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Hypoglycaemia detection using fuzzy inference system with intelligent optimiser

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ABSTRACT

Hypoglycaemia is a medical term for a body state with a low level of blood glucose. It is a common and serious side effect of insulin therapy in patients with diabetes. In this paper, we propose a system model to measure physiological parameters continuously to provide hypoglycaemia detection for Type 1 diabetes mellitus (TIDM) patients. The resulting model is a fuzzy inference system (FIS). The heart rate (*HR*), corrected *QT* interval of the electrocardiogram (ECG) signal (QT_c), change of *HR*, and change of QT_c are used as the input of the FIS to detect the hypoglycaemic episodes. An intelligent optimiser is designed to optimise the FIS parameters that govern the membership functions and the fuzzy rules. The intelligent optimiser has an implementation framework that incorporates two wavelet mutated differential evolution optimisers to enhance the training performance. A multi-objective optimisation approach is used to perform the training of the FIS in order to meet the medical standards on sensitivity and specificity. Experiments with real data of 16 children (569 data points) with TIDM are studied in this paper. The data are randomly separated into a training set with 5 patients (l99 data points), a validation set with 5 patients (177 data points) and a testing set with 5 patients (193 data points). Experiment results show that the proposed FIS tuned by the proposed intelligent optimiser can offer good performance of classification.

1. Introduction

In this paper, a fuzzy inference system (FIS) is developed to model the relationship between four physiological parameters and the episodes of hypoglycaemia. Hypoglycaemia is a medical term for a body state with a low level of blood glucose. It is a result of mismatch between the action of insulin, the ingestion of food and the energy expenditure. Hypoglycaemia is not common in non-diabetic persons, but can occur at any age [1]. It can be caused by excessive insulin produced in the body, inborn errors, medications and poisons, alcohol, hormone deficiencies, prolonged starvation, alterations of metabolism associated with infection, and organ failure [2]. Some study reported that diabetic patients, who have been treated with insulin, have high risk of developing hypoglycaemia. Most surveys reported that the tighter the glycaemia control, and the younger the patient, the greater frequency of both mild and severe hypoglycaemia would occur [3,4].

Hypoglycaemia may be defined differently for different people in terms of blood glucose in different circumstances and for different purposes. Most of the healthy adults maintain a fasting glucose level at above 70 mg/dL (3.9 mmol/L), and develop symptoms of hypoglycaemia when the glucose level falls below 55 mg/dL (3.3 mmol/L) [2,5]. Several studies reported that hypoglycaemic episodes are defined as blood glucose levels being below 50 mg/dL (2.8 mmol/L), and the patients are advised to take necessary medical treatment immediately.

The symptoms of hypoglycaemia are often unaware by the patients. Nocturnal hypoglycaemia is particularly dangerous because it may obscure autonomic counter-regulatory responses, so that any initially mild episodes may become severe. 50% of all severe episodes occur at night time. Deficient glucose counter-regulation can lead to severe hypoglycaemia even with the modest insulin elevations. Regulation of nocturnal hypoglycaemia is further complicated by the dawn phenomenon [7]. This is a consequence of nocturnal changes in insulin sensitivity secondary to growth hormone secretion: a decrease in insulin requirement approximately between midnight and 5 am followed by an increase in requirement between 5 am and 8 am. Thus, hypoglycaemia is one of the complications of diabetes most feared by patients. As a result, constructing a model for the detection of hypoglycaemia with respect to some physiological parameters are very important for patients to perform real-time monitoring of their blood glucose level especially at night time [6,8,11,12]. In this paper, a fuzzy

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inference system is developed to model the relationship between four physiological signals and the episodes of hypoglycaemia. The physiological signals are the heart rate (*HR*), the change of *HR* with time (ΔHR), the corrected *QT* interval (QT_c) of the electrocardiogram (ECG) signal, and the change of QT_c with time (ΔQT_c). These four signals are used as the inputs for the classification.

In this paper, a fuzzy inference system (FIS) is employed to perform the modelling of the hypoglycaemic episodes. Fuzzy inference is a process of making decisions by using fuzzy logic and fuzzy rules. The data for the hypoglycaemic detection are real-time body signals from patients. A lot of noise and error can be present during the measurement process. Fuzzy logic (FL) can be applied to obtain a good model for processing those body signals. Thanks to the linguistic rule base, any human knowledge can readily be absorbed into the FIS.

Before the FIS works as a classifier for hypoglycaemia episodes for Type 1 diabetes mellitus patients, it has to be trained by some data set with known class labels. The training is a kind of supervised learning. The major objective is to determine the best parameter values for the FIS's rules and membership functions. The training can be realised as an optimisation process. Traditional optimisation methods like the least square algorithm and gradient descent methods have the potential problem of trapping in some local optima of the solution space. Hence, evolutionary optimisation algorithms are considered in this paper.

Differential evolution (DE) has been well accepted as a powerful evolutionary computation algorithm for handling optimisation problems during the last decade. It is a population based stochastic optimisation algorithm that searches the solution space by using the weighted difference between two population vectors to determine a third vector [9,17,18]. Owing to the population-based strategy, DE is less possibly getting trapped in some locally optimal solution. In [22], an improved version of DE with double wavelet mutations (DWM-DE) is employed to the training process of the hypoglycaemia problem. The result shows that DWM-DE performs well in the training process. The details of the performance and comparison after using the wavelet mutation in DE were reported in [25]. However, the performance of DWM-DE still depends quite much on some control parameters' values and the setting of the initial conditions. To reduce these limitations, a further improved intelligent optimiser is introduced, which is designed based on DWM-DE. In the intelligent optimiser, a fuzzy controller is employed to adjust the parameter values adaptively during the progress of searching. To reduce the dependence on the initial conditions of the optimisation algorithm, a parallel implementation framework involving two wavelet-mutated differential evolution (WM-DE) engines is proposed. Moreover, to reduce the number of control parameters as a compensation for the increase of complexity brought by the fuzzy controller, we use a single wavelet operation instead of two. The resulting system consists of two WM-DE engines running in parallel with different initial conditions to tackle the same optimisation problem. The fuzzy controller in the proposed intelligent optimiser captures the on-line population information from the two WM-DE engines. The information is analysed and compared by the Student *T*-test, which is a method to assess whether two groups of data are statistically different from each other in terms of the mean fitness values. The individual populations' information and the result of the Student *T*-test act as the inputs of a fuzzy controller to determinate the next iteration (generation) values of the control parameters of the DE engines. The two DE engines in the intelligent optimiser act as a pairing system with additional searching information shared between them. The result is a closed-loop adaptive control system that supports the intelligent optimiser for better performance. Thanks to the changes brought by the intelligent optimiser, the solution reliability can be enhanced when the fuzzy controller tries to minimise the *t*-value. By applying the wavelet function in the DE's crossover, we can have the solution space to be more widely explored in the early stage of the search; and are more likely to obtain a fine-tuned global solution in the later stage of the search by setting a smaller searching space. The wavelet function's properties enable us to improve the performance of DE in terms of convergence speed, solution quality and solution reliability statistically [22].

In this paper, sensitivity and specificity are used to measure the performance of the classification. The sensitivity measures the proportion of actual positives that are correctly identified; and the specificity measures the proportion of actual negatives that are correctly identified. As common clinical classification requirements, the sensitivity should be higher than 70% and the specificity should be higher than 50% in order to obtain a reliable classification. Based on these clinical requirements, we have two objectives to achieve in the training process. As a result, a multi-objective optimisation approach using the proposed intelligent optimiser should be employed to realise the training process. Besides, overtraining is another key problem that affects the classification performance when constructing the FIS model. Overtraining refers to the reduction of the generalisation ability that can occur as a system is trained. In this paper, a validation strategy is employed to reduce the risk of overtraining [20,21,23]. This strategy is embedded in the training operation and the formulation of the fitness functions in the proposed intelligent optimiser. The details will be given in Section 2.

The organisation of this paper is as follows: in Section 2, the details of the development of the FIS and the proposed intelligent optimiser are presented. The experiment results of detecting nocturnal hypoglycaemic episodes in TIDM patients are discussed in Section 3. A conclusion is drawn in Section 4.

2. Fuzzy inference system with the proposed intelligent optimiser

To realise the detection of hypoglycaemic episodes for the type-1 diabetes mellitus (T1DM) cases, an FIS tuned by the proposed intelligent optimiser with two wavelet-mutated differential evolution (WM-DE) engines is employed. A block diagram of the FIS is shown in Fig. 1. It is a 4-input and 1-output learning and modelling system. The physiological inputs are the heart rate (*HR*), the corrected *QT* interval of the electrocardiogram signal (QT_c), the change of heart rate (ΔHR), and the change of QT_c (ΔQT_c). The output is the binary state of hypoglycaemia (*h*), which takes the value of true (+1) or false (−1). The major role of the FIS is to model the relationship of *HR*, QT_c, ΔHR and ΔQT_c to *h* so as to perform classification.

Two of the inputs of the FIS are obtained from the ECG signal. The ECG signal being investigated involves the parameters in the depolarisation and repolarisation stages of electrocardiography. An example ECG signal (with two cycles) is shown in Fig. 2. In this study, the concerned points are the *Q* points, *R* peak, *T* wave peak (T_p), and the *T* wave end (T_e). The *QT* interval is between the *Q* point

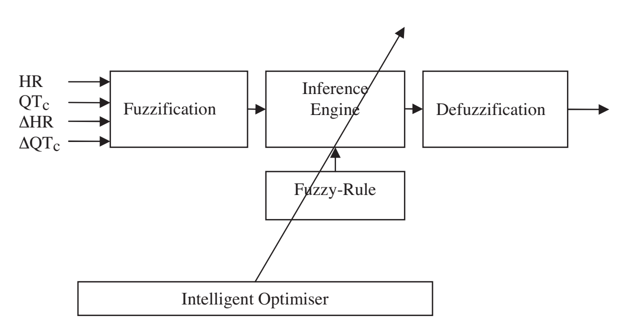

Fig. 1. Fuzzy inference system (FIS).