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Article

Investigating the mechanisms of drama therapy's effects on adult mood swings using time series analysis

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Abstract: The role of art healing is gradually being emphasized by modern people. And with the maturity of physiological signal processing technology, combining technology with art brings more possibilities for the application of art healing. In this paper, while choosing drama therapy as a modality for adult emotional healing, a physiological signal feature extraction model based on contrast learning (TS-TWC) is introduced. Using the Time-Wavelet Contrast Module and Three-View Contrast Module, the emotional fluctuation features of the subjects were extracted according to the time series, and the emotional changes during the drama therapy were restored. After the drama treatment, the mean scores of the three emotion expression indicators of the 10 drama treatment participating adults increased to more than 85, and the mood fluctuation scores of depression/anxiety decreased to less than 70, and the emotional health was improved.

Keywords: TS-TWC; time series; feature extraction; drama therapy; mood swings

1. Introduction

Drama therapy is a process-oriented, concrete action-oriented healing experience that is an interdisciplinary combination of theater and psychology [1-2]. Since the 20th century, the boundaries between drama and life have become more and more blurred, with dramatic performances becoming increasingly lifelike and everyday life increasingly artistic, and despite the fact that the means of drama therapy originated in the theater, its core goal remains therapeutic [3-4]. Drama is not only an appendage of literature, but also becomes an art of action. As drama increasingly focuses on the process of performance, the concept of theater has been transformed, which has had a profound impact on drama therapy [5-6].

Drama therapy is mainly based on psychodrama theory, humanistic psychology and artistic expression theory [7]. From the perspective of theater, Stanislavsky believed that the “identification” of the character is crucial, and he proposed the concept of “magic if”, that in the rehearsal stage, the actor should recall the moments in his own life related to the character, in order to stimulate the required emotions, thus revealing the “magic if” of the character. This reveals the “inner truth” of the character [8-10]. In contrast, the German dramatist Bertolt Brecht advocated a distance between the actor and the character in order to prevent the audience from becoming passive recipients, and he used the effect of “strangeness” to keep the audience calm and reflective during the performance [11-12]. Polish director Grotowski, influenced by Stanislavski and French theater theorist Aalto, put forward the concept of “sacred actor”, emphasizing the actor's “self-penetration” in the role, so as to make the theater exploration deep inside.

Drama therapy consists of two parts: “drama” and “therapy”. Drama is a kind of art that reflects various conflicts in social life through the performance of stories by actors, and it is a synthesis of literature, music, dance and other arts centered on performing arts [13-14]. And therapy is aimed at healing and curing physical and mental rehabilitation [15]. Drama therapy is the use of drama mode to complete the process of psychological healing of the case, in China still need a certain social acceptance of the process, in recent years in the application of the rise of the theater on the dissemination of drama therapy has played a positive role in the promotion [16-17].

Mood fluctuations in adults are often reflected in the fluctuation of hormone levels and the perfection of brain function, so that their emotions are easy to rise and fall, sometimes excited and thrilled, sometimes anxious and depressed [18]. With the enhancement of self-awareness and the gradual establishment of independence, they are also more prone to conflicts and confusion when facing problems such as academic pressure, interpersonal relationships and self-identity. Emotional problems are particularly prominent in this period, and emotional disturbances, such as anxiety, depression, anger, and feelings of inferiority, have become a common phenomenon in the adult population, and these emotional problems not only affect the quality of adults' learning and life, but also may have long-term effects on their physical and mental health [19-20].

As an important method for analyzing temporal data, time series analysis methods have been widely used in various fields, including the Internet, financial engineering, etc. [21-22]. The traditional time series analysis method emphasizes that the changes of time series are regarded as compounded by a variety of factors, such as seasonal variation factors, etc., and when conducting the analysis, it tries to find the influence of each factor variable on the changes of time series, while the modern time series is to regard this sequence as a stochastic process, aiming to find the rule of change therein and get the corresponding conclusions through the analysis [23-25]. The rational use of time series analysis is of great practical significance in studying the mechanism of the influence of drama therapy on mood swings in adults.

The use of time series analysis technology in drama therapy is mainly to analyze the changes of physiological signal data of participants during mood fluctuations, so as to scientifically reflect the treatment effect and timely adjust the treatment. In this paper, we propose a TS-TWC model based on the MoCov3 contrast learning framework, which processes time series data in stages through two modules. In the first stage, the time-wavelet comparison module converts the original time series data into four-view wavelet sequences by means of dual encoders. After combining the Sigmoid function to calculate the conversion loss value and enhancing the view features by using the Attention-based Feature Augmentation (AFA) structure, the data features are extracted by contrasting the data in separate views. In the second stage, shallow-deep feature fusion of the extracted features is performed by the adjustment module (three-view comparison module), and after calculating the view similarity by using the contrast loss function of MoCov3, the mood swings of the participants are obtained and the categorized mood set is constructed. Based on the features of the mood fluctuation data obtained in the two stages, the details of the drama treatment were adjusted to heal the depression/anxiety of adults in three dimensions: emotional catharsis, emotional projection, and emotional memory.

2. Time series in drama therapy and adult mood swings

2.1. Feature extraction algorithm for physiological signals based on comparative learning

Physiological signal data records a sequence of values over time and has a similar form to data such as behavioral detection signals and mechanical vibration signals. These data can be collectively referred to as time series. Currently, many generalized models based on self-supervised learning have emerged in the field of time series processing, working to improve the performance and generality of time series feature extraction. A deep learning model that can process time series is general enough to learn features of various physiological signals. Therefore, this chapter proposes a feature extraction algorithm for physiological signals based on comparative learning (TS-TWC), which is capable of processing a wide range of time series signals including physiological signals. The algorithm first performs a wavelet transform on the time series, splices its scale coefficients and detail coefficients, and calls it a wavelet sequence; then performs self-supervised learning by comparing the time series with the wavelet sequence; and finally uses the learned features for a downstream task. This chapter utilizes migration learning and classification tasks to examine the model's ability to process time series and the quality of the features obtained. Sample datasets used include ECG signals, skin electrical signals, EEG signals, mechanical vibration signals, and behavioral detection signals.

2.1.1. Time-wavelet comparison module

The time-wavelet contrast module is constructed based on the MoCov3 contrast learning framework. Figure 1 shows the structure of the time-wavelet contrast module. Currently, most contrast learning frameworks are only applicable to two views, but the present algorithm needs to process four views at the same time.MoCov3 can be regarded as a combination of the SimSiam and MoCo frameworks.The SimSiam framework does not use negative samples, and trains the student network model by completing the agent task of permutation prediction. In this paper's algorithm, the SimSiam network is responsible for processing data from the same original view, and the MoCo framework's input is information from different original views.

To introduce the specifics, first a brief overview of the MoCov3 contrast learning framework is given.MoCov3 uses two encoders f_q and f_k to encode two randomly augmented views v_1 and v_2. Let $q_1 = f_q(v_1)$, $q_2 = f_q(v_2)$, $k_1 = f_k(v_1)$, and $k_2 = f_k(v_2)$, then the symmetric loss is $loss = ctr(q_1,k_2)+ctr(q_2,k_1)$, and the contrast loss function $ctr(x,y) = 2\tau \cdot L_q$, where L_q uses a contrast loss function in the form of InfoNCE as shown below:

$$L_q = -\log \frac{\exp(q \cdot k^+ / \tau)}{\exp(q \cdot k^+ / \tau) + \sum_{k^-} \exp(q \cdot k^- / \tau)} \tag{1}$$

The set k^+ is the output of the encoder f_k on the input sample q, called the positive sample of q. The set $\{k^-\}$ represents the output of f_k on samples other than q in the same mini-batch, called negative samples of q, and τ is the temperature hyperparameter.

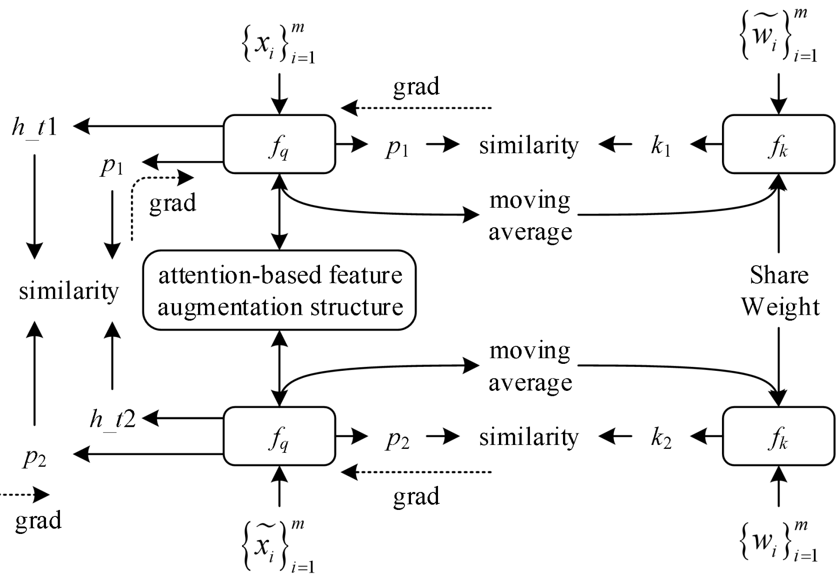

Figure 1. Structure of the Time-Wavelet contrasting module

The encoders f_q and f_k are structurally identical. In the training phase, the parameters of f_q are updated with the gradient back propagation, while the parameters of f_k are updated with momentum in the form of moving average, denoting the parameters of f_q as θ_q and the parameters of f_k as θ_k, θ_k is updated in the following way: $\theta_k = m \cdot \theta_k + (1-m) \cdot \theta_q$, where m tends to 1.0.

Let the time series $\{x_i\}_{i=1}^m$ be one of the original views, then its corresponding wavelet series is $\{w_i\}_{i=1}^m$, and the respective randomly enhanced views are $\{\tilde{x}_i\}_{i=1}^{mm}$ and $\{\tilde{w}_i\}_{i=1}^m$, and the four views are encoded using two encoders, f_q and f_k. The f_q consists of a backbone network (e.g., a one-dimensional ResNet) denoted as g_q and a projection header, and f_q shares weights between the two views $\{x_i\}_{i=1}^m$ and $\{\tilde{x}_i\}_{i=1}^m$. A prediction header h is used to transform the output of one of the views and match it to the other. Notate the two output vectors as $p_1 \triangleq h\left(g_q\left(\{x_i\}_{i=1}^m\right)\right)$ and $z_2 \triangleq g_q\left(\{\tilde{x}_i\}_{i=1}^m\right)$, and relatively symmetrically, there exists $p_2 \triangleq h\left(g_q\left(\{\tilde{x}_i\}_{i=1}^m\right)\right)$ and $z_1 \triangleq g_q\left(\{x_i\}_{i=1}^m\right)$.

The stop-gradient operation plays a crucial role in preventing the collapse of contrast learning. f_q constitutes one of the encoders of the SimSiam network, and following the loss function of MoCov3, the symmetric loss is $loss1 = ctr\left(p_1, stopgrad\left(z_2\right)\right) + ctr\left(p_2, stopgrad\left(z_1\right)\right)$. The parameters of f_k are updated by moving averaging the parameters and sharing the weights between the two views of $\{w_i\}_{i=1}^m$ and $\{\tilde{w}_i\}_{i=1}^m$. Denote the two output vectors as $k_1 = f_k\left(\{w_i\}_{i=1}^m\right)$, $k_2 = f_k\left(\{\tilde{w}_i\}_{i=1}^m\right)$, then the symmetric loss is $loss2 = ctr\left(p_1, k_2\right) + ctr\left(p_2, k_1\right)$.

If the model has difficulty distinguishing between positive and negative samples in the feature space, the contrast learning loss will fall slowly. These difficult negative samples force the model to learn a better representation. The Sigmoid function has a small gradient in regions greater than 1.0, which approximates the effect of difficult negative samples. And in the experiments, the Sigmoid function has no negative effect on the results of transfer learning. Therefore, in this stage $loss_{att} = Sigmoid\left(loss1\right) + Sigmoid\left(loss2\right)$ is used as the loss function for the entire time-wavelet comparison module.

An Attention-based Feature Augmentation (AFA) structure was added to the SimSiam network with the same structure as the AA structure and with no trainable parameters in it. $\{x_i\}_{i=1}^m$ and augmented view $\{x_i\}_{i=1}^m$ are used as two inputs to the Siamese network and are further augmented by the AFA structure after two convolutional layers. Contrast learning usually requires the input data to contain two different augmented views of the same sample to facilitate the learning of invariant representations. However, the proposed data enhancement method has the probability that the two enhancement sequences are identical. To avoid this, the AFA structure is used to augment the feature maps of the original data.

The backbone network of f_a in this chapter is a one-dimensional CNN with three convolutional layers. The convolutional kernel size, step size and padding are set as hyperparameters whose exact values depend on the length and type of the time series. Thus, the choice of model is not limited to a specific range. However, given the use of shallow-deep feature fusion, the range of model choices used mainly includes CNNs, ResNet and other networks that use convolutional operations.

In the next section, the first and third convolutional layers of the encoder are used for shallow-deep feature fusion. Therefore, the AFA structure is placed after the second convolutional layer in this chapter. Shallow-Deep feature fusion preserves the initial features in the final output of the encoder and prevents the enhanced feature maps from deviating too much from their original information. With this operation, the contrast learning process transitions from the time-wavelet contrast module to the three-view contrast module.

2.1.2. Three-view comparison module

In convolutional neural networks, feature maps of different layers have different information. Specifically, shallow features contain geometric information and deep features contain semantic information. The shallow-deep feature fusion method reshapes the shape of the shallow feature maps through an adjustment module (adj) and adds it to the deep feature maps, and ultimately this result is used as an input to the three-view comparison module.

The MoCov3 framework requires large batch sizes to learn good representations. However, the fine-tuned dataset for migration learning is small in many cases. A triple network is proposed which reduces the batch size by adding augmented views appropriately in the comparison learning. The scale factor and detail factor are different for different wavelet bases. Thus, one wavelet basis corresponds to one wavelet sequence and multiple wavelet sequences can be used to generate multiple views. Wavelet bases with short vanishing moments have a similar effect and in this section Daubechies wavelet base and Haar wavelet base are used to create two different views. The goal is to reduce the batch size in pre-training and fine-tuning and to learn more transform invariant representations. Figure 2 shows the structure of the three-view comparison module. The three-view comparison module first selects two of the three views without duplication, which are augmented with data and fed into the time-wavelet comparison module.

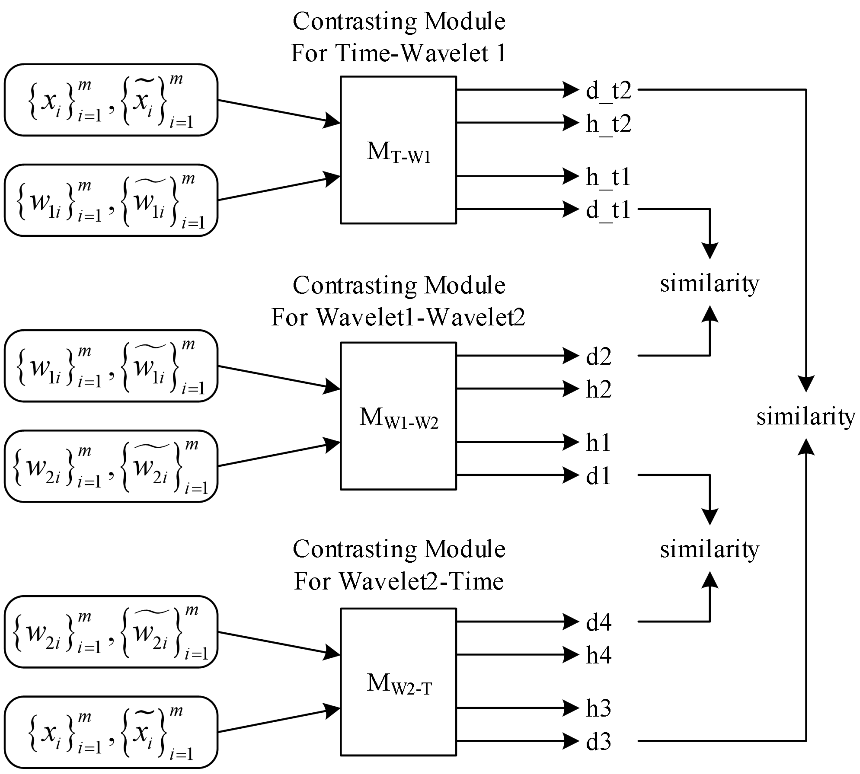

Figure 2. The framework of the triple-view contrasting module

If the wavelet sequence is generated by the Daubechies wavelet basis, its corresponding view is notated as $\{w_{1i}\}_{i=1}^m$. Similarly, $\{w_{2i}\}_{i=1}^m$ represents the wavelet sequence view of the Haar wavelet basis, and $\{x_i\}_{i=1}^m$ remains the original batch data. Let $(\{x_i\}_{i=1}^m, \{w_{1i}\}_{i=1}^m)$ represent one of the three kinds of inputs in Fig. 2, the other two sets can be written as $(\{w_{1i}\}_{i=1}^m, \{w_{2i}\}_{i=1}^m)$ and $(\{w_{2i}\}_{i=1}^m, \{x_i\}_{i=1}^m)$. Where $(\{x_i\}_{i=1}^m, \{w_{1i}\}_{i=1}^m)$ has inputs of $\{x_i\}_{i=1}^m$ and $\{x_i\}_{i=1}^m$ on the SimSiam structure. If its output shallow-deep feature fusion feature map is noted as (d_t1, d_t2) , the fusion feature maps of the other two input methods can be expressed as $(d1, d2)$ and $(d3, d4)$. At the same time, the output representations of the SimSiam structure when shallow-deep feature fusion is not performed are retained, denoted as (h_t1, h_t2), $(h1, h2)$ and $(h3, h4)$. The similarity between the three views is computed using MoCov3's contrast loss function, denoted as $loss3 = ctr(d\_t1, d2)$, $loss4 = ctr(d1, d4)$, and $loss5 = ctr(d3, d\_t2)$. After the Sigmoid function processing, the three-view comparison loss is shown below:

$$loss_{triplet} = Sigmoid(loss3) + Sigmoid(loss4) + Sigmoid(loss5) \tag{2}$$

According to the discussion in Section 2.1.1, $loss_{ar,all}$ can denote $(\{x_i\}_{i=1}^m, \{w_{1i}\}_{i=1}^m)$, $(\{w_{1i}\}_{i=1}^m, \{w_{2i}\}_{i=1}^m)$ and $(\{w_{2i}\}_{i=1}^m, \{x_i\}_{i=1}^m)$ the sum of their respective comparative learning losses, the overall comparative loss function L can be Determine:

$$L = loss_{ar,all} + loss_{triplet} \tag{3}$$

Since (h_t1, h_t2) is extracted from the original time series view $\{x_i\}_{i=1}^{m}$, h_t1 and h_t2 are summed as a characterization of $\{x_i\}_{i=1}^{m}$. Similarly, $h1+h2$ and $h3+h4$ can be obtained, corresponding to $\{w_{1i}\}_{i=1}^{m}$ and $\{w_{2i}\}_{i=1}^{m}$, respectively. In the inference phase, to fully utilize the three-view representations, h_t1+h_t2, $h1+h2$ and $h3+h4$ are input to a three-view fusion module to obtain the final feature vectors to be used in the classification task. However, shallow-deep feature fusion results can also be selected as inputs. In order to explore the difference between these two cases, a detailed ablation experiment was performed. In particular, when h_t1+h_t2, $h1+h2$ and $h3+h4$ are used as inputs, the resulting three-view fusion structure is called a fusion head h; and when d_t1+d_t2, $d1+d2$ and $d3+d4$ are used as inputs, it is called a fusion head d.

Figure 3 shows the specific components of the three-view fusion structure. First, it projects the input vectors into a feature space of the same dimension using a fully connected layer and a relu activation function. The projected vectors are denoted as m_x, m_y and m_z. They are then concatenated into a single vector that will be normalized by the SN layer, and a fully connected layer is added to reduce one of its dimensions to 3. Processing by the Sigmoid function yields weight1, weight2 and weight3, which assign different importance to m_x, m_y and m_z. The weighted vectors will be normalized by SN layer respectively. The results are superimposed on the input vectors x, y and z. Finally, the obtained vectors are connected together again and their lengths are adjusted by means of a fully connected layer.

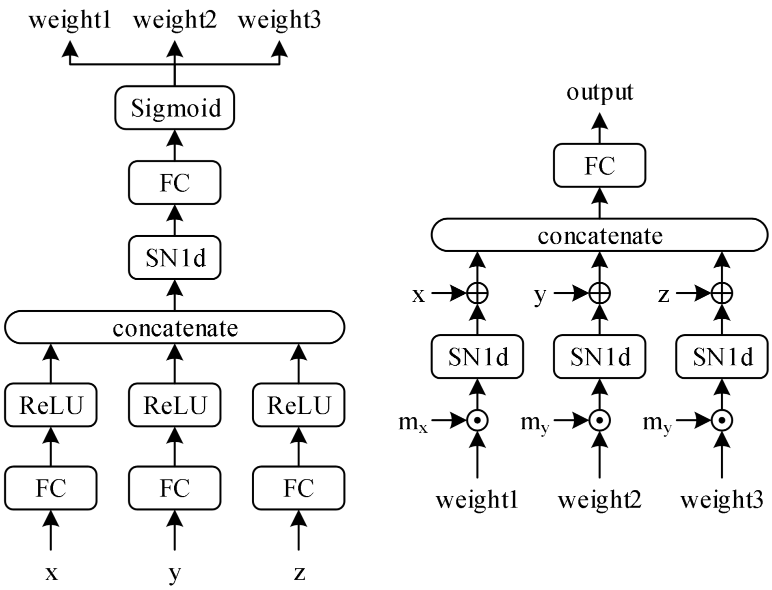

Figure 3. Tri-view fusion structure

2.2. Links between drama therapy and emotion regulation

2.2.1. Drama therapy and emotional catharsis

Drama therapy methods are linked to adult emotional regulation in three main ways. First of all drama therapy is an effective way of emotional catharsis. When people watch a tragedy, they will be triggered by fear and pity because of the fate of the characters in the play, so that these two negative emotions can be released and peace of mind can be obtained. Emotional catharsis is the release of repressed and pent-up negative emotions from the heart in order to avoid their adverse effects on the body. Negative emotions are inevitable for everyone, but many times they cannot be released in time due to social constraints, and can be harmful to the body when accumulated over time. Drama therapy, however, can provide a safe, secluded space for adults to leave behind all social roles and fully release their inner emotions without fear. In addition, the dramatization of the virtual background of the story allows adults to see the whole event from a certain distance, to avoid over-involvement in the emotions and get hurt.

2.2.2. Drama therapy and emotional projection

Secondly drama therapy can provide space and time for adults to project emotionally. “Emotional projection is a psychological process of imagining that someone else feels the same way as he does, or even that someone else is him.” In the process of drama therapy, especially group drama therapy, adults not only tell and interpret their own stories, but also sometimes act as supporters to help others to complete their performances or just as witnesses to their performances. In acting out the role of another person's story, adults use the specific space and time constructed by drama therapy for empathy and personal emotional projection, and adults need to think in the mode of thinking of the narrator. This also provides the adult with a new way of looking at things, so that he or she can have a more pluralistic view of different situations, rather than only from his or her own subjective point of view. When adults merely act as spectators to witness others' stories, they can not only observe the psychological activities and entanglements of others' subjective worlds through emotional projection, but also rationally scrutinize the whole story from an outsider's point of view, and understand how the conflict between adults' subjective thoughts and the objective environment of reality is caused, so as to provide a way of thinking for solving the dilemma of their own reality. In addition, in the improvisation between the adult and his/her partner in different situations, the adult can explore a variety of possibilities for the same situation, change his/her one-dimensional response to the situation, reevaluate his/her own relationship with the situation, and achieve the enhancement of his/her psychological acceptance and development. Overall, drama therapy can provide adults with a comprehensive, multi-angle understanding of the situation and their own spatial world and an opportunity for cognitive reassessment, so that they can calm down, use a certain amount of time to re-examine their own relationship with the environment, and ultimately accept and face it in a positive state of mind.

2.2.3. Drama therapy and emotional memory

Finally, Drama Therapy provides adults with a rich source of emotional memory, allowing them to break away from the monotony of negative emotions and focus instead on the positive emotional experiences that have recently arisen. Emotional memory is a psychological term and an important concept in the Stanislavski system of performance theory. Emotional memories are emotional experiences that are stored in our minds. In moments of major emotional fluctuations, the brain spontaneously records the neural circuits of the moment. This way, when people recall the situation again, even if the specific people, events and objects are blurred, the neural circuits are evoked to make our emotional and psychological experience very clear. Through the use of different roles in drama therapy, an adult can have a variety of emotional experiences to dissolve his/her internalized single solidified negative emotional feelings. In social life, every person assumes a variety of roles, such as father-family roles, professional roles, political roles, and so on. And each role will have his social attributes of emotional characteristics, the expression of these emotions is also a prerequisite or necessary content of communication and exchange between the role and the role, a lack of role-free emotional experience and memory of the person, is unable to produce normal communication with others. Such as autism, neurosis patients, etc., most of them are caused by too many single emotional experience.

2.3. Research methodology

2.3.1. Recruitment of subjects

Through online recruitment, students from a university were called to participate in the depression and anxiety mood test, and 12 students and faculty with mild or moderate symptoms of depression/anxiety were initially screened. After time coordination and willingness to participate, 10 students finally participated in the whole drama therapy and mood intervention. Among them, 5 were females and 5 were males with an age range of 20 to 25 years old. At the same time, a control group was recruited with the same format and criteria, and eventually 10 participants with moderate or mild depression/anxiety were enrolled in the control group (screened for access to the subsequent intervention group). Interviews with the 10 participants in the experimental group revealed that they all talked about depression, anxiety, and work/school stress due to change, which is consistent with the theory of "emerging adulthood" that focuses on self-development and construction of one's own life, and is full of unknowns, contradictions, and changes, and the quest for the value of life and the challenges of life's changes are the most important factors in the development of the adult. The pursuit of life's values and the challenges of life's changes are the main sources of mood swings.

2.3.2. Data collection

The present study measured participants' depression and anxiety levels in the pre-, mid-, and post-intervention phases. Participants were subjected to semi-structured interviews before and after the intervention, with the pre-interviews revolving around recent emotional feelings and experiences of participating in the program, and the post-interviews including recent emotional feelings, experiences of the drama therapy sessions, and gains in mind-body integration, thinking styles, behavioral habits, and emotional management. The interviews lasted no less than 60 minutes.

2.3.3. Treatment procedures

This study conducts clinical practice of physiological signaling of participants with follow-up research and interviews. It was conducted 3 times a week for about 60 minutes at a time for 5 months. A total of 5 therapists participated in the practice portion of this study, with 3 surrogate leaders leading the entire process of completing the drama therapy. The group activity practice took place offline.

This study mapped the 3 entry points of emotional catharsis, emotional projection, and emotional memory to drama therapy, a type of creative arts therapy. In drama therapy, participants tell and interpret their own stories and help others to perform their own stories, from which empathy, observation and other therapies are carried out, so that participants can improve their self-perception ability, experience more emotions of self and others, increase the perspective of problems, soothe suppressed emotions, improve brain function, deepen self-understanding, and learn the skills of emotional regulation, and ultimately realize the in-depth analysis of their own personality traits The ultimate goal is to deeply analyze one's personality characteristics and social relationships, and to look forward to the ideal state, so as to move from a depressed and anxious emotional state to a healthy emotional state.

3. Drama therapy practice supported by time series analysis

3.1. Data collection and processing and model performance testing

3.1.1. Physiological signal acquisition and processing

In order to test the feature extraction performance of the TS-TWC model for participants' physiological signals and to ensure that the model can successfully reflect the participants' emotional changes in the course of drama therapy, this section takes the physiological signal data processing of Participant A as an example to test the application value of the model. Figure 4 shows the raw EEG signal data of Participant A. After being processed by the time-wavelet contrast module of the model, the raw EEG signal of Participant A is converted into the 4-band waveform view of Figure 5. The EEG signal of Participant A during the drama treatment was feature-enhanced using the time-wavelet module, which resulted in the segmentation into 4 frequency band waveforms. It can be seen that the detailed features of the 4-band waveforms after processing by the Time-Wavelet module are clearer, which facilitates the subsequent three-view comparison module to learn the features of the EEG signals.

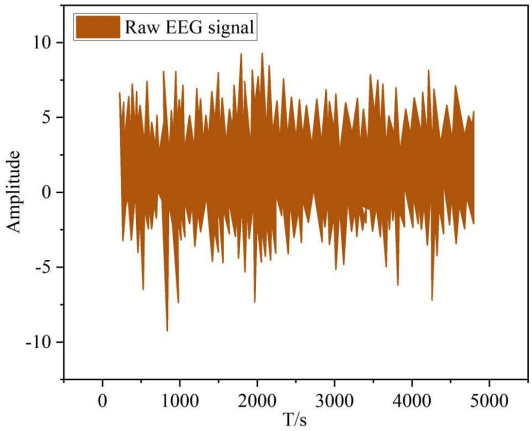

Figure 4. The raw electroencephalogram data of Participant A

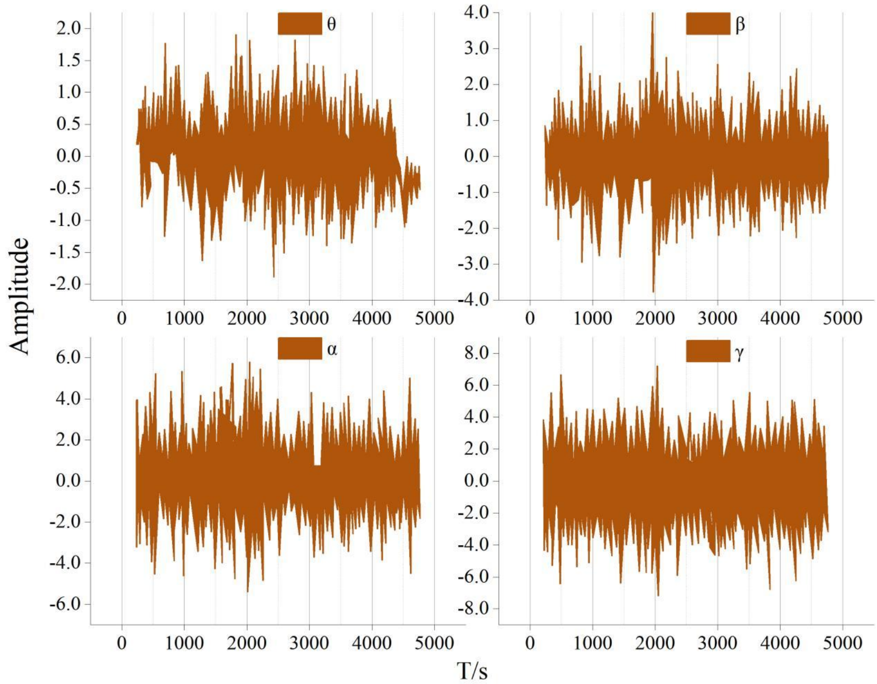

Figure 5. Waveform of 4 frequency bands after time-wavelet module processing

3.1.2. Emotion Sample Set Construction

After the characterization of the EEG signals was extracted using the three-view comparison module, the emotion classification was performed based on the extracted results. The classified EEG signals were time-sliced according to the electrode channels selected for the different emotional dimensions of Participant A. Only the EEG encoding results of the channels with high feature weights were retained, and the pulse time sequences of individual experiments were divided into time slices based on a 3-second time window to construct an emotional sample set. Figure 6 shows some of the pulse time series splitting results for Participant A. In the 20th, 40th, and 60th time slices of Participant A's first drama treatment, it can be seen that when the participant senses external stimuli and generates corresponding impulse signals, the TS-TWC model can accurately detect and extract the emotional changes in this time series, and restore the participant's emotional fluctuations.

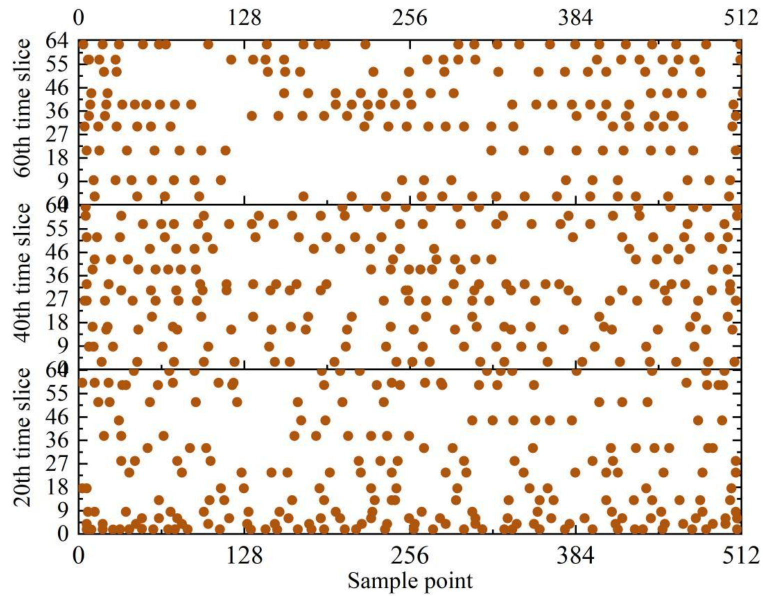

Figure 6. Split results of the partial pulse time series of participant A

3.1.3. Model performance validation

The physiological signals of mood swings of 10 participants in the experimental group during the drama therapy were collected, and the dataset was constructed to test the model performance. Figure 7 shows the accuracy of the TS-TWC model for physiological signal feature extraction and mood swing reduction in the dataset. The accuracy of the TS-TWC model exceeded 90% for both physiological signal feature extraction and mood fluctuation reduction, with the highest physiological signal feature extraction accuracy being able to reach 98.54% (Participant F) and the highest mood fluctuation reduction accuracy being able to reach 95.46% (Participant C). This indicates that the model can better provide the therapist with the participants' emotional data, and assist the therapist to adjust and improve the drama therapy method in time.

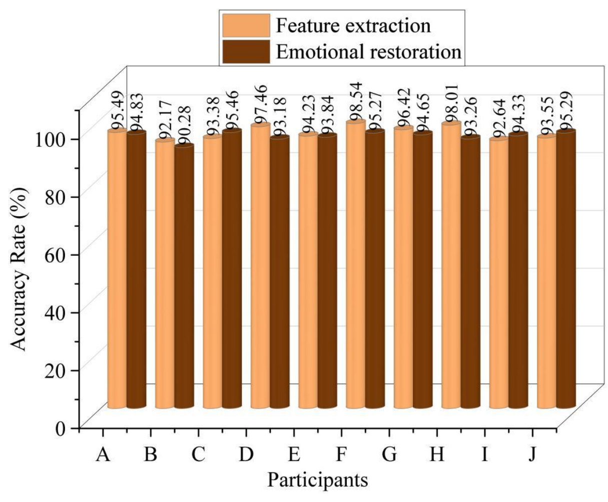

Figure 7. The performance of the TS-TWC model on the dataset

3.2. Comparison of Adult Emotional Expression and Mood Swings Before and After Drama Therapy

3.2.1. Comparison of Emotional Expressions

The emotional expression of the participants before and after the drama therapy was compared and an independent samples t-test was conducted to determine the actual effectiveness of the model in aiding drama therapy. Table 1 shows the results of comparing the pre- and post-test differences in emotional expression between the test group and the control group. Before the drama treatment, the mean scores of the three emotion expression indicators of the experimental group and the control group were around 50, with P greater than 0.01, and the participants in the two groups were at a comparable level, which met the control requirements. And after the drama treatment, the mean scores of the experimental group increased to 85.94, 86.37, and 88.26, but the mean scores of the control group only increased to about 60. The p-value of all three emotion expression indicators is 0.00, indicating that after the drama treatment, the experimental group's ability to express emotions is much better than the control group.

Table 1. Comparison of differences in emotional expression before and after test

		Pre-test		
Indicators	Experimental group	Control group	T	P
Emotional release	50.58	51.02	0.48	0.392
Emotional projection	51.23	51.29	0.52	0.284
Emotional memory	51.95	51.67	0.43	0.461
	Post-test			
Indicators	Experimental group	Control group	T	P
Emotional release	85.94	60.39	0.19	0.00
Emotional projection	86.37	61.27	0.26	0.00
Emotional memory	88.26	61.86	0.17	0.00

3.2.2. Comparison of mood swings

Table 2 shows the comparison of depression mood swings before and after the drama treatment for the 10 participants in the experimental group. Table 3 shows a comparison of anxiety mood swings before and after the drama treatment for the 10 participants in the test group. Since the adults who participated in the drama therapy were in a mild/moderate depressed or anxious mood state, they all scored 80 or higher on mood swings on the pre-test. After 5 months of prolonged drama therapy, the depression/anxiety mood swing scores of all 10 adult participants dropped below 70, and mood swings returned to normal. Using the model to extract the characteristics of adult mood swings, we were able to visualize the situation during the drama treatment, which greatly facilitated the adoption of targeted measures and was the key reason why this drama treatment was able to achieve good results.

Table 2. The fluctuation of depressive mood before and after drama therapy

Participants	**Pre-test**	**Pre-test level of depression**	**Post-test**	**Post-test depression level**	**Difference scores**
A	85.03	Moderate	60.49	Normal	24.54
B	86.27	Moderate	61.84	Normal	24.43
C	81.34	Mild	62.01	Normal	19.33
D	88.48	Moderate	60.37	Normal	28.11
E	86.27	Moderate	61.22	Normal	25.05
F	83.53	Mild	62.05	Normal	21.48
G	84.27	Mild	61.43	Normal	22.84
H	85.66	Moderate	60.28	Normal	25.38
I	88.93	Moderate	62.16	Normal	26.77
J	80.29	Mild	60.49	Normal	19.80

Table 3. The fluctuation of anxiety levels before and after drama therapy

Participants	**Pre-test**	**Pre-test level of anxiety**	**Post-test**	**Post-test level of anxiety**	**Difference scores**
A	85.43	Moderate	61.29	Normal	24.14

B	88.57	Moderate	63.85	Normal	24.72
C	81.38	Mild	60.23	Normal	21.15
D	80.52	Mild	65.46	Normal	15.06
E	81.46	Mild	62.81	Normal	18.65
F	82.09	Mild	60.09	Normal	22.00
G	81.64	Mild	65.73	Normal	15.91
H	88.49	Moderate	64.56	Normal	23.93
I	89.52	Moderate	67.52	Normal	22.00
J	81.27	Mild	61.38	Normal	19.89

4. Conclusion

In this paper, a physiological signal feature extraction model based on comparative learning (TS-TWC) was applied to analyze participants' mood fluctuations during drama therapy. The feature extraction and emotion reduction accuracy of the model was consistently >90%. With the accurate monitoring of mood fluctuations, the therapist can see the participants' mood changes in each session of drama therapy in time. Through continuous adjustment and improvement, eventually all 10 adults who participated in drama therapy came out of mild/moderate depression/anxiety mood states, mastered healthier ways of expressing emotions, and reduced the intensity of mood fluctuations (meaning: scores in 3 categories of emotion-expressive behaviors improved to between 85.94-88.26; scores of depression/anxiety states reduced to less than 70). This drama therapy experiment also well verified that the time series analysis technique has the potential to be applied in art healing, and subsequent in-depth research can be considered.

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