Motion and Noise Artifact-Resilient Atrial Fibrillation Detection Algorithm for a Smartphone

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***Abstract*—We have developed a motion and noise artifact (MNA)-resilient atrial fibrillation (AF) detection algorithm for smartphones that eliminates MNAs, and then detects AFs in smartphone camera recordings. MNA-corrupted episodes are observed to have larger values of turning point ratio (TPR), pulse slope, or Kurtosis compared to clean AF and normal sinus rhythm (NSR) episodes. On the other hand, AFs are shown to have larger root mean square of successive RR differences (RMSSD) and Shannon Entropy (ShE) [1]. Our developed AF algorithm is capable of separating MNAs, NSRs, AFs, which enhances the specificity of AF detection. We have recruited 88 subjects having AF at baseline and NSR after electrical cardioversion, and 11 subjects having MNA-corrupted NSRs to evaluate the performance of our AF algorithm. The clinical tests show that the proposed AF algorithm gives higher accuracy, sensitivity and specificity of 0.9667, 0.9765, 0.9714 compared to the previous AF algorithm [1].**

I. Introduction

Recently, use of smartphones has been gaining attention in the prediagnosis and management of AF patients [1]. AF monitoring is important since complications of AF can be severe, e.g., stroke, heart failure, and death [2]. However, motion and noise artifacts (MNAs) may cause false positive AF since smartphone signals of MNAs and AFs have similar characteristics. Hence, the accuracy of the AF detection may decrease by misclassifying normal sinus rhythm (NSR) signals corrupted by MNAs as AF.

Our previous AF detection application for smartphones detected AF with 96 % accuracy [3] on MNA-free signals. However, the accuracy of previous AF detection algorithm is observed to decrease when more than twelve MNA beats present among sixty beats by misclassifying MNA-corrupted NSR signals as AF. The authors are not aware of any studies proposing MNA-resilient AF detection methods for smartphones.

In this paper, we propose an MNA-tolerant AF detection algorithm for iPhone 4S/5S/6S, which discriminates MNA episodes from smartphone signals, and then detects AF episodes from clean smartphone signals. Time- and space-domain parameters are used for MNA discrimination: signal slope changes, turning point ratio (TPR) changes, and color distribution changes. We adopt our previous AF detection algorithm based on Root Mean Square of Successive RR Differences (*RMSSD*) and Shannon Entropy (*ShE*) to detect AF beats among clean segments. MNA-corrupted and MNA-free signals, or NSR and AF signals are classified using a support vector machine (SVM) concept. We evaluated the performance of our proposed algorithm on MNA-free NSR, MNA-free AF, MNA-corrupted NSR, and MNA-corrupted AF subjects who were recruited at the University of Massachusetts Medical Center (UMMC), Worcester Polytechnic Institute (WPI), and University of Connecticut (UConn).

II. Materials

We collected smartphone data using video cameras of iPhone 4S/5S/6S. As shown in Fig. 1, smartphone signals were obtained from a subject's fingertip on a video camera of iPhones. A subject's fingertip was recorded at a sampling rate of 30 frames with 640x480 pixel resolution. After two minutes of recordings, the green band from the video was used because our recent results show that the green band gives the best signal quality [4]. We make an average of the upper 320x480 pixels to obtain a signal value. Preprocessing such as interpolation, sudden DC change elimination, two stages of band pass filter, pulse beat-to-beat detection, and pulse slope detection were performed to detect MNAs and AFs.

We collected NSR and AF signals from 88 patients of UMMC and MNA-corrupted signals from 11 healthy subjects. The subjects were asked to place their fingertip on the iPhone's lens. For MNA-corrupted signals, *fingertip misplacement* and *hand movement* were considered. *Fingertip misplacement* MNAs is obtained by moving the position of a fingertip away from the smartphone's lens during the recording. On the other hand, *hand movement* MNAs were collected by moving a hand in a random way with placing a fingertip on a correct position.

III. Methods

A. Fingertip Misplacement MNA Detection

An example of video recordings from NSR or AF subjects is shown in Fig. 2(a), which contains a whole fingertip image. However, an example from fingertip misplacement MNA subjects is shown in Fig. 2(c), where a fingertip is recorded

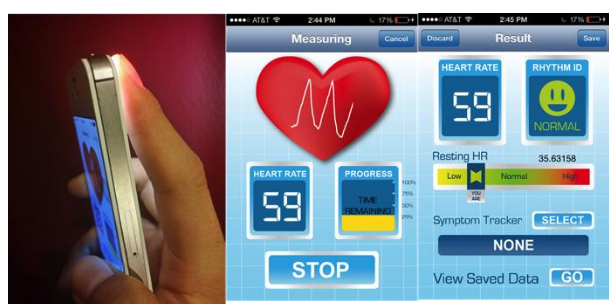

Figure 1. Our developed smartphone application for smartphone data recording.

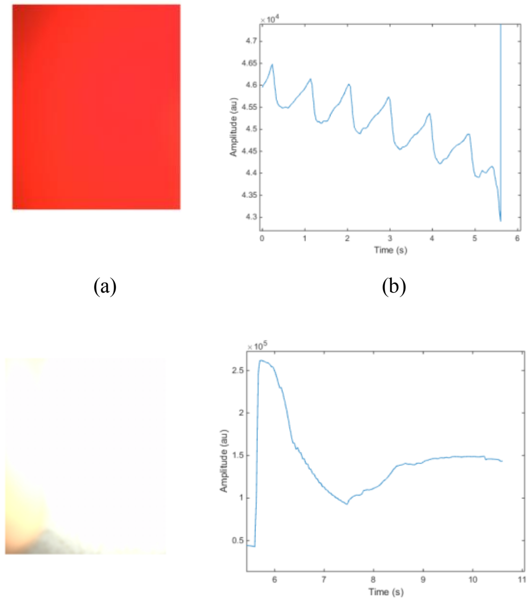

Figure 2. Examples of representative fingertip placements on a smart phone lens (left) with their corresponding distributions of luma differences (ΔY). (a)-(b) lens fully-covered by a fingertip: correct placement and (c)-(d) less than a half coverd: misplacement.

with a background. We utilize following metrics to detect finger misplacement MNAs.

1) Pulse amplitude changes

We denote by $A_{n,i}$ the pulse amplitude at the i^{th} pulse of the n^{th} segment and calculated $A_{n,i}$ by subtracting the $(i+1)^{th}$ trough value from the i^{th} peak value at the n^{th} segment. The smartphone signal of static background without a fingertip image due to totally misplaced fingertip is expected to make $A_{n,i}$ smaller than clean NSRs, clean AFs, or hand movement MNAs.

2) Color distribution changes

A video camera of an iPhone gives YUV images, which consist of one luma (or brightness), Y, and two chrominance components, U and V. Among Y, U, and V components, the Y component is used to detect fingertip misplacement MNAs. We denote by $\Delta S_{i,j}$ the gradient at the pixel (i,j) and is defined by:

$$\Delta S = < S_{i-1,j} - S_{i,j}, S_{i,j+1} - S_{i,j} > \quad (5)$$

where $S_{i,j}$ denotes the Y-luma at the pixel (i,j). The smartphone signals with a partial fingertip image due to partially misplaced fingertip are expected to have larger ΔS values than NSRs, AFs, or hand movement MNAs at the boundary between fingertip and background images compared to NSR, AF, or hand movement MNAs.

B. Hand movement MNA Detection

For both of NSR and AF episodes, we observed the steep slope in the systole and the gradual slope. On the other hand, hand movement MNAs do not follow this slope patterns since the smartphone signals from hand movement MNAs are not incurred by heart pumping.

We denote by $\Delta A_{n,i}$ the slope between the i^{th} sample and the next $(i+1)^{th}$ of the n^{th} segment and is defined by:

$$\Delta A_{n,i} = A_{n,i} - A_{n,i-1} \quad (1)$$

where $A_{n,i}$ is the peak-to-peak interval at the i^{th} sample of the nth segment. We denote the positive maximal slope and the negative minimal slope in the n^{th} segment by P_n and N_n, respectively, and are defined by:

$$P_n = \max_{i\in S_n, \Delta A_{n,i}>0} \Delta A_{n,i} \quad (2)$$

$$N_n = \min_{i\in S_n, \Delta A_{n,i}<0} \Delta A_{n,i} \quad (3)$$

where S_n is a set of sample index in the n^{th} segment. The max/min slope ratio R_n of the n^{th} segment is defined as:

$$R_n = |P_n/N_n| \quad (4)$$

where $|x|$ denotes the absolute value of x. The R_n of MNAs are expected to be time-variant while NSRs and AFs are not.

C. AF Detection from MNA-Free AF and MNA-Free NSR Subjects

We adopted our previous AF detection algorithm [3] to detect AF episodes from MNA-free smartphone signals. The previous AF algorithm gave the AF detection accuracy of 95 % for MNA-free smart phone signals by utilizing the *RMSSD* and *ShE* of the pulse-to-pulse intervals (PPIs).

IV. Results

A recording duration of iPhones is basically two minutes. However, it is automatically extended when the number of MNA-free episodes in the recording is less than 20. We evaluated our MNA-resilient AF detection algorithm by comparing it to the previous AF algorithm. We consider the accuracy, sensitivity, and specificity as performance metrics.

A. Detection of MNA

1) Fingertip misplacement MNA

The proposed algorithm first detects fingertip misplacements. An image of uniform background without a fingertip (see Fig. 2c) gives smaller and non-periodic time series (see Fig. 2d) compared to an image from a correct fingertip placement (see Figs. 2a and 2b). Fig. 3 shows the color distributions of correct placement (see Fig. 3a) and misplacements (see Fig. 3c). Using the statistics of pulse amplitude changes and the distribution of ΔS, the fingertip misplacement MNA was detected with an accuracy of 100%.

2) Hand movement MNA

Fig. 4 compares max/min slope ratio, turning point ratio (TPR), standard deviations of max and min slopes of NSR, AF, and hand movement MNA. As expected in Section II, max/min slope ratio, TPR, standard deviation of maximum (or minimum) slope values are different between hand movement MNA and other categories. We adopted a support vector machine (SVM) to detect hand movement MNAs emanating from smart phone signals. Note that the SVM boundaries between hand movement MNAs and other categories (NSRs and AFs) noticeable in Figs. 4(a)-(b) while the values of AF and NSR are similar. To obtain the optimal boundaries for each parameters, we considered segment lengths of

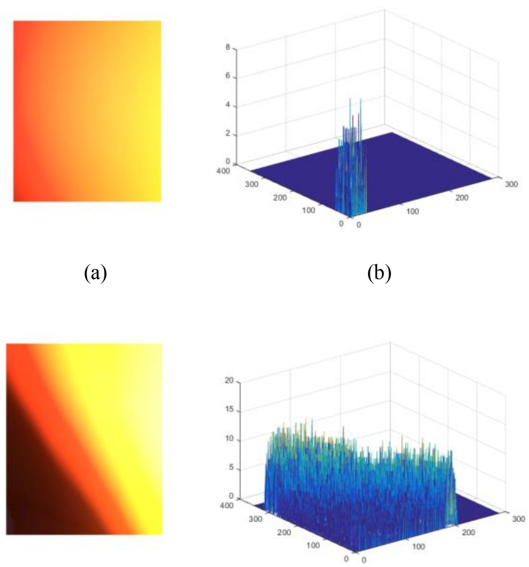

Figure 3. Fingertip placement on a smart phone lens (left) with their corresponding distributions of luma differences (ΔY). (a)-(b) fully-covered by a fingertip: correct placement and (c)-(d) half coverd: misplacement.

L_{max/min_slope_ratio} 1s, L_{tpr} 1 s, L_{slope_max} 14 s, and L_{slope_min} 14 s.

B. Detection of AF from MNA-Free Smart Phone Data.

Table I is a confusion matrix of our proposed algorithms on AF, NSR, MNA Type 1 (hand movement) and MNA Type 2 (finger misplacement) subjects. For the 91 NSR subjects, 6 FNs were changed to 1 FN after our algorithm; thus, specificity increased from 93.41% to 98.84%. Table II compares the AF detection performance of the conventional and proposed algorithms. Using our proposed algorithm, the accuracy, sensitivity, specificity increased from 0.9560, 0.7905, 0.8673 to 0.9667, 0.9765, 0.9714, respectively.

V. DISCUSSION

We developed an MNA-resilient AF detection algorithm that has capabilities of detecting whether a subject's finger is misplaced or not as well as discriminating hand movement from AF. To implement these MNA detection capabilities, we utilized the statistics of image distributions and light intensity from the successive camera images. As a result, we have enhanced the AF detection performance by reducing these types of MNAs before AF detection. Given the growing popularity of smartphones, our approach to MNA-resilient AF detection using a smart phone will result in higher sensitivity and specificity. A clinical trial testing of the proposed AF detection is currently ongoing.

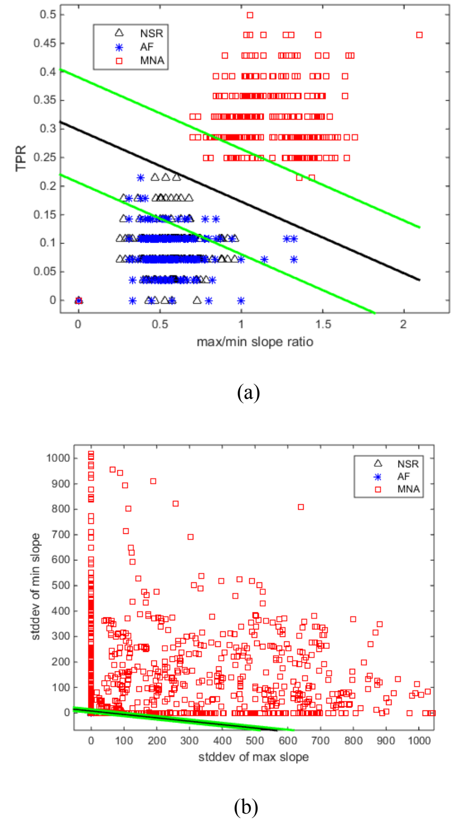

Figure 4. Parameter value comparison between NSR, AF, and hand movement MNA (MNA1) signals.

TABLE I. CONFUSION MATRIX OF OUR MNA-RESILIENT AF DETECTION ON AF, NSR, MNA TYPE 1, MNA TYPE 2 SUBJECTS

		Predicted Class			
		AF	**NSR**	**MNA type 1**	**MNA type 2**
Actual Class	**AF**	87	3	1	0
	NSR	2	83	6	0
	MNA type 1	0	0	7	0
	MNA type 2	0	0	0	7

TABLE II. COMPARISON OF AF DETECTION PERFORMANCE BETWEEN CONVENTIONAL AND PROPOSED ALGORITHMS

	AF Detection without MNA Discrimination [11]	**AF Detection with MNA Discrimination**
Sensitivity	0.9560	0.9667
Specificity	0.7905	0.9765
Accuracy	0.8673	0.9714

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