Article

An Approach for Vigilance Assessment using Hidden Markov Model

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Abstract: Purpose: To construct a hidden Markov model (HMM) for vigilance assessment to improve the real-time performance and accuracy of current vigilance measurement. Methods: ECG signal was collected by sensors, while the noise and baseline drift was eliminated from the original ECG signal. 10 volunteers were randomly selected. Their heart rate variability (HRV) were measured and trained parameters of the modified Hidden Markov model for vigilance assessment. Then, these data were collected to optimize using the Baum-Welch algorithm and obtained the state transition probability matrix $\hat{A}$ and the observation probability matrix $\hat{B}$. Finally, the data of three volunteers with different transition patterns of mental state were selected randomly and used the Viterbi algorithm to find the optimal state, which compared with the actual state. Results: The constructed vigilance assessment model had a high accuracy rate the accuracy rate of data prediction for these three volunteers exceeded 80%. Conclusion: The Hidden Markov model for vigilance assessment can accurately predict the vigilance level and indicate broad application prospects.

Keywords: hidden Markov model; vigilance; HRV; wearable device; PVT; VST

1. Introduction

Internet of Things (IoT) and sensor technologies promote products' properties to monitor and evaluate the personal status[1] To better understand the physiological situation in our working status, we should design an accessible product for people to easily know the measured data of the current working status.

Vigilance can be defined as the ability to achieve and maintain a state of high sensitivity to incoming stimuli. It is a measure of perceiving and responding to subtle changes that occur at random time intervals in a particular environment[2]. Vigilance is a special form of attention[3]. Continuous vigilance is related to types of work, such as aerospace, navigation, driving, etc[4–6], Caldwell found that official statistics indicate that low vigilance caused fatigue is involved in at least 4–8% of aviation mishaps[7]. However, Vigilance measurement is not directly available, which is taken by three main modalities: the subjective scale, experimental paradigm, and physiological signals[8].

Since the level of vigilance is often linked to the fatigue rate, some subjective scales for fatigue rate assessment are often used to assess the level of vigilance. The most commonly used scales are: Karolinska Sleepiness Scale (KSS) and Stanford Sleepiness Scale (SSS). Nine levels are used in KSS to describe the degrees of fatigue, 1 = extremely awake, 5 = neither awake nor sleepy, 9 = very drowsy (taking a great effort to stay awake)[3]; Seven levels are utilized in SSS to describe the degrees of fatigue, 1 = fully awake, 3= awake, 7 = close to sleep[9].

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The experimental paradigm is always used to evaluate the level of vigilance to study the impact on vigilance due to sleep deprivation or human rhythm variation. The commonly used methods include the Psychomotor Vigilance Task (PVT) and the Mackworth clock test (MCT). The PVT experiment was firstly used to assess the decreased level of vigilance because of sleep deprivation[10] and measure the speed of the subject's psychomotor reaction[11]. It depends on the subject's responsiveness to stimuli. The main index is the response time of the participant, and the results are obtained through repeated sampling of random stimuli[12]. At the same time, PVT detects the vigilance of subjects accurately using the signal detection methods such as ECG which lasts 10 minutes. Common indicators of PVT include the grand mean, the PVT fastest RTs, the PVT slowest 10%, and the PVT lapse frequency[13].

MCT is used to record the subjects' response time in small probability events and the exact rate of response to target events to evaluate the current subjects' levels of vigilance(14). MCT is also involved in the field of experimental psychology that explores the influence of long-term vigilance on signal detection[14].

At present, the relatively mature physiological parameters for vigilance detection mainly include ECG signals, EEG signals, and pulse wave. the electrocardiogram (ECG) changes with the successive excitation of the pacemaker, atrium, and ventricle during each beat of the heart. The contraction of the heart produces a pulsation, which generates an electrical signal that can be conducted from the body inside to the body surface along special cardiomyocytes and detected by an ECG device. Yu et al. found that the R wave of the ECG signal can effectively distinguish the two states of sleep and wakefulness[15]. Zhao et al. measured drivers' ECG and EEG during driving, and pointed out a correlation between the increase in driving duration and the decrease in driver's vigilance level and HR because the standard deviation of the RR interval tends to increase[16]. HRV (Heart Rate Variablity) separating from ECG signal also contains a large amount of human physiological and psychological information. Many studies have pointed out that HRV signals can be effectively used to distinguish sleeping and waking states, Zhang pointed out that the main wave, the amplitude of the heavy wave, and the conduction time of the pulse wave show obvious differences between waking and sleeping states[17].

HMM is a typical dynamic Bayesian network model, which is used to estimate the probability distribution of state transition in the dynamic sequence of the measurement process and the probability of measurement output[18]. HMM rests on the assumption that time-changing observations are produced by underlying processes with discrete hidden states. The measured process variable is regarded as the realization of the underlying stochastic process[19]. The difficulty lies in determining the hidden parameters of the process from the observable parameters and using these parameters for further analysis.

However, existing studies on the vigilance mainly distinguish between sleep and wakefulness and focus on the variation of signal characteristics in typical vigilance tasks such as MCT. Few studies have introduced new models to improve the accuracy of vigilance measurement. Therefore, the purpose of our study was to systematically examine the feasibility of using ECG signal and HMM for vigilance detection from the perspective of time- and frequency-domain characteristics, and to improve the accuracy and broaden the application prospects of wearable products for vigilance monitoring.

2. Methods

In this section, we will introduce how we collected the HRV feature data of volunteers using wearable ECG signal sensor during they conducting PVT and VST paradigms as dataset. The dataset was used for training the HMM. And then, we verified the accuracy of the model by choosing three volunteers' data and comparing with SVM.

2.1. HMM for vigilance assessment

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2.1.1. Collection of experimental data

In order to realize the classification of vigilance level, one needs to extract the signal features related to the state of vigilance. This paper adopted the ECG as the object signal for extraction, which is closely related with vigilance, and the measurement of ECG now can effectively circumvent the complexity of the EEG signal extraction process and the interference to participants.

PVT is a visual response time measure that objectively quantifies vigilance and thus fatigue in humans by measuring the time of a visual response to a simple and salient signal. In order to acquire data more conveniently, we chose the 10 min standard PVT experiment as the experimental paradigm. In the PVT experiment, as shown in Figure. 1a, at the beginning of each trial, the screen appeared blank for 1000 to 6000 ms until a number of count came out. The volunteer was asked to react by pressing the space bar as soon as possible upon seeing the number appear on the screen. The number corresponds to the current time in milliseconds from the beginning of the digital presentation. Whether the volunteer pressed the space bar or gave no response 5000 ms, the experiment automatically entered the next test trial[13].

The Visual Search Task (VST) is mainly used to stimulate the cognitive load of the volunteers to change their vigilance level artificially. In each trial, as shown in Figure. 1b, an 800 ms "+" fixation point was presented first, followed by a visual search stimulus that was presented until the volunteers responded with a key press and the search stimulus disappeared, whereafter the screen appeared blank for 500 ms. The volunteers were instructed by a guiding letter to search for stimuli presented at the visual search interface. When judging the color of the lowercase letter 'p', the volunteers were asked to press the key 'F' key if it was red, or the key 'J' otherwise. Before formal experiments the volunteers performed a 12-trial exercise session, and the practice section similarly contained the stimuli for all conditions. After the volunteers understood the experimental procedures, and when the correct rate exceeded 80%, the formal experiments started.

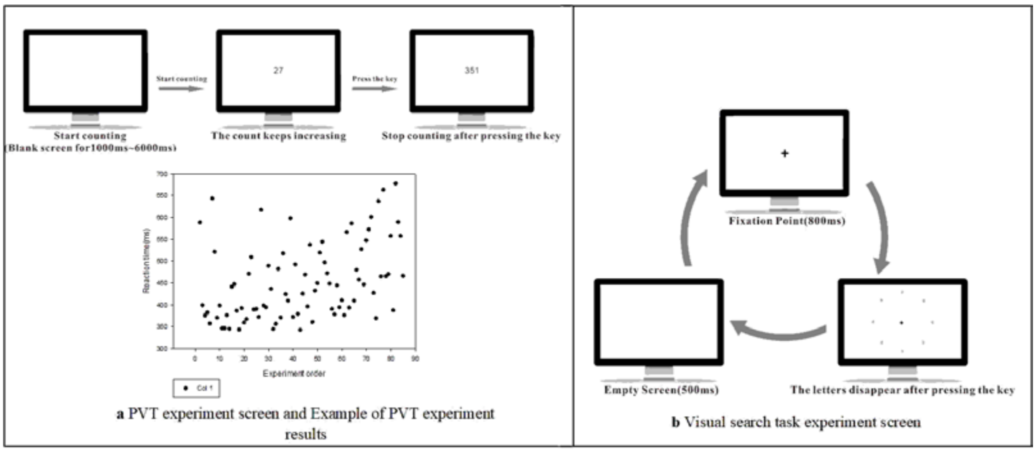

Figure 1. PVT experiment and Visual search task experiment. (**a**)PVT experiment screen and example of PVT experiment results; (**b**)Visual search task experiment screen.

The participants in the experiment were 20 undergraduates, including 9 males and 11 females (age range 18-32; m = 24; SD = 2.6). None of them had a history of smoking, and they all reported normal hearing, vision, or corrected vision. The participants were required to maintain a regular sleep-wake period at least one week before the commencement of the experiment and not to consume alcohol or functional beverages and not to do any high-intensity physical sports on the day of the experiment. The participants read and signed an informed consent. They were also informed that they had the right to quit the experiment anytime. All data were analyzed and reported in an anonymous manner.

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The experiment was conducted in a quiet environment where the natural light was completely shielded using shade drapes and completely replaced with fixed artificial light sources. The device for ECG signal acquisition was EQ02 LifeMonitor (EquivitalTM, Cambridge, UK), whose sampling frequency was set to 256 Hz. A well-established commercial finger clip heart rate oximeter was used to simultaneously measure the heart rate of the volunteers and compare it with the heart rate calculated from the experimental data.

In order to obtain vigilance data for different fatigue conditions, we artificially reduced the volunteers' vigilance level using the visual search task, in which the volunteers were asked to attend the laboratory for data acquisition during three time periods: 8:00 – 11:10 am, 14:30 – 5:40 pm, and 19:30 – 22:40 pm. The volunteers entered the laboratory on the day of the experiment and were first tested for subjective levels of vigilance and drowsiness using the SSS (Table 2). Next, they underwent a standard PVT trial for a duration of 10 minutes using a laptop computer. Immediately after that, they performed the visual search task, and once again following the visual search task, vigilance was rated using PVT with a cycle of ten trials ending at the end of the simultaneous experiment. Measurements and the volunteers' heart rate and HRV were recorded and combined into the volunteers' physiological performance[20]. From this, the experimentally recorded state sequence was obtained. Figure. 2 shows the experimental flowchart with three segments of state sequence data for a total duration of 30 mins. The SSS, PVT, and VST experiments were all completed on the computer. Specific data are introduced in section Datasets.

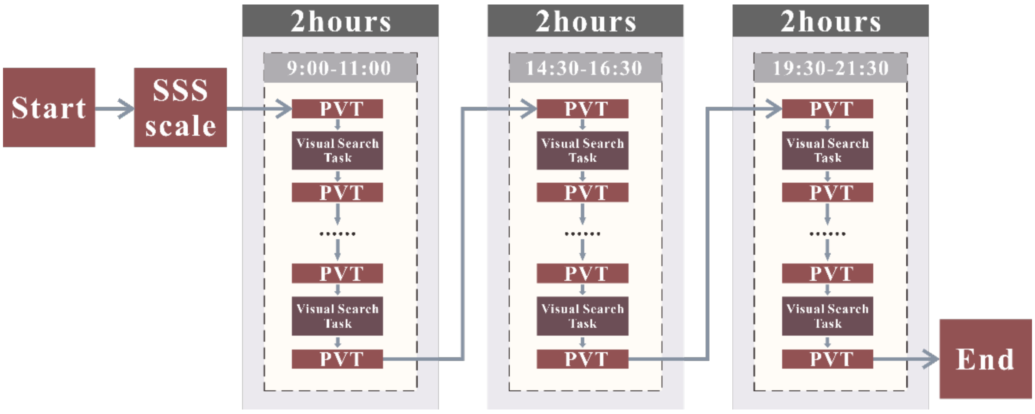

Figure 2. Experimental flowchart.

During the experiment, the volunteers kept their limbs still and their breath even, and away from sources of electromagnetic interference such as mobile phones, desk lamps, and electric drills. The collected ECG data were transferred to a computer through a cross-talk and saved into a table form to facilitate the subsequent computerized processing. The acquisition scenes are shown in Figure. 3

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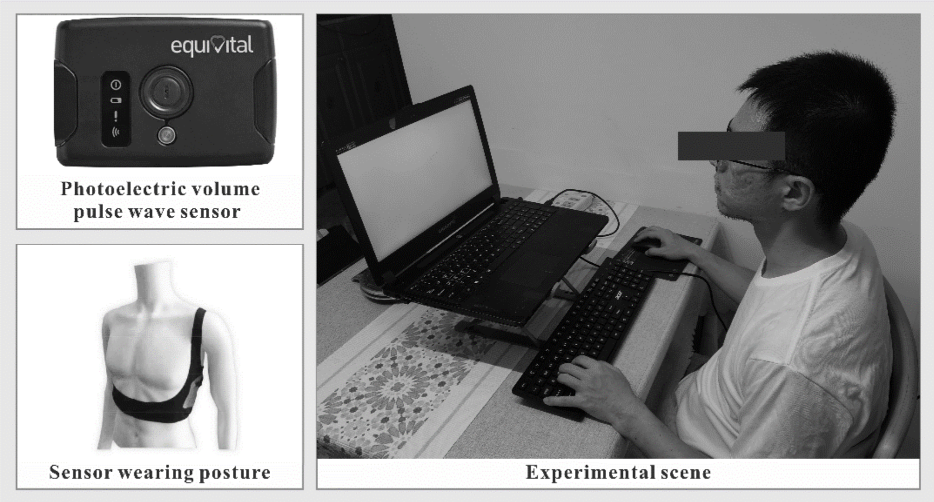

Figure 3. Experimental scene.

ECG data cannot be directly used in HMM model construction, so it is necessary to extract HRV features. The key to extracting the HRV features from the raw signal is to determine the peak position of the main wave in the R-R cycle. To do so, we used the differential threshold method. Next, N cardiac cycles (i.e., the periodic time sequence of N heartbeats), each of which is denoted as $t(n)$, n∈{1, N}, were selected on the ECG waveform of the volunteers. Then the instantaneous heart rate $HR(n)$, the mean heart rate HR_MEAN; the difference between cardiac cycles was recorded as $\delta_{(n)} = t_{(n)} - t_{(n\text{-}1)}$. SDNN and RMSSD can be expressed in terms of the average cardiac cycle $\bar{\delta}$. The indicator LFP was used to calculate the integrated power in the low-frequency band of 0.04 Hz – 0.15 Hz after performing a spectral transformation on the R-R interval sequence of N cardiac cycles; the indicator HFP is to calculate the integrated power in the high-frequency band of 0.15 Hz – 0.4 Hz. Shown in Table 1 for HRV features used in this paper.

Table 1. Heart Rate Features.

Feature	Feature type	Meaning	Calculation
HR(n)	Heart rate indicator	Instantaneous heart rate	$HR(n) = \frac{60}{t_{(n)}}$
HR_MEAN	Heart rate indicator	Mean heart rate	$HR\_MEAN = \overline{HR}_{(n)}$
SDNN	Heart rate variability indicator	Standard deviation of the R-R (peak) interval	$SDNN = \sqrt{\frac{1}{N-1}\sum_{n=2}^{N}\left(\delta_{(n)} - \bar{\delta}\right)^2}$
RMSSD	Heart rate variability indicator	Root mean square of the difference between adjacent R-R intervals	$RMSSD = \sqrt{\frac{1}{N-2}\sum_{n=3}^{N}\left(\delta_{(n)} - \delta_{(n-1)}\right)^2}$
LFP	Heart rate variability indicator	Low frequency (0.04 Hz – 0.15 Hz) power	$LFP = \sum P_{(W)}, \quad 0.04 < W < 0.15$
HFP	Heart rate variability indicator	High frequency (0.15	$HFP = \sum P_{(W)}, \quad 0.15 < W < 0.4$

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		Hz – 0.4 Hz) power	
LFP/HFP	Heart rate variability indicator	High frequency (0.15 Hz – 0.4 Hz) power	/

As vigilance declined, SDNN, LF, and LFP/HFP increased significantly, and HF decreased significantly, all showing significant linearities. Hence, we chose SDNN from among the above indicators, which was carried in as an observation matrix parameter in HMM.

2.1.2. Markov chain determination and characteristic parameter processing

To build the HMM for vigilance assessment, first, the initial model parameters $\lambda = (\pi, A, B)$ were determined; second, the Baum-Welch algorithm was used to train the initial model parameters to obtain the appropriate ones $\hat{\lambda} = (\hat{\pi}, \hat{A}, \hat{B})$; finally, the Viterbi algorithm was used to input the observed value sequence into the established HMM for vigilance assessment to obtain the optimal state sequence, which was compared with the actual state sequence to estimate the accuracy of the model. The whole modeling process is shown in Figure. 4.

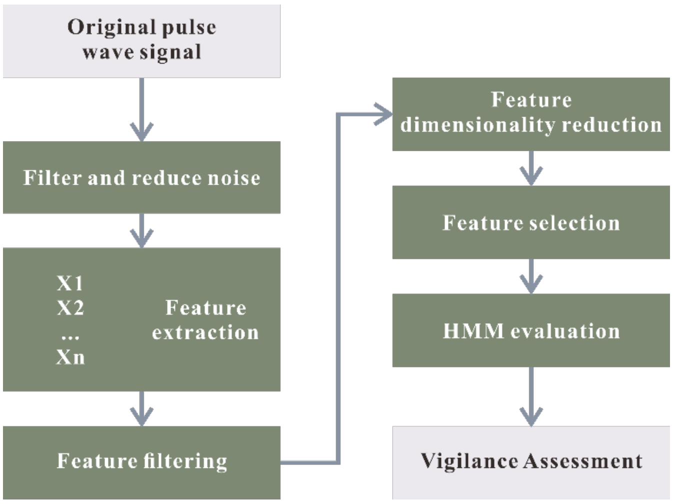

Figure 4. Modeling process of HMM for vigilance assessment.

Since the purpose of this study was to determine the level of vigilance during working, the hidden states were associated with three levels, namely, the high vigilance level, the medium vigilance level, and the low vigilance level. Considering the possibility that an individual may get into the native state or any other state from the current state at some point, the HMM allows for the transition of each state into the next or the current state. Thus, the number of states of the Markov chain in the HMM for vigilance assessment was set to 3 in the manuscript, as shown in Figure. 5. State S1 denotes the state of low vigilance level, state S2 denotes the state of medium vigilance level, and state S3 denotes the state of high vigilance level.

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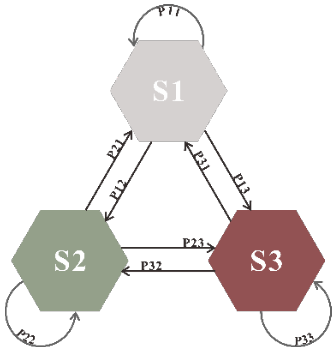

Figure 5. Schematic diagram of the Mar-kov chain.

In the HMM for vigilance assessment established in the manuscript, the three hidden states were defined as above, and accordingly, three states corresponding to the observed variables were also classified, namely state 1, state 2, and state 3. Boxplots can accurately and steadily reflect the discrete distribution of data, so this manuscript used boxplots to perform statistical analysis based on the experimental data to determine the threshold of SDNN state segmentation. Previous study [21] found that the PVT fastest 10% of responses that were optimally represented depend on the activation of ongoing attention networks and motor system cortex, and that the fastest 10% of responses reflect the volunteer's level of sustained attention. So we classified the states of vigilance level into three levels based on subjective scales and the fastest 10% of responses of PVT results, and finally established the relationship between vigilance and SDNN. Specific classification results will be presented in the section Datasets.

2.2. Determination of the initial parameters of the HMM

Since the initial values of entries in the initial state probability matrix ◎ and the state transition probability matrix A had little effect on the model training results, we only needed to meet the following conditions.

$$\pi_i = P(q_i = S_i), 1 < i < N \tag{1}$$

$$\sum_{i=1}^{N} \pi_i = 1, \qquad 0 \le \pi_i \le 1 \tag{2}$$

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1N} \\ \vdots & \ddots & \vdots \\ a_{N1} & \cdots & a_{NN} \end{bmatrix} \tag{3}$$

$$\sum_{i=1}^{N} a_{ij} = 1, \qquad 0 \le a_{ij} \le 1 \tag{4}$$

The values of entries in ◎ and A can be considered randomly selected or uniformly taken. Since a left-right model is usually adopted in pattern recognition, the initial state probability vector π, without making an estimate, is set to:

$$\pi_1 = 1 \tag{5}$$

$$\pi_i = 0, \qquad i = 2, 3, \ldots, N \tag{6}$$

The values of entries in A were initialized by the principle of uniform distribution by the following formula:

$$a_{ij} = \frac{1}{\begin{array}{c}\text{The number of transfer}\\ \text{paths on the Markov chain}\\ \text{that move out of state } i\end{array}} \tag{7}$$

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From the above analysis, the number of Markov chains is 3, namely, the high vigilance level, the medium vigilance level, and the low vigilance level. The number of transfer paths connecting these states is 3, so $a_{ij} = 1/3$, i.e., the initial state transition probability matrix A is:

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1N} \\ \vdots & \ddots & \vdots \\ a_{N1} & \cdots & a_{NN} \end{bmatrix} = \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \end{bmatrix} \tag{8}$$

Let S1, S2, and S3 represent the low, medium, and high vigilance levels, respectively. Each entry in A denotes the probability of transferring from a certain vigilance level to another vigilance level. For example a_{13} represents the probability of transferring from S1 to S3, whereas a_{31} represents the probability of transferring from S3 to S1, and a_{22} represents the probability of transferring from S2 to S2.

The initial values of entries in the initial observation probability matrix B were determined from the experimental data. The acquired ECG signal was analyzed and SDNN data were extracted, the sample database making up the HMM for vigilance assessment was constructed, and the values of the individual entries b_{ij} in B, which denote the probability that the observed value is j when the state is i, were calculated by mathematical statistical means.

For example, to calculate b_{11} in B, select a sequence of observed values with a length of 30 as the statistical data sample:

O = *[2, 3, 2, 2, 1, 2, 1, 2, 2, 2, 2, 3, 3, 1, 1, 2, 1, 1, 2, 2, 2, 1, 2, 3, 2, 3, 2, 3, 3, 1]*

The state sequence of the corresponding experiment record at this time is:

Q = *[2, 2, 1, 3, 2, 2, 3, 1, 2, 2, 2, 1, 1, 2, 1, 2, 2, 2, 3, 2, 3, 1, 3, 1, 2, 2, 2, 2, 2, 1]*

b11 represents the probability that the observed variable is in state 1 when the human body is in the low vigilance level, namely, the probability that the value in O is 1 when the value in Q is 1. In the above sequence of states, the number of 1s is 8, the number of state 1s and the observed value 1s is 3, hence b11 = 3/8 = 0.375. The same method was used to determine the values of other entries in the observation probability matrix B.

Each volunteer was given a sequence of observed values of length 30 and a state sequence upon completion of the trial. To avoid the influence of the training results of a single special datum on the model, in this paper, 10 sets of data were randomly selected using the above method for value initialization, to obtain a sequence of observations of length 300 and an experimentally recorded state sequence for modeling, and the initial observation probability matrix B. The specific result of B is described in the section Datasets.

$$B = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \tag{9}$$

We adopted the UMDHMM (hidden Markov model Toolkit) lightweight C language version HMM package developed by Dr. tapas Kanungo, the chief application scientist of Microsoft, on PC to implement the algorithm. In the modeling process, the values of entries in B were optimized. The optimized results are described in the section Datasets.

2.3. Datasets and training

First, the length of the data was determined. The international standard duration of short-lasting data is generally 5 minutes, which has many characteristics, such as easiness of grasp, easiness of control, and less susceptibility to external interference. It is widely used in many studies and clinical trials to analyze HRV data. In our study, the changes in vigilance are sensitive and susceptible to stimuli, so the data were divided into multiple 1-minute-long bins for processing and analysis by being intercepted to 6000 sampling sites

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in length. To clarify the raw signal waveform changes before and after processing, only data intercepted to 3000 sampling sites in length were elaborated in the manuscript.

Then, the collected raw data were processed after noise reduction. Considering the size, real-time performance, and easiness of implementation, a simple real-time noise suppression method based on double median filtering was used in this study.

Threshold segmentation is also needed for SDNN-vigilance level. In general, the higher the HRV, the more active the vagus nerve and hence the vigilance. We divided the sampled fastest 10% of response into three phases, statistically analyzed the scale results, and set a threshold to the PVT results, at which the vigilance was higher and the PVT fastest 10% of responses was lower. The PVT fastest 10% of responses was divided into three levels, < 400 ms, 400 ms ~ 500 ms, and > 500 ms, based on questionnaire results, corresponding to high, moderate, and low levels of vigilance, respectively. A boxplot of the SDNN numerical statistics results versus vigilance levels is shown in Figure 6.

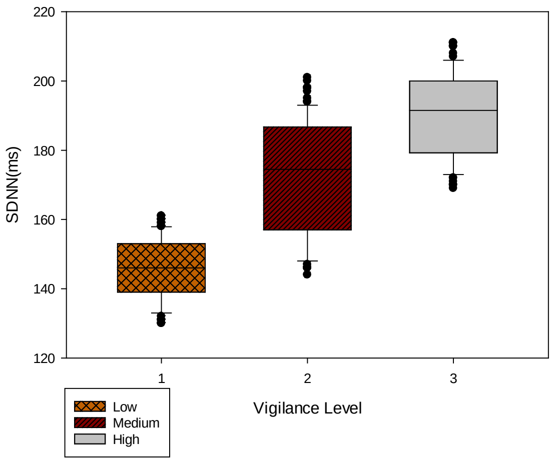

Figure 6. SDNN numerical statistics results.

It can be seen from Figure 6 that the upper quartile of the low vigilance level is less than 153, whereas the lower quartile of the medium vigilance level is higher than 156, so the level segmentation threshold of SDNN was set to 155; the upper quartile of the medium vigilance level is 186, and the lower quartile of the high vigilance level is 179. Since this manuscript was committed to verifying whether the HMM could be used to predict the change in vigilance level, the state segmentation threshold of SDNN was set to 182. More precise vigilance threshold segmentation methods will be explored in the follow-up studies. The states of low, medium, and high vigilance levels were set to S1, S2, and S3, respectively, for subsequent programming and postprocessing.

The matrix B in formula (9) also needs to be calculated. The exact calculated result of B is

$$B = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} = \begin{bmatrix} 0.36 & 0.46 & 0.27 \\ 0.24 & 0.51 & 0.24 \\ 0.29 & 0.45 & 0.26 \end{bmatrix}$$

Lastly, $\hat{a}_{ij}$ and $\hat{b}_j(k)$ were estimated by Baum Welch algorithm using a sequence of observations of length 300 chosen in the previous section, $O = [o_1, o_2, \ldots, o_T]$, to achieve the optimal solutions $\hat{A}$ and $\hat{B}$ for the state transition probability matrix A and the observed probability matrix B, respectively.

$$\hat{A} = \begin{bmatrix} 0.00690844 & 0.62553189 & 0.36755967 \\ 0.08648997 & 0.00769783 & 0.9058122 \\ 0.36374147 & 0.15714435 & 0.47911419 \end{bmatrix}$$

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$$\hat{B} = \begin{bmatrix} 0.30776675 & 0.2082504 & 0.48398284 \\ 0.69870426 & 0.01570709 & 0.28558865 \\ 0.01910991 & 0.85105961 & 0.12983048 \end{bmatrix}$$

2.4. Validation experiment and result

Considering that the setup conditions (e.g., stimulus duration and inter stimulus interval) of the task have the potential to influence the experimental results, the results obtained by PVT and visual search task experiments were contrasted with those obtained by the HMM as reference.

During the experiment it was found that the way mental states transform differs from individual to individual. A volunteer's state of vigilance level within a single experiment will form 10 consecutive states based on the PVT experimental results. The volunteer will produce a state sequence with a length of 30 after completing the experiment on that day, such as the experimentally recorded state sequence Q = [3, 1, 2, 2, 2, 1, 2, 2, 2, 3, 1, 3, 2, 2, 2, 2, 3, 1, 2, 1, 1, 1, 3, 3, 2, 1, 1, 2] , which shows the change of vigilance level in the three experiment trials.

In order to evaluate the accuracy of our approach based HMM in predicting vigilance, we invited three volunteers to participate in the model evaluation through the PVT experiment. The observed values of the volunteers in the PVT experiment were input into the HMM to obtain the prediction of vigilance. The results are shown in Table 2 and Figure. 7. By comparing them with the state values in the PVT experiment, we got an average accuracy rate of 87.78%, a proof that our method is effective. Therefore, the vigilance assessment model based on the HMM constructed in this paper can detect the change of human vigilance state very accurately without producing large deviations due to the different modes of human mental state transition.

Table 2. Validation results.

Experimentally recorded observation sequence	Experimentally recorded state value sequence	HMM state prediction value sequence	Accuracy
2 2 2 2 3 2 2 1 2 2 2 1 3 3 3 2 2 2 3 2 3 2 3 2 3 2 2 3 2 1	2 2 2 3 2 1 2 1 2 2 2 2 3 2 1 2 1 2 2 2 3 2 2 1 2 3 2 3 1 3	2 2 2 3 2 1 2 1 2 2 **1** 2 3 2 1 2 1 **1** 2 2 3 2 **1** 1 2 3 2 **2** 1 3	86.67%
1 2 1 1 3 2 2 2 1 2 2 3 1 2 2 3 2 3 1 2 3 3 3 1 2 2 1 2 3 1	2 2 1 3 3 1 2 2 1 2 2 2 3 3 2 2 1 1 2 3 2 3 2 2 1 3 1 3 3 2	2 2 1 **2** 3 **2** 2 2 1 2 2 2 3 3 2 2 **2** 1 2 3 2 3 2 2 1 3 1 3 3 2	90.00%
2 2 3 1 2 1 2 2 2 2 2 1 2 2 1 2 3 2 1 2 1 2 3 1 2 1 2 1 2 1	2 3 3 3 2 3 2 2 2 2 3 2 2 1 2 3 2 2 3 1 3 3 2 2 1 2 3 1 2 2	2 3 3 **2** 2 3 2 **1** **1** 2 3 2 2 1 2 3 2 2 3 1 3 3 2 **1** 1 2 3 1 2 2	86.67%

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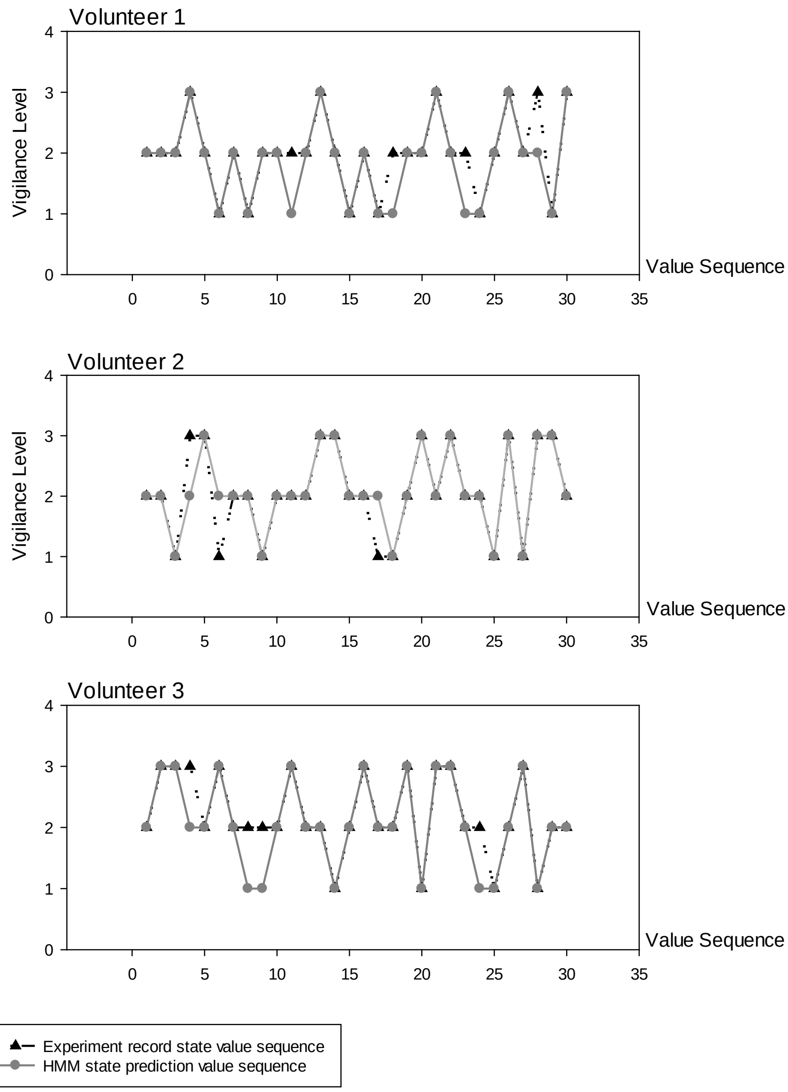

Figure 7. Validation results.

In order to contrast the differences between the HMM and other algorithms, we used the SVM algorithm to make predictions according to the same section of experimentally recorded observation sequence. The results of accuracy contrast are shown in Table 3, suggesting that the method adopted in our paper is superior to the SVM algorithm.

Table 3. Results of contrast between HMM and SVM.

	HMM										SVM									
Experimental record observation sequence	2	2	2	2	3	2	2	1	2	2	2	2	2	2	3	2	2	1	2	2
	2	1	3	3	3	2	2	2	3	2	2	1	3	3	3	2	2	2	3	2
	3	2	3	2	3	2	2	3	2	1	3	2	3	2	3	2	2	3	2	1
Experiment record state value sequence	2	2	2	3	2	1	2	1	2	2	2	2	2	3	2	1	2	1	2	2
	2	2	3	2	1	2	1	2	2	2	2	2	3	2	1	2	1	2	2	2
	3	2	2	1	2	3	2	3	1	3	3	2	2	1	2	3	2	3	1	3
prediction value sequence	2	2	2	3	2	1	2	1	2	2	2	2	2	**2**	2	1	2	1	2	2
	1	2	3	2	1	2	1	**1**	2	2	**1**	2	3	2	1	2	1	**1**	2	2
	3	2	**1**	1	2	3	2	**2**	1	3	3	2	**1**	1	2	3	2	**2**	1	3
Accuracy	86.67%										83.33%									

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3. Discussion

In this section, we first introduce the evaluation metric in this paper. Then we review the related work. Finally, we discuss the limitation of our works.

3.1. Evaluation Metric

We adopt the PVT and VST as our evaluation metric. Given that the focus of this paper is primarily on vigilance variation, the fastest 10% reaction time of PVT was chosen as the measure of the model. Although there are various statistical techniques for PVT to assess the level of vigilance, it has been verified that the fastest 10% reaction time was essentially consistent with the subjects' subjective feelings of fatigue, it raised with the increase of task duration and was not affected by the task level[13].

We selected VST to modify the vigilance level of volunteers because there was little variation in the level. According to the results, the vigilance level seemed to be changed irregularly, with respect to this phenomenon, we believe that the change of vigilance level by VST showed some kind of periodicity. The vigilance level may affected by VST and other personal condition of volunteers, for PVT has no practice effect, we believe that personal condition such as rest well or not before experiment and other work is loading, etc. and will influence vigilance level in conjunction with VST. We will try to conduct analyses of data to find out the periodicity in future work.

Segmentation thresholds of vigilance levels are divided into wakefulness and fatigue (sleepiness) only, in most of the current literatures. But during the experiment process we learned that different states of vigilance levels could still have an impact on work performance even in the waking state. Therefore, further studies are needed to determine more precise demarcation criteria.

PVT has significant effects on volunteers' mind, behavior, and physiology. It may cause subjective drowsiness and mental fatigue in volunteers, and autonomic function and changes in the central nervous system. This manuscript highlights the use of physiological methods for vigilance measurement. Changes in vigilance level were monitored based on indicators of autonomic nerve function, such as HRV. Changes in vigilance level have a close relationship with physiological parameters, which serve as indicators of vigilance. The HMM proves to be an effective vigilance level estimator.

3.2. Related Works

Vigilance is the ability to sustain attention and remain alert to a particular stimulus over a prolonged period of time[21]. Numerous jobs in the fields of industry, the military, medicine, and education demand constant attention with varied levels of cognitive workload. Security personnel[22], workers in charge of watching security cameras or baggage screening experts, operating vehicles, real classroom settings [23], as well as industrial and air traffic control [24], are examples of applications that require ongoing attention. For these tasks to be completed with a sufficient level of cognitive efficiency, a certain range of arousal is required. How to achieve vigilance assessment is an important problem.

In the past decade, machine learning methods, Zheng et.al have played important roles in the vigilance assessment[25]. Generally, these methods have five different phases to achieve vigilance assessment: (i) a sample acquisition focused on each task, (ii) signal pre-processings like band-pass filtering, (iii) a feature extraction stage, (iv) a classification or regression step, and (v) a feedback phase[26]. For example, to achieve vigilance assessment, previous works propose the neural network methods for mental fatigue monitoring, such as BP neural network and LRNN neural network[27]. However, these works could not deal with the continued vigilance assessment scenarios.

Such neural network based methods have over-fitting problem due to the few-shot examples of each task.

To address such problem, we consider the HMM method, that utilizes HRV parameters can meet the need for continued vigilance assessment.

According to literature[28], Performance in monotonous tasks is associated with an increase in the LF component of HRV. The low-frequency power spectrum of HRV reflects both sympathetic and parasympathetic activities, which jointly control the heart. This is the theoretical basis for our research. And the average correct rate of identification for out HMM method is up to 87.78% in this paper. Therefore, the method proposed in this paper is a promising one for vigilance level prediction, which may play a role in improving work performance and preventing the staff from suffering accidents in special posts by combining wearable devices with prompt prewarning function.

For general evaluation products already in application, the relevant monitoring of mental fatigue focuses on stress, but apart from stress, work performance is associated with several factors and is more intuitive to vigilance level measurement[29]. With advances in ECG sampling technology, the method of obtaining HRV indicators by measuring ECG is also more convenient and easier to deploy in work scenarios than the traditional method before.

Some other literature used a combination of ECG and EMG signals to develop a system that could simultaneously detect low vigilance manifestations such as drowsiness and inattention[30]. The KNN method, linear discriminant analysis, and quadratic discriminant analysis have been used to classify the features, with the maximum accuracy of 96.75%. However, compared with the method in our study, they need more sensors, and a larger number and type of sensors is a great challenge to wearable device design.

We also compared our approach with SVM, and results have shown that the gap of accuracy of different algorithms is not apparent. But still, HMM has a higher accuracy than SVM. HMM can analyze the dynamic signals of time series, complete pattern recognition according to the relationship between adjacent states, and reflect the similarity between categories to a greater extent while the differences between categories are ignored. By mapping the linearly inseparable samples in the low-dimensional space to the high-dimensional space, SVM separates similar samples with the largest possible Euclidean distance, which reflects the difference between categories to a greater extent. Both models have their own advantages, besides there have been studies combining the two algorithms to extract speech feature or recognize driving intention. Thus in the further research, we may explore the way of HMM and SVM cascade algorithm to further enhance the accuracy of vigilance assessment. Our study is aimed at workers on key positions of special industries such as Manned deep submersible or Nuclear Industry, which need to be high concentration of attention to deal with monotonous repetitive work.

3.3. Limitation

The study's limitations include the small sample size and the narrow range of vigilance levels. Finding statistically significant results is challenging due to the limited sample size, which also restricts the analytical capacity. And we did not conduct further analysis of the data changes during collecting for considering that the purpose of this paper is to comprehensively examine the availability of HMM for assessing vigilance.

The collection device of ECG in our study now is only applicable in lab environment, which is still a gap from practical. We will test other devices and signals that more convenient for real working environment in future work.

4. Conclusions

In this paper, we have extracted the HRV information of the human body by experimentally collecting ECG signal from the human body and recording the mental state of volunteers at the same time, preprocessed ECG signal and extracted the HRV information of the human body, and built an HMM for vigilance assessment. The experimental results have shown that the model has a high correct rate and can be used in wearable products to improve their functionality of vigilance level assessment.

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