A Real-time Detection and Warning of Cardiovascular Disease LAHB for a Wearable Wireless ECG Device

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***Abstract*—According to the World Health Organization, an estimated 17 million people die annually due to cardiac disease, which accounts for 30% of the global deaths. Current studies on cardiac diseases indicate that 15% of the people have Left Anterior Hemiblock (LAHB), which ranks third after Right Bundle Branch Block (RBBB) and Left Bundle Branch Block (LBBB). To our knowledge, a reliably consistent disease detection and warning algorithm is not currently available for LAHB although various ECG morphologies can be monitored for real-time detection of LAHB. The objective of this research is to develop a real-time detection and warning of LAHB. The presented work describes the design of a weighted feature-based disease classification algorithm, which can be run in a resource constrained mobile environment for effective real-time diagnosis. The testing and evaluation of the algorithm indicates that it is able to detect LAHB with an accuracy of 95.3% and specificity of 100%.**

I. Introduction

Heart Disease is the single leading cause of death globally. Cardiovascular disease includes a group of disorders of the heart and blood vessels [1]. According to the American Heart Association, 17 million people die due to cardiac disease annually, and this figure is expected to grow to over 23.6 million by 2030. According to the survey and studies described in the reference paper [2], LAHB occurs in 3% to 5% of patients after an acute heart attack. The cardiac death rate is 4.9% in patients with LAHB.

Left anterior hemiblock occurs when the anterior half of the left bundle branch becomes defective, causing delay in the transmission of the signal along the upper and anterior part of the left ventricle [7].

Current diagnosis methodologies focus on the use of electrocardiograms (ECG) to detect cardiac diseases. Several algorithms have been developed to automatically detect various cardiac diseases based on ECG morphologies. While some ECG based disease detection systems store and process data offline, others use remote processing techniques. Existing resting ECG machines provide initial diagnosis based on ECG morphology. However, similar algorithms cannot be used for real-time diagnosis in a wearable system due to resource constraints. Power, processing and transmission requirements need to be considered when designing real-time diagnosis and warning algorithms.

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Here, we present our work on the development of a real-time ECG monitoring and disease detection algorithm to detect LAHB for wearable ECG devices. In our system, the patient wears a 3 lead ECG monitoring device, which is connected to a smartphone over Bluetooth. The mobile device runs algorithms for analysis and detection of LAHB. Upon detection, the smartphone based warning system generates a warning and sends it to all the stakeholders.

There are various approaches for analysis and diagnosis based on the ECG data. Some of the proven approaches [3-5] include the use of Support Vector Machines (SVM), Artificial Neural Networks (ANN) and k-nearest neighbor (kNN) to classify abnormal ECGs from normal ones. The diagnosis is usually based on standard rules for ECG diagnosis such as the one discussed by Becker [6]. In this work, we have adopted a novel method, combining multiple techniques for detection and classification. This method uses Support Vector Machines (SVM) and a weighted mathematical model, which is based on doctor feedback to increase the accuracy of diagnosis.

II. Left Anterior hemiblock

Left anterior hemiblock, which is also known as left anterior fascicular block (LAFB), is primarily identified by the presence of rS complexes in inferior leads (II, III and aVF), which results in left axis deviation. It also introduces the presence of qR complexes in leads I and aVL, which suggests LAHB along with an inferior wall myocardial infarction [7]. It is also commonly associated with anterior wall myocardial infarction. Isolated LAHB cases are scarce. The occurrence of LAHB after a myocardial infarction is quite high.

III. System Architecture

The diagnosis platform performs real time acquisition of ECG using a wearable device called 'Amrita Spandanam' [8], which is a low power, low weight wearable 3 channel ECG sensing device, developed by our research team. It is capable of recording up to 8000 samples per second and has a Bluetooth transmitter, which sends ECG data to a smartphone. The data obtained through the Bluetooth receiver is used to display, process and provide a warning and summary on an Android smartphone. The processing module performs the ECG feature extraction and LAHB detection. The ECG signal is preprocessed to avoid unwanted noises such as power line interference, baseline wandering and noise due to muscle movement. Also, since this is a wearable ambulatory device, the preprocessing includes motion artifact removal based on wavelet decomposition using a db2 wavelet filter. The feature extraction is performed on the preprocessed filtered ECG signal for increasing the accuracy of detection.

The processing module includes 5 sub-modules: 1) QRS axis calculation, 2) QRS detection, 3) QRS duration calculation, 4) R peak time calculation, and 5) qR and rS complex detection. The decision support module uses a mathematical model in order to arrive at a suitable decision. Upon the detection of a suspected LAHB condition, it sends out a warning message to the patient and the doctor from the smartphone. Further, the recorded ECG signal is stored on a server for offline diagnosis. Over time, the mathematical model may be altered dynamically based on data analysis, which spans multiple patients and temporal variations in the specific patient data. The work presented in this paper primarily deals with the processing and decision support modules. The complete system architecture is depicted in Fig. 1.

IV. METHODOLOGY

For the detection of LAHB, many ECG morphological feature criteria were considered based on literature and doctor feedback. Table I lists the features that differentiate LAHB signal from a normal ECG. For the training and testing of the algorithm, data from Massachusetts General Hospital/Marquette Foundation (MGH/MF) Waveform Database [9] was obtained from PhysioNet [9]. This database includes 250 patient recordings of about one hour in length were examined (13 male patients and 1 female patient, aged 50 to 80 years). ECG signals from lead I and lead II were obtained from the database, from which other leads were derived. Ten ECG datasets from MIT-BIH normal sinus rhythm [9] were used as the normal reference signals.

TABLE I. ANALYSIS OF LAHB FEATURES

	QRS Axis (deg)	QRS duration (ms)	R peak time (ms)	qR complex	rS complex
Normal	-30 to 90	70 - 100	< 45	Absent	Absent
LAHB	90	100 - 120	> 45	Present	Present

V. ALGORITHM

The LAHB ECG features are detected using an algorithm as shown in Fig. 2. Based on the result of the detection, a score is updated at each step. The scores are updated based on a predefined mathematical model, which is described in the next section. After the completion of ECG feature detection, the cumulative score is compared against a threshold to decide the likelihood of LAHB.

In addition to the SVM based feature detection system, a mathematical model is introduced, which helps in decision support. Let the LAHB ECG features be denoted as X_1, X_2, X_3, X_4 and X_5. A corresponding weight W_1, W_2, W_3, W_4 and W_5 is assigned depending upon its prognostic significance in the detection of LAHB. The weights are decided based on the inputs from the doctors. The variables X_i and the values of W_i are defined as follows.

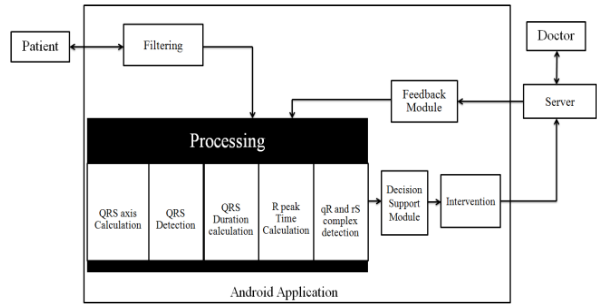

Fig. 1. System architecture showing different modules for the detection and warning of LAHB occurrences.

X_1 – Presence of qR complex in leads I and aVL
X_2 – QRS duration
X_3 – QRS axis
X_4 – Presence of rS complex in leads II, III and aVF
X_5 – R peak time

$W_1 = 0.3$
$W_2 = 0.2$
$W_3 = W_4 = W_5 = 0.166$

It is to be noted that X_1 and X_4 take discrete values (1=true, 0=false), while X_2, X_3 and X_5 are z-score normalized values of the corresponding ECG feature. Feature X_1 has a greater importance in the prediction of LAHB, and hence the weight of X_1 (denoted by W_1) is assigned 0.3. Similarly, feature X_2 has minor importance compared to X_1, but is considered to be more important compared to other features, and hence its weight $W_2$is assigned 0.2. The remaining features have an equal prognostic significance, and hence their weights are assigned the value 0.166. We define a utility function, U, which is calculated using (1), as given below.

$$U = \sum_{i=1}^{5} WiXi \qquad (1)$$

A threshold limit is applied to the utility function to decide the likelihood of LAHB. In order to find out the threshold, the existing LAHB and normal sinus rhythm data were used to calculate the corresponding utility function (U) values.

VI. IMPLEMENTATION

The algorithm was implemented and tested in Matlab R2013a. The algorithm was validated using the PhysioNet ECG database [9]. For the QRS duration calculation, the QRS complex was detected using the Pan-Tompkins algorithm. The R wave amplitude and location was calculated using the Pan-Tompkins algorithm and was used later to detect the S wave and Q wave for the QRS duration calculation and the R peak time calculation. The Q wave was detected by finding the local minimum point within the 50ms points from the R wave. The S wave was located by finding the local minimum value from the 100ms after the R wave. The QRS axis was calculated using the ECG signals from lead I and aVF.

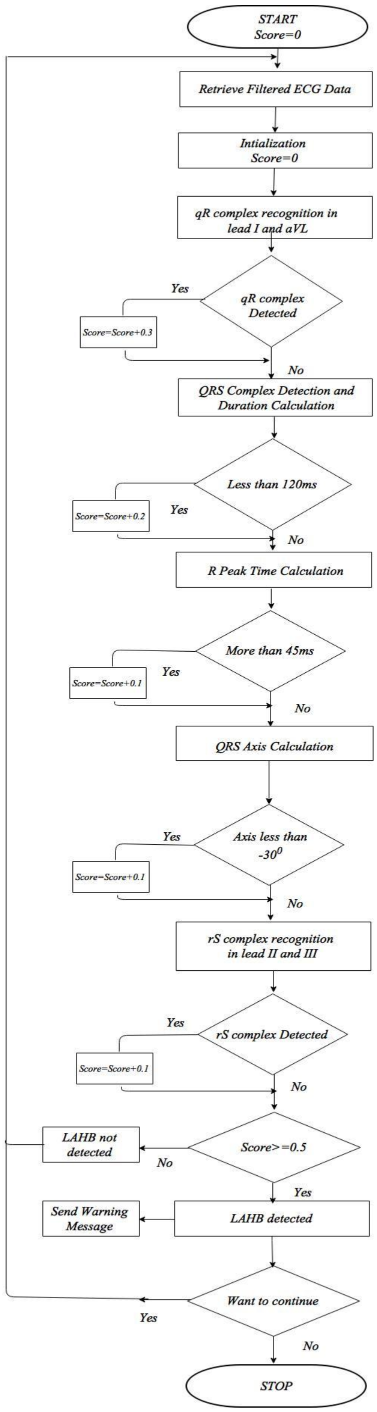

Fig.2. Flow chart of the algorithm for LAHB detection.

The qR and rS complexes were detected using an SVM based classifier. The SVM classifier has the advantage of high performance even with a smaller learning data than any other classifier and has a faster implementation [5]. The SVM classifier was implemented in Matlab using libsvm 3.20. The SVM was trained using 18 training sets and was then tested using the test data while accuracy was observed. Table II and Table III list these observations. The utility function based classification was also implemented in Matlab, which took the inputs from the above modules and used the mathematical model to arrive at a decision.

VII. EVALUATION

For the evaluation of the algorithm, MGH/MF and MIT-BIH database were used. The ECG signals from both the databases were downloaded and read using the WFDB toolbox for Matlab. A set of 32 ECG signals were used for training and testing: 14 LAHB signals from the MGH/MF database and 18 normal ECG signals from MIT-BIH normal Sinus rhythm database. We evaluated the system in three parts. First, the QRS measurements, including QRS axis, duration and R-peak time, were evaluated to identify if these measures can be used for an accurate classification. Second, we evaluated the performance of the SVM classifier for qR and rS detection. Finally, the utility function-based algorithm was evaluated to classify LAHB from the normal signals for different threshold values.

By statistically comparing the normal ECG signals and LAHB signals, it was observed that QRS axis, QRS duration and R peak time alone could not be used as a classification criterion.

We used an SVM classifier to differentiate LAHB signals having qR and rS complexes from normal signals. The performance of the SVM classifier was measured separately for qR signals and rS signals. We split the whole dataset of 14 LAHB and 18 normal sinus rhythm data into 3 sets: A, B and C, each containing 7 normal and 7 LAHB signals. In order to classify qR, we used Lead I signals from LAHB and normal sinus rhythm to train and test. A threefold cross validation was done. The accuracy, specificity and sensitivity of SVM for classifying qR from normal signals are summarized in Table II.

For rS complex classification, lead aVF was used from LAHB and normal sinus rhythm databases. Similar to the qR test, 7 ECG signals from LAHB and the normal database were used during each test. A threefold cross validation was performed. The results of the SVM classifier for rS detection are summarized in Table III. It can be noted that the average detection accuracy of the SVM was above 80% in both qR and rS signals. The specificity of the classifier was 100% in the former and 85% in the latter case. The utility function was also evaluated using the above sets A, B and C. For each data in the set, all the five LAHB features were measured. Values for X2, X3 and X5 were z-score normalized while X1 and X4 values (0 or 1) were used to compute the U value according to equation (1). The computed U values were normalized between 0 and 1. A threshold limit T was then used to classify a given dataset as LAHB or normal. Table IV summarizes the performance of the utility function for three datasets with the value of T=0.5. Table V shows the results, when the value of T is 0.3 on the same 3 datasets.

TABLE II. SVM QR COMPLEX DETECTION RESULTS USING LEAD I SIGNALS.

Test Set	Accuracy	Specificity	Sensitivity
Set A	92.86 %	100%	83.33%
Set B	78.57%	100%	57.14%
Set C	85.71%	100%	66.67%
Average	85.73%	100%	69.13%

TABLE III. SVM RS COMPLEX DETECTION USING LEAD AVF.

Test Set	Accuracy	Specificity	Sensitivity
Set A	78.57%	75%	80%
Set B	92.87%	100%	83%
Set C	71.43%	80%	50%
Average	80.97%	85%	71%

TABLE IV. PERFORMANCE MATRIX OF THE UTILITY FUNCTION FOR DIFFERENT DATASETS WITH T=0.5.

Utility function performance matrix (T = 0.5)			
	Accuracy	**Sensitivity**	**Specificity**
Set A	93%	86%	100%
Set B	100%	100%	100%
Set C	93%	86%	100%
Average	95.3%	90.7%	100%

TABLE V. PERFORMANCE MATRIX OF THE UTILITY FUNCTION FOR DIFFERENT DATASETS WITH T=0.3.

Utility function performance matrix (T = 0.3)			
	Accuracy	**Sensitivity**	**Specificity**
Set A	93%	100%	86%
Set B	93%	100%	86%
Set C	86%	100%	71%
Average	90.7%	100%	81%

On an average, the utility function had an accuracy of 95.3%, sensitivity of 90.7% and specificity of 100%, when the threshold was 0.5. At T=0.3, though the sensitivity was 100%, the specificity reduced to 81%. In case of disease detection, since the aim is to minimize false positives, T = 0.5 was considered to be the optimum threshold value. Our team is currently implementing and testing this algorithm on Smartphones.

VIII. CONCLUSION AND FUTURE WORK

A design and implementation of the algorithm to detect and warn about left anterior hemiblock is proposed and evaluated here. We may conclude that a combination of the QRS parameter calculation, the SVM based qR and rS detection, and the utility function based on the weight of ECG features can be used in order to efficiently classify LAHB from the normal ECGs. The results from the present work are quite encouraging. We hope to develop suitable real-time algorithms for detection of other cardiovascular diseases as well. We also plan to conduct a large field trial in order to evaluate the efficacy of the current algorithm, when run in a mobile resource constrained environment.

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