Towards understanding emotional experience in a componential framework

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Towards Understanding the Underlying Mechanism of Emotional Experience: A Componential View

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***Abstract*—Emotions are complex, multifaceted phenomena affecting our perception, cognition, memory and action. Hence they modify our behavior in response to the outside world, to a great extent. Although most empirical studies have been dominated by two theoretical models including discrete categories of emotion and dichotomous dimensions, results from neuroscience approaches suggest a multi-processes mechanism underpining emotional experience with a large overlap across different emotions. While these findings are consistent with the influential theories of emotion in psychology that emphasise a role for multiple component processes to generate emotion episodes, few studies have systematically investigated the relationship between discrete emotions and full componential view. This paper is an attempt to study the emotional experience from a full componential view using a data-driven approach. Results suggests at least six latent dimensions to capture the differences between different types of emotions. In addition, the link between discrete emotions and component model is explored and results show that a componential model with limited number of descriptors is still able to predict the level of experienced discrete emotion(s) to a satisfactory level.**

***Index Terms*—emotion, component model, emotion mechanism, dimensions, data-driven approach, computational modelling, emotional experience, emotion recognition**

I. Introduction

Emotion are complex phenomena, at the centre of human interactions, which not only affect the feeling state but also shape one's perception [24], cognition [2], memory [23], [40] and action [38]. Therefore, the ability to recognise emotion in others and respond appropriately is vital to maintain any relationships [4], [16]. Despite the great efforts in conceptualising emotion experience, various theories have remained debated [32]. However, there is a general consensus that emotions are multi-componential phenomena consisting of appraisal of an event followed by motivation to take action(s), face and body expression, changes in physiology and subjective feeling [21]. Nevertheless, most of the previous works on emotion recognition or neural circuitry of emotion have mainly focused on changes in the feeling component either in the form of discrete emotions or dimensional model [13], [14], [43]. Discrete model of emotion postulates a small set of basic emotions, shared across cultures, that each represents a distinct feeling with a unique facial expression [21]. The most popular set of basic emotions was introduced by Ekman and his colleague which has six basic emotions of anger, disgust, fear, happiness, sadness and surprise [3], [5], [41]. In contrast, dimensional model of emotion describes any feeling state according to one or more dimensions like valence and arousal [29]. Although such models of emotion are very useful in many areas, they neglect the complexity of emotions altogether, and reduce an emotional experience to either a fixed label or a point in valence -arousal space. Whilst feeling component, as an integrated awareness of the changes in other components, holds an exceptional position in componential model of emotion, yet it doesn't represent the involved processes led to that awareness. Therefore, to better understand the underpining mechanism of different emotional states, it is important to consider the full componential view.

In this paper, we first present a dataset, collected by inducing a wide range of emotions in an effort to spans the componential space, well. Then we apply unsupervised learning methods to learn about the underlying dimensions of emotional experience. And finally, computational analysis is used to study the link between discrete emotions and componential model of emotion. The main contributions of this work are as follows: first,this study is among the first works that study the mapping between discrete emotions and the full componential model using a data-driven approach; second, most previous studies have only focused on empirical assessments of discrete emotions in terms of semantic profiles rather than reporting on actual emotional experience which is the focus of this work; and finally, this work goes beyond just labelling each profile with one discrete emotion and instead predicts the degree to which each discrete emotion is felt.

II. BACKGROUND

A. Component Process Model

According to component process model of emotion, every emotional experience arises from coordinated changes in several components which starts with 1) appraisal component that involves evaluating the event/situation with respect to personal significance, implications, coping potentials, novelty and compatibility with norms; the changes in this component triggers changes in the other four main components;

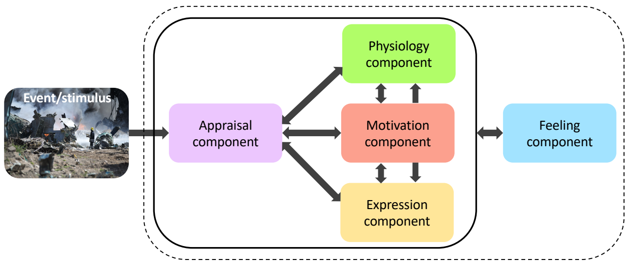

Fig. 1. Component Model of Emotion, suggested by Scherer

2) motivational component that defines changes in action tendencies (e.g. fight or flight); 3) physiological component that encompasses changes in peripheral autonomic activity (e.g. changes in heart rate or respiratory rate); 4) expression component that implies changes in expressive motor behavior such as facial expression, body gestures/postures; and finally 5) feeling component that reflects the conscious experience associated with changes in all other components and people usually describe this feeling with some categorical labels (like anger, happiness, sadness and so on) [34]. (see Figure 1)

B. Related works

The relationship between different emotions and the underlying components are studied in two ways of theory-driven and data-driven modeling; in the former the componential emotion theorists propose a particular profile for each discrete emotion (a top-down model) whereas in the latter the data is used to define the link between discrete emotion and their representation in componential space (a bottom-up model). Most of the data-driven approaches have only focused on the relationship between discrete emotions and appraisal component and only few works have looked into the full componential process model. Some of these studies have focused on discriminative power of appraisal component for discrete emotion categories and their reported accuracy varies between 27% to 80% depending on the number of emotion categories they have taken into account [7], [8], [20], [27], [30]. Other studies investigated the link between specific emotions and specific appraisals by either manipulating the appraisal [17], [28], [39] or observed data [15], [35], [36]. There is only one recent study that has taken similar approach with a different experimental setup, using virtual reality for emotion elicitation [19]. This work has modelled two categories of fear and joy as a function of a set of component model descriptors. They have applied a multilevel models using forward stepwise modelling. For fear, the best model with 9 descriptors has achieved a marginal R^2 of 0.62 and conditional R^2 of 0.69 and for joy the best model is achived with 3 predictors, resulting a marginal R^2 of 0.26 and conditional R^2 of 0.66.

III. Approach

This section presents the material used in this study and also elaborates on the types of assessments collected along with experimental design.

A. Material & Assessment

To elicit different emotions we made use of film excerpts. The use of film excerpts for emotion elicitation has been well established in empirical studies of affects due to their desirable characteristics including being dynamic, readily standardized, accessible and ecologically valid [10]. Several studies have already shown the efficacy of film stimuli in inducing different emotions [9], [10], [31], [33]. Moreover, films are considered as naturalistic stimuli which can induce even complex emotions like nostalgia and empathy [26] .

To select a set of emotionally engaging film excerpts a collection of 139 video clips from the well-known literatures on emotions elicitation was selected [9], [10], [33], [37] based on the availability. The emotion assessment was done in terms of discrete emotions and componential model descriptors. We used a modified version of Differential Emotion Scale to evaluate 14 discrete emotions namely fear, anxiety, anger, shame, warm-hearted, joy, sadness, satisfaction, surprise, love, guilt, disgust, contempt, calm [12], [18]. For component model we used a questionnaire with 39 descriptive items, a subset of CoreGRID instrument with 63 items representing activity in all five major components [7]. The item selection was performed based on the applicability to the emotion elicitation scenario which is emotional response to an event in a video clip, rather than an active involvement in a situation such that the collected items represent all five major components (appraisal, motivation, expression, physiology and feeling). Table 1 summarises the items used in the experiment.

B. Experimental Setup

The assessment was done through a web interface using CrowdFlower, a crowdsourcing platform which allows accessing an online workforce to perform a task. The selected workforce was limited to native English speakers from USA or UK and the reward was set for an effective hourly wage of 6$. The quality control of the assessments was taken care of by means of some test questions about the content of the clip.

Participants were required to first self-assess their personality using the Big Five Inventory 10 (BFI-10) questionnaire [25], then watch the video clip and finally completing the GRID and discrete emotion questionnaires by rating how much each question describes their feeling or experience on a 5-points likert-scale with 1 associated to “not at all” and 5 associated to “strongly”. Participants were instructed to let themselves to freely feel the emotions and express them rather than controlling the feelings and then reflect on what they felt in the assessment. In a pilot study, a set of 5 assessments was collected per each clip and 99 video clips from the original set were selected based on the power of emotion they induced and the emotion discreteness. In the second round of assessments, 10 more judgments were collected for each clip to provide a higher statistical power for inference of emotionality. No clip with high ratings for shame, warm-hearted, guilt and contempt were found, so these four emotions were excluded

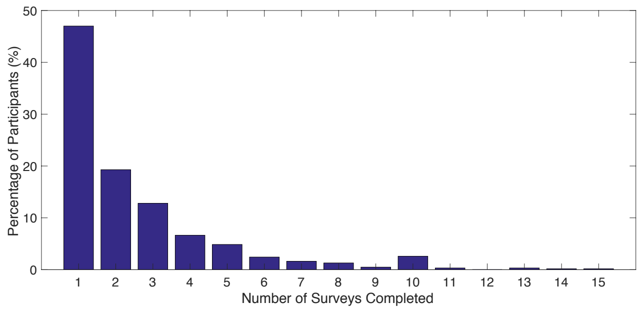

Fig. 2. Distribution of number of surveys completed per participant. The chart shows the percentage of participants completing the survey a given number of times..

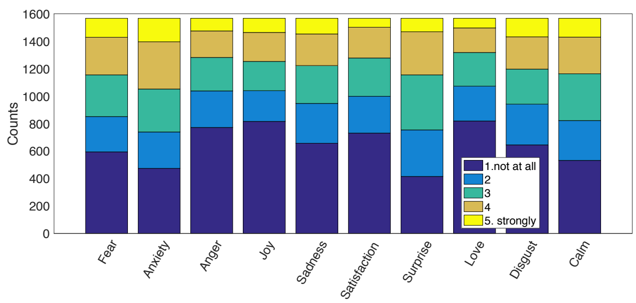

Fig. 3. Distribution of rankings in each discrete emotion. Each colour shows the proportion of samples with corresponding ranking.

from the list of elicited emotions. The total duration of the dataset is about 3.7 hours with an average length of 133.8 seconds for each clip. Overall 1792 validated survey results from 638 workers were collected from which 1567 surveys belonged to the 99 selected clips with at least 15 assessment per each video clip gathered from 617 participants (workers with unique ID). Figure 2 show the distribution of number of surveys completed per worker. To evaluate the power of selected video clips in inducing a wide range of emotions, Figure3 represent the portion of samples within each ranking group across all discrete emotions. Overall, the ratings cover the whole range of the continuum, however it is more skewed towards the lower end particularly for anger, joy, satisfaction and love.

IV. Analysis & Results

This section presents analyses performed to evaluate the validity of the paradigm as well as the modelling approach to find the factors underlying emotional space and the mapping between discrete emotions and component model.

A. Cluster Analysis

To investigate the similarity between different discrete emotions in componential space, we ran a clustering analysis on the componential profile of discrete emotions. The componential profile of each discrete emotion was estimated using a weighted average of normalised GRID-feature ratings where

	Big Five Inventory 10 (BFI-10)	
1	This person is reserved	
2	This person is generally trusting	
3	This person tends to be lazy	
4	This person is relaxed, handles stress well	
5	This person has few artistic interests	
6	This person is outgoing, sociable	
7	This person tends to find fault with others	
8	This person does a thorough job	
9	This person gets nervous easily	
10	This person has an active imagination	
	GRID Questionnaire	Component
	While watching this movie, did you...	
1	think it was incongruent with your standards/ideas?	Appraisal
2	feel that the event was unpredictable ?	Appraisal
3	feel the event occurred suddenly?	Appraisal
4	think the event was caused by chance?	Appraisal
5	think that the consequence was predictable?	Appraisal
6	feel it was unpleasant for someone else?	Appraisal
7	think it was important for somebody?s goal or need?	Appraisal
8	think it violated laws/social norms?	Appraisal
9	feel in itself was unpleasant for you?	Appraisal
10	want the situation to continue?	Motivation
11	feel the urge to stop what was happening?	Motivation
12	want to undo what was happening?	Motivation
13	lack the motivated to pay attention to the scene?	Motivation
14	want to destroy s.th.?	Motivation
15	want to damage, hit or say s.th. that hurts?	Motivation
16	want to tackle the situation and do s.th.?	Motivation
17	have a feeling of lump in the throat?	Physiology
18	have stomach trouble?	Physiology
19	experience muscles tensing?	Physiology
20	feel warm?	Physiology
21	sweat?	Physiology
22	feel heartbeat getting faster?	Physiology
23	feel breathing getting faster?	Physiology
24	feel breathing slowing down?	Physiology
25	produce abrupt body movement?	Expression
26	close your eyes?	Expression
27	press lips together?	Expression
28	have the jaw drop?	Expression
29	show tears?	Expression
30	have eyebrow go up?	Expression
31	smile?	Expression
32	frown?	Expression
33	produce speech disturbances?	Expression
34	feel good?	Feeling
35	feel bad?	Feeling
36	feel calm?	Feeling
37	feel strong?	Feeling
38	feel an intense emotional state?	Feeling
39	experience an emotional state for a long time?	Feeling
	Discrete Emotions	
	While watching this movie, did you feel...	
1	fearful, scared, afraid?	
2	anxious, tense, nervous?	
3	angry, irritated, mad?	
4	warm, hearted, gleeful, elated?	
5	joyful, amused, happy?	
6	sad, downhearted, blue?	
7	satisfied, pleased?	
8	surprised, amazed, astonished?	
9	loving, affectionate, friendly?	
10	guilty, remorseful?	
11	disgusted, turned off, repulsed?	
12	disdainful, scornful, contemptuous?	
13	calm, serene, relaxed?	
14	ashamed, embarrassed?	

TABLE I
THE QUESTIONNAIRE USED IN THE EXPERIMENT OF THIS WORK WHICH INCLUDED THREE PARTS INCLUDING ASSESSMENT OF PERSONALITY, GRID FEATURE AND DISCRETE EMOTION

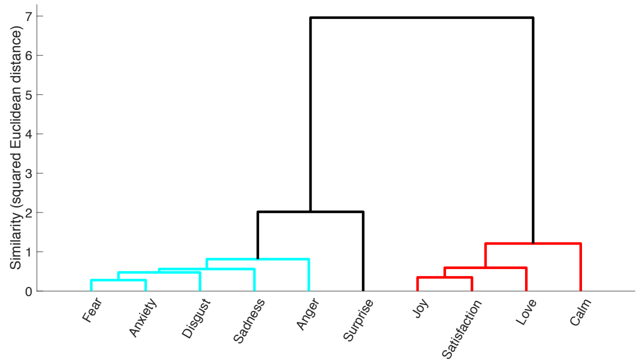

Fig. 4. Clustering of discrete emotion profile in componential space using hierarchical clustering

the weight for each observation is proportional to its rating for that specific discrete emotion. For example, if there is a set of n ratings for GRID features $\{\mathbf{r}_1, \ldots, \mathbf{r}_n\}$, where each vector is described by $d = 39$ ratings ($\mathbf{r}_i \in \mathbb{R}^{39}$) and a corresponding set of n ratings for discrete emotions $\{\mathbf{w}_1, \ldots, \mathbf{w}_n\}$ where each vector is described by $d = 10$ ratings ($\mathbf{w}_i \in \mathbb{R}^{10}$) and $\mathbf{w}_{ij}$ is the rating for discrete emotion j in sample i, the componential profile (CP) for discrete emotion j is defined as:

$$CP_j = \frac{\sum_{i=1}^{n} \mathbf{w}_{ij}\mathbf{x}_i}{\sum_{i=1}^{n} \mathbf{w}_{ij}} \tag{1}$$

Each CP_j is a vector representing the class centroid corresponding to one discrete emotions j. A hierarchical clustering analysis based on Ward's method, which applies an agglomerative hierarchical clustering procedure over squared Euclidian distance, was performed on the class centurions [22]. At the high-level, our results suggest a clear distinction between positive versus negative emotions, while five main clusters are observed at the lower level (Figure 4). These included clusters for happiness (joy, satisfaction, love), serenity (calm), distress (fear, anxiety, disgust, sadness), anger, and surprise. These findings demonstrate theoretically meaningful clusters, derived from our set of features, and thus validates the experimental paradigm and its success in eliciting different emotion categories with expected characteristics.

B. Dimensional Analysis

In the second step to reveal the main factors underpining an emotional experience with greatest variance, we applied a Principal Component Analysis (PCA) to the GRID features [42]. We selected the first six principal components which accounted for about 59% of the total variance. The reason for choosing only six components was due to gaining little variance by retaining more components. A Varimax rotation was applied to simplify the interpretation of each sub-dimension in terms of just few major items. The interpretation of these six dimensions is based on their relationships with the GRID features. Figure 5 demonstrates the coefficients for each of the six components. The first component loads mostly on items related to motivation (e.g. tendency to destroy something or say something), expressions (e.g closing eyes, showing tears) and changes in physiology which can be interpreted as action tendency. The second component which is mainly correlated with items in feeling component (e.d feeling good, not feeling bad, feeling calm), smile and feeling warm seems to encode pleasant feeling (vs. unpleasant feeling). The third component encodes appraisal of suddenness and unpredictability that together can be interpreted as novelty checks. The forth component is heavily loaded on appraisal items related to violation of norms and standards which is unpleasant for self and others, that can represent the valuation of norms. The fifth component has high correlation with long and intense emotional experience with high breathing rate and fast heartbeat that together represent the arousal state. The sixth component which has been characterised by a relatively high loadings on relevance for somebody's goal in appraisal component and high motivation for taking some actions without high loadings in body and physiological changes that comes with feeling strong can be interpreted as appraisal of goal relevance. These factors are in line with the findings of previous studies based on similar component models [6], and confirm that in order to characterise different emotional experience, more than two dimensions of valence and arousal are needed to capture the commonality and specificity of different types of emotions.

C. Modeling

The last step consists in modelling and predicting the categorical emotion label from the GRID features. To evaluate the capacity of using GRID features to predict the categorical emotions, first we simplified the problem to a binary classification. To do so, we grouped the ratings for each categorical emotion into two classes of *"high"* (equal or above the median) and *"low"* (below the median). One *Logistic Regression* classifier per each categorical emotion was trained and tested using k-fold cross validation method with $k = 10$. At each iteration of training, one fold was left out as the test set to evaluate the generalisability of the model to unseen data. The folds were selected such that the samples from one assessor appear only in one fold to ensure that the training and test sets are independent. Figure 6 shows the accuracy of the binary classification for each category and the corresponding baseline. For all categories, accuracy is significantly higher than baseline ($p < 0.001$), however the best performances are for joy, satisfaction and calm which share very similar characteristics given that the calm category in our dataset comes with more positive valence (see Figure 4). The binary classification results demonstrated the capacity of GRID features in making distinction between *high* and *low* values of each categorical emotion. However, the assessments of discrete emotions are in the form of qualitative ratings of individual items (e.g. "not at all" to "strongly"). Although no explicit measure of distance can be defined between adjacent categories, the ratings posses properties of ordinality. Therefore to find the mapping between each discrete emotion and their representation in GRID space,

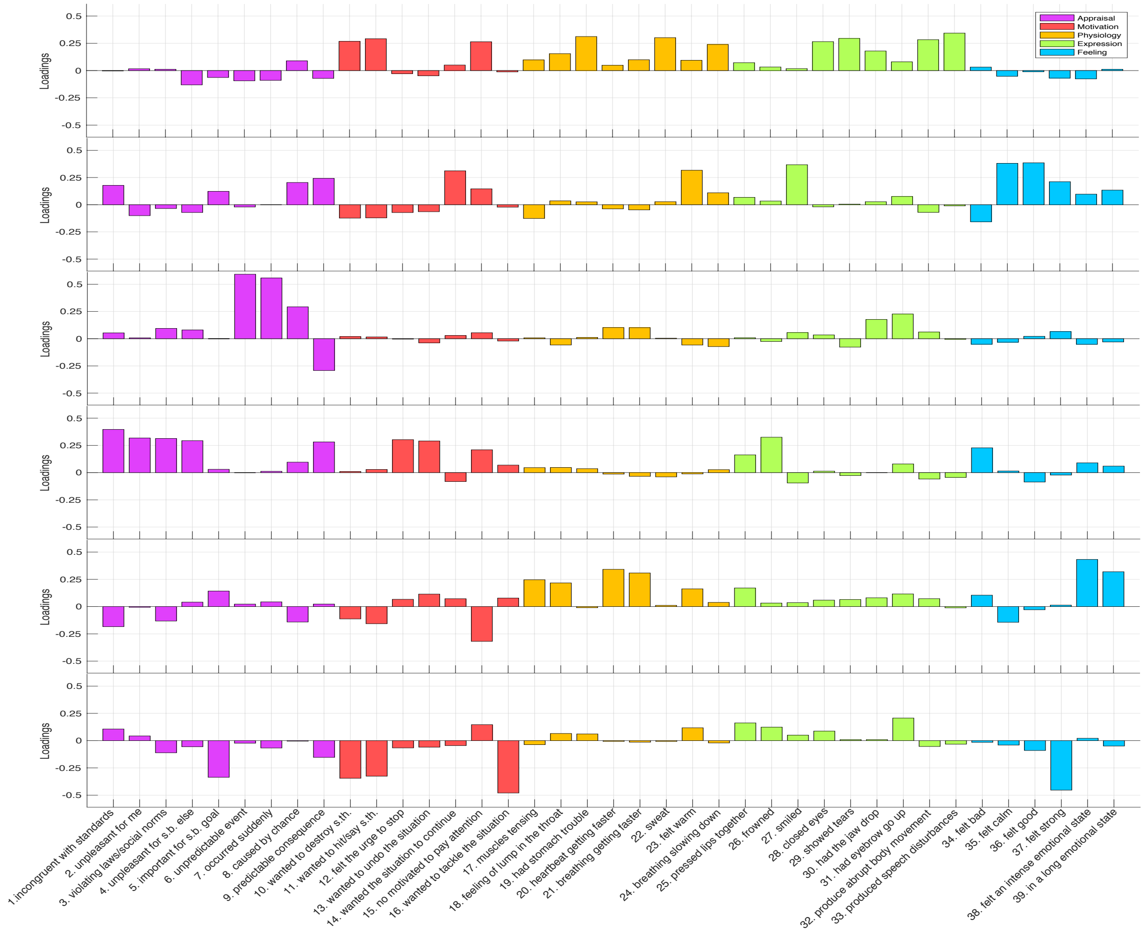

Fig. 5. Component Loadings of the PCA for the first six components when applied on GRID features. The top graph corresponds to the first component and the bottom corresponds to the sixth component.

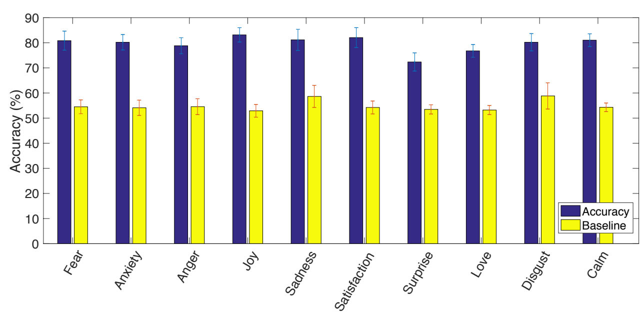

Fig. 6. Accuracy of *Logistic Regression* for binary classification of the discrete emotions using GRID features. Error bars represent standard deviation of the accuracy from 10-fold cross validation.

we used *Ordinal Regression* based on *Proportional Odds* model.

Ordinal Regressionl (OR) is a well suited approach for automatically predicting an ordinal variable [11]. In OR, a set of n samples $\{\mathbf{x}_1, \ldots, \mathbf{x}_n\}$, each described by d features ($\mathbf{x}_i \in \mathbb{R}^d$), is associated with a set of labels $\{y_1, \ldots, y_n\}$ selecting one of r ordered categories in $C = \{1, \ldots, r\}$ representing the ranking of the corresponding inputs. Let $\mathbf{y} = (y_1, \ldots, y_n)^{\mathrm{T}}$ and X be the $n \times d$ matrix obtained by stacking the input vectors by row.

Proportional Odds Model (POM) uses cumulative probabilities as follows:

$$\log \left[\frac{p(y \leq h|\mathbf{x})}{p(y > h|\mathbf{x})} \right] = \alpha_h + \mathbf{x}^T \boldsymbol{\beta}, \qquad (2)$$

which assumes that the logarithm of proportional odds on the left hand side can be expressed as a linear combination of covariates with parameters $\boldsymbol{\beta}$ and a bias term α_h which depends on h, with $\boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_r)$. It can be shown that the above is equivalent to:

$$p(y \leq h|\mathbf{x},) = \frac{1}{1 + \exp[-(\alpha_h + \mathbf{x}^{\mathrm{T}} \boldsymbol{\beta})]} = l(\alpha_h + \mathbf{x}^T \boldsymbol{\beta})$$

where $l(z)$ is the *logistic function* and the probabilities for the observed y_i can be obtained from:

$$p(y_i = h|x_i) = l(\alpha_h + \mathbf{x}_i^T \boldsymbol{\beta}) - l(\alpha_{h-1} + \mathbf{x}_i^T \boldsymbol{\beta}). \qquad (3)$$

	Fear	Anxiety	Anger	Joy	Sad	Satisfied	Surprise	Love	Disgust	Calm
Appraisal	1.08	1.01*	1.21	1.54	1.31	1.29	1.04**	1.49	0.98*	1.2
Motivation	1.07*	0.97**	1.07*	1.45	1.18	1.16	1.26	1.52	1.09*	1.09
Physiology	0.92**	0.88**	1.33	1.43	1.30	1.29	1.29	1.23	1.29	1.13
Expression	1.04**	0.91*	1.09*	0.81**	1.15	0.86**	1.13	1.04*	1.09	1.14
Feeling	0.95**	0.86**	1.06	0.98*	0.92**	0.82**	1.22	0.99*	1.10	0.80**
All Components	**0.77****	**0.73****	**0.83****	**0.70****	**0.83****	**0.69****	**0.89****	**0.86****	**0.89****	**0.78****

TABLE II

PERFORMANCE OF *Ordinal Regression* FOR PREDICTION OF EACH DISCRETE EMOTION RANKING FROM GRID FEATURES OF ONE COMPONENT OR ALL COMPONENTS TOGETHER. NUMBERS REPRESENT MAE^M AND THE BASELINE MAE^M FOR TRIVIAL ORDINAL RANKING MODEL IS 1.2 FOR ALL OR MODELS. ASTERISKS SHOW LEVEL OF SIGNIFICANCE WHERE * MEANS $p < 0.01$ AND ** MEANS $p < 0.001$. NUMBERS IN BOLD SHOW THE BEST PERFORMANCE FOR EACH DISCRETE EMOTION.

This last equation holds for $h > 1$ and $p(y_i = h) = l(\alpha_1 + \mathbf{x}_i^T\boldsymbol{\beta})$ for $h = 1$. The parameters of the model $\boldsymbol{\beta}$ are estimated using *Maximum Likelihood* and can be used to interpret the relation between features and the response variable

For each discrete emotion category we performed six OR models to predict the rating from all GRID features or features from one component at the time (e.g. appraisal, expression, etc.) to evaluate the predictive power of different components for each discrete emotion separately. To evaluate the performance of the model we used macro-averaged mean absolute error (denoted as MAE^M) which is a modified version of mean absolute error (MAE) to account for imbalanced data classes. MAE is the average of absolute deviation of predicted rank y_i^* from the actual rank y_i:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - y_i^*| \tag{4}$$

and MAE^M is the average of absolute error across classes:

$$MAE^M = \frac{1}{n}\sum_{j=1}^{r}\frac{1}{T_j}\sum_{x_i \in T_j}|y_i - y_i^*| \tag{5}$$

where T_j is the set of samples, x_i, whose true rank is j. Although MAE is the most common measure for evaluating ordinal regression models, it is not robust against imbalanced dataset. Therefore, we use MAE^M which is a more rigorous metric to account for imbalanced ordinal classes [1]. Table II reports the evaluation of the model on each discrete emotion. Results suggests that although *expression*, the most dominant component in the field of *automatic emotion recognition*, is a powerful component to predict most of the categories, it may not be as discriminative for some of the categories such as sadness, surprise, disgust and calm. This means that such categories can be more of an internal state without any external expression. However, for sadness and calm, *feeling* component which mainly captures valence and arousal in our experiment is more predictive. For surprise and disgust, *appraisal* component is the most informative component due to capturing the internal evaluation of unpredictability and anti-sociality. *Physiology* component shows high distinction power for fear and anxiety and low distinction power for joy. As expected *Motivation* component is more discriminative for fear, anxiety, anger and disgust, where people usually show more action tendencies to tackle or stop the situation. And finally, using all components result significant improvements in all emotion categories emphasising the importance of taking the full componential model into account. All together, these findings suggests that no single component is enough to capture the difference of all categories and adding components like appraisal and motivation which can be captured to some extent by including context can potentially improve the results significantly.

V. CONCLUSION

This paper analysed the relationship between discrete emotions and componential model of emotion which postulates five major components underlying emotional experience: appraisal, motivation, physiology, expression and feeling. A set of 1576 surveys of emotional experience assessment was used in the analysis. The survey included a subset of 39 GRID features that evaluates the changes in each of the five components along with an assessment of 10 discrete emotions that participants had to respond after watching video clips with emotional content. To the best of our knowledge this is among the first studies that evaluated the relationship between discrete emotions and component model of emotion using all five components. Moreover, previous studies have mostely focused on empirical assessment of semantic profile of emotion whereas this study has focused on the assessment of actual emotional experience using a data-driven approach.

Three types of analyses were carried out starting by clustering the discrete emotion profiles in componential space, which yielded a clear distinction between positive and negative emotions in the high level and separate clusters of happiness, serenity, distress, anger and surprise in the low level.

In the second analysis, we performed a dimensional reduction technique to reveal the most important dimensions underlying the emotional experience. Six dimensions were retained that represent action tendency, pleasantness, novelty, valuation of norms, arousal and goal relevance. These dimensions suggest that more than two dimensions of valence and arousal are needed to distinguish between different types of emotional experience.

Finally, we predicted the rating of each discrete emotion category from GRID features, first by utilising one component at a time and then combining all components. Results are higher than chance level with high statistical significance for all discrete emotions if we use all components, however using individual components decrease the performance significantly in all categories. Results also suggest that different components contribute differently to the prediction of each emotion category.

Future work will take three main directions: The first is to limit the emotional assessment to shorter episodes to have a more accurate assessment. The second direction is to analyse the potential interaction between GRID features which can both improve the predictive capacity and our understanding of emotion production processes. Therefore, it is necessary that the current analyses, limited to linear mappings between the GRID features and discrete emotions, to be revised and include nonlinearity and potential interactions. And finally, assessment of emotional experience during events with self relevance rather than passive experience of emotion like during watching events in video which has a passive nature without having any implications for self.

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