Heterogeneous Face Recognition Framework using Multiple Filters for Person Identification

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Abstract—Face recognition is the task of identifying an already detected face as known or unknown face and has attracted much attention due to its potential value in security, biometrics and law enforcement applications. One of the most difficult challenges in automated face recognition is computing facial similarities between face images which are acquired in alternate modalities. To address this problem Heterogeneous Face recognition comes takes place. Heterogeneous face recognition (HFR) involves matching two face images from alternate imaging modalities, such as sketch to a photograph or an infrared image to a photograph. The Proposed work is based on experimentation using Heterogeneous Face Recognition framework using Prototype Random Subspace Approach for both probe and gallery images which are represented in terms of nonlinear similarities to a collection of prototype face images. The proposed work will be evaluated on various performance parameters with accuracy as the main focus and pre-processing time required for filtering the images using DOG, GF, and CSDN filters. This framework performs equally well for different modalities whereas the focus of the study is specifically for Face Photo-Sketch Recognition Accuracy and Recognition time required using DOG, GF, and CSDN filters. The accuracy of this nonlinear prototype representation is improved by projecting the features with the help of PCA The outcome of this work will be useful in the areas like forensic sciences, video surveillance etc. The paper also shows a comparative study of Heterogeneous Face Recognition framework for both probe and gallery images which are represented in terms of nonlinear similarities to a collection of prototype face images and an approach to Heterogeneous face recognition which needs feature descriptors that are effective within each domain.

Key words: Heterogeneous Face Recognition, Difference of Gaussian, Gaussian Filter, Center Surround Divisive Normalization, Principle of Component Analysis

I. INTRODUCTION

Automated face recognition is a rapidly growing field that uses computer algorithms to measure the similarity between two face images. Face recognition has made dramatic progress over the past decade [03]. Automating this process of facial identification has enormous implications towards improving public safety and security. An emerging topic in face recognition is matching between two heterogeneous image modalities. Heterogeneous face recognition involves matching two face images which are acquired in different modalities. The motivation behind heterogeneous face recognition is that circumstances exist in which face image to be identified is available only in a respective modality. For example, when a subject's face can only be acquired in night time environments, the use of infrared imaging may be the only modality for acquiring a useful face image of a subject.

One of the most challenging tasks in automated face recognition is matching between two face images that have been observed in either alternate imaging modalities or in different sensing Environments and time called heterogeneous face recognition and is of substantial interest. [01]. Therefore, it is necessary to solve the heterogeneous matching problem, which enables the utilization of all the images in various modalities for recognition.

This paper presents Prototype random subspace approach samples the patches of images randomly which are extracted with different feature descriptors. In this Paper, Kernel Prototype approach is used. This approach represents images from each modality as a vector of their similarities to a common set of prototypes.

The paper proposes PRS [01] algorithm to heterogeneous face recognition to achieve following objectives:

- To study the process of achieving high leading Accuracy.
- To study the recognition time required using combination of filters
- To reduce Computation Cost in terms of using filters.
- Reduce false acceptance rate (FAR)

This section provides an overview of heterogeneous face recognition and automated face recognition. The main focus will be on the Accuracy of face recognition through face representation and feature extraction stages and to calculate the recognition time required for face recognition using combination of DOG, GF and CSDN filters. This is because the research on heterogeneous face recognition has generally relied on improvements in these two stages to increase recognition accuracies between heterogeneous face images.

The remainder of the paper is organized as follows.

Section II gives the Literature survey of Heterogeneous face recognition. In section III, details of HFR are described. Section IV describes Experimentation and Section V gives Comparative results and Applications of Heterogeneous Face Recognition. In section VI followed by the conclusion.

II. LITERATURE SURVEY

In face recognition systems, face images may be captured in more than one modality. For examples, the NIR based face recognition methods [08] have been developed to overcome the illumination variation problem; sketch images drawn by artists based on the recollection of an eyewitness have been used in the retrieval of a sketch from the police mug shot databases. Therefore, heterogeneous face recognition is a current topic of interest. The survey summarizes following different approaches for face recognition.

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A. Heterogeneous Face Recognition using Kernel Prototype Similarities:

In this paper the author presents kernel prototype approach to heterogeneous face recognition, and extends existing methods in face recognition. The kernel prototype approach is similar to the object recognition method. Kernel PCA and Kernel LDA approaches to face recognition have used a similar approach, where a face is represented as the kernel similarity to a collection of prototype images in a high dimensional space. The use of a kernel similarity representation is well suited for the HFR problem because a set of training subjects with an image from each modality can be used as the prototypes, and, depending on the modality of a new image (probe or gallery), the image from each prototype subject can be selected from the corresponding modality. The method is effective even when different feature descriptors are used in the probe and gallery domains. By representing images from alternate modalities with their non-linear similarity to a set of prototype subjects who provide images from each corresponding modalities, the need to directly compare face images from alternate modality is eliminated. This property generalizes the algorithm, called Prototype Random Subspaces (P-RS), to any HFR scenario [01].

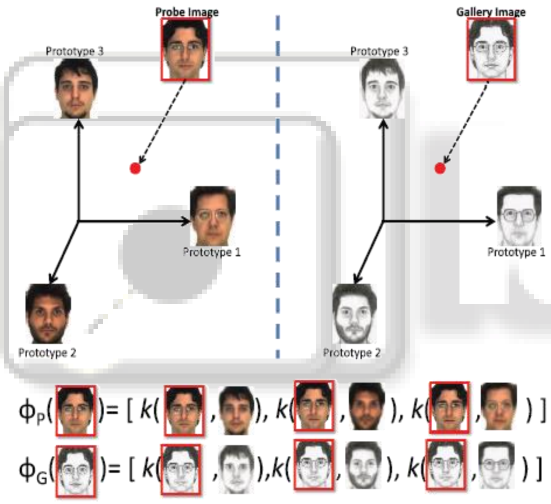

Fig. 1: Kernel Prototype based approach as a vector of their similarity to a set of common prototypes [01].

B. Matching Composite Sketches to Face Photos: A Component-Based Approach:

Composite sketches are the sketches which are computer software generated facial photographs and are matched against a face photo. Component-based representation (CBR) [11] approach is used to measure the similarity between a composite sketch and mugshot. First automatically detect facial landmarks in composite sketches and face photos using an active shape model (ASM). Features are then extracted for each facial component using multiscale local binary patterns (MLBPs), and after that per component similarity are calculated. Finally, the similarity scores obtained from individual facial components are fused together, yielding a similarity score between a composite sketch and a face photo. Matching performance is further improved by filtering the large gallery of mugshot images using gender information.

C. Matching Forensic Sketches to Mug Shot Photos:

Forensic sketches are the sketches drawn based on the verbal description of an eyewitness or a victim. Matching a forensic sketch to a gallery of mug shot images is addressed in Forensic sketch framework which differs from viewed sketches in drawn by a police sketch artist using the description of the subject provided by an eyewitness. Matching forensic sketches is a very difficult problem in heterogeneous face recognition for two main reasons. (1) Forensic sketches are often an incomplete portrayal of the subject's face. (2) Matching across image modalities since the gallery images are photographs and the probe images are sketches. One of the key contributions of this paper is using SIFT and MLBP feature descriptors to represent both sketches and photos. To handle the combination of a large feature size and small sample size and to increase accuracy, Local feature discriminant analysis is proposed [05]. LFDA offers considerable improvements in matching forensic sketches to the corresponding face images. The authors were able to further improve the matching performance using race and gender information to reduce the target gallery size.

D. Regularized Discriminative Spectral Regression Method for Heterogeneous Face Matching:

In this paper, the author proposes a new method, the Discriminative Spectral Regression (DSR), for heterogeneous face recognition. The DSR method finds the projective mappings which map heterogeneous face images of the same person to similar representations and map images from different persons to significantly different representations. The DSR maps heterogeneous face images into a common discriminative subspace in which robust classification can be achieved. In the proposed method, the subspace learning problem is transformed into a least squares problem [19].

E. Coupled Information-Theoretic Encoding for Face Photo-Sketch Recognition:

The author proposed a coupled information-theoretic encoding based descriptor for face photo-sketch recognition and introduced coupled information-theoretic projection forest to maximize the mutual information between the encoded photo and encoded sketch of the same subject. Face photo-sketch recognition is to match a face sketch to one of many face photos in the database. In this, the authors propose a new inter-modality face recognition approach by reducing the modality gap at the feature extraction stage. A new face descriptor based on coupled information-theoretic encoding is used to capture discriminative local face structures and to effectively match photos and sketches. Coupled encoding achieved by proposed randomized coupled information theoretic projection forest learns by Maximum Mutual Information Tree criterion [02].

III. DETAILS OF HETEROGENEOUS FACE RECOGNITION FRAMEWORK

A. Heterogeneous Face Recognition:

Heterogeneous face recognition is an effective framework which involves matching two face images from alternate imaging modalities. Heterogeneous face recognition Framework for person identification involves matching two face images from alternate imaging modalities. The

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proposed work is based on experimentation using Heterogeneous Face Recognition framework using Prototype Random Subspace Approach for both probe and gallery images which are represented in terms of nonlinear similarities to a collection of prototype face images. The propose method, the Prototype Random Subspace Approach (PRS), for heterogeneous face recognition is to improve recognition accuracy of a face image. The PRS method samples the patches of images randomly which are extracted with different feature descriptors. In this Paper, Kernel Prototype approach is used. This approach represents images from each modality as a vector of their similarities to a common set of prototypes [01].

HFR based framework gives solutions for multiple scenarios.

- NIR to Photograph
- Thermal to Photograph
- Viewed Sketch to Photograph
- Forensic Sketch to Photograph

Fig. 2: Pictorial representation of Heterogeneous faces recognition Framework for person identification [19].

B. *Steps Require For Image Pre-processing:*

1) *Face Detection:*

Must first find a face to perform face recognition. Face detection takes place with the help of Viola Jones Algorithm [13] having three phases to enable a fast and accurate detection:

- Introduction of a new image called" Integral image"
- Classifier is used Adaboost for Alignment and feature selection.
- Cascading is done for efficient computational resource allocation.

2) *Face Alignment:*

Geometric Normalization: The first step in representing face images using feature descriptors is to geometrically normalize the face images with respect to the location of the eyes. This step reduces the effect of scale, rotation, and translation variations. The eye locations for the face images from all modalities are automatically estimated using Cognate's Face VACS SDK [14].

3) *Image Filtering:*

Face images are filtered with three different image filters. These filters are intended to help compensate for both intensity variations within an image domain (such as non-uniform illumination changes), as well appearance variations between image domains.

Images are filtered with three different Filtering techniques:

a) Difference of Gaussian:

DOG is a feature enhancement algorithm where high frequency details noise is removed. A difference of Gaussian (DoG) image filter has been used to improve face recognition performance in the presence of varying illumination

b) CSDN:

CSDN stands for Centre Surround Divisive Normalization It is interactions between centres and surround regions of the receptive fields. The CSDN filter divides the value of each pixel by the mean pixel value in the neighbourhood surrounding the pixel.

c) Gaussian Filter:

The Gaussian smoothing filter has long been used in image processing applications to remove noise contained in high spatial frequencies while retaining the remainder of the signal.

4) *Feature Extraction:*

Features are extracted with the help of different descriptors:

a) SIFT (Scale Invariant Feature Transform):

It is an algorithm to detect and describe local features. For any object in an image, interesting points on the object can be extracted to provide a "feature description" of the object. This description, extracted from a training image, can then be used to identify the object when attempting to locate the object in a test image containing many other objects

b) MLBP (Multi-scale Local Binary Pattern):

It is an algorithm to detect and describe local features. Multi-scale local binary patterns are a variant of the LBP descriptor to slightly improved face recognition accuracy using MLBP.

5) *Random Sampling:*

The features which are extracted are randomly sampled with the random subspace method and create a subset of features and perform training in this reduced feature space. Multiple sets (or bags) of randomly sampled features are generated, and for each bag the parameters are learned. This approach is similar to the classical bagging classification scheme [16], where the training instances are randomly sampled into bags multiple times and training occurs on each bag separately.

6) *Linear discriminant analysis (LDA):*

LDA [15] seeks to reduce dimensionality while preserving as much of the class discriminatory information as possible to increase accuracy.

7) *Face Matching:*

Similarity measure facilitates recognition using a threshold for a binary verification scenario or a nearest neighbour matcher for an identification scenario.

8) *Feature Recognition:*

In this, Recognition of image takes place as Yes or No.

C. *Proposed Methodology:*

The input images which are considered are probe images as well as the gallery images. i.e. P & G.

Here discriminative analysis is done using T1 as sift and LBP as the feature descriptor and T2 is LDA as feature descriptor. These feature descriptor is applied on the both Probe & Gallery images. These T1 set of images and T2 set images produces R & W set of features after using kernel similarity prototype frame work.

How this done as follows:

- Input training images: T1= {p1, g1, p2, g2...}

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- Then apply SIFT and LBP feature extractor on T1.
- Then apply kernel similarity prototype transform on SIFT &LBP transformed T1 image set which will give R as output.
- Take same input images in T2= {p1, g1, p2, g2...}
- Then apply LDA transform to features on T2.
- Then apply kernel similarity prototype transform on LDA transformed T2 image set which will produce W as output.

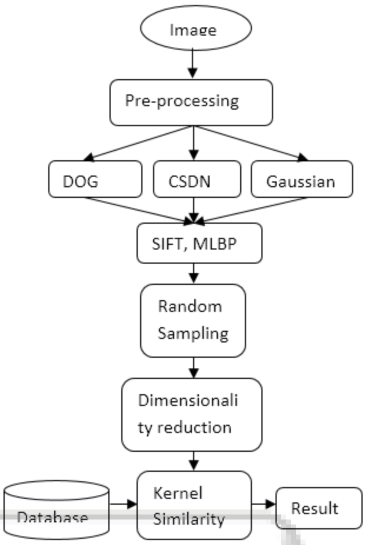

Fig. 3: System Architecture

D. Dataset Used:

Sketch photos: A viewed sketch is a hand drawn sketch of a face which is drawn while looking at a photograph of the subject. Viewed Sketch to Visible is used for CUHK sketch dataset2, which was used by Tang and Wang the CUHK dataset consists of 606 subjects with a viewed sketch image for probe and a visible photograph for gallery. The photographs in the CUHK dataset are from the AR, XM2VTS, and CUHK student datasets.

The CUHK dataset is publicly available for download at http://mmlab.ie.cuhk.edu.hk/facesketch.html.

Standard Photos: These are face images which are captured from driver license photos, passport photos etc.

IV. EXPERIMENTATION

In this section, the filtering of image takes place with the help of Difference of Gaussian, Centre Surround Divisive Normalization and Gaussian filters and also shows featured Extracted images with the help of LBP and SIFT methods:

A. DOG Filtered Image:

Total time required: 0.425 sec

B. Gaussian Filtered Image:

Total time required: 0.395 sec

C. CSDN Filtered Image:

Total time required: 0.685 sec

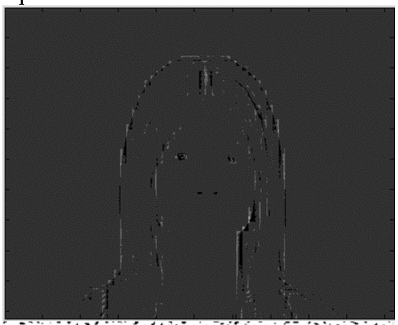

Fig: 5 LBP Feature Extracted image of Gaussian filtered image

Fig. 6: LBP Feature Extracted image of CSDN filtered image

Fig. 7: SIFT Feature Extracted image of DOG filtered image

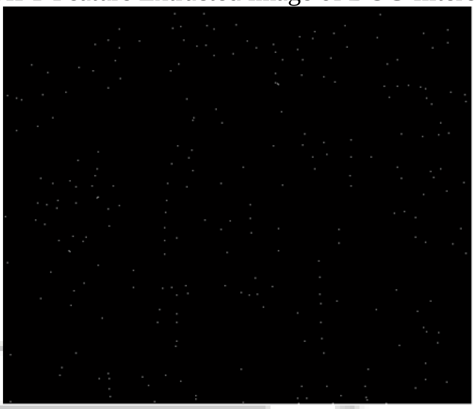

Fig. 8: SIFT Feature Extracted image of Gaussian filtered image

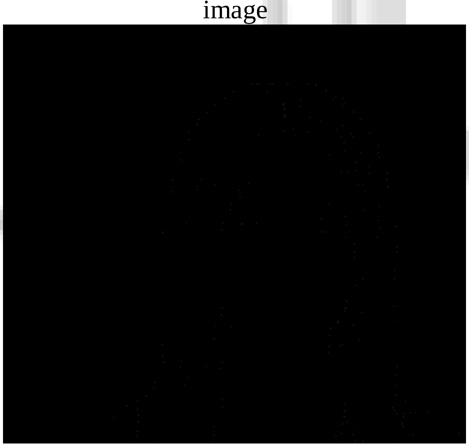

Fig. 9: SIFT Feature Extracted image of CSDN filtered image

V. RESULTS

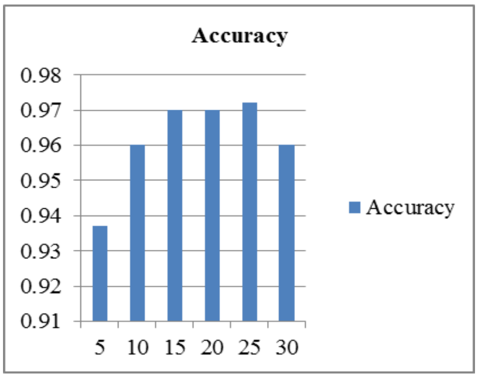

Fig. 10: Graph: 1. No of Images vs. Accuracy (%) applying three filters

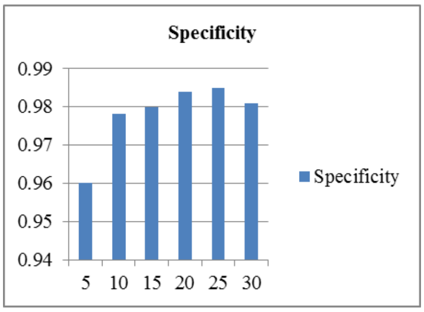

Fig. 11: Graph: 2. No of Images vs. Specificity (%) applying three filters

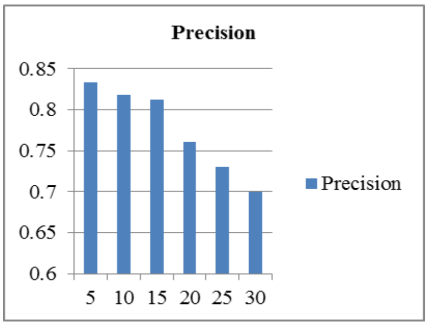

Fig. 12: Graph: 3. No of Images vs. Precision (%) applying three filters

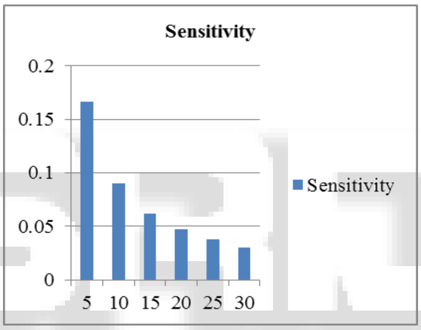

Fig. 13: Graph: 4. No of Images vs. Sensitivity (%) applying three filters

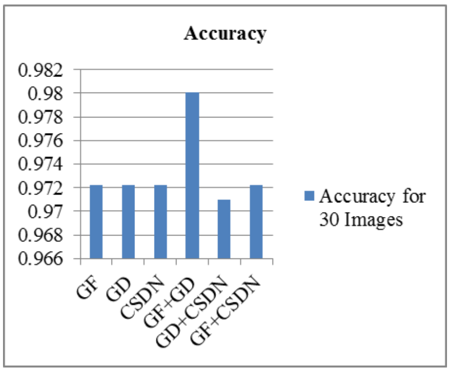

Fig. 14: Graph: 5. Combination of filters vs. Accuracy

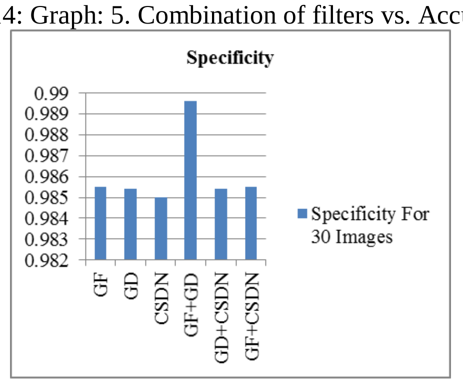

Fig. 15: Graph: 6. Combination of filters vs. Specificity (%)

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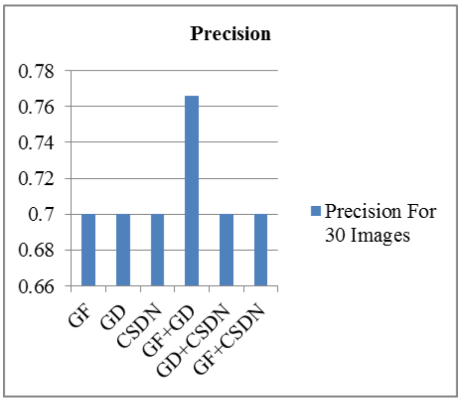

Fig. 17: Graph: 7. Combination of filters vs. Precision (%)

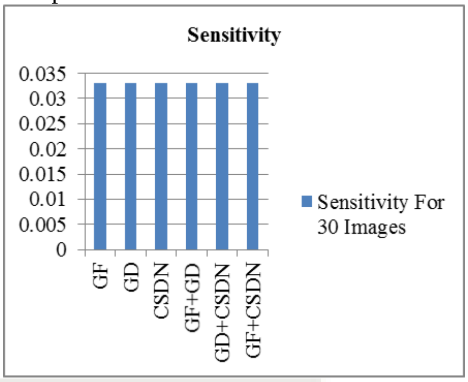

Fig. 18: Graph: 8. Combination of filters vs. Sensitivity (%)

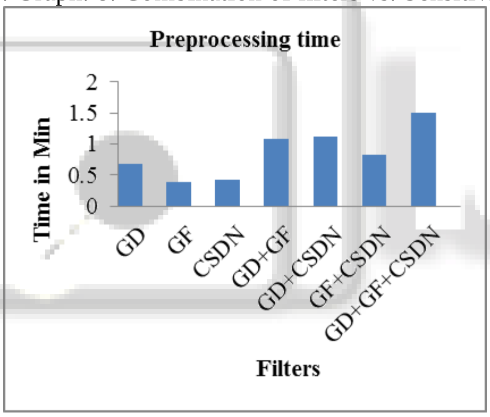

Fig. 19: Graph: 9. Combination of filters vs. preprocessing time.

Filters`	Pre-processing time
GD	0.685
GF	0.395
CSDN	0.425
GD+GF	1.08
GD+CSDN	1.11
GF+CSDN	0.82
GD+GF+CSDN	1.5

Table 1: Preprocessing time (min) required for combination of filters

No of Images	Accuracy			
5	0.937	0.96	0.833	0.166
10	0.96	0.978	0.818	0.09
15	0.97	0.98	0.812	0.062
20	0.97	0.984	0.761	0.047
25	0.972	0.985	0.73	0.038
30	0.96	0.981	0.7	0.03

Table 2: Accuracy (%) achieved with varying number of images for three filters

Filters	Specificity	Accuracy	Precision	Sensitivity
GF	0.9855	0.9722	0.7	0.033
GD	0.9854	0.9722	0.7	0.033
CSDN	0.985	0.9722	0.7	0.033
GF+GD	0.9896	0.9801	0.766	0.033
GD+CSDN	0.9854	0.971	0.7	0.033
GF+CSDN	0.9855	0.9722	0.7	0.033

Table 3: Parameters (%) achieved with varying number of filters

No of Images	GD	GF	CSDN	GD-GF	GD-CSDN	GF-CSDN	ALL
3	2.55	2.61	2.63	4.74	4.98	5.1	9.2
6	5.1	5.22	5.26	9.48	9.96	10.2	18.5
9	7.65	7.83	7.89	14.22	14.94	15.3	27.8
12	10.2	10.44	10.54	18.96	19.92	20.4	37
15	12.75	13.05	13.15	23.7	24.9	25.5	46.1
18	15.3	15.66	15.78	28.44	29.8	30	55
21	17.8	18.27	18.41	33.18	34.8	35.7	64.1
24	20.4	20.88	21.04	37.9	39.84	40.8	74.2
27	22.95	23.49	23.67	42.6	44.82	45	83
30	25.5	26.1	26.31	47.4	49.8	51	92

Table 4: Recognition time (min) required for combination of filters across number of images

VI. APPLICATIONS

A. Law Enforcement:

Video surveillance, Suspect tracking, Suspect identification. Biometrics: Automated identity verification.

B. Access Management:

Secure access authentication, permission based system

C. Information Security:

Access security, Data privacy, User authentication.

VII. CONCLUSION

This paper presents the proposed work which is based on experimentation using Heterogeneous Face Recognition framework using Prototype Random Subspace Approach.

The proposed work will be evaluated on various performance parameters with accuracy as the main focus and pre-processing time required for filtering the images using DOG, GF, and CSDN filters. This framework performs equally well for different modalities whereas the focus of the study is specifically for Face Photo-Sketch The Accuracy achieved using DOG, GF and CSDN filters for photo sketch recognition is 96% whereas accuracy achieved using only DOG and GF filter is 98%. Pre-processing time required for filtering the images using DOG, GF, and CSDN filters is more as compared to DOG and GF filters. Hence recognition time using DOG and GF filter is less as compared to using DOG, GF, CSDN filters The outcome of this work will be useful in the areas like forensic sciences, video surveillance etc.

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