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Monitoring Driving Psychological Fatigue Through Unconstrained Heartbeat Signal Extraction by Using Pressure Sensor Array

SUN HONGCHANG [1,2], ZHANG ZHIJING [1], JIN XIN [1], DENG SANPENG [2], JIANG YONGXIANG [2], AND ZHENG ZHONGPENG [1]

[1]School of Mechanical Engineering, Beijing Institute of Technology, Beijing 100081, China
[2]Institute of Robotics and Intelligent Equipment, Tianjin University of Technology and Education, Tianjin 300090, China

Corresponding author: Jin Xin (goldking@bit.edu.cn)

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ABSTRACT The feasibility of monitoring driving psychological fatigue through unconstrained heartbeat extraction by using pressure sensors array was investigated. The pressure signals were obtained by close contact between subject's back and backrest of car seat. Correlation coefficients of electrocardiogram signals and pressure signals were used to select the optimal monitoring point due to the unavoidable adjustment of sitting posture during long times of driving. Lifting wavelet transform was applied for de-noising. J-J interval signals, which represent heartbeat signals, were extracted. The correlation dimension of heartbeat signals, reflecting the complicated degree and the chaotic level of a nonlinear dynamic system, was used as the indicator to determine the psychological fatigue. Its validity was verified by the consistency of correlation dimension with R-R interval (represents cardiac cycle). Finally, questionnaires during driving were administered. The effectiveness of this method to judge driver psychological fatigue was confirmed. This finding indicates that driving psychological fatigue can be monitored through unconstrained heartbeat signal extraction by using the pressure sensor array.

INDEX TERMS Pressure sensor array, correlation coefficients, heartbeat signals, unconstrained heartbeat extraction, correlation dimension.

I. INTRODUCTION

Fatigue driving is one of the most important factors causing traffic accidents [1]. According to its mechanism, this condition can be divided into three categories, namely, cyclic fatigue, physiological fatigue, and psychological fatigue. Although all kinds of driving fatigue can influence the emergency response ability, their mechanisms are different. Cyclic fatigue is mainly caused by insufficient sleep that is manifested as drowsiness in driving [2]. physiological fatigue is caused by heavy load of the shoulder blades, lumbar spine, and muscle in long times of driving sitting posture. Unreasonable body pressure distribution aggravates the sense of physiological fatigue. When facing an emergency, the response reduction caused by body stiffness. Psychological fatigue is caused by high intensity work in nerve center, as well as the response reduces caused by distraction.

Driving fatigue is usually a combination of those three types. Therefore, whether driving fatigue is caused by insufficient sleep, distraction or body stiffness is able to be determined by categorizing cyclic, physiological and psychological fatigue types. The corresponding fatigue control strategies are capable to be proposed for further research. This research is focus on discriminate psychological fatigue from hybrid fatigue.

A. THE MECHANISM OF CYCLIC FATIGUE AND MONITORING METHOD

In the state of cyclic fatigue, drivers often yawn, their percentage of eyelid closure over time is significant different from non-fatigue. Driver state monitoring system employing computer vision technologies have been developed and some

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of them are in practical use. Toyota Motors adopted cameras to measure the distance between the upper and lower eyelids of the driver to determine whether the driver is falling into a sleepy state [3]. Percentage of eyelid closure over time is relatively a reliable method to determine alertness level [4]. But strong light from the vehicles running on the opposite lane may cause false determination because the method needs an ideal light condition. Moreover, when the driver wears sunglasses, the camera system may yield invalid results.

B. THE MECHANISM OF PHYSIOLOGICAL FATIGUE AND MONITORING METHOD

During driving, the shoulder blades, lumbar spine, and muscle take heavy load in sitting posture. The driver feels stiffness and frequently adjusts the sitting posture to improve physical comfort. Therefore, physiological driving fatigue can be obtained by detecting the body pressure distribution [5]. Driving posture can be pattern recognized using pressure sensor arrays. Physiological fatigue can be monitored by evaluating driving comfort and the frequency of driving posture adjustment. Sammonds *et al.* [6] measured seat comfort for up to a 2h driving and identified the correlation between the amount of movement in a car seat and the comfort level.

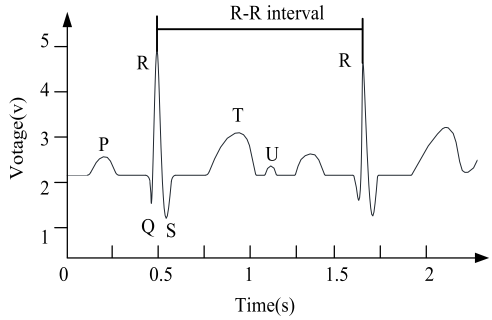
When physiological fatigue occurs, the driver's control ability decreases, the change of speed, gear, throttle, and other driving behaviors becomes fast, and the range of front wheel angle decreases. Multisensor data fusion method [7] is widely used to improve the accuracy of physiological fatigue detection. Support vector machine algorithm was previously employed to monitor multiple behaviors [8]. Several sensors need proper layout for monitoring physiological fatigue. The data fusion algorithm is complex and time consuming and thus do not meet the needs of real-time monitoring.

C. THE MECHANISM OF PSYCHOLOGICAL FATIGUE AND MONITORING METHOD

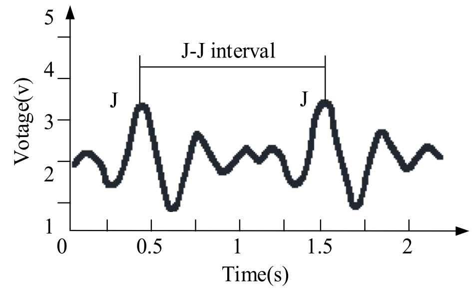
Psychological fatigue is mainly caused by high-intensity work in the nervous center. The main manifestation is that the driving spirit is negligent, and the judgment ability of driving emergencies is weakened.

Monitoring methods for psychological fatigue have been widely researched. Subjective feelings are the most effective indicators to evaluate psychological fatigue, those can be measured by subjective questionnaire, response times and flash fusion frequency experiment [9]. Electroencephalo(EEG) is believed a gold standard of measuring psychological fatigue [10]. Wang [11] reported that heart rate variability (HRV) is an effective indicator to judge psychological fatigue. Wu and Wu [12] stated the sensitivity and effectiveness of physiological signals, such as electroencephalogram, electromyogram, electrocardiogram (ECG), and breath, in monitoring psychological fatigue. These psychological fatigue monitoring methods have referential importance to driving application.

Conventional monitoring methods for psychological fatigue detection require attaching electrodes to the body of the subjects, resulting in restraint to the body and incompatibility for actual driving. Pressure signals can be obtained through the close contact between the subject's back and backrest of car seat in an unconstrained way by installing the pressure sensor array on the backrest of the car seat. The methods of extracting heartbeat signals by using the unconstrained way have achieved satisfactory results, providing possibilty to monitor psychological fatigue by the pressure sensor array.



(a) ECG signals



(b) BCG signals

FIGURE 1. ECG signals and BCG signals.

D. UNCONSTRAINED HEARTBEAT EXTRACTION METHOD BY USING PRESSURE SENSORS

The heart undergoes volumetric changes during each cardiac cycle while pumping blood through the cardiovascular system. These changes are then reflected in the periodical movement of the chest and contain important features that reflect the state of the heart. The composition of standard ECG signals and ballistocardiograph (BCG) signals are shown in Figure 1. Figure 1(a) displays the significant ECG features, such as the P-wave, QRS complex, T-wave, and U-wave. Figure 1(b) presents the wave components of the BCG signals similar to those of ECG. R wave and J wave are the most energetic components of ECG and BCG signals. R-R interval and J-J interval represent cardiac cycle signal and heartbeat signal, respectively.

Unconstrained heartbeat acquisition methods by using radar [13], Wi-Fi radio [14], and audio [12] are effective. The signals are transmitted and propagate in the monitoring space. Returning signals carrying information about heartbeat are then received. However, those methods restrict only one person in the monitoring space and therefore not suitable for driving fatigue monitoring because the driver and passengers are in an extremely close contact in a relatively small space. Another type of proposed unconstrained heartbeat acquisition method using acceleration [15] and pressure sensors is by installing the sensors on the seat belt [16], steering wheel, and driving seat [17]. Ear-hanging measurement method [18] and wearable heart monitoring method [19] have also been studied.

In their research on pressure sensor-based heartbeat extraction, Yu and his group conducted a continuous study and extracted heartbeat signals from micromovement sensitive mattress and used these signals for driving fatigue [20] and sleeping health [21] monitoring. Posture is inevitably adjusted during driving. Deploying multiple acceleration sensors for optimal monitoring point adjustment is impossible due to the high cost. Pressure sensors can be easily fabricated into a large area flexible pressure sensor array. Jiang *et al.* [22] studied the effects of driving posture on heartbeat signal extraction by using a pressure sensor array. The abovementioned unconstrained measurement methods are easily affected by environment noise because road bump and body movement of the driver are inevitable during driving. Therefore, if the heartbeat de-nosing is effective in high noise environment during driving, then unconstrained heartbeat extraction based on pressure sensor array is promising.

E. DRIVING FATIGUE MONITORING BASED ON BCG-RELATED SIGNALS

ECG and BCG signals are correlated that it considers BCG signals as indicators instead of ECG signals [23]. Therefore, ECG signals can be replaced by BCG signals as indicators for determining driving psychological fatigue. Eilebrecht *et al.* [24] revealed that heartbeat recording in car is feasible without attaching adhesive electrodes, thus making this vital sign potentially available for driving fatigue monitoring. Heartbeat signals for driving fatigue monitoring are easily affected by environment noise because of the inevitable vibration and body movement of the driver. Thus, extracting the heartbeat signals with abundant information is impossible as shown in Figure 1(a). However, the J peak is the positive maximum of heartbeat signals. Therefore, the extraction of only J-J interval is feasible and provides a promising way for fatigue driving determination.

Many studies showed that driving fatigue can be detected by observing the changes of HRV extracted by the R-R interval. HRV describes the variations between consecutive heartbeats. The regulation mechanisms of HRV originated from sympathetic and parasympathetic nervous systems. Thus, HRV can be used as a quantitative marker of autonomic nervous system [25]. HRV analysis methods can be divided into time-domain, frequency-domain, and nonlinear methods as follows.

Time-domain parameters are the simplest ones calculated directly from the raw R-R interval time series. The simplest time domain measures are the mean and standard deviation of the R-R intervals. In addition, reference [6] mentioned the standard deviation of the differences between consecutive R-R intervals (SDSD), the number of consecutive R-R intervals differing more than 50 ms (NN50), and the percentage value of NN50 intervals (pNN50). Although time-domain algorithms are simple, these algorithms are not suitable for driving fatigue monitoring due to the simplicity and inaccuracy in high noise background.

Frequency-domain parameters include the powers of extremely low frequency, low frequency (LF), high frequency (HF) bands in absolute and relative values, the normalized power of LF and HF bands, and LF to HF ratio. Zhao *et al.* [26] reported that the lower and upper bands of HRV power are significantly different before and after driving fatigue. Michail *et al.* [27] showed that the power spectral analysis of the drivers' heart rate can evaluate driving fatigue. Frequency domain filtering can be used to reduce noise, and the accuracy is higher than that of using time domain. However, the frequency domain analysis of HRV is not sufficiently stable to reflect the driving fatigue status of different groups of people [28].

HRV is a typical nonlinear discrete time series and the "fractal" series of R-R intervals manifesting nonlinear dynamics. Under fatigue, the fractal feature of the R-R intervals is converted to a regular and linear pattern [29]. Therefore, driving fatigue can be monitored by extracting an index quantity of the change of fractal structure. Michail *et al.* [27] reported that the variations of fractal dimension can provide important information for the assessment of the driving situation. Xie *et al.* [30] presented the nonlinear dynamics and chaotic activity of HRV by computing the correlation dimension of the R-R interval. Li *et al.* [31] introduced sample entropy to distinguish fatigue, drunk, and normal driving and proved its validity.

Basing on the above mentioned research and the existing problem, this study focuses on solving the following problems.

1) The traditional unconstrained heartbeat monitoring method strictly restricts the body movement during monitoring. The placement of sensors should be adjusted accordingly due to the varying sitting postures. Therefore, the methods using acceleration and pressure sensors are not universally applicable. In this study, the sensor array was placed between the driver and the seat back, and the optimal monitoring point can be adjusted based on the correlation coefficient. The corresponding relationship between sitting posture and optimal monitoring points can be obtained by further studying the sitting posture recognition based on pressure distribution. This result confirms the applicability of the real-time adjustment method for practical use.

2) The signal-to-noise ratio of the BCG signals is extremely low due to the road bump and body movement during driving, thus making the extraction of pressure signals difficult. Therefore, few studies were conducted on fatigue driving monitoring using pressure sensors. The present study extracted heartbeat signals from BCG signals. The variability of J-J intervals, a nonlinear discrete time series, was also

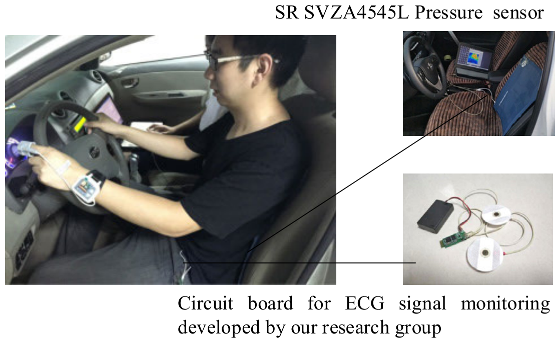


FIGURE 2. Experimental setup for the measurement of heartbeat signal during driving.

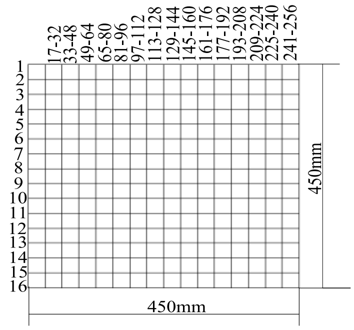


FIGURE 3. Distribution of pressure sensor array.

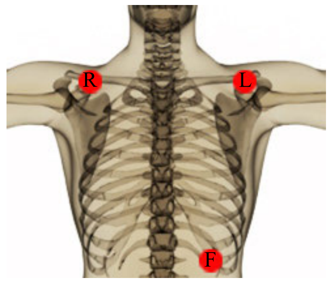


FIGURE 4. Schematic diagram of ECG sensors attached on the volunteer's body [22].

analyzed. This process provides possibility to monitor fatigue based on heartbeat signals during driving.

II. EXPERIMENT DESIGN

A. EXPERIMENT EQUIPMENT

1) PRESSURE SENSOR ARRAY FOR HEARTBEAT EXTRACTION

Pressure sensor arrays, which are manufactured by the Tokai Rubber Industries, Ltd. in Komaki, Japan, were used to extract heartbeat signal because of its excellent low frequency response characteristics. The resistance strain type pressure sensor array was set on the surface of the car seat and between the driver and backrest (Figure 2). The 16 × 16 pressure sensor array is arranged by 256 pressure sensors, and the available measuring area is 450 mm × 450 mm. The sensors were numbered from 1 to 256 as shown in Figure 3 [32].

The equipment is powered by a Universal Serial Bus(USB) with low power consumption and is suitable for installation on automobiles. Real-time image of pressure distribution was acquired by its own software. Pressure data were obtained by COM debug assistant software.

2) EQUIPMENT FOR ECG SIGNAL MONITORING

The ECG signals were monitored to verify the accuracy of extracted heartbeat signals and search the optimal monitoring point from 256 sensors on the pressure sensor array. In addition, the R-R interval of the ECG signals was used to verify the J-J interval extracted from the pressure sensor array. A circuit board for ECG signal monitoring developed by our research group is also shown in Figure 2. The diameter of the electrode patch is 3cm. Three electrodes of ECG sensors were attached to the R(the edge of right subclavian chest wall), L(the edge of left subclavian chest wall), and F(bottom rib of the left chest wall) positions in the subject's body as shown in Figure 4. The accuracy of heart rate monitoring was verified in our previous research [32].

B. EXPERIMENTAL ARRANGEMENT

The experiment was conducted on an actual automobile, and the pressure signals and ECG signals were monitored. A highway with insignificant traffic was selected to ensure driving safety. Ten healthy male and ten healthy female subjects were involved under controlled conditions to ensure the consistency of subjects' physical condition. The ages of the subjects ranged from 20 years to 25 years, the mean and standard deviation of the subjects' weight and height were 63.15±6.61kg and 167.88±5.75cm, the weight and height distribution of subjects were shown in Figure 5. All the subjects were asked to have a good rest in the previous night and forbidden to consume tobacco, wine, tea, coffee, and any other food and drugs that might affect heart rate from the previous day. A 2h long time driving experiment was designed from 9:00 am to 11:00 am, which is usually the most energetic time of the day, to record the state from non-fatigue to fatigue.

Fatigue driving judgment by heartbeat signal is made every 10 minutes. Therefore, heartbeat signals extracted from pressure sensor arrays and ECG signals were chosen in driving state without acceleration, turning or large ground turbulence, aiming at minimize the impact of ground truth on the heartbeat signal.

Fatigue level was judged by the driving fatigue questionnaire. The investigator conducted an oral questionnaire every 10 min and recorded the questionnaire while the subjects were driving. In the questionnaire sheet, four groups of words were selected to describe the subjective feelings. The words representing psychological fatigue were "Uncomfortable/Comfortable," "Distracted/ Concentrated," "Anxious/Quite," and "Bleary/Clear." As mentioned above, driving fatigue is commonly hybrid fatigue, in order to verify the accuracy of psychological fatigue judgment under hybrid fatigue, two groups of words were selected to describe

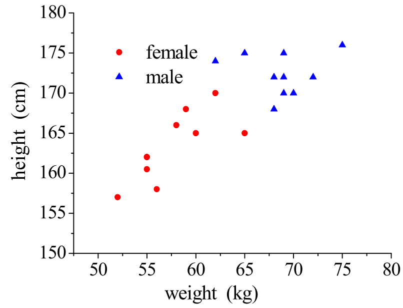


FIGURE 5. Weight and height distribution of subjects.

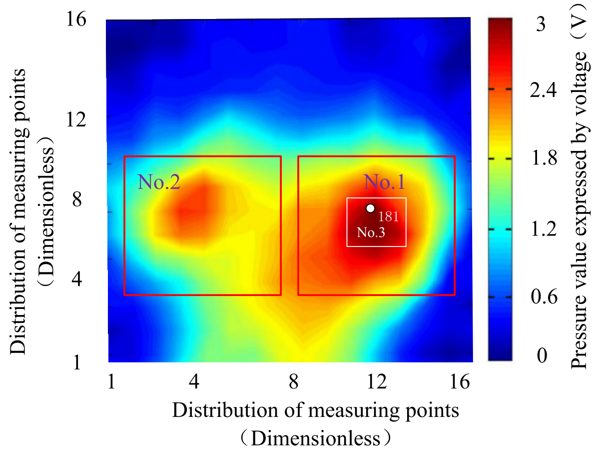


FIGURE 6. Color contour distribution of pressure between the subject's back and backrest.

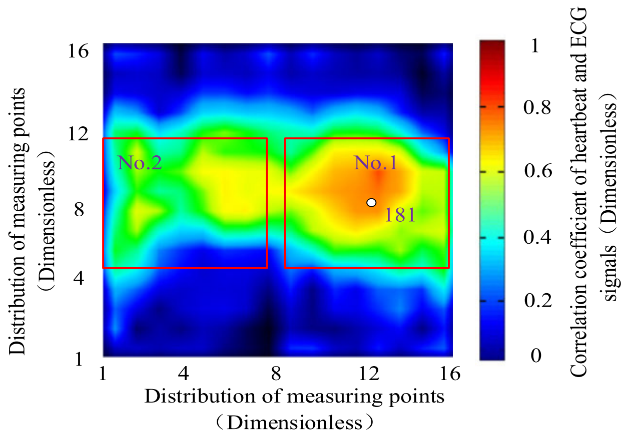


FIGURE 7. Correlation coefficient analysis of heartbeat and ECG signals.

objective narrative, The words "Body stiff/Body flexible" and "Sleepy/Energetic" represent physiological fatigue and cyclic fatigue respectively. These words can be divided into seven grades defined as "special fatigue, general fatigue, slightly fatigue, no impact, slightly sober, generally sober, and special sober." The evaluation was based on a 7-point scale from −3 to +3.

III. HEARTBEAT EXTRACTION FROM PRESSURE SENSOR ARRAY

There are two steps to extract heartbeat signal. The first step is to select the optimal monitoring point by using correlation coefficient analysis method, the influence of sitting posture on the selection of the optimal monitoring point is also discussed. The second step is the pressure signal denoising from the optimal monitoring point.

A. SELECTION OF OPTIMAL MONITORING POINT IN PRESSURE SENSOR ARRAY BASED ON CORRELATION ANALYSIS

The optimal monitoring point from 256 sets of pressure sensors should be chosen by the correlation coefficient between the ECG signals and pressure signals due to the various sitting postures and statures of subjects. The correlation coefficient is a statistical index used to reflect the degree of close correlation between variables as follows:

$$|\rho xy| = \frac{\sum_{i=1}^{n}(x_i-\overline{x})(y_i-\overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\overline{x})^2\cdot\sum_{i=1}^{n}(y_i-\overline{y})^2}} \tag{1}$$

where $|\rho_{xy}|$ is the correlation coefficient, x_i and y_i are the two sets of data to evaluate the degree of concordance. $\overline{x}$ and $\overline{y}$ are the mean value of x_i and y_i, respectively. $|\rho_{xy}| = 1$ indicates a strong correlation between the two signals, and $|\rho_{xy}| = 0$ when the two signals are independent.

During the 2h driving experiment, the correlation coefficient is calculated every 10 minutes for each subjects. Therefore, the optimal monitoring point for extracting heartbeat of each subject with driving time is able to be selected. The pressure distributes of subject 1 at the first 10 min of the driving experiment is shown in Figure 6 [33]. The areas with high pressure were distributed in the regions marked No. 1 and No. 2. The 181 sensor in pressure sensor array achieved the highest pressure value. According to Figure 6, the high pressure of regions No. 1 and No. 2 is caused by the close contact of the subject's back and backrest. The position of the heart of the subject in the regions marked No. 3.

The correlation coefficient between the ECG signals and heartbeat at the first 10 min was displaced by color contour and is shown in Figure 7. Noncorrelation existed outside of regions No. 1 and No. 2, wherein the value of correlation coefficient is small. The pressure signals in region No. 2 was large according to Figure 6. However, the correlation between the pressure signals and heartbeat signals was not significant in region No. 2, which is relatively distant from the heart according to Figure 6. The 181 sensor in the pressure sensor array also obtained the highest correlation coefficient. Therefore, the optimal monitoring point of subject 1 at the first 10 min was located in the 181 sensor of region No. 1 with the maximum correlation coefficient.

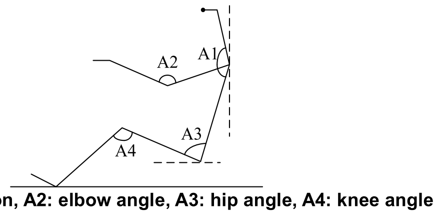


FIGURE 8. Postural angle model.

TABLE 1. Range of comfort and typical driving posture for the postural angle.

Postural Angle	Driving Posture 1(°)	Driving Posture 2(°)	Driving Posture 3(°)	Driving Posture 4(°)
A1:	145–155	130–135	135–145	155–160
A2:	115–120	114–120	116–122	112–116
A3:	102–106	98–102	102–108	109–110
A4:	124–130	124–130	124–130	124–130

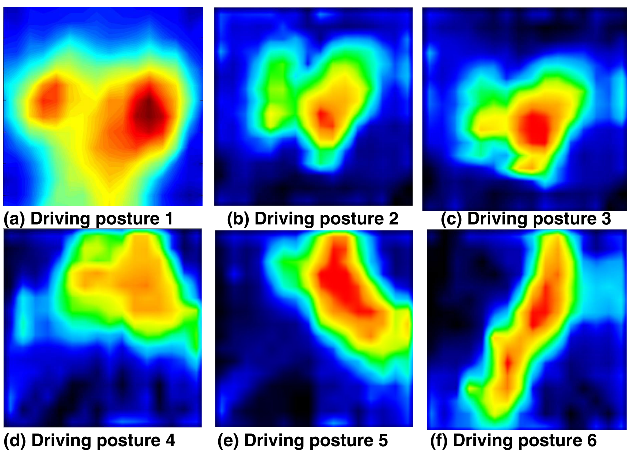


FIGURE 9. Sitting posture and pressure distribution of subject 1.

B. CORRELATION BETWEEN HEARTBEAT SIGNAL AND ECG IN VARIED SITTING POSTURES

A postural angle model is shown in Figure 8. Cervical flexion, elbow angle, hip angle, and knee angle were selected as dependent variables to evaluate the driving posture [34].

According to the questionnaire, the first four comfort ranges of the postural angle were chosen as driving postures 1–4 and are summarized in Table 1 based on the questionnaire.

In order to discuss the applicability of the unconstrained monitoring method for heartbeat signals measurement under an unsuitable sitting posture, the body tends to the left at 10° and the body tends to the right at 10° in the driving posture 1 (postural angle A1:145–155, A2: 115–120, A3: 102–106, A4: 124–130) were chosen as driving postures 5 and 6. Take subject 1 as an example, the pressure distribution in driving posture 1 is shown in Figure 9.

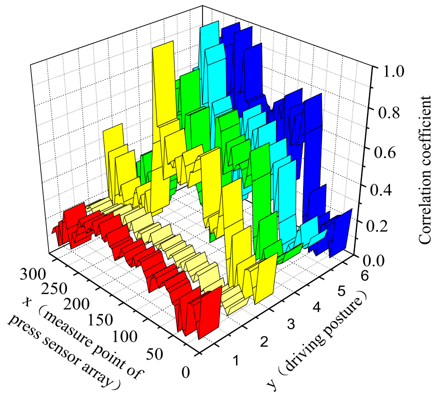


FIGURE 10. Correlation coefficient analysis in varied driving postures.

The analysis leads to obtain the optimal measure point considering the varied driving postures, the correlation coefficient between the ECG and heartbeat signals are illustrated in Figure 10. From driving postures 1–4 in the y-coordinate, the change in the maximum pressure point caused by the driver's posture corresponds to the maximum correlation coefficient. Thus, the heartbeat signals in the four driver postures can be extracted from the pressure signal. In driving postured 5 and 6, the correlation coefficients in all measuring points were below 0.4, thereby indicating that heartbeat signal can be hardly extracted in the two driving positions.

According to the subjective questionnaire, the pressure sensors array is capable of producing reliable driver fatigue information in most cases. For exceptional cases, when the correlation coefficient is small, the monitoring system able to remind the driver to maintain a comfortable sitting posture. It is not only to ensures the heartbeat signal acquisition, likewise to ensure comfortable sitting posture and delay driving fatigue.

C. HEARTBEAT EXTRACTION BY LIFTING WAVELET TRANSFORM

Given that road bump and body movement in driving is inevitable, weak heartbeat signals in a large noise background are acquired during driving. The noise of pressure signals are random signals with low frequency. Thus, the de-nosing method in the frequency domain is inappropriate to evaluate the change of J-J interval. Therefore, the time-frequency domain analysis method based on lifting wavelet was studied.

The lifting scheme has three steps: "Split", "Predict", and "Update". Following the three steps is the reconstruction of the lifting wavelet by reverse lifting. "Split" is to split the original signal into two disjoint data sets, namely, even sample set and odd sample set. "Predict" is to build an operator to predict one sample set by using the other by evaluating the correlation and closeness of the two disjoint sample sets. "Predict" has two functions. One is to separate high frequency components, and the other is to compress the data. "Update" is to correct the sample set generated by

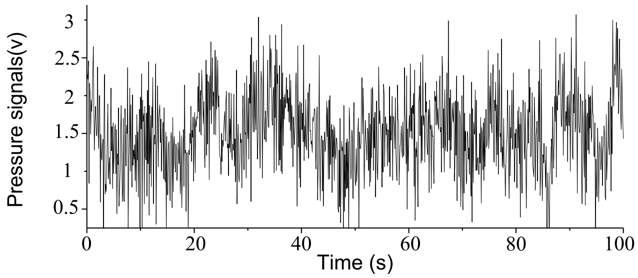


FIGURE 11. Press signals measured during driving experiment.

"Split" to make its characteristics consistent with the original signal.

1) SPLIT (S)

"Split" splits the sample into two disjoint sets: the even sample ($x_e(n)$) and the odd sample ($x_o(n)$).

$$x(n) = \text{Split}(x_e(n), x_o(n)) \tag{2}$$

2) PREDICT (P)

Provided that the even sample set and odd sample set are correlated, we can build a prediction operator P that is independent of the samples to predict the odd sample set $x_o(n)$ by the even sample set $x_e(n)$.

$$d(n) = x_o(n) - P(x_e(n)) \tag{3}$$

If the differenceis sufficiently small, then the prediction is accurate and invertible. $x_o(n)$ can be recovered from $d(n)$ and $x_e(n)$. This lifting operation has two functions. One is to separate the high frequency components of the sample $x(n)$, and the other is to compress the data.

3) UPDATE (U)

Given that the sample set $x_e(n)$ generated by "Split" may deviate from the original data, "Update" is required. As shown in Eq. (3), "Update" is to modify $x_e(n)$ with $d(n)$ to make the modified sample to have only low frequency components of $x(n)$.

$$c_e(n) = x_e(n) + U(d(n)) \tag{4}$$

where $c_e(n)$ represents the modified even sample set.

Reconstruction of the lifting wavelet by reverse lifting consists of

$$\text{Reverse“Update}'' : x_e(n) = c_e(n)\text{-}U(d(n)) \tag{5}$$

$$\text{Reverse“Predict}'' : x_o(n) = d(n) + P(x_e(n)) \tag{6}$$

$$\text{“Merge}'' : x(n) = \text{Merge}(x_e(n), x_o(n)). \tag{7}$$

Here, "Merge" means reconstructing $x(n)$ by $x_o(n)$ and $x_e(n)$.

According to correlation coefficient analysis, the signals of No. 181 sensor marked by Figure 6 in region No. 1 were chosen as the optimal measure point. Figure 7 shows the press signals measured by No. 181 sensor in the first 10 min during

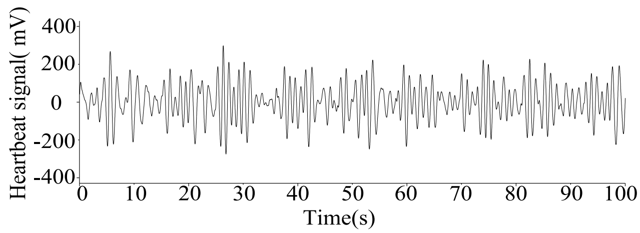


FIGURE 12. Heartbeat extraction from press signals by wavelet noise reduction.

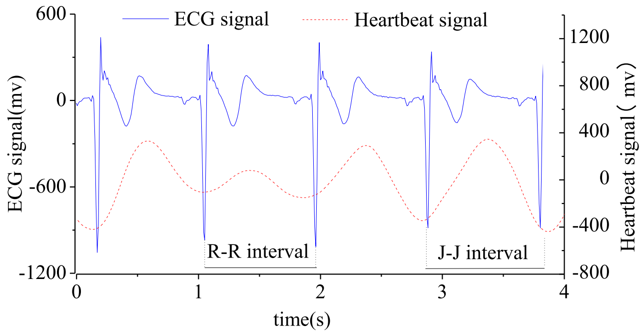


FIGURE 13. ECG signals measured simultaneously for verifying the J-J interval.

driving experiment. Figure 11 presents the signals filtered by the lifting wavelet, and Figure 12 is the ECG signals acquired simultaneously. In Figure 11, the heartbeat was submerged in the noise, and no periodic signals can be seen. In Figure 12, the heartbeat signals can be extracted regardless of the detail components of the BCG signals. Four second heartbeat signals were intercepted from Figure 12 and indicated by dotted lines in Figure 13. The solid line indicates the ECG signals acquired simultaneously. The frequency of cardiac cycles expressed by the two curves is similar. Therefore, heartbeat can be unconstrainedly extracted during driving from high noise background.

IV. DRIVING FATIGUE DETERMINATION BASED ON CORRELATION DIMENSION OF J-J INTERVAL

A. CORRELATION DIMENSION

The term chaos is used to describe the erratic time-dependent changes in certain physical processes, such as HRV. The chaotic systems are "fractal" (i.e., having fractional dimensions that exceed their integer topological dimensions) and "low dimensional" (i.e., only having a few independent variables). Correlation dimension D2 is used to estimate the dimension and describe the complicated degree of chaos. Thus, high dimension means several variables are needed to describe the dynamic characteristics of the system and the complex the system is. Given that the J-J interval and R-R interval have the same frequency characteristics, the correlation dimension of the J-J interval can be used to evaluate the psychological fatigue.

A common technique to probe the system is to measure a single scalar function of the system state and reconstruct the dynamics in an m-dimensional space by using the time delay coordinate, called phase space reconstruction. Given a time series

$$x(t) = \{x_1, x_2, \ldots x_N\}, \quad (8)$$

where $x(t)$ represents the time series of J-J interval signals, and N is the size of the data set. Then, $x_1, x_2, x_3, \ldots x_N$ can be embedded into a reconstruction matrix by using delay time coordinates.

$$X = \{X_i | X_i = [\mathbf{x}_i, \mathbf{x}_{i+\tau}, \ldots, \mathbf{x}_{i+(m-1)\tau}]\}^T, \quad i = 1, 2, \ldots, M, \quad (9)$$

where m represents the embedding dimension, and τ is the delay time. $M = N - (m-1)\tau$ is the number of embedded points in the m-dimensional space.

Considering this m-dimensional dynamical system that exhibits a chaotic attractor, a probability measure r can be defined on the attractor as follows. Let $x \in Rn$ be a point on the attractor, and B be an n-dimensional hypercube centered at x. The probability measure contained in B, $r(B)$, is then defined to be the fraction of time a typical trajectory spends in the cube.

The correlation dimension introduced by Grassberger and Procaccia is widely used in many fields for the characterization of strange attractors. The correlation integral for the embedded time series is as follows: [30]

$$C(m, N, r, t) = \frac{2}{M(M-1)} \sum_{1 \le i \le j \le M} \Theta(r - \|x_i - x_j\|) \quad (10)$$

where $C(m, N, r, t)$ represents the correlation integral; t is the index lag; $||\ldots||$ denotes the sup-norm, and Θ represents a Heaviside step function. The summation (Σ) and the Heaviside function count the distance $||xi\text{-}xj||$ with an interdistance smaller than r.

If the limit of $C(m, N, r, t)$ as $N \to \infty$ exists for each r, then the fraction of all state vector points that are within r of each other is denoted by $C(m, r, t) = \lim N \to \infty C(m, N, r, t)$, and the correlation dimension is defined as

$$D_2(m, t) = limr_{\to 0}[logC(m, r, t)/logr] \quad (11)$$

Given that N remains finite for data sets, then, we cannot let r proceed to 0. Instead, we look for a linear region of slope $D_2(m, t)$ in the plot of log $C(m, N, r, t)$ vs. log r.

The estimated correlation dimension of the reconstructed attractor typically increases with m and reaches a plateau (on which the dimension estimate is relatively constant) for a range of large enough m values. The plateaued dimension value is then assumed to be an estimate of D2 for the attractor in the original full phase space [35].

B. PSYCHOLOGICAL FATIGUE MONITORING BASED ON HEARTBEAT CORRELATION DIMENSION

The 120 min heartbeat and ECG signals were acquired and divided into 12 segments. The curve D2 in Figure 14 is the heartbeat correlation dimension in No. 181 measuring points.

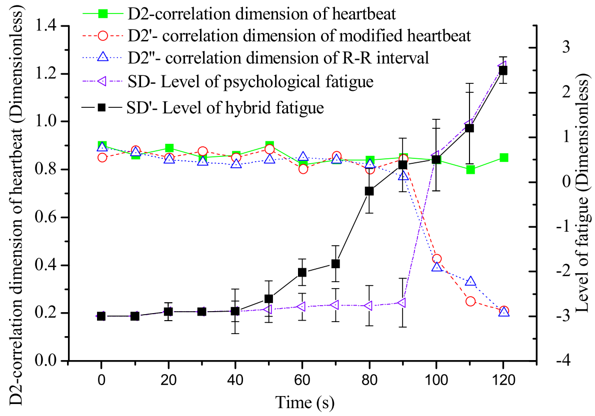


FIGURE 14. D2 and SD curve to evaluate driving psychological fatigue.

Considering the unavoidable adjustment of driver's sitting posture in the experiment, the correlation dimension was calculated by the heartbeat signal acquired in the optimized measure point by using the correlation coefficient calculation. The modified correlation dimension curve, for compensate the change of the optimal monitoring point, was subsequently drawn and is expressed by D2′. The R-R interval of ECG signals was used to simultaneously calculate the correlation dimension and verify the accuracy of driving fatigue judgment by heartbeat, and the curve is expressed by D2''. In addition, SD curve represent the level of psychological fatigue, providing the average score of the 20 subjects according to four group of words in driving fatigue questionnaire. SD' curve represent the level of hybrid fatigue by six group of words. Their confidence intervals are plotted in Figure 14. The analysis of D2, D2′, D2'', SD and SD' curve is summarized as follows:

1)In the period between 0 and the 40th minute, the changes in D2, D2′, and D2'' were flat. In addition, the large value of correlation dimension exhibited the complexity of heartbeat signal, indicating a result of non-fatigue. The level of psychological and hybrid SD curve were basic agree and flat, and the mean value was close to −3, which is defined as special sober. These results have good consistency in proving non-fatigue driving. The confidence interval is the range of the estimate in this study and was observed to be maintaining a narrow range. According to investigation, all the subjects answered general sober or slightly sober within this period. The most extreme confidence interval is (−3, −3) in the first and third 10 min. Accordingly, all the subjects felt special sober. The results show that subjects' subjective feelings of non-fatigue are consistent at the beginning of the driving test.

2)In the period between 40th and the 90th minute,level of psychological fatigue curve is flat, however, level of hybrid fatigue curve showing an upward trend. The changes in D2, D2′, and D2'' were flat and unaffected by physiological fatigue and cyclic fatigue.

3)In the period between the 90th and the 110th minutes, D2′ and D2'' rapidly decreased, indicating that the chaotic level was decreasing. The downward trend of D2 curve was opposite to that of D2′ and D2'', showing an upward trend. After long time of driving, some subjects began to adjust their sitting posture because of body stiffness, resulting in inaccurate data of D2. D2′ is modified correlation dimension curve, it is calculated by the heartbeat signal obtained under the optimal monitoring point selected by the correlation coefficient analysis. Therefore, the level of D2′ and D2'' were curve efficiently corresponded. Although the level of psychological and hybrid SD curve is consistent with the results of correlation dimension, the confidence interval was in a wide range possibly due to the subjective feelings in fatigue-resistance state.

4)After the 110th minute from the beginning of the test, D2′ and D2'' reached their lowest value, and the curve became smooth, indicating a general fatigue state. Level of psychological fatigue curve and hybrid fatigue curve overlap well, indicating all the three type of fatigue appear. The level of fatigue evaluation index was increased to the highest. The confidence interval range became narrow again because all the subjects answered fatigue in this period.

V. CONCLUSIONS

This study proposed a monitoring method for driving fatigue through unconstrained heartbeat extraction by using a pressure sensor array. With the correlation coefficient of ECG signals and pressure signals as the indicator, the influence of driving posture adjustment on the optimal monitoring point selection was investigated.

BCG signals are weak signals on the large noise background during driving. Therefore, retaining all of the components after de-nosing is difficult. In this research, heartbeat signals and the maximum components J-J interval were used as data source for fatigue monitoring. This condition reduces the difficulty of de-noising. In addition, LWT was employed to extract the heartbeat signals.

Correlation dimension was used as an indicator of driver psychological fatigue extracted from heartbeat signals. The heartbeat correlation dimension D2′ obtained by the modified monitoring point is proven effective compared with the correlation dimension of the R-R interval of ECG and the SD subjective evaluation in real driving experiment.

This research is able to recognize psychological fatigue from hybrid fatigue using unconstrained pressure sensor array.

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SUN HONGCHANG received the master's degree in mechanical engineering from the Beijing University of Technology, in 2006, where he is currently pursuing the Ph.D. degree in mechanical engineering. He is also an Associate Professor. He has published 20 articles and edited three textbooks and holds 12 patents. His research interests include precision motion control, mechatronics system development, and robot technology. He has rich experience in engineering and project development. He is responsible for the research programs funded by Tianjin Science and Technology Commissioner Project.

ZHANG ZHIJING is currently a Professor and also a Doctoral Supervisor with the Beijing University of Technology. He has published more than 150 SCI/EI articles and holds 30 patents. His research interests include precision micromechanical manufacturing and assembly technology. He is in charge of more than 20 funded research programs by the National Major Safety Project, National Natural Science Foundation project, and National Major Project. His achievements are in the fields of precision micro-structure composite processing technology, precision micro-structure flexible automation assembly technology, and precision assembly theory researches. "Precision Miniature Turning and Milling Composite Processing Equipment and Technology" has been one of the "Twelfth Five-Year Plan" technology promotion projects in the science and technology industry. He has received five ministerial science and technology awards.

JIN XIN received the Ph.D. degree in engineering from the Beijing University of Technology, in 2005. She is currently a Professor with the Beijing University of Technology. She has published 23 SCI/EI articles and holds 26 invention patents and obtained three provincial and ministerial appraisal results. Her research interests include precision sensor detection technology, micro-electromechanical equipment control, and detection technology. She is in charge of several research programs funded by the National Natural Science Foundation Surface Project, the Natural Science Foundation Joint Foundation Key Project, and the Beijing Outstanding Talents Subsidy Program. Her group developed the first high-speed ultraprecision turning and milling machine tool in China. In the past five years, she has undertaken 9 million Yuan research fund.

DENG SANPENG received the Ph.D. degree in mechanical engineering from the Beijing University of Technology, in 2015. He is currently a Professor and a Doctoral Supervisor with the Tianjin University of Technology and Education. He has published 100 articles and edited ten textbooks and holds 50 authorized patents. His research interests include robot sensor system integration and intelligent manufacturing equipment design. He is in charge of more than ten research programs at the provincial and ministerial level. He has received one second prize and two third prizes from the Tianjin Science and Technology Progress Award.

JIANG YONGXIANG received the Ph.D. degree in engineering from Tianjin University, in 2010. She is currently an Associate Professor and a Master's Supervisor with the Tianjin University of Technology and Education. She has published 20 articles and edited three textbooks and holds 12 authorized patents. Her research interests include signal processing, robot system integration, and intelligent manufacturing equipment design. She is in charge of two research programs funded by the Tianjin Natural Science Foundation and the Tianjin Science and Technology Commissioner Project.

ZHENG ZHONGPENG received the master's degree in mechanical engineering from Xi'an Technological University, in 2017. He is currently pursuing the Ph.D. degree with the Beijing University of Technology. His research interests include advanced manufacturing technology, machine assembly, and ultraprecision sensor deign.