Clustering Approach to Characterize Haptic Expressions of Emotions

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Several studies have investigated the relevance of haptics to physically convey various types of emotion. However, they use basic analysis approaches to identify the relevant features for an effective communication of emotion. This paper presents an advanced analysis approach, based on the clustering technique, that enables the extraction of the general features of affective haptic expressions as well as the identification of specific features in order to discriminate between close emotions which are difficult to differentiate. This approach was tested in the context of affective communication through a virtual handshake. It uses a haptic device which enables the expression of 3D movements. The results of this research were compared to those of the standard Analysis of Variance method in order to highlight the advantages and limitations of each approach.

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1. INTRODUCTION

Nonverbal communication, such as prosody or gestures, corresponds to the major part of the interpersonal communication [A. Mehrabian and S.R. Ferris 1967]. The expression of emotions uses these different communication channels [Scherer 2000]. Joy, surprise, or fear are emotions that everybody can understand without specific learning [Ekman 1992]. They play an essential role in interpersonal and affective communication with other people [Scherer 2005; Parkinson et al. 2004]. Even though the expression of emotions includes and uses several modalities, existing papers mainly focus on the study of facial expressions [Ekman and Friesen 1975; Ahn et al. 2009; Courgeon et al. 2009] and gestural expressions [Dael et al. 2011; Wallbott 1998; Coulson 2004]. Affective Computing, which is the scientific field that studies the recognition and simulation of human affects, has proposed several solutions for mediated communication [Picard 1997], for instance, with virtual avatars [Courgeon et al. 2008]. Unfortunately, these approaches are not yet able to reproduce the full potential of human–human affective communication and often remain limited to some basic emotions such as joy and anger.

Several papers have investigated the potential of touch for affective communication. For instance, Hertenstein et al. [Hertenstein et al. 2006] showed how haptic expressions can effectively convey several emotions through direct contact between two humans. Olausson et al. [Olausson et al. 2008] highlighted specific biological systems dedicated to the expression of emotions through this modality. Bailenson et al. [Bailenson et al. 2007] proposed a complete platform for recording and rendering affective expressions with a haptic channel through motor expressions. However, all these papers adopted a basic analysis of variance (ANOVA) to identify the discriminative physical features of the emotion investigated. In fact, this approach can process only two emotions with one feature. However, affective communication involves a great number of emotions, and each emotion requires the identification of its unique features in order to discriminate this emotion from other emotions.

This paper introduces an advanced analysis method, based on a clustering technique, in order to identify the discriminating features of haptic expressions corresponding to several emotions. This paper focuses on the study of pairs of close emotions which are difficult to distinguish. A corpus of affective haptic expressions, corresponding to a set of eight emotions, was collected for this study. Based on this corpus, two studies were carried out. The first uses the standard ANOVA and the second uses the clustering technique. The objective of this comparative study is to highlight the advantages and limitations of the proposed analysis approach compared to the conventional method.

This paper is organized as follows. Section 2 introduces the existing analysis methods used for the classification and recognition of emotions. Section 3 describes the corpus of haptic expressions collected for the study. Section 4 presents a first analysis of the haptic corpus with the ANOVA. Section 5 presents a second analysis of the haptic corpus with the clustering technique. Finally, Section 6 presents a detailed discussion in order to compare the two analysis approaches.

2. RELATED WORKS

The methods for the analysis of affective communication have been investigated in several fields. The techniques involved mainly depend on the nature of the processed signal. This review focuses on the analysis of haptic and speech expressions.

2.1 Analysis of haptic expressions of emotions

Several studies have investigated the role of a haptic channel in conveying several classes of emotions. Basic researches use predefined kinematical and physical behaviors, identified in previous works investigating motor expressions for different emotions (e.g., a swinging movement for happiness, a tapping movement for disgust) [Tsetserukou and Neviarouskaya 2010; Bonnet et al. 2011]. However, these approaches are limited to a few basic emotions.

Bailenson et al. [Bailenson et al. 2007] proposed a complete approach to identify the haptic features for a wide range of emotions. They presented three complementary steps. First, the creation of a haptic corpus. This consists of asking a given population to express different emotions according to detailed descriptions. Second, the mean value for different measures, such as the speed and amplitude along two axes, are calculated for each expressions. Third, based on the calculated mean values, an ANOVA analysis was carried out to identify the discriminative features between the emotions. However, this approach compared emotions by pairs and for one feature. Thus, it not possible to identify one feature which can discriminate one emotion from all the other emotions.

Other papers have investigated advanced analysis approaches. Eisenstein et al. [Eisenstein et al. 2001] used clustering techniques to recognize hand signs from haptic gestures. This approach enables the simultaneous management of several features. However, it compares emotions by pairs. Knight et al. [Knight et al. 2009] proposed an approach to recognize gestures (as hugs or tickles) applied to a robot equipped with capacitive sensors. This approach is based on the Fourier transform of signals. By comparing the importance of resulting frequencies observed in a database, it is possible to recognize a gesture. Chang et al. [Chang et al. 2010; Yohanan and Maclean 2011] used a probabilistic Markovian model to recognize affective haptic expressions applied on the Haptic Creature device. Beyond the simultaneous management of several features, this approach enables the processing of dynamic features of haptic expressions such as the size of the interaction surface and the applied pressure. This last approach can also predict the next gesture based on the previous one. Both previous approaches are able to recognize several different gestures almost in real-time.

2.2 Analysis of speech expressions of emotions

A lot of research has investigated the use of speech analysis to identify emotions and related features. Dellaert et al. [Dellaert et al. 1996] compared several statistical methods for this type of analysis. They concluded that the clustering method of K-nearer neighbors was the most efficient, compared to a maximum likelihood Bayes classifier and a kernel regression. Vogt and Andr [Vogt and André 2005] proposed to analyze an important number of features (1280 features) extracted from speech. They used the correlation-based feature selection (CFS) evaluator to remove correlated features. Ververidis et al. [Ververidis et al. 2004] used a sequential forward selection method (SFS) coupled to a principal component analysis (PCA) to select representative features extracted from pitch and energy. These features enabled the classification of speech expressions with a Bayes classifier.

Some works use neural networks [Nicholson et al. 2000; Bhatti et al. 2004; Polzehl et al. 2009] to learn the identification of emotions according to the features involved. However, it can not manage dynamic features of speech expressions. The use of statistical methods such as hidden Markow models [Nwe et al. 2003; Schuller et al. 2003] gives access to this type of analysis (i.e., dynamic features). Mower and Narayanan combine feature filtering, static–dynamic modeling of expressions, emotion profiles representing characteristics of affective expressions, and hidden Markov models to recognize emotion[Lu et al. 2007; Mower and Narayanan 2011]. This enables the comparison of stimuli and profiles of several emotions. The results showed a better accuracy for emotion classification than with basic static or dynamic analysis strategies.

2.3 Synthesis

In summary, the majority of previous research uses the ANOVA for the analysis of haptic expressions. However, this approach has several limitations. First, this analysis technique compares emotions by pairs, and cannot compare one emotion with the rest of the emotions. Second, it processes only one feature between the compared emotions. Thus, it is not possible to identify a group of specific features that enables a discrimination between emotions. Moreover, the ANOVA cannot correlate the analysis of individual features. Third, and most important of all, the ANOVA cannot identify the multiple ways of expressing a given emotion. In fact, advanced analysis techniques applied to other modalities suggest different ways to express the same emotion [Dael et al. 2011].

On the other hand, the related work on speech analysis showed that the clustering technique is an alternative relevant to these issues. In fact, it enables the simultaneous comparison of several emotions presenting several features. This allows the identification of specific features for each emotion for discrimination from the rest of the emotions. Moreover, the clustering technique can detect several subpopulations in a given population which should highlight several ways to express the same emotion.

3. HAPTEMO: CORPUS OF AFFECTIVE HAPTIC EXPRESSIONS

3.1 The emotions investigated

The first step of this research consisted of creating a haptic corpus for a given set of emotions. First, we identify pairs of semantically close emotions which are difficult to differentiate with visual cues. In fact, the aim of this work consisted of finding discriminative haptic features to improve the differentiation of these close emotions.

The dimensional approach for emotion (PAD emotional state model [Russell and Mehrabian 1977]) representation suggests that emotions can be described using three uncorrelated and continuous dimensions:

—Pleasure (P): degree of well-being.

—Activation (A): degree of mental or physical activity.

—Dominance (D): degree of control of a situation.

Pair	Emotion	Pleasure	Arousal	Dominance
Pair 1	Joy	0.76	0.48	0.35
	Elation	0.50	0.42	0.23
Pair 2	Disgust	−0.60	0.35	0.11
	Contempt	−0.23	0.31	0.18
Pair 3	Anxiety	0.01	0.59	−0.15
	Fear	−0.64	0.60	−0.43
Pair 4	Irritation	−0.58	0.4	0.01
	Rage	−0.44	0.72	0.32

Table I. : Four pairs of emotions and their corresponding values in the PAD model [Russell and Mehrabian 1977].

Based on this 3D continuous representation, it is possible to calculate the Euclidean distance between the different emotions, and to select emotions which are close to each other. Four pairs of emotions were selected according to the PAD model (see Table I).

3.2 Creation of the corpus

Multiple protocols were defined in order to collect affective expressions in several modalities. They use two main classes of expressions: acted and spontaneous. This paper uses the acted expressions of emotions since they are easier to express and collect in an experimental study. Moreover, this approach provides haptic expressions that unambiguously convey a given emotion to the user. This approach consists of asking participants to express emotions defined with a textual description. In this experiment, the participants express several emotions with a 6 DoF haptic device.

3.2.1 *Experimental Platform.* The experimental platform used to collect the HAPTEMO corpus is based on a Sensable PHANToM Desktop device[1]. This haptic device enables the recording and subsequent rendering of haptic expressions. Moreover, this device enables the expression of 3D movements, which gives access to the depth component for the movement. It may exert forces of up to 7.9 N, which enables the generation of fast and jerky haptic expressions. All these features should increase the number and the type of haptic expressions compared to the standard 2D and 1D devices used in previous works [Bailenson et al. 2007] [Smith and Maclean 2007].

The experimental platform includes two computers. The client supports the manager module which manages the progress of the experiment, and controls the overall software platform. Moreover, this module records the haptic expressions, several measures, and information related to the participants. A GUI displays the instructions to the participants and processes their keyboard and mouse inputs. Accordingly, the manager module sends the records and displaying requests to the server which manages the haptic device. The haptic device was connected to a dedicated computer in order to prevent haptic instabilities due to the calculation latency of the manager module. The haptic device is controlled with a low-level module (haptic module) based on the OpenHaptics library. This module also includes a recalibration procedure in order to recalibrate the device if participants apply movements presenting an important velocity. The client–server configuration uses a UDP connection in a local network. The mean delay time is around 32 ms. This delay being too large for a stable haptic display of recorded movements, the recorded haptic expressions are sent from the manager module to the haptic module before the rendering.

[1] `http://www.sensable.com/haptic-phantom-desktop.htm`

3.2.2 *Participants.* Forty subjects (eight women and thirty-two men), ages twenty and fifty-three with an average age of thirty-one (SD = 8) completed the experiment.

We did not analyze the influence of gender, handedness, or education on the collected haptic expressions due to a majority of European right-handed males (thirty-three subjects were right-handed and thirty-five had received a European education).

3.2.3 *Procedure.* The participants were seated in front of a desk on which there was a screen, a keyboard, and a haptic device (Fig. 1). They were instructed to hold the haptic device with the dominant hand and keep the same body position during the whole experiment. The graphic interface, displayed on the screen, explained the experiment and how they should proceed to express the haptic expressions with the haptic device. The participants were asked to hold the device as if they were holding someone's wrist.

The experiment included three steps. During the first step, the participants filled out a questionnaire about their age, gender, and whether they had already used a haptic arm. The second step corresponded to the training. The participants were asked i) to explore the workspace of the haptic device, and ii) to express a given emotion with the haptic device (Surprise). The third step corresponded to the effective experiment. Participants were asked to express the eight emotions. The order of presentation of the emotional labels was randomized across subjects. A textual description of a relevant emotional situation, selected from the MindReading database [Witten and Frank 2005], was displayed along with each emotional label. It was intended to ensure a common understanding of the meaning of the emotions [Wallbott 1998]. The form that the participants used to record the haptic expressions of emotions is shown in Fig. 2.

Participants had ten seconds to express the target emotion using the haptic device. Afterwards, the recorded haptic signal was rendered to the participant through the same haptic device. Then, participants had to report via a seven point Likert scale their level of confidence about the expressed emotion. Participants had only one trial to record each emotion. This was intended to decrease the duration of the whole experiment and to ensure a minimum spontaneity in the collected data. Forty haptic expressions were collected for each of the eight emotions. The HAPTEMO corpus is thus made of $40 \times 8 = 320$ haptic expressions of emotions.

3.2.4 *Measures.* For each haptic signal collected, we computed several measures that were used in previous studies and observed to be relevant for finding out the discriminating features of emotional gestures [Bailenson et al. 2007; Castellano 2008] (see Table II). These measures were computed from the sequence of 3D-points $[(x, y, z)_1, (x, y, z)_2, ..., (x, y, z)_n]$ corresponding to the recorded movement. The sampling rate was 1 ms.

Besides those 12 main measures, Distance, Mean Speed, Fluidity, Amplitude and Contraction Index are also analyzed according to the three left-right, up-down and depth axes separately (secondary measures). This leads to 27 measures for each recorded haptic signal.

In addition to these objective measures, we considered the confidence level reported by each participant for each of his/her haptic expressions, evaluated on a seven point Likert scale. Before the analysis, the corpus was filtered in order to keep only the haptic expressions which possess a high level of confidence. The applied threshold is 5/7 on the seven point Likert scale. For the rest of this paper, the term haptic expression refers to the 194 expressions that fulfilled this criterion.

4. ANALYSIS OF VARIANCE

The analysis of affective expressions is a complex process used to highlight the differences or similarities between expressions of different emotions. ANOVA is a common approach to identifying the differences between two emotions according to a given measure [Lemmens et al. 2009; Bailenson et al. 2007]. We decided to conduct an ANOVA for the following reasons:

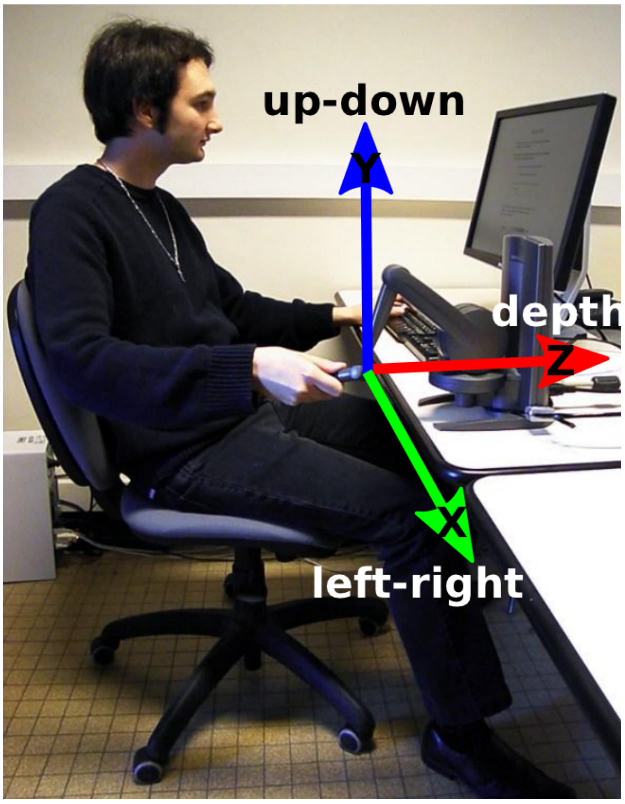


Fig. 1: A participant interacting with the platform. He moves his hand holding the device as if he were holding someone's hand.

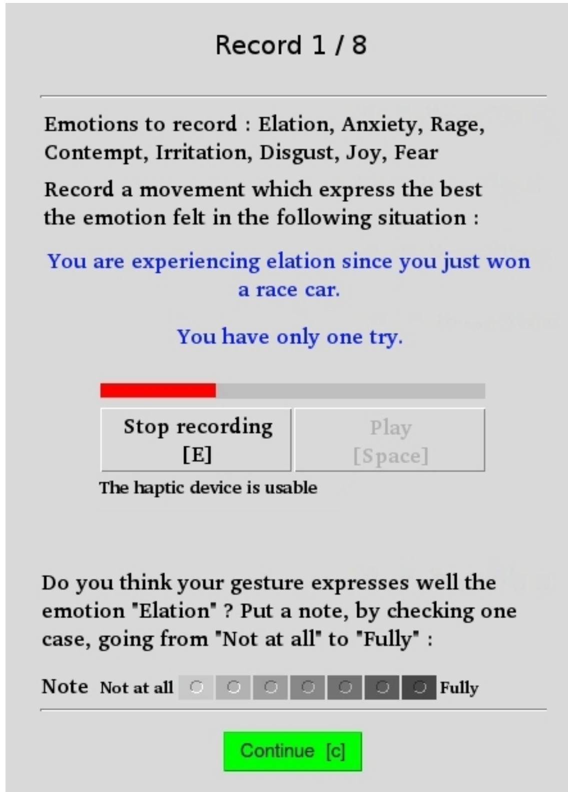


Fig. 2: English version of the form displayed on screen to the participants. The original form was in French.

(1) To compare our results with those of other studies. If our analysis gives similar results to those of other studies, that would suggest the existence of a common way to express emotions using haptics.

(2) To study new emotions which were not analyzed in previous works. We compare close emotions which present some difficulties for discrimination.

(3) To investigate the limits of ANOVA and to propose a new method which enables going beyond those limitations.

A Wilcoxon signed-rank test was used for this analysis in order to compare populations with different sizes. The filtering step based on the level of confidence provides sets presenting different numbers of haptic expressions for each emotion. Besides, populations do not respect a normal distribution. The pairwise test was not used to give a better clue to compare two specific emotions. Thus, when a given emotion has a higher score than other emotions, this means it is significantly above all those emotions taken separately.

The Wilcoxon test revealed numerous significant differences (p-value $< .05$) between emotions on most measures. Figure 3 shows the boxplots for the main measures. Table III displays mean values and standard deviations observed for all measures.

Measure	Description
Duration	Overall duration of the haptic signal.
Distance	Overall traveled distance with the device's end-effector (participant's hand): $\sum_{t=1}^{n-1} d(p_t, p_{t+1})$, with $d(p_t, p_{t+1})$ the Euclidean distance between points taken at times t and $t+1$. A low score would mean that the participant did not move the haptic device a lot.
Mean speed	Average speed of the end-effector: Distance / Duration. A low value means that the participant performed a slow gesture.
Fluidity	Degree of smoothness of the expression: $\sum_{t=0}^{n-1} \lvert a(t+1) - a(t) \rvert \ / \ n$, with $a(t)$ the acceleration at time t.
Amplitude	Distance between the two farthest corners of the bounding box containing the haptic expression.
Contraction Index	Degree of contraction and expansion of the haptic expression [Castellano 2008]: $\sum_{t=0}^{n} d(p(t), \text{isobar}) \ / \ n$, with $d(p_t, \text{isobar})$ the Euclidean distance between point taken at time t and the isobarycenter of the expression. A low value for the contraction index means that the movement is concentrated.
Major Axis (left–right, up–down, and depth)	Major axis of the gesture, computed with a Singular Value Decomposition (SVD) [Klema and Laub 1980]. Each coordinate is considered as an independent measure.
Weight of Major Axis	Prevalence of the major axis on the movement (based on SVD).
Weight of Second Major Axis	Prevalence of the second major axis on the movement (based on SVD).
Repetitivity	Estimate of the repetitive phases of the signal [Hartmann et al. 2006]. After computing the barycenter of the haptic expression and Major Axis, all the points describing the expression on the major axis are projected. Then, one repetition is counted each time the barycenter is crossed two times by the projection.

Table II. : Measures collected from haptic signals. $d(p_i, p_j)$ is the Euclidean distance between p_i and p_j.

4.1 General features of affective haptic expressions

The following list summarizes the general features of the investigated emotions (see Table III for complete data). These results were compared with those obtained in previous works on affective haptic [Basori et al. 2008; Bailenson et al. 2007] and gestural expression of emotions [Castellano 2008]. This comparison aims at highlighting the general features independently of the interaction technology and population tested.

4.1.1 *Joy.* It has a high mean duration, amplitude, contraction index, use of the left-right axis, and weight of the second major axis. It has a medium distance and mean speed. It has low use of the up-down axis, use of the depth axis, fluidity, weight of the major axis, and repetitivity.

In the related works that deal with Joy, Basori et al. [Basori et al. 2008] and Bailenson et al. [Bailenson et al. 2007] also noticed long distances and fast movements. Castellano [Castellano 2008] also observed a high speed and scattered movements (i.e., high contraction index), which is in accord with our results. Finally, our results showed that the participants mainly use the left-right axis to express Joy, while Bailenson observed important use of the up-down axis (which for this study, was mainly is the case for Elation). The proximity of these two emotions might explain this result.

4.1.2 *Elation.* It has a high distance, mean speed, amplitude, contraction index), use of the up-down axis, weight of the second major axis, and repetitivity. It has a medium fluidity and weight of the major axis. It has low use of the left-right and the depth axes. Some participants explained us that they used the up-down axis for movement because it is linked to the up-down movements of arms expressed when they hear very good news.

Table III. : Exhaustive means and standard deviations for each measure, according to the expressed emotion. Values in the highest third for a measure are in bold font. Values in the lowest third for a measure are underlined. Emotions are abbreviated as follows: Joy=Joy, Ela=Elation, Dis=Disgust, Con=Contempt, Anx=Anxiety, Fea=Fear, Irr=Irritation, Rag=Rage. X, Y and Z axes correspond respectively to left-right, up-down and depth axes.

	Joy	**Ela**	**Dis**	**Con**	**Anx**	**Fea**	**Irr**	**Rag**
duration (s)								
M	**6.4**	5.2	5.6	*4.6*	*5.1*	**6.0**	5.3	*5.1*
SD	**2.7**	2.8	3.0	*2.6*	*2.9*	**3.1**	2.5	*2.6*
distance (m) - then X, Y, Z axes alone								
M	1.30	**1.6**	*0.80*	*0.60*	*0.79*	1.0	*0.82*	**1.8**
SD	0.71	**1.1**	*0.66*	*0.54*	*.70*	1.2	*0.64*	**1.5**
$\mathbf{M_X}$	**0.78**	0.72	*0.50*	*0.43*	*0.46*	0.64	*0.48*	**0.94**
$\mathbf{SD_X}$	**0.45**	0.74	*0.54*	*0.46*	*0.44*	0.84	*0.40*	**0.91**
$\mathbf{M_Y}$	**0.83**	**1.1**	*0.41*	*0.25*	*0.45*	*0.53*	*0.46*	**1.1**
$\mathbf{SD_Y}$	**0.48**	**0.81**	*0.27*	*0.22*	*0.52*	*0.66*	*0.49*	**1.2**
$\mathbf{M_Z}$	0.26	**0.35**	*0.24*	*0.15*	*0.20*	0.27	*0.19*	**0.43**
$\mathbf{SD_Z}$	0.19	**0.24**	*0.23*	*0.14*	*0.29*	0.23	*0.17*	**0.45**
mean speed ($m.s^{-1}$) - then X, Y, Z axes alone								
M	0.23	**0.32**	*0.15*	*0.13*	*0.14*	*0.16*	*0.16*	**0.33**
SD	0.17	**0.18**	*0.092*	*0.089*	*0.075*	*0.13*	*0.10*	**0.19**
$\mathbf{M_X}$	0.13	0.13	*0.085*	*0.093*	*0.078*	*0.095*	*0.094*	**0.17**
$\mathbf{SD_X}$	0.097	0.095	*0.057*	*0.076*	*0.058*	*0.085*	*0.071*	**0.15**
$\mathbf{M_Y}$	0.15	**0.24**	*0.089*	*0.061*	*0.085*	*0.091*	*0.086*	**0.21**
$\mathbf{SD_Y}$	0.12	**0.15**	*0.072*	*0.049*	*0.066*	*0.087*	*0.086*	**0.15**
$\mathbf{M_Z}$	*0.047*	**0.071**	*0.042*	*0.034*	*0.033*	0.048	*0.037*	**0.076**
$\mathbf{SD_Z}$	*0.042*	**0.041**	*0.024*	*0.022*	*0.029*	0.037	*0.030*	**0.051**
fluidity ($m.s^{-2}$) - thenX, Y, Z axes alone								
M	*4.1*	6.0	*3.8*	*2.7*	*3.6*	*4.3*	*3.0*	**11**
SD	*3.1*	13	*3.0*	*0.89*	*2.4*	*4.7*	*0.67*	**19**
$\mathbf{M_X}$	3.4	3.5	*3.1*	*2.2*	*2.3*	*3*	*2.3*	**6.2**
$\mathbf{SD_X}$	2.5	4.5	*2.4*	*0.81*	*0.56*	*1.7*	*0.64*	**11**
$\mathbf{M_Y}$	*3.5*	5.7	*3.0*	*2.2*	*3.1*	*3.8*	*2.5*	**8.8**
$\mathbf{SD_Y}$	*2.0*	12	*1.3*	*0.87*	*2.3*	*4.0*	*0.77*	**14**
$\mathbf{M_Z}$	*2.6*	3.2	*2.8*	*2.3*	*2.5*	*3.0*	*2.5*	**4.5**
$\mathbf{SD_Z}$	*0.49*	1.5	*0.75*	*0.75*	*0.80*	*2.0*	*0.56*	**3.8**
amplitude (m) - then X, Y, Z axes alone								
M	**0.24**	**.23**	**0.22**	0.17	*0.16*	*0.16*	*0.13*	**0.21**
SD	**0.095**	**0.080**	**0.077**	0.089	*0.093*	*0.10*	*0.075*	**0.093**

	Joy	**Ela**	**Dis**	**Con**	**Anx**	**Fea**	**Irr**	**Rag**
amplitude (m) - then X, Y, Z axes alone								
$\mathbf{M_X}$	**0.18**	0.12	0.14	0.12	*0.095*	*0.098*	*0.088*	0.13
$\mathbf{SD_X}$	**0.083**	.081	0.066	0.082	*0.079*	*0.078*	*0.068*	0.087
$\mathbf{M_Y}$	**0.15**	**0.17**	0.13	*0.090*	*0.10*	*0.096*	*0.073*	**0.14**
$\mathbf{SD_Y}$	**0.057**	**0.051**	0.067	*0.056*	*.071*	*0.075*	*0.046*	**0.063**
$\mathbf{M_Z}$	**0.061**	**0.059**	**0.066**	**0.056**	*0.045*	0.063	*0.035*	0.064
$\mathbf{SD_Z}$	**0.031**	**0.031**	**0.029**	**0.042**	*0.039*	0.044	*0.024*	0.044
contract. index (m) - then X, Y, Z axes alone								
M	**0.071**	**0.059**	**0.059**	0.051	0.042	*0.041*	*0.027*	0.054
SD	**0.033**	**0.025**	**0.032**	0.032	0.030	*0.030*	*0.023*	0.034
$\mathbf{M_X}$	**0.050**	0.028	0.034	0.034	*0.023*	*0.023*	*0.017*	0.028
$\mathbf{SD_X}$	**0.029**	0.021	0.022	0.027	*0.022*	*0.020*	*0.015*	0.024
$\mathbf{M_Y}$	**0.039**	**0.042**	**0.037**	0.024	0.025	*0.022*	*0.014*	**0.036**
$\mathbf{SD_Y}$	**0.019**	**0.021**	**0.028**	0.019	0.022	*0.023*	*0.014*	**0.026**
$\mathbf{M_Z}$	**0.014**	**0.013**	**0.015**	**0.015**	0.010	**0.014**	*.007*	**0.014**
$\mathbf{SD_Z}$	**0.007**	**0.008**	**0.007**	**0.015**	0.011	**0.012**	*.006*	**0.011**
major axis, X, Y, Z axes alone								
$\mathbf{M_X}$	**0.73**	*0.42*	**0.66**	**0.68**	*0.51*	0.57	0.58	0.61
$\mathbf{SD_X}$	**0.33**	*0.30*	**0.24**	**0.3**	*0.31*	0.30	0.33	0.30
$\mathbf{M_Y}$	*0.40*	**0.74**	*0.50*	*0.42*	0.59	*0.48*	*0.48*	0.52
$\mathbf{SD_Y}$	*0.33*	**0.31**	*0.31*	*0.32*	0.33	*0.29*	*0.31*	0.33
$\mathbf{M_Z}$	*0.24*	*0.22*	0.34	0.34	**0.37**	**0.43**	**0.39**	0.32
$\mathbf{SD_Z}$	*0.21*	*0.21*	0.23	0.26	**0.24**	**0.32**	**0.30**	0.24
weight of the major axis								
M	*0.58*	0.63	0.66	**0.69**	0.67	**0.72**	**0.71**	0.64
SD	*0.11*	0.11	0.097	**0.13**	0.13	**0.14**	**0.14**	0.13
weight of the second major axis								
M	**0.29**	**0.29**	**0.26**	0.23	**0.26**	*0.21*	*0.20*	**0.27**
SD	**0.074**	**0.096**	**0.077**	0.092	**0.11**	*0.11*	*0.093*	**0.091**
repetitivity								
M	*2.7*	**5.2**	*2.4*	*1.4*	*3.0*	3.4	4.9	**7.1**
SD	*1.9*	**6.6**	*2.2*	*2.1*	*3.1*	4.5	4.2	**9.1**

4.1.3 *Disgust.* It has a high amplitude, contraction index, and use of the left-right axis. It has medium use of the depth axis and weight of the major axis. It has a low distance, mean speed, fluidity, use of the up-down axis, and repetitivity.

This is in line with the results observed by Basori et al. [Basori et al. 2008], who noticed a low distance measure for Disgust.

4.1.4 *Contempt.* It has high use of the left-right axis and weight of the major axis. It has a medium amplitude, contraction index, and weight of the second major axis. It has a low duration, distance, mean speed, fluidity, use of the up-down axis, and repetitivity.

4.1.5 *Anxiety.* It has high use of the depth axis. It has a medium contraction index, use of the up-down axis, and weight of the major axis. It has a low distance, mean speed, fluidity, amplitude, and weight of the major axis.

4.1.6 *Fear.* It has high use of the depth axis and weight of the major axis. It has a medium distance, use of the left-right axis, and repetitivity. It has a low mean speed, fluidity, amplitude, contraction index, use of the up-down axis, and weight of the second major axis.

This is in line with the results observed by Basori, who noticed a low value for the distance measure for Fear.

4.1.7 *Irritation.* It has high use of the depth axis and weight of the major axis). It has a medium repetitivity. It has a low distance, mean speed, fluidity, amplitude, contraction index, use of the up-down axis, and weight of the second major axis.

4.1.8 *Rage.* It has a high distance, mean speed, fluidity, amplitude, weight of the second major axis, and repetitivity. It has a medium contraction index, use of the left-right axis, use of the up-down axis. Finally, this emotion has low weight of the major axis, which means the movements were not focused on the main axis.

In the related papers that deal with Anger, Bailenson noticed a high mean speed for this emotion [Bailenson et al. 2007]. However, Bailenson and Castellano highlighted a high fluidity for Anger [Bailenson et al. 2007; Castellano 2008].

This study highlights many features of the investigated emotions. Moreover, some results are similar to those found in previous research. This supports the hypothesis that there is a common way to express the different emotions. However, as explained above, the identified features discriminate a given emotion from only a set of emotions and not from all other emotions. This limits the scope of these results since they do not allow a global characterization of emotions. One exception was observed for Joy. The analysis highlighted a significant difference from all emotions, using the contraction index on the left-right axis (a secondary measure).

4.2 Discriminative features between close emotions

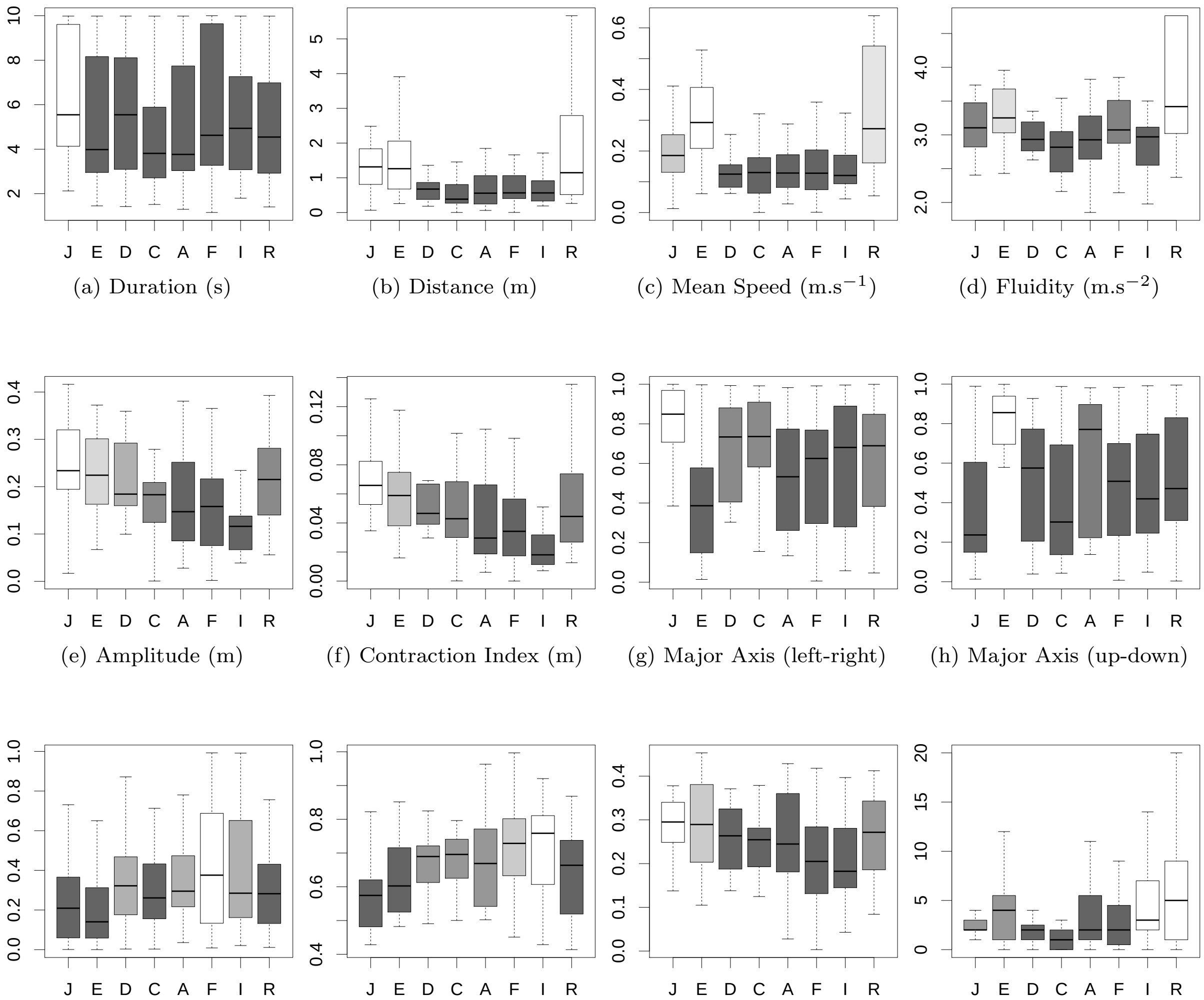
In this section we compare the emotions by pairs according to their proximity in the PAD space. Based on these features (see Table III for all details), typical haptic expressions could be proposed for differentiating pairs of emotions.

4.2.1 *Discriminative features between Joy and Elation.* This mainly concerns the mean speed and the major axes. Elation corresponds to fast movements on the up-down axis, while Joy corresponds to slow movements on the left-right axis. Several other discriminative features were observed for secondary measures such as fluidity and the contraction index .

4.2.2 *Discriminative features between Disgust and Contempt.* This only concerns the traveled distance on the up-down axis, which is a secondary measure. This means that Disgust and Contempt present large and small movements, respectively, along the up-down axis.

4.2.3 *Discriminative features between Anxiety and Fear.* This only concerns the distance along the depth axis which is a secondary measure. This means that Anxiety and Fear present small and large movements respectively according the depth axis.

4.2.4 *Discriminative features between Irritation and Rage.* It concerns the distance, the mean speed, the amplitude, the fluidity, the contraction index, the weight of the major axis, and the weight of the second major axis. This means that Irritation corresponds to small, slow and smooth movements, while Rage corresponds to large, fast and jerky movements. Several other discriminative features were observed for secondary measures.



(a) Duration (s) (b) Distance (m) (c) Mean Speed (m.s^{-1}) (d) Fluidity (m.s^{-2})

(e) Amplitude (m) (f) Contraction Index (m) (g) Major Axis (left-right) (h) Major Axis (up-down)

(i) Major Axis (depth) (j) Weight of MA (k) Weight of SndMA (l) Repetitivity

Fig. 3: Boxplots of the main computed measures extracted from the HAPTEMO corpus. The lighter the color of an emotion, the higher the corresponding measure ($p < .05$). For instance, fluidity (d) of Disgust, Anxiety, Fear and Irritation have low values, while Rage is significantly above most emotions, just ahead of Elation. Outliers are not displayed to show only important results.

4.3 Limitations of the standard ANOVA

The ANOVA analysis is easy to apply to the extracted measures and to interpret. However, it has two main limitations. First, the standard method manages only one measure per emotion at a time. This prevents finding possible correlations among different measures or groups of measures describing well a given emotion. For example, there is a linear correlation between distance, mean speed, and the duration of an expression. Due to the ANOVA, these links overestimate the differences between the expressions of two distinct emotions.

This limitation can be bypassed with an extended analysis using a multivariate ANOVA or an analysis of covariance (ANCOVA) with post hoc tests.

The second major limitation concerns the analysis of population. In fact, this method compares the whole populations, but cannot find subpopulations inside them, which can be useful to identify the different ways to express a given emotion. For instance, in the HAPTEMO corpus, people do not express Joy in the same way. Some people use slow movements, while others use fast movements. This explains in part why the measures described in Table III have high standard deviations and high interquartile distances in Fig. 3. Thus, the ANOVA deals only with the main trend, but cannot detect the different groups of expressions. The next section proposes a method that overcome these limitations.

5. CLUSTERING-BASED APPROACH

We investigated a new method, based on the clustering technique, which enables the identification of multiple expressions for the same emotion. The application of this method enables determining i) general features of affective haptic expressions and ii) the discriminative features between close emotions.

5.1 Proposed approach

The proposed approach includes four main steps:

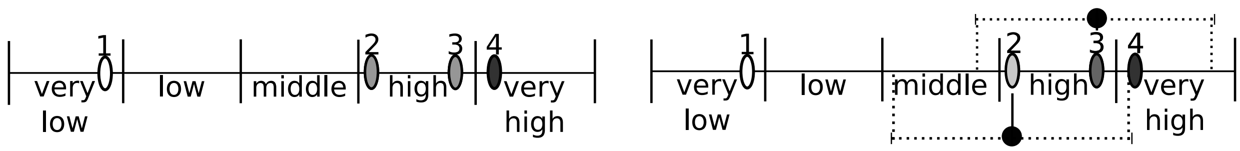
(1) Extraction of different ways to express each emotion.
(2) Selection of relevant measures describing each cluster for each emotion.
(3) Comparison between two clusters according to one measure.
(4) Characterization of clusters.

The following sections present these steps in detail.

Step 1: *Extraction of different ways to express each emotion.* The objectives of the first step are i) to identify emotions having multiple expressions and ii) to identify the different types of expressions. We used the Expectation-Maximization (EM) clustering algorithm [Dempster et al. 1977] implemented with the Weka platform [Golan et al. 2006] which is a well-known data mining tool. The EM algorithm finds clusters by determining a mixture of Gaussians that fit a given data set. This algorithm enables estimating the optimal number of clusters using the cross-validation method. In fact, in our case, this number is not known a priori. Furthermore, this algorithm captures the correlations and dependencies between attributes.

The EM algorithm highlights possible multiple expressions dependence among attributes. Thus, the algorithm is applied to each emotion separately. In consequence, the number of clusters found for each emotion corresponds to the different ways that participants express this emotion. The results of clustering are synthesized in Table IV. The results showed only one cluster for Joy, Anxiety and Fear. The other emotions present two distinct clusters per emotion. This suggests that there are at least two different ways in which participants express those emotions.

Step 2: *Selection of relevant measures describing each cluster for each emotion.* The objective of this step is to check the relevance of measures corresponding to the different clusters identified in step 1. The relevant measures should form the set of discriminative features to differentiate effectively emotions. For example, Table IV suggests that only expressions of cluster 1 of Rage present a very high mean speed for the Z-axis. Thus, this measure should be kept for the analysis of discriminative features. However, since the clustering simultaneously uses all measures for the classification, it does not allow the highlighting of the relevant subsets of the measures for the different clusters. Thus, this step was added to determine which measures are representative for each cluster. The adopted solution used the attribute selection algorithm, and more



(a) Method 1: comparison by belonging to a class. (b) Method 2: comparison by Euclidean distance.

Fig. 4: Two different class comparison methods. In Method 1 (a), elements 2 and 3 are indistinguishable since they are both in the high class. In contrast, 3 and 4 are distinguishable since they are not in the same class. This is illogical since the value of 4 is nearer to 3 than to 2. However, in Method 2 (b), couples 2 and 3 as well as 3 and 4 are indistinguishable since the distance between them is lower than a class length.

specifically the correlation-based feature with the best first method, for each cluster separately [Casale et al. 2010] [Vogt and André 2005].

Table IV presents the results of this step. The gray cells correspond to the relevant, kept measures, while the white cells correspond to the irrelevant, removed measures. As expected, the results show that some measures are irrelevant. For example, the mean speed on the Z-axis is not a relevant measure for Rage. Thus, it must be removed from the subset of discriminative features of this emotion and from the corresponding cluster.

Step 3: *Comparison between two clusters according to one measure.*

The objective of this step is to present the method adopted for comparing two clusters according to one measure. The result should establish whether the analyzed measure discriminates or not for the two clusters considered.

The proposed approach consists of comparing the values for a given feature of the centroids of two clusters. The use of the centroids' values aims at limiting the effect of outsiders, which can bias the comparison. However, the direct comparison of two values makes no sense statically. In fact, statistical analyses compare two populations and not two values. In order to overcome this limitation, a relative comparison of clusters is used. It consists in comparing the distance between the two considered clusters (d) and the global distance between the minimum and maximum centroids' values observed for all clusters (D). This comparison implies the definition of a threshold (T) above which the two compared values can be evaluated as different.

The adopted threshold corresponds to one-fifth of the global distance between the minimum and maximum centroids' values ($T = \frac{1}{5} \times D$). This threshold provides five equal parts, each one corresponding to a class commonly used for such classifications (i.e., very low, low, medium, high, and very high) [Castellano 2008]. These classes provide an explicit criterion for comparing two clusters. Two clusters belonging to different classes are considered different (clusters 1 and 2 in Fig. 4a)).

However, this method has an important limitation. Close clusters belonging to two neighboring classes are evaluated as different (clusters 3 and 4 in Fig. 4a)). Conversely, distant clusters belonging to the same class are not evaluated as different values (clusters 2 and 3 in Fig. 4a)).

To overcome this limitation, the distance between the clusters concerned is compared with the threshold that corresponds to the size of one class. If this distance is smaller than the threshold ($d < T$), the two values are indistinguishable, and, thus, the feature is considered as not discriminating between the two clusters (see Fig. 4b). This implies that if a feature is identified as characteristic of a given cluster, the value of this feature for this cluster should not be found in other clusters.

Step 4: *Characterization of clusters.*

The objective of this step is to introduce the method adopted for the identification of all subsets of discriminative features for all clusters. This step aggregates the results of steps 1, 2, and 3.

The relevant features for each cluster, identified in step 2, correspond to a unique combination of features. However, considering simultaneously all these features can restrict the recognition of expressions, since they should match with all values of the features. Thus, it is necessary to minimize the number of required features to characterize a given cluster. The smaller the number of discriminative features, the higher the weight of the features.

The overall comparison process consists in comparing each subset of relevant features for a given cluster with the subsets of relevant features for all other clusters. Several subsets of relevant features, for each cluster, are compared with those of other clusters. The features are compared by pairs according the method presented in step 3. If a combination of features is identified as specific for a given cluster, then it is considered as characteristic for this cluster and enables its discrimination from the rest of clusters.

For example, we want to discriminate Rage (cluster 1) from Joy (cluster 1) and Elation (cluster 1). One subset including two relevant features was identified for these emotions (step 2): the mean speed and the weight of the major axis. Based on the comparison procedure developed in step 3, the mean speed of Rage is compared with the mean speed of Joy, and thus with the mean speed of Elation. The same comparison procedure is used for the weight of the major axis. Suppose that Rage and Joy have only different mean speeds, and Rage and Elation have only different weights of major axis. Then these feature are not discriminative individually. However, the simultaneous use of these features is characteristic of Rage.

Nevertheless, this last step has a drawback. The analysis of all possible combinations of features among all clusters has an exponential complexity. However, the complexity can be reduced in two ways. In order to increase the weight of the relevant features, we need to minimize the number of required features to characterize a given cluster. Thus, the size of the subsets can be limited in order to keep only the most general characterizations. Second, it is possible to filter the results when the size of the subsets is high. For example, if duration characterizes Elation, it is obvious that any combination of features including duration enables the discrimination of this emotion. Thus, such combinations are ignored.

5.2 General features of affective haptic expressions

Based on the analysis approach presented above, the following list summarizes the features, and corresponding values, that allow the discrimination of each cluster from the rest of the clusters of emotions investigated. If a feature is discriminative for a given cluster, it allows also the discrimination of the corresponding emotion from the rest of the emotions. Some clusters and emotions are not mentioned since the adopted method did not identify characteristic features compared to the rest of the clusters and emotions. Each emotion is followed by a number which corresponds to the analyzed cluster (Elation 1 means cluster 1 of Elation).

— *"Elation 1"* has the highest duration (7.8 s), a medium fluidity on the left-right axis (12. $m.s^{-2}$), and the highest number of repetitions (9.6).
— *"Elation 2"* has the lowest use of the left-right axis (0.37) and the highest use of the up-down axis (0.77).
— *"Disgust 2"* has low use of the depth axis (0.21).
— *"Contempt 1"* has the lowest mean speed on the depth axis (0.0027 $m.s^{-1}$), fluidity on the depth axis (0.69 $m.s^{-2}$), amplitude (0.030 m), amplitude on the left-right axis (0.023 m), and amplitude on the up-down axis (0.016 m). It also has the highest weight of the major axis (0.92) and the lowest weight of the second major axis (0.070).
— *"Irritation 1"* has a low amplitude (0.087 m), a high weight of the major axis (0.78), and a low weight of the second major axis (0.16).
— *"Rage 1"* has the highest fluidity on the left-right (9.8 $m.s^{-2}$) and the depth (5.4 $m.s^{-2}$) axes.
— *"Rage 2"* has a high fluidity (8.5 $m.s^{-2}$).

Table IV. : Barycenters' features for all emotions (step 1 and 3). The clustering-based approach enables highlighting of similarities and differences between the different expressions of the studied emotions. Values with gray cases are those where the corresponding measure is relevant for the cluster (step 2). Values in white on black are discriminative for the corresponding cluster (step 4, with subsets containing a single measure). "- -" corresponds to very low, "-" corresponds to low, "0" corresponds to medium, "+" corresponds to high, and "+ +" corresponds to very high. Emotions are abbreviated as follows: Joy=Joy, Ela=Elation, Dis=Disgust, Con=Contempt, Anx=Anxiety, Fea=Fear, Irr=Irritation Rag=Rage. X, Y and Z axes correspond respectively to left-right, up-down and depth axes.

	Joy 1	**Ela 1**	**Ela 2**	**Dis 1**	**Dis 2**	**Con 1**	**Con 2**	**Anx 1**	**Fea 1**	**Irr 1**	**Irr 2**	**Rag 1**	**Rag 2**
distrib.	100%	29%	71%	53%	47%	13%	87%	100%	100%	64%	36%	45%	55%
	duration												
-	+	+ +	- -	- -	+	- -	- -	-	0	- -	+	0	- -
	distance												
All axes	0	+ +	-	- -	-	- -	-	-	-	- -	0	+ +	-
***X* axis**	0	+ +	-	- -	0	- -	-	-	-	- -	0	+ +	-
***Y* axis**	0	+ +	-	- -	0	- -	-	-	-	- -	0	+ +	-
***Z* axis**	0	+ +	-	- -	-	- -	- -	-	-	- -	0	+ +	-
	mean speed												
All axes	0	+ +	0	- -	0	- -	-	-	-	-	0	+ +	0
***X* axis**	0	+ +	-	- -	0	- -	-	-	-	-	0	+ +	-
***Y* axis**	0	+ +	+	- -	0	- -	-	-	-	- -	0	+ +	0
***Z* axis**	-	+	0	-	0	- -	-	-	0	-	0	+ +	-
	fluidity												
All axes	-	+ +	- -	- -	-	- -	- -	- -	-	- -	- -	+ +	0
***X* axis**	-	0	-	- -	-	- -	-	- -	-	- -	-	+ +	-
***Y* axis**	-	+ +	-	- -	-	- -	- -	-	-	- -	-	+ +	+
***Z* axis**	0	+	0	-	0	- -	-	-	0	-	0	+ +	+
	amplitude												
All axes	+	+ +	0	0	+ +	- -	0	0	0	-	0	+ +	0
***X* axis**	+ +	+ +	-	-	+ +	- -	0	-	-	- -	+	+ +	-
***Y* axis**	+	+ +	+	-	+ +	- -	0	0	0	- -	0	+ +	0
***Z* axis**	+	+ +	0	0	+ +	- -	+	0	+	- -	0	+ +	-
	contraction index												
All axes	+ +	+ +	+	0	+ +	- -	+	0	0	- -	0	+ +	0
***X* axis**	+ +	+ +	-	0	+ +	- -	+	-	-	- -	0	+ +	- -
***Y* axis**	+	+	+	0	+ +	- -	0	0	-	- -	0	+ +	0
***Z* axis**	+	+ +	0	+	+	- -	+	-	+	- -	0	+ +	-
	major axis of movement												
***X* axis**	+ +	0	- -	+	+ +	-	+ +	0	0	0	+	+ +	0
***Y* axis**	- -	+	+ +	- -	0	+ +	- -	0	-	-	-	-	0
***Z* axis**	-	- -	0	+ +	-	- -	+	+	+ +	+ +	+	0	+
	weight of the major axis												
-	- -	- -	-	-	-	+ +	-	-	0	+	- -	- -	0
	weight of the second major axis												
-	+ +	+ +	+	+	+	- -	+	+	0	-	+ +	+ +	0
	repetitivity												
-	-	+ +	-	- -	-	- -	- -	-	-	-	+	+ +	-

5.3 Discriminative features between close emotions

This section presents the features which discriminate between the expressions of close emotions. As presented above, the emotions are compared by pairs according to their proximity in the PAD space. Based on these features, typical haptic expressions are proposed for differentiating the pairs of emotions.

As shown above, each emotion might possess several clusters. The identification of the discriminative features between two emotions (e_1 and e_2) consists in finding at least one relevant feature for one cluster of e_1 different from all clusters of e_2.

5.3.1 *Discriminative features between Joy and Elation.* For Joy 1, these features are the duration and the major axis (left-right and up-down coordinates). For Elation 1, it concerns the duration, the distance, the mean speed, the fluidity, the amplitude, the major axis of movement (left-right and up-down coordinates), and the repetitivity. For Elation 2, it concerns the duration, the major axis of movement (left-right and up-down coordinates), the weight of the second major axis of movement), and the repetitivity.

Thus, Elation 1 has more discriminative features from Joy 1 than Elation 2. This means that Elation 1 has the least ambiguty with Joy 1. Based on the identified features, it can be said that Elation 1 corresponds to very fast, jerky, and repetitive movements. It has a very important duration and distance and mainly uses the up-down axis. On the other hand, Joy 1 corresponds to movements that have a long duration, which mainly use the left-right axis.

5.3.2 *Discriminative features between Disgust and Contempt.* For Disgust 1, it concerns the contraction index and the major axis of movement (left-right and depth coordinates). For Disgust 2, these features are the duration), the mean speed, the amplitude, and the major axis of movement (all coordinates). For Contempt 1, it concerns the duration, the amplitude, the contraction index, the major axis of movement, the weight of the major axis, the weight of the second major axis, and the repetitivity. For Contempt 2, it concerns the duration, the contraction index, and the major axis of movement (depth coordinate).

Thus, Disgust 2 possesses more discriminative features from Contempt (both clusters) than Disgust 2. Besides, Contempt 1 has more discriminative features from Disgust (both clusters) than Contempt 2. This means that Disgust 2 has the least ambiguity with Contempt 1. Based on the identified features, it can be said that Disgust 2 corresponds to medium speed movements with a very important amplitude in a short time. It mainly uses the left-right axis. On the other hand, Contempt 1 corresponds to very concentrated movements with a very low duration, amplitude, and repetitivity.

5.3.3 *Discriminative features between Anxiety and Fear.* For Anxiety 1, these features are the duration, the major axis of movement (left-right and up-down coordinates), the weight of the major axis of movement, and the weight of the second major axis of movement. For Fear 1, it concerns the distance, the contraction index, and the major axis of movement (up-down coordinate).

Based on the identified features, it can be said that Anxiety 1 corresponds to short time movements which use both the left-right and up-down axis, while Fear 1 corresponds to moderately concentrated movements involving short distances.

5.3.4 *Discriminative features between Irritation and Rage.* For Irritation 1, it concerns the mean speed, the fluidity, the amplitude, the contraction index, the major axis of movement up-down coordinate), the weight of the major axis of movement, and the weight of the second major axis of movement. For Irritation 2, it concerns the fluidity and the weight of the second major axis of movement. For Rage 1, it concerns the duration, the distance, the mean speed, the fluidity, the contraction index, and the major axis of movement (depth coordinate). For Rage 2, it concerns the mean speed, the fluidity, the major axis of movement, the weight of the major axis of movement, and the repetitivity.

Thus, Irritation 1 has more discriminative features from Rage than Irritation 2. Besides, Rage 1 has more discriminative features from Irritation than Rage 2. This means that Irritation 1 has the least ambiguity with Rage 1. Based on the identified features, it can be said that Irritation 1 corresponds to smooth movements with medium amplitudes, speeds, and concentrations, while Rage 1 corresponds to very high speed, jerky, and concentrated movements with important distances.

6. OVERALL ADVANTAGES OF THE CLUSTERING APPROACH

This section presents the advantages of the proposed analysis approach compared to ANOVA. First, we discuss the advantages of dealing simultaneously with several measures using the proposed comparison approach. Second, we discuss the advantages of dealing with several ways of expression using the clustering approach.

6.1 Simultaneous use of the measures

Dealing simultaneously with several measures has three main objectives.

6.1.1 *Identification of several ways to express an emotion.* With the ANOVA, the comparison of emotions may lead to identifying general features which do not take into consideration the several ways of expressing an emotion. For instance, the analysis of Joy highlighted duration as a discriminative feature from the other emotions. However, the clustering analysis showed that this feature is not relevant for discriminating Joy from one of the two clusters of Disgust. On the other hand, the clustering method highlighted other relevant features, which may be combined with the duration (such as the Y component of major axis), that allows an efficient discrimination of these emotions.

6.1.2 *Combination of information.* With the ANOVA, it is not possible to combine independent measures that are not relevant individually, in order to find a relevant combination that enables an efficient discrimination between emotions. For instance, the contraction index on the left-right axis and the contraction index on the Y-axis are not relevant individually, with either ANOVA or clustering methods, for discriminating Elation 2 from the other emotions. However, clustering can combine these two measures and provide a relevant combination of features that enables the discrimination of Elation 2 from the other emotions.

6.1.3 *Identification of sets of features with different levels of relevancy.* With the ANOVA, it is not possible to identify independent sets of relevant features since this method deals only with one measure at a time. Since the proposed approach (see step 4, Section 5) allows the simultaneous management of several measures, it is possible to find sets of relevant features. However, these sets have different levels of relevance, depending on the size of the sets. The smaller the size of the set, the more important is the weight (see step 4, Section 5). For instance, the analysis of Disgust 2 highlighted two sets of discriminative features. First, the depth component of major axis (set 1). Second, the combination of the left-right component of major axis and the Y component of major axis (set 2). Set 1 has the largest weight, which leads to a more general discrimination from the other emotions.

The results presented previously cannot be found with an ANOVA-based approach. Besides, the combination of measures also gives clues on the kinematic properties of the relevant expressions.

6.2 Several ways of expressing emotions

Dealing with several ways to express a given emotion has two main objectives.

6.2.1 *Identification of representative measures.* With the ANOVA, all expressions of a given emotion are mixed in a single population. This may lead to large standard deviations for some measures. The clustering approach identifies the different groups of expressions which provide more representative measures, with a less scattered population, for each cluster. This leads to finding more significant differences, and thus more discriminative features, between the emotions. For instance, the general analysis of Rage found a mean speed of 0.33 $m.s^{-1}$ with a standard deviation of 0.19. The clustering analysis highlighted two clusters for this emotion. The first cluster has a mean speed of 0.48 $m.s^{-1}$ with a standard deviation of 0.15. The second cluster has a mean speed of 0.21 $m.s^{-1}$ with a standard deviation of 0.12.

6.2.2 *Extraction of groups of expressions.* Since the clustering method groups the expressions according to their similarity, the resulting clusters correspond to different expressions for a given emotion. This property of clustering is very useful for the automatic recognition of emotions.

7. CONCLUSION

This paper introduced a new classification method to extract discriminative features of 3D affective haptic expressions. A classical ANOVA approach applied to our corpus of expressions confirmed the results found by related studies. However, this approach has several limitations, such as the impossibility of managing multiple ways to express a given emotion, and the impossibility of correlating several analyzed measures.

To overcome these limitations, we proposed a clustering-based approach. It includes four main independent steps which deal with different analytic issues. The main advantages are 1) the management of several expressions for a single emotion and 2) the management of several features and emotions at the same time. The analysis of the results highlighted several general features of affective haptic expressions for each emotion, and provided relevant discriminative features between close emotions. Moreover, the proposed approach found specific combinations of features for each emotion studied. This could be useful, for example, for the creation of synthetic affective haptic expressions.

The proposed approach has nevertheless a limitation: as in the ANOVA, the measures computed are static. Recent studies in speech recognition of emotions suggest that dynamic features are better for the automatic recognition of emotions. Future research will also compare the results obtained with acted emotions used herein to those obtained from spontaneous emotions.

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