Electrocardiographic T wave peak-to-end interval for Hypoglycaemia detection

Nuryani, S. H. Ling, *Member, IEEE* and Hung T. Nguyen, *Senior Member, IEEE*

***Abstract*—Electrocardiographic T wave peak-to-end interval (TpTe) is a parameter of T wave morphology containing important indicators for hypoglycaemia. This paper shows the corrected TpTe ($TpTe_c$) interval as one of the important inputs to detect hypoglycaemia. In this paper, support vector machine (SVM) and fuzzy support vector machine (FSVM) utilizing radial basis function (RBF) are as the classification method. By comparing the classification systems with the inputs of corrected QT interval (QT_c) and heart rate only, the results indicate that including $TpTe_c$ perform better results to detect hypoglycaemia in term of sensitive, specificity and accuracy.**

I. INTRODUCTION

Hypoglycaemia is a common complication of type 1 diabetic patients and as one of factors causing death [1, 2]. A study shows that mild and severe hypoglycaemia occur in 58% and 26%, respectively, of insulin-treated diabetic patients [3].

ECG parameters have been applied in the hypoglycaemia detection systems. RR (distance of two nearest R points), RT_c (interval from R point to peak of T wave with bazzet correction) , T wave amplitude, T wave skewness and T wave kurtosis have also been applied to detect onset of hypoglycaemia [4], [5]. Interval from the peak of T wave to its end (TpTe) is one of T wave morphology parameters in electrocardiographic signal. The interval is started from the peak of T wave and is ended at the end of T wave. Furthermore, a corrected TpTe or $TpTe_c$ is TpTe with correcting factor by heart rate using bazzet formula.

TpTe interval is suggested as transmural dispersion of repolarization [6],[7]. It can happen because there are the differences in the repolarization time of three myocardial cells: epicardial, endocardial and midmyocardial M cells, as illustrated in Fig 1. The rising side of T wave is on account of the deviation between epicardial and the M cells action potentials and, in another side, the deviation between endocardial and the M cells action potential decreases T wave until its end coinciding with fully repolarization of the M cells [7].

A number of studies show that TpTe interval increases in patients with QT interval prolongation. It is reported in [8] that TpTe interval is the important parameter in identification of patient with long QT syndrome. Furthermore, ratio of TpTe interval and QT interval is a potentially significant index for arrhythmic event [9]. These results imply that QT interval is not only one parameter in ventricular repolarization.

QT interval represents the duration of ventricular depolarization and subsequent repolarization and, in electrocardiogram, is depicted as the interval from the start of the Q wave to the end of the T wave. Corrected QT interval (QT_c) is potentially meaningful for hypoglycaemia diagnosis. Hypoglycaemia results altered ventricular repolarization or prolonged QT_c interval [10-12] and is predicted on account of sympathoadrenal stimulation [11]. Therefore hypoglycaemia detection system researchers utilize QT_c as an input in the detection system [13].

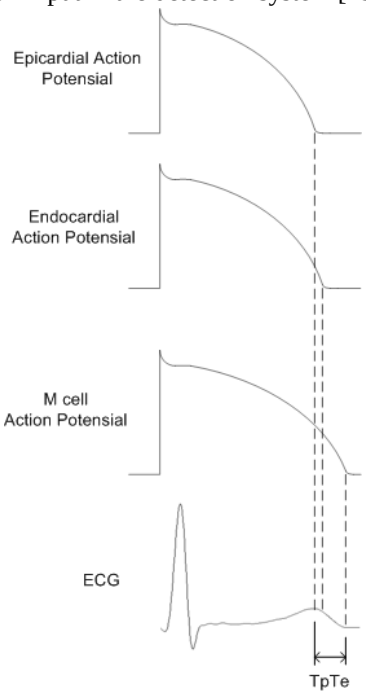


Fig. 1. Epicardial, endocardial and the M cell action potentials and correlated TpTe interval in ECG.

In hypoglycaemia detection research, TpTe interval is not yet investigated. In this paper, we will demonstrate the significant of the TpTe and a hypoglycaemia detection system without TpTe interval is given for comparison purpose. Support vector machine (SVM) and fuzzy support vector machine (FSVM) classifications techniques are investigated into the hypoglycaemia detection. FSVM is a further classification technique of support vector machine (SVM) basing on the concept of decision planes that separate different class objects. SVM based classifications have ability to generalize well even with small size sample [14]. In

Manuscript received March, 2010. Nuryani, S. H. Ling and Hung T. Nguyen are with the Centre for Health Technologies, Faculty of Engineering and Information Technology, University of Technology, Sydney, Broadway, NSW 2007, Australia. e-mail contact: nnuryani@eng.uts.edu.au.

the FSVM technique, a fuzzy membership is introduced to each training sample and therefore different training points can differently contribute to the learning of decision surface [15, 16].

The rest of this paper is organized as follows. Methods consisting of features extraction of the ECG signals and the SVM and FSVM classifications are described in section II. Section III presents the experimental results and the conclusion for this research is drawn in Section IV.

II. METHODS

This work, firstly, creates preprocessing for ECG signals and then extracts it to obtain QT intervals, heart rates and TpTe intervals. Heart rate, QT_c (defined as QT/√RR), and $TpTe_c$ (defined as TpTe/√RR) are then used as inputs for hypoglycaemia detection.

This paper uses two classifiers, SVM and FSVM. The following are the descriptions of SVM and FSVM. The more detail discussions of SVM can be found in [17, 18] and of FSVM in [16, 19].

1) SVM classifier

An SVM is a classifier that constructs an optimal hyperplane separating binary class data. The optimal hyperplane is found through maximization of margin between the two classes. Suppose there are N dimensional data $\mathbf{x}_i \in R^N$ positively or negatively labelled with $y_i \in \{+1,-1\}$, $i = 1,\ldots,n$. SVM algorithm then looks for the hyperplane $(\mathbf{w}\cdot\mathbf{x}+b)$, that maximally separates the positive and negative the training data.

For the binary data, training data satisfy equation of $y_i(\mathbf{w}\cdot\mathbf{x}+b)-1\geq 0$, where $\mathbf{w}$ is its normal, and support vectors are the data that lie in equality of the equation. SVM algorithm looks for the optimum separating hyperplane that maximize distance, that is referred as margin, between two hyperplanes: $(\mathbf{w}\cdot\mathbf{x}+\mathrm{b})-1\geq+1$ and $(\mathbf{w}\cdot\mathbf{x}+\mathrm{b})-1\geq-1$.

When the object is not separable data, the algorithm introduce positive slack variable ξ_i and then the maximization of the margin can be found by minimization of

$$C\sum \xi_i + \frac{1}{2}\|\mathbf{w}\|^2 \qquad (1)$$

subject to $y_i(\mathbf{w}\cdot\mathbf{x}+b)\geq 1-\xi_i$ where the C is a constant to control the trade-off between complexity and proportion of nonseparable data.

Searching the optimal hyperplane can be formulated through maximize

$$L(\alpha) = \sum_{i=1}^{k}\alpha_i - \frac{1}{2}\sum_{i=1}^{k}\sum_{j=1}^{k}\alpha_i\alpha_j y_i y_j (\mathbf{x}_i\cdot\mathbf{x}_j) \qquad (2)$$

subject to

$$0\leq\alpha_i\leq C \text{ and } \sum y_i\alpha_i = 0$$

Inner product in equation above need to be replaced by a kernel function to map the input data to higher dimensional space and so that nonlinearly separable data can be linearly classified. Radial basis function (RBF) kernel function

$$K(\mathrm{x}_i,\mathrm{x}_j) = \exp\left(-\frac{\|\mathrm{x}_i-\mathrm{x}_j\|}{2\sigma^2}\right) \qquad (3)$$

is applied in the SFM and FSVM classifiers in this paper.

Finally, the output of the classification for $\mathbf{x}\in R^N$ is given by

$$y = \mathrm{sgn}(\sum \alpha_i y_i K(\mathrm{x}_i,\mathrm{x})) \qquad (4)$$

2) FSVM classifier

Another classifier used in this paper is FSVM. The FSVM introduces a fuzzy membership $0< s_i<1$ to each data point $\mathbf{x}_i$. The optimal hyper plane problem can be regarded as the solution through minimizing

$$C\sum_{i=1}^{k} s_i\zeta_i + \frac{1}{2}\mathbf{w}\cdot\mathbf{w} \qquad (5)$$

subject to same constraints as in the SVM. That minimization can be transformed to (2) and subject to $0\leq\alpha_i\leq s_i C$ and $\sum y_i\alpha_i = 0$.

In this paper the fuzzy membership output s_i is created in form of triangular membership function as function of blood glucose level (BGL) value β of the patients. The peak of the membership function is at β equal to 3.30 mmol/l with s_i = 1. More precisely of the output membership function is described below:

$$s_i = \begin{cases} 0, & \textbf{for } \beta \leq 2.2201 \\ \dfrac{(\beta-2.2201)}{(3.3-2.2201)}, & \textbf{for } 2.2201 < \beta < 3.3 \\ \dfrac{(6.2201-\beta)}{(6.2201-3.3)}, & \textbf{for } 3.3 \leq \beta < 6.2201 \\ 0, & \textbf{for } \beta \geq 6.2201 \end{cases} \qquad (6)$$

III. EXPERIMENTAL RESULT

This work results ECG parameters that are QT_c, heart rate and $TpTe_c$ of the five type-1 diabetic patients with age of 16±0.7 years. It is an overnight monitoring for the natural occurrence of nocturnal hypoglycaemia. The parameters are then formed as the matrix data with three columns that represent QT_c, heart rate and $TpTe_c$. Each row of the matrix correlates with the blood glucose level (BGL) that classed to hypoglycaemia or normal; the lower than 3.3 mmol/l is defined as hypoglycaemia and that of higher level is for normal.

A leave-one-out cross-validation scheme is used to evaluate the performance of the classification. In this scheme, the dataset is divided into 5 subsets (first patient to fifth patient) with one used for testing and the remaining subsets used to train and to construct the classification decision surface. The performances are measured in terms of sensitivity, specificity and accuracy:

$$Sensitivity = \frac{TP}{TP+FN},$$
$$Specificity = \frac{TN}{TN+FP}, \quad (7)$$
$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN},$$

where *TP* (true positive) is number of the inputs that correspond to hypoglycaemia classified as hypoglycaemia. *FP* (false positive) is number of the inputs that correspond to normoglycaemia classified as hypoglycaemia. *TN* (true negative) is number the inputs that correspond to normoglycaemia classified as normoglycaemia. *FN* (false negative) is the inputs that correspond to hypoglycaemia classified as normoglycaemia. Average of sensitivity, specificity, and accuracy of the cross-validation are used for comparison among the classification techniques,

RBF kernel function has been applied in the both classifiers and the comparison of performances in the cross-validations between the SVM and FSVM using the three variables and the two variables is described in Table 1. The classifiers apply the kernel function with variation of kernel parameter σ (kernel width). Parameter of σ is varied from 51 to 131 with step of 10.

This table shows that the classifier with the best performance among the classifiers is the FSVM using the three inputs, including $TpTe_c$, where the sensitivity, specificity and accuracy are 74.19%, 59.08% and 63.55% respectively. It also shows that the classification for the hypoglycaemia using FSVM performs better. These results indicated the $TpTe_c$ which is a potential ECG parameter to improve the performance for hypoglycaemia detection.

TABLE 1
OPTIMUM VALUE OF THE LEAVE-ONE-OUT CROSS-VALIDATION USING THE THREE AND TWO INPUTS

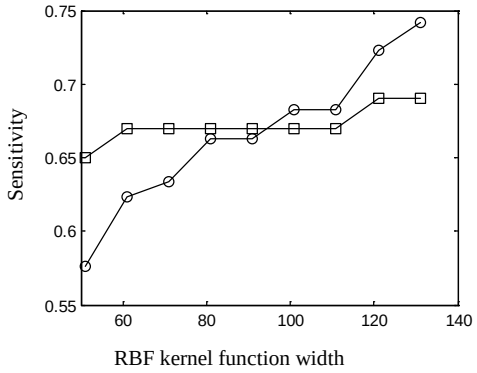
Classifier	Input	Sens.	Spec.	Acc.
FSVM	HR, QTc, $TpTe_c$	74.19%	59.08%	63.55%
	HR, QTc	65.00%	50.63%	56.35%
SVM	HR, QTc, $TpTe_c$	72.43%	54.40%	59.30%
	HR, QTc	64.00%	50.12%	55.87%

Sens: Sensitivity; *Spec*: Specificity; *Acc*: Accuracy

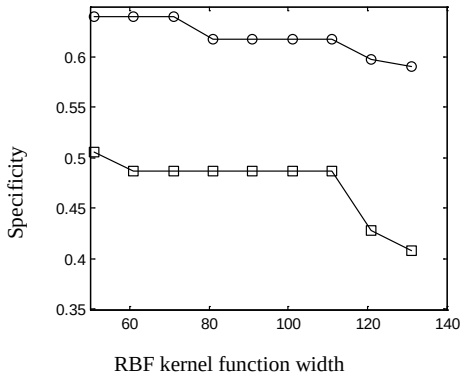
The graphs in Fig. 2 and Fig. 3 show that the performances of the classifiers in the cross-validation can vary on account of the different kernel parameter values and this kind result is also reported in other papers [20, 21]. It indicates that choosing kernel function parameters in the FSVM and SVM classifiers is crucial to find a good performance in a classification. In these classifications, the FSVM with the RBF kernel parameter of 131 achieves highest performance in terms of sensitivity and accuracy. All graphs indicate that the classifiers using the three inputs perform higher performances than that of classifiers using the two inputs except the sensitivity of the FSVM with the kernel parameters of 91 and less.

IV. CONCLUSION

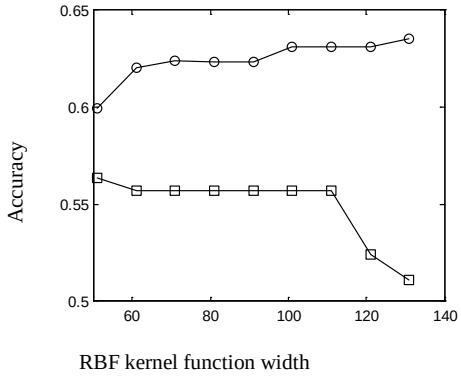
This paper has compared the hypoglycaemia classification applying the ECG parameters with and without $TpTe_c$. The result shows that $TpTe_c$ is an important input for hypoglycaemia detection. Furthermore, a comparison between SVM and FSVM are given. As conclude, the best performance of the classification is the FSVM including $TpTe_c$, as the sensitivity and specificity are 74.19% and 59.08% respectively.



(a) Sensitivity of the FSVM classification

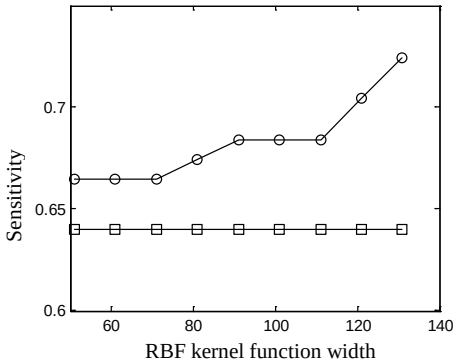


(b) Specificity of the FSVM

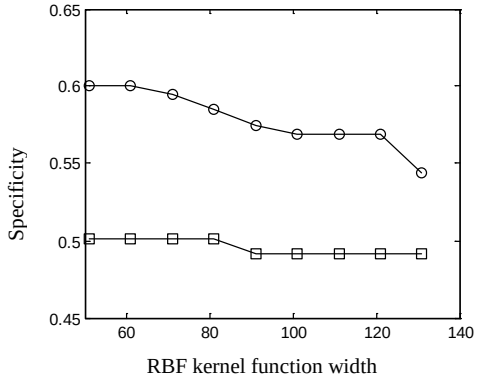


(c) Accuracy of the FSVM classification

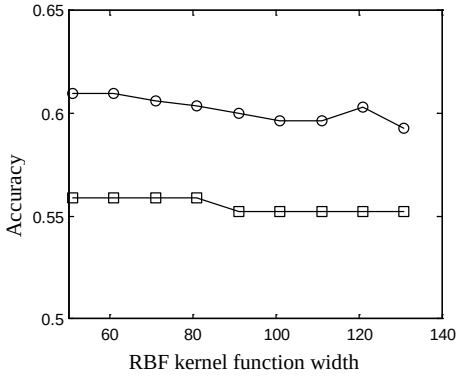
Fig. 2. Performance comparisons of the FSVM classifiers. "o" for the classifiers with $TpTe_c$ as one of the inputs and "□" for the classifiers without $TpTe_c$.



(a) Sensitivity of the SVM classification



(b) Specificity of the FSVM



(c) Accuracy of the FSVM classification

Fig. 3. Performance comparisons of the SVM classifiers – "o" for the classifiers with $TpTe_c$ as one of the inputs and "□" for the classifiers without $TpTe_c$.

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