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A Predictive Control Approach For Nonlinear Systems

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Abstract: - The theory of artificial neural networks has been successfully applied in control systems. In this paper, a neural-network-based controller structure is proposed and applied to an unknown non-linear system that is affected by unmeasured disturbances. The controller structure includes three neural-network modules: the disturbance estimator, the system model, and the optimizer. The controller provides control actions according to the estimated values of unmeasured disturbances, and predictions of the future behavior of the system. The overall performance of the controller is improved continuously during its work so that a near disturbance rejection control is obtained. This strategy allows the controller to adapt to the behavior of a specific system and to any changes in it during the control process.

Key Words: Neural networks, adaptive control, predictive control.

1. Introduction

Neural-network-based control systems have a great scientific interest, as they are being able to approximate any non-linear function. Most control systems exhibit certain types of nonlinearities [1]. Neural Networks are able to estimate various system functions especially for unknown systems or systems that have complex mathematic functions. It worth mentioning that there are many works aimed to develop control systems based on neural networks [1,2,3].

The widely used structures of neural-network-based control systems use neural networks to approximate the system function and to apply a feedback control based on the results of estimation of the values of the system output. A neural network controller is continuously training in parallel with the work of the whole system to minimize the difference between the predicted and actual output of the system in order to closely approximate the system function.

In this paper, we examine a neural network adaptive control model and apply it to the problem of control of physiological systems (PS). PSs are very complex, and they are characterized by unstable response to changes in their input parameters. These systems include the control of blood pressure, blood-glucose concentration, and others. PSs are also complicated by the presence of unmeasured disturbances.

There were many approaches for the control of PSs, which has been attempted. These control models are related to the PS processes that require a stable value of a PS parameter. The PS self-control may be lost partially or completely because of specific diseases. If the self-control of a PS is lost, it must be utilized by an external control mechanism that must be very accurate. Poor control of these parameters may lead to many complications and risks of life [3,4].

One of the most important control approaches is the one based on the mathematical modeling of PS dynamics [5,6,7]. However, this approach requires a complete understanding of all physiological processes that affect the controlled object. This task usually leads to complex unsolved mathematical equations. Other approaches use probabilistic models based on the probability distribution of the control system parameters [9,13]. These systems are very sensitive to the incompleteness of available information.

The basic model for the control of PS is defined in terms of the classical cybernetic closed loop [1,8,11]. However, the inclusion of a delay in system response, an unmeasured disturbance, and individual PS variations of response amount and time much complicates the problem. This motivates to adopt an adaptive control approach with an ability to predict changes in the system state depending on the estimation of unmeasured disturbances and an approximation system model. The control strategy based on a prediction of the values of unmeasured disturbances is called a predictive control strategy.

2. The Neural Network Controller

The main common neural network based controller uses a neural network to predict the system output (Y'(t+1)) in order to determine a suitable control action for the system [1]. Later on, the controller finds the error between the predicted (1) and the measured values of the system output (δy) to train the neural network to minimize this error (Fig. 1).

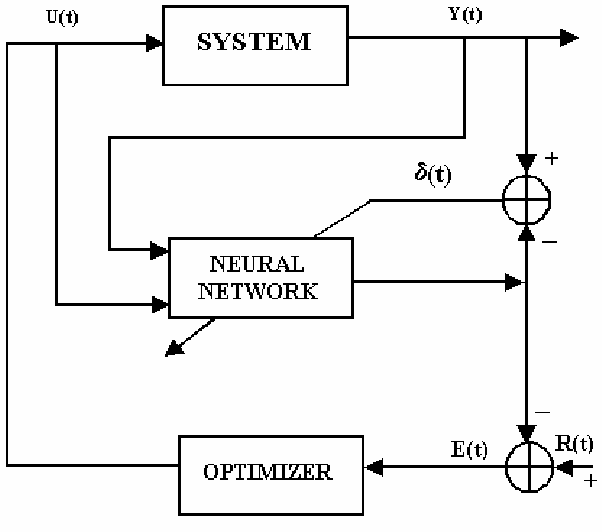

Fig. 1. A NEURAL NETWORK CONTROLLER

$$Y'(t+\Delta t) = g(Y(t), Ua(t-\Delta t), X(t), \Delta t) \quad (1)$$

$$\delta y = Y(t+1) - Y'(t-m) \quad (2)$$

Where Y(t) is the current system output, U(t) is the actual control action, and g(…) is the transition function of the system that the neural network approximates. The suitable control action is determined according to the difference between the predicted value and the goal value of system output δc; (3) .

$$\delta c = Yg(t+1) - Y'(t+1) \quad (3)$$

Where, Yg(t+1) is the goal value of the system output.

The neural network learns to predict Y(t+1) by Y(t), U(t), and their previous values. This value is not only a function of these two parameters, but also a function of the unmeasured disturbance X(t). Applying X(t) to the system affects its output and increases |δy|. Any changes of the amount of disturbance in the system allow the neural network to adapt to these new circumstances. This may take a time delay until |δy| is minimized, introducing instability in the system. The difference δy in non-linear systems does not provide enough information to determine the appropriate control signal to stabilize the system output because of the delay of the system response, which characterizes PSs. Consequently, it is valuable to introduce a neural network control structure that makes a great effort of the mapping and approximation properties of neural networks to be applied to complex unknown systems such as PS.

3. The Extended Control Structure

An extended adaptive control structure includes three neural network modules: a Neural Network Disturbance Estimator (NNDE), a Neural Network System Model (NNSM), and a Neural Network Optimizer (NNO), (fig. 2). The NNDE is used to estimate the amount of disturbance present to the system by previous and current measured values of the system output (Y(t-Δt), Y(t)), and the accumulative effective control action value - Ua(t-Δt); (5).

$$X(t) = f(Y(t-\Delta t), Y(t), Ua(t-\Delta t)) \quad (4)$$

$$Ua(t) = \sum_{t_i = t-te, t} \beta(t-t_i)\, U(t_i) \quad (5)$$

Where $\beta(t-t_i)$ is a constant defined by the control latency profile (Fig. 3); $t_i \geq 0$; Δt is the time interval since the last sample. Ua(t-Δt) determines the effect of previous control actions. The effect of each previous control action is attributed by β(t-te); where (te) is the duration of the control action effect in the system.

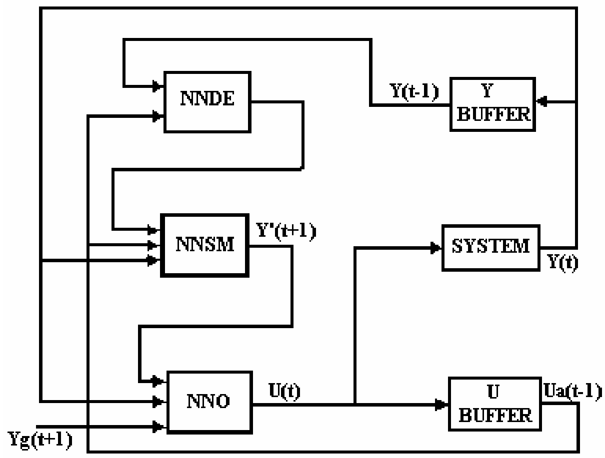

Fig. 2. An Extended Control Structure

The NNSM approximates the behavior of the system and it is used to predict the value of the latter system output by the following system inputs: Y(t), Ua(t-1), X'(t), and Δt; (1). This allows the controller to issue a suitable control to prevent predicted unacceptable states of the system output. The NNO is used to determine the appropriate control signal depending on the following parameters: Y(t), Y(t-1), and Ua(t-1); (6).

$$U(t)=h((Y(t)-Yg(t)),(Y'(t+\Delta t)-Yg(t)),X(t), Ua(t-\Delta t)) \quad (6)$$

All three neural network modules are initially trained using an experimental data set, and then they are put together in the work with a real system; (fig.2). During the work of the controller, the neural networks adapt to an individual system behavior according to the training algorithm of the control structure to optimize the system stability.

4. Training Algorithm

The training algorithm of the controller is designed to support discreet time control, where time is divided into fixed slices. In the (t+Δt) time slice the controller determines the error of control – δc; (3). If this error is not acceptable: ($|\delta c| > \varepsilon$) then the controller enters the training mode in order to adapt to the system being controlled. ε- is the error tolerance of the controller.

In the first stage, the NNDE is trained by using the Backpropagation Delta Rule to minimize the error of estimation |δx|. δx is found as a component of δy, hence δx has an influence on this error (7).

$$\delta x = \alpha_1 \, \delta y \quad (7)$$

Where α_1 is a constant defined as follows: $0<|\alpha_1|\leq(X_{avr}/Y_{avr})$, $\alpha_1>0$; if Y is directly proportional to X, and $\alpha_1<0$ if Y is inversely proportional to X; X_{avr} and Y_{avr} are the average values of X and Y respectively. This procedure is repeated until NNDE produces $X'(t) + \delta x \pm \varepsilon$.

$$Y'_{new}(t+\Delta t)=g(Y(t),Ua(t-\Delta t),X'_{new}(t),\Delta t) \quad (8)$$

$$\delta u = \alpha_2 \, \delta c \quad (9)$$

Where: α_2 - a small constant defined by: $0<|\alpha_2|\leq(U_{avr}/Y_{avr})$, and $\alpha_2<0$; if Y is directly proportional to U, and $\alpha_2>0$; if Y is inversely proportional to U. δu is backpropagated through the NNO and a new value of U(t) is obtained and it is included in Ua(t).

An error δy causes an error in determining the suitable control action (δu); (9). Moreover, an error δy may be caused by the NNSM itself. Finally, the NNO may cause an error δy because any error in determining U(t) will affect Y(t+Δt) causing an increase in |δc|; (3). |δc| is minimized by training all three neural network modules. In the second stage, $X'_{new}(t)$ is applied to the NNSM to make anew prediction $Y'_{new}(t+\Delta t)$; (8). Then the error of prediction δy is found, and this error is backpropagated through the NNSM and a new prediction of Y(t+Δt) is obtained and applied to the NNO to determine the new control signal. Then Ua(t) is given to the NNSM and another value of δy is obtained and backpropagated through the NNSM and so on.

The NNSM and the NNO must be trained repeatedly until the control error (δc) is acceptable. Both modules are trained interchangeably forming a closed loop training system where they interchange the latest their outputs. As soon as the training of these two modules is complete, the controller must be able to decide a suitable control signal to stabilize the system.

5. Application To A Physiological System

The neural network controller is applied to the problem of control of diabetes in human diabetic patients. The insulin dependent diabetes mellitus (IDDM) is a wide spread chronic disorder that is characterized by hyperglycemia. The primary defect of IDDM is inadequate insulin secretion by pancreatic beta cells, which results in hyperglycemia, and many other complications. The IDDM patients are dependent on insulin to survive for the duration of their lives [4]. The goal of insulin treatment is to maintain blood-glucose concentration (BGC) within a normal range in order to prevent the risks of hyperglycemia and hypoglycemia. The management of IDDM is considered an optimal control problem of the BGC. Poor diabetic control may lead to many complications like retinopathy, neuropathy, and nephropathy, while an insulin overdose may result in hypoglycemia that leads to coma The patient self-treatment and the physician control are useful, but not accurate and have many risks. This problem is much more complicated in ICU patients. A great deal of research effort ha been devoted to attempting to achieve an effective management of this disease [5,6,8,12].

In normal healthy person, the natural internal control of BGC is achieved by a feedback control mechanism. In diabetics, this mechanism must be utilized by an external control mechanism that must be very accurate [9,10]. Here we apply the proposed control structure to the control of BGC by specifying suitable doses of insulin in the right moments. This system may be used as advisory system or may be accompanied by an insulin infusion pump in a direct control mode.

All three neural networks of the controller are implemented as three layer backpropagation networks with the binary sigmoid activation function. These neural networks were given the following learning rates: α_x=0.1, α_y=0.05, α_u=0.01. The component parameters of the system output are assigned the following values: α_1=0.021, α_2= -0.054. Neural networks are initially trained using a clinical database of IDDM patients. This database records contain the daily follow-up of 70 patients for periods of (2-7) months. It includes information about BGC, insulin types, insulin doses, meals, amounts of exercise, and times of BGC measures. Hence, the control module is defined by seven parameters: current and latter BGC, disturbance, accumulative insulin dose, time interval between measures, and the recommended by physicians dose of insulin. The accumulative insulin dose is found by (5); where βi constants are determined according to insulin profile; (fig.3).

6. Testing The Control Model

The controller must gradually adapt to a specific individual diabetic patient characteristics of organism if it is applied to control his BGC. These characteristics include: the degree of defect in the patients internal control of BGC, the amounts and time of response to changes in the meals and exercise, the style of his life and diet, etc.

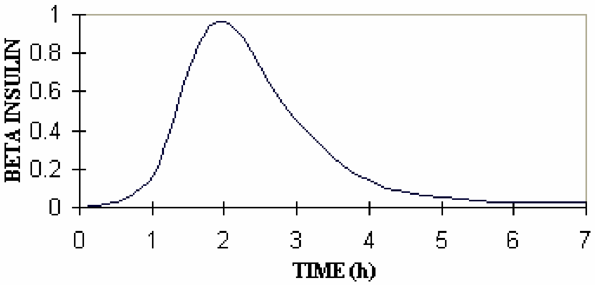

Fig. 3. The Insulin Profile

The controller is trained using the clinical database to be able to control an average patient BGC. Then it is given a series of inputs from the patients' records data-58 to enforce it to adapt to this arbitrarily selected patient. This series includes periods between BGC measures, disturbance values, insulin doses, and the initial BGC of this patient at the beginning of his recorded clinical treatment. Working in the control mode the controller is fed by disturbances and the periods between BGC samples. The controller specifies insulin doses for the patient and if necessary, it switches to the learning mode to adapt to the system.

The results of the work of the controller are demonstrated in (fig. 5). The actual data base entries that show the physician's management is illustrated in (fig.4). It can be seen from (fig.5), that the control efficiency of the controller is improving rapidly by the time as the neural networks adapt to the characteristics of the specific patient. Note that (fig.4) encounters a high peek of BGC that mount to 350 mg/dL, while (fig.5) includes only the same as the first peek of BGC of fig.4 (300 mg/dL). Other peeks of BGC gradually decrease by time.

The results of this test show a temporal increase of the system stability, so that a near disturbance rejection control is obtained. However, there are still limited fluctuations of the BGC resulting from disturbances, these fluctuations of BGC are normal in healthy persons depending on the meal, stress, and exercise. We can see that the fluctuation of the system state is within the acceptable range of the BGC for the most of control time, and the fluctuation out of the acceptable range happens only in short time periods which is normal even in healthy organisms.

7. Conclusion

A neural-network based adaptive control approach is presented and an adaptive predictive control structure is proposed in this work. This approach is completely based on the estimation and approximation properties of neural networks. It uses three neural network modules: the disturbance estimator, the system model, and the optimizer.

The disturbance estimator bases its estimations on previous and current measures of the system state and the issued control actions. The system model emulates the system function and makes predictions of the system output to the optimizer. The optimizer issues control actions to prevent unpreferable predicted system states from occurring. The neural-network modules of the controller are trained by using a clinical database of diabetic patients, and then they are trained additionally during the control process in order to adapt to the system behavior and to enhance the control quality. The system model is trained directly according to the backpropagation of its output errors. The disturbance estimator and the optimizer are trained by their partial influence error on the system model. This approach capitalizes the ability of the controller to adapt to the system behavior, and to improve its control strategy.

The neural-network modules extract the system characteristics from their experience during the control process. As this experience increases by time, the system stability is improved. The physician treatment of diabetes is not able to keep a high stability due to the high complexity of the problem of control of diabetes. The control system behavior in some way- is similar to behavior of a junior physician who accumulates experience and rapidly improves his performance and accuracy of management of a disease. Real application to specific patients based on the clinical database of diabetic patients has demonstrated the efficiency and stability of the control system. However, a difficulty remains with the definition of values for the amounts of the partial influence error components of the system output, and other controller parameters. Further investigation is needed in this manner.

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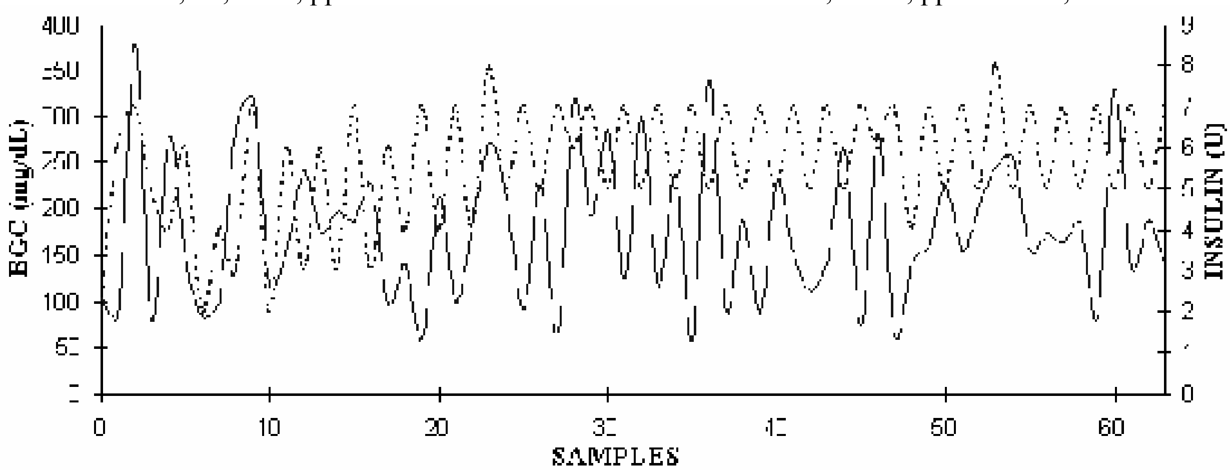

Fig. 4. PHYSICIANS MANAGEMENT OF A DIABETIC PATIENT

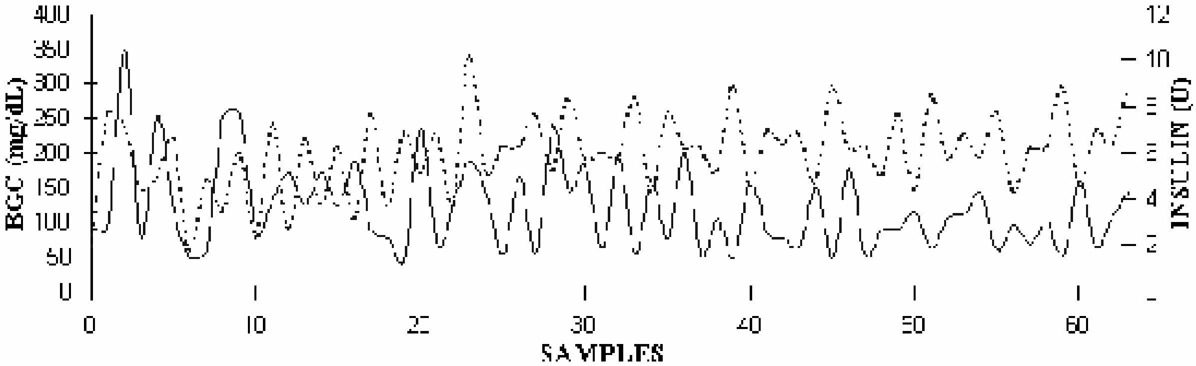

Fig. 5. SIMULATED NEURAL-NETWORK MANAGEMENT OF A DIABETIC PATIENT