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Automated System for Recognizing Human Face Expression

[1]Meenakshi.R.P,[2]Krithika.R,[3]Mrs.V.Shivakrithika
[1][2]Computer Science and Engineering
[1][2][3]TRP Engineering College, Triruchirapalli , Tamilnadu
[1]r.p.meenakshi@gmail.com,[2]krithiraj.cse@gmail.com

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Abstract — : **In this paper we introduce a new approach for facial expression recognition and emotional state recognition for human. 2D features were used in the existing system whereas the 3D features are used in the proposed system and dynamic analysis for natural interaction. In this survey automatic recognition is done through video sequence. The image processing is done by detecting the facial regions and 26 fiducial points are calculated which is taken as input frames. Based on the fiducial points facial expressions are recognized. Elastic Body Spline (EBS) is used for emotion classification with the feature extraction which depends on the 3Dmodel. This extracts the feature from realistic emotion expression and it is also applied in Driver's Drowsiness Detection, Human Computer Interface, Psychological studies in Robotics which is automatically recognized through video sequence. The emotions are recognized from the fiducial points. Those emotions are taken as the input frame for human machine interface and Psychological studies in robotics as well as virtual reality. Facial scan technology acquires face from any static camera or video system that generates images of sufficient quality with high resolution. The facial expressions are recognized with the recognition rate average of 91% in the existing system. The recognized emotions are classified by using Elastic Body Spline(EBS) with the feature extraction which depends on the 3Dmodel. This extracts the feature from realistic emotion expression.**

I. INTRODUCTION

Facial expressions are also among the most universal forms of body language. The expressions used to convey fear, anger, sadness, and happiness are similar throughout the world. A facial expression is motions of the muscles under the skin of the face. These movements states the emotions of an individual to observers. Facial expressions are a form of nonverbal communication. It is accurate and it requires no physical interaction on behalf of the users. Humans facial expression either voluntarily or involuntarily produced. The neural mechanisms controls the expression which differs from case to case. Some Voluntary facial expressions are socially conditioned and they are followed by cortical route in the brain whereas involuntary facial expressions are innate and they are sub cortical route in the brain. Emotion plays a vital role in human-to-human interaction, allowing people to express themselves beyond the verbal domain and understand each other from various modalities. Emotions are discrete, physiologically distinct. Emotions are a complex state of feeling that results in physical and psychological changes that influence our behavior. Some emotions motivate human actions, and others are the medium for communication. Here we introduce automatic recognition from video sequence. A physical or behavioral sample is captured. Unique data is extracted by the image processing technique. The 26 fiducial points are taken as input frames. Based on the fiducial points facial expressions are recognized. This

emotions are applied in many areas like Robotics and human machine interface. The input can be recorded in the form of video or image. Once the face is detected and it is localized or normalized. The facial expressions are recognized of 91% in the existing system. Elastic Body Spline(EBS) for emotion classification is used here. It extracts the feature from realistic emotion expression.

I. RELATEDWORKS

Affective computing is the study of systems and devices that can recognize, interpret, process, and simulate human affects. It is a field of spanning cognitive science Engineering and computer science, Sociology, Physiology, Psychology and many more. In the last few decades most of the research was based on data of spontaneous as well as posed data acquired in the laboratory setting for affect recognition. The different affective states like thinking, embarrassment or depression can be considered complex affective states and expressed via dozens of anatomically possible facial expression or body gesture.

This framework is to predict the emotion from audio-visual modalities. The correlation between different emotions improves the performance. Two machine learning techniques are compared here (i.e. Support Vector Machine and Multilayer Perceptron) for continuous affect prediction . In real life Facial expressions, convey non-verbal communication cues in face-to-face interactions. These cues may also complement speech by helping the listener to elicit the intended meaning of spoken words. And it matters that how easy we can communicate. In human to human communication non-verbal cues are often used like facial expression and variations in voice tones. Emotions plays a vital role in human communication to recognize the human feelings.

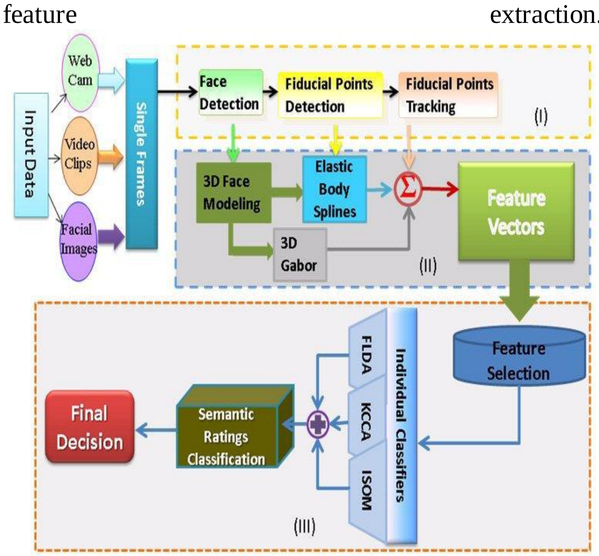
Beyond the nature of facial expressions in spoken communication between people, they play a important role in communication with sign language. Many phrases in sign language include facial expressions. Facial expression recognition are based on Facial Action Coding System (FACS) introduced by Ekman and Friesen. It is the most common method used for facial expression recognition. Every expression is identified by the action unit (AU).

The Existing system for solving the human facial expressions recognition[9] are based on 2D spatiotemporal data. It may be either 2D static images or 2D video sequences. In the past 20 years, there has been much research into recognizing emotion through facial expressions. Unfortunately, such approaches have difficulty in handling pose variations, lighting illumination, and subtle facial behavior and the performance of 2D based algorithms remains unsatisfactory, and is often unreliable under adverse conditions. Therefore, the 2D based approaches are limited to certain constrained environment. To achieve more robust performance, we introduce the proposed system 3D.Using 3D visual feature method is more robust approach for human emotion recognition which is automatically analyzing facial expressions for human emotion recognition in video sequences. It is also a challenging task due to the fact that current techniques for the detection and tracking of facial expressions are sensitive to head pose, clutter and variations in lighting conditions. To find the emotional states, the facial feature extraction attempts to find the most appropriate way to represent the facial expressions.

The representations of expression is more important for feature extraction[7] and classification. If there is any change it will affect the performance of an emotion recognition system. A good representation should have characteristics such as small within-class variations, large between-class variations, and robust to transformations without changing the class labels. The extraction should not depend much on manual operation. *Active deformation analysis.* We use the Elastic Body Spline (EBS) technique for human emotion classification system with Active Deformation Analysis. It is applied on the 3D face mesh model to generate a smooth warp which reflects control point and it extracts the deformation feature of the realistic expression from the neutral face. Very few existing studies have been made of the context-dependent interpretation of the observed facial expressions. The proposed EBS method can function as an interpolation approach to generate corresponding intrinsic geometries of the facial expressions and investigate the interpretation of emotional space.

II. PROPOSED SYSTEM

The proposed EBS method automatically generates facial expressions using a 3-D physically based DM model according to a deformable feature perspective executed with the control points within an acceptable time for emotion recognition. We present a new 3D emotion recognition method using geometric features and the color/density information. The main contribution of this work consists of applying the3D for feature extraction.



Figure[4]
It Automatically detects and tracks the fiducial points which extract the prominent characteristics of facial expressions with the distances between points and the relative sizes of the facial components to form the feature vector. On the other hand, finding feature points appropriately on the face can best represent the most important characteristics of the expressions and extract features more easily.

III. METHODOLOGY

The performance of the proposed system is checked by two facial expression video datasets method: Mind Reading database and RML Emotion database .The RML Emotion database was originally recorded for language and context independent. It recognizes emotions with the six fundamental emotional states: happiness, sadness, anger, disgust, fear and surprise. It includes eight subjects in frontal view(2 Italian, 2 Chinese, 2 Pakistani, 1 Persian, and 1 Canadian) and total of 520 video sequences. Each video captures a single emotional expression and ends at the apex of that expression . The first frame of every video sequence shows a neutral face. Video sequences from neutral to target display are digitized into 320×340 pixel arrays with 24-bit color values.

A. Preprocessing

The faces are non rigid and have a high degree of variability in location, color, and pose, several facial features which are uncommon. The other pattern detection issues make facial detection more complex. Occlusion and lighting distortions and illumination conditions can also change the overall appearance of a face. We detect facial regions in the input video sequence consisting of feature selection and classification based on a local normalization technique.

We choose 26 fiducial points on the face region

Fiducial Points Description			
1	Top of the head	14	Top of the left eyebrow
2	Tip of the chin	15	Left eyebrow outer corner
3	Left of the head	16	Right eyebrow inner corner
4	Right of the head	17	Top of the right eyebrow
5	Left eye inner corner	18	Right eyebrow outer corner
6	Top of the left eye	19	Top of the nose
7	Left eye outer corner	20	Left nose corner
8	Bottom of the left eye	21	The medial point between left and right nostril centres
9	Right eye inner corner	22	Right nose corner
10	Top of the right eye	23	Left corner of the mouth
11	Right eye outer corner	24	Top of the upper lip
12	Bottom of the right eye	25	Right corner of the mouth
13	Left eyebrow inner corner	26	Bottom of the lower lip

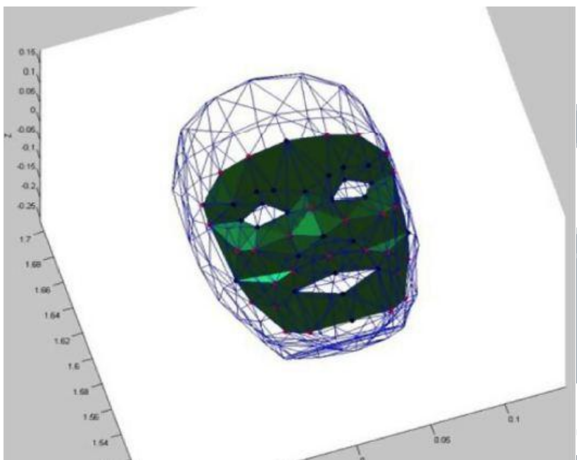
B. Fiducial Point Detector

Automatically fiducial points are detected successfully in facial region which plays a significant role in numerous facial image interpretation tasks. We propose an automatic and robust fiducial point detection method using the scale invariant feature. After the facial region is located from the face detection step, candidate points are selected over the facial region using local scale space extrema detection. The scale invariant feature of each candidate point is extracted for examination. All the candidate points in the facial region are examined through these detectors, and the 26 fiducial points can be detected.
Using fiducial points for facial expressions recognition is a challenge in computer vision systems. Most of the automatic feature point detection algorithms are implemented in such a way that every pixel in the input image is examined through feature detectors one by one to construct the feature vectors. Then the classifications are applied to the feature vectors to perform the feature point detection. Practically, the number of feature points, or equivalently, the number of times the classification will be processed, is typically in the tens of thousands, depending on the image size and demagnification factor. We propose to use the scale space extrema method to efficiently detect the locations of candidate points in the facial region from the face detection step. Compared with common automatic

feature point detection algorithm, our proposed method does not need to classify every pixel of the input image and thus speeds up the processing.

c.EBS spline:

Spline is the curve that connects two or more points. EBS is Elastic Body Spline which connects the fiducial points using NCC algorithm. EBS forms the morphed images. The face model is actually a mesh wireframe model consisting of characteristic feature points and deformable polygons with the EBS structure. We can deform the wireframe model to best fit a human face with or without any expressions. The 3D affine transformation realizes the facial expressions by facial muscular actions. It formulates the deforming rules according to the FACS coding system by considering the 26 fiducial points as the control points.



Figure[2]

D.D-Isomap:

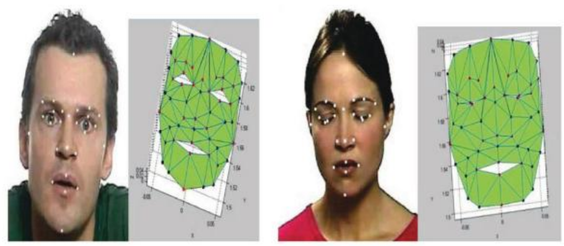
After establishing the deformable facial features , we use D-Isomap based method for emotion classification. D- Isomap was proposed by Tenenbaum and is one of the most popular manifold learning techniques for promising nonlinear dimensionality reduction. It learns complex embedding manifolds using local geometric metrics within a single global coordinate system. The geodesic distances is used in Isomap algorithm. The distance between points are taken instead of simply taking Euclidean distances, thus manifold structure of the input space into distances is encoded. The geodesic distances are computed by constructing a sparse graph. Here, each node is connected only to its closest neighbors. The length of the shortest path in the graph is calculated by the geodesic distance between each pair of node in which the graph is connected . These approximated geodesic distances are then used as input to classical multidimensional scaling (MDS).

The Isomap algorithm has three steps: Construct neighborhood graph, Compute shortest paths, and Construct D-dimensional embedding. The low dimensional embedding of the data is obtained by Classical MDS which is applied to the matrix of graph distance. The difference between MDS and Isomap is the use of geodesic distances in Isomap. The original prototype Isomap does not discriminate data acquired from multi-class data, several isolated sub-graphs will result in undesirable embedding. When the number of classes is less than three, the Extended Isomap can only be used. If the number of classes becomes larger, the classes may construct their own spatially intrinsic structure. The intrinsic structures of the high-dimensional are not recovered by Extended Isomap and improved version. The facial configurations are varied during emotional expressions, and then these points can be embedded in a lower dimensional space.

e. D-Isomap classifier:

EBS face model is constructed with different Poisson's ratio a male anger face, a female sadness face, a female anger face, a male happiness face.

It is constructed using the spline which connects the fiducial points using nearest class center algorithm. once the spline is constructed, we will get the morphed image of the person.



Figure[1]

Using EBS transform the positions are interpolated of characteristic feature points such that the 3D face model of an expressive expression can be generated from the input video frame. Based on the arrangement of facial muscle fiber, our EBS model calculates elastic characteristics for each emotional face by modeling the facial muscle fiber as elastic body. The affine or rigid elastic body coordinate transformation is fitted to the displacements of the facial expression with the continuity condition. The spline is obtained by mathematically identical to the computed coefficients from the original displacements of the control points directly. The overall co ordinate transformations obtained from the resulting spline which is added to the initial mesh of the elastic body transformation. Simulation results show that the face model generated by our method demonstrates good performance under the availability of control point positions.

Once the spline is constructed using EBS, the morphed image is obtained figure[2]. using the Euclidean and geo distance spline calculations are made and data sets are being trained. when the image is tested, the data sets are compared and using patter matching technique. using D-Isomap classifier the emotions are classified.

CONCLUSION

In this paper, we presented an automatic emotion recognition method from video sequences using the 3-D active deformable information. From the experimental results, we found that the significant features to distinguish one individual emotion from the other emotions were different. Some of the features selected in a global scenario were redundant, while some of the other features might contribute to the classification of specific emotion. Another observation was that there was no single feature which was significant for all the classes. This actually revealed the nature of human emotion; there were no sharp boundaries between the emotional states. Any single emotion may share similar patterns to other emotions, but not all. The human perception of emotion was based on the integration of different patterns.

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