Gaussian Hermite Moments are used for 3D face recognition

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Abstract:

In the subject of pattern recognition, the issue of face recognition is an intriguing one. Using three-dimensional depth data, we provide an approach for face recognition that is both accurate and fast. The goal is to get the absolute minimum of attributes while yet achieving good identification rates for those qualities. Following the extraction of 3D clouds points from the VRML face database, the nose tip of each sample is identified and is used as the new origin of the coordinate system, which is defined as the place where the 3D clouds points intersect. To characterise each person, Gaussian Hermite Moments are employed, and a back propagation neural network is used for the recognition job to finish the extraction process, after which the data is extracted. Following the studies, it was discovered that Gaussian Hermite moments combined with global depth information outperformed another strategy that was based on local depth information. A approach based on local depth information is compared to another method based on ratios of distances and angles between manually chosen facial fiducial sites in this research, and it is shown to perform much better.

Keywords GaussianHermite Moments, 3D Face Recognition, Back Propagation Neural network

1.INTRODUCTION

Given the fact that it is non-intrusive, face recognition is one of the several biometric identication modalities that are now accessible, and it rates highly on the list of subject preferences. However, from the standpoint of the operator, face recognition encounters a number of significant challenges, such as the vast diversity of emotions, ages, positions, lighting, and occlusion that may be seen in the real world. Numerous academics have worked on this problem for years, with the goal of developing a technique that is very accurate at facial recognition. A significant lot of research has been done on it. Several commercial face recognition algorithms are examined in the Vendor Test 2006 [1, which is held every two years and evaluates the performance of several commercial face recognition algorithms. There are three types of face recognition procedures, each of which is classed according to the kind of data that is employed in the recognition process. The first category consists of approaches that are used in two-dimensional space. When applied in a controlled setting, the performance of these technologies is outstanding. Methods that make use of three-dimensional information are classified as belonging to the second category. The integration of both 2D and 3D facial data results in the creation of the third kind of face data. There is a general summary of various techniques offered in [2][3, which is separated into two sections]. Because of the rapid development of 3D collecting technology in recent years, 3D capture has become easier to do, faster to complete, and more resistant to fluctuations in lighting conditions.
There are two ways to 3D face recognition systems that we may distinguish: global and local approaches. Face matching across the whole face is performed using global techniques, although it is computationally inefficient. Also noteworthy is that it is local in the sense that it divides the face surface into regions and extracts pertinent descriptors for each of those areas. A 3D face recognition system is often used to identify and categorise individuals by analysing depth information and surface properties [4][5][6] as well as other characteristics. It has been established that several different techniques for reporting on the importance of specific areas have been developed. These techniques are based on the geometric features

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of local facial landmarks/fiducial points and the Euclidean distances, ratios of distances, or angles between them that are calculated. Consider the following example: in[7], fifty-three non-independent features representations have been extracted from twelve anchor points, yielding a total of 53 non-independent features representations: a total of 53 non-independent features representations. In cases when distance and angle computations are conducted locally, the depth information available in the area is utilised to identify the multiple features present. The 20 most discriminating anthropometric Euclidean and geodesic distance characteristics obtained from the existing research on anthropometric face proportions, as published in [8,] were found by Gupta et al. based on the current literature on anthropometric face proportions. It has been shown that orthogonal moments are very beneficial in a range of applications, including pattern recognition and image processing. [9] [10]. Because of their mathematical orthogonality and effectiveness in defining local aspects of the signal[11], the Gaussian-Hermite moments were used to generate geometric invariants, which provide rich representation due to their mathematical orthogonality and efficacy in defining local aspects of the signal[12], and which are useful in characterising local details of the signal[13]. [12] Xu et al. proposed using Gaussian Hermitemoments as local descriptors in combination with a global mesh as a local descriptor in order to describe the local environment. A set of global features based on Gaussian-Hermite Moments is created and utilised to represent face data for the purpose of portraying it. In this paper, we compare the experimental results with a local technique that is based on the calculation of distances and angles using fiducial points that have been discovered around the subject's nose and eyes regions. It is proposed that the remainder of this work be organised as follows: This section explains how to construct feature extraction vectors and how to use them in the feature extraction process. The Gaussian Hermite Moments are discussed in detail in Section 3 of this document. To be more specific, Sections 4 and 5 cover the identification technique in detail as well as the experimental results. Section 6 of this article finishes the discussion by offering a summary of the results.

2.FACIAL FEATURES EXTRACTION

It is customary to assume that a nose's proximity to the camera will result in it having the biggest value in terms of z-axis values. However, this is not always the case. However, this assumption is not always valid, despite the fact that it has the potential to drastically reduce the complexity of an algorithm (like some examples in Fig 1). For this reason, we propose that the search for the nose tip be limited to the lowest two-thirds of the model in order to avoid confusion.

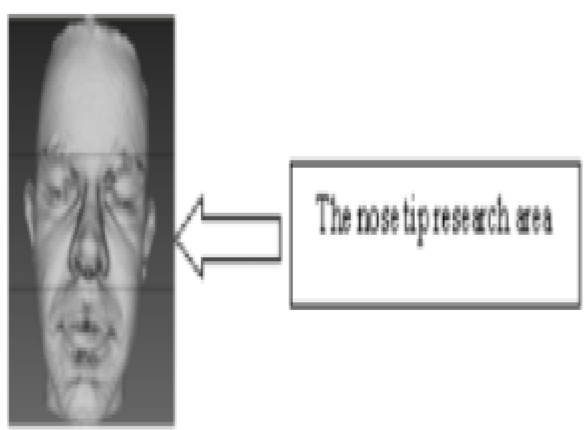
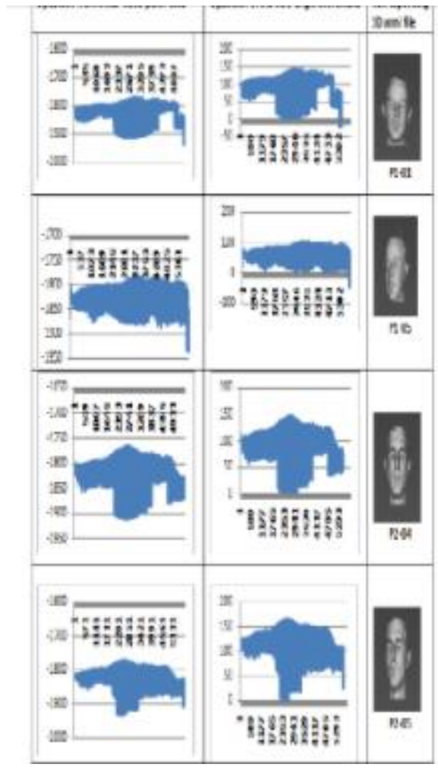


Fig 1: the nose tip research area



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3.GAUSSIAN–HERMITE MOMENTS

According to the information presented in the introduction section, moments and functions of moments have been widely employed in a variety of domains of image analysis during the last few decades. Among the many different types of moment-based feature descriptors are Cartesian geometrical moments, rotational moments, orthogonal moments, and complex moments, to mention a few examples. In the introduction to moments, the geometric moment is the first of the sorts of moments that are discussed, and it is the one that has been used the most often because of its evident geometry importance. Using direct explanation of moment invariants in a formalised way, Hu was the first to make use of this technique. [13] In Hu's theory, the most major flaw is that it does not allow for the possibility of any kind of generalisation. Moments such as Legendre and Zernike were used to portray the image in order to provide a more accurate depiction. It has been shown that orthogonal moments and their inverse transformations may be used to some extent in pattern representation, image analysis, and picture reconstruction, with variable degrees of success in each of these domains. With the high computational cost of moments, especially when a larger degree of moments is employed[14], their employment provides a substantial hurdle in practical applications. In fact, it was J. Shen[15] who made the first proposal for the notion of Gaussianl-Hermite Moments (GHM). [16]

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$$g(x,\sigma)=(2\pi\, \sigma^2)^{-1/2} \exp(-x^2 / 2\, \sigma^2)$$

The n^{th} order smoothed Gaussian Hermite Moments of a signal $S(x)$ is defined as:

$$GHM_n(x,S(x))= \int_{-\infty}^{+\infty} g(t,\sigma) H_n(t/\sigma) S(x+t)dt$$

With $H_n(t)$ is a scaled Hermite polynomial function of order n.defined as: $H_n(t/\sigma)= (-1)^n \exp(t^2) \dfrac{d^n \exp(-t^2)}{dt^n}$

The GHM_0 and GHM_1 can be calculated in the discret domain as follows:

$$GHM_0(x,S(x))= g(x,\sigma)*S(x)= \sum_{i=0}^{n} S(i) g(x-i)$$

$$GHM_1(x,S(x))=2\sigma \frac{d[g(x,\sigma)*S(x)]}{dx} =2\sigma \frac{d[g(x,\sigma)]}{dx} * S(x)$$

4.THE RECOGNITION PROCESS

As previously indicated in the preceding section, we investigate GHM in order to get features that may be used to solve the classification issue in question. These qualities are then used as input data by the classifier, which processes them. This is accomplished via the deployment of a back propagation neural network. The supervised learning network in this scenario is composed of multiple layers and is based on the gradient descent learning method, which is used to train the network. As part of the training process, we evaluate the network's capacity to react properly to input patterns that have already been used for training, as well as its ability to respond effectively to input patterns that are similar to those used in the testing database, among other things.

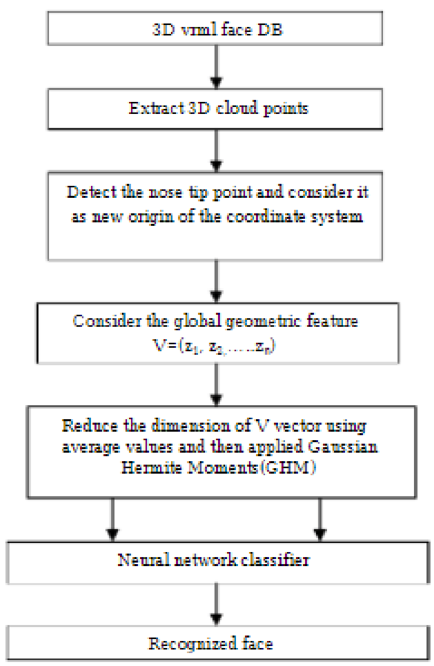

Fig3: The architecture of the proposed solution

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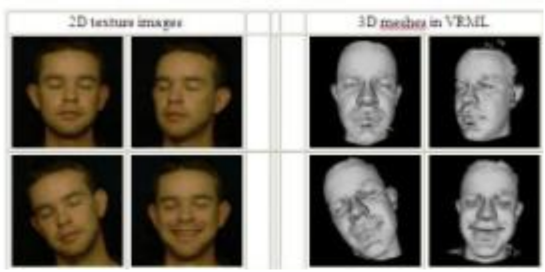
5. EXPERIMENTAL RESULTS

5.1 Using GHM

Label	Type of image
01 - 04	Frontal
05 - 06	Right turn 25º (respect to Y axis)
07 - 08	Left turn 5º (respect to Y axis)
09	Severe right turn (respect to Z axis)
10	Soft left turn (respect to Z axis)
11	Smiling face
12	Open mouth
13	Looking upwards (turn respect to X axis)
14	Looking downwards (turn respect to X axis)
15 - 16	Frontal view with lighting changes

Table1: description of the acquisition order



Six samples (1,2,6,12,13,14) were used for training and the rest for test. We train our neural network with the following setting: 100 inputs per pattern, 75 hidden neurons, 10 outputs neurons, and the error is set to 0.0001 for stopping condition. Comparison between n=0, n=1 and n=2 and without GHM.

Results:

FRAV 3D	Using only z-coordinate	GHM 0	GHM 1	GHM 2
80 Samples	95%	95%	Not interesting	93%
160 Samples	46%	89%	Not interesting	84%

Table2: the rate of recognition

5.2 Using Distances and angles between anthropometric facial points

Craniofacial anthropometry is a method used in physical anthropology to create parametric models of human faces[18]. It is a technique that is used to create parametric models of human faces. Multiple anthropometric face proportions have been suggested throughout the years, and researchers have gathered data on their values from diverse human populations[19] and evaluated them to determine their significance. In this investigation, anthropometric face points from the Texas 3D Data base [20] were utilised to collect data. We chose seven fiducial locations that are invariant to isometric deformations and take use of the symmetry of the face in order to do our measurements.

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Fig4: Fiducial point location:P1:Left Outer Eye; P2: Left Inner Eye; P3: Head base point; P4: Upper nose point; P5: Nose Tip; P6: Right Nose Base; P7: Left Nose Base;

X1 = ang(P3,P4,P5);

X2 = ang(P2,P4,P5);

X3 = ang(P7,P4,P5);

X4= ang(P6,P5,P7);

X5=dist(P2,P5)/dist(P4,P5);

X6=dist(P6,P7)/dist(P4,P5);

X7=dist(P1,P4)/ dist(P4,P5);

X8=dist(P2,P4)/dist(P7,P5);

The trials were carried out and assessed on the basis of numerous conditions from ten sets of faces from 3D Texas DB; each person of the selected folks was subjected to 23 distinct circumstances, including neutral, facial expression, and lighting. Ten photographs were utilised for training, with the remaining images being used for testing. The rate of identification is 82 percent for a data set consisting of 230 samples, according to the results. In particular, we see that findings from the first technique are more accurate than those from the second, despite the fact that samples in the Frav3D DB exhibit greater variances than those in the Texas DB. We may also conclude that methods based on global information provide better outcomes than methods based on local information.

6. Conclusion:

An innovative 3D face recognition system is presented in this research. For each sample in the database, 3D cloud points are first retrieved, followed by the consideration of 1D feature vectors based on depth information, and finally the application of Gaussian-Hermite Moments (GHM). The Back Propagation neural network was utilised to do the classification job, and the features obtained from the results were used as input vectors. Comparisons are made between the findings of this study and those obtained when looking into the utilisation of features comprised of angle and distance measurements of manually chosen 3D anthropometric face fiducial points. Experiments have demonstrated that the results obtained by using GHM are more effective.

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