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A Facial Recognition System Survey Paper

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Abstract:

A computer programme called a facial recognition system may recognise a person from a digital image or a video frame from a video source. Connecting specific facial features from the image and a face database is one approach to accomplish this. Lately, biometrics, computer vision, and network multimedia information access have all given face recognition a lot of attention. There are numerous techniques for it. People have compared numerous face recognition methods in their research. Yet as of now, there isn't a method that has consistently produced excellent outcomes in all circumstances. Comparative analysis of various Facial Recognition System approaches is presented in this research.

Keywords: PCA, LDA, LBP, Face Recognition, and Biometric

I. INTRODUCTION

Throughout the last three decades, one of the most fascinating and significant study areas has been computer vision and image processing. It is not easy to examine any facial recognition system in detail. As a result, only a group of the most beneficial systems will be covered in this work. The need for automated recognition and surveillance systems, interest in facial recognition technology, and interface design for human-computer interaction are the causes. Facial identification and verification are both possible with face recognition.

A face recognition system automatically recognises faces in movies and photos. It is divided into two groups:

a. Facial authentication or face verification

b. Facial recognition or Face identification

A one-to-one similarity between a question face picture and a template face image whose identification is being asserted is used in face verification or validation. A one-to-many similarity relation is used in face identification or recognition to compare a query face image to every template face image in the database in order to identify the query face image. A watch-list check is another facial identification situation in which an inquiry face is compared to a suspect list. Since the creation of the first automated facial recognition system, face recognition systems' efficiency has greatly increased [1]. A person can be recognised by their facial pictures in a variety of ways, such as by taking a visible spectrum photo of their face with a cheap camera or by analysing the infrared heat emission patterns from their face. Using a variety of cameras, visible light facial recognition systems generally model key features from the centre region of the facial image. These systems take features from the recorded images that do not change over time while avoiding trivial features like facial emotion or hair. Principle Component Analysis (PCA) [2], local feature analysis [3], neural network [4], and multiresolution research are a few techniques to analyse face pictures in the visual range. Reduce the effect of varying lighting and find a cover or picture are two challenges for face identification in the visible range.

Many systems use a real-time method to identify a person's head and find the face automatically, but some facial recognition systems may need a fixed or positioned user in order to record a picture. The fact that face recognition is non-intrusive, hands-free, constant, and well-liked by most users are its main advantages. The majority of facial identification studies can be divided into two primary categories: feature-based and comprehensive [4]. Holistic methods gained popularity in the 1990s with the well-known Eigen-faces approach. Feature-based approaches [6] to face recognition basically rely on the detection and characterization of individual facial features and their geometrical relationships. Geometric approaches predominated in the 1980s where simple measurements such as the distance between the eyes and shapes of lines connecting facial features were used to recognise faces. Typically, these characteristics include the lips, nostrils, and eyes. These methods are resistant to spatial changes of the faces in the input picture because people and their characteristics are detected before authentication or identification is carried out. On the other hand, holistic or global methods of face identification [7] entail storing the complete facial picture and considering the resulting facial "code" as a point in a high dimensional space.

As a result, they presumptively believe that all features are limited to specific sizes, locations, and angles. Although holistic methods [8] like neural networks are more difficult to implement than their geometric equivalents, their application is much simpler because an entire image segment can be reduced to a few key values for comparison with other stored key values, and no precise measurements or knowledge, like the locations of the eyes or the presence of moustaches, is required. The issue with this "take all" strategy was that, despite the fact that noise, occlusions like spectacles, and other non-face picture attributes are not specific to features, the holistic algorithm could learn them and include them in the identification outcome.

Early efforts to automate facial identification were more frequently based on feature-based techniques. In some of this earlier work, people and their characteristics were detected using very basic image processing methods [8, 9]. A large circular shape was matched to an edge map that was first taken from an input picture in [9], with potential adjustments to size and location. Then, by looking for borders at predicted positions of specific characteristics like the eyes and lips, the existence of a visage was verified. With the aid of heuristic planning and a better edge detection, Kelly et al. [8] were able to accurately extricate a person's head's shape from a variety of backdrops.

The structure of the current document is as follows. The associated study is described in part (II), and the findings are presented in section (III).

II. RELATED WORK

Principal Component Analysis typically employs eigenfaces, requiring that the query and exhibition pictures be of equal size and adjusted to align the subjects' eyes and mouths in the images. By computing the distance between each pair of feature vectors in a probe and exhibition picture, the results of the comparison are then made public. This method's primary benefit is that it can reduce the amount of data required to recognise a particular to 1/1000th of the data displayed. Principle Component Analysis can be used to determine how effective a facial recognition system is, and neural networks are used for identification back propagation [2].

An appearance-based method for dimensionality reduction that excels at facial identification is linear discriminant analysis [10]. It gives us a select group of characteristics that contain the most crucial data for categorization. SVM is a categorization method [11] that divides two data sets with the greatest possible distance. The idea is to increase the divisibility between classes by using a conformal projection to increase the spatial precision around the margin. When some of the characteristics (facial images) are obscured, SVM cannot be used directly. The numbers for those measures aren't known in this situation. When the feature vectors describing our data have absent elements, SVM cannot be used.

SIFT descriptor [12] is extremely unique and impervious to scale, rotation, linear translation, noise, and occlusions. Finding scalespace extrema is the first stage in SIFT features' four main detection and representation processes, which are followed by key point localisation and filtration, orientation assignment, and key point description.

The SURF descriptor, which is immune to scale and in-plane rotation characteristics, is created by H. Bay et al. in 2008 [13]. Interest point detection and interest point identifier are two of its two stages. Find the focus point in the picture in the first phase, then use the Hessian matrix to discover an approximation of the finding in the second phase.

A new approach to estimating population density at the patch level was put forth by Hajer Fradi et al. [14], in which the area of each patch changes to account for viewpoint errors. instead of using the raw LBP feature vector, to learn a discriminatory subset of the high-dimensional Local Binary Pattern (LBP). Second, a different multiclass SVM method based on significance ratings is suggested. The PETS dataset is used to assess the efficacy of the suggested strategy, and the findings show how the low-dimensional compressed depiction of LBP affects categorization accuracy.

A straightforward method for person identification on low resolution pictures is presented by Ahmed Boudissa et al. in [15]. Although the LBP feature extractor and edge orientations make up the system's structure, a new method of threshold selection is presented. This level greatly reduces processing time and increases discovery rate. Additionally, it makes the system resistant to consistently noisy backdrops, light changes, and crowded backgrounds.

A brand-new technique of object-based colour and texture feature merging based on kernel PCA was suggested by Zhengrong Li et al. in [16]. The technique has been put to the test in a plant categorization application involving overhead photography. According to the testing findings, combining colour and material characteristics improves discernment compared to using them separately. Additionally, the suggested nonlinear feature fusion strategy has significantly outperformed the serial fusion strategy in terms of dimensionality reduction, processing efficiency, noise removal, and discriminative strength.

For strong facial identification, Li Liu et al. [7] suggested a straightforward, innovative, but incredibly powerful technique. This method created a very basic structure to combine the suggested descriptors for the issue of facial recognition. It also expanded a collection of LBP-like descriptors. The following are our key conclusions: The enhanced performance obtained by fused descriptors is evidence that I the suggested ELBP descriptors exploit the majority of the information that is locally available and do contain complementary information with one another; (ii) the traditional uniform patterns approach does not apply to the proposed descriptors; and (iii) the WPCA technique can further enhance the recognition performance of the fused proposed features.

By utilising the cooccurrence data, Cong Wang et al. [8] suggested a technique to fully utilise the potential of Gabor phase features. On the FERET and AR datasets, the proposed histogram of cooccurrence of Gabor phase patterns (HCGPP) is thoroughly examined and contrasted with existing approaches. The suggested description HCGPP has a high dimensions issue, though.

A block-based speed-up technique for foot recognition was suggested by Won-Jae Park et al. in their study [19]. The suggested method gets nearly the same precision as the traditional method and is about three times quicker than HOG-LBP. Additionally, the proposed method is a rejecter with reduced complexity using the chosen blocks and the re-classification process.

The powerful LBP descriptor can be used in the suggested framework with two kernels based on the 2 distance and the Hamming distance, according to Cuicui Kang et al's [10] proposal for a novel kernel coordinate descent (KCD) algorithm based on the covariance update technique for the l1 minimization problem in the kernel space. This technique also applied the new algorithm in the sparse representation classification framework for face recognition.

A. Porebski et al. [11] suggested a score-based LBP histogram selection method for classifying colour textures. It entails giving each histogram a number that evaluates how well it can describe how the patterns match up within the various groups. The most distinctive histograms are then chosen and ordered according to the suggested score in order to create a low-dimensional pertinent region for the classifier to work in.

A modified Local Binary Pattern (LBP) feature extraction method was proposed by Yunyun Cao et al. for pedestrian detection in low-light conditions. The method consists of three steps: I using the magnitude component to weight the LBP code; (ii) using multiresolution to reduce the impact of noise; and (iii) utilising multi-scale information to obtain more co-occurrence information of the grey scale patterns.

The LBP spread of various tiny areas within the same texture picture may vary, according to Yonggang He et al[13] .'s presentation. The LBP statistic characteristic in local areas was not taken into account by the traditional LBP methods, which only computed the LBP distribution across the entire picture. To fully utilise local binary patterns, rotation-invariant LBP histograms were taken from small areas in order to learn the LBP texton vocabulary for texture description. The incidence of textons, rather than the frequency, was used to symbolise every background picture.

In order to recognise facial expressions, Zhou Lubing et al. [14] suggested a new facial description based on LGIP. The LGIP operator incorporates the benefits of regular, gradient, and LDP designs. It shows a local increase in luminosity tendency and exhibits acceptable noise and non-monotonic light shift stability. The face description built on the LGIP histogram includes data at the individual, local, and global levels. In order to classify expressions, the description thus demonstrates promising discriminativeness.

A brand-new training free rotation invariant texture categorization method, called M-LBP, was put forth by Lin Zhang et al. [5]. It blends the conventional uniform LBP operator with two Rotation invariant measures, the local phase and the local surface type obtained by the first- and second-order Riesz transforms.

Three different types of oriented statistical characteristics were suggested by Zhenhua Guo et al. [11]. The adjustable factors to reduce the local differences as well as the mean value and standard variation of the local directional differences. The LBP histogram distances were weighted for texture categorization using these statistical characteristics.

By fusing the LBP and SQMV features, Ching-Te Chiu et al. [7] suggested a novel face description for facial identification. In addition, to reduce the computational complexity of the facial identification technique, the features are only taken from the eye areas rather than the entire face picture.

In order to obtain a higher identification rate than the initial LBP methods and further decrease processing complexity, a quick and efficient facial recognition method based on texture categorization and LBP is first suggested.

An adaptive local ternary derivative pattern is suggested by Vinh Dinh Nguyen et al. [18] to record more discerning information and to withstand noise better than LBP and LDP. The differential quality of BP in CBD is greatly improved by the suggested approach, according to experimental results for BP using three datasets.

An innovative smoke recognition technique was introduced by Hidenori Maruta et al. [9] and was based on anisotropic LBP descriptors and AdaBoost. Anisotropic LBP descriptions are made with excellent handling of smoke information in mind.

In other words, anisotropic LBP descriptors are thought to be effective to changes in light and they can manage smoke deformation due to external factors. A new texture description was suggested by Marcelo Musci [10] by joining the histograms of a local variance estimate and a texture binary code (either LBP or LPQ).

Jie Chen et al. [11] suggested a brand-new paradigm for spatiotemporal features-based dynamic texture segmentation.

Super histogram was suggested by Jianfeng Ren et al. [12] in order to increase dependability. The super histogram receives some of the time information.

A novel feature set called MS-LTP for face recognition was suggested by Zhe Wei et al. As feature sets for facial recognition, Haar, LBP, LTP, MB-LBP, and MS-LTP are compared.

A plaque classification technique for IVUS pictures was put forth by Gonzalo Vegas-Sanchez-Ferrero et al. [14] and is based on the probability behaviour of speckle in each tissue class in various tissue kinds. Because it performed better than the Rayleigh and Nakagami distributions under the downsampling and blending of the echo envelope procedures, a gamma distribution is assumed for the probability description of the speckle.

A GMM is used to represent each class because varying echogenic material can be found in various plaque types. To overcome the drawbacks of Local Binary Pattern (LBP) and Non-Redundant LBP, Amit Satpathy et al. [15] suggested a new edge-texture feature called Discriminative Robust Local Binary Pattern (DRLBP) for human identification (NRLBP). A vibrant person can be distinguished from a black backdrop using LBP, and vice versa. This difference increases the intra-class variance of people for human identification. By selecting the smallest LBP code and its supplement, NRLBP lessens the impact of LBP. NRLBP, on the other hand, maps LBP codes and their counterparts within a block to the same code. As a result, NRLBP misrepresents some systems. Additionally, LBP and NRLBP's representations ignore contrast information. As a consequence, associated feature expression is evident in comparable areas with varying contrast. This is undesirable for human identification because the human shape holds the most important data. The shape cannot be successfully distinguished by the characteristics because they disregard the contrast information.

The brand-new feature, DRLBP, takes into account both the numerical difference between the bins of the LBP codes and their corresponding supplement codes as well as the gradient weighted total of the bins. DRLBP helps to solve these issues with LBP and NRLBP for human recognition. A. Porebski et al. [16] suggested a score-based LBP histogram selection method for classifying colour textures. It entails giving each histogram a number that evaluates how well it can describe how the patterns within each class fit. The most distinctive histograms are then chosen and ordered according to the suggested score in order to create a low-dimensional pertinent region for the classifier to work in.

Olgun Gulden et al. [17] developed a novel method to describe and categorise pictures of gastrointestinal tissue. Local object patterns, a novel class of high-level texture identifiers, are introduced in this method. Moreover, describe these characteristics on tissue objects, which roughly correspond to the histopathological tissue's constituent parts. To capture the geographic configurations of the objects within the defined local neighbourhoods, specify a collection of neighbourhoods with various location ranges and create a binary text for each of these neighbourhoods. Additionally, describe tissue objects using their decimal versions of their binary counterparts as identifiers, and create a bag-of-words depiction of a picture using the described objects.

III. CONCLUSION

We summarised the most significant facial detection algorithms in this article. A fascinating and crucial identification method is face recognition. The user-friendliness of the facial detection strategy is one of its major advantages over other biometric methods. We have provided an overview of facial detection technology in this article.

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This essay can give readers a better grasp of different facial recognition algorithms, and we urge those who are particularly interested in this subject to look up more information in the sources.

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