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A Dimensional Model for the Classification of Human Emotions in Affective Systems The Russel-Salah-Abdullahi Space

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Abstract
The identification of human emotions in affective computer systems is usually performed through discrete class identification, such a procedure makes the identification of outlying emotions difficult, it also attempts to reduce the continuum of emotions into discrete classes, sometimes unsuccessfully.

This paper presents a dimensional classification scheme for human emotions. It shows that by representing affective data using a continues Cartesian space, identification can be done much more accurately and with reduced computational costs. Tests conducted using a normal multi class neural network indicates that classification based on the proposed scheme provides a substantial improvement in classification accuracy.

Keywords: Affective Computing; Emotion Representation; Emotion Classification; Artificial Neural Networks

INTRODUCTION
Affective Computing is an inter disciplinary field which attempts to utilize computer systems for the interpretation and or simulation of human emotions. It harnesses the methods and tools or artificial intelligence and studies in psychology, neuro science and other cognitive sciences in order to propose a science of artificial emotions (Picard 1995). Researches in the field which seek to map expressions to emotions using models such as the FACS are based discrete assumptions about the emotional continuum. The Action units 6 + 12 (Cheek Raiser, Lip Corner Pull) for instance, which denote happiness in the Ekman model assume a discrete activation of a set facial muscles, these however do not account for the degree of activation of such muscles which might result in the variability of expression inference among cultures. Despite researches claiming the universality of emotion inference, researches like Lim(2016) have continued to suggest that cultural difference playing an important rule in expression perception. Others like Matsumoto (1999) suggest that the difference are not in inference but in the identification of emotional intensity and subjectivity. These researches suggest that action unit based emotion recognition systems might actually not only be culturally subjective, but also inadequate as such discrete action units do not accommodate for the intensity of the defined actions.

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Conventional feature recognition systems that seek to identify features from defined emotional classes also face the same problems. Labelled emotional datasets are prone to cultural bias and do not accommodate for the wide variability of emotional class expressions across different cultures.
To face these challenges, this paper proposes a dimensional model for the recognition of human emotions in intelligent agents. Using valence, Arousal and stress (shame) as vectors in a Cartesian space, we show that an efficient model of emotion recognition could be constructed that could potentially accommodate for class occlusion and compensate for problems such as cultural discrepancies in emotional perception. The emotional information being on a continuum and not in discrete classes, the proposed model is also able to accommodate intensity based variations.

Contemporary Affective Computing systems classify human facial emotions using Facial Expressions in the form of Action Units or a selection of mathematical features extracted from such expressions. In a majority of cases, the mapping from Expressions either in the form of action units or other features was done with apriori assumptions about the universality of human emotional-expression inference. These assumptions, we have shown, have been challenged by more contemporary works.

Facial Action Based Systems

Emotion recognition systems that model facial emotions as a set of discrete actions usually do so by harnessing the Facial Action Coding System (FACS) of Ekman ands Friesen (1977). The FACS model attempts to build of framework of human facial emotions by constructing a library of minute facial actions called action units, these actions are then used to describe various facial configurations which might infer emotional affect. In time dependent systems, the evolutionary chain of action units, divided along neutral affect, affect onset, apex and offset are used to build a resilient framework of emotional inference (Ambadar and Schooler, 2005). Cohn and Schmidt (2004) as proposed that some emotions might be better modelled when these four temporal segments are alternated with some beginning at the apex phase and others at the offset phase. Further credence is given to the FACS model by Lucy *et al.* (2011) who suggested that Action Units could be used to distinguish posed emotions from genuine emotion behaviour in uncontrolled conditions.

The disadvantage of the FACS model however is that it was constructed on apriori assumptions that the human brain is hard-wired to display only six basic emotions: happiness, sadness, surprise, fear, disgust and anger (Ekman ands Friesen, 1977). These assumptions have been challenged by more recent theories which give a much larger categorization of emotional classes (Gunes and Schuller, 2013; Plutchik,1997). Izzard (1983) proposed a different facial movement coding system called the Maximally Descriptive Facial Movement Coding System. Its focuses on less details than FACS. A single movement in FACS can be decomposed into several movement in FACS.

Besides facial movement based emotion recognition models, some models attempt to derive judgements directly from emotional states. This is because an array of expressions facial, vocal or posture can actually imply a singular emotion, thereby making efforts to record movement or expressions redundant. In this regard some researches have attempted to extend FACs to cover a description of emotional affect in a model known as EMFACS (Tron *et al.* 2016). Others like Izard (1983) have proposed a completely different system called Automatic Affect Expression System AFFEX .

The dimensional model of human emotions represents affect by projecting emotions unto a two dimensional spectrum, with each class being a measure of the likely outcome of its emotional family (Greenwald, Cook and Lang, 1998). Although it creates an extremely large emotional space, this model is used for systems that attempt the ambitious task of describing even minute elements of emotional display.

Non-Action Unit Based Recognition schemes

Feature based recognition models attempt to identify emotions across classes by identifying the features common to each class. Although Facial Actions are not emphasized, it stands to reason that the various mathematical feature selection methodologies do actually harness segments of facial actions when classifying facial expressions. The degree of information absorption however depends on the mathematical representation scheme and feature selection method (Bartlet et al. 2005). Textual based method for instance might harness selective fiducial curves and not the entire information stored in an action unit (Gunes et al. 20013).

The inherent disadvantage of these schemes lies in their attempt at discrete classification of emotions. While most of these rely of trained datasets to select features, conventional researches have always attempted to label data sets across emotional classes and not using other continuum based methods.

PROPOSED MODEL

To create a suitable model for the classification of emotions, we drew inspiration from the Russel/Circumplex classification scheme (Russel, 1980)

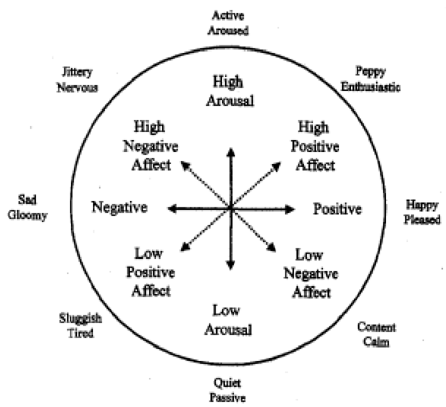

Figure 1: The russel space (remington et al. 2000)

The Russel scheme grades emotion across a two dimensional space with Arousal and Valence being the defining vectors.

While taking into cognizance the unique cultural orientation of Sudanic Africa, tests, while compiling the Sudanic Database of Affective Data showed classification could be better achieved by including a third "Stress" dimension. The dimension will represent the component of shyness or nervousness, which is a major component of non verbal dialogue in Muslim and sudanic Africa (Olofson, 1974).

In general, this proposes a space, in which each emotional class is a point P (a, b, c). Using Cartesian coordinate system, the position of any class or point in the three-dimensional space is therefore given by an ordered triple of real numbers.

Thus, for any emotional class, the set R^3 consists of all emotions and each emotional class x in R^3 is given by $x= (x,y,z)$ where x,y and z are real numbers.

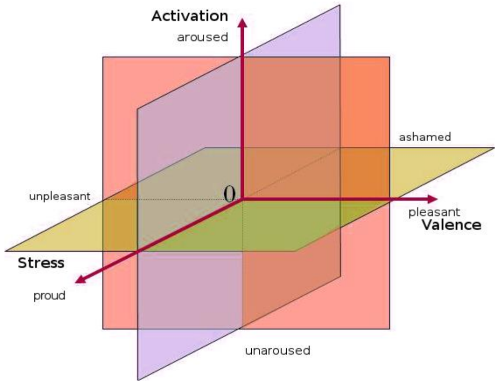

Figure 2: The proposed Russel-Salah-Abdullahi Space

METHODOLOGY AND TOOLS

A multi class neural network (MCNN) was used to test the proposed model and compare its accuracy with the classical labels model. The Extended Cohn Kanade dataset CK+
The MCNN was programmed using matlab R2015 and configured on a Windows 2000, Intel Core i5-8400 Processor, an 8GB RAM and Graphics Card Nvidia GTX 1050 Ti GPU.
Normal back propagation was used to train the MCNN with activation function set at Transg.
Features were selected using Principal Component analysis and Independent Component Analysis and both results were compared.
Validation of both models was performed using three factor cross validation with the data divided evenly across training, testing and validation subsets. Using data from published researches, we also compared the accuracy of proposed model on the CK+ and other recognitions systems and representation models.

TESTS

327 discreetly labeled images of the cohn Kanade dataset (Angry 45, Contempt 18, Disgust 59, Fear 25, Happy 69, Sadness 28, Surprise 83) were re-labeled using the proposed classification scheme. Individuals were asked to grade each image on a scale 1 to 20 and 1 to 10 for each of the three vectors (Valence, Arousal and stress). For the 10X10 space, this gives N=1000 possible emotional classes.

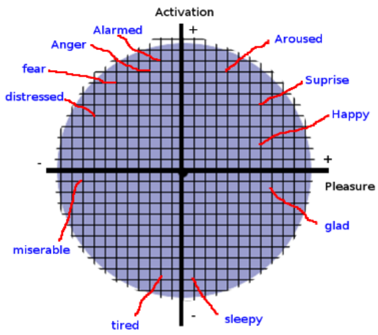

Figure 3: Transformation of classical emotional labels in the proposed dimensional model.

The conventional classes published in the cohn-Kanade dataset (neutral, sadness, surprise, happiness, fear, anger, contempt and disgust) were projected unto the Russel space using published data and responses of subjects while constructing the Sudanic Database of Affective Data.

Figure 4: Samples of labelled pictures from the Cohn-Kanade dataset

Tests were performed using a standard feed forward network with Independent component analysis and Principal component analysis.

While there are 7 traditional class labels in the cohn-kanade dataset, the Russel-Salah-Abdullahi scheme has 10 X 10 X 10= 1000 classes.

To allow for a translation of the Russel Classes to the traditional 7 labels, normal euclidean distances in the 3 dimensional Cartesian space are computed.

$$d=\sqrt{((x_2-x_1)^2+(y_2-y_1)^2+(z_2-z_1)^2)} \quad \ldots\ldots \quad (1)$$

Thus, points that are closest to the assigned points of the traditional class labels will be given the same labels. The mappings are highlighted in Table 1

Table 1: Mappings of the Russel-Sallah-Space to the conventional classification labels

Conventional classical labels	Russel-Sallah-Abdullahi Classification maps
Fear	(-8, 6, 2)
Anger	(-3, 7, 1)
Happiness	(7, 3, 0)
Sadness	(-3, -5, -2)
Surprise	(7, 6,-1)
Disgust	(-2, -1, -1)
Contempt	(-8, 6,- -5)

Feature Selection

Principal Component Analysis

Principal Components Analysis employs a stochastic procedure to extract principal factors from data in the form of vectors. It extracts the variability within the data and presents it as a set of eigenvectors. (Li and Jain, 2005). The procedure, according to Li and Jain (2005) remains statistically sound unless while in a very large and complex data sets where the accumulation of intricate dependencies may require an excessively large set of components and may thus negate the objectives of the procedure.

Independent Component Analysis

Independent Component Analysis differs from PCA in the determination of multivariate relationships. It analyses data-sets with each component being treated as an independent variable. It thus decomposes the data into a set of linear combinations. This allows ICA to negate some of the second order deficiencies found in PCA (Abdullahi, 2016). In this research, FastICA developed by Aapo Hyvarinen is employed for the Independent Component Analysis.

Classification System- Multi -Class Neural Network

To test the proposed representation scheme, we employed a multi-class neural network which according Uglov *et al.* (2008) is a technique of training feed forward neural networks to classify multivariate data sets according to different factor classes. These as shown by Uglov *et al.* (2008) have provided optimal performances when classifying small datasets, especially those with well defined class boundaries.

RESULTS AND COMPARISON

Tests were performed on the Cohn-Kanade dataset using a Multi-Class Neural Network, using both a labelled classification which annotates seven emotional labels to facial expressions and the proposed classification scheme, which gradates the pictures as degrees in the three vectors used in the scheme. Features were selected in both instances using Principal components Analysis and Independent components analysis. A standard 50 hidden neurons were used in both instances, and performance were calculated using mean square error. For the classical classification scheme, each class data was divided in to 5 folds while three folds were used in the proposed classification scheme,. This reduction is due to the small amount of class data in the Russel-Salah-Abdullahi framework. Table 2 and 3 shows the performances recorded by the networks. When independent component analysis was used for feature selection, the classical classification scheme resulted in an average performance accuracy of 22% over the seven emotional classes. The Russel Salah Scheme however yielded a performance of 79%.

This increase in performance was also recorded when PCA was used for feature selection. The Russel Salah scheme yielded an accuracy of 91% while the classical scheme resulted in a 33% accuracy.
These tests indicate that a change in the classification methodology of affective systems alone can yield a 3 factor increase in accuracy.

Table 2: Experiments using Independent Component Analysis 50 hidden neurons, ICA, Tansig

Emotional Class	**Traditional Classification (mse)**	**Russel-Sallah-Abdullahi Classification** (mse)
Anger	**0.49**	**0.751**
Contempt	**0.37**	**0.51**
Disgust	**0.31**	**0.841**
Fear	**0.25**	**0.869**
Happiness	**0.030**	**0.877**
Sadness	**0.030**	**0.883**
Suprise.	**0.032**	**0.883**

Table 2: Results of tests using Principal Component Analysis 50 hidden neurons, PCA, Tansig

Emotional Class	**Traditional Classification (mse)**	**Russel-Sallah-Abdullahi Classification (mse)**
Anger	**0.33**	**0.92**
Contempt	**0.03**	**0.77**
Disgust	**0.28**	**0.91**
Fear	**0.34**	**0.92**
Happiness	**0.35**	**0.93**
Sadness	**0.34**	**0.93**
Suprise.	**0.65**	**0.99**

COMPARISON WITH OTHER RECOGNITION SYSTEMS AND MODELS

A comparison of the performance of the multi class neural network using the different classification methodologies demonstrated the efficiency gain of the system when using the proposed classification scheme.

This performance gain is not limited to the multi class neural network. Published results in researches that tested recognition systems on the Cohn-Kanade data set indicate that a normal multi-class neural network, when using the proposed classification scheme, outperforms many recognition models. One of the highest published recognition performances was by Shan *et al.* (2012) with recorded an average recognition accuracy of 88.9% as opposed to an average accuracy of 91% recorded with the proposed classification scheme. Table 4 below gives a comparison of other systems tested on the Coh-Kanade.

Table 3: Performance Comparison of Different Systems with Different Classification Schemes

Research	Accuracy	Classification Scheme	Features	Recognition Method
-	91.00%	Russel-Salah-Abdullahi classification	PCA	Multi Class Neural Network
Shan *et al.* (2005)	79.1	Action Units	LBP	Template Matching
Barret *et al* . (2005)	86.9	Emotional Labels	Naive Bayesian Patterns	Geometric
Shan *et al.* (2009)	88.9	Action Units	LBP	Support Vector Machines
Shan *et al* .(2009)	86.9	Action Units	Gabor Filters	Support Vector Machines

The performances indicate the efficacy of the proposed system. This is especially true for neural networks where a sizeable amount of data is usually required in order to attain this level of accuracy.

CONCLUSION

The proposed dimensional model for emotion classification has proven effective in increasing the accuracy of affective systems. Inspired by a circumplex representation of emotions, the Russel-Salah-Abdullahi space reduces human emotion classification into a geometric problem and allows for a more accurate analysis by the various classification systems. Tests performed in the CK+ dataset indicate that the proposed model offers a robust improvement in emotional classification using a multi class neural network.

The solutions presented in this paper also suggest that a geometric interpretation of some of the major problems of neural computation could prove advantageous. This could feasibly be extended into research in artificial consciousness and other areas of artificial intelligence.

For temporal representation schemes, an affine transformation in the proposed space could feasibly reduce the computational requirements of Temporal systems. If the marginal three factor increase in performance is replicated, it could make real-time systems extremely competitive in affect recognition. A future research endeavour could address this.

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