Assessing systemic vascular resistance using arteriolar pulse transit time based on multi-wavelength photoplethysmography

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Abstract
Objective. Sympathetic nerve activity affects blood pressure by contracting the arteriole, which can increase systemic vascular resistance (SVR). Consequently, SVR is a key factor affecting blood pressure. However, a method for measuring SVR continuously is lacking. This paper formulated and experimentally validated a method that uses the arteriolar pulse transmit time (aPTT) to track changes in SVR.

Approach. multi-wavelength photoplethysmogram (PPG), electrocardiogram (ECG), and galvanic skin response (GSR) data were simultaneously gathered using a measurement system designed by this study. Blood perfusion was monitored by laser Doppler. Least mean square (LMS) is an adaptive filtering algorithm. Our LMS-based algorithm formulated in this study was used to calculate the aPTT from the multi-wavelength PPGs. A cold stimulation experiment was conducted to verify the relationship between aPTT determined by algorithm and arteriole vasodilation. An emotinal stimulation experiment conducted, in which GSR was employed to further verify the relationship between aPTT and SVR. Twenty healthy young participants were asked to watch movie clips, which excited their sympathetic nerves. The dynamic time warping (DTW) distance is applied to evaluate between correlation of GSR and aPTT. Main results. The changes in aPTT was extracted using our LMS-based method. During the recovery period after cold stimulation, aPTT decreased with the average slope of −0.2080, while blood perfusion increased with the average slope of 0.7046. Meanwhile, 70% participants’ DTW distances median between aPTT and GSR were significantly smaller than that between PTT and GSR during emotion stimulation. Significance. Our method uses aPTT, a continuous measurable parameter, to closely reflect SVR, as verified through experiments.

1. Introduction

Hypertension is the main cause of stroke, cardiovascular, and kidney disease. With the increase of blood pressure (BP), the probability of cardiovascular disease and stroke will greatly increase (Hao et al 2017, Herrington et al 2017). Thus, BP must be monitored and managed to prevent these diseases. However, because BP is constantly changing throughout the day, continuous ambulatory BP monitoring, which is essential for patients with hypertension (Pickering et al 2008), is difficult and has drawn much research attention.

Recent methods for continuously measuring ambulatory BP have done so based on the pulse transit time (PTT). However, previous PTT-based methods yield inaccurate PTT calculations and do not completely account for all factors affecting blood pressure (Forouzanfar et al 2015, Kachuee et al 2016, Esmaili et al 2017, Miao et al 2017). PPG is collected at the far end of the heart, like fingers or wrist (He et al 2014, Song et al 2019). Therefore, the time interval between the R wave peak of the ECG signal and the peak of the next PPG signal is actually equivalent to the pulse arrival time (PAT) (Elgendi et al 2019). The PAT spans two periods: pre-ejection period (PEP) and PTT. By contrast, because arteries, arterioles, and capillaries are often distributed in the remote...
Table 1. Five main factors affecting arterial blood pressure.

| Main factors                                      | Noninvasive continuous measurable physiological parameters |
|--------------------------------------------------|-------------------------------------------------------------|
| Stroke volume (SV)                               | HR and SV                                                   |
| Heart rate (HR)                                  | Time interval between R wave peaks of ECG                   |
| Systemic vascular resistance (SVR)               | Arteriolar PTT                                               |
| The elasticity of the arterial wall              | Arterial PTT                                                 |
| The ratio of circulating blood volume to blood vessel volume | Can be considered as a constant                             |

PPG collection site, the collected PPG signal includes the reflection signals associated with these three vascular layers. Furthermore, the previous PAT measurement cannot accurately reflect the change in the elasticity of the arterial wall especially when the smooth muscles of small arteries contract or relax (Yang and Tavassolian 2017). For this change to be reflected more accurately, the arterial PPG should be extracted from the detected PPG signals, as illustrated in figure 5. Thus, this paper proposes a multi-wavelength PPG (MWPPG) method for extracting the arterial PPG signal and the capillary PPG signal from the detected mixed PPG signal.

BP is primarily affected by five factors (Westerhof et al 2009, Salvi 2012): stroke volume (SV), systemic vascular resistance (SVR), heart rate (HR), elasticity of the arterial wall, and ratio of circulating blood volume to blood vessel volume (see table 1). Among five major factors, only the ratio of circulating blood volume to blood vessel volume remains constant in the absence of a sudden event (such as a massive haemorrhage or shock); thus, this ratio can be considered to be constant under normal circumstances. HR can be calculated by the R wave peak interval of an ECG signal, as illustrated in figure 5. In addition, SV can be expressed in terms of HR and SVR (Liu et al 2018). The aforementioned PTT-based methods only reflect the elasticity of the arterial wall (Ding et al 2016, Zhang et al 2017, Ripoll and Vellido 2019). Therefore, we must formulate a method that can use a continuous measurable parameter to indicate SVR.

SVR is a quantity that indicates the left ventricular afterload. It refers to the resistance to blood flow exerted by the entirety of the systemic vasculature excluding the pulmonary vasculature. SVR reflects changes in the arterioles, which can affect the emptying of the left ventricle. Pulsatility decreases as the blood flows into smaller arteries and arterioles (Klabunde 2011). Changes in vascular resistance reflect changes in arteriolar tone or changes in the viscosity of blood. Obviously, SVR can be reflected by the characteristics of arterioles.

Liu et al were the first to propose the arteriolar PTT (aPTT) measurement, which is calculated from MWPPG signals (Ray et al 2021), and indicates SVR (Liu et al 2015, 2016, 2018). Compared with traditional arterial PTT-based methods, the use of BP calculation model with the calculated aPTT yields more accurate results in patients with hypertension who are taking antihypertensive drugs that can change their SVR. As part of their method, a PCA-based multi-wavelength PPG algorithm is applied to obtain the arterial PPG and capillary PPG (Liu et al 2020). In theory, the components obtained from principal component analysis (PCA) are unrelated to each other, but PPG signals of different wavelengths are inevitably correlated with each other. To address the problem, we formulated an LMS-based multi-wavelength PPG algorithm that find the aPTT more explanatory. Our method separated PPGs while preserving some correlation. We also conducted experiments to validate whether the aPTT obtained by the algorithm accurately indicates SVR.

If one assumes that the fluid is not viscous, the pulse transit time in the elastic pipe can be calculated using the M–K equation (Chandran et al 2006). In microcirculation, the blood viscosity is pronounced, and the Womersley number is of great importance. Liu et al (2018) establish the relationship between aPTT and SVR using an equation that includes the Womersley number. However, this equation may not be applicable when one accounts for the blood viscosity and arteriole thickness (Chandran et al 2006). Therefore, this paper tries to experimentally verify the relationship between aPTT and SVR.

The cold stimulation cause the finger vessels to contract, including the arterioles. When the finger is placed in room temperature after cold stimulation, the vasodilation of finger vessels will increase the blood perfusion mainly dependent on nitric oxide (NO) generation (Minson et al 2001), and meanwhile be involved in the decrease in SVR (Stamler et al 1994). Therefore, the arteriole vasodilation will lead to the increase in blood perfusion and the decrease in SVR as illustrated in figure 1. In this paper, both the blood perfusion and aPTT are detected during the recovery periode of cold stimulation. The variation trend of both parameters will be analyzed.

Excitement of the sympathetic nerves can cause many changes in the body, such as sweat gland secretion and arteriole contraction. Sweat gland secretion can lead to changes in skin impedance, which can through detected by the GSR method (figure 1). This method has been used in many studies to measure emotional changes in individuals (Wen et al 2014, Goshvarpour et al 2017, Nourbakhsh et al 2017). Under emotional stimulation, GSR is increased (Westerink et al 2008). Emotional changes can also excite the sympathetic nerves leading to vasoconstriction (Hayashi et al 2009). As illustrated in figure 1, emotional stimulation can increase SVR through...
vasoconstriction (Delong and Sharma 2019). Based on the above theoretical basis, GSR and SVR have a certain relevance. As mentioned, researchers have recently proposed that aPTT can be used to indicate SVR (Liu et al 2018). In doing so, this study is the first to experimentally demonstrate that aPTT can be used as a parameter for tracking SVR driven by sympathetic nerves.

In this paper, a measurement system was first developed to collect multi-wavelength PPG, ECG, and GSR readings simultaneously. The participants then watched a movie clip that generated the emotion of fear, and their measurements were collected. We then applied our LMS-based multi-wavelength algorithm to separate the PPG signals associated with a given vascular layer from the collected multi-wavelength PPG signals. In the cold stimulation experiment, the participants’ aPTT and blood perfusion was monitored during the recovery period. As mentioned, PTT is related with the elasticity of the arterial wall among the five major factors affecting BP. In the emotion experiment, we compared the aPTT’s dynamic time warping (DTW) distance with the PTT’s DTW distance. Our aim is to demonstrate that aPTT is a non-invasive parameter that can track SVR. We are the first to provide evidence for the mechanism underlying the association between aPTT and SVR driven by sympathetic nerves.

2. Materials and methods

In this section, we detail our measurement system and our LMS-based multi-wavelength PPG algorithm. The overall parameter extraction process is summarised in figure 2.

2.1. Measurement system

We constructed a novel measurement system to simultaneously collect multi-wavelength PPG, ECG, and GSR readings (figure 3). This measurement system featured infrared (940 nm), yellow (591 nm), and blue (470 nm) LEDs, whose light penetrated into the arterial layer, arteriolar layer, and capillary layer, respectively, per the principle that light of longer wavelength penetrates human tissue more deeply. These LEDs were denoted IR_PPG, Y_PPG, and B_PPG, respectively. We used an analog front-end (AFE4404, Texas Instruments, Dallas, TX, USA) to drive the LEDs and receive photodiode signals. The current of each LED could be adjusted individually. One photodiode was used to detect the reflected light from each LED. The photodiodes had a sensitivity that depended on the wavelength of light. Subsequently, different feedback resistances on the
trans-impedance amplifier, which were adjustable at the analog front-end, were required for the different LEDs to obtain signals of a similar amplitude. The PPG signals were sampled and converted by the sample and hold circuit and by the ADC in AFE4404, respectively. All signals were sampled at 500 Hz and transmitted using a bluetooth low energy module.

2.2. Experiments

In the cold stimulation experiment, five participants (age: 25 ± 1 years; gender: 5 men) were asked to put their fingers into the ice water (0 °C) for 30 s. Subsequently, three PPG signals and were collected by the measurement system on the left index finger at room temperature for 60 s while the blood perfusion was collected by the PeriFlux 5000 laser Doppler on the right index finger for 60 s. Blood perfusion measured by laser Doppler is a relative value (semi-quantitative). It represents the number of relative moving blood cells that cause the Doppler shift, and the relative cell moving speed. This value is expressed as perfusion unit (PU). As indicated in figure 4, PeriFlux 5000 laser Doppler was collecting the blood perfusion while our measurement system was collecting PPG readings during the recovery period.

In the emotion experiment, 20 healthy young participants (age: 28 ± 5 years; gender: 15 men, 5 women) without any history of cardiovascular disease watched the same 11 movie clips from the MediaEval 2018 Emotional Impact of Movies collection (Larson et al. 2020). These clips were 60 s long including fear annotations. Before the experiment, each subject undertook spontaneous breathing for at least 1 min until they felt at ease. Subsequently, the participants were instructed to focus on the clip being played and feel whatever emotions they did naturally before watching the clips. The participants rested for 60 s every two clips for them to regain their emotional equilibrium. When the movie clips were playing, three PPG signals, lead I ECG and GSR signals, were recorded at the sampling rate of 500 Hz. Each participant watched 11 movie clips, and each set of data was collected over 60 s. We directly removed the excessively noisy data to ensure that the overall data was valid. To determine the correlations between GSR and aPTT and between GSR and PTT, we first normalised these values to be between 0 and 1 and then calculated the distance between their trajectories.

The cold stimulation and emotion experiments were approved by an institutional review board (SIAT-IRB-190615-H0348).
2.3. Signal preprocessing
A fourth-order Butterworth bandpass filter (0.2–5 Hz) is applied to the multi-wavelength PPGs for noise removal and baseline wander removal. To accurately detect the R peaks of the recorded ECG signals, after a fourth-order Butterworth lowpass filter (40 Hz) was applied, we applied a MATLAB implementation of a Pan–Tompkins ECG QRS detector (Pan and Tompkins n.d., Sedghamiz 2014). As illustrated in figure 5, PTT is the time interval between the R wave peak of the ECG signal and the peak point of the arterial PPG signal. aPTT is the time interval between the peak point of the arterial PPG signal and the capillary PPG signal. HR can be calculated using the R wave peak interval in ECG measurements.

Empirical mode decomposition, first introduced by Huang et al (1998), was used to decompose a signal into intrinsic mode functions (IMFs). Compared with general filters, IMFs based on local properties of the signal allow for the instantaneous frequency to be meaningfully interpreted. GSR signals are decomposed into eight IMFs, and the eighth IMF contains the lowest frequency’s component of the GSR. Therefore, we applied the eighth IMF as the GSR feature to calculate the correlation.

2.4. LMS-based PPG algorithm
A PPG signal comprises three parts. The ambient part is due to the reflection of the ambient light during measurement and should be subtracted from the overall signal. The DC part is due to the reflection off nonpulsatile tissue and pulsatile blood at a constant volume. Finally, the AC part is determined by the changes in volume of the blood vessels. In this study, we were only interested in the AC part. According to the modified Beer–Lambert law, the absorbance of a liquid is proportional to the product of the concentration of the
Using the aforementioned method, we obtained the arterial PPG signal:

\[ \Delta A(t) = k b \Delta c(t), \]  

(1)

where \( k \) is the proportionality constant related to the properties of the absorbing substances, the wavelength of the light, and the temperature; \( b \) is the average path length of the diffused photons from the light source to the detector; \( \Delta c(t) \) is the change in volume of the blood vessels (see figure 6). Per the principle that the depth of penetration of a light wave depends on its wavelength, the absorbance for a given wavelength is as follows (Fabbri et al 2004):

\[ \Delta A^\lambda(t) = \sum_{i=1}^{N} [R_i^\lambda b_i^\lambda \Delta c_i(t)], \]

(2)

where \( N \) is the number of vascular layers, \( R_i^\lambda \) is the depth ratio of each layer’s transmission for the current wavelength of light \( \lambda \), \( k \) is related to the wavelength, and \( b \) is related to both the wavelength and vascular layer. Subsequently, we can obtain the absorbance of vessels for every light wave as follows:

\[
\begin{align*}
\Delta A^\lambda(t) &= k^\lambda b_1^\lambda \Delta c_1(t) + R_2^\lambda k^\lambda b_2^\lambda \Delta c_2(t) \\
\Delta A^\lambda(t) &= k^\lambda b_1^\lambda \Delta c_1(t) + k^\lambda b_2^\lambda \Delta c_2(t) + R_3^\lambda k^\lambda b_3^\lambda \Delta c_3(t) \\
\Delta A^\lambda(t) &= k^\lambda b_1^\lambda \Delta c_1(t) + k^\lambda b_3^\lambda \Delta c_3(t) + R_2^\lambda k^\lambda b_3^\lambda \Delta c_3(t),
\end{align*}
\]

(3)

where \( A^\lambda(t) \), \( A^\gamma(t) \), and \( A^\nu(t) \) are the detected PPG signals for the three LEDs. The specific changes in volume in every layer (\( \Delta c_1(t) \), \( \Delta c_2(t) \), and \( \Delta c_3(t) \)) must be calculated from these signals. If we set the weights \( w_1 \) and \( w_2 \), then we obtain the following:

\[
\begin{align*}
\Delta A^\lambda(t) &= w_1 \Delta A^\lambda(t) - w_2 \Delta A^\gamma(t) \\
&= (k^\lambda b_1^\lambda - w_1 k^\gamma b_1^\gamma - w_2 k^\nu b_1^\nu) \Delta c_1(t) \\
&+ (k^\lambda b_2^\lambda - w_1 k^\gamma b_2^\gamma - w_2 R_2^\lambda k^\lambda b_2^\nu) \Delta c_2(t) \\
&+ (R_3^\lambda k^\lambda b_3^\lambda - w_1 R_3^\nu k^\lambda b_3^\nu) \Delta c_3(t).
\end{align*}
\]

(4)

If \( (k^\lambda b_1^\lambda - w_1 k^\gamma b_1^\gamma - w_2 k^\nu b_1^\nu) \) and \( (k^\lambda b_2^\lambda - w_1 k^\gamma b_2^\gamma - w_2 R_2^\lambda k^\lambda b_2^\nu) \) are 0, then \( \Delta A^\lambda(t) = w_1 \Delta A^\lambda(t) - w_2 \Delta A^\gamma(t) \propto \Delta c_1(t) \). However, because the number of unknown parameters is too large, it is impossible to directly calculate \( w_1 \) and \( w_2 \). We thus employed LMS adaptive algorithm to find the optimised \( w_1 \) and \( w_2 \). LMS algorithm is basically a nonlinear feedback control system (Haykin 2008). We use the correlation coefficient to feed back the system. When \( \Delta A_3(t) = \Delta A^\lambda(t) - w_1 \Delta A^\lambda(t) - w_2 \Delta A^\gamma(t) \propto \Delta c_3(t) \) has the lower correlation with \( \Delta A^\lambda(t) \). Thus, \( w_2 \) can be adjusted by the LMS algorithm to be:

\[ w_2(t + 1) = w_2(t) + \mu \Delta A_3(t) \Delta A^\gamma(t), \]

(5)

where \( \mu \) is the learning rate. Because \( R_3^\lambda \gg R_3^\nu \), when \( \Delta A_3(t) \propto \Delta c_3(t) \), \( \Delta A_3(t) \) also has a smaller correlation with \( \Delta A^\nu(t) \). Subsequently, \( w_1 \) can be adjusted to the following:

\[ w_1(t + 1) = w_1(t) + \mu \Delta A_3(t) \Delta A^\lambda(t). \]

(6)

Using the aforementioned method, we obtained the arterial PPG signal: \( \Delta A_3(t) \). Using the same method, we obtained the arteriolar PPG signal.

Figure 6. Distribution of vascular layers and light penetration paths. MWPPG signal includes those from \( \lambda_1 \) (blue), \( \lambda_2 \) (yellow) and \( \lambda_3 \) (infrared). The specific changes in volume in every layer are \( \Delta c_1(t) \), \( \Delta c_2(t) \) and \( \Delta c_3(t) \).
In the LMS-based MWPPG algorithm, the weights stabilise with every iteration, and the correlation coefficients decrease and stabilise with every iteration. The convergence speed can be adjusted by the learning rate $\mu$. The best weights should have the minimum correlation between the layer PPG signals of every two layers.

2.5. Correlation evaluation

As is well-known, the aPTT is calculated between the PPGs of the artery and capillary layers for each beat. Therefore, in the 60 s emotion experiment, the aPTT is discrete according to the HR of the subjects. However, GSR is a continuous signal with a sampling rate of 500 Hz. Thus, it is difficult to calculate their correlation coefficients. To address the problem, we treated different signal curves as trajectories and applied the DTW distance to measure their similarity in terms of their correlation.

The DTW distance is a widely applied measure for detecting patterns in inherently temporal data, and the goal of doing so is to determine the warping path between two trajectories that incurs the minimum warping cost (Keogh and Ratanamahatana 2005). Given the aPTT as represented by the point set $aPTT = \{a_1, a_2, a_3 \cdots a_m\}$ and the GSR as represented by the point set $GSR = \{b_1, b_2, b_3 \cdots b_n\}$, the distance $d(a_i, b_j)$ between the two points $a_i$ and $c_j$ is

$$d(a_i, b_j) = (a_i - b_j)^2.$$  

A warping path $W$ is a contiguous set of matrix elements that defines a mapping between aPTT and GSR, and the $k$th element of $W$ is defined as $w_k = (i, j)_k$, where
We are only interested in the path that minimizes the warping cost:

$$\text{DTWcost} (\text{aPTT}, \text{GSR}) = \min \left( \sum_{k=1}^{K} w_k \right).$$

This path can be obtained using dynamic programming, and we defined the cumulative distance $D(i,j)$ as follows:

$$D(i,j) = d(a_i, b_j) + \min\{D(i-1, j-1), D(i-1, j), D(i, j-1)\}.$$  

(15)

PTT responds to the elasticity of the arterial wall among the five major factors affecting BP. It has no connection with sympathetic nerve excitement and thus, in theory, has no correlation with GSR. Because we cannot quantitatively analyse the correlation, we compare the correlation between GSR and aPTT with the correlation of GSR and PTT. In general, the smaller the distance between two signals, the greater the correlation between them. Using such a method, we could investigate whether aPTT better represents sympathetic nerve activity than PTT does. If the distance between GSR and aPTT was found to be smaller than GSR and PTT, this would provide evidence that aPTT could have greater utility for assessing SVR.

3. Results

To accurately separate the PPG signal of each vascular layer, we obtained the arterial PPG signal ($A_3$), arteriolar PPG signal ($A_2$) and capillary PPG signal ($A_1$) by using our LMS-based MWPPG algorithm.

3.1. Result of cold stimulation experiment

In the cold stimulation experiment, the vessels on the finger contracted and then recovered 60 s at room temperature. The calculated aPTTs and blood perfusion for participants collected at the same time are illustrated in figure 8. The slope values of aPTT and blood perfusion are shown in the table 2. During the recovery period after cold stimulation, aPTT decreased with the average slope of $-0.2080$ (s/ per pulse), while blood perfusion increased with the average slope of $0.7046$ (PU s$^{-1}$). It shows that the overall blood perfusion is an upward trend and the overall aptt is in a downward trend. The experimental results are consistent with the theoretical analysis introduced previous. The blood perfusion and aPTT show opposite trends. Therefore, the result indirect provide the evidence for the relationship between aPTT and SVR.
3.2. Result of emotional stimulation experiment

As indicated in Figure 11(a), when the participants watched the movie clips, the measurement system could monitor the participants’ physiological response in a timely manner. Figure 11(b) illustrates the signals collected by the measurement system over one movie clip. When the participant experienced fright, the GSR signals exhibited obvious fluctuations. When the participant experienced fright, sympathetic nerve excitement causes sweat gland secretion and vasoconstriction, which change the GSR and SVR, respectively. GSR was particularly well-reflect of its eighth IMF, where tracking this IMF was equivalent to tracking the SVR. Thus, in the following calculation of the distance between the trajectories, we use the eighth IMF instead of GSR.

The distance for each participant is illustrated in Figure 9. For all except six participants, each participant’s DTW distance’s median between aPTT and GSR were smaller than that between PTT and GSR, which accounted for 70%. Considering that some participants are not sensitive to emotional stimuli, this proportion is already high. Even among participants whose DTW distance’s median between aPTT and GSR is not smaller, the overall distribution is smaller. Subjects 3, 8, 10, 12 and 13 were female and there was no significant difference between them and male subjects. As shown in Figure 10, furthermore, to control for the different effect exerted by different movie clips, we also calculated the DTW distance for each movie clip. On the basis of the aforementioned findings, we conclude that compared with the PTT and GSR, the aPTT and GSR were more correlated; thus, the aPTT can better reflect changes in SVR due to sympathetic nerve activity.

The level of shock differed between the participants. Figure 12(a) presents the signals collected when the participant 10 was watching a movie clip starting from the 45th second of MEDIAEVAL18_08. After the movie was edited, the original videos fear annotations were at 7–14, 24–28, 35–93, and 51–53 s into the video. Participant 11 reported to us that they were more frightened at the first annotation (714 s), which was consistent with the fluctuation in their GSR. Figure 12(b) presents the signals collected when participant 13 was watching a movie clip starting from the 75th second of MEDIAEVAL18_10. After the movie was edited, the original videos fear annotation was at 20–50 s into the video. Using the raw data obtained by our measurement system, we determined that GSR signals fluctuated when the participant was is frightened. Because the participants differed physiologically, their reaction time (from when the fearful stimuli was presented to when they felt fear) and degree of fear differed; this meant that the fear annotations were not completely accurate, as reflected in

Figure 9. Boxplot of each participant’s DTW distance.

Table 2. The slope values of aPTT and blood perfusion.

| Subject no. | Blood perfusion slope (PU s⁻¹) | aPTT slope (s/ per pulse) |
|-------------|--------------------------------|--------------------------|
| 1           | 0.8760                         | −0.1217                  |
| 2           | 0.6316                         | −0.2002                  |
| 3           | 1.2891                         | −0.3342                  |
| 4           | 0.2232                         | −0.3135                  |
| 5           | 0.5031                         | −0.0705                  |
Nonetheless, and most importantly, aPTT tracked GSR and, by consequence, SVR better than PTT did.

4. Discussion

In non invasive continuous BP measurement, the change in SVR, a factor caused by sympathetic nerve activity, has been neglected in the literature. Parameters in existing BP models characterise changes in SVR poorly. Thus, to better measure sympathetic-driven BP, in this study, we formulated a multi-wavelength PPG detection method to reflect systemic vasoconstriction and our experiments verified that aPTT can track SVR very well.

Our method features an LMS adaptive algorithm for optimising the weights in equations (4), (7) and (10). Compared with the methods used in Liu et al (2016, 2020), our method accounts for the correlation between the signals of each vascular layer and can be realised in real time. The weight updating of weights can also be an

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Figure 10. Boxplot of each clip’s DTW distance.

Figure 11. (a) Participant number 16 watching movie clips from MediaEval 2018 Emotional Impact of Movies collection while our measurement system was collecting physiological signals. (b) Signals collected by our measurement system. MWPPG signal includes those from IR_PPG(infrared), Y_PPG(yellow), and B_PPG(blue).

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automatically convergent process. To increase the convergence rate, one can increase the learning rate or use the recursive least squares adaptive algorithm. Although the proportional constant \( k \) and the path parameter \( b \) in equation (1) depend mainly on the particular person at a given, the different usage of the same participant, such as the movement of the finger, also induces changes in these two parameters, especially the path parameter \( b \). Therefore, calibration for a given individual conducted only at the initial stage does not guarantee the accuracy of the model. The adaptive algorithm can calibrate the parameters in real time according to the current situation, which increases the flexibility of the model.

Liu et al (2018) theoretically deduced that arteriole PTT can be used to track changes in SVR and there should be an inverse relationship between them, which is contrary to our experimental results. They used the relationship between the aPTT and SVR and between SVR and BP to construct an aPTT-based BP calculation model. Their results indicated that compared with traditional PTT-based methods, their method has better accuracy when used for patients with hypertension who are taking antihypertensive drugs that can change their SVR. However, they did not experimentally verify the mechanism underlying the correlation between aPTT and SVR. In general, arteries where microcirculation occurs are difficult to analyse theoretically because of their characteristics. Thus, we experimentally determined the relationship between aPTT and SVR.

In the cold stimulation experiment, the aPTT changed during the recovery period after cold stimulation, and the observed trends were identical with those predicted in the theoretical analysis. These experimental results demonstrated that aPTT was closely related to SVR. However, our cold stimulation experiment has a small number of subjects and are all male and still need to be improved. We can also perform cold stimulation experiments on the whole body.

In our emotion experiment, because all the participants were young, their physiological response was relatively obvious and their physiological signals were relatively clear. Our experiment demonstrated that aPTT tracks SVR well. Many drugs for high BP are aimed at regulating SVR. Therefore, follow-up experiments can recruit participants who take hypertension drugs that change their SVR. With regard to the movie clips watched by the participants, we selected the movies in the MediEval 2018 Emotional Impact of Movies collection and used the fear annotations in them. However, some participants stated to us that some movie clips were not scary enough, which may leave their sympathetic nerves to unexcited. Conversely, if the subject receives constant shock, the break time between movie clips should be lengthened accordingly. Follow-up experiments can have participants watch movies over a long period and collect their signals continuously.

Figure 12. (a) Signals collected when participant 10 was watching a movie clip starting from the 45th second of MEDIAEVAL18_08. (b) Signals collected when the participant 13 was watching a movie clip starting from the 75th second of MEDIAEVAL18_10. Both PTT and aPTT were calculated based on the participant’s pulse in a 60 s movie clip. The overall frequency differed between participants because their heart rate differed.
5. Conclusion

In this paper, we propose an LMS-based multi-wavelength PPG algorithm that is based on the correlation of the PPG signals between each vascular layer to more accurately extract PTT and aPTT parameters. Based on the principles that cold stimulation increases SVR and that sympathetic nerve activity changes SVR and GSR simultaneously, experiments were conducted to verify the mechanism underlying the correlation between aPTT and SVR. In the cold stimulation experiment, aPTT decreased while blood perfusion increased during the recovery period after cold stimulation. The mean value of aPTT’s slope is $-0.2080$ while the mean value of blood perfusion’s slope is $0.7046$. In the emotional stimulation experiment, $70\%$ participants’ DTW distances median between aPTT and GSR were significantly smaller than that between PTT and GSR during emotion stimulation.

To the best of our knowledge, this is the first study to experimentally verify such a mechanism driven by sympathetic nerves. The result of cold stimulation experiment indicated that the decrease in aPTT was correlated with arteriole vasodilation. The result of emotional stimulation experiment indicated that aPTT was correlated (and more correlated than PTT was) with GSR, thus demonstrating that aPTT can be used to track SVR.

SVR is a key factor affecting BP but has received little scholarly attention. In general, we identify the aPTT as a measurable parameter that is useful for continuously measuring changes in BP induced by sympathetic nerve activity.

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