Cardiovascular Signal Synchronization Based on Mutual Information and Cross-Recurrence Plots

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***Abstract*—Cardiovascular data provides valuable information into daily health, and the increasing adoption of wearable devices, such as photoplethysmography (PPG), promises extensive diagnosis and analysis capabilities. However, validation through established clinical standards like electrocardiogram (ECG), either simultaneously or closely aligned with PPG, remains essential for validating cardiac disease diagnosis. This paper introduces a novel approach to synchronize ECG and PPG recordings based on the cardiac variability dynamics and non-linear techniques. Through a "proof of concept" analysis on a controlled dataset of 13 patients, the efficacy of mutual information (MI) versus linear correlation (LC) is compared. The findings underscore the superior performance of MI over the traditional LC method, thereby highlighting immediate opportunities for further research on signal synchronization, particularly in scenarios involving the physical collection of cardiovascular data from different devices.**

I. Introduction

Photoplethysmography (PPG) is a non-invasive optical technique for sensing microvascular blood volume changes on the skin [1]. The technology behind PPG was first described in the 1930s, and it was subsequently tested for applications in peripheral vascular disease from the 1940s onward. PPG technology has evolved over the years, finding applications in various fields, including medical diagnostics, wearable devices, and continuous health monitoring [2]. Despite its widespread use, challenges such as signal quality assessment and motion artifacts persist [3]. For this reason, the gold standard for evaluating the signal quality of PPG is through simultaneous or synchronized electrocardiogram (ECG), a non-invasive medical test that records the electrical activity of the heart [4].

While recording both PPG and ECG simultaneously is feasible using the same acquisition system, challenges in signal synchronization arise when integrating data from different devices [5]. For instance, holter ECG with pulse oximeter (conventional finger tip location), or ECG bands with wristband-based PPG. As a general rule, synchronization is performed manually, by overlaying as near as possible the cardiac rhythms or events between recordings. This is an endeavor task and requires plenty human intervention, thus hampering the clinical analysis on the collected data. Furthermore, the synchronization accuracy may also depend on the quality of the data acquisition system and technology. While not always perfect, such approximation remains valuable for understanding the temporal relationships and variations between recordings, extracting relevant information about cardiac activity, as well as the general health status [6].

Previous works on automatic signal synchronization can be found in many other areas, especially when it comes to dealing with dynamic or chaotic systems [7], being the meteorological and geophysical applications the most relevant domains in the field [8]. However, in the cardiovascular domain, there is still a scarcity of research in the matter. In fact, cardiovascular signal synchronization appears to hold a minor role within the signal processing section of determined studies, varying from acceleration-based methods [9], to measuring differences on cardiac rhythms through correlation methods [10]. Most recently, Vollmer et al. [11] presented an exhaustive method for signal synchronization consisting in two stages, a first rough heart beat alignment to a reference recording, and then performing a finer back and forward search to perfectly match the cardiovascular dynamics between recordings. This was followed by a non-linear sampling frequency correction and plenty manual intervention for assuring the highest accuracy.

In this latter regard, the most appealed method for cardiovascular data synchronization is through the heart rate variability (HRV), a clinical measure widely used, not only for heart disease diagnosis, but also for better understanding of the underlying cardiovascular dynamics [12]. HRV is usually extracted from a single lead of ECG but there exist a surrogate magnitude that can be extracted from the PPG as well, known as the pulse rate variability (PRV) [13]. Therefore, by searching for the linear correlation (LC) coefficients between the HRV and PRV, it is possible to find potential locations of synchronization [10]. It is known, however, that traditional LC methods have shown limitations in capturing the nonlinear characteristics inherent in dynamic systems, such as cardiovascular data [14], thus leading to potential false correlation positives.

All things considered, in view of the scarcity of research in cardiovascular data synchronization and the limitations shown by traditional LC methods, this study aims to address this gap by investigating a novel approach based on the self-similarity effect of cross-recurrence plots (CRP). This technique, which explores the nonlinear relationships between cardiovascular signals, offers promising potential to enhance the accuracy of data synchronization and unveil hidden patterns in cardiac records. With the help of mutual information (MI) for image similarity assessment, the effectiveness of this method will be evaluated compared to traditional LC techniques.

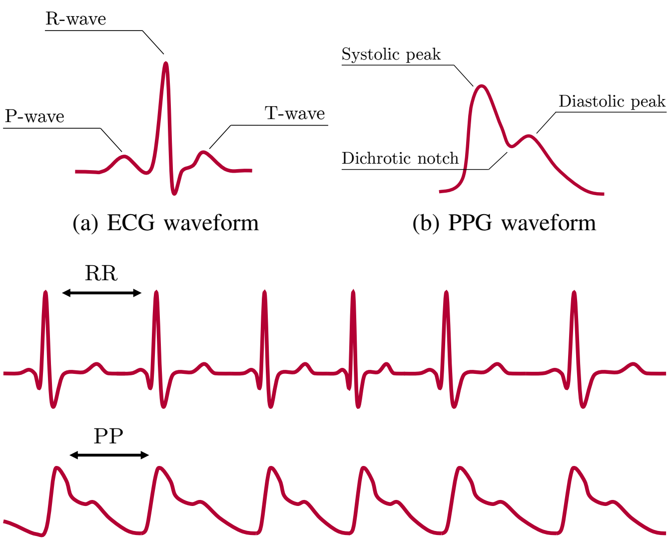
II. Dataset

The *Simultaneous physiological measurements with five devices at different cognitive and physical loads* (SPM), publicly available on PhysioNet's official repository [11], has been selected for the present study. The SPM database consists of 13 subjects (7 female, and 6 male), with simultaneous recordings from multiple devices re-sampled at 256Hz. Such recordings were manually synchronized under an event-wise procedure described in previous works [15]. The dataset included a five minute baseline measurement, five minute walking on the treadmill, a five minute cognitive audio test, and a five minute uphill walking on a treadmill. In this study, the selection was limited to PPG and ECG signals corresponding to the SOMNOtouch NIBP device, within the five minutes of baseline measurement (subjects at rest). Consequently, a subset of 13 entries with simultaneous PPG and ECG recordings was constituted for the proposed experiments.

III. Methodology

A. Cardiovascular morphology

Although distinct, ECG and PPG waveforms share similar information about the cardiac cycle. A simplified breakdown of ECG and PPG waveforms is represented in Figure 1. As can be seen, a healthy reference ECG (Figure 1a) mainly consists in the electrical depolarization of the atria (P-wave), a strong ventricular response (R-wave), and the subsequent ventricular repolarization (T-wave). On the other hand, the typical PPG waveform (Figure 1b) can be broken down into a systolic peak (highly correlated with the R-wave of ECG), and a diastolic peak (atria depolarization), normally separated by a dichrotic notch [16]. Therefore, as illustrated in Figure 1c, the relationship between ECG and PPG waveforms becomes evident when considering R to R or pulse to pulse distances. This correlation is often referred to as heart rate variability (HRV) in the context of ECG, and pulse rate variability (PRV) in the case of PPG [13]. Eventually, the importance of HRV and PRV lies in their widely sustained relationship with the autonomous nervous system, which provides valuable information for the early identification and clinical diagnosis of cardiovascular diseases [12].



(a) ECG waveform (b) PPG waveform

(c) ECG and PPG waveforms overview

Fig. 1: ECG and PPG waveforms overview.

B. Signal processing

The ECG recordings were treated with a second-order Chebyshev filter (0.5 - 100 Hz cut-off frequencies), preserving the original signal's characteristics [17]. Then, R-peak detection was performed under the Pan-Tompkins algorithm [18], followed by an automatic R-peak correction for potential delays. Ultimately, the HRV was obtained as the consecutive difference between R-peaks.

On the other hand, the PPG recordings were processed by applying a fourth-order, band-pass, forward-backwards filter with zero-phase distortion between 0.5 and 5 Hz, which is deemed to facilitate systolic peak detection [19]. Then, peak detection was performed by half-rectifying the filtered signal and then finding local maxima with a minimum peak height based on the median value of the signal, a minimum peak distance of 0.25 seconds, and a minimum peak width of 5% of the sampling frequency. Then, the PPV was obtained as the consecutive difference between systolic peaks.

C. Non-linear characterization tools

In the present study, recurrence plot (RP) and cross-recurrence plot (CRP) constitute the foundations for ECG and PPG synchronization. Both RP and CRP are non-linear tools for the visualization of the phase-space trajectories of dynamical systems [8]. In simple terms, a phase-space is a mathematical construction that allows representing the set of positions and their respective moments of a determined dynamical system. One way to visualize such positions and moments is the RP, and when it comes to comparing two phase-spaces, CRP can be employed. The principle of synchronization presented in this work consists in comparing two plots, i.e., the RP of a reference HRV segment (extracted from ECG), and the CRP obtained between the reference HRV and a PRV segment taken in different times.

D. Mutual information and linear correlation

Mutual information (MI) is a measure that represents how much knowing the value of one distribution can tell about the value of another one [20]. In simpler terms, it quantifies the amount of information shared between two variables. If the mutual information is high, knowing the value of one variable gives more information about the other variable, whereas if it is low, there is less shared information between them. Moreover, the normalized information coefficient (NIC) was calculated to compare images, which indicates a normalized notion of similarity between the evaluated image and the reference image. Ultimately, the correlation coefficient (R) was also employed, as a reference notion, to compare the original HRV series from ECG and the PPV series from PPG.

E. Synchronization method

The proposed synchronization method draws inspiration from Marwan's research on synchronizing geological and meteorological data, as documented in [14]. In Marwan's work on recurrence analysis, CRP is considered a generalized form of RP. Namely, when applying CRP to a data series aligned with itself, the resulting CRP closely resembles into its RP under the same parameters. This resemblance manifests when trajectories show similarly, in a form of a diagonal pattern in the CRP, also known as *line of synchronization*

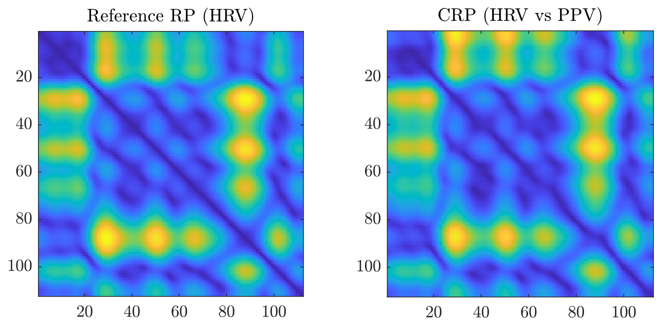


Fig. 2: Synchronized cardiac cycles (NIC = 0.59).

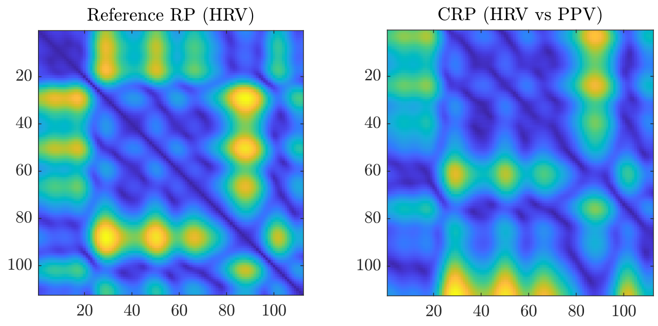


Fig. 3: Non-synchronized cardiac cycles (NIC = 0.049).

(Figure 2). However, any time dilation or compression of one of these similar trajectories introduces a distortion to this diagonal structure [14] (Figure 3). Then, the key for synchronization consists in finding the CRP that closely aligns with the reference RP. This is accomplished by employing a look-up process wherein an overlapping PPV window is swept over the HRV signal until it best aligns with the reference HRV segment.

F. Validation framework

The synchronization process was validated by measuring the lag between the reference HRV section and the chosen PRV segment, obtained after the look-up analysis. This lag is denoted as a "shift" measured in seconds, computed as the subtraction of the timestamps of the reference and chosen sections. A negative shift indicates that the chosen PPV segment was located to the right of the reference HRV section, while a positive shift indicates that the chosen PPV segment was located to the left of the reference HRV section (Figure 4). These measurements were taken for both MI and LC methods.

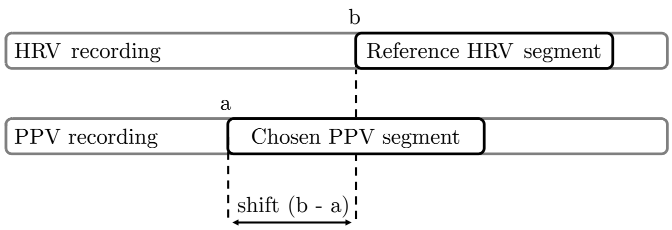


Fig. 4: Validation system overview.

IV. Results

A total of 13 HRV and PPV recordings were synchronized using both MI and LC methods. The measured shifts per method (in seconds) and their corresponding values (R and NIC) are presented in Table I. In general, the MI-based method demonstrated equal or superior performance compared to the LC-based method. Specifically, there was a 31% improvement observed compared to the LC method (in 4 over 13 cases, MI did improve). Additionally, Figure 5 and Figure 6 depict the evolution of the iterative sweep for both methods in the patient that exhibited the highest shift difference between methods (patient x010).

TABLE I: Table of results.

	Linear correlation		Proposed method	
Patient	R	Shift (s)	NIC	Shift (s)
x001	0,99	-0,67	0,72	-0,67
x002	0,99	-1,21	0,69	-1,21
x003	0,87	-0,76	0,45	-0,76
x004	0,65	**-32,05**	0,20	**7,88**
x005	0,99	-1,44	0,72	-1,44
x006	0,99	-0,34	0,67	-0,34
x007	0,86	-49,66	0,40	-49,66
x008	0,86	-165,36	0,29	-165,36
x009	0,78	**52,44**	0,18	**41,46**
x010	0,94	**109,81**	0,51	**-1,71**
x011	0,99	-1,52	0,67	-1,52
x012	0,90	-1,23	0,40	-1,23
x013	0,85	**0,48**	0,42	**-0,01**

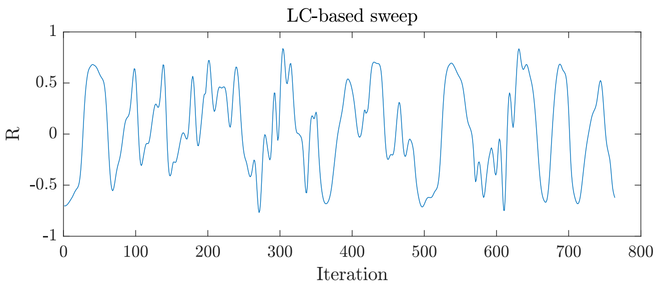


Fig. 5: LC-based synchronization (patient x010).

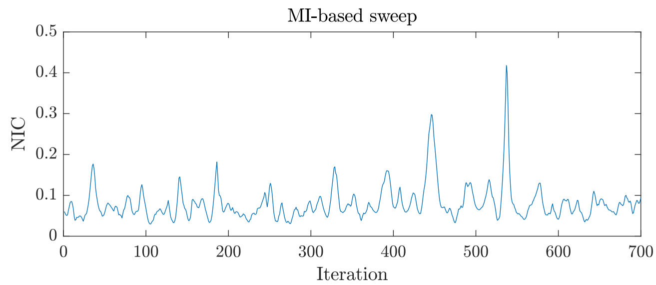


Fig. 6: MI-based synchronization (patient x010).

V. Discussion

The presented cardiovascular signal synchronization method has proven to be more effective than traditional LC when comparing HRV and PPV. Despite the 31% improvement disclosed by the proposed method over reference LC, there remains an opportunity for further research on ECG and PPG synchronization based on their rhythm variability forms.

The synchronization patterns observed in the LC-based method exhibit more variability and less easily discernible absolute maxima (as depicted in Figure 5) compared to those shown by the NIC-based method (Figure 6). This observation could explain the improved performance of the proposed method in identifying the correct synchronization window compared to LC. This superiority can be attributed to MI's capacity to penalize dissimilar entities while assigning greater significance to images demonstrating higher similarity [20] [21]. However, in those cases where HRV and PPV series already exhibit high similarity, both MI and LC-based methods yielded identical results. Therefore, it is in the most uncertain scenarios that the proposed method proves its value, offering more significant insights into the actual synchronization window.

Additionally, the potential of this method transcends the presented application, particularly in scenarios where signals may share information across different dimensional planes. In such cases, traditional LC analysis often fails to detect any significant relationship or correlation [8], further underscoring the advantages of the proposed approach.

Last, but not least, it is important to note that the experiments in this study were conducted on a limited number of subjects at rest. Consequently, the presented results should be interpreted with caution, particularly in contexts that require synchronizing PPG and ECG signals for ambulatory blood pressure measurement, as suggested in previous studies utilizing single-device ECG and PPG recordings [4].

VI. Conclusions

The present paper has introduced a novel method for the automatic synchronization of electrocardiogram and photoplethysmogram recordings through their cardiac rhythm variability forms (i.e., heart rate variability and pulse rate variability). The results obtained demonstrate the superiority of mutual information over traditional linear correlation analysis in achieving cardiovascular signal synchronization.

Acknowledgements

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