1. Introduction

The main purpose of remote Cardiovascular Disease (CVD) monitoring system is to create an alarm whenever an abnormality is detected during long-term monitoring. The system is mainly characterised from a limited number of available leads (i.e. channels) and, in particular, limited processing capabilities. The trade-off between accuracy and computational complexity is made to derive the best strategy for classifying Electrocardiogram (ECG) signal.

2. ECG & On-Sensor Classification

ECG trace comprises of five electrical waves (PQRST) that occur sequentially during a heart cycle, as shown in Fig. 1. They physically represent cardiac activities, which are of great clinical importance.

As the conventional implementation of remote monitoring system, ECG signal is captured and transmitted continuously to centralised server for complex signal processing and sophisticated classification. However, energy-constrained sensor cannot afford long-term signal transmission as battery would die soon. To maintain continuous monitoring, a new approach of low-complexity on-sensor processing has been proposed, which particularly focuses on the trade-off between accuracy and computational complexity for classification.

3. Feature Generation & Classifier

To quantify the electrical activities of the heart for classification, spectral energy of the specific waves/complexes of interest is considered as the primary feature. Discrete Wavelet Transform (DWT) is used as the signal processing tool to extract this type of feature, as it is well-known suitable for biomedical (non-stationary) signal analysis. The procedure of feature generation is shown below.

On classification side, five classifiers covering conventional and state-of-the-art learning algorithms are utilised to investigate various classification performance, namely Linear/Quadratic Discriminant Analysis, Support Vector Machine with Linear/Quadratic kernel and k-Nearest Neighbour as shown in Fig. 4.

4. Experimental Analysis & Results

Having set the practical limitation of number of participating leads (lead scenario) in remote system to be 5 as maximum, investigation of searching the most effective features is made. Following Fig. 5, the most optimal feature combination in each lead scenario for each classifier with the highest accuracy can be achieved. With these features, final accuracy can then be obtained.

Moreover, training of the classifiers is done off-line and any parameters achieved are used in on-line prediction. Hence, only the computational complexity involved in on-line prediction (thus power consumption) is considered. In particular, since the number of Support Vectors (#SVs) proportionally affects the computational complexity, two cases of SVM Lin and SVM Quad are considered: (1) highest accuracy without any concern of #SVs, which can exhibit significantly high complexity; (2) trade-off between accuracy and #SVs, which enjoys low complexity while retains comparative accuracy. In this way, comparison among classifiers can be made.

Finally, Fig. 6 illustrates the accuracy and computational complexity both along with the number of participating leads. Interestingly, LDA achieves comparative accuracy to the best classifier (SVM Quad) in lead scenario not less than 3, while maintains the lowest computational complexity compared to the other four.

5. Conclusion

To summarise, LDA is capable of providing comparative accuracy to the best performing classifier in normal/abnormal ECG classification, while achieves the lowest computational complexity. This renders LDA as a practically suitable classifier for on-sensor classification in remote CVD monitoring systems.

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