Journal of Network Intelligence ©2025 ISSN 2414-8105
Taiwan Ubiquitous Information Volume **10**, Number **4**, November **2025**

A Data-Driven Study on Monitoring and Assessment of Psychological Stress in Athletes' Training

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Received July 10, 2024, revised January 29, 2025, accepted August 12, 2025.

Abstract. *With the development of competitive sports, athletes face increasing psychological stress during training and competition, and this stress not only affects athletic performance, but may also endanger health. However, traditional psychological stress assessment methods mostly rely on subjective reports or simple physiological monitoring, making it difficult to capture the psychological state of athletes during high-intensity training in real time and accurately. To solve this problem, this paper proposes an athlete psychological stress monitoring and assessment method based on multiple physiological signals and Harris Hawk Optimization-K Nearest Neighbour (HHO-KNN) algorithm. Firstly, this paper adopts the International Affective Preconditioning Picture Store (IAPS) as the main tool for emotion elicitation, and designs and implements an emotion elicitation experiment in a laboratory environment, where multiple physiological signals of athletes are collected in real time, including heart rate (HR), galvanic skin conductance (GSR), respiratory rate (RR), and blood oxygen saturation (SpO2). These signals are acquired synchronously with high-precision equipment to ensure data integrity and accuracy. Next, in data pre-processing, we denoised and baseline corrected the physiological signals to extract key features that could reflect psychological stress. Then, the HHO algorithm is used to optimally select these features and determine the optimal parameters of the KNN classifier. The accuracy of feature selection and the performance of the classifier can be effectively enhanced by the global search capability of HHO. Eventually, the HHO-KNN classifier is used for recognition and classification of emotional states. The experimental results show that the system is able to accurately distinguish the psychological stress of athletes in different emotional states, and especially performs well in distinguishing high arousal emotions such as anger and fear.*
Keywords: multi-physiological signals; harris hawk optimisation; K-nearest neighbors; emotion recognition; psychological stress monitoring

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1. **Introduction.** The monitoring and assessment of psychological stress has received increasing attention in modern athlete training [1, 2]. As the level of competitive sports continues to rise, athletes not only have to face intense physical confrontation and technical challenges, but also have to cope with great psychological stress. Excessive psychological stress not only affects athletes' competitive status, but also may lead to serious health problems [3]. Therefore, how to accurately monitor and assess the psychological stress state of athletes during training has become an important research topic in the field of sports science and psychology.

In recent years, data-driven approaches have shown great potential in psychological stress monitoring and assessment. With the help of advanced physiological signal acquisition technology, we can acquire multidimensional physiological data of athletes in real time, such as heart rate, skin conductance, respiratory rate and blood oxygen saturation. These physiological signals are closely related to psychological states [4], and by analysing these signals, we can reveal the changes of psychological stress in athletes under different training intensities and environments. The aim of this study is to explore how multiple physiological signals and advanced machine learning algorithms, such as Harris Hawk Optimization (HHO) [5, 6] and K-Nearest Neighbors (KNN) [7, 8, 9], can be used to achieve accurate identification and assessment of psychological stress in athletes.

The research in this paper not only has important theoretical value, but also has a wide range of prospects in practical application. Through accurate psychological stress monitoring and assessment, we can provide personalised training advice to athletes to help them better manage stress, optimise training effects and enhance competitive performance. Meanwhile, the results of this study can also be applied to other high-stress occupations, such as firefighters, military personnel, and pilots [10, 11, 12], to provide scientific support for their mental health. Overall, this study is significant in promoting the cross-fertilisation of sports science and psychology, and facilitating intelligent and data-driven mental health management.

1.1. **Related work.** Emotion recognition, as a technique capable of understanding and decoding human emotional states, has a wide range of applications in the fields of psychology, computer science and biomedical engineering [13, 14]. Traditional emotion recognition methods mainly rely on single physiological or behavioural signals, such as facial expressions, speech features and simple physiological data. However, these methods have many limitations in practical applications.

Early emotion recognition research focused on the analysis of facial expressions and speech signals, and pioneering work by Gaebel and Wölwer [15] demonstrated the theoretical basis on which facial expressions could be used to recognise basic emotions, with their "basic emotion theory" highlighting the direct correlation between a number of facial expressions and specific emotions. This research has led to many subsequent emotion recognition systems relying on facial expression analysis. However, one of the main problems with the use of facial expressions for emotion recognition is their dependence on ambient lighting and camera equipment, and the difficulty of obtaining stable recognition results in non-static scenes.

Physiological signals as an important source of data for emotion recognition have received more and more attention in recent years, and the study of Singh et al. [16] demonstrated the possibility of using physiological signals such as HRV, GSR, etc., to recognise the emotional state of a driver. They found that physiological signals are more distinctive in response to high stress and tension, which lays the foundation for emotion recognition based on physiological signals. However, the accuracy of emotion recognition based on a single physiological signal is limited and easily affected by individual differences.

With the advancement of technology and the increase of application requirements, the current research direction of emotion recognition has gradually shifted to multimodal and multidimensional data fusion, especially the data-driven methods that combine multiple physiological signals [17, 18].

Pinto et al. [19] proposed a method to combine multiple physiological signals (e.g., heart rate, skin conductance, and electromyographic signals) for emotion recognition. It was shown that the fusion of multiple physiological signals significantly improved the accuracy of emotion recognition, especially when dealing with complex emotional states. However, the heterogeneity of the signals and the management of high-dimensional features became major challenges, requiring effective feature selection and dimensionality reduction techniques. Since then, Alam et al. [20] further investigated the combination of multi-physiological signals with machine learning models using traditional classifiers such as Support Vector Machines (SVMs) and Random Forests (RFs) to deal with high-dimensional data, and despite some successes, the optimisation and real-time performance of the models still need to be improved.

In recent years, feature selection and parameter optimisation based on intelligent optimisation algorithms have become a hot research topic. Gao et al. [21] used particle swarm optimisation (PSO) algorithm to select physiological signal features and combined with convolutional neural network (CNN) to improve the accuracy of emotion recognition. It was shown that the global search capability of PSO can effectively reduce the complexity of the feature space, but the algorithm is computationally expensive when dealing with high-dimensional data. To address these issues, Kanwal and Asghar [22] combined Genetic Algorithm (GA) and Deep Learning methods to optimise the performance of emotion recognition systems by finding the optimal subset of features and model parameters through multiple rounds of evolutionary search, however, the complexity and computational overhead of this method is still large. In the current research, Harris Hawk Optimization (HHO), as an emerging intelligent optimisation algorithm [23], is beginning to be applied in the field of feature selection and parameter optimisation due to its efficient global search capability.

1.2. **Motivation and contribution.** Although current research on emotion recognition has made significant progress in theory and application, it still faces many challenges in practical application. Most emotion recognition systems rely on a single type of physiological signal or simple multimodal fusion, which makes it difficult to accurately recognise athletes' emotional states in complex and dynamic environments. The heterogeneity and high dimensionality of physiological signals, as well as the optimisation problem of classifier parameters, are key challenges that emotion recognition systems need to overcome in terms of efficiency and accuracy. To address these challenges, this paper proposes an emotion recognition method based on multiple physiological signals and the HHO-KNN algorithm. The main innovations and contributions of this paper include:

(1) **Integration and optimisation of multi-physiological signals:** Aiming at the limitations of the single physiological signal approach, this paper proposes a multi-physiological signal integration scheme, which combines multiple physiological signals, such as Heart Rate (HR), Galvanic Skin Response (GSR), Respiration Rate (RR) and Blood Oxygen Saturation (SpO2). Through the fusion of multiple signals, the multi-dimensional physiological response characteristics of different emotional states are captured, which improves the accuracy and robustness of emotion recognition.

(2) **Feature selection and KNN parameter optimisation based on HHO algorithm:** In this paper, HHO algorithm is introduced for feature selection and parameter optimisation of the KNN classifier. The global search capability of HHO makes it able

to find the optimal subset of features efficiently in high-dimensional feature space and optimise the parameter K of the KNN, which significantly improves the accuracy and efficiency of emotion recognition.

2. Data-driven multi-physiological signal processing in athletes.

2.1. Emotion category analysis. In the field of psychological emotion recognition in athletes, the study of emotion categories is the foundation of an emotion recognition system. The accuracy of emotion recognition relies on the precise definition and classification of emotion categories. The field of psychology has a rich history of research on emotions, but a unified system for defining and classifying emotions has not yet been developed. In this paper, in the study of psychological emotion recognition in athletes, the more widely accepted emotion classification method is used to analyse and classify emotions in detail in combination with actual sports scenarios.

2.1.1. *Overview and categorisation.* Psychologists usually classify emotions into two main categories: discrete emotion models and continuous emotion models. The discrete emotion model views emotions as several separate basic emotions, such as anger, fear, and happiness. Each basic emotion is expressed through specific physiological responses and behaviours. In this model, complex emotional states can be viewed as different combinations and variants of basic emotions.

Continuous emotion models, on the other hand, view emotions as a multidimensional continuum in which emotions are mapped to points in a multidimensional space. Commonly used two-dimensional models include the Valence dimension and the Arousal dimension. The Valence dimension indicates a positive or negative evaluation of the emotion, such as pleasant or unpleasant, while the Arousal dimension indicates the degree of physiological arousal, such as whether one is calm or agitated.

2.1.2. *Specific application.* In the study of this paper, for the special environment and stress state of athletes, we adopted the continuous emotion model and combined some features of the discrete emotion model to specifically analyse the categories of emotions in the stress state. In particular, emotions under stress states are usually expressed as positive (e.g., excitement) or negative (e.g., anxiety) responses, which can be distinguished and analysed by changes in physiological signals.

In Figure 1, we show a coordinate system for emotions based on valence and arousal dimensions. Emotions with high arousal with positive valence, such as anger and pleasure, typically exhibit higher heart rate and skin conductance responses. Whereas emotions with low arousal with negative valence, such as calmness and boredom, show lower levels of physiological activation.

In order to better describe and recognise emotions, we quantify and classify the features of physiological signals. Let V denote the potency dimension and A denote the arousal dimension, the emotion E can be expressed as: $E = (V, A)$. The specific features of different emotions are described as follows:

$$E_i = \sum_{j=1}^{n} w_j S_j \tag{1}$$

where E_i is the i-th emotion, w_j is the weight of the physiological signal S_j, and n is the number of signals. By weighting and summing the eigenvalues of different physiological signals, the eigenvector of a particular emotion can be derived.

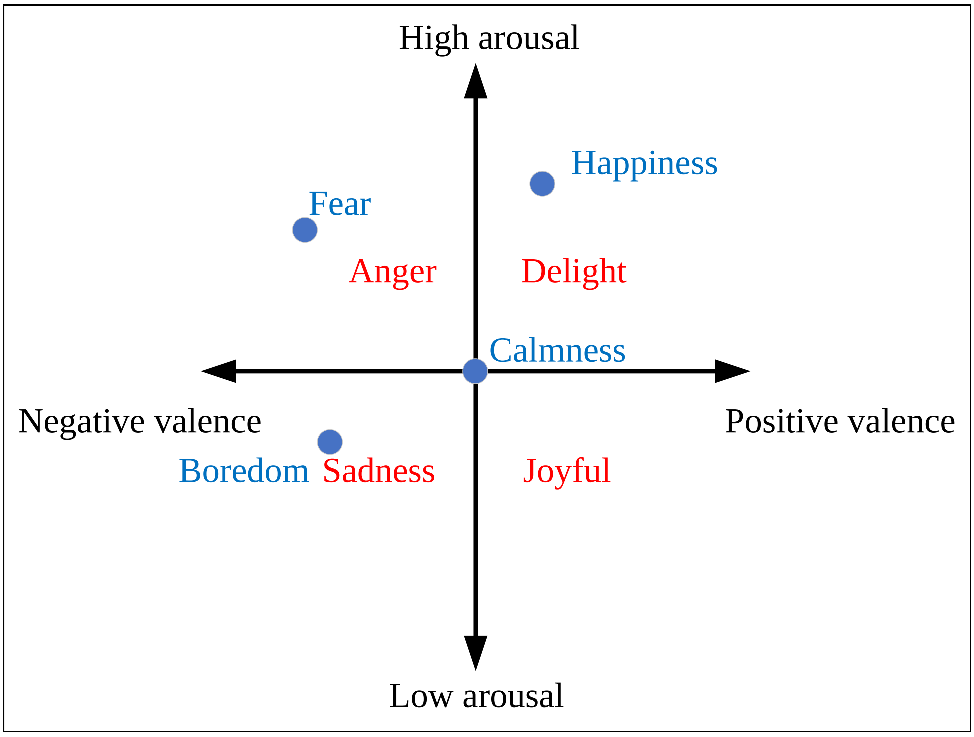

Figure 1. Emotion latitude coordinate

2.2. **Acquisition of physiological signals.** The acquisition of physiological signals is a crucial step in the psycho-emotional recognition system of athletes. Accurate physiological signal data is the basis for efficient and accurate emotion recognition. In this paper, we designed and implemented a complete physiological signal acquisition scheme to capture the physiological responses of athletes in different emotional states. These signals include heart rate, skin conductance, respiration rate and oxygen saturation [24]. The following section details the physiological signal acquisition process and the equipment used.

2.2.1. *Acquisition equipment and parameters.* In order to obtain high quality physiological signal data, we used an advanced multi-channel physiological signal acquisition device. This device is capable of recording multiple physiological signals synchronously and providing highly accurate data output. The selection of multiple physiological signals is as follows:

(1) **Heart Rate (HR):** indicates the number of times the heart beats per minute. Changes in heart rate can reflect the degree of excitement of the emotional state. The device used has a highly sensitive ECG sensor with a heart rate sampling frequency of 1000 Hz.

(2) **Galvanic Skin Response (GSR):** Measurement of changes in skin conductance to reflect sympathetic nervous system activity, often used to detect stress and emotional responses. The sampling frequency is 1000 Hz.

(3) **Respiration Rate (RR):** Indicates the number of breaths per minute, reflecting the changes in respiration during emotional stress. A high-precision respiratory sensor with a sampling frequency of 1000 Hz is used.

(4) **Blood Oxygen Saturation (SpO2):** Indicates the degree of oxygen saturation in the blood, which usually changes during emotional stress. It is collected by pulse oximetry with a sampling frequency of 1000 Hz.

These signals are acquired synchronously over multiple channels to provide a comprehensive view of the athlete's emotional state. The equipment used and its key parameters are shown in Table 1.

Table 1. Physiological Signal Acquisition Devices and Parameters

Signal Type	Equipment Name	Model Number	Sampling Frequency	Description of the Main Parameters
HR	High Precision Electrocardiograph	BioPac MP160	1000 Hz	Measuring range 30–240 times/minute, error $\leq 2\%$
GSR	Skin Conductivity Meter	Shimmer GSR+	1000 Hz	Conductivity range 10μS–100μS with error $\leq 3\%$
RR	Respiratory Rate Sensor	Vernier Go Direct	1000 Hz	Measurement range 0–100 times/minute, error $\leq 5\%$
SpO_2	Pulse Oximeter	Nonin WristOx2	1000 Hz	Measuring range 70–100% with error $\leq 2\%$

The BioPac MP160 is a high-precision physiological signal acquisition system that is widely used in biomedical research. It is equipped with multi-channel recording capability, which allows simultaneous acquisition of multiple physiological signals. Its ECG module provides high-resolution heart rate data, which helps to accurately detect heart rate fluctuations during emotion changes.

The Shimmer GSR+ specialises in the precise measurement of skin conductance for the assessment of psychological stress and emotional responses. Lightweight and easy to wear, it is suitable for prolonged physiological signal monitoring. Highly sensitive electrodes capture subtle skin conductance changes, reflecting small differences in emotional state.

The Vernier Go Direct is a portable respiratory rate sensor for use in a wide range of physiological laboratory environments. It is capable of recording changes in respiratory rate in real time, providing accurate analysis of respiratory patterns. The device is easy to operate and highly stable, making it suitable for both laboratory and field collection.

The Nonin WristOx2 is used to monitor blood oxygen saturation in a wide range of medical and sports science applications. The wrist-worn design facilitates continuous monitoring during training or competition. Provides highly accurate blood oxygen and pulse rate data, reflecting the effects of emotional and physiological stress on blood oxygen levels.

2.2.2. *Acquisition process.* In physiological signal acquisition, we designed a set of standardised experimental processes to ensure the accuracy and consistency of the data. The whole process includes the following steps:

(1) **Experiment preparation:** Before the experiment started, firstly, let the athletes fully understand the purpose and process of the experiment and sign the informed consent form. Ensure good contact between all sensor devices and the athlete's body to avoid the influence of motion artefacts on the data.

(2) **Resting state baseline acquisition:** Physiological signals of the athlete in the resting state are recorded as baseline data before the emotion is evoked. The resting baseline data helps the accuracy of subsequent data denoising and emotion recognition.

(3) **Emotional evocation and data acquisition:** The target emotional state of the athlete is evoked by playing specific emotional evocation material (e.g., stimulating videos or pictures) [25]. At the same time, physiological signals such as heart rate, skin conductance, respiratory rate and oxygen saturation are recorded in real time.

(4) **Emotional calming period:** At the end of each set of emotion-evoking experiments, athletes were given a period of time for emotional calming. Physiological signals during the emotional calming period were recorded to ensure that the athlete returned to a state close to baseline when moving on to the next set of experiments.

To describe and analyse the acquired physiological signals, we use the following mathematical representation:

$$S(t) = \{HR(t), GSR(t), RR(t), SpO_2(t)\} \quad (2)$$

where $S(t)$ denotes the vector of physiological signals acquired at time t, containing heart rate $HR(t)$, skin conductance $GSR(t)$, respiratory rate $RR(t)$ and oxygen saturation $SpO_2(t)$. By capturing and analysing these signals, physiological response characteristics can be obtained at each time point for subsequent emotion recognition.

2.3. **Pre-processing of physiological signals.** In athletes' mental-emotional recognition, the raw physiological signals collected often contain noise and irrelevant information, and these interfering factors will affect the subsequent feature extraction and emotion recognition. Therefore, preprocessing of physiological signals is crucial. In this paper, the process of physiological signal preprocessing will be described in detail, including signal denoising, baseline signal removal and other steps.

2.3.1. *Signal denoising.* Physiological signals are interfered with by a variety of noises during the acquisition process, including environmental noise, electrical interference and motion artefacts. In order to improve the quality of the signal and the accuracy of subsequent analyses, the raw signal must be denoised. We used several common signal processing methods as follows.

A **Low-Pass Filter (LPF)** is used to remove high-frequency noise such as power supply noise and high-frequency interference. The cut-off frequency f_c is set and a band of 0.5–30 Hz is usually chosen to preserve the main signal components such as heart rate and respiratory rate. The transfer function of the low-pass filter can be expressed as follows:

$$H_{LP}(f) = \frac{1}{1 + (f/f_c)} \tag{3}$$

where $H_{LP}(f)$ is the frequency response of the low-pass filter and f_c is the cutoff frequency.

The **High-Pass Filter (HPF)** is used to remove low-frequency noise such as baseline drift and slow breath fluctuations. The cut-off frequency f_c is usually set in the range of 0.01–0.5 Hz. The transfer function of a high-pass filter can be expressed as follow:

$$H_{HP}(f) = \frac{(f/f_c)^2}{1 + (f/f_c)^2} \tag{4}$$

where $H_{HP}(f)$ is the frequency response of the high-pass filter.

A **Band-Pass Filter (BPF)** combines low-pass and high-pass filters and is used to extract signal components in a specific frequency range, such as the frequency range of heart rate. The transfer function of a band-pass filter can be expressed as follows:

$$H_{BP}(f) = H_{LP}(f) \cdot H_{HP}(f) \tag{5}$$

where $H_{BP}(f)$ is the frequency response of the bandpass filter, combining the characteristics of both the high-pass and low-pass filters.

An **Adaptive Filter** automatically adjusts the filter parameters according to the statistical characteristics of the input signal to minimise the noise component. Commonly used algorithms include the Least Mean Squares (LMS) algorithm with the update rule:

$$w(n + 1) = w(n) + \mu x(n)e(n) \tag{6}$$

where $w(n)$ is the filter weight at the n-th iteration, μ is the step factor, $x(n)$ is the input signal, and $e(n)$ is the error signal.

Through these filtering and denoising techniques, the noise component of the physiological signal can be significantly reduced, preserving the main features of the signal and providing clear input data for subsequent feature extraction and emotion recognition.

2.3.2. *Baseline signal removal.* Baseline drift is a common problem when performing analysis of physiological signals [26]. Baseline drift is caused by slow signal changes, such as respiration, position changes, etc., which may affect the true characteristics of the signal. Therefore, baseline signal removal is an integral part of signal preprocessing.

First, baseline signal modelling and estimation is required. For simple baseline drift, we use a low order polynomial to fit and remove the baseline drift. As an example of linear fitting, the baseline signal $B_{poly}(t)$ can be expressed as follow:

$$B_{poly}(t) = a_0 + a_1 t \tag{7}$$

where a_0 and a_1 are the fit coefficients; t is the time.

For more complex baseline drifts, we used a higher order polynomial or spline function to fit. The higher order polynomial fit can be expressed as follow:

$$B_{poly}(t) = \sum_{k=0}^{N} a_k t^k \tag{8}$$

where N is the order of the polynomial and a_k is the fitting coefficient.

Sliding window averaging is a simple and effective method of removing baseline drift. Slowly changing baseline drift can be removed by averaging the signal over a window of time and subtracting it from the original signal. The method of sliding window averaging is shown as follow:

$$B_{avg}(t) = \frac{1}{2M+1} \sum_{k=-M}^{M} S(t+k) \tag{9}$$

where M is the window size, $S(t)$ is the original signal, and $B_{avg}(t)$ is the signal after baseline removal.

A high-pass filter can be used to effectively remove the baseline drift component at low frequencies, such as filtering at a cutoff frequency of 0.01 Hz. Refer to the previous section on high-pass filters for specific filter design. By baseline signal removal, slow changes in the physiological signal can be eliminated, making the changes in the signal more reflective of the true fluctuations in emotion. This step is crucial for improving the accuracy of emotion recognition.

Ultimately, the mathematical description of the physiological signal preprocessing is shown as follows:

$$S_{clean}(t) = S(t) - N(t) \tag{10}$$

where $S_{clean}(t)$ is the denoised signal, and $N(t)$ is the noise signal.

The signal after removing the baseline drift is:

$$S_{baseline}(t) = S_{clean}(t) - B(t) \tag{11}$$

where $B(t)$ is the estimated baseline signal, obtained by polynomial fitting or sliding window averaging as described above.

During physiological signal preprocessing, it is important to select appropriate baseline removal methods for different types of physiological signals. Different signal characteristics and noise properties determine the applicability of using polynomial fitting or sliding window averaging methods. The baseline removal methods for the four types of physiological signals are shown in Table 2.

Table 2. Baseline Removal Methods for Four Physiological Signals

Physiological signal	Baseline removal methods	Descriptions
HR	Sliding window average	Removal of low-frequency drift and short-term fluctuations to preserve heart rate variability characteristics.
GSR	Polynomial fit	Removing slow changes and capturing emotionally induced rapid changes.
RR	Sliding window average	Removal of low-frequency baseline drift in periodic fluctuations and preservation of periodic characteristics.
SpO_2	Polynomial fit	Removes slow baseline drift and maintains signal smoothness.

HR signals usually appear as rapidly fluctuating pulsed signals that are susceptible to low-frequency disturbances such as motion artefacts and breathing. The sliding window averaging method is effective in smoothing out short-term fluctuations in the heart rate signal and removing low-frequency baseline drift. GSR signals typically vary slowly, and this variability may be due to factors such as emotion changes or skin moisture. Polynomial fitting is effective in capturing and removing these slow baseline drifts. The RR signal exhibits periodic fluctuations and is often affected by baseline drift and low-frequency noise. The sliding window averaging method is suitable for removing these low-frequency baseline drifts while maintaining the periodicity of the respiratory rate. The SpO_2 signal is usually smooth, but slow baseline drifts occur during prolonged monitoring. Polynomial fitting methods are effective in removing these slow baseline changes and maintaining the overall trend of the signal.

Selecting appropriate baseline removal methods based on the properties of different physiological signals can significantly improve the effectiveness of signal processing and the accuracy of subsequent emotion recognition.

2.4. **Feature extraction and selection of physiological signals.** Feature extraction and selection of physiological signals is a crucial step in the emotion recognition process. By extracting meaningful features from preprocessed physiological signals, we can convert complex raw signals into low-dimensional data that are easy to be processed by classifiers. These features not only capture the important information in the physiological signals, but also enhance the accuracy and robustness of emotion recognition.

The purpose of feature extraction is to extract key parameters from physiological signals that characterise the emotional state. These features can usually be classified into time-domain features, frequency-domain features and non-linear features. For the time-domain features of multi-physiological signals, Mean μ, Standard Deviation σ and Peak Value are used.

The mean value μ of the signal is calculated as:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} S(t_i) \tag{12}$$

where $S(t_i)$ is the signal value of the i-th sampling point and N is the total number of sampling points.

The Standard Deviation σ signal is the degree of volatility within a specific time window:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(S(t_i) - \mu)^2} \tag{13}$$

The Peak Value signal is the maximum or minimum value within a specific time window:

$$Peak = \max_{1\le i\le N} S(t_i) \tag{14}$$

For the frequency domain characteristics of multi-physiological signals, Power Spectral Density (PSD) and major frequency components were used. For the non-linear features of multi-physiological signals, sample entropy is adopted. With the above feature extraction methods, we can extract the key features that can characterise the emotional state from the physiological signals to form the feature vector $F = \{f_1, f_2, \ldots, f_n\}$, where f_i is the i-th feature extracted from the physiological signals and n is the total number of features.

After feature extraction, we may get a large number of features. However, not all features are useful for emotion recognition. The purpose of feature selection is to select the most useful part of the extracted features for emotion recognition in order to reduce the dimensionality and computational complexity of the data while improving the accuracy of classification. In this paper, Lasso regression regularisation is used for feature subset selection:

$$F_{selected} = \min_{w}\{Loss(w, F) + \lambda\|w\|_1\} \tag{15}$$

where w is the model weights, F is the feature matrix, and λ is the regularisation parameter.

By feature selection, we can select the subset of features that best reflect the emotional state from the extracted features: $F_{selected} = \{f_{i1}, f_{i2}, \ldots, f_{im}$ where f_k is the k-th selected feature and m is the number of features selected, usually $m < n$. These features will be used for subsequent emotion recognition.

3. **HHO-KNN based psycho-emotional recognition of athletes.**

3.1. **HHO Principle.** For effective classification of features of physiological signals in the recognition of mental emotions in athletes, we used the HHO algorithm to optimize the parameters and feature selection of the KNN classifier. HHO is an intelligent optimization algorithm based on group behaviour, inspired by the cooperative strategy of Harris Hawk groups during hunting.

The HHO algorithm simulates the dynamic hunting behaviour of the Harris Hawk, which mainly consists of four phases: Exploration, Tracking, Encircling and Attack. Through these phases, HHO is able to efficiently find the global optimal solution in the multidimensional search space. The basic idea of HHO is to gradually approximate the target solution by continuously adjusting the positions of the flock members (i.e., candidate solutions). In the initialisation phase, initial eagle group positions are randomly generated in the search space to form a set of candidate solutions. The position vector X_i (where i denotes the i-th eagle) of each eagle is set, and the objective function $f(X)$ is used to evaluate the position of each candidate solution.

During the reconnaissance phase, Harris hawks fly randomly during the reconnaissance phase, searching for possible prey locations. The hawks explore extensively in the search space to avoid falling into local optima. The position of the hawk is updated as shown below:

$$X_i(t+1) = X_i(t) + J(X_i(t) - X_j(t)) \cdot R \tag{16}$$

where $X_i(t)$ is the position of the i-th eagle at time t, J is the random jump amplitude, $X_j(t)$ is the position of the j-th eagle (chosen at random), and R is the random number matrix.

During the tracking phase, the Harris Hawk concentrates on tracking potential prey, adjusting its position to gradually approach the prey. The hawk's position is updated as follows:

$$X_i(t+1) = X_i(t) + r_1(X_{prey}(t) - X_i(t)) \tag{17}$$

where $X_{prey}(t)$ is the position of the prey, and r_1 is a random number controlling the direction and distance the hawk moves.

During the encircling phase, as the eagles approach the prey, they will begin to circle around the prey, gradually closing in on the prey's position. The position of the eagles is updated as follows:

$$X_i(t+1) = X_{prey}(t) - A|X_{prey}(t) - X_i(t)| \tag{18}$$

where A is the convergence factor to control the intensity of the encircling.

During the attack phase, the Harris Hawk captures and lifts its prey by moving quickly, eventually finding the globally optimal solution. The position of the hawk is updated as follows:

$$X_i(t+1) = X_{prey}(t) - r_2|X_{prey}(t) - X_i(t)| \tag{19}$$

where r_2 is the random number that controls the final position adjustment.

Through these stages, the HHO algorithm is able to efficiently search and approximate the global optimal solution in the search space, which is suitable for high-dimensional and complex optimisation problems. By applying HHO to the optimisation of KNN classifiers, we are able to find the optimal subset of features and classification parameters in the high-dimensional physiological signal feature space, thus improving the accuracy and efficiency of emotion recognition.

3.2. **KNN.** In the study of mental emotion recognition in athletes, choosing an appropriate classifier is one of the cores of emotion recognition system. KNN classifier, as a simple and effective non-parametric classification method, is widely used in various pattern recognition tasks because of its easy to understand and implement. KNN classifier is an instance-based learning algorithm that stores all the training data and makes predictions when classifying by using a distance metric. The core idea of KNN is: given a sample to be classified, find the closest K samples by calculating their distances from each sample in the training set, vote based on the category information of these K samples, and ultimately assign the sample to be classified to the category that receives the most votes.

Emotion recognition systems usually deal with multidimensional physiological signal data such as HR, GSR, RR and SpO_2. These signals are extracted and processed to form high-dimensional feature vectors. KNN classifiers are able to classify efficiently in these high-dimensional feature spaces by assigning each sample to the appropriate emotion category through distance metrics and voting mechanisms.

In practical applications, the performance of KNN classifiers can be further improved by combining feature selection and parameter optimisation. For example, in this paper, using the HHO algorithm for feature selection and optimisation of K values can significantly improve the accuracy and efficiency of KNN classifiers in emotion recognition.

3.3. **HHO-KNN based sentiment recognition.** In applications of emotion recognition, KNN classifiers are widely used due to their intuition and flexibility. However, the performance of KNN relies heavily on feature selection and optimisation of the parameter K. To improve the accuracy and efficiency of KNN classifiers in emotion recognition, this paper uses the HHO algorithm to optimise feature selection and parameter K. Through the global search capability of the HHO algorithm, the optimal feature subset and the best K value can be effectively selected, which significantly improves the performance of the KNN classifier.

3.3.1. *Feature selection and optimisation.* The goal of feature selection is to select a subset from the original feature set such that the KNN classifier performs best on that subset. Let $F = \{f_1, f_2, \ldots, f_n\}$ be the original feature set, and feature selection can be expressed as a binary vector $X = [x_1, x_2, \ldots, x_n]$ where $x_i \in \{0, 1\}$ indicates whether feature f_i is selected.

The HHO algorithm represents the position vector of each eagle as X, where X has the same dimension as the number of features n. For feature selection, the value of the position vector is either 0 or 1, indicating whether the corresponding feature is selected or not.

The parameter K of a KNN classifier is the number of neighbours and has a significant impact on the performance of the classifier. The goal of optimising K is to find the best value that minimises the classification error. In the HHO algorithm, we include K as a continuous variable in the position vector X, denoted as a real number, which is then converted to an integer by rounding for use.

The HHO algorithm optimises feature selection and K values by minimising an objective function. The objective function can be defined as the classification error of the KNN classifier on the validation set:

$$Objective(X) = Error(K, F_{selected}) \tag{20}$$

where $Error(K, F_{selected})$ denotes the classification error of the KNN classifier when using the K value and the selected feature subset $F_{selected}$.

3.3.2. *HHO Algorithm Optimisation Process.* The optimisation process of the HHO algorithm in the emotion recognition task can be described as follows:

During the initial process, initial position vectors X_i of the eagle flock are randomly generated, each position vector $X = [X_{features}, K]$ contains the feature selection vector $X_{features}$ and K value K_i. Set the size of the hawk population N and the maximum number of iterations T. The initial hawk flock position is as follows:

$$X_i(0) = [X_i^{features}(0), K_i(0)] \tag{21}$$

where $X_i^{features}(0)$ is the feature selection vector and $K_i(0)$ is the initial K value.

The iterative updating process updates the position of each eagle in each iteration based on the current optimal position X_{best} and the prey position X_{prey}. The formula for position update is based on the four different phases of the HHO algorithm (Exploration, Tracking, Encircling and Attack).

During the position correction process, for the feature selection part of the update process $X_{features}$, the real values in the position vector are converted to binary values (0 or 1) to indicate whether the feature was selected or not. For the K value K_i, round the real values in the position vector to the nearest integer and ensure that the K value is within a reasonable range (typically 1 to 20).

Calculate the objective function value corresponding to each position vector, i.e., the classification error of the KNN classifier on the validation set. Update the optimal position X_{best} and the prey position X_{prey}, so that their corresponding objective function values are minimised.

Eventually, if the convergence conditions are satisfied (e.g., the maximum number of iterations is reached or the classification error rises to a predetermined threshold), the iteration is stopped and the optimal feature selection and K value are output.

The global search capability of the HHO algorithm makes it able to find the optimal feature subset and the best K value in the high-dimensional search space, which effectively avoids the local optimal problem. The HHO algorithm is able to adaptively adjust the combination of feature selection and K value to adapt to the change of different datasets and emotion categories, which has good generality. By optimising feature selection, HHO is able to reduce the number of features, lower the computational complexity, and improve the efficiency of the KNN classifier. The pseudo-code for emotion recognition based on multi-physiological signals and HHO-KNN is shown in Algorith 1.

Algorithm 1 Emotion recognition based on multiple physiological signals and HHO-KNN

Input: training set $\mathbf{D_{train}}$, test set $\mathbf{D_{test}}$, the eagle population size in HHO N, maximum number of iterations T, KNN parameter range $[K_{min}, K_{max}]$.
Output: emotional labels.

begin
Initialize eagle flock location $\mathbf{X_i} = [\mathbf{X_i^{features}}, \mathbf{K_i}]$ $(i = 1, 2, ..., N)$ ▷ Includes feature selection vectors and K-values
$\mathbf{X_{best}} = null$, $bestFitness = \infty$
for $t = 1$ to T **do**
  for each eagle i in N **do**
    Evaluate fitness of $\mathbf{X_i}$ using KNN classifier on validation set
    if $fitness(\mathbf{X_i}) < bestFitness$ **then**
      $\mathbf{X_{best}} = \mathbf{X_i}$
      $bestFitness = fitness(\mathbf{X_i})$
    end if
  end for
  for each eagle i in N **do**
    Update $\mathbf{X_i}$ position based on HHO rules
    if in Exploration Phase **then**
      $\mathbf{X_i}(t+1) = \mathbf{X_i}(t) + J(\mathbf{X_i}(t) - \mathbf{X_j}(t)) \cdot R$
    else if in Tracking Phase **then**
      $\mathbf{X_i}(t+1) = \mathbf{X_i}(t) + r_1(\mathbf{X_{prey}}(t) - \mathbf{X_i}(t))$
    else if in Encircling Phase **then**
      $\mathbf{X_i}(t+1) = \mathbf{X_{prey}}(t) - A|\mathbf{X_{prey}}(t) - \mathbf{X_i}(t)|$
    else if in Attacking Phase **then**
      $\mathbf{X_i}(t+1) = \mathbf{X_{prey}}(t) - r_2|\mathbf{X_{prey}}(t) - \mathbf{X_i}(t)|$
    end if
    Correct $\mathbf{X_i}$ to ensure valid feature selection and K value
  end for
end for
Use optimal $\mathbf{X_{best}}$ (selected features and K) to train KNN classifier on $\mathbf{D_{train}}$
for each sample in $\mathbf{D_{test}}$ **do**
  Predict emotion label using optimized KNN classifier
end for
return predicted emotion labels
end

4. Experiments and analysis of results.

4.1. **Sample of emotion-evoked physiological data.** In the study of psychological emotion recognition in athletes, the emotion evoked experiment is a key step in obtaining physiological signal data. In order to be able to effectively analyse and identify physiological responses under different emotional states, the International Affective Picture System (IAPS) [27], an internationally recognised emotion-evoking tool, was used in this study. This section describes in detail the emotion-evoking materials used in the experiment, the experimental design and the physiological data samples collected.

Developed by the NIMH Center for the Study of Emotion and Attention at the University of Florida, the International Affective Precipitation Picture Stack (IAPS) is a standardised collection of images designed to elicit and study human emotional responses.

The IAPS contains over 1,000 carefully selected images, each of which has been standardised to assess its effectiveness in eliciting specific emotional responses. The images cover a range of emotional dimensions from extremely positive to extremely negative, as well as different levels of arousal, making it an ideal tool for studying emotional responses.

In this study, we selected pictures from IAPS that could represent four typical emotional states (happy, angry, fearful, and calm), as shown in Table 3. These pictures were explicitly scored on the dimensions of emotional potency (Valence) and arousal to ensure that the target emotions could be accurately induced.

Happiness (Positive High Arousal): select images rated as highly effective and highly arousing, such as celebration scenes and beautiful nature.

Anger (Negative High Arousal): images rated as low potency and high arousal, such as scenes of conflict and violence, were selected.

Fear (Negative High Arousal): pictures rated as low potency and high arousal were selected, such as dangerous animals and disaster scenes.

Calmness (Positive Low Arousal): selects images rated as highly efficient and low arousal, such as quiet landscapes and cosy indoor scenes.

Table 3. Parameters for the four typical emotions in IAPS

Emotion	**Valence**	**Arousal**
Happiness	5.0 ± 0.4	5.5 ± 0.4
Anger	3.5 ± 0.4	4.5 ± 0.5
Fear	3.0 ± 0.4	6.0 ± 0.6
Calmness	4.0 ± 0.6	5.5 ± 0.5

A special experimental design was conducted to obtain data on physiological signals in different emotional states. During the preparation phase of the experiment, subjects were first informed about the purpose and procedure of the experiment and signed an informed consent form upon entering the laboratory. Before the start of the experiment, it was ensured that all physiological signal acquisition devices (HR, GSR, RR and SpO_2) were properly connected and calibrated. Subjects were asked to remain quiet and relaxed in order to record baseline physiological signals.

During the emotion-evoking experiment, each subject viewed different categories of IAPS pictures in turn, with each set of pictures presented for 10 seconds. After the presentation of the pictures of each emotional category, a period of time (e.g., 30 seconds) was given to the subjects for emotional recovery in order to avoid confusion of emotional states. HR, GSR, RR and SpO_2 physiological signals were recorded in real time throughout the emotional evocation process.

During the data acquisition phase, physiological signals were recorded for each subject in different emotional states, and the data included baseline data, data during emotional evocation, and data during emotional recovery. A high sampling rate (1000 Hz) device was used to ensure the accuracy and integrity of the data.

4.2. **Emotion recognition results and analyses.** In the emotion-evoking experiment, we collected a total of physiological signal data from 30 healthy adult volunteers. Data were collected under four different emotional states for each volunteer. The resting physiological signals of the subjects were recorded within 30 seconds prior to the emotional evocation in each group as baseline data. The baseline data were used for baseline drift correction and signal normalisation in subsequent analyses. After the presentation of each set of pictures, the subjects' physiological signal recovery process was recorded, usually for 30 seconds.

According to the steps of the HHO-KNN algorithm proposed in this paper, the implementation of mental emotion recognition for athletes was carried out. The experimental test platform was: 2.93 GHz Intel Core Duo processor, Windows 10, 4 GB RAM. Programming software: MATLAB (R2018b).

Table 4. Sentiment Recognition Results for the HHO-KNN Algorithm

Physiological signal	Raw feature count	Number of optimal subset features		Best recognition rate/%		Average recognition rate/%	
		No baseline removed	Baseline removed	No baseline removed	Baseline removed	No baseline removed	Baseline removed
HR	6	2	2	52.00	66.67	50.13	64.51
GSR	6	2	1	58.33	66.67	56.09	64.26
RR	6	3	3	59.21	69.31	58.33	66.67
SpO_2	6	1	1	32.09	34.73	31.35	32.91
ALL	33	7	7	66.67	75.00	64.04	73.62

ALL: HR, GSR, RR, SpO2

The results shown in Table 4 indicate that the HHO-KNN classifier is able to effectively identify and distinguish between different emotional states, and especially performs well in distinguishing between high arousal and low arousal emotions. To gain a deeper understanding of the performance of the HHO-KNN classifier in emotion recognition, we analysed the confusion matrix of the model on the test set, as shown in Figure 2. The confusion matrix provides classification results for each emotion category, showing the model's recognition errors across categories.

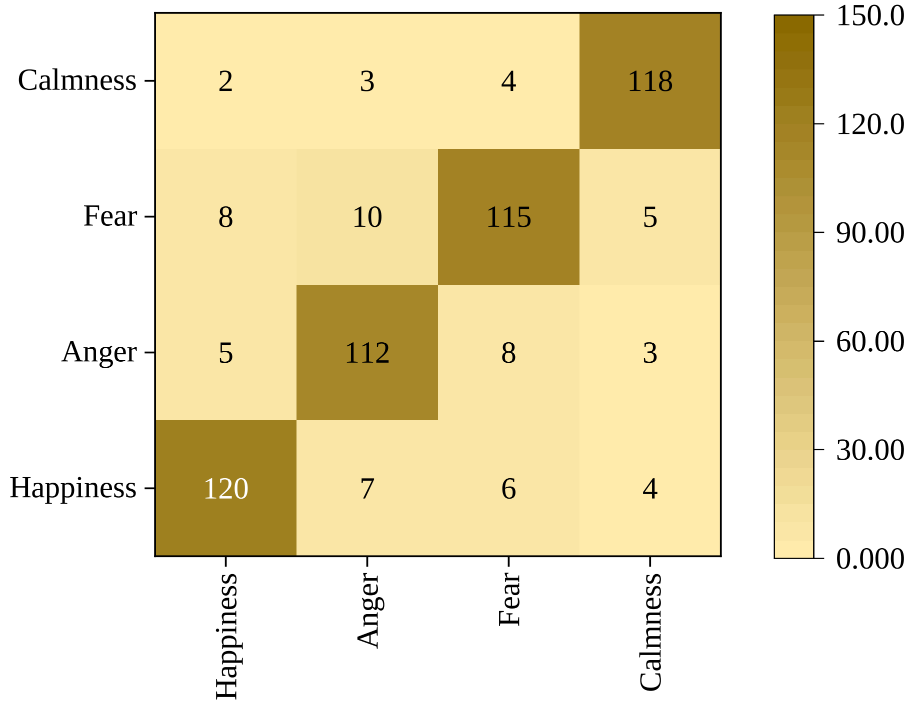

Figure 2. Confusion matrix analysis.

As shown in Figure 2, most of the emotion categories (especially "happiness" and "calmness") have high accuracy in being predicted as the corresponding categories, indicating that the HHO-KNN is better at recognising these emotional states. A few emotional samples (e.g., "anger" and "fear") were misclassified as other emotions. These misclassifications mainly occurred between emotional states with high arousal, which may be due to the fact that these emotions are more similar in terms of their physiological signatures.

5. **Conclusion.** In this paper, we developed an innovative emotion recognition method focused on real-time monitoring and assessment of athletes' psychological stress states during training and competition. Different emotional states of the athletes were successfully induced using IAPS and four physiological signals were captured simultaneously. The HHO algorithm was used for feature selection and parameter optimisation of the KNN classifier during feature extraction and classification. The HHO algorithm can find out the most discriminative feature subset and the best classifier parameters.

Experimental results show that the HHO-KNN based emotion recognition method significantly improves the classification accuracy, especially in recognising complex and high arousal emotional states such as anger and fear. Compared with traditional emotion recognition methods, the multi-physiological signal integration and optimisation strategy proposed in this paper demonstrates significant advantages. The combination of multi-physiological signals enables the system to capture richer emotional features, while the application of the HHO algorithm effectively solves the challenges of high-dimensional feature selection and parameter optimisation.

However, some of the misclassifications between emotional states mainly occurred between emotions with high arousal (e.g., anger and fear), which may be due to the fact that these emotions have more similar features on physiological signals and are difficult to be distinguished by a simple distance metric. Future work could consider introducing more complex classifiers or fusing multiple physiological signal features to improve these misclassifications.

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