Original Article

Ideal of Fuzzy Inference System and Manifold Deterioration Using Genetic Algorithm and Particle Swarm Optimization

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ABSTRACT

Ideal of Fuzzy Inference System and Manifold Deterioration Using Genetic Algorithm and Particle Swarm Optimization is presented. Hypoglycaemia or low blood glucose often occurs with patients that take insulin therapy for diabetes. Hypoglycaemia is serious and causes unconsciousness, seizures or even death. The proposed system uses ECG signal for the detection of hypoglycemia. To find the presence of the hypoglycaemic episodes the system uses heart rate (HR), corrected QT interval, change of HR and change of corrected QT interval of the ECG signal. The system is developed using multiple regression with fuzzy inference system (FIS). Genetic algorithm and particle swarm optimization is used to optimize the parameters of FIS and multiple regressions. Fuzzy Inference System is used to estimate the hypo level based on the physiological parameters. The physiological parameters are heart rate and corrected QT interval. Multiple regressions are used to fine tune the performance of the hypoglycemic detection based on the estimated hypo level and the change of the HR and corrected QT interval. Thus estimate the presence of hypoglycemia using the FIS and multiple regressions with genetic algorithm and also with particle swarm optimation and finally comparing the performance of both techniques.

Keywords: Fuzzy inference system (FIS), Hypoglycemia, Multiple regression, Genetic algorithm, Particle swarm optimization (PSO).

INTRODUCTION

Hypoglycemia is a condition that occurs when your blood sugar (glucose) is too low. Hypoglycemia can result in unconsciousness, seizures or even death, are common and can cause serious side effect in insulin therapy[1]. Hypoglycemic episodes are suggested as those in which the patient had blood glucose (BG) levels less than 3.3

mmol/l (60 mg/dl)[2]. Hypoglycemia develops when rates of glucose entry into the systemic circulation are reduced relative to glucose uptake by tissues. As glucose levels continue to fall, a number of redundant glucose counter-regulatory factors are sequentially activated at specific thresholds to ensure sufficient glucose uptake to the brain and other central nervous system tissue metabolism[3]. In patients with Type 1 diabetes mellitus (T1DM) undergoing intensive insulin therapy, falling plasma glucose concentrations often do not elicit counter-regulatory responses at normal glycemic thresholds, allowing glucose levels to drop to dangerously low values. Studies in T1DM patients have demonstrated that as few as two episodes of antecedent hypoglycemia can blunt responses to subsequent hypoglycemia[4]. Nocturnal hypoglycemia is particularly dangerous because sleep reduces and may obscure autonomic counter-regulatory responses so that an initially mild episode may become severe[5]. Regulation of nocturnal glycemia is further complicated by the dawn phenomenon. This is a consequence of nocturnal changes in insulin sensitivity secondary to growth hormone secretion: a decrease in insulin requirements approximately between midnight and 5 A.M. followed by an increase in requirements between 5 and 8 A.M. In this paper, we develop a fuzzy inference system with multiple regressions for the detection of hypoglycemia episodes using physiological parameters such as heart rate, corrected QT interval, change of heart rate and change of QT interval.

Fuzzy inference system

To realize the detection of hypoglycemic episodes in patients, multiple regressions with fuzzy inference system (FIS) is developed as shown in Fig. 1. The inputs are the HR, corrected QT interval of the ECG signal (QT*c)*, change of HR (ΔHR), and the change of corrected QT interval (ΔQT*c)*; and the output is the binary level of hypoglycemia (low level represents hypo and high level represents non hypo). The ECG parameters that will be investigated in this research involve the parameters in depolarization and repolarization stages of electrocardiography. The concern points are Q point, R peak, T wave peak, and T wave end, as can be seen in Fig. 2. The peak of T wave is searched in the section of 300 ms after R peak. In this section, the maximum peak is defined as the peak of T wave. Q point is searched in the section of 120 ms in left side of R peak. The Q point is found by investigating the sequential gradients of negative–negative–positive/zero–positive/zero from the right side[6]. QT is interval between Q and Tp points. QT*c* is QT/ $\sqrt{}$ (*RR*) in which *RR* is the interval between R peaks. HR is 60/*RR*. Based on the linear correction analysis, HR and QT*c* have a medium correlation with hypoglycemia, and the ΔHR and ΔQT*c* have a slight correlation with hypoglycemia. With the result of correction analysis, the hypoglycemic episodes detector system is combined with two subsystems and, namely, FIS and multiple regression models are proposed.

Referring to Fig. 1, the FIS is used to realize the approximated correlation between the physiological parameters (HR and QTc*)* and hypo index (*υ*).

Due to the highly correlation of the input HR and QTc[7]. The index *υ* is in the range of 0–1. Larger value of *υ* is implied that the possibility of hypoglycemia is higher. The fuzzy detection system consists of three components: fuzzification, inferencing, and defuzzification.

Fuzzification

The first step is to take the inputs, and determine the degree of membership they

belong to each of the appropriate fuzzy sets. The membership function is defined as 1) $\mu_{N_z^k}(z($which a bell-shaped function is given by:

$$\mu_{N_z^k}\left(z(t)\right) = e^{\frac{-(z(t)-m_z^k)^2}{2\sigma_z^k}} \quad ..(1)$$

where $\mathbf{z}(t)$ = [HR(t) QT(t)] in which $\mathbf{z}(t)$ denotes the non fuzzy input, k = 1, 2,. . .m_f in which m_f denotes the number of membership functions, t = 1, 2,. . .,n_d in which n_d denotes the number of input–output data pairs, and parameters m_z^k and σ_z^k are the mean value and the standard deviation of the member function, respectively. If the input value is less than the minimum of the mean value or higher than the maximum of mean value, the degree of membership is set to 1.

Inferencing

The task of the inferencing process is to map the fuzzified inputs to the rule base, and to produce a fuzzified output for each rule. The fuzzy if-then rules in the rule base are of the following format:

Rule r: If HR (t) is N_{HR}^k(HR (t)) and QT (t) is N_{QT}^k(QT (t)) then υ (t) is w_{r}....(2)

where N_{HR}^k (HR(t)) and N_{QT}^k (QT(t)) are fuzzy terms, γ = 1,2,. . .,n_r in which n_r denotes the number of rules and is equal to $(m_f)^{n_{in}}$ here $n_{in} = 2$ is the number of inputs of the FIS. Aggregation is then used to obtain the output of each rule γ as a fuzzy value. The output for each rule is defined as:

1) $$\mu_r = \left(\mu_{N_{HR}^k}\left(HR(t)\right)\right) \times \left(\mu_{N_{QT}^k}\left(QT(t)\right)\right) \quad .....(3)$$

r=1, 2... n_r

Defuzzification

Defuzzification is the process of translating the outputs of the fuzzy rules into a value. The output of the Defuzzification process is given by:

$$\upsilon(t) = \frac{\sum_{\gamma=1}^{n_r} \omega_\gamma \mu_\gamma}{\sum_{\gamma=1}^{n_r} \mu_\gamma} \quad .....(4)$$

Where $\omega_r \in$ [0, 1] is the fuzzy singleton in Ruler.

Multiple Regression Model

Multiple regression models that are used to classify the presence of hypoglycemia based on the approximated υ, ΔHR, and ΔQTc. This model is used to fine-tune the hypoglycemic detection performance due to the slight correction of ΔHR and ΔQTc[8]. A multiple regression model is introduced to find the relationship between the system's inputs and the presence of hypoglycemic episodes. Referring to Fig. 1, the inputs are: 1) υ that is estimated by the FIS; 2) change of HR (ΔHR); and 3) the change of corrected QT interval (ΔQTc). ΔHR and ΔQTc are used to fine-tune the performance of the system. In general, multiple regression model procedures will be estimated as the following form:

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i^2 + \cdots + \beta_2 X_i^\eta \quad .....(5)$$

Where the $\mathbf{Y}_i$ is the output to represent the binary status of hypoglycemic.

When $\mathbf{Y}_i \geq 0$, which represents positive (sick), and appositively, when $\mathbf{Y}_i < 0$, which represents negative (healthy). $\mathbf{X}_i$ is the inputs of the system, i.e., $\mathbf{X}_i$ = [υ_i ΔHR_i ΔQT_i], i = 1, 2, *nd;* $\boldsymbol{\beta}$ denotes the parameters of the regression model; and η denotes the number of order.

Genetic algorithm

To optimize the fuzzy membership functions and rules (the values of m, ς and w), the Genetic Algorithm (GA) is used. The GA process is shown in algorithm1.

In this paper, Blend-α[10] is used as the operation of crossover, which has a good searching ability and can handle multimodal and separability problem effectively. For the Blend-α crossover, the resulting offspring is chosen randomly from the-

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==========================================
begin
    τ⟶0                  // τ: iteration number
    initialize P (τ)     // P(τ): population for iteration τ
    evaluate f(P (τ))    // f(P (τ)): fitness function
while (not termination condition) do
    begin
            τ⟶ τ+1
            select 2 parent p1 and p2 from P(τ-1)
            perform crossover operation
            perform mutation operation
            reproduce a new P (τ)
            evaluate f(P (τ))
    end
end
end
==========================================
```

Algorithm 1: Basic steps in GA

Interval $[X^1_j, X2j]$ following the uniform distribution, where

$$X_j^1 = \min(p_{1j}, p_{2j}) - \alpha d_j$$

And

$$X_j^2 = \min(p_{1j}, p_{2j}) + \alpha d_j \quad \ldots(6)$$

Where dj = $|p_{1j} - p_{2j}|$, p_{1j} and p_{2j} are the jth elements of p1 and p2, respectively, and α is a positive constant.

GA is employed to optimize the fuzzy rules by finding out the best parameters m^k_{HR}, σ^k_{HR}, $m^k_{QT}\sigma^k_{QT}$, and w_γ of the FIS. GA is used to learn the input output relationship of HR, QTe interval and hypo index value. The input output relationship is described by,

$$v^d(t) = \mathbf{g}(\mathbf{z}^d(t)), \mathbf{z}^d(t) = [HR^d(t)\ QT^d(t)] \ldots(7)$$

Where $\mathbf{z}^d(t)$ and $v^d(t)$ are the given physiological inputs and the desired hypo index output of a nonlinear function $\mathbf{g}(\cdot)$, respectively. When BG levels are less than 3.3 mol/l, $v^d(t)$ will set to 1, otherwise, set to 0. Referring to (5) of the GA, the fitness function is defined as,

$$\text{fitness} = -\frac{1}{n_d}\sum_{t=1}^{n_d}(v^d(t) - v(t))^2 \quad \ldots\ldots(8)$$

The objective is to maximize the fitness function of (8) (minimize the mean square error between the desired $v^d(t)$ and the $v(t)$ from FIS using the GA by setting the chromosome to be $[m^k_{HR}, \sigma^k_{HR}, m^k_{QT}, \sigma^k_{QT}, w_j]$ for all j, k. After the training, an optimized FIS is found.

Tune the parameters of multiple regressions using GA

The objective of the multiple regression models is to detect the hypoglycemic episodes accurately based on the output of trained FIS, ΔHR, and ΔQTc. To measure the performance of the biomedical classification test, sensitivity and specificity are introduced[11]. The sensitivity measures the proportion of actual positives that are correctly identified and the specificity measures the proportion of negatives that are correctly identified. The definitions of the sensitivity (ς) and the specificity (κ) are given as follows:

$$\varsigma = \frac{N_{TP}}{N_{TP} + N_{FN}} \quad \ldots\ldots(9)$$

$$\kappa = \frac{N_{TN}}{N_{TN} + N_{FP}} \quad \ldots\ldots(10)$$

where N_{TP} is the number of true positives that means the sick people are correctly diagnosed as sick; N_{FN} is the number of false negatives that means the sick people are wrongly diagnosed as healthy; N_{FP} is the number of false positives that means the healthy people wrongly diagnosed as sick; and N_{TN} is the number of true negatives that means the healthy people are correctly diagnosed as healthy.

The objective of the system is to maximize the sensitivity and the specificity; thus, the fitness function is defined as follow:

$$fitness = \lambda\varsigma + (1 - \lambda)\kappa + \rho \quad \ldots\ldots(11)$$

$$\rho = \begin{cases} 1 & if\ \varsigma \geq 0.7\ and\ \kappa \geq 0.5 \\ 0, & otherwise \end{cases}$$

Where ρ is penalty value.

A larger value of the λ gives a strong force to the system to maximize the sensitivity; however, it will reduce the performance of the specificity.

Particle swarm optimization

Particle swarm optimization (PSO) is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. Each particle's movement is influenced by its local best known position and is also guided toward the best known positions in the search-space, which are

updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions[12]. PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. At every iteration, all particles are updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. This value is called pbest. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called gbest. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called lbest.

RESULTS AND DISCUSSION

The detection of hypoglycemic episodes (BG<=3.3 mmol/l) by using these variables is based on a GA-based multiple regression with FIS developed from the obtained clinical data. In effect, it estimates the presence of hypoglycemia at sample period k_s based on the basic of the data at sampling period k and the previous data at sampling period k_s−1. In general, the sampling period is 5 min.

There are two steps to develop the proposed multiple regression with FIS to T1DM problem. The first step is to determine the optimized fuzzy rules and membership function of the FIS to approximate the relationship between the inputs HR, QTc, and υ. Once the optimized FIS is developed, the second step is to develop a multiple regression model to detect the hypoglycemia with the inputs υ, Δ HR, and ΔQTc.

In the FIS, the number of the membership function is set to 5 (m_f = 5); thus, the total number of fuzzy rules n_r is equal to 25. After the training process, the tabulated fuzzy rule is shown in Table 1. There are five fuzzy terms, namely, VL (very low), L (low), M (middle), H (high), and VH (very high). The value of the fuzzy singleton w_γ for different fuzzy terms is optimized and shown in Fig. 3, and higher value that represents the presence of hypo is "VH." With these set of fuzzy parameters, 25 fuzzy if–then rules are developed. Give one rule as an example: IF HR (t) is "VH" AND QT (t) is "VH," THEN υ (t) is "VH" (or w_γ = 0.9807).

Once an optimized FIS is developed, a multiple regression is used to fine-tune the hypoglycemic Detection performance with the inputs of Δ HR and ΔQTc for comparison and analysis purpose, first order (liner), second order and third order of the multiple regression models are used. According to (5), η is set to 1–3, respectively.

The figure 3 illustrates ECG signal for a non hypoglycemic person for 5 minutes.

The heart rate is calculated from the ECG signal using the formula 60/RR where RR is the interval between R peaks of the signal. Thus calculated heart rate value from the ECG signal is 60.8519, 60.1806, 62.2407, 61.5385, and 59.3472.

The corrected QTe value is calculated using the formula QT/√RR where QT is the interval between the Q and Tp points. The calculated corrected QTe value is 0.2437., 2283, .2628, 0.2420, and 0.2626. After calculating the heart rate and corrected QT interval value membership function value of each are calculated. The membership value lies between 0 and 1. The calculated membership function of each heart rate and QTe interval is shown in figure 3.

After finding the membership function value of each heart rate and corrected QTe interval inference rule is applied. The rule is ' If HR(t) is VH and QTe (t) is VH then w_r is 0.9807'. Based on the fuzzy rule table shown in the table 1.

Inference rule value for the heart and corrected QTe interval is shown in the figure 5.

Based on the inferencing rule and membership function value defuzzified value is calculated. This value is called as hypo index value. The defuzzified value is 0.4433.

After calculating the hypo index value multiple regressions in done based up on (5) .The calculated value for multiple regressions is -1.6583. The result shows that the person is not hypoglycemic.

CONCLUSION

In this paper, multiple regressions with FIS detection algorithm are developed to recognize the presence of hypoglycemic episodes. The aforementioned results indicate that hypoglycemia can be detected noninvasively, continuously, and effectively from the real-time physiological responses. A multiple regression with FIS is proposed to detect the presence of hypoglycemic episodes. To optimize the fuzzy rules and the regression model, genetic algorithm and particle swarm optimization can be used. Finally the performance of the system with genetic algorithm and the system with particle swarm optimization are compared.

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Table 1. Fuzzy rule table

QTc \ HR	VL	L	M	H	VH
VL	0.0177	0.2433	0.3733	0.5600	0.5581
L	0.0805	0.3045	0.1749	0.4465	0.5718
M	0.1192	0.4433	0.6938	0.8495	0.6853
H	0.2044	0.4157	0.9764	0.9854	0.7058
VH	0.2592	0.3308	0.9910	0.9126	0.9807

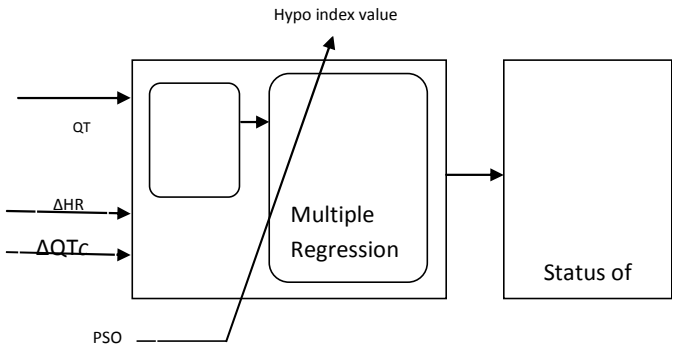

Figure 1. Hypoglycemic episodes detection system

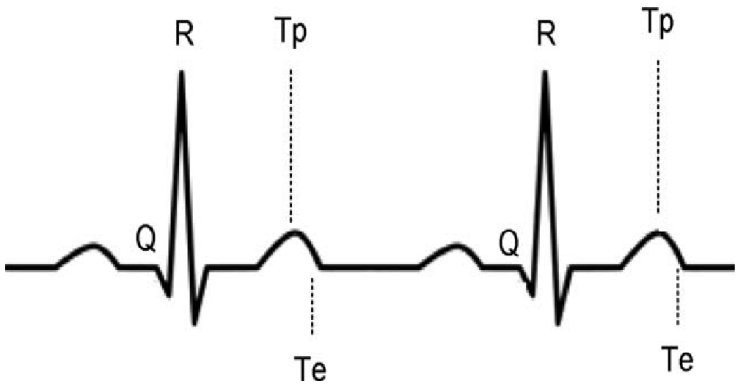

Figure 2. Concerned points: Q, R, Tp, and Te that are used to find the ECG parameters

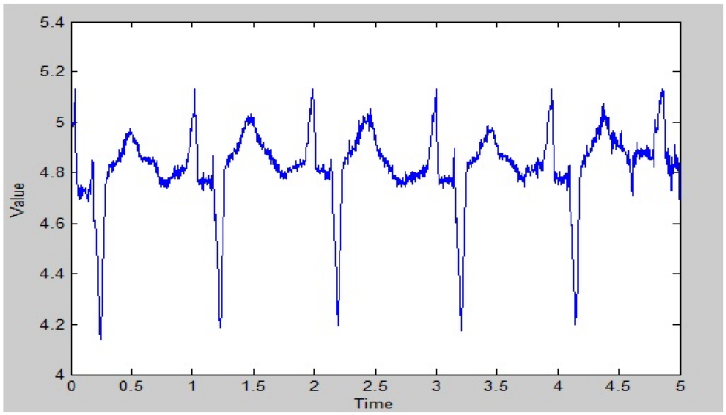

Figure 3. ECG signal

Membership function value

hr	qt
0.9998	0.9994
0.8290	0.9871
0.4157	0.9925
0.8018	0.9988
0.3773	0.9927

Figure 4. Membership function value

inferencing output

0.9807	0.9807	0.9807	0.9807	0.9807
0.9807	0.9807	0.9807	0.9807	0.9807
0.9910	0.9910	0.9910	0.9910	0.9910
0.9807	0.9807	0.9807	0.9807	0.9807
0.4433	0.4433	0.4433	0.4433	0.4433

Figure 5. Inferencing rule output