An Affect Extraction Method in Personal Fabrication Based on Laban Movement Analysis

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Abstract. Affect extraction in personal fabrication will become indispensable in enhancing the recent advances in the field, because we can provide that information to the fabricators and let the fabricators enjoy the experience. In this study, we proposed an extraction method of affect in personal fabrication based on Laban Movement Analysis by using the motion data of fabricators. As a result of evaluation, the average of the correctly extracted affects was approximately 80 %.

Keywords: Laban Movement Analysis · Personal fabrication · Decision tree

1 Introduction

A revolution in manufacturing is approaching, and it could change the style of fabrication. Extracting affects in personal fabrication will become indispensable in enhancing the recent advances in the field, because we can provide that information to the fabricators and let the fabricators enjoy the experience. In this study, we proposed an extraction method of affect in personal fabrication based on Laban Movement Analysis (LMA) [1] by using the motion data of fabricators.

2 Related Studies

Many studies on extracting an affect in various situations have been performed, but most of them limit the target situations. This means that such studies are not sufficiently suitable for personal fabrication, where we use various tools and various movements are dependent on the tools.

LMA is known as a method for interpreting human movement. It is a tool used by dancers and actors. Moreover, it can be applied to movement generation of CG characters and robots. For example, Chi et al. have developed EMOTE, which is a 3D character animation system based on LMA [2]. Nakata et al. have adopted the method for generating the motions of a robot and analyzed its impressions [3]. Here, we should note that both studies are applied to generating motions.

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However, though LMA was proposed as a method to extract affects from body movement, it has been difficult. LMA was composed of several characteristic elements, such as Space (Direct/Indirect), Weight (Light/Strong), and Time (Sudden/Sustained), although they were not defined numerically. Recently, as the technology on motion sensors has shown progress, research has been conducted on analyzing motions and computing the elements [4]. In addition, some methods of extracting affects are reported [5, 6]. However, they could not be applied to personal fabrication.

3 Experiment

We conducted an experiment on personal fabrication before proposing an extraction method because we do not have data sets of motions and affects. Here, we performed an experiment by using the electronic building blocks termed littleBits. We asked participants to arrange their original synthesizer in pairs by using littleBits. We shot the motions of participants by using a motion capture system (Bonita 10, Vicon) and video camera (HVR-A1J, SONY), as shown in Fig. 1. We also measured the heart rate of the participants (WHS-2, UNION TOOL). The participants were six male and six female Japanese students.

Fig. 1. Example scene of making synthesizer

We classified affects by using the affect grid by Russel [7], and asked participants to recall and select a suitable affect and its intensity (5 grades) after fabrication. Figure 2 shows an example of the result. We classified the results into strong and weak based on the average intensity. The blue bar shows a strong affect by one of the participants.

4 Affect Extraction Method

4.1 Amount of Characteristics of Laban Movement Analysis

We then defined the amount of characteristics of Laban Movement Analysis, Space, Weight and Time as shown in Fig. 3. Space was computed by the area between the

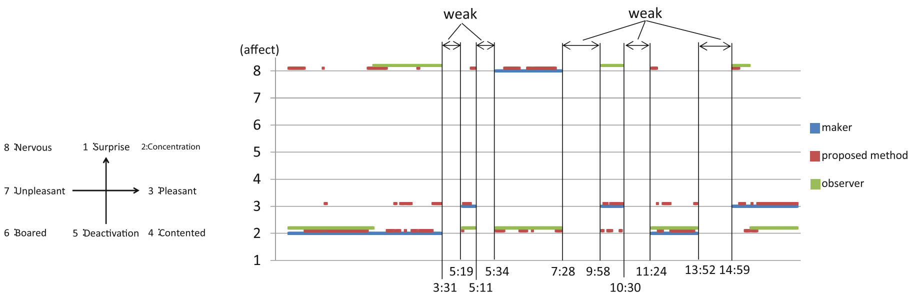

Fig. 2. An example of affect (Color figure online)

head and both wrists. Weight was the vertical position of head. Time was the sequence of the speed of the wrists for 60 s.

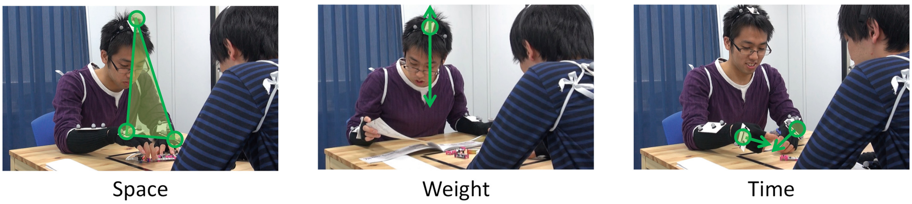

Fig. 3. The amount of characteristics for Laban Movement Analysis; Space, Weight and Time

4.2 Estimation of Interval of Strong Affect

First, we estimated the interval of a strong affect. Here, we used the parameters of 4.1 and heart rate. We introduced a decision tree by using the value of Space, Weight, Time, and heart rate for each person. For each value, we normalized all the parameters in advance. We used Weka and J48 decision tree. As a result, the estimation of the strong interval of affects was 71.3 % of recall (Fig. 4).

4.3 Classification of Affect

We then classified the affects by using a decision tree based on Space, Weight and Time for each participant. Figure 5 shows an example of the tree. As shown in the figure, we could classify different motions at the same affect. As a result, the average of the correctly classified instances was 58.1 %. In addition, 46.2 % of incorrect results were observed when the affect of the participants changed. This means that the correctly extracted affect would be approximately 80 %.

Table 1 shows the result of the classified affect. As shown in the table, concentration and boredom could be classified at approximately 70 %. However, classifying surprise was difficult.

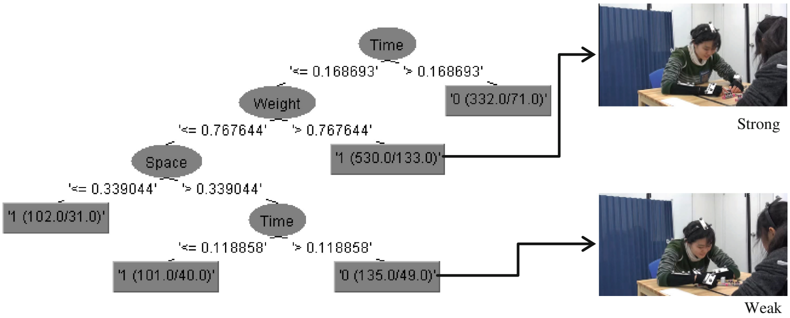

Fig. 4. Example of estimation of strong affect

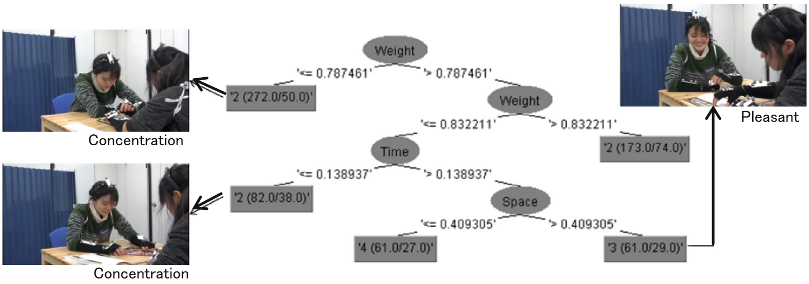

Fig. 5. An example of the decision tree

Table 1. Classified affect by proposed method

				Classified value							
				1	2	3	4	5	6	7	8
			Total	Surprise	Concentration	Pleasant	Contented	Deactivation	Bored	Unpleasant	Nervous
True value		Total	8165	694	3249	1279	514	0	1425	653	351
			100.0%	8.5%	39.8%	15.7%	6.3%	0.0%	17.5%	8.0%	4.3%
	1	Surprise	799	296	256	63	19	0	50	81	34
			9.8%	37.0%	32.0%	7.9%	2.4%	0.0%	6.3%	10.1%	4.3%
	2	Concentration	2757	108	2037	259	31	0	151	105	66
			33.8%	3.9%	73.9%	9.4%	1.1%	0.0%	5.5%	3.8%	2.4%
	3	Pleasant	1324	89	400	647	74	0	29	75	10
			16.2%	6.7%	30.2%	48.9%	5.6%	0.0%	2.2%	5.7%	0.8%
	4	Contented	656	7	158	114	271	0	82	19	5
			8.0%	1.1%	24.1%	17.4%	41.3%	0.0%	12.5%	2.9%	0.8%
	5	Deactivation	58	10	0	2	2	0	36	8	0
			0.7%	17.2%	0.0%	3.4%	3.4%	0.0%	62.1%	13.8%	0.0%
	6	Bored	1326	86	146	84	74	0	908	28	0
			16.2%	6.5%	11.0%	6.3%	5.6%	0.0%	68.5%	2.1%	0.0%
	7	Unpleasant	658	24	76	90	37	0	108	323	0
			8.1%	3.6%	11.6%	13.7%	5.6%	0.0%	16.4%	49.1%	0.0%
	8	Nervous	587	74	176	20	6	0	61	14	236
			7.2%	12.6%	30.0%	3.4%	1.0%	0.0%	10.4%	2.4%	40.2%

(frame %)

Fig. 6. Experimental scenery

5 Estimation by Human

As a reference, we performed an experiment for affect estimation by human participants. Here, we asked observers to classify the affect of participants, as shown in Fig. 6. Ten Japanese students participated in the experiment.

As a result, the correct rate was 21.1 %, which was lower than that of the proposed method. Table 2 shows the result of the classified affects. As shown in the table, humans could classify pleasant or unpleasant affects. However, it was difficult to distinguish between activated and deactivated in Russel's affect grid.

Table 2. Classified affect by human

			Observed value								
				1	2	3	4	5	6	7	8
			Total	Surprise	Concentration	Pleasant	Contented	Deactivation	Bored	Unpleasant	Nervous
True value	Total		1970	44	1026	334	35	33	366	34	98
			100.0%	2.2%	52.1%	17.0%	1.8%	1.7%	18.6%	1.7%	5.0%
	1	Surprise	250	3	137	55	5	1	26	4	19
			12.7%	1.2%	54.8%	22.0%	2.0%	0.4%	10.4%	1.6%	7.6%
	2	Concentration	580	8	323	100	7	10	96	14	22
			29.4%	1.4%	55.7%	17.2%	1.2%	1.7%	16.6%	2.4%	3.8%
	3	Pleasant	410	15	194	92	12	7	62	5	23
			20.8%	3.7%	47.3%	22.4%	2.9%	1.7%	15.1%	1.2%	5.6%
	4	Contented	120	2	54	31	2	2	26	0	3
			6.1%	1.7%	45.0%	25.8%	1.7%	1.7%	21.7%	0.0%	2.5%
	5	Deactivation	20	2	10	4	3	0	1	0	0
			1.0%	10.0%	50.0%	20.0%	15.0%	0.0%	5.0%	0.0%	0.0%
	6	Bored	250	5	112	28	2	5	77	8	13
			12.7%	2.0%	44.8%	11.2%	0.8%	2.0%	30.8%	3.2%	5.2%
	7	Unpleasant	190	5	100	13	2	5	49	2	14
			9.6%	2.6%	52.6%	6.8%	1.1%	2.6%	25.8%	1.1%	7.4%
	8	Nervous	150	4	96	11	2	3	29	1	4
			7.6%	2.7%	64.0%	7.3%	1.3%	2.0%	19.3%	0.7%	2.7%

(frame)
(%)

6 Summary

We proposed a novel affect extraction method in personal fabrication based on Laban Movement Analysis by using the motion data of fabricators. We proposed a method for extracting affects by defining the amount of characteristics of LMA, and by introducing a decision tree. The method was relatively simple, and the results of the experiments demonstrated the effectiveness of the method.

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