Pulse Harmonic Strength of Facial Video Signal for the Detection of Atrial Fibrillation

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Abstract

It is estimated that 3.2 million people have developed atrial fibrillation (AF) in the United States and 30% of AF patients are unaware of their diagnosis (silent AF). We tested a new technology for contactless detection of AF based on facial video recordings in patients undergoing electrical cardioversion for AF. The proposed technique uses the facial video signal to extract the beat-to-beat variations of the skin color reflecting the cardiac pulsatile signal. We developed the concept of Pulse Harmonic Strength (PHS) to capture AF patterns from this signal. Also, we quantified the variability of the heart rate and pulse rate using additional measurements of heart rate variability. Eleven subjects (65±6 years, 8 males) were enrolled in the study and 407 epochs of 15 sec. were acquired simultaneously with ECG and facial video signals. PHS was associated with a 20% detection error rate of AF in reference to human interpretation while the error rates of the automatic ECG-based measurements ranged between 17% and 29% across the investigated HRV parameters.

1. Introduction

Atrial fibrillation (AF) represents a significant health and economic challenge because it is a major cause of stroke, heart failure, emboli, diminished quality of life, and death. It is accepted worldwide that approximately 8% of the aging population develop AF based on the clinical trials conducted this past decennia: 8.3% in Rotterdam study (age >55 yrs) and 7.9% in the Screening for Atrial Fibrillation in the Elderly (SAFE) trial (age>65 yrs).[1-2] Importantly, the "Prevention of Atrial Fibrillation After Cardioversion" trial (PAFAC) have shown that 54% of the 188,634 ECGs recorded in 1,033 patients were asymptomatic AF episodes (silent AF), and 70% of the 191,103 recordings from 383 patients enrolled in the 'Suppression of Paroxysmal Atrial Tachyarrhythmias' trial (SOPAT) suffer from the silent form of the disease. Therefore, it is of paramount importance to develop novel monitoring technologies that could enable ubiquitous monitoring and diagnostic of individuals for AF. Currently, the mobile cardiac outpatient telemetry systems are available but these technologies rely on standard ECG recording systems which require a physician's prescription and hence the presence of a symptomatology.

We propose to evaluate a method to extract variability of pulse from a new non-contact video-based technology, so–called facial videoplethysmography (VPG) [3,4], as an inexpensive, safe, and easily portable solution to the challenge of AF diagnosis and prevention. It is expected that an early detection of AF will maximize the use of current therapeutic strategies, improve AF prevention, reduce mortality and morbidity, and finally improve quality of life of AF patients.

2. Method

2.1. Videoplethysmography and pulse harmonic strength

The pioneering work on non-contact video monitoring was developed for the monitoring of respiration and heart rate using digital RGB cameras. The basic concept of VPG is to find the observed RGB traces associated with the heart activity pumping blood to and from the face. It was observed that the green channel of the RGB signal features the strongest plethysmographic signal because it corresponds to the absorption peak of ambient light by hemoglobin. Poh M.Z. et al. [6] improved the accuracy of such method by applying blind source separation using independent component analysis and incorporating face tracking to automatically capture the face of a single or multiple patients. This type of monitoring was recently

expanded by the same group to include measurements of other parameters such as the Heart Rate Variability (HRV) based on the independent component analysis approach. [7].

In our method, we implemented a set of pre-processing steps during which a region of interest (ROI) is selected in each frame; pixels in each ROIs are then spatially averaged to create a time-series signal. This green trace is detrended and band-pass filtered within the frequency range of human heart rate. Cubic interpolation is then applied to up sample the signal. Constrained independent component analysis is then computed to extract oscillatory signals within the physiologically-acceptable range. This process is applied on a continuous basis and coupled with peak and valley detection algorithm to ultimately extract the pulse rate on a beat-to beat basis. [3].

A power spectral density is computed across all frequencies within the VPG signal to facilitate an identification of a fundamental frequency and at least its first harmonic. Pulse harmonic strength (PHS)" is a ratio of signal strength at the fundamental frequency and harmonics to the strength of a base signal. A 0.2 Hz frequency band around the fundamental and its harmonics is considered.

Figure 1. Panel A is a picture of the Holter recording device (Mortara Instruments, Milwaukee, WI) used to record the 12-lead ECG signals that includes the video-ECG synchronizing device (located on the right of the ECG recorder). Panel B is a picture of the cardioversion room where the web cam is mounted on a pole above the head of the patient. The laptop stores the video signal throughout the cardioversion procedure.

The power of the fundamental frequency and its harmonic reasonances between 0.05Hz and 3 Hz are integrated and denoted P_{sign}. The power in all remaining bands are integrated separately denoted P_{nois} . The pulse harmonic strength is therefore given by the ratio:

$$PHS = \frac{P_{sign}}{P_{nois}} \quad \text{with} \quad P_{nois} = P_{total} - P_{sign}$$

Where P_{total} is the total energy of the signal in the frequency band of interest. Therefore, one expects PHS to measure the total strength of the cardiac pulsatile signal. The highest the PHS value the less variability is present in the VPG-based pulsatile signal.

2.2. Study design

We enrolled adult AF patients who underwent direct current electrical cardioversion in the Electrophysiology Laboratory at Strong Memorial Hospital (Rochester, NY). During the procedure, a RGB web camera (Microsoft LifeCam Cinema, Microsoft Inc., Redmond, WA) was placed above the head of the patients (when supine) at a distance of 1 meter. Camera was connected to a laptop (Dell Precision M6400, Dell, Round Rock, TX) to record the face of the patient during the overall procedure (see Figure 2, panels B and C). We recorded 12-lead ECG using a Holter recorder (Mortara Instrument Inc., Milwaukee, MN). The internal clock of the Holter recorder and the video camera were not precise enough to ensure adequate synchronization. Therefore, we developed a synchronization light-sensitive apparatus placed between the lead cables and the Holter recorder connectors to disconnect the ECG lead from the recorder (flat signals) when illuminated by a flashlight (see Figure 1, panel A). We synchronize the ECG and video signals by aligning the time of the first video frame with the flashlight to the time of ECG signal interruption generated by the apparatus. The video recording device was a standard web camera providing 15/30 frames per second video signals (66.7/33.3 ms time precision). After extracting pulsating signals from each video data signals were upsampled to 180 samples per second. The camera resolution varied between VGA (640x480) to HD (1280x720). The ECG recorder provided a signal with a 1,000 samples per second and ~5microV amplitude resolution. ECG computations were done 180 samples per second. The duration of the recordings depended on several factors: the procedure success (single and multiple shocks procedure) and the time to sedation.

2.3. VPG and ECG processing

Examples of VPG and ECG signals in patients during sinus rhythm and during AF are provided in Figure 2. Both signals were processed to extract the beat-to-beat pulse and heart rates. A commercial Holter Scanning software (HScribe, Mortara Instruments, Milwaukee, WI) was used for the analysis of the ECG signal, and a MATLAB procedure (Mathworks, Natick, MA) for the extraction of the pulse rate from the VPG signals.

We investigated standard ECG factors used to measure heart rate variability: 1) three parameters from the time-domain: SDNN, RMSSD, and pNN50; and 2) two parameters from the Lorenz plot method: SD1, SD2. The parameters SD1 and SD2 are robust markers of the presence of AF, they measured the short- and long-term dispersion of the RR interval durations, respectively. [8].

Finally, the interpretation of the 15-sec ECG signal was conducted by ECG experts from the Heart Research Follow-up Program (University of Rochester, NY). The identification of AF by these experts was considered as the gold standard for the interpretation of the 15-sec ECG recordings.

3. Results

The Table 1 and 2 provide the means and standard deviations of the heart rate and pulse variability for the set of 15-sec epochs of ECG and VPG recordings, respectively. We extracted all RR intervals (n=2,676) from 143 epochs during AF, and 3543 RR intervals from 264 epochs during sinus rhythm. The VPG method was found to be more accurate during sinus rhythm. Precisely, less than 1% (0.9%) of cardiac beats were over sensed by the VPG method, and 17.7% were undetected. During sinus rhythm, we found 1.3% over sensed beats and 5.0% undetected beats during SR. When evaluating the error due to VPCs, we counted 23 supraventricular beats and VPCs during AF and 259 post-ablation, 20% of VPCs were missed by the VPG method in SR and 65% during AF.

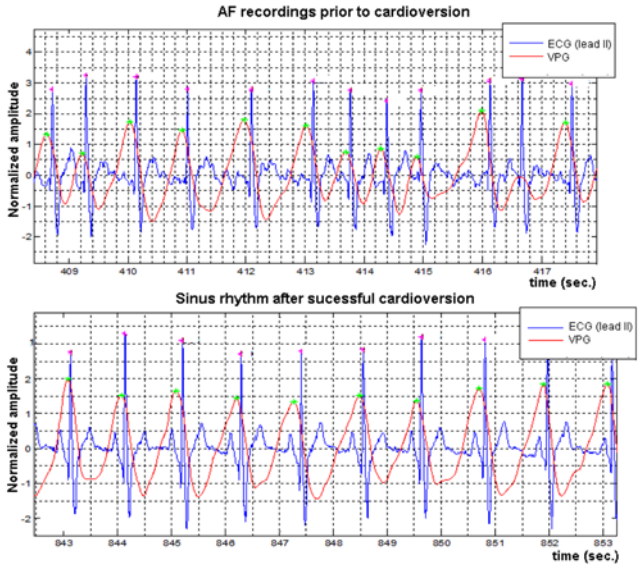

Figure 2. The two tracings present ECG and VPG signals extracted from the video of a patient's face. The facial VPG signals were shifted to have the peak of the first pulse aligned with the R waves of the first QRS complex, i.e., deletion of the pulse transit time between heart contraction and facial blood flow. In both AF examples (upper panel) and in sinus rhythm (lower panel) the maxima on the VPG signals remain well synchronized with R-waves from the ECG signals.

We used a leave-one-subject-out cross-validation to estimate the classification error rate (CER) of each methods (ECG vs. VPG) for detecting AF rhythm using human annotation as reference. This was done by selecting the threshold that optimized the epoch-level CER for 10 training subjects; computing the empirical CER for the epochs from the 1 test subject, using the training threshold; and computing the weighted average of the 11 subject-specific cross-validated error rates, weighted by the number of epochs per subject. This procedure was used to estimate the error rate of the various parameters at classifying the epochs in the two groups AF and sinus rhythm. The results of the process delivered the results described in Table 1 and 2 for the ECG and VPG signals, respectively.

ECG (gold standard)	Sinus	AF	P value
HR (bpm)	74±25	55±12	**0.008**
SDRR (ms)	128±56	19±23	**0.002**
RMSSD (ms)	172±69	19±20	**0.002**
SD1 (ms)	124±48	16±13	**0.002**
SD2 (ms)	155±58	25±20	**0.002**

Table 1: Measurements of heart rate variability from ECG-based factors.

VPG	Sinus	AF	P value
PR (ppm)	73±23	54±12	**0.006**
SDRR (ms)	133±89	51±24	**0.002**
RMSSD (ms)	176±90	70±34	**0.002**
SD1 (ms)	129±58	51±23	**0.002**
SD2 (ms)	139±74	46±17	**0.002**

Table 2: Measurements of pulse rate variability from VPG-based factors.

The estimated error rate (ER) for the PHS parameter was equal to 20% while the ERs for the ECG-based parameters were equal to 17%, 21%, 24%, 25%, and 29% for PNN50, SDNN, SD1, RMSSD , and SD2, respectively. When considering the ECG-based parameters after manual annotation, i.e., non-sinus beats were marked and eliminated from the computation of HRV parameters, the ER for the same factors were equal to 8%, 15%, 15%, 16%, and 16%.

4. Discussion

We propose a new concept for detecting the presence of AF from the video recordings of an individual by using a technology extracting the subtle variation of skin color attributed to the changes in blood volume underneath the thin facial skin (beat-to-beat flushing).

This is a pioneering work in which one attempts to detect the presence of cardiac arrhythmias without any direct physical contact with the subject. Estimation of the heart rate using facial flushing has been implemented and commercialized using various technologies. Most of those are embedded in smartphone and tablet using Android.

These technologies are limited to an estimated heart rate because they do not deliver a beat-to-beat detection of cardiac pulse. Our technology goes beyond these existing methods by measuring the beat-to-beat pulse [3,4] and therefore enabling the measurements of heart rate variability and its increase in patients with AF.

The unique advantage of the technology is its potential for being embedded in any device loaded with a digital camera delivering video signal with at least 30 frames per sec. The current performances of the technology is too low (20% error rate) to expect clinical acceptance. Hence, we are currently conducting additional investigations to better understand how VPG could be used to discriminate pulse waves due to sinus of non-sinus cardiac beats and improving both their detection and classification. Our study showed that ventricular premature beats (VPBs) were generally not detected from the VPG signal when they were recorded during AF (65% were missed), while only 20% were missed during sinus rhythm. The speculative explanation for this higher detection rate during sinus rhythm involves the role of the hemodynamic impact of the arrhythmia, precisely the VPBs during AF are expected to generate weaker blood pulse signal. This is supported by the documented presence of pulse deficit in patients with AF.

Also, this pulse deficit is likely to play a role in the large difference in values of HRV factors between ECG-based and VPG-based signals during AF rhythm. We are currently testing this hypothesis using simultaneous recordings of ECG, VPG and standard plethysmographic signals during electrophysiology testing procedures.

Finally and importantly, the head movements of the subjects have been one of the most challenging and impactful factor in our experiment despite the fact that patients were sedated during the procedure. Body movement during the cardioversion shocks, snoring during sedation, and other unconscious movements of the subject's body were associated with loss of the VPG signal. Our algorithm scans the face of the patient and extracts a ROI of the facial video images that carries the strongest pulsatile signal. Once this ROI has been lost because the head changes position and/or its angle with the camera is modified (this specific case occurred during our study when the pillow of the patient was readjusted during sedation), then the subject requires new scanning and identification of a new ROI. A face tracking algorithm is likely to help stabilizing these measures but is not likely to be sufficient to solve the issue of changes of the angle between the patient's face and the video camera.

5. Conclusion

We describe a proof-of-concept study in which we analyzed 15-sec facial video and ECG recordings from patients during AF and sinus rhythms, i.e., before and after successful cardioversion. The proposed technology enabled the identification of the presence of AF in 15-sec facial video recordings with an estimated error rate of 20% without any physical contact with the patient.

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