Optimizing Central Pattern Generators to Generate Rhythmic for Arm Movement

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الملخص

تحلل هذه الدراسة التركيبة الرياضية لمولدات الأنماط المركزية وتحليل الاستقرار. تتناول هذه الورقة أيضًا كيفية تحسين مولد النمط المركزي لتوليد أنماط إيقاعية للذراع البشرية باستخدام الخوارزمية الجينية بالدالة الهجينة. كما يركز على تحسين مولد النمط المركزي ثنائي الاتجاه في المنطقة المستقرة لإنشاء أنماط إيقاعية مماثلة للأنماط الإيقاعية المستمدة من البيانات الحقيقية دون أي مدخلات .

الكلمات المفتاحية:
مولدات الأنماط المركزية ، نمذجة الذراع الواحدة ، تحليل الاستقرار ، الخوارزمية الجينية.

Abstract.

This study analyses the mathematical structure of the central pattern generators (CPGs) and their stability analysis. This paper also discusses how to optimizing the CPGs to generate rhythmic patterns for human arm by using the genetic algorithm (GA) with hybrid function. It also focuses on optimizing bidirectional two CPGs in the stable region to generate rhythmic patterns similar to the rhythmic patterns derived from real data without any input or sensory feedback.

Keywords: Central Pattern Generators (CPGs), Modelling of One Arm, Stability analysis, Genetic Algorithm (GA).

1- Introduction

Recently, many studies are shown the basic movement patterns of biological systems are produced by a central nervous system that is referred to as a Central Pattern Generator [1], [2] and [3]. In the biology, the CPGs consider as the inspired networks of nonlinear oscillating neurons that are able to produce rhythmic patterns without any sensory feedback, which is located at the spinal cord, and we are also able to generate it to rhythmic commands for the muscles [1].

One of the facts that, the CPGs are existed in the spine of both vertebrate and invertebrate animals and burst signal from the brainstem induces a periodic activity in the CPG [4] and [5]. Some studies are also defined the CPG as a small neural network and also receives inputs from higher parts of the central nervous system [6], which is contradicted with the study are mentioned above. In general, the CPGs will be considered a set of nonlinear oscillators and each of the set of nonlinear oscillators is forced by the output of a sensor, which gives a time-indexed to the first-order information on the motion [3], the previous definitions of the CPGs are considered to represent continuous the cyclic motion of this system. Many physical structures of the limbs and arms mostly have been modelled, whereas the control systems are now being copied to regenerate the same move patterns in the robots as seen in nature. The CPG starts to use synchronizing with body movement and accordingly send motor commands to motor neurons at an appropriate time in a movement cycle [4] and [7]. The CPG gives signals to each joint [8] and [9].

There are many different mathematical CPGs, which have different reflexes, where these reflexes are phase-dependent for instance; they will have different effects relying on the timing within locomotors cycle [10], [11] and [12]. In this part of our study investigates the arm's movement during dart throwing and motor skill to develop medical or sports applications. In many previous studies, the dart-throwing motion has been analyzed to throw accurately. In [13] tested tennis players in a whole body in order to show that the preparatory motion of a slight vertical jump shortened the time required to move a certain distance.

Another study in [14] showed the preparatory motion of the basketball players diminished the time required to travel a certain distance, which is similar the previous study. It is concluded by those two studies that; the preparatory motion is improving the performance of aiming movements. Despite of the preparatory motion of those two studies have different motion, in [13] the participants performed the preparatory motion in a discrete manner. Whereas in [14] the preparatory motion was rhythmic motion movement. The relationship between discrete and rhythmic motions has been studied previously [15] and [16]. In both studies, they focusing on term of the brain activity during the flexion and extension of the wrist joint. They found that rhythmic movements were not concatenated discrete movement as observed in brain activation. Another study, they showed that, there were small differences in movement time and peak velocity between trails and continuous motion conditions [17]. We choose the dart throwing because of it is simplicity, the movement of the arm during the dart throwing is totally executed by a single upper limb without whole body movement, another reason is that, the previous studies have chosen dart throwing in order to estimate factors affecting motor performance in both the field of the human motion and attention studies [18], [19] and [20].

It combines both oscillators to control the arm movement of the kinematic model of a single one arm with two degrees of freedom (DOF).

The mathematical analysis for the optimization of the CPG can be another novelty in this paper. Based on the cost function, this paper uses a developmental algorithm to find the optimum parametric values for bidirectional two CPGs only, it is predicted that the bidirectional two CPGs will give the best results.

The paper is organized as follows: The kinematic model has been discussed in the next section. A strategy to couple two CPGs and the stability analysis are given in Section 3. In Section 4, the real data is discussed. Section 5 is devoted to the optimization results. In Section 6, some conclusions are drawn and suggestions for future research are given.

2 -The kinematic Model of the Arm

Let us describe human arm as a 'machine' of 3 levers attached to each other by 2 joints or 'hinges', and with 1 joint attaching it to a fixed point as in the figure 1.

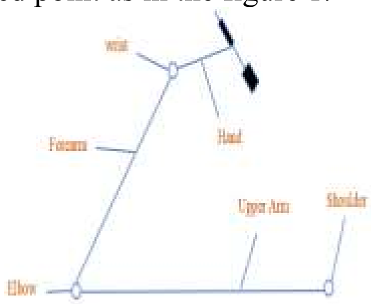

Figure 1: Modelling of human Arm during dart throwing

By looking at the figure.1, Actual, we have here the fixing joint is the shoulder, the two attaching joints are elbow and wrist, while the 3 levers are the upper arm, the forearm and the hand. It can theoretically draw every possible curve within its range when the levers are moved properly, and although the human arm is slightly less movable the parabolic curve is not an easy task to find. Kinematic model is derived to perform basic analysis.

Figure 1 shows the arm movement during dart throwing. Let us consider L_1 and L_2 are presented the lengths of the arm and forearm respectively, and θ_1 and θ_2 are presented the first arm and the body for the shoulder joint. The second angle is between the first arm and the second arm for elbow. Let us also assume that (x_S, y_S) is denoted the first coordinate of the shoulder, let (x_E, y_E) is denoted the second coordinate of the elbow. The figure 2 shows planar arm with three joints during dart throwing in 2DOF.

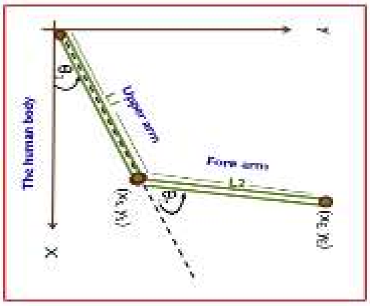

Figure 2: Modelling of human Arm during dart throwing

The simple kinematic equations are

$$\left.\begin{aligned} x_S &= L_1 cos\theta_1 \\ y_S &= L_1 sin\theta_1 \end{aligned}\right\} \quad (1)$$

$$\left.\begin{aligned} x_E &= L_1 cos\,\theta_1 + L_2 cos\,(\theta_1 + \theta_2) = x_s + L_2 cos\,\,(\theta_1 + \theta_2) \\ y_E &= L_1 sin\,\theta_1 + L_2 sin\,(\theta_1 + \theta_2) = y_s + L_2 cos\,\,(\theta_1 + \theta_2) \end{aligned}\right\} \quad (2)$$

One needs to just the simple kinematic equation during the optimization part and it is not needed the Lagrange or Newton equations and we will here focus only on two DOF in this study. The main idea of this study to select the movements of arm without using brain, and also how the arm can move by using the output of CPGs, let us consider the following steps.

The normal movement of the upper arm part is started from the body (angle 0) until almost to the top of the shoulder (angle 90) as shown in this Figure 3.

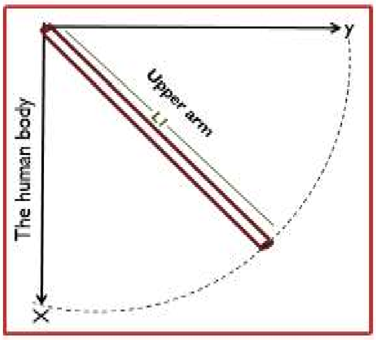

Figure 3: The normal movement of the upper arm part

The normal movement of the forearm part as first angle (θ_1) is between the body and the upper arm (zero until 90). The second angle (θ_2) is between the upper arm and the forearm for elbow as in the Figure 4.

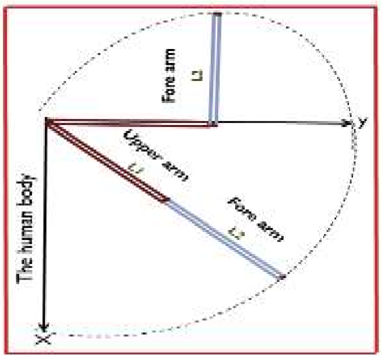

Figure 4: The normal movement of the forearm arm part

3- Central Pattern Generators (CPGs)

In introduction of this paper, the CPGs are defined explicitly. The mathematical differential equations are presented the CPGs in general formula in [10],[12] and [21]. By comparing all the results and studies that have done here, we pick that one has been studied by [12]. That one is called standalone nonlinear oscillator. Some experiments show that sinusoidal signals are well suited for locomotion control. Here, it briefly discusses about this type.

$$x = Asin(2\pi ft + \varphi)$$

Where A is the amplitude, f and φ are the frequency and the phase respectively. By taking the first and the second derivative of x, a first order differential equation can be derived:

$$\tau\dot{x} = v, \tau\dot{v} = -x \text{ where } \tau = \frac{1}{2\pi f}$$

The amplitude A is only implicitly defined by this linear differential equation. A depends on the initial conditions and perturbations of the state variables will have an effect on it. We must therefore add a new term that drives the system to a limit cycle with precise amplitude. It consists of the following differential equations:

$$\left.\begin{aligned} \tau\dot{x} &= v \\ \tau\dot{v} &= -\frac{\alpha}{E}(x^2 + v^2 - E)v - x \end{aligned}\right\} \quad (3)$$

The parameters τ, α and E are positive constants. The expression $x^2 + v^2$ represents the actual energy of the oscillator and $x^2 + v^2 - E$ is the energy error of the oscillator. Therefore, the nonlinear term may be understood as the normalized energy error multiplied by α and v. The positive constant α can be used for tuning the attracting force to the limit cycle. The bigger α, the faster the convergence. The above system is for a single CPG. The system for these types of oscillators is given by

$$\left.\begin{aligned} \tau\dot{x}_i &= v_i \\ \tau\dot{v}_i &= -\frac{\alpha}{E_i}({x_i}^2 + {v_i}^2 - E_i)v_i - x_i + \sum_j (a_{ij}x_j + b_{ij}v_j) \end{aligned}\right\} \quad (4)$$

Where τ, α and E_i are positive constants, a_{ij} and b_{ij} are constants that determine how oscillator j influences oscillator i. Where $i, j = 1,2$ and $i \neq j$. Note that, the sensory inputs be negligent here.

Certain forms of outputs are possible by changing the numerical values of parameters, more detail with different CPGs [8]. By deriving the equation (4), we obtain three types of CPGs, Uncoupled, Unidirectional and Bidirectional CPGs respectively.

$$\left.\begin{aligned} \tau\dot{x}_1 &= v_1 \\ \tau\dot{v}_1 &= -\frac{\alpha}{E_1}({x_1}^2 + {v_1}^2 - E_1)v_1 - x_1 \\ \tau\dot{x}_2 &= v_2 \\ \tau\dot{v}_2 &= -\frac{\alpha}{E_2}({x_2}^2 + {v_2}^2 - E_2)v_2 - x_2 \end{aligned}\right\} \tag{5}$$

$$\left.\begin{aligned} \tau\dot{x}_1 &= v_1 \\ \tau\dot{v}_1 &= -\frac{\alpha}{E_1}({x_1}^2 + {v_1}^2 - E_1)v_1 - x_1 + a_{12}x_2 + b_{12}v_2 \\ \tau\dot{x}_2 &= v_2 \\ \tau\dot{v}_2 &= -\frac{\alpha}{E_2}({x_2}^2 + {v_2}^2 - E_2)v_2 - x_2 \end{aligned}\right\} \tag{6}$$

$$\left.\begin{aligned} \tau\dot{x}_1 &= v_1 \\ \tau\dot{v}_1 &= -\frac{\alpha}{E_1}({x_1}^2 + {v_1}^2 - E_1)v_1 - x_1 + a_{12}x_2 + b_{12}v_2 \\ \tau\dot{x}_2 &= v_2 \\ \tau\dot{v}_2 &= -\frac{\alpha}{E_2}({x_2}^2 + {v_2}^2 - E_2)v_2 - x_2 + a_{21}x_1 + b_{21}v_1 \end{aligned}\right\} \tag{7}$$

Figure 5 shows One CPGs structure in Simulink.

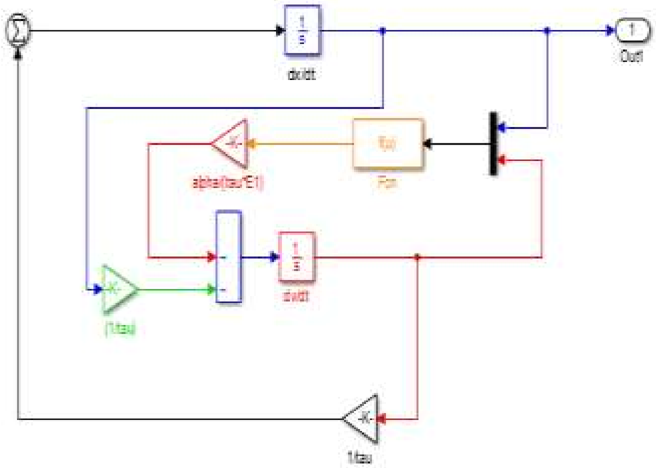

Figure 5: Internal Dynamics of single CPGs

The outputs of the systems are $x_1 = \theta_1$ and $x_2 = \theta_2$, where θ_1 and θ_2 are previously defined in our model. For the stability and bifurcation part, they have done in more details by [12]. We here omit both cases Uncouple and Unidirectional two CPGs in this study, we just focus on the stability bidirectional two CPGs, consider the equation (7), this system has four equations, it is a clear that, the equilibrium point is the origin point (0,0,0,0). The Jacobian matrix at the origin point is

$$J(0,0,0,0) = \begin{bmatrix} 0 & 1/\tau & 0 & 0 \\ -1/\tau & \alpha/\tau & a_{12}/\tau & b_{12}/\tau \\ 0 & 0 & 0 & 1/\tau \\ a_{21}/\tau & b_{21}/\tau & -1/\tau & \alpha/\tau \end{bmatrix}$$

The characteristic polynomial is

$$\lambda^4 - \frac{2\alpha\lambda^3}{\tau} + \frac{(-b_{21}b_{12} + 2 + \alpha^2)\lambda^2}{\tau^2} - \frac{(a_{21}b_{12} + b_{21}a_{12} + 2\alpha)\lambda}{\tau^3} - \frac{a_{21}}{a_{12}\tau^4} = 0 \qquad (8)$$

We can impose more conditions to extract some information from this equation (8) and simplified equation (8): For example, one can Set $\mu_1 = a_{12} = b_{12}$ and $\mu_2 = a_{21} = b_{21}$, the equation (8) becomes

$$\lambda^4 - \frac{2\alpha\lambda^3}{\tau} + \frac{(-\mu_1\mu_2 + 2 + \alpha^2)\lambda^2}{\tau^2} - \frac{2(\mu_1\mu_2 + \alpha)\lambda}{\tau^3} - \frac{\mu_2}{\mu_1\tau^4} = 0 \qquad (9)$$

One of the eigenvalues in the equation (9) must be the real part positive, according to that we will focus only on the equation (8). The equation (8) is not easily to analysis it manually, we used both simulation and optimization to compare with these eigenvalues be in stable or not.

4- Obtaining Real Data

Obtaining real data involves different objectives. One of the major objectives, for instance, is to learn whether the output of CPGs may be endorsed. Another important and legitimate inquiry is whether manipulating CPGs would establish rhythmic patterns for the shoulder, elbow, and waist angles akin to those seen in nature. The Figure 6 below explain how real data can be obtained under different circumstances along with their analysis. The data were obtained through video recording by using High speed Camera, as described in the Figure 6.

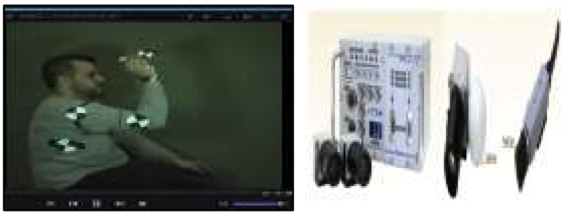

Figure 6: Video-recorded data and High-speed Camera

In fact, in order for us to be able to analyze the video-recorded real data, the researchers used the Tema Motion software. Results of using Tema Motion to establish real data for the shoulder and elbow angles are shown in Figure 7, where θ_S and θ_E stand for the angles of shoulder, elbow of the real data respectively.

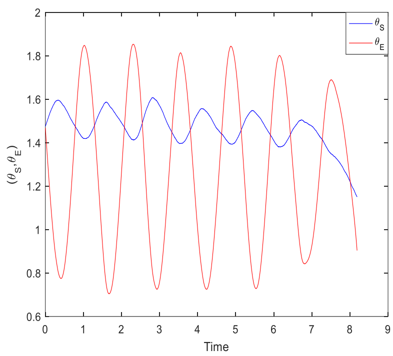

Figure 7: Angles of the shoulder and elbow that are collected by real data.

5- Optimizing Movement of arm during dart throwing

There are three cases, each pattern generator outputs angular patterns for each joint. To evaluate arm generation, actually it is needed to find the optimal parameter sets by using central pattern generators, which means that, how the angular of the shoulder and the elbow should vary with time to generate motion similar to real data that is obtained in the Figure 7. For each case, parameter sets for each joint's central pattern is given below. $P_1 = \{\tau, \alpha, E_1, E_2\}$. Uncoupled Case, $P_2 = \{\tau, \alpha, E_1, E_2, a_{12}, b_{12}\}$.

Unidirectional case and $P_3 = \{\tau, \alpha, E_1, E_2, a_{12}, b_{12}, a_{21}, b_{21}\}$. Bidirectional case. By using genetic algorithm (GA) and hybrid function (patterns search or minimization function (fmincon) to find the optimal parameter sets [5] and [22]. In this study, there is one cost function is utilized; to obtain arm movement as dart throwing, it should be depended on this cost function below.

$$J_1 = \sum_{k=1}^{n}((\theta_1(k) - \theta_S(k))^2 + (\theta_2(k) - \theta_E(k))^2) \qquad (10)$$

Translating the aforementioned equation into words indicates that θ_1 and θ_2 are the outputs of the CPGs as defined before, where θ_S and θ_E are the angles of shoulder and elbow of the real data respectively, and that n is the total number of step times.

The conclusive goal here is to minimize differences between the outputs of the CPGs and the real data for the angles of the shoulder and the elbow in the region captured by stability analysis (see [12]).

In addition, the equation above unfolds two constraints, namely $0 \le \theta_1 \le \frac{2\pi}{3}$ and $0 \le \theta_2 \le \frac{3\pi}{2}$. In the present study, a hybrid function was used during the optimization process, an optimization function that runs after the GA terminates in order to improve the value of the fitness function**.** The significance of the hybrid function stems from the fact that it uses the final point from the GA as its initial point which can be specified in the Hybrid function options.

One can set the initial conditions in the CPGs as variables which are determined by Ga optimization, and where the mutation rate and crossover fraction are predicted to be 0.05 and 0.2, respectively. As described in Figures 8, 9, 10,11 and 12 below. The CPGs in these figures corresponding to the values $\alpha = 0.0027$, $\tau = 0.2082$, $E_1 = 0.0004$, $a_{12} = 1.4728$, $b_{12} = 0.0355$, $E_2 = 0.5599$, $a_{21} = 1.2675$, $b_{21} = -10.3977$ and the initial conditions, $x_1(0) = 1.4472$, $v_1(0) = 4.1830$, $x_2(0) = 1.4202$, $v_1(0) = 0.0001$.

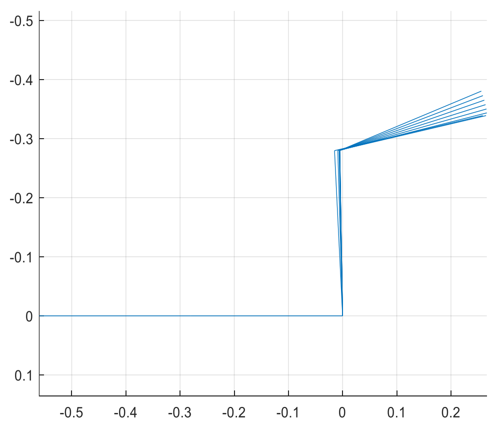

Figure 8: One Arm animation

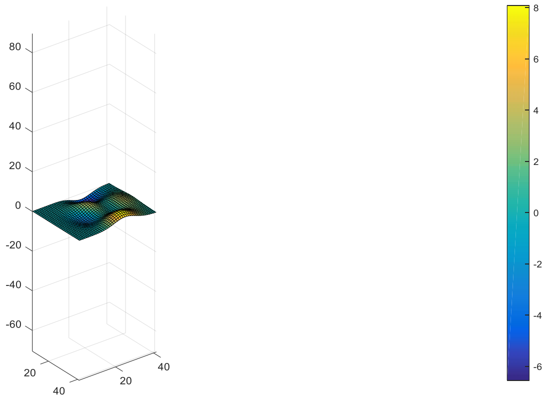

Figure 9: The outputs of the CPGs in 3D

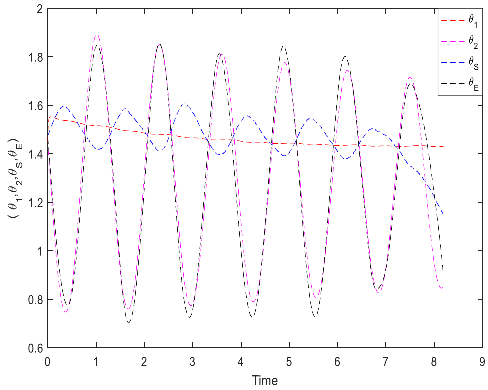

Figure 10: Outputs of the CPGs and real data

e_1 and e_2 are the errors between each angle, respectively, as shown in the figure 11:

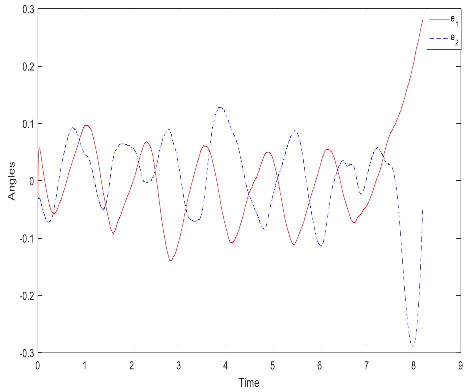

Figure 11: Errors between the outputs of the CPGs and the real data at each angle

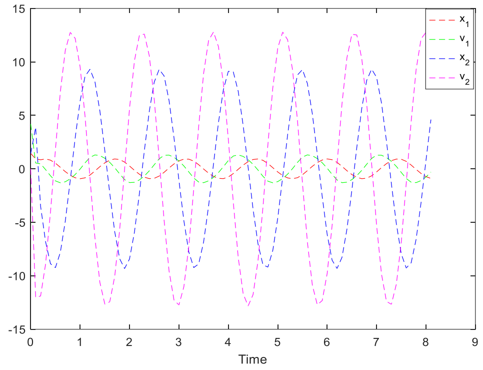

Figure 12: Numerical solution corresponding to the same values in Fig 8.

To reduce the error more than before on the objective function, it should not be focusing only the Genetic algorithm, we should look at the parameters. Final part of the study, we focused on optimizing the parameters of the CPGs especially the first one since the big error comes from it.

The results reveal that the most effective parameters are τ and α; where the parameter τ stands for the number of oscillations. In order to verify the results, we repeated the optimization of arm movement shown in Figures 8 and 9, and started changing the value of τ with fixed some of the parameters such as $E_2 = 0.5599$, $a_{21} = 1.2675$, $b_{21} = -10.3977$. Table 1 summarizes these results, let us start to change τ only and keep α,E_1,a_{12} and b_{12} are determined by Genetic algorithm:

Table 1: Values of J for different choices of α,E_1,a_{12} and b_{12}

τ	α	E_1	a_{12}	b_{12}	J
0.2082	0.0027	0.0004	1.4728	0.0355	98.1252
0.4082	0.0037	0.0001	1.2512	1.0355	1225.8
0.5082	0.003	0.0003	1.2512	1.0355	1299.1

Table 2 summarizes these results, let us fix τ and α, and start to optimize E_1, a_{12} and b_{12}

Table 2: Values of J for different choices of α,E_1,a_{12} and b_{12}

τ	α	E_1	a_{12}	b_{12}	J
0.2082	0.0027	0.0003	1.2512	0.0355	279.010
0.2082	0.0027	0.0002	1.2675	-0.1781	388.7878
0.2087	0.0027	0.0001	1.2491	-0.4181	691.2655

Any increasing or decreasing in some value of the parameters in the bidirectional CPGs, it leads to effect outputs of the CPGs, Sine the bidirectional CPGs are connecting to each other in this case, we will just try to increase both E_1 and E_2 and by repeat the optimization using both Genetic algorithm and hybrid function to get better results such as in the Figures 13 and 14, the outputs of the CPGs in the Figures 13 and 14 correspond to the values $\alpha = 0.0014$, $\tau = 0.9601$, $E_1 = 0.2000$, $a_{12} = -0.4794$, $b_{12} = 0.0401$, $E_2 = 0.0100$, $a_{21} = 2.1196$, $b_{21} = 0.0538$ and the initial conditions, $x_1(0) = 1.4472$, $v_1(0) = 4.1830$, $x_2(0) = 1.4202$, $v_1(0) = 0.0001$, these results are much better compare with the study had done (see [19].

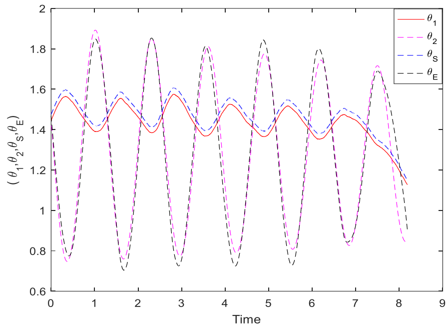

Figure 13: The Outputs of the CPGs and real data

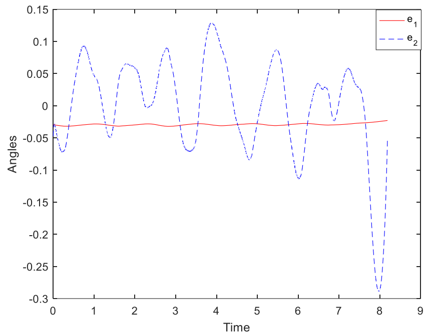

Figure 14: Errors between the outputs of the CPGs and the real data

It is a clear that, the optimization results identity the stability analysis, where the solution here is site in stable domain. Although, there exist some error during to optimization of the bidirectional two CPGs, as a result of the genetic algorithms works just to find local minimum, and also, the cameraman who recorded the video did not put the sign in exact place lead us to get in small incorrect data.

6- Conclusion and Future Directions

In this paper, the bidirectional two CPGs are used to generate motion similar to the rhythmic patterns derived from real data for arm with two degrees of freedom, the arm starts moving normally as dart throwing during the optimization in stable domain, which lead us to think about the future work to use the CPGs to control some different part of the body or generate different movements of arms by using different algorithm.

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