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A Multi-level Heart Rate Fatigue Recognition Framework Based on CNN-LSTM for Air Traffic Controllers

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Abstract. Fatigue is an important factor of air accidents caused by air traffic controllers. The conventional fatigue features extraction and recognition algorithms focus on individual behavioral and perceptual data, while ignoring the physiological conditions. Furthermore, the state-of-the-art heart rate detection method didn't consider the issue of timing correlation. Therefore, this paper proposes a multi-level heart rate fatigue recognition model based on CNN-LSTM, which realizes fatigue recognition from static and dynamic features respectively. It achieved a high accuracy in recognizing air traffic controllers' fatigue in complex environmental backgrounds, which are up to 95.5%. The experimental results demonstrated that the feature of heart rate is closely related to fatigue.

Keywords: heart rate, fatigue feature extraction, LSTM, CNN, air traffic controller

1. Introduction

The work of air traffic controllers mainly ensures the safety and orderly take-off and landing of aircraft, preventing collisions between air and ground. The work process requires continuous high vigilance. Long term mental pressure and shift system can easily cause fatigue, increase safety risks and even the possibility of accidents, prompting scholars to strengthen research on controllers' fatigue. However, current research on fatigue tends to focus more on individual behavioural data, including speech, facial, etc., ignoring the physiological data that most directly reflects fatigue and mental fatigue led attention failure is associated with accidents causing injuries and fatigue[1]. Therefore, this paper aims to explore the impact of physiological data on fatigue. Research has found that fatigue is not induced by a single mechanism, and a large number of internal physiological and external environmental factors can lead to fatigue[2]. In recent years, scholars have conducted extensive research on mental workload using electrocardiogram (ECG) indicators. Sun et al.[3] found that heart rate (HR) is related to the workload of controllers. M. Matabuena et al.[4] used functional data to predict maximum heart rate (MHR). Sugimoto et al.[5] used the normal heart rate R-R interval value SDNN and low/high frequency value to evaluate the mental load level of workers. Heart rate variability (HRV) is used to describe the fluctuations in HR caused by the efferent activity of the sympathetic and parasympathetic branches of the autonomic nervous system. Considering that heartbeats have timing features, many scholars have used HRV to evaluate the mental fatigue induced by different methods. Lu et al.[6] found that HRV is a timing features of HR and a key indicator for detecting the fatigue of workers. Masum et al.[7] used long short-term memory (LSTM) network to predict time series data of HR. Lin Haijun et al.[8] combined LSTM with fully connected neural networks with attention mechanisms to construct long-term relationships for HR data. M. Panwar et al.[9] proposed a deep learning model PP-Net based on LRCN for extracting and recognizing HR features. Moshawrab et al.[10] constructed a HR recognition model based on deep neural networks to recognize the features of HRV. In addition, attention mechanisms can ignore invalid information, especially improving the performance of time series prediction. Ding et al.[11] proposed an LSTM model based on attention mechanism to dynamically adjust features weights in spatial and temporal dimensions. Lin et al.[12] proposed a new method for heart rate prediction based on LSTM-BiLSTM-Att model, which utilizes LSTM to construct long-term relationships of heart rate data and extract high-dimensional features of heart rate.

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This paper proposes a multi-level heart rate fatigue features extraction and recognition model, which extracts static statistical features and dynamic timing features respectively. Based on the combination of convolutional neural network and long short-term memory network (CNN-LSTM), deepening the dynamic features extraction effect and proving the superiority of the proposed method.

The rest of this paper is organized as follows: Section 2 introduces heart rate signals and related physiological parameters. Section 3 introduces a multi-level heart rate features extraction recognition model. Section 4 evaluates the proposed method on a real collected dataset. Finally, a summary of this study was provided in Section 5.

2. Parameters of Heart Rate

ECG is a method of recording cardiac electrical activity and is widely used in clinical diagnosis and research. The electrocardiogram signal is obtained by recording the electrical activity of the heart through electrodes placed on the surface of the skin. It presents a series of periodic waveforms, mainly including P waves, QRS complexes, T waves, etc., which reflect the changes in electrical activity of various parts of the heart at different time.

HR refers to the number of beats per minute of the heart, which is a specific indicator extracted from ECG. It is obtained by measuring the time interval between the peaks of adjacent QRS complexes in the ECG, known as the RR interval, and converting it. The RR interval is the time difference between two consecutive R waves, denoted as$RR_{interval}$, usually expressed in seconds. The formula for calculating heart rate is:

$$HR = \frac{60}{RR_{interval}} \tag{1}$$

HRV is an indicator used to measure changes in HR, which is a dynamic analysis of heart rate changes. It refers to the phenomenon of continuous fluctuations in the interval between adjacent heartbeats, which is the small changes in the RR interval. HRV reflects the function of the autonomic nervous system in regulating cardiac activity, reflecting small fluctuations and irregularities between heart rates. HRV is a complex physiological indicator that is not only related to the autonomic regulation mechanism of the heart, but also influenced by various factors such as environment, emotions, and lifestyle. Therefore, its changes are of great significance in the early diseases' diagnosis and fatigue risk assessment.

3. Multi-level Heart Rate Features Extraction and Recognition Model

3.1. Date Preprocessing

Before the experiment, it is necessary to preprocess the heart rate data to meet the input requirements, including cleaning, time alignment, standardization, and normalization, as shown in Fig.1. Firstly, check whether there are missing or abnormal values in the heart rate data. Secondly, a unified time ensures that all heart rate data has a consistent time and sampling frequency. Finally, standardize and normalize the heart rate data to conform to a standard normal distribution.

Fig. 1: Heart rate data preprocessing

3.2. Static Statistical Features Extraction

The static statistical features of heart rate refer to the statistical measures extracted from heart rate that reflect the distribution features of heart rate. Static statistical features are obtained through direct statistical calculations of heart rate, reflecting the central trend and global trend of heart rate. Therefore, this paper extracts the static features of heart rate based on statistical principles. The static statistical features that need to be extracted are shown in Table 1.

Table 1: Static statistical features

Feature code	Feature	Explanation
Mean_hr	Mean heart rate	The average value of heart rate, describing the overall heart rate level.
Max_hr	Maximum heart rate	The extreme value of heart rate, reflects the upper limit of heart rate.
Min_hr	Minimum heart rate	The extreme value of heart rate reflects the lower limit of heart rate.
Std_hr	Standard deviation of heart rate	Reflects the fluctuation amplitude of heart rate.
Median_hr	Median heart rate	Reflects the central trend of heart rate.
CV	Coefficient of variation	The standard deviation of heart rate divided by the mean, represents the relative variability of heart rate.
Range	Heart rate fluctuation range	Reflects the overall fluctuation range of heart rate

3.3. Dynamic Timing Features Extraction

After extracting static statistical features from heart rate data, while these features effectively reflect the overall trend, they fail to capture the timing dependencies inherent in time-series data. To address this, this paper utilize the advantages of convolutional neural networks (CNNs) in extracting local features. Specifically, a 1D CNN layer was used to extract local timing features and capture short-term dependencies in heart rate. Since heart rate spans a long-time range, this paper employs a LSTM network to extract long-term timing features and capture long-term dependencies, combines with CNN to form the CNN-LSTM model proposed in this paper. Additionally, to enhance the model's focus on key time steps, a temporal pattern attention mechanism to improve attention to dynamic features.

The dynamic features of heart rate are mainly determined by HRV, which can reflect the activity of the autonomic nervous system, as well as the balance and coordination of sympathetic and vagus nerves. It is sensitive to mental load and fatigue status of the body. The R-R interval can be used to measure the regularity of cardiac rhythm through means, standard deviations and percentiles Therefore, this paper analysis and extracts HRV features from both time and frequency domains.

The time domain analysis of HRV is a mathematical calculation of the extracted R-R intervals of continuous heartbeats to evaluate the autonomic nervous system's regulation of heart rate changes. The time domain features and calculation formulas used in this paper are as follows, where N represents the heartbeat cycle, each heartbeat cycle is denoted as $t(n), \mathrm{n} \in \{1, N\}$, the average heartbeat cycle is δ, and $\Delta t(n)$ represents the difference between adjacent heartbeat cycles.

- Mean R-R interval ($Mean\_nni$):

$$Mean_{nni} = \frac{1}{N}\sum_{i=1}^{N} t(i) \tag{2}$$

- Standard deviation of R-R peak interval ($SDNN$):

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{n=2}^{N}\left(\delta(n) - \bar{\delta}\right)^2} \tag{3}$$

- Root mean square of R-R interval difference ($RMSSD$):

$$RMSSD = \sqrt{\frac{1}{N-2}\sum_{n=3}^{N}\left(\delta_{(n)} - \delta_{(n-1)}\right)^2} \tag{4}$$

- Standard deviation of the difference between adjacent R-R intervals ($SDSD$):

$$\Delta t(n) = t(n+1) - t(n), \quad n = 1,2,\cdots,N-1 \tag{5}$$

$$SDSD = \sqrt{\frac{1}{N-2}\sum_{n=1}^{N-1}(\Delta t(n) - \delta)^2} \tag{6}$$

The frequency domain analysis of HRV is to decompose the HRV into frequency domain components of different energies, and observe the activity changes of sympathetic and vagus nerve functions by analyzing the distribution of signal energy with frequency. The frequency domain features and calculation formula used in this paper are as follows, where the spectrum of the R-R interval sequence $t(n)$ for N cardiac cycles is $F(\omega)$:

- Power spectral density:

$$P_{(\omega)} = \left|F_{(\omega)}\right|^2 \tag{7}$$

- Low frequency:

$$LF = \sum P_{(\omega)}\text{,}\quad 0.04 < \omega < 0.15 \tag{8}$$

- High frequency:

$$HF = \sum P_{(\omega)}\text{,}\quad 0.15 < \omega < 0.4 \tag{9}$$

- LF to HF power ratio:

$$\mathrm{LF/HF} = \frac{LF}{HF} \tag{10}$$

3.4. Multi-level Features Recognition Network

Extracting static statistical features and dynamic timing features from heart rate through a multi-level pattern to compensate for the problem of static statistical features not considering the timing correlation of continuous heart rate. The features extracted from the two levels are concatenated and fused into feature vectors to achieve comprehensive extraction of heart rate. Input the fused heart rate features into the fully connected layer and softmax classifier to achieve the final fatigue recognition. As shown in Fig.2.

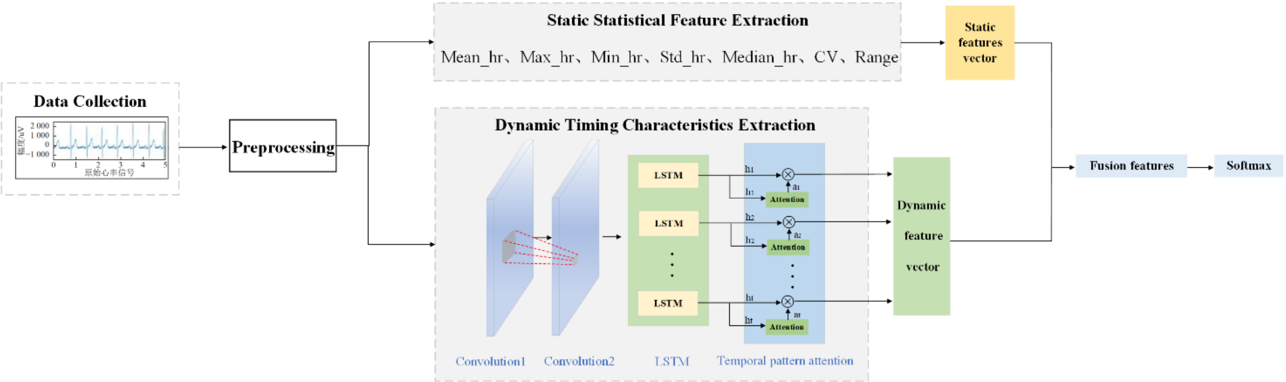

Fig. 2: Multi-level fatigue recognition network

4. Experiments and Performance Analysis

4.1. Experimental Setup

Data were collected within a highly realistic ATC simulation chamber equipped with an advanced civil aviation ATC simulation system replicating diverse flight scenarios. Traditional ECG measurements require sensors to be tightly attached to the skin, which can be intrusive for controllers. Therefore, to ensure portability and acceptance, participants wore physiological watch equipped with optical heart rate sensors on the back of the watch to collect heart rate data during their work. Twenty controllers (10 males and 10 females) each with more than 3 years of work experience were recruited from Jiangsu air administrative bureau. The controllers alternated as primary operators on different days to ensure data diversity. Prior to the experiments, participants were required to rest adequately (>7 hours) for 2 nights and were prohibited from consuming food and alcohol that may have affected the experimental results. All were aware of the experimental content and that they had the right to withdraw from participating in an experiment at any time. The simulation training mission included both low and high traffic densities, during which different control situations were arranged irregularly, ensuring a realistic reflection of the fatigue accumulation process.

4.2. Results and Analysis

Considering the different control load pressures caused by the working mode of air traffic controllers and changes in flight scenarios, a correlation analysis was conducted between heart rate data and work time. Due to the special nature of air traffic controllers' work, it was assumed in the experiment that each controller would start working from 00:00. The results are shown in Fig.3.

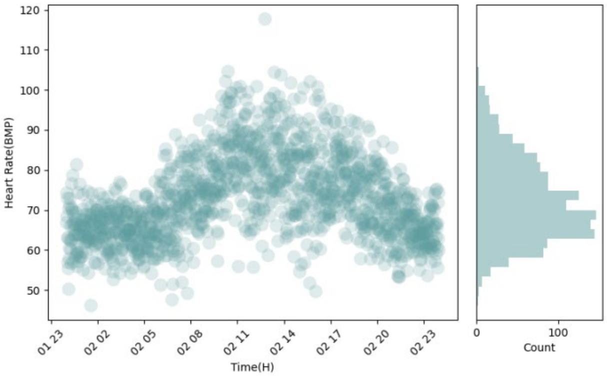

Fig. 3: The fluctuation state of heart rate over time

The results show the changes in heart rate of air traffic controllers at different times during a 24-hour period with increasing working hours. It can be seen that during the initial working stage, heart rate is mostly concentrated between 55-70 beats per minute, indicating that the body is in a baseline adaptive state. As work begins, the heart rate gradually increases, but not excessively, as the body gradually enters an active state and sympathetic nervous system activity increases. But as the working hours continue to increase, physical and mental fatigue gradually accumulates in the period after lunch. At this time, the heart rate fluctuates greatly and its stability decreases, manifested as scattered distribution of heart rate data points with abnormally high values in the figure. Afterwards, as work pressure decreased, the heartbeat gradually returned to baseline levels. Fully demonstrates the correlation between heart rate and mental fatigue.

The loss, accuracy, and model confusion matrix obtained through multi-level heart rate features recognition network for fatigue recognition of controllers are shown in Fig.4 and Fig.5.

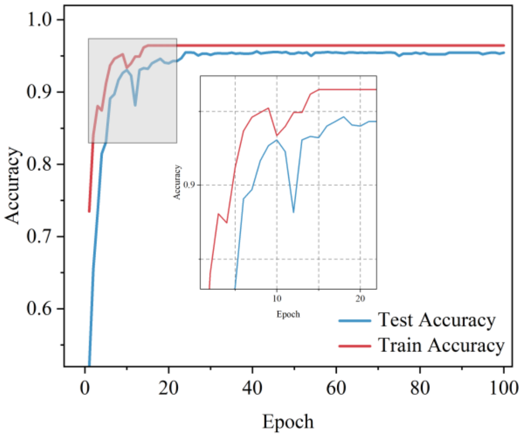

Fig. 4: Recognition accuracy

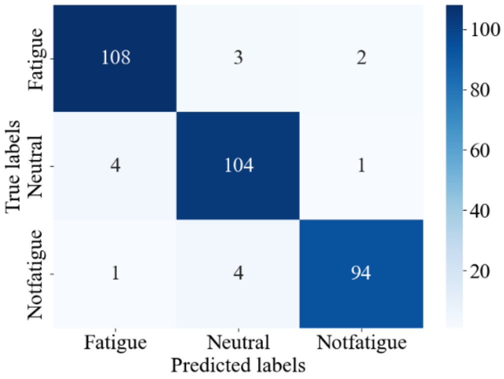

Fig. 5: Confusion matrix results

From the figure, it can be seen that the recognition accuracy of the training and testing sets gradually improves and remains stable with the increase of iteration epoch, ultimately reaching a recognition accuracy of 95.5%. The confusion matrix also shows a diagonal distribution, reflecting the robustness of the model's recognition and classification.

5. Conclusion

A multi-level heart rate fatigue features extraction and recognition algorithm was proposed to add physiological features in controllers' fatigue recognition. By combining CNN with LSTM to extract dynamic timing features, the local and global features of the heart rate data can be more easily focused. In addition, by fusing static statistical features with dynamic timing features, the model can more suitable to analysis the fatigue state. The experimental results on the heart rate dataset collected from on-duty controllers show that the proposed algorithm achieved a recognition accuracy of 95.5%.

In future research, both individual behavioural and physiological data of air traffic controllers will be considered to achieve accurate assessment of fatigue from multiple perspectives.

6. Acknowledgement

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