Fatigue Monitoring and Recognition During Basketball Sports via Physiological Signal Analysis

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ABSTRACT

Fatigue is a feeling that appears after the human body undergoes excessive physical or mental work. The fatigue may reduce the ability to complete work. When sport fatigue occurs, the athlete’s heart load continues to increase, muscles become sore, flexibility is reduced, thinking and judgment become slow, and the athlete is easily irritated. Thus, it is necessary to monitor the athlete’s status during sports, such as playing basketball. Generally, the ion current in the body will change when the athlete suffers fatigue. That means the sport fatigue may cause changes in the bioelectric signals of the human body. This paper adopts bioelectric signals to analyze athlete status to prevent sport fatigue during basketball. The experiments on a basketball sport dataset demonstrate the effectiveness of the proposed method.

KEYWORDS

Electrocardiograph Signal, Electromyography Signal, Fatigue Recognition, Physiological Signal, Support Vector Machine

1. INTRODUCTION

With the rapid development of society and the continuous improvement of people’s living standards, sport and exercise have become an indispensable part in people’s daily living. Exercise can strengthen the body and make people feel happy, but excessive exercise may cause physical damage and injury. There are also some special occupations, such as athlete, soldier, who requires a lot of sports training every day. Excessive training will weaken the training effect, and may lead to more serious consequences such as syncope, muscle damage and even sudden death (da Rocha 2019).

Fatigue is a kind of discomfort felt by humans. It is a feeling that appears after the human body undergoes a lot of physical or mental work. It will reduce people’s ability to complete work. Generally speaking, fatigue is divided into mental fatigue, physical fatigue and pathological fatigue. The sport fatigue is defined as that the body cannot maintain the function at a certain level, or cannot maintain a predetermined exercise intensity. When sport fatigue occurs, the athlete’s heart load will continue to increase, become more irritable than usual, muscle aches and flexibility decreases, and the necessary thinking ability in competitive sports such as judgment and reaction will also decrease.
Therefore, sports fatigue is a comprehensive physical and mental fatigue that combines mental, psychological, and physical strength.

Exercise fatigue is bound to cause changes in the biochemical conditions in the human body. Therefore, it will change the ion current in the human body. The associated bioelectric signals are easy to collect (Durant 2019). This paper adopts bioelectric signals to analyze sport fatigue.

The research about sport fatigue monitoring and recognition can classified as subjective evaluation (GÖKER 2018) and objective evaluation (Kelly 2017). The objective evaluation utilizes objective human biochemical and bioelectrical indicators to analyze sport fatigue, such as electrocardiogram, myoelectricity, blood lactic acid, blood oxygen concentration, body temperature, skin electricity, brain electricity, eye electricity, facial expression recognition, respiration. It is called physiological fatigue assessment (Yu 2019). The subjective evaluation analyzes the degree of fatigue of the human body by combining self-fatigue feeling and fatigue scale. As traditional exercise fatigue assessment, the subjective assessment is quick, direct and effective. However, it lacks objectivity merely adopting subjective evaluation. The sport fatigue analysis is a complicated process. It is difficult to comprehensively and accurately analyze and evaluate sport fatigue merely using subjective assessment. This paper combines objective evaluation and subjective evaluation to analyze sport fatigue to explore the relationship between physical fatigue indicators and mental fatigue during sports and overcome the weakness in subjective evaluation. In objective assessment, we adopt electrocardiograph (ECG) (Bhardwaj 2018) and electromyography (EMG) (Jebelli 2019).

In electrocardiograph related sport fatigue, it is generally used the heart rate variability (HRV) for analysis. The HRV changes with the degree of sport fatigue and is sensitive to sport fatigue. When the sport deepens, the high-frequency power peak gradually increases. That means the main energy of HRV gradually shifts to the right during sports. The intensity of sport just has a positive correlation with the sport fatigue level. The electrocardiograph is an effective indicator to reflect the intensity of sport fatigue.

The muscles are the direct source of the power during sports. The electromyography (EMG) signals, especially the surface EMG signals (Enoka 2019), is an important way to analyze the fatigue during sports. By analyzing the relation between muscle fatigue and surface electromyography (sEMG), the myoelectric value (IEMG) in the time domain can reflect the degree of muscle fatigue, whilst the average power frequency (MPF) in the frequency domain can reflect the change of fatigue better than the median frequency (MF). The MPF and MF of sEMG decrease with the increasing of muscle fatigue. Compared with the power spectrum of the sEMG signal before and after fatigue, the power spectrum after fatigue is shifted to the left than before fatigue.

In all, both ECG and EMG bioelectrical signals are highly correlated with sport fatigue. This paper adopts ECG signals and EMG signals to analyze sport fatigue in human daily exercise. For ECG signals and EMG signals, we consider the characteristics in both time domain and frequency domain. A flowchart of the fatigue recognition is illustrated in Figure 1.

The rest of the paper is organized as follows. The feature extraction for electrocardiograph and electromyography signals are provided in Section 2. The experimental results are reported in Section 3. The last Section is the conclusion and discussion.

2. THE FEATURE REPRESENTATION OF ELECTROCARDIOGRAPH AND ELECTROMYOGRAPHY SIGNALS

The heart is the most important organ in human body. Under the effect of the cyclical changes in the balance of external anion and cation concentration in the cell membrane, the cardiomyocytes regularly depolarize and repolarize to form a galvanic couple with the adjacent cell membrane and generate regular current pulses in the heart. The pulse can excite the muscle cells in the ventricles and atria and cause the heart to contract and relax periodically. The heart becomes the blood pump to allow blood to circulate around the body with sufficient power to maintain the normal operation of human body.
In each cardiac cycle, the depolarization and repolarization process of each cardiomyocyte can be regarded as a dipole field. The human body has conductivity and can be regarded as a volume conductor. There is a potential difference when an electric field is generated in the human body. The potential difference can be collected on the surface of the human body through special electrodes and amplifiers.

A whole cardiac cycle of ECG signal includes P wave, T wave, U wave and QRS complex. The P wave, T wave and U wave are smooth, whilst the QRS complex is steep. The peak point of QRS complex is called R peak. In general, the R peak is also the peak point of the entire cardiac cycle. The RR interval is the time interval between the R peaks of two adjacent cardiac cycles. An illustration of a cardiac cycle is shown in Figure 2.

The ECG signal is a very weak bioelectric signal. The amplitude is generally between 0-4mv, whilst the spectral energy is between 0.5-100 Hz. Most of the energy is distributed in 0.5-20 Hz. The noise in ECG signal includes power frequency interference, baseline drift, motion artifacts, and myoelectric interference. The power frequency interference mainly comes from the 220 V alternating current in the power supply, and its frequency is generally 50 Hz or a multiple of 50 Hz. The myoelectric interference comes from the muscle contraction during the exercise. The baseline drift mainly comes from the human breathing and signal acquisition equipment. The frequency of baseline drift is generally between 0.1 Hz and 2 Hz. It is low-frequency interference. The motion artifact is a kind of peculiar noise of bioelectricity in the process of human movement, whose frequency is seriously overlapped with the main energy of ECG signal. The motion artifact will seriously affect the heart waveform of electrical signal and the analysis result.

This paper adopts fast median filtering (Ataman 1980) to remove the baseline drift in ECG signals. The median filtering is based on the idea of sorting statistics to process nonlinear signals. It
is effective to remove the impulse noise. While removing noise, it can still protect the edges of useful signals to prevent being blurred. For a signal \( x \), we set a filter window with length \( 2t + 1 \). The filter window is initialized by \( y = [x(n - t), \ldots, x(n), \ldots, x(n + t)] \). The sequence \( y = [x(n - t), \ldots, x(n), \ldots, x(n + t)] \) is sorted in ascending order as \( z = [z(1), \ldots, z(2t + 1)] \). The middle element in \( z \) is selected as output and the filter window is moved one bit backward in \( x \). Then, it removes an element in \( z \) and adds \( x(n + t + 1) \) into sequence \( z \) to sort again. The middle element in the new sort sequence is used as output. The procedure is repeated until the filter window reaches the end of signal \( x \).

The methods to filter out motion artifacts in ECG signals include wavelet decomposition, periodic element analysis, and adaptive filtering. The wavelet decomposition may cause the distortion of the signal. The periodic element analysis cannot identify the motion artifacts effectively. This paper adopts adaptive filtering to remove motion artifacts in ECG signals.

The adaptive filter can update its filtering coefficient in real time according to the input signal and feedback error signal at each time. Thus, it can achieve good filtering effect with the change of noise. In this paper, the three-axis acceleration signal is used as the reference signal for adaptive filtering to remove motion artifacts in ECG signals. Least Mean Square (LMS) Filter (Sathesh 2020) is an adaptive filtering algorithm based on the idea of random gradient descent. It tries to minimize error mean square between the expected response and the output signal. The noisy ECG signal is used as the expected response. It adopts an estimated step vector in the iteration of input signal to update adaptive filter weight coefficients until reaching the optimal terminate condition.

Let \( r(n) \) represent the noisy input signal, \( x(n) \) represent the triaxial acceleration signal, \( y(n) \) represent the output signal of the filter, \( e(n) \) represent the error signal, and \( w(n) \) represent the weight coefficient vector of the filter at each time. Then, the following equations hold:
\[ y(n) = x(n) \ast w(n)^T \]  \hspace{1cm} (1)

\[ e(n) = r(n) - y(n) = r(n) - x(n) \ast w(n)^T \]  \hspace{1cm} (2)

The cost function is defined as the mean square of error signal, which is written as follows:

\[ J = E(e(n)^2) \]  \hspace{1cm} (3)

Since the adaptive filtering adjusts the filtering parameters to adapt the new unknown noise according to error signal \( e(n) \), the expected operation in cost function can be omitted and the cost function can be rewritten as follows:

\[ J = e(n)^2 \]  \hspace{1cm} (4)

The gradient of Equation (4) is written as follows:

\[ \nabla J(n) = \frac{\partial J(n)}{\partial w(n)} = -2e(n)x(n) \]  \hspace{1cm} (5)

The update rule for filter coefficients is written as follows:

\[ w(n+1) = w(n) - \frac{1}{2} \mu \nabla J(n) \]  \hspace{1cm} (6)

Substituting equation (5) into equation (6), the following equation holds:

\[ w(n+1) = w(n) + \mu e(n)x(n) \]  \hspace{1cm} (7)

The weight coefficients in LMS filter are updated according to equation (1), (2) and (7). The \( \mu \) is step constant, which satisfies \( 0 < \mu < 2 \). For LMS filter, if the \( \mu \) is set too large, the filter will converge quickly and the steady state error will also be large; otherwise, the filter will converge slowly and the error is steady.

The power frequency interference in ECG signal mainly concentrates in the vicinity of 50 Hz or an integral multiple of 50 Hz. It does not coincide with the main frequency band of ECG signal and can be removed by a Butterworth low-pass filter.

The heart rate variability (HRV) is the time sequence of intervals between adjacent cardiac cycles, which reflects the changes of each cardiac cycle. The HRV contains lots of information related to human cardiovascular system. When human body is during sports, the cardiovascular system will change greatly and HRV behaves obvious and regular changes. In this paper, the HRV signals are represented as the features in time domain, frequency domain, and nonlinearity. The features in time domain includes the standard deviation of NN intervals (SDNN), root mean square of successive
differences (RMSSD), standard deviation of successive differences (SDSD), nnvgr, the proportion of NN50 (pNN50) and HR. The features in frequency domain include low frequency power (LF), high frequency power (HF), total power (TP) and low frequency / high frequency power ratio (LF / HF).

According to the ion current theory, the repolarization and depolarization of muscle cell membrane is the reason to form the electromyography (EMG). The cell membrane is semi permeable. Under the muscle relaxation status, the cation concentration outside the cell membrane is higher than that inside the membrane through the effect of ion pump. The outer potential difference of muscle cell is high, whilst the inner potential difference of muscle cell is low. The polarization forms. Under the muscle contraction status, the cell membrane is stimulated, whilst the permeability of cell membrane changes. More sodium channels open. Thus, massive sodium ions flow into the cell membrane. The potential difference between the inside and outside of the membrane reaches 0 mV (depolarization) to + 30 mV (hyperpolarization). The muscle electricity is generated by above potential difference changes. When the muscle relaxes, the sodium ion quickly flows out and the channel closes until the resting potential is restored. That is repolarization. The potential difference changes are the source of muscle electricity.

Since the human body is a good conductor, the muscle electricity generated by the above process can be transmitted to the human epidermis through the human tissue. We can directly collect the muscle electricity generated by muscle contraction from the human skin. That is the surface EMG signal (sEMG). Compared with needle electrode EMG signals, the sEMG signals are noninvasive, convenient, and can be obtained by multi-channel. This paper adopts sEMG signals to recognize fatigue status.

EMG signal is the bioelectrical signal produced during muscle contraction. When muscle relaxes, no EMG signal is detected. The spectrum energy distribution of EMG is wider than that of EEG. The main energy distributes in the band 20-150 Hz. The amplitude is generally in the range 0-4 mV. The EMG signal is a kind of non-stationary random signal. Its mechanism determines that it has strong uncertainty and high individual differences.

Before utilizing EMG signals to analyze the fatigue status, it is necessary to filter the noises in EMG signals. The noises in EMG signals include power frequency interference, motion artifact, and baseline drift. The power frequency interference is filtered by Butterworth low pass filter and Babbitt band stop filter. The motion artifact and baseline drift are filtered by high pass Babbitt filters.

The denoised EMG signals are represented by the features in time domain and the features in frequency domain. Time domain features include: average rectified value (ARV), integral electromyography value (iEMG) and root mean square value (RMS). The ARV, iEMG and RMS are represented by equation (8), (9), and (10), respectively:

\[
ARV = \frac{1}{t_2 - t_1} \int_{t_1}^{t_2} e(t) dt
\]

\[
iEMG = \int_{t_1}^{t_2} e(t) dt
\]

\[
RMS = \sqrt{\frac{1}{t_2 - t_1} \int_{t_1}^{t_2} e(t)^2 dt}
\]
The frequency domain features include median frequency (MF) and average power frequency (MPF) and total electromyography power (TP). The MF, MPF and TP are represented by equation (11), (12), and (13), respectively:

$$\int_0^{MF} psdemg(f) df = \int_0^\infty psdemg(f) df$$  \hspace{1cm} (11)

$$MPF = \frac{\int_0^\infty f \cdot psdemg(f) df}{\int_0^\infty psdemg(f) df}$$  \hspace{1cm} (12)

$$TP = \int_0^\infty psdemg(f) df$$  \hspace{1cm} (13)

After obtaining the features of ECG signal and EMG signal, we adopt AI technology to learn a classifier as the oracle to predict the athlete’s future status through a training set that consists of massive historical samples. The common used classification model includes support vector machine, random forest, Gaussian processing, k-nearest neighbors, linear discriminant analysis etc. In this paper, we adopts weighted support vector machine as the classification algorithm which is an improved version of classical support vector machine.

Both classical support vector machine (Suthaharan 2016) and weighted support vector machine (Zhu 2016) are only suitable for two-class classification problem. In order to solve multi-class classification, we need to adopt either one-to-one strategy or one-to-rest strategy (Franc 2002). In one-to-one strategy, each pair of classes is converted as a two-class classification problem. Then, a multi-class classification problem with \(c\) classes is converted as \(\frac{c(c-1)}{2}\) two-class classification problems. The final classification result is devoted by these \(\frac{c(c-1)}{2}\) two-class classifiers. In one-to-rest strategy, a multi-class classification problem with \(c\) classes is converted as \(c\) two-class classification problems. In each two-class classification problem, one class is used as positive class, whilst the rest classes are all used as negative classe. In one-to-one strategy, when the number of classes is large, it will require to learn massive two-class classifiers. In one-to-rest strategy, the negative samples would be much more than positive samples due to the negative samples are from \(c-1\) classes. The two-class classification in one-to-rest strategy is an unbalance problem which may lead poor performance. In this paper, we adopts one-to-one strategy for multi-class classification in fatigue recognition.

3. EXPERIMENTS AND SIMULATIONS

In this section, we will verify the proposed fatigue monitoring and recognition scheme. First, we collect the ECG signals and EMG signals from 40 volunteers. For each volunteer, the collected ECG signal and EMG both last 5 minutes and the collection is repeated several times to cover different fatigue states including mild fatigue, moderate fatigue, severe fatigue, and no fatigue. Lastly, we collect 352 mild fatigue records, 297 moderate fatigue records, 318 severe fatigue records, and 786 no fatigue records. All collected records are randomly split as training part and test part. The training
part is used to learn classification model, whilst the test part is used to evaluate the proposed fatigue recognition model.

Then, the features of ECG signals, the features of EMG signals, and the fusion of features from ECG signals and EMG signals are used to construct learning model, respectively. In weighted support vector machine, the Gaussian function is adopted as kernel function. The parameter $\sigma$ in Gaussian function, penal factor $C$ in weighted support vector machine are tuned by grid search to ensure the best accuracy in the range $\{2^{-1}, 2^0, \ldots, 2^7\}$ for $\sigma$ and $\{2^{-3}, 2^{-4}, \ldots, 2^3\}$ for $C$. The instance-weights are obtained by extended nearest neighbor chain which is proposed in (Zhu 2016, Zhu 2017). The accuracy of fatigue recognition is reported in Table 1, Table 2, and Table 3 for features from ECG signals, features from EMG signals, and fused features, respectively.

In Table 1, 2, and 3, we also compare the weighted support vector machine (WSVM) with classical support vector machine (SVM). The OvsR represents that the one-to-rest strategy is adopted for multi-class classification problem, whilst OvsO represents that the one-to-one strategy is adopted for multi-class classification problem.

### Table 1. The accuracy of fatigue recognition merely using features of ECG signals

|                  | SVM (OvsR) (%) | SVM (OvsO) (%) | WSVM (OvsR) (%) | WSVM (OvsO) (%) |
|------------------|----------------|----------------|-----------------|-----------------|
| Mild fatigue     | 90.24          | 90.86          | 92.04           | 92.68           |
| Moderate fatigue | 89.11          | 89.93          | 91.34           | 90.91           |
| Severe fatigue   | 89.23          | 90.17          | 91.03           | 92.14           |
| No fatigue       | 90.94          | 91.35          | 92.62           | 94.51           |
| total            | 90.49          | 90.97          | 92.36           | 93.07           |

### Table 2. The accuracy of fatigue recognition merely using features of EMG signals

|                  | SVM (OvsR) (%) | SVM (OvsO) (%) | WSVM (OvsR) (%) | WSVM (OvsO) (%) |
|------------------|----------------|----------------|-----------------|-----------------|
| Mild fatigue     | 89.81          | 90.35          | 91.51           | 91.61           |
| Moderate fatigue | 88.87          | 89.22          | 90.87           | 91.24           |
| Severe fatigue   | 88.93          | 89.37          | 91.07           | 91.89           |
| No fatigue       | 90.41          | 90.44          | 92.15           | 93.59           |
| total            | 89.93          | 90.27          | 91.83           | 92.35           |

### Table 3. The accuracy of fatigue recognition when using fused features of ECG and EMG signals

|                  | SVM (OvsR) (%) | SVM (OvsO) (%) | WSVM (OvsR) (%) | WSVM (OvsO) (%) |
|------------------|----------------|----------------|-----------------|-----------------|
| Mild fatigue     | 93.53          | 94.28          | 94.82           | 95.58           |
| Moderate fatigue | 92.59          | 93.37          | 93.18           | 94.79           |
| Severe fatigue   | 93.01          | 93.42          | 93.52           | 95.34           |
| No fatigue       | 94.37          | 95.09          | 95.19           | 96.63           |
| total            | 93.84          | 94.69          | 94.87           | 95.61           |
From Table 1, it can be found that the accuracy of fatigue recognition achieves 90.49%, 90.97%, 92.36%, and 93.07% for SVM (OvsR), SVM (OvsO), WSVM (OvsR), and WSVM (OvsO) when using features of ECG signals, respectively. The WSVM (OvsO) performs better than others merely using features of ECG signals. From Table 2, it can be found that the accuracy of fatigue recognition achieves 89.93%, 90.27%, 91.83%, and 92.35% for SVM (OvsR), SVM (OvsO) WSVM (OvsR), and WSVM (OvsO) when using features of EMG signals, respectively. The WSVM (OvsO) also performs better than others merely using features of EMG signals. From Table 3, it can be found that the accuracy of fatigue recognition achieves 93.84%, 94.69%, 94.87%, and 95.61% for SVM (OvsR), SVM (OvsO), WSVM (OvsR), and WSVM (OvsO) when using fused features of ECG signals and EMG signals. The WSVM (OvsO) performs better than others as well when using fused features of ECG signals and EMG signals. Compare with features of ECG signals and features of EMG signals, the fused features of ECG signals and EMG signals can increase 3 to 4 percent. The F1-measure and Recall when using WSVM (OvsO) are reported in Figures 3 and 4, respectively.

From the results in Figures 3 and 4, we can obtain the same conclusion that the fused features of ECG signals and EMG signals preforms better than merely using features of ECG signals or EMG signals.

4. CONCLUSION

The fatigue recognition is an important topic in the community of smart health exercise, which can avoid injuries or incidents caused by excessive exercises or sports. In order to implement automatically fatigue recognition, this paper proposes a framework to recognize fatigue state in sports with the help of

![Figure 3. The F1-measure of fatigue recognition when using WSVM (OvsO) as classification model](image)

![Figure 4. The recall of fatigue recognition when using WSVM (OvsO) as classification model](image)
signal processing technology and AI technology. First, the ECG signals and EMG signals are collected by wearable devices. Second, the collected signals are processed by signal processing technology, such as fast median filtering, least mean square (LMS) filter, Butterworth filter, and Babbitt filter, to remove the noises in ECG signals and EMG signals. Third, the denoised signals are represented as the features in time domain and the features in frequency domain. Fourth, the extracted features are used to learn a classifier that is used to predict future fatigue state. The experimental results show that the proposed method can identify more than 95% fatigue states.

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