QRS axis based classification of electrode interchange in wearable ECG devices

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ABSTRACT

Wearable ECG monitoring is becoming a convenient way for patients as well as doctors, in tracking and diagnosing heart diseases among large population in rural areas. Wearable ECG devices along with the smartphones are used to capture and transmit ECG data to hospitals where medical practitioners diagnose and make suitable interventions. ECG electrode cable misplacement poses significant challenge when untrained population is the end-user. We present a real-time lead misplacement detection system for Mason-Likar lead configuration to provide immediate feedback to patients. It reduces chances of pseudo-disease diagnosis as well as the need for technicians to confirm the validity and quality of captured ECG data. The field test results show that six different Mason-Likar electrode misplacement can be detected and differentiated from a normal one with a confidence value p=0.05.

Categories and Subject Descriptors

J.3 [**LIFE AND MEDICAL SCIENCES**]: Medical information systems

General Terms

Algorithms, Experimentation

1. INTRODUCTION

Wearable ECG devices are becoming popular and relevant, especially in remote health monitoring in rural areas in developing countries. In this scenario, ECG measurements are usually taken by primary health workers (PHW) or patients themselves and then sent for professional diagnosis to doctors in urban hospitals.

Hede et al. [5] and many other studies have concluded that about 2% to 3% of all ECG readings taken in clinical setting suffer from lead misplacements and other human errors. Garcia et al. [3] describes most of the lead misplacements in a clinical setting. Remote health monitoring applications would suffer from these errors more, given the fact that primary health workers or patients would not have received professional training. In order to give the patients or the PHW an instant feedback about the quality of the recorded ECG, the signal needs to be analysed for basic defects such as, zero leads, electrode contact loss, misplaced electrodes and electrode reversal. In case of lead reversals, providing a real-time feedback about the validity of ECG to the patient through his smartphone would help him change the leads and place it in the correct position. This will in turn prevent recording incorrect ECG data, which otherwise would only be detected by the doctor or a technician, or in the worst case lead to a pseudo-disease diagnosis.

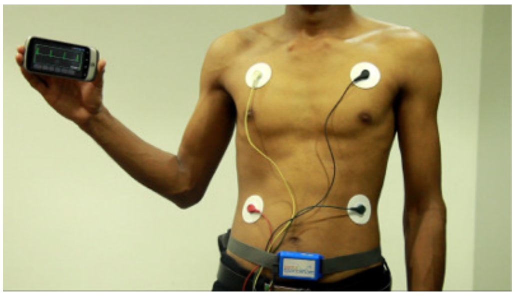

Figure 1: Wearable ECG device along with the 4 electrode cables connected according to Mason-Likar placement. The smartphone shows the live ECG data.

Such unassisted electrode placements may result in electrode misplacements thereby leading to false positive disease morphologies. In case of resting ECG measurements, many techniques exists such as those discussed in [7, 5, 2]. The wearable ECG devices use a different placement of electrodes, the Mason-Likar configuration, which allows the patients to continue his activities even while the ECG is monitored. This change of position of electrodes is accompanied by characteristic changes in the ECG morphology and along with it challenges in detecting any misplacement. A mobile device that gathers the data from the wearable ECG device should be able to provide instant feedback to patients, which tells the patients to check the misplaced electrode cables. In our knowledge, such a system is not present which is able to differentiate six different lead misplacements including all the four leads: LA, LL, RA and RL.

We present a QRS axis measurement based algorithm to

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MOBIHEALTH 2015, October 14-16, London, Great Britain

DOI 10.4108/eai.14-10-2015.2261647

Table 1: **Characteristics of ECG morphology in Standard and Mason-Likar lead placement.**

Placement	RA-RL	LA-RL	Dual
Standard ECG	$II = 0, -I$	$III = 0, aVR \approx -II$	$I = 0, -III, aVF \approx III$
ML ECG	$-I$	$aVR \approx -II$	$-III, aVF \approx III$

detect and differentiate lead misplacements. Using this algorithm, the mobile device will be able to provide immediate feedback to patients. We foresee that this will have multiple advantages for the patients as well as doctors. It will reduce the need for technicians and doctors to provide feedback on the validity and quality of the captured ECG data. Also, upon getting immediate feedback, the patients can themselves correct the lead misplacements. We expect that, this will result in lesser visits to hospitals for the patients and reduced load on technicians.

2. RELATED WORK

Batchvarov et al. [1], in their study, has analyzed all the possible electrode misplacement along with their consequence on the resulting ECG morphology. From a medical perspective this is one of the most extensive studies. Various methods as suggested in [6, 5, 7, 2] have been used to detect lead misplacement automatically. Some of the techniques include using ANN (Artifical Neural Networks), SVM (Support Vector Machine) and decision tree to train and detect misplacement morphology. Though these techniques are effective, they are primarily designed to work with standard ECG electrode placement. Since the wearable devices require the use of ML configuration, it is noted that it fails in many cases, due to the inherent changes in ECG signal brought about by ML.

Han et al.'s [4] general algorithm that detects misplacement in both standard and ML ECG signals have not considered right leg electrodes. The current literature also lacks a detailed study on the effects of right leg electrode misplacement. We also present some of our observations related to right leg electrode misplacemnt in a separate section below.

3. ML VS. STANDARD ECG

The detection of ECG electrode misplacement makes use of the characteristic differences in morphologies when the electrodes are reversed. The various ECG features that shows difference include amplitude, phase and polarity. In some cases, the lead amplitude becomes zero, in some others QRS becomes equiphasic and in few others certain leads show high similarity. Mason-Likar lead placement changes these characteristic features too when compared to standard ECG signal. In comparison, some of the evident effects are: 1) Reduction in lead I amplitude and 2) Increase in lead II amplitude. Hence, the measurement of various parameters used for lead change detection in standard setup is different compared to ML system. We present our observation about these differenced in Table 1.

It may be noted that there are not many changes in case of LA-LL, RA-LL and LA-RA. The differences are more pronounced when RL is involved in the interchange. In standard lead placement, lead I, II and III are zero potential in case of Dual, RA-RL and LA-RL interchange respectively. But these signs are absent in case of ML. Fig 2 shows leads I, II, III of ML ECG signal having RA-RL interchange.

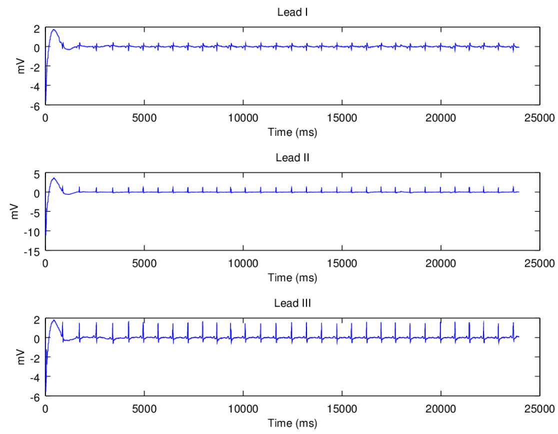

Figure 2: Leads I, II and III when RA and RL are interchanged. In standard lead placement, lead II should be zero potential, while in ML, it is having high amplitude.

4. SYSTEM

We use a 3 lead (4 electrode) wearable ECG device, developed by our research group, to capture ambulatory ECG from patients. Electrode cables are placed according to the Mason-Likar placements, i.e., arm electrodes (RA and LA) at the infraclavicular fossae and the leg electrodes (RL and LL) on the lower abdomen. This is aimed at recording the ECG even while the patients are involved in any activity. Fig 1 shows a subject with ECG device worn as a belt and the 4 electrodes placed on the torso using contact electrodes. The wearable is connected to a mobile device over bluetooth which runs an Android app. This app can automatically trigger the wearable to start and stop the capture at regular intervals, or when the patient is ready for the capture. The captured ECG signal is then automatically sent to a hospital server over data network, where a doctor can later analyze the signal and provide necessary feedback to the patient, if required. The lead misplacement algorithm runs on the Android smartphone and interfaces with the wearable device. In case of detection, the phone would initiate an alert to the patient, before sending the data to the hospitals. In this study, we consider six major electrode misplacements: LA-LL, RA-LL, LA-RA, RA-RL, LA-RL and Dual (LA-LL and RA-RL together) and their detection possibility from QRS axis measurement.

5. METHOD

5.1 Data Collection

We obtained ECG data from 7 healthy subjects in the age group of 23-37 with no history of heart diseases. Readings were taken by placing the electrodes in the correct Mason-

Table 2: QRS axis measurement: normal and six different electrode misplacements.

QRS Axis	Normal	LA-LL	RA-LL	LA-RA	RA-RL	LA-RL	Dual
Avg	75.1	24.1	147.6	105.5	123.9	55.7	53.5
$(\pm Sn * t)$	(± 1.4)	(± 5.5)	(± 5.1)	(± 2.2)	(± 10.2)	(± 5.8)	(± 9.8)

Likar configuration for 20s. An electrode reversal will have time indepedent effect on the ECG morphology and hence 20s of data is sufficient for analysis. The Android app, interfaced with the wearable device captured and stored the data. The electrodes were then manually misplaced, one at a time and the procedure repeated for all the six different lead misplacements that we consider here. The stored data was later analyzed using Octave. Since the wearable device provided only lead I and lead II data, we derived other leads from the available ones using mathematical transformations. The average of ten R peak amplitudes of lead I and aVF was used to calculate the QRS axis. The QRS axis measurements for all the seven readings, 1 normal and 6 misplaced electrode configuration was compiled and analyzed for all the 7 subjects. Table 2 summarizes the data.

5.2 Analysis

QRS axis for different lead configurations is shown in Fig 3. Each bar represents standard error of means (SEM) with p=0.05 (Average $\pm Sn * t$). QRS axis of normal ECG is 75.079 ($\pm$1.38) and is statistically different from all other lead misplacement configurations. It may be noted that there is significant difference between LA-LL, RA-LL, LA-RA and RA-RL. Therefore, these four misplacements can be differentiated between themselves and also from the normal placement. RA-LL, LA-RA and RA-RL showed significant right axis deviation too. The QRS axis for LA-RL and Dual are 55.66 ($\pm$5.81) and 53.46 ($\pm$9.81) respectively. Though these two can be differentiated from correct placement, there is overlap between their values, and hence we could not categorize whether the electrode misplacement is due to LA-RL or Dual. Hence, we have six categories for classifying any given ML ECG signal based on QRS axis.

6. ALGORITHM

Based on these results, we propose a QRS axis based classification algorithm. The ECG signal from the wearable device is transmitted to the mobile device over bluetooth. This signal is filtered using a high pass, low pass and notch filter to denoise the signal and remove baseline wandering. The filtered data consists of lead I and lead II data. Other four leads (III, aVR, aVL and aVF) are then derived from the available data. The average of ten R peaks each in lead I and aVF is used to calculate QRS axis. The R peaks are detected using a dynamic thresholding function. Based on the calculated QRS axis, we could classify the lead misplacements into six categories: Normal (75.1 ($\pm$1.4)) , LA-LL (24.1 ($\pm$5.5)), RA-LL (147.6 ($\pm$5.1)), LA-RA (105.5 ($\pm$2.2)), RA-RL (123.9 ($\pm$10.2)), LA-RL or Dual (53.5 ($\pm$9.8)). The last two could not be differentiated and hence part of the same category. Our team is currently implementing this algorithm in Android smartphone for larger field trial.

7. CONCLUSION

The use of QRS axis as a measurement to detect and classify electrode misplacements in Mason-Likar configuration

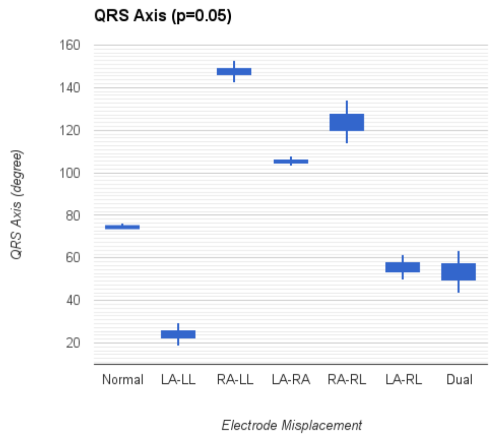

Figure 3: QRS axis measurement for normal and 6 electrode misplacements. The bars are based on SEM (p=0.05, N=7).

shows promising results. Currently, the proposed smartphone based analysis and lead misplacement detection system can classify 6 different lead misplacements in ML configuration and provide instant feedback to patients. We have also presented our observations on the effect of ML placements on ECG morphology which shows that there is significant deviation from the standard resting ECG readings. Coupled with these two, we expect that further research in the direction of feedback systems for cardiac patients will help expand the use of wearable health monitoring devices in rural areas.

8. FUTURE WORK

Further research needs to be done to analyze the correlation between ECG morphologies in lead misplacements and disease conditions. This might require a larger study group, including healthy and non-healthy high risk cardiac patients.

9. ACKNOWLEDGEMENT

We would like to extend our deepest gratitude to our Chancellor Sri Mata Amritanandamayi Devi for guiding, inspiring and supporting us in carrying out research for betterment of healthcare delivery among rural population. We also acknowledge the contribution of volunteers who supported us in the data collection process.

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