Pattern Classification of Time Plane Features of ECG Wave from Cell-Phone Photography for Machine Aided Cardiac Disease Diagnosis

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Abstract— **This article reports a robust technique for extracting time plane features of Electrocardiogram (ECG) from digital images of ECG paper strips. We concluded this article reporting performance evaluation of the system developed for machine aided cardiac disease detection. Mostly paper based ECG recordings are used in developing countries and digital photographs of different leads could easily be taken and sent with a mediocre cellular phone set. Apart from extracting the features, the proposed system detects cardiac axis deviation and diagnose if Left or Right Bundle Branch Blockage (LBBB or RBBB) is present while fed with the digital photographs of different leads of ECG strips. Pre-processing of the low-resolution images involves background grid line noise removal, adaptive image binarization by Sauvola's method and Bresenham's line joining algorithm to link the ECG signature, if broken. Pattern extraction mainly delineate the time plane features like P wave, QRS complex and T wave using water reservoir based pattern recognition techniques and Discrete Wavelet Transform (DWT). Cardiac axis deviation detection is done by checking the overall voltage levels of QRS complexes of lead I, II and III. Having the knowledge of cardiac axis completes the requirements to comment on the cardiac blockage like Left or Right Bundle Branch Blockage (LBBB or RBBB). Thus, the proposed algorithm is primarily developed for machine aided diagnosis of LBBB or RBBB from the digital photographs of ECG paper strips.**

Keywords- Bresenham Line Joining Algorithm, Cardiac Axis Detection, ECG Feature extraction, LBBB and RBBB, Sauvola Binarization technique, Water Reservoir feature.

I. INTRODUCTION AND PAST WORK

Heart diseases are the major silent killers of people for both developed and developing countries. "Today, one of every 2.6 Americans will die of some cause related to their heart," as reported by Columbia University Medical Center [1]. Also, report from Center for Disease Control and Prevention informs in their "preliminary data for 2011" that heart disease is the leading cause of death in the whole of United States [2]. Developing countries like India, Pakistan or Bangladesh show almost same trend of statistics on human death due to cardiac diseases. Again the developing countries are in serious dearth of qualified cardiologists, especially in rural parts of these countries. Hence an automated cardiac diagnosis system is needed for preliminary heart monitoring for common people. Of different heart diseases cardiovascular diseases (CVDs) prevail and ECG is the most prevalently used diagnostic aid for CVDs. Hence we chose to work on ECG data. One advantage of an expert ECG classifier system is that it will serve a large number of users in day-to-day self cardiac monitoring. Clicking images from ECG strips and feed those to an automated disease classifier are user friendly and hassle free. It classifies various patterns occurred in different leads of ECG records and subsequently diagnose disease like LBBB or RBBB. Here a small numbers of features are carefully chosen to get the best result.

In last couple of publications we have exclusively focused on digital images of ECG strips [3,4]. Many articles report a wide spectrum of applications of different pattern classification and machine learning algorithms on ECG signal but ECG strip records are rarely considered for machine aided clinical diagnosis system development [5-8]. It is easy to take the snap of one's ECG strips with basic PDA camera and use those images as the input to our algorithm for instant diagnosis. Thus this form of ECG records attracted our research interest and we analyzed with different techniques and perspective for classification task. A few approaches employ multi-layered perceptron network for classification of bundle branch blocks but they are not enough for image ECG data of paper based ECG strip [9]. Machine learning methods, support vector machine and extreme learning machine have been tried to classify four different types of heart beats including LBBB, RBBB along with premature ventricular contraction [10]. But most pattern recognition techniques are either applied on electrical signal of ECG or good quality images (scanned copied). The novelty of our approach lies in the fact that we have selected low quality photographs of ECG strips taken with cell-phone cameras. An advantage of using cell-phone photographs is that these photographs of ECG records can readily be sent to a remote server for analysis.

II. ECG TIME PLANE FEATURES

A typical ECG system has 12 leads which are placed on hands, feet and chest of human body to record the electrical actions of the heart. Those electrodes give traces of ECG signature representing the electrical activity of human heart.

In Fig. 1, different time-plane features of an ECG wave are shown [3]. The first major feature is P wave, generated when the depolarization wave propagates from Sino Auricular node (SA node). QRS complex is the most important time plane feature which represents the depolarization of ventricles. After that when the ventricles re-polarize, it generates T wave and as the ventricular re-polarization takes longer time than depolarization, T wave duration is longer than that of QRS duration. Some time-intervals of clinical importance are measured and interpreted, namely PR interval, QRS width & ST interval. Another important component of ECG wave is its ST segment.

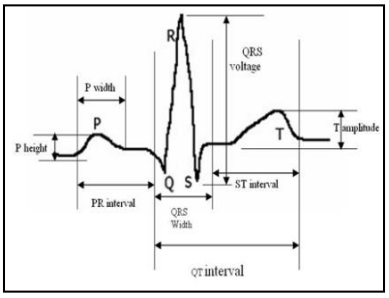

Figure 1. Different time plane features of ECG

QRS complex is an interesting research topic due to its high information content. Apart from the depolarization and re-polarization activities of cardiac muscles, we can calculate the direction of cardiac axis useful for diagnosis of some diseases.

The cardiac axis is the average direction of the depolarization wave of the cardiac muscles. In Fig. 2 we have schematically shown the required lead vectors and the normal range of the cardiac axis with the right axis deviation (RAD) and left axis deviation (LAD). The normal cardiac axis direction typically ranges from the -30° to +90° (measurement convention is clockwise from the direction of Lead 1 which is at 0°). But in case of RAD, as shown in the Fig. 2, the resultant cardiac vector deviates from the normal range and falls in the range of +90° to +180°. On the other hand, LAD occurs when the cardiac vector falls in the range of -30° to -90°. The fourth quadrant is termed as no man's land and the cardiac axis does not fall in that quadrant except in some special cases [11].

Features of axis deviation: LAD: In case of normal cardiac axis, say +60°, we find strong QRS complex in lead I, II and III. As the cardiac axis moves towards the aVL, the lead III and lead II generates significant S waves and as the cardiac axis moves towards lead I, this lead shows a strong R wave. When the cardiac axis reaches exactly the aVL which is perfectly orthogonal to lead II hence lead II eventually becomes iso-electric while the R and S wave of lead II are equal in magnitude. Now when the cardiac axis moves further in the abnormal region, the QRS complexes of lead III and lead II become overall negative and that of lead I becomes positive. RAD: On the other hand, when the cardiac axis moves beyond the aVF, towards unsafe RAD region, QRS complex of lead I becomes overall negative but in lead III & II QRS complexes remain strongly positive.

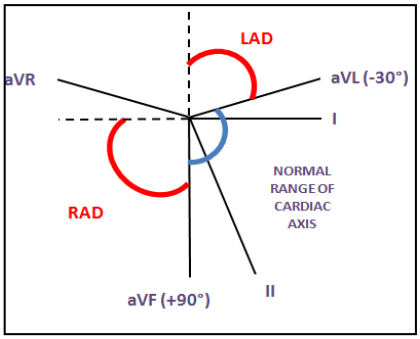

Figure 2. Cardiac Axis Deviation detection

In Fig. 3 an exclusive feature of QRS complex to prompt the presence of BBB is shown. For LBBB we find 'M-pattern', as shown in Fig. 3, in leads V6, V5 or V4 and for RBBB the 'M-pattern' occurs in leads V1, V2 or V3. M pattern is basically the pattern of QRS complex where it looks like the English alphabet 'M' . In Fig. 3 the M patterns have occurred in Lead V2 and V3. Although these are the sufficient features to detect LBBB or RBBB usually LAD is found in the case of LBBB and RAD for RBBB [12].

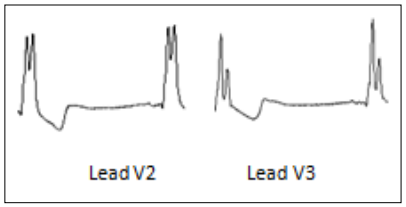

Figure 3. Single cardiac cycle with 'M' pattern in QRS. ECG of patient 204(0425), PTB database

III. Methodology

Now we briefly discuss the process-flow which involves filtering of noisy images of ECG strip, subsequent feature extraction and decision making. The entire system can be broadly categorized into three sub-modules. Image pre-processing, features delineation from binarized image and baseline and axis deviation detection. However the logic behind the final decision making module of LBBB and RBBB diagnosis is somewhat clear after the last section. A part of the procedure is repeated below.

A. Image pre-processing: The photographs of ECG strips taken with ordinary cell-phone camera are not only of low resolution but also perturbed with different kinds of noise. The insufficient light, blurring, shadows of the camera etc are the sources of noise. Thus the pre-processing of image must involves techniques eradicate the noises. We removed the background grids by RGB color thresholding technique to get ECG trace with white background

[Fig.4]. Sauvola's approach is used to determine local threshold for binarization of images [13]. The reader can observe the cases where the images are perturbed with blurring, shadows and insufficient light in Fig. 4. The formula for threshold T(x,y) is given by:

$$T(x,y) = m(x,y)[1 + k(\frac{s(x,y)}{R} - 1)]$$

where m(x,y) is the local mean, s(x,y) is the local standard deviation, R is the dynamic range of standard deviation and k is a positive constant [14]. We got optimum result by keeping the k value in the range of 0.35 to 0.42. Bresenham line join algorithm is used to complete the ECG signatures if it is broken during binarizaion.

B. Featres deleniation from binarized image : To delineate the QRS complex, we compute local maxima, applying second order derivative. This algorithm identifies two consecutive maxima that may be considered as R peaks. We did wavelet analysis using wavelet 'db2' to decompose the ECG signal into lower and higher freqency components. The thoretical logic behind choosing a mother wavelet is that if the signal under consideration has a consistent behavior with n-th degree polynomial within a certain interval, to have wavelet coefficient of zero on that interval we need to use a wavelet with vanishing moments N. Now to find the QRS complex more accurately, a class of feature called water reservoir was used for labeling the crest portion as R and the trough portions as S or Q. The idea is like the two dimensional equivalent of water reservoir. Water falling on a concave region will be stored as if in a reservoir [15,16]. The QRS regions will hold much water from above or below. Features like area, width or depth of reservoir can be used for classification.

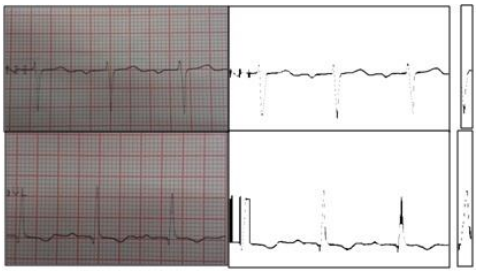

Figure 4. Two different sample photographs and the out put after the pre-processing like denoisification and binarization. The right-most two images are the delineated QRS components.

By measuring the water reservoir size we locate the start and end point of the QRS complex, depth of the Q or S wave and height (voltage) of R wave etc. The QRS, RS, RSR etc are the different possible shapes for QRS complexes. These patterns are thus detected easily and accurately using the features discussed above. P wave and T wave are also extracted using those features.

C. Base line detection and Axis deviation detection: An easy way to detect the base line of an ECG signature from its digital image is histogram plotting [17]. Once the base line is detected, the algorithm must look for the over all voltage levels of QRS complex of lead I, II and III. Here the overall voltage lebel is the resultant voltage level with respect to the base line of the ECG signature of the lead. The water reservoir algorithm helps us to delineate the QRS complex, the depth and width of the trough and even the rate of change of curvature of the trough which may have some medical implications. The difference of the depths of the deepest troughs which are formed in the lower part of the baseline (Q wave and S wave) and that of the upper part of the base line (R wave) gives the overall voltage level.

In our algorithm two major functions do these jobs. *AxisDeviation*(LI ,LII, LIII) which gives whether the patient has LAD or RAD. Next function *QRSPattern*(lead) gives the output whether the input lead shows "M-pattern" or not. The *BBBDiagnosis*(Output from *AxisDeviation*) checks whether RAD or LAD is reported and accordingly calls *QRSPattern*(lead) for three times for V4,V5,V6 for LAD and V1,V2,V3 for RAD. If M patterns occur in V4, V5 or V6 with LAD then that is a case of complete LBBB on the other hand if M patterns occur in V1, V2 or V3 with RAD then that is a case of complete RBBB. We had to consider another prime factor which is the duration of the QRS complex greater than 120 mS. All these considerations lead to the decision of bundle branch blockage. Thus we design our system to check for wide QRS (more than 120ms) and the axis deviation and if found axis deviation along with the 'M pattern' in selected leads our system infers complete BBB. It is a simplified morphological approach to diagnose with complete BBB. Although the broadening of QRS without any significant LBBB or RBBB features may be inferred as Intra-Ventricular Conduction Delay(IVCD).

TABLE I. A PORTION OF RESULT SHEET

PTB Data base id	Cardiac Axis Deviation	M PATTERN IN VI/V2/V3	M PATTERN IN V4/V5/V6	QRS DURATION (mS)	BBB DETECTION
175	In Normal Range	YES	NO	97	INCOMPLETE RBBB
202(0421)	In Normal Range	YES	NO	105	INCOMPLETE RBBB
204(0425)	In Normal Range	YES	NO	148	INCOMPLETE RBBB
209(0431)	LAD	NO	YES	135	COMPLETE LBBB
213	LAD	YES	NO	102	INCOMPLETE RBBB
219(0441)	LAD	NO	YES	132	COMPLETE LBBB

IV. RESULTS AND DISCUSSIONS

In this section we briefly showcase the performance evaluation of the developed system. For BBB diagnosis we have used the PTB ECG database available online [18]. As the previous section reveals the importance of cardiac axis detection in BBB diagnosis, a separate result table is built to show the findings of the algorithm. Table II shows the cardiac axis deviation computed by the algorithm. So far we found only 0.32% cases where our algorithm computed this deviation wrongly. The main reason of failure was severe drift in baseline leading to erroneous computation of overall voltage level of the QRS complexes. Table I is a portion of the complete diagnosis result. The key features which are clinically important to comment on bundle branch blockage are the presence of 'M Pattern' in certain leads, the duration of the 'QRS complex' of Lead 2 and the cardiac axis deviation [11]. Thus, Table I shows the detected or computed output of the algorithm for feature extraction and subsequent decision making for BBB diagnosis. In this final performance evaluation we found 98.62% correct diagnosis of BBB has been made by the algorithm. We need to associate other different and rare types of ECG traces and re-evaluate the performance for other disease diagnosis in near future for a reliable, easy to use machine aided cardiac disease diagnosis system.

TABLE II. A PORTION OF AXIS DEVIATION DETECTION RESULT SHEET

PTB Data base ID	Cardiac Axis Deviation computed by the Algorithm
175	In Normal Range
202(0421)	In Normal Range
204(0425)	LAD
206	In Normal Range
209(0431)	LAD
213	In Normal Range
219(0441)	LAD
220	In Normal Range
225	LAD
228	In Normal Range

V. CONCLUSION

In this article we have shown the performance of the proposed technique for machine aided diagnosis of LBBB and RBBB. In future this can be extended for other heart diseases which can be reported from ECG record. At this stage we extract the pattern information of each leads as well as the overall cardiac vector information. In near future we shall start work on machine aided diagnosis of cardiac diseases like myocardial infarctions from ECG image. Moreover we are actually working on to reduce the complexities involved in many modules of this sequential algorithm to make it further efficient. We envisage a more robust system associating other image processing techniques which can correct a defocused and blurred image, rectify the overshadowed or over illuminated images, rectify the base line drift due to noise etc. At the same time we need to ensure a more computationally faster, less memory consuming and less time complex algorithm to build fast and reliable ECG diagnosis app for smart PDAs in near future.

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