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Feasibility of Authenticating Medical Data Using Photoplethysmography(ppg) as Signature Mark

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Abstract—This paper presents a new human verification approach using photoplethysmography (PPG) signals that can be obtained easily from the fingertip. PPG signals can be easily obtained with low cost and have great potential to serve as biometric identification mechanism. These characteristics are unique identifiers specific to different persons while they are similar enough to recognize the same person. The different signal processing, feature extraction methods are described in this paper. Hence PPG signal can be used as signature mark to authenticate medical data with high security and Confidentiality.

Keywords— Biometrics, Photoplethysmography, Identification, filter, feature.

I INTRODUCTION

Automatic human identification using biometrics is gaining more importance. Its potential application can be great in many different areas such as telemedicine or ebanking. Nowadays, most systems that control access to financial transactions, computer networks, or secured locations still identify authorized persons by recognizing passwords, or ID cards. These systems are not reliable enough, because the information is easy to be stolen or forged. Being able to eliminate such common problems, biometric systems, which use unique human physical or behavioural characteristics to automatically identify a person, can ensure much greater security or confidentiality.

Certain characteristics of our bodies or features of our behaviors have been studied as means of human identification, such as fingerprint, face [l], voice [2], retina/iris [3], lip movement [4], gait motion [5],electroencephalograph (EEG) [6], and electrocardiograph (ECG) [7]. New applications based on these biometric approaches would provide us with a promising and irrefutable future of human identification. However, fingerprint can be recreated in latex, face recognition can be fooled by a photo, voice can be imitated [10], and the methods based on EEG or ECG are to some extent cumbersome because several electrodes are required to pick up the bio-signals.

In this paper, we propose to use PPG signals for human verification. Compared with other biometric approaches, PPG technique has several distinct advantages including low development cost, easy to use without any complicated procedure or special skill, and conveniently accessible to various sites of human body, such as finger, ear lobe, wrist[8] or fore head[9]. The specific aim of this work is to investigate the feasibility of acquiring PPG from fingertip, more advantageous than the other methods because of the increased motion artifacts.

Compared to traditional method, PPG was a novel non-invasive method with the advantages of convenience and accuracy. Until now, PPG has been widely used for the detection of many basic physiological parameters, such as blood oxygen, heart rate, breath and blood pressure. Besides, PPG could also reflect some other important cardiovascular parameters, such as atherosclerosis etc.[10] So there's great meaning to make a deep analysis of the PPG signal in order to extract various physiological parameters containing in it with high accuracy. PPG can be used as signature mark to authenticate medical data and transmit it securely.

II PPG SIGNAL FEATURES

PPG signal is generated by periodic ejection of the heart, so it has a close relationship with the ejection period, from which the heart rate (HR) could be extracted. In another aspect, the blood flowing in the vessels is affected by the vessel elasticity and blood viscosity. So that many cardiovascular information, such as the degree of angiosclerosis, could also be picked up from the PPG signal. All the physiological parameters could be reflected in PPG signal feature points, as shown in Fig.1

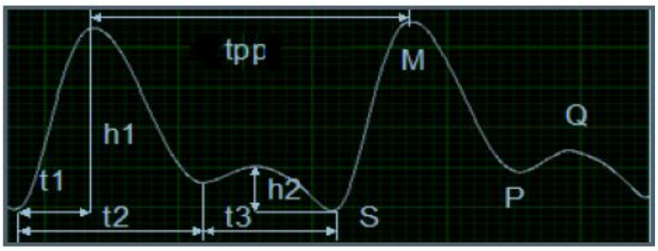


Fig 1: Standard PPG signal and its feature points

As noted, in the typical PPG signal, the section from point S to M represents the rapid ejection phase; from M to P is the late phase. Point M is the main peak of the signal. At this point, the blood pressure (BP) is highest in the whole period. Another crest Q is called dicrotic wave, which could reflect the compliance of the arteriola; point P is called dicrotic notch. HR could be obtained from the interval of two main peaks (TPP); time interval of M-Q is an index of arteriosclerosis. However, due to the presence of various factors, the feature points for real PPG signals were always hard to get directly. So there's great meaning to find efficient and practical pre-processing and feature extraction methods to pinpoint the PPG signal[10].

III PPG SIGNAL PROCESSING ALGORITHMS

Processing procedure of the PPG signal primarily contains two parts: signal conditioning and feature extraction [10].There are many signal processing algorithms present, in which three of them are discussed. NLMS algorithm [8],the signal conditioning algorithm design- procedure consists three main steps: removing singular values, FIR low-pass filtering and baseline drift elimination. Signal feature extraction aims to extract all the feature points of the PPG signal, based on which the physiological parameters would be derived.

A. NLMS algorithm

In the standard form of a least-mean-square (LMS) filter[16], the adjustment of filter coefficients is directly proportional to the tap-input vector u(n) . Therefore, when u(n) is large, the LMS filter suffers from a gradient noise amplification problem. To solve this problem, the normalized LMS filter is used. The normalized LMS filter is exactly the same as the standard LMS filter but differ only in the way in which the weight controller is mechanized in structural terms.

Let u(n) represent the M-by-l tap-input vector. An output y(n) is subtracted from the desired response d (n) to produce the error signal (estimation error), e(n). The weight controller applies weight adjustment to the transversal filter in response to the product of the input vector and the error signal. This process is repeated for a number of iterations until the filter reaches the steady state. The normalized LMS algorithm is summarized as follows :

Parameters:

M = *number of taps (i.e., filter length)*

μ = *adaptation constant*

$$0 < \mu < 2\frac{E\left[|u(n)|^2 \mathcal{D}(n)\right]}{E\left[|e(n)|^2\right]},$$

where

$E\left[|e(n)|^2\right]$ = *error signal power*

$E\left[|u(n)|^2\right]$ = *input signal power*

$\mathcal{D}(n)$ = *mean-square deviation*

$= E\left[\|\varepsilon(n)\|^2\right]$

$\varepsilon(n)$ = *weight-error vector*

$= \mathbf{w} - \hat{\mathbf{w}}(n)$

$\mathbf{w}$ = *model's unknown parameter vector*

$\hat{\mathbf{w}}(n)$ = *tap-weight vector*

Algorithm:

Initialization: *If prior knowledge about the tap-weight vector* $\hat{w}(n)$ *is available, use that knowledge to select an appropriate value for* $\hat{w}(0)$. *Otherwise, set* $\hat{w}(0) = 0$.

Data:

(a) Given: $u(n)$ = *M-by-1 tap input vector at time n*

$u(n)$ = *desired response at time step n*

(b) To be computed: $\hat{w}(n+1)$ = *estimate of tap-weight vector at time step n+1*

Computation: *For n=0, 1, 2,...,compute*

$$e(n) = d(n) - \hat{w}^H(n)u(n) \ ,$$

$$\hat{w}(n+1) = \hat{w}(n) + \frac{\mu}{\|u(n)\|^2} u(n)e^*(n) \ ,$$

where H denote the hermitian and * denote the conjugate transpose.

B. Signal conditioning algorithm design

Median filtering is an efficient method for removing singular values from the signal with sharp noise. The maximum and minimum points could be kicked off to make the signal smoother. In experiment, a 5×5 template was used for median filtering.

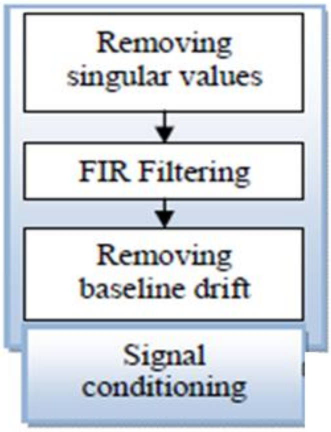


Fig 2. The signal processing algorithm(flow chart)

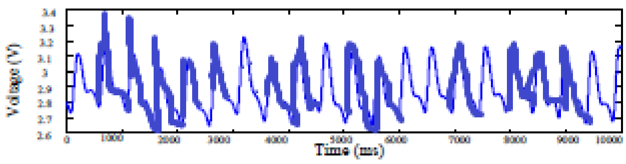
Nevertheless, median filtering could only reduce the singular values in the signal, but not effective for the high frequency noise. So an FIR filter is added after median filtering. FIR filter with linear phase is very important for extracting time features from the PPG signal. The window function used is a modified Hamming window as shown below, whose weighting coefficient could suppress the sidelobe noise effectively.

$$w(n) = [0.54 - 0.46\cos(\frac{2\pi n}{N})] \qquad (1)$$

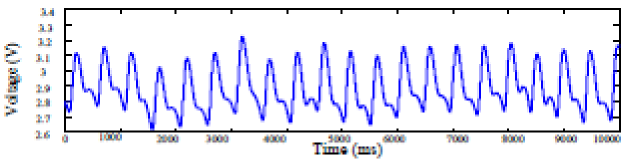
A Hamming window with 21 orders is used to eliminate the high-frequency noise containing in the original PPG signals. Sampling frequency *fs* of the signal is 500Hz, cut-off frequency *fc* is set to 30Hz, so the digital filter index *wc* = 2* *fc*/ *fs* =0.12. The combining filtering result is shown in Fig.3.

As shown in Fig.3, the filtered signal became smooth enough, but still with obvious baseline drift. This drift was mainly caused by breathe signal and motion artifact. Frequency band of the breathe signal is within 0.3~1Hz, which was overlapped with the PPG signal. So that traditional frequency analysis methods were ineffective to eliminate this drift.

Wavelet transform (WT) is one of the modern spectral analysis tools, which can not only analyse the frequency domain features of short time-domain process but also can analyze the time domain features of local frequency domain[12]. An orthogonal wavelet decomposition method was proposed to eliminate the influence of the breathe signal [13]. The main procedure is to make the signal pass through a series of low-pass filter and high-pass filter. The low frequency part is decomposed further. Wavelet reconstruction was a reverse procedure, as shown in Fig.4.



(a) Original signal



(b) Filtered signal

Fig 3. Median filtering and FIR filtering result compared to original signal

In Fig.4, A is approximation coefficient obtained through a low pass filter; D was detail coefficient generated by high pass filter. "↓2" represent subsample and "↑2" represent subsample interpolation. The algorithm was shown in the following equations.

$$A_{jk} = \sum_n h0(n-2k)A_{(j-1)k}$$
$$D_{jk} = \sum_n h1(n-2k)A_{(j-1)k} \qquad (2)$$

In experiment, "sym8" wavelet is chosen as the basic function to decompose the filtered signal. For the signal, the baseline is a slowly varying component. It could be eliminated by reconstructing the signal after the approximation components were deleted. The processing result was shown in Fig.5. As shown in Fig.5, the blue curve is the filtered signal; the red one represent the approximate signal, that is the baseline caused by breathe and motion artifact with the bandwidth about 0.3~1Hz. The reconstructed signal with baseline eliminated was shown as the green one. Compared to the blue curve, the processed signal was much more steady and regular. This is significant and necessary for picking out the feature points from the PPG signal accurately.

C. Feature extraction algorithm design

After pre-processed, most noises and baseline drift had been eliminated. A differential threshold method is then used to extract feature points from the regular signal. This method consists chiefly of three steps: interpolation, differentiation and extreme point extraction.

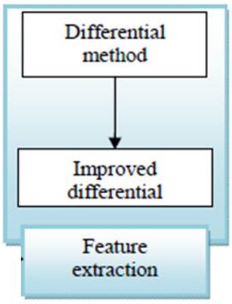
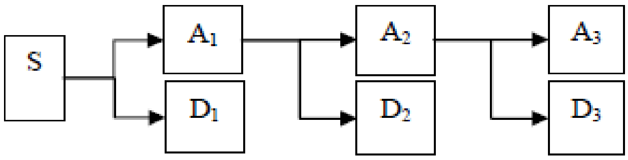


Fig 4: Feature extraction algorithm(flow chart)

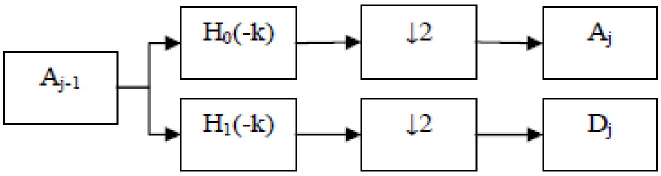
The interpolation algorithm was quite important for digital differential. The cubic spline interpolation method was used, which was shown in Equation(3).

$$S_i(x) = y_i + y_{i,i+1}(x - x_i) + \frac{1}{6}(x - x_i)(x - x_{i+1})$$

$$y'_{i,i+1} = \frac{y_{i+1} - y_i}{x_{i+1} - x_i} \qquad (3)$$

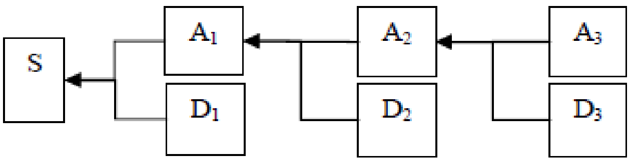


Decomposition illustration

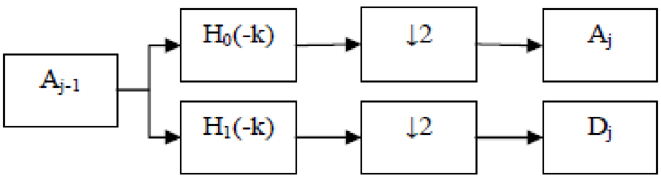


Decomposition procedure

(a) Decomposition



Reconstruction illustration



Reconstruction procedure

(b) Reconstruction

Fig 5. Decomposition and reconstruction procedure of WT used for baseline drift elimination

The cubic spline interpolation method could ensure that *S(x)* had continuous first and second derivative, which was profitable for the later differential action. Normally, the extreme points of PPG signal could be obtained from the nearest zero points in the first derivative curve. These extreme points included the start point of rapid ejection phase S, main peaks M, dicrotic notch P and dicrotic wave peak Q. The extreme points of second derivative were related to the compliance and elasticity of the blood vessel. It could be a supplementary means for the feature points extraction. The curve of first and second derivative was showed in Fig.6.

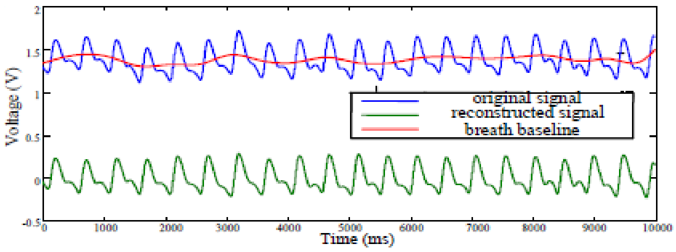


Fig 6. Baseline drift elimination result by WT method

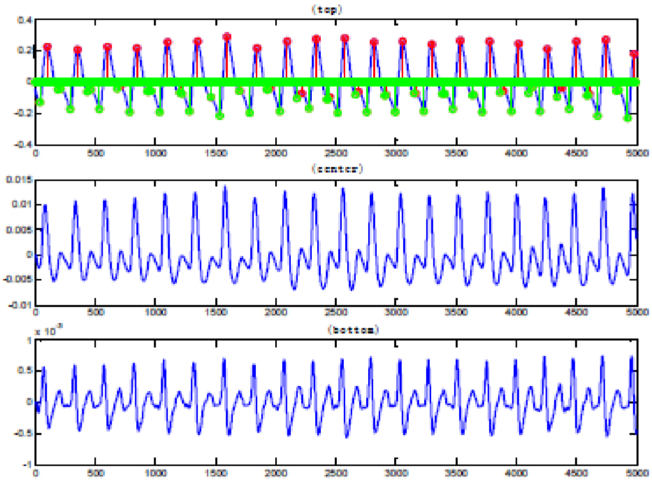


Fig 7. First(center) and second derivative (bottom) result of the filtered PPG signal(top)

Actually, every extreme points could be detected by the differential method. However, in many applications, e.g. pulse wave translation time (PTT) detection, only the start point or the main peak should be picked up. The other extreme points near the required point would be negative for its accurate locating[10].

To solve this problem, an improved differential algorithm was proposed. The main strategy was to cut the signal across zero points before differential. By this way, only one extreme point could be detected in every section. The main flow chart was showed in Fig.8.

As can be seen, after cut by zero-crossing point, only one extreme point could be located in every section. This method could ensure that the time interval features of PPG signal could be accurately calculated. The experiment results by the two methods were displayed in Fig.9.

With the traditional method, 3 mistake points was got in a 50s PPG signal, the error rate was about 4.1%. When the improved method is used, there is no mistake appeared. Because the proposed differential method could eliminate the false positives caused by signal jitter effectively, it is advantageous to the detection of the physiological parameters, such as HR, PTT etc.

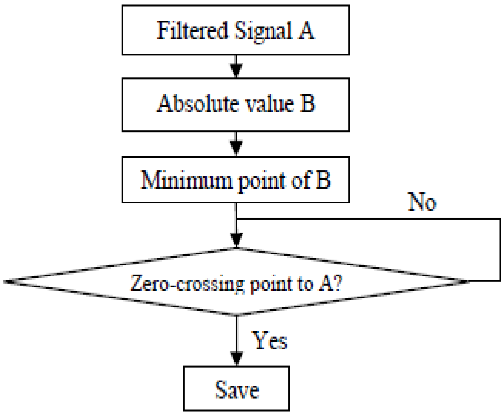


Fig 8. Flow diagrams of the improved differential algorithm

D. PPG as Signature Mark to Authenticate Medical Data:

For transmitting an EPR over the Internet, an EPR typically contains the health history of a patient, including demographic data, physical examinations, laboratory tests, treatment procedures, prescriptions, radiology examinations, historic pathology, etc.,An EPR transmitted through the Internet is especially important since it contains a highly private material of medical information for a person. to transmit different types of EPRs via the Internet data are first converted into several files. The EPR data are then received and acknowledged by authorized physicians or administrators.

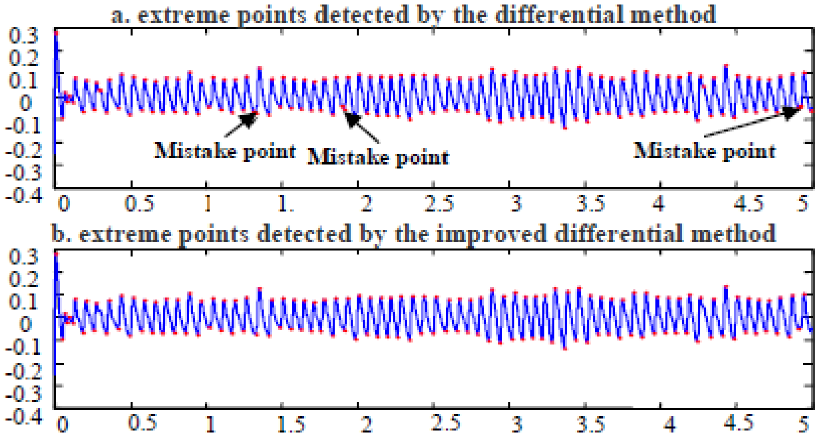


Fig 9. Comparison of feature extraction result by the differential algorithm and the improved one

The implementation steps for data-hiding and data-extracting methods using PPG as signature mark are stated in the following[15].

1) Data Hiding:

Step 1) Generating the hiding base.

First, image of size r×c is chosen. A JPEG lossy image generated from the mark image is then produced. The hiding base, i.e., bipolar TER(tolerance error range) base, is, therefore, obtained by taking the differences of these two images.

Step 2) Reorganizing data.

A digital PPG values is randomized through a pseudorandom process. A diagnostic report or a digital ECG signal is converted into numerical data.

Step 3) Hiding data into the hiding base.

The doctor and hospital bilevel digital signatures are hidden into the Base1. The diagnostic report and a segment of the ECG signal with significant symptoms are hidden into Base2, followed by key chains for different types of hidden data.

Step 4) Formatting the hidden image.

Finally, the hidden image is constructed by adding the original mark image and the new bipolar TER base values.

2) Data Extracting:

Step 1) Generating the default TER Base and modified TER base. The default TER base is produced by taking the differences between the original mark image and its JPEG decompressed image. The modified TER base is generated by taking the differences between the original mark image and hidden image.

Step 2) Using the key chains to find out the locations of hidden data. According to different numbers of zeros in Base2 and Base2 , the locations of different types of hidden data in the hidden image are obtained.

Step 3) Extracting the data.

According to the locations specified in the key chain (key1 or key), the location of the digital signature is obtained by subtracting each pixel value in the hidden image from one. For extracting a diagnostic report and a segment of the ECG signal, the pixel values in the received image are subtracted from the modified TER base values based on the key-chain that indicates the number of temporary values converted.

Step 4) Restoring the data.

The inverse pseudorandom process is taken to restore the digital signatures. The inverse number conversion is processed to find the corresponding hidden data.

V CONCLUSIONS

As noted, PPG is a novel noninvasive method with the advantage of convenience and accuracy. It could reflect many physiological parameters and functions, such as heart function, blood vessel elasticity, blood viscosity and so on. However, the original signal was usually interfered by many other factors, such as high-frequency noise, baseline drift and so on. In the present work, many practical methods including median filtering and FIR filtering was used to remove most noises from the original signal. A new algorithm based on wavelet transformation was proposed for eliminating the baseline drift caused by breathes and motion artifact. Feature points extraction was another key issue. An improved differential algorithm was used to solve this problem. By this way, all the feature points of PPG signal could be extracted accurately. It is possible to identify a person by information extracted from PPG signals given that signals were collected under controlled environment and with accurate sensors. Hence PPG can be used as a signature mark to authenticate medical data transmit it securely and confidentially.

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