INTERNATIONAL JOURNAL OF ADVANCE RESEARCH, IDEAS AND INNOVATIONS IN TECHNOLOGY

ISSN: 2454-132X
Impact factor: 4.295
(Volume3, Issue3)
Available online at www.ijariit.com

Averaging Representation of Standard Face Images and Recognition by KPCA and GFMT

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Abstract: Face recognition has received substantial attention from both research communities and the market, but still remained very challenging in real-time applications. This texture mapping of the face images to be morphed to a standard shape. Triangulation of face images with face key points image averaging technique to derive abstract representations of known faces. This standard shape improves the probability of recognition of faces. Glasgow Face Matching Test (GFMT) and Kernel PCA on image averages appear to preserve face information. Thus the approach with KPCA and GFMT has improvement in efficiency with constraints.

Keywords: Face recognition, KPCA, GFMT, Triangulation, Morphing, and Averaging.

I. INTRODUCTION

Humans often use faces to recognize individuals and advancements in computing capability over the past few decades now enable similar recognitions automatically. Early face recognition algorithms used simple geometric models, but the recognition process has now matured into a science of sophisticated mathematical representations and matching processes. Major advancements and initiatives in the past ten to fifteen years have propelled face recognition technology into the spotlight. Face recognition can be used for both verification and identification.

The major challenges in face recognition are scale changes, illumination changes, image noise, background clutter and identification and real-time performance. Face recognition involves the identification of correct face from the database. So face verification need algorithms to match the correct face and reject the unfamiliar face images in the database.

In this paper, we convert every face image to standard face and using the averaging technique to represent face image of every person. Finally, we describe how K-PCA on image averages appears to preserve identity-specific face information while eliminating non-diagnostic pictorial information. We, therefore, suggest that this is a good candidate for a robust face representation.

II. MAJOR PROCESSES

The major processes which are holding the recognition using averaging and GFMT explained in the next part.

2.1 Standard Shape

Since the face recognition is facing the problems with angle, illumination, emotional expression, facial hair, make-up, aging, different lights conditions and different characteristics of the camera. Face standard shape image of a single person is obtained from different face images in terms of angle, expression, time, illumination etc. And morph all these faces to a standard shape for the purpose of averaging. This is performed in a graphics program by overlaying an image of a face with a grid. The face is then morphed to a standard shape by applying triangulation calculation with face key points of the face image.

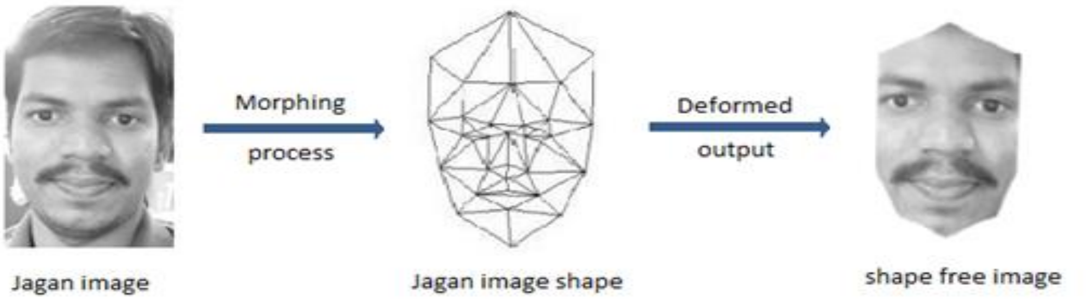

Fig. 1: Standard shape morphing process

2.2 Averaging Technique

Face standardized images of every person are averaged to a single face image by simple averaging of every image and represent it as the face image of that person in the database. All database images morphed and brought to be a single image with triangulation. Triangulation of face images with face key points image averaging technique to derive abstract representations of known faces. Since every standardized face images contain same face parts in the same location, averaging image can represent without any loss in the feature of a person.

The face is then deformed (morphed) to a standard shape, which will be used for all faces in the study. In this way, the same part of each image will contain the mouth, the eyes, and so forth. The resultant images are called “shape-free” in the literature. Finally, we describe how K-PCA on image averages appears to preserve identity-specific face information while eliminating non-diagnostic pictorial information. We, therefore, suggest that this is a good candidate for a robust face representation.

Fig. 2: Ten images of Jagankumar

Fig. 3: The results of morphing each of these images to a standard shape.

Fig. 4: The image-average of these shape-standardized images.

2.3 Kernel-PCA
Database of average face images is representing by kernel PCA for recognition. PCA is a statistical approach used for reducing the number of variables in face recognition and image compression and is a common technique for finding patterns in data of high dimension. The performance of PCA is improving using applying kernel filter in the covariance matrix. In PCA, every image in the training set is represented as a linear combination of weighted eigenvectors called Eigenfaces. These eigenvectors are obtained from the covariance matrix of a training image set. The weights are found out after selecting a set of most relevant Eigenfaces. Recognition is performed by projecting a test image onto the subspace spanned by the Eigenfaces and then classification is done by measuring minimum Euclidean distance. Here we are selecting least three Euclidean distanced average face images from databases. The main purposes of a principal component analysis are the analysis of data to identify patterns and finding patterns to reduce the dimensions of the dataset with minimal loss of information.

The Important steps involved in K-PCA are,

- Normalize the data.
- Calculate the covariance matrix.
- Find the eigenvectors of the covariance matrix.
- Translate the data to be in terms of the components.

2.4 Glasgow Face Matching Test
The task in face recognition not only limited to select most related face image from the database but also required to reject unfamiliar input face image of databases. One of the main disadvantages of PCA is that it selecting the recognition of face identity by using the minimum Euclidean distance between projected test image data and projected PCA face data sets. Here we have to select three most closely projected face image in PCA data and applying Glasgow Face Matching Test with input face image which selecting the matched image as output. We have examined a commonplace match, two full-face views in good lighting, in an attempt to mimic situations in which one is trying to optimize the accuracy of a photo ID, not to make it difficult.

III RESULT AND DISCUSSION
The shape-free morphing, plus histogram equalization, brings the images more closely into alignment than the originals. In order to match on a Mahalanobis distance, or on a Mahalanobis distance within calipers, one has to first combine covariates into a matrix of Mahalanobis distances (or list of such matrices). The use of a Mahalanobis distance match is also very important. Under this technique, all dimensions (i.e., principal components) are standardized to have the same variance, prior to Euclidean matching. The technique has been used commonly in PCA research and has been shown significantly to improve performance. The second point of note is that the image-average systems consistently outperform the instance-based versions, even though the same test images were used across all systems.

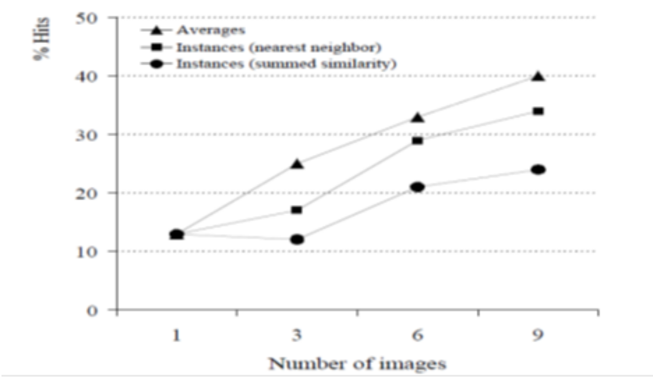

Fig.-5: Hit rate (% recognition) as a function of the number of images constituting

The above figure shows the hit rate as a function of the number of images contributing to the average. There is clear improvement in hits as more images of each face are averaged together. Indeed there is a simple monotonic improvement in performance as the images contributing to each average increases.

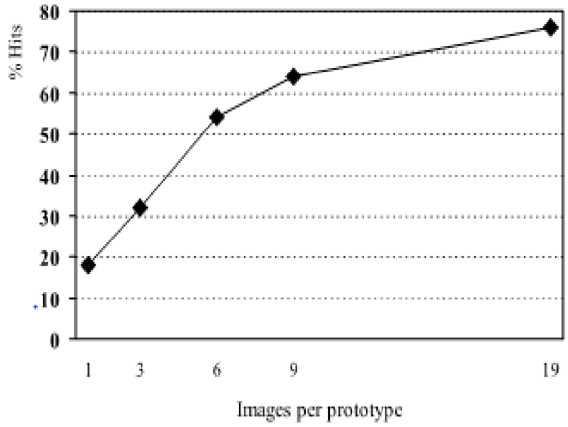

Fig. 6: Hit rate (% recognition) as a function of the number of images constituting each average representation

The matching test described above reveals substantial individual differences in a task that, at first glance, might appear relatively easy. In order to establish whether this variation reflects more general variation in visual- processing abilities, we also examined our subjects' performance on three more commonly used tests of visual matching and memory. Analyze above also contributed measures on three further tests:

(1) Recognition memory for faces,
(2) The Matching Familiar Figures Test (MFFT), and
(3) A visual short-term memory test.

Table 1 shows the overall performance levels for the GFMT and the three tests.

TABLE I
THE OVERALL PERFORMANCE LEVELS FOR THE GFMT AND THE THREE TESTS

First, the highest		**Performance on Four Tests of Matching and Memory**		
	GFMT	**Recognition memory for faces**	**Matching familiar figures**	**Visual short-term memory**
Mean	89.9	62.4	66.3	62.9
SD	7.3	10.0	21.9	9.4

Correlation with the GFMT is the MFFT. Notably, the GFMT involves a yes/no response to pairs of faces, whereas the MFFT involves a line-up of six options. Furthermore, the MFFT contains only target-present items; a match always exists.

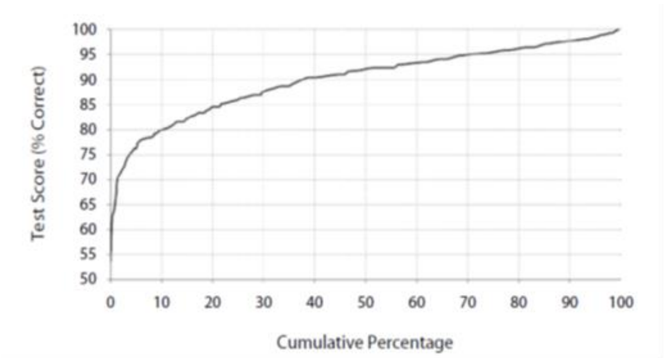

Fig. 7: Cumulative frequency of accuracies for the short version of the Glasgow Face Matching Test

CONCLUSION

Accuracy and performance of face recognition is improved by proposed methods. Firstly the outline solution of face representation is achieved by averaging of face images after standardizing of face images using morphing in a grid with position orientation. Also, the performance of traditional PCA method is improving by using kernel implementation in PCA. Finally, the problem of rejecting unknown input face images are achieving by GFMT matching with the result of projected face image from PCA data.

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ACKNOWLEDGEMENT

The authors would like to acknowledge the moral support, encouragement and technical guidance of Mrs. Shanthi M and Mr.Arun Kumar P V in this research.

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