**University of Technology Sydney**

**Faculty of Engineering and Information Technology**

# ELECTROCARDIOGRAM AND HYBRID SUPPORT VECTOR ALGORITHMS FOR DETECTION OF HYPOGLYCAEMIA IN PATIENTS WITH TYPE 1 DIABETES

**By**

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# CERTIFICATE OF AUTHORSHIP/ORIGINALITY

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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## List of Abbreviations

| | | |
|---|---|---|
| DCCT | : | Diabetes Control and Complications Trial |
| ECG | : | Electrocardiographic |
| FIS | : | Fuzzy Inference system |
| FMR | : | Fuzzy Inference System Multiple Regression |
| Gm | : | Geometric mean |
| IDDM | : | Insulin-dependent diabetes mellitus |
| MR | : | Multiple regression |
| PSO | : | Particle swarm optimization |
| PSOWM | : | Particle swarm optimization with wavelet mutation |
| RBF | : | Radial basis function |
| ROC | : | Receiver operating characteristic |
| rSVML | : | SVM (with linear kernel function) in which their parameters are determined randomly. |
| rSVMP | : | SVM (with polynomial kernel function) in which their parameters are determined randomly. |
| rSVMR | : | SVM (with RBF kernel function) in which their parameters are determined randomly. |
| rSVMS | : | SVM (with sigmoid kernel function) in which their parameters are determined randomly. |
| Sensitivities | : | Sensitivity |
| SFSVM | : | Swarm based fuzzy inference system support vector machine |
| SMR1 | : | Swarm based multiple regression (order 1) |
| SMR2 | : | Swarm based multiple regression (order 2) |
| SMR3 | : | Swarm based multiple regression (order 3) |
| Specificity | : | Specificity |
| SSVML | : | Swarm based support vector machine with linear kernel function |
| SSVMP | : | Swarm based support vector machine with polynomial kernel |

| | | |
|---|---|---|
| | | function |
| SSVMR | : | Swarm based support vector machine with RBF kernel function |
| SSVMRF | : | Swarm based support vector machine with RBF kernel function with the input of ECG parameter corrected using Fridericia formula |
| SSVMS | : | Swarm based support vector machine with sigmoid kernel function |
| SSVMw | : | Swarm based support vector machine without weight optimization |
| SVM | : | Support vector machine |
| SVML | : | Support vector machine with linear kernel function |
| SVMP | : | Support vector machine with polynomial kernel function |
| SVMR | : | Support vector machine with RBF kernel function |
| SVMS | : | Support vector machine with sigmoid kernel function |

## List of Symbols

| | | |
|---|---|---|
| $Q$ | : | the start of $QRS$ complex |
| $R$ | : | the peak of $QRS$ complex |
| $S$ | : | the end of $QRS$ complex |
| $To$ | : | the starting point of $T$-wave |
| $Tp$ | : | the peak of $T$-wave |
| $Te$ | : | the end of $T$-wave |
| $TpTe_c$ | : | interval from the peak of $T$-wave $Tp$ to the end of T-wave $Te$ |
| $ToTe_c$ | : | the interval from the beginning of $T$-wave $To$ to the end of T-wave $Te$ |
| $RTp_c$ | : | the interval from $R$ point to the peak of T-wave $Tp$ |
| $QTe_c$ | : | the interval from $Q$ point to the end of T-wave $Te$ |
| $QTp_c$ | : | the interval from $Q$ point to the peak of T-wave $Tp$ |
| $STo_c$ | : | the interval from $S$ point to the beginning of $T$-wave $To$ and |
| $D$ | : | polynomial degree of polynomial kernel function |
| $\gamma$ | : | The width of RBF kernel function |
| $\alpha$ | : | Lagrangain multiplier |
| $k()$ | : | Kernel function |
| $\xi$ | : | A slack variable introduced for soft margin SVM |
| $C$ | : | The SVM parameter "*cost*" |
| $\tilde{z}$ | : | Personal best position in particle swarm optimization |
| $\hat{z}$ | : | Global best parameter in particle swarm optimization |
| $\varphi$ | : | Inertia weight in particle swarm optimization |
| $\varphi_{max}$, $\varphi_{min}$ | : | Upper and lower bound of inertia weight |
| $c_1$, $c_2$ | : | Acceleration constants in particle swarm optimization |
| $\beta$ | : | Coefficient of independent variables of multiple regression |
| $m$ | : | Mean of Gaussian membership function |
| $\sigma$ | : | Standard deviation of Gaussian membership function |
| $\eta$ | : | The output of fuzzy inference system |
| $h$ | : | The fuzzy singleton in the if-then part of the inference engine (FIS) |

| | | |
|---|---|---|
| $\rho$ | : | Rule number of rules in the if-then part of the inference engine (FIS) |
| $q$ | : | Constriction factor in particle swarm optimization with wavelet mutation (PSOWM) |
| $\rho_{\mathrm{max}}$, $\rho_{\mathrm{min}}$ | : | The upper and lower boundary, respectively, of the element of particle. |
| $\vartheta_{tr}$, $\vartheta_{v}$ | : | Sensitivity of training and validation, respectively |
| $\mathcal{S}_{\mathrm{tr}}$, $\mathcal{S}_{\mathrm{v}}$ | : | Specificity of training and validation |
| $\delta$ | : | Morlet wavelet function |
| $\wp_{max}$, $\wp_{min}$ | : | The upper and lower boundary of the element of particle in PSOWM |
| $\beta_{wm}$ | : | The shape parameter of the monotonic increasing function in PSOWM |

# ABSTRACT

Hypoglycaemia is the most acute and common complication of type 1 diabetes. Physiological changes occur when blood glucose concentration falls to a certain level. A number of studies have demonstrated that hypoglycaemia causes electrocardiographic (ECG) alteration.

The serious harmful effects of hypoglycaemia on the body motivate research groups to find an optimal strategy to detect it. Detection of hypoglycaemia can be performed by puncturing the skin to measure the blood glucose level. However, this method is unsuitable as frequent puncturing may produce anxiety in patients and periodic puncturing is difficult to conduct, not to mention inconvenient, while the patient is sleeping. Therefore, a continuous and non-invasive technique can be considered for hypoglycaemia detection. Several techniques have been reported, such as reverse iontophoresis and absorption spectroscopy.

Another approach to hypoglycaemia detection is based on the physiological effects of hypoglycaemia on the various parts of the body such as the brain, heart and skin. Physiological effects of hypoglycemia to the brain are studied by investigating electroencephalography (EEG) features. Hypoglycemic effects to the heart include alteration of electrocardiographic (ECG) parameters such as heart rate, *QT* intervals and *T*-wave amplitude alteration.

Several algorithms were developed to process ECG parameters for hypoglycemia detection. The algorithms include neural network and fuzzy system based intelligent algorithms. Furthermore, hybrid systems were also developed, such as fuzzy neural network and genetic-algorithm-based multiple regression with fuzzy inference systems.

So far, hypoglycaemia detection systems which are based on the physiological effects still require extensive validation before they can be adopted for worldwide clinical practices.

The research in this thesis introduces several ECG parameters especially which relate to the repolarization phase and could contribute to hypoglycaemia detection. Furthermore, this research aims to introduce novel computational intelligent techniques for hypoglycaemia detection. The detection is based on electrocardiographic (ECG) parameters. A support vector machine (SVM) is the first algorithm introduced for hypoglycaemia detection in this research. The second algorithm is a hybrid of SVM with particle swarm optimization (PSO), which is called an SSVM algorithm. This algorithm is intended to improve the performance of the first algorithm. PSO is an evolutionary technique based on the movement of swarms. It is employed to optimize SVM parameters in order that the SVM perform well for hypoglycaemia detection. The third algorithm is for the improvement of the second algorithm where a fuzzy inference system (FIS) is included. This algorithm involves SVM, FIS and a PSO, which is called SFSVM. The FIS is used to process some ECG parameters to find a better performance of hypoglycaemia detection. FIS is an effective intelligent system which employs fuzzy logic and fuzzy set theory. Its frameworks are based on the concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. In addition, the proposed algorithms are compared with the other algorithms. All the algorithms are investigated with clinical electrocardiographic data. The data is collected from a hypoglycaemia study of type 1 diabetic patients.

This study shows that the selected ECG parameters in hypoglycaemia differ significantly from those in nonhypoglycaemia ($p$<0.01). This difference might consider that the ECG parameters are part of repolarization, in which repolarization prolongs hypoglycaemia. It implies that the ECG parameters are important parameters which possibly contribute to hypoglycaemia detection. Therefore, the ECG parameters are used for inputs of hypoglycaemia detection in this study.

The result also shows that the hypoglycaemia detection strategy which uses SSVM performs better than that which uses SVM (80.04% vs. 73.63%, in terms of geometric mean). Furthermore, the SFSVM performs better than the SSVM (87.22% vs. 80.45% in terms of sensitivity and 79.41% vs. 79.64% in terms of specificity). In summary, SFSVM performs better than the other two algorithms (SVM and SSVM), with acceptable sensitivity, specificity and geometric mean of 87.22%, 79.41% and 83.22%, respectively.