Facial Signs and Psycho-physical Status Estimation for Well-being Assessment

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Abstract: Stress and anxiety act as psycho-physical factors that increase the risk of developing several chronic diseases. Since they appear as early indicators, it is very important to be able to perform their evaluation in a contactless and non-intrusive manner in order to avoid inducing artificial stress or anxiety to the individual in question. For these reasons, this paper analyses the methodologies for the extraction of respective facial signs from images or videos, their classification and techniques for coding these signs into appropriate psycho-physical statuses. A review of existing datasets for the assessment of the various methodologies for facial expression analysis is reported. Finally, a short summary of the most interesting findings in the various stages of the procedure are indicated with the aim of achieving new contactless methods for the promotion of an individual's well-being.

1 INTRODUCTION

Although well-being is a subjective term, which refers to how individuals perceive their quality of life, there are objective conditions such as health that influence this judgement. A healthy status combined with low risk factors for developing chronic diseases is essential to the well-being. However, human way of living in modern societies induces psycho-physical states such as stress and anxiety which may lead to the origin of various illnesses.

Stress is a state being present as a part of pressures of accelerated life rhythms. Stressors are perceived by the human body as threats mobilizing all of its resources to face them. Recurrent incidents of stress can also cause heart attack, due to the increase of the heart rate (Stress.org).

Anxiety is, in general terms, the unpleasant feeling of worrying, fear and uneasiness when a perceived threat is present (Lox 1992). It is correlated with many other disorders such as attention-deficit hyperactive disorder, oppositional defiant disorder, and obsessive-compulsory disorder. Under certain circumstances, anxiety can be conceived as a mental disorder called generalized anxiety disorder, characterized by a disproportionate uncontrollable and irrational worry in common life activities (Rowa et al. 2008).

The detection of stress and anxiety in their early stages turns to be of great significance, especially if achieved without the excessive use of sensors or other monitoring equipment, which may by themselves cause extra stress or anxiety to the individual. Anxiety and stress are reflected in the human face, similarly to emotional states, where global categories of facial expressions of emotions exist, overcoming cultural differences (Ekman et al. 2003). Hence, facial expression recognition can be a useful non-invasive technique for studying anxiety and stress. A preliminary study towards this direction has already been presented in (Chiarugi et al. 2013).

Facial expressions are among the most significant parts of non-verbal communication of human emotions. Several studies have been published, using facial expressions in the recognition of 6 basic emotions (Ekman et al. 2002), but only few studies report approaches of stress and anxiety recognition.

In this paper it is assumed that facial expressions for different psycho-physical statuses can be characterised through compositions of different facial signs, such as eye blinking, trembling of lips

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etc. The scope is to review the state of the art in facial expression analysis methods and to give insights towards a non-invasive assessment of well-being, through the analysis of facial features or expressions for stress and anxiety.

2 FACIAL SIGNS OF STRESS AND ANXIETY

Symptoms of stress can be linked with fluctuations either in physiological (e.g. heart rate, blood pressure, galvanic skin response) or in physical measures, as well as with facial features. In fact, gaze spatial distribution, saccadic eye movement, pupil diameter increase and high blink rates carry information that indicates increased stress levels (Sharma et al. 2012). Additionally, jaw clenching, grinding teeth, trembling of lips, and frequent blushing are also signs of stress (Stress.org).

Lerner et al. (Lerner et al. 2007), in their experiment, induced stress to their subjects by assigning them difficult mental arithmetic tasks. With the help of the EMotional Facial Action Coding System (Friesen et al. 1983) they coded facial expressions of fear, anger and disgust. Their results showed that anger and fear can be well correlated to action units (AUs, see Section 3) linked to upper-face areas. They found anger and disgust to be negatively correlated with cardiovascular and cortisol stress responses. Fear on the contrary, can be directly associated with the aforesaid physiological signals.

Anxiety affects the total psycho-emotional human state triggering both psychological and physical symptoms. It is considered a composite feeling that is affected mainly by fear (Harrigan et al. 1996). Therefore, when individuals are experiencing anxiety, facial signs of fear would be expected. In addition, it is argued that anxiety and fear separation is not reachable by using just psychometric means (Perkins et al. 2012).

Although facial signs of anxiety can be ambiguous and literature is not consistent yet, main effects of anxiety on human face are considered reddening, lip deformations, and eye blinking. Further facial symptoms include strained face, facial pallor, dilated pupils, and eyelid twitching (Hamilton 1959). Eye blink rate has also been correlated with an anxiety personality (Zhang et al. 2006). Accordingly, eyelid response was found to differentiate anxious and non-anxious groups (Huang et al. 1997). Finally, Simpson et al. (Simpson et al. 1971) found significant effect on pupil size as a result of audience anxiety.

3 FACIAL PARAMETER REPRESENTATION SYSTEMS

Over the years, various measurement systems for facial parameters have been proposed, the most remarkable of which are the facial action coding system (FACS) (Ekman et al. 2002), the facial animation parameters (FAPs) (Pandzic et al. 2003), the facial expression spatial charts (Madokoro et al. 2010) and the maximally discriminative facial movement coding system (MAX) (Izard 1979).

FACS is a comprehensive system, standardizing sets of muscle movements known as action units (AUs) that produce facial expressions. It consists of 44 unique AUs and their combinations, each of which reflects distinct momentary changes in facial appearance. However, due to its subjective nature, FACS may be biased and image annotation is time consuming (Hamm et al. 2011).

The next coding system is defined by the Moving Picture Expert Group in the formal standard ISO/IEC 14496 (MPEG-4). The MPEG-4 standard supports facial animation by providing 66 low-level "*FAPs*". The FAPs represent a complete set of facial actions, along with head motion, tongue, eye and mouth control, which deform a face model from its neutral state. The FAP value indicates the magnitude of the deformation caused on the model.

Facial expression spatial charts is a system able to incorporate intensity levels of facial expression organized as happiness, anger and sadness quadrants. It was applied to represent stress levels and profiles (Madokoro et al. 2010).

MAX is a system that describes selected changes in facial expressions in infants. It assumes continuity of emotion expressions from infancy through adulthood and identifies facial expressions hypothesized to be indexes of discrete emotion in infants (Izard 1979).

4 FACIAL FEATURE EXTRACTION METHODS

In order to evaluate facial expressions for emotion or psycho-physical status recognition, specific facial features need to be extracted. Stable facial features are characteristics of the face like lips, mouth, eyes and furrows that have become permanent with age and may be deformed due to facial expressions. Transient facial features are features not present at rest, which appear with facial expressions as a result of feelings or emotional states mainly in regions surrounding the mouth, the eyes and the cheeks.

There are various methods in the literature, extracting facial features towards facial expression recognition. Most of them can be applied either to the whole face (holistic approach) or to specific regions of interest like mouth, nose or eyes (local approach). Although the holistic approach provides a complete picture of facial information, in cases where a facial expression affects only specific regions, a local approach gives more detailed and distinguishable information. Facial feature extraction methods can be categorised in: *muscle/geometric based*, *model/appearance based*, *motion based* and their combination as *hybrid methods* (Figure 1).

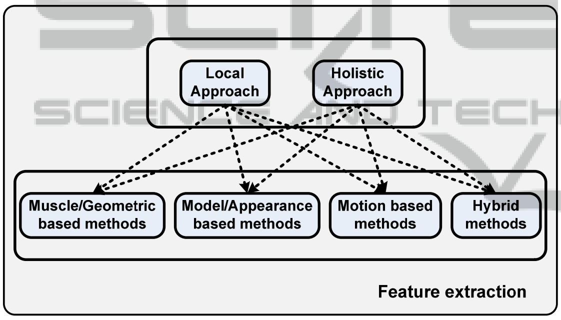

Figure 1: Categorization of facial features extraction methods.

4.1 Muscle based Methods

Muscle/geometric based techniques of feature extraction estimate facial muscle deformation from videos and images. A facial expression is a result of one or more facial features due to the contraction of the muscles of the face. Facial features change either their motion or position (eye, eyebrows, nose and mouth) or their geometric characteristics and shape.

In this context, dependencies between AUs, like “inner brow raiser” and “outer brow raiser”, can be exploited (Tong et al. 2010). Hence, the presence or absence of either AU can help to infer the state of the other AU, under ambiguous situations. Furthermore, expert systems of emotion recognition from facial expression using distance and geometric features can be developed (Pantic et al. 2000).

In another study (Aleksic et al. 2006) FAPs have been utilized as facial features, extracted by the active contour method. In the FAP extraction process the outer-lip and eyebrow contours are tracked for each frame and compared to the corresponding contours of the neutral frame of the sequence in order to calculate FAPs in terms of facial animation parameter units. In another approach a landmark template is created in order to extract geometric features of a test face (Hamm et al. 2011). The face is aligned to the template by similarity transformations to suppress intra-subject head pose variations and inter-subject geometric differences.

4.2 Model based Methods

Model (appearance) based methods depend on the general appearance of the face or/and specific regions (skin texture, wrinkles, furrows etc.) for fitting 2D or 3D face models. The most known are CANDIDE (Rydfalk 1978), the anatomical and physical model of the face (Terzopoulos et al. 1993), the canonical wire-mesh face model (Pighin et al. 2006) and the wireframe face model (Wiemann 1976).

Active appearance models (AAMs) (Cootes et al. 2001) provide a consistent representation of the shape and appearance of the face and have been used for facial expression classification (Hamilton 1959). Active shape models (ASMs) were used to track 2D and 3D facial information from a model in order to quantify facial actions and subsequently expressions (Tsalakanidou et al. 2010).

Additionally, facial texture information and shape analysis using a 3D model was performed for feature extraction (Boashash et al. 2003). The fusion of texture and shape information was applied in (Feng et al. 2005) providing good results. Many studies have employed local binary patterns (LBP) (Kämäräinen et al. 2011; Shan et al. 2009) in extracting facial texture information. LBP followed by linear programming (Eisert et al. 1997), support vector machine (SVM) (Ojala et al. 1996), kernel discriminant isomap (Zhao et al. 2011) was used in facial expression with remarkable recognition results.

4.3 Motion based Methods

Motion based methods utilize features derived from movements, extracted from image sequences of either facial components or the whole face.

Optical flow (Mase et al. 1991) is the method adopted by the majority of facial motion analysis systems. An extension of FACS, the FACS+, which enables the coding of expressions also by means of motion, was established using this method along with geometric dynamic models (Essa et al. 1997).

A local optical flow approach for facial features or expression recognition was used in another study (Rosenblum et al. 1996).

As an alternative, Gabor wavelets can be employed in facial motion analysis. A fully automatic system based on motion analysis was proposed in (Littlewort et al. 2006) with automatic face detection, Gabor representation and SVM classification.

4.4 Hybrid Methods

Hybrid methods use features from local and holistic approaches in order to improve the results. These approaches reflect the human perception that utilizes both local face signs and the whole face to recognize a facial expression.

A combination of muscle based and appearance based methods was presented by Zhang et al. (Zhang et al. 1998) and a combination of appearance based methods using model and shape perspectives by Kotsia et al. (Kotsia et al. 2008). Another promising perspective is to combine motion information with spatial texture information (Donato et al. 1999).

5 FACIAL EXPRESSION CODING

5.1 Dimensionality Reduction of Facial Features

Automatic facial expression recognition systems aim to classify transient and permanent facial features into the desired classes. The classification performance mainly depends on the technique of feature selection and whether appropriate discriminant features were extracted reliably and accurately. An important factor affecting the classifier optimality is the amount of data which are to be analysed. In most cases, the feature extraction methods produce a large bundle of features which increase the computational cost for classification. Thus, methods for dimension reduction must be used to project those data into a lower dimensional feature subspace, still obtaining robust and accurate classification.

The most common techniques for data reduction are principal component analysis (PCA), independent component analysis (ICA) and linear discrimination analysis (LDA). PCA is a well-established technique for dimensionality reduction that performs data mapping from a higher dimensional space to a lower dimensional space (Jolliffe 2005). A generalization of PCA is ICA, in which the goal is to find a linear representation of data so that the reduced components are statistically independent, or as independent as possible (Hyvarinen 1999). LDA searches for those vectors in the underlying space that best discriminate among classes in order to provide a small set of features that carry the most relevant information for classification purposes (Etemad et al. 1997).

5.2 Classification of Facial Features

In a recent overview (De la Torre et al. 2011) of emotion detection algorithms, the classification techniques were divided into supervised and unsupervised approaches. Some of the proposed supervised learning methods are hidden Markov models, dynamic Bayesian networks and naive Bayes classifiers. The main proposed unsupervised learning methods are geometric-invariant clustering, aligned cluster analysis and AAMs to learn the dynamics of person-specific facial expression models.

According to Whitehill et al. (Whitehill et al. 2013), the main kinds of approaches for converting the extracted features into a facial expression class are machine learning classifiers and rule-based systems such as the one proposed by Pantic et al. (Pantic et al. 2006). The main machine learning classifiers can be linear or multiclass and include SVMs, AdaBoost or GentleBoost, k-nearest neighbours, multivariate logistic regression and multilayer neural networks.

In general, as mentioned before, the choice of the classifier is strictly correlated to the selection of features since the classification performance depends both on the extraction of features with high discriminative capability and on the choice of an appropriate highly discriminant classifier.

5.3 Coding Classes into Psycho-physical Statuses

There has been a lot of research that endeavoured to classify human emotions into specific categories. The early philosophy of mind posited that all emotions can be categorized into basic classes (e.g. pleasure and pain), but since then more in depth theories have been put forth (Handel 2011).

A conception of emotions, called the “wheel of emotions”, demonstrates how different emotions can blend into one another and create new emotions (Plutchik 2001). In this study, eight basic and eight advanced emotions, classified as opposite emotions, define more complex emotions based on their differences in intensities (Figure 2). A theory consisting of a tree type structured list (including over 100 emotions) leading to the classification of deeper emotions as primary, secondary and tertiary is described in (Parrott 2001).

Facial expressions can show aspects of internal psychology, reflective emotions such as delight, anger, sorrow and pleasure (Kazuhito 2013). Stress and anxiety might be measured by using a combination of the emotions described in (Plutchik 2001; Parrott 2001). Based on their categorization of emotions it is possible to assess secondary or tertiary emotions (such as anxiety) derived from the primary.

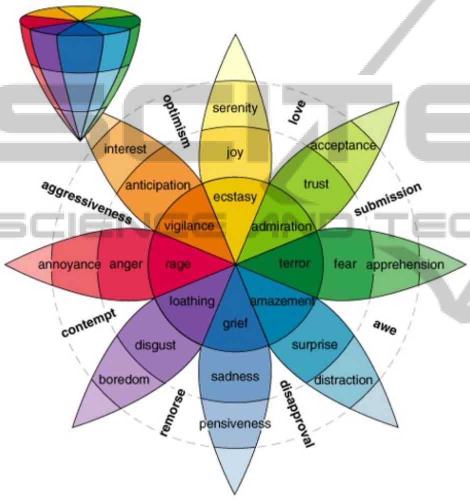

Figure 2: Plutchik's wheel of emotion.

Action units can be divided into primary (AUs or AU combinations that can be clearly classified to one of the six basic emotions without ambiguities) and auxiliary (AUs that can be only additively combined with primary AUs to provide supplementary support to the facial expression classification). Their combination formulates a facial expression. Interpretation of AUs related to the psycho-physical statuses of anxiety and stress does not appear explicitly in the literature, but as aspects of fear. However, fear seems to vary among studies as it can be considered as the combination of various non-identical AU subsets (Ekman et al. 2003; Lewis et al. 2008; Zhang et al. 2005).

5.4 Assessment through Available Datasets

Annotated datasets for assessing the psycho-physical statuses are necessary to reach the objective of any related study, which in the current research is the identification of stress and anxiety. The majority of existing datasets focus on basic emotions (McIntyre 2010; van der Schalk et al. 2011). "*MMI*" is an exhaustive database of 79 series of expressions based on combination of AUs (Valstar et al. 2010). Studies examining depression severity (AVEC2013) are also of great interest, since depression is closely related to anxiety. Few approaches have been made for stress assessment (Sharma et al. 2014). To the best of the authors' knowledge, none of the existing datasets covers entirely the needs of the current research.

The different expressions required for the dataset creation can be obtained either by asking the subjects to fake the emotion or by inducing it to the subjects. Emotion can be elicited by showing videos as affective stimuli (Koelstra et al. 2012; McIntyre 2010; Soleymani et al. 2012). Protocols like the "Trier Social Stress Test" (Kirschbaum et al. 1993) can be used for the induction of stress.

For the image acquisition, the use of a colour camera is common (Koelstra et al. 2012; McIntyre 2010; Valstar et al. 2010), while extending to multiple views is becoming more and more popular (Soleymani et al. 2012; van der Schalk et al. 2011) in an effort to achieve pose invariance. Infrared imaging has also been employed in stress assessment (Sharma et al. 2014). Image resolutions used for the acquisitions include 640x480 and 720x576, while frame rates range from 25 to 60 fps (Koelstra et al. 2012; Sharma et al. 2014; Soleymani et al. 2012; Valstar et al. 2010; van der Schalk et al. 2011). Illumination in most cases is controlled with only one case relying on natural lighting (Valstar et al. 2010).

Facial signs indicating stress and anxiety, as explained in detail in Section 2, include small particulars in eye and lips movements. Thus, it is important to have a high frame rate, in order to allow the accurate evaluation of the eye blinking rate and the lips trembling (25 fps is considered satisfactory), and a resolution higher than 800x600 with the face taking about one fourth of the screen in frontal position in order to capture pupil dilation. Good illumination conditions are of high importance, since skin colour information is also valuable.

6 DISCUSSION AND CONCLUSIONS

This paper gives an account of the facial signs of stress and anxiety, as well as of methodologies for the extraction of these signs. Various ways of characterizing facial expressions as compositions of these facial signs are described. Furthermore, the coding of facial expressions into psycho-physical statuses is presented. Finally, existing datasets or requirements for creating specifically annotated datasets are examined towards the suitability for the assessment of stress and anxiety.

It is worth noting that, while the relations between basic emotions and facial expressions are strongly consolidated in the literature, a definite understanding of the relations existing among individuals' psycho-physical statuses and facial expressions is still lacking and is an open field for further scientific investigation. However, there are promising research directions that can be exploited in order to non-invasively estimate the psycho-physical states under investigation with respect to well-being assessment.

Considering the facial expression of stress and anxiety it has been identified that gaze spatial distribution, saccadic eye movement, pupil dilation, as well as high blink rates carry information that indicates increased stress levels (Sharma et al. 2012). Jaw clenching, grinding teeth, trembling of lips, and frequent blushing are also useful signs of stress (Stress.org). For anxiety, pupil dilation/size, eye blinking, strained face, facial colour (reddening/pallor), lip deformations, eyelid twitching and response have been reported as facial signs of significant interest. These signs can be represented through existing well-assessed representation systems such as FACS and FAPs with the addition of colour information.

As reflected in the wide research area of facial expression analysis, the reported feature extraction methods produce satisfactory results (De la Torre et al. 2011) that, in some cases, can be enhanced using hybrid methods. The selection criteria are mainly defined by the application environment. Moreover, the choice of facial features delegates the technique required for their extraction, but is also a function of image/video data quality and resource constraints of the domain. In a similar manner, the choice of the classifier is strictly correlated to the selection of features since the classification performance depends both on the extraction of features with high discrimination capability and on the choice of an appropriate highly discriminant classifier.

Stress and anxiety might be measured by using a combination of the basic emotions, such as those defined by Plutchik (Plutchik 2001) and Parrott (Parrott 2001). A possible approach is to assess anxiety and stress as secondary or tertiary emotions derived from the primary.

Finally, to the best of the authors' knowledge, none of the existing datasets covers completely the needs of the current research related to stress and anxiety facial expression analysis. For this reason, some requirements for the acquisition of a specifically targeted dataset have also been provided in this study.

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