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Partially Occluded Face Recognition Using Dynamic Approach

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Abstract-- Partial occlusion is one of the most challenging problems for recognizing faces captured in unconstrained conditions. In uncontrollable environments, the occlusion detection is generally difficult. This paper focuses on direct face recognition in the presence of the partial occlusion. To solve partial occlusion problem, a method based on Dynamic Programming is proposed. This method involves dividing both gallery (database) and probe face images into sub-patches and then to combine all the patches to form a patch sequence. Euclidean distance is calculated between the patch sequences and then Dynamic Time Warping alignment is applied to find the minimum matching path between the probe and gallery sequences. Image-to-Image and Image-to-Class matching have been performed by the proposed method. The proposed method performance has been evaluated by the experiments on face databases like ORL and IAB database containing occluded faces. This method provides optimal solution and gives better recognition rate. This method works better even if the images are having occlusion and has good performance.

***Index Terms*—**Dynamic Time Warping, Image-to-Image, Image-to-Class, Occlusion, Patch.

I. INTRODUCTION

Face recognition is a biometric technique capable of automatically verifying or identifying a person. In image analysis and understanding, automatic face recognition has received increasing attention in various applications like access control, law enforcement, surveillance, security, etc. An efficient face recognition system can be developed by considering the factors such as the acceptable system speed, high recognition accuracy, and easily upgradable system based on the progression in technology.

Partial occlusion is one of the challenges associated with face Recognition. In real world scenarios, faces are easily occluded by the objects in active or passive ways. Faces may be partially occluded by the subjects themselves. For example, people wear facial accessories such as mask, sunglasses, hat, and scarves for personal or traditional reasons. Sometimes the objects that are in front of the face, for example other's faces, hand, food, mobile phone, and pets. Faces can also be affected by environmental conditions like extreme illumination, limited field of view, and poor image quality. In crime or security related scenarios, people tend to occlude their faces to hide their identity, which will make the face recognition task difficult. Fig.1 shows some examples of partially occluded faces.

Two face image distance will increase when the discriminating facial features are distorted by the occlusion. This reduces the performance of the recognition. Occlusion of facial landmarks leads to registration errors, which will degrade the recognition rate [1]. There are two cases to be considered in face recognition with occlusions, one is occluded area detection and second is the occluded area restoration. In real-world scenarios, it is not always necessary for detection of occlusion [3], [4] since no availability of prior information and unpredictable occlusions types. Recognition of face with occlusions directly is very practical in many applications. Research into the occluded face recognition problem is very important since it is an overlooked problem in face recognition.

II. LITERATURE REVIEW

There are several face recognition systems under controlled environments. These systems are based on three approaches: Feature, Holistic, and Hybrid. The popular existing methods for face recognition are Eigen faces [5], [6], Fisher faces, Linear discriminant analysis [7], [8], and local binary patterns [9] etc.

Eigen faces is the first successful method for facial recognition [6]. This involves projecting an input image into

Fig.1. Partially occluded faces

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a new dimension called face space (eigen space) and then computing the distance between the projected and known faces. Principal component analysis is used for calculating eigen vectors and eigen values, which represents the eigen space [5]. This method is simple and the most commonly used, but it is not invariant to changes in poses and scales.

Face recognition using the Linear Discriminant analysis is called the fisher face method [7], [8]. Eigen face uses linear PCA. It is not optimal to distinguish one face class from others. The fisher face method finds a linear transformation to higher the between-class scatter and lower the within-class scatter. Test results show that LDA is better than Eigen face using linear PCA. Ahonen et al. Applied local binary patterns for the task of face recognition [9]. LBP is a texture descriptor. In this, a binarised pattern is used as features. The face image is divided into many sub-blocks (patches), and the histograms of the local pixel-wise patterns are calculated for every patch. Weighted, finally, classification is done.

Face recognition under controlled environments has been in scene for the past many years, but recognition under uncontrolled conditions like illumination, expression, pose variation and partial occlusion is a current issue. Therefore, different strategies have to be adopted to solve these problems. There are three different types of approaches for the direct recognition in presence of partial occlusion. Reconstruction based approaches are the first type. Sparse representation based clarification (SRC) [10], Gabor feature based SRC [11], and SRC with Markov random fields [12] are some of the approaches comes under reconstruction based, these consider the occluded facial recognition as the reconstruction problem. These approaches have high computational cost and require many samples to represent a test image. The second type is local matching based approaches, Local probabilistic subspace [13], self organizing map(SOM) [14], and partial Distance [15] are some of the examples, these approaches require training. Local matching involves dividing a false image is into multiple small regions (patches, small circles or ellipses), and analyzing the affected and unaffected parts of the face in isolation. The third type is an occlusion insensitive feature based, Local nonnegative matrix factorization [16], and Local salient independent component analysis [17] are some of the examples extract the local occlusion insensitive features from face images.

The sparse representation based classification [10] involves reconstruction of a clean image from an occluded probe image through a linear combination of gallery images and occlusion dictionary of the basis vectors, and then assigning the occluded image to the class with the best reconstruction. The classification is done based on the most accurate reconstruction of the probe image. This method requires pixel-level alignment of images. M Yang et.al [11] proposed a method to improve the SRC model for face recognition. Compressed Gabor-features of the image are used to form an occlusion dictionary. This method reduces the computational cost of SRC. Zhou et al. [12] used a Markov Random Fields (MRF) model (SRC-MRF) to find the contiguous occlusions, which improves SRC's performance. There is no prior information on location, size, shape, color, or number of the occluded regions; the only prior information is about the occlusion is that the corrupted pixels are likely to be adjacent to each other in the image plane. The performance of the SRC-MRF drops when the probe images are not well aligned.

Martinez proposed a local probabilistic method [13] which divides a face into k local parts, then learns k eigenspaces from database images. Then all database images are projected onto these subspaces and each class is modeled using k Gaussian mixture models (GMM). A test image is also divided into k parts and projected onto the corresponding subspaces. Then the local distances (i.e., probabilities) to each GMM of a specific class can be computed and the sum of local distances can be used as the similarity measure between a given probe and a specific class. Tan et al. [14] proposed self-organizing maps (SOM) instead of the mixture of Gaussians to model each class. SOM is trained such that a single SOM map was trained for all samples and then a separate SOM map was trained for each class. K-nearest neighbor classifier is used for recognition. In this, pre-training is required before face recognition. Tan et al. [15] further applied the partial distance (PD). It gets the significant partial similarities between face images, which can reduce the negative impacts of the unreliable features due to occlusions.

A Selective Local Non-Negative Matrix Factorization (S-LNMF) based method for occlusion based face recognition was proposed in [16]. This involves dividing a face image into non-overlapping parts, applying PCA to each part and then detecting distortions using 1 NN. J Kim et. al [17] proposed Local salient technique using ICA (LS-ICA) for face recognition with partial occlusion. It is a local part based representation. Kurtosis maximization was used for creating part-based local basis of the image and then the LS-ICA was used for basis image selection which contained only discriminate localized features like lips, chin, eyes, nose etc. for face recognition.

In this proposed approach for the occluded Face Recognition, recognition is performed with and without the presence of the occlusions. An approach using method Dynamic Time Warping (DTW) for Image-to-Image and Image-to-Class matching is proposed and this is a local matching based approach and training is not required. This approach involves dividing both gallery and probe face images into sub-patches and then to form a concatenated sequence in the raster scan order. In this way, a face is represented by a patch sequence which has order information on facial features. DTW distance is calculated between the probe sequence and gallery (database) sequences.

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III. PROPOSED APPROACH

The proposed approach uses DTW based on dynamic programming for matching. Fig. 2. Shows the proposed system model. In the proposed approach, query (probe) image is partitioned into K non-overlapping sub-patches of m×m pixels. All the sub-patches are then

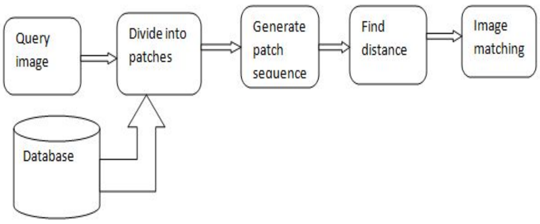


Fig.2. Proposed system model

(a)

(b)

Fig.3. (a) Dividing a face into patches (b) Patch Sequence

concatenated in raster scan in order to form a single sequence called patch sequence. Similarly for all the database images, patches are generated and also patch sequences (shown in Fig.3.) are generated. Then the distance between the query image and the images in the database is calculated using local distance measures like Euclidean distance. And then optimal alignment is performed with DTW. Finally, classification is based on the similarity measure and the recognized image is retrieved. The proposed work uses alignment methods DTW as a similarity measure.

IV IMPLEMENTATION USING DYNAMIC PROGRAMMING

A nonlinear mapping produces a more intuitive similarity measure, allowing similar patterns to match even if they are out of phase in the time axis. A linear mapping aligns the k-th point on one time series with the k-th point on the other will produce a poor similarity score. DTW is a non-linear mapping technique based on dynamic programming.

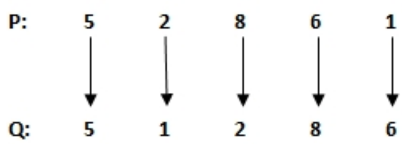
Dynamic programming is an optimization approach that transforms a complex problem into a sequence of simpler problems. Its essential characteristic is the multistage nature of the optimization procedure. More than the optimization techniques described previously, dynamic programming provides s general framework for analyzing several types of problems. A variety of optimization techniques can be employed within this framework to solve particular aspects of a more general formulation. Usually creativity is required before we can recognize that a particular problem can be often subtle insights are necessary to restructure the formulation so that it can be solved effectively. Dynamic time warping can be solved using dynamic programming which always gives an optimal solution.

Image matching is implemented by defining a similarity measure between patch sequences. Once the sequence of patches is at hand, matching is performed between the patch sequences by using the robust sequence alignment method such as Dynamic Time Warping (DTW). Recognition is done using a nearest-neighbor classification scheme based on the similarity measure obtained by means of DTW [13]. DTW matches all the patches in both query and database images. This method reduces the effect of occlusion by means of non-linear matching and it is shown in Fig.4.

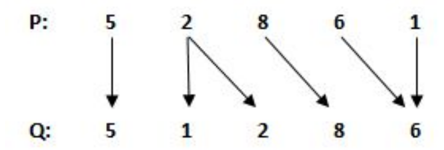
Initially, given two sequences P and Q lengths x and y, a local cost (distance) matrix R is created with size (x×y). Then this matrix is used for further procedure. This work uses Euclidean distance as local distance measure. In other words the cost of matching two individual patches is calculated using Euclidean distance or cosine distance. For each patch in the query image, best matching patch of the image in the database is found by using the Euclidean distance between the patches. Patch pair with small distance represent matching patches.

Dynamic Time Warping (DTW) calculates the distance between two time sequences by finding the optimal alignment between them with the minimal overall cost. Unlike other distance functions, DTW breaks the limitation of one-to-one mapping, and also supports non-equal length sequence. Different from the point-wise matching, DTW tries every possible warping path, then selects the one with minimal cost. So the warping path with large distance error is not considered. Warping path can be determined using dynamic programming. It is a non-linear matching algorithm. DTW allows us to find a non-linear mapping between two sequences with certain restrictions. Following constraints are considered in warping path:

(1) Boundary
(2) Monotonicity
(3) Continuity
(4) Window constraint



(a)



(b)

Fig.4. (a) Linear matching (b) Non-linear matching

Solving dynamic time warping (DTW) using dynamic programming always gives an optimal solution. Optimal matching cost between two difference patch sequences can be calculated using dynamic programming with the following recurrence relation.

D(i,j)=min{D(i-1,j-1),D(i-1,j),D(i,j1)}+d(i,j)

Here d(i, j) local cost (distance) matrix which is the Euclidean distance between the patches i and j.

Algorithm1: Dynamic Time Warping distance for Image-to-Image

Input: Probe and Gallery sequence I and M of n, m patches respectively

Output:

DTW_dist: the image-to-image distance between P and G;

Set each element in D to ∞

D[0,0]=0;

Compute local distance matrix d;

for i= 1 to n do

 for j= 1 to m do

  D[i,j]=min{D(i-1,j-1), D(i-1,j), D(i,j- 1)}+d[i,j];

 end for

end for

DTW_dist= D[n,m];

return DTW_dist

DTW can also perform matching between the query image and all the images that belong to a particular class. In DTW for Image-to-Class, occlusions are not directly removed, but by means of warping. In this, a patch of the query image can be matched to patches of database images of the same class. Because the chance that patches at the same location of all images of the same class are occluded is low, the chance that a patch of query image is compared to an un-occluded patch of database image is thus higher. The Image-to-Image distance may be larger in the case of occluded images. By exploiting the information from different database images, DTW is able to reduce the effect of occlusions.

In this, instead of performing the match between two sequences, match is performed between a query sequence and a sequence set of a particular class, so the number of possible warping path is more when compared to DTW for Image-to-Image, this can also be solved in the same way as that of DTW for Image-Image using dynamic programming. Image-to-Class mapping is shown in Fig.5.

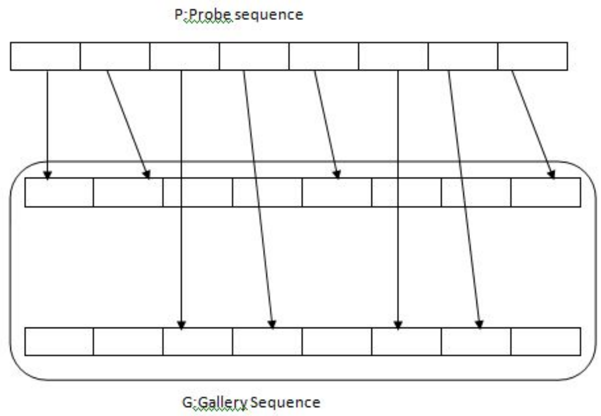


Fig.5. DTW Image- to-Class mapping

To compute DTW_dist_c(P,G), one could test every possible warping path, but with a high computational cost. Fortunately, it can be solved efficiently by Dynamic programming. A three dimensional matrix D is used to store the cumulative distance. The element $D_{n,m,k}$ store the cost of the optimal warping path of matching the first n probe patches to the set of first m patches of each gallery sequence and at the same time the m'th patch p_m is matched to the patch from the k-th gallery image. The calculation of the final optimal cost DTW_dist_c(P,G) is based on the results of a series of predecessors. D can be computed recursively as:

D(i,j,k)=min{D(i-1,j-1,1:K),D(i-1,j,1:K),D(i,j-1,1:K)}
 + d(i,j,k)

Here d(i,j,k) local cost(distance) matrix which is the Euclidean distance between the patch i of query image and patch j of gallery image of class k.

Algorithm 2: Dynamic Time Warping distance for Image-to-Class

Input: Probe and Gallery sequence I and M of n, m patches respectively

Output:

DTW_dist_c: the image-to-class distance between P and G;

Set each element in D to ∞

D[0,0,1:K]=0;

Compute local distance matrix d;

for i= 1 to n do

 for j= 1 to m do

  D[i,j,k] = min{D(i-1,j-1,1:K), D(i-1,j,1:K),D(i,j-1,1:K)}+d[i,j,k];

 end for

end for

DTW_dist_c= min[D[n,m,1:K]};

return DTW_dist_c;

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V. EXPERIMENTAL ANALYSIS

In this work all the algorithms are implemented using MATLAB. MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation.

The proposed method is evaluated using two databases ORL, and IAB (Image Analysis and Biometrics lab) databases. The Face Recognition task is performed according to two cases (without occlusion and with occlusion). ORL database consists of 400 images from 40 subjects each with 10 images. These images contain variations such as the lighting, facial expressions (open/ closed eyes, smiling / not smiling) and facial details, etc. Some sample images of the dataset are shown in Fig.6. IAB database consists of cropped and occluded face images provided by IIT (Indraprastha Institute of Information Technology) Delhi [14],[15]. This database consists of 684 images 75 subjects with different kinds of disguise variations,

i.e. occluded and un-occluded images. Some sample images of the dataset are shown in Fig.7.

Fig.6. Sample images from ORL database

Fig.7. Sample images from IAB database

1) DTW for Image-to-Image matching

DTW for Image-Image matching is tested with the ORL database. In this experiment, one image from each subject, a total of 40 images taken as database images. For testing, 5 images from 40 subjects of ORL database, i.e. total of 200 images are taken. We compared proposed approach with PCA for face recognition.Out of 200 testing images PCA recognized correctly 120 faces, whereas DTW recognized 156 faces correctly.So,the recognition rate of DTW is **78%** which is better than PCA's recognition rate of **60%.**

2) DTW for Image-to-Class matching

a) Face Recognition without occlusion

DTW for Image-Class matching for face recognition without occlusion is tested with the ORL face database. In this experiment, the database images are divided into 2 sets. The first set, consisting of 40 subjects with first 5 images, is used for training. For testing, database of 40 subjects with last 5 images and 60 non database images of total 260 images are taken. All images are re-sized to 60*45 pixels and the patch size is 5*5 pixels.

Implementation of DTW using dynamic Programming shows accuracy of about 87.3. Table I shows the confusion matrix for DTW. The first cell shows the number of true positive (TP) instances which is 191. It indicates the number of instances that are correctly identified. Second cell shows the number of false negative (FN) instances. Third cell indicates the number of false positive (FP) instances and fourth is the number true negatives (TN).

Table I: DTW for Image-to-Class matching
Without occlusion

191	9
24	36

Precision =TP/(TP+FP)=88.83%
False positive rate=FP/FP+TN=40%
True Positive rate =TP/(TP+FN)= 95.5%
Accuracy=(TP+TN)/(TP+TN+FP+FN)=87.3%

b) Face Recognition with occlusion

The proposed method for occlusion case is tested with IAB database. This database is tested under two scenarios, one with 30 classes, each with 5 images as training set and a test set with 271 images from both database and non database. Second with 20 classes with each 5 images as training set and test set of 181 images from both database and non database.

For number of classes=30 and number of images per each class=5, implementation of DTW using dynamic Programming shows accuracy of about 72.3. Table II shows the confusion matrix in this case. The first cell shows the number of true positive instances which is 181. It indicates the number of instances that are correctly identified. Second cell shows the number of false negative instances. Third cell indicates the number of false positive instances and fourth is the number true negatives.

Table II: DTW-Image-to-Class matching
(With occlusion, classes=30)

181	53
20	15

Precision =TP/(TP+FP) =90%
False positive rate=FP/FP+TN=57.14%
True Positive rate = TP/(TP+FN) =76.69%
Accuracy= (TP+TN) /(TP+TN+FP+FN) =72. 3%

For number of classes=20 and number of images per each class=5, implementation of DTW using dynamic Programming shows accuracy of about 75.69. Table III shows the confusion matrix in this case. The first cell shows the number of true positive instances which is 122. It indicates the number of instances that are correctly identified. Second cell shows the number of false negative instances. Third cell indicates the number of false positive instances and fourth is the number true negatives.

Table III: DTW-Image-to-Class matching
(With occlusion, classes=20)

122	24
20	15

Precision =TP/(TP+FP)=85.9%
False positive rate=FP/FP+TN=57.14%
True Positive rate =TP/(TP+FN)= 83.56%
Accuracy=(TP+TN)/(TP+TN+FP+FN)=75.69%

VII. CONCLUSION

In this work, Face recognition, which is robust to partial occlusion is developed using DTW as a similarity measure. Faces are divided into patches,then patch sequences are generated. DTW is applied to query and test patch sequences to find the minimum matching path. DTW for Image-to-class matching greatly reduces the effect of occlusion by means of Image-to-Class mapping. DTW for Image-to-Image and Image-to-Class are determined by using dynamic programming. This work is tested with two databases ORL and IAB. The experimental results showed that the proposed algorithms produced the best recognition rate. This work can be used in various fields like forensic and surveillance system. This work can also be implemented using linear programming which has proven to give the best solution always.

REFERENCES

[1] H. K. Ekenel and R. Stiefelhagen "Why is facial occlusion a challenging problem?" in Proc. IAPR 3rd International Conference Biometrics (ICB), pp. 299-308, 2009.
[2] X. Wei, C.-T. Li, Z. Lei, D. Yi, and S. Z. Li, "Dynamic image-to-class warping for occluded face recognition," IEEE Transactions on Information Forensics and Security, vol. 9, no. 12, pp. 2035- 2050, Dec. 2014
[3] R. Min, A. Hadid, and J.-L. Dugelay, "Improving the recognition of faces occluded by facial accessories," in Proc. IEEE International Conference Automatic Face Gesture Recognit. (FG), pp. 442447, Mar. 2011.
[4] H. Jia and A. M. Martinez, "Face recognition with occlusions in the training and testing sets," in Proc. IEEE International Conference Automatic Face Gesture Recognit. (FG), pp. 16, Sep. 2008.
[5] M. Kirby, L. Sirovich, Application of the Karhunen–Loève procedure for the characterization of human face, IEEE transactions on pattern analysis and machine intelligence. Vol. 12, January 1990.
[6] M.A. Turk, A.P. Pentland, Face recognition using eigen faces, in: Proceedings of the IEEE Conference on CVPR, 1991, pp. 586–591.
[7] Sushma Jaiswal, Dr. (smt.) Sarita Singh Bhadauria, Dr. Rakesh Singh Jadon," comparison between face recognition algorithm-eigenfaces, fisherfaces and elastic bunch graph matching", volume 2, no. 7, July 2011 journal of global research in computer science.
[8] P.N. Belhumeur, J.P. Hespanha, D.J. Kriegman, again faces vs. fishy faces: recognition using class specific linear projection, IEEE transactions on pattern analysis and machine intelligence, vol. 19, no. 7, July 1997,pp. 711–720.
[9] T. Ahonen, A. Hadid, M. Pietikainen, face description with local binary patterns: application to face recognition, IEEE transactions on pattern analysis and Machine Intelligence, Vol. 28, No. 12, December 2006,pp. 2037–2041.
[10] J. Wright, A. Y. Yang, A. Ganesh, S. S. Sastry, and why. Ma, "Robust face recognition via sparse representation," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 31, no. 2, pp. 210 – 227, Feb. 2009.
[11] M. Yang and L. Zhang, "Gabor feature based sparse representation for face recognition with Gabor occlusion dictionary," in European Conference Computer Vision (ECCV), vol. 6316, 2010, pp. 448 – 461.
[12] Z. Zhou, A. Wagner, H. Mobahi, J. Wright, and Y. Ma, "Face recognition with contiguous occlusion using Markov random fields," in IEEE International Conference Computer Vision (ICCV), Oct. 2009, pp. 1050 – 1057.
[13] A. M. Martinez, "Recognizing imprecisely localized, partially occluded, and expression variant faces from a single sample per class," IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 6, pp. 748–763, Jun. 2002.
[14] X. Tan, S. Chen, Z.-H. Zhou, and F. Zhang, "Recognizing partially occluded, expression variant faces from single training image per person with SOM and soft k-NN ensemble," IEEE Transactions on Neural Networks, vol. 16, no. 4, pp. 875 – 886, 2005.
[15] X. Tan, S. Chen, Z.-H. Zhou, and J. Liu, "Face recognition under occlusions and variant expressions with partial similarity," IEEE Transactions on Information Forensics and Security, vol. 4, no. 2, pp. 217 – 230, Jun. 2009.
[16] Oh H., Lee K., and Lee S., "Occlusion Invariant Face Recognition using Selective Local Nonnegative Matrix

Factorization Basis Images," Image and Vision Computing, vol. 26, no. 11, pp. 1515-1523, 2008.

[17] J. Kim, J. Choi, J. Yi, and M. Turk, "Effective representation using ICA for face recognition robust to local distortion and partial occlusion," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 27, no. 12, pp. 1977 – 1981, Dec. 2005.

[18] Hong Cheng, Zhongjun Dai, Zicheng Liu, Image-to-class dynamic time warping for 3D hand gesture recognition, In: IEEE ICME, 2013.

[19] T. I. Dhamecha, R. Singh, M. Vatsa, and A. Kumar, Recognizing DisguisedFaces: Human and Machine Evaluation, PLoS ONE, 9(7): e99212, 2014.

[20] T. I. Dhamecha, A. Nigam, R. Singh, and M.Vatsa Disguise Detection and Face Recognition in Visible and Thermal Spectrums, In Proceedings of International Conference on Biometrics, 2013.