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Control of Nonlinear Heartbeat Models under Time-Delay-Switched Feedback Using Emotional Learning Control

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Abstract— **In this paper, we adopt the Zeeman nonlinear heart model to discuss its stability and control its operation using emotional learning control (ELC). We also demonstrate the control of the heart model under threats of possible time delay introduced in the sensing loop. We compare the robustness of the ELC with other control methods such as the classical PID and the model predictive control (MPC) for the heart model under time delay attack. We have showed that ELC is more robust than the classical PID and the MPC.**

Index Terms— **Emotional learning controller, TDS attack, nonlinear heartbeat model**

I. Introduction

There are many design and analysis techniques developed for linear time-invariant (LTI) systems [1, 2]. However, for nonlinear systems which could possibly be time-varying, one needs different methodology. A major part of nonlinear control theory studies how to extend the well-known methods for liner systems to nonlinear systems.

One of the most complex but robust nonlinear systems is the human heart. Electrocardiogram (ECG) records potential differences between two electrodes located on the skin at predetermined positions on the chest to measure the electrical activities in cardiac tissue. A solitary cycle of ECG consists of the activities of relaxation and contraction of the heart (called the heart pumping actions). One can identify an ECG signal by its P, Q, R, S, and T peaks, PR and ST segments, PR and QT intervals, and QRX complex. Characteristic information took out from ECG can be used to assess cardiac health and identify potential heart problems. For example, important information extracted from ECG recording is the time between successive R-peaks which is stated to as an RR-interval. The changeability of the series of RR-intervals, known as heart rate variability (HRV), is being used to measure heart functions: identifying patients risk for a cardiovascular failure [3], as "an indicator for mortality following myocardial infraction" [4], and as a measure of the contacts between different control mechanisms of physiology like respiratory sinus arrhythmia.

The development of mathematical models of heartbeat (ECG) with appropriate PQRST peaks, QRX complex, (PR, ST) segments, (PR, QT) intervals and HRV spectra has been and continue to be the subject of wide investigations with varying degrees of successes. A good model of ECG will make available a valuable tool for analyzing the various physiological conditions effects on the outlines of the ECG and for the assessment of diagnostic ECG signal processing devices.

The form of ECG signal is the result of the propagation of electrical activities in myocardium and HRV is the result of physiological and neurological controls. In 1972 Zeeman presented a set of nonlinear dynamical

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equations for heartbeat modeling [5-7] based on the Van der Pol-Lienard equation. These models are based on pace making generated by the Sino-Atrial (SA) node, which is the dominant pacemaker as compared with the slower one produced by the Atrio-Ventricular (AV) junction. Furthermore, these models did not take into consideration of sympathetic and parasympathetic modulations responsible for HRV generation [8].

In [9], the Zeeman's 2^{nd}-order ordinary differential equation (ODE) of the heartbeat model was modified by incorporating a switch (on/off) control variable demonstrating the pacemaker's mechanism of the contraction-relaxation for the heart. Whereas Jafarnia-Dabanloo et al in 2007 [10] modified the 3^{rd}-order nonlinear Zeeman model by adding control parameters that affect the frequency of the oscillation to control the HRV by using a neural network to produce the ECG signal.

Yet another well-known approach to model the cardiac rhythms is based on the Van der Pol oscillators. In contrast to the Zeeman models, the coupled Van der Pol oscillator models at AV node making it have a more active role in pace making [11]. This model allows us to consider the effect of the coupling between the SA and the AV pacemakers in normal electrophysiological dynamics.

In this paper, we study the stability of the heartbeat model that has been developed by Zeeman [5]. This model captures, at least qualitatively, three essential characteristics of cardiac dynamics: (i) a stable equilibrium, (ii) a threshold for triggering the action potential, and (iii) a return to equilibrium. The model consists of a 2^{nd}-order nonlinear ODE of the Liénard-type representing heartbeat dynamics [15].

In this era of pervasive communication technology, distant monitoring and follow-up of patients implanted with pacemakers (PMs) and implantable cardioverter-defibrillators (ICDs) is becoming very common. Most companies fit PMs and ICDs with wireless capability that communicates information to home transmitters then to physicians. These systems are widely used in the USA and are being introduced in Europe. Only recently, a tiny wireless pacemaker is launched in Europe by Nanostim [12]. The security of current and future biomedical devices is going to draw a major concern of public health in the future. Recently the U.S. Department of Homeland Security underscored some threats affecting almost 300 medical devices [13]. New revolution in wireless pacemakers [14] can further plan of attackers intending to access and sabotage biomedical devices. Attacks such as false data injection, denial of service and other types of attacks can make people's life who depend on these wireless enabled devices (e.g. pacemakers), difficult and dangerous. Therefore, it is reasonable to model the heartbeat pacemaker system under time-delay-switch (TDS) attacks and provide a possible solution. TDS attacks is a switched action "Off/Delay-by-τ", where τ specifies some random delay time, of the sensed system states or control signals of a system. We are going to model the TDS attack on the heartbeat control system (Fig.1) as a hybrid system. Then, we will provide a solution using emotional learning control to temper the effects of such an attack on the control of heartbeats.

The first section of the paper introduces a common nonlinear model of heartbeat, i.e. Zeeman models. Also we discuss the stability of 2^{nd}-order heartbeat model using the indirect method. In the next section, we present the method of the emotional learning controller for control of the 2^{nd}-order heartbeat model. Note that, controllability and observability are assumed and have been studied and discussed elsewhere [15]. Based on nonlinear feedback Emotional Learning PI control technique and schematic method, Section 3 organizes the control of the system. Finally, it presents experiments to verify that this method works well. The conclusion section shows that this method is powerful to track the ECG signal and is more robust compare to other control methods under TDS attack or random delay in the sensing loop.

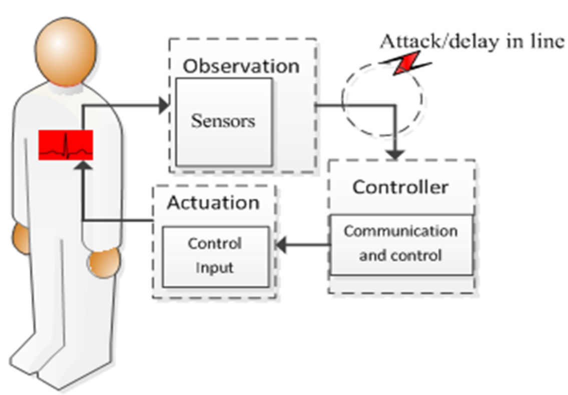

Figure 1. Heart beat control model with possible control attack

II. NONLINEAR HEARTBEAT MODEL

Based on [6], the second-order nonlinear heartbeat model is given by:

$$\begin{bmatrix} \dot{X}_1(t) \\ \dot{X}_2(t) \end{bmatrix} = \begin{bmatrix} -\frac{1}{\varepsilon}\{X_1^3(t) - TX_1(t) + X_2(t)\} \\ X_1(t) - x_d \end{bmatrix}, \qquad T > 0 \qquad (1)$$

where the states $X_1(t)$ and $X_2(t)$ represent the length of a muscle fiber and a state related to electrochemical activities, x_d indicates a typical muscle fiber length, ε is a small positive constant which plays a role in fast eigenvalues of the system, and finally T shows tension in the muscle fiber. Parameter values are given in Table 1.

TABLE 1 PARAMETERS VALUE OF MODEL (1)

Parameter	x_d	T	ε
value	1.024	1	0.2

Values in Table 1 have been checked by analyzing the equilibrium point stability using the well-known Lyapunov indirect stability theorem [16]. For this purpose, let A be the Jocobian matrix of Equation 1 at the origin.

$$A = \begin{bmatrix} \frac{\partial \dot{X}_1}{\partial X_1} & \frac{\partial \dot{X}_1}{\partial X_2} \\ \frac{\partial \dot{X}_2}{\partial X_1} & \frac{\partial \dot{X}_2}{\partial X_2} \end{bmatrix}\Bigg|_{X=0} = \begin{bmatrix} -\frac{1}{\varepsilon}(3X_1^2 - T) & -\frac{1}{\varepsilon} \\ 1 & 0 \end{bmatrix}\Bigg|_{X=0} = \begin{bmatrix} \frac{T}{\varepsilon} & -\frac{1}{\varepsilon} \\ 1 & 0 \end{bmatrix} \qquad (2)$$

For the parameter $x_d = 0$, the eigenvalues of A have the values of 3.618 and 1.382. Both are positive and show that the origin is not stable.

The condition for the real part of the eigenvalue to be negative is $3X_1^2 - T > 0$. So the system can be stable if $X_1 \geq \sqrt{\frac{T}{3}}$, and $X_1 \leq -\sqrt{\frac{T}{3}}$. These conditions can be satisfied if the value of x_d be 1.024. For $x_d = 1.024$, the stable equilibrium point is at $(1.024, -0.0497)$ in the state space. In this case, all of the trajectories, irrespective to their primary conditions, go to the diastolic equilibrium point.

The system stays at the stable equilibrium point endlessly, until the equilibrium point is stable, except there is an exterior excitation that forces the system move to a new equilibrium point. Based on this new stable system, a control input is added to the system (1) as shown below:

$$\begin{bmatrix} \dot{X}_1(t) \\ \dot{X}_2(t) \end{bmatrix} = \begin{bmatrix} -\frac{1}{\varepsilon}\{X_1^3(t) - TX_1(t) + X_2(t)\} \\ (X_1(t) - x_d) + (x_d - x_s)u(t) \end{bmatrix} \qquad (3)$$

where, when heart is in systolic state, x_s is an additional parameter representing a typical fiber length and $u(t)$ shows the cardiac pacemaker controls mechanism that leads heart into diastolic and systolic states. The feedback controller can be found in the form

$$u(t) = -K\hat{X} \qquad (4)$$

and the new state after the attack (or random delay of feedback line) can be modeled by

$$\hat{X} = X(t - \tau) \qquad (5)$$

In Equation 5, τ is the time-delay and a positive integer. When time-delay is zero, the system works in its normal operation. The adversary can access to the communication line and delay the communication line. This model is true also for the small value of delay which can happen in the nature of the wireless sensor.

III. EMOTIONAL LEARNING CONTROLLER (ELC)

Emotional learning controller was presented by Moren and Balkenious for the first time. They started to evolve computational models for parts of the human brain that carry out emotional functioning. In [17], a new computational model of brain emotional learning included amygdala, orbitofrontal cortex, and thalamus and finally sensory cortex has been presented, (Figure 2).

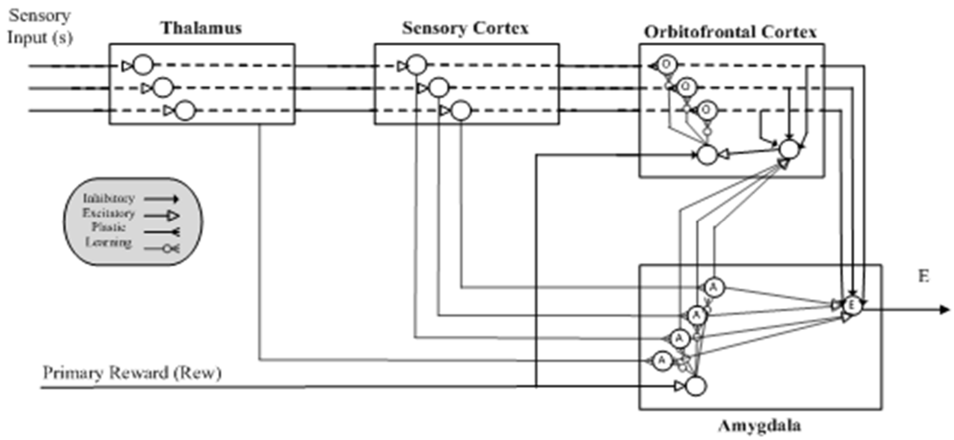

Figure 2 Scheme of detail presented brain emotional learning model

Amygdale is a small unit in the brain, which is involved in emotional evaluation of the stimuli. These emotional states and reactions derive attention signals and ultimately motor control commands. Some of inherent exciters are: hunger, pain, certain smells, etc. can excite the amygdale. The amygdale response to these stimulants is used in learning. On the other hand, the orbitofrontal cortex plays the role of a modifier of inappropriate responses and reactions of the amygdale. Numerous experiments on patients with damaged orbitofrontal-cortex have revealed that they are not able to adapt themselves to new conditions [18], in the other words, previous learning does not let them understand and response to new conditions.
The ELC consists of two stages which carry out the learning and control process: one corresponds to information processed by the amygdala and the other by the orbitofrontal cortex. Basically, input stimuli (signals) are processed and used as a gain control of coefficients (synaptic efficacies) to affect future processing of stimuli and motor control commands.
By ignoring some details of Figure 2, the computational emotional learning model of amygdale-orbitofrontal can be proposed in Figure 3.

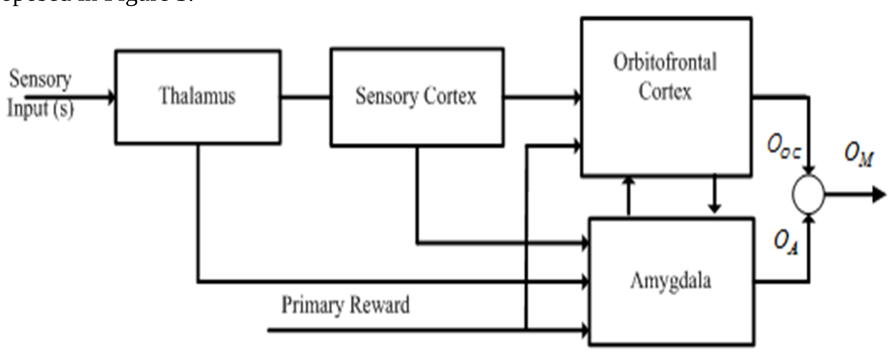

Figure 3 Overall computational model of ELC

The output of the computational model can be found as:

$$O_M = O_A - O_{OC} \quad (6)$$

where O_M is the model output, O_A and O_{OC} are the amygdale and the orbitofrontal cortex unit output, respectively.
The outputs of the amygdale and orbitofrontal units are described by

$$O_A = G_A \cdot I_S \tag{7}$$

$$O_{OC} = G_{OC} \cdot I_S \tag{8}$$

where G_A is the amygdale gain, I_S is the sensory input, and G_{OC} is the orbitofrontal cortex gain. The amygdale and orbitofrontal learning laws can be modeled as:

$$\Delta G_{OC} = k_1 \cdot (O_M - I_{PR}) \tag{9}$$

$$\Delta G_A = k_2 \cdot Max\{0, I_{PR} - O_A\} \tag{10}$$

where I_{PR} is the primary reward, k_1 and k_2 are rates of learning related to orbitofrontal and amygdale, respectively. The Equation (10) shows that the amygdale learning uses Max operation, therefore the amygdale gain is forced to have a consistently increasing deviation. This emphasizes the physiological fact of the amygdale unit which memorizes what it has been learned.

Now, let us use Equations 6, 7 and 8 to find a general formula:

$$O_M = (G_A - G_{OC}) I_S \tag{11}$$

Based on Equation 11, we can conclude that the output for emotional learning system of the amygdale-orbitofrontal unit depends on the amygdale and orbitofrontal gains and the sensory inputs. It should be noted that these gains depend on the primary reward signal.

In this paper, the sensory input of emotional learning system has been formulated by a format similar to self-tuning PID:

$$I_S(t) = K_P e(t) + K_D \dot{e}(t) + K_I \int_0^t e(t)\, dt \tag{12}$$

where K_P, K_D and K_I are the proportional gain, the derivative gain and the integral gain, respectively. The signal $e(t)$ is the difference value between the tracking error and the output value at any time instant. However, to get a better response in front of noise, we used PI instead of PID as our sensory input to the amygdale-orbitofrontal emotional learning system. In the next section we will show that this controller improves the performance of the system in the attack operations and also track the reference ECG signal very well.

IV. Results And Comparison

We have simulated the 2nd order heartbeat model to track the ECG signal using the Emotional Learning PI Controller (ELPIC). Then an external TDS attack or random feedback delay is applied to the model from a start time t_S until a final time t_F to show the performance of the ELPIC, which is compared with the classical PID and the model predictive controller (MPC).

Figure 4 shows the ECG reference tracking $X_2(t)$ using the ELPIC. The line shows the output of the model controlled by the ELPIC and the points indicate the patient's ECG referenced signal [19]. The result shows that the ELPIC tracks the reference signal accurately.

The TDS attack or feedback delay has been applied to the model from $t_S = 0.4\sec$ until $t_S = 0.45\sec$ with time-delay of $\tau = 0.01s$. For the purpose of visual comparison, the attack period and the amount of attack have been selected small because for larger period and time-delay value, the classical PI and MPC controllers goes out of visual bound. Figures 5 and 6 compare the ELPIC with the classical PI and the Matlab MPC. The results clearly show that ELPIC is more robust in front of TDS attack or unwanted random feedback delay.

V. Conclusion

In summary, we have shown that the ELC applied to Zeeman nonlinear heart model is able to track the ECG signal with high fidelity. Furthermore, the robustness of the ELC to control Zeeman heart model under time-delay switch attack was demonstrated. Its stability and control of its operation was evaluated. We have also showed that ELC is more robust than other common control schemes such as the classical PID and the model predictive control (MPC).

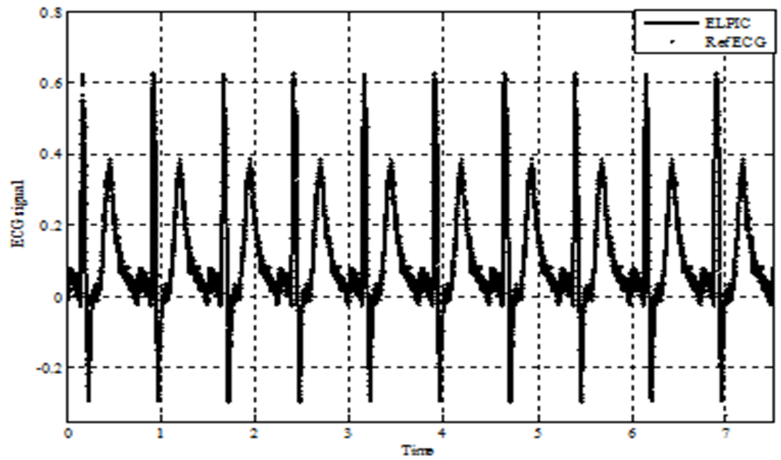

Figure 4 Simulation result of ECG tracking for second-order heartbeat model based on ELPIC pacemaker signal

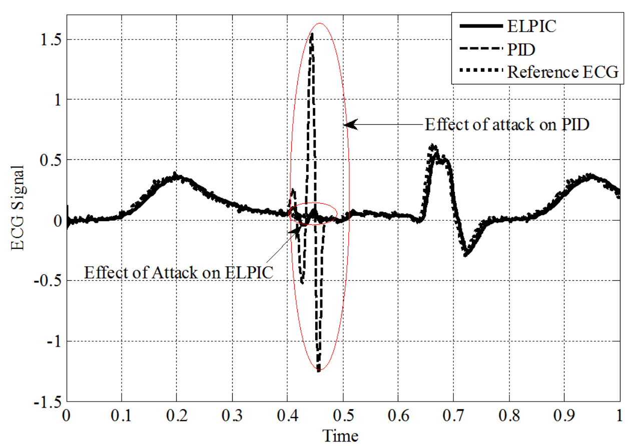

Figure 5 Comparison of the ELPIC and the classical PID for ECG tracking under TDS attack

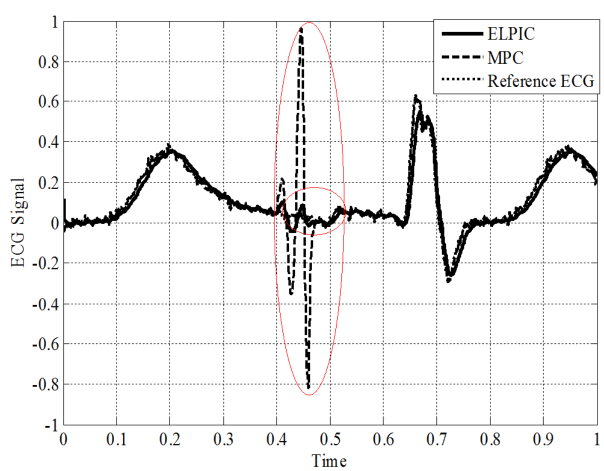

Figure 6 Comparison of the ELPIC and the MPC for ECG tracking under TDS attack

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