Feature Extraction and Classification of Electrocardiogram (ECG) Signals Related to Hypoglycaemia

C Alexakis[1], HO Nyongesa[1], R Saatchi[1], ND Harris[2], C Davies[3], C Emery[3], RH Ireland[4], SR Heller[3]

[1]Schools of Computing & Engineering, Sheffield Hallam University, Sheffield, UK
[2]University of Bath, Bath, UK, [3]University of Sheffield & [4]Weston Park Hospital, Sheffield, UK

Abstract

Nocturnal hypoglycaemia has been implicated in the sudden deaths of young people with diabetes. Experimental hypoglycaemia has been found to prolong the ventricular repolarisation and to affect the T wave morphology. It is postulated that abnormally low blood glucose could in certain circumstances, be responsible for the development of a fatal cardiac arrhythmia.

We have used automatic extraction of both time-interval and morphological features, from the Electrocardiogram (ECG) to classify ECGs into normal and arrhythmic. Classification was implemented by artificial neural networks (ANN) and Linear Discriminant Analysis (LDA). The ANN gave more accurate results. Average training accuracy of the ANN was 85.07% compared with 70.15% on unseen data.

This study may lead towards the demonstration of the possible relationship between cardiac function and abnormally low blood glucose.

1. Introduction & background

The aim of this work is to detect the onset of nocturnal hypoglycaemia indirectly through analysis of the Electrocardiogram (ECG) of type 1 diabetics. In order to achieve this, ECG feature extraction is performed and the features produced are classified according to their corresponding glucose levels.

Nocturnal hypoglycaemia has been implicated in the sudden deaths of diabetics, especially those of an early age, a syndrome known as "Dead in Bed" [1]. The mechanism and cause of such deaths is still not very clear. The diabetics were well the night before and were found dead in an undisturbed bed the following morning. There was no brain damage, a symptom of profound hypoglycaemia, hence the deaths were caused by a different mechanism. It is suspected that deaths were caused by a fatal cardiac arrhythmia. It has been shown that experimental hypoglycaemia prolongs the ventricular repolarisation (VR) and hence it affects the rythmicity of the heart [2].

The 3-lead ECG was used for the purposes of this research. A typical ECG cycle is presented in figure 1. The T wave corresponds to the ventricular repolarization of the myocardium. During hypoglycaemia, the counter-regulatory responses cause the release of adrenaline and a fall in potassium, which delays repolarisation. These changes may be reflected on the ECG by changes in T wave morphology. If these changes can be automatically identified it may provide a warning of hypoglycaemia or of a potentially pro-arrhythmogenic condition.

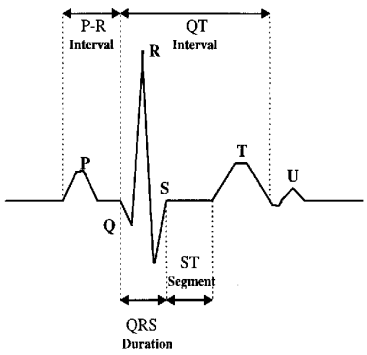

Fig 1: a typical ECG

2. Methods

2.1. Data acquisition

The data used in this study consisted of both the ECG traces and their corresponding blood glucose levels. They were obtained from eleven type 1 diabetic patients, with mean (sd) age 35.9 (14.53), recruited by the Diabetic Clinic of the Royal Hallamshire Hospital in Sheffield. The ECG data were recorded in the patient's own environment by a custom-built system that captures data from the YY' orthogonal lead [3]. One-minute worth of recording was captured every 15 minutes. Blood glucose was recorded by an implantable glucose sensor (MiniMed CGMS) [4] that measures glucose in the trancutaneous tissue every 5 minutes. The above acquisition was carried out for two successive nights and produced a data-set of paired ECG-glucose readings. This data-set was used for offline feature extraction and classification.

2.2. ECG features

An illustration of the time-interval features that can be extracted from an ECG cycle is given in figure 1. The QT was considered in this study since it describes the duration of VR. Correction of QT for heart rate was carried out using Bazett's formula ($QTc = QT/\sqrt{RR}$) [5]. Besides the time interval features, other features describing the amplitude, morphology or area of certain waves were considered.

Five ECG features were used in this study namely: RR, RTc, T wave amplitude (Tampl), T wave skewness (skew) and T wave kurtosis (kurt). These features were extracted using automatic algorithms. The onset and end of the T wave were detected using the tangent method [6,7].

RT is the time interval from the R peak to the end of the T wave. RTc is the corrected version using Bazzett's formula. The RT interval was chosen for this study, instead of the QT, since R point detection is more robust than Q point detection especially in the presence of noise. Moreover the RT interval still describes the process of ventricular repolarisation satisfactorily. RT has been used before [8] but to a lesser extend than the QT.

Skewness is used to evaluate the symmetry of the T wave shape. Kurtosis is used to quantify the degree of peakedness of the T wave shape. Traditionally skewness and kurtosis are used to evaluate the symmetry and peakedness of statistical distributions but in this study they are used for the shape analysis of the T waveform [9].

2.3. Neural network classification

Artificial Neural Networks (ANN) are computational models inspired by the functioning of the human brain. They consist of simple but highly interconnected computing devices, each of which imitates the biological neuron. The ANN "learns" by adapting connections between its computational neurons to match input-output combinations.

The neural network architecture used in this study for classifying ECG traces was the Multi-Layer Perceptron (MLP). Classification was binary, into normal and arrhythmic (corresponding to hypoglycaemia) ECG records. The ANN mapped normal ECG records as negative and arrhythmic ones as positive. A threshold of 2.5 mmol/lt was used to distinguish euglycaemia from hypoglycaemia. ECG traces corresponding to glucose equal or below 2.5 mmol/lt were classed as arrhythmic (hypoglycaemic) while those corresponding to the glucose interval [4 8] mmol/lt were classed as normal (euglycaemic). Records belonging to the interval (2.5 4) were excluded since they belong in the transition region between the normal and the hypoglycaemic class. Hyperglycaemic records (defined as: glucose> 8mmol/lt) were also excluded.

The 5 ECG features produced were combined in two combinations of 4 features namely RR, RTc, Tampl, skew and RTc, Tampl, skew, kurt. Apart from the above features, a third combination was considered. It consisted of a total of 10 ECG features, including the above 5. The extra 5 features were: RT, Tduration, corrected Tduration (using Bazett's formula), area under T and ratio of areas under T on either side of T peak. These 10 features were preprocessed using Principal Component Analysis (PCA) to produce an orthogonalised set of features and reduce the dimensionality of the input vector (i.e. the number of features used). Any feature with less than 2% contribution to the variation in the data set was discarded by the PCA algorithm. PCA typically reduced the 10 initial features into 4 or 5 orthogonalised features. Neural networks were trained using the above three feature combinations and comparisons were made in order to identify the best one.

A classifier was trained for each patient considered in the study. Alternatively a single classifier could have been trained to work on all patients. The second approach was not preferred because of inter-patient variability problems. Such variability is common when dealing with physiological data, making it difficult for the classifiers to generalise on unseen data, across the population of all patients. Some parameters that are typically varying across patients are: age, sex, duration of diabetes, level of glycaemic control, fitness level etc. By allowing a classifier to focus on the dynamics of a single patient the problem of inter-patient variability is overcome and the only problem we are faced with is that of intra-patient variability.

Producing a classifier for each patient means that each classifier only sees data from a single patient. This introduces the problem of small data-sets since the data has to be partitioned per patient. In order to maximise the data available five-fold cross-validation was applied and the results were averaged over 5. Data-sets consisted of a maximum of 66 feature vectors, each vector consisting of four (or more for PCA) features. Since the length of the data-sets was short, the size (number of neurons) of the ANNs was kept small to avoid overfitting. A maximum of 5 neurons was used in the single hidden layer. For the same reason, the number of input ECG features was limited to 4 although more features were available. The preprocessing of the features included removal of outliers (using the mean ± 2sd criterion) and normalisation in the interval [-1 1].

The performance measures used to evaluate the performance of the classifiers were: accuracy, hitrate (sensitivity), false-alarm-rate, true-negatives-ratio (tnratio) and missed-hypos (false-negatives ratio). They are defined as:

- Accuracy = tp + tn / (tp+tn+fp+fn) *(1)*
- Hitrate = tp / (tp +fn) *(2)*

- False-alarm-rate = fp / (fp +tn) *(3)*
- Tnratio = tn / (tn + fp) (4)
- Missed-hypos = fn / (fn + tp) (5)

where *tp*, *tn*, *fp* and *fn* stand for: true positives, true negatives, false positives and false negatives respectively. Positive refers to hypoglycaemia while negative refers to euglycaemia.

Hitrate describes the number of arrhythmic traces classified correctly while false-alarm-rate describes the number of normal traces that were classified as arrhythmic (i.e. false alarms). Tnratio describes the number of normal traces classified correctly while missed-hypos describes the number of arrhythmic traces classified as normal, i.e. the number of hypoglycaemic events that were missed.

3. Results

Neural network classification results for the 11 subjects and for features RTc, Tampl, skew, kurt are given in table 1. The table contains performance measures for both the training and testing datafiles.

Table 1: ANN classification results (RTc Tampl skew kurt)

patient	TRAIN					TEST				
	accuracy (%)	hitrate (%)	false alarm (%)	tnratio (%)	missed hypos (%)	accuracy (%)	hitrate (%)	false alarm (%)	tnratio (%)	missed hypos (%)
202	89.82	100.00	3.53	89.26	0.00	71.52	73.85	24.29	74.29	24.75
203	93.78	98.46	10.90	89.10	1.54	87.50	90.46	26.67	73.33	9.54
204	77.08	100.00	0.00	77.22	0.00	58.33	62.00	37.00	58.67	34.00
208	88.30	94.86	3.50	90.33	4.80	66.00	71.00	29.00	66.00	26.67
212	83.50	100.00	0.00	79.00	0.00	77.66	85.45	16.67	83.33	12.73
216	79.15	93.89	29.26	70.07	5.88	76.82	85.61	57.00	39.33	14.13
220	83.89	97.78	0.00	83.89	2.22	65.19	70.87	16.67	50.00	27.14
223A	82.19	96.19	0.95	79.76	3.81	69.11	84.00	21.90	68.33	13.33
227	93.17	100.00	4.86	89.33	0.00	62.00	65.86	27.00	68.67	30.17
229	78.21	81.88	6.41	78.21	17.18	64.19	60.00	29.69	65.14	38.33
244	86.67	100.00	0.00	86.67	0.00	73.28	80.60	28.00	58.00	18.60
mean	85.07	96.64	5.40	82.99	3.22	70.15	75.43	29.72	64.10	22.67
std	5.79	5.38	8.63	6.59	5.10	8.36	10.41	10.95	12.17	9.58
min	77.08	81.88	0.00	70.07	0.00	58.33	60.00	16.67	39.33	9.54
max	93.78	100.00	29.26	90.33	17.18	87.50	90.46	57.00	83.33	38.33

To allow comparisons, Linear Discriminant Analysis (LDA) was also used for classification of the ECG records in normal and arrhythmic. LDA works by minimising the Mahalanobis distance [10] which is a multivariate measure of the separation of a data set from a point in space. The same ECG features that were fed into the ANN were used in LDA. Five-fold cross-validation was applied and the results were averaged over 5. Partitioning of the data into training and testing was exactly the same as for the ANN. The classification results for RTc, Tampl, skew, kurt obtained from LDA are tabulated in table 2.

Overall the ANN were superior to the LDA. The weakest point of LDA was the percentage of missed-hypos. This ratio was high even for the training data-set.

For both the ANN and the LDA, the hitrate was greater than the tnratio for both training and test results. This means that both classifiers were better in classifying hypoglycaemic records correctly than in classifying normal records correctly.

Table 2: LDA Classification results (RTc Tampl skew kurt)

patient	TRAIN					TEST				
	accuracy (%)	hitrate (%)	false alarm (%)	tnratio (%)	missed hypos (%)	accuracy (%)	hitrate (%)	false alarm (%)	tnratio (%)	missed hypos (%)
202	83.42	86.99	20.15	79.85	13.01	69.62	72.58	37.14	62.86	27.42
203	91.35	92.05	9.36	90.64	7.95	82.92	86.52	34.67	65.33	13.48
204	70.56	66.11	25.00	75.00	33.89	50.67	26.67	25.33	74.67	73.33
208	73.40	70.17	23.37	76.63	29.83	63.67	46.67	19.33	80.67	53.33
212	100.0	100.00	0.00	100.0	0.00	89.96	92.00	60.00	40.00	8.00
216	77.28	82.28	27.72	72.28	17.72	69.88	71.67	36.67	63.33	28.33
220	68.89	90.83	53.06	46.94	9.17	87.10	89.77	100.00	0.00	10.23
223A	64.90	76.86	47.05	52.95	23.14	56.25	84.76	65.28	34.72	15.24
227	65.95	51.14	19.24	80.76	48.86	44.09	39.33	41.33	58.67	60.67
229	79.68	87.18	27.82	72.18	12.82	36.33	45.00	64.49	35.51	55.00
244	87.78	97.78	22.22	77.78	2.22	83.44	90.68	61.33	38.67	9.32
mean	78.47	81.94	25.00	75.00	18.06	66.72	67.79	49.60	50.40	32.21
std	11.24	14.75	14.92	14.92	14.75	18.24	23.95	23.18	23.18	23.95
min	64.90	51.14	0.00	46.94	0.00	36.33	26.67	19.33	0.00	8.00
max	100.0	100.00	53.06	100.0	48.86	89.96	92.00	100.00	80.67	73.33

For some patients the test figures for false-alarm-rate (for both the ANN and the LDA) were extremely high while the accuracy and hitrate were also high. This can be understood by looking at equations 1-3 in the previous section. If in the data-set there exist very few *tn* compared to the number of *fp* the false-alarm-rate will be high. At the same time the accuracy and hitrate can be high if *tp* is much higher than *fp* and *fn*. If the data-sets were sufficiently large there would not be such a problem.

4. Discussion

Classification of ECG traces was carried out by MLP and LDA. Both are supervised classification methods but the way they work is not the same. The LDA is a linear

statistical classifier while the MLP is non-linear. Both types of classifiers had reasonable performance with the MLP performing better than the LDA. Longer data-sets will be necessary for obtaining a clearer picture of the differences in performance of the two classifiers.

The three feature combinations used had very similar performance when considering the average performance metrics. Looking at individual patients, the three feature combinations did not have systematic performance for the various patients.

For the given data-sets and input features, the performance of LDA cannot, because of its nature, be improved further. However, in the neural network case the performance could be further improved. Many different parameters are involved which have not been explored fully. By tuning the parameters better classification performance could be possible.

5. Conclusion

This paper focused on automatic feature extraction and classification of ECG signals for detection of the delayed ventricular repolarisation, a cardiac arrhythmia that is suspected to be introduced by hypoglycaemia. ECG features were used that describe both the duration and morphology of the relevant ECG components. Classification was carried out using multi-layer perceptrons and statistical classifiers (LDA). The two types of classifiers performed quite closely to each other, with the ANN being more accurate. The ANN can be further improved to achieve even better performance, because of the nature of its architecture being multi-parametric. It is suspected that the optimal neural network recipe has not been found yet.

Future work will focus on improving the ANN classification and also on experimenting with other feature combinations and probably the introduction of new features. Non-linear PCA may be used instead of PCA in order to, more effectively, reduce the dimensionality of the input space. Fuzzy logic will also be considered in order to offer transparency to the classification process.

Regarding data acquisition, data sets from adolescent and prepubescent type 1 diabetic patients will be used in the near future. The incidence of sudden death is highest in young people or those with a short duration of diabetes and these data may show more pronounced changes.

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Address for correspondence:

Charilaos Alexakis
School of Engineering, Sheffield Hallam University
City Campus, Sheffield, England, S1 1WB
Email: c.alexakis@shu.ac.uk