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A Pilot Study on Using Derivatives of Photoplethysmographic Signals as a Biometric Identifier

Jianchu Yao, *Member, IEEE*, Xiaodong Sun, and Yongbo Wan

***Abstract*—Photoplethysmographic (PPG) signals are easy to obtain with low cost, which enhances its potential to server as biometric identification mechanism for various applications. This paper examines two important issues in applying derivatives of PPG signals as discriminants to identify and verify subjects: consistency within an individual subject and discriminability between different subjects. The experimental results demonstrate that, by employing statistical tools, derivatives can precisely describe the features of an individual's PPG signal and be used as bio-measures for identification purposes.**

***Keywords*—Attributes, consistency, discriminability, derivatives, photoplethysmographic (PPG) signal.**

I. Introduction

Identification / verification / authentication is critical for security systems such as homeland security, airports, immigration checkpoints, finance and healthcare infrastructures. Traditional identification mechanisms (e.g. signatures and fingerprints) can barely meet these extensive and growing security requirements. Various biometric measures have been investigated for identification/ verification purposes, including iris and retina [1-3], face complexion [4, 5], lip movements [6], hand/finger geometry [7, 8], and ECG [9, 10], among others. These approaches present different levels of accuracy, user friendliness, system complexity, and cost, and consequently find applications in diverse scenarios. Compared to these biological identification approaches, photoplethysmographic (PPG) signals can be obtained non-invasively with minimal cost from a variety of body locations [11]. PPG signals reflect the pulsative action of arteries through the interaction between oxygenated-hemoglobin and photons. The feasibility of applying PPG signals as a biological discriminant has been preliminarily studied [12, 13]. These studies applied an approach to represent the pulses using four quantities: the peak number M, upward slope k_1, downward slope k_2, and the time interval from the bottom to the peak t_1. This approximation ignores higher-order derivative information contained in the pulse and, therefore, does not take full advantage of the potential of PPG signals to improve identification accuracy and reliability. Methods employing signal features that can better describe periodic pulses should be able to obtain better identification performance in practical use.

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Jianchu Yao is with the Department of Engineering, East Carolina University, Greenville, NC 27858 USA (phone: 252-737-1029; fax: 252-737-1041; e-mail: yaoj@ecu.edu).

Xiaodong Sun is with the Department of Technology Systems, East Carolina University, Greenville, NC 27858 USA (e-mail: sx1215@ecu.edu).

Yongbo Wan is with the Electrical Engineering Department, Shaanxi University of Science and Technology, Weiyang District, Xi'an, Shaanxi 710021 China (e-mail: wanyongbo@sust.edu.cn).

This paper presents the preliminary study of using local maximum/minimum points and inflection points of a PPG waveform as a biometric identification mechanism. Specifically, the scope of the paper is to address two important factors that enable a signal as an effective biometric discriminant: statistical **consistency** of the used attributes within individual subjects and their **discriminability** between different subjects. After this introduction, the METHODS section describes the process of data collection, fitting, and statistical analysis, followed by the RESULTS section where the efficacy of the proposed measures are reported. Potential impacts of this derivative approach on other applications and future work are also discussed.

II. Methods

A. Mathematical Representation of PPG Pulses

A photoplethysmographic pulse can be modeled using a variety of mathematical schemes represented by different sets of parameters. In this context, a set of parameters used to represent PPG pulse curves is called *attributes*. Figure 1 demonstrates a simple approach using two straight lines to approximate a PPG pulse. Possible attributes for this representation can be triples of different quantities such as

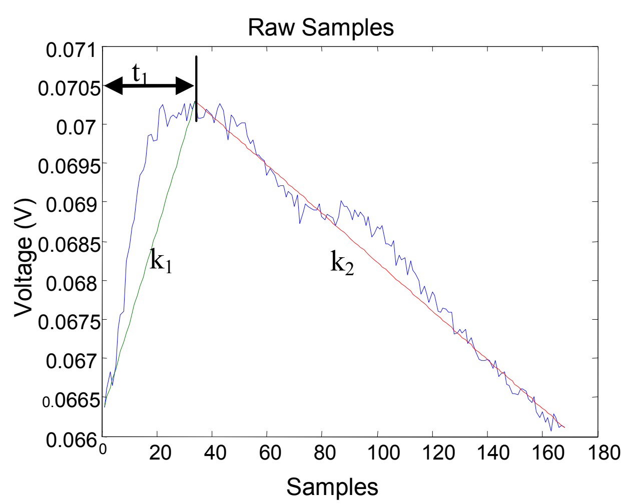

Figure 1. A pulse modeled by two straight lines.

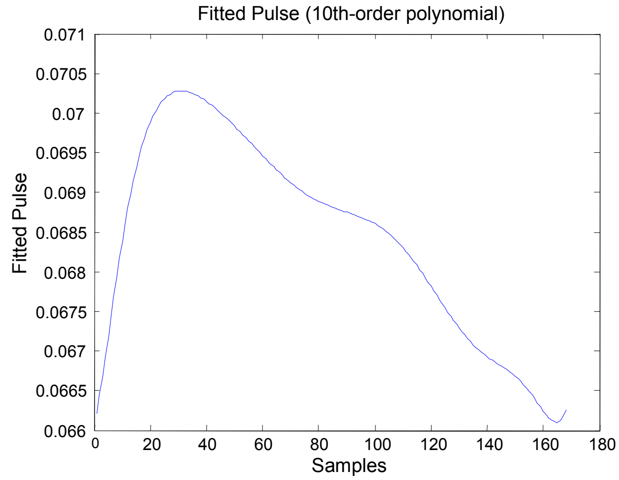

Figure 2. A PPG pulse fitted by a 10th-order polynomial.

the slopes of the two straight lines k_1, k_2 and the time from the bottom to the peak t_1. Discriminant algorithms can evaluate these attributes against certain criteria to identify individual subjects. An improved presentation was discussed in [12, 13], where the number of peaks M has been included to describe the pulse in a greater detail. However, this description is still coarse: the higher-order derivatives of the signals (which contain finer information about the pulses that can potentially be used as discriminants) are overlooked. The identification performance of the PPG signal can be impaired by the coarse approximation.

In this paper, we propose to use local maximum/minimum points and inflection points of PPG pulses and the time intervals between these points as attributes to discriminate subjects. The 1st- and 2nd-order derivatives of a pulse signal fitted by a polynomial (shown in Figure 2) are first taken. The maximum/minimum points of the pulse and the time intervals between them can be found from the 1st-order derivative (Figure 3); the inflection points and the time intervals between them can be obtained from the 2nd–order derivative (Figure 4). The number of maximum/minimum points and inflection points, along with the time interval between these points, precisely describes the features of a PPG pulse. Therefore, we can use these attributes as statistical discriminants to identify subjects from each other.

B. Data Acquisition

A simple pulse oximeter sensor (see Figure 5) was built to collect PPG data. This sensor uses an amplification circuit adopted from [11] with the following modifications:

1. An optical probe consisting of an infrared LED with a wavelength of 940 nm.
2. The sample rate was increased to 300 Hz in order to maintain a more complete spectrum of information contained in the acquired PPG pulses.
3. The system architecture was simplified by eliminating the microcontroller used in the original design. A LabVIEW-DAQ card directly sampled and digitized analog signals, which allow reliable data acquisition and flexible real-time signal processing.
4. Improved amplification circuits to obtain good pulse signals [14].

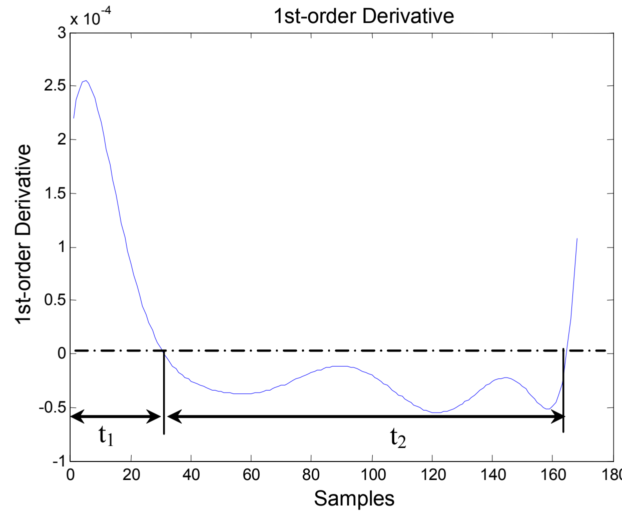

Figure 3. First-order derivative curve and time intervals between maximum/minimum points.

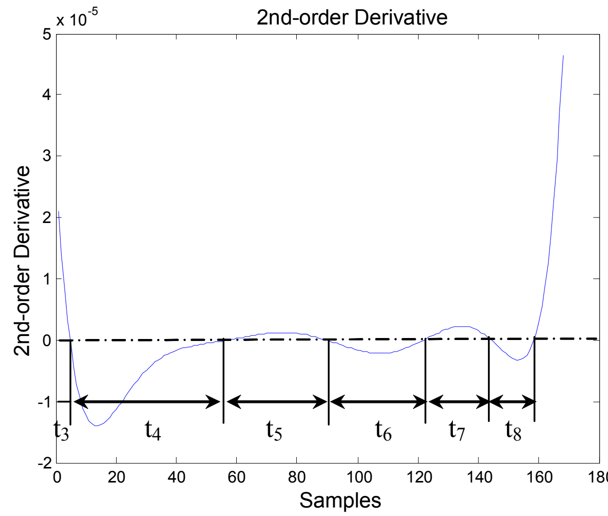

Figure 4. Second-order derivative and time intervals between inflection points.

Limited by time and funding, only three subjects were used to collected data from. Three groups of data from each subject were collected, resulting in nine datasets for further statistical analysis. Each dataset represents around 70 seconds worthy of data (70~80 pulses).

In this pilot study, the subjects were required to sit without movements when taking measurements to prevent artifact/noise factors from interfering with the physiological pulsatile signals. The data collected in LabVIEW were saved into Excel spreadsheet files which can be accessed by a MATLAB program for further processing.

C. Attributes Extraction

The MATLAB program employed nine steps (described below) to extract the attributes from the PPG pulses that can be used for statistical analysis.

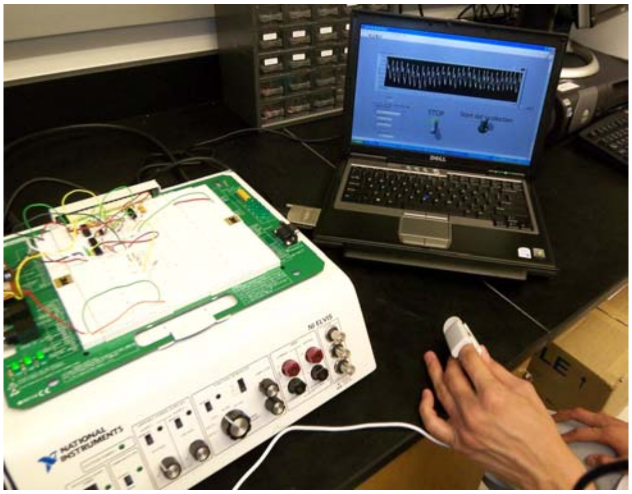

Figure 5. PPG data collection setup.

1. Filters the raw data with a Chebyshev low-pass filter to remove 60 Hz noise from the power source and ambient light;
2. Randomly picks up one complete pulse from a data set. The pulse cycle starts and ends at two consecutive valley points;
3. Fits the pulse curve with a polynomial (so that we can take derivatives of the function);
4. Takes the 1st- and 2nd-order derivatives of the polynomial;
5. Finds the number of maximum/minimum points (N_1) and the number of inflection points (N_2) from the 1st- and 2nd-order derivatives, respectively;
6. Finds the time intervals between consecutive maximum/minimum points ($t_1 \sim t_{N_1}$) and inflection points ($t_{(N_1+1)} \sim t_{(N_1+N_2)}$), including the time interval from the start point to the first maximum and inflection point;
7. Saves (a) the number of maximum/minimum points (N_1), (b) the number of inflection points (N_2), and (c) the time intervals ($t_1 \sim t_{(N_1+N_2)}$) as attributes;
8. Repeat steps 2 through 7 thirty times. This extracts attributes from 30 pulses for a subject. No pulse was selected more than once during this repetition.
9. Repeat step 8 three times. This extracts attributes from the three datasets collected for a subject.

The same process was applied to the three subjects. Note that in step 4, N_1 and N_2 might vary between subjects and therefore, the total number of attributes ($N_1 + N_2 + 2$) for different subjects might vary as well.

D. Statistic analysis

To this point we verified the consistency of the attributes obtained previously within the same subject and analyzed their discriminability between two different subjects. Within a subject, given that N_1 and N_2 for a minority portion of pulses may be different from that of the others; we first used

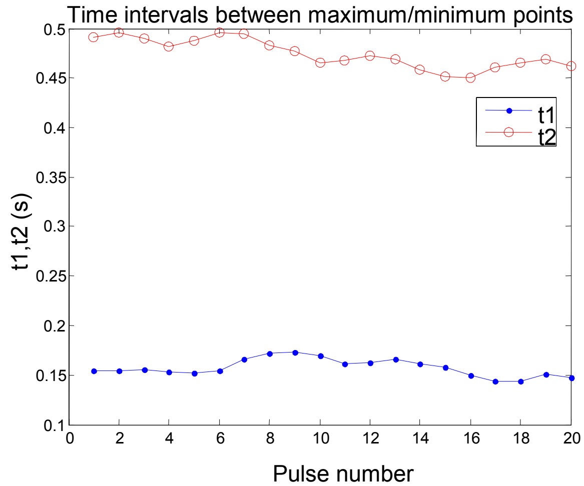

Figure 6. Time intervals between maximum/minimum points.

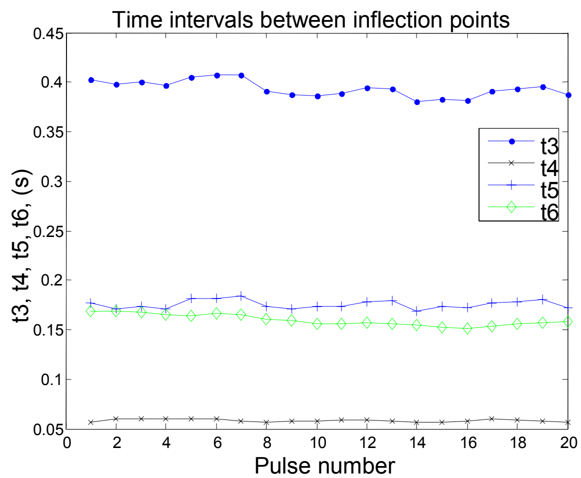

Figure 7. Time intervals between inflection points.

N_1 and N_2 of the majority pulses as the number of time intervals to be examined. The correlations of the same subject's time intervals and that of two different subjects are then obtained.

TABLE 1. STATISTICAL FEATURES OF THE TIME INTERVALS.

	T_1	T_2	T_3	T_4	T_5	T_6
Mean (s)	0.1575	0.4745	0.3934	0.0583	0.1755	0.1597
STD (s)	0.0087	0.0146	0.0081	0.0013	0.0041	0.0056
%	5.53	3.07	2.05	2.20	2.35	3.49

III. RESULTS

Figures 6 and 7 show the time intervals extracted from one of the datasets of subject 1. Since the majority of pulses have two maximum/minimum points and four inflection points, two and four time intervals were obtained, respectively. Results in Table 1 demonstrate that the same subject's time intervals, although vary in small ranges, are statistically consistent.

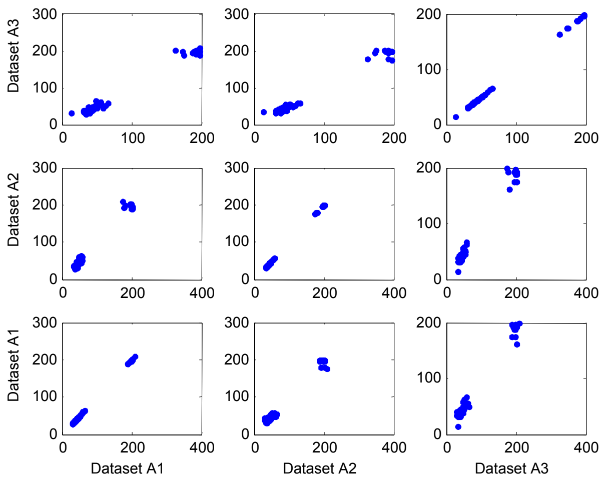

Figure 8. Correlations between datasets for the same subject.

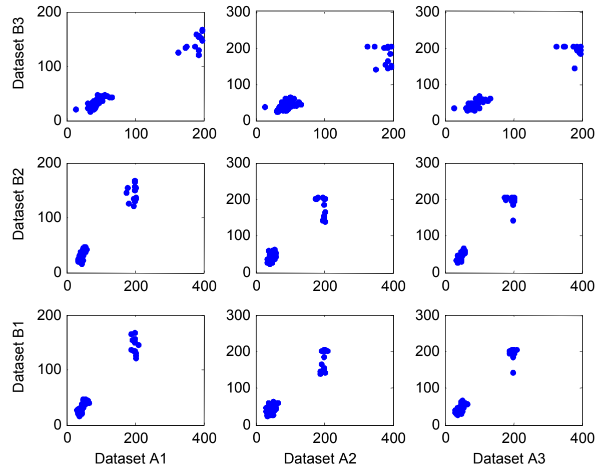

Figure 9. Correlations between datasets for two different subjects.

Figures 8 and 9 illustrate the correlations between the three datasets for the same subject and two different subjects, respectively. These figures indicate that the correlation within a subject is stronger than that between two subjects.

IV. Discussion

With the consistency and correlation features the attributes studied earlier, it is possible to apply these attributes as biometric identification discriminants. However, significant work is still required based on this pilot study before this method can be applied to real identification applications. Specifically, the following issues deserve further discussion:

1. Using the attributes discussed here as discriminants, find the best discriminant techniques (e.g. [10, 12]) that can be used for decision making.
2. When performing identification, it is important to assign appropriate weight to individual attributes. Generally, attributes about higher-order derivatives are more discriminative yet more sensitive to noises; attributes about lower-derivatives are more robust but not as sensitive. It is desired to assign weights to each attribute with these characteristics considered.
3. The signal acquired in this study was weak and noisy. One subject's data could barely be used for comparison due to noise distortion. We plan to improve the hardware setup in the future (this work has been done by the time of revision).
4. Other future work includes studying the attribute consistency and discriminability under conditions that the PPG signals are corrupted by motion artifacts and other noises.
5. We will also validate this identification method using a larger subject population.
6. The approach that uses derivative features of PPG signals might be applied to describe other physiological signals (ex. ECG).

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