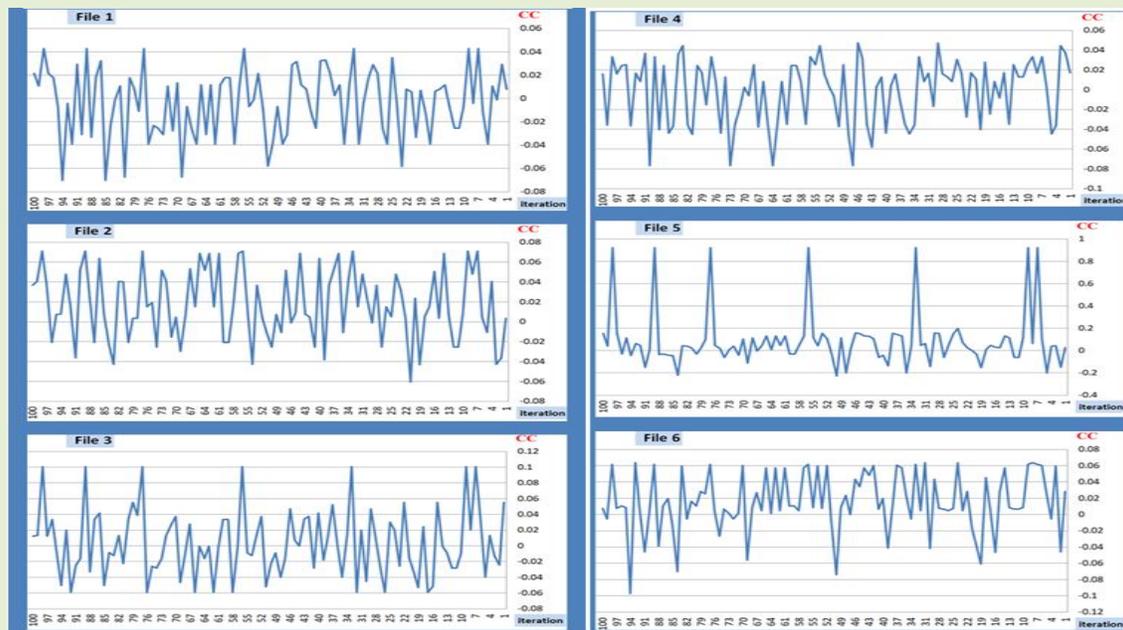


Figure (4.8) Accessing the Best and Worst Values for Test Speech Descrambler Based on Parameter Estimation

Figures (4.7,4.8) show results of test speech descrambling based on the estimation of the two parameters (K, Ω) , were used two measures to measure recovered speech are SNR and CC measures when the SNR is high, the recovered speech signal is good, and when $CC = -1$ then both samples (original speech and recovered speech) go in an opposite direction, and if $CC = +1$ then both samples (original speech and recovered speech) goes in an equal direction.

The researcher check the speech signal using subjective tests as listeners for six audio files that are taken for this test. Figures (4.9, 4.10) show the waveform difference between the original and scrambled speech signal, and the difference between the scrambled and descrambled speech signal.



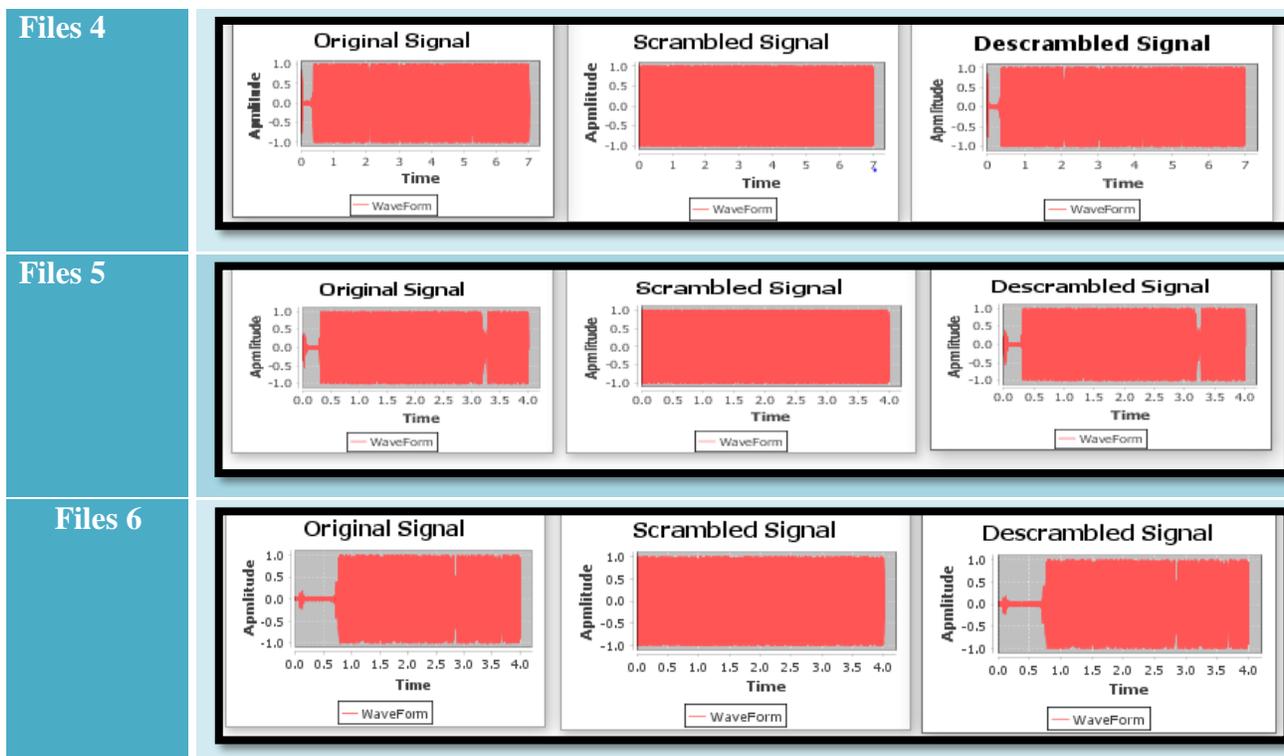
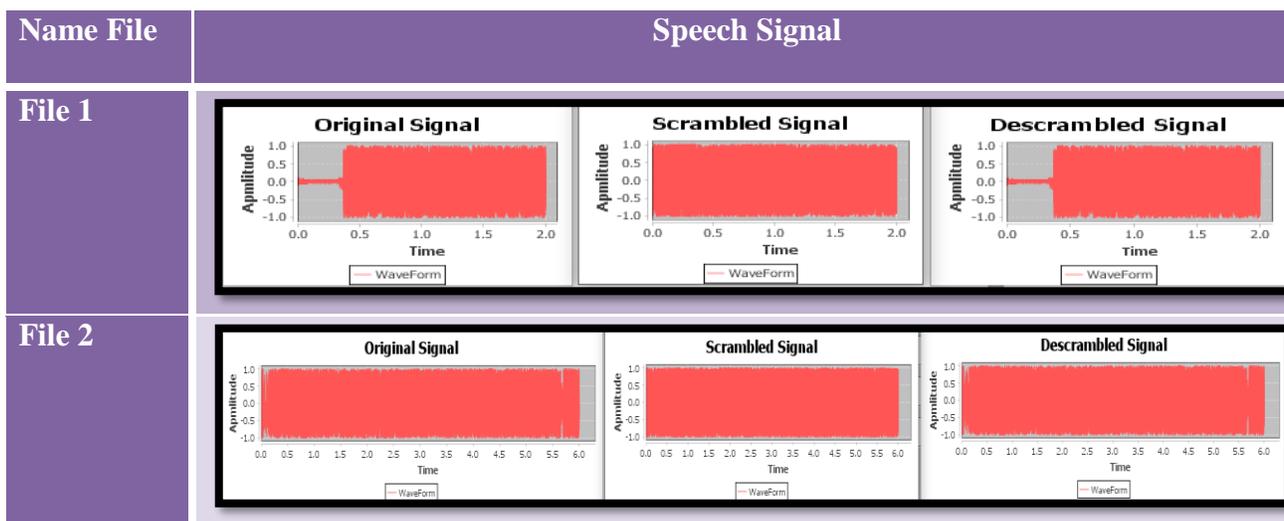


Figure (4.9) Original, Scrambled, and Descrambling Speech.

The figure (4.9) shows result the speech scrambling based on the logistic map, which is used as a secret key , where $r = 3.9$, in descrambling process, which is based on an estimate of a parameter (r), so that the same value would appear.



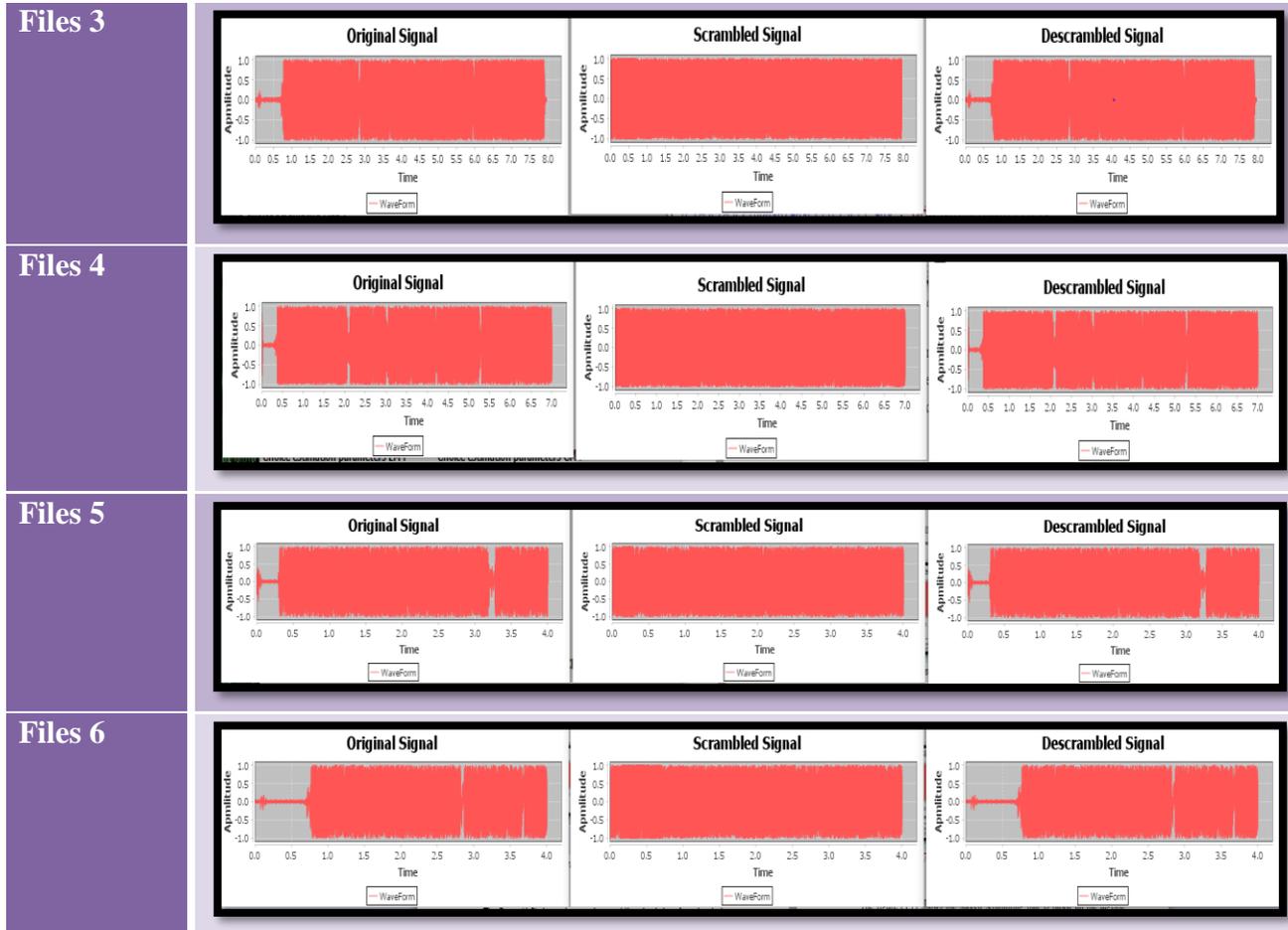


Figure (4.8) Original, Scrambled, and Descrambling Speech.

The figure (4.8) shows result the speech scrambling based on the circle map, which is used as a secret key , where $K=0.712$, $\Omega=0.5$, in descrambling process, which is based on two and an estimation of the parameters (K , Ω), so that the same values would appear.

Chapter Five

Conclusion and Future Works

*Chapter five**Conclusion and Future Works***5.1 Conclusions**

Parameters estimation of chaotic systems was modeled as a one-dimensional chaotic map. This thesis introduced a system of the chaotic parameters estimation based on meta-heuristic algorithms: speech descrambling case study. The two meta-heuristic algorithms used are particle swarm optimization(PSO) and the quantum particle swarm optimization(QPSO) algorithms of the estimation of the parameters of chaotic maps are logistic map and circle map. The minimum the mean square error (MSE) and the sum square error (SSE) are used as the PSO and QPSO algorithms' fitness functions. The researcher concludes the following:-

1. The QPSO algorithm is better than the PSO algorithm in the process of estimating the logistic parameter (r), but the PSO algorithm is better than the QPSO algorithm in the process of estimating the logistic parameter if the value (r) has two values after the separator (ex. $r=3.66$), then the PSO algorithm is better at the parameter estimation process of the logistic map.
2. The PSO algorithm is better than the QPSO algorithm in the process of estimating the two parameters (k and ω) in a circle map.
3. Statistical measurements between speech signals (original, scrambled, and recovered) show the good performance of the proposed system.

5.2 Future Work

Based on the results that are achieved in this thesis, the researcher can be extended in the future according to the following suggested items:

1. Using more chaotic maps to estimate parameters that have three or more parameters using meta-heuristic algorithms.
2. Using more meta-heuristic algorithms to estimate the parameters of chaotic maps.
3. Using more metrics to measure speech signals.

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Appendix A

The Published Paper

1st Babylon International Conference on Information Technology and Science 2021 (BICITS 2021)- Babil- IRAQ

Speech Descrambling Based on Chaotic Parameter Estimation

Duaa Abdulrida
Department of Software, College of IT
University of Babylon
Babil, IRAQ
duaa.rida@student.uobabylon.edu.iq

Nidaa A. Abbas
Department of Software, College of IT
University of Babylon
Babil, IRAQ
nidaa.abbas@uobabylon.edu.iq

Abstract—The growth of wireless technologies and the use of computer networks have compromised data. Speech scrambling is an essential method of understandable speech elimination and improves information protection in wireless communication applications. The scrambling and descrambling methods have an opposite relation. A chaotic system is a dynamic and deterministic nonlinear system. Its performance is almost random, and states produce chaotic systems dependent on the initial conditions and system parameters and are essential for scrambling speech applications because of their characteristics. This paper suggested using an estimate of the chaotic map parameter, including a logistic map for descrambling speech, and an estimate of the parameter using the meta-heuristic method, including particle swarm optimization (PSO) and quantum particle swarm optimization (QPSO). We suggested minimizing mean square error (MSE) as an objective function. The simulation results show that QPSO is better than PSO for a logistic map's estimated parameter. The signal-to-noise ratio (SNR) was used to measure speech quality.

Keyword—Descrambling Speech, Chaotic Map, Parameter, Particle Swarm Optimization, Quantum Particle Swarm Optimization estimate.

I. INTRODUCTION

With the rapid developments of wireless communication, network attack tools and techniques have been developed, so wireless security methods have been developed to protect people's communications [1]. Encoding schemes suggest many algorithms to protect multimedia data, such as speech signals, photographs, and video clips [2].

The scrambling method can be categorized as analog and digital scrambling. Scrambling speech is a technique used to convert intelligible speech into unintelligible speech. It is hard to decode in the absence of a key; it is used to avoid attackers and eavesdroppers. It also plays an essential role in securing speech when transmitted through insecure channels [3].

Chaos is a characteristic that can be categorized for nonlinear systems and is an unstable restrained dynamic behavior that shows a sensitive dependence on primary conditions and includes infinitely unstable periodic motions [4]. In previous decades, many scientists focused on controlling and synchronizing a chaotic system applied to a wide field of information security [5]. Several strategies operate under the assumption that chaotic systems are known in advance. It is challenging to define parameters in the real world due to the complexity of chaotic systems [6]. Besides, not all dynamic parameters are known despite physical information for these systems [7].

The problem study of parameter estimation has a long history. In this system, the chaotic logistical system's parameter estimation is proposed. The logistic map is One-dimensional and was discovered by Pierre Verhulst in 1845 [8].

The meta-heuristic algorithm is one of the most popular methods of effectively estimating chaotic system parameters. It is characterized by good durability and ease of implementation, such as Genetic Algorithm (GA) Particle Swarm Optimization Algorithm (PSO), PSO Hybrid Algorithm, etc. However, all of these

systems want to get the original system's primary values. It changes parameter estimation to an optimization problem, and prior knowledge for estimating parameters only takes some pseudo-random sequences resulting from chaotic systems as samples [5, 9].

The particle swarm algorithm (PSO) starts with collecting random solutions in the search space and is scanning for an ideal solution by transforming potential solutions across generations [10]. Through the PSO, the perfect solution will be obtained. In PSO, there are two types of (solution) particles, i.e., the best and universally fine particles. The quantum particle swarm optimization (QPSO) algorithm is a probabilistic algorithm. It requires fewer parameters than PSO and is easier to implement, needs no particle velocity vectors [10]. The optimal solution using two algorithms be obtained by detecting the lowest error rate (fitness function) using the minimum mean square error (MSE) [11]. Using PSO and QPSO, this paper estimates the logistic map's chaotic map parameter. The logistic map is the key to encoding the original speech in the scrambling process. In the descrambling process, the logistic map is used based on an estimate of the parameter to detect original speech. The SNR is used to calculate speech signal after descrambling process; if the SNR is high will remain the estimated value is the same; Otherwise, it will be replaced.

II. RELATED WORK

In [12] proposed parameter estimation method with three completely unknown parameters of the chaotic system (Lorenz and Rossler Chaotic System) applying evolutionary algorithms fireworks algorithm (FWA) showed computational performance well, accuracy better, and robustness. FWA is a better estimate for parameters.

In [13], the proposed algorithm for parameter identification problems is the Parallel Chaos Optimization Algorithm (PCOA) master-slave model (PCOA) (referred to as MSM-PCOA) is a new global optimization algorithm. MSM-PCOA is implemented to identify two complex systems: a bi-directional inductive power transmission system and chaotic systems. Simulations, outcomes, and compared with other optimization algorithms show that MSM-PCOA has a better performance for parameter identification.

In [5] proposed improving a parameter estimation method with unknown primary values using a new algorithm named the Chaos Behavior particle swarm improvement algorithm. The results of the algorithm were reasonable compared to other algorithms.

In [14] proposed parameter estimation for a one-dimensional chaotic system for parameter estimation by using two steps: the first step is preprocessing of the measures through the guaranteed method, and the results of the guaranteed estimation are interval estimates for unknown variables (the primary condition and parameter of the chaotic map). The second step is to reduce the objective function by using particle swarm optimization. The

Appendix B

The parameter estimation program was implemented 100 times for estimating 'r' in the logistic equation where $r = 3.9$ based on meta-heuristic algorithms (PSO/QPSO), used (MSE/SSE) as a fitness function with PSO and QPSO algorithms, then entered the parameter (r) in the descrambling speech process, then the recovered speech signal is measured by SNR and CC.

▪ Case study 1:

Table 1: Accessing the best and worst values for test speech descrambler based on parameter estimation(logistic map) .

(a) MSE is Fitness Function., File 1 is Audio File.

No	r/PSO/MSE	File 1/SNR	File 1 / Rc	r/QPSO/MSE	File 1 / SNR	File 1/ Rc
1	3.9	0.00032	0.04265	3.9	0.00032	0.04265
		
12	3.9	0.00032	0.04265	3.9	0.00032	0.04265
13	3.9	0.00032	0.04265	2.5	0.000028	0.02146
14	3.9	0.00032	0.04265	3.9	0.00032	0.04265
		
28	3.9	0.00032	0.04265	3.9	0.00032	0.04265
29	-1322775.3	0.000022	0.01822	3.9	0.00032	0.04265
	-1212210.5	0.000022	0.01822	3.9	0.00032	0.04265
31	-1925732.8	0.000022	0.01822	3.9	0.00032	0.04265
32	202492.7	0.000047	0.03803	3.9	0.00032	0.04265
33	3.9	0.00032	0.04265	3.9	0.00032	0.04265
		
43	3.9	0.00032	0.04265	3.9	0.00032	0.04265
44	3.9	0.00032	0.04265	2.5	0.000028	0.02146
45	3.9	0.00032	0.04265	3.9	0.00032	0.04265
79	3.9	0.00032	0.04265	3.9	0.00032	0.04265
80	-26091.4	0.000022	0.01822	3.9	0.00032	0.04265
81	3.9	0.00032	0.04265	3.9	0.00032	0.04265
		
84	3.9	0.00032	0.04265	3.9	0.00032	0.04265
85	3.03360952E7	0.000047	0.03803	3.9	0.00032	0.04265
86	2.58500963E7	0.000047	0.03803	3.9	0.00032	0.04265
87	-5.10244393E7	0.000022	0.01822	3.9	0.00032	0.04265
88	-1.924944138E8	0.000022	0.01822	3.9	0.00032	0.04265
89	-2.41967731E7	0.000022	0.01822	3.9	0.00032	0.04265
90	-9447410.9	0.000022	0.01822	3.9	0.00032	0.04265
91	-1467272.6	0.000022	0.01822	3.9	0.00032	0.04265
92	-986878.4	0.000022	0.01822	3.9	0.00032	0.04265
93	-6389896.6	0.000022	0.01822	3.9	0.00032	0.04265
94	559223.0	0.000047	0.03803	3.9	0.00032	0.04265
95	3.9	0.00032	0.04265	3.9	0.00032	0.04265
		

100	3.9	0.00032	0.04265	3.9	0.00032	0.04265
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(b) SSE is Fitness Function, File 1 is Audio File.

No.	r/PSO/ SSE	File 1/ SNR	File1/ Rc	r/QPSO/SSE	File 1/ SNR	File 1/ Rc
1	3.9	0.00032	0.04265	3.9	0.00032	0.04265
		
9	3.9	0.00032	0.04265	3.9	0.00032	0.04265
10	3.9	0.00032	0.04265	2.5	0.000028	0.02146
11	3.9	0.00032	0.04265	3.9	0.00032	0.04265
		
21	3.9	0.00032	0.04265	3.9	0.00032	0.04265
22	-341964.6	0.000022	0.01822	3.9	0.00032	0.04265
23	52689.8	0.000047	0.03803	3.9	0.00032	0.04265
24	3.9	0.00032	0.04265	3.9	0.00032	0.04265
		
90	3.9	0.00032	0.04265	3.9	0.00032	0.04265
91	8299830.4	0.000047	0.03803	3.9	0.00032	0.04265
92	2.0536991E7	0.000047	0.03803	3.9	0.00032	0.04265
93	1.77950045E7	0.000047	0.03803	3.9	0.00032	0.04265
94	2.54796405E7	0.000047	0.03803	3.9	0.00032	0.04265
95	5831634.0	0.000047	0.03803	3.9	0.00032	0.04265
96	1795970.7	0.000047	0.03803	3.9	0.00032	0.04265
97	972531.8	0.000047	0.03803	3.9	0.00032	0.04265
98	643826.1	0.000047	0.03803	3.9	0.00032	0.04265
99	2422843.6	0.000047	0.03803	3.9	0.00032	0.04265
100	-2864020.1	0.000022	0.01822	3.9	0.00032	0.04265

▪ Case study 2 :

Table 2: Accessing the best and worst values for test speech descrambler based on parameter estimation(logistic map) .

(a) MSE as Fitness Function, File 2 is Audio File

No	r/PSO/MSE	File 2 / SNR	File 2 / Rc	r/QPSO/MSE	File 2 / SNR	File 2/ Rc
1	3.9	-0.00028	0.000093	3.9	-0.00028	0.000093
		
12	3.9	-0.00028	0.000093	3.9	-0.00028	0.000093
13	3.9	-0.00028	0.000093	2.5	0.00119	-0.03712
14	3.9	-0.00028	0.000093	3.9	-0.00028	0.000093
		
28	3.9	-0.00028	0.000093	3.9	-0.00028	0.000093
29	-1322775.3	-0.00023	-0.01587	3.9	-0.00028	0.000093
30	-1212210.5	-0.00023	-0.01587	3.9	-0.00028	0.000093
31	-1925732.8	-0.00023	-0.01587	3.9	-0.00028	0.000093
32	202492.7	-0.00092	-0.06344	3.9	-0.00028	0.000093
33	3.9	-0.00028	0.000093	3.9	-0.00028	0.000093
		
43	3.9	-0.00028	0.000093	3.9	-0.00028	0.000093
44	3.9	-0.00028	0.000093	2.5	0.00119	-0.03712
45	3.9	-0.00028	0.000093	3.9	-0.00028	0.000093
79	3.9	-0.00028	0.000093	3.9	-0.00028	0.000093
80	-26091.4	-0.00023	-0.01587	3.9	-0.00028	0.000093
81	3.9	-0.00028	0.000093	3.9	-0.00028	0.000093
		
84	3.9	-0.00028	0.000093	3.9	-0.00028	0.000093
85	3.03360952E7	-0.00092	-0.06344	3.9	-0.00028	0.000093

86	2.58500963E7	-0.00092	-0.06344	3.9	-0.00028	0.000093
87	-5.10244393E7	-0.00023	-0.01587	3.9	-0.00028	0.000093
88	-1.924944138E8	-0.00023	-0.01587	3.9	-0.00028	0.000093
89	-2.41967731E7	-0.00023	-0.01587	3.9	-0.00028	0.000093
90	-9447410.9	-0.00023	-0.01587	3.9	-0.00028	0.000093
91	-1467272.6	-0.00023	-0.01587	3.9	-0.00028	0.000093
92	-986878.4	-0.00023	-0.01587	3.9	-0.00028	0.000093
93	-6389896.6	-0.00023	-0.01587	3.9	-0.00028	0.000093
94	559223.0	-0.00092	-0.06344	3.9	-0.00028	0.000093
95	3.9	-0.00028	0.000093	3.9	-0.00028	0.000093
		
100	3.9	-0.00028	0.000093	3.9	-0.00028	0.000093

(b) SSE as Fitness Function, *File 2 is Audio File.*

No	r/ PSO/ SSE	File 2 /SNR	File 2 /Rc	r/QPSO/SSE	File 2 / SNR	File 2 / Rc
1	3.9	-0.00028	0.000093	3.9	-0.00028	0.000093
		
9	3.9	-0.00028	0.000093	3.9	-0.00028	0.000093
10	3.9	-0.00028	0.000093	2.5	0.00119	-0.03712
11	3.9	-0.00028	0.000093	3.9	-0.00028	0.000093
		
21	3.9	-0.00028	0.000093	3.9	-0.00028	0.000093
22	-341964.6	-0.00023	-0.01587	3.9	-0.00028	0.000093
23	52689.8	-0.00092	-0.06344	3.9	-0.00028	0.000093
24	3.9	-0.00028	0.000093	3.9	-0.00028	0.000093
					
90	3.9	-0.00028	0.000093	3.9	-0.00028	0.000093
91	8299830.4	-0.00092	-0.06344	3.9	-0.00028	0.000093
92	2.0536991E7	-0.00092	-0.06344	3.9	-0.00028	0.000093
93	1.77950045E7	-0.00092	-0.06344	3.9	-0.00028	0.000093
94	2.54796405E7	-0.00092	-0.06344	3.9	-0.00028	0.000093
95	5831634.0	-0.00092	-0.06344	3.9	-0.00028	0.000093
96	1795970.7	-0.00092	-0.06344	3.9	-0.00028	0.000093
97	972531.8	-0.00092	-0.06344	3.9	-0.00028	0.000093
98	643826.1	-0.00092	-0.06344	3.9	-0.00028	0.000093
99	2422843.6	-0.00092	-0.06344	3.9	-0.00028	0.000093
100	-2864020.1	-0.00023	-0.01587	3.9	-0.00028	0.000093

▪ **Case study 3:**

Table 3: Accessing the best and worst values for test speech descrambler based on parameter estimation (logistic map) .

(a) MSE as Fitness Function, *File 3 is Audio File.*

No	r/PSO/MSE	File 3 /SNR	File 3 /Rc	r/QPSO /MSE	File 3 /SNR	File 3 / Rc
1	3.9	0.0182	0.10087	3.9	0.0182	0.10087
		
12	3.9	0.0182	0.10087	3.9	0.0182	0.10087
13	3.9	0.0182	0.10087	2.5	-0.02635	-0.04786
14	3.9	0.0182	0.10087	3.9	0.0182	0.10087
		
28	3.9	0.0182	0.10087	3.9	0.0182	0.10087
29	-1322775.3	-0.00023	0.07855	3.9	0.0182	0.10087
30	-1212210.5	-0.00023	0.07855	3.9	0.0182	0.10087
31	-1925732.8	-0.00023	0.07855	3.9	0.0182	0.10087

32	202492.7	-0.00007	-0.02907	3.9	0.0182	0.10087
33	3.9	0.0182	0.10087	3.9	0.0182	0.10087
		
43	3.9	0.0182	0.10087	3.9	0.0182	0.10087
44	3.9	0.0182	0.10087	2.5	-0.02635	-0.04786
45	3.9	0.0182	0.10087	3.9	0.0182	0.10087
79	3.9	0.0182	0.10087	3.9	0.0182	0.10087
80	-26091.4	-0.00023	0.07855	3.9	0.0182	0.10087
81	3.9	0.0182	0.10087	3.9	0.0182	0.10087
		
84	3.9	0.0182	0.10087	3.9	0.0182	0.10087
85	3.03360952E7	-0.00007	-0.02907	3.9	0.0182	0.10087
86	2.58500963E7	-0.00007	-0.02907	3.9	0.0182	0.10087
87	-5.10244393E7	-0.00023	0.07855	3.9	0.0182	0.10087
88	-1.924944138E8	-0.00023	0.07855	3.9	0.0182	0.10087
89	-2.41967731E7	-0.00023	0.07855	3.9	0.0182	0.10087
90	-9447410.9	-0.00023	0.07855	3.9	0.0182	0.10087
91	-1467272.6	-0.00023	0.07855	3.9	0.0182	0.10087
92	-986878.4	-0.00023	0.07855	3.9	0.0182	0.10087
93	-6389896.6	-0.00023	0.07855	3.9	0.0182	0.10087
94	559223.0	-0.00007	-0.02907	3.9	0.0182	0.10087
95	3.9	0.0182	0.10087	3.9	0.0182	0.10087
		
100	3.9	0.0182	0.10087	3.9	0.0182	0.10087

(b) SSE as Fitness Function, File 3 is Audio File..

No.	r/ PSO/ SSE	File 3/SNR	File 3 / Rc	r /QPSO/SSE	File 3 / SNR	File 3 / Rc
1	3.9	0.0182	0.10087	3.9	0.0182	0.10087
		
9	3.9	0.0182	0.10087	3.9	0.0182	0.10087
10	3.9	0.0182	0.10087	2.5	-0.02635	-0.04786
11	3.9	0.0182	0.10087	3.9	0.0182	0.10087
		
21	3.9	0.0182	0.10087	3.9	0.0182	0.10087
22	-341964.6	-0.00023	0.07855	3.9	0.0182	0.10087
23	52689.8	-0.00007	-0.02907	3.9	0.0182	0.10087
24	3.9	0.0182	0.10087	3.9	0.0182	0.10087
					
90	3.9	0.0182	0.10087	3.9	0.0182	0.10087
91	8299830.4	-0.00007	-0.02907	3.9	0.0182	0.10087
92	2.0536991E7	-0.00007	-0.02907	3.9	0.0182	0.10087
93	1.77950045E7	-0.00007	-0.02907	3.9	0.0182	0.10087
94	2.54796405E7	-0.00007	-0.02907	3.9	0.0182	0.10087
95	5831634.0	-0.00007	-0.02907	3.9	0.0182	0.10087
96	1795970.7	-0.00007	-0.02907	3.9	0.0182	0.10087
97	972531.8	-0.00007	-0.02907	3.9	0.0182	0.10087
98	643826.1	-0.00007	-0.02907	3.9	0.0182	0.10087
99	2422843.6	-0.00007	-0.02907	3.9	0.0182	0.10087
100	-2864020.1	-0.00023	0.07855	3.9	0.0182	0.10087

Case study 4:

Table 4: Accessing the best and worst values for test speech descrambler based on parameter estimation (logistic map) .

(a) MSE as Fitness Function, File 4 is Audio File.

No	r/PSO /MSE	File 4 / SNR	File 4 / Rc	r /QPSO /MSE	File 4 / SNR	File 4 / Rc
1	3.9	0.0025	0.03337	3.9	0.0025	0.03337
		
12	3.9	0.0025	0.03337	3.9	0.0025	0.03337
13	3.9	0.0025	0.03337	2.5	0.0011	0.00719
14	3.9	0.0025	0.03337	3.9	0.0025	0.03337
		
28	3.9	0.0025	0.03337	3.9	0.0025	0.03337
29	-1322775.3	-0.000005	-0.0006	3.9	0.0025	0.03337
30	-1212210.5	-0.000005	-0.0006	3.9	0.0025	0.03337
31	-1925732.8	-0.000005	-0.0006	3.9	0.0025	0.03337
32	202492.7	-0.00023	0.0011	3.9	0.0025	0.03337
33	3.9	0.0025	0.03337	3.9	0.0025	0.03337
		
43	3.9	0.0025	0.03337	3.9	0.0025	0.03337
44	3.9	0.0025	0.03337	2.5	0.0011	0.00719
45	3.9	0.0025	0.03337	3.9	0.0025	0.03337
79	3.9	0.0025	0.03337	3.9	0.0025	0.03337
80	-26091.4	-0.000005	-0.0006	3.9	0.0025	0.03337
81	3.9	0.0025	0.03337	3.9	0.0025	0.03337
		
84	3.9	0.0025	0.03337	3.9	0.0025	0.03337
85	3.03360952E7	-0.00023	0.0011	3.9	0.0025	0.03337
86	2.58500963E7	-0.00023	0.0011	3.9	0.0025	0.03337
87	-5.10244393E7	-0.00023	-0.0006	3.9	0.0025	0.03337
88	-1.924944138E8	-0.00023	-0.0006	3.9	0.0025	0.03337
89	-2.41967731E7	-0.00023	-0.0006	3.9	0.0025	0.03337
90	-9447410.9	-0.00023	-0.0006	3.9	0.0025	0.03337
91	-1467272.6	-0.00023	-0.0006	3.9	0.0025	0.03337
92	-986878.4	-0.00023	-0.0006	3.9	0.0025	0.03337
93	-6389896.6	-0.00023	-0.0006	3.9	0.0025	0.03337
94	559223.0	-0.00023	0.0011	3.9	0.0025	0.03337
95	3.9	0.0025	0.03337	3.9	0.0025	0.03337
		
100	3.9	0.0025	0.03337	3.9	0.0025	0.03337

(b) SSE as Fitness Function, File 4 is Audio File

No	r/ PSO/ SSE	File 4 / SNR	File 4 / Rc	r/QPSO/SSE	File 4 / SNR	File 4 / Rc
1	3.9	0.0025	0.03337	3.9	0.0025	0.03337
		
9	3.9	0.0025	0.03337	3.9	0.0025	0.03337
10	3.9	0.0025	0.03337	2.5	0.0011	0.00719
11	3.9	0.0025	0.03337	3.9	0.0025	0.03337
		
21	3.9	0.0025	0.03337	3.9	0.0025	0.03337
22	-341964.6	-0.000005	-0.0006	3.9	0.0025	0.03337
23	52689.8	-0.00023	0.0011	3.9	0.0025	0.03337
24	3.9	0.0025	0.03337	3.9	0.0025	0.03337
		
90	3.9	0.0025	0.03337	3.9	0.0025	0.03337
91	8299830.4	-0.00023	0.0011	3.9	0.0025	0.03337
92	2.0536991E7	-0.00023	0.0011	3.9	0.0025	0.03337
93	1.77950045E7	-0.00023	0.0011	3.9	0.0025	0.03337
94	2.54796405E7	-0.00023	0.0011	3.9	0.0025	0.03337
95	5831634.0	-0.00023	0.0011	3.9	0.0025	0.03337
96	1795970.7	-0.00023	0.0011	3.9	0.0025	0.03337
97	972531.8	-0.00023	0.0011	3.9	0.0025	0.03337

98	643826.1	-0.00023	0.0011	3.9	0.0025	0.03337
99	2422843.6	-0.00023	0.0011	3.9	0.0025	0.03337
100	-2864020.1	-0.000005	-0.0006	3.9	0.0025	0.03337

▪ **Case study 5:**

Table 5: Accessing the best and worst values for test speech descrambler based on parameter estimation (logistic map) .

(a) MSE as Fitness Function, File 5 is Audio File

No	r/PSO /MSE	File 5 / SNR	Files 5 / Rc	r/QPSO /MSE	File 5 / SNR	File 5 / Rc
1	3.9	0.92329	0.4457	3.9	0.92329	0.4457
		
12	3.9	0.92329	0.4457	3.9	0.92329	0.4457
13	3.9	0.92329	0.4457	2.5	-0.1171	-0.0037
14	3.9	0.92329	0.4457	3.9	0.92329	0.4457
		
28	3.9	0.92329	0.4457	3.9	0.92329	0.4457
29	-1322775.3	-0.00023	-0.02106	3.9	0.92329	0.4457
30	-1212210.5	-0.00023	-0.02106	3.9	0.92329	0.4457
31	-1925732.8	-0.00023	-0.02106	3.9	0.92329	0.4457
32	202492.7	-0.00027	-0.04903	3.9	0.92329	0.4457
33	3.9	0.92329	0.4457	3.9	0.92329	0.4457
		
43	3.9	0.92329	0.4457	3.9	0.92329	0.4457
44	3.9	0.92329	0.4457	2.5	-0.1171	-0.0037
45	3.9	0.92329	0.4457	3.9	0.92329	0.4457
79	3.9	0.92329	0.4457	3.9	0.92329	0.4457
80	-26091.4	-0.00023	-0.02106	3.9	0.92329	0.4457
81	3.9	0.92329	0.4457	3.9	0.92329	0.4457
		
84	3.9	0.92329	0.4457	3.9	0.92329	0.4457
85	3.03360952E7	-0.00027	-0.04903	3.9	0.92329	0.4457
86	2.58500963E7	-0.00027	-0.04903	3.9	0.92329	0.4457
87	-5.10244393E7	-0.00023	0.07855	3.9	0.92329	0.4457
88	-1.924944138E8	-0.00023	0.07855	3.9	0.92329	0.4457
89	-2.41967731E7	-0.00023	0.07855	3.9	0.92329	0.4457
90	-9447410.9	-0.00023	0.07855	3.9	0.92329	0.4457
91	-1467272.6	-0.00023	0.07855	3.9	0.92329	0.4457
92	-986878.4	-0.00023	0.07855	3.9	0.92329	0.4457
93	-6389896.6	-0.00023	0.07855	3.9	0.92329	0.4457
94	559223.0	-0.00027	-0.04903	3.9	0.92329	0.4457
95	3.9	0.92329	0.4457	3.9	0.92329	0.4457
		
100	3.9	0.92329	0.4457	3.9	0.92329	0.4457

(b) SSE as Fitness Function, File 5 is Audio File.

No.	r/ PSO/ SSE	File 5 / SNR	File 5 / Rc	r /QPSO/SSE	File 5 / SNR	File 5 / Rc
1	3.9	0.92329	0.4457	3.9	0.92329	0.4457
		
9	3.9	0.92329	0.4457	3.9	0.92329	0.4457
10	3.9	0.92329	0.4457	2.5	-0.1171	-0.0037
11	3.9	0.92329	0.4457	3.9	0.92329	0.4457
		
21	3.9	0.92329	0.4457	3.9	0.92329	0.4457
22	-341964.6	-0.00023	-0.02106	3.9	0.92329	0.4457
23	52689.8	-0.00027	-0.04903	3.9	0.92329	0.4457

24	3.9	0.92329	0.4457	3.9	0.92329	0.4457
					
90	3.9	0.92329	0.4457	3.9	0.92329	0.4457
91	8299830.4	-0.00027	-0.04903	3.9	0.92329	0.4457
92	2.0536991E7	-0.00027	-0.04903	3.9	0.92329	0.4457
93	1.77950045E7	-0.00027	-0.04903	3.9	0.92329	0.4457
94	2.54796405E7	-0.00027	-0.04903	3.9	0.92329	0.4457
95	5831634.0	-0.00027	-0.04903	3.9	0.92329	0.4457
96	1795970.7	-0.00027	-0.04903	3.9	0.92329	0.4457
97	972531.8	-0.00027	-0.04903	3.9	0.92329	0.4457
98	643826.1	-0.00027	-0.04903	3.9	0.92329	0.4457
99	2422843.6	-0.00027	-0.04903	3.9	0.92329	0.4457
100	-2864020.1	-0.00023	-0.02106	3.9	0.92329	0.4457

▪ **Case study 6:**

Table 6: Accessing the best and worst values for test speech descrambler based on parameter estimation (logistic map).

(a) MSE as Fitness Function, File 6 is Audio File .

No	r/PSO /MSE	File 6 / SNR	File 6 / Rc	r/QPSO /MSE	File 6 / SNR	File 6 / Rc
1	3.9	0.00531	0.06168	3.9	0.00531	0.06168
		
12	3.9	0.00531	0.06168	3.9	0.00531	0.06168
13	3.9	0.00531	0.06168	2.5	0.0011	0.00719
14	3.9	0.00531	0.06168	3.9	0.00531	0.06168
		
28	3.9	0.00531	0.06168	3.9	0.00531	0.06168
29	-1322775.3	-0.00009	0.03543	3.9	0.00531	0.06168
30	-1212210.5	-0.00009	0.03543	3.9	0.00531	0.06168
31	-1925732.8	-0.00009	0.03543	3.9	0.00531	0.06168
32	202492.7	-0.0001	-0.07143	3.9	0.00531	0.06168
33	3.9	0.00531	0.06168	3.9	0.00531	0.06168
		
43	3.9	0.00531	0.06168	3.9	0.00531	0.06168
44	3.9	0.00531	0.06168	2.5	0.0011	0.00719
45	3.9	0.00531	0.06168	3.9	0.00531	0.06168
79	3.9	0.00531	0.06168	3.9	0.00531	0.06168
80	-26091.4	-0.00009	0.03543	3.9	0.00531	0.06168
81	3.9	0.00531	0.06168	3.9	0.00531	0.06168
		
84	3.9	0.00531	0.06168	3.9	0.00531	0.06168
85	3.03360952E7	-0.0001	-0.07143	3.9	0.00531	0.06168
86	2.58500963E7	-0.0001	-0.07143	3.9	0.00531	0.06168
87	-5.10244393E7	-0.00009	0.03543	3.9	0.00531	0.06168
88	-1.924944138E8	-0.00009	0.03543	3.9	0.00531	0.06168
89	-2.41967731E7	-0.00009	0.03543	3.9	0.00531	0.06168
90	-9447410.9	-0.00009	0.03543	3.9	0.00531	0.06168
91	-1467272.6	-0.00009	0.03543	3.9	0.00531	0.06168
92	-986878.4	-0.00009	0.03543	3.9	0.00531	0.06168
93	-6389896.6	-0.00009	0.03543	3.9	0.00531	0.06168
94	559223.0	-0.0001	-0.07143	3.9	0.00531	0.06168
95	3.9	0.00531	0.06168	3.9	0.00531	0.06168
		
100	3.9	0.00531	0.06168	3.9	0.00531	0.06168

(b) SSE as Fitness Function, File 6 is Audio File.

No.	r/ PSO / SSE	File 6/ SNR	File 6 / Rc	r/QPSO/SSE	File 6 / SNR	File 6 / Rc
1	3.9	0.00531	0.06168	3.9	0.00531	0.06168
		
9	3.9	0.00531	0.06168	3.9	0.00531	0.06168
10	3.9	0.00531	0.06168	2.5	0.0011	0.00719
11	3.9	0.00531	0.06168	3.9	0.00531	0.06168
		
21	3.9	0.00531	0.06168	3.9	0.00531	0.06168
22	-341964.6	-0.00009	0.03543	3.9	0.00531	0.06168
23	52689.8	-0.0001	-0.07143	3.9	0.00531	0.06168
24	3.9	0.00531	0.06168	3.9	0.00531	0.06168
					
90	3.9	0.00531	0.06168	3.9	0.00531	0.06168
91	8299830.4	-0.0001	-0.07143	3.9	0.00531	0.06168
92	2.0536991E7	-0.0001	-0.07143	3.9	0.00531	0.06168
93	1.77950045E7	-0.0001	-0.07143	3.9	0.00531	0.06168
94	2.54796405E7	-0.0001	-0.07143	3.9	0.00531	0.06168
95	5831634.0	-0.0001	-0.07143	3.9	0.00531	0.06168
96	1795970.7	-0.0001	-0.07143	3.9	0.00531	0.06168
97	972531.8	-0.0001	-0.07143	3.9	0.00531	0.06168
98	643826.1	-0.0001	-0.07143	3.9	0.00531	0.06168
99	2422843.6	-0.0001	-0.07143	3.9	0.00531	0.06168
100	-2864020.1	-0.00009	0.03543	3.9	0.00531	0.06168

Tables (1,2,3,4,5, and 6) show the results measures used for the test speech descrambling are SNR and CC, when the SNR is high, the recovered speech signal is good, and when $CC = -1$ then both samples(original speech ,recovered speech) go in an opposite direction, and if $CC = +1$ then both samples(original speech ,recovered speech) goes in an equal direction.

The parameters estimation program was implemented 100 times for estimating (K, Ω) in the circle equation where $K = 0.712$, $\Omega = 0.5$ based on meta-heuristic algorithms (PSO/QPSO), used (MSE/SSE) as a fitness function with PSO and QPSO algorithms, then entered the parameters (K, Ω) in the descrambling speech process, then the recovered speech signal is measured by SNR and CC.

▪ Case study 1

Table 7: Accessing the best and worst values for test speech descrambler based on parameter estimation (circle map).

(a) MSE as Fitness Function, File 1 is Audio File.

NO	PSO/MSE	File 1 / SNR	File 1 / CC	QPSO/MSE	File 1 / SNR	File 1 / CC
1.	0.712 ,0,5	0.00032	0.04265	0.699 , 0,5	-0.00005	-0.0309
2.	0.712 ,0,5	0.00032	0.04265	0.704 , 0,5	0.00001	0.01348
3.	0.712 ,0,5	0.00032	0.04265	0.703 , 0,5	0.00005	0.03214
4.	0.712 ,0,5	0.00032	0.04265	0.711 , 0,5	0.00002	0.0117
5.	0.712 ,0,5	0.00032	0.04265	0.715 , 0,5	0.000026	0.02149
6.	0.712 ,0,5	0.00032	0.04265	0.721 , 0,5	0.000074	0.05597
7.	0.712 ,0,5	0.00032	0.04265	0.697 , 0,5	-0.000045	-0.03329
8.	0.712 ,0,5	0.00032	0.04265	0.712 , 0,5	0.00032	0.04265
9.	0.712 ,0,5	0.00032	0.04265	0.709 , 0,5	-0.00006	-0.03915
10.	0.712 ,0,5	0.00032	0.04265	0.711 , 0,5	0.00002	0.0117
11.	0.712 ,0,5	0.00032	0.04265	0.699 , 0,5	-0.00005	-0.0309
12.	0.712 ,0,5	0.00032	0.04265	0.698 , 0,5	-0.000015	-0.0109
13.	0.712 ,0,5	0.00032	0.04265	0.711 , 0,5	0.00002	0.0117
14.	0.712 ,0,5	0.00032	0.04265	0.712 , 0,5	0.00032	0.04265
15.	0.712 ,0,5	0.00032	0.04265	0.711 , 0,5	0.00002	0.0117
16.	0.712 ,0,5	0.00032	0.04265	0.726 , 0,5	0.00004	0.03033
17.	0.712 ,0,5	0.00032	0.04265	0.711 , 0,5	0.00002	0.0117
18.	0.712 ,0,5	0.00032	0.04265	0.708 , 0,5	0.0000002	-0.0013
19.	0.712 ,0,5	0.00032	0.04265	0.704 , 0,5	0.00001	0.01348
20.	0.712 ,0,5	0.00032	0.04265	0.71 , 0,5	-0.00001	-0.007
21.	0.712 ,0,5	0.00032	0.04265	0.726 , 0,5	0.00004	0.03033
22.	0.712 ,0,5	0.00032	0.04265	0.703 , 0,5	0.00005	0.03214
23.	0.712 ,0,5	0.00032	0.04265	0.712 , 0,5	0.00032	0.04265
24.	0.712 ,0,5	0.00032	0.04265	0.726 , 0,5	0.00004	0.03033
25.	0.712 ,0,5	0.00032	0.04265	0.708 , 0,5	0.0000002	-0.0013
26.	0.712 ,0,5	0.00032	0.04265	0.706 , 0,5	0.000006	0.0024
27.	0.712 ,0,5	0.00032	0.04265	0.713 , 0,5	0.00003	0.0349
28.	0.712 ,0,5	0.00032	0.04265	0.712 , 0,5	0.00032	0.04265
29.	0.712 ,0,5	0.00032	0.04265	0.695 , 0,5	-0.00006	-0.0231
30.	0.712 ,0,5	0.00032	0.04265	0.697 , 0,5	-0.000045	-0.03329
31.	0.712 ,0,5	0.00032	0.04265	0.713 , 0,5	0.00003	0.0349
32.	0.712 ,0,5	0.00032	0.04265	0.712 , 0,5	0.00032	0.04265
33.	0.712 ,0,5	0.00032	0.04265	0.723 , 0,5	0.00004	0.03155
34.	0.712 ,0,5	0.00032	0.04265	0.711 , 0,5	0.00002	0.0117
35.	0.712 ,0,5	0.00032	0.04265	0.71 , 0,5	-0.00001	-0.007
36.	0.712 ,0,5	0.00032	0.04265	0.696 , 0,5	-0.00005	-0.03912
37.	0.712 ,0,5	0.00032	0.04265	0.711 , 0,5	0.00002	0.0117
38.	0.712 ,0,5	0.00032	0.04265	0.71 , 0,5	-0.00001	-0.007
39.	0.712 ,0,5	0.00032	0.04265	0.714 , 0,5	0.000004	-0.02548
40.	0.712 ,0,5	0.00032	0.04265	0.698 , 0,5	-0.00001	-0.0109
41.	0.712 ,0,5	0.00032	0.04265	0.698 , 0,5	-0.00001	-0.0109
42.	0.712 ,0,5	0.00032	0.04265	0.711 , 0,5	0.00002	0.0117
43.	0.712 ,0,5	0.00032	0.04265	0.714 , 0,5	0.000004	-0.02548
44.	0.712 ,0,5	0.00032	0.04265	0.711 , 0,5	0.00002	0.0117
45.	0.712 ,0,5	0.00032	0.04265	0.724 , 0,5	0.00004	0.03522
46.	0.712 ,0,5	0.00032	0.04265	0.704 , 0,5	0.00001	0.01348
47.	0.712 ,0,5	0.00032	0.04265	0.696 , 0,5	-0.00005	-0.03912
48.	0.712 ,0,5	0.00032	0.04265	0.708 , 0,5	0.0000002	-0.0013
49.	0.712 ,0,5	0.00032	0.04265	0.713 , 0,5	0.00003	0.0349
50.	0.712 ,0,5	0.00032	0.04265	0.711 , 0,5	0.00002	0.0117
51.	0.712 ,0,5	0.00032	0.04265	0.706 , 0,5	0.000006	0.0024
52.	0.712 ,0,5	0.00032	0.04265	0.708 , 0,5	0.0000002	-0.0013
53.	0.712 ,0,5	0.00032	0.04265	0.722 , 0,5	0.00005	0.03597
54.	0.712 ,0,5	0.00032	0.04265	0.71 , 0,5	-0.00001	-0.007
55.	0.712 ,0,5	0.00032	0.04265	0.715 , 0,5	0.000026	0.02149
56.	0.712 ,0,5	0.00032	0.04265	0.714 , 0,5	0.000004	-0.02548
57.	0.712 ,0,5	0.00032	0.04265	0.708 , 0,5	0.0000002	-0.0013
58.	0.712 ,0,5	0.00032	0.04265	0.712 ,0,5	0.00032	0.04265

59.	0.712 ,0,5	0.00032	0.04265	0.698 , 0,5	-0.00001	-0.0109
60.	0.712 ,0,5	0.00032	0.04265	0.699 , 0,5	-0.00005	-0.0309
61.	0.712 ,0,5	0.00032	0.04265	0.698 , 0,5	-0.00001	-0.0109
62.	0.712 ,0,5	0.00032	0.04265	0.713 , 0,5	0.00003	0.0349
63.	0.712 ,0,5	0.00032	0.04265	0.703 , 0,5	0.00005	0.03214
64.	0.712 ,0,5	0.00032	0.04265	0.723 , 0,5	0.00004	0.03155
65.	0.712 ,0,5	0.00032	0.04265	0.711 , 0,5	0.00002	0.0117
66.	0.712 ,0,5	0.00032	0.04265	0.714 , 0,5	0.000004	-0.02548
67.	0.712 ,0,5	0.00032	0.04265	0.708 , 0,5	0.0000002	-0.0013
68.	0.712 ,0,5	0.00032	0.04265	0.696 , 0,5	-0.00005	-0.03912
69.	0.712 ,0,5	0.00032	0.04265	0.726 , 0,5	0.00004	0.03033
70.	0.712 ,0,5	0.00032	0.04265	0.726 , 0,5	0.00004	0.03033
71.	0.712 ,0,5	0.00032	0.04265	0.709 , 0,5	-0.00006	-0.03915
72.	0.712 ,0,5	0.00032	0.04265	0.715 , 0,5	0.000026	0.02149
73.	0.712 ,0,5	0.00032	0.04265	0.698 , 0,5	-0.00001	-0.0109
74.	0.712 ,0,5	0.00032	0.04265	0.726 , 0,5	0.00004	0.03033
75.	0.712 ,0,5	0.00032	0.04265	0.712 ,0,5	0.00032	0.04265
76.	0.712 ,0,5	0.00032	0.04265	0.726 , 0,5	0.00004	0.03033
77.	-0.667,0,5	0.00276	-0.02776	0.703 , 0,5	0.00005	0.03214
78.	0.712 ,0,5	0.00032	0.04265	0.715 , 0,5	0.000026	0.02149
79.	0.712 ,0,5	0.00032	0.04265	0.712 ,0,5	0.00032	0.04265
80.	0.712 ,0,5	0.00032	0.04265	0.71 , 0,5	-0.00001	-0.007
81.	0.712 ,0,5	0.00032	0.04265	0.709 , 0,5	-0.00006	-0.03915
82.	0.712 ,0,5	0.00032	0.04265	0.71 , 0,5	-0.00001	-0.007
83.	0.712 ,0,5	0.00032	0.04265	0.708 , 0,5	0.0000002	-0.0013
84.	0.712 ,0,5	0.00032	0.04265	0.722 , 0,5	0.00005	0.03597
85.	0.712 ,0,5	0.00032	0.04265	0.723 , 0,5	0.00004	0.03155
86.	0.712 ,0,5	0.00032	0.04265	0.712 ,0,5	0.00032	0.04265
87.	0.712 ,0,5	0.00032	0.04265	0.7 , 0,5	-0.00001	0.07919
88.	0.712 ,0,5	0.00032	0.04265	0.696 , 0,5	-0.00005	-0.03912
89.	0.712 ,0,5	0.00032	0.04265	0.71 , 0,5	-0.00001	-0.007
90.	0.712 ,0,5	0.00032	0.04265	0.708 , 0,5	0.0000002	-0.0013
91.	0.712 ,0,5	0.00032	0.04265	0.711 , 0,5	0.00002	0.0117
92.	0.712 ,0,5	0.00032	0.04265	0.708 , 0,5	0.0000002	-0.0013
93.	0.712 ,0,5	0.00032	0.04265	0.699 , 0,5	-0.00005	-0.0309
94.	0.712 ,0,5	0.00032	0.04265	0.715 , 0,5	0.000026	0.02149
95.	0.712 ,0,5	0.00032	0.04265	0.708 , 0,5	0.0000002	-0.0013
96.	0.712 ,0,5	0.00032	0.04265	0.709 , 0,5	-0.00006	-0.03915
97.	0.712 ,0,5	0.00032	0.04265	0.726 , 0,5	0.00004	0.03033
98.	0.712 ,0,5	0.00032	0.04265	0.712 ,0,5	0.00032	0.04265
99.	0.712 ,0,5	0.00032	0.04265	0.726 , 0,5	0.00004	0.03033
100.	0.712 ,0,5	0.00032	0.04265	0.726 , 0,5	0.00004	0.03033

(b) SSE as Fitness Function, File 1 is Audio File.

NO	PSO/SSE	File 1 / SNR	File 1 / CC	QPSO/SSE	File 1 / SNR	File 1 / CC
1.	0.712 ,0,5	0.00032	0.04265	0.716,0,5	0.00008	0.07941
2.	0.712 ,0,5	0.00032	0.04265	0.725,0,5	0.00003	0.02928
3.	0.712 ,0,5	0.00032	0.04265	0.708,0,5	0.0000002	-0.0013
4.	0.712 ,0,5	0.00032	0.04265	0.707,0,5	0.00002	0.010803
5.	0.712 ,0,5	0.00032	0.04265	0.696,0,5	-0.00005	-0.03912
6.	0.712 ,0,5	0.00032	0.04265	0.704,0,5	-0.00001	-0.0109
7.	0.712 ,0,5	0.00032	0.04265	0.712 , 0,5	0.00032	0.04265
8.	0.712 ,0,5	0.00032	0.04265	0.705,0,5	-0.000004	-0.00418
9.	0.712 ,0,5	0.00032	0.04265	0.712 , 0,5	0.00032	0.04265
10.	0.712 ,0,5	0.00032	0.04265	0.71,0,5	-0.00001	-0.007
11.	0.712 ,0,5	0.00032	0.04265	0.714,0,5	0.000004	-0.02548
12.	0.712 ,0,5	0.00032	0.04265	0.714,0,5	0.000004	-0.02548

13.	0.712,0,5	0.00032	0.04265	0.71,0,5	-0.00001	-0.007
14.	0.712,0,5	0.00032	0.04265	0.711,0,5	0.00002	0.0117
15.	0.712,0,5	0.00032	0.04265	0.716,0,5	0.00008	0.07941
16.	0.712,0,5	0.00032	0.04265	0.668,0,5	0.00008	0.06398
17.	0.712,0,5	0.00032	0.04265	0.709,0,5	-0.00006	-0.03915
18.	0.712,0,5	0.00032	0.04265	0.666,0,5	-0.00001	-0.01253
19.	0.712,0,5	0.00032	0.04265	0.719,0,5	-0.0071	-0.04329
20.	0.712,0,5	0.00032	0.04265	0.697,0,5	-0.000045	-0.03329
21.	0.712,0,5	0.00032	0.04265	0.673,0,5	0.00001	0.00567
22.	0.712,0,5	0.00032	0.04265	0.716,0,5	0.00008	0.07941
23.	0.712,0,5	0.00032	0.04265	0.687,0,5	-0.00007	-0.05835
24.	0.712,0,5	0.00032	0.04265	0.705,0,5	-0.000004	-0.00418
25.	0.712,0,5	0.00032	0.04265	0.713,0,5	0.00003	0.0349
26.	0.712,0,5	0.00032	0.04265	0.709,0,5	-0.00006	-0.03915
27.	0.712,0,5	0.00032	0.04265	0.714,0,5	0.000004	-0.02548
28.	0.712,0,5	0.00032	0.04265	0.715,0,5	0.000026	0.02149
29.	0.712,0,5	0.00032	0.04265	0.701,0,5	0.00004	0.02906
30.	0.712,0,5	0.00032	0.04265	0.676,0,5	0.00001	0.01766
31.	0.712,0,5	0.00032	0.04265	0.705,0,5	-0.000004	-0.00418
32.	0.712,0,5	0.00032	0.04265	0.709,0,5	-0.00006	-0.03915
33.	0.712,0,5	0.00032	0.04265	0.712,0,5	0.00032	0.04265
34.	0.712,0,5	0.00032	0.04265	0.707,0,5	0.00002	0.010803
35.	0.712,0,5	0.00032	0.04265	0.696,0,5	-0.00005	-0.03912
36.	0.712,0,5	0.00032	0.04265	0.711,0,5	0.00002	0.0117
37.	0.712,0,5	0.00032	0.04265	0.706,0,5	0.000006	0.0024
38.	0.712,0,5	0.00032	0.04265	0.715,0,5	0.000026	0.02149
39.	0.712,0,5	0.00032	0.04265	0.72,0,5	0.00003	0.03283
40.	0.712,0,5	0.00032	0.04265	0.703,0,5	0.00005	0.03214
41.	0.712,0,5	0.00032	0.04265	0.714,0,5	0.000004	-0.02548
42.	0.712,0,5	0.00032	0.04265	0.704,0,5	-0.00001	-0.0109
43.	0.712,0,5	0.00032	0.04265	0.7,0,5	-0.00001	0.07919
44.	0.712,0,5	0.00032	0.04265	0.711,0,5	0.00002	0.0117
45.	0.712,0,5	0.00032	0.04265	0.723,0,5	0.00004	0.03155
46.	0.712,0,5	0.00032	0.04265	0.701,0,5	0.00004	0.02906
47.	0.712,0,5	0.00032	0.04265	0.699,0,5	-0.00005	-0.0309
48.	0.712,0,5	0.00032	0.04265	0.696,0,5	-0.00005	-0.03912
49.	0.712,0,5	0.00032	0.04265	0.71,0,5	-0.00001	-0.007
50.	0.712,0,5	0.00032	0.04265	0.691,0,5	-0.00006	-0.03756
51.	0.712,0,5	0.00032	0.04265	0.692,0,5	-0.00007	-0.05792
52.	0.712,0,5	0.00032	0.04265	0.704,0,5	-0.00001	-0.0109
53.	0.712,0,5	0.00032	0.04265	0.715,0,5	0.000026	0.02149
54.	0.712,0,5	0.00032	0.04265	0.708,0,5	0.0000002	-0.0013
55.	0.712,0,5	0.00032	0.04265	0.71,0,5	-0.00001	-0.007
56.	0.712,0,5	0.00032	0.04265	0.712,0,5	0.00032	0.04265
57.	0.712,0,5	0.00032	0.04265	0.711,0,5	0.00002	0.0117
58.	0.712,0,5	0.00032	0.04265	0.709,0,5	-0.00006	-0.03915
59.	0.712,0,5	0.00032	0.04265	0.702,0,5	0.00002	0.01775
60.	0.712,0,5	0.00032	0.04265	0.702,0,5	0.00002	0.01775
61.	0.712,0,5	0.00032	0.04265	0.711,0,5	0.00002	0.0117
62.	0.712,0,5	0.00032	0.04265	0.709,0,5	-0.00006	-0.03915
63.	0.712,0,5	0.00032	0.04265	0.711,0,5	0.00002	0.0117
64.	0.712,0,5	0.00032	0.04265	0.699,0,5	-0.00005	-0.0309
65.	0.712,0,5	0.00032	0.04265	0.711,0,5	0.00002	0.0117
66.	0.712,0,5	0.00032	0.04265	0.709,0,5	-0.00006	-0.03915
67.	0.712,0,5	0.00032	0.04265	0.686,0,5	-0.00003	-0.02555
68.	-0.661,0,5	-0.00321	-0.01745	0.71,0,5	-0.00001	-0.007
69.	0.712,0,5	0.00032	0.04265	0.69,0,5	-0.00009	-0.06741
70.	0.712,0,5	0.00032	0.04265	0.704,0,5	-0.0109	-0.00001
71.	0.712,0,5	0.00032	0.04265	0.681,0,5	-0.00003	-0.02804
72.	0.712,0,5	0.00032	0.04265	0.707,0,5	0.00002	0.010803
73.	0.712,0,5	0.00032	0.04265	0.699,0,5	-0.00005	-0.0309
74.	0.712,0,5	0.00032	0.04265	0.714,0,5	0.000004	-0.02548
75.	0.712,0,5	0.00032	0.04265	0.652,0,5	-0.00003	-0.02331

76.	0.712 ,0,5	0.00032	0.04265	0.709,0,5	-0.00006	-0.03915
77.	0.712 ,0,5	0.00032	0.04265	0.712,0,5	0.00032	0.04265
78.	0.712 ,0,5	0.00032	0.04265	0.698,0,5	-0.00001	-0.0109
79.	0.712 ,0,5	0.00032	0.04265	0.716,0,5	0.00008	0.07941
80.	0.712 ,0,5	0.00032	0.04265	0.702,0,5	0.00002	0.01775
81.	0.712 ,0,5	0.00032	0.04265	0.693,0,5	-0.00012	-0.06738
82.	0.712 ,0,5	0.00032	0.04265	0.707 , 0,5	0.00002	0.010803
83.	0.712 ,0,5	0.00032	0.04265	0.708,0,5	0.0000002	-0.0013
84.	0.712 ,0,5	0.00032	0.04265	0.695,0,5	-0.00006	-0.0231
85.	0.712 ,0,5	0.00032	0.04265	0.685,0,5	-0.00008	-0.07013
86.	0.712 ,0,5	0.00032	0.04265	0.703,0,5	0.00005	0.03214
87.	0.712 ,0,5	0.00032	0.04265	0.702,0,5	0.00002	0.01775
88.	0.712 ,0,5	0.00032	0.04265	0.697,0,5	-0.000045	-0.03329
89.	0.712 ,0,5	0.00032	0.04265	0.712 , 0,5	0.00032	0.04265
90.	0.712 ,0,5	0.00032	0.04265	0.699,0,5	-0.00005	-0.0309
91.	0.712 ,0,5	0.00032	0.04265	0.725,0,5	0.00003	0.02928
92.	0.712 ,0,5	0.00032	0.04265	0.709,0,5	-0.00006	-0.03915
93.	0.712 ,0,5	0.00032	0.04265	0.705,0,5	-0.000004	-0.00418
94.	0.712 ,0,5	0.00032	0.04265	0.685,0,5	-0.00008	-0.07013
95.	0.712 ,0,5	0.00032	0.04265	0.71,0,5	-0.00001	-0.007
96.	0.712 ,0,5	0.00032	0.04265	0.702,0,5	0.00002	0.01775
97.	0.712 ,0,5	0.00032	0.04265	0.715,0,5	0.000026	0.02149
98.	0.712 ,0,5	0.00032	0.04265	0.712 , 0,5	0.00032	0.04265
99.	0.712 ,0,5	0.00032	0.04265	0.707 , 0,5	0.00002	0.010803
100.	0.712 ,0,5	0.00032	0.04265	0.715 , 0,5	0.000026	0.02149

▪ Case study 2 :

Table 8: Accessing the best and worst values for test speech descrambler based on parameter estimation (circle map).

(a) MSE as Fitness Function, File 2 is Audio File.

NO	PSO/MSE	File 2 / SNR	File 2/ CC	QPSO/MSE	File 2 / SNR	File 2/ CC
1.	0.712 ,0,5	0.00028	0.01585	0.699, 0,5	-0.00085	-0.0373
2.	0.712 ,0,5	0.00028	0.01585	0.704 , 0,5	-0.00078	-0.04089
3.	0.712 ,0,5	0.00028	0.01585	0.703 , 0,5	0.00016	0.04195
4.	0.712 ,0,5	0.00028	0.01585	0.711 , 0,5	-0.00008	-0.00445
5.	0.712 ,0,5	0.00028	0.01585	0.715 , 0,5	0.00021	0.002
6.	0.712 ,0,5	0.00028	0.01585	0.721 , 0,5	-0.00018	-0.01179
7.	0.712 ,0,5	0.00028	0.01585	0.697 , 0,5	-0.00146	--0.06883
8.	0.712 ,0,5	0.00028	0.01585	0.712 , 0,5	0.00028	0.01585
9.	0.712 ,0,5	0.00028	0.01585	0.709 , 0,5	-0.00011	-0.00512
10.	0.712 ,0,5	0.00028	0.01585	0.711 , 0,5	-0.00085	-0.0373
11.	0.712 ,0,5	0.00028	0.01585	0.699 , 0,5	-0.00085	-0.0373
12.	0.712 ,0,5	0.00028	0.01585	0.698 , 0,5	-0.00042	-0.01346
13.	0.712 ,0,5	0.00028	0.01585	0.711 , 0,5	-0.00008	-0.00445
14.	0.712 ,0,5	0.00028	0.01585	0.712 , 0,5	0.00028	0.01585
15.	0.712 ,0,5	0.00028	0.01585	0.711 , 0,5	-0.00008	-0.00445
16.	0.712 ,0,5	0.00028	0.01585	0.726 , 0,5	-0.00045	-0.02762
17.	0.712 ,0,5	0.00028	0.01585	0.711 , 0,5	-0.00008	-0.00445
18.	0.712 ,0,5	0.00028	0.01585	0.708 , 0,5	-0.0011	-0.05969
19.	0.712 ,0,5	0.00028	0.01585	0.704 , 0,5	-0.00078	-0.04089
20.	0.712 ,0,5	0.00028	0.01585	0.71 , 0,5	-0.00023	-0.0123
21.	0.712 ,0,5	0.00028	0.01585	0.726 , 0,5	-0.00045	-0.02762
22.	0.712 ,0,5	0.00028	0.01585	0.703 , 0,5	0.00016	0.04195
23.	0.712 ,0,5	0.00028	0.01585	0.712 , 0,5	0.00028	0.01585
24.	0.712 ,0,5	0.00028	0.01585	0.726 , 0,5	-0.00045	-0.02762
25.	0.712 ,0,5	0.00028	0.01585	0.708 , 0,5	-0.0011	-0.05969

26.	0.712 ,0,5	0.00028	0.01585	0.706 , 0,5	-0.00048	-0.02757
27.	0.712 ,0,5	0.00028	0.01585	0.713 , 0,5	0.00025	0.0028
28.	0.712 ,0,5	0.00028	0.01585	0.712 , 0,5	0.00028	0.01585
29.	0.712 ,0,5	0.00028	0.01585	0.695 , 0,5	-0.00044	-0.01939
30.	0.712 ,0,5	0.00028	0.01585	0.697 , 0,5	-0.00146	-0.06883
31.	0.712 ,0,5	0.00028	0.01585	0.713 , 0,5	0.00025	0.0028
32.	0.712 ,0,5	0.00028	0.01585	0.712 , 0,5	0.00028	0.01585
33.	0.712 ,0,5	0.00028	0.01585	0.723 , 0,5	-0.0005	-0.03205
34.	0.712 ,0,5	0.00028	0.01585	0.711 , 0,5	-0.00008	-0.00445
35.	0.712 ,0,5	0.00028	0.01585	0.71 , 0,5	-0.00023	-0.0123
36.	0.712 ,0,5	0.00028	0.01585	0.696 , 0,5	-0.00048	-0.02363
37.	0.712 ,0,5	0.00028	0.01585	0.711 , 0,5	-0.00008	-0.00445
38.	0.712 ,0,5	0.00028	0.01585	0.71 , 0,5	-0.00023	-0.0123
39.	0.712 ,0,5	0.00028	0.01585	0.714 , 0,5	0.0001	0.00669
40.	0.712 ,0,5	0.00028	0.01585	0.698 , 0,5	-0.00042	-0.01346
41.	0.712 ,0,5	0.00028	0.01585	0.698 , 0,5	-0.00042	-0.01346
42.	0.712 ,0,5	0.00028	0.01585	0.711 , 0,5	-0.00008	-0.00445
43.	0.712 ,0,5	0.00028	0.01585	0.714 , 0,5	0.0001	0.00669
44.	0.712 ,0,5	0.00028	0.01585	0.711 , 0,5	-0.00008	-0.00445
45.	0.712 ,0,5	0.00028	0.01585	0.724 , 0,5	0.0002	0.0139
46.	0.712 ,0,5	0.00028	0.01585	0.704 , 0,5	-0.00078	-0.04089
47.	0.712 ,0,5	0.00028	0.01585	0.696 , 0,5	-0.00048	-0.02363
48.	0.712 ,0,5	0.00028	0.01585	0.708 , 0,5	-0.0011	-0.05969
49.	0.712 ,0,5	0.00028	0.01585	0.713 , 0,5	0.00025	0.0028
50.	0.712 ,0,5	0.00028	0.01585	0.711 , 0,5	-0.00008	-0.00445
51.	0.712 ,0,5	0.00028	0.01585	0.706 , 0,5	-0.00048	-0.02757
52.	0.712 ,0,5	0.00028	0.01585	0.708 , 0,5	-0.0011	-0.05969
53.	0.712 ,0,5	0.00028	0.01585	0.722 , 0,5	0.00014	0.0104
54.	0.712 ,0,5	0.00028	0.01585	0.71 , 0,5	-0.00023	-0.0123
55.	0.712 ,0,5	0.00028	0.01585	0.715 , 0,5	0.00021	0.002
56.	0.712 ,0,5	0.00028	0.01585	0.714 , 0,5	0.0001	0.00669
57.	0.712 ,0,5	0.00028	0.01585	0.708 , 0,5	-0.0011	-0.05969
58.	0.712 ,0,5	0.00028	0.01585	0.712 ,0,5	0.00028	0.01585
59.	0.712 ,0,5	0.00028	0.01585	0.698 , 0,5	-0.00042	-0.01346
60.	0.712 ,0,5	0.00028	0.01585	0.699 , 0,5	-0.00085	-0.0373
61.	0.712 ,0,5	0.00028	0.01585	0.698 , 0,5	-0.00042	-0.01346
62.	0.712 ,0,5	0.00028	0.01585	0.713 , 0,5	0.00025	0.0028
63.	0.712 ,0,5	0.00028	0.01585	0.703 , 0,5	0.00016	0.04195
64.	0.712 ,0,5	0.00028	0.01585	0.723 , 0,5	-0.0005	-0.03205
65.	0.712 ,0,5	0.00028	0.01585	0.711 , 0,5	-0.00008	-0.00445
66.	0.712 ,0,5	0.00028	0.01585	0.714 , 0,5	0.0001	0.00669
67.	0.712 ,0,5	0.00028	0.01585	0.708 , 0,5	-0.0011	-0.05969
68.	0.712 ,0,5	0.00028	0.01585	0.696 , 0,5	-0.00048	-0.02363
69.	0.712 ,0,5	0.00028	0.01585	0.726 , 0,5	-0.00045	-0.02762
70.	0.712 ,0,5	0.00028	0.01585	0.726 , 0,5	-0.00045	-0.02762
71.	0.712 ,0,5	0.00028	0.01585	0.709 , 0,5	-0.00011	-0.00512
72.	0.712 ,0,5	0.00028	0.01585	0.715 , 0,5	0.00021	0.002
73.	0.712 ,0,5	0.00028	0.01585	0.698 , 0,5	-0.00042	-0.01346
74.	0.712 ,0,5	0.00028	0.01585	0.726 , 0,5	-0.00045	-0.02762
75.	0.712 ,0,5	0.00028	0.01585	0.712 ,0,5	0.00028	0.01585
76.	0.712 ,0,5	0.00028	0.01585	0.726 , 0,5	-0.00045	-0.02762
77.	-0.667,0,5	-0.0001	-0.00736	0.703 , 0,5	0.00016	0.04195
78.	0.712 ,0,5	0.00028	0.01585	0.715 , 0,5	0.00021	0.002
79.	0.712 ,0,5	0.00028	0.01585	0.712 ,0,5	0.00028	0.01585
80.	0.712 ,0,5	0.00028	0.01585	0.71 , 0,5	-0.00023	-0.0123
81.	0.712 ,0,5	0.00028	0.01585	0.709 , 0,5	-0.00011	-0.00512
82.	0.712 ,0,5	0.00028	0.01585	0.71 , 0,5	-0.00023	-0.0123
83.	0.712 ,0,5	0.00028	0.01585	0.708 , 0,5	-0.0011	-0.05969
84.	0.712 ,0,5	0.00028	0.01585	0.722 , 0,5	0.00014	0.0104
85.	0.712 ,0,5	0.00028	0.01585	0.723 , 0,5	-0.0005	-0.03205
86.	0.712 ,0,5	0.00028	0.01585	0.712 ,0,5	0.00028	0.01585
87.	0.712 ,0,5	0.00028	0.01585	0.7 , 0,5	0.000012	0.00812
88.	0.712 ,0,5	0.00028	0.01585	0.696 , 0,5	-0.00048	-0.02363

89.	0.712 ,0,5	0.00028	0.01585	0.71 , 0,5	-0.00023	-0.0123
90.	0.712 ,0,5	0.00028	0.01585	0.708 , 0,5	-0.0011	-0.05969
91.	0.712 ,0,5	0.00028	0.01585	0.711 , 0,5	-0.00008	-0.00445
92.	0.712 ,0,5	0.00028	0.01585	0.708 , 0,5	-0.0011	-0.05969
93.	0.712 ,0,5	0.00028	0.01585	0.699 , 0,5	-0.00085	-0.0373
94.	0.712 ,0,5	0.00028	0.01585	0.715 , 0,5	0.00021	0.002
95.	0.712 ,0,5	0.00028	0.01585	0.708 , 0,5	-0.0011	-0.05969
96.	0.712 ,0,5	0.00028	0.01585	0.709 , 0,5	-0.00011	-0.00512
97.	0.712 ,0,5	0.00028	0.01585	0.726 , 0,5	-0.00045	-0.02762
98.	0.712 ,0,5	0.00028	0.01585	0.712 ,0,5	0.00028	0.01585
99.	0.712 ,0,5	0.00028	0.01585	0.726 , 0,5	-0.00045	-0.02762
100.	0.712 ,0,5	0.00028	0.01585	0.726 , 0,5	-0.00045	-0.02762

(b) SSE as Fitness Function, File 2 is Audio File.

NO	PSO/SSE	File 2 / SNR	File 2 / CC	QPSO/SSE	File 2 / SNR	File 2 / CC
1.	0.712 ,0,5	0.00028	0.01585	0.716,0,5	0.00023	0.01909
2.	0.712 ,0,5	0.00028	0.01585	0.725,0,5	0.00048	0.00362
3.	0.712 ,0,5	0.00028	0.01585	0.708,0,5	0.0011	0.05969
4.	0.712 ,0,5	0.00028	0.01585	0.707,0,5	-0.00108	-0.0549
5.	0.712 ,0,5	0.00028	0.01585	0.696,0,5	-0.00048	0.02363
6.	0.712 ,0,5	0.00028	0.01585	0.704,0,5	-0.00078	-0.04089
7.	0.712 ,0,5	0.00028	0.01585	0.712 , 0,5	0.00028	0.01585
8.	0.712 ,0,5	0.00028	0.01585	0.705,0,5	-0.00075	-0.05649
9.	0.712 ,0,5	0.00028	0.01585	0.712 , 0,5	0.00028	0.01585
10.	0.712 ,0,5	0.00028	0.01585	0.71,0,5	-0.00023	-0.0123
11.	0.712 ,0,5	0.00028	0.01585	0.714,0,5	0.0001	0.00669
12.	0.712 ,0,5	0.00028	0.01585	0.714,0,5	0.0001	0.00669
13.	0.712 ,0,5	0.00028	0.01585	0.71,0,5	-0.00023	-0.0123
14.	0.712 ,0,5	0.00028	0.01585	0.711 ,0,5	-0.00008	-0.00445
15.	0.712 ,0,5	0.00028	0.01585	0.716,0,5	0.00023	0.01909
16.	0.712 ,0,5	0.00028	0.01585	0.668,0,5	-0.00042	-0.02723
17.	0.712 ,0,5	0.00028	0.01585	0.709,0,5	-0.00512	-0.00011
18.	0.712 ,0,5	0.00028	0.01585	0.666,0,5	-0.00047	-0.03147
19.	0.712 ,0,5	0.00028	0.01585	0.719,0,5	0.00019	0.01315
20.	0.712 ,0,5	0.00028	0.01585	0.697,0,5	-0.00146	--0.06883
21.	0.712 ,0,5	0.00028	0.01585	0.673,0,5	-0.00055	-0.03514
22.	0.712 ,0,5	0.00028	0.01585	0.716,0,5	0.00023	0.01909
23.	0.712 ,0,5	0.00028	0.01585	0.687,0,5	-0.00079	-0.05754
24.	0.712 ,0,5	0.00028	0.01585	0.705,0,5	-0.00075	-0.05649
25.	0.712 ,0,5	0.00028	0.01585	0.713,0,5	0.00025	0.0028
26.	0.712 ,0,5	0.00028	0.01585	0.709,0,5	-0.00512	-0.00011
27.	0.712 ,0,5	0.00028	0.01585	0.714,0,5	0.0001	0.00669
28.	0.712 ,0,5	0.00028	0.01585	0.715,0,5	0.002	0.00021
29.	0.712 ,0,5	0.00028	0.01585	0.701,0,5	0.000043	0.00304
30.	0.712 ,0,5	0.00028	0.01585	0.676,0,5	0.000013	0.00153
31.	0.712 ,0,5	0.00028	0.01585	0.705,0,5	-0.00075	-0.05649
32.	0.712 ,0,5	0.00028	0.01585	0.709,0,5	-0.00512	-0.00011
33.	0.712 ,0,5	0.00028	0.01585	0.712,0,5	0.00028	0.01585
34.	0.712 ,0,5	0.00028	0.01585	0.707,0,5	-0.00108	-0.0549
35.	0.712 ,0,5	0.00028	0.01585	0.696,0,5	-0.00048	0.02363
36.	0.712 ,0,5	0.00028	0.01585	0.711 ,0,5	-0.00008	-0.00445
37.	0.712 ,0,5	0.00028	0.01585	0.706,0,5	-0.02757	-0.00048
38.	0.712 ,0,5	0.00028	0.01585	0.715,0,5	0.002	0.00021
39.	0.712 ,0,5	0.00028	0.01585	0.72 , 0,5	-0.00108	-0.0549
40.	0.712 ,0,5	0.00028	0.01585	0.703,0,5	0.00016	0.04195
41.	0.712 ,0,5	0.00028	0.01585	0.714,0,5	0.0001	0.00669
42.	0.712 ,0,5	0.00028	0.01585	0.704,0,5	-0.00078	-0.04089
43.	0.712 ,0,5	0.00028	0.01585	0.7,0,5	0.000012	0.00812

44.	0.712 ,0,5	0.00028	0.01585	0.711 ,0,5	-0.00008	-0.00445
45.	0.712 ,0,5	0.00028	0.01585	0.723,0,5	-0.0005	-0.03205
46.	0.712 ,0,5	0.00028	0.01585	0.701,0,5	0.000043	0.00304
47.	0.712 ,0,5	0.00028	0.01585	0.699,0,5	-0.0373	-0.00085
48.	0.712 ,0,5	0.00028	0.01585	0.696,0,5	-0.00048	0.02363
49.	0.712 ,0,5	0.00028	0.01585	0.71,0,5	-0.00023	-0.0123
50.	0.712 ,0,5	0.00028	0.01585	0.691,0,5	-0.00015	-0.00966
51.	0.712 ,0,5	0.00028	0.01585	0.692,0,5	-0.00107	-0.05645
52.	0.712 ,0,5	0.00028	0.01585	0.704,0,5	-0.00078	-0.04089
53.	0.712 ,0,5	0.00028	0.01585	0.715,0,5	0.002	0.00021
54.	0.712 ,0,5	0.00028	0.01585	0.708,0,5	0.0011	0.05969
55.	0.712 ,0,5	0.00028	0.01585	0.71,0,5	-0.00023	-0.0123
56.	0.712 ,0,5	0.00028	0.01585	0.712,0,5	0.00028	0.01585
57.	0.712 ,0,5	0.00028	0.01585	0.711 ,0,5	--0.00008	-0.00445
58.	0.712 ,0,5	0.00028	0.01585	0.709,0,5	-0.00512	-0.00011
59.	0.712 ,0,5	0.00028	0.01585	0.702,0,5	0.00022	0.01057
60.	0.712 ,0,5	0.00028	0.01585	0.702,0,5	0.00022	0.01057
61.	0.712 ,0,5	0.00028	0.01585	0.711 ,0,5	-0.00008	-0.00445
62.	0.712 ,0,5	0.00028	0.01585	0.709,0,5	-0.00008	-0.00445
63.	0.712 ,0,5	0.00028	0.01585	0.711 ,0,5	-0.00008	-0.00445
64.	0.712 ,0,5	0.00028	0.01585	0.699,0,5	-0.00085	-0.0373
65.	0.712 ,0,5	0.00028	0.01585	0.711 ,0,5	-0.00008	-0.00445
66.	0.712 ,0,5	0.00028	0.01585	0.709,0,5	-0.00512	-0.00011
67.	0.712 ,0,5	0.00028	0.01585	0.686,0,5	-0.00078	-0.05042
68.	-0.661, 0,5	-0.0002	-0.01757	0.71,0,5	-0.00023	-0.0123
69.	0.712 ,0,5	0.00028	0.01585	0.69,0,5	-0.00039	-0.02679
70.	0.712 ,0,5	0.00028	0.01585	0.704,0,5	-0.00078	-0.04089
71.	0.712 ,0,5	0.00028	0.01585	0.681,0,5	-0.00024	-0.01514
72.	0.712 ,0,5	0.00028	0.01585	0.707,0,5	-0.00108	-0.0549
73.	0.712 ,0,5	0.00028	0.01585	0.699,0,5	-0.00085	-0.0373
74.	0.712 ,0,5	0.00028	0.01585	0.714,0,5	0.0001	0.00669
75.	0.712 ,0,5	0.00028	0.01585	0.652,0,5	-0.00031	-0.01686
76.	0.712 ,0,5	0.00028	0.01585	0.709,0,5	-0.00512	-0.00011
77.	0.712 ,0,5	0.00028	0.01585	0.712,0,5	0.00028	0.01585
78.	0.712 ,0,5	0.00028	0.01585	0.698,0,5	-0.00042	-0.01346
79.	0.712 ,0,5	0.00028	0.01585	0.716,0,5	0.00023	0.01909
80.	0.712 ,0,5	0.00028	0.01585	0.702,0,5	0.00022	0.01057
81.	0.712 ,0,5	0.00028	0.01585	0.693,0,5	-0.00051	-0.02777
82.	0.712 ,0,5	0.00028	0.01585	0.707 , 0,5	-0.00108	-0.0549
83.	0.712 ,0,5	0.00028	0.01585	0.708,0,5	0.0011	0.05969
84.	0.712 ,0,5	0.00028	0.01585	0.695,0,5	-0.01939	-0.00044
85.	0.712 ,0,5	0.00028	0.01585	0.685,0,5	-0.00144	-0.09747
86.	0.712 ,0,5	0.00028	0.01585	0.703,0,5	0.00016	0.04195
87.	0.712 ,0,5	0.00028	0.01585	0.702,0,5	0.00022	0.01057
88.	0.712 ,0,5	0.00028	0.01585	0.697,0,5	-0.00146	--0.06883
89.	0.712 ,0,5	0.00028	0.01585	0.712 , 0,5	0.00028	0.01585
90.	0.712 ,0,5	0.00028	0.01585	0.699,0,5	-0.00085	-0.0373
91.	0.712 ,0,5	0.00028	0.01585	0.725,0,5	0.000049	0.00362
92.	0.712 ,0,5	0.00028	0.01585	0.709,0,5	-0.00512	-0.00011
93.	0.712 ,0,5	0.00028	0.01585	0.705,0,5	-0.00075	-0.05649
94.	0.712 ,0,5	0.00028	0.01585	0.685,0,5	-0.00144	-0.09747
95.	0.712 ,0,5	0.00028	0.01585	0.71,0,5	-0.00023	-0.0123
96.	0.712 ,0,5	0.00028	0.01585	0.702,0,5	0.00022	0.01057
97.	0.712 ,0,5	0.00028	0.01585	0.715,0,5	0.002	0.00021
98.	0.712 ,0,5	0.00028	0.01585	0.712 , 0,5	0.00028	0.01585
99.	0.712 ,0,5	0.00028	0.01585	0.707 , 0,5	-0.00108	-0.0549
100.	0.712 ,0,5	0.00028	0.01585	0.715 , 0,5	0.002	0.00021

▪ Case study 3

Table 9: Accessing the best and worst values for test speech descrambler based on parameter estimation (circle map).

(a) MSE as Fitness Function, File 3 is Audio File.

NO	PSO/MSE	File 3 / SNR	File 3/ CC	QPSO/MSE	File 3 / SNR	File 3/ CC
1.	0.712 ,0,5	0.0182	0.10087	0.699, 0,5	-0.000054	-0.0163
2.	0.712 ,0,5	0.0182	0.10087	0.704 , 0,5	0.0001	0.03749
3.	0.712 ,0,5	0.0182	0.10087	0.703 , 0,5	0.00016	0.04195
4.	0.712 ,0,5	0.0182	0.10087	0.711 , 0,5	-0.000002	-0.00024
5.	0.712 ,0,5	0.0182	0.10087	0.715 , 0,5	0.00003	0.01234
6.	0.712 ,0,5	0.0182	0.10087	0.721 , 0,5	0.000027	0.01133
7.	0.712 ,0,5	0.0182	0.10087	0.697 , 0,5	-0.00009	-0.0329
8.	0.712 ,0,5	0.0182	0.10087	0.712 , 0,5	0.0182	0.10087
9.	0.712 ,0,5	0.0182	0.10087	0.709 , 0,5	-0.00019	-0.0592
10.	0.712 ,0,5	0.0182	0.10087	0.711 , 0,5	-0.000002	-0.00024
11.	0.712 ,0,5	0.0182	0.10087	0.699 , 0,5	-0.000054	-0.0163
12.	0.712 ,0,5	0.0182	0.10087	0.698 , 0,5	0.00011	0.03875
13.	0.712 ,0,5	0.0182	0.10087	0.711 , 0,5	-0.000002	-0.00024
14.	0.712 ,0,5	0.0182	0.10087	0.712 , 0,5	0.0182	0.10087
15.	0.712 ,0,5	0.0182	0.10087	0.711 , 0,5	-0.000002	-0.00024
16.	0.712 ,0,5	0.0182	0.10087	0.726 , 0,5	0.00023	0.08217
17.	0.712 ,0,5	0.0182	0.10087	0.711 , 0,5	-0.000002	-0.00024
18.	0.712 ,0,5	0.0182	0.10087	0.708 , 0,5	-0.00003	-0.01245
19.	0.712 ,0,5	0.0182	0.10087	0.704 , 0,5	0.0001	0.03749
20.	0.712 ,0,5	0.0182	0.10087	0.71 , 0,5	-0.00003	-0.00893
21.	0.712 ,0,5	0.0182	0.10087	0.726 , 0,5	0.00023	0.08217
22.	0.712 ,0,5	0.0182	0.10087	0.703 , 0,5	0.00016	0.04195
23.	0.712 ,0,5	0.0182	0.10087	0.712 , 0,5	0.0182	0.10087
24.	0.712 ,0,5	0.0182	0.10087	0.726 , 0,5	0.00023	0.08217
25.	0.712 ,0,5	0.0182	0.10087	0.708 , 0,5	-0.00003	--0.01245
26.	0.712 ,0,5	0.0182	0.10087	0.706 , 0,5	0.0003	0.05264
27.	0.712 ,0,5	0.0182	0.10087	0.713 , 0,5	0.00006	0.03038
28.	0.712 ,0,5	0.0182	0.10087	0.712 , 0,5	0.0182	0.10087
29.	0.712 ,0,5	0.0182	0.10087	0.695 , 0,5	-0.00003	-0.00852
30.	0.712 ,0,5	0.0182	0.10087	0.697 , 0,5	-0.00009	-0.0329
31.	0.712 ,0,5	0.0182	0.10087	0.713 , 0,5	0.00006	0.03038
32.	0.712 ,0,5	0.0182	0.10087	0.712 , 0,5	0.0182	0.10087
33.	0.712 ,0,5	0.0182	0.10087	0.723 , 0,5	0.00001	0.00772
34.	0.712 ,0,5	0.0182	0.10087	0.711 , 0,5	-0.000002	-0.00024
35.	0.712 ,0,5	0.0182	0.10087	0.71 , 0,5	-0.00003	-0.00893
36.	0.712 ,0,5	0.0182	0.10087	0.696 , 0,5	-0.00012	-0.04006
37.	0.712 ,0,5	0.0182	0.10087	0.711 , 0,5	-0.000002	-0.00024
38.	0.712 ,0,5	0.0182	0.10087	0.71 , 0,5	-0.00003	-0.00893
39.	0.712 ,0,5	0.0182	0.10087	0.714 , 0,5	-0.00007	-0.02815
40.	0.712 ,0,5	0.0182	0.10087	0.698 , 0,5	0.00011	0.03875
41.	0.712 ,0,5	0.0182	0.10087	0.698 , 0,5	0.00011	0.03875
42.	0.712 ,0,5	0.0182	0.10087	0.711 , 0,5	-0.000002	-0.00024
43.	0.712 ,0,5	0.0182	0.10087	0.714 , 0,5	-0.00007	-0.02815
44.	0.712 ,0,5	0.0182	0.10087	0.711 , 0,5	-0.000002	-0.00024
45.	0.712 ,0,5	0.0182	0.10087	0.724 , 0,5	0.00005	0.02141
46.	0.712 ,0,5	0.0182	0.10087	0.704 , 0,5	0.0001	0.03749
47.	0.712 ,0,5	0.0182	0.10087	0.696 , 0,5	-0.00012	-0.04006
48.	0.712 ,0,5	0.0182	0.10087	0.708 , 0,5	-0.00003	--0.01245
49.	0.712 ,0,5	0.0182	0.10087	0.713 , 0,5	0.00006	0.03038
50.	0.712 ,0,5	0.0182	0.10087	0.711 , 0,5	-0.000002	-0.00024
51.	0.712 ,0,5	0.0182	0.10087	0.706 , 0,5	0.0003	0.05264
52.	0.712 ,0,5	0.0182	0.10087	0.708 , 0,5	-0.00003	--0.01245
53.	0.712 ,0,5	0.0182	0.10087	0.722 , 0,5	0.00003	0.01337

54.	0.712 ,0,5	0.0182	0.10087	0.71 , 0,5	-0.00003	-0.00893
55.	0.712 ,0,5	0.0182	0.10087	0.715 , 0,5	0.00003	0.01234
56.	0.712 ,0,5	0.0182	0.10087	0.714 , 0,5	-0.00007	-0.02815
57.	0.712 ,0,5	0.0182	0.10087	0.708 , 0,5	-0.00003	--0.01245
58.	0.712 ,0,5	0.0182	0.10087	0.712 ,0,5	0.0182	0.10087
59.	0.712 ,0,5	0.0182	0.10087	0.698 , 0,5	0.00011	0.03875
60.	0.712 ,0,5	0.0182	0.10087	0.699 , 0,5	-0.000054	-0.0163
61.	0.712 ,0,5	0.0182	0.10087	0.698 , 0,5	0.00011	0.03875
62.	0.712 ,0,5	0.0182	0.10087	0.713 , 0,5	0.00006	0.03038
63.	0.712 ,0,5	0.0182	0.10087	0.703 , 0,5	0.00016	0.04195
64.	0.712 ,0,5	0.0182	0.10087	0.723 , 0,5	0.00001	0.00772
65.	0.712 ,0,5	0.0182	0.10087	0.711 , 0,5	-0.000002	-0.00024
66.	0.712 ,0,5	0.0182	0.10087	0.714 , 0,5	-0.00007	-0.02815
67.	0.712 ,0,5	0.0182	0.10087	0.708 , 0,5	-0.00003	--0.01245
68.	0.712 ,0,5	0.0182	0.10087	0.696 , 0,5	-0.00012	-0.04006
69.	0.712 ,0,5	0.0182	0.10087	0.726 , 0,5	0.00023	0.08217
70.	0.712 ,0,5	0.0182	0.10087	0.726 , 0,5	0.00023	0.08217
71.	0.712 ,0,5	0.0182	0.10087	0.709 , 0,5	-0.00019	-0.0592
72.	0.712 ,0,5	0.0182	0.10087	0.715 , 0,5	0.00003	0.01234
73.	0.712 ,0,5	0.0182	0.10087	0.698 , 0,5	0.00011	0.03875
74.	0.712 ,0,5	0.0182	0.10087	0.726 , 0,5	0.00023	0.08217
75.	0.712 ,0,5	0.0182	0.10087	0.712 ,0,5	0.0182	0.10087
76.	0.712 ,0,5	0.0182	0.10087	0.726 , 0,5	0.00016	0.04195
77.	-0.667,0,5	-0.03399	0.01512	0.703 , 0,5	0.00016	0.04195
78.	0.712 ,0,5	0.0182	0.10087	0.715 , 0,5	0.00003	0.01234
79.	0.712 ,0,5	0.0182	0.10087	0.712 ,0,5	0.0182	0.10087
80.	0.712 ,0,5	0.0182	0.10087	0.71 , 0,5	-0.00003	-0.00893
81.	0.712 ,0,5	0.0182	0.10087	0.709 , 0,5	-0.00019	-0.0592
82.	0.712 ,0,5	0.0182	0.10087	0.71 , 0,5	-0.00003	-0.00893
83.	0.712 ,0,5	0.0182	0.10087	0.708 , 0,5	-0.00003	--0.01245
84.	0.712 ,0,5	0.0182	0.10087	0.722 , 0,5	0.00003	0.01337
85.	0.712 ,0,5	0.0182	0.10087	0.723 , 0,5	0.00001	0.00772
86.	0.712 ,0,5	0.0182	0.10087	0.712 ,0,5	0.0182	0.10087
87.	0.712 ,0,5	0.0182	0.10087	0.7 , 0,5	0.00011	0.03394
88.	0.712 ,0,5	0.0182	0.10087	0.696 , 0,5	-0.00012	-0.04006
89.	0.712 ,0,5	0.0182	0.10087	0.71 , 0,5	-0.00003	-0.00893
90.	0.712 ,0,5	0.0182	0.10087	0.708 , 0,5	-0.00003	--0.01245
91.	0.712 ,0,5	0.0182	0.10087	0.711 , 0,5	-0.000002	-0.00024
92.	0.712 ,0,5	0.0182	0.10087	0.708 , 0,5	-0.00003	--0.01245
93.	0.712 ,0,5	0.0182	0.10087	0.699 , 0,5	-0.000054	-0.0163
94.	0.712 ,0,5	0.0182	0.10087	0.715 , 0,5	0.00003	0.01234
95.	0.712 ,0,5	0.0182	0.10087	0.708 , 0,5	-0.00003	--0.01245
96.	0.712 ,0,5	0.0182	0.10087	0.709 , 0,5	-0.00019	-0.0592
97.	0.712 ,0,5	0.0182	0.10087	0.726 , 0,5	0.00023	0.08217
98.	0.712 ,0,5	0.0182	0.10087	0.712 ,0,5	0.0182	0.10087
99.	0.712 ,0,5	0.0182	0.10087	0.726 , 0,5	0.00023	0.08217
100.	0.712 ,0,5	0.0182	0.10087	0.726 , 0,5	0.00023	0.08217

(b)SSE as Fitness Function, File 3 is Audio File.

No	PSO/SSE	File 3 / SNR	File 3 / CC	QPSO/SSE	File 3 / SNR	File 3 / CC
1.	0.712 ,0,5	0.0182	0.10087	0.716,0,5	0.00012	0.05517
2.	0.712 ,0,5	0.0182	0.10087	0.725,0,5	-0.00006	-0.02424
3.	0.712 ,0,5	0.0182	0.10087	0.708,0,5	-0.00003	-0.01245
4.	0.712 ,0,5	0.0182	0.10087	0.707,0,5	0.00005	0.01319
5.	0.712 ,0,5	0.0182	0.10087	0.696,0,5	-0.00012	-0.04006
6.	0.712 ,0,5	0.0182	0.10087	0.704,0,5	0.0001	0.03749
7.	0.712 ,0,5	0.0182	0.10087	0.712 , 0,5	0.0182	0.10087
8.	0.712 ,0,5	0.0182	0.10087	0.705,0,5	0.00005	0.02001

9.	0.712,0,5	0.0182	0.10087	0.712,0,5	0.0182	0.10087
10.	0.712,0,5	0.0182	0.10087	0.71,0,5	-0.00003	-0.00893
11.	0.712,0,5	0.0182	0.10087	0.714,0,5	-0.00007	-0.02815
12.	0.712,0,5	0.0182	0.10087	0.714,0,5	-0.00007	-0.02815
13.	0.712,0,5	0.0182	0.10087	0.71,0,5	-0.00003	-0.00893
14.	0.712,0,5	0.0182	0.10087	0.711,0,5	-0.000002	-0.00024
15.	0.712,0,5	0.0182	0.10087	0.716,0,5	0.00012	0.05517
16.	0.712,0,5	0.0182	0.10087	0.668,0,5	-0.00013	-0.05141
17.	0.712,0,5	0.0182	0.10087	0.709,0,5	-0.00019	-0.0592
18.	0.712,0,5	0.0182	0.10087	0.666,0,5	0.000064	0.02445
19.	0.712,0,5	0.0182	0.10087	0.719,0,5	-0.00012	-0.05271
20.	0.712,0,5	0.0182	0.10087	0.697,0,5	-0.00009	-0.0329
21.	0.712,0,5	0.0182	0.10087	0.673,0,5	-0.00005	-0.01539
22.	0.712,0,5	0.0182	0.10087	0.716,0,5	0.00012	0.05517
23.	0.712,0,5	0.0182	0.10087	0.687,0,5	-0.00006	-0.02584
24.	0.712,0,5	0.0182	0.10087	0.705,0,5	0.00005	0.02001
25.	0.712,0,5	0.0182	0.10087	0.713,0,5	0.00006	0.03038
26.	0.712,0,5	0.0182	0.10087	0.709,0,5	-0.00019	-0.0592
27.	0.712,0,5	0.0182	0.10087	0.714,0,5	-0.00007	-0.02815
28.	0.712,0,5	0.0182	0.10087	0.715,0,5	0.00003	0.01234
29.	0.712,0,5	0.0182	0.10087	0.701,0,5	0.00012	0.04704
30.	0.712,0,5	0.0182	0.10087	0.676,0,5	-0.0001	-0.04518
31.	0.712,0,5	0.0182	0.10087	0.705,0,5	0.00005	0.02001
32.	0.712,0,5	0.0182	0.10087	0.709,0,5	-0.00019	-0.0592
33.	0.712,0,5	0.0182	0.10087	0.712,0,5	0.0182	0.10087
34.	0.712,0,5	0.0182	0.10087	0.707,0,5	0.00005	0.01319
35.	0.712,0,5	0.0182	0.10087	0.696,0,5	-0.00012	-0.04006
36.	0.712,0,5	0.0182	0.10087	0.711,0,5	-0.000002	-0.00024
37.	0.712,0,5	0.0182	0.10087	0.706,0,5	0.0003	0.05264
38.	0.712,0,5	0.0182	0.10087	0.715,0,5	0.00003	0.01234
39.	0.712,0,5	0.0182	0.10087	0.72,0,5	-0.00004	-0.01818
40.	0.712,0,5	0.0182	0.10087	0.703,0,5	0.00016	0.04195
41.	0.712,0,5	0.0182	0.10087	0.714,0,5	-0.00007	-0.02815
42.	0.712,0,5	0.0182	0.10087	0.704,0,5	0.0001	0.03749
43.	0.712,0,5	0.0182	0.10087	0.7,0,5	0.00011	0.03394
44.	0.712,0,5	0.0182	0.10087	0.711,0,5	-0.000002	-0.00024
45.	0.712,0,5	0.0182	0.10087	0.723,0,5	0.00001	0.00772
46.	0.712,0,5	0.0182	0.10087	0.701,0,5	0.00012	0.04704
47.	0.712,0,5	0.0182	0.10087	0.699,0,5	-0.0163	-0.000054
48.	0.712,0,5	0.0182	0.10087	0.696,0,5	-0.00012	-0.04006
49.	0.712,0,5	0.0182	0.10087	0.71,0,5	-0.00003	-0.00893
50.	0.712,0,5	0.0182	0.10087	0.691,0,5	-0.00002	-0.02257
51.	0.712,0,5	0.0182	0.10087	0.692,0,5	-0.00013	-0.05176
52.	0.712,0,5	0.0182	0.10087	0.704,0,5	0.0001	0.03749
53.	0.712,0,5	0.0182	0.10087	0.715,0,5	0.00003	0.01234
54.	0.712,0,5	0.0182	0.10087	0.708,0,5	-0.00003	-0.01245
55.	0.712,0,5	0.0182	0.10087	0.71,0,5	-0.00003	-0.00893
56.	0.712,0,5	0.0182	0.10087	0.712,0,5	0.0182	0.10087
57.	0.712,0,5	0.0182	0.10087	0.711,0,5	-0.000002	-0.00024
58.	0.712,0,5	0.0182	0.10087	0.709,0,5	-0.00019	-0.0592
59.	0.712,0,5	0.0182	0.10087	0.702,0,5	0.00008	0.03335
60.	0.712,0,5	0.0182	0.10087	0.702,0,5	0.00008	0.03335
61.	0.712,0,5	0.0182	0.10087	0.711,0,5	-0.000002	-0.00024
62.	0.712,0,5	0.0182	0.10087	0.709,0,5	-0.00019	-0.0592
63.	0.712,0,5	0.0182	0.10087	0.711,0,5	-0.000002	-0.00024
64.	0.712,0,5	0.0182	0.10087	0.699,0,5	-0.000054	-0.0163
65.	0.712,0,5	0.0182	0.10087	0.711,0,5	-0.000002	-0.00024
66.	0.712,0,5	0.0182	0.10087	0.709,0,5	-0.00019	-0.0592
67.	0.712,0,5	0.0182	0.10087	0.686,0,5	0.00008	0.02767
68.	-0.661,0,5	-0.00219	0.00502	0.71,0,5	-0.00003	-0.00893
69.	0.712,0,5	0.0182	0.10087	0.69,0,5	-0.00013	-0.0468
70.	0.712,0,5	0.0182	0.10087	0.704,0,5	0.0001	0.03749
71.	0.712,0,5	0.0182	0.10087	0.681,0,5	0.00006	0.02659

72.	0.712 ,0.5	0.0182	0.10087	0.707,0.5	0.00005	0.01319
73.	0.712 ,0.5	0.0182	0.10087	0.699,0.5	-0.000054	-0.0163
74.	0.712 ,0.5	0.0182	0.10087	0.714,0.5	-0.00007	-0.02815
75.	0.712 ,0.5	0.0182	0.10087	0.652,0.5	-0.00007	-0.02603
76.	0.712 ,0.5	0.0182	0.10087	0.709,0.5	-0.00019	-0.0592
77.	0.712 ,0.5	0.0182	0.10087	0.712,0.5	0.0182	0.10087
78.	0.712 ,0.5	0.0182	0.10087	0.698,0.5	0.00011	0.03875
79.	0.712 ,0.5	0.0182	0.10087	0.716,0.5	0.00012	0.05517
80.	0.712 ,0.5	0.0182	0.10087	0.702,0.5	0.00008	0.03335
81.	0.712 ,0.5	0.0182	0.10087	0.693,0.5	-0.00007	-0.02251
82.	0.712 ,0.5	0.0182	0.10087	0.707 ,0.5	0.00005	0.01319
83.	0.712 ,0.5	0.0182	0.10087	0.708,0.5	-0.00003	-0.01245
84.	0.712 ,0.5	0.0182	0.10087	0.695,0.5	-0.00003	-0.00852
85.	0.712 ,0.5	0.0182	0.10087	0.685,0.5	-0.00011	-0.0504
86.	0.712 ,0.5	0.0182	0.10087	0.703,0.5	0.00016	0.04195
87.	0.712 ,0.5	0.0182	0.10087	0.702,0.5	0.00008	0.03335
88.	0.712 ,0.5	0.0182	0.10087	0.697,0.5	-0.00009	-0.0329
89.	0.712 ,0.5	0.0182	0.10087	0.712 ,0.5	0.0182	0.10087
90.	0.712 ,0.5	0.0182	0.10087	0.699,0.5	-0.000054	-0.0163
91.	0.712 ,0.5	0.0182	0.10087	0.725,0.5	-0.00006	-0.02424
92.	0.712 ,0.5	0.0182	0.10087	0.709,0.5	-0.00019	-0.0592
93.	0.712 ,0.5	0.0182	0.10087	0.705,0.5	0.00005	0.02001
94.	0.712 ,0.5	0.0182	0.10087	0.685,0.5	-0.00011	-0.0504
95.	0.712 ,0.5	0.0182	0.10087	0.71,0.5	-0.00003	-0.00893
96.	0.712 ,0.5	0.0182	0.10087	0.702,0.5	0.00008	0.03335
97.	0.712 ,0.5	0.0182	0.10087	0.715,0.5	0.00003	0.01234
98.	0.712 ,0.5	0.0182	0.10087	0.712 ,0.5	0.0182	0.10087
99.	0.712 ,0.5	0.0182	0.10087	0.707 ,0.5	0.00005	0.01319
100.	0.712 ,0.5	0.0182	0.10087	0.715 ,0.5	0.00003	0.01234

■ Case study 4

Table 10: Accessing the best and worst values for test speech descrambler based on parameter estimation (circle map).

(a) MSE as Fitness Function, File 4 is Audio File.

NO	PSO/MSE	File 4 / SNR	File 4/ CC	QPSO/MSE	File 4 / SNR	File 4/ CC
1.	0.712 ,0.5	0.0025	0.03337	0.699 , 0.5	-0.00057	-0.07672
2.	0.712 ,0.5	0.0025	0.03337	0.704 , 0.5	0.00001	0.00259
3.	0.712 ,0.5	0.0025	0.03337	0.703 , 0.5	-0.00037	-0.04387
4.	0.712 ,0.5	0.0025	0.03337	0.711 , 0.5	-0.00046	-0.03495
5.	0.712 ,0.5	0.0025	0.03337	0.715 , 0.5	0.00008	0.01615
6.	0.712 ,0.5	0.0025	0.03337	0.721 , 0.5	0.00024	0.04203
7.	0.712 ,0.5	0.0025	0.03337	0.697 , 0.5	-0.00025	-0.04034
8.	0.712 ,0.5	0.0025	0.03337	0.712 , 0.5	0.0025	0.03337
9.	0.712 ,0.5	0.0025	0.03337	0.709 , 0.5	-0.00008	0.00835
10.	0.712 ,0.5	0.0025	0.03337	0.711 , 0.5	-0.00046	-0.03495
11.	0.712 ,0.5	0.0025	0.03337	0.699 , 0.5	-0.00057	-0.07672
12.	0.712 ,0.5	0.0025	0.03337	0.698 , 0.5	-0.0001	-0.01534
13.	0.712 ,0.5	0.0025	0.03337	0.711 , 0.5	-0.00046	-0.03495
14.	0.712 ,0.5	0.0025	0.03337	0.712 , 0.5	0.0025	0.03337
15.	0.712 ,0.5	0.0025	0.03337	0.711 , 0.5	-0.00046	-0.03495
16.	0.712 ,0.5	0.0025	0.03337	0.726 , 0.5	-0.00018	-0.02945
17.	0.712 ,0.5	0.0025	0.03337	0.711 , 0.5	-0.00046	-0.03495
18.	0.712 ,0.5	0.0025	0.03337	0.708 , 0.5	0.00027	0.04441
19.	0.712 ,0.5	0.0025	0.03337	0.704 , 0.5	0.00001	0.00259
20.	0.712 ,0.5	0.0025	0.03337	0.71 , 0.5	0.00019	0.02531
21.	0.712 ,0.5	0.0025	0.03337	0.726 , 0.5	-0.00018	-0.02945
22.	0.712 ,0.5	0.0025	0.03337	0.703 , 0.5	-0.00037	-0.04387

23.	0.712 ,0,5	0.0025	0.03337	0.712 , 0,5	0.0025	0.03337
24.	0.712 ,0,5	0.0025	0.03337	0.726 , 0,5	-0.00018	-0.02945
25.	0.712 ,0,5	0.0025	0.03337	0.708 , 0,5	0.00027	0.04441
26.	0.712 ,0,5	0.0025	0.03337	0.706 , 0,5	-0.00013	-0.01074
27.	0.712 ,0,5	0.0025	0.03337	0.713 , 0,5	-0.00228	-0.0346
28.	0.712 ,0,5	0.0025	0.03337	0.712 , 0,5	0.0025	0.03337
29.	0.712 ,0,5	0.0025	0.03337	0.695 , 0,5	-0.00041	-0.03563
30.	0.712 ,0,5	0.0025	0.03337	0.697 , 0,5	-0.00025	-0.04034
31.	0.712 ,0,5	0.0025	0.03337	0.713 , 0,5	-0.00228	-0.0346
32.	0.712 ,0,5	0.0025	0.03337	0.712 , 0,5	0.0025	0.03337
33.	0.712 ,0,5	0.0025	0.03337	0.723 , 0,5	0.00004	0.03155
34.	0.712 ,0,5	0.0025	0.03337	0.711 , 0,5	-0.00046	-0.03495
35.	0.712 ,0,5	0.0025	0.03337	0.71 , 0,5	0.00019	0.02531
36.	0.712 ,0,5	0.0025	0.03337	0.696 , 0,5	-0.00029	-0.04461
37.	0.712 ,0,5	0.0025	0.03337	0.711 , 0,5	-0.00046	-0.03495
38.	0.712 ,0,5	0.0025	0.03337	0.71 , 0,5	0.00019	0.02531
39.	0.712 ,0,5	0.0025	0.03337	0.714 , 0,5	0.00006	0.01273
40.	0.712 ,0,5	0.0025	0.03337	0.698 , 0,5	-0.0001	-0.01534
41.	0.712 ,0,5	0.0025	0.03337	0.698 , 0,5	-0.0001	-0.01534
42.	0.712 ,0,5	0.0025	0.03337	0.711 , 0,5	-0.00046	-0.03495
43.	0.712 ,0,5	0.0025	0.03337	0.714 , 0,5	0.00006	0.01273
44.	0.712 ,0,5	0.0025	0.03337	0.711 , 0,5	-0.00046	-0.03495
45.	0.712 ,0,5	0.0025	0.03337	0.724 , 0,5	0.00028	0.0484
46.	0.712 ,0,5	0.0025	0.03337	0.704 , 0,5	0.00001	0.00259
47.	0.712 ,0,5	0.0025	0.03337	0.696 , 0,5	-0.00029	-0.04461
48.	0.712 ,0,5	0.0025	0.03337	0.708 , 0,5	0.00027	0.04441
49.	0.712 ,0,5	0.0025	0.03337	0.713 , 0,5	-0.00228	-0.0346
50.	0.712 ,0,5	0.0025	0.03337	0.711 , 0,5	-0.00046	-0.03495
51.	0.712 ,0,5	0.0025	0.03337	0.706 , 0,5	-0.00013	-0.01074
52.	0.712 ,0,5	0.0025	0.03337	0.708 , 0,5	0.00027	0.04441
53.	0.712 ,0,5	0.0025	0.03337	0.722 , 0,5	0.00031	0.04929
54.	0.712 ,0,5	0.0025	0.03337	0.71 , 0,5	0.00019	0.02531
55.	0.712 ,0,5	0.0025	0.03337	0.715 , 0,5	0.00008	0.01615
56.	0.712 ,0,5	0.0025	0.03337	0.714 , 0,5	0.00006	0.01273
57.	0.712 ,0,5	0.0025	0.03337	0.708 , 0,5	0.00027	0.04441
58.	0.712 ,0,5	0.0025	0.03337	0.712 ,0,5	0.0025	0.03337
59.	0.712 ,0,5	0.0025	0.03337	0.698 , 0,5	-0.0001	-0.01534
60.	0.712 ,0,5	0.0025	0.03337	0.699 , 0,5	-0.00057	-0.07672
61.	0.712 ,0,5	0.0025	0.03337	0.698 , 0,5	-0.0001	-0.01534
62.	0.712 ,0,5	0.0025	0.03337	0.713 , 0,5	-0.00228	-0.0346
63.	0.712 ,0,5	0.0025	0.03337	0.703 , 0,5	-0.00037	-0.04387
64.	0.712 ,0,5	0.0025	0.03337	0.723 , 0,5	0.00004	0.03155
65.	0.712 ,0,5	0.0025	0.03337	0.711 , 0,5	-0.00046	-0.03495
66.	0.712 ,0,5	0.0025	0.03337	0.714 , 0,5	0.00006	0.01273
67.	0.712 ,0,5	0.0025	0.03337	0.708 , 0,5	0.00027	0.04441
68.	0.712 ,0,5	0.0025	0.03337	0.696 , 0,5	-0.00029	-0.04461
69.	0.712 ,0,5	0.0025	0.03337	0.726 , 0,5	-0.00018	-0.02945
70.	0.712 ,0,5	0.0025	0.03337	0.726 , 0,5	-0.00018	-0.02945
71.	0.712 ,0,5	0.0025	0.03337	0.709 , 0,5	-0.00008	0.00835
72.	0.712 ,0,5	0.0025	0.03337	0.715 , 0,5	0.00008	0.01615
73.	0.712 ,0,5	0.0025	0.03337	0.698 , 0,5	-0.0001	-0.01534
74.	0.712 ,0,5	0.0025	0.03337	0.726 , 0,5	-0.00018	-0.02945
75.	0.712 ,0,5	0.0025	0.03337	0.712 ,0,5	0.0025	0.03337
76.	0.712 ,0,5	0.0025	0.03337	0.726 , 0,5	-0.00018	-0.02945
77.	-0.667,0,5	-0.00053	-0.01401	0.703 , 0,5	-0.00037	-0.04387
78.	0.712 ,0,5	0.0025	0.03337	0.715 , 0,5	0.00008	0.01615
79.	0.712 ,0,5	0.0025	0.03337	0.712 ,0,5	0.0025	0.03337
80.	0.712 ,0,5	0.0025	0.03337	0.71 , 0,5	0.00019	0.02531
81.	0.712 ,0,5	0.0025	0.03337	0.709 , 0,5	-0.00008	0.00835
82.	0.712 ,0,5	0.0025	0.03337	0.71 , 0,5	0.00019	0.02531
83.	0.712 ,0,5	0.0025	0.03337	0.708 , 0,5	0.00027	0.04441
84.	0.712 ,0,5	0.0025	0.03337	0.722 , 0,5	0.00031	0.04929
85.	0.712 ,0,5	0.0025	0.03337	0.723 , 0,5	0.00004	0.03155

86.	0.712 ,0,5	0.0025	0.03337	0.712 ,0,5	0.0025	0.03337
87.	0.712 ,0,5	0.0025	0.03337	0.7, 0,5	-0.00042	-0.05812
88.	0.712 ,0,5	0.0025	0.03337	0.696 , 0,5	-0.00029	-0.04461
89.	0.712 ,0,5	0.0025	0.03337	0.71 , 0,5	0.00019	0.02531
90.	0.712 ,0,5	0.0025	0.03337	0.708 , 0,5	0.00027	0.04441
91.	0.712 ,0,5	0.0025	0.03337	0.711 , 0,5	-0.00046	-0.03495
92.	0.712 ,0,5	0.0025	0.03337	0.708 , 0,5	0.00027	0.04441
93.	0.712 ,0,5	0.0025	0.03337	0.699 , 0,5	-0.00057	-0.07672
94.	0.712 ,0,5	0.0025	0.03337	0.715 , 0,5	0.00008	0.01615
95.	0.712 ,0,5	0.0025	0.03337	0.708 , 0,5	0.00027	0.04441
96.	0.712 ,0,5	0.0025	0.03337	0.709 , 0,5	-0.00008	0.00835
97.	0.712 ,0,5	0.0025	0.03337	0.726 , 0,5	-0.00018	-0.02945
98.	0.712 ,0,5	0.0025	0.03337	0.712 ,0,5	0.0025	0.03337
99.	0.712 ,0,5	0.0025	0.03337	0.726 , 0,5	-0.00018	-0.02945
100.	0.712 ,0,5	0.0025	0.03337	0.726 , 0,5	-0.00018	-0.02945

(b)SSE as Fitness Function, File 4 is Audio File.

No.	PSO/SSE	File 4 / SNR	File 4 / CC	QPSO/SSE	File 4 / SNR	File 4 / CC
1.	0.712 ,0,5	0.0025	0.03337	0.716,0,5	0.00008	0.01713
2.	0.712 ,0,5	0.0025	0.03337	0.725,0,5	0.00019	0.03688
3.	0.712 ,0,5	0.0025	0.03337	0.708,0,5	0.00027	0.04441
4.	0.712 ,0,5	0.0025	0.03337	0.707,0,5	-0.00031	-0.03574
5.	0.712 ,0,5	0.0025	0.03337	0.696,0,5	-0.00029	-0.04461
6.	0.712 ,0,5	0.0025	0.03337	0.704,0,5	0.00001	0.00259
7.	0.712 ,0,5	0.0025	0.03337	0.712 , 0,5	0.0025	0.03337
8.	0.712 ,0,5	0.0025	0.03337	0.705,0,5	0.0001	0.01657
9.	0.712 ,0,5	0.0025	0.03337	0.712 , 0,5	0.0025	0.03337
10.	0.712 ,0,5	0.0025	0.03337	0.71,0,5	0.00019	0.02531
11.	0.712 ,0,5	0.0025	0.03337	0.714,0,5	0.00006	0.01273
12.	0.712 ,0,5	0.0025	0.03337	0.714,0,5	0.00006	0.01273
13.	0.712 ,0,5	0.0025	0.03337	0.71,0,5	0.00019	0.02531
14.	0.712 ,0,5	0.0025	0.03337	0.711 ,0,5	-0.00046	-0.03495
15.	0.712 ,0,5	0.0025	0.03337	0.716,0,5	0.00008	0.01713
16.	0.712 ,0,5	0.0025	0.03337	0.668,0,5	-0.00005	-0.00837
17.	0.712 ,0,5	0.0025	0.03337	0.709,0,5	-0.00008	0.00835
18.	0.712 ,0,5	0.0025	0.03337	0.666,0,5	-0.00014	-0.02461
19.	0.712 ,0,5	0.0025	0.03337	0.719,0,5	0.00013	0.02795
20.	0.712 ,0,5	0.0025	0.03337	0.697,0,5	-0.00025	-0.04034
21.	0.712 ,0,5	0.0025	0.03337	0.673,0,5	0.00007	0.01068
22.	0.712 ,0,5	0.0025	0.03337	0.716,0,5	0.00008	0.01713
23.	0.712 ,0,5	0.0025	0.03337	0.687,0,5	-0.00016	-0.02785
24.	0.712 ,0,5	0.0025	0.03337	0.705,0,5	0.0001	0.01657
25.	0.712 ,0,5	0.0025	0.03337	0.713,0,5	-0.00228	-0.0346
26.	0.712 ,0,5	0.0025	0.03337	0.709,0,5	-0.00008	0.00835
27.	0.712 ,0,5	0.0025	0.03337	0.714,0,5	0.00006	0.01273
28.	0.712 ,0,5	0.0025	0.03337	0.715,0,5	0.00008	0.01615
29.	0.712 ,0,5	0.0025	0.03337	0.701,0,5	0.00028	0.04723
30.	0.712 ,0,5	0.0025	0.03337	0.676,0,5	-0.00009	-0.0168
31.	0.712 ,0,5	0.0025	0.03337	0.705,0,5	0.0001	0.01657
32.	0.712 ,0,5	0.0025	0.03337	0.709,0,5	-0.00008	0.00835
33.	0.712 ,0,5	0.0025	0.03337	0.712,0,5	0.0025	0.03337
34.	0.712 ,0,5	0.0025	0.03337	0.707,0,5	-0.00031	-0.03574
35.	0.712 ,0,5	0.0025	0.03337	0.696,0,5	-0.00029	-0.04461
36.	0.712 ,0,5	0.0025	0.03337	0.711 ,0,5	-0.00046	-0.03495
37.	0.712 ,0,5	0.0025	0.03337	0.706,0,5	-0.00013	-0.01074
38.	0.712 ,0,5	0.0025	0.03337	0.715,0,5	0.00008	0.01615
39.	0.712 ,0,5	0.0025	0.03337	0.72, 0,5	0.00021	0.00392
40.	0.712 ,0,5	0.0025	0.03337	0.703,0,5	-0.00037	-0.04387

41.	0.712 ,0,5	0.0025	0.03337	0.714,0,5	0.00006	0.01273
42.	0.712 ,0,5	0.0025	0.03337	0.704,0,5	0.00001	0.00259
43.	0.712 ,0,5	0.0025	0.03337	0.7,0,5	-0.00042	-0.05812
44.	0.712 ,0,5	0.0025	0.03337	0.711 ,0,5	-0.00046	-0.03495
45.	0.712 ,0,5	0.0025	0.03337	0.723,0,5	0.00004	0.03155
46.	0.712 ,0,5	0.0025	0.03337	0.701,0,5	0.00028	0.04723
47.	0.712 ,0,5	0.0025	0.03337	0.699,0,5	-0.00057	-0.07672
48.	0.712 ,0,5	0.0025	0.03337	0.696,0,5	-0.00029	-0.04461
49.	0.712 ,0,5	0.0025	0.03337	0.71,0,5	0.00019	0.02531
50.	0.712 ,0,5	0.0025	0.03337	0.691,0,5	-0.00026	-0.03741
51.	0.712 ,0,5	0.0025	0.03337	0.692,0,5	-0.00003	-0.00626
52.	0.712 ,0,5	0.0025	0.03337	0.704,0,5	0.00001	0.00259
53.	0.712 ,0,5	0.0025	0.03337	0.715,0,5	0.00008	0.01615
54.	0.712 ,0,5	0.0025	0.03337	0.708,0,5	0.00027	0.04441
55.	0.712 ,0,5	0.0025	0.03337	0.71,0,5	0.00019	0.02531
56.	0.712 ,0,5	0.0025	0.03337	0.712,0,5	0.0025	0.03337
57.	0.712 ,0,5	0.0025	0.03337	0.711 ,0,5	-0.00046	-0.03495
58.	0.712 ,0,5	0.0025	0.03337	0.709,0,5	-0.00008	0.00835
59.	0.712 ,0,5	0.0025	0.03337	0.702,0,5	0.00183	0.02445
60.	0.712 ,0,5	0.0025	0.03337	0.702,0,5	0.00183	0.02445
61.	0.712 ,0,5	0.0025	0.03337	0.711 ,0,5	-0.00046	-0.03495
62.	0.712 ,0,5	0.0025	0.03337	0.709,0,5	-0.00008	0.00835
63.	0.712 ,0,5	0.0025	0.03337	0.711 ,0,5	-0.00046	-0.03495
64.	0.712 ,0,5	0.0025	0.03337	0.699,0,5	-0.00057	-0.07672
65.	0.712 ,0,5	0.0025	0.03337	0.711 ,0,5	-0.00046	-0.03495
66.	0.712 ,0,5	0.0025	0.03337	0.709,0,5	-0.00008	0.00835
67.	0.712 ,0,5	0.0025	0.03337	0.686,0,5	-0.00024	-0.03769
68.	-0.661, 0,5	-0.00165	-0.03994	0.71,0,5	0.00019	0.02531
69.	0.712 ,0,5	0.0025	0.03337	0.69,0,5	-0.00004	-0.00617
70.	0.712 ,0,5	0.0025	0.03337	0.704,0,5	0.00001	0.00259
71.	0.712 ,0,5	0.0025	0.03337	0.681,0,5	-0.0001	-0.01804
72.	0.712 ,0,5	0.0025	0.03337	0.707,0,5	-0.00031	0.03574
73.	0.712 ,0,5	0.0025	0.03337	0.699,0,5	-0.00057	-0.07672
74.	0.712 ,0,5	0.0025	0.03337	0.714,0,5	0.00006	0.01273
75.	0.712 ,0,5	0.0025	0.03337	0.652,0,5	-0.00028	-0.04408
76.	0.712 ,0,5	0.0025	0.03337	0.709,0,5	-0.00008	0.00835
77.	0.712 ,0,5	0.0025	0.03337	0.712,0,5	0.0025	0.03337
78.	0.712 ,0,5	0.0025	0.03337	0.698,0,5	-0.0001	-0.01534
79.	0.712 ,0,5	0.0025	0.03337	0.716,0,5	0.00008	0.01713
80.	0.712 ,0,5	0.0025	0.03337	0.702,0,5	0.00183	0.02445
81.	0.712 ,0,5	0.0025	0.03337	0.693,0,5	-0.00035	-0.04515
82.	0.712 ,0,5	0.0025	0.03337	0.707,0,5	-0.00031	0.03574
83.	0.712 ,0,5	0.0025	0.03337	0.708,0,5	0.00027	0.04441
84.	0.712 ,0,5	0.0025	0.03337	0.695,0,5	-0.00041	-0.03563
85.	0.712 ,0,5	0.0025	0.03337	0.685,0,5	-0.00018	-0.03649
86.	0.712 ,0,5	0.0025	0.03337	0.703,0,5	-0.00037	-0.04387
87.	0.712 ,0,5	0.0025	0.03337	0.702,0,5	0.00183	0.02445
88.	0.712 ,0,5	0.0025	0.03337	0.697,0,5	-0.00025	-0.04034
89.	0.712 ,0,5	0.0025	0.03337	0.712 , 0,5	0.0025	0.03337
90.	0.712 ,0,5	0.0025	0.03337	0.699,0,5	-0.00057	-0.07672
91.	0.712 ,0,5	0.0025	0.03337	0.725,0,5	0.00019	0.03688
92.	0.712 ,0,5	0.0025	0.03337	0.709,0,5	-0.00008	0.00835
93.	0.712 ,0,5	0.0025	0.03337	0.705,0,5	0.0001	0.01657
94.	0.712 ,0,5	0.0025	0.03337	0.685,0,5	-0.00018	-0.03649
95.	0.712 ,0,5	0.0025	0.03337	0.71,0,5	0.00019	0.02531
96.	0.712 ,0,5	0.0025	0.03337	0.702,0,5	0.00183	0.02445
97.	0.712 ,0,5	0.0025	0.03337	0.715,0,5	0.00008	0.01615
98.	0.712 ,0,5	0.0025	0.03337	0.712 , 0,5	0.0025	0.03337
99.	0.712 ,0,5	0.0025	0.03337	0.707 , 0,5	-0.00031	0.03574
100.	0.712 ,0,5	0.0025	0.03337	0.715 , 0,5	0.00008	0.01615

▪ **Case study 5 :**

Table 11: Accessing the best and worst values for test speech descrambler based on parameter estimation (circle map).

(a) MSE as Fitness Function, File 5 is Audio File.

NO	PSO/MSE	File 5 / SNR	File 5/ CC	QPSO/MSE	File 5/ SNR	File 5/ CC
1.	0.712 ,0.5	0.92329	0.4457	0.699 , 0.5	0.00006	0.01
2.	0.712 ,0.5	0.92329	0.4457	0.704 , 0.5	0.00061	0.10417
3.	0.712 ,0.5	0.92329	0.4457	0.703 , 0.5	-0.00033	-0.04108
4.	0.712 ,0.5	0.92329	0.4457	0.711 , 0.5	0.00162	0.13042
5.	0.712 ,0.5	0.92329	0.4457	0.715 , 0.5	0.0008	0.15424
6.	0.712 ,0.5	0.92329	0.4457	0.721 , 0.5	0.00031	0.05711
7.	0.712 ,0.5	0.92329	0.4457	0.697 , 0.5	-0.00019	-0.03293
8.	0.712 ,0.5	0.92329	0.4457	0.712 , 0.5	0.92329	0.4457
9.	0.712 ,0.5	0.92329	0.4457	0.709 , 0.5	0.00031	0.04703
10.	0.712 ,0.5	0.92329	0.4457	0.711 , 0.5	0.00162	0.13042
11.	0.712 ,0.5	0.92329	0.4457	0.699 , 0.5	0.00006	0.01
12.	0.712 ,0.5	0.92329	0.4457	0.698 , 0.5	0.00063	0.10192
13.	0.712 ,0.5	0.92329	0.4457	0.711 , 0.5	0.00162	0.13042
14.	0.712 ,0.5	0.92329	0.4457	0.712 , 0.5	0.92329	0.4457
15.	0.712 ,0.5	0.92329	0.4457	0.711 , 0.5	0.00162	0.13042
16.	0.712 ,0.5	0.92329	0.4457	0.726 , 0.5	0.00024	0.0428
17.	0.712 ,0.5	0.92329	0.4457	0.711 , 0.5	0.00162	0.13042
18.	0.712 ,0.5	0.92329	0.4457	0.708 , 0.5	0.00024	0.04222
19.	0.712 ,0.5	0.92329	0.4457	0.704 , 0.5	0.00061	0.10417
20.	0.712 ,0.5	0.92329	0.4457	0.71 , 0.5	0.00085	0.114
21.	0.712 ,0.5	0.92329	0.4457	0.726 , 0.5	0.00024	0.0428
22.	0.712 ,0.5	0.92329	0.4457	0.703 , 0.5	-0.00033	-0.04108
23.	0.712 ,0.5	0.92329	0.4457	0.712 , 0.5	0.92329	0.4457
24.	0.712 ,0.5	0.92329	0.4457	0.726 , 0.5	0.00024	0.0428
25.	0.712 ,0.5	0.92329	0.4457	0.708 , 0.5	0.00024	0.04222
26.	0.712 ,0.5	0.92329	0.4457	0.706 , 0.5	0.00169	0.14381
27.	0.712 ,0.5	0.92329	0.4457	0.713 , 0.5	0.00348	0.04305
28.	0.712 ,0.5	0.92329	0.4457	0.712 , 0.5	0.92329	0.4457
29.	0.712 ,0.5	0.92329	0.4457	0.695 , 0.5	-0.00239	-0.06702
30.	0.712 ,0.5	0.92329	0.4457	0.697 , 0.5	-0.00019	-0.03293
31.	0.712 ,0.5	0.92329	0.4457	0.713 , 0.5	0.00348	0.04305
32.	0.712 ,0.5	0.92329	0.4457	0.712 , 0.5	0.92329	0.4457
33.	0.712 ,0.5	0.92329	0.4457	0.723 , 0.5	0.00085	0.15042
34.	0.712 ,0.5	0.92329	0.4457	0.711 , 0.5	0.00162	0.13042
35.	0.712 ,0.5	0.92329	0.4457	0.71 , 0.5	0.00085	0.114
36.	0.712 ,0.5	0.92329	0.4457	0.696 , 0.5	-0.00126	-0.19914
37.	0.712 ,0.5	0.92329	0.4457	0.711 , 0.5	0.00162	0.13042
38.	0.712 ,0.5	0.92329	0.4457	0.71 , 0.5	0.00085	0.114
39.	0.712 ,0.5	0.92329	0.4457	0.714 , 0.5	-0.00031	-0.06025
40.	0.712 ,0.5	0.92329	0.4457	0.698 , 0.5	0.00063	0.10192
41.	0.712 ,0.5	0.92329	0.4457	0.698 , 0.5	0.00063	0.10192
42.	0.712 ,0.5	0.92329	0.4457	0.711 , 0.5	0.00162	0.13042
43.	0.712 ,0.5	0.92329	0.4457	0.714 , 0.5	-0.00031	-0.06025
44.	0.712 ,0.5	0.92329	0.4457	0.711 , 0.5	0.00162	0.13042
45.	0.712 ,0.5	0.92329	0.4457	0.724 , 0.5	0.00087	0.15221
46.	0.712 ,0.5	0.92329	0.4457	0.704 , 0.5	0.00061	0.10417
47.	0.712 ,0.5	0.92329	0.4457	0.696 , 0.5	-0.00126	-0.19914
48.	0.712 ,0.5	0.92329	0.4457	0.708 , 0.5	0.00024	0.04222
49.	0.712 ,0.5	0.92329	0.4457	0.713 , 0.5	0.00348	0.04305
50.	0.712 ,0.5	0.92329	0.4457	0.711 , 0.5	0.00162	0.13042
51.	0.712 ,0.5	0.92329	0.4457	0.706 , 0.5	0.00169	0.14381
52.	0.712 ,0.5	0.92329	0.4457	0.708 , 0.5	0.00024	0.04222
53.	0.712 ,0.5	0.92329	0.4457	0.722 , 0.5	0.00088	0.14224

54.	0.712 ,0,5	0.92329	0.4457	0.71 , 0,5	0.00085	0.114
55.	0.712 ,0,5	0.92329	0.4457	0.715 , 0,5	0.0008	0.15424
56.	0.712 ,0,5	0.92329	0.4457	0.714 , 0,5	-0.00031	-0.06025
57.	0.712 ,0,5	0.92329	0.4457	0.708 , 0,5	0.00024	0.04222
58.	0.712 ,0,5	0.92329	0.4457	0.712 ,0,5	0.92329	0.4457
59.	0.712 ,0,5	0.92329	0.4457	0.698 , 0,5	0.00063	0.10192
60.	0.712 ,0,5	0.92329	0.4457	0.699 , 0,5	0.00006	0.01
61.	0.712 ,0,5	0.92329	0.4457	0.698 , 0,5	0.00063	0.10192
62.	0.712 ,0,5	0.92329	0.4457	0.713 , 0,5	0.00348	0.04305
63.	0.712 ,0,5	0.92329	0.4457	0.703 , 0,5	-0.00033	-0.04108
64.	0.712 ,0,5	0.92329	0.4457	0.723 , 0,5	0.00085	0.15042
65.	0.712 ,0,5	0.92329	0.4457	0.711 , 0,5	0.00162	0.13042
66.	0.712 ,0,5	0.92329	0.4457	0.714 , 0,5	-0.00031	-0.06025
67.	0.712 ,0,5	0.92329	0.4457	0.708 , 0,5	0.00024	0.04222
68.	0.712 ,0,5	0.92329	0.4457	0.696 , 0,5	-0.00126	-0.19914
69.	0.712 ,0,5	0.92329	0.4457	0.726 , 0,5	0.00024	0.0428
70.	0.712 ,0,5	0.92329	0.4457	0.726 , 0,5	0.00024	0.0428
71.	0.712 ,0,5	0.92329	0.4457	0.709 , 0,5	0.00031	0.04703
72.	0.712 ,0,5	0.92329	0.4457	0.715 , 0,5	0.0008	0.15424
73.	0.712 ,0,5	0.92329	0.4457	0.698 , 0,5	0.00063	0.10192
74.	0.712 ,0,5	0.92329	0.4457	0.726 , 0,5	0.00024	0.0428
75.	0.712 ,0,5	0.92329	0.4457	0.712 ,0,5	0.92329	0.4457
76.	0.712 ,0,5	0.92329	0.4457	0.726 , 0,5	0.00024	0.0428
77.	-0.667,0,5	0.00054	0.01244	0.703 , 0,5	-0.00033	-0.04108
78.	0.712 ,0,5	0.92329	0.4457	0.715 , 0,5	0.0008	0.15424
79.	0.712 ,0,5	0.92329	0.4457	0.712 ,0,5	0.92329	0.4457
80.	0.712 ,0,5	0.92329	0.4457	0.71 , 0,5	0.00085	0.114
81.	0.712 ,0,5	0.92329	0.4457	0.709 , 0,5	0.00031	0.04703
82.	0.712 ,0,5	0.92329	0.4457	0.71 , 0,5	0.00085	0.114
83.	0.712 ,0,5	0.92329	0.4457	0.708 , 0,5	0.00024	0.04222
84.	0.712 ,0,5	0.92329	0.4457	0.722 , 0,5	0.00088	0.14224
85.	0.712 ,0,5	0.92329	0.4457	0.723 , 0,5	0.00085	0.15042
86.	0.712 ,0,5	0.92329	0.4457	0.712 ,0,5	0.92329	0.4457
87.	0.712 ,0,5	0.92329	0.4457	0.7 , 0,5	0.00086	0.1263
88.	0.712 ,0,5	0.92329	0.4457	0.696 , 0,5	-0.00126	-0.19914
89.	0.712 ,0,5	0.92329	0.4457	0.71 , 0,5	0.00085	0.114
90.	0.712 ,0,5	0.92329	0.4457	0.708 , 0,5	0.00024	0.04222
91.	0.712 ,0,5	0.92329	0.4457	0.711 , 0,5	0.00162	0.13042
92.	0.712 ,0,5	0.92329	0.4457	0.708 , 0,5	0.00024	0.04222
93.	0.712 ,0,5	0.92329	0.4457	0.699 , 0,5	0.00006	0.01
94.	0.712 ,0,5	0.92329	0.4457	0.715 , 0,5	0.0008	0.15424
95.	0.712 ,0,5	0.92329	0.4457	0.708 , 0,5	0.00024	0.04222
96.	0.712 ,0,5	0.92329	0.4457	0.709 , 0,5	0.00031	0.04703
97.	0.712 ,0,5	0.92329	0.4457	0.726 , 0,5	0.00024	0.0428
98.	0.712 ,0,5	0.92329	0.4457	0.712 ,0,5	0.92329	0.4457
99.	0.712 ,0,5	0.92329	0.4457	0.726 , 0,5	0.00024	0.0428
100.	0.712 ,0,5	0.92329	0.4457	0.726 , 0,5	0.00024	0.0428

(b)SSE as Fitness Function, File 5 is Audio File.

No	PSO/SSE	File 5 / SNR	File 5 / CC	QPSO/SSE	File 5 / SNR	File 5 / CC
1.	0.712 ,0,5	0.4457	0.92329	0.716,0,5	0.00011	0.02548
2.	0.712 ,0,5	0.4457	0.92329	0.725,0,5	-0.00076	-0.14855
3.	0.712 ,0,5	0.4457	0.92329	0.708,0,5	0.00024	0.04222
4.	0.712 ,0,5	0.4457	0.92329	0.707,0,5	0.00032	0.03992
5.	0.712 ,0,5	0.4457	0.92329	0.696,0,5	-0.00126	-0.19914
6.	0.712 ,0,5	0.4457	0.92329	0.704,0,5	0.00061	0.10417
7.	0.712 ,0,5	0.4457	0.92329	0.712 , 0,5	0.4457	0.92329
8.	0.712 ,0,5	0.4457	0.92329	0.705,0,5	0.00411	0.06343
9.	0.712 ,0,5	0.4457	0.92329	0.712 , 0,5	0.4457	0.92329

10.	0.712 ,0,5	0.4457	0.92329	0.71,0,5	0.00085	0.114
11.	0.712 ,0,5	0.4457	0.92329	0.714,0,5	-0.00031	-0.06025
12.	0.712 ,0,5	0.4457	0.92329	0.714,0,5	-0.00031	-0.06025
13.	0.712 ,0,5	0.4457	0.92329	0.71,0,5	0.00085	0.114
14.	0.712 ,0,5	0.4457	0.92329	0.711 ,0,5	0.00162	0.13042
15.	0.712 ,0,5	0.4457	0.92329	0.716,0,5	0.00011	0.02548
16.	0.712 ,0,5	0.4457	0.92329	0.668,0,5	0.00016	0.02889
17.	0.712 ,0,5	0.4457	0.92329	0.709,0,5	0.00031	0.04703
18.	0.712 ,0,5	0.4457	0.92329	0.666,0,5	0.000045	0.00825
19.	0.712 ,0,5	0.4457	0.92329	0.719,0,5	-0.00071	-0.15263
20.	0.712 ,0,5	0.4457	0.92329	0.697,0,5	-0.00019	-0.03293
21.	0.712 ,0,5	0.4457	0.92329	0.673,0,5	-0.00001	-0.00212
22.	0.712 ,0,5	0.4457	0.92329	0.716,0,5	0.00011	0.02548
23.	0.712 ,0,5	0.4457	0.92329	0.687,0,5	0.00038	0.07081
24.	0.712 ,0,5	0.4457	0.92329	0.705,0,5	0.00411	0.06343
25.	0.712 ,0,5	0.4457	0.92329	0.713,0,5	0.00348	0.04305
26.	0.712 ,0,5	0.4457	0.92329	0.709,0,5	0.00031	0.04703
27.	0.712 ,0,5	0.4457	0.92329	0.714,0,5	-0.00031	-0.06025
28.	0.712 ,0,5	0.4457	0.92329	0.715,0,5	0.0008	0.15424
29.	0.712 ,0,5	0.4457	0.92329	0.701,0,5	0.00452	0.05277
30.	0.712 ,0,5	0.4457	0.92329	0.676,0,5	-0.00072	-0.14157
31.	0.712 ,0,5	0.4457	0.92329	0.705,0,5	0.00411	0.06343
32.	0.712 ,0,5	0.4457	0.92329	0.709,0,5	0.00031	0.04703
33.	0.712 ,0,5	0.4457	0.92329	0.712,0,5	0.4457	0.92329
34.	0.712 ,0,5	0.4457	0.92329	0.707,0,5	0.00032	0.03992
35.	0.712 ,0,5	0.4457	0.92329	0.696,0,5	-0.00126	-0.19914
36.	0.712 ,0,5	0.4457	0.92329	0.711 ,0,5	0.00162	0.13042
37.	0.712 ,0,5	0.4457	0.92329	0.706,0,5	0.00169	0.14381
38.	0.712 ,0,5	0.4457	0.92329	0.715,0,5	0.0008	0.15424
39.	0.712 ,0,5	0.4457	0.92329	0.72, 0,5	-0.00069	-0.13477
40.	0.712 ,0,5	0.4457	0.92329	0.703,0,5	-0.00033	-0.04108
41.	0.712 ,0,5	0.4457	0.92329	0.714,0,5	-0.00031	-0.06025
42.	0.712 ,0,5	0.4457	0.92329	0.704,0,5	0.00061	0.10417
43.	0.712 ,0,5	0.4457	0.92329	0.7,0,5	0.00086	0.1263
44.	0.712 ,0,5	0.4457	0.92329	0.711 ,0,5	0.00162	0.13042
45.	0.712 ,0,5	0.4457	0.92329	0.723,0,5	0.00085	0.15042
46.	0.712 ,0,5	0.4457	0.92329	0.701,0,5	0.00452	0.05277
47.	0.712 ,0,5	0.4457	0.92329	0.699,0,5	0.00006	0.01
48.	0.712 ,0,5	0.4457	0.92329	0.696,0,5	-0.00126	-0.19914
49.	0.712 ,0,5	0.4457	0.92329	0.71,0,5	0.00085	0.114
50.	0.712 ,0,5	0.4457	0.92329	0.691,0,5	-0.00151	-0.22686
51.	0.712 ,0,5	0.4457	0.92329	0.692,0,5	-1.75646	-0.03234
52.	0.712 ,0,5	0.4457	0.92329	0.704,0,5	0.00061	0.10417
53.	0.712 ,0,5	0.4457	0.92329	0.715,0,5	0.0008	0.15424
54.	0.712 ,0,5	0.4457	0.92329	0.708,0,5	0.00024	0.04222
55.	0.712 ,0,5	0.4457	0.92329	0.71,0,5	0.00085	0.114
56.	0.712 ,0,5	0.4457	0.92329	0.712,0,5	0.4457	0.92329
57.	0.712 ,0,5	0.4457	0.92329	0.711 ,0,5	0.00162	0.13042
58.	0.712 ,0,5	0.4457	0.92329	0.709,0,5	0.00031	0.04703
59.	0.712 ,0,5	0.4457	0.92329	0.702,0,5	-0.00016	-0.03107
60.	0.712 ,0,5	0.4457	0.92329	0.702,0,5	-0.00016	-0.03107
61.	0.712 ,0,5	0.4457	0.92329	0.711 ,0,5	0.00162	0.13042
62.	0.712 ,0,5	0.4457	0.92329	0.709,0,5	0.00031	0.04703
63.	0.712 ,0,5	0.4457	0.92329	0.711 ,0,5	0.00162	0.13042
64.	0.712 ,0,5	0.4457	0.92329	0.699,0,5	0.00006	0.01
65.	0.712 ,0,5	0.4457	0.92329	0.711 ,0,5	0.00162	0.13042
66.	0.712 ,0,5	0.4457	0.92329	0.709,0,5	0.00031	0.04703
67.	0.712 ,0,5	0.4457	0.92329	0.686,0,5	0.000014	-0.002861
68.	-0.661, 0,5	-0.00122	-0.01705	0.71,0,5	0.00085	0.114
69.	0.712 ,0,5	0.4457	0.92329	0.69,0,5	-0.00006	-0.11229
70.	0.712 ,0,5	0.4457	0.92329	0.704,0,5	0.00061	0.10417
71.	0.712 ,0,5	0.4457	0.92329	0.681,0,5	-0.00022	-0.04207
72.	0.712 ,0,5	0.4457	0.92329	0.707,0,5	0.00032	0.03992

73.	0.712 ,0,5	0.4457	0.92329	0.699,0,5	0.00006	0.01
74.	0.712 ,0,5	0.4457	0.92329	0.714,0,5	-0.00031	-0.06025
75.	0.712 ,0,5	0.4457	0.92329	0.652,0,5	0.00012	0.02062
76.	0.712 ,0,5	0.4457	0.92329	0.709,0,5	0.00031	0.04703
77.	0.712 ,0,5	0.4457	0.92329	0.712,0,5	0.4457	0.92329
78.	0.712 ,0,5	0.4457	0.92329	0.698,0,5	0.00063	0.10192
79.	0.712 ,0,5	0.4457	0.92329	0.716,0,5	0.00011	0.02548
80.	0.712 ,0,5	0.4457	0.92329	0.702,0,5	-0.00016	-0.03107
81.	0.712 ,0,5	0.4457	0.92329	0.693,0,5	0.00015	0.0219
82.	0.712 ,0,5	0.4457	0.92329	0.707 , 0,5	0.00032	0.03992
83.	0.712 ,0,5	0.4457	0.92329	0.708,0,5	0.00024	0.04222
84.	0.712 ,0,5	0.4457	0.92329	0.695,0,5	-0.00239	-0.22004
85.	0.712 ,0,5	0.4457	0.92329	0.685,0,5	-0.00022	-0.04575
86.	0.712 ,0,5	0.4457	0.92329	0.703,0,5	-0.00033	-0.04108
87.	0.712 ,0,5	0.4457	0.92329	0.702,0,5	-0.00016	-0.03107
88.	0.712 ,0,5	0.4457	0.92329	0.697,0,5	-0.00019	-0.03293
89.	0.712 ,0,5	0.4457	0.92329	0.712 , 0,5	0.4457	0.92329
90.	0.712 ,0,5	0.4457	0.92329	0.699,0,5	0.00006	0.01
91.	0.712 ,0,5	0.4457	0.92329	0.725,0,5	-0.00076	-0.14855
92.	0.712 ,0,5	0.4457	0.92329	0.709,0,5	0.00031	0.04703
93.	0.712 ,0,5	0.4457	0.92329	0.705,0,5	0.00411	0.06343
94.	0.712 ,0,5	0.4457	0.92329	0.685,0,5	-0.00022	-0.04575
95.	0.712 ,0,5	0.4457	0.92329	0.71,0,5	0.00085	0.114
96.	0.712 ,0,5	0.4457	0.92329	0.702,0,5	-0.00016	-0.03107
97.	0.712 ,0,5	0.4457	0.92329	0.715,0,5	0.0008	0.15424
98.	0.712 ,0,5	0.4457	0.92329	0.712 , 0,5	0.4457	0.92329
99.	0.712 ,0,5	0.4457	0.92329	0.707 , 0,5	0.00032	0.03992
100.	0.712 ,0,5	0.4457	0.92329	0.715 , 0,5	0.0008	0.15424

▪ Case study 6

Table 12: Accessing the best and worst values for test speech descrambler based on parameter estimation (circle map).

(a) MSE as Fitness Function, File 6 is Audio File.

No	PSO/MSE	File 6 / SNR	File 6/ CC	QPSO/MSE	File 6 / SNR	File 6 / CC
1.	0.712 ,0,5	0.00531	0.06168	0.699, 0,5	0.000004	0.00117
2.	0.712 ,0,5	0.00531	0.06168	0.704 , 0,5	0.00018	0.06022
3.	0.712 ,0,5	0.00531	0.06168	0.703 , 0,5	0.00008	0.0196
4.	0.712 ,0,5	0.00531	0.06168	0.711 , 0,5	0.00036	0.05748
5.	0.712 ,0,5	0.00531	0.06168	0.715 , 0,5	0.00019	0.07434
6.	0.712 ,0,5	0.00531	0.06168	0.721 , 0,5	0.00001	0.00619
7.	0.712 ,0,5	0.00531	0.06168	0.697 , 0,5	-0.00011	-0.03858
8.	0.712 ,0,5	0.00531	0.06168	0.712 , 0,5	0.00531	0.06168
9.	0.712 ,0,5	0.00531	0.06168	0.709 , 0,5	0.00001	0.00449
10.	0.712 ,0,5	0.00531	0.06168	0.711 , 0,5	0.000004	0.00117
11.	0.712 ,0,5	0.00531	0.06168	0.699 , 0,5	0.000004	0.00117
12.	0.712 ,0,5	0.00531	0.06168	0.698 , 0,5	0.00008	0.02563
13.	0.712 ,0,5	0.00531	0.06168	0.711 , 0,5	0.00036	0.05748
14.	0.712 ,0,5	0.00531	0.06168	0.712 , 0,5	0.00531	0.06168
15.	0.712 ,0,5	0.00531	0.06168	0.711 , 0,5	0.00036	0.05748
16.	0.712 ,0,5	0.00531	0.06168	0.726 , 0,5	0.00006	0.02284
17.	0.712 ,0,5	0.00531	0.06168	0.711 , 0,5	0.00036	0.05748
18.	0.712 ,0,5	0.00531	0.06168	0.708 , 0,5	-0.00004	-0.01549
19.	0.712 ,0,5	0.00531	0.06168	0.704 , 0,5	0.00018	0.06022
20.	0.712 ,0,5	0.00531	0.06168	0.71 , 0,5	0.00003	0.00849
21.	0.712 ,0,5	0.00531	0.06168	0.726 , 0,5	0.00006	0.02284
22.	0.712 ,0,5	0.00531	0.06168	0.703 , 0,5	0.00008	0.0196

23.	0.712 ,0,5	0.00531	0.06168	0.712 , 0,5	0.00531	0.06168
24.	0.712 ,0,5	0.00531	0.06168	0.726 , 0,5	0.00006	0.02284
25.	0.712 ,0,5	0.00531	0.06168	0.708 , 0,5	-0.00004	-0.01549
26.	0.712 ,0,5	0.00531	0.06168	0.706 , 0,5	0.00039	0.06849
27.	0.712 ,0,5	0.00531	0.06168	0.713 , 0,5	0.00017	0.07613
28.	0.712 ,0,5	0.00531	0.06168	0.712 , 0,5	0.00531	0.06168
29.	0.712 ,0,5	0.00531	0.06168	0.695 , 0,5	-0.00038	-0.07026
30.	0.712 ,0,5	0.00531	0.06168	0.697 , 0,5	-0.00011	-0.03858
31.	0.712 ,0,5	0.00531	0.06168	0.713 , 0,5	0.00017	0.07613
32.	0.712 ,0,5	0.00531	0.06168	0.712 , 0,5	0.00531	0.06168
33.	0.712 ,0,5	0.00531	0.06168	0.723 , 0,5	0.00009	0.03428
34.	0.712 ,0,5	0.00531	0.06168	0.711 , 0,5	0.00036	0.05748
35.	0.712 ,0,5	0.00531	0.06168	0.71 , 0,5	0.00003	0.00849
36.	0.712 ,0,5	0.00531	0.06168	0.696 , 0,5	-0.00026	-0.08511
37.	0.712 ,0,5	0.00531	0.06168	0.711 , 0,5	0.00036	0.05748
38.	0.712 ,0,5	0.00531	0.06168	0.71 , 0,5	0.00003	0.00849
39.	0.712 ,0,5	0.00531	0.06168	0.714 , 0,5	0.0001	0.00669
40.	0.712 ,0,5	0.00531	0.06168	0.698 , 0,5	0.00008	0.02563
41.	0.712 ,0,5	0.00531	0.06168	0.698 , 0,5	0.00008	0.02563
42.	0.712 ,0,5	0.00531	0.06168	0.711 , 0,5	0.00036	0.05748
43.	0.712 ,0,5	0.00531	0.06168	0.714 , 0,5	0.0001	0.00669
44.	0.712 ,0,5	0.00531	0.06168	0.711 , 0,5	0.00036	0.05748
45.	0.712 ,0,5	0.00531	0.06168	0.724 , 0,5	0.00015	0.05504
46.	0.712 ,0,5	0.00531	0.06168	0.704 , 0,5	0.00018	0.06022
47.	0.712 ,0,5	0.00531	0.06168	0.696 , 0,5	-0.00026	-0.08511
48.	0.712 ,0,5	0.00531	0.06168	0.708 , 0,5	-0.00004	-0.01549
49.	0.712 ,0,5	0.00531	0.06168	0.713 , 0,5	0.00017	0.07613
50.	0.712 ,0,5	0.00531	0.06168	0.711 , 0,5	0.00036	0.05748
51.	0.712 ,0,5	0.00531	0.06168	0.706 , 0,5	0.00039	0.06849
52.	0.712 ,0,5	0.00531	0.06168	0.708 , 0,5	-0.00004	-0.01549
53.	0.712 ,0,5	0.00531	0.06168	0.722 , 0,5	0.00014	0.0104
54.	0.712 ,0,5	0.00531	0.06168	0.71 , 0,5	0.00003	0.00849
55.	0.712 ,0,5	0.00531	0.06168	0.715 , 0,5	0.00019	0.07434
56.	0.712 ,0,5	0.00531	0.06168	0.714 , 0,5	0.0001	0.00669
57.	0.712 ,0,5	0.00531	0.06168	0.708 , 0,5	-0.00004	-0.01549
58.	0.712 ,0,5	0.00531	0.06168	0.712 ,0,5	0.00531	0.06168
59.	0.712 ,0,5	0.00531	0.06168	0.698 , 0,5	0.00008	0.02563
60.	0.712 ,0,5	0.00531	0.06168	0.699 , 0,5	0.000004	0.00117
61.	0.712 ,0,5	0.00531	0.06168	0.698 , 0,5	0.00008	0.02563
62.	0.712 ,0,5	0.00531	0.06168	0.713 , 0,5	0.00017	0.07613
63.	0.712 ,0,5	0.00531	0.06168	0.703 , 0,5	0.00008	0.0196
64.	0.712 ,0,5	0.00531	0.06168	0.723 , 0,5	0.00009	0.03428
65.	0.712 ,0,5	0.00531	0.06168	0.711 , 0,5	0.00036	0.05748
66.	0.712 ,0,5	0.00531	0.06168	0.714 , 0,5	0.0001	0.00669
67.	0.712 ,0,5	0.00531	0.06168	0.708 , 0,5	-0.00004	-0.01549
68.	0.712 ,0,5	0.00531	0.06168	0.696 , 0,5	-0.00026	-0.08511
69.	0.712 ,0,5	0.00531	0.06168	0.726 , 0,5	0.00006	0.02284
70.	0.712 ,0,5	0.00531	0.06168	0.726 , 0,5	0.00006	0.02284
71.	0.712 ,0,5	0.00531	0.06168	0.709 , 0,5	0.00001	0.00449
72.	0.712 ,0,5	0.00531	0.06168	0.715 , 0,5	0.00019	0.07434
73.	0.712 ,0,5	0.00531	0.06168	0.698 , 0,5	0.00008	0.02563
74.	0.712 ,0,5	0.00531	0.06168	0.726 , 0,5	0.00006	0.02284
75.	0.712 ,0,5	0.00531	0.06168	0.712 , 0,5	0.00531	0.06168
76.	0.712 ,0,5	0.00531	0.06168	0.726 , 0,5	0.00006	0.02284
77.	-0.667,0,5	-0.0001	-0.00736	0.703 , 0,5	0.00008	0.0196
78.	0.712 ,0,5	0.00531	0.06168	0.715 , 0,5	0.00019	0.07434
79.	0.712 ,0,5	0.00531	0.06168	0.712 , 0,5	0.00531	0.06168
80.	0.712 ,0,5	0.00531	0.06168	0.71 , 0,5	0.00003	0.00849
81.	0.712 ,0,5	0.00531	0.06168	0.709 , 0,5	0.00001	0.00449
82.	0.712 ,0,5	0.00531	0.06168	0.71 , 0,5	0.00003	0.00849
83.	0.712 ,0,5	0.00531	0.06168	0.708 , 0,5	-0.00004	-0.01549
84.	0.712 ,0,5	0.00531	0.06168	0.722 , 0,5	0.00014	0.0104
85.	0.712 ,0,5	0.00531	0.06168	0.723 , 0,5	0.00009	0.03428

86.	0.712 ,0,5	0.00531	0.06168	0.712 ,0,5	0.00531	0.06168
87.	0.712 ,0,5	0.00531	0.06168	0.7, 0,5	0.00016	0.04833
88.	0.712 ,0,5	0.00531	0.06168	0.696 , 0,5	-0.00026	-0.08511
89.	0.712 ,0,5	0.00531	0.06168	0.71 , 0,5	0.00003	0.00849
90.	0.712 ,0,5	0.00531	0.06168	0.708 , 0,5	-0.00004	-0.01549
91.	0.712 ,0,5	0.00531	0.06168	0.711 , 0,5	0.00036	0.05748
92.	0.712 ,0,5	0.00531	0.06168	0.708 , 0,5	-0.00004	-0.01549
93.	0.712 ,0,5	0.00531	0.06168	0.699 , 0,5	0.000004	0.00117
94.	0.712 ,0,5	0.00531	0.06168	0.715 , 0,5	0.00019	0.07434
95.	0.712 ,0,5	0.00531	0.06168	0.708 , 0,5	-0.00004	-0.01549
96.	0.712 ,0,5	0.00531	0.06168	0.709 , 0,5	0.00001	0.00449
97.	0.712 ,0,5	0.00531	0.06168	0.726 , 0,5	0.00006	0.02284
98.	0.712 ,0,5	0.00531	0.06168	0.712 ,0,5	0.00531	0.06168
99.	0.712 ,0,5	0.00531	0.06168	0.726 , 0,5	0.00006	0.02284
100.	0.712 ,0,5	0.00531	0.06168	0.726 , 0,5	0.00006	0.02284

(b) SSE as Fitness Function, File 6 is Audio File.

No	PSO/SSE	File 6 / SNR	File 6 / CC	QPSO/SSE	File 6 / SNR	File 6 / CC
1.	0.712 ,0,5	0.00531	0.06168	0.716,0,5	0.00006	0.02845
2.	0.712 ,0,5	0.00531	0.06168	0.725,0,5	-0.00011	-0.04615
3.	0.712 ,0,5	0.00531	0.06168	0.708,0,5	0.0011	0.05969
4.	0.712 ,0,5	0.00531	0.06168	0.707,0,5	-0.00002	-0.0056
5.	0.712 ,0,5	0.00531	0.06168	0.696,0,5	-0.00026	0.02363
6.	0.712 ,0,5	0.00531	0.06168	0.704,0,5	0.00018	0.06022
7.	0.712 ,0,5	0.00531	0.06168	0.712 , 0,5	0.00531	0.06168
8.	0.712 ,0,5	0.00531	0.06168	0.705,0,5	0.00019	0.06377
9.	0.712 ,0,5	0.00531	0.06168	0.712 , 0,5	0.00531	0.06168
10.	0.712 ,0,5	0.00531	0.06168	0.71,0,5	0.00003	0.00849
11.	0.712 ,0,5	0.00531	0.06168	0.714,0,5	0.0001	0.00669
12.	0.712 ,0,5	0.00531	0.06168	0.714,0,5	0.0001	0.00669
13.	0.712 ,0,5	0.00531	0.06168	0.71,0,5	0.00003	0.00849
14.	0.712 ,0,5	0.00531	0.06168	0.711 ,0,5	0.00036	0.05748
15.	0.712 ,0,5	0.00531	0.06168	0.716,0,5	0.00006	0.02845
16.	0.712 ,0,5	0.00531	0.06168	0.668,0,5	-0.00012	-0.04638
17.	0.712 ,0,5	0.00531	0.06168	0.709,0,5	0.00001	0.00449
18.	0.712 ,0,5	0.00531	0.06168	0.666,0,5	0.00012	0.04505
19.	0.712 ,0,5	0.00531	0.06168	0.719,0,5	-0.00014	-0.06102
20.	0.712 ,0,5	0.00531	0.06168	0.697,0,5	-0.00011	-0.03858
21.	0.712 ,0,5	0.00531	0.06168	0.673,0,5	-0.00006	-0.01751
22.	0.712 ,0,5	0.00531	0.06168	0.716,0,5	0.00006	0.02845
23.	0.712 ,0,5	0.00531	0.06168	0.687,0,5	0.00001	0.00467
24.	0.712 ,0,5	0.00531	0.06168	0.705,0,5	0.00019	0.06377
25.	0.712 ,0,5	0.00531	0.06168	0.713,0,5	0.00017	0.07613
26.	0.712 ,0,5	0.00531	0.06168	0.709,0,5	0.00001	0.00449
27.	0.712 ,0,5	0.00531	0.06168	0.714,0,5	0.0001	0.00669
28.	0.712 ,0,5	0.00531	0.06168	0.715,0,5	0.00019	0.07434
29.	0.712 ,0,5	0.00531	0.06168	0.701,0,5	0.00012	0.04352
30.	0.712 ,0,5	0.00531	0.06168	0.676,0,5	-0.0001	-0.04176
31.	0.712 ,0,5	0.00531	0.06168	0.705,0,5	0.00019	0.06377
32.	0.712 ,0,5	0.00531	0.06168	0.709,0,5	0.00001	0.00449
33.	0.712 ,0,5	0.00531	0.06168	0.712,0,5	0.00531	0.06168
34.	0.712 ,0,5	0.00531	0.06168	0.707,0,5	-0.00002	-0.0056
35.	0.712 ,0,5	0.00531	0.06168	0.696,0,5	-0.00026	0.02363
36.	0.712 ,0,5	0.00531	0.06168	0.711 ,0,5	0.00036	0.05748
37.	0.712 ,0,5	0.00531	0.06168	0.706,0,5	0.06849	0.00039
38.	0.712 ,0,5	0.00531	0.06168	0.715,0,5	0.00019	0.07434
39.	0.712 ,0,5	0.00531	0.06168	0.72, 0,5	-0.0001	-0.04111
40.	0.712 ,0,5	0.00531	0.06168	0.703,0,5	0.00008	0.0196
41.	0.712 ,0,5	0.00531	0.06168	0.714,0,5	0.0001	0.00669

42.	0.712 ,0,5	0.00531	0.06168	0.704,0,5	0.00018	0.06022
43.	0.712 ,0,5	0.00531	0.06168	0.7,0,5	0.00016	0.04833
44.	0.712 ,0,5	0.00531	0.06168	0.711 ,0,5	0.00036	0.05748
45.	0.712 ,0,5	0.00531	0.06168	0.723,0,5	0.00009	0.03428
46.	0.712 ,0,5	0.00531	0.06168	0.701,0,5	0.00012	0.04352
47.	0.712 ,0,5	0.00531	0.06168	0.699,0,5	0.00117	0.000004
48.	0.712 ,0,5	0.00531	0.06168	0.696,0,5	-0.00026	0.02363
49.	0.712 ,0,5	0.00531	0.06168	0.71,0,5	0.00003	0.00849
50.	0.712 ,0,5	0.00531	0.06168	0.691,0,5	-0.00024	-0.07394
51.	0.712 ,0,5	0.00531	0.06168	0.692,0,5	-0.00002	-0.00959
52.	0.712 ,0,5	0.00531	0.06168	0.704,0,5	0.00018	0.06022
53.	0.712 ,0,5	0.00531	0.06168	0.715,0,5	0.00019	0.07434
54.	0.712 ,0,5	0.00531	0.06168	0.708,0,5	0.0011	0.05969
55.	0.712 ,0,5	0.00531	0.06168	0.71,0,5	0.00003	0.00849
56.	0.712 ,0,5	0.00531	0.06168	0.712,0,5	0.00531	0.06168
57.	0.712 ,0,5	0.00531	0.06168	0.711 ,0,5	-0.00036	0.05748
58.	0.712 ,0,5	0.00531	0.06168	0.709,0,5	0.00001	0.00449
59.	0.712 ,0,5	0.00531	0.06168	0.702,0,5	0.00022	0.01057
60.	0.712 ,0,5	0.00531	0.06168	0.702,0,5	0.00022	0.01057
61.	0.712 ,0,5	0.00531	0.06168	0.711 ,0,5	0.00036	0.05748
62.	0.712 ,0,5	0.00531	0.06168	0.709,0,5	0.00036	0.00449
63.	0.712 ,0,5	0.00531	0.06168	0.711 ,0,5	0.00036	0.05748
64.	0.712 ,0,5	0.00531	0.06168	0.699,0,5	0.000004	0.00117
65.	0.712 ,0,5	0.00531	0.06168	0.711 ,0,5	0.00036	0.05748
66.	0.712 ,0,5	0.00531	0.06168	0.709,0,5	0.00001	0.00449
67.	0.712 ,0,5	0.00531	0.06168	0.686,0,5	0.00008	0.02673
68.	-0.661, 0,5	-0.0002	-0.01757	0.71,0,5	0.00003	0.00849
69.	0.712 ,0,5	0.00531	0.06168	0.69,0,5	-0.00017	-0.05601
70.	0.712 ,0,5	0.00531	0.06168	0.704,0,5	0.00018	0.06022
71.	0.712 ,0,5	0.00531	0.06168	0.681,0,5	0.000002	0.00119
72.	0.712 ,0,5	0.00531	0.06168	0.707,0,5	-0.00002	-0.0056
73.	0.712 ,0,5	0.00531	0.06168	0.699,0,5	0.000004	0.00117
74.	0.712 ,0,5	0.00531	0.06168	0.714,0,5	0.0001	0.00669
75.	0.712 ,0,5	0.00531	0.06168	0.652,0,5	-0.00007	-0.02653
76.	0.712 ,0,5	0.00531	0.06168	0.709,0,5	0.00001	0.00449
77.	0.712 ,0,5	0.00531	0.06168	0.712,0,5	0.00531	0.06168
78.	0.712 ,0,5	0.00531	0.06168	0.698,0,5	0.00008	0.02563
79.	0.712 ,0,5	0.00531	0.06168	0.716,0,5	0.00006	0.02845
80.	0.712 ,0,5	0.00531	0.06168	0.702,0,5	0.00022	0.01057
81.	0.712 ,0,5	0.00531	0.06168	0.693,0,5	0.00006	0.01641
82.	0.712 ,0,5	0.00531	0.06168	0.707,0,5	-0.00002	-0.0056
83.	0.712 ,0,5	0.00531	0.06168	0.708,0,5	0.0011	0.05969
84.	0.712 ,0,5	0.00531	0.06168	0.695,0,5	-0.00038	-0.07026
85.	0.712 ,0,5	0.00531	0.06168	0.685,0,5	-0.00003	-0.01278
86.	0.712 ,0,5	0.00531	0.06168	0.703,0,5	0.00008	0.0196
87.	0.712 ,0,5	0.00531	0.06168	0.702,0,5	0.00022	0.01057
88.	0.712 ,0,5	0.00531	0.06168	0.697,0,5	-0.00011	-0.03858
89.	0.712 ,0,5	0.00531	0.06168	0.712 , 0,5	0.00531	0.06168
90.	0.712 ,0,5	0.00531	0.06168	0.699,0,5	0.000004	0.00117
91.	0.712 ,0,5	0.00531	0.06168	0.725,0,5	0.00004	-0.04615
92.	0.712 ,0,5	0.00531	0.06168	0.709,0,5	0.00001	0.00449
93.	0.712 ,0,5	0.00531	0.06168	0.705,0,5	0.00019	0.06377
94.	0.712 ,0,5	0.00531	0.06168	0.685,0,5	-0.00144	-0.09747
95.	0.712 ,0,5	0.00531	0.06168	0.71,0,5	0.00003	0.00849
96.	0.712 ,0,5	0.00531	0.06168	0.702,0,5	0.00022	0.01057
97.	0.712 ,0,5	0.00531	0.06168	0.715,0,5	0.00019	0.07434
98.	0.712 ,0,5	0.00531	0.06168	0.712 , 0,5	0.00531	0.06168
99.	0.712 ,0,5	0.00531	0.06168	0.707 , 0,5	-0.00002	-0.0056
100.	0.712 ,0,5	0.00531	0.06168	0.715 , 0,5	0.00019	0.07434

Tables (7,8,9,10,11, and 12) show the results measures used for the test speech descrambling are SNR and CC, when the SNR is high, the recovered speech signal is good, and when $CC = -1$ then both samples(original speech ,recovered speech) go in an opposite direction, and if $CC = +1$ then both samples(original speech ,recovered speech) goes in an equal direction.

الخلاصة

النظام الفوضوي هو نظام غير خطي ديناميكي وحتمي. أداءه غير دوري ، ويعتمد على الظروف الأولية ومعالم النظام و انظمه فوضويه ضرورية لتطبيقات خط الكلام سبب خصائصها . في هذه الأطروحة ، يتم استخدام الخوارزميات الامثليه لتقدير المعالم النظام الفوضوي التي تمتاز بالمتانة الجيدة وسهولة التنفيذ. استخدمت هذه الأطروحة تقدير معالم خرائط فوضوية ، بما في ذلك تقدير المعلم (r) في الخريطة اللوجستية وتقدير المعالم (k, Ω) في الخريطة الدائرية ، وتم عمليه تقدير لمعالم باستخدام خوارزميات الامثليه ، بما في ذلك تحسين سرب الجسيمات (PSO) وتحسين سرب الجسيمات الكمومية (QPSO) . يُستخدم الحد الأدنى لمتوسط الخطأ التربيعي (MSE) ومجموع الخطأ التربيعي (SSE) كوظائف ملاءمة لخوارزميات PSO و QPSO . تظهر نتائج المحاكاة أن خوارزمية QPSO أفضل من خوارزمية PSO للمعلم المقدره للخريطة اللوجستية (r) ، لكن خوارزمية PSO تكون هي الأفضل إذا كانت القيمة (r) لها قيمتان بعد الفاصله مثال $(r = 3.6)$. تعد خوارزمية PSO أفضل من خوارزمية QPSO في تقدير المعلمين (k, Ω) لخريطة الدائرة. تم استخدام نسبة الإشارة إلى الضوضاء (SNR) ومعاملات الارتباط (CC) لقياس جودة إشارات الكلام .



جمهورية العراق
وزارة التعليم العالي والبحث العلمي
جامعة بابل
كلية تكنولوجيا المعلومات - قسم البرمجيات

تقدير المعالم الفوضوية استناداً الى الطرائق الامثلية :
فك تشفير الاصوات كحالة دراسية

رسالة مقدمة إلى

مجلس كلية تكنولوجيا المعلومات - جامعة بابل كجزء من متطلبات
نيل درجة الماجستير في تكنولوجيا المعلومات / البرمجيات

من قبل

دعاء عبدالرضا رحيم محمد

بإشراف

أ.د. نداء عبدالمحسن عباس حسن