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Estimation of Emotional State in Personal Fabrication

Analysis of Emotional Motion based on Laban Movement Analysis

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***Abstract*—In personal fabrication, novel fabrication frameworks that promote fabrications that satisfy individuals' creative preferences will become indispensable. To realize such a framework, it is necessary to study the following: (1) estimation of the emotion that is expressed when performing the creative work and (2) adaptive recommendations based on those emotion estimates. In this study, we performed a Laban Movement Analysis to show how emotions are expressed through movement when performing a creative work. The results show that each emotion was expressed through unique movement features for quantities such as Time, Weight, and Space. We confirmed that the features corresponding to each emotion differed between individuals. This suggests that, in emotional expression, the features include information on personal preference and behavioral propensity.**

Keywords—Emotional Expression, Emotional Motion, Personal Fabrication, Laban Movement Analysis

I. INTRODUCTION

Recently, the digital fabrication culture has begun to spread, as digital tools such as personal 3-D printers have become more widely available [1]. In addition, technologies that support digital fabrication have been developed, including FabNavi [2], Fabtable [3], and Fabble [4]. These technologies provide both an easy tool for recording the fabrication process and a web platform for sharing knowledge.

For the promotion of this new fabrication culture, it is important that it cater to individual preferences—unlike mass production, which meets general consumer needs. Achieving this requires a framework that suggests digital fabrication recipes based on user preferences. This system should be controlled by measuring the emotions expressed after completing the digital fabrication, including pleasure, displeasure, satisfaction, and worry. For example, the system might provide a complex recipe that requires significant trial and error to a user who takes pleasure in the fabrication process.

Developing such a system requires novel analysis techniques that enable the estimation of emotional states based on the emotional movements made during the fabrication process. Kim et al. studied Laban Movement Analysis (LMA) [5,6] for the estimation of emotional states, proposing the use of LMA-based features to represent emotional movements in the context of human–robot interaction. They then showed that rejoicing and lamenting represented different features [7].

In our study, we aim to extend this idea to human–human interaction and thus realize the real-time estimation of emotions expressed during creative activities. Previously, we proposed the use of LMA-based features in the context of creative activities and evaluated these features' ability to estimate emotions using a decision-tree analysis. From this evaluation, we found that the estimation accuracy was about 60% [8]. However, we could not fully clarify the characteristics of the proposed feature values because of certain properties of the decision-tree analysis for determining the separation hyperplane.

In this paper, we study the relationships between the proposed features and emotional states using Russell's circumplex model [9]. The goal of the paper is to clarify the characteristics of the proposed features with respect to analyses of emotional movements during creative activities. In addition, we evaluate the accuracy of emotional-state estimation that is based on emotional movements and that uses a support vector machine (SVM), which generally has greater estimation accuracy than a decision-tree analysis.

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Fig. 1. Example of synthesizer construction.

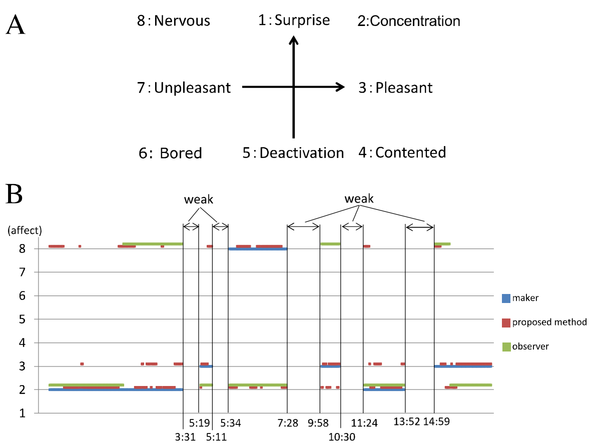

Fig. 2. Example results. A shows the emotions that can be selected on the questionnaire. B shows the time series of the selected emotion.

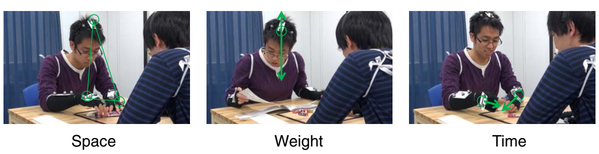

Fig. 3. The characteristics used for Laban Movement Analysis: Space, Weight and Time.

II. Related Studies

Many studies have been performed on the estimation of emotional states in various situations [10, 11], but most were limited in their target situations. This means that these studies are not very suitable for personal fabrication, for which various tools (with distinct movements) are used.

LMA is a method for interpreting human movement. Dancers and actors often use LMA, and it can be applied to generate movements for CG characters and robots. For example, Chi et al. developed EMOTE, a 3 D character animation system based on LMA [12]. Nakata et al. adopted LMA to generate a robot's motions and to analyze its impressions [13, 14]. Both of these studies are applied to the generation of motion.

Although LMA has been proposed as a method for estimating emotional states from body movements, applying it in this area has been difficult. In particular, LMA is composed of several characteristic elements—Space (direct or indirect), Weight (light or strong), and Time (sudden or sustained)—but these have not been numerically defined. Recently, due to progress in motion-sensor technology, some researches have used LMA to analyze motion and determine its elements [15]. Some approaches for representing emotional motion have also been reported [7, 16]. However, they cannot be applied to personal fabrication in human–tool interaction.

III. Previous Work

A. Subject and Experimental Environment

We conducted an experiment regarding personal fabrication before proposing an extraction method because we lacked data on the relationship between motions and emotions. We performed this experiment using the electronic building blocks called littleBits. We asked participants to create original synthesizers in pairs using littleBits. We captured the participants' motions using a motion-capture system (Bonita 10, Vicon) and video (HVR-A1J, SONY), as shown in Fig. 1. We also measured heart rate (WHS-2, UNION TOOL). The participants were 6 male and 6 female Japanese students.

We classified affect using the affect grid proposed by Russel [9]; after fabrication, we asked participants to recall and then select both a suitable emotion and its intensity (graded from 1 to 5). Fig. 2 shows an example of the resulting emotional change. We classified the results as strong or weak based on the intensity of the emotion. Below, we analyze the relationships between the proposed features and the strong emotions (which are indicated by the blue bar).

B. Proposed Features of Emotional Motion

We then defined the LMA-based features—Space, Weight and Time—as shown in Fig. 3. We computed space using the distance between the head and the wrists. Weight represented the vertical position of head, and time was the speed of the wrists across 60 s.

C. Decision-Tree Analysis

Estimation of intervals with strong emotion

First, we estimated which intervals had strong emotions. We introduced a decision tree using the values of Space, Weight, Time for each person. We normalized each value in advance and used Weka and J48 decision trees. As a result, estimating intervals with strong emotions was 71.3% of recall.

Classification of emotion

We then estimated the emotional states using a decision-tree analysis based on Space, Weight and Time for each participant. We classified the various motions for each emotion. As a result, about 60% of the instances were correctly classified.

IV. Feature-Based Analysis of Emotional Expression

A. Whole Data Set Analysis

We visually analyzed the relationships between the proposed features and the emotions using a self-organizing map (SOM) [17]. The SOM is a clustering visualization that presents the distance between each feature by mapping high-dimensional data to a two-dimensional space (called the output layer). In this case, each emotion forms an independent region on the SOM output layer SOM, thus validating the analysis from section III.A. Using this method, the authors of [18] analyzed the

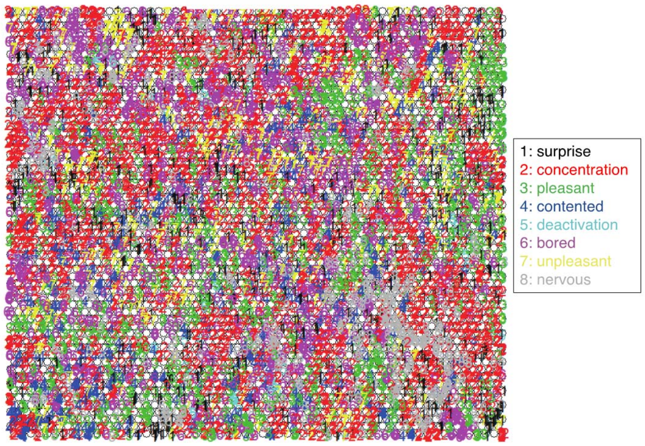

Fig. 4. Distribution of emotional states on the output layer (calculated using the data set). Each color corresponds to a particular emotion: Black is surprise, red is concentration, green is pleasantness, blue is contentment, light blue is deactivation, purple is boredom, yellow is unpleasantness, and gray is nervousness.

TABLE I. CLUSTERING RESULTS OF USER-SUBTYPE.

ID	Group	Rate of Standard Deviation		
		Space	Weight	Time
A	Balance	0.609	0.208	0.183
B	Balance	0.696	0.190	0.114
C	Balance	0.564	0.264	0.172
D	Balance	0.583	0.261	0.156
E	Balance	0.575	0.239	0.185
F	Weight	0.544	0.305	0.151
G	Weight	0.571	0.306	0.123
H	Weight	0.545	0.351	0.104

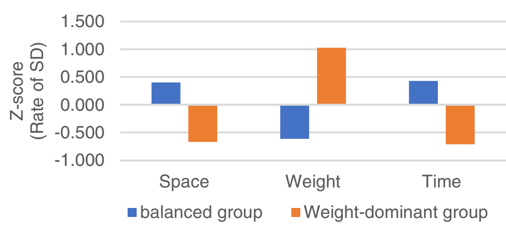

Fig. 5. Sensitivity of each group's proposed features. The blue bars are the balanced group, and the orange bars are the Weight-dominant group.

relationships between facial expressions and the emotional states of the core affect. To conduct our SOM analysis, we also used the Kohonen package implemented in R.

We analyzed the entire data set (approximately 8000 samples) using the classical Kohonen SOM. The features of the emotions were clustered in the corresponding elements of a 60 × 60 matrix (Fig. 4). In this figure, each color corresponds to an emotional state. Many emotional states—for example, concentration—have clusters in multiple regions. This result suggests that each emotional state is associated with several types of emotional shifts.

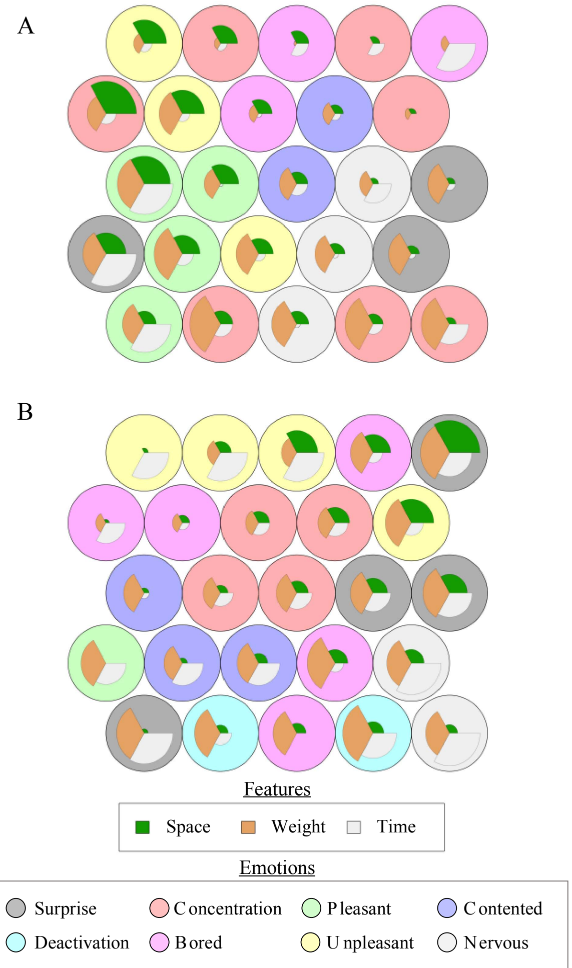

Fig. 6. Distribution of features and emotions in each group's output layer. A is the balanced group, and B is the weight-dominant group. Each circle is a node of SOM; each node's background color indicates the corresponding emotion.

B. *Types of Emotional Expression*

We classified emotional expressions based on their feature variances. The impact of an emotional expression is indicated by the feature difference between that emotion and the other emotions in a sensitivity analysis. Hence, we quantified the influence of each feature using its normalized standard deviation, with the normalization factor equal to the sum of the standard deviations of the individual features.

Table 1 shows the z-scores of all participants' influence quantities. We identified two groups of emotional expression by processing the vector-of-influence quantities (Table 1) using a hierarchical clustering method in Ward. Fig. 5 presents each group's average influence quantity and characteristics group. In the Weight-dominant group, weight strongly contributes to emotion estimation, whereas in the balanced group, all feature elements contribute to the emotion estimation.

TABLE II. ESTIMATION RESULTS AND OPTIMIZED PARAMETERS.

	Accuracy [%]	gamma	C	N
Whole	62.7	15.9	6.3	5089
Balance	70.8	10.0	2.5	2897
Weight	68.4	10.0	6.3	2192

C. Comparisons between the Emotional Expression Types

To evaluate the differences among the emotional expressions in each group, we used SOM to visually analyze the data derived from each group. The Weight-dominant and balanced groups contained 2172 and 2897 samples, respectively. For each group, the features of each emotion clustered around the corresponding element of the 5 × 5 matrix.

Fig. 6 shows the output layers for the balanced and Weight-dominant groups. The background color for each node indicates the emotion. The LMA features corresponding to each node of the output layer are visualized in polar bar graphs. We confirmed that, for each emotion, the features differed between the groups. However, some emotions, such as pleasure and contentment, had particular features in common. Moreover, concentration has some features in common with the Weight-dominant group but many more in common with the balanced group.

These results confirm that multiple subtypes of emotional motions exist during creative work. They also suggest that the number of emotional motions differs between emotions.

V. EVALUATION OF ESTIMATION CAPABILITY

To clarify each emotion's representation capability in terms of the proposed features, we evaluated the estimation capability of the discriminator that was constructed with a SVM [19]. We trained the SVM-based discriminator with the radial basis function using the e0171 package and implemented it in R. Moreover, we performed tenfold cross-validations and optimized the adjustment parameters (gamma and C).

We trained the discriminator separately for the entire data set, for the balanced group and for the Weight-dominant group using the corresponding data. The optimized parameters and the estimations' accuracy rates are shown in Table 2. The results suggest that multiple subtypes exist, as the discriminator of the entire data set is less accurate than the other discriminators. Because the estimation's accuracy is not high, the results also suggest that multiple other subtypes exist.

VI. CONCLUSIONS

We clarified the characteristics of the proposed features using a SOM analysis and an evaluation of the capability for estimating the emotions; we suggested that, during creative work, each emotion's motion comprises multiple subtypes. It would be pertinent to conduct further research on the various types of emotional motion. Moreover, we hope that the proposed features can be applied to analyses of other cultural movements, as the proposed features enable easy analyses of emotional motion.

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