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Block Based Neural Network for Hypoglycemia Detection

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Abstract— **In this paper, evolvable block based neural network (BBNN) is presented for detection of hypoglycemia episodes. The structure of BBNN consists of a two-dimensional (2D) array of fundamental blocks with four variable input-output nodes and weight connections. Depending on the structure settings, each block can have one of four different internal configurations. To provide early detection of hypoglycemia episodes, the physiological parameters such as heart rate (HR) and corrected QT interval (QTc) of electrocardiogram (ECG) signal are used as the inputs of BBNN. The overall structure and weights of BBNN are optimized by an evolutionary algorithm called hybrid particle swarm optimization with wavelet mutation (HPSOWM). The optimized structures and weights of BBNN are capable to compensate large variations of ECG patterns caused by individual and temporal difference since a fixed structure classifiers are easy to fail to trace ECG signals with large variations. The ECG data of 15 patients are organized into a training set, a testing set and a validation set, each of which has randomly selected 5 patients. The simulation results shows that the proposed algorithm, BBNN with HPSOWM can successfully detect the hypoglycemic episodes in T1DM in term of testing sensitivity (76.74%) and test specificity (50.91%).**

I. INTRODUCTION

Current technologies used in the diabetes diagnostic testing and self-monitoring market have already been improved to some extent. However, technology advancement in the market is expected to have non-invasive glucose meter with the use of novel design concepts. There is a limited number of non-invasive blood glucose monitoring systems currently available in the market but each of them has its own drawbacks in terms of functioning, cost, reliability and obtrusiveness. Intensive research has been devoted to the development of hypoglycemia alarms, exploiting principles that range from detecting changes in the electroencephalogram (ECG) or skin conductance (due to sweating) to measurements of subcutaneous tissue glucose concentrations by glucose sensors. However, none of these have proved sufficiently.

To carry out modeling and classification for medical diagnose purposes of ECG and EEG [1] much of attention have been devoted to computational technologies such as fuzzy system [2], support vector machine [3] and neural networks [4]. Each technology has its own advantages, for example, fuzzy system is famous because of its decision making ability. Due to its human experts representation, the system's output can be determined by a set of linguistic rules which can be understood with an easy manner. In [5] neural network (NNs) has been applied to develop classification models for medical diagnosis due to its merit of generalization ability in addressing both nonlinear and fuzzy nature of patients data. Support vector machine (SVM) has been used in classification of cardiac signal [6] according to its special feature in tackling binary classification problems.

To generate classification models for heart disease [7] in term of polynomial forms, the genetic programming with least square algorithm [8] has been used. According to fuzziness of measures, it is unavoidable that the patients' data involves uncertainty. Since the genetic programming with least square algorithm does not consider the fuzziness of uncertainty during measurement, it cannot give the best classification model for diagnosis purpose.

For modeling and design of a non-invasive hypoglycemia monitor with physiological responses, a significant contribution is devoted in this paper, by using evolvable block based neural networks (BBNN). In the proposed system, the psychological parameters, HR and QTc are used as the inputs because of its higher correlation with hypoglycemia. Since the classifier with fixed structure are often fail to trace the large variation in ECG signal, BBNN with evolvable structures and weights [9] are proposed due to its merit in approximation of higher correlation between the physiological parameters. To optimize the structure and weights of BBNN, a global learning optimization algorithm called hybrid particle swarm optimization with wavelet mutation (HPSOWM) [10] is introduced.

The organization of this paper is as follows: In Section II, block based neural networks and their training procedures by the use of HPSOWM is introduced. To show the effectiveness of our proposed methods, the results of early detection of nocturnal hypoglycemic episodes in T1DM are discussed in Section III before a conclusion is drawn in Section IV.

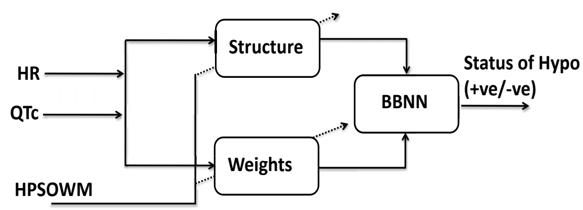

Fig. 1. PSO based block based neural network for hypoglycaemia detection

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II. METHODS

To realize the detection of hypoglycemic episodes in T1DM, an evolvable block based neural network (BBNN) with 2 inputs and 1 output system is developed for the early detection of hypoglycemia episodes as shown in Figure. 1. The two inputs are the psychological input: the heart rate (HR) and the corrected QT interval (QTc) of electrocardiogram (ECG) signal while the output is the presence of hypoglycemia (h) in which $+1$ represents hypoglycemia and -1 is non-hypoglycemia. In this proposed system, the structure and the weights of BBNN are optimized by HPSOWM [10] and the detail structure of BBNN with HPSOWM are presented in this section.

A. Block Based Neural Network (BBNN)

A block based neural network (BBNN) is a network design that is more flexible to change the structure depending on the signal flow between blocks. In [11], it has been proposed an effective network structure to solve ECG classification problem due to the significant improvement of the sensitivity, specificity and accuracy rate. It can be represent by 2-D array of blocks and each individual neuron blocks work as a basic signal processing unit that is composed of a feedforward neural network having four variable input/output nodes. A block is connected to its neighboring blocks with signal flow represented by arrows: $\downarrow$ represent as 0 while $\uparrow$ and $\rightarrow$ assign as 1. As shown in Fig. 2, the structure of BBNN is organized with m rows and n columns of blocks which is labeled as B_{ij}, in which $(i = 1, \ldots m)$ and $(j = 1, \ldots, n)$.

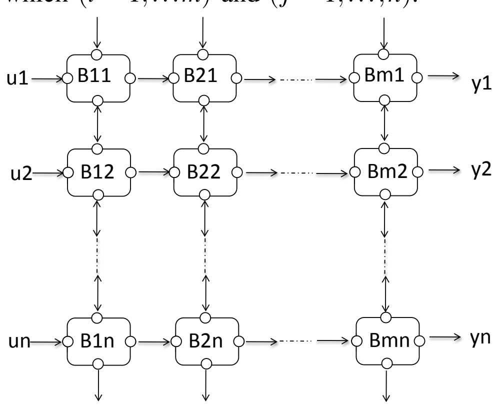

Fig. 2. Structure of Block-Based Neural Network

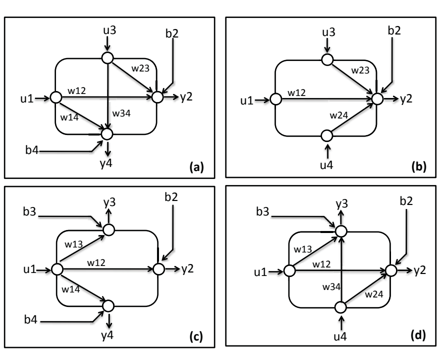

Fig. 3. Internal configurations of block based neural network

The first column of blocks, $B_{11}, B_{12}, \ldots, B_{1m}$ is determined as the input layer of BBNN network structure while the last column of blocks, $B_{m1}, B_{m2}, \ldots, B_{mn}$ is represented as output layer. The output of BBNN network $(y = y_1, y_2, y_3, \ldots, y_n)$ is a function of summation of weighted inputs and a bias. A constant input value is given to redundant input nodes and un-used output nodes are ignored. Due to modular characteristics, BBNN can be easily expanded to be a larger network.

In this paper, the connections between layers will only be considered as feedforward configuration in forward direction. The structure of BBNN is determined by automatically internal configuration or input-output connection of basic blocks. According to the input-output connections of the network structure, the block has four different types of internal configuration. Fig. 3 (a) and (d) represent for two input and two output with different internal configurations while (b) and (c) correspond to one input-three outputs and three-output configurations. The capability of generalization is improved through various internal configurations of a block. Even though each basic block should be one input and three output (1/3), three inputs and one output (3/1), two inputs and two outputs (2/2), the extreme cases of all input nodes (4/0) or all output nodes (0/4) are considered as invalid configurations.

For each basic block consists of four nodes and each nodes inside the block are connected with each other through connection of weights, w_{ij}. A block can have up to maximum of six connection weights including the biases. For the case of two inputs and two outputs in Fig. 3 (b) and (d), there are four weights and two biases. Same as the case in Fig. 3 (c), one input and three outputs structure has three weights and and three biases. For three inputs and one output cased in Fig. 3 (a), it belongs to three weights and one biases. Each node of a block can be an input or an output according to internal configuration which is determined by the signal flow. An incoming arrow to a block is defined as the input nodes and its associated outputs are considered as the block outputs with outgoing arrows. The output of each block is connected to the another block as the input signal. The output of the block is calculated by the summation of weighted inputs and biases corresponded to a feedforward NN as follows:

$$y_j = \sum_{i \in I} w_{ij} u_i + b_j, \quad j \in J \tag{1}$$

where u_i is the input to node i, b_J is the biases of j, I and J are the two index set for input and output nodes. For $(1/3)$ block $I = 1$ and $J = 2, 3, 4$. For block type of $(3/1)$, $I = 1, 3, 4$ and $J = 2$ while the $(2/2)$ block type has $I = 1, 4$ and $J = 2, 3$. For each node, it is characterized by the following activation function:

$$\phi(y) = \alpha \left(\frac{2}{1 + e^{-\beta y}} - 1 \right) \tag{2}$$

where the parameter α and β will be optimized by HPSOWM [10].

B. Hybrid Particle Swarm Optimization with Wavelet Mutation (HPSOWM)

In HPSOWM, a swarm $X(t)$ is constituted with the number of particles. Each particle $\mathbf{x}^p(t) \in X(t)$ contains κ elements $x_j^p(t)$ at the t-th iteration, where $p = 1,2,...,\theta$ and $j = 1,2,...,\kappa$; θ denotes the number of particles in the swarm and κ is the dimension of a particle. First, the particles of the swarm are initialized and then evaluated by a defined fitness function. The objective of HPSOWM is to minimize the fitness function (cost function) $f(X(t))$ of particles iteratively. The position $x_j^p(t)$ and velocity $v_j^p(t)$ used in HPSOWM [10] are given as follows:

$$\begin{aligned} x_j^p(t) &= x_j^p(t-1) + v_j^p(t) \\ v_j^p(t) &= k.\left(w.v_j^p(t-1) + \varphi_1 r_1\right).\left(\tilde{x}_j - x_j^p(t-1)\right) \\ &+ \varphi_2 r_2 \left(\hat{x}_j - x_j^p(t-1)\right) \end{aligned} \tag{3}$$

where$\tilde{x}^p = \left[\tilde{x}_1^p, \tilde{x}_2^p, \ldots, \tilde{x}_k^p\right]$ and $\hat{\mathbf{x}} = [\ \hat{x_1}\ \ \hat{x_2}\ \ ,...\hat{x_\kappa}\ ]$, $j = 1,2,...,\kappa$. The best previous position of a particle is recorded and represented as $\tilde{x}$; the position of best particle among all the particles is represented as $\hat{x}$; w is an inertia weight factor; r_1 and r_2 are acceleration constants which return a uniform random number in the range of [0,1]; w is inertia weight factor and k is a constriction factor which detail derivation is discussed in [10].

$$\overline{x}_j^p(t) = \begin{cases} x_j^p(t) + \sigma \times \left(\rho_{\max}^j - x_j^p(t)\right) & ,\sigma > 0 \\ x_j^p(t) + \sigma \times \left(x_j^p(t) - \rho_{\min}^j\right) & ,\sigma < 0 \end{cases} \tag{4}$$

where $j \in 1,2,\ldots,\kappa$ and κ denotes the dimension of particles. The value of σ is governed by Morlet wavelet function as presented in [10].

C. Fitness Function and Training

The performances of classifications are measured in terms of sensitivity and specificity. The performance of proposed detection system is measured in terms of Sensitivity, $\xi = \frac{N_{TP}}{N_{TP}+N_{FN}}$ and Specificity, $\eta = \frac{N_{TN}}{N_{TN}+N_{FP}}$ in which N_{TP} is defined as number of true positive which implies the sick people correctly diagnosed as sick; N_{FN} is number of false negative which implies the sick people wrongly diagnosed as healthy; N_{FP} is number of false positive which implied healthy people wrongly diagnosed as sick; and N_{TN} is number of true negative which implied healthy people correctly diagnosed as healthy. The values of these are within 0 to 1. The objective is to maximize the fitness function of (5) which equivalent to maximize the sensitivity and the specificity. To meet the objective of the system the fitness function $f(\xi,\eta)$ is defined as follow:

$$f(\xi,\eta) = \xi + \frac{\eta_{\max} - \eta}{\eta_{\max}} \tag{5}$$

where $\eta_{\max}$ is a upper limit of the specificity. Each particle of HPSOWM contains the structure (s_l) and weights (w_k^l) parameters of BBNN and transfer function parameters a and b from eq. (2) which is in the form of $\mathbf{x} = [s_l\ w_k^l\ a\ b]$, where l and k are number of layers and weights of BBNN (up to 12 connection weights for each layer). In (5), the specificity is limited by a maximum value $\eta_{\max}$. The parameter $\eta_{\max}$ is used to fix the region of specificity and find the optimal sensitivity in this region. In particularly, the $\eta_{\max}$ can set from 0 to 1 and different sensitivity with different specificity value can be determined.

III. RESULT AND DISCUSSION

To study the natural occurrence of nocturnal hypoglycemia, 15 children with T1DM is monitored for the 10-hour overnight at the Princess Margaret Hospital for Children in Perth, Western Australia, Australia. The required physiological parameters are measured by the use of non-invasive monitoring system in [12], while the actual blood glucose levels (BGL) are collected as reference using Yellow Spring Instruments. The main parameters which is used for the detection of hypoglycemia are the heart rate (HR) and corrected QT (QTc) interval.

The responses from 15 children with T1DM exhibit significant changes during the hypoglycemia phase against the non-hypoglycemia phase. Normalization is used to reduce patient-to-patient variability and to enable group comparison by dividing the patient's heart rate and corrected QT interval by his/her corresponding values at time zero. The study shows that the hypoglycemia episodes (BGL $\leq 3.3 mmol/l$) is detected using these variables based on a hybrid PSO with wavelet mutation based block based neural network model.

To find the optimized structure and weights of BBNN, the parameters of HPSOWM are chosen as: swarm size $\theta = 50$, constant value c_1 and c_2 = 2.05, maximum velocity $v_{\max}$ = 0.3, probability of mutation μ_m = 0.7, the shape parameter of wavelet mutation ζ_{wm} = 2, the constant value g of wavelet mutation = 10000 and the number of iteration T=2000.

The training performance of proposed detection has been analyzed by means of ROC curve in which the sensitivity (true positive rate) and the 1-specificity (false positive rate) are relatively plotted. The corresponding ROC curve areas for proposed block based neural network is 0.7101(71.01%) while the other comparison methods, FWNN and MR gives 0.6695(69.95%) and 0.6597(65.97%).

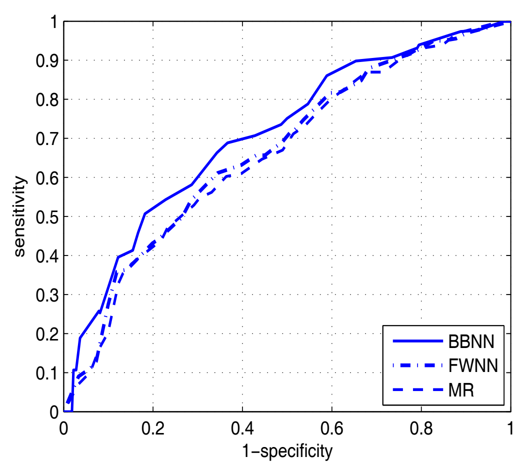

Fig. 4. ROC curve: Sensitivity versus 1-Specificity

TABLE I
MEAN VALUE OF TRAINING, VALIDATION AND TESTING RESULTS: SPECIFICITY (TRAINING)= 40 %

Method	Training		Validation		Testing		
	Sen	Spec	Sen	Spec	Sen	Spec	gm
BBNN	83.64%	40.35%	87.34%	40.13%	76.28%	52.40%	63.22%
FWNN	81.06%	41.26%	76.41%	41.44%	65.93%	50.09%	57.46%
MR	85.76%	40.89%	73.28%	40.00%	63.37%	59.74%	61.52%

TABLE II
BEST TESTING RESULT FOR HYPOGLYCEMIA DETECTION WITH DIFFERENT APPROACHES

Method	Sensitivity(Testing)	Specifcity(Testing)	gm
BBNN	76.74%	50.91%	63.06%
FWNN	67.44%	54.55%	60.65%
MR	62.79%	60.91%	61.84%

The results of hypoglycemic detection are presented in Table I - II, in which proposed block based neural networks with 2 inputs (BBNN4), feedforward neural networks with 2 input (FWNN) and multiple regression with 2 inputs (MR) are compared and analyzed. In clinical study, the sensitivity of the detection system is most important than the specificity because it mainly represents the performance of classifier for patients with hypoglycaemia. Thus, it is vital to classify the abnormal condition for patients with hypoglycemia efficiently. If the proposed detection system can correctly detect the status of hypoglycemia accurately, the value of sensitivity will be higher. The higher sensitivity represents the better performance of detection system.

In order to analyze the optimum sensitivity and specificity, the cut-off point is set at 0.6 ($1-\eta_{\max}$=60%) which is equivalent to maximum specificity, $\eta_{\max}$=40% based on the ROC curve in Fig. 4. At the defined cut-off point, the average (mean) training, the validation and the testing results in terms of the sensitivity and specificity are tabulated in Table I. The results are evaluated in terms of mean values which is calculated by averaging over 20 runs.

In Table I, the average (mean) testing result of proposed BBNN model gives satisfactory sensitivity, 76.28% and specificity, 52.40% which is outperformed other models such as FWNN and MR whose sensitivity and specificity are (65.93% and 50.09%) and (63.67% and 59.74%) respectively. In addition, the performance of proposed BBNN are assessed in terms of geometric mean, ($gm = \sqrt{\xi \times \eta}$). In Table I, the proposed BBNN approach performs approximately 2% and 3% better than that of FWNN and MR approaches.

As tabulated in Table II, after the training process the optimized block based neural network (BBNN) model gives the best testing sensitivity, 76.74% and acceptable specificity, 50.91%. The obtained BBNN result outperform conventional classification techniques such as feedforward neural network (FWNN) (67.44% of testing sensitivity and 54.55% of testing specificity) and multiple regression (MR) (62.79% of testing sensitivity and 60.91% of testing specificity). From Table II, it can be clearly seen that only proposed BBNN is able to meet the requirement of diagnosis which sensitivity and specificity are ($\geq$ 70% and $\geq$ 50%). Besides, the proposed BBNN gives better geometric mean value of 63.06% while FWNN and MR only have 60.65% and 61.84%.

IV. CONCLUSIONS

A hybrid particle swarm optimization based block based neural network (BBNN) is developed for detect the hypoglycemia episodes for diabetes patients. The result in Section III indicate that the hypoglycemia episodes in T1DM children can be detected non-invasively and continuously from the real-time physiological responses (heart rate,corrected QT interval). To optimize the structure and weight of BBNN, a hybrid particle swarm optimization is presented where wavelet mutation operation is introduced to enhance the optimization performance. An actual T1DM study illustrated that the proposed algorithm gives better sensitivity and specificity than other conventional algorithms, feedforward and multi regression. In short, the proposed evolved BBNN can effectively detect hypoglycemic episodes by giving satisfactory sensitivity and specificity 76.74% and 50.91%.

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