IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received August 17, 2019, accepted August 28, 2019, date of publication September 11, 2019, date of current version September 30, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2940378

A Hybrid Biological Data Analysis Approach for Students' Learning Creative Characteristics Recognition

SHIH-YEH CHEN[1], CHIN-FENG LAI[2], (Senior Member, IEEE), AND CHI-CHENG CHANG[3]

[1]Department of Computer Science and Information Engineering, National Taitung University, Taitung 950, Taiwan
[2]Department of Engineering Science, National Cheng Kung University, Tainan 701, Taiwan
[3]Department of Technology Application and Human Resource Development, National Taiwan Normal University, Taipei 106, Taiwan

Corresponding author: Chi-Cheng Chang (samchang@ntnu.edu.tw)

This work was supported by the Ministry of Science and Technology, Taiwan, under Grant 106-2511-S-143-002-MY2, in part by the Ministry of Science and Technology, Taiwan, under Grant 106-2511-S-143-002-MY2 and Grant 107-2622-S-006-001-CC3, and in part by the Ministry of Science and Technology, Taiwan, under Grant 108-2511-H-143-002 and and Grant 108-2511-H-006-004-MY2.

ABSTRACT Regarding the effectiveness evaluation of students' creativity learning, most of the past studies have proposed teaching strategies to improve the creativity of students. For example, teachers use traditional questionnaires to evalute students' creativity learning effectiveness after implementing teaching strategies. However, most traditional questionnaires lack automated methods to provide immediate feedback to help teachers understand the current learning status of students instantly. Based on the above problem description, a hybrid biological data analysis approach is proposed that the teachers can analysis the students' learning status in the learning process through the wearable biological monitoring devices. Hybrid biological data such as the degree of course participation and creativity growth of the students is collected to be analyzed for recognizing students' learning creative characteristics. In the experiment results, we observed that the changes in brainwave values and heartbeats echoed the students' creativity status.

INDEX TERMS Biological data analysis, learning creative, characteristics recognition.

I. INTRODUCTION

With the advances of information technologies (IT) in recent years, the cultivation of talents in the IT industry has been listed as one of the priorities of education reform in many countries. However, traditional education methods have led most engineers lack the innovative ability to design new products. How to design innovative learning mechanisms through creative education combined with IT for improving the engineers' creativity becomes an important issue for the cultivation of government talents. Hence, this study mainly addressed two problems as follows.

A. TEACHERS CAN GRASP THE STUDENTS LEARNING STATUS AT ANY TIME

Many education scholars have recently discussed the value and quality of school education based on capstone courses. For capstone courses, the main way of learning is to see what difficulties a team meets during problems solving and what the team can learn from overcoming the difficulties. Fincher thought that the overall goal of capstone courses is to integrate the concepts and skills that students have earned by implementing a group project [2]. In the period of implementing a project, teachers ask students to solve problems spontaneously. Nevertheless, in such a learning environment, it is still difficult for teachers to understand the problems students have encountered and what they have learned in the capstone course because the teacher can not grasp the learning status of each student at any time.

B. COMBINATION OF BIOLOGICAL DATA ANALYSIS TECHNOLOGIES AND SOCIAL RESEARCH MECHANISMS

College education has always paid attention to the training of students' individual professional ability, but neglected to cultivate students' innovative thinking. Most companies have constantly pointed out that innovation is one of the significant indicators of recruitment. Many researchers in the past adopted social research methods (qualitative interviews or quantitative questionnaires) to determine the effectiveness of creativity, but it is often difficult to analyze innovation and creativity among members in a quantitative manner.

The associate editor coordinating the review of this manuscript and approving it for publication was Mu-Yen Chen.

In this study, we not only propose the hybrid biological data analysis approach that combines biological monitoring devices and data analysis technologies to recognize students' learning creative characteristics, but also adpot the project-based learning strategy and cooperative learning theory to stimulate students' creativity. The overall goal is to record and analyze the interaction among group students in detail during development of final projects. To identify which cooperation models are effective, the models to groups with low efficiency or poor interaction will be fed back for observation and improvement. The verified models provide the valid teaching assessment for teachers who are able to adjust their teaching strategies to improve students' learning performance.

The remainder of this study is organized as follows: Section II analyzes the related achievements in the fields of creativity and biological data. Section III presents the hybrid biological data analysis computing to recognize students' learning creative characteristics and illustrate the detailed explanation of each phase. In the Section IV, we design the experiments to verify the feasibility of the proposed approach and analyze the results. Finally, the conclusion and further study is given in the Section V.

II. RELATED WORKS

A. CREATIVITY AND ASSESSMENT OF CREATIVITY

What is creativity? There is no unified definition of creativity, In other words, it has hundreds of definitions so far. Some scholars asserted that creativity is a kind of mental ability or a personal quality [3], [4], and some tended to evaluated creativity with the indicator of work. For instance, Gruber assumed that creative works must be original, purposeful, and compliant with specific needs and values [5]. Rhodes spent five years to collect, read, and summarize 40 researches on creativity. He argued that, though scholars had different views on creativity, their definitions were not in conflict. Even most of the views are overlapping or related to each other. He proposed the 4P Theory of Creativity based on these researches, whereby 4P refers to person, process, product, and press [6]. The research of Rhodes, Wu, and Liu et al. is summarized in Table 1.

Because creativity is complex and cannot be explained by a single definition, it is extremely difficult to quantify an individual's creativity. It makes most scholars assessed creativity based on products and idea. Amabile considered that products or observable responses are the proof of creativity [7] and proposed the consensual assessment techniques that have been widely adopted. The consensual assessment techniques mean that "A group of experts in one field have a consensus on a definition. That is if a group of experts agrees that a product or an idea is creative, the product or the idea is creative. Hence, in this study, we chose students' creative products as a basis to assess creativity with the consensual assessment techniques. Teachers were asked to score students' works with fairness and professionalism. Other than this, the scoring standard is based on the principle of intelligent structure

TABLE 1. Rhodes's 4p theory of creativity.

4P	Definition	Assessment Method
Person	It stands for distinctive personality traits of creators, including knowledge and behavioral motivation.	Thinking Style Questionnaire, Concept Generation, and Attitude Scale
Process	It means the process from identifying or solving problems to producing outcomes.	TTCT, Time Sampling, and Log
Product	It means novel and appropriate products.	Consensual Assessment Techniques
Press	It means that creativity is derived from the stress in the external environment.	KEYS, Creative Atmosphere Scale

proposed by Guilford. He thougth that divergent thinking can reflect an individual's creativity. Different from convergent thinking, divergent thinking is a way of thinking with outward expansion, which can explore many possible solutions [8]. From the viewpoint of divergent thinking, creativity includes four qualities, i.e.: fluency, originality, flexibility, and elaboration [9]. Therefore, this paper scored students' works with the four qualities of creativity as shown as Table 2.

TABLE 2. The four qualities of creativity proposed by Guilford.

Quality	Explanation
Fluency	It refers to the ability to produce many ideas and respond quickly in the face of problems, including length of time for producing ideas or answers, number of ideas or answers, and the correlation among ideas or answers. Fluency is classified into four categories: ideational fluency, associational fluency, expressional fluency, and word fluency.
Originality	It means the ability to generate distinctive or novel and practical ideas.
Flexibility	It stands for the ability to flexibly change the way of thinking and solve problems from various perspectives.
Elaboration	It means the prudence of thinking and the ability to complete or execute a plan or the retouch or addition of details.

B. BIOLOGICAL DATA FOR MEASURING CREATIVITY

Psychologists have long believed that positive emotions contribute to creativity, because positive emotions make the mind more open. On the other hand, negative emotions can narrow a person's attention and are not conducive to creativity. Individuals' emtions are closely related to the Autonomic Nervous System [11] composed of the Sympathetic Nervous System (SNS) and the Parasympathetic Nervous System (PNS). It controls important biological functions of individuals, such as heartbeat, breathing, and blood pressure, that cannot be controlled by human will and directly reflect biological phenomena responding to the influences of the external environment. The SNS controls individuals' reactions to tension, fear, and stress, while the PNS controls the reactions after relaxation, sleep, and tension. These emotion states trigger the Autonomic Nervous System to initiate the instinctual protection mechanism. Hence, we can infer individuals' emtions from biological data.

Biological data screened out by researches on emtions can in general be easily obtained. Non-invasive measurement instruments can be used. Moreover, when an emotional state changes, signals change obviously. This paper referred to four biological data that are the most closely related to emotions and easy to obtain in past studies: galvanic skin response (GSR), electromyography (EMG), heart rate (HR), and electroencephalogram (EEG). The four biological phenomena are introduced as follows.

1) GALVANIC SKIN RESPONSE

GSR measures the changes in resistance of an individual's skin under current flow - also known as electrodermal activity (EDA), electrodermal response (EDR), and skin conductance response (SCR). Skin conductance is the most sensitive biological parameter of sympathetic excitability changes [12], which cannot be easily and directly inhibited by cerebral cortex consciousness. Measuring skin conductance can be calculated to get the arousal amplitude variation of emotions [13]. Because the SNS controls skin conductance, the SNS will be stimulated to increase activities and GSR when the arousal level increases[14]. This biological feature is frequently used in researches on emtion computing since Bradley and Lang confirmed that GSR is closely associated with emotions [15]. However, if you want to accurately determine which kind of emotion, other biological data must be referred. During the measurement of GSR, it is suggested that the site to obtain GSR are the second knuckles of the index finger and the middle finger [16]. At the same time, it is also necessary to prevent the subject's hand movements from being as static as possible. Otherwise, the measured values may be affected.

2) ELECTROMYOGRAPHY

EMG denotes the epidermal electrical potential differences during muscle contraction [17]. Some scholars thought measuring the EMG of face is associated with emotions [18], because when one's emotion changes, his/her changes in facial expression are obvious. As a result, EMG can be regarded as an important indicator for studies on emotions. When measuring EMG, it is necessary for electrode patches to affix facial muscles corresponding to emotions since different emotions affect different facial muscles. For instance, positive emotions are related to zygomaticus major muscle, while negative emotions are related to corrugator supercilii muscles [19], [20]. However, in this study, subjects are asked to have discussions. That will affect the correctness of read values derived from the measurement of facial muscles. Thus, according to the previous study [21], we changed the measurement site to trapezius muscle to avoid affecting measured values.

3) HEART RATE

The valence level of emotions can be measured by the HR. When one's SNS and PNS are active, the change in HR is the most obvious [22]. Studies demonstrated that the HR during a negative emotion is slower than that during a positive emotion [23]. Therefore, it is common to use HR as a reference in emotional experiments. HR can be obtained via electrocardiogram or photoplethysmography (PPG). These five waveforms, P, Q, R, S, and T, can be obtained to constitute a heartbeat cycle. The interval between two adjacent R waves is called the R-R Interval. Based on the R-R Interval, heart rate variability (HRV) can be calculated, and then frequency domain analysis can be conducted on HRV. The high-frequency region of frequency domain analysis reflects the activity of the PNS, and the low-frequency region reflects the activity of both SNS and PNS. As a result, HRV can be used as one of the main references of emotions. This study obtained participants' HR through PPG and used an optical sensor to measure the changes in blood volume along with heartbeat [24]. Generally, the sensor is clipped to ears or fingers for measurement. It is more convenient than wearable ECG devices.

4) ELECTROENCEPHALOGRAM

EEG is a current pulse that the brain generates. Hans Berger was the first person who recorded the discharge process in the human brain. The record of discharge process is called EEG and is regarded as electric wave changes recording brain activities [25]. The international organization of societies for electrobiological technology developed several common brainwaves based on frequencies, including four major waves: alpha (α), beta (β), theta (θ), and delta (δ) waves. Table 3 lists human states reflected by the four waves and indicates that different waves can reflect different physical and mental states [26], [27]. If we further classify brainwave frequency in each brain wave, corresponding states are able to be analysed more precisely. For example, the beta wave can be classified into high beta and low beta. High beta wave reflects excitement and anxiety. Low beta wave reflects a relaxed yet concentrated state.

There are two methods presently to measure EEG. The first method obtained brain waves through electrodes on the scalp surface. Subjects were asked to wear specific headgears, or the skins on their heads were covered with electric patches. This method is limited to location, but the values recorded are fine. The other method adopted brain wave headsets or easy-to-wear headbands. This method is cheaper and easier to set up, but the first one is more accurate.

III. A HYBRID BIOLOGICAL DATA ANALYSIS APPROACH TO RECOGNIZE STUDENTS' LEARNING CREATIVE CHARACTERISTICS

In this paper, we introduced a project-based learning method to allow students to increase their interests in real problems they encounter. Students not only acquire knowledge through

TABLE 3. Introduction to common brain waves and corresponding body states.

Brain Wave	Frequency (Hz)	Speed	Human Body State
δ wave	< 4	The slowest wave	It is the band when one's consciousness is interrupted and one enters deep sleep. It is an unconscious state.
θ wave	4-7	Slow wave	It is especially obvious during deep meditation. It is a wave at the subconscious level and can facilitate deep and long-term memory.
α wave	8-15	Stable wave	It is obvious when one reduces his/her concentration but remains conscious. It is a bridge for communication between consciousness and subconsciousness. It is also the best brain wave for learning and thinking.
β wave	16-31	Fastest wave	When one is conscious, most brain waves are β. When one concentrates on thinking or shoulders great pressure or is nervous, the β wave increases significantly. It is a wave at the conscious level.

learning by doing to improve their problem-solving ability, but also cultivate a good learning attitude and imagination. During project-based learning stage, students could effectively utilize information technology. Through group discussion, students would select a project that they were interested in and intended to develop. And students try to collect and analyis information from books or internet, asked each other questions, proposed and summarized ideas, and share hands-on experience to develop the selected project. From the viewpoint of teaching, project-based learning is a good learning strategy that can effectively guide students to actively engage in learning activities and encourage students to interact with others in the classroom. In addition to cultivating students' professional technical skills, it also trains teamwork and allows students to study independently, exercise innovative and multi-dimensional ways of thinking, and acquire the problem-solving ability. However, early researches on creativity mainly assessed the degree of creativity of individuals through scales or tests. This study employed six creative teaching strategies (i.e. sudoku analysis method, catalog technique, attribute listing method, focused conversation method, scamper method, and six thinking hats) to guide students' creativity. Furthermore, it combined the data on the characteristics of learning behaviors and perception data obtained from field teaching to design the Factorial Hidden Markov Model (FHMM). Through analysing the creativity characteristics of the original hybrid biological data, it formed characteristics of learning behaviors as input parameters of the auxiliary detection model. The original hybrid biological data have many dimensions, high data redundancy, and insufficient descriptions of teaching and education knowledge. Therefore, we first parametrized the knowledge of expert education and experience of field teaching under each model related to student learning as the expectations of inference model training and confirmed the number of nodes and expected values of the output layer. After the inference model training was completed, the perceived biological parameters of each model were automatically extracted and converted into biological characteristics that can describe creative thinking.

A. SUBJECTS

The subjects were students of an engineering course at a university in Taiwan. At the beginning of the semester, the students were told that the course would be accompanied by an experiment measuring biological information. The experiment was conducted with the consent of the students. A total of 44 students between 21 and 25 years old participated in the experiment. In terms of grouping of the innovative IoT project, 2 to 4 students formed one group. There were 13 groups. Before the experiment, it was confirmed that there were no special biological abnormalities of each student participating in the measurement to ensure that no errors were caused by any biological problems.

B. EXPERIMENTAL INSTRUMENTS

This study adopted four biological instruments: pulse sensor (upper left in Figure 1), Grove GSR sensor (upper right in Figure 1), Grove EMG sensor (lower left in Figure 1), and NeuroSky MindWave Brain Wave Headset (lower right in Figure 1). With respect to biological data recording, Pulse, GSR, and EMG recorded once every 20 milliseconds. Each entry of data contained recording time followed by biological signal values. The pulse sensor also recorded three types of information: BPM, IBI, and pulse signal. For EEG measurement, because the official App assessment did not match with this experiment, this experiment used an unofficial eegID Android App as the measurement tool. It can completely record brain wave information, including Alpha, Beta, Gamma, and Theta waves.

FIGURE 1. Experimental instruments.

C. EXPERIMENTAL PROCEDURES

The experiment regarded one semester as the unit, ranging from the beginning to the end of the semester. The course of the entire semester was mainly designed based on the ADDIE model, including five stages: analysis, design, development, and implementation, as shown below.

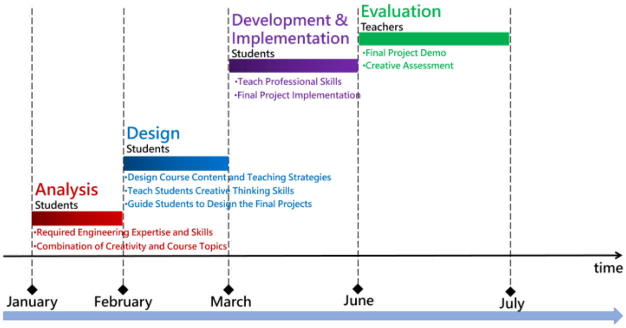

FIGURE 2. Semester course diagram designed based on the ADDIE model.

During these five stages, various teaching activities were introduced, including professional guidance on theory and practice, introduction of methods related to creative thinking, creative development of projects with creative thinking, and mid-term and final project projects. Lastly, the students presented their results of creative projects, which were then scored.

D. CREATIVE THINKING INTRODUCED DURING AND AT THE END OF THE SEMESTER

Creative thinking methods were introduced during the semester. GSR, EEG, HR, and EMG of the students were measured for follow-up analysis of emotions. Six methods of creative thinking were introduced to the students to figure out directions of creative projects. The students could use one or more methods. At the end of the semester, tests were also conducted during creative thinking. Six creative thinking methods and wearable measurement devices of GSR, EEG, HR, and EMG were included. The students were mainly asked to solve the problems they encountered during projects. The students were allowed to use one or more creative thinking methods that they considered effective. After the test, they were asked to fill in the satisfaction questionnaire including five questions. The Likert five-point scale was adopted for the first four questions. Question 5 was a multiple-choice question. They were asked to select useful creative thinking methods, as shown in Table 4.

Question 1 (Q1) was designated to understand that these creative thinking methods were actually helpful to the students. Q2 was to learn that these creative thinking methods were interesting to the students. If students felt that they were not interesting, we then interviewed them to learn the reasons for future improvement. Q3 was negative to Q1 to avoid invalid feedback due to careless answering. Q4 was to see if the students would use the creative thinking methods to help solve problems after the training. Q5 was to check which creative thinking methods were the most helpful for them in order to learn which creative thinking methods were suitable to apply to works at the end of the semester and make adjustment in future courses.

TABLE 4. Questions of the satisfaction questionnaire.

Question	Strongly Agree	Agree	Fair	Disagree	Strongly Disagree
1. The creative thinking methods can help me think about creative topics and solve difficulties during practice.					
2. The creative thinking methods are interesting.					
3. I do not think that the creative thinking methods are helpful.					
4. In the future, if I face challenges requiring creativity, I will use creative thinking methods to help myself again.					
5. Which are the most helpful, among all the creative thinking methods? (multiple-choice question) A. Sudoku analysis method B. Catalog technique C. Attribute listing method D. Focused conversation method E. Scamper method F. Six thinking hats					

E. MID-TERM AND FINAL REPORTS

In the mid-term report the students were supposed to report their project topics, expected works, and creative thinking methods used for creative project development. After the course on IoT for one semester, the students must realize the expected works described in the mid-term report and needed to make a final report. Both reports were submitted by groups and scored by the teacher and one expert in the field. Scoring items covered professional skills, practicality, expected benefits, reporting, and presentation, as shown in Table 5. Creativity was assessed from the four qualities of creativity proposed by Guilford, including fluency, originality, flexibility, and elaboration. As this paper only discussed creativity, the scores of items in Table 5 were not included in the final analysis. When reporting was over, the students were asked to complete an intra-group mutual assessment form. They were expected to fill in their contributions to reports and contributions to works and creativity of themselves and their teammates. The data were helpful to make adjustments and give a score to each student rather than just one score for a whole group. For the format of intra-group mutual assessment form, please refer to Table 6.

TABLE 5. Scoring items for final project.

Scoring Item	Note
Professional skills	If a project is combined with the professional skills of students.
Practicality	A project is practical or commercially feasible.
Expected benefits	Impact of a work on the industry or forward-looking technologies.
Report and presentation	It contains oral presentation and poster. Reporting skills, presentation skills, and works (works, schematic models, or multimedia) were scored.

TABLE 6. Intra-group mutual assessment form.

<table>
<tr><td>Scorer</td><td colspan="2">Please describe your major contributions to this report. You may list your ideas proposed, difficulties solved, or amount of time devoted.</td></tr>
<tr><td>Student A</td><td colspan="2"></td></tr>
<tr><td>Teammate</td><td>Scoring Item</td><td>Score (1-10 Points)</td></tr>
<tr><td rowspan="2">Student A</td><td>Contributions to work and report</td><td></td></tr>
<tr><td>Contribution to creative thinking</td><td></td></tr>
<tr><td rowspan="2">Student B</td><td>Contributions to work and report</td><td></td></tr>
<tr><td>Contribution to creative thinking</td><td></td></tr>
</table>

F. CREATIVITY ANALYSIS METHOD

According to past studies, the alpha wave is the most closely related to creativity among all brain waves. The alpha wave of a group with higher creativity was significantly lower than that of a group with lower creativity. Studies also demonstrated that beta and gamma waves increase in a group with a higher score of creativity, while theta and delta waves drop. One's HR rises significantly during creative thinking. The responses of EMG and GSR to creativity were not distinctive. EMG and GSR could be high or low regardless of the score of creativity. This study also discussed the possible correlation between EMG & GSR and creativity. We analyzed the records on creative thinking of students and their biological signals including EEG, EMG, HR, and GSR. In other words, experts scored the creative performance recorded during creative thinking at each stage. Based on such scores, coupled with biological information, we conducted pre-training with the analysis model. The method to analyze the students' characteristics of creativity in this study contained two steps. First, FHMM was used to conduct preliminary analysis and prediction. Second, based on the preliminary results, this study extracted the characteristics s of biological signals and analyzed the students' characteristics of creativity. The three steps are described in detail below.

1) STAGE-1 FORECAST WITH FHMM

In the Factorial Hidden Markov Model (FHMM), time-series observed values are used. Possible outcomes were guessed based on internal conversion probability and initial probability in a continuous time. Under the Gaussian mixture model (GMM), the probability of an individual state is usually assessed by Log Likelihoods. For instance, in Eq. 1, Σ means Covariance Matrix, μ is the average of each Gaussian distribution, M is the number of GMM, and x means observed value.

$$P_{GMM}(X) = -\frac{M}{2}\ln(2\pi) - \frac{1}{2}\ln|\Sigma| - \frac{1}{2}(x-\mu)^T\,\Sigma^{-1}(x-\mu) \tag{1}$$

In FHMM each layer of HMM is established on the premise of a Gaussian distribution. When the number of layers is greater than two, the structure naturally becomes a GMM. After individual HMM learning is completed with the EM algorithm, HMMs are merged into one FHMM. The most important step next is to perform a probability prediction. In combination with the basic GMM probability Eq. 1, suppose that the observed value at different times is X, the initial probability is π, and the transition probability in the hidden state is A. Log Likelihoods are assessed in two situations, as shown in Eqs. 2 and 3.

- $t = 1$:

$$P(X) = P_{GMM}(X) + \ln\pi \tag{2}$$

- $t > 1$:

$$P(X) = \ln A + viterbi\,[\mathrm{t}-1] \tag{3}$$

Viterbi array is the Log Likelihoods at t-1 and when P(X) is the biggest, which means that the P(X) probability at t will be affected by Log Likelihoods at *t-1*. For the convenience of follow-up introduction, a set H was defined here. Its subsets are $k(k \geq 1)$ types of sets guessed at T of FHMM, as shown in Eq. 4.

$$\mathrm{H}_T = \{C_1, C_2, C_3, \ldots\ldots, C_k\}, \quad k \geq 1 \tag{4}$$

The Log Likelihood of multi-biologically perceived signal combination predicted by each FHMM is P(C_i), $1 \leq i \leq k$. Eq. 5 indicates that, in each multi-biologically perceived signal combination, there are $m(m \geq 1)$ types of biologically perceived signal status.

$$\mathrm{C}_i = \{S_1, S_2, S_3, \ldots\ldots, S_m\}, \quad m \geq 1,\ k \geq i \geq 1 \tag{5}$$

This study regarded the observed values at FHMM as the fluctuations of biologically perceived signals. Viterbi Algorithm was used as the internal prediction method; it uses dynamic planning to identify the maximum probability at each time point. However, for a certain time point, each state of FHMM will have a probability value - that is, Log Likelihoods in GMM. For this study, the stage-1 prediction of multi-biologically perceived signal combination based on FHMM contained two key points. Different Log Likelihoods were given to each biologically perceived signal combination at T. What is more important is the selection of characteristics, that is the selection of the best characteristics s for different multi-biologically perceived signal combinations.

2) SELECTION OF CHARACTERISTICS OF A BIOLOGICALLY PERCEIVED SIGNAL

During the course, each biologically perceived signal combination was learned and filed. The data storage space grew exponentially with the increase in the number of biologically perceived signals, which not only prolonged the learning time, but also increased the time for analyzing characteristics of creativity. In this study, for all load states Si in set U, there were T types of characteristics s of biologically perceived signal. $S_i = \{f_1, f_2, \ldots, f_T\}, 1 \leq i \leq N$. Two sets, F_{SD} and F_{mean}, are defined here, as shown in Eqs. 6 and 7. For the T types of characteristics s of biologically perceived signal, F_{mean} is the average of characteristics s of biologically perceived signals of all the states in set U. FSD is the standard deviation of each characteristics of biologically perceived signal.

$$F_{SD} = \left\{f_1^{SD}, f_2^{SD}, \ldots, f_T^{SD}\right\} \tag{6}$$

$$F_{mean} = \left\{f_1^{mean}, f_2^{mean}, \ldots, f_T^{mean}\right\} \tag{7}$$

This system used the concept of retaining the standard score, but the numerator was changed. This study defined it as Biological Features Standardization (BFS), as shown in Eq. 8.

$$\mathrm{BFS}(f_i) = \frac{|f_i - f_i^{mean}|}{f_i^{SD}}, \quad 1 \leq i \leq N,\ f_i^{SD} \neq 0 \tag{8}$$

This thus study utilized a perceptual information merger mechanism to record the original biological perceived information during creative thinking, merged the state waveforms included in the combinations predicted by FHMM, and regarded the merged waveforms as a profile. In this way, we could quickly obtain the characteristics s of biologically perceived signals of all state combinations and significantly reduce the time complexity during identification. In order to verify the feasibility of this mechanism, this study compared the merged waveforms with the original measurement results. The waveforms generated by this mechanism completely approximated the measured results. After the merger of biological information at this stage was completed, all characteristics s of biologically perceived signals could be calculated based on the merged waveforms to facilitate the last stage of analysis of characteristics of students' creativity.

We now shall explain some other contents on the selection of characteristics of biologically perceived signal - that is, score and selection of characteristics of biologically perceived signal. This section will discuss the determination of scores for all characteristics s of biologically perceived signals in multi-biologically perceived signal combinations predicted by FHMM. A function was defined here, Biological Features Composition Score (BFCS), the purpose of which is to use the multi-biologically perceived signal combinations predicted by FHMM at the first stage to calculate the scores for the T types of composite scores of Characteristics s of biologically perceived signals. Take C_i, a combination of biologically perceived signals predicted by FHMM for instance. Biological Features Standardization (BFS) defined in Eq. 8 previously was used to aggregate T types of Characteristics s of biologically perceived signals under all biologically perceived signal states, S_j, $1 \leq j \leq m$, as shown in Eq. 9. Figure 3 supplements the interpretation of Eq. 9 with a tree diagram.

$$\mathrm{BFCS}(f_i) = \sum_{j=1}^{m} \mathrm{BFS}(f_i)\ in\ S_j, \quad 1 \leq i \leq T \tag{9}$$

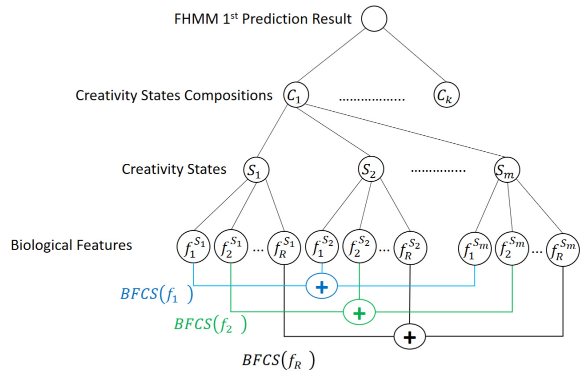

FIGURE 3. The interpretation of Eq. 9 with a tree diagram.

After the T types of characteristics s of biologically perceived signals of the combination were assessed, coupled with Eq. 9, a set, Load Composition Score Set (LCSS), was defined. This set represents the aggregation of T types of characteristics s of biologically perceived signals in combination C_i, as shown in Eq. 10.

$$\mathrm{LCSS}(C_i) = \{\mathrm{BFCS}(f_1), \mathrm{BFCS}(f_2), \mathrm{BFCS}(f_3), \ldots\ldots, \mathrm{BFCS}(f_T)\} \tag{10}$$

Lastly, in the part of the selection of the characteristics of biologically perceived signal, this study defined a set, as shown in Eq. 11.

$$\mathrm{Top}(k\%, C_i), \quad k \in N^+ \tag{11}$$

This set collected the top $(T \times k\%)$ types of characteristics s of biologically perceived signals in score for LCSS (C_i). The number of elements in this set was $(T \times k\%)$.

3) ANALYSIS OF CHARACTERISTICS OF CREATIVITY OF STUDENTS AND FINAL RESULTS

This part explains the analysis of characteristics of creativity of students and final results. First, the concept of error is discussed. As long as there is measurement, an error is inevitable. Errors may be caused by improper human operation, wrong data recorded, or poor quality of measurement by a system. Quantitative data like absolute error, relative error, and percentage error can be used to judge the degree of errors. For example, suppose a profile value is A, and a testing value is B. The absolute error is shown in Eq. 12, while the relative error is Eq. 13, and the percentage error in Eq. 14.

$$\text{AbsoluteError} = |B - A| \tag{12}$$

$$\text{RelativeError} = \frac{|B - A|}{|A|}, \quad A \neq 0 \tag{13}$$

$$\text{PercentageError} = \frac{|B - A|}{|A|} \times 100\%, \quad A \neq 0 \tag{14}$$

This study used percentage error as the baseline of measurement. Two kinds of data were defined. The first was the waveform to be tested, Test, which means current and voltage waveforms measured by the system in real time. The second was the standard self-simulated waveform of the system, Profile - that is, the combination predicted by FHMM. Coupled with the characteristics s of biologically perceived signals mentioned above, the method to merger current information was selected. Signal waveform merger was conducted on the biologically perceived signal combinations of internal elements. Additionally, for the combinations of biologically perceived signals predicted by each FHMM, Profile analog waveforms were re-estimated and compared with Test for error estimation. According to $(T \times k\%)$ types of characteristics s selected by Eq. 10 Top $(\mathrm{k}\%, C_i)$, characteristics conversion was conducted on the *Test* and *Profile* waveforms. The sets after the conversion of the two waveforms were defined, as shown in Eqs. 15 and 16.

$$\text{Biological\_Features}(\mathit{Test}) \tag{15}$$

$$\text{Biological\_Features}(\mathit{Profile}) \tag{16}$$

Through the conversion of characteristics s, the sets of characteristics s of biologically perceived signals of Test and Profile waveforms were obtained. For the sake of follow-up error assessment, a set, *Error*, was defined, as shown in Eq. 17.

$$\text{Error} = \frac{|\text{Power\_Features}(\mathit{Test}) - \text{Power\_Features}(\mathit{Profile})|}{|\text{Power\_Features}(\mathit{Profile})|} \times 100\% \tag{17}$$

In the set Error, the number of elements was $(T \times k\%)$. It was used to see the difference in characteristics s of biologically perceived signals of Test and Profile waveforms after conversion. The average error of T x k% characteristics s of biologically perceived signals was defined, as shown in Eq.18.

$$\text{Error}\,(C_i) = \mathit{Average}\,(\text{Error}) \tag{18}$$

Function Error(C_i) was designated to obtain the average of all elements in set Error calculated based on C_i predicted by FHMM. As mentioned in Eqs. 4 and 5, when FHMM was used for stage-1 analysis of the characteristics of creativity of students, set C_i containing several biologically perceived signal combinations would be guessed. In each set, a Log Likelihood probability, P (C_i), was given to each set P (C_i) that represented the probability of this set predicted by FHMM, compared with other biologically perceived signal sets predicted. By multiplying P (C_i) and Error $(C_i$i), we can compare which probability is bigger and regard the bigger probability as the final result for the prediction of characteristics of creativity, as shown in Eq. 19.

$$\mathit{Finial}_{\mathit{Result}} = \mathit{Max}\,(P\,(C_i) \times (1 - \text{Error}\,(C_i))) \tag{19}$$

IV. EXPERIMENT RESULTS

The pre-test on creativity of this study was supported by College of Education, National Chung Cheng University. It referred to Abbreviated Torrance Test for Adults compiled by Chang-yi Chen according to Kathy Goff and E. Paul and the Taiwanese norm. Issued by Taiwan Psychological Publishing, the original TTCT included a Chinese Test (in A and B forms) and image test (in A and B forms). This revised version combined the two types of tests and simplified them into an Abbreviated Torrance Test for Adults. Subjects were asked to answer the questions by writing and drawing for the assessment of their creativity. In addition, the reliability of various creativity indicators was between 0.34 and 0.68. The reliability among scorers was between 0.31 and 0.97, indicating that the test has good stability. In terms of validity, the scores relating to "test of creativity in problem solving" were 0.37 and 0.46. Both reached the confidence level of 0.05, implying that the test has good validity.

The results on creativity were mainly based on the comparison between the TTCT creativity pre-test score and the comprehensive creativity score in the Report on Project & Creative Thinking. The reason why the TTCT creativity post-test was not compared with the pre-test is because the teacher at the College of Education held that there was only one type of questions in TTCT. As the questions were already used in the pre-test, it would be inappropriate to use them again in the post-test. Therefore, as a trade-off, the qualities of creativity used in TTC were used to assess the Final Report on Project and Creative Thinking. A comprehensive score was given as the score for the post-test. The post-test score was the average of the sum of scores of the eight reviewers (rounded to the first two decimal points).

The results are shown in the Tables 7 and 8. We can see that, after guidance with creative thinking methods, the average post-test score of the subjects (74.58) was bigger than that of the pre-test (62.50). The significance value p = 0.000

TABLE 7. Statistics with TTCT pre-test and Creativity post-test.

	Number	Mean	Standard Deviation	Standard Deviation of Average
TTCT pre-test	44	62.50	6.116	1.304
Creativity post-test	44	74.58	5.18337	1.1051

TABLE 8. Sample test with TTCT pre-test and creativity post-test.

Item	Variable difference					t	degree of freedom	Sig.
	Avg.	STD	SEM	Confidence interval				
				lower bound	Upper bound			
TTCT pre-test Creativity post-test	-12.08273	7.44367	1.58700	-15.38307	-8.78239	-7.614	21	.000

($p < 0.01$). The upper and lower limits of the 95% confidence interval did not contain 0. It means that the assumption that the averages of pre-test and post-test were equal is not valid. Both illustrated that the pre-test and the post-test are significantly different.

A. QUESTIONNAIRE RESULTS

The satisfaction questionnaire consisted of five items. Four were positive items (higher average means better result), while the remaining item was the reverse (lower average means better result). The Likert 5-point scale was used to obtain the score to each item of each student. SPSS was utilized to analysis the average, standard deviation, and reliability. For the reliability analysis of the four positive questions, Cronbach's alpha = 0.597. The statistical data are shown in the Table 9. We can see that the averages of positive Questions 1, 4, and 5 were high and above 4 (the full score of a question was 5), implying that most respondents have a positive attitude toward the practicality and potential of the creative thinking methods. For Q1, only two students disagreed that the creative thinking methods were helpful, while the rest deemed that the methods were indeed helpful. The scores of creativity of the two students were prominently lower than those of other students. It can be inferred that perhaps these students did not use the creative thinking methods or did not know how to apply them. Q2 was subjective. It asked the students if they felt the creative thinking methods were interesting. Six students did not think they were interesting. Creative thinking methods can be helpful and also not be interesting. In order to prevent students from answering questions in the questionnaire without carefully reading the questions, we designed the negative problem Q3 in this questionnaire. Q3 also showed that the two students who believed the creative thinking methods were not helpful were exactly the same two students who gave negative answers to Q1. Hence, they would no longer be discussed herein. In terms of the willingness to use creative thinking methods to help solve problems again, only four students disagreed. They thought that it was troublesome to learn too many creative thinking methods. Therefore, in order to raise students' intention to apply creative thinking methods, some more appropriate creative thinking methods shall be applied in future courses.

TABLE 9. Satisfaction questionnaire.

	Number	Min	Max	Avg	Standard Deviation
(1) The creative thinking methods can help me think about creative topics.	44	3	5	4.05	0.653
(2) The creative thinking methods are interesting.		3	5	3.86	0.710
(3) I do not think that the creative thinking methods are helpful.		1	3	2.32	0.568
(4) I am willing to try other creative thinking methods to help improve my creative thinking.		3	5	4.18	0.588
(4) In the future, if I face challenges requiring creativity, I will use creative thinking methods to help myself again.		3	5	4	0.436

B. COMPARISON OF CREATIVE THINKING PERFORMANCE BEFORE AND AFTER THE INTRODUCTION OF CREATIVE THINKING METHODS

In this study, Paired Sample t test was adopted to assess whether students' creative thinking performance before and after the introduction of creative thinking teaching was significantly different. In terms of the tests before and after the introduction of creative thinking methods, the creative thinking performances of only five students in the pre-test

TABLE 10. Paired sample statistics.

	Number	Mean	Standard Deviation	Standard Deviation of Average
Before introducing creative thinking skills	44	61.5909	14.52835	2.19023
After introducing creative thinking skills	44	78.7773	9.40656	1.41809

TABLE 11. Paired sample verification.

Item	Variable difference					t	degree of freedom	Sig.
	Avg.	STD	SEM	Confidence interval				
				lower bound	Upper bound			
Before introducing creative thinking skills After introducing creative thinking skills	-17.18636	15.75391	2.37499	-21.97599	-12.3967	-.7236	43	.000

TABLE 12. Random biological feature to recognize result.

Course	3 features				4 features
	GSR, EEG, HR	GSR, HR, EMG	GSR, EEG, EMG	EEG, HR, EMG	GSR, EEG, HR, EMG
Analysis Stage: 1st class	92.16	82.23	83.27	93.51	93.86
Analysis Stage: 2nd class	89.24	84.17	80.56	90.15	90.43
Analysis Stage: 3rd class	86.89	70.85	72.14	87.76	88.82
Analysis Stage: 4th class	82.11	72.25	78.19	83.54	84.58
Design Stage: 1st class	96.89	86.27	86.27	97.52	96.89
Design Stage: 2nd class	95.51	86.07	84.94	95.51	94.38
Design Stage: 3rd class	82.8	72.8	79.17	85.99	89.81
Design Stage: 4th class	82.84	72.25	78.17	88.17	86.98
Development Stage: 1st class	95.61	85.61	86.05	95.61	96.93
Development Stage: 2nd class	97.87	87.52	87.87	97.16	96.1
Development Stage: 3rd class	96.77	87.7	86.77	97.7	98.16
Development Stage: 4th class	95.11	85.65	86.74	95.11	96.74

were higher than those in the post-test. However, their differences were not bigger than five points. The creative thinking performances of other students in the post-test were significantly better than those in the pre-test. The averages of the two tests were M (before introduction) = 61.59 and M (after introduction) = 78.78 shown in the Table 10. The pairwise sample t-test was conducted on both tests, with $t\ (44) = -.7.236$, $p < 0.05$, and 95% CI [−21.98, −12.40]. The lower limit of 95% CI was −21.98, while the upper limit was −78.78. The range between the lower and the upper limits did not contain 0. It means that the performances in the two tests are significantly different, which is consistent to the result of significance, $p < 0.05$ shown in the Table 11. The results prove that creative thinking methods are conducive to enhancing individuals' creativity.

C. THE RELATIONSHIP BETWEEN BIOLOGY AND CREATIVITY

In this section, we focused on analyzing students' creative biology characteristics during the stages of design and development after the creavity thinking course. This is divided into two kinds of analysis conditions for discussion, including three randomly biological characteristics and all of the characteristics. The results of the analysis are shown in Table 12. In the students' brainwave data, We also observed that the changes in brainwave values echoed the students' creativity.

In terms of the number of heartbeats, the number of heartbeats has increased during the students are analysising, designing or developping their projects. As for GSR and EMG, it cannot be proved here that the two characteristics are related to the creativity thinking. In the table that randomly selects three kinds of characteristics, the accuracy of the analysis that includes both the GSR and EMG features will be inferior to other groups.

V. CONCLUSION

After the design and implementation of experiment, this study identified many aspects worthy of discussion and improvement. Several problems are explored. First, during measurement, when students moved obviously, the devices they wore tended to fall off. Thus, students who lacked biological data could not be included in the analysis. As a result, the data of many students could not be used. Therefore, the sensors must be fixed with a bandage or breathable tape, or a device with better fixation can be adopted. Second, during creative thinking, we asked the students to provide a discussion. The best sites for EMG measurement are zygomaticus major muscle and corrugator supercilii muscle. Both sites are on the face. We were concerned that the movement of facial muscles during any discussion might influence the results on emotions. Thus, by referring to past studies, we changed the site to trapezius muscle. Consequently, the data measured were not as obvious as expected. Hence, it is suggested that if there is no need for a discussion, then the face is a better choice as the site for measurement.

REFERENCES

[1] J. Khatena, "The khatena-torrance creative perception inventory for identification diagnosis facilitation and research," *Gifted Child Quart.*, vol. 21, no. 4, pp. 517–525, Dec. 1977.

[2] S. Fincher, M. Petre, and M. Clark, *Computer Science Project Work: Principles and Pragmatics*, London, U.K.: Springer-Verlag, 2001.

[3] J. S. Robert, *The Nature of Creativity: Contemporary Psychological Perspectives*. Cambridge, U.K.: Cambridge Univ. Press, 1988.

[4] J. P. Guilford and R. Hoepfner, *The Analysis of Intelligence*. New York, NY, USA: McGraw-Hill, 1971.

[5] D.B. Wallace and H.E. Gruber, *Creativity and Human Survival. Creative People At Work: Twelve Cognitive Case Studies*. New York, NY, USA: Oxford Univ. Press, 1992.

[6] M. Rhodes, "An analysis of ceativity," *Phi Delta Kappan*, vol. 42, no. 7, pp. 305–310, Apr. 1961.

[7] T. M. Amabile, "The social psychology of creativity: A componential conceptualization," *J. Personality Social Psychol.*, vol. 45, no. 2, pp. 357–376, 1983.

[8] J. P. Guilford, "The nature of human intelligence," *Science*, vol. 162, no. 3857, pp. 990–991, 1968.

[9] D. W.Chang, "Analyze and infer the traits of creativity based on the brainwave signal: Take the IoT course combined with creative thinking for example," National Chung Cheng University, Minxiong, Taiwan, Tech. Rep., 2015.

[10] R. W. Levenson, P. Ekman, K. Heider, and W. V. Friesen, "Emotion and autonomic nervous system activity in the Minangkabau of west sumatra," *J. Personality Social Psychol.*, vol. 62, no. 6, p. 972, 1992.

[11] S. W. Chae and K. C. Lee, "Physiological experiment approach to explore the revelation process for individual creativity based on exploitation and exploration," in *Proc. Int. Conf. Adv. Comput. Sci. Inf. Technol.*, Seoul, Korea, Sep. 2011, pp. 295–304.

[12] M. Bradley and P. Lang, "Affective reactions to acoustic stimuli," *Psychophysiology*, vol. 37, no. 2, pp. 204–215, Mar. 2000.

[13] I. C. Christie and B. H. Friedman, "Autonomic specificity of discrete emotion and dimensions of affective space: A multivariate approach," *Int. J. Psychophysiol.*, vol. 51, no. 2, pp. 143–153, Jan. 2004.

[14] M. J. Christie, "Electrodermal Activity in the 1980s: A Review," *J. Roy. Soc. Med.*, vol. 74, no. 8, pp. 616–622, 1981.

[15] P. J. Lang, "The emotion probe: Studies of motivation and attention," *Amer. Psychologist*, vol. 50, no. 5, pp. 372–385, 1995.

[16] J. Kim, "Bimodal emotion recognition using speech and physiological changes," *Robust Speech Recognit. Understand.*, vol. 15, pp. 265–281, Jun. 2007.

[17] M. J. Lee and M. Shin, "Fear versus humor: The impact of sensation seeking on physiological, cognitive, and emotional responses to antialcohol abuse messages," *J. Psychol.*, vol. 145, no. 2, pp. 73–92, 2011.

[18] S.-L. Brown and G. E. Schwartz, "Relationships between facial electromyography and subjective experience during affective imagery," *Biol. Psychol.*, vol. 11, no. 1, pp. 49–62, Aug. 1980.

[19] T. D. Blumenthal, B. N. Cuthbert, D. L. Filion, S. Hackley, O. V. Lipp, and A. Van Boxtel, "Committee report: Guidelines for human startle eyeblink electromyographic studies," *Psychophysiology*, vol. 42, no. 1, pp. 1–15, 2005.

[20] J. Kim and E. André, "Emotion recognition based on physiological changes in music listening," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 30, no. 12, pp. 2067–2083, Dec. 2008.

[21] M. Häggström, "Medical gallery of Mikael Häggström 2014," *Wikiversity J. Med.*, vol. 1, no. 2, p. 8, Dec. 2015.

[22] N. Ravaja, "Contributions of psychophysiology to media research: Review and recommendations," *Media Psychol.*, vol. 6, no. 2, pp. 193–235, 2004.

[23] P. D. Bolls, A. Lang, and R. F. Potter, "The effects of message valence and listener arousal on attention, memory, and facial muscular responses to radio advertisements," *Commun. Res.*, vol. 28, no. 5, pp. 627–651, Oct. 2001.

[24] Y. Maeda, M. Sekine, and T. Tamura, "The advantages of wearable green reflected photoplethysmography," *J. Med. Syst*, vol. 35, pp. 829–834, Oct. 2011.

[25] S. Sampedro, L. Parra-López, C. Sampedro-Abascal, and J. C. Muñoz-Rodríguez, "Atrial flutter EKG can be useless without the proper electrophysiological basis," *Int. J. Cardiol.*, vol. 179, pp. 68–69, Jan. 2015.

[26] L. F. Haas, "Hans berger (1873-1941), richard caton (1842-1926), and electroencephalography," *J. Neurol., Neurosurgery Psychiatry.*, vol. 74, no. 1, p. 9, 2003.

[27] W. O. Tatum, "Ellen r. grass lecture: Extraordinary EEG," *Neurodiagnostic J.*, vol. 54, no. 1, pp. 3–21, 2014.

SHIH-YEH CHEN received the Ph.D. degree in engineering science from National Cheng Kung University, Tainan, Taiwan, in 2016. He was a Lecturer with the General Education Center, National Chung Cheng University, from 2014 to 2016. He is currently an Assistant Professor with the Department of Computer Science and Information Engineering, National Taitung University, Taitung, Taiwan. He received the Best Paper Award from CETE 2011, the IEEE CIT 2012, and GCCIL 2017. His main research interests include e-learning education, social interactions, and mobile networking.

CHIN-FENG LAI (SM'09) received the Ph.D. degree from the Department of Engineering Science, National Cheng Kung University, Taiwan, in 2008, where he is currently an Associate Professor with the Department of Engineering Science. He has been with the Department of Computer Science and Information Engineering, National Chung Cheng University, since 2016. He received the Best Paper Award from the IEEE 17th CCSE, the 2014 International Conference on Cloud Computing, the IEEE 10th EUC, and the IEEE 12th CIT. He has more than 100 paper publications and four papers selected to TOP 1% most cited articles by essential science indicators (ESI). He is an Associate Editor-in-Chief of the *Journal of Internet Technology*. He serves as an Editor or Associate Editor for *IET Networks*, the *International Journal of Internet Protocol Technology*, *KSII Transactions on Internet and Information Systems*, and the *Journal of Internet Technology*. He is TPC Co-Chair for EmbeddedCom 2012, CIT 2012ICESS 2013, FC 2013, FCST 2014, ICS 2014, and the Interest Group on Multimedia Services and Applications over Emerging Networks of the IEEE Multimedia Communication Technical Committee, from 2012 to 2017. His research interests include the Internet of Things, body sensor networks, E-healthcare, mobile cloud computing, cloud-assisted multimedia networks, and embedded systems.

CHI-CHENG CHANG received the Ph.D. degree in workforce education and development from Pennsylvania State University, USA. He is currently a Chair Professor with the Department of Technology Application and Human Resource Development, National Taiwan Normal University, Taipei. He received the National Outstanding Research Award from the Taiwan Ministry of Science and Technology (MOST), in 2014. His current research interests include e-learning, e-assessment, learning technology, and STEM/STEAM integrated education.