A Particle Swarm Optimization-based Neural Network for Detecting Nocturnal Hypoglycemia Using Electroencephalography Signals

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Abstract— For patients with Type 1 Diabetes Mellitus (T1DM), hypoglycemia or the state of low blood glucose level is a very common but dangerous complication. Hypoglycemia episodes can lead to a large number of serious symptoms and effects, including unconsciousness, coma and even death. The variety of hypoglycemia symptoms is originated from the inadequate supply of glucose to the brain. By analyzing electroencephalography (EEG) signals from five T1DM patients during an overnight study, we find that under hypoglycemia, both centroid theta frequency and centroid alpha frequency change significantly against non-hypoglycemia conditions. Furthermore, a neural network is developed to detect hypoglycemia using the mentioned two EEG features. A standard particle swarm optimization strategy is applied to optimize the parameters of this neural network. By using the proposed method, we obtain the classification performance of 82% sensitivity and 63% specificity. The results demonstrate that hypoglycemia episodes can be detected non-invasively and effectively from EEG signals.

Keywords- hypoglycemia detection; EEG; neural network; particle swarm optimization

I. INTRODUCTION

Type 1 Diabetes Mellitus (T1DM) is a form of diabetes which is caused by the loss of insulin-producing beta cells in the pancreas leading to insulin deficiency. T1DM can cause a variety of serious complications [1]. The intensive insulin therapy is the most efficient treatment for T1DM patients which can delay the onset and reduce the risk of acute diabetic complications like retinopathy, nephropathy and neuropathy. On the other hand, it also increases, by three times, the incidence of hypoglycemia among patients with T1DM over conventional therapy. Hypoglycemia is the medical term for the state produced by an abnormally lower than normal level of blood glucose level (BGL). This is considered as the most common but dangerous complication for T1DM patients and a barrier which limits the glycemic control therapy for diabetes patients.

Hypoglycemia can produce a variety of symptoms, from mild to severe episodes [2, 3]. Mild hypoglycemia causes sweating, nervousness, heart plumping, confusion, anxiety, etc. It can be alleviated by eating or drinking glucose-rich food. If left untreated, hypoglycemia can become severe and lead to seizures, coma, and even death. One of the most dangerous effects of hypoglycemia is hypoglycemia unawareness. This is caused by frequent episodes of hypoglycemia which can lead to changes in the response of patients’ bodies. In unawareness situations, patients’ bodies do not release the hormone epinephrine which is the origin of early warning symptoms for patients like sweating, hunger, anxiety. Because of no warning, patients normally cannot realize the occurrence of hypoglycemia until it becomes severe and could lead to fatal damage. Nocturnal hypoglycemia is also especially fearful for T1DM patients as sleep can make the symptoms unclear. It was reported previously that almost 50% of all episodes of severe hypoglycemia occur at night during sleep [4]. Because of the severity of hypoglycemia, a large number of studies have been conducted in order to develop systems that can detect the onset of hypoglycemic episodes and give alarm to provide enough time for patients and carers to take action.

The variety of hypoglycemia symptoms is originated from an inadequate supply of glucose, which is the primary metabolic fuel to the brain. Since the electroencephalogram (EEG) is directly related to the metabolism of brain cells, hypoglycemia is believed to cause early changes in EEG that can be detected non-invasively.

Previous studies have showed important evidences of different changes in EEG signals of T1DM patients due to hypoglycemia [5-9]. Similarly, in a recent study, we reported significant changes found under hypoglycemia conditions [10, 11]. In this study, we also proposed a method of feature extraction using Fast Fourier Transform (FFT) and classification using neural network to detect nocturnal hypoglycemic episodes. Results of this study showed that hypoglycemia can be detected using EEG signals. However, in order to develop a system that can be applied into real clinical situations, the overall accuracy of the proposed method needs to be improved. This improvement can be done by using an efficient training technique which can provide a better estimation of the neural network model.
Recently, particle swarm optimization (PSO) has been employed widely in training and evolving neural network models [12]. This is a stochastic optimization technique which was inspired by the social behavior of birds flocking. Applying PSO in training neural network has been proved to provide better performance with fast and stable convergence rate.

The main objective of this paper is to develop a PSO-based neural network to detect hypoglycemic episodes non-invasively using EEG signals. Using FFT, different EEG parameters are extracted and analyzed to find important features that significantly change under hypoglycemia conditions. These features are used as inputs for a neural network to classify patients’ conditions into two states: hypoglycemia or non-hypoglycemia. The developed neural network structure is optimized by using a global learning optimization algorithm based on PSO. Section II provides an overview of the methodology used in our study. Results of the study will be mentioned in Section III. A conclusion for this study is drawn in Section IV.

II. METHODS

A. Study

EEG signals were acquired from five adolescent patients with T1DM (between the ages of 12 and 18 year old) who volunteered for the overnight hypoglycemia study at the Princess Margaret Hospital for Children in Perth, Australia. During the study, signals were continuously recorded and stored using Compumedics system with the sampling rate of 128 Hz. The EEG sensors were positioned at 4 channels which are O1, O2, C3 and C4 according to the International 10/20 system, referenced to A1 with left-side positions and A2 with right-side positions. There were also two sensors placed at patients’ chins to measure the electromyogram (EMG) signals and two sensors placed near patients’ eyes to measure the electrooculogram (EOG) signals. During the study, the actual blood glucose levels (BGLs) from patients were also routinely collected to be used as reference. BGLs were acquired using Yellow Spring Instruments with the general sampling period of 5 minutes. Data were collected with the approval of the Women’s and Children’s Health Service, Department of Health, Government of Western Australia, and with informed consent.

B. Feature extraction

After finalizing the signal acquiring step, signal processing is carried out using EEGLAB [13]. The data are segmented into 30-second epochs before being processed. In EEGLAB, EEG signals from patients are filtered using an IIR highpass filter with a cut-off frequency of 2Hz to get rid of low frequency artifacts. A notch filter at 50Hz is also applied to remove power noise.

These 30-seconds epochs after being processed are labeled as hypoglycemia or non-hypoglycemia according to the BGL data. Epochs which correspond with BGL lower than 3.3mmol/l are defined as hypoglycemia. Conversely, they are labeled as non-hypoglycemia epochs. Then, non-artifact 30-second EEG epochs are subdivided into 5-second non-overlapping segments. By using Fast Fourier Transform (FFT), these segments are transformed into the frequency domain which results in the power spectrum \( P(f_i) \). The power spectrum is then subdivided into 3 frequency bands: theta (\( \theta: 3.5-7.5\text{Hz} \)), alpha (\( \alpha: 8-13\text{ Hz} \)) and beta (\( \beta: 13.5-30\text{Hz} \)).

From the power spectrum of each frequency band, different EEG parameters are estimated as following.

Power (\( P \)): The power level within each frequency band has been shown as a common feature in EEG research. Previous studies indicate that there are changes in the power level of theta and alpha bands caused by hypoglycemia onset [7-9]. In our study, the power level within each frequency band is estimated from the power spectrum \( P(f_i) \) by using a numerical integration technique (the trapezoidal rule). Because the power levels are very different between patients, an appropriate normalization strategy is used to reduce the variability of these features and to enable group comparison. To do this, we normalize each patient’s power levels against their corresponding values at time zero.

Centroid Frequency (CF): This feature can be referred as the center of gravity of the spectrum within each band. It is estimated as the frequency which subdivides the area under the spectral curve into identical parts.

\[
CF = \frac{\sum f_i P(f_i)}{\sum P(f_i)}
\]

As a result, a total set of 24 EEG features (2 different kinds of feature x 4 channels x 3 frequency bands) are estimated for each epoch. For comparison and classification purposes, approximately 25 data points are used for each patient. Each data point is corresponding to the 5-minute duration of each blood glucose sampling episode. The combined data set from all five patients consists of 107 episodes which include 47 hypoglycemia episodes.

The Student’s \( t \)-test is then applied to each feature to estimate the significance of differences between hypoglycemia and non-hypoglycemia conditions. Probability values (\( p \)-value) less than 0.05 are considered to be significant. The statistically significant features will be used as inputs for the classification.

C. Classification

1) Neural network

Artificial neural networks have been employed popularly in biomedical area as a powerful tool of classification and pattern recognition. It has been recognized that neural network is a successful method in classifying complex situations. Neural networks can effectively model non-linear relationships between inputs and outputs.

Considering the final aim of developing a real-time detecting system which requires reducing the computational cost, in this study, a neural network with feed-forward three-layer structure is developed and employed as classification unit. This network consists of one input layer which includes...
the features extracted from EEG signals, one hidden layer and one output layer.

The structure of the neural network is shown in Fig. 1. From this figure, the input-output relationship of the neural network can be written as follows:

\[
y = \sum_{i=1}^{S} v_i \tan \sigma \left( \sum_{j=1}^{R} w_{ij} x_j - b_{i1} \right) - b_2
\]  

(2)

where \( w_{ij}, i = 1, 2, ..., S; j = 1, 2, ..., R \) is the weight of the link between \( i \)-th hidden node and the \( j \)-th input; \( v_i \) is the weight of the link between \( i \)-th hidden node and the output; \( b_{i1}, b_2 \) are the biases for the input layer and hidden layer respectively; \( S \) is the number of hidden nodes; \( R \) is the number of inputs; \( \tan \sigma \) is the hyperbolic tangent sigmoid transfer function of hidden layer:

\[
\tan \sigma(a) = \frac{e^a - e^{-a}}{e^a + e^{-a}}
\]  

(3)

The overall data are grouped into a training set and a testing set. The developed neural network is trained by using the training set. The number of hidden nodes will be selected as the one which gives the best classification performances. PSO is applied as the weight learning algorithm to find the optimized network parameters (including \( w_{ij}; b_{i1}; v_i; b_2 \)). A detail about PSO is provided in the later session.

After determining the optimized neural network, the Receiver Operating Characteristic (ROC) curve will be found based on the training set. By definition, a ROC curve presents the tradeoff between the true positive rate versus false positive rate (equivalently, sensitivity versus 1–specificity) for different thresholds of the classifier output. It can be used to find the threshold that can improve the classification performance. The area under ROC curve (AuR) is an important measure that presents the performance of the classification. The higher the AuR, the better the classification. A random classification gives an AuR of 0.5, while an ideal classification gives an AuR of 1.

Finally, based on the derived structure as well as the output threshold of neural network, the test set will be applied to test the performance of the developed neural network. These performances are determined in terms of sensitivity and specificity of the classification results:

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \tag{4}
\]

\[
\text{Specificity} = \frac{TN}{TN + FP} \tag{5}
\]

where True Positive (TP) is the number of hypoglycemic episodes which are correctly classified as hypoglycemia; True Negative (TN) is the number of non-hypoglycemic episodes which are correctly classified as non-hypoglycemia; False Positive (FP) is the number of non-hypoglycemic episodes which are wrongly classified as hypoglycemia; False Negative (FN) is the number of hypoglycemic episodes which are wrongly classified as non-hypoglycemia.

2) Particle swarm optimization

Since it was first introduced by Kennedy and Eberhard in 1995 [14], PSO has been employed into various applications, including neural network training [15]. In PSO, individuals or particles represent possible solutions to the optimization problem. Each particle flies through the search space, using information of best position estimated by itself as well as by the whole swarm or population, to adjust its velocity and position. The objective of this adjustment is getting closer to a target defined by a fitness function.

To perform a training on neural network, a swarm of \( P \) particles is initialized first. Each of these particles consists of \( N \) dimensions which are equivalent to \( N \) parameters of neural network model. Each dimension is represented by two parameters: position and velocity. The mean squared error function of neural network is considered as fitness function. The PSO travels though the search space to optimize the fitness function. At each iteration of this travelling, each dimension updates its position and velocity based on its own best experience as well as the whole swarm's best experience. This update can be expressed as follows:

\[
v_{id}(t) = \mu v_{id}(t - 1) + c_1 \phi_1 \left( p_{id}^{\text{best}} - p_{id}(t - 1) \right) + c_2 \phi_2 \left( g^{\text{best}} - p_{id}(t - 1) \right)
\]  

(6)

\[
p_{id}(t) = p_{id}(t - 1) + v_{id}(t)
\]  

(7)

where \( p_{id} \) denotes position of the \( d \)-th dimension of the \( i \)-th particle, and \( v_{id} \) denotes the velocity of the \( d \)-th dimension of the \( i \)-th particle, \( i = 1, 2, ..., P \); \( d = 1, 2, ..., N \); \( c_1, c_2 \) are acceleration factors; \( \phi_1, \phi_2 \) are uniformly distributed random numbers in the range of \((0,1)\); \( \mu \) is inertial weight factor; \( p_{id}^{\text{best}} \) represents the best position that the \( d \)-th dimension of the \( i \)-th particle can reach, \( g^{\text{best}} \) represents the global best position that the whole population can reach.
In (6), the velocity adjustment includes three different parts. The first part keeps the adjustment of each iteration out of abrupt changes. The second part represents the adjustment based on the learning experience of each dimension in each particle. The last part is considered as global part, which represents the adjustment based on the best flying experience of the whole swarm. The selection of factors $\mu_1, c_1, c_2$ keeps the balance between local and global searching ability of PSO.

### III. RESULTS

The actual BGL profiles of five patients which were collected by the Yellow Spring Instruments during the study are shown in Fig. 2. The reference (Ref line in Fig. 2) is set at 3.3mmol/l which is used as the BGL threshold of hypoglycemia.

![Figure 2. Actual blood glucose level profiles in 5 T1D children](Image)

EEG responses from all five patients show significant changes during the hypoglycemia state against non-hypoglycemia state. Statistical results of channel O1 and C3 are presented in Tables I and II. Significant features are reported in bold. The results show that there is a similarity between channels in the same brain area (i.e. O1 and O2; C3 and C4).

There are some slight changes in alpha power and theta power at channels O1 and O2. The beta power levels at all channels except C3 do not change significantly between non-hypoglycemia and hypoglycemia states. Because these responses are not consistent with all patients, we conclude that they are caused by the changes in sleep stages of patients during night.

The study shows that the centroid alpha frequency is the most significant feature. Under hypoglycemia conditions, the centroid alpha frequency of 5 patients reduces significantly at all four channels ($p \leq 0.0001$). The results also show an increase in centroid beta frequency at all channels ($p = 0.026$ at O2, 0.007 at C3 and 0.006 at C4). There is no significant change in the centroid beta frequency across all four channels ($p = 0.037$ at channel C3 and $p > 0.05$ at others). These results demonstrate that during the hypoglycemia onset, there is a power shift to the border area between alpha band and theta band in the power spectra of EEG signals. This is an important finding that should be explored more in future studies to find other features which can enhance the performance of hypoglycemia classification.

| TABLE I
<p>| CHANGES UNDER HYPOGLYCEMIA CONDITION – CHANNEL C3 |</p>
<table>
<thead>
<tr>
<th>Feature</th>
<th>Normal State</th>
<th>Hypoglycemia State</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power $\theta$</td>
<td>1.5435 ± 0.7411</td>
<td>1.4107 ± 0.6309</td>
<td>$p = 0.01$</td>
</tr>
<tr>
<td>Power $\alpha$</td>
<td>0.8802 ± 0.3596</td>
<td>0.8510 ± 0.3147</td>
<td>$p = 0.242$</td>
</tr>
<tr>
<td>Power $\beta$</td>
<td>0.7694 ± 0.1965</td>
<td>0.8284 ± 0.4013</td>
<td>$p = 0.011$</td>
</tr>
<tr>
<td>CF $\theta$</td>
<td>5.2347 ± 0.2304</td>
<td>5.2800 ± 0.2323</td>
<td>$p = 0.007$</td>
</tr>
<tr>
<td>CF $\alpha$</td>
<td>10.2910 ± 0.3107</td>
<td>10.1531 ± 0.3415</td>
<td>$p \leq 0.0001$</td>
</tr>
<tr>
<td>CF $\beta$</td>
<td>19.8080 ± 0.7664</td>
<td>19.9430 ± 0.8253</td>
<td>$p = 0.037$</td>
</tr>
</tbody>
</table>

| TABLE II
<p>| CHANGES UNDER HYPOGLYCEMIA CONDITION – CHANNEL O1 |</p>
<table>
<thead>
<tr>
<th>Feature</th>
<th>Normal State</th>
<th>Hypoglycemia State</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power $\theta$</td>
<td>1.3392 ± 0.7256</td>
<td>1.3177 ± 0.7793</td>
<td>$p = 0.691$</td>
</tr>
<tr>
<td>Power $\alpha$</td>
<td>1.1012 ± 0.4812</td>
<td>1.0982 ± 0.4117</td>
<td>$p = 0.928$</td>
</tr>
<tr>
<td>Power $\beta$</td>
<td>0.8907 ± 0.2827</td>
<td>0.9305 ± 0.3601</td>
<td>$p = 0.078$</td>
</tr>
<tr>
<td>CF $\theta$</td>
<td>5.2318 ± 0.2128</td>
<td>5.2757 ± 0.2377</td>
<td>$p = 0.006$</td>
</tr>
<tr>
<td>CF $\alpha$</td>
<td>10.2688 ± 0.3136</td>
<td>10.1619 ± 0.3221</td>
<td>$p \leq 0.0001$</td>
</tr>
<tr>
<td>CF $\beta$</td>
<td>20.0541 ± 0.8664</td>
<td>20.1644 ± 0.8197</td>
<td>$p = 0.074$</td>
</tr>
</tbody>
</table>

Based on these statistical results, the centroid theta frequency and the centroid alpha frequency from each channel are selected as inputs of classification. The final set has 8 features.

A neural network is developed using these features as inputs. The structure of neural network has 8 input nodes which are 8 mentioned EEG features. There is 1 output node which indicates the state of hypoglycemia or non-hypoglycemia. The desired output is set at 1 in case of hypoglycemia and -1 in case of non-hypoglycemia. The neural network has $S$ hidden nodes. $S$ is varied from 4 to 10 to select the one that gives the best performance. As a result, in our application, $S = 6$ produces the best classification. Thus, following reported results are corresponding to the neural network structure of 6 hidden nodes. The total number of parameters in neural network is $(8 + 1) \times 6 + 7 = 61$.

The overall data are grouped into a training set and a testing set, with ratio of 3 : 2 patients. Using the training set, the developed neural network is trained by PSO in which each particle has corresponding 61 dimensions. To train neural network, the parameters of PSO are selected as following: swarm size 30, inertial weight factor $\mu$ keeps $\in [12, c, c]$, acceleration factors $c_1, c_2$ are set at 2, $\mu$ is set at 0.8. The maximum number of iterations is 1000.

The ROC Curve for the training set is plotted in Fig. 3. The corresponding ROC Curve area (AUROC) for the training set is 0.77. With this ROC curve, the most suitable cut-off point is selected as the threshold to distinguish between the hypoglycemia and normal states. In the application of detecting hypoglycemia, the sensitivity or the true positive rate is very important. So in our study, the condition for cut-off point is producing sensitivity higher than 80%. At that point, the combined training and validation results of 81% sensitivity and 56% specificity are gained.
To find the contribution of different channels to the performance of classification, different neural networks are developed using inputs corresponding to data from each EEG channel as well as from two EEG channels separately. For the consideration of the results from two EEG channels, we evaluate the results from various two channels at different sides and different areas of the brain (C3 and O2, C4 and O1). All results are presented in Table III. These reported results are the best performance over 30 runs for each case.

The classification using data from all four EEG channels results in a sensitivity of 82% and specificity of 63% which indicate a potential ability of detecting hypoglycemia from EEG signals. With these results, it is proved that centroid theta frequency and centroid alpha frequency are two important EEG features in hypoglycemia detection. The results also indicate that neural network optimized by PSO can produce excellent performance with good generalization (training results of 81% and specificity of 56%, compared with testing results of 82% and specificity of 63%). This is very important for detecting hypoglycemia using EEG signals, because of the variation between patients and patients is very big.

The classification results from smaller group of channels also show acceptable results for detecting hypoglycemia. The case of using data from channel C3 and O2 can give comparable testing results with 74% sensitivity and 64% specificity.

<table>
<thead>
<tr>
<th>Inputs</th>
<th>AuR</th>
<th>Sensitivity Training</th>
<th>Specificity Training</th>
<th>Sensitivity Testing</th>
<th>Specificity Testing</th>
</tr>
</thead>
<tbody>
<tr>
<td>4 channels</td>
<td>0.77</td>
<td>81</td>
<td>56</td>
<td>82</td>
<td>63</td>
</tr>
<tr>
<td>O1</td>
<td>0.65</td>
<td>71</td>
<td>51</td>
<td>79</td>
<td>40</td>
</tr>
<tr>
<td>O2</td>
<td>0.70</td>
<td>71</td>
<td>67</td>
<td>84</td>
<td>48</td>
</tr>
<tr>
<td>C3</td>
<td>0.75</td>
<td>75</td>
<td>59</td>
<td>79</td>
<td>43</td>
</tr>
<tr>
<td>C4</td>
<td>0.69</td>
<td>71</td>
<td>53</td>
<td>69</td>
<td>42</td>
</tr>
<tr>
<td>O2,C3</td>
<td>0.76</td>
<td>82</td>
<td>72</td>
<td>74</td>
<td>64</td>
</tr>
<tr>
<td>O1,C4</td>
<td>0.71</td>
<td>71</td>
<td>60</td>
<td>69</td>
<td>48</td>
</tr>
</tbody>
</table>

With the classification results of 82% sensitivity and 63% specificity, it indicates that hypoglycemia episodes can be detected effectively and non-invasively using parameters from scalp EEG signals. The above results also show that PSO-based neural network can produce good performance of classifying T1DM patients’ conditions into hypoglycemia and non-hypoglycemia.

Based on achieved results, a more advanced algorithm of PSO neural network will be investigated in future research to further improve the study’s performance.

IV. CONCLUSION

In this paper, a method of detecting episodes of hypoglycemia using parameters extracted from EEG signals is introduced. Statistical results of study show that under nocturnal hypoglycemia, the centroid alpha frequency significantly decreases in all five patients with T1DM. A slightly significant increase in centroid theta frequency is also found. Using these two parameters as inputs, a neural network is proposed for the purpose of classification. PSO is applied to train this neural network to achieve the optimized parameters. The developed neural network is trained using data from three patients and tested using data from the other two patients.

REFERENCES


