Comparison of Statistical Methods for the Analysis of Affective Haptic Expressions

Yoren Gaffary[1], Victoria Eyharabide[2], Yacine Tsalamlal[1], Jean-Claude Martin[1], and Mehdi Ammi[1]

[1] CNRS/LIMSI, Bâtiment 508, Université de Paris-Sud, 91403 Orsay Cedex, France
firstname.lastname@limsi.fr
[2] STIH, Université Paris-Sorbonne, 28 rue Serpente, 75006 Paris, France
maria-victoria.eyharabide@paris-sorbonne.fr

Abstract. Several studies were conducted to show the relevance of haptics for conveying emotions to users. These studies usually cover recognition rate of emotions from haptic expressions. Surprisingly, the analysis of features of these haptic expressions has been in counterpart often limited to a classical analysis of variance. This method is limited since it can neither highlight multiple possible expressions of a given emotion nor compare several emotions or features simultaneously. This paper presents a methodological approach for collecting and analyzing haptic expressions of emotions. We compare three statistical methods, namely analysis of variance, principal component analysis, and clustering. Over this study we will highlight the advantages and drawbacks of each method for the analysis of haptic expressions of emotions.

Keywords: Emotion, Haptics, Experimental Study, Statistics

1 Introduction

Emotions play an important role in human-human communication [12]. The capabilities of some modalities as facial expressions to express emotions during human-computer interactions are addressed in multiple studies [13].

Recently, several works have investigated the role of haptics to improve the recognition and discrimination of some emotions expressed with facial expressions [3,2,14,7]. These works were based on the identificati on of discriminative features in haptic expressions for each investigated emotion. These studies have exploited the analysis of variance (ANOVA) as a mainstream statistical method to exhibit these discriminative features. However, classical ANOVA suffers from three main limitations. First, emotions are compared pairwise. It is thus not possible to compare simultaneously more than two emotions. Second, features of haptic expressions are considered one at a time and it is not possible to identify the correlations between these features. Third, these studies do not focus on multiple ways to express a given emotion, while studies in other modalities have observed and suggest multiple and different expressions of the same emotion [5].

To overcome these limitations of ANOVA, we have explored its complementarity with two other statistical methods. The first method is based on the Principal Components Analysis (PCA) [10] which allows the highlighting of correlations between features. The second method is based on the clustering analysis (using the Expectation-Maximization (EM) algorithm [6]) to analyze multiple groups of emotions in a given set of haptic expressions.

This paper starts with the description of a corpus of haptic expressions that we collected. The next section introduces the results of the three statistical methods applied to the collected data. Finally, we summarize the advantages and drawbacks of each method, and highlight the complementarity between the three methods.

2 HAPTEMO: a Corpus of Affective Haptic Expressions

The first step of this study concerns the creation of a corpus of haptic expressions corresponding to different emotions. This implies i) the selection of a set of emotions, and ii) the definition of an experimental protocol to collect corresponding haptic expressions. We propose to study pairs of close emotions in order to identify haptic features that enable an efficient recognition and discrimination.

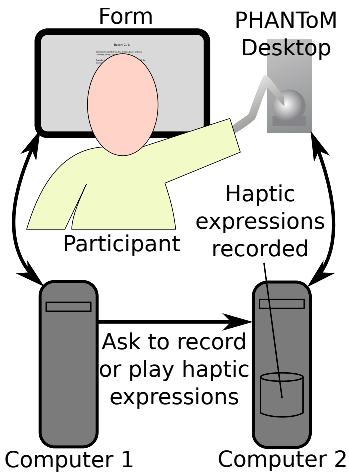
The dimensional representation of emotions suggests that emotions can be represented using three continuous and orthogonal dimensions : Pleasure (degree of well-being), Arousal (degree of mental or physical activity) and Dominance (degree of control of a situation) [11].

This dimensional approach enables to compute a distance between two emotions and compare features expressing emotions that are either close or far from each other. Thus, we have selected the following emotions (according to the PAD axes as observed in a previous study [11]): "Joy", "Elation", "Disgust", "Contempt", "Anxiety","Fear", "Irritation" and "Rage".

Multiple protocols, using realistic acted or spontaneous expressions, have been defined for collecting expressions of emotions in several modalities. We propose to use the acted approach since we want to analyze haptic expressions, and their related features, that conveys without ambiguity a single emotion to users.

2.1 Experimental Platform

The experimental platform is based on a PHANToM Desktop haptic arm. This device enables recording and rendering of 3D Kinesthetic expressions. The platform includes two computers (see Fig. 1). The main computer displays instructions to users with a screen and process keyboard's inputs. It also includes the UDP protocol to support the communication with the second computer which records and render haptic expressions. This configuration ensures a better stability for haptic rendering.



(a) experimental set-up.

(b) a participant interacting with the platform.

Fig. 1: Experimental platform to collect haptic expressions of emotions.

2.2 Participants

Forty subjects (eight women, thirty-two men), aged between twenty and fifty-three, thirty-one average age (SD = 8) participated in this experiment. We did not analyze the influence of gender, handedness or education on the collected haptic expressions. This is due to the high majority of European, right-handed (thirty-three subjects were right-handed, and thirty-five received a European education) and males.

2.3 Procedure

The experimental procedure includes the three following steps :

Step 1 Participants have filled a form asking for their age, gender, dominant hand, if they have already used an haptic device, and their cultural education.

Step 2 They had five minutes of training session, during which participants were asked to explore the workspace of the haptic device and to express an emotion that was not in the investigated set ("Surprise").

Step 3 Once this training session was finished, participants were asked to express each of the eight emotions ("Joy", "Elation", "Disgust", "Contempt", "Anxiety", "Fear", "Irritation" and "Rage"). The order of presentation of the emotional labels was counterbalanced across subjects. A textual description of a relevant emotional situation, selected from the MindReading database [8], was displayed with each emotional label in order to ensure a common understanding of the meaning of the emotional labels.

Participants had ten seconds to express the requested emotion using the haptic device. We have asked them to hold the stylus of the haptic device as if it was the hand of somebody else. Subjects freely moved their hand, by holding the stylus, inside the workspace of the haptic device. They had only one trial for each emotion in order to collect spontaneous haptic expressions. Afterwards, the recorded haptic expression was rendered to the participant with the same haptic device. Then, the participant had to assess, via a seven point Likert scale, his level of confidence about the expressed emotion.

Forty haptic expressions corresponding to forty subjects were collected for each of the eight emotions. The HAPTEMO corpus is thus made of $40 \times 8 = 320$ haptic expressions of emotions.

2.4 Measures

For each collected haptic expression, we have computed several measures derived from studies investigating haptic and gestural affective expressions [1,4]:

- **M1** *Distance*: overall traveled distance by the participant's hand (end-effector of the haptic device) between the beginning and the end of the haptic expression.
- **M2** *Mean speed*: average speed of the participant's hand.
- **M3** *Fluidity*: degree of suppleness of the expression given by the following equation: $\frac{\sum_{t=0}^{duration} |a(t+1)-a(t)|)}{duration}$. Where $a(t)$ corresponds to the acceleration at t ($(t+1)-t = \Delta t \approx 1$ ms), and *duration* corresponds to the overall duration of the expression. Notice that a low level for this measure corresponds to movements with a high fluidity.
- **M4** *Amplitude*: distance between the two farthest corners of the bounding box containing the haptic expression.
- **M5** *Expansion Index*: degree of expansion of the haptic expression given by the following equation: $\frac{\sum_{t=0}^{duration} d(p(t),\text{isobar})}{duration}$. Where $d(p_1, p_2)$ corresponds to the distance between positions p_1 and p_2, $p(t)$ corresponds to the position of the end-effector at t ($(t+1)-t = \Delta t \approx 1$ ms), *isobar* corresponds to the isobarycenter of the expression, and *duration* corresponds to the duration of the expression.
- **M6** *Duration*: overall duration of the haptic expression.
- **M7** *Major Axis (X coordinate, Y coordinate, Z coordinate)*: major axis of the gesture, computed with a Singular Value Decomposition (SVD) [9].
- **M8** *Weight of Major Axis*: prevalence of the major axis on the movement (based on SVD).
- **M9** *Weight of Second Major Axis*: prevalence of the second major axis on the movement (based on SVD).
- **M10** *Repetitivity*: estimation of the repetitive phases of the expression. This is obtained by calculating the barycenter of the haptic expression and the major axis. We use the projection of each point of the trajectory on this axis and the barycenter and count 1 repetition each time the barycenter is crossed two times by the projection.

Measures M1 to M5 are also computed using a single axis of movement (left-right, up-down and depth). This leads to a total of 27 measures.

In addition to these objective measures, we propose a evaluate the level of confidence reported by the participant, for each haptic expression (a 7-points Likert scale). It indicates if the participant thinks his/her expression expresses well the targeted emotion.

3 Analyzes of the Haptic Expressions

The goal of this study is to highlight the similarities and differences in expressions of different emotions. We have investigated three statistical methods: an ANOVA, a PCA and an EM-cluster analysis. For each method, we have highlighted the main advantages and drawbacks.

Before the analysis, we filtered the corpus to keep only haptic expressions which present a positive level of confidence (minimum 5/7). For the rest of this paper, the term "haptic expressions" refers to the 194 expressions out of a total 320 expressions (equal to 60% of the total, corresponding between 47% and 75% of expressions collected for each emotion) that fulfilled this criterion.

3.1 Analysis of Variance

The commonly used ANOVA method enables to identify differences between two emotions according to a given measure. The previous filtering step provides sets with different numbers of haptic expressions for each emotion. Thus, we used a Wilcoxon test that enables the comparison of populations with different sizes.

The Wilcoxon test was applied to each quantitative measure of two compared emotions. Table 1 summarizes the number of measures presenting a significant difference ($p < 0.05$) between two emotions. This table shows that some pairs of emotions (bold values) present more differences than the mean number of differences (mean of 9.4). This means that those pairs of emotions are statistically more different using the identified measures. For instance, "Elation" and "Disgust" present many significant differences for the following measures: M1 (component of movement along the up-down axis), M2 (along up-down and depth axes), M3 (along up-down and depth axes), M4 (along up-down axis) and M7 (along all three axes).

Advantage of ANOVA. The ANOVA expresses the level of difference (i.e., significant difference or non significant difference) between two emotions according to a given dimension. If there is a significant difference between measured values for two different emotions, we consider that the mean value of this measure for each emotion is a discriminative feature for this pair of emotions.

Drawbacks of ANOVA. The ANOVA approach presents two limitations. First, ANOVA can not be applied to non-homogeneous populations, and can not deal with subpopulations). For instance, some emotions can be expressed, by some

Table 1: Number of measures presenting significant differences when applied to two emotions. The number of similarities can be obtained by calculating the difference between the total number of measures (i.e., 27 measures) and the number of measures presenting significant differences. Bold and italic values correspond to pairs of emotions presenting more and less differences respectively than the overall mean number of differences (mean of 9.4 measures).

	Elation	**Disgust**	**Contempt**	**Anxiety**	**Fear**	**Irritation**	**Rage**
Joy	*8*	*7*	**19**	**16**	**14**	**17**	*5*
Elation	↳	**12**	**14**	**15**	**15**	**21**	*2*
Disgust	-	↳	*1*	*5*	*3*	*9*	*9*
Contempt	-	-	↳	*1*	*4*	*5*	**13**
Anxiety	-	-	-	↳	*1*	*1*	**11**
Fear	-	-	-	-	↳	*5*	**11**
Irritation	-	-	-	-	-	↳	**18**

participants, with a first category of movements (e.g., slow movements), while the rest of the participants express the same emotion with a different category of movement (e.g., fast movements). In this case, the ANOVA can not find statistical differences between emotions, even if the different populations of movement include specific features for the same emotions (e.g. elation is expressed with two categories of movements: vertical and horizontal movements).

The second limitation of ANOVA concerns the number of emotions compared, which is limited to two emotions at a time. If a multivariate ANOVA can correct this (if the measures are not too correlated), it remains not possible to simultaneously compare a given emotion to several other emotions. For instance, it is irrelevant to compare the speed of expressions of "Irritation" and "Rage" simultaneously to the speed of "Joy" by mixing the expressions of the first two emotions for the ANOVA. Indeed, there is a huge difference between the speed of expressions between "Irritation" and "Rage" (means of = 0.16m.s^{-1} and = 0.33m.s^{-1} respectively).

3.2 Principal Components Analysis

Compared to ANOVA, a PCA simultaneously deals with all quantitative measures and emotions. Besides, it also highlights linear correlations between linear measures. For instance, it highlighted in our data set an inverse correlation between the weight of major and second axes of movements. High weight for the major axis implies low weight for the second major axis. Using these correlations, a PCA can reduce the dimensionality of the data set by mixing elementary correlated measures in new axes called factorial axes. This operation simplifies the set to keep only useful information to describe the data set.

In a second step, we applied a PCA to keep only the two main factorial axes. These two factorial axes cover 55% of the whole information contained in all quantitative measures. This revealed that barycenters of "Joy", "Elation" and

Table 2: Distance between the barycenters of each pair of emotion category in the space computed by the PCA. Distances higher than the mean are displayed in bold.

	Elation	Disgust	Contempt	Anxiety	Fear	Irritation	Rage
Joy	**1.629**	1.414	1.431	**1.624**	**1.734**	**1.633**	**1.822**
Elation	↳	**1.740**	**1.961**	**1.528**	**1.905**	**1.698**	**1.483**
Disgust	-	↳	1.139	1.045	1.138	1.304	1.422
Contempt	-	-	↳	1.091	1.199	1.220	**1.740**
Anxiety	-	-	-	↳	1.241	0.915	**1.457**
Fear	-	-	-	-	↳	1.055	**1.463**
Irritation	-	-	-	-	-	↳	**1.528**

"Rage" are far from the barycenters of other emotions. This corroborates the results obtained by the ANOVA, which displayed many significant differences for these emotions compared to other emotions.

Advantages of PCA. The PCA presents two advantages compared to ANOVA. First, it enables the computation of explicit Euclidean distances between the barycenters of emotions in the space provided by the PCA (i.e., with uncorrelated dimensions, see Table 2). This distance, including all factorial axes, explicitly determines how much the haptic expressions of different emotions are close.

The second contribution of the PCA is the highlighting of subpopulations of haptic expressions for a given emotion. The haptic expressions for a given emotion might not concentrate on a single point but spreads across several ones.

Drawbacks of PCA. The PCA approach presents also two limitations. First, a PCA creates factorial axes which are the combination of different measures. Thus, this method must deal with at least two different measures. For example, contrary to ANOVA, PCA can not deal with only the measure of duration.

The second limitation of PCA is that it can not process the highlighted subpopulations (i.e. multiple expressions for a given emotion). For example, the two main factorial axes revealed two main ways used to express for "Rage" : one is near from expressions of other negative emotions, while one is isolated from all other emotions. But we need an external algorithm to determine to which set each expression belongs to.

3.3 EM-cluster analysis

Considering the limitations of PCA, we investigate here a clustering approach that enables the identification of subsets in the same group of data. This method groups in clusters haptic expressions presenting similar features (i.e. similar on most values of our measures), regardless of the emotion labels.

We decided to use the EM algorithm implemented in the Weka platform for clustering since this algorithm enables the estimation of the optimal number of clusters from the data. In our case, this number is not known a priori.

The clustering results of the haptic expressions in the HAPTEMO data set are displayed in tables 3 and 4. Table 3 shows the percentage of an emotion in a cluster against the total number of emotions in this cluster. Table 4 shows the distribution of each emotion across the different clusters.

Table 3: Percentage of emotions per cluster. The most representative emotions in each cluster are highlighted.

	clust. #0	**clust. #1**	**clust. #2**	**clust. #3**	**clust. #4**	**clust. #5**
Joy	5%	11%	11%	14%	**29%**	0%
Elation	0%	11%	**32%**	14%	**18%**	9%
Disgust	0%	**18%**	18%	9%	6%	0%
Contempt	16%	**20%**	4%	0%	12%	11%
Anxiety	**21%**	5%	18%	5%	6%	14%
Fear	16%	**20%**	11%	9%	9%	14%
Irritation	**32%**	5%	4%	5%	6%	**34%**
Rage	11%	9%	4%	**45%**	15%	17%
TOTAL	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

This technique produced six different clusters for the eight emotions. In Table 3, the most representative emotion of each cluster is highlighted (white font, dark background). The predominance of an emotion in a cluster means that the haptic expressions of that emotion differ from those of other emotions. For instance, Table 3 shows that cluster #4 includes mainly expressions of positive emotions (”Joy” and ”Elation”). However, cluster #2 mainly includes expressions of ”Elation”. This means that cluster #2 represents haptic expressions that are specific to ”Elation”, while cluster #4 includes haptic expressions of ”Elation” that are closer to expressions of the ”Joy” emotion.

Table 4: Percentage of clusters by emotion. The most representative clusters of each emotion are highlighted.

	clust. #0	**clust. #1**	**clust. #2**	**clust. #3**	**clust. #4**	**clust. #5**	TOT.
Joy	4%	26%	13%	13%	**43%**	0%	**100%**
Elation	0%	22%	**33%**	11%	22%	11%	**100%**
Disgust	0%	**53%**	26%	11%	11%	0%	**100%**
Contempt	13%	**48%**	4%	0%	17%	17%	**100%**
Anxiety	20 %	15%	**25%**	5%	10%	**25%**	**100%**
Fear	11%	**41%**	11%	7%	11%	19%	**100%**
Irritation	24 %	12%	4%	4%	8%	**48%**	**100%**
Rage	7%	17%	3%	**34%**	17%	21%	**100%**

In contrast, some clusters do not present a dominant emotion (i.e., they contain haptic expressions of several emotions). This means that the mixed emotions in that cluster display similarities in their haptic expressions. This is the case of cluster #1 that contains expressions of "Disgust", "Contempt" and "Fear".

Advantages of Clustering. Clustering presents two advantages. First, this approach simultaneously analyzes a large number of haptic expressions and measures. However, an extraction of the principal features from data (as correlations between measures) would improve the EM procedure.

Second, clustering enables the determination of specific haptic expressions characterizing a given emotion. EM is based on the similarities between haptic expressions and not on the emotion labels to identify the clusters. This explains that a cluster could include a mix of haptic expressions corresponding to different emotions without the prevalence of one emotion. In contrast, the dominance of expressions of a single emotion can correctly describe this emotion.

Drawbacks of clustering. The main limitation of the clustering approach is the difficulty to identify emotions that are not dominant in any cluster. In that case, it is impossible to determine the main features of corresponding haptic expressions. There are two emotions which are not represented by a single cluster: "Disgust" and "Anxiety". In order to detect which cluster is the most representative of these emotions, it is helpful to calculate the percentage of these emotions in each cluster. Table 4 displays those percentages. On one hand, we observe that 53% of haptic expressions of "Disgust" are in cluster #1 which is the cluster for "Contempt" and "Fear". On the other hand, we found that "Anxiety" is spread in cluster #2 and cluster #5 (25% in each one of these two clusters). This means that the algorithm could not find a clear pattern for the expressions of this emotion. Besides, these two emotions display the two lowest quantities of haptic expressions: only nineteen and twenty expressions respectively. Few participants were confident in the way they expressed these two emotions. This could also explain why a cluster for these emotions could not be found.

4 Conclusion

This paper has compared three statistical methods to determine similarities and differences between haptic expressions corresponding to different emotions. These methods have produced different but complementary results. Table 5 summarizes the advantages and drawbacks of each method.

It could be interesting to combine those methods to overcome their individual limitations. For instance, the PCA is an efficient pre-processing before applying the EM-cluster analysis as it is designed to extract the principal features of a data set. Then, by considering the resulting clusters, the ANOVA analysis (or a derivative method) should be more efficient than a single ANOVA to highlight differences between clusters for the examined measures.

Future works consist in collecting more spontaneous haptic expressions of emotions and comparing them with the acted data described in this article. Features extracted could be used to recognize emotions from users's haptic expressions, or to synthesize haptic expressions for the eight investigated emotions.

Table 5: Advantages and limitations of each method we studied in this paper.

Method	Advantages	Limitations
ANOVA	• Gives specific features for two emotions if there is a significant difference between these features.	• Can not highlight non-homogeneous populations. • Can not compare groups of emotions
PCA	• Determines distances of several emotions explicitely. • Highlights subpopulations of haptic expressions for a given emotion.	• Deals with at least two measures. • Can not process subpopulations.
EM	• Analyze simultaneously several haptic expressions and measures. • Determine specific haptic expressions for a given emotion.	• Can not identify features of emotions that are not dominant in any cluster.

References

1. Bailenson, J.N., Yee, N., Brave, S., Merget, D., Koslow, D.: Virtual Interpersonal Touch: Expressing and Recognizing Emotions Through Haptic Devices. Human-Computer Interaction 22(3), 325–353 (2007)
2. Bickmore, T.W., Fernando, R., Ring, L., Schulman, D.: Empathic Touch by Relational Agents. IEEE Transactions of Affective Computing 1(1), 60–71 (2010)
3. Bonnet, D., Ammi, M., Martin, J.c.: Improvement of the recognition of facial expressions with haptic feedback. In: IEEE Haptic Audio Visual Environments and Games International Workshop. pp. 81 – 87. Hebei, China (Oct 2011)
4. Castellano, G.: Movement expressivity analysis in affective computers: from recognition to expression of emotion. Ph.D. thesis, University of Genoa, Italy (2008)
5. Dael, N., Mortillaro, M., Scherer, K.R.: Emotion Expression in Body Action and Posture. Emotion 12(5), 1085–1101 (2011)
6. Dempster, A.P., Laird, N.M., Rubin., D.B.: Maximum Likelihood from Incomplete Data via the EM algorithm. Journal of the Royal Statistical Society. Series B (Methodological) 39(1), 1–38 (1977)
7. Gaffary, Y., Eyharabide, V., Martin, J.C., Ammi, M.: Comparison of Statistical Methods for Analysis of Affective Haptic Expressions. In: ACM Symposium on Applied Perception. p. 128. Los Angeles, California, U.S.A. (2012)
8. Golan, O., Baron-Cohen, S., J., H.: The Cambridge Mindreading Face-Voice Battery: Testing Complex Emotion Recognition in Adults with and without Asperger Syndrome. Journal of Autism and Developmental Disorders 36(2), 169–183 (2006)
9. Klema, V., Laub, A.: The singular value decomposition: Its computation and some applications. IEEE Transactions on Automatic Control 25(2), 164–176 (1980)
10. Pearson, K.: LIII. On lines and planes of closest fit to systems of points in space. Philosophical Magazine Series 6 2(11), 559–572 (1901)
11. Russell, J.A., Mehrabian, A.: Evidence for a three-factor theory of emotions. Journal of Research in Personality 11(3), 273–294 (Sep 1977)
12. Scherer, K.R.: What are emotions? And how can they be measured? Social Science Information 44(4), 695–729 (Dec 2005)
13. Surakka, V., Hietanen, J.K.: Facial and emotional reactions to Duchenne and non-Duchenne smiles. International journal of psychophysiology : official journal of the International Organization of Psychophysiology 29(1), 23–33 (Jun 1998)
14. Tsalamlal, M.Y., Ouarti, N., Ammi, M.: Psychophysical study of air jet based tactile stimulation. In: to appear in IEEE World Haptics. Daejon, Korea (Apr 2013)