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A New approach to Recognize Human Face Under Unconstrained Environment

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Abstract

Human face is considered as one of the most useful traits in biometrics, and it has been widely used in education, security, military and many other applications. However, in most of currently deployed face recognition systems ideal imaging conditions are assumed; to capture a fully featured images with enough quality to perform the recognition process. As the unmasked face will have a considerable impact on the numbers of new infections in the era of COVID-19 pandemic, a new unconstrained partial facial recognition method must be developed. In this research we proposed a mask detection method based on HOG (Histogram of Gradient) features descriptor and SVM (Support Vector Machine) to determine whether the face is masked or not, the proposed method was tested over 10000 randomly selected images from Masked Face-Net database and was able to correctly classify 98.73% of the tested images. Moreover, and to extract enough features from partially occluded face images, a new geometrical features extraction algorithm based on Contourlet transform was proposed. The method achieved 97.86% recognition accuracy when tested over 4784 correctly masked face images from Masked Face-Net database.

Keywords*: Facial Recognition, Unconstraint conditions, masked faces, HOG, Support Vector Machine.*

1 Introduction

Over the last years face recognition systems as one developed biometric application gained a noticed attention from researchers, since the face is considered as one of the biometric factors, which contains a huge information about the human identity [1]. Many studies have focused on creating, implementing, evaluation and testing algorithms and methods for such type of systems.

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The task of these systems are based on identifying the person identity by his biometrical characteristics. This method can overcome the several disadvantages of other methods such as forgetting the password or codes.

Many studies and researches have agreed that imaged based face recognition can be classified into three classes: 1) local approach: classified by specific facial features, 2) holistic approach: It uses the entire face as input data and 3) hybrid approach, which uses the local and global features for more recognition accuracy [1, 3, 4,].

As shown in fig1. Face recognition system is consisting of several phases:

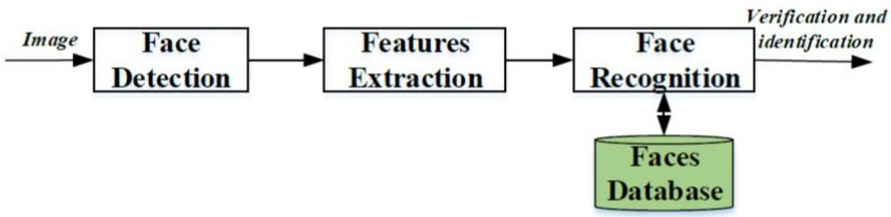

Fig. 1 The main phases of face recognition systems. [2]

Face detection is the first step after acquisition the image into the recognition system, for determining whether the image is containing a face or not by preprocessing and extracting the face part from the image. Typically, this algorithm starts by searching the boundaries and face features, such as, eyes, mouth, nose and iris etc... [5, 6]. Face features extraction can be performed by image segmentation image. Once the face is detected, additional test is applied for confirming that a face is detected inside the image [7]. Different algorithms are used such as Voila Jones and histogram of oriented gradient (HOG), and principal component analysis (PCA) can be used in this phase.

Features Extraction is the most critical phase in face recognition system, since it focusses on identifying the features of the face after detection [7]. Eyes, nose, ears and their geometry are the most important inherent features that could be used to describe the face. Different algorithms and techniques are used to determine face features such as (SIFT), Histogram of Oriented Gradients (HOG) and multi-scale weighted Local Binary Patterns (WLBP) feature descriptors as mentioned in [7,8]. According to [9], extraction is based on local and global features. Techniques on global features bases on Eigenface algorithm based on (PCA), Fisherface algorithm based on the (LDA) and Two-Dimensional Principal Component Analysis (2DPCA), While for local feature extraction algorithm, LBP is more effective.

Face recognition in this phase, a specific and distinctive extracted feature such as distance between eyes, eyebrow, shape of chin etc. Converted to mathematical form and compared with stored images in the face recognition databases [10]. This phase can be classified as identification or verification task according to the goal of recognition as offered by [1] early. In identification process, face is compared with all the know faces images that stored in databases to identify the image, while verification is performed by comparing it with the face data of the claimed identity in the database. As presented in [11], several issues take place with this phase, like the face pose, glasses wearing, expressions, illumination variances, facial hair etc. Local binary pattern (LBP), linear discriminant analysis (LDA), conventional neural networks and k-nearest neighbor (K-NN) are mostly used algorithms in this phase.

Nowadays, the masked face recognition is gained a significant importance because of the necessary of wearing masks to protect people from pandemic COVID-19. Regardless of type, size and color of the mask, any identity verification system will face a serious problem to identify the person who wear a mask, since the mask occludes the deterministic features of the face [12]. As a result, the accuracy rate of face recognition will be decreased. For that, a huge number of researches are implemented to improve the efficiency of recognition systems, whether it aim to detect of the face is masked or not, or to recognize the person face.

2 Related Work

Face detection and recognition is considered as the most important issues in tracking and recognition systems, regardless the sources were a surveillance, digital camera or video.

One of the most prominent challenges facing systems specialized in discovering and recognizing faces, and it constitutes a challenge that still constitutes a research material in this field is the factors affecting face images such as pose variation, different locations, illumination, expression variation and partially occluded faces as mentioned in [13]. The research for resolving such problems was based in using several approaches that use LBP (Local Binary Pattern), Voila Jones and Histogram.

Evaluating efficiency and performances of these algorithms are presented in many studies, where authors in [13] presented a comparative study to review the performance of these three algorithms and focused in their study on False Negative rate [FNR] and True Positive Rate [TPR]. According to their study as well as in [14], Hog face algorithm founded as the most accurate and effective with (92%) accuracy. The capability of Hog descriptor for overcoming the most detection problems is conducted by [15]. The proposed approach focuses on extracting orderless features from the image. The proposed approach based on converting numerical vectors to “codewords” since the descriptors are presented as numerical vectors to produce what called a codebook”. Representing histogram could be achieved through mapping of each image feature to the “codeword”.

The use of histogram has contributed as a basis for many of the research that contributed to the development of facial expression recognition systems. In [16]. Here, authors proposed a W_HOG feature in their framework which based on several stages, face detection and normalizing, transforming spatial domain feature into frequency domain using (DWT), then feature extraction by retrieving (HOG) feature as W_HOG feature. Multiclass SVM has been used for recognition. Such approach has been tested for different dataset [17], [18], [19]. The new approach shows a significant improvement and better performance regarding the accuracy and time for recognition.

In spite of the progress that achieved last decades in face recognition systems, it still a hot topic for researchers because of the variation in different factors which should be considered as mentions early. The Local Binary Pattern (LBP) played a significant role in this field. Image recognition is based on labeling the pixels of an image by thresholding the 3x3-neighbourhood of each pixel with the center value and considering the result as a binary code. As shown in [20], Authors proposed to divide the face image into facial regions then extract LBP and construct a global feature histogram that represents both the statistics of the facial micro-patterns and their spatial locations. The nearest neighbor classifier in the computed feature space with $\chi 2$ as a dissimilarity measure for face recognition. For improving accuracy, authors in [21] presented a hybrid LDP+ELBP Feature Extractor with a voting classifier operators for recognizing facial images where the face area is divided into small region from which LBP/LDP histogram could be extracted.

According to [22], LBP descriptor has a major disadvantage, the sensitivity to noise and characterizing different structural pattern to the same code, consequently, reduction the discriminability. Authors proposed a new approach where a robust framework called (CRLBP). The proposed approach based on replacing each center pixel with its saver age local gray level which leads to more robustness and stability. An impressive result to noise reduction was achieved during the experiment from four texture databases.

Authors in [23] proposed a mask- aware face recognition system for identifying images with and without mask. Several hand-craft descriptors are evaluated (LBP, HOG, LDOP) with using support vector machine (SVM). A deep learning dynamic model proposed to recognize the facial mask image. Real-World Masked Face Recognition Dataset (RMFRD) that consisting of 426 subject, 1945 with facial mask and 88500 without. LDOP descriptor for facial mask detection gave a high accuracy around 99:60%, where 24% the performance degradation was reported for deep learning based ResNet-50 face recognition model in the presence of facial mask.

In [24], different methods were used for face recognition. Authors proposed (VGG16, and MobileNetV2) as deep learning architecture and (HOG) technique for extracting features from images. Classification is performed using a SoftMax and (SVM). Different assessments using different approaches and models on unmasked faces dataset and mixture (masked and unmasked) dataset are provided. The results showed that the best accuracy of 96.8% was achieved with MobileNetV2 and SoftMax layer on mixture dataset.

3 Proposed Methods

The proposed face recognition framework has 3 main steps see Figure 2; first the face area is detected from whole image using Dlip C++ library to determine 86 landmark points that represent the face area coordinates that will be used for segmentation. In the second step, a mask detection algorithm based on HOG features descriptors followed by SVM to classify the image as masked or unmasked face image are applied to the segmented images, and finally the template matching method is applied.

1. HOG is one of the best algorithms that have been developed to overcome the object detection problem regarded to size, shape and orientations, it provides an effective grid-based descriptor that are very influential to recognize and detect faces with illumination changes, pose and occlusions.

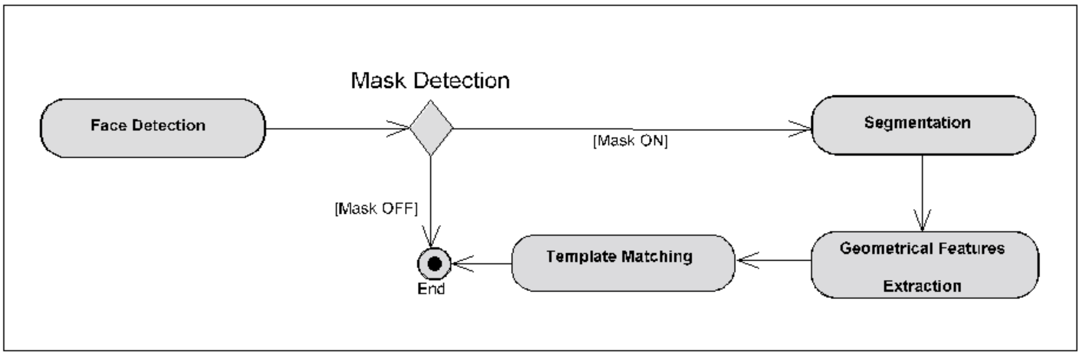

Fig. 2 the main steps of our proposed recognition system

After the HOG features are extracted from face images, these features are applied to SVM classifier for label prediction. Our proposed system utilizes SVM because it is one of the most powerful approaches to perform machine learning tasks, due to its mathematical foundation for statistical learning SVM is used for feature reduction, classification, novelty detection tasks and regression. In our unconstrained face recognition system SVM was used to find a discriminant function that can predict correct labels for new instances form independent and identically distributed (iid) HOG features dataset. SVM can be used as a discriminant technique, it solves the problems in an analytical way, and it always provides optimal hyper plane parameters. For a given training set, a training will return a uniquely defined SVM model parameters using data from the input space to the feature space. Moreover, the masked images are applied to segmentation process to define the coordinates of the unmasked partition of the face (eyes area) based on the landmarks extracted from the DLip code.

2. In the second main step a geometrical feature extraction technique based on Contourlet transform is applied to extract a robust discriminating feature from the segmented images. As the traditional transforms are very smooth and effective to detect discontinuity in a one dimensional pricewise, it represents signal discontinuities as point of discontinuities. Wavelets like transforms are effective in isolating discontinuities at the edge points, but their representations fail in detecting smoothness within the contour. Many methods were developed to improve this problem, the Pyramidal Directional Filter-Bank [26] solve the block-based approach of Curvelet Transform by applying directional filter bank to the whole scales at every resolution, which solve the curve discontinuities representation but with high redundancy. Utilization of Contourlet Transform outperforms the weakness of other transforms in term of curve representation with acceptable redundancy rate. The Contourlet can be used to transform images that cannot provide separable wavelets, as it is a multiscale transform and can be used in directional decomposition of a single, it uses a combination of modified Laplacian Pyramid [27, 28] to detect low frequencies into several directional sub-bands (stop leaking) and a Directional Filter Bank to detect high frequency components (directionality).

3. Finally, in the last step the distance between extracted face template and stored templates are calculated using Euclidian distance to accept or reject the claim.

4 Implementation and Experimental Results

To test our proposed algorithm, we used the Masked Face-Net dataset [32] with 10000 randomly selected images (out of 133,783 images) from both correctly masked faces (CMFD) and incorrectly masked faces (IMFD) sets, as it is the only database in the literature that permits to check if the face worn a mask correctly or not. First, and to detect the face area, the DLip method (dlib C++ Library) was applied over selected dataset of 10000 images, the method extract the face features using HOG descriptor and feeds the descriptor data to linear SVM to segments the face area see fig 3. The face detector was able to correctly segments 4784 images from CMFD and 4777 images from IMFD sets.

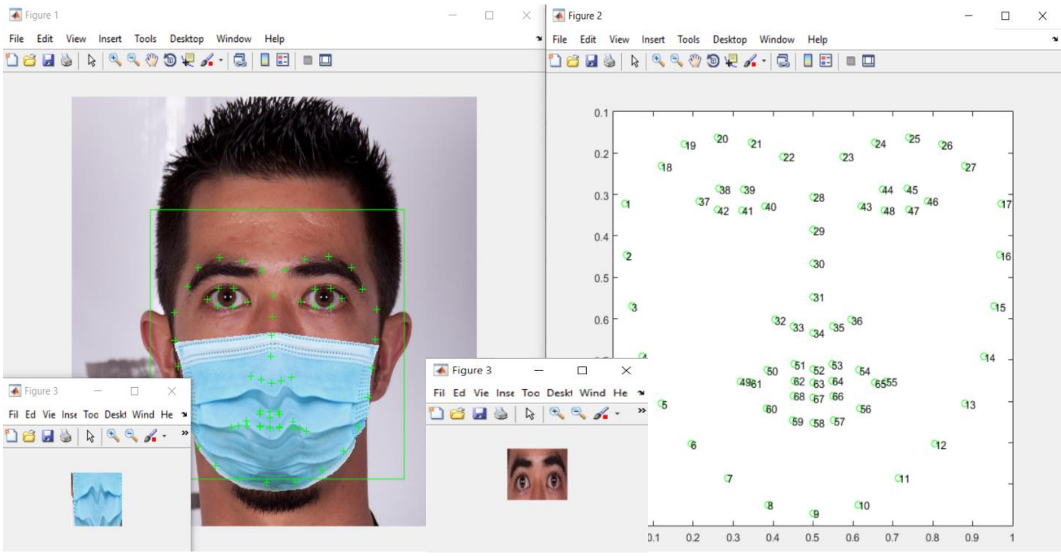

Fig.3 Face Detection and Landmarks Descriptor

As shown in the above figure, the 86 landmarks extracted from face detector steps were utilized to define and segment the lower mask area and the upper partial face area from face images. After the segmentation process the masked part of the was applied to HOG algorithm to extract oriented gradient descriptors as following:

$$Magnitude = \sqrt{{f_x}^2 + {f_y}^2}$$

$$Direction = \text{atan}\left(\frac{f_y}{f_x}\right)$$

Where, f_x and f_y is the function of gradient in both x and y direction. A sliding windows of 16×16 were used which produce a total of 324 HOG descriptor. For classification and to predict weather the face is wearing mask correctly or not, the extracted HOG feature vectors of the lower face area from 4784 CMFD and 4777 IMFD images (see fig 4) were applied to SVM.

(a) (b)

Fig. 4 (a) CMFD (b) IMFD

The SVM classifier is a supervised learning algorithm which is used to define the margin area between two different sets and defined as:

$$y = sign\left(\sum_{i=1}^{n} y_i a_i K(x, x_i) + b\right)$$

Where

where x is the feature vector of HOG feature, $y \in \{+1, -1\}$ is a label of correctly or incorrectly masked image, x_i the feature vector of the i_{th} training sample which is 80% of the selected dataset, n is the number of training samples, and $K(x, x_i)$ is the used kernel function. The testing were held on 20% of the dataset and the SVM was able to correctly classify 98.73% from the testing images.

Once the face images were classified, the unmasked part of the face which represent the upper side of the whole face image should be passed to a feature extraction method, in this research we proposed to utilize a geometrical feature extraction technique based on Contourlet transform [26]. As the resulting face images have a partial portion of the face without main discriminating nose, lips and chin textural and structural features, a geometrical feature extraction method should be applied. Contourlet transform have many advantages over older method such as Curvelet and Ridgelet transforms in term of redundant features where Contourlet transform have less than 33% redundancy of the original image data.

Curve discontinuities are better approximated with directional Contourlet than traditional Wavelet like transform see fig 5, the Contourlet transform follows the standard scenario of all directional transforms

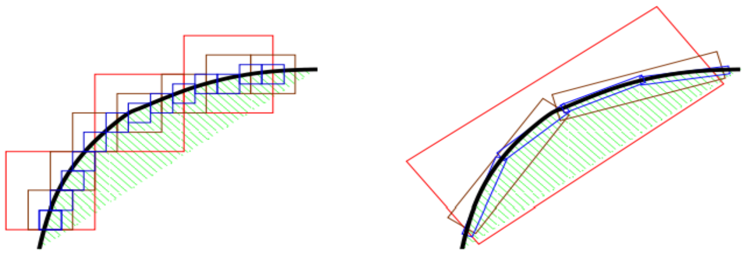

Fig.5 Wavelet representation (left) and Contourlet representation (right)

for edge representation (Multiresolution, Localization, Directionality and Anisotropy), which means the image should be decomposed at different resolution, and each edge have to be localized in both time and frequency domain.

Moreover, edge features are calculated at different orientations and finally the specific edge windows should obey the anisotropic scaling low where $width \approx length^2$. fig 6 shows the Contourlet transform.

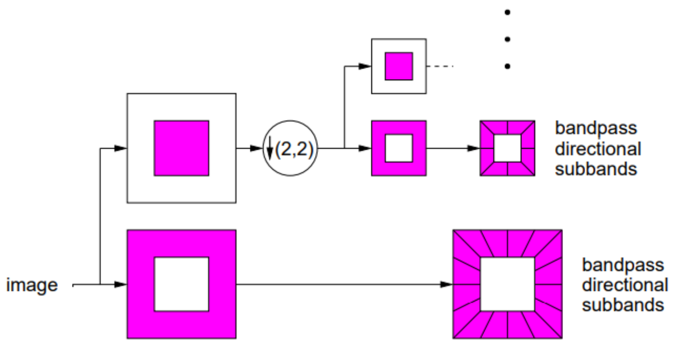

Fig .6 Contourlet Filter Bank

First, Laplacian pyramid (LP) is computed over a multiscale decomposition in octave bands directions, and then a directional filter bank is applied to each band-pass channel. In our implementations of Contourlet transform we used 4 level of decomposition and 7 biorthogonal filter, from each level and to eliminate the redundancy the extracted features from each level were sorted in descending order as a discriminating coefficients will have the highest value when a curve feature fit inside a directional wedge. Finally, the first $\frac{1}{4}$ (25%) of directional features that represent the highest discriminating features from each level were stored for matching process.

Finally, and to reduce the matching time introduced by using a complex matching methods [33], a simple Euclidian Distance was used to find the similarity between the claim and the stored face template as following

$$L_0(a,b) = ||a-b||_0 = \sum_{i=1}^{n} \frac{\mathbb{1}(diff(a,b) \leq m)}{n}$$

$$\text{Where } \mathbb{1}(a=b) = \begin{cases} 1 & if\ (a-b) \leq m \\ 0 & if\ (a-b) \geq m \end{cases}$$

Where n is the features vector size, the distance will be in the range between 0-1, where 1 = no match and 0 = complete match. We used a threshold distance of 0.31, and we got 97.86% correctly recognized images over the selected subset of Masked Face-Net database.

Table 1: the results of the comparison between the proposed method and some recent method

Method	Recognition Rate
HOG + Deep Learning [24]	96.8%
Codeword HOG [15]	92%
CNN + features weight [30]	93.8%
AlignedReID + ResNet-50 [31]	91.46%
Our proposed method	97.86%

Authors in [15] improved face recognition by proposing a new function namely fair loss, the method reinforce machine learning to learn margin adaptive strategy using CosFace to get competitive results from imbalanced datasets. While authors in [30] applied CNN architecture on MaskedNet to generate different feature to map the occluded face images, by assigning lower weight to hidden units and higher weight to non-occluded facial parts.

In [31], authors proposed a new method that extracts local and global features using AlignedReID method to re-identify faces from surveillance scenarios to define the masked and not-masked faces, ResNet-50 is used to extract feature map from the input images, then a global features and local features are generated to measure the similarity of distance between unmasked images and masked images. Based on the obtained results, the use of multiresolution geometrical features extraction method outperforms the non-robust features extracted using a textural features extraction methods.

5 Conclusion

In this research a complete unconstrained face recognition framework was introduced. The proposal starts with reliable mask detection algorithm based on extracted HOG features fed to SVM to classify face images as masked or unmasked. Then we proposed a segmentation method to locate the eyes partition from masked faces by utilizing the landmark points coordinates extracted using a well-known DLip face detection method. Moreover, a multi-scale 2D features extraction technique based on Contourlet transform was applied to extract discriminating geometrical features from noisy face images. Both segmentation and feature extraction methods were tested on the Masked Face-Net database and achieved a 97.86% recognition rate.

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