

Received August 30, 2020, accepted September 9, 2020, date of publication September 28, 2020, date of current version October 9, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3026833

# Development of Radial Artery Pulse Audiogram Sensing System for Fast Detection of Atrial Fibrillation and Pulse Amplitude Variation

JU-YI CHEN<sup>1</sup>, CHOU-CHING K. LIN<sup>2,5</sup>, (Senior Member, IEEE),

CHE-WEI LIN<sup>3,5</sup>, (Member, IEEE), FAN-MING YU<sup>4</sup>, KUAN-JUNG LI<sup>5</sup>, AND LIANG-MIIN TSAI<sup>1,6</sup>

<sup>1</sup>Division of Cardiology, Department of Internal Medicine, National Cheng Kung University Hospital, College of Medicine, National Cheng Kung University, Tainan City 701, Taiwan (R.O.C)

<sup>2</sup>Department of Neurology, National Cheng Kung University Hospital, College of Medicine, National Cheng Kung University, Tainan City 701, Taiwan (R.O.C)

<sup>3</sup>Department of Biomedical Engineering, College of Engineering, National Cheng Kung University, Tainan City 701, Taiwan (R.O.C)

<sup>4</sup>Department of Aeronautics and Astronautics, College of Engineering, National Cheng Kung University, Tainan City 701, Taiwan (R.O.C)

<sup>5</sup>Medical Device Innovation Center, National Cheng Kung University, Tainan City 701, Taiwan (R.O.C)

<sup>6</sup>Department of Internal Medicine, Tainan Municipal Hospital (Managed by Show Chwan Medical Care Corporation), Tainan City 701, Taiwan (R.O.C)

Corresponding author: Liang-Miin Tsai (tsailm@mail.ncku.edu.tw)

This work was supported by the SPARK Program, National Cheng Kung University (NCKU) /Medical Device Innovation Center (MDIC), National Cheng Kung University (NCKU) from the Featured Areas Research Center Program within the framework of the Higher Education Sprout Project by the Ministry of Education (MoE) in Taiwan/Ministry of Science and Technology, Taiwan, under Grant MOST-108-2628-E-006-003-MY3.


**ABSTRACT** **Background:** A new wearable pulse audiogram (PAG) of radial artery was developed with the main purpose to quickly screen atrial fibrillation (AF) and monitor pulse amplitude variation. **Methods:** Subjects with sinus rhythm (SR), AF, ectopic arrhythmia (EA), and a pacemaker rhythm (PM) were recruited to measure the PAG of radial artery. In total, 91 subjects were recruited: SR ( $n = 45$ ), AF ( $n = 21$ ), EA ( $n = 11$ ), and PM ( $n = 14$ ). For signal processing, the inter-pulse interval (IPI) and pulse height (PH) were extracted. Then, an automatic classification algorithm combining fuzzy c-means (FCM) or sample entropy (CEn) with an adaptive-network-based fuzzy inference system was constructed. The PAG data were divided into different segment lengths (10 to 30 beats) to investigate the robustness of the algorithm in short intervals. Furthermore, linear regression was performed to evaluate the relation between the normalized IPI and PH in the AF group. **Results:** The identification rate of AF increased with the number of beats and decreased with the number of classified types of arrhythmia. Results of combining CEn and FCM, or of FCM alone were better than those of CEn alone. When the combined method was used for the two types of arrhythmia and the number of beats was greater than 10, the rate of successful identification was greater than 90%, validating the technique. Furthermore, for the AF group, PH increased with IPI, while the amplitude of electrocardiogram (ECG) did not. **Conclusions:** Results indicated that our PAG can effectively identify AF, even in a time window as short as 10 beats. In addition, PAG can monitor the trend of pulse amplitude, possibility that cannot be offered by an ECG.

**INDEX TERMS** Atrial fibrillation, pulse audiogram, fuzzy C-means, sample entropy, pulse blood pressure.

## I. INTRODUCTION

Atrial fibrillation (AF), the most common arrhythmia type with increasing age, accounts for 15% to 20% of ischemic strokes and contributes to higher mortality rates [1]. Patients with AF may be completely asymptomatic [2], and AF is notoriously tricky to detect in clinical practice [3]. Asymp-

tomatic AF has been associated with similar morbidity and mortality rates as symptomatic AF [4]. Recently, AF has also been linked to silent cerebral infarcts among young patients without a history of cerebrovascular diseases [5]. Current guidelines on primary prevention of AF-related strokes strongly recommend opportunistic pulse detection for patients of age higher than 65 years [6]. In the outpatient department setting, early and accurate diagnosis of AF can reduce the transfer time and the total public-health

The associate editor coordinating the review of this manuscript and approving it for publication was Mouloud Denai .

burden of treating AF related strokes or cardiovascular events [6].

The gold-standard method for the determination of AF is a 12-lead electrocardiogram (ECG) [7]. However, for measuring ECG, at least two electrodes (use of three electrodes is more reliable) on two limbs, or the anterior chest wall are needed, hence its convenience is an issue. In addition to the 12-lead standard ECG, plenty of alternative measurements such as single-lead ECG, photoplethysmography (PPG), inertial signal, ballistocardiogram (BCG), seismocardiography (SCG), mechanocardiograms, and ultra-wideband, have been developed for AF screening.

Single-lead ECG is a well-known technology for AF screening, with Apple watch and Verily's study watch being representative examples of this technology to detect AF [8]. In addition to single-lead ECG, photoplethysmography (PPG) is another conventional technology utilized for heart rhythm detection. Light beams and light sensors are used to measure the blood volume variation caused by the peripheral pulse. PPG is convenient for accessing the heart rhythm and is also employed in AF screening [9]–[11]. PPG can not only access the heart rhythm but also the pulse amplitude. However, the normal frequency range of PPG is 0.5-5 Hz [12]. To develop another alternative for monitoring hemodynamics is one of the research aim in this study. Furthermore, based on our literature survey, existing researches relies on the heart rhythm variation to detect the AF. However; AF is easily to cause pulse deficit [13] and existing technologies are hard to visualize the pulse deficit. Although PPG can also provide pulse amplitude, the normal frequency range of PPG is 0.5 Hz to 5 Hz [12]. The pulse audiogram provides wider frequency band (0-50 Hz) in the proposed study.

In addition to using ECG and PPG to represent irregular heart contraction of AF, mechanical-related sensor signals were also used to screen AF [14], [15]. Contactless sensing is another technology for screening for AF; Lee *et al.* found that the RR interval obtained from ultra-wideband radar (UWB) was highly correlated to the RR interval obtained from electrocardiography, indicating the potential of using UWB in AF screening [16].

The radial artery is close to the skin surface and in an ideal location to detect the heart rhythm and pulse amplitude. However, radial artery measurements are hard to perform, owing to individual anatomical variations. Joshi *et al.* utilized piezoelectric sensors to sense the radial artery pulse and these sensors were adopted for diagnosis by Ayurvedic practitioners [17]–[20].

There have been many documented algorithms for detecting AF [21], [22], with some showing the possibility of implementation in real-time operations [23], [24]. Most of the methods can be categorized into those based on rhythm irregularity [25] and those based on morphological features of waves. A study compared the performance of methods of these two categories and concluded that the methods based on rhythm irregularity were more robust against noises and had higher specificity and sensitivity. For methods of this

category, non-linear methods, such as those based on sample entropy, performed better. However, these studies mainly aimed to detect paroxysmal AF, such as, transient AF in long segments of regular rhythm. Besides, in most of these studies, other types of arrhythmias such as ventricular premature beats and atrial flutters were removed before testing the efficiency of the algorithm in detecting AF. This pre-processing increased the accuracy of differentiating between AF and sinus rhythm but reduced the practicability. In general, longer duration of evaluation improves the performance of the detection algorithms, while a shorter duration facilitates clinical acceptability, especially for quick evaluation at an outpatient department or a general practitioner clinic. A study investigated the efficiency of detecting AF using evaluations of very short duration and claimed that some algorithms performed well even for duration as short as 5 s [26].

To develop a convenient tool for quick evaluation and screening for AF, the sensing technique should require only one contact point on the body surface (unlike ECG which requires two or more electrodes). In addition, development of an algorithm that only needs a few cardiac beats to detect AF is also desirable. This paper proposed a pulse audiogram (PAG) of the radial artery that could detect peripheral arterial pulses conveniently, using a simple device that measured the vibration of the wrist radial artery, representing the pulse and blood flow. The PAG measurement device consisted of a condenser microphone, a resonant cavity, an amplification/filtering circuit, and an analog to digital (A/D) converter. Radial artery vibration could be measured by attaching the condenser microphone on the skin surface of the radial artery. The resonant cavity was used to enhance the pulse vibration collected by the condenser microphone. The analog PAG signal was transformed into digital, for automated data processing. The main goal of this study was to evaluate the feasibility of applying this PAG with the associated signal processing algorithm, to quickly identify arrhythmias, and especially AF. Operation of the PAG is not difficult, the operator can first sense the location of the subject's radial artery by finger and then place the PAG transducer on the wrist artery, generally it can sense the PAG of the radial artery.

## II. DATA COLLECTION AND METHODS

### A. SUBJECTS

Candidate subjects were recruited from the outpatient clinics of Cardiology at National Cheng Kung University Hospital (NCKUH). The recruitment criteria were for candidates to be of age between 20 and 80 years old and have full consciousness. Patients with both regular and irregular rhythms were recruited. The study complied with the Declaration of Helsinki and the study protocol was approved by the NCKUH ethics committee on human subject study (approval number B-BR-106-030). Before experiments took place, the purpose, potential hazards and experimental procedures were fully explained to the subjects. All participants signed written informed consent forms. The types of cardiac rhythms were

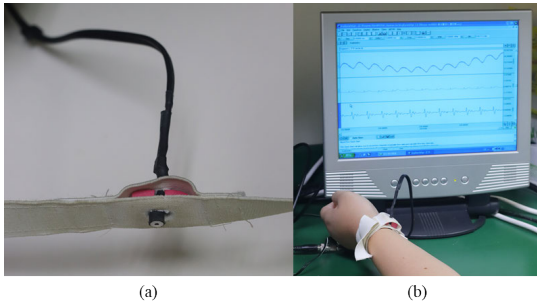


FIGURE 1. (a) Custom-made audiometric device and (b) the device in use.

confirmed by two senior cardiologists, by inspecting a long-run of ECG recording. The patients (total of 91 subjects) were classified into 4 groups, namely those with SR ( $n = 45$ ), AF ( $n = 21$ ), ectopic arrhythmia (EA,  $n = 11$ ), and a pacemaker rhythm (PM,  $n = 14$ ). The EA group included subjects with atrial or ventricular premature contraction.

**B. EXPERIMENT SETUP FOR PAG CLASSIFICATION FROM SR/AF/EA/PM SUBJECTS**

A PAG sensing device was developed in this study as shown in FIGURE 1 (a). The core of the PAG was composed of a commercially available capacitive microphone (Panasonic WM-61A) with an integrated amplifier. A tailored short silicone tube was fixed on the periphery of the microphone, so that when the microphone was pressed on the skin the silicone tube could act as a compression zone of the microphone. A closed air chamber was formed for better audio signal collection. During data collection, subjects were in sitting position, with their forearm and hand placed on a table (as shown in FIGURE 1 (b)). The subjects were instructed to relax but not to fall asleep. The PAG probe was gently placed on the distal forearm over the radial artery, adjusted to obtain proper waveforms, and fixated with a Velcro tape. The ECG signal was recorded for reference and comparison to PAG, using three tape electrodes placed at distal parts of the upper extremities and the left lower extremity respectively. The ECG signal was amplified by a biopotential amplifier (ECG 100C, Biopac System Inc., www.biopac.com). The PAG (without amplification) and ECG signals were digitized and recorded on a PC by a commercial analog-to-digital conversion system (MP100, Biopac System Inc., www.biopac.com) at a sampling rate of 1000 Hz/channel, for a duration of 10 minutes. An example of time-/frequency-domain PAG collected from sinus rhythm condition is shown in FIGURE 2, the frequency range of sinus rhythm PAG is range from 0-50 Hz.

**C. EXPERIMENT SETUP FOR PAG COLLECTION IN AN INTENSIVE CARE UNIT FOR INVESTIGATING PAG PULSE HEIGHT AND BLOOD PRESSURE**

In order to investigate the relationship between PAG pulse height (PH) and blood pressure (BP), a similar setup to

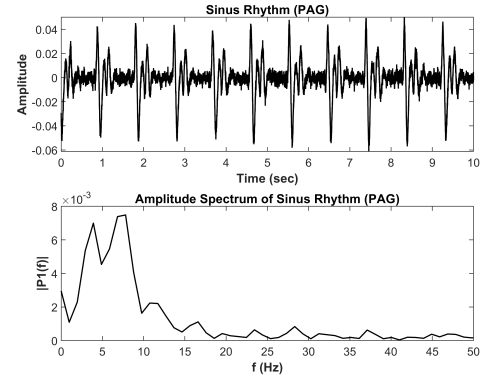


FIGURE 2. Time- and frequency-domain example of a sinus rhythm PAG.

that for PAG and ECG measurements was combined with a commercial monitor (Philips IntelliVue MP70 Patient Monitor, Avante, avantehs.com) to measure the arterial BP from arterial catheterization of a patient in the environment of intensive care unit. During data collection of PAG and EKF, data of continuous arterial blood pressure was synchronously digitized using the same analog-to-digital conversion system (MP100) mentioned in section II B.

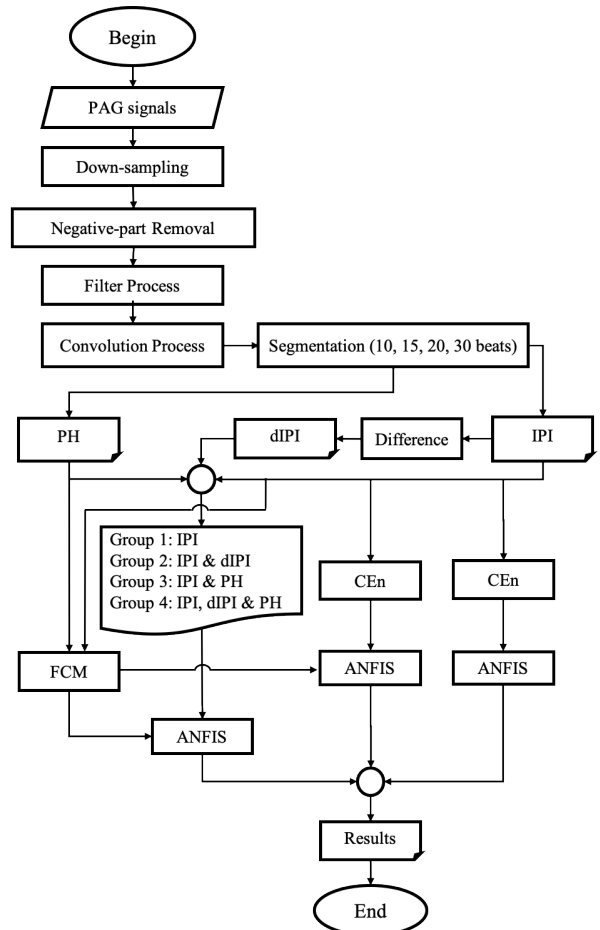
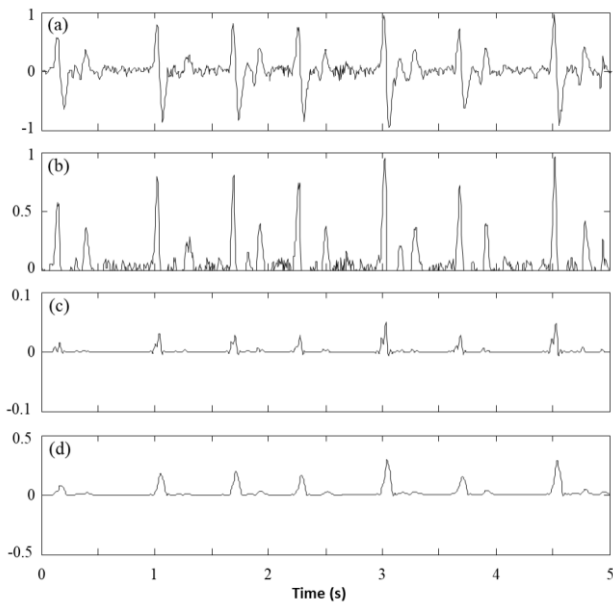


FIGURE 3. Algorithm flowchart of the proposed signal processing.



**FIGURE 4.** An intermediate processing example of the signal processing results in diagrams, (a) raw data after down sampling to 200 Hz, (b) after half-wave rectification, (c) after bandpass filtering, squaring and low-pass filtering, and (d) after convolution.

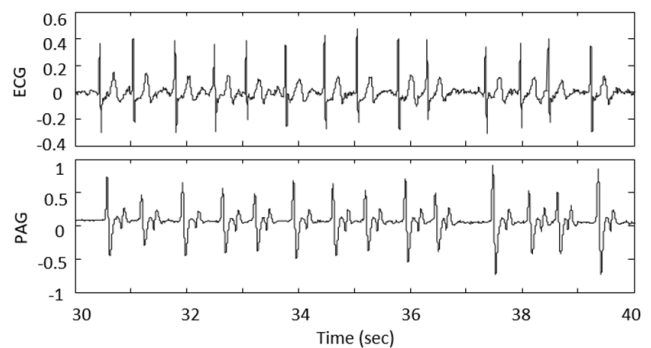
**D. SIGNAL PROCESSING FOR SR/AF/EA/PM PAG CLASSIFICATION**

In order to classify the PAG signals collected from SR/AF/EA/PM subjects, the algorithm flowchart of the proposed signal processing for SR/AF/EA/PM PAG classification is shown in FIGURE 3, an intermediate example of signal processing is shown in FIGURE 4, and the pseudo code is shown in FIGURE 5. The PAG signal was first downsampled to 200 Hz, and then a half-wave rectifier is used to remove the signal with the negative part. Then the signal peaks corresponding to heart beats were identified by an algorithm similar to the one used for the construction of tachogram for ECG. In brief, the signal was band-pass filtered between 5 to 35 Hz by a Butterworth with filter zero phase shift, squared, again low-pass filtered with a cutoff frequency of 30 Hz by a Butterworth with filter zero phase shift, and finally, convoluted with a sequence of ten points of one. A height threshold was empirically determined for searching peaks. A sequence of inter-spike interval (IPI) and associated pulse height (PH), i.e., the amplitude of pulse, was obtained. The next step was to differentiate SR/AF/EA/PM in a short period of time. In order to investigate the performance of rhythmicity quantification algorithms in different lengths of beats, the sequence was segmented into 10, 15, 20 and 30 beats, respectively. Two algorithms were implemented for quantifying the rhythmicity of heart beats. These were fuzzy c-means (FCM) [21], first adopted by us for this purpose, and coefficient of sample entropy (CEn) [26], [27], also adopted from other researchers and used here for comparison. FCM

```

For i = 1 to number of Preprocessing signals
    [IPI, PH, AMP] = DataCalculation()
    dIPI = difference of IPI
    For j = 1 to Number of subtypes of IPI
        [Dmax(i, j), Rdm(i, j)] =
        FCMAgorithm(IPI)
        [dDmax(i, j), dRdm(i, j)] =
        FCMAgorithm(dIPI)
        CEn(i, j) = CEnAlgorithm(IPI)
    End
    % Group 1
    G1(i) = Dmax, Rdm
    % Group 2
    G2(i) = Dmax, Rdm & dDmax, dRdm
    % Group 3
    G3(i) = Dmax, Rdm & PH
    % Group 4
    G4(i) = Dmax, Rdm & dDmax, dRdm & PH
End
% Input to Network
% Only CEn
ANFIS(CEn)
% CEn + PCM
ANFIS(CEn + Dmax, Rdm)
% Only PCM
ANFIS(G1)
ANFIS(G2)
ANFIS(G3)
ANFIS(G4)
3: Output: Accuracy of this research.
    
```

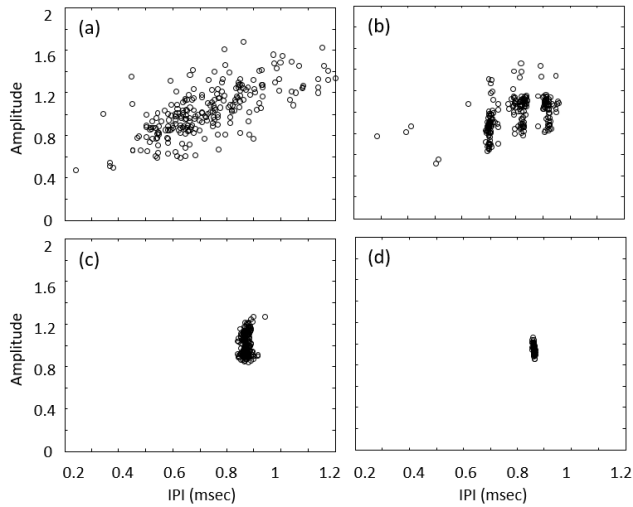
**FIGURE 5.** Pseudo code of the proposed signal processing.



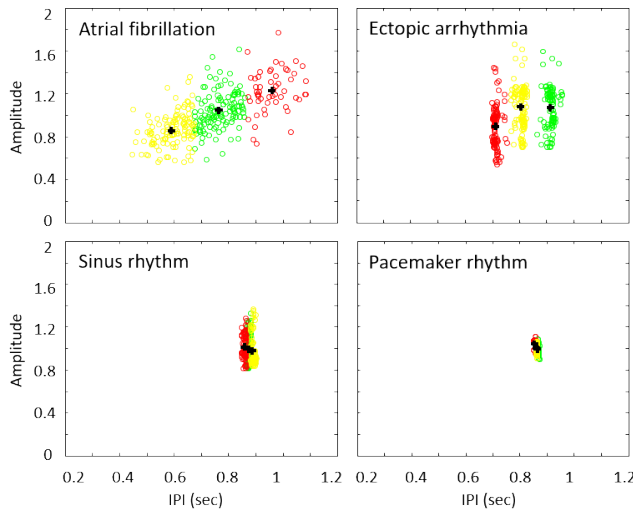
**FIGURE 6.** An example of ECG and PAG recordings of a case of AF, showing a good correspondence between the pulses.

was used to minimize the following objective function (*J*),

$$J = \text{mean}_k \left( \sum_{i=1}^N \sum_{j=1}^C w_{ijk}^m |x_{ik} - c_{jk}|^2 \right) \quad (1)$$



**FIGURE 7.** Examples of the relationship between IPI and amplitude in patients with (a) AF, (b) EA, (c) SR, and (d) PM.



**FIGURE 8.** Classification results by FCM of the example data shown in FIGURE 5. The classification algorithm was set to classify the data points into tree clusters, with randomly assigned yellow, green, and red color for clarity. It is clear that the distances between the centers of clusters (the black dots) are largest for AF, followed by those of EA, SR and PM, respectively.

where  $N$  was the number of peaks in a segment,  $k$  was the number of segments,  $C$  was the number of clusters,  $m$  was the degree of fuzzy overlap,  $x_{ik}$  was the time of  $i^{th}$  peak in the  $k^{th}$  segment,  $c_{jk}$  was the center of  $j^{th}$  cluster in the  $k^{th}$  segment and  $w_{ijk}$  was the degree of membership of  $x_{ik}$  in  $j^{th}$  cluster of the  $k^{th}$  segment. It was assumed that the times of peaks could be clustered into three clusters, and two parameters ( $D_{max}$  and  $R_{dm}$ ) were defined from the results.  $D_{max}$  was the mean over all  $k$  segments of the maximal distance between the centers of clusters,

$$D_{max} = \text{mean}_k \left( \text{Max}_{i,j \in \{1,2,3\}} (|c_{ik} - c_{jk}|) \right) \quad (2)$$

and  $R_{dm}$  was the measure of the evenness of the degree of membership among the three clusters, averaged over all peaks in a segment and then over all  $k$  segments,

$$R_{dm} = \text{mean}_{k,N} \left( \left( w_{i1}^2 + w_{i2}^2 + w_{i3}^2 \right)^{1/2} \right) \quad (3)$$

CEn was defined as

$$\text{CEn} = -\ln \left( \frac{A}{B} \right) - \ln(2r) - \ln(u) \quad (4)$$

where  $A$  and  $B$  were determined as explained in the original paper,  $r$  was initially set as 30 ms and  $u$  was the mean IPI.

The adaptive-network-based fuzzy inference system (ANFIS) was used for automatic grouping of patients with different cardiac rhythms [28]. Sugeno type fuzzy system was adopted [29]. In order to study the effects of variable numbers fed to the ANFIS (input), four sets of inputs were defined and fed to ANFIS respectively. The first set was only IPI, the second set was IPI and the difference of IPI (dIPI), the third set was IPI and PH, and the fourth set was a combination of the IPI, dIPI and PH. While for single input three membership functions were assigned, for more than one input two membership functions were assigned to each input. A generalized bell shape was adopted as a membership function. The effect of patient grouping on algorithm performance was investigated by comparing the accuracy rates obtained upon removal of some groups, such as the PM or EA group. A hybrid training algorithm was used and the output was the linear combination of weighted membership functions. The error tolerance was set at 0.02 and the number of iterations was set at 40. Half of the collected data was used for training and the other half for validation.

Alternatively, linear regression was performed to quantify the relationship between IPI and PH in the AF group. IPI and PH were first normalized by the individual mean of IPI and PH. Linear regression was performed to obtain the slope ( $S$ ), i.e.,

$$\text{normalized (PH)} = S \cdot \text{normalized (IPI)} + b, \quad (5)$$

where  $b$  is a constant representing the vertical intercept. The group mean  $S$  was tested by Student t-test to check whether it was significantly different from zero with a confidence level of 0.05. All of the calculations were performed using the commercial software Matlab (www.mathworks.com) on a PC.

### III. RESULTS

#### A. PATTERNS OF RHYTHMICITY AND PULSE AMPLITUDE

An example of the recorded data obtained via ECG and PAG measurements for an AF case is shown in FIGURE 6. It can be seen that although the wave forms were different, the PAG peaks lagged behind and followed the ECG peaks well. It is worth noting that the PAG amplitude changed, but was not in accordance with the amplitude of the ECG peaks. On the contrary, the amplitude of PAG peak was larger when the leading IPI was larger, take for example the PAG peak at

around 37.5 s. Examples of typical plots of PAG IPI versus peak amplitude are shown in FIGURE 7. As expected in the AF case, IPI spread over a relatively wide range. There was a tendency of positive correlation between IPI and peak amplitude. In the EA case, IPI was divided into three clusters, while in the SR and PM cases, IPI merged into one cluster. The cluster formed in the PM case was tighter than that of SR case. Although there was also some spreading in amplitudes, the range of IPI was much smaller in the latter three groups, compared to AF.

### B. QUANTIFICATION OF RHYTHMICITY

Classification of results by FCM for data shown in FIGURE 7 as example, is shown in FIGURE 8. The group results of rhythmicity quantification are shown in FIGURE 9. For  $D_{max}$  and  $R_{dm}$ , the group tendency was robust enough to allow for segment length change from 30 to 10 beats, though the difference in groups tended to be smaller when the segment length decreased. Visually, while  $D_{max}$  could be used to separate the AF and EA groups from the SR and PM groups,  $R_{dm}$  could be used to separate the AF from the EA group. The SR and PM groups stayed close together for both parameters. For CEn, the separation of groups was better for a segment length of 30 beats, compared with  $D_{max}$  or  $R_{dm}$ , respectively. However, the overlap between groups became larger when the segment length decreased, and the pattern changed when the segment length was 10 beats, for example the value for AF group became smaller than that of other groups. For FCM, when the included variables increased from only IPI to the combination of IPI, diPI and amplitude, the group trend did not change (FIGURE 10). The difference of  $D_{max}$  among groups remained similar, but that of  $R_{dm}$  became larger. In other words, incorporating more variables as inputs marginally improved the performance.

### C. AUTOMATIC GROUPING

The accuracy of automatic grouping by ANFIS with 10-fold cross validation are summarized in TABLE 1. In general, the performance of FCM method was better than that of CEn. However, as described above, using more variables in FCM did not consistently increase the accuracy. FCM was more robust for short segment length, but CEn performed better for longer segment length. Combining FCM and CEn increased the accuracy for all segment lengths, but only marginally. Dividing subjects with regular rhythms into SR and PM groups reduced the accuracy. For only AF and SR groups, both FCM and CEn + FCM achieved near 100% accuracy, even for a segment length as short as 10 beats.

### D. PH AND IPI

In the AF group, the individual slope ( $S$ ) of normalized PH versus normalized IPI was significantly different from zero ( $p < 0.05$  by Student t-test) in all but one subject. The group mean  $S$  was 1.31, which meant PH increased with the preceding IPI. Student t-tests showed that the group mean  $S$  was also significantly different from zero ( $p < 0.05$ ).

### E. PAG PH AND BP

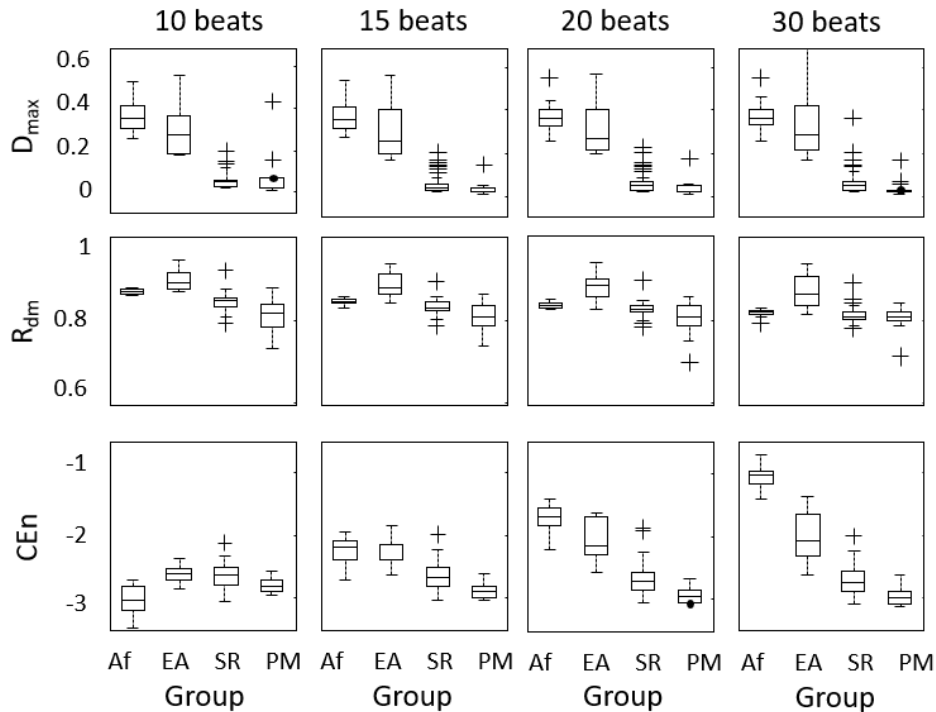
FIGURE 11 shows the recording of a patient of paroxysmal AF with pulse deficit. In addition to ECG and PAG, systolic BP was also continuously monitored through an arterial catheter. Plots in the upper half show the arrhythmic phase. It can be seen that ECG amplitude did not change prominently in AF, while PAG PH and BP did. The arrows indicate two pulse deficits where ECG peaks are visible, without the associated PAG or BP peaks. Systolic BP increases with PH (upper right plot). In the rhythmic phase (plots in the lower half), the amplitude variations of ECG, PAG PH and BP are modest. Systolic BP also has a tendency to increase with PH (lower right plot). However, because PH is less variable, the variation of systolic BP is also much smaller. Results obtained for this patient indicate that PAG PH has a better correlation with BP change than ECG peak does.

## IV. DISCUSSION

The results of this study show that PAG can be used to identify cardiac arrhythmia. When only two groups are to be differentiated (AF and SR), FCM achieved accuracy greater than 94%, and CEn was in the range of 85% to 100%, depending on the segment length chosen. Although we did not perform head-to-head comparisons between the performance of PAG and ECG, the results are compatible with the reported results based on ECG. CEn becomes less satisfactory when the heart beat segment length is short, though some authors claimed that CEn performed well even when the segment length was as short as 5 s [26]. It is known that when  $A$  (in Equation 4) is small, the performance of CEn deteriorates. Combination of FCM and CEn improved the performance and change of segment length became more robust.

Segment length as short as 10 beats was tested. In clinical practice, such short duration of AF may not be necessary. AF ablation guidelines suggest considering any episode exceeding 30 s as a recurrence [30] and several studies found that an AF burden greater than 5-6 minutes is associated with a higher risk of ischemic stroke [31], [32]. We chose such a small segment length in order to test the limits of identification algorithms, and also for convenience as a screening test in outpatient clinics (in a range of 20-30 beats). Longer segment length increases the true positive detection rates and reduces false positive detections.

The information about PAG peak amplitude was added as an input variable as a case in FCM, as hinted by the trend of AF (FIGURE 7 (a)), such as the tendency of peak amplitude to increase with IPI. However, the identification results indicated that adding the peak amplitude as a variable did not significantly improve the performance of differentiation. This can be explained by peak amplitude being possibly unstable due to movements of upper limb, hence leading to a systemic bias. It would be useful to improve hardware, so that the effect of movement can be reduced in the future. Difference of IPI (diPI) was also added as an input variable as a case in FCM, as suggested by other researchers claiming that using both IPI



**FIGURE 9.** Results of quantification of rhythmicity. First two rows show the results of FCM, with  $D_{max}$  and  $R_{dm}$  (see section II D for the definition of these two parameters). Third row shows the results of CEn coefficient. The numbers above the plots indicate the segment lengths used for the analysis. The groups include AF (atrial fibrillation), EA (ectopic arrhythmia), SR (sinus rhythm) and PM (pacemaker).

and dIPI could achieve a better and more robust performance in differentiating between AF and SR [21]. Results shown herein did not support this claim, as the performance with and without dIPI was found similar. The discrepancy may be due to the different algorithms adopted, as we did not implement the algorithm that these researchers used, nor compared the algorithms.

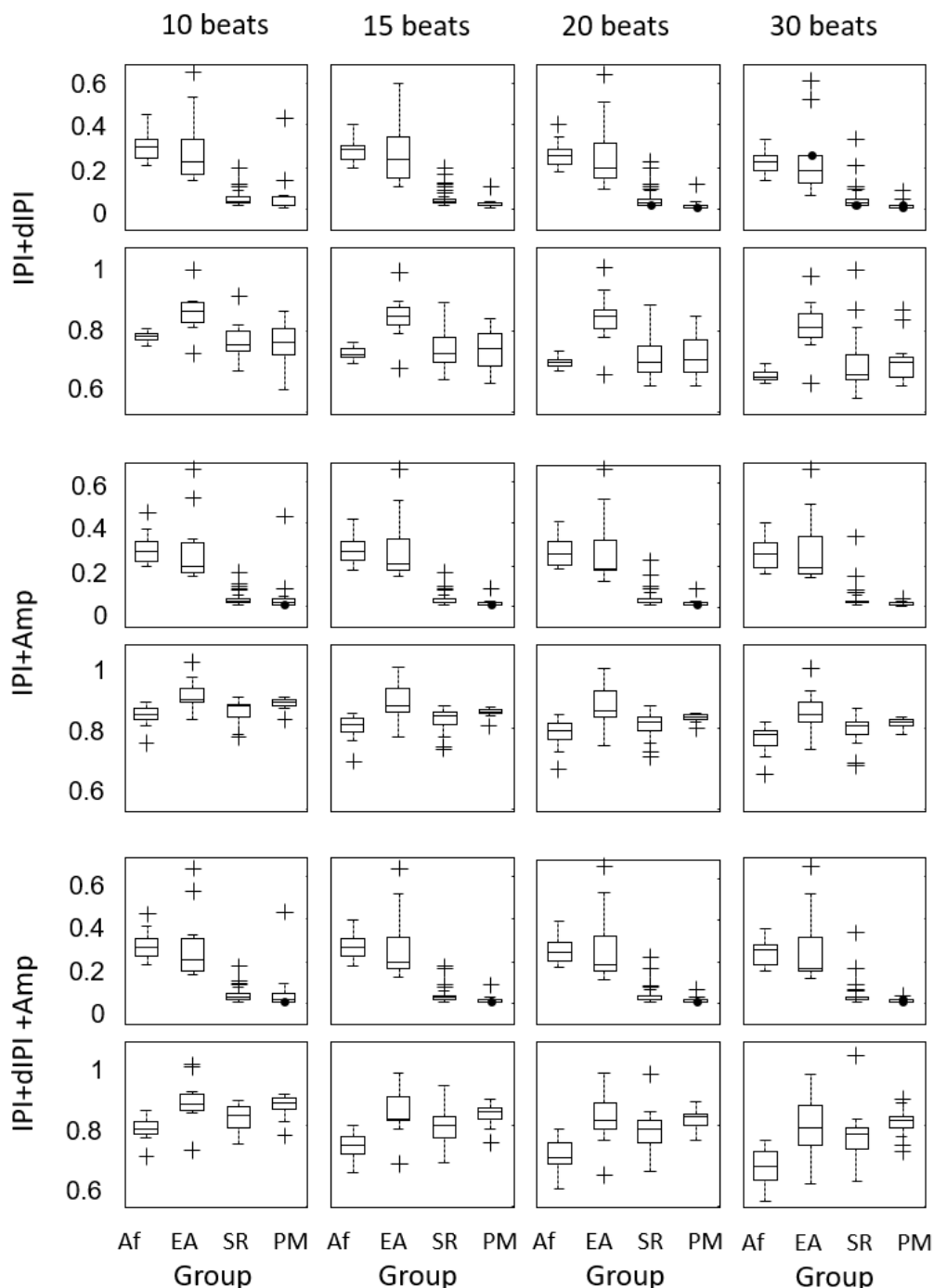
When three groups were to be differentiated (AF, EA and SR), the success rates dropped, as expected. We intentionally added the EA group, because the main targeted application was a quick screening test in the outpatient clinic. For this purpose, the doctor could differentiate arrhythmia from SR by manual palpation and, then, PAG could be utilized to differentiate between AF and EA. Intuitively, for EA with infrequent ectopic beats and short segment length, some segments were actually as regular as SR. On the other hand, for EA with frequent ectopic beats, some segments might mimic AF. Therefore, differentiation is inherently difficult and a longer segment length is needed. We did not include patients with atrial flutter or multifocal atrial tachycardia, which are also differential diagnoses of AF, due to their rarity.

PM was also included in this analysis for the same reason. In specific cases, doctors may want to know whether the rhythm originates naturally, or from an artificial pacemaker. ECG may not be helpful for very small pacing trigger artifacts. However, the rhythms for some patients with SR might be less variable due to autonomic dysfunction. The obtained

margin between SR and PM groups was very narrow and the differentiation was difficult.

Results showed that our PAG can be used to identify AF over several other scenarios. When three groups were included in the differentiation experiment (AF, EA and SR), the accuracy were around 90%, and for four groups (AF, EA, SR and PM) the accuracy were around 80%. The goal of developing a PAG was not to replace ECG, but to provide a simple alternative for quick screening. PAG has some advantages over ECG, including only one position needed for detection, no need of skin preparation or gel presence, information about mechanical properties of the cardiovascular system, and resistance to electromagnetic noises. PAG's disadvantages include less available experience and available database, inability for further arrhythmia classification, and vulnerability to movement.

Because PAG monitors mainly the mechanical properties of the cardiovascular system, while ECG records electrical properties, PAG may provide some additional information that ECG cannot offer. Such information is the pulse amplitude variation and the contractile efficiency of the heart. In FIGURE 6, PAG showed that a longer leading IPI, by a longer ventricular filling time, leads to a larger PAG peak amplitude (PH). The mean slope of linear regression showed positive correlation between IPI and PH of PAG in AF patients. The extreme case of pulse amplitude variation is the so-called pulse deficit, which may lead to wrong estimation



**FIGURE 10.** Results of analyses using FCM with different input variables. The conventions are identical to those in FIGURE 8. First two rows ( $D_{max}$  and  $R_{dm}$ ) used IPI (inter-pulse interval) and dIPI (difference of IPI) as the input variables, middle two rows used IPI and amplitude (Amp) and bottom two rows used IPI, dIPI and amplitude.

of heart rate and mismatch between the estimated rates by palpation and by ECG. When the heart beat is very fast and irregular as in AF, some of the beats are not strong enough to open the aortic valve, hence a pulse is not felt. This usually occurs when there is a short cardiac cycle with little time for diastolic filling of the ventricle. Highly premature ectopic

beats can also produce pulse deficit for the same reason. A pulse deficit of more than 10 per minute is more likely to occur in AF [33]. We found by visual inspection that 10 out of the 21 patients in this study showed large variation of pulse amplitude, indicating the existence of pulse deficit. As described in section E of results, FIGURE 11 shows a case of



**TABLE 1. Accuracy (%) of automatic grouping of cardiac rhythms.**

	CEn <sup>#1</sup>		CEn + FCM		FCM							
					F1 <sup>#2</sup>		F2		F3		F4	
	T <sup>#3</sup>	V	T	V	T	V	T	V	T	V	T	V
C1 <sup>#4</sup> (n=46/45)	59 <sup>#5</sup>	54	99	65	88	79	82	77	84	74	88	79
	56	52	98	57	88	83	83	73	81	67	89	84
	73	71	97	62	85	79	79	67	82	72	87	82
	80	76	94	69	82	72	81	68	82	71	85	79
C2 (n=46/45)	60	54	100	79	100	93	98	90	94	83	94	84
	56	47	98	73	99	93	94	85	93	81	94	85
	79	78	99	69	98	90	93	83	93	82	95	88
	88	84	99	75	94	85	91	79	93	81	93	81
C3 (n=33/33)	87	82	100	100	100	99	100	99	100	99	100	92
	84	73	100	94	100	100	100	99	100	96	99	97
	99	94	100	99	100	97	100	99	100	95	100	95
	100	100	100	97	100	97	100	96	100	94	98	97

<sup>#1</sup> CEn: coefficient of sample entropy; FCM: fuzzy c-means.

<sup>#2</sup> Inputs used for FCM. F1: IPI; F2: IPI and dIPI; F3: IPI and PH; F4: IPI, dIPI and PH.

<sup>#3</sup> Data set used for testing ANFIS. T: training; V: validation.

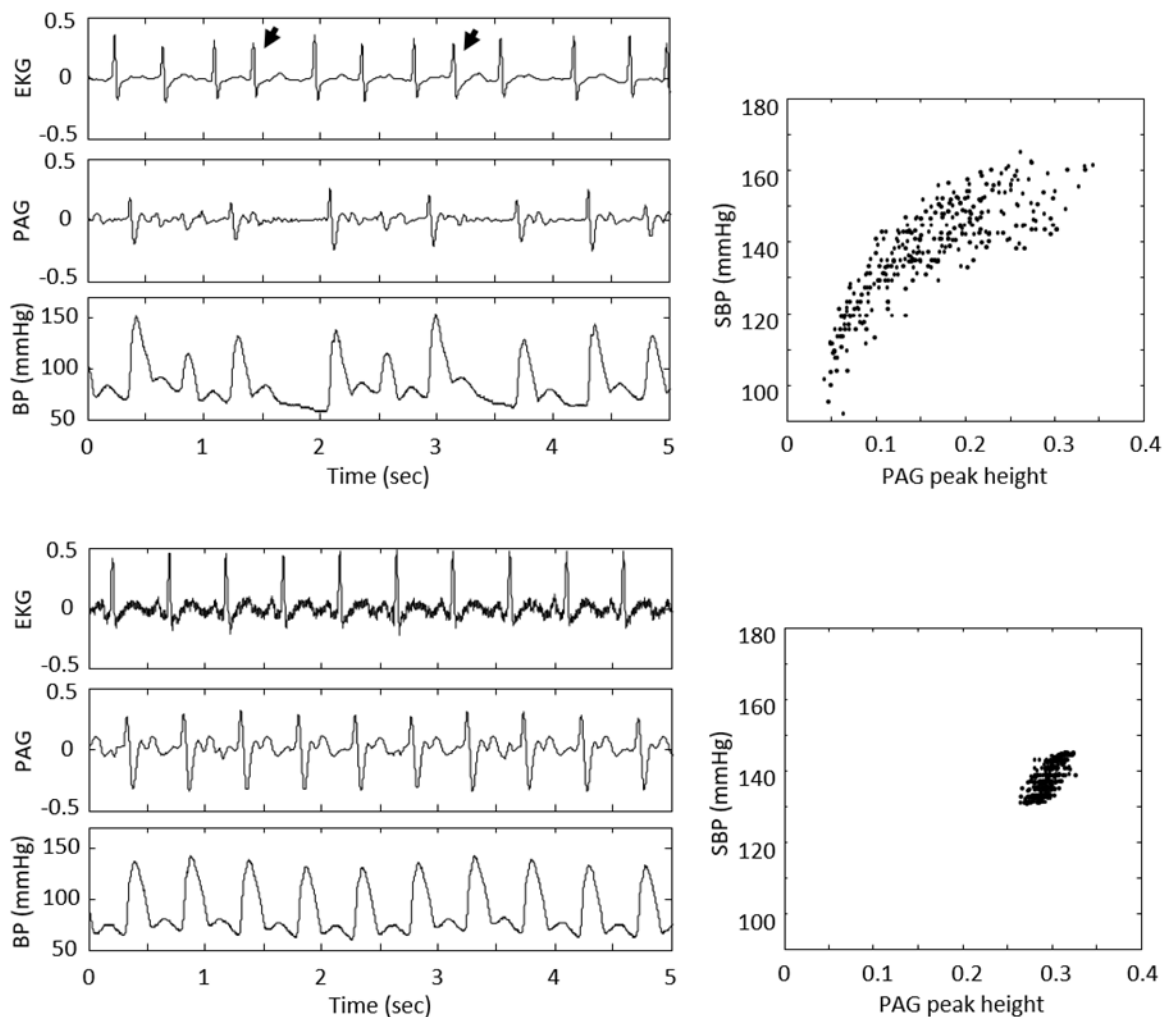
<sup>#4</sup> Included patient groups included. C1: AF, EA, SR and PM; C2: same as C1, except SR and PM were merged; C3: AF and SR. *n*: patient numbers in training and validation data sets, respectively.

<sup>#5</sup> From top to bottom, values in a cell show the result of 10, 15, 20 and 30 beats, respectively.

paroxysmal AF with pulse deficit, in which ECG amplitude did not change prominently among peaks, while PAG PH and BP did. Muntinga *et al.* [34] reported that beat-to-beat interval may influence the left ventricular systolic performance. On the other hand, the left ventricular contractility was significantly reduced in the cases with pulse deficit [35]. In the absence of cardiac monitoring, the assessment of the apex beat (with the radial pulse) is an important aspect for the management of a patient with AF. A wide apex-radial pulse deficit indicates inefficient cardiac contraction [33]. ECG cannot reflect the variation of pulse amplitude. Although a

previous study [36] reported that the sensitivity and specificity of the simple manual peripheral pulse measurement by health care professionals was 96.5% and 94.0%, respectively, our new developed device PAG provides simultaneous objective recordings of pulse amplitude and intervals. Therefore, we think PAG, complementary to ECG, may be useful in some conditions, such as the process of cardiac resuscitation.

Even though the techniques of signal processing used in this study may appear complicated, the processing time is less than a second using a typical personal computer. The whole sequence of algorithms can be automated, embedded in



**FIGURE 11.** An example of paroxysmal AF with pulse deficits. The upper left plots show the arrhythmic phase, in which the arrows indicate the places where the pulse deficits occur. The lower plots show the rhythmic phase. The right plots show that the systolic blood pressure (SBP) increase with the peak height of PAG. Because the PAG peak height spreads wider in the arrhythmic phase (upper right plot, compared to lower right plot), the relationship becomes more evident.

a microprocessor, and implemented in real time. As described in the experimental methods section, the hardware of PAG is simple. In conclusion, PAG can be a simple device for real-time screening of arrhythmias, especially AF.

**V. CONCLUSION**

A new wearable PAG of the radial artery was developed with the main purpose of quickly detecting AF and monitoring pulse amplitude variation. Results indicated that our PAG can identify AF satisfactorily, even in a time window as short as 10 beats. In addition, PAG can monitor the trend of pulse amplitude, which cannot be offered by ECG. For patients with AF, left ventricular contractility was significantly reduced in the cases with pulse deficit. Also, PAG peak height spread wider in the arrhythmic phase, and the relationship of SBP increase with the peak height of PAG became more evident. Our PAG device could sensitively detect this scenario. The individual slope of normalized PH versus normalized IPI

and PH increased with the preceding IPI were significantly different from zero ( $p < 0.05$  by Student t-test) in the AF group. Both FCM and CEn + FCM achieved near 100% accuracy of differentiation between AF and SR groups, with the segment length being as short as 10 beats. The limitations of the proposed PAG device are that lack of large-scale validation in its effectiveness and susceptibility of the method to the environmental noise, to improve these limitations can be future works of our research. Hence, to measure the PAG and ECG simultaneously in the future may be beneficial for capturing pulse deficit and measuring the differences of the number of pulses and heart rate during AF, which is possible to investigate insight of hemodynamics of atrial fibrillation.

**ACKNOWLEDGMENT**

(*Ju-Yi Chen and Chou-Ching K. Lin are co-first authors.*)

## REFERENCES

- [1] P. S. Jagadish and R. Kabra, "Stroke risk in atrial fibrillation: Beyond the CHA<sub>2</sub>DS<sub>2</sub>-VASc score," *Current Cardiol. Rep.*, vol. 21, no. 9, p. 95, Sep. 2019.
- [2] R. W. Rho and R. L. Page, "Asymptomatic atrial fibrillation," *Prog. Cardiovascular Diseases*, vol. 48, no. 2, pp. 79–87, Sep. 2005.
- [3] N. R. Jones, C. J. Taylor, F. D. R. Hobbs, L. Bowman, and B. Casadei, "Screening for atrial fibrillation: A call for evidence," *Eur. Heart J.*, vol. 41, no. 10, pp. 1075–1085, Mar. 2020.
- [4] G. C. Flaker, K. Belew, K. Beckman, H. Vidaillet, J. Kron, R. Safford, M. Mickel, and P. Barrell, "Asymptomatic atrial fibrillation: Demographic features and prognostic information from the atrial fibrillation follow-up investigation of rhythm management (AFFIRM) study," *Amer. Heart J.*, vol. 149, no. 4, pp. 657–663, Apr. 2005.
- [5] R. Marfella, F. C. Sasso, M. Siniscalchi, M. Cirillo, P. Paolisso, C. Sardu, M. Barbieri, M. R. Rizzo, C. Mauro, and G. Paolisso, "Brief episodes of silent atrial fibrillation predict clinical vascular brain disease in type 2 diabetic patients," *J. Amer. College Cardiol.*, vol. 62, no. 6, pp. 525–530, Aug. 2013.
- [6] C. T. January, L. S. Wann, H. Calkins, L. Y. Chen, J. E. Cigarroa, J. C. Cleveland, Jr., P. T. Ellinor, M. D. Ezekowitz, M. E. Field, K. L. Furie, P. A. Heidenreich, K. T. Murray, J. B. Shea, C. M. Tracy, and C. W. Yancy, "2019 AHA/ACC/HRS focused update of the 2014 AHA/ACC/HRS guideline for the management of patients with atrial fibrillation: A report of the American College of cardiology/American heart association task force on clinical practice guidelines and the heart rhythm society," *J. Amer. College Cardiol.*, vol. 74, no. 1, pp. 104–132, 2019.
- [7] P. Kirchhof, S. Benussi, D. Kotecha, A. Ahlsson, D. Atar, B. Casadei, M. Castella, H. Diener, H. Heidbuchel, J. Hendriks, G. Hindricks, A. S. Manolis, J. Oldgren, B. A. Popescu, U. Schotten, B. V. Putte, and P. Vardas, "2016 ESC guidelines for the management of atrial fibrillation developed in collaboration with EACTS," *Eur. Heart J.*, vol. 37, no. 38, pp. 2893–2962, 2016.
- [8] N. Isakadze and S. S. Martin, "How useful is the smartwatch EKG?" *Trends Cardiovascular Med.*, vol. 30, no. 7, pp. 449–450, 2020.
- [9] K. Lee, H. O. Choi, S. D. Min, J. Lee, B. B. Gupta, and Y. Nam, "A comparative evaluation of atrial fibrillation detection methods in Koreans based on optical recordings using a smartphone," *IEEE Access*, vol. 5, pp. 11437–11443, 2017.
- [10] C. Yang, C. Veiga, J. J. Rodríguez-Andina, J. Fariña, A. Iñiguez, and S. Yin, "Using PPG signals and wearable devices for atrial fibrillation screening," *IEEE Trans. Ind. Electron.*, vol. 66, no. 11, pp. 8832–8842, Nov. 2019.
- [11] L. M. Eerikainen, A. G. Bonomi, F. Schipper, L. R. C. Dekker, H. M. de Morree, R. Vullings, and R. M. Aarts, "Detecting atrial fibrillation and atrial flutter in daily life using photoplethysmography data," *IEEE J. Biomed. Health Informat.*, vol. 24, no. 6, pp. 1610–1618, Jun. 2020.
- [12] S. Bagha and L. Shaw, "A real time analysis of PPG signal for measurement of SpO<sub>2</sub> and pulse rate," *Int. J. Comput. Appl.*, vol. 36, no. 11, pp. 45–50, 2011.
- [13] Y.-E. M. Portnoy and L. D. Richardson, "Pulse deficit as a new, innovative, non-invasive measure to risk-stratify atrial fibrillation patients," *Circulation*, vol. 138, no. 1, 2018, Art. no. A11244.
- [14] O. Lahdenoja, M. Pankaala, T. Koivisto, T. Hurnanen, Z. Iftikhar, S. Nieminen, T. Knuutila, A. Saraste, T. Kiviniemi, T. Vasankari, and J. Airaksinen, "Atrial fibrillation detection via accelerometer and gyroscope of a smartphone," *IEEE J. Biomed. Health Informat.*, vol. 22, no. 1, pp. 108–118, Jan. 2018.
- [15] X. Wen, Y. Huang, X. Wu, and B. Zhang, "A feasible feature extraction method for atrial fibrillation detection from BCG," *IEEE J. Biomed. Health Informat.*, vol. 24, no. 4, pp. 1093–1103, Apr. 2020.
- [16] Y. Lee, J.-Y. Park, Y.-W. Choi, H.-K. Park, S.-H. Cho, S. H. Cho, and Y.-H. Lim, "A novel non-contact heart rate monitor using impulse-radio ultra-wideband (IR-UWB) radar technology," *Sci. Rep.*, vol. 8, no. 1, p. 13053, Dec. 2018.
- [17] A. B. Joshi, A. E. Kalange, D. Bodas, and S. A. Gangal, "Simulations of piezoelectric pressure sensor for radial artery pulse measurement," *Mater. Sci. Eng., B*, vol. 168, nos. 1–3, pp. 250–253, Apr. 2010.
- [18] S. Zang, Q. Wang, Q. Mi, J. Zhang, and X. Ren, "A facile, precise radial artery pulse sensor based on stretchable graphene-coated fiber," *Sens. Actuators A, Phys.*, vol. 267, pp. 532–537, Nov. 2017.
- [19] D. Jia, J. Chao, S. Li, H. Zhang, Y. Yan, T. Liu, and Y. Sun, "A fiber Bragg grating sensor for radial artery pulse waveform measurement," *IEEE Trans. Biomed. Eng.*, vol. 65, no. 4, pp. 839–846, Apr. 2018.
- [20] D. Lin, A. Zhang, J. Gu, X. Chen, Q. Wang, L. Yang, Y. Chou, G. Liu, and J. Wang, "Detection of multipoint pulse waves and dynamic 3D pulse shape of the radial artery based on binocular vision theory," *Comput. Methods Programs Biomed.*, vol. 155, pp. 61–73, Mar. 2018.
- [21] J. Lian, L. Wang, and D. Muessig, "A simple method to detect atrial fibrillation using RR intervals," *Amer. J. Cardiol.*, vol. 107, no. 10, pp. 1494–1497, May 2011.
- [22] E. R. Pfeiffer, J. R. Tangney, J. H. Omens, and A. D. McCulloch, "Biomechanics of cardiac electromechanical coupling and mechanoelectric feedback," *J. Biomech. Eng.*, vol. 136, no. 2, Feb. 2014.
- [23] X. Zhou, H. Ding, B. Ung, E. Pickwell-MacPherson, and Y. Zhang, "Automatic online detection of atrial fibrillation based on symbolic dynamics and Shannon entropy," *Biomed. Eng. OnLine*, vol. 13, no. 1, p. 18, 2014.
- [24] X. Zhou, H. Ding, W. Wu, and Y. Zhang, "A real-time atrial fibrillation detection algorithm based on the instantaneous state of heart rate," *PLoS ONE*, vol. 10, no. 9, Sep. 2015, Art. no. e0136544.
- [25] N. Larburu, T. Lopetegui, and I. Romero, "Comparative study of algorithms for atrial fibrillation detection," in *Proc. Comput. Cardiol.*, Sep. 2011, pp. 265–268.
- [26] P. Langley, M. Dewhurst, L. Y. Di Marco, P. Adams, F. Dewhurst, J. C. Mwita, R. Walker, and A. Murray, "Accuracy of algorithms for detection of atrial fibrillation from short duration beat interval recordings," *Med. Eng. Phys.*, vol. 34, no. 10, pp. 1441–1447, Dec. 2012.
- [27] D. E. Lake and J. R. Moorman, "Accurate estimation of entropy in very short physiological time series: The problem of atrial fibrillation detection in implanted ventricular devices," *Amer. J. Physiol.-Heart Circulatory Physiol.*, vol. 300, no. 1, pp. H319–H325, Jan. 2011.
- [28] H. Yin, Y. Zeng, J. Zhang, and Y. Pan, "Application of adaptive noise cancellation with neural-network-based fuzzy inference system for visual evoked potentials estimation," *Med. Eng. Phys.*, vol. 26, no. 1, pp. 87–92, Jan. 2004.
- [29] K. Tanaka and H. O. Wang, *Fuzzy Control Systems Design and Analysis*. New York, NY, USA: Wiley, 2004.
- [30] H. Calkins, J. Brugada, D. L. Packer, R. Cappato, S. A. Chen, H. J. Crijns, R. J. Damiano, Jr., D. W. Davies, D. E. Haines, M. Haissaguerre, and Y. Iesaka, "HRS/EHRA/ECAS expert consensus statement on catheter and surgical ablation of atrial fibrillation: Recommendations for personnel, policy, procedures and follow-up: A report of the Heart Rhythm Society (HRS) task force on catheter and surgical ablation of atrial fibrillation," *Heart Rhythm: Off. J. Heart Rhythm Soc.*, vol. 9, no. 6, pp. 335–379, 2007.
- [31] G. Boriani, T. V. Glotzer, M. Santini, T. M. West, M. De Melis, M. Sepsi, M. Gasparini, T. Lewalter, J. A. Camm, and D. E. Singer, "Device detected atrial fibrillation and risk for stroke: An analysis of more than >10,000 patients from the SOS AF project (Stroke Prevention Strategies Based on Atrial Fibrillation Information from Implanted Devices)," *Eur. Heart J.*, vol. 35, no. 8, pp. 508–516, 2014.
- [32] J. S. Healey, S. J. Connolly, M. R. Gol, C. W. Israel, I. C. Vam Gelder, A. Capucci, C. P. Lau, E. Fain, S. Yang, C. Bailleul, and C. A. Morillo, "Subclinical Atrial Fibrillation and The Risk of Stroke," *New England J. Med.*, vol. 366, no. 2, pp. 120–129, 2012.
- [33] M. E. Williams, *Geriatric Physical Diagnosis: A Guide to Observation and Assessment*. California, NC, USA: McFarland, 2010.
- [34] H. J. Muntinga, A. T. M. Gosselink, P. K. Blanksma, P. J. De Kam, E. E. V. D. Wall, and H. J. G. M. Crijns, "Left ventricular beat to beat performance in atrial fibrillation: Dependence on contractility, preload, and afterload," *Heart*, vol. 82, no. 5, pp. 575–580, Nov. 1999.
- [35] K. Mawatari, J. Sanada, N. Kuroiwa, K. Okumiya, K. Nakamura, and S. Hashimoto, "Mechanism of production of pulse deficit in atrial fibrillation: Assessment by blood flow dynamics," *J. Cardiol.*, vol. 18, no. 1, pp. 197–205, 1988.
- [36] B. Kallmunzer, T. Bobinger, N. Kahl, M. Kopp, N. Kurka, M.-J. Hilz, L. Marquardt, S. Schwab, and M. Kohrmann, "Peripheral pulse measurement after ischemic stroke: A feasibility study," *Neurology*, vol. 83, no. 7, pp. 598–603, Aug. 2014.



cardiac implantable electric devices.

**JU-YI CHEN** was born in Tainan, Taiwan, in 1974. He received the M.S. degree from Chang Gung University, Taoyuan City, Taiwan, in 1999, and the Ph.D. degree from the National Cheng Kung University, Tainan, Taiwan, in 2013. He is currently an Associate Professor, since 2013, with the Department of Internal Medicine, National Cheng Kung University, Tainan. His current research activities involve the cardiovascular diseases, including arrhythmias, hypertension, arterial stiffness, and



Cheng Kung University, Taiwan. His research area of interest is experimental aerodynamics.

**FAN-MING YU** received the B.S. degree in mechanical engineering from National Cheng Kung University, Taiwan, the M.S. degree in mechanical engineering from National Taiwan University, Taiwan, the degree in aerospace engineering from the University of Tennessee, USA, and the Ph.D. degree in aerospace engineering from the University of Tennessee, USA. He is currently an Adjunct Professor with the Department of Aeronautics and Astronautics, National



Cheng Kung University, Tainan, Taiwan. His areas of interest include functional MRI, brain-computer interface (BCI), brain stimulation, and neural network modeling.

**CHOU-CHING K. LIN** (Senior Member, IEEE) received the bachelor's degree in medicine from National Yang-Ming University, Taipei, Taiwan, in 1988, and the M.Sc. and Ph.D. degrees in biomedical engineering from Case Western Reserve University, Cleveland, OH, USA, in 1994 and 1997, respectively. He is currently a Professor and a Chairman with the Department of Neurology and an Adjunct Professor with the Department of Biomedical Engineering, National



**KUAN-JUNG LI** received the Ph.D. degree in biomedical engineering from Chung Yuan Christian University, Taiwan. He is currently a Research Assistant Professor with the Medical Device Innovation Center, National Cheng Kung University, Taiwan. His research areas of interests include cardiovascular risk, blood pressure, cardiovascular medicine, pulse wave analysis, cardiac function, ambulatory blood pressure monitoring, osteoblast, and internal medicine.



Innovation Center, National Cheng Kung University, Tainan City, Taiwan (R.O.C). His research interests include the biomedical signal analysis using deep learning algorithms, virtual reality rehabilitation system, the surgical assistive device development, and artificial intelligence wearable technology.

**CHE-WEI LIN** (Member, IEEE) was born in Hualien, Taiwan, in 1984. He received the B.Eng. degree in electrical and control engineering from National Chiao Tung University (NCTU), Hsinchu City, Taiwan (R.O.C), in 2006, and the Ph.D. degree from the Department of Electrical Engineering, National Cheng Kung University, Tainan City, Taiwan (R.O.C), in 2011. Since 2016, he has been an Assistant Professor with the Department of Biomedical Engineering/Medical Device



primary intervention therapy, critical care medicine, and medical informatics.

**LIANG-MIIN TSAI** was born in Kaohsiung, Taiwan, in 1958. He received the M.D. degree from Taipei Medical University, Taipei, Taiwan, in 1984. He had been Professor of medicine with the College of Medicine, National Cheng Kung University, Tainan, Taiwan, from 1998 to 2019. He is currently the Superintendent of Tainan Municipal Hospital (Managed by Show Chwan Medical Care Corporation), Tainan, Taiwan. His research interest includes echocardiography, coronary

• • •