Face Expressional Recognition using Geometry and Behavioral Traits

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ABSTRACT

Tremendous growth in the use of biometric technologies in high-security applications has motivated the requirement for highly dependable face recognition systems with expressional robustness. Current standards demonstrated that the accuracy of state-of-the-art algorithms is fairly high under constrained conditions, but degrades significantly for images exhibiting facial expression variations. The previous works try to achieve insensitivity to such variations leads to the motivation in classifying the physiological properties of the facial expressions and mapping it to the behavioral traits underlying the expression. The system developed in this paper describes and evaluates a resilient face expressional recognition system using a geometric structural representation of the various expressions like sad, angry, disguise, happy etc and mapping it to the behavioral traits stored in the form of either hidden or exposed property in the genes adopted in genetic algorithm model. The experimental evaluations are conducted with initial taking of 10 expression samples of each and every faces of 63 humans (21 men and 42 women). The geometric structure linking to the expressions are identified and store it the training samples template. The behavior pattern mapping of the expressions are associated with the genetic properties. The matching phenomenon is tested with the training template to evaluate the recognition and its rate of matching.

Keywords:

Biometrics, Face Recognition, Face Expressions, Geometry Methods, Behavioral Characteristics, Genetic Algorithms.

1. INTRODUCTION

Researchers from a number of fields of psychology and biometric security have been interested in facial expressions of emotion. Social psychologists studying person perception have often focused on the face. Recent research is examining the relative weight given to the face as compared to other sources of information, the relationship between encoding and decoding, and individual differences.

Developmental psychologists are examining the age at which infants first show what can be considered as an emotion, whether this age precedes or follows an infant's ability to recognize emotions, and the sequencing of expressions between caregiver and infant. Physiological psychologists have been concerned with the role of the right hemisphere in the recognition and, more recently, in the production of facial expression, and in the relationship between facial and autonomic measures of arousal [2].

These are but a few examples of the many divergent questions that involve consideration of facial expression. Most of these questions are not new. They were subject to considerable research a few decades ago, although sometimes the questions were phrased differently. Unfortunately, little progress was made. The most basic questions were not answered, and methods for measuring facial expression were not well developed. In the last decade, progress has been made both on methods and on a set of fundamental questions [6].

1.1 Facial Expression as an Adaptive Communications Mechanism

Some theorists have focused on the power of emotional expression to convey messages about the expressor as the center of their theories about emotion [2]. Charles Darwin cast the topic of emotional expression, and especially facial expressions, into a modern scientific treatment in the mid-nineteenth century, and provided a basis for considering facial expressions as behaviors that evolved as a mechanism of communication. Although Darwin himself put little emphasis on the communicative potential of facial expression of emotion as an object of adaptive selection, the thrust of his general work suggests this connection and encouraged later scientists to elaborate upon this mechanism

1.2 Facial Feature Extraction and Recognition

The proposed method in this paper, deals with two types of features extraction i.e., geometric features and behavioral features. Geometric features present the

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shape and locations of facial components (including mouth, eyes, brows, and nose). The facial components or facial feature points are extracted to form a feature vector that represents the face geometry.

Research shows that using hybrid features can achieve better results for some expressions. To remove the effects of variation in face scale, motion, lighting and other factors, one can first align and normalize the face to a standard face (2D or 3D) manually or automatically and then obtain normalized feature measurements by using a reference image (neutral face) [1].

2. LITERATURES

Neither emotion nor its expression is concepts universally embraced by psychologists. The term "expression" implies the existence of something that is expressed. Some psychologists deny that there is really any specific organic state that corresponds to our naive ideas about human emotions; thus, its expression is a non sequitur. Other psychologists think that the behaviors referenced by the term "expression" are part of an organized emotional response, and thus, the term "expression" captures these behaviors' role less adequately than a reference to it as an aspect of the emotion reaction. Still other psychologists think that facial expressions have primarily a communicative function and convey something about intentions or internal state, and they find the connotation of the term "expression" useful [3].

Regardless of approach, certain facial expressions are associated with particular human emotions. Research shows that people categorize emotion faces in a similar way across cultures, that similar facial expressions tend to occur in response to particular emotion eliciting events, and that people produce simulations of emotion faces that are characteristic of each specific emotion [4]. Despite some unsettled theoretical implications of these findings, a consensus view is that in studies of human emotions, it is often useful to know what facial expressions correspond to each specific emotion, and the answer is summarized briefly below.

To match a facial expression with an emotion implies knowledge of the categories of human emotions into which expressions can be assigned. For millennia, scholars have speculated about categories of emotion, and recent scientific research has shown that facial expressions can be assigned reliably to about seven categories, though many other categories of human emotions are possible and used by philosophers, scientists, actors, and others concerned with emotion [6]. The recent development of scientific tools for facial analysis, such as the Facial Action Coding System, has facilitated resolving category issues.

3. METHODOLOGY

3.1 Facial Expression on Behavior

The system developed works on the basic principal set of Facial Action Coding System (FACS) that measures all visible facial movements. FACS would differentiate every change in muscular action, but it is limited to what a user can reliably discriminate when movements are inspected repeatedly, in stopped and slowed motion. It does not measure invisible changes (e.g., certain changes in muscle tonus) or vascular and glandular changes produced by the autonomic nervous system.

Limiting FACS measurement to visible movements was consistent with an interest in those behaviors which may be social signals, usually detected during social interactions. FACS can be applied to any reasonably detailed visual record of facial behavior. If the technique were to measure invisible or autonomic nervous system (ANS) activity, it would be limited to situations were sensors were attached (e.g., EMG electrodes) or special sensing and recording methods were used (e.g., thermography).

The primary goal in adopting FACS for face recognition system was comprehensiveness, a technique that could measure all possible, visible discriminable facial actions. Comprehensiveness was important because many of the fundamental questions about the universe and nature of facial expressions cannot be answered if just a subset of behaviors is measurable. FACS was derived from an analysis of the anatomical basis for facial movement. A comprehensive system was obtained by discovering how each muscle of the face acts to change visible appearances. With this knowledge it is possible to analyze any facial movement into anatomically based, minimal action units.

3.2 Geometry on Expressions

The geometry of the intensity of facial expressional emotions had been studied and analyzed to have an effective, flexible and objective method for facial recognition system. The applicability of the approach has been demonstrated on various expressions at varying levels of intensity. It has also been able to associate a pixel-wise shape value corresponding to an expression change, based on the expansion/contraction of that region.

The creation of this pixel-wise association makes it evident that the method can quantify even subtle differences on a region-wise basis, for expressions at all levels of intensity. This is important for any facial expression analysis, as a single number quantifying the whole face is of limited significance because various regions of the face undergo different changes in the same expression of emotion.

3.3 3D Face model

The 3D model is fitted to the first frame of the sequence by manually selecting landmark facial features such as corners of the eyes and mouth. The generic face model, which consists of 16 surface patches, is warped to fit the selected facial features. To estimate the head motion and deformations of facial features, a two-step process is used. The 2D image motion is tracked using template matching between frames at different resolutions. From the 2D motions of many points on the face model, the 3D head motion then is estimated by solving an over determined system of equations of the projective motions in the least-squares sense.

3.4 Genetic Feature selection

Create a 3D facial model database by modifying a generic facial model to customize each individual face, given a front view and a side view of one face. This approach is based on recovering the structure of selected feature points in the face and then adjusting a generic model using these control points to obtain the individualized 3D facial model. Each individualized facial model consists of 295 vertices. Our 3D face model database is generated using 32 pairs of face images from 10 subjects. These source image pairs are mainly chosen from the databases and some additional images are captured from our local community.

For each subject, there are two or three pairs of frontal and profile images, which were taken under different imaging conditions. In order to better characterize 3D features of the facial surface, each vertex on the individual model is labeled by one of eight label types. Therefore, the facial feature space is represented by a set of labels. A cubic approximation method is explored to estimate the principal curvatures of each vertex on the model. Then the eight typical curvature types (i.e., convex peak, convex cylinder/cone, convex saddle, minimal surface, concave saddle, concave cylinder/ cone, concave pit and planar) are categorized according to the relation of the principal curvatures.

Among the set of labels, only the labels located in certain regions are of our most interest. Some non-feature labels could be noises that may blur the individual facial characteristics. Therefore, need to apply a feature screening process to select features in order to better represent the individual facial traits for maximizing the difference between different subjects while minimizing the size of the feature space. In order to select the optimal features, partition the face model into 15 sub-regions based on their physical structures (there are overlaps between some of the regions), which is similar to the region components.

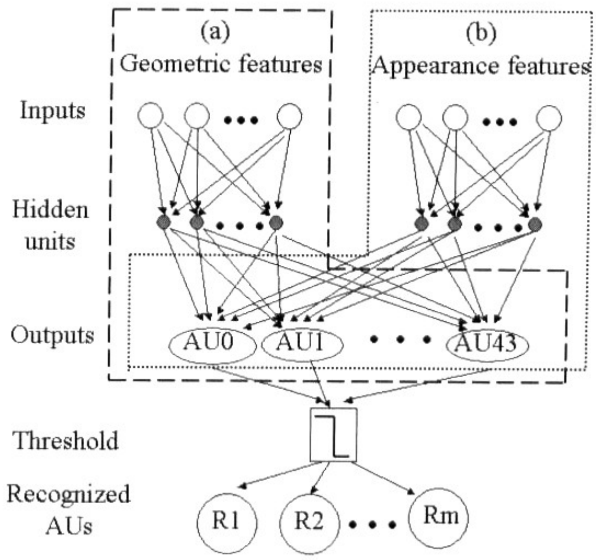

Fig 1: Recognized of facial expression units

Since not all the sub - regions contribute to the recognition task, and not all the vertices within one sub-region contribute to the classification, need to select the best set of vertex labels and the best set of sub-regions. The purpose of the feature selection is to remove the irrelevant or redundant features which may degrade the performance of face classification. The Genetic Algorithms (GA) is used successfully to address this type of problem. So choose to use a GA-based method to select the components that contribute the most to our face recognition task.

4. EXPERIMENTAL EVALUATION

The main focus of the paper is to exploit 3D information to cope with expressional variations. The system presented techniques that take input as a pair of 2D and 3D images, to produce a pair of normalized images depicting frontal pose. Resilient to matching the variations is achieved not only by using a combination of a 2D color and a 3D image of the face, but mainly by using face geometry information and allele of gene mapping variations that inhibit the performance of 3D face recognition.

A face normalization approach is proposed, which unlike state-of-the-art techniques is computationally efficient and does not require an extended training set. Experimental results on a large data set show that template-based face recognition performance is significantly benefited from the application of the proposed normalization algorithms prior to classification

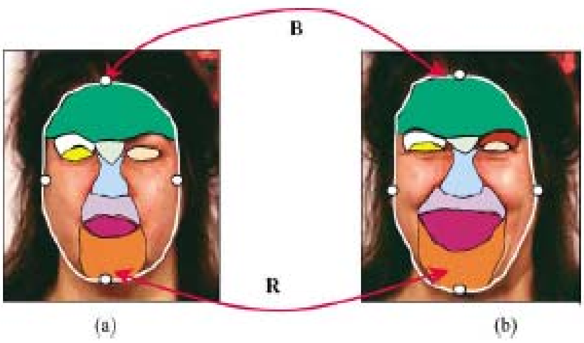

Fig. 2: Regions demarcated in the face. B depicts one of the boundaries and R indicates one of the regions. (a) is the neutral face chosen as the template and (b) is the happy face taken as the subject

Fig. 3: Quantification of intensities of happiness

5. CONCLUSIONS

The Facial Expression Recognition System presented in this paper contributes a resilient face recognition model based on the mapping of behavioral biometry with the physiological biometric characteristics. The physiological characteristics of the human face with relevant to various expressions such as happy, sad, angry, disguise etc are associated with geometrical structures as restored as base matching template for the recognition system.

The behavioral aspect of this system relates the attitude behind different expression as property base. The property bases are alienated as exposed and hidden category in genetic algorithmic genes. The gene training set evaluates the expressional uniqueness of individual faces and provide a resilient expressional recognition model in the field of biometric security.

The exhaustive experimental evaluation of the face expressional system shows a superior face recognition rates. Having examined techniques to cope with expression variation our aim in the future is to investigate in more depth the 3D face classification problem and optimal fusion of color and depth information.

Further study can be laid down in the direction of allele of gene matching to the geometric factors of the facial expressions. The genetic property evolution framework for facial expressional system can be studied to suit the requirement of different security models such as criminal detection, governmental confidential security breaches etc.,

TABLE 1: GENE PROPERTY MAPPING VALUES ON FACE EXPRESSIONAL (X –HAPPY, Y – SADNESS, Z – SURPRISE, A – ANGRY, B - DISGUISE) OF 32 HUMANS

HUMAN FACES	X	Y	Z	A	B
1	2.67	2.80	1.53	1.80	2.00
2	3.00	2.67	1.53	2.00	1.87
3	2.67	2.73	1.67	2.20	2.40
4	4.67	1.13	1.27	1.13	1.13
5	4.53	1.20	1.13	1.00	1.00
6	4.07	1.07	1.13	1.00	1.13
7	4.87	1.00	1.13	1.00	1.00
8	4.33	1.33	1.20	1.13	1.13
9	1.47	3.67	1.60	2.27	2.80
10	1.07	3.67	1.73	2.67	3.33
11	1.33	4.20	1.73	2.60	3.33
12	1.33	4.33	1.20	2.07	2.87
13	1.53	3.67	1.53	2.40	4.07
14	1.93	1.60	4.80	1.47	1.47
15	3.13	1.47	4.93	1.47	1.40
16	2.87	1.73	4.80	1.40	1.47
17	1.67	2.20	1.53	4.27	3.60
18	1.47	2.60	1.33	4.13	4.00
19	1.27	2.60	1.40	4.40	3.87
20	1.47	1.73	1.53	4.13	4.73

NOTE: Values of expressional parameter indicates the mapping sequence of faces with the gene property function

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