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Article

Training biomechanics into emotion recognition of athletes based on time series change characteristics of expression

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Abstract: Emotion management is a critical psychological skill for athletes, deserving significant attention during the foundational training phase. Early intervention in athletes' emotional states allows coaches to devise effective training plans, ultimately enhancing competition performance. Emotions can be evaluated through facial expressions and physiological signals, providing a basis for detecting athletes' training emotions. This study explores the biomechanical characteristics of facial expressions to recognize emotions. First, the relationship between facial expressions and facial Action Units (AUs) is analyzed, identifying AU combinations that effectively represent facial expressions. Considering the temporal and spatial dynamics of facial expressions, AUs are used as feature inputs for an SVM model to classify athletes' training emotions. Subsequently, emotional expressions are mapped to corresponding emotional states, introducing an emotion index to quantify athletes' training emotions. Finally, quantitative emotion recognition is achieved based on transient facial expressions observed during training. This research provides a theoretical framework for coaches and athletes to enhance emotional management through biomechanically informed training approaches.

Keywords: biomechanics; temporal dynamics; facial Action Units; emotion recognition; athlete training; emotional management in sports

1. Introduction

From the current research situation, emotion recognition research has not only achieved fruitful results in the field of management, but also penetrated into sociology, pedagogy, physical education and other disciplines [1]. Among them, in the field of physical education, More and more scholars have made rich research on the emotional aspects of athletes' training, it mainly involves athletes' emotion management before competition, emotion management during competition, emotion influence mechanism, emotion management strategy and so on. However, the research on emotion management during athletes' training is rare, and most of its contents are literature review and experience summary, while experimental and confirmatory research is relatively few. As an important psychological skill, athletes' emotion recognition should be paid enough attention in the basic training stage [2]. Only by intervening in advance, cultivating and training athletes' emotion management skills can they have better training effect and improve their own skill level in training. At present, the technologies related to athletes' condition monitoring mainly focus on image collection and recognition, feature extraction, big data mining and deep learning [3]. And most of the research on athletes' behavior models tend to fatigue training and distraction training, and the research on emotional problems is slightly insufficient [4]. Although the method based on quantitative data has the advantages of non-invasiveness and accurate parameter acquisition, it is easy to be affected by individual or environmental differences, resulting in large discrimination errors [5].

Biomechanics, the discipline that studies the relationship between body movement and force, offers a new perspective on athlete emotion recognition. Changes in emotional states affect not only the psychological level but also directly impact the muscle activity and performance of athletes. By analyzing the muscle activity patterns of athletes under different emotional states, we can gain a deeper understanding of the impact of emotions on athletic performance, thereby providing a scientific basis for training emotion management.

Based on this, this paper will use non-invasive data collection method (camera), take the comprehensive identification of athletes' training status as the breakthrough point, take multiple facial information as the analysis object, and use big data analysis and machine learning technology to realize the comprehensive detection of athletes' training emotions. The research results can be applied to the actual sports training process, and play an important role in making training plans for coaches and improving athletes' skill level. This study combines biomechanical features with the time series variation characteristics of expression to achieve more accurate recognition of athletes' training emotions. By analyzing the facial muscle activity and physiological indicators of athletes under different emotional states, we can extract biomechanical features related to emotional changes. These features include not only the dynamic changes of facial expressions but also changes in physiological indicators such as heart rate and respiratory frequency. By comprehensively analyzing these biomechanical features, we can more fully understand the emotional state of athletes, thereby providing more effective strategies for training emotion management.

2. Related work

2.1. Research on sports athletes' training emotion

Athletes' emotional fluctuations will not only affect the daily training effect; Moreover, during the competition, the athletes' emotional changes and emotional management ability directly affect the exertion of sports skills, and finally affect the competition results. In the existing research literature, researchers have done a lot of research on athletes' emotions before and during competitions and during training.

Domestic scholars take martial arts routine athletes as the research object, anatomize the pre-competition emotional state and influencing emotional factors, and put forward methods to strengthen pre-competition adaptation training and physical emotional regulation [6]. Some scholars believe that in the daily training of shooters, coaches will always imperceptibly transfer their emotions to athletes, and the emotional adjustment of coaches and athletes in training classes is divided into pre-class adjustment, in-class adjustment and after-class adjustment [7]. You scholars defined the concept of boredom, and high-level figure skaters boredom of the causes of the analysis, according to the boredom of the mechanism put forward targeted suggestions [8]. The level of emotional state directly affects the competition performance of the fighting athletes, and the individual emotional experience of the fighting athletes is often the integration of stimulation factors, physiological factors and cognitive factors [9]. It is proposed that the emotional adjustment can be carried out by adaptive training and biofeedback training.

Foreign scholars believe that athletes from different cultures can reliably judge spontaneously expressed emotions, while among subjects from different cultural backgrounds, the lower absolute consistency rate is related to the noise caused by non-emotional facial behaviors [10]. In addition, subjects from different cultural backgrounds used the same facial cues when judging emotions, and the signal value of facial expressions was similar in different cultures. Scholars have discussed the attention patterns related to positive and negative emotions in sports competitions, and athletes' perceptions of the impact of these attention changes on attention and performance, confirming that excitement requires more attention than negative emotions, but positive emotions are thought to be more likely to lead to performance-related attention and automatic body movements, both of which are conducive to attention concentration and performance [11]. Scholars study the possible relationship between emotion and confidence and different competitive sports in Greece. In terms of functional pleasure emotion and self-confidence, there is no statistically significant difference in sports. Emotional content and intensity are different in training practice and competition, and they are different in pre-competition, middle-competition and post-competition performance.

In recent years, the application of biomechanics in the field of emotion recognition has been increasing. Studies have shown that changes in emotional states are closely related to physiological indicators such as muscle tension, heart rate, and respiratory frequency. These physiological indicators can be measured and analyzed using biomechanical methods, providing objective data support for emotion recognition. For example, by analyzing the muscle activity patterns of athletes during training, we can identify biomechanical characteristics associated with specific emotional states, which is significant for understanding the impact of emotions on the execution of athletic skills.

According to the previous literature, the research contents mainly focus on the influencing factors of athletes' emotions, emotional regulation and strategies during competitions, and the correlation verification between athletes' emotions and another external variable. There are few in-depth studies on how the internal dimensions of athletes' emotions affect the external variables, and it is even less to apply structural equation model to the study of athletes' emotions.

2.2. Research on facial behavior of athletes

At present, the detection of facial motion units includes recognition and intensity estimation. Recognition of facial motion unit refers to judging whether it appears or not, including single recognition of facial motion unit, combined recognition, coupling recognition of facial motion unit and expression, recognition of facial motion unit dependence and so on [12]. Intensity estimation of facial motion unit refers to judging the motion degree of its corresponding muscles, and accurately estimating it can greatly increase the richness of information and help to determine more complex facial behaviors. But up to now, most of the work on facial motion unit detection is focused on facial motion unit recognition, but there is little research on intensity estimation. This is mainly because intensity estimation is a more challenging task than recognition [13]. First of all, the perception of facial motion unit intensity depends on the facial shape and expressive force of the observed object to a great extent. Secondly, the symbiosis of facial motor units affects the scoring standard of its intensity. Third, changes in lighting, head position and instantaneous shadows all give people the impression of different facial motor unit intensities [14]. Fourthly, the labeling of facial motion unit intensity is more challenging. However, considering the complexity of detection, including a large number of categories, more subtle models and slight differences among facial motion units, the detection of facial motion units is still an open challenge.

Biomechanics plays a crucial role in understanding and analyzing the relationship between physical motion and emotional states, particularly in the context of athletic training and performance. Prior research has extensively explored the biomechanics of specific motions, such as wrist and elbow movement in sign language [15], running dynamics [16], and gait analysis for patients with neurological disorders [17]. These studies demonstrate the ability of biomechanical assessments to quantify motion characteristics, providing valuable insights into movement efficiency, joint stability, and potential areas of intervention. Moreover, advancements in motion capture systems, such as smartphone-based tools, have expanded access to biomechanical evaluations in clinical and sports settings [18]. Biomechanics has also been applied to model joint movement through nonlinear dynamics, offering insights into system stability and behavior under perturbations [19]. In the context of emotion recognition, the integration of biomechanical models enables the precise quantification of facial movements and expressions, bridging the gap between physical motion and psychological states. By leveraging techniques such as dynamic analysis and motion modeling, these studies highlight the potential of biomechanics to improve emotional detection and management strategies in athletic training, thereby fostering better performance and psychological resilience.

In the past decades, the research on automatic analysis of facial motion units has been continuously developed, but it is limited by the size of training database. Under the limitation of small database, people often use methods with simple model and few parameters to detect facial motion units, such as support vector machine, decision tree, linear regression, rule learning and so on. With the development of computer technology, image technology and storage technology, it is possible to make and store large-scale databases, which makes the application of large-scale deep network possible. With the increase of training data, the accuracy and generalization ability of facial motion unit detection are greatly improved.

3. Research on training emotion recognition of athletes based on time series change characteristics of expression

3.1. Facial AU characteristics of expression

In the description of expression and facial AU in FACS, it is mentioned that any expression is obtained by the combination of some facial AUs. Therefore, this paper based on Bosphorus database with expression tags, mining the relationship between facial AU and expression. Using the facial AU intensity estimation model, the data statistics of samples under various expressions in the database (**Table 1**) are carried out.

Table 1. Sample size of basic expression.

Expression	Fear	Angry	Happiness	Grieve	Surprise	Aversion
Sample size	69	70	105	63	70	68

After mining the relationship between facial AU and expression, we can see that the facial AU stimulated by different expressions is different, so combining facial AU stimulated by different expressions can get a facial AU feature set that can represent all expressions. Based on the cumulative intensity of AU under each expression, this paper classifies the facial AU under each expression by Otsu binarization method, and screens the key facial AU features that can represent the expression. Finally, all the key facial AU features are combined into a facial AU feature set that can represent all expressions. According to statistics, the key facial AU stimulated by each expression is shown in **Table 2**. This set is the input feature of facial expression recognition model.

Table 2. Facial AU stimulated by basic expression.

Expression	Excited facial AU	Number
Fear	AU25, AU5, AU1, AU26, AU2	5
Angry	AU4, AU7	5
Happiness	AU25, AU12, AU7	3
Grieve	AU7, AUL, AU4, AU17, AU15	5
Elegant	AU25, AU5, AU2, AU1, AU26, AU27	6
Aversion	AU7, AU25, AU10, AU4, AU9	5
Collection	AU1, AU2, AU4, AU5, AU7, AU9, AU10, AU12, AU15, AU17, AU25, AU26, AU27	13

3.2. Temporal and spatial characteristics of expression

3.2.1. Spatial characteristics

Because of the randomness of head posture and face orientation, the orientation of face samples collected in practice is different from that of face samples used in model training, which leads to the poor robustness of recognition algorithm. Therefore, in order to eliminate the influence of face orientation or head movement on facial expression recognition, before facial expression recognition, the key points of the face are affine transformed, so that no matter whether the original face orientation or head posture is frontal or not, the faces described by the facial feature points are frontal. The affine transformation formula is:

$$(X', Y', Z', 1) = (X, Y, Z, 1)\begin{bmatrix} \cos\beta & 0 & -\sin\beta & 0 \\ 0 & 1 & 1 & 0 \\ \sin\beta & 0 & \cos\beta & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{1}$$

3.2.2. Time characteristic

Another intrinsic characteristic of expression is its time pattern. In addition, the expression from scratch is a time process. When the expression appears, the related AU of the face is activated. When the expression reaches its peak, some AU also reaches its peak. When the expression gradually disappears, the related facial AU also disappears, as shown in **Figure 1**. Among them, there are two dynamic changes of expressions, that is, from expressionless to happy or angry, and then return to expressionless. The red part in the figure is the happy or angry state detected by the existing algorithm. The abscissa is the corresponding frame number, and the ordinate is the facial AU intensity.

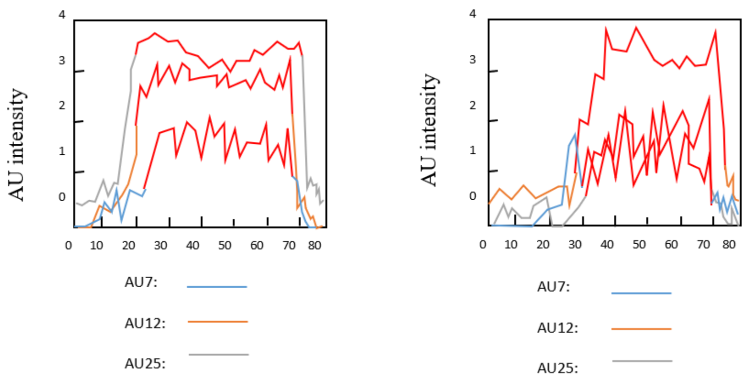

Figure 1. Temporal characteristics of expressions (left: happy, right: angry).

As can be seen from the above figure, with the gradual increase of AU intensity, expression appears, and with the decrease of AU intensity, expression disappears, but face and AU are not synchronized, and facial AU appears before expression, and expression disappears before facial AU.

3.3. Transient expression recognition

Universal machine learning model, the idea of model construction is to minimize the observed training error, that is, to minimize the empirical risk, so that the model performs well in the sample space. Different from most models, Support Vector Machine (SVM) constructs support vectors which can classify samples by using the differences between different kinds of samples, and constructs hyperplane with support vectors, so as to realize the classification of samples. **Figure 2** is a schematic diagram of two-dimensional sample classification based on support vector machine algorithm. The horizontal and vertical coordinates are the two-dimensional input data of samples, red is the positive sample, blue is the negative sample, and the circle is the support vector needed to build the model.

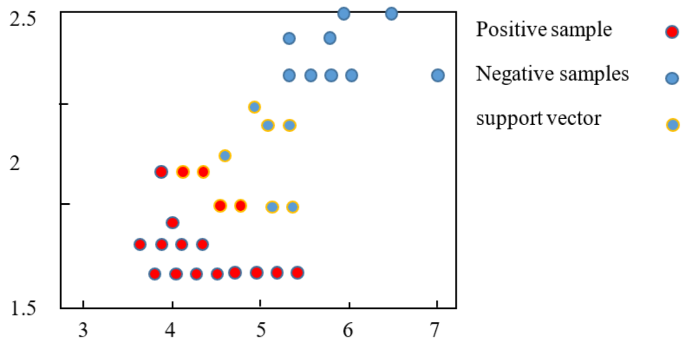

Figure 2. Schematic diagram of support vector machine algorithm.

Because expression is one of the external expressions of people's subjective emotions, Has the overall expression form of thousands of people, Individual expression varies from person to person, so the application of machine learning in emotion recognition should avoid over-fitting results. Therefore, this paper chooses to build emotion recognition model based on time series characteristics, whose essence is to observe and minimize generalization errors between samples, so as to minimize structural risks of the model. As far as universality is concerned, the model constructed by support vector machine is stronger than other models in robustness on high-dimensional small samples. Relevant data show that any expression of facial emotion can be decomposed into a combination of multiple facial motion units. Therefore, based on six basic expressions in Bosporus database, this paper constructs an expression recognition algorithm using support vector machine algorithm with facial AU feature set as input features.

To ensure the practical applicability of the proposed system in real-time environments, the computational requirements and processing speed were evaluated. The system was implemented on a workstation equipped with an Intel Core i7-12700 K processor, 32 GB of RAM, and an NVIDIA GeForce RTX 3080 GPU. Optimization of the processing pipeline, including feature extraction and SVM classification, allowed the system to achieve an average processing time of approximately 15 ms per frame. This ensures a real-time operational capacity with a frame rate exceeding 60 FPS, making it suitable for use in live training environments.

3.4. Model validation

In this paper, the Bosporus database is fitted and verified using a 50% cross-validation method. The data split was stratified by subject to ensure that both training and testing sets contained a balanced representation of facial expressions from each individual. This approach minimizes potential biases and improves the generalizability of the results by accounting for individual differences in facial expressions. The recognition results are shown in **Table 3**.

Table 3. Expression recognition accuracy.

Expression	**Fear**	**Angry**	**Happiness**	**Grieve**	**Surprise**	**Aversion**
Accuracy	88.1%	93.9%	98.4%	95.3%	90.3%	93.5%

As can be seen from **Table 3** above, under the 50% cross-validation, the recognition rate of other emotions except fear is over 90%, and the overall accuracy rate of the model is 93.25%. At the same time, compared with other algorithms, the results are shown in **Table 4**. From the table data, we can see that the expression recognition algorithm constructed in this paper is higher than other popular algorithms.

Table 4. Comparison of recognition effects of various algorithms.

Algorithm	Fear	Angry	Happiness	Grieve	Surprise	Aversion	Overall
KNN	86.50%	89.70%	97.10%	88.80%	87.40%	89.40%	89.80%
LDA	84.90%	93.30%	98.00%	92.40%	89.20%	92.10%	91.70%
LR	84.70%	93.00%	97.10%	90.60%	89.40%	90.80%	90.90%
DT	86.70%	92.10%	96.40%	92.10%	89.00%	92.10%	91.40%
This article	88.10%	93.90%	98.40%	95.30%	90.30%	93.50%	93.30%

The notably lower accuracy rate for fear recognition (88.1%) compared to other emotions could be attributed to several factors. First, fear-related facial expressions involve subtle changes in facial AUs, which may overlap with expressions associated with other emotions, such as surprise; Second, individual differences in expressing fear, coupled with cultural variations in interpreting fear-related cues, could introduce additional complexity; Lastly, the dataset may have fewer samples for fear expressions, leading to a less robust training of the model. Future improvements could include augmenting the dataset with more diverse and balanced fear-related samples and refining the feature extraction process to enhance the model's sensitivity to subtle AU changes.

4. Experimental analysis of sports athletes' training emotion recognition based on expression time series change characteristics

4.1. Emotional recognition of expression

Expression is the external expression of emotion, and emotion is the internal experience of expression, which is also the most commonly used and intuitive emotional expression in human daily life. Many scholars have scientifically proved six basic expressions of human coexistence: Anger, fear, happiness, sadness, disgust and surprise (the seventh one was generally recognized later: contempt). These six basic emotions are innate, and they have commonalities among different regions and cultures. The facial muscle changes caused by them are roughly the same, and the expression of emotions is subconscious, which is basically difficult to suppress or conceal. Human emotion is the comprehensive embodiment of human emotion, but there are many external manifestations of emotion, and facial expression is only one of its external manifestations, as shown in **Figure 3**. The external expression of emotion is called expression, but the expression here refers to the broad expression, which includes verbal expression and gesture expression besides facial expression, which is divided according to the different body parts when people express emotions.

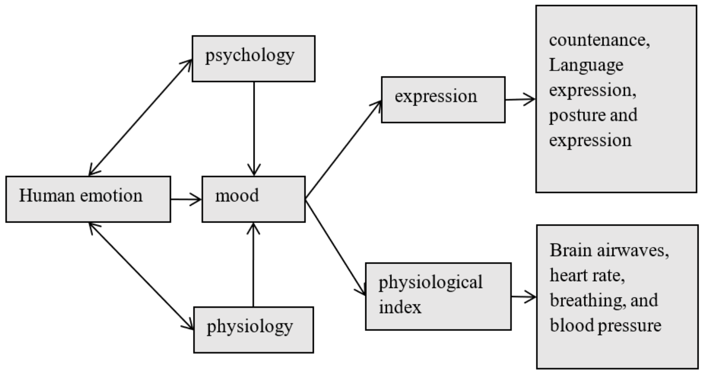

Figure 3. Manifestations of emotions.

Although facial expressions can be used to recognize emotions, because the change of human emotions is a continuous process, and the extraction and recognition of facial expressions are instantaneous, the facial expressions recognized at a certain moment cannot be directly regarded as the result of emotion recognition. Therefore, in order to solve the problem of emotion recognition of athletes during training, in this paper, a method of emotion recognition based on temporal features of transient facial expressions is proposed, and the concept of emotion index of athletes is put forward, which can reflect the emotional state of athletes, realize the continuous expression of transient facial expressions, and finally realize the objective evaluation of athletes' emotions.

Correspondence between emotion and expression

It is difficult to quantify people's emotions, which are mainly reflected in the following two points: First, there are many difficulties in identifying emotions; Second, different people express the same emotions differently. There are two common modeling expressions of emotions, one is discrete description model, and the other is emotion dimension model. The discrete description model aims to describe specific emotions with basic expressions, such as happiness, anger, sadness, etc., but this method has certain fuzziness and is difficult to express complex emotions; The emotional dimension model refers to describing emotions from different dimensions, such as the popular AV (Arousal-Valence) model, which uses Arousal and Valence to form a two-dimensional plane, and the speaker can quantify his emotions in four quadrants, as shown in **Table 5**. In the model, excitement refers to the intensity of a certain emotion, while pleasure refers to the nature of a certain emotion, that is, positive emotion and negative emotion.

Table 5. Two-dimensional model of emotion.

Activity	Negative pleasure	Positive pleasure
High activation	Fear, anger	Surprised, happy
Low activation	Sad, disgusted	Calm, calm

Based on the idea of two-dimensional model of emotion, usually, during the training period of athletes, the emotions that are helpful to driving training can be classified as positive emotions (or positive emotions), and the emotions that are unfavorable to athletes' training can be classified as negative emotions (negative emotions). Among them, positive emotion means that the subject of emotion has positive and positive psychological tendency, which is a benign psychological state. Individuals in this emotion will show positive optimism psychologically or physiologically when facing external stimuli, and are not prone to excessive behavior.

If training is carried out in this emotional state, the training actions of athletes will be more standard, and the judgment ability of technical actions and environment in the training process will be more rational. Negative emotion means that the subject of emotion has negative and negative psychological tendency, which is a bad psychological state. In this mood, when the individual is stimulated by the outside world, his psychology or physiology will be negative and pessimistic, and it is easy to produce some excessive reactions. For example, training in this emotional state, due to the influence of emotions, athletes are difficult to maintain normal thinking and often lose rational judgment ability, which is prone to aggressive behavior, thus affecting the training environment. In addition, in addition to the above two emotions, there is also a neutral emotion, that is, the subject of emotion is in a calm state physically or psychologically. In this state, athletes have correct judgment, normal training behavior and can keep normal training. Based on the above analysis, the basic correspondence between various emotions and facial expressions is shown in **Table 6**.

Table 6. Influence of emotion on training emotion of athletes.

Emotional state	Corresponding facial expressions	Influence on athletes
Positive emotion	Happiness, surprise	Contribute to training
Negative emotions	Sadness, fear, anger, contempt	Not conducive to training
Neutral emotion	Neutral, disgusting	Do not affect training

The facial expressions and emotions are normalized and quantified, as shown in **Table 7**. That is to say, according to the influence of emotion on driving safety, the positive emotion is quantified as 1, the negative emotion is quantified as −1, and the neutral emotion is quantified as 0, which respectively represent three situations: beneficial to training, unfavorable to training and normal training. The quantitative value of facial expression is consistent with its corresponding emotional state.

Table 7. Normalized assignment of facial expression and emotion.

Emotional state	Quantified value of emotional state	Corresponding facial expressions	Quantified value of facial expression
Positive emotion	1	Happiness	1
Positive emotion	1	Surprise	1
Negative emotion	−1	Grieve	−1
Negative emotion	−1	Fear	−1
Negative emotion	−1	Angry	−1
Negative emotion	−1	Contempt	−1
Neutral emotion	0	Neutral	0
Neutral emotion	0	Aversion	0

4.2. Sports athletes train sentiment index

Although the three emotional states are set as three quantitative values related to athletes' training, it is not very appropriate to analyze the real situation. Because emotions are not three fixed states, there are strong and weak points in the same emotional state, for example, there are joy and ecstasy in positive emotional state, and anger and rage in negative emotional state. In addition, the three emotional states also have a transformation relationship, and they can transform each other. Therefore, simply setting the three emotional states as three fixed quantitative values can not reflect the internal relations of emotional states, and it is difficult to truly reflect the emotional states of athletes.

Therefore, this paper combines the time characteristics of facial expressions described above, and restricts the time within a certain time range. Based on the statistical data of transient facial expressions within this time range, this paper puts forward an index that can express athletes' emotions, that is, athletes' emotion index, and its calculation formula is:

$$I_{\text{feeling}} = \frac{\sum_{i=1}^{\text{freq}\times t} f(\text{Emotion}_i)}{\text{freq} \times t} \tag{2}$$

According to the quantitative indicators of facial expressions above, the continuous frame expressions are accumulated, and finally normalized, that is, the sentiment index of sports training mobilization training within a certain period of time is obtained.

In practical implementation, the real-time processing capabilities of the proposed system were tested and validated. Using the specified hardware configuration, the system demonstrated the ability to process frames continuously with negligible latency. The average processing time per frame, including preprocessing, AU feature extraction, and classification, was approximately 15 ms, enabling a consistent real-time performance. This ensures that the system can be seamlessly integrated into live sports training scenarios without compromising the flow of activities.

4.3. Analysis of experimental results

In this paper, one minute is the time constraint, one second is the sliding window step, and three groups of training data were collected using a camera with a sampling frequency of 30 Hz and a resolution of 1920 × 1080 pixels. The camera was positioned at a fixed distance of 2 m, directly facing the athlete at eye level to ensure full facial capture. The experiments were conducted in a controlled indoor environment with standardized lighting provided by overhead LED lights (color temperature: 5000 K, illumination level: ~500 lux) to ensure uniform facial visibility. A plain, neutral-colored backdrop was used to minimize distractions and avoid interference with facial expression recognition.

The data collection involved 20 participating athletes (12 males, 8 females) aged between 18 and 30 years (mean age: 24.5 years). The athletes represented a range of sports disciplines, including basketball, swimming, track and field, and gymnastics, to ensure diversity in emotional expression patterns. All participants were non-professional athletes but had at least 3 years of competitive experience. This demographic and sports diversity ensures the study's findings are representative across various physical training contexts. Facial expressions were recorded during specific training scenarios, including endurance drills, technical skill development, and strength exercises. This ensured that emotional responses could be observed under a variety of physical and mental demands.

To ensure the practical applicability of the proposed system in real-time environments, the computational requirements and processing speed were evaluated. The system was implemented on a workstation equipped with an Intel Core i7-12700 K processor, 32 GB of RAM, and an NVIDIA GeForce RTX 3080 GPU. Optimization of the processing pipeline, including feature extraction and SVM classification, allowed the system to achieve an average processing time of approximately 15 ms per frame. This ensures a real-time operational capacity with a frame rate exceeding 60 FPS, making it suitable for use in live training environments.

Using the collected data, emotion recognition calculations were conducted based on the sentiment index of sports athletes. **Figure 4** shows the changes in emotional indices over time for two representative scenarios. The first group starts with negative emotions (e.g., angry), transitions to neutral emotions during the middle phase, and concludes with positive emotions (e.g., happiness). Conversely, the second group transitions from positive to neutral emotions and eventually to negative emotions. These results illustrate the system's ability to continuously monitor and quantify athletes' emotions during training.

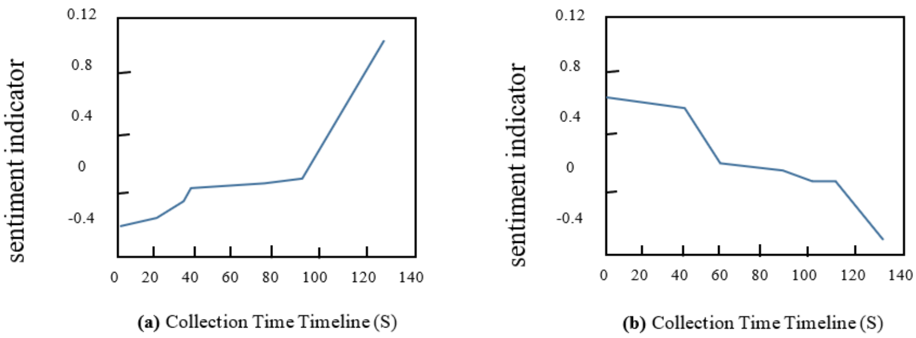

Figure 4. Emotion recognition calculation results.

The selection of a one-minute time window for emotion index calculation was based on balancing temporal granularity and computational feasibility. A one-minute duration provides sufficient temporal resolution to capture significant emotional trends during typical training drills while minimizing computational overhead. This duration was also chosen to align with the structure of many training routines, where exercises and rest periods often span similar lengths. However, the applicability of this duration may vary across sports and training intensities, and future studies could explore adaptive time windows tailored to specific sports or scenarios to enhance precision.

It is worth noting that the fear recognition accuracy (88.1%) was lower than other emotions. This discrepancy could stem from several factors. First, fear-related facial expressions involve subtle changes in facial AUs that may overlap with other emotions like surprise. Second, individual differences in expressing fear and cultural variations in interpreting fear-related cues add complexity. Lastly, the dataset might have fewer samples for fear expressions, leading to a less robust training of the model. Future work could focus on expanding the dataset, refining feature extraction methods, and improving model sensitivity to subtle AU changes.

5. Conclusion

Athletes' emotion is an important part of sports training class. Once athletes are in negative training emotion, both the training effect and quality will be significantly reduced. Therefore, it is very important to use data mining technology to accurately identify athletes' emotions in the training process. On the basis of consulting a large number of relevant documents at home and abroad, By comparing and analyzing the research results of emotion recognition and detection of athletes at present, Using multiple facial information, The multi-state detection of emotion, fatigue and distraction is realized, and the following work is carried out: through big data analysis and mining of facial AU representations under basic expressions, based on the cumulative intensity of AU under each expression, the key representations of AU under basic expressions are extracted, and finally a facial AU index set that can represent the changes of basic expressions is formed. Considering the characteristics of high-dimensional and small samples of data set, combined with the temporal and spatial characteristics of expressions, support vector machine algorithm is selected to realize the recognition of transient expressions of athletes. Time recognition of facial expressions will be beneficial to the realization of quantitative expression of athletes' emotions. Secondly, by recognizing the transient facial expressions of athletes, this paper analyzes the temporal and spatial characteristics of facial expressions, and considers and puts forward an emotional quantitative index based on the temporal characteristics of transient facial expressions of athletes: emotional index of athletes, which realizes the continuous expression of transient facial expressions, and then realizes the objective evaluation of athletes' emotions. The introduction of biomechanics provides a new research path for athlete emotion recognition. Future studies can further explore the relationship between biomechanical features and emotional states, as well as how these features affect performance. By combining biomechanics and emotion recognition technology, we can develop more precise emotion monitoring tools to provide more scientific support for athletes' emotion management.

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