CreativeBioMan

A Brain- and Body-Wearable, Computing-Based, Creative Gaming System


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by Min Chen, Yingying Jiang, Yong Cao, and Albert Y. Zomaya

Current artificial intelligence (AI) technology is used mainly in rational work, i.e., computational and logical analysis. How to best make the machine as aesthetic and creative as humans has gradually gained attention. This article presents a unique, creative game system called *CreativeBioMan*. This system combines brain wave and multimodal emotion data and uses an AI algorithm for intelligent decision fusion, which can then be used in artistic creation with the goal being to separate the artist from repeated labor creation.

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To imitate humans' artistic creation, the creation process of the algorithm is related to artists' previous artworks and emotions. Electroencephalogram (EEG) data are used to analyze the style of artists and match them with a style

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from a data set of historical works. Universal AI algorithms are then combined with each artist's unique creativity, which evolves into a personalized creation algorithm. According to the results of cloud emotion recognition, the artworks' colors are corrected in such a way that the artists' emotions are fully reflected in their works, thus creating novel works of art. This allows for the machine to integrate the understanding of past art and emotions with the ability to create new art forms in the same manner as that of humans.

This article introduces the system architecture of CreativeBioMan from two aspects: 1) data collection from the brain- and body-wearable devices and 2) the intelligent decision-making fusion of models. A testbed platform is built for an experiment, and the creativity of the works produced by the system is analyzed.

Electroencephalogram data are used to analyze the style of artists and match them with a style from a data set of historical works.

AI Applications

With the development of AI technology, machines have surpassed humans in many ways. Nevertheless, current AI technology is primarily applied in rational fields of work. The computing and logical analysis abilities of AI are particularly better than those of humans. People usually think that the appreciation and creation of beauty is an exclusive peculiarity of humans; however, rapidly developing AI has demonstrated its specific aesthetic perception and creativity while imitating the skills of humans. Current AI can not only compute, it can also generate creative digital images. For example, in [1], the authors apply a neural style transfer to redraw key scenes in *Come Swim* in the same style as that of the impressionistic painting that inspired the film. It is also possible to apply AI in fashion; e.g., the work of Jiang and Fu [2] can automatically generate a clothing image with a particular style in real time using a neural-fashion style generator. In [3], the authors present a novel approach for generating new clothing on a wearer through the use of generative adversarial learning, while at the same time keeping the wearer and her/his pose unchanged. To solve the visual creation process problem and allow for nonprofessionals to participate in artistic creation, brain waves and multimodal emotion data offer new trains of thought for the art creation process.

Cognitive biometrics continues to attract attention; e.g., EEG and electrocardiogram signal measurements can detect the reaction of the brain and record various electromagnetic, untouchable neural oscillations [4]. Emotion data add more personalized elements to art creation, which endow soul to the created work. The AI algorithm can be used to process the style of artistic contents created by the artist according to a combination of the artist's brain wave and her/his emotion. Thus, the efficiency of the art creation process will be increased significantly if an artist is liberated from repetitive labors.

On this basis, and for the first time, we present CreativeBioMan, which jointly encodes brain wave and multimodal emotion data and applies them to creative games. The machine has creativity similar to that of humans for drawing paintings and creating artwork; in this context, *creative* denotes a creative algorithm. *BioMan* means a humanoid biological robot, which can collect the user's biological signals and design the algorithm according to the human cognitive process; it is a coalition of machine and human and includes a virtual and creative AI entity.

Compared with the aforementioned existing work, we not only innovatively used EEG data for artistic creation, we also incorporated user emotions into the artwork, which enriched its meanings. In addition, as presented in this article, we performed a systematic integration to build a complete, creative system platform. Our main contributions are as follows:

- We present CreativeBioMan, which, for the first time, develops a creative game using brain wave and multimodal emotion data, completes decision fusion and superposition using an AI algorithm, and converts their respective, complementary advantages into something that advances toward a personalized, creative algorithm.
- We introduce the two important components of CreativeBioMan in detail, i.e., brain-wearable devices and wearable clothes were used by an emotional robot to collect brain wave and multimodal emotion data, respectively. Styles were then matched based on a motor imagery model that helps artists form their creation.
- We describe the construction of the CreativeBioMan experimental platform. In addition, to verify the creativity of system, an experiment was designed for an expert to analyze the fidelity of artworks generated by the machine to that of artworks created by humans.

Related Work

With the development of computer and mobile terminal technology, more and more game systems are flooding people's lives. General entertainment games not only take up a lot of users' time but also easily lead to addiction as players cannot extricate themselves, and thus, the games can impact their normal lives. Unlike entertainment games, creative games are human–computer interactive activities with enlightening and educational significance. AlphaGo, developed by Google's DeepMind team, is an important step in the development of creative games. Through more and more accurate and fast-learning algorithms, AlphaGo has won in all previous battles with human chess players.

As early as 2003, Freeman et al. [5] proposed an algorithm to translate the lines of a painting into any style that users want. The authors used a simple and traditional linear-fitting interpolation method for training and testing.

In [6], the authors developed a body interactive creative game called "Word Out." This game is aimed mainly at 4–7-year-old children to help them learn to recognize and spell letters independently while playing the game, stimulate their active learning, and fully tap into their imagination and creativity. During the game, the alphabet first appears on the screen. After the user selects a word, the body's contour is matched with the words on the screen when the user manipulates the pose. The game can also be completed by the cooperation of multiple people working together as creatively as possible.

The machine has creativity similar to that of humans for drawing paintings and creating artwork.

Chatain et al. [7] designed an application for users to design and create games themselves. First, users draw on paper the elements of the game that they want to develop, including which types of instances the game has. Then, they take a picture of the paper through the tablet camera and integrate it into the application. Next, users can design the level, and the event-based visual programming language is used to define the logic and rules of the game. Finally, users can test their own curated and designed games. At any stage of the game's entire development process, users can skip or test to fully utilize their imagination and creativity.

The related work of the creative games introduced above can enhance the creativity of users, but these games do not take into account the users' emotional attributes and personality characteristics. With the development of deep learning and emotional computing, the characteristics of more users are integrated into the creative game, and additional complex deep learning algorithms are adopted to make the creative game system more intelligent, which has attracted our attention.

Conversely, for their research methods, Fink et al. [8] collected EEG signals of professional dancers during improvisational dancing. They observed that, during the generation of alternative uses, professional dancers showed stronger alpha synchronization in posterior parietal brain regions than did novice dancers. Fortino et al. [9]–[11] proposed a completely new architecture that supports the development of novel, smart wearable systems for cyberphysical, pervasive computing environments. And, in [12], the authors introduced an augmented convolutional neural network (CNN) architecture that bridged the gap between generative algorithms and pixel-labeling NNs. Gatys et al. [15] used neural representations to separate and recombine the content and style of arbitrary images, which provided a neural algorithm for creating artistic images.

System Architecture

The system architecture includes five modules: a user data acquisition module, a historical creation data set, a landscape data acquisition module, a cloud processing module, and an artwork publishing module. First, during the system design process, we used an expressive robot of brain-wearable devices and wearable clothes to collect data. Second, we collected different styles of paintings created by users and employed CNNs to extract the style features of paintings [14]. The third part, i.e., the landscape data acquisition module, is utilized when users are outdoors and do not want to create. They can then use the camera to take pictures, and the system extracts the content features of the artworks. Then, an AI algorithm was deployed in the cloud. After completing the intelligent decision fusion and creating artwork in the cloud, the results were sent to the intelligent terminal and displayed. This system architecture is shown in Figure 1.

Data Collection of Brain- and Body-Wearable Devices

EEG Data

For the CreativeBioMan creativity game, we used an independently designed, brain-wearable device to collect users' brain wave data. In our research findings, varying neural activity generated a different brain wave pattern [13]. For example, when a human was idle or in a state of artistic creation, the brain wave was a theta wave at a frequency between 4 and 8 Hz.

Real-Time Artistic Creation

As for the drafting of real-time artistic works created by artists, in this article, it is called the *content feature data* of artworks. The drawing board configured for the wearable-clothing expressive robot can be used to collect data in real time. Accordingly, the image data can be transmitted to the cloud in real time. The wearable-clothing expressive robot is a good tool for recording the creativity of artists who have divergent thinking, are good at improvisation, and want to capture inspiration at a certain moment. When artists travel and are inspired to paint a picture but there are no painting supplies available, the wearable-clothing expressive robot can complete the creation for them.

Multimodal Emotion Data

An affective interaction through wearable computing and cloud technology (AIWAC) box is an embedded hardware product independently developed by our laboratory. It can be used for real-time voice interaction with users, detection of users' emotional information, and analysis of users' emotional states based on AI algorithms. The AIWAC box is configured in the wearable-clothing expressive robot as the hardware core of emotional recognition and interaction and is used mainly to collect the artists' multimodal emotion data and upload them to the cloud. The peripheral modules of the wearable-clothing expressive robot include a communication module, a camera module for image collection, a microphone (MIC), and a playing module related to voice data collection and interaction. The wearable-clothing robot that integrates the AIWAC box has nine personality characteristics: courage, prudence, sincerity, virtuousness, confidence, modesty, tenacity, foresight, and optimism. It can also recognize 21 different human emotions. As emotion is the soul of an artwork, after the multimodal data collected by the wearable-clothing expressive robot are recognized and

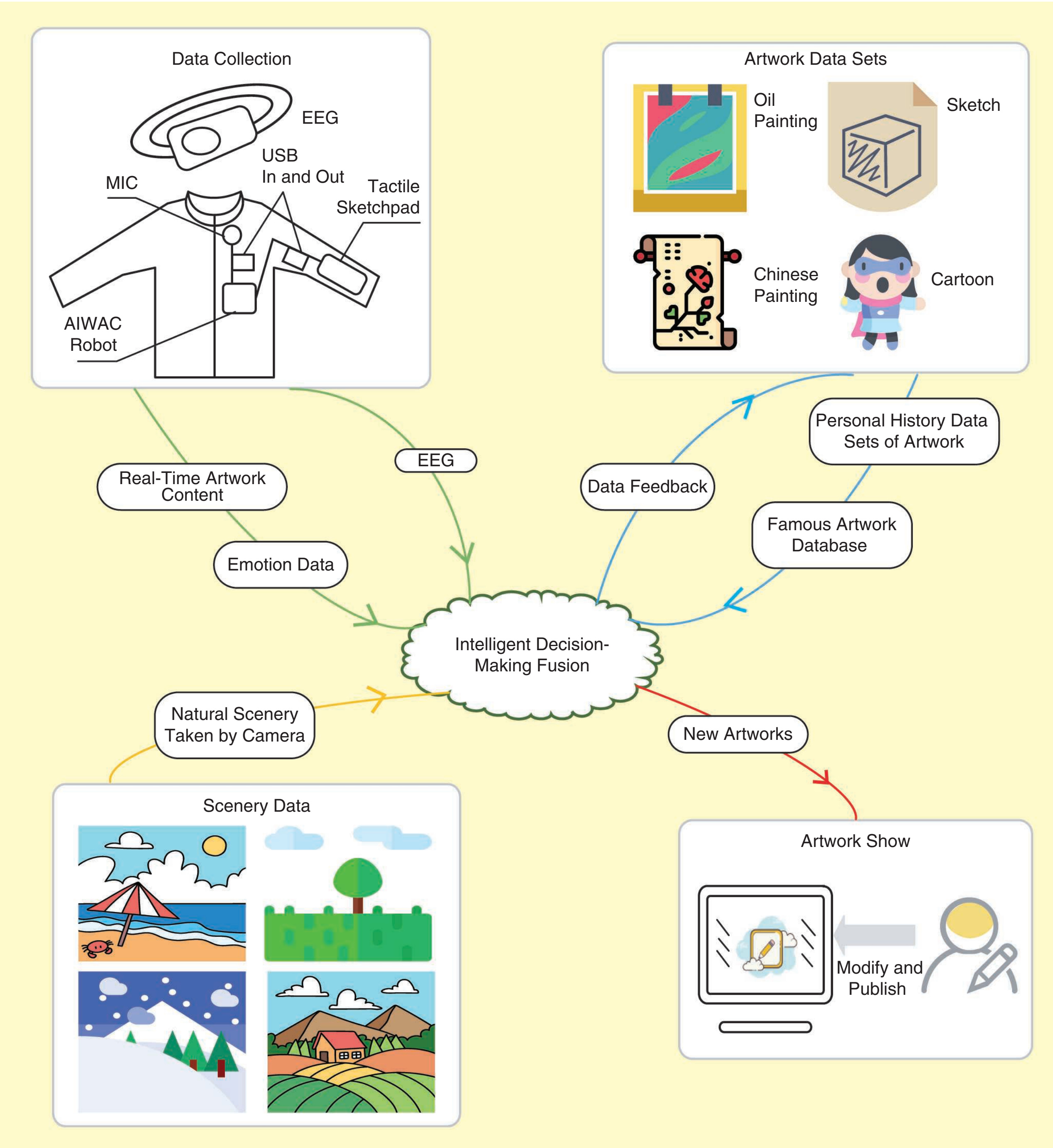

Figure 1. The CreativeBioMan system architecture. MIC: microphone; USB: universal serial bus. (Source: Flaticon.)

analyzed in the cloud, the artists' emotion is conveyed to the artwork by adjusting its lines and colors.

Artwork Data Sets

The artwork data sets include a personal, historical works data set for each artist. Aside from content feature, brain wave, and multimodal emotion data of brain-wearable devices as well as the wearable-clothing emotional robot that serves as the data source for the artistic creations of machines, an original, large-quantity artwork data set can also be input into the system. The data sets are classified according to the different creation styles of artists. After the motor imagery model is used to classify the style features of EEG data, they match them to the style features of the historical works data set. In this way, the styles of the content features can be transferred to create artworks with specific styles and contents. The algorithm learns and is trained by combining the historical data set, EEG data, and emotion data. The system can generate paintings in specific emotional themes and styles. Because this is a digital game, it can be used to present AI creativity. Artwork data sets integrate the data of famous artists, which form a rich database of works. The system can recommend style features for ordinary users and match the style of the user's EEG sports imagination to extract the style features.

Intelligent Decision Fusion and Creative Game Production

It is necessary to rapidly transmit the data to the cloud for intelligent decision fusion after obtaining EEG data, the content feature data of real-time artistic creation, and multimodal emotion data. First, the cloud uses a motor imagery algorithm to classify the style features of EEG data and analyze the styles desired by the artists. In this article, the style features are divided into four classes: oil paintings, traditional Chinese paintings, sketches, and cartoons. They are then matched with the style features of the historical artworks, which were previously uploaded to the cloud. After the EEG data styles are matched to that of the corresponding historical data set, the system confirms the actual style of the artistic creation. The content features are determined by the work draft created by the artists in real time.

To form an artwork with specific contents and styles, the Visual Geometry Group (VGG) 19 network algorithm is deployed in the cloud to extract and rebuild content and style features. In addition, the AI algorithm in the cloud includes an attention-based recurrent neural network (RNN) algorithm, which is used for recognizing and analyzing emotion data. The RNN algorithm can effectively memorize the relevant feature information according to a specific context. By introducing an attention mechanism into the RNN algorithm framework, a new weight-pooling strategy can be implemented into the network to project the part of the voice that has intense emotional features. After the artists' emotion is recognized in the cloud, the artworks are rectified with contents and style. The changing of the lines and color are used to express the artists' state of mind when creating artworks.

The Algorithm Model

The CreativeBioMan system's creativity is determined by the performance of the AI algorithm, which is deployed in the cloud. As described in this article, a motor imagery model is used to classify the styles of EEG data. A VGG-19 network is then used to rebuild style and contents to create a new artwork. An attention-based RNN algorithm is employed to raise the accuracy rate of emotion recognition to analyze and recognize emotion data. The system rectifies the colors and lines of artworks, which are created according to the emotion-recognition result, and fuses the emotion into the works. The systematical algorithm procedures are depicted in Figure 2.

EEG Data Processing and Motor Imagery Model

The common spatial pattern (CSP) method is frequently used in brain–computer interface (BCI) research based on EEG data. A data set is required to have a label and its class is known in each experiment. For the task of brain signal classification, the data collected in a single experiment are a matrix the size of $N \times P$ and noted as E_i, where N is the number of channels for signal collection, P is the number of samples of single channel, and i signifies the ith class. If there are M experiments in the ith class, then there will be M E_i matrixes. Because it is different from the traditional mean-normalization method used for obtaining the covariance of the class, the M E_i matrixes in the same class are linked in the direction of the row vector to obtain the entire EEG signal data, T_i, in the ith class in size $N \times (M \times P)$. The corresponding space covariance is then obtained according to the T_i matrix in the ith class, displayed as

$$C_i = \frac{T_i T_i^T}{tr(T_i T_i^T)}. \tag{1}$$

The $i \in \{1, 2\}$ CSP method is used to obtain the space-filtering matrix W of the two classes and validates (2) and (3):

$$W^T C_1 W = \Lambda_1, \tag{2}$$
$$W^T C_2 W = \Lambda_2. \tag{3}$$

The artwork style in this article is a four-class problem. A one-to-one strategy is chosen to build the CSP in multiple classes. The four classes are combined anew in pairs, and six space-filtering matrixes W will be obtained. The best six-column vectors are chosen for each space-filtering matrix, with each column vector seen as a filter. There are 36, i.e., 6×6, column vectors in total; therefore, the $36 \times N$, mixed, space-filtering matrix

$\bar{W}$ can finally be obtained. It is notable that $\bar{W}$ shall be saved. For the test, testing data directly use the mixed, space-filtering matrix obtained from set training for filtering. The mixed space filter $\bar{W}$ is used to finally filter the EEG data, E_i, in a single experiment and obtain X_i of $36 \times T$:

$$X_i = \bar{W} E_i. \tag{4}$$

As a result, the features of signal X_i are extracted after space filtering. First, the variances of the row vectors of X_i are obtained. Because of the variance among single EEG signals, the difference among some of the eigenvalues is large; therefore, the logarithm of variance is used to alleviate the difference among data, as displayed in (5):

$$v_i = \log(\mathrm{var}(X_i)), \tag{5}$$

where v_i is the eigenvector of a single experiment E_i. There are six eigen elements in total; in other words, each sample contains six eigenvalues. Then, long short-term memory (LSTM) is used to train and build a classifier.

Artwork Contents and Style-Processing Model Based on VGG-19

The processing of artworks consists of extracting its particular creation style. The works in the same class are extended, the contents of the works are extracted, and artworks are created. The VGG19 network in [15] is used to extract and rebuild the features of contents and styles, which involves 16 convolutional layers and five pooling layers. For the extraction of content features, a CNN of five layers is used for convolution. Mean pooling is conducted after each convolutional layer, and a content feature matrix is finally generated. As for the extraction of style features, first, all of the feature maps at a certain layer are processed after being put in the network. There is large quantity of feature maps at each layer, and, accordingly, the inner product of each pair of the feature maps and the style feature matrix that contains the texture and color information of the maps are obtained. After the content and style features are extracted, artistic paintings are created. Content and style features as well as white noise images are input into the VGG19 network. The gradient descent method is used to solve the total loss function, i.e., the minimum value of (6). The output result of the white noise image is used to update x constantly and uses the VGG19 network to rectify the result. To decrease the total loss, a painting based on a creation of the artist can finally be obtained:

$$L_{\text{total}}(\bar{p}, \bar{a}, \bar{x}) = \alpha L_{\text{content}}(\bar{p}, \bar{x}) + \beta L_{\text{style}}(\bar{a}, \bar{x}), \tag{6}$$

where $L_{\text{content}}(\bar{p}, \bar{x})$ is the loss of contents, $L_{\text{style}}(\bar{a}, \bar{x})$ is the loss of style, and α, β is the factor of influence.

Attention-Based RNN Emotion Analysis Model

In this article, we use an attention-based RNN model to evaluate a human's emotion, and, the higher of the

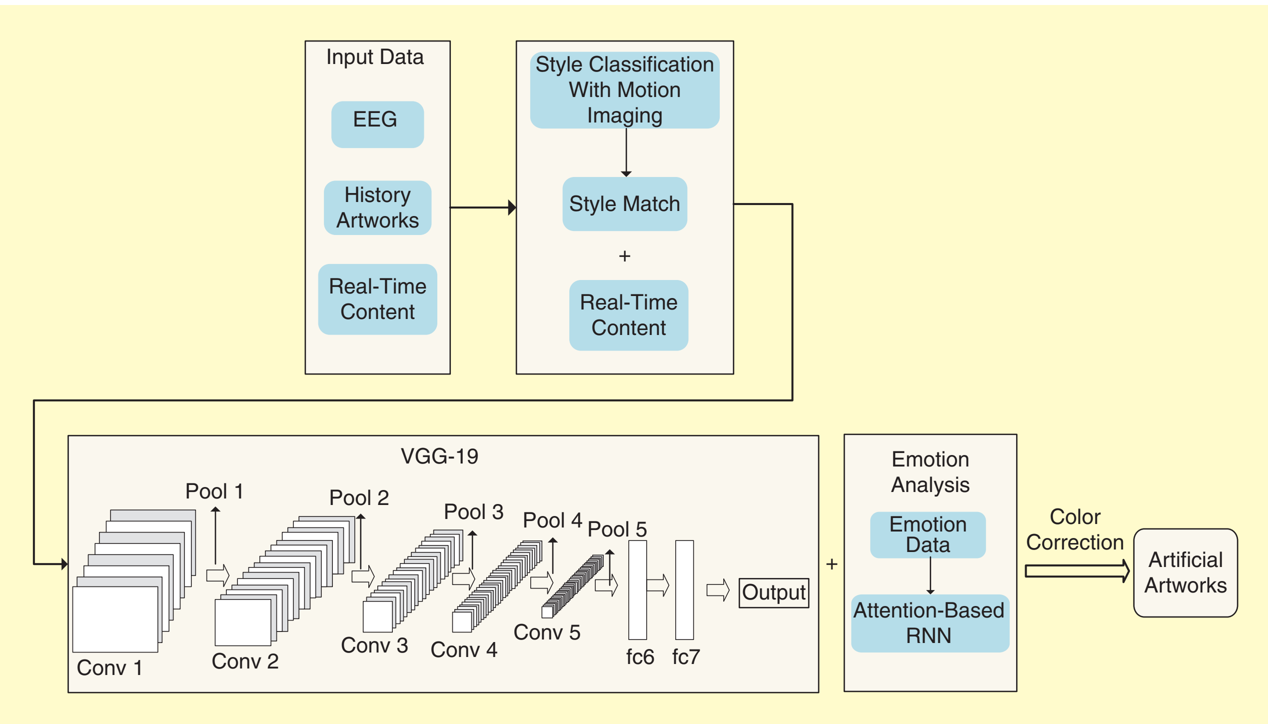

Figure 2. The CreativeBioMan algorithm flowchart. conv: convolution; fc: full connection.

similarity between the current input and the target state, the greater the weight that will be assigned to the current input. Moreover, the softmax function is introduced to calculate the output of parameter α_t, which is defined as

$$\alpha_t = \frac{\exp(\mu^T y_t)}{\sum_{t=1}^{T} \exp(\mu^T y_t)}. \tag{7}$$

Therefore, the attention model's output is

$$z = \sum_{t=1}^{T} \alpha_t y_t. \tag{8}$$

A different wave signal in the time domain corresponds to a different weight. In an area with concentrated emotional information, α_t is large, whereas in a blank frame or in an area without emotional information, α_t is small. Basic acoustical features are mapped to be discrete, emotion feature labels through the pooling layer, and softmax through RNN and attention computing.

Testbed and Experiment

System Testbed

We built a testbed for the CreativeBioMan system, which included brain-wearable devices, a wearable-clothing expressive robot, and a data center in the cloud, as displayed in Figure 3. For brain wave signal collection, we chose Texas Instruments' ADS1299-8 and CH559L as the chip and main control chip, respectively. The wearable-clothing expressive robot integrated the AIWAC box, the intelligent drawing board, and the MIC voice collection module. Wireless communication was used for data communication with the whole system. The Inspur Big Data Center in the cloud was equipped with two management nodes and seven data nodes. A data amount of 253 TB could be saved onto it, which offered a sufficient hardware guarantee to the real-time computing and analysis of the AI algorithm.

The EEG signal-sampling frequency was 512 Hz, and the EEG signal was collected in three creation processes for each test subject. Simultaneously, a user's emotion

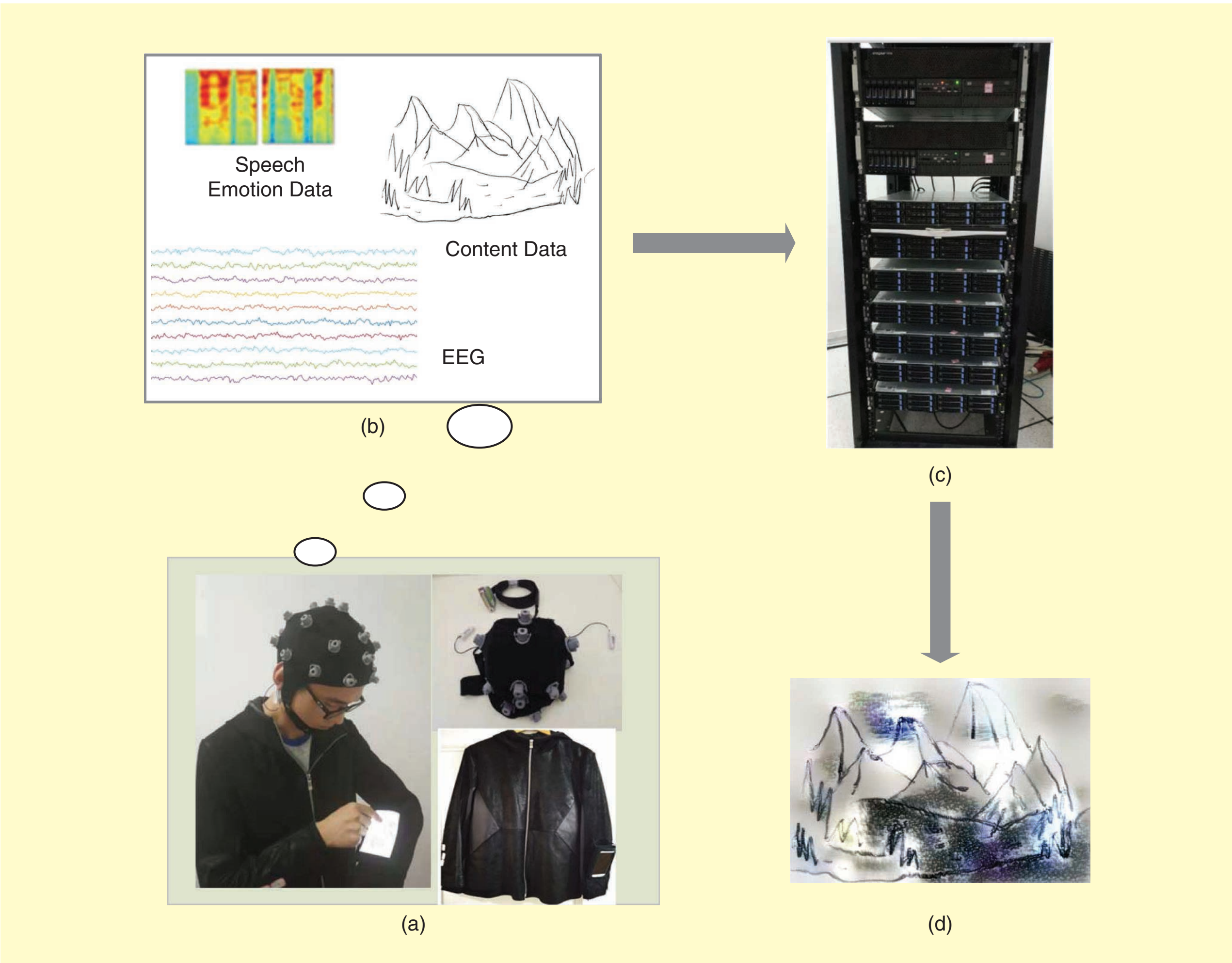

Figure 3. The CreativeBioMan system testbed. The (a) real brain and body devices, (b) collected data, (c) cloud, and (d) generated artwork.

was recognized utilizing the wearable-clothing expressive robot. After obtaining a user's emotion data, the hue of the final works could be slightly adjusted according to the user's emotion. If the user's emotion was positive, then the hue of the work was set at "warm"; if his or her emotion was to the contrary, then it would be set to "cold." The duration of each monitoring session lasted 8–15 min.

After each test, users labeled the signal of their whole creation process to mark the style of painting desired. The data set was used to train the imagine classification model for different painting styles to match the painting styles in the users' historical works. The data sets built were used to train the users' personalized creation process.

We first preprocessed the 22 EEG signals paths for each user. A five-order, low-pass Butterworth filter with $fz = 50\,\text{Hz}$ was used to filter the radio-frequency component. The EEG signal was divided into frames, and the size of a window was 256 pixels. A short-time, discrete Fourier transform was utilized to extract the rhythm bands of the EEG signal, thereby obtaining the energy values of δ, θ, α, and β as the approximate entropy, largest Lyapunov index, and the Kolmogorov entropy as the signal features of the EEG, respectively. These values were then input into the LSTM network for classification and to obtain the corresponding labeling result.

We collected between five to 10 works of users in different styles and marked the painting style of each work. The labels were divided into four classes: oil paintings, traditional Chinese paintings, sketches, and cartoons. Histogram equalization was used to obtain the luminance image in the whole luminance range. All users' historical works were resized to be the same size and were then uploaded to the server.

Experimental Results and Analysis

By establishing the aforementioned platform and data set, the CreativeBioMan system could generate paintings using the users' style. Our work assessed the system according to the picture effect generated by the system and the fidelity of artworks.

To define the artwork's creation fidelity, the works generated by the computer were mixed with those created by real artists and other painters to distinguish and select them. If the painters could not select the works created by the computer, this was an indication that the computer had a similar creativity to that of real painters, i.e., the fidelity of the creation was very high. Concretely, it can be expressed by the following mathematical formula:

$$\text{life\_like} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} \text{goal}_{i,j}}{n \times m} \times \text{non\_machine} \times 100\%. \quad (9)$$

The formula $goal\_i, j$ equals 0 if the ith judge finds the work created by computer in the jth test set; otherwise, it equals 1. In addition, m means m test sets, n means n judges, and *non_machine* is the proportion of painting works in the test set that were not created by the computer. The experimental results are shown in Figure 4. From Figure 4(a), it is clear that, for testing the artworks of the 10 test subjects, the fidelity rate of the system's creation corresponding to nine test subjects was higher than 50%. The fidelity rate corresponding to test subject seven was 90%, which indicates that the creativity of the system we built is high. In addition, we also tested the running-time delay of the system, with the results displayed in Figure 4(b). The data transmission delay time was 0.6–0.8 s, the training time model was 1–1.3 s, while the model test time was less than 50 ms. Accordingly, deploying the algorithm in practical applications is feasible.

Conclusion

The AI rapidly being developed is not limited to use in computing and logical analysis. To transfer the aesthetic judgment and creativity of a human to a machine, the creative game system CreativeBioMan was introduced in this article.

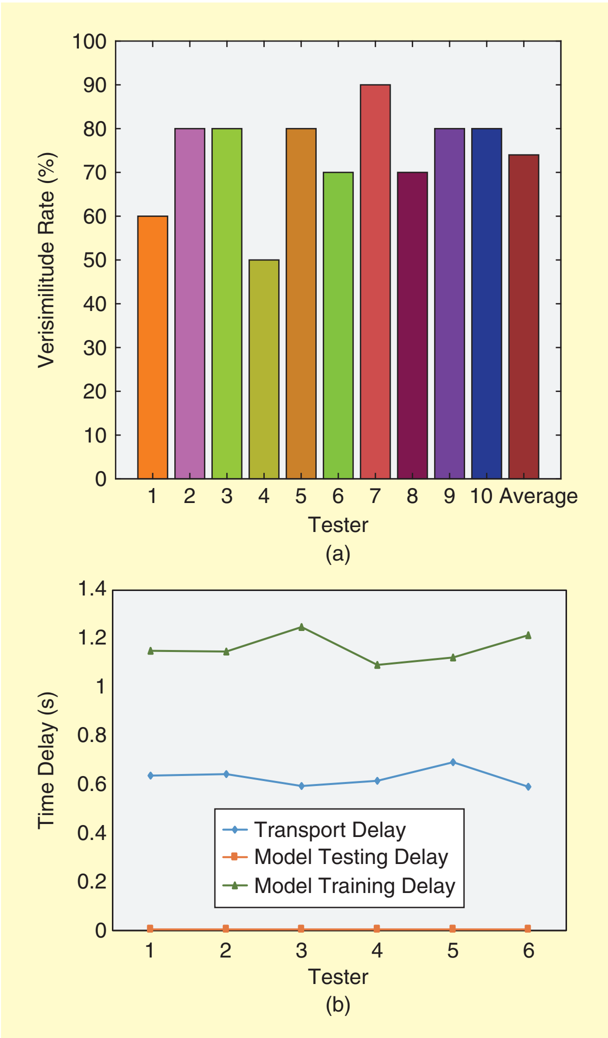

Figure 4. The experiment results: (a) verisimilitude rate and (b) time delay of the CreativeBioMan system.

Brain-wearable devices and a wearable-clothing emotional robot were used during the artists' creation to collect the EEG and multimodal emotion data, respectively. By combining the artists' previous artworks and utilizing the AI algorithm in the cloud for decision fusion, artists were assisted with artwork creation. An AI algorithm model was also detailed in this article, including EEG data processing; style classification based on motor imagery models; style and content reconstruction models based on the VGG-19 network; and the attention-based, RNN emotion-recognition model.

Finally, we described in detail a testbed platform of the creative game and analyzed the fidelity rate of the works generated by the system and its creativity. In future work, we will consider using EEG data to record the brain state of a user's creation, read out the brain's awareness, and create a more intelligent and creative game system.

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