# S-HRVM: Smart Watch-based Heart Rate Variability Monitoring System

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## Abstract

Continuous heart rate variability (HRV) monitoring can monitor a user's health and help them make adjustments and treatments. The current methods of using ECG or externally mounted sensors are accurate, but inconvenient for the user. Other methods of using computer vision rely on ambient lighting conditions, and there are issues that may violate user privacy. Mobile devices such as smart watches and smartphones hold the promise of providing a more convenient, practical, and non-invasive method of detection. In this paper, we propose *S-HRVM*, a smart watch-based heart rate variability monitoring system. The basic idea behind *S-HRVM* is to combine the physiological representation and motion state of user. In physiological representation, we propose SP-HR method to process heart rate data and extract HRV features. The motion state, which can be derived by using accelerometer data of smart watch, is used to reduce the power consumption. In addition, the HRV features are used as calculation parameters of G-MSPC (the general health monitoring model based on MSPC), which can be used to detect mental states and diseases associated with autonomic function. Extensive experimental results demonstrate the effectiveness of the proposed methods.

## 1 Introduction

Heart rate (HR) is a very important function indicator of the human body. Numerous studies have shown that ubiquitous heart rate sensing can provide possibilities for enabling clinical-grade services [5]. Short-term heart rate variability (HRV) monitoring in terms of the RR-intervals(RRI) is particularly useful, and it is often used to track human body mental states such as stress and fatigue [1], which are important for driving safety and personal well-being.

Previous work has taken many approaches, including electrocardiograms, and cameras, sometimes combined to get heart rate data from people. Electrocardiogram (ECG) or photoplethysmography (PPG) is currently the most advanced and most commonly used method of heart rate monitoring, it can directly reflect changes in the heart rate of the human body. However, this method requires special equipment used in medical diagnosis or research, which is costly and inconvenient to carry, and has poor practicality. The accuracy of the method using the camera depends on the ambient lighting conditions. The data collected during the day and night may vary greatly which cannot truly reflect the user's heart rate changes, and it may involve the privacy of the user.

Thus, we want to design an accurate and portable monitoring system with strong robustness, embedding on mobile devices, to detect HRV of user. Fortunately, heart rate sensors are widely embedded in mobile devices such as smart watches, we can collect the user's heart rate data by smart watch. Heart rate can be used to estimate the HRV, which is the RRI fluctuation of an ECG, as an important physical indicator. In addition, other sensing data (e.g. accelerometer and gyroscope) from smart watches can be used to assist the detection system and reduce power consumption.

There are two key technical challenges. The first challenge is how to reduce the power consumption of the heart rate sensor. The most common method of measuring heart rate in smart watches is the reflective optoelectronic method, which measures heart rate by measuring the blood flow at the bottom of the LED, the heart rate sensor is the same as all sensor nodes in WSNs, energy can be quickly depleted if kept working for a long time [2]. Moreover, heart rate measurements will be more accurate in relatively static situations. Considering these two aspects comprehensively, we propose SSPA (static state prediction algorithm) which detects the relative static state of the human body using the inertial measurement unit (accelerometer and gyroscope, etc.) in the smart watch as a starting mechanism for the heart rate sensor. The heart rate sensor starts working only when it detects that the user is in a relatively static state.

The second challenge is how to obtain the HRV from the heart rate data. The traditional HRV is obtained from the ECG. In our work, we only obtain the heart rate data from the smart watch, and we can't get the interval between two adjacent heartbeats like an ECG. To address this challenge, we propose the SP-HR (statistical processing of heart rate) which utilize the statistics to calculate the RR-interval between two adjacent heartbeats, then calculate HRV features

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based on these RR intervals. We further perform statistical results as a threshold on real-time processing of heart rate data.

Since the fluctuations in the RRI of the electrocardiogram reflect autonomic function, the disease and physical state associated with the autonomic nervous system can be monitored by monitoring RRI data, such as epilepsy [9], ischemic stroke [11], stress and other mental states. According to the fact that the autonomic nervous function affects heart rate variability, we design a general health monitoring model based on MSPC (Multivariate Statistical Process Control), G-MSPC, which uses multiple HRV features from RRI analysis as input variables. In G-MSPC, detection and recognition of outliers are very important, we adopt Yang et.al work [10] to define and identify outliers. In the experiment, we collected a large number of heart rate data of different people in both awake and drowsy state, the awake data sets as modeling data of G-MSPC, the two statistic $Q$ and $T^2$ are used to detect whether the user is drowsy.

The contributions of this paper are summarized as follows:

1) We design a relatively static state prediction algorithm SSPA as the starting mechanism for the heart rate sensor to reduce power consumption and obtain more accurate heart rate data.

2) We propose the SP-HR method to process heart rate data, and then extract HRV features that reflects the autonomic function.

3) We propose a general health monitoring model based on MSPC (G-MSPC) to monitor the user's physical condition related to the autonomic nervous system.

4) We implement *S-HRVM* and evaluate its performance in a simulated driving environment. The experiment results demonstrate the effectiveness of *S-HRVM*.

In the rest of this paper, we will present the preliminaries in Section II. Then we describe architecture of *S-HRVM* in Section III. We elaborate the design details of *S-HRVM* in Section IV and evaluate its performance in Section V. We will introduce the related work in Section VI. Section VII concludes the whole paper.

# 2 PRELIMINARIES

## 2.1 Heart Rate Variability

Since HRV reflects autonomic activity which changes during stress, extreme fatigue, and sleepiness episodes. HRV analysis has been used for stress or sleepiness estimation and cardiovascular disease monitoring. In this section, the commonly used HRV features are briefly described.

**RR-interval (RRI):** A typical electrocardiographic trajectory of the cardiac cycle (standard lead II) consists of several peaks, the highest of which is called the R wave. The RRI [ms] is the interval between the R wave and the next R wave.

The following time domain features are calculated directly from the raw RRI data.

**meanNN:** Mean of RRI.

**SDNN:** Standard deviation of RRI.

**rMSSD:** Root mean square of difference of adjacent RRI, it reflects the rapid change of HRV.

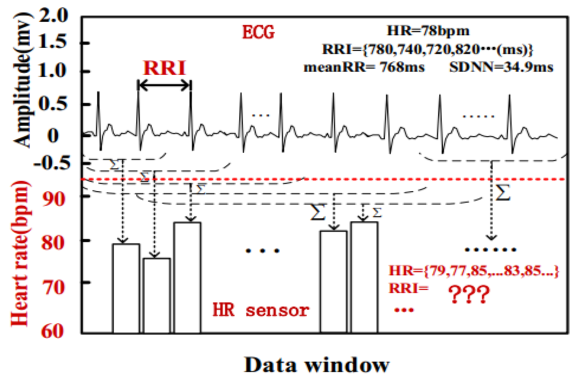


Figure 1: **Comparison of ECG and heart rate sensor.**

**NN50:** The number of pairs of adjacent RRI whose difference is more than 50 msec.

**pNN50:** The number of pairs of adjacent RRI, whose difference is more than 50 msec, divided by the total number of RRI.

**TP:** Total power, the variance of RRI.

The frequency domain features are mainly the following:

**LF:** Power in the low frequency range (0.04 Hz - 0.15 Hz) of PSD. It reflects sympathetic nervous system activity and parasympathetic nervous system activity.

**HF:** Power in the high frequency range (0.15 Hz - 0.4 Hz) of PSD. HF reflects the activity of parasympathetic nervous system.

**LF/HF:** Ratio of LF to HF. LF/HF represents the balance between sympathetic and parasympathetic nervous system activities.

As shown in Figure.1, the RRI can be obtained directly from the ECG, and then the time domain and frequency domain features can be calculated from the RRI. However, when using a smart watch to monitor heart rate, we can't directly get these parameters, the first challenge we face when getting these parameters is how to get RRI from heart rate data. The proposed SP-HR is used to solve this problem, and the detailed content is in section IV.

## 2.2 Built-in Sensors

The heart rate sensor detects heart rate by PPG (Photoplethysmography). Its principle is that the LED behind the watch can emit green light, and the photodiode can determine the instantaneous blood flow by detecting the absorption of green light. When the heart contracts, blood flow velocity increased, so the amount of green light absorption is also large. Conversely, when the heart is dilated, the blood flow decreased, and the amount of green light absorption is also small. The smart watch can measure the heart beat by detecting hundreds of green light exposures per second and changes in the regularity of green light absorption.

The accelerometer is an inertial sensor, which is triaxial accelerometer used to detect the acceleration on the x, y and z axes of equipment, always embedded in the smart phone and smart watch. The essence of the accelerometer is to measure the deformation of the sensitive components inside the sensor caused by the force, and transform the deformation into an electrical signal output with the relevant circuit to

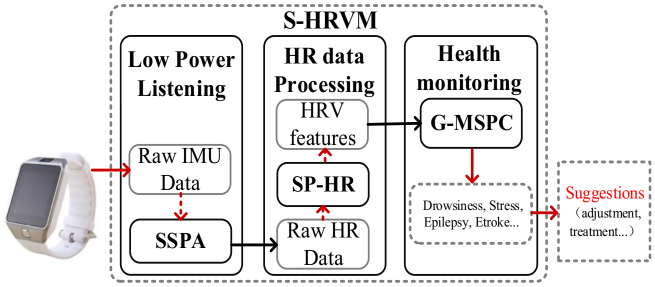


Figure 2: **Overview of *S-HRVM*.**

obtain the corresponding acceleration signal. The three-axis acceleration sensor can fully and accurately reflect the motion properties of the object.

## 3 Overview

In this part, we introduce the processing flow of the system. The overview of system is shown in Figure.2. *S-HRVM* is mainly composed of three modules: low power listening module, heart rate data processing module and health monitoring module.

**Low power listening module:** Considering the power consumption of the heart rate sensor and the more accurate heart rate detection at rest, we design SSPA, a static state prediction algorithm which process acceleration data are extracted from the IMU sensor of the smart watch and smartphone to predict whether the user is in a relatively stationary state for a short period of time. If the user is in a relatively static state, the heart rate sensor works, otherwise, low power listening in a cycle.

**Heart rate data processing module:** After the heart rate sensor is activated. We extract heart rate data from the smart watch in real time, then process them by our proposed SP-HR method and extract HRV features.

**Health monitoring module:** In this part, the multiple HRV features extracted from the heart rate data processing module as input variables for our proposed the general health detection model, G-MSPC. The model uses two statistics in the multivariate statistical process to measure the degree of deviation of the sample from the modeling data. Since our data sets are all composed of normal samples, when any statistic exceeds the corresponding control limit and is judged to be abnormal. Therefore, G-MSPC can monitor the user's physical status such as stress, drowsiness, epilepsy, stroke, and other cardiovascular diseases.

## 4 SYSTEM DESIGN

In this section, we will introduce the design details of *S-HRVM*.

### 4.1 Static state prediction algorithm(SSPA)

In order to reduce the power consumption of the heart rate sensor, and measure the heart rate data more accurately. We designed a relative static state prediction algorithm (SSPA) as a heart rate sensor startup mechanism. In *S-HRVM*, A smartphone placed around the user is used to monitor the dynamics of the environment, while a smart watch on the user's wrist tracks the movement of the user's hand. For example, in a traveling vehicle environment, a smartphone placed in the car is used to monitor the movement of the vehicle. *S-HRVM* continuously samples the accelerometers of smart phone and smart watch at a sampling rate of 50Hz to collect motion data. Each sample contains an acceleration vector $\overrightarrow{a}$.

Usually the variance of $\overrightarrow{a}$ can be used to detect whether a device is moving, but it is ineffective in a driving environment where $\overrightarrow{a}$ is disturbed by the movement of the vehicle. We solve this problem by comparing the $\overrightarrow{a}$ of the smart phone and the smart watch. Due to the inconsistent coordinates of smart phone and smart watch, we cannot directly compare $\overrightarrow{a}$. However, an important observation is that if there is no relative motion between these devices, the $|\overrightarrow{a}|$ in these devices should be similar [4]. Based on this, *S-HRVM* determines if the user is in a relatively static state by comparing each device's $\overrightarrow{a}$ and checking the following formula:

$$\frac{\sum_{i=1}^{L} \left||\overrightarrow{a_{i,swatch}}| - |\overrightarrow{a_{i,sphone}}|\right|}{L} > \xi \qquad (1)$$

Here L is the window length, when equation (1) is satisfied, *S-HRVM* considers that the user to be in a relatively static state. The size of $\xi$ determines the performance of the detector, because a small $\xi$ will reduce the robustness of the classifier and increase the false alarm rate when there are noisy motion signals. If $\xi$ is too large, *S-HRVM* may not detect relative static state, which will reduce the detection rate. In our experiments, $\xi = 1.0m/s^2$ performs best in most cases.

### 4.2 Statistical processing of heart rate(SP-HR)

The HRV signal is usually calculated by analyzing the time series of beat-to-beat intervals measured by electrocardiogram (ECG) or PPG waveform. However, due to the complexity of the equipment and the discomfort of wearing, the practicality of these two methods is very low. In our work, we use smart watch to monitor heart rate data and obtain HRV signals that can be further analyzed. In this section, we mainly introduce SP-HR method, which can obtain the RRI from the heart rate data to calculate the HRV features.

We obtain a large number of HR data from a smart watch under different scenarios. According to the HRV analysis guidelines, RRI data should be measured for at least 2 to 5 minutes for accurate frequency analysis. We use a sliding window $w_h$ to extract the heart rate sequence, and $w_h = 300$, which is about five minutes long.

The sliding window $w_h = 300$, represents 300 consecutive heart rate data. Assume that the heart rate data sequence is $H_n = \{h_n, h_{n-1}, h_{n-2}, \ldots, h_{n-(w_h-1)}\}$. The average of the $w_h$ data is the average heart rate of $H_n$, denoted as R, and $R = (h_n + h_{n-1} + h_{n-2} + \cdots + h_{n-(w_h-1)})/w_h$. The total number of heartbeats in five minutes is $5R$, and the number of RRI is 5R-1. We first calculate the reciprocal of $w_h$ data separately, and then multiply the result after the reciprocal by 60, $H_n = \{h_n, h_{n-1}, h_{n-2}, \ldots, h_{n-(w_h-1)}\}$ becomes $H'_n = \{60/h_n, 60/h_{n-1}, 60/h_{n-2}, \ldots, 60/h_{n-(w_h-1)}\}$. The $H'_n$ represents $w_h$ RR intervals. The remaining $5R - 1 - w_h$ RR intervals are generated by two methods, one is the mean value of $w_h$ RR intervals. Another method is to calculate the maximum and minimum values of $w_h$ RR intervals, and then use the random number generator to generate random numbers in the range of minimum and maximum values. The step size of the random number is obtained from the statistics of a large amount of data.

We have made sufficient statistics on the large amount of data collected from 28 different individuals. Including RRI mean, minimum RRI value, maximum RRI value and step size for different genders, different age groups, different heart rate ranges. At the same time, they were corrected with the data collected by the ECG. The corrected statistics are used to process the heart rate data collected in real time.

RRI data is not directly used for clinical testing, and further extraction of HRV time and frequency domain features is required. As mentioned before, time domain features include meanNN, SDNN, rMSSD, etc. They are calculated by the following formulas:

$$\text{meanNN} = \left(\sum_{i=1}^{N} RRI_i\right) \Big/ N \tag{2}$$

$$SDNN = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (RRI_i - meanNN)^2} \tag{3}$$

$$rMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N} (RRI_{i+1} - RRI_i)^2} \tag{4}$$

Commonly used frequency domain features are LF, HF, and LF/HF, which are typically obtained by power spectral density of resampled RRI data.

### 4.3 The general health monitoring model based on MSPC (G-MSPC)

MSPC, as a useful technique for multivariate process monitoring, has a wide range of applications [8, 17]. The main content is to build a multivariate statistical model (PCA, PLS model), to map a large number of highly relevant process variables to the low-dimensional space defined by a small number of hidden variables through multivariate statistical methods, and to use $T^2$ and $Q$ indicate the degree of deviation of the sample from the pivot model. If the statistic control limit is exceeded, the sample is considered abnormal. The application of MSPC to health detection fully considers the time and frequency domain features of HRV.

Let X denote the normal data set, and N and M denote the number of samples and variables, respectively. Then we need to construct the PCA model based on X and project the multivariable data into the low-dimensional feature space defined by a few hidden variables by using the correlation between variables. First, the singular value decomposition of X is recorded as:

$$\begin{aligned} \mathrm{X} &= U\Sigma V^T \\ &= [U_R\ U_0] \begin{bmatrix} \sum_R & 0 \\ 0 & \sum_0 \end{bmatrix} [V_R\ V_0] \end{aligned} \tag{5}$$

In principal component analysis, $V_R$ is the right singular matrix of X, and the column space of $V_R$ is the subspace spanned by principal components, R ($\leq M$) represents the number of principal components retained in the PCA model. $T_R \in \Re^{N\times R}$, which is the projection of X on the subspace spanned by principal components, is given by

$$T_R = XV_R \tag{6}$$

X can be reconstructed or estimated from $T_R$ by linear transformation of $V_R$.

$$\hat{X} = \mathrm{T}_R V_R^T = XV_R V_R^T \tag{7}$$

The loss of information (that is errors) caused by dimensional compression, is written as

$$E = X - \hat{X} = X(I - V_R V_R^T) \tag{8}$$

According to the errors, the Q statistic is defined as

$$Q = \sum_{m=1}^{M} (x_m - \hat{x}_m)^2 = x(I - V_R V_R^T)x^T \tag{9}$$

Where $x$ is a newly measured sample, The Q statistic is the squared distance between the sample and the subspace composed of the principal components. That is, the Q statistic measures the difference between the sample and the modeling data from the perspective of the correlation between the variables.

In addition, Hotelling's $T^2$ statistic is used to monitor anomalies in the subspace composed of principal components.

$$\mathrm{T}^2 = \sum_{r=1}^{R} \frac{t_r^2}{\sigma_{t_r}^2} = xV_R \sum\nolimits_R^{-2} V_R^T x^T \tag{10}$$

Where $\sigma_{t_r}$ denotes the standard deviation of the rth score $t_r$. The $T^2$ statistic represents the Mahalanobis distance from the origin in the subspace composed of the principal components. When the $T^2$ statistic is small, it indicates that the sample is close to the mean of the modeling data. When the $T^2$ or Q statistic exceeds the corresponding control limit, it indicates that the current sample is abnormal. Since G-MSPC is constructed using only normal HRV data, G-MSPC can be used for user's physical condition detection.

Particularly, in the study of drowsiness detection, many studies have shown that drowsiness is a cumulative process, that is, the drowsiness at the current moment is related to the previous drowsiness condition. When calculating the deviation between the current sample and the modeling data using the $T^2$ and $Q$ statistic, we take the deviation of the sample from the previous moment into the sample at the current moment. The $Q$ and $T^2$ can be formalized as:

$$Q_i = \alpha x_i(I - V_R V_R^T)x_i^T + (1-\alpha)Q_{i-1} \tag{11}$$

$$T_i^2 = \beta x_i V_R \sum\nolimits_R^{-2} V_R^T x_i^T + (1-\beta)T_{i-1}^2 \tag{12}$$

The values of $\alpha$ and $\beta$ are 0.9 in our implementation, $T^2$ and Q statistic have different thresholds.

## 5 IMPLEMENTATION AND EVALUATION

In this section, we conduct experiments to evaluate the performance of the proposed system. In order to verify our drowsiness detection model, twelve healthy subjects with at least one year of driving experience (including 9 males and 3 females, with an average age of $38 \pm 15$ yr) are recruited to participate in our experiments. They do not have any sleep disorders, sleep apnea and other related diseases that may affect the results of the analysis. Subjects are asked to fill out survey forms before and after the experiment. We performed our experiments on a driving simulator, and each participant had two to three hours before the formal experiment to simulate the system. We conducted experiments during the day and night to collect data. And the total dataset, which is divided into awake data sets and sleepy data sets, 70% is used for training and 30% is used for testing. During the exper-

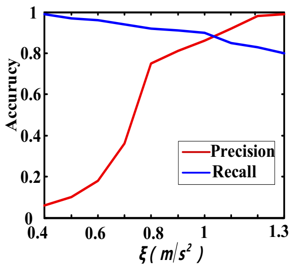


Figure 3: **The effect of ξ.**

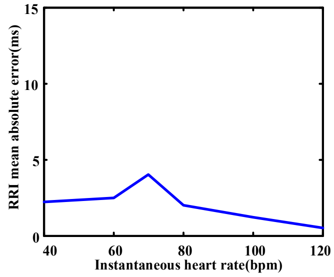


Figure 4: **RRI mean absolute error.**

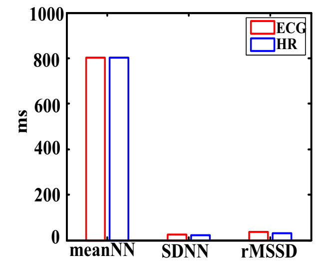


Figure 5: **HRV time domain features extracted.**

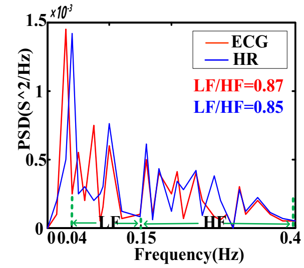


Figure 6: **HRV frequency domain features extracted.**

iment, we obtain the ground truth of the subjects through video.

We use these metrics to quantify the performance of *S-HRVM*.

**Precision**: The percentage of samples accurately detected by *S-HRVM* in the total sample.

**Recall**: The percentage of correctly detected samples in all relevant samples.

## 5.1 Performance of SSPA

**1)The effect of ξ to SSPA:** According to equation (1), the performance of the user's relatively static state detection depends on ξ, Figure.3 presents the accuracy of hand movement detection at different values of ξ. We can observe that as ξ increases, the precision gradually increases and the recall decreases slowly and the precision exceeds 90% when $\xi = 1m/s^2$. $\xi = 1m/s^2$ is considered to be the most appropriate setting to detect the user's relative static state.

**2)Power consumption:** One of the biggest challenges in using a heart rate sensor is power consumption. In the experiment, we used a power monitor to test the power consumption during heart rate detection. When the heart rate start algorithm is not used, the smart watch has only 8 hours of standby time. However it can last for 13.5 hours when using the startup algorithm, the life time of the smart watch is greatly extended compared to the case where the startup mechanism is not used, which is enough to monitor the user's heart rate throughout the day.

## 5.2 Performance of SP-HR

**1)RRI mean absolute error:** RRI (RR-interval) is the time interval between two adjacent heartbeats. In order to validate the performance of our proposed SP-HR, we obtain RRI from the heart rate data collected from the smart watch by SP-HR, and the RRI in the electrocardiogram is used as a reference for comparison. RRI mean absolute errors corresponding to different instantaneous heart rates are obtained. From Figure.4, we can see that the maximum RRI mean absolute error is less than 4ms, and the average is about 1.5ms, which is a relatively low level. It explains that our SP-HV method can be used to extract RR-interval from heart rate data, which has a good effect on HRV analysis.

**2)Time and frequency domain features of HRV:** We also compare the time and frequency domain features of HRV extracted from ECG and HR data using SP-HR method. Figure.5 and Figure.6 show that several HRV features extracted from the ECG and from HR data are approximately equal, and several other features have similar results. The results show that the SP-HR method proposed in this paper has higher accuracy as the HRV analysis method of heart rate data.

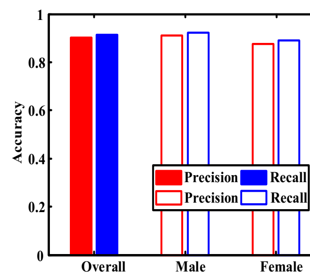


Figure 7: **Accuracy of G-MSPC.**

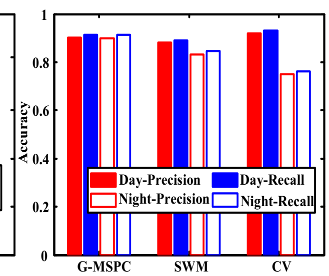


Figure 8: **Comparison with other methods.**

## 5.3 G-MSPC for drowsiness detection

**1)Overall accuracy:** We use the methods proposed in the *S-HRVM* to process awake data sets and drowsiness data sets from different drivers. The HRV features extracted from these data are processed to obtain the model G-MSPC, and the corresponding Q, T thresholds. The overall accuracy of G-MSPC is shown in Figure.7. We can see that the G-MSPC has achieved 90.3% precision and 91.5% recall. The performance of the system in different gender groups is similar, and the male group is closer to the total accuracy. The lower accuracy of the female group is mainly due to the smaller number of samples used for training, however, the detection accuracy is still higher than 87.5%.

**2)Performance comparison between methods during the day and night:** We compare the performance of G-MSPC during day and night with the method of steering wheel movement (SWM) and computer vision (CV) in Figure.8. We can see that the accuracy of both SWM and CV methods has decreased at night, especially the CV method is very obvious, mainly because the CV method relies heavily on ambient lighting, and the light at night is much worse than during the day, which seriously affects the performance of the system. The performance of the SWM method is not much different between day and night, but the overall accuracy is not high, mainly due to the small number of features detected, which cannot fully reflect the state of the driver. Compared to them, G-MSPC is highly accurate and robust, whether day or night, because our system measures human physiological characterization.

## 6 Related Work

**Heart rate monitoring Methods:** Various methods of monitoring heart rate have been explored. A common method is to use electrocardiogram (ECG) and PPG sensors [16]. These methods generally require installation, allowing direct skin contact between the user and the sensor, although their performance is promising, but such installation requirements prevent widespread use of these methods.

Other heart rate measurement methods include the use of capacitive sensors in the seat, high-resolution cameras to capture skin tone fluctuations, and thermal imaging. Although these methods work well in the static environment of the laboratory, they are affected by (such as light, vibration, etc.) in environments such as vehicles. These methods cannot accurately measure a single heartbeat interval [6,18], this is not useful for user stress and fatigue inference.

**Drowsiness detection methods:** Physiological signals are considered to be an accurate indicator of drowsiness because they are strongly related to fatigue [3, 16]. Electroencephalogram (EEG) is widely regarded as one of the most reliable physiological indicators [15]. Electrocardiogram (ECG) is another widely used method to detect sleepiness [14, 16]. Although these methods provide effective detection of physiological and cognitive states of the human body. However, the feasibility of these methods in the actual environment is severely limited due to the wearability of the equipment. In addition, the computer vision method mainly uses image processing technology to detect the driver's behavior characteristics to judge the driver's drowsiness [7]. The performance of this method is greatly affected by the ambient light intensity and other factors [19], the reliability of such methods is low, although they are non-invasive.

The motion sensor method mainly detects the steering wheel movement, speed variability, lane departure of the vehicle through sensors [12, 13]. These measures are highly dependent on road conditions and their performance is limited, they require a lot of training.

## 7 Conclusions

This paper presents *S-HRVM*, a smart watch-based heart rate variability monitoring system. *S-HRVM* obtains the RR interval between adjacent heartbeats and extracts HRV features from heart rate data by SP-HR, and the HRV features are used as the input of the general health monitoring model G-MSPC to detect the user's physical condition. The acceleration data collected from smart phone and smart watch is used to detect if the driver is in a relatively static state which acts as a starting mechanism for turning on the heart rate sensor, it reduces the power consumption of the system while measuring heart rate data is more accurate. A large number of experimental results showed the effectiveness of *S-HRVM*.

## 8 Acknowledgments

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