On the Trade-off of Accuracy and Computational Complexity for Classifying Normal and Abnormal ECG in Remote CVD Monitoring Systems

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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 composes 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**.

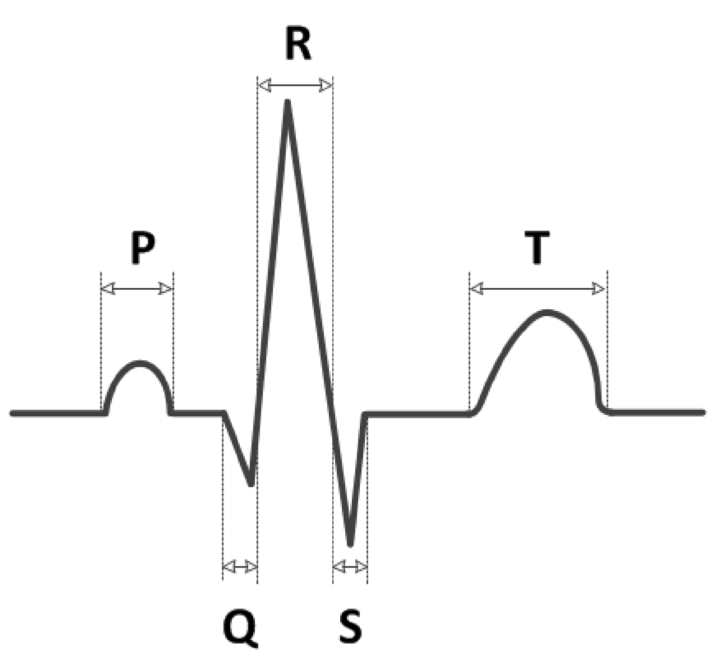


Fig. 1 ECG wave

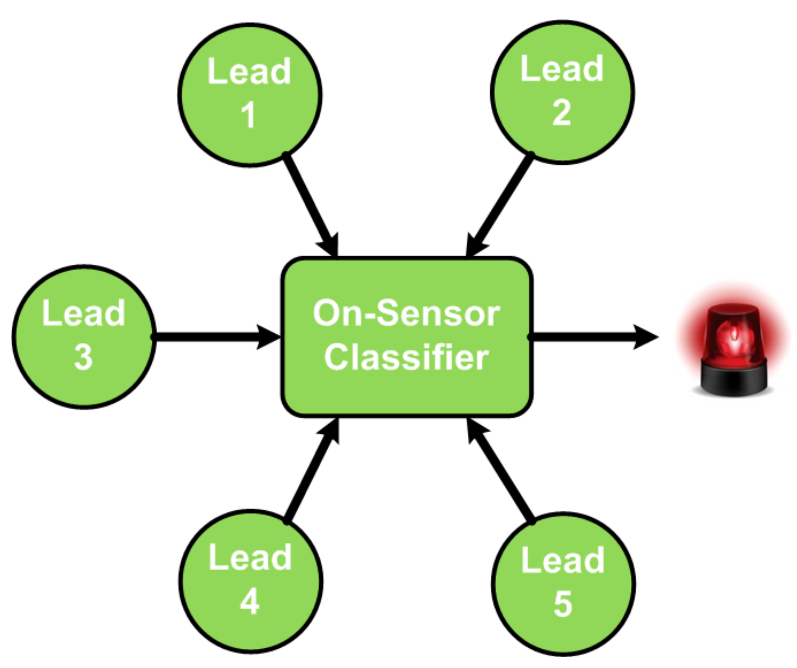
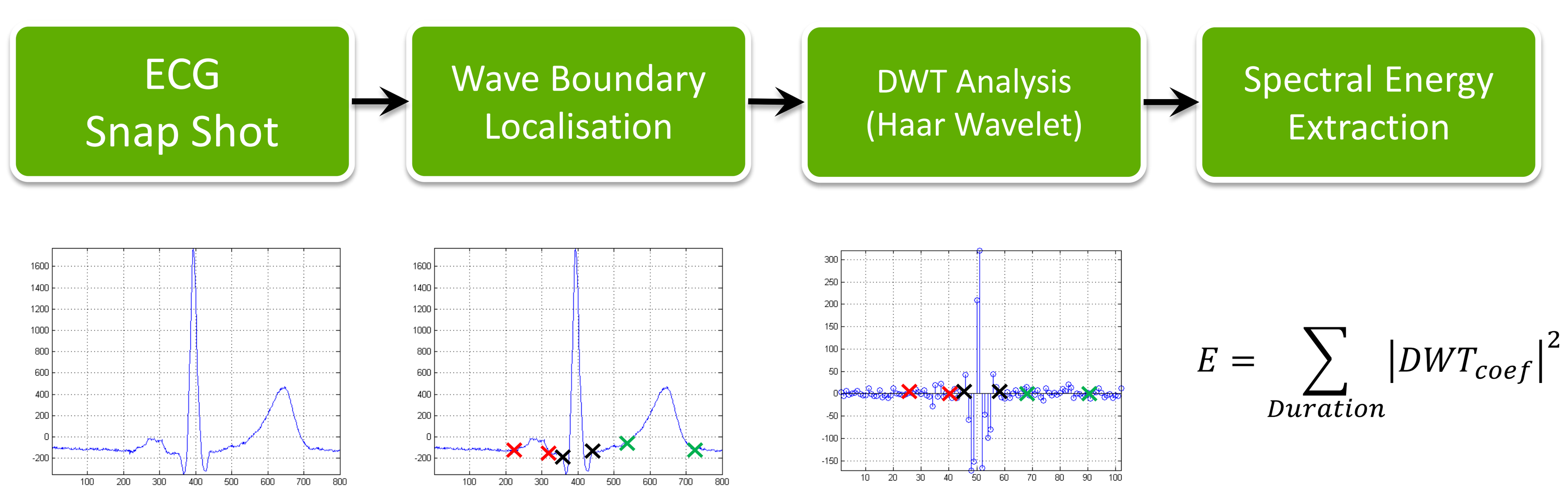


Fig. 2 On-sensor classifier

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 out soon**. To maintain continuous monitoring, a new approach of low-complexity on-sensor processing has been proposed, which particularly focus on the **trade-off** between accuracy and computational complexity for classification.

3. Feature Generation & Classifier

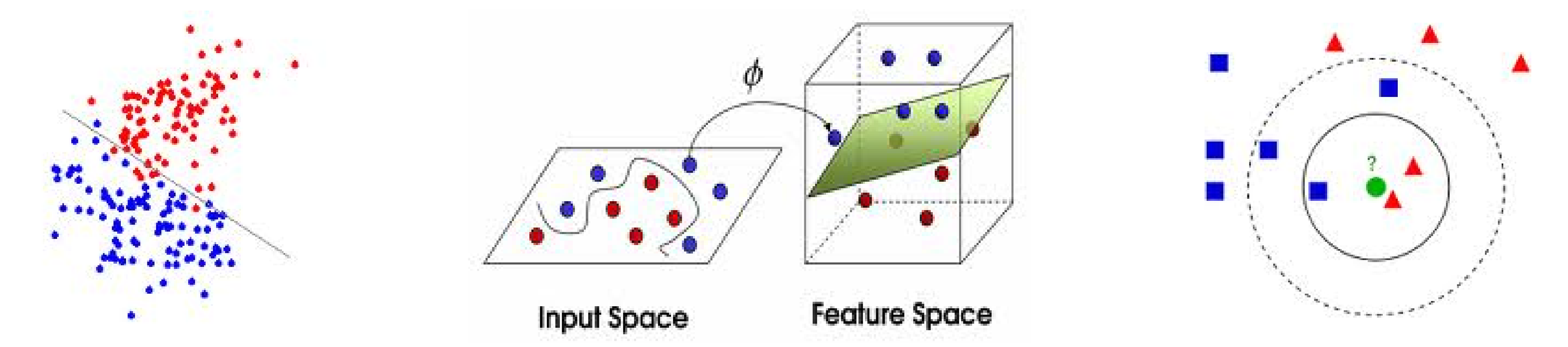
To quantify the electrical activities of the heart for classification, **spectral energy** of the specific waves/complexes of interest is considered as the primary feature. **Discrete Wavelet Transform** (DWT) is used as the signal processing tool to extract this type of feature, as it is well-known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



$$E = \sum_{Duration} |DWT_{coef}|^2$$

Fig. 3 Procedure of feature generation of spectral energy

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.



(a) LDA/QDA (b) SVM Lin/Quad (c) k-NN

Fig. 4 Five types of classifiers investigated

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.

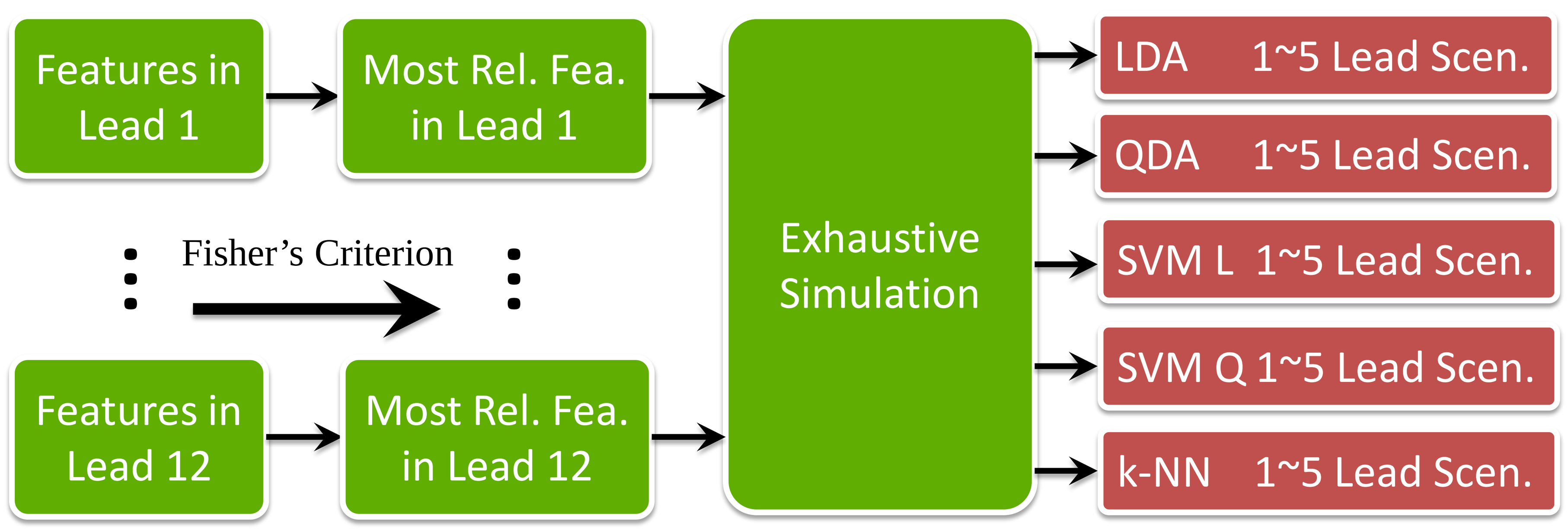
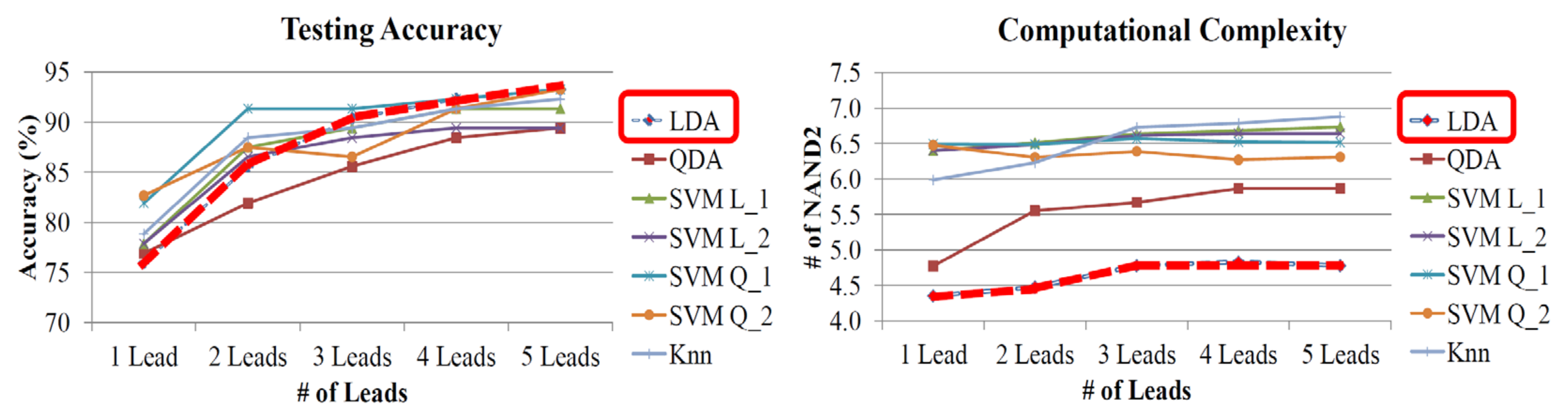


Fig. 5 Flow chart of obtaining the optimal feature combination in each lead scen. for classifiers

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.



(a) Accuracy V.S. # of Leads (b) Comp. Comp. V.S. # of Leads

Fig. 6 Accuracy and computational complexity for the five classifiers

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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