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Research paper

Partially Occluded Face Recognition using Dynamic Time Wrapping

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Abstract

It is evident that the research contributions in the domain of partially occluded image are quite sparse. This paper presents a novel method, termed as Partially Occluded Face Recognition (POFR) using Maximally Stable External Regions (MSER) feature sets and Dynamic Time Wrapping (DTW). This proposed system works in two phases: Phase-I, creates an annotated database using the non-occluded images, and Phase-II focuses on the detection and recognition of partially occluded probe image, which is also annotated using the mechanism of phase-I. Hence, POFR selectively and dynamically calibrates the annotated database as per the annotation of the probe image. Further, the similarity between the feature sets of the annotated database images and the probe image is computed, using the principle of DTW. The POFR is tested on the face images from University of Stirling dataset and the average accuracy of face recognition is recorded as 88%. This method promises a computational advantage for partially occluded face recognition without any prior reconstruction or synthesis. The POFR finds direct applications in surveillance and security systems.

Keywords: *Partial Occlusion; Face Recognition; Dynamic Time Wrapping; Maximally Stable External Regions (MSER).*

1. Introduction

Last four witnessed has shown tremendous growth in the field of machine vision. Human face recognition has evolved as a potential branch of machine vision. The applications of computer vision has received remarkable attention in face tracking [1-2], crowd analysis [3], steganography [4], facial expression [5], driver fatigue detection [6] and many more. Automated face recognition is a natural and accessible passive biometric practice in the field of machine vision. The capability of face recognition in an unconstrained environment demonstrates system robustness. The major applications of face recognition spans from law enforcement/securities to commercial applications. Face recognition is primarily classified into Face Identification and Face Verification. The face identification is a one-to-many problem, where the probe (test subject) face image is matched with all the images in the target database. Generally, the common features of probe image is matched with those of database images, for face identification. Face identification can be of two types: closed set and open set identification. If the probe image is identified amongst the available database images, identification is in closed set otherwise it falls under open set. Face verification is termed as one-to-one matching problem that compares a probe face image with the target database image.

2. Face Recognition Methods

Face recognition methods are broadly classified into three categories: Holistic, Local and Hybrid methods. In holistic methods, the feature set is generated from the entire face and is represented by a single dimension feature vector and this feature vector is also called global face feature vector. The major challenges of holistic method are illumination variation, orientation and scaling factor. Turk M. *et al*. [6] proposed utilization of Eigenfaces for face recognition. Face recognition using Fisherfaces was suggested by Belhumeur P. *et al*. [7]. Pentland A. *et al*. [8] applied view-based Eigenfaces approach for face recognition.

Featured based methods are synonym of Local Methods which utilize the location and local statistics of facial features such as nose, mouth, eyes, chin, and forehead outline. Generally, Local methods outperform holistic methods in terms of classification accuracy and are more robust against the variation in facial expressions, illumination difference and partial occlusion. The pioneer of local methods were Timo *et al*. [9] who used texture analysis for face local features. Utilization of Discrete Cosine Transform (DCT) individually on the non-overlapping face patches for face recognition was proposed by Chen W. *et al*. [10] and Ekenel and Stiefelhagen [11]. Hybrid colour space and hybrid Gabor-LBP-DCT based face recognition was proposed by Liu Z. and Liu C. [12]. Patch-based Gabor features using local classifier for high resolution images was suggested by Su Y. *et al*. [13].

The combination of global and local methods is called Hybrid methods. The hybrid methods are designed on the principle of human perception. Hybrid methods are used to consider local as well as global features to achieve the robust face recognition. The computational complexity of hybrid methods is usually high due to overburden of global and local features matching simultaneously. Fang Y. *et al*. [14] proposed the hybridization of global Principal Component Analysis (PCA) and component-based local feature extraction by Harr wavelets. Wiskott L. *et al*. [15] presented Elastic Bunch Graph Matching model for face recognition. The combination of multi-scale and multi-orientation Gabor filter and

Local Binary Pattern (LBP) was investigated by Zhang W. *et al*. [16]. The hybridization of local features obtained from Gabor and global features from Fourier suggested by Su Y. [13].

2.1. Dynamic Time Wrapping

Dynamic Time Wrapping (DTW) algorithms are used for measuring the similarity between two temporal sequences. DTW can be applied on any data which transforms into a linear sequences, such as video, audio and graphics data. DTW is successfully implemented for automatic speech recognition, on a varying degree of speaking speed and can be utilized for partially shape matching. DTW can calculate optimal match between two temporal sequences [17-18]. DTW is effectively applied in Handwriting recognition [19, 20], signature verification [20, 21], and finger print verification [22-24]. An optimal wrapping path can increase the speed of DTW using four constraints namely *Monotonicity*: Assures that features are not repeated in the alignment, *Continuity*: Promises that the alignment does not omit important features, *Boundary*: Bonds the alignment and does not consider partially one of the sequences, and *Wrapping Window*: Guarantees that the alignment does not try to skip different features and gets stuck at similar features.

Although several techniques has been proposed in the field of face recognition, research contribution on face recognition in partially occluded images is quite sparse. The challenges in partially occluded face recognition, offer scope for the development of newer and better-performing computational algorithms as well as an automated Partially Occluded Face Recognition (POFR) system [25].

3. Proposed method: POFR-DTW

The POFR techniques, based on the human intervention can be classified into two classes: semi-supervised and fully-automated face recognition [26]. In a semi-supervised approach, the occluded region is manually guided for detection, whereas in its counterpart, the system will automatically detect the occluded face based on the non-occluded face region. Proposed method falls under later category where system will automatically detects occluded face and recognizes the partially occluded face based on partially available face information. Dynamic Time Wrapping is used to compute similarity between two image profiles. The DTW algorithm is used to find the optimum alignment and score between two signals. Rather than Euclidean distance, DTW is a robust distance measure for time series. It allows similar shapes to match even if they are out of phase in time axis [27].
POFR-DTW works in two phases:

Phase-I : Annotated Database Creation and
Phase-II : POFR using DTW.

The Partially Occluded Face Detection (POFD) and annotation is done using [28]. Phase-I is done based on the devised algorithm in [28] that aims to automatically detect face components individually and it starts mostly from un-occluded face component called Nose. It is very hard to cover up without drawing suspicions. Keeping nose component as a reference, algorithm searches the surrounding area for other major facial features, if any. Once face parts qualify facial geometry, those parts are normalized (scale and rotational) and tagged as an annotation about each facial features so that partial face recognition algorithm can be adapted accordingly with the test image. Maximally Stable External Regions (MSER) features (FL, FR, FN and FM) are extracted from each facial component and are stored in an annotated database along with the extracted face components such as left-eye (LE), right-eye (RE) nose (N), and mouth (M), (Fig. 1). MSER is used to find the corresponding image elements between two images with different viewpoints [29]. MSER extracts a comprehensive number of corresponding image elements that contribute to the effective matching in object recognition algorithms. Phase-II deals with recognition phase as depicted in Fig. 2.

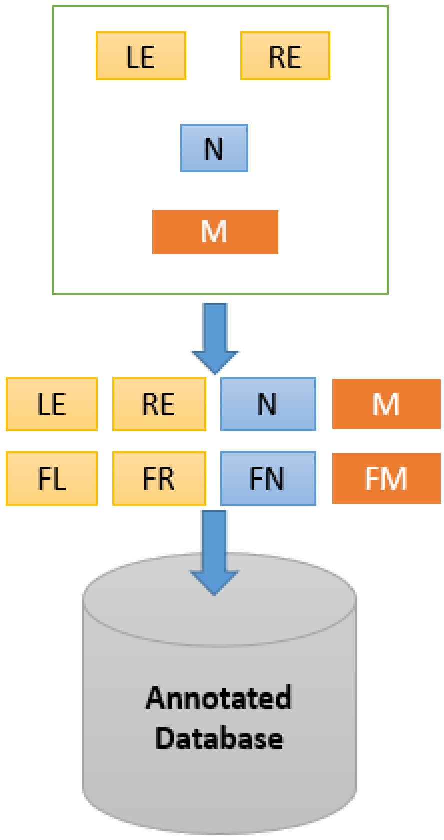

Fig. 1: Annotated Database Creation (Phase-I).

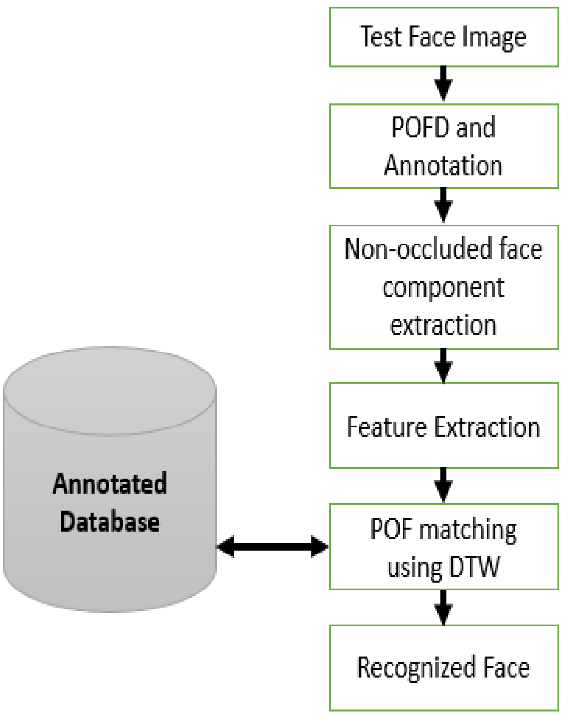

Fig. 2: POF matching using DTW (Phase-II).

An algorithm for partially occluded face recognition is given here:
Algorithm for partially occluded face Recognition
Algorithm: Face recognition using DTW
Input: Probe image I, Annotated Database

Output: Recognized Face

Step 1: Find occlusion and annotation tag
Step 2: Exclude occluded region from database and test image
Step 3: Extract feature sets for non-occluded face components
Step 4: Compute distances using DTW
Step 5: List the five top matches found in Step 4
Step 6: Most frequent match from database is a recognized face.

The occluded region detection and tagging of probe image and feature extraction is done using Phase – I. Once occluded region is identified, faces features of database is customized as per probe image. The database customization as per probe image, on the go is called as database calibration and it does not change anything in the physical database. Database calibration works on logical level. For example, if left-eye is missing in probe image then left-eye feature from all database image feature set shall be excluded during matching process. After database calibration according to probe face image, distance measure for the feature sets of probe image vs. database is calculated using DTW. If more than one feature set of face images is available in database for each subject then as per step 5 and 6 in above mentioned algorithm, most frequent match found in database is recognized as identified face. More than one features set of each subject in database increases the probability of accurate face recognition by increasing the repetition of matching frequency, as in step 6 of the algorithm. If database contains only one feature set of each subject then top most match found in step 5 shall be considered as recognized face. The efficiency of proposed method is to recognize face from partially available feature set itself. It does not require synthesis stitching or artificial building of occluded part of probe image for face recognition.

4. Results and Discussion

The POFR model is devised using Matlab on Core i5, 2.4 GHz CPU with 8GB of RAM. The experiment is restricted with four major face components features (i.e. Nose, Right Eye, Left Eye and Mouth) and the performance of POFD is evaluated using a series of experiments on standard Face Datasets [30] and on profile image database constructed by the authors, from various public domain images. The sample results shown in Fig. 3 are from 2D face images dataset of University of Stirling [30]. This dataset contains 687 Colour faces between 1 and 18 images of 90 individuals with varying illumination, resolution and have eight varied viewpoint. The authors have selected only those individuals' which have at least four face images per subject. Out of four images, three images of each individual (subject) is stored in databases along with MSER extracted feature sets. One face image per subject is taken as test image which has slight illumination and viewpoint variation. The results of randomly selected partially occluded face images, where the mouth feature and the left eye is occluded as shown in Fig. 3 and Fig. 4 respectively. In Fig. 3, the first column of rows 1-3 shows the non-occluded facial components of probe image in which mouth feature is occluded (column 1, row 4). Similarly, in Fig. 4, the first column of rows 1-3 shows the non-occluded facial components of the probe image in which left eye feature is occluded (column 1, row 4). Corresponding top four matching of facial components are shown in column 2 - 5 of rows 1- 3. Last row shows full faces voted by top four face components matching as depicted in step 6 of the proposed algorithm. The intermediate results of the proposed algorithm varies based on type of feature occlusion, see row 4 of Fig. 4. This issue is taken care by voting mechanism, the most frequent matching of face is considered as recognized face.

Fig. 3: POFR using DTW; Column 1 and Rows 1, 2 and 3 shows automatic detected non-occluded face component named T-Nose, T-LEye and T-Reye of test image. Column 2 to 5 of Rows 1 to 3 shows corresponding top four match find in database using DTW. Column 2 to 5 of Fourth row show corresponding face match in database. T-Face is a probe image in which mouth feature is occluded.

Fig. 4: POFR using DTW; Column 1 and Rows 1, 2 and 3 shows automatic detected non-occluded face component named T-Nose, T-Mouth and T-Reye of test image. Column 2 to 5 of Rows 1 to 3 shows corresponding top four match find in database using DTW. Column 2 to 5 of Fourth row show corresponding face match in database. T-Face is a probe image in which Left Eye feature is occluded.

5. Conclusion

In this paper, a partially occluded face recognition technique using dynamic time wrapping is presented. This approach recognizes face from partially available features set and does not requires synthesis or reconstruction of occluded face part for face recognition. More than one set of face features of each individual are helpful to increase the accuracy of POFR-DTW. Through the experiment, it is evident that partially occluded face recognition using DTW exhibits promising results and find places in surveillance and security applications.

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