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On Recognizing Face Images With Weight and Age Variations

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ABSTRACT With the increase in age, there are changes in skeletal structure, muscle mass, and body fat. For recognizing faces with age variations, researchers have generally focused on the skeletal structure and muscle mass. However, the effect of change in body fat has not been studied with respect to face recognition. In this paper, we incorporate weight information to improve the performance of face recognition with age variations. The proposed algorithm utilizes neural network and random decision forest to encode age variations across different weight categories. The results are reported on the WhoIsIt database prepared by the authors containing 1109 images from 110 individuals with age and weight variations. The comparison with existing state-of-the-art algorithms and commercial system on WhoIsIt and FG-Net databases shows that the proposed algorithm outperforms existing algorithms significantly.

INDEX TERMS Face recognition, biometrics, facial aging.

I. INTRODUCTION

Face recognition has been studied for several decades and majority of the research has focused on covariates such as pose, illumination, expression, aging, disguise, and plastic surgery [1]– [3]. Among all, facial aging is one of the most challenging and fascinating ones. With time, we, *homo sapiens*, age thereby leading to changes in our facial appearances. This is a natural process and is affected by several factors such as environment and life style. It is often observed that with age variations, the weight of an individual also changes. However, there is no direct relationship between the two. Within a limited period of time, there can be significant weight changes and within a long period of time, the weight may not change at all. Fig. 1 shows face images of four individuals with age and weight variations. In the first two columns, even with large age variations, there is almost no change in weight. The next two columns show that over small age variation, weight can change significantly. The combination of weight and age variations makes the problem a lot more challenging. With increasing age, the weight can increase or decrease depending on several factors such as medical conditions and changes in lifestyle. Since there is no defined structure to these weight variations, it is challenging to model them using existing anthropometric or modeling based techniques.

(a) (b)

FIGURE 1. Face images with (a) very little weight variation over a long period of time and (b) large weight variation over a small period of time.

The algorithms for age invariant face recognition can be broadly categorized into discriminative and generative approaches [4]. Discriminative approaches utilize the information available for matching whereas generative approaches use the information to model other variations. Ramanathan *et al.* presented a review of existing algorithms for addressing age variations [5] in 2009. A review of some of the recent papers after the survey are presented in Table 1.

TABLE 1. Literature review of recent papers on age invariant face recognition.

Author	Technique	Rank-1 Accuracy and Database
Guo et al. [6]	Soft biometrics and PCA+ EBGM + SOFT	52.09% on MORPH-II
Park et al. [4]	3D shape and texture spaces from 2D images	37.4% on FG-Net, 66.4% on Morph Album 1 and 28.1% on BROWNS
Mahalingam & Kambhamettu [7]	Gaussian mixture model and graph technique	25.4% for (18,69) years and 29.2% for (0,69) years on FG-NET
Xia et al. [8]	Age simulation: filling algorithm	14.63% on (10,12) years and 18.29% on (7,9) years on FG-NET
Li et al. [9]	SIFT and LBP with MFDA	47.50% on FGNET and 83.9% on MORPH Album 2
Xu et al. [10]	WLBP, UDP: periocular region	100% on FG-NET
Wang et al. [11]	"C1-S"-based on "HMAX" model and shape features	33.92% on FG-NET
Chen et. al. [12]	Learning Gabor features for facial age estimation	Age estimation mean absolute error of about 6 years on UIUC PAL
Yadav et al. [13]	Bacteria foraging fusion algorithm	64.5%: Oldest probe and 31.2%: Youngest probe on FG-NET. 54.3% :Oldest probe and 33.3%: Youngest probe on IIIT-D.

To the best of our knowledge, weight information has not been incorporated with aging in face recognition. Therefore, the contributions of this research are two fold: (1) since none of the existing face databases contains weight information, we have prepared the WhoIsIt (WIT) face database that contains age separated images of 110 subjects with both age and weight variations and (2) a learning-based algorithm is proposed that uses neural network and random decision forest to address the age and weight variations for improved recognition performance. Section 2 presents the WhoIsIt database along with baseline experiments to establish that *weight variations* affect face recognition performance. Section 3 describes the proposed face recognition algorithm. Finally, Section 4 presents the results on the WhoIsIt database along with results on the FG-Net face database [14].

II. WHOISIT DATABASE: ESTABLISHING WEIGHT AS A COVARIATE

Due to the lack of an existing database that contains both age and weight information along with face images, we have created the WhoIsIt database using public figures while trying to capture weight variations over a period of time. The images are taken from the Internet and they are mainly frontal images with minor pose and expression variations. The database consists of 1109 images pertaining to 110 subjects. Every subject has a minimum of 10 and maximum of 12 images. The age ranges from 1 to 81 years and the average is 30.95 years with an average age difference of 23 years in the images of one subject. Since exact weights of the celebrities are not available, the photos are classified in three weight groups: thin, moderate, and heavy. This categorization is performed manually depending on the visual perception of the body. For instance, face image associated with a thin body structure is categorized as thin.

There are 537 images corresponding to thin weight category, 448 images corresponding to moderate, and 124 heavy weight images. The mean age of each group is 28.03, 32.87 and 36.28 years respectively whereas the median age is 27, 32 and 35 years respectively for thin, moderate and heavy weight categories. Table 2 summarizes the information about the database and Fig. 2 shows sample images from the database. The database will be publicly available for the research community at our website.[1]

TABLE 2. WhoIsIt face database description.

Number of subjects	110
Range of age	1 – 81
Average Age	30.95 years
Images per subject	[10, 12]
Total number of images	1109
Number of images in each weight type	Thin - 537, Moderate - 448 Heavy - 124

A. ESTABLISHING WEIGHT AS A COVARIATE FOR FACE RECOGNITION

Over the years, several researchers have shown that age variations affect the performance of both human and automatic face recognition. However, the effect of weight on face recognition performance has not been established yet. To validate our assertion that along with age, weight also affects the performance of face recognition, we have performed three sets of experiments.

- *Experiment 1*: This experiment is performed to study the effect of weight variation with very small age difference. We selected two pairs of images for each subject. The first pair contains images within the age gap of one year and correspond to the same weight category such as thin-thin and medium-medium, while the second pair contains images within the age gap of one year and correspond to two different categories such as thin-heavy and heavy-moderate. In both cases, the two images must

[1] https://research.iiitd.edu.in/groups/iab/facedatabases.html

FIGURE 2. Sample images from the WhoIsIt face database.

be within the age gap of one year only. To ensure that there is no bias because of multiple occurrences of a person and the results are comparable, only one pair is chosen from one subject and same number of pairs are selected for the two sets. In the WIT database, we found 84 subjects for whom such pairs are available and therefore, we have 168 such pairs. One image from each pair is used as gallery and the other as probe.

- *Experiment 2*: This experiment is performed to study the effect of weight variation with a comparatively larger age difference of 3-4 years. Similar to the first experiment, two pairs of images are chosen - one corresponding to no weight variation and the second with weight variations. We have 188 pairs of images in both the categories; one image from each pair is used as gallery and the other as probe.
- *Experiment 3*: This experiment is performed to study the effect of weight variation for any age difference greater than one year. Similar to the first two experiments, two pairs of images are chosen - one corresponding to no weight variation and the second with weight variations. We have 208 pairs of images in both the categories combined; one image from each pair is used as gallery and the other as probe.

Fig. 3 shows sample face pairs for all three experiments. To analyze the face recognition results for these three experiments, we use a commercial system, VeriLook [15], on these pairs. The results obtained are reported in terms of rank-1 identification accuracy in Fig. 4. It is to be noted that we can only compare the two bars in individual figures (with weight variations and without weight variations) and not the three figures (corresponding to less than 1 year, 3-4 years, more than 1 year) because the number of image pairs in all three experiments are different. The results show that for all

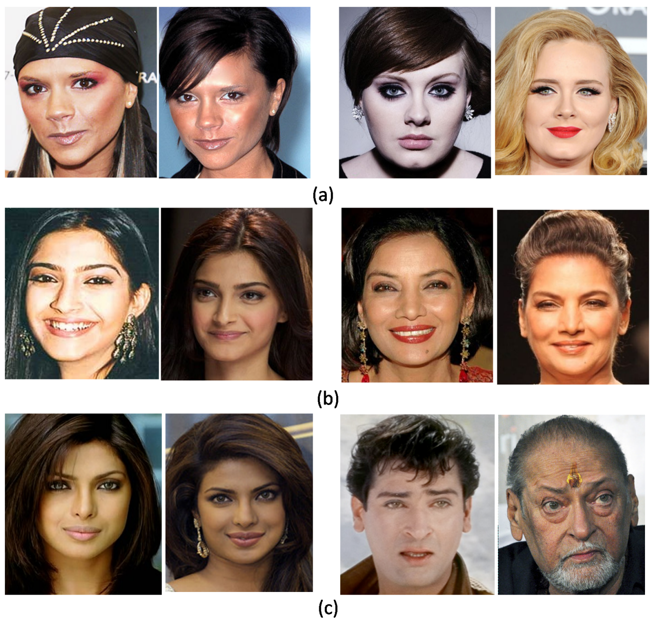

FIGURE 3. Sample images corresponding to three experiments performed with age difference of (a) less than 1 year, (b) 3-4 years, and (c) more than 1 year. The first two columns present samples from the first pair (no weight variation) and the last two columns show the samples from the second pair (weight variations). Verilook system includes face detection and preprocessing stages and it utilizes only facial region for recognition, the background information is discarded.

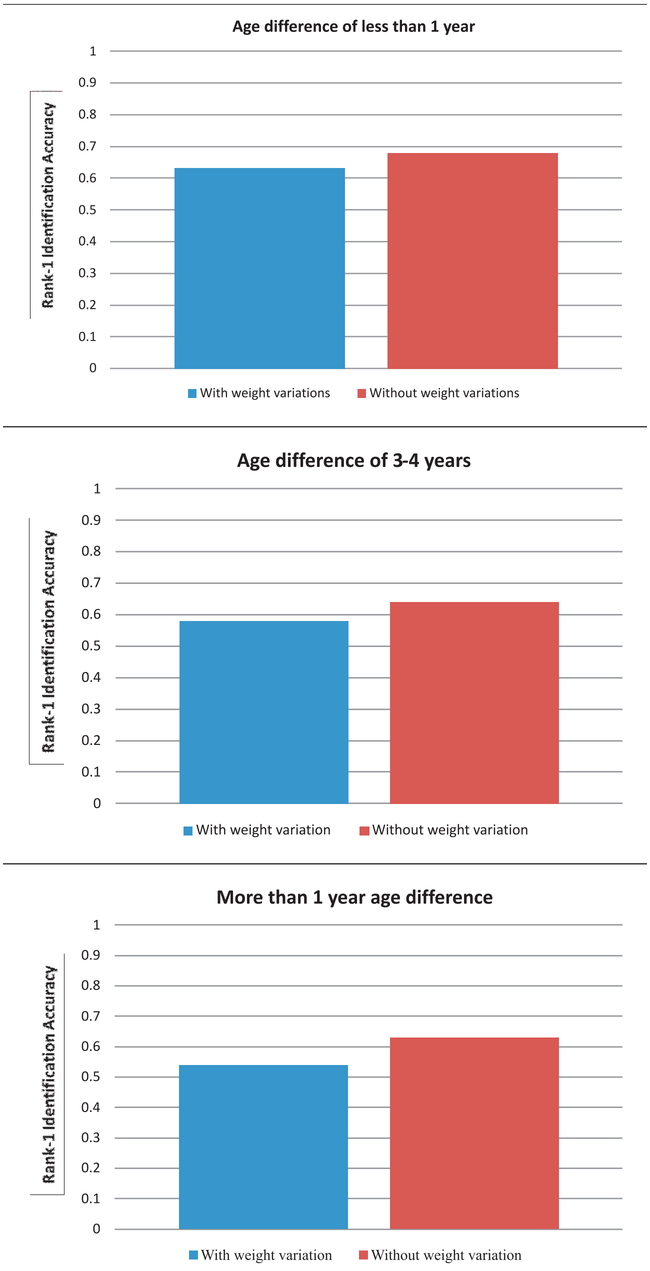

FIGURE 4. Identification results demonstrating the effect of weight variations on the WIT database. The results correspond to the three experiments performed with age difference of less than 1 year, 3-4 years, and more than 1 year.

the experiments, in-spite of the age differences, presence of weight variation reduces the identification accuracy by 7–8%. This validates our assertion that weight is also an important covariate of face recognition and the research community should address it in conjunction with aging effect.

III. PROPOSED FACE RECOGNITION ALGORITHM

This research also presents an algorithm that attempts to recognize images with variations due to weight changes. Fig. 5 illustrates the block diagram of the proposed algorithm. Designing a generative model that incorporates both weight and age variations requires significant amount of training data with all combinations of age and weight. Unfortunately, the databases available for studying age and weight variations are rather limited and therefore, in this research, we propose a discriminative algorithm. The proposed algorithm incorporates the effect of weight by training three different neural networks, one for each weight category. Since it is a learning-based algorithm, it is primarily divided into two parts: training and testing. Both the parts are explained in detail below.

A. TRAINING

Let $\mathbf{I} = \{I^i, i = 1, \ldots, N\}$ be the set of training images where N is the total number of images in the training database. As mentioned previously in Section II, The training data is divided into three categories: thin, moderate and heavy. Using all the thin images in the training database, a mean thin weight image (m_T) is created. Similarly, mean moderate (m_M) and mean heavy (m_H) weight images are also created from the training database. Fig. 6 shows mean images of the three weight categories along with mean image of the entire training database.

All the images in the training database are registered with the mean thin image, m_T, using normalized mutual information (nMI) [16], [17] to generate the registered images $\mathbf{I_{TR}} = \{I^i_{TR}, i = 1, \ldots, N\}$. nMI is computed as

$$nMI(m_T, I^i) = \frac{H(m_T) + H(I^i)}{H(m_T, I^i)} \tag{1}$$

$$H(m_T) = -\sum_{x \in m_T} p(x) log_b p(x) \tag{2}$$

$$H(I^i) = -\sum_{y \in I^i} p(y) log_b p(y) \tag{3}$$

$$H(m_T, I^i) = -\sum_{x \in m_T} \sum_{y \in I^i} p(x, y) log_b p(x, y) \tag{4}$$

where $H(\cdot)$ represents the entropy of the image and $H(m_T, I^i)$ represents the joint entropy of m_T and I^i. Equation 1 suggests that registering m_T and I^i requires $H(m_T)$ and $H(I^i)$ to be maximized and $H(m_T, I^i)$ to be minimized. In an affine registration space R, an optional parameter set R^+ is obtained such that

$$R^+ = argmax_{(R)}\{nMI(m_T, I^i)\} \tag{5}$$

The optimized parameters are then used to register I^i with respect to m_T and I^i_{TR} is generated. The registration approach minimizes the variations between the mean thin face and face images in $\mathbf{I}$. This can also be viewed as a preprocessing scheme to reduce the spatial variations between the mean face and training images.

For gallery images, it is feasible to assume that the weight parameter is known. However, with probe image, we cannot assume that weight category is known and it is challenging to estimate the weight category by only using face information. Therefore, the proposed algorithm registers the training

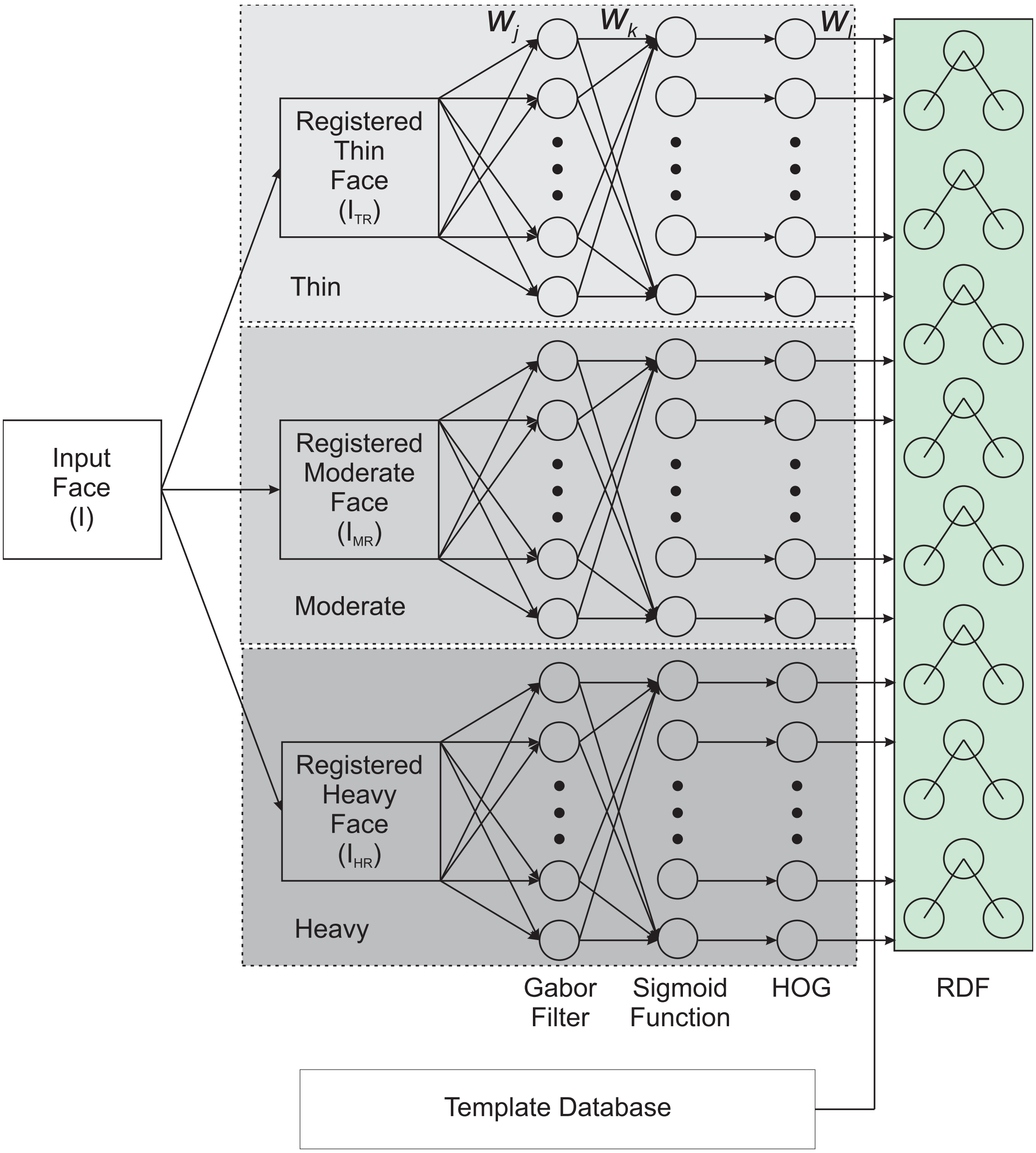

FIGURE 5. Illustrating the steps involved in the proposed face recognition algorithm.

image with respect to mean face of all three weight categories. Similar to thin category, the images are registered with respect to mean moderate face image (m_M) and mean heavy weight face image (m_H) to generate the registered face images $\mathbf{I_{MR}} = \{I^i_{MR}, i = 1, \ldots, N\}$ and $\mathbf{I_{HR}} = \{I^i_{HR}, i = 1, \ldots, N\}$ respectively.

As shown in Fig. 5, three neural networks are jointly trained, one for each weight category. The nodes in the first hidden layer of the network are composed of Gabor filters with variations in scale and orientation parameters. In the sub-network (for each weight category), 64 Gabor filters with 8 scale (s) and 8 orientation (θ) parameters are used to compute the Gabor coefficients, $G_{s,\theta}$. Therefore, total $64 \times 3 = 192$ filters are used in the complete network. The output $(\sum w_j(I^i_t * G_{s,\theta}), t = \{\mathbf{TR}, \mathbf{MR}, \mathbf{HR}\})$ of this hidden layer in a weighted fashion is used as input to the second hidden layer which applies a sigmoid function. At each node, the output of this layer is $\left(\varphi\left(\sum w_k(\sum w_j(I^i_t * G_{s,\theta}))\right)\right)$. Here, w_j and w_k represent the weights of the two layers of the neural network and φ represents sigmoid (logistic) function. The number of nodes in the output layer is same as the first hidden layer, i.e., 192. Each response is then encoded via Histogram of Oriented Gradients (HOG) [18] of size 81. Overall, the size of a feature vector is 81×192. Finally, in place of using a threshold unit for classification, a random decision forest classifier [19] is applied.

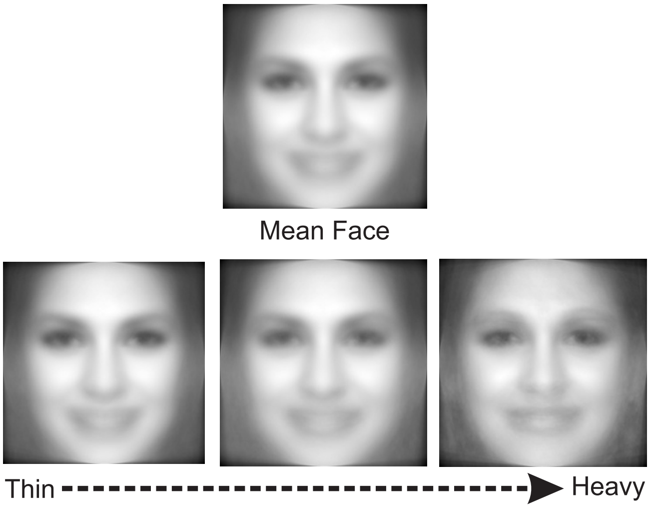

FIGURE 6. The first row shows mean face computed from the training set of the WIT database and the second row shows the mean faces of the three groups: thin, moderate and heavy.

RDF is an ensemble based multiclass classifier which is fast to train and classify. It can handle non-linearity as well as large number of classes, details of RDF can be found in [19]. Input to RDF is weighted HOG descriptors (weights being w_l) and output is *class* label. The parameters of RDF (i.e., the number of trees in the forest) and weights of the network, w_j, w_k and w_l, are trained using stochastic back propagation learning [20] and descending epsilon technique [21] with rank-1 accuracy as fitness function for improved generalization and faster convergence. Here, all three sub-networks and RDF are trained in a cohesive manner that encodes the variations due to thin, moderate and heavy weight variations over a period of time.

B. TESTING

At the probe level, a query face image is given as input and three registered images are created with respect to the three mean faces obtained during training. Gabor convoluted sigmoid outputs are used for HOG feature extraction which is provided to RDF for classification. RDF provides a probabilistic match score for each class which denotes the probability with which the query belongs to the particular class. The class with the maximum probability is selected as the final class of the image.

IV. EXPERIMENTAL RESULTS

The experiments are performed on the WhoIsIt database and the FG-Net database [14]. The results of the proposed algorithm are compared with the following algorithms:

- HOG [18],
- Local Binary Patterns (LBP) [22],
- Sparse variation dictionary learning (SVDL) [23] which is a recently proposed algorithm,[2]
- Discriminative model (DM) [9], which is the current state-of-the-art for face recognition with age variations,[3] and
- a commercial face recognition system Verilook [15] (referred to as COTS).

Face images are detected using Voila Jones face detector [24] and normalized to 200 $\times$ 200 with inter eye distance of 90 pixels. The results obtained on the two databases are analyzed in the following two subsections.

A. RESULTS ON WHOISIT DATABASE

The WIT database is partitioned into two equal unseen sets: training and testing. Images pertaining to 50% subjects are used for training and the remaining subjects are used for testing. This train-test partitioning is repeated five times for random subsampling based cross validation. The training database is divided into three parts depending on the weights: thin, moderate and heavy. In the testing database, the youngest image is taken as gallery and the remaining images are taken as probe. Rank-1 accuracies are reported in Table 3 and Fig. 7 shows the cumulative match curves (CMC). Key observations are as follows:

- The proposed algorithm yields 28.53% rank-1 identification accuracy which is at least 3.4% better than

[2]Source code is available on author's website.

[3]Since the source code is not available, we have implemented this algorithm.

TABLE 3. Average identification accuracies along with standard deviation on the WhoIsIt database.

Algorithm	Rank-1 Accuracy (%)
HOG [18]	10.50 $\pm$ 1.04
LBP [22]	8.19 $\pm$ 0.92
COTS (Verilook) [15]	25.09 $\pm$ 3.70
DM [9]	24.56 $\pm$ 0.98
SVDL [23]	24.12 $\pm$ 1.57
Proposed Algorithm	28.53 $\pm$ 1.03

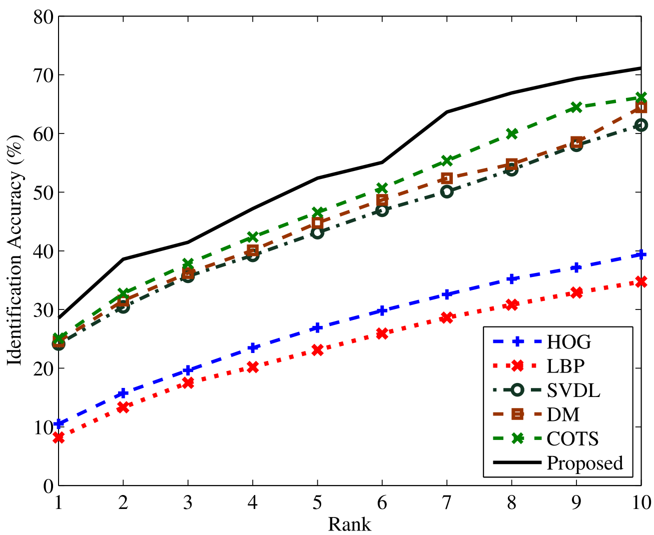

FIGURE 7. CMC curves on the WhoIsIt database.

existing approaches. Individual descriptors, i.e. HOG and LBP, are not able to provide more than 10.5% identification accuracy whereas existing algorithms yield around 25% accuracy. This suggests that mitigating the effect of age and weight variations requires learning these variations from the data.

- Discriminating model based algorithm [9] is able to encode aging variations but it fails to effectively encode weight variations. As mentioned earlier, weight variations can significantly affect the facial appearance and therefore, for recognition, both aging and weight variations should be learnt, as in the case of the proposed algorithm.
- To analyze the performance of individual components involved in the proposed algorithm, three experiments are performed: (1) network with 192 Gabor filters but without RDF, i.e., threshold units are used in place of RDF, (2) network with RDF classification without thin, moderate and heavy weight variations (i.e. a network with 64 Gabor filters instead of 192 filters), and (3) 64 filter network with threshold units instead of RDF (i.e, the difference between (2) and (3) is the use of RDF or threshold units). Using the same experimental protocol, average rank-1 identification accuracy for these three experiments are 20.97%, 16.04%, and 13.65% respectively. These experiments show that incorporating three weight variations coupled with RDF classifier helps in improving the performance significantly.
- It is interesting to note that skeletal structure can change only with major age variations but body fat can change within a small time interval as well. Therefore, incorporating weight information for face recognition can help in improving the performance at smaller time intervals as well.
- While the architecture seems complex and training the network is a time consuming task, at probe level, the proposed algorithm is computationally fast. On an Intel Quad Core 2.7 GHz processor with 8 GB RAM, under MATLAB programming environment, the proposed algorithm requires about 2 seconds for identifying a probe image.

B. RESULTS ON FG-NET DATABASE

The FG-Net Aging database contains 1002 images of 82 subjects. On an average, each subject has 12 images and the age range of the entire database is from 0 to 69 years. Similar to the WhoIsIt database, the FGNet database is also partitioned into two equal unseen sets: training with 50% subjects and testing on non-overlapping (remaining) 50% subjects. Since the FG-Net database does not contain weight information, one mean face image is computed for all the training images and a single network is trained (i.e. a network with 64 Gabor filters instead of 192 filters). The input image is registered with the mean face image obtained from the training dataset. In the testing phase, the youngest image for each subject is taken as gallery (single gallery) and the remaining images are used as probe. The experiment is repeated five times for random sub-sampling based cross validation. The results are reported in Table 4 and Fig. 8. The key observations on the FG-NET dataset are as follows:

TABLE 4. Average identification accuracies along with standard deviation on the FG-NET database.

Algorithm	Rank-1 Accuracy (%)
HOG [18]	6.17 ± 1.74
LBP [22]	6.13 ± 1.86
COTS (Verilook) [15]	3.17 ± 0.37
DM [9]	14.12 ± 0.21
SVDL [23]	14.84 ± 0.95
Proposed Algorithm	20.34 ± 0.47

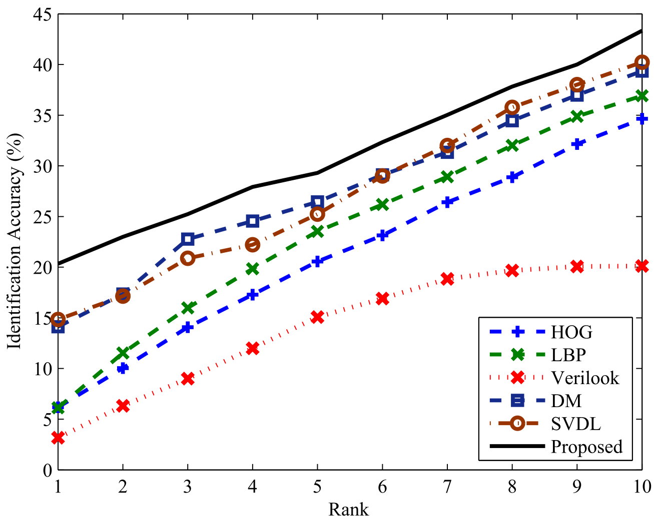

FIGURE 8. CMC curves on the FGNet face database.

- The proposed algorithm yields 20.34% rank-1 identification accuracy which is at least 6% better than existing approaches. The existing algorithms provide the best rank-1 accuracy of around 14% and the accuracy of individual descriptors such as HOG and LBP is less than 7%. This suggests that the proposed algorithm yields better results even without incorporating the knowledge of weight variations of images.
- The commercial system, Verilook, has inbuilt quality check mechanism which ensures that only those images which are better than a predefined quality threshold are processed and all the remaining images are considered as failure to process (FTP). With a high FTP rate of 40%, Verilook yields a very low rank-1 identification accuracy of 3.17%.
- Results pertaining to the proposed algorithm, DM, and SVDL suggest that for improved recognition performance, the algorithm should incorporate both age and weight variations, which can be learnt from the training data.

V. CONCLUSION

This research presents weight variations as a specific challenge for addressing face recognition with age variations.

Even with small age difference, an individual can have significant weight variations and with large age variations, the weight variations can be small. We propose a neural network and random decision forest based classification algorithm that learns the age variations for different weight variations to recognize the identity of a given face image. Due to the unavailability of a public database containing both age and weight information, we have also created a new database, WhoIsIt database, and the results are reported on this database along with the already available FG-Net database. The performance of the proposed algorithm is compared with several existing face recognition algorithms including a commercial system. The results show that incorporating weight information for recognizing age separated face images improves the identification performance. In future, we plan to extend the database and improve the algorithm with age and weight invariant feature extraction.

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