Resource-Aware ECG Analysis on Mobile Devices

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ABSTRACT
In this paper, we present our experience in developing and evaluating a resource-aware time-series analysis for ECG data on mobile devices using SAX (Symbolic Aggregate Approximation).

Keywords
Mobile ECG analysis, Time Series, SAX

1. INTRODUCTION
In recent years, the number of people who suffer from cardiovascular diseases has significantly increased [1]. A growing area of work is real-time monitoring systems using bio-sensors and mobile devices like PDAs/Smart Phones [9]. Studies such as [4] have shown that the key to effective analysis on mobile devices is to perform "resource-aware adaptation".

In this paper, we introduce our resource-aware adaptation [6] of Symbolic Aggregate Approximation (RA-SAX) and experimentally demonstrate its performance in respect to the battery life of a mobile device. We evaluate the use of RA-SAX in conjunction with K-Nearest Neighbor (K-NN) for classification purpose. In particular, we group and cluster incoming data streams, and adopt this method instead of individual incoming streams over K-NN.

2. PROPOSED FRAMEWORK: ECG CLASSIFICATION WITH RA-SAX
Our proposed framework consists of three elements namely, (*i*) SAX, (*ii*) Lightweight Clustering, and (*iii*) K-NN. These elements are attached to our resource-adaptation scheme that aims to intelligently control the classification parameters following the resource's state of the system.

Symbolic Aggregate Approximation (SAX) [6]: is a time series representation that has proved to be the state-of-the-art technique in time series representation and has been successfully applied in a number of applications [2, 3].

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Lightweight Clustering (LWC)[5]: is a cost effective clustering algorithm which is designed to cater for the requirements of ubiquitous, mobile and embedded systems which are bound to limited levels of resources. It is computationally efficient and specially structured to be adapted to streaming environments [8].

K-Nearest Neighbor (K-NN): is to find a group of *k* objects that are closest to the test object. The algorithm uses a distance metric to compute the distances between the test object and all the other samples and identifies the k closest samples.

Our choice of K-NN in this paper is partially due to the fact that SAX has been used with K-NN for ECG classification in a non-mobile setting [7].

2. RESOURCE-AWARE ECG ANALYSIS
Our resource-aware ECG monitoring framework, shown in Figure 1, is designed to provide local ECG analysis and classification on the mobile device (i.e. smart phone).

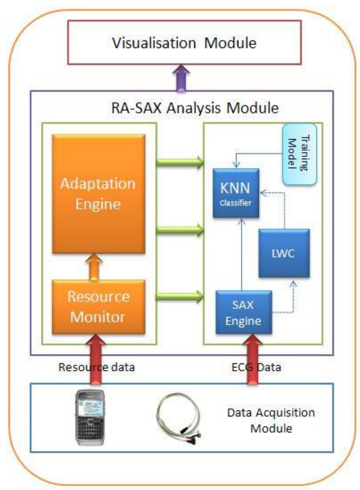

Figure 1. System Architecture

As depicted in Figure 1, RA-Analysis receives ECG signals from the data acquisition module, and feeds them to the SAX engine for SAX strings conversion. As the battery levels change, the Adaptation Engine controls the resource demands of SAX Engine by increasing and decreasing the alphabet and segment size. LWC, subsequently, clusters the converted incoming ECG signals, which reduces the data rate flowing to K-NN classifier. This is expected to minimize the cost of checking/classification for every instance. Finally, K-NN classifier performs classification and detects abnormalities either using each incoming signal or the cluster centroids, which are in the form of SAX converted time series.

3. IMPLEMENTATION AND EVALUATION

A prototype of the Resource-Aware ECG Classification has been developed on the Android Developer phone version 1.5. For the experiments, a total of 18 normal samples and 29 abnormal samples of ECG data were used.

Figure 2 shows a conspicuous decline in the classification time for each of the abnormal samples while reducing the number of segments from 300 to 100 and keeping the alphabet size constant. Figure 3 shows the battery drain for each segment size. Figure 4 shows the effect of clustering algorithm to the classification time.

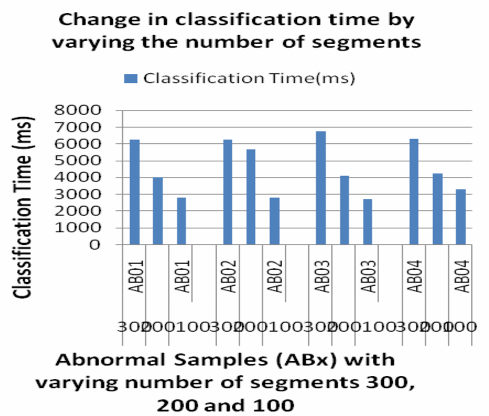

Figure 2. Classification time by varying number of segments

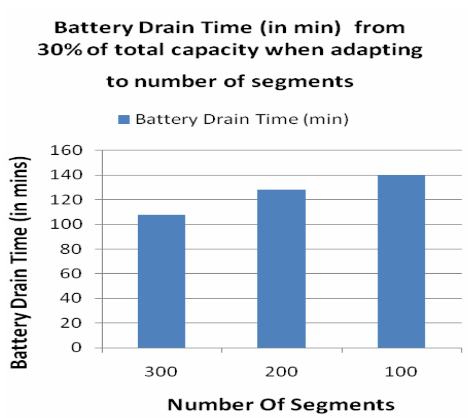

Figure 3. Battery drain by varying number of segments

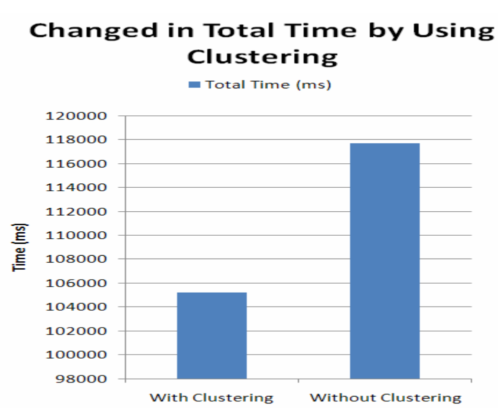

Figure 4. Classification time: with/without clustering

4. CONCLUSION AND FUTURE WORK

We have presented our resource-aware architecture for mobile ECG analysis using SAX, Lightweight Clustering and K-NN. Our experiments showed that the proposed approach is potentially effective to reduce the classification time, which eventually leads to a longer battery lifetime. For future work, we intend to measure the accuracy of the clustering model, and investigate a number of clustering algorithms to further improve the accuracy, classification time, and battery life of the mobile device.

5. REFERENCES

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