Face Recognition Using Pattern Recognition Algorithms

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Abstract- *The face is the preferable biometrics for person recognition or identification applications because person identifying by face is a human connate habit. In contrast to 2D face recognition, 3D face recognition is practically robust to illumination variance, facial cosmetics, and face pose changes. Traditional 3D face recognition methods describe shape variation across the whole face using holistic features. In spite of that, taking into account facial regions, which are unchanged within expressions, can acquire high performance 3D face recognition system .We present an approach to the detection and identification of human faces and describe a working, near-real-time face recognition system which tracks a subject's head and then recognizes the person by comparing characteristics of the face to those of known individuals. Our approach treats face recognition as a two-dimensional recognition problem, taking advantage of the fact that faces are normally upright and thus may be described by a small set of 2-D characteristic views. Face images are projected onto a feature space "face space" that best encodes the variation among known face images. The face space is defined by the "Eigen faces", which are the eigenvectors of the set of faces; They do not necessarily correspond to isolated features such as eyes, ears, and noses. The framework provides the ability to learn to recognize new faces in an unsupervised manner.*

Keywords- Facial recognition, Non-negative matrix factorisations , principal component analysis, Face Detection

I. INTRODUCTION

Biometric traits are physical or behavioural human characteristics that can be classified in pre-defined categories established by humans with the aim of differentiating individuals [1, 2]. The face is one of the most revealing parts of the human body. Besides being our way of communicating emotions and intentions, it also contains information about the identity of a person, like sex, age, ancestry, weight, etc. The study of the human face is one of strong interest in the shape modelling community under the heading of morphometric. Morpho metric studies comprise the quantitative analysis of human head size and face shape. To some degree, certain variations in our face appearance are local. For Example, The shape of our eyes is independent of the shape of our lips. Even for a feature as simple as the lips, there are many different subtle variations, such as their width, curvedness, length, etc. therefore, within the context of face recognition, a further distinction can be made into holistic and part- based approaches. The effect of part-based face perception in humans has revealed in studies such as the Thatcher illusion [3]. In this study, a portrait photo has edited by placing the eyes and mouth upside down, with respect to the face. Although the inversion of the parts can be readily observed, the shapeless effect it has on the facial appearance as a whole. In machine recognition, a part-based representation can be advantageous, because traits within part are highly correlated with each other, but relatively independent of traits in other part [4]. Therefore, in 3D face recognition, it can provide robustness to facial expression by excluding affected parts [5], or by including only parts of interest [6]. In reconstruction and animation, the expressiveness of a face can be improved by modelling individual parts [7]. Consequently, in this research we study the relation between the face modules (segments) and face recognition. Non-negative Matrix Factorisation (NMF) is used to segment the face to different number of modules, and then the effect of these modules in face recognition accuracy is investigated. The main contribution of this research is using NMF for 3D face segmentation for face recognition purpose. The experimental results are recorded . Finally, concludes the achievements of the proposed method, and it comprise suggestions for future research.

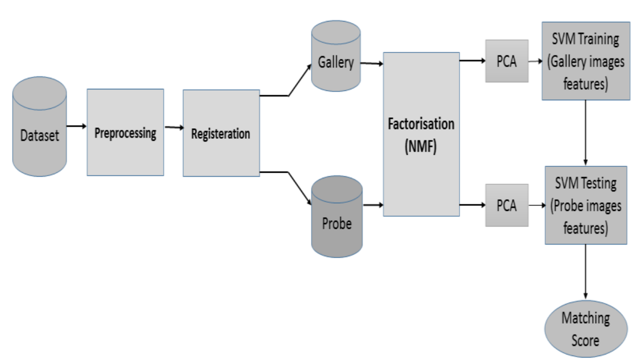

Fig. 1. Block-diagram of the proposed face recognition system

Facial recognition system:

A facial recognition system is a technology capable of identifying or verifying a person from a digital image or a video frame from a video source. There are multiple methods in which facial recognition systems work, but in general, they work by comparing selected facial features from given image with faces within a database. It is also described as a Biometric Artificial Intelligence based application that can uniquely identify a person by analysing patterns based on the person's facial textures and shape.

While initially a form of computer application, it has seen wider uses in recent times on mobile platforms and in other forms of technology, such as robotics. It is typically used as access control in security systems and can be compared to other biometrics such as fingerprint or eye iris recognition systems. Although the accuracy of facial recognition system as a biometric technology is lower than iris recognition and fingerprint recognition, it is widely adopted due to its contactless and non-invasive process. Recently, it has also become popular as a commercial identification and marketing tool. Other applications include advanced human-computer interaction, video surveillance, automatic indexing of images, and video database, among others.

Dataset

The data used in experimental work come from the FRGCv2 dataset. This data set contains 3D facial images of 466 persons, with 22 images per subject, the total number of images are 4007. The Minolta Vivid 910 camera is used to register these images [20]. In this dataset, 2469 3D face images are classified as neutral expression, while the rest of the 4007 images have non-neutral expressions E.g., disgust, happiness, surprise. Neutral images are used, 80% randomly used for training and the rest for testing. A total of 1975 images were used as a gallery training images and 494 images were used for probing testing images. Pre-processing operations are aimed to improve the extraction of object information in the given images. The data from 3D scanners frequently suffer from imperfections. These imperfections are generally in the form of noise or holes. Therefore, data preprocessing is a vital and non-trivial step. All scans in FRGCv2 database are preprocessed by using 3DFaceModelsPreprocessingTool [21], to eliminate noise and remove some undesired parts such as clothes, neck, ears, and hair from the scanned images. The denoising images were smoothed by using the medium filter, which removes the noise spikes. The holes are detected by searching vertices that have less than eight adjacent vertices, and filled by fitting square surfaces.

Registration

The aims of the registration process are alignment of all faces and find mesh dense correspondence between them. The technical details and algorithms that are used for dense surface model generation are provided in [22]. The following steps give an informal summary for the registration process:

A random face is taken from the database as an initial template or base mesh.

Five landmarks annotated manually on the 3D facial image (medial canthus of the right eye, medial canthus of the left eye, nasal tip, right labial commissure, left labial commissure).

Following the manual landmarks placing on all 3D face surfaces, the mean landmarks for the set is calculated using the Generalized Procrustes Algorithm (GPA) [23].

Each surface is warped with the mean landmarks using the Thin-Plate Spline (TPS) technique [24], to bring the corresponding landmarks on each face into accurate alignment.

A k-Nearest Neighbour Rule [25] is used to assign dense mesh correspondences with the vertices of a base mesh.

Non-negative matrix factorisations

The massive interest in NMF is the newly discovered ability of NMF to solve challenging clustering problems [26]. NMF has been shown to be a useful tool for analysing multivariate data. In machine learning, the approximation of a matrix by two factorizing low-rank matrices has many clear benefits. Among these benefits are discovering a structure in data, as well as reducing dimensionality and making a way for better generalization. In particular, the non-negativity constraint induces sparsity, causing selection of the variables into groups. In the field of facial analysis, it has shown to combine spatially nearby vertices into coherent parts [27]. Formally, the non-negative Factorisation of a matrix $V \approx WH$, of size $(n\times m) = (n\times k)\ (k\times m)$, can only be exact if $k \geq \mathrm{rank}(V)$. In practice, k is usually chosen much smaller, and so the Factorisation approximates the original data with a residual matrix that can contain both positive and negative elements.
Assume each column of V is an image of m vertices. Then, by using the approximation $V \approx WH$, one may say that the columns of W correspond to a basis image. Each column of H, on the other hand, corresponds to the encoding of each image in terms of the basis images. Non-negativity constraints on V, W, and H implicitly make for more interpretable and parts-

based representation of the data. *W*, *H*0 implies that each element *Vij* = *wihj*, is a weighted addition of positive vectors. By limiting both the basis and the encoding to non-negative values, NMF forces the Factorisation to an additive weighted structure (encoding), of non-negative building blocks (bases) [28].

Principal Component Analysis (PCA)

Principal Component Analysis, or PCA, is a dimensionality-reduction method that is often used to reduce the dimensionality of large data sets, by transforming a large set of variables into a smaller one that still contains most of the information in the large set. Reducing the number of variables of a data set naturally comes at the expense of accuracy, but the trick in dimensionality reduction is to trade a little accuracy for simplicity. Because smaller data sets are easier to explore and visualize and make analyzing data much easier and faster for machine learning algorithms without extraneous variables to process. So to sum up, the idea of PCA is simple reduce the number of variables of a data set, while preserving as much information as possible. The purpose of this post is to provide a complete and simplified explanation of Principal Component Analysis, and especially to answer how it works step by step, so that everyone can understand it and make use of it, without necessarily having a strong mathematical background.PCA is actually a widely covered method on the web, and there are some great articles about it, but only few of them go straight to the point and explain how it works without diving too much into the technicalities and the 'why' of things. That's the reason why i decided to make my own post to present it in a simplified way. Before getting to the explanation, this post provides logical explanations of what PCA is doing in each step and simplifies the mathematical concepts behind it, as standardization, covariance, eigenvectors and eigenvalues without focusing on how to compute them.

The sub regions feature vector is extracted and dimensionally reduced using PCA. In general, PCA aims to search for the best vector for the distribution of images, and to use this vector to define the subspace of range images. All face images in training group are projected into the principle components space to find out a set of coefficients, which describes the contribution of each face vector in the face space. For identifying a testing face image, it is projected to the trained face space to achieve the corresponding set of coefficients. The vectors of PCA are known as eigenvectors, which correspond to the largest eigenvalues. Meanwhile, the eigenvectors are also known as eigenfaces. Usually, the input images represented as *n*-dimension feature vectors are reduced to a feature vector of *d*-dimensional, because the eigenvectors corresponding to smaller eigenvalues are mostly noise and they usually are neglected [29].

II. FACE DETECTION

The face detection system can be divided into the following steps:

Pre-Processing:

To reduce the variability in the faces, the images are processed before they are fed into the network. All positive examples that is the face images are obtained by cropping images with frontal faces to include only the front view. All the cropped images are then corrected for lighting through standard algorithms.

Classification:

Neural networks are implemented to classify the images as faces or nonfaces by training on these examples. We use both our implementation of the neural network and the Matlab neural network toolbox for this task. Different network configurations are experimented with to optimize the results.

Localization:

The trained neural network is then used to search for faces in an image and if present localize them in a bounding box. Various Feature of Face on which the work has done on:

Position
Scale
Orientation
Illumination

Machine learning

Machine learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. Machine learning focuses on the development of computer programs that can access data and use it learn for themselves. The process of learning begins with observations or data, such as examples, direct experience, or instruction, in order to look for patterns in data and make better decisions in the future based on the examples that we provide. The primary aim is to allow the computers learn automatically without human intervention or assistance and adjust actions accordingly.

Some machine learning methods

Machine learning algorithms are often categorized as supervised or unsupervised.

Supervised machine learning algorithms can apply what has been learned in the past to new data using labeled examples to predict future events. Starting from the analysis of a known training dataset, the learning algorithm produces an inferred function to make predictions about the output values. The system is able to provide targets for any new input after sufficient training. The learning algorithm can also compare its output with the correct, intended output and find errors in order to modify the model accordingly.

In contrast, unsupervised machine learning algorithms are used when the information used to train is neither classified nor labeled. Unsupervised learning studies how systems can infer a function to describe a hidden structure from unlabeled data. The system doesn't figure out the right output, but it explores the data and can draw inferences from datasets to describe hidden structures from unlabeled data.

Semi-supervised machine learning algorithms fall somewhere in between supervised and unsupervised learning, since they use both labeled and unlabeled data for training – typically a small amount of labeled data and a large amount of unlabeled data. The systems that use this method are able to considerably improve learning accuracy. Usually, semi-supervised learning is chosen when the acquired labeled data requires skilled and relevant resources in order to train it / learn from it. Otherwise, acquiring unlabeled data generally doesn't require additional resources.

Reinforcement machine learning algorithms is a learning method that interacts with its environment by producing actions and discovers errors or rewards. Trial and error search and delayed reward are the most relevant characteristics of reinforcement learning. This method allows machines and software agents to automatically determine the ideal behavior within a specific context in order to maximize its performance. Simple reward feedback is required for the agent to learn which action is best; this is known as the reinforcement signal.

Machine learning enables analysis of massive quantities of data. While it generally delivers faster, more accurate results in order to identify profitable opportunities or dangerous risks, it may also require additional time and resources to train it properly. Combining machine learning with AI and cognitive technologies can make it even more effective in processing large volumes of information.

The Support Vector Machine (SVM) is a supervised learning approach that is used in pattern recognition. SVM maps an input sample to high dimensional feature space and works on finding the optimal hyperplane that can minimise the classification error for the training data using the non-linear transformation function. The classifier tries to find the optimal one by maximizing the margin. This margin, as shown in Fig. 2 is the minimal distance between the hyperplane and the training data [30].

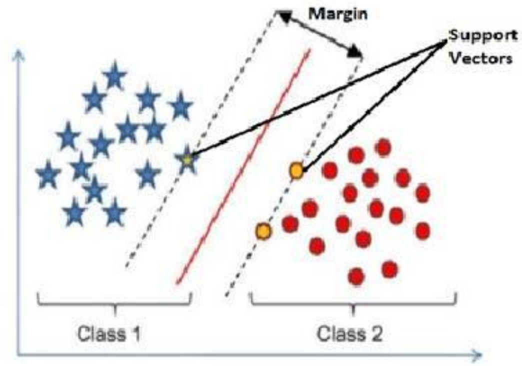

Fig. 2. Margin, supports vectors and hyperplane for SVM

Cross-validation method (N-fold) is used for evaluating the recognition performance. In this research, the dataset is divided into five subsets. Each time, one of the five subsets are used as the test set and the rest sets are used for training, after that the average error across all five trials is calculated [31].

III. RESULTS

Although the segmentation method is unsupervised in the sense that there is no example segmentation to learn from, the choice of the number of parts, *K*, is a controlling parameter. In fact, the number of parts is the main controlling parameter for the segmentation of the face. The number of parts defines a scale ranging from 1 (whole face) up to intermediate values of parts to the total number of vertices. Progression along this scale means a reduction for information per part. This reduction is an offset against an increase of information found in the relations between parts. Fig. 3 visualises the full segmentation based on 10 parts, while Fig. 4 visualizes the segmentation based on 20 parts. As the number of parts increases, the size of the features decreases. A range of *K* value is tested, increasing *K* value over 20 produce very small parts that might be better combined with other parts. In fact, for the segmentation in more than 35 regions, the face is divided in small contiguous regions that separate different anatomical aspects, but the results are less intuitive to interpret since the regions are small. For a smaller number of parts, remarkable result in the 2-region division is that mouth and nose are combined into one region. According to this result, some relation exists between these anatomical structures. As they coincide in the same region, there must be higher covariance between them, and less interaction with the parts in the other region as shown in Fig. 5. The vertices of 10 parts, 20 parts and 35 parts are used as features for face recognition purpose. Table 1 shows the recognition rate and error rate for 3D face recognition using SVM, while Fig. 6 illustrates the relation between the accuracy and the number of regions.

Fig. 3. Visualization of 10 parts

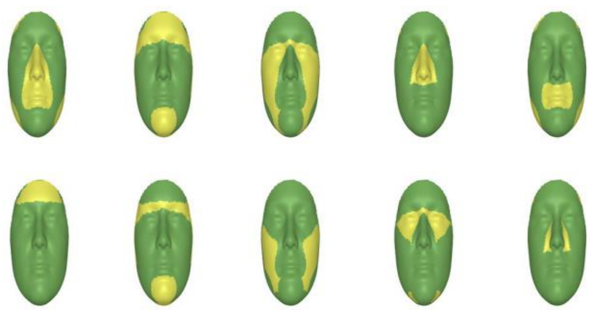

Fig. 4. Visualization of 20 parts

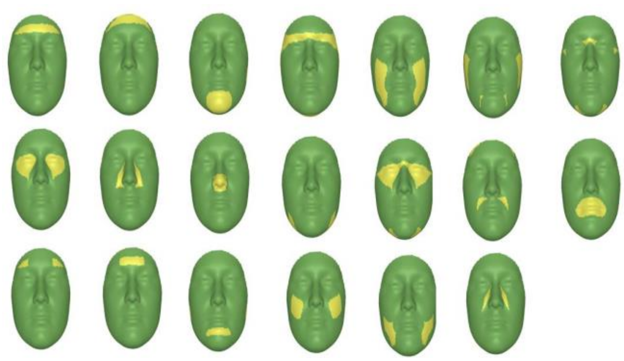

Fig. 5. Visualization of two parts

Number of parts	Recognition rate	Error rate
10 parts	92.7%	5.2%
20 parts	96.4%	2.7%

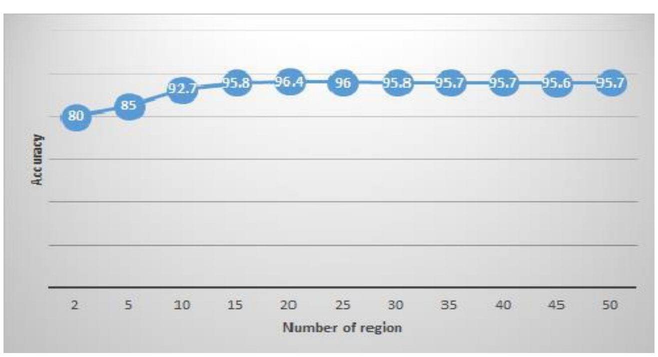

Fig. 6. The recognition accuracies for different number of face regions

IV. DISCUSSION

Facial detection via the Viola-Jones algorithm is a common method used due to its high detection rate and fast processing speed. The algorithm can be summed up in four steps: feature selection, feature evaluation, feature learning to create a classifier, and cascading classifiers. Simple features are used, inspired by Haar basis functions, which are essentially rectangular features in various configurations. A two-rectangle feature represents the difference between the sum of the pixels in two adjacent regions of identical shape and size. This idea can be extended to the three-rectangle and four-rectangle features. In order to quickly compute these rectangle features, an alternate representation of the input image is required, called an integral image.

Non-negative matrix Factorisation is suited for decomposition of the whole face. NMF results in sparser basis vectors that group strongly correlating vertices. The strongest correlation is found among local groups of vertices. Consequently, the basis vectors obtained can be used to define a statistical decomposition of the face into parts. Face Factorisation is unsupervised segmentation process, the selection of the number of segments is an essential parameter for any segmentation algorithm to avoid under-segmentation and over-segmentation problems. Under-segmentation, in which the segments appear to describe more than one part of the face. Over-segmentation when segments appear to describe only part of the part. Therefore, an open question remains: what is the correct number of parts that is sufficient for face recognition. Logically, more parts mean smaller parts and vice versa, but further experiments are needed to find a proper criterion for the evaluation. A general trend that can be seen from the results. It is the increase in accuracy when the number of regions is increased, but this is followed by a drop-in performance due to over fitting. The increasing performance when segmenting the face in more regions, suggests that investigating the face from a region perspective enhances the recognition rate. Experimental tuning for the *k* value yield 96.4% recognition rate when *k* =20.

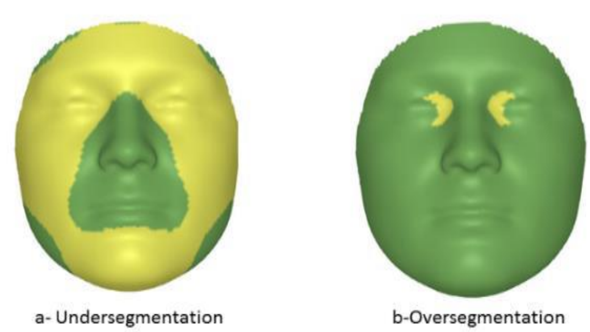

Fig. 7. Under segmentation and over segmentation

A number of studies have investigated face recognition performance using face parts conducted on FRGCv2 dataset. Chang, Bowyer and Flynn [14] divide the 3D face into regions; the center of these regions is the nose. These regions are used for comparison instead of the whole frontal face region. While, Zhong, Sun and Tan [15] divided the frontal face into two regions, the upper and the lower face region. They used K-means clustering technique for face segmentation and nearest neighbor classifier for the classification. For the same purpose, Lei, Bennamoun and El-Sallam [32] collected features from the eyes, forehead and nose regions, these features are represented as a histogram. They used fusion of feature level for evaluation. Compare the recognition performance of the proposed approach with respect to the performance obtained in other states of art 3D face recognition systems. We can notice the high performance of 3D face recognition system based on face Factorisation. The major novelty in this paper is the automatic face segmentation.

Reference	Recognition rate	Number of regions	Data set
Flatmier,bowyer and Flynn [33]	93.2	28	FRGCv2
Cook,Chandran And Fookes[34]	92.3	147	FRGCv2
Lei,Bennamoun And El-Sallam[32]	95.6	3	FRGCv2
Zhong,sun and Tan[15]	95.9	40	FRGCv2
Spreeuwers[13]	95.9	30	FRGCv2

V. CONCLUSION

This paper proposes a novel 3D face recognition approach based on face Factorisation. The experimental study is performed on how discrete regions across the face affect the ability of a subject recognition. The increase in recognition performance occurred when segmenting the face in more regions, corresponds with the hypothesis mentioned in the introduction that it is an interesting approach to split the face into local modules instead of examining the face as a whole. The region-based 3D face recognition approach is assessed on the FRGCv2 data set containing 4007 3D face scans from 466 unique subjects, representing a variety of facial expressions. The results of the proposed algorithm outperform those reported by many other state of the arts publication results on the same data set. For future work, this study will be extended to explore gender variations and ethnicity, also work on investigating other methods for data clustering and apply them for 3D face segmentation

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