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Matching Forensic Sketches to Mug Shot Photos using Speeded Up Robust Features

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Dr. S. K. Rath
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May 14, 2012

Certificate

This is to certify that the work in the thesis entitled *Matching Forensic Sketches to Mug Shot Photos using Speeded Up Robust Features* by *Dileep Kumar Kotha*, bearing Roll No. 108CS015, is a record of an original research work carried out by him under my supervision and guidance in partial fulfilment of the requirements for the award of the degree of *Bachelor of Technology* in *Computer Science and Engineering*. Neither this thesis nor any part of it has been submitted for any degree or academic award elsewhere.

Dr. S. K. Rath
(Supervisor)

Acknowledgment

If I have seen a little further it is by standing on the shoulders of Giants.

- Sir Isaac Newton

This thesis would not have been possible without the support and guidance of many people. Even though mere words would not be sufficient to thank them, I will try to express my gratitude in this feeble manner.

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Dileep Kumar Kotha

Abstract

The problem that is dealt in the project is to match a forensic sketch against a gallery of mug shot photos. Research in past decade offered solutions for matching sketches that were drawn while looking at the subject (viewed sketches). In this thesis, emphasis is made on matching the forensic sketches, which are the sketches drawn by specially trained artists in police department based on the description of subject by an eyewitness. Recently, a method for forensic sketch matching using LFDA (Local Feature based Discriminant Analysis) was published. Here, the same problem is addressed using a novel preprocessing technique combined with a local feature descriptor called SURF (Speeded Up Robust Features). In our method, first, the images are preprocessed using a novel preprocessing technique suitable for forensic sketch matching that is based on the cognitive research on human memory. After the preprocessing, SURF is used for matching. SURF extracts features in the form of 64-variable vectors for each image. Then all these vectors of one image are combined to form the SURF descriptor vector for that image. These descriptor vectors are then used for matching. This method of forensic sketch matching was applied to match a dataset of 64 Forensic Sketches against a gallery of 1058 photos. From our experiments, it was observed that our approach of image preprocessing combined with SURF had shown promising results with a good accuracy.

Keywords: **Sketch Recognition, viewed Sketches, forensic Sketches, SURF, matching, Preprocessing.**

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List of Acronyms

CMC Cumulative Match Curve

CUHK Chinese University of HongKong

Fa type Frontal images from FERET color database

FERET FacE REcognition Technology

GCC GNU Compiler Collection

GIMP GNU Image Manipulation Program

GNU GNU is Not Unix

LFDA Local Feature based Discriminant Analysis

NIR Near Infra red Images

SIFT Scale Invariant Feature Transform

SURF Speeded Up Robust Features

VIS Visible Light Images

Chapter 1

Introduction

Today, advances in biometric technology have provided law enforcement agencies additional tools in the identification of criminals. In addition to the incidental evidence, if a dormant fingerprint is found at the scene of crime or a surveillance camera captures an image of the face of a suspect, then these clues are used in determining the suspect using biometric identification techniques. However, many crimes occur where none of the above discussed information is present. Also, the lack of technology to effectively capture the biometric data like finger prints within a short span after the scene of crime, is a routine problem in remote areas. Despite these repercussions, many a times, an eyewitness account of the crime is available who had seen the criminal. The Police department deploys a forensic artist to work with the witness in order to draw a sketch that limns the facial appearance of the culprit. These sketches are known as forensic sketches. Once the sketch is ready, it is sent to the law enforcement officers and media outlets with the hope of catching the suspect. Here, two different scenarios may arise for the culprit:

1. The person may have already been convicted once or

2. The person has not been convicted even once or this is the first time, he may be committing felony.

This thesis deals with the first type scenario. If the criminal has been convicted at-least once, a mug shot photo (photo taken, while the person is being sent to jail) is available. Using an efficient forensic sketch matching system, the police can narrow down the potential suspects which will reduce the future crimes by the same criminal drastically. Also, consider a party with a camera at the entrance door, which captures the image of everyone entering the hall with a predetermined calibration. If some crime happens inside the party, and someone sees the criminal, he and the photos initially captured can act as eye witness and mug shot photos respectively, can be used to catch the criminal using forensic sketch matching. In this thesis, we provide a novel preprocessing technique combined with the detector and descriptor powers of Speeded Up Robust Features (SURF) to create a forensic sketch matching system.

1.1 Sketches

Sketches are the figures, drawn by trained artists on a piece of white paper with a single pencil or a bunch of pencils. In general, sketches are classified into two categories: viewed sketches (Figure 1.1) and forensic sketches (Figure 1.2)

1. **Viewed Sketches:** These are the sketches drawn by an artist, directly looking at the subject or the photograph of the subject

2. **Forensic Sketches:** These are the sketches drawn by specially trained artists based on the description of subject by an eye witness

Since viewed sketches are drawn, by directly looking at the subject or the photograph of the subject, they carry a very good detail of the original subject in terms of accuracy. On the other hand, since forensic sketches are drawn, just based on the verbal description, their accuracy is considerably low. It is succinct to say that the accuracy of forensic sketches is directly proportional to the remembrance capability of the eye witness.

1.2 Sketch recognition

Even though there existed multiple face recognition schemes since the past two decades, research on sketch to photo matching started only a decade ago. This is because of the difficulty in the problem compared to traditional recognition. And also, the best recognition

Figure 1.1: Example of viewed sketch and it's corresponding photograph

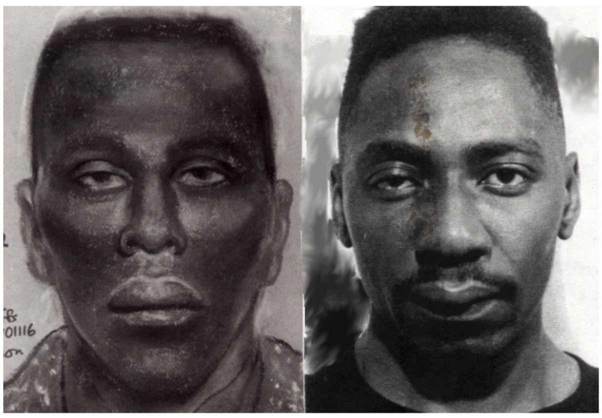


Figure 1.2: Example of forensic sketch and it's corresponding photograph

levels in photo matching, came only at the onset of past decade. The sketches are mainly drawn using pencils and for a sketch, atmost 4-5 pencils are used pertaining to different darkness levels. So a sketch has atmost 4-5 grey levels. The photographs on the other hand are taken with a camera that can capture 256 grey levels (If a colour image is present, it could be easily converted to a 256 grey level image). So to match 4-5 grey levels against 256 grey levels is a near impossible problem. Contrast stretching, in which we convert the 256 grey levels into 3-4 grey levels is tried by various researchers, but proven to be ineffective to solve the problem. Through out the past decade, scientists have been trying various methods like synthetic photograph generation, spectral regression, using feature based descriptors etc., out of which some have proven to be fruitful. Based on the past research in sketch recognition, and the research done on the cognitive ability of human mind, a new method is proposed by us, that could effectively solve the problem of sketch recognition to a great extent. Experiments were conducted on the two kinds of sketches that are available (viewed and forensic sketches). But we emphasize on matching of forensic sketches, since it has a practical purpose in apprehending criminals [1]. Nevertheless, viewed sketches acted as a baseline for forensic sketches and helped us perform continuous experiments on them, before proceeding to experiment with forensic sketches.

1.3 Motivation

The main motivation behind the undertaking of this project is that there are a lot of problems in forensic sketch recognition compared to normal face recognition (in which both probe and gallery images are photographs). The textures of sketches, whether they may be viewed or forensic are quite different from that of the gallery of photographs that were being matched against. Previous work in sketch matching is done only on viewed sketches [2], [3], [4], [5], [6], even though most real world scenarios involve forensic sketches only. Forensic sketches have additional problems compared to viewed sketches. Due to the petulant nature of the memory, the exact appearance of the criminal cannot be remembered by the witness. This leads to an incomplete and inaccurate depiction of the sketches which reduces the recognition performance substantially.

1.4 Thesis Organization

The rest of the thesis is organised as follows. In Chapter 2, the different methods, already in use for sketch recognition are discussed. Our proposed approach, along with the motivations that led to it are also discussed in this chapter. In Chapter 3 we discuss the experimental results that are obtained using both viewed and forensic sketches, along with the databases and technologies used. Chapter 4 concludes the thesis explaining the future work that can be extended from this thesis.

Chapter 2

Methods

Research in sketch matching started only a decade ago. This is because the accuracy of sketch recognition is very low, compared to traditional face recognition. This is inturn due to a large texture difference, between a sketch and a photo. Since researchers struggled to get good results with photo to photo recognition till the onset of past decade, sketch recognition is not undertaken as a serious problem till then. But after that, the research started to spread like a forest fire, where the academicians all over the world, started digging the problem. Even though all the methods that are applicable to viewed sketches, are also applicable to forensic sketches, the unavailability of a public database for forensic sketches led to a lack of standard test procedure on the latter one. That is why, most of the early work consists of tests on viewed sketches only. In the first section, we talk about the different methods applied for sketch recognition. In the second section our proposed approach, along with the motivations that led to it are discussed.

2.1 Related Work

Research on sketch matching started only a decade ago. Due to the unavailability of standard public database for forensic sketches, through out the past decade, the research is done on viewed sketches only.

On viewed sketches, most of the early work is done by Tang *et al*. [3], [4], [6]. A synthetic photograph is generated from the sketch in these works; And then matching is performed with standard face recognition algorithms.

In the recent years, research on sketch matching is done using feature based descriptors. Klare and Jain published a Scale Invariant Feature Transform (SIFT) based approach [2] for the sketch to photo matching. Other methods similar to this such as Coupled Spectral Regression [7], Local Binary Patterns [8], [9], [10] are used for matching near-infrared images (NIR) to visible light images (VIS).

Only one paper is published in forensic sketch matching till date. Klare and Jain [11] published a Local Feature based Discriminant Analysis (LFDA) approach for matching forensic sketches to mug shot photos. It is claimed as the first large scale experiment conducted on forensic sketch matching in which 159 forensic sketches are matched against 10159 mug shot photographs. We propose a technique based on Speeded Up Robust features (SURF) that could solve the problem of forensic sketch matching in a much better manner. Our results are compared to LFDA; since it is reported to be the one with highest accuracy till date in forensic sketch matching. We also compare our results to faceVACS, a commercially off the shelf system for traditional face recognition. We show experimentally, that with a novel preprocessing technique, combined with the detector and descriptor powers of SURF [12], a better accuracy than LFDA can be achieved.

2.2 Proposed Approach

This section is divided into two subsections giving an overview of matching experiments conducted. In a recognition experiment, the images are preprocessed first and then matching is performed. In the first subsection, we describe a novel preprocessing technique that is applied to both sketches and photographs and the motivations that led to it. In the second subsection, we discuss about the SURF in a detailed manner, finally giving an algorithm for the matching step.

2.3 Preprocessing

A novel preprocessing technique is discussed in this section. This preprocessing is different from the conventional face recognition preprocessing techniques where the face

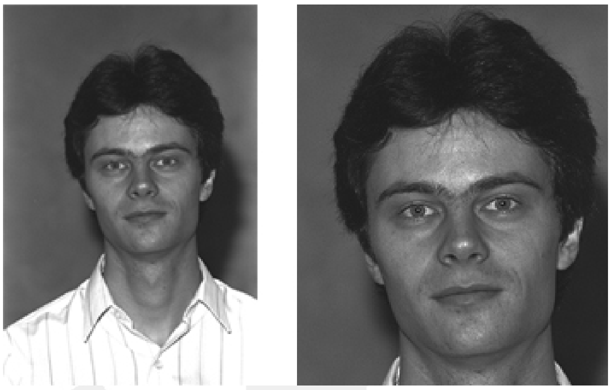


Figure 2.1: Example of the image preprocessing, done with our proposed method. The external features of the face are not lost in the preprocessed image

is preprocessed so that the region only from forehead to chin and cheek to cheek is visible (internal features of the face). Here, we preprocess the images, so that the hairline and neck region along with the ears are also visible (as shown in Figure 2.1). This is due to two reasons:

1. Experiments conducted by Frowd *et al.* [13] showed that human beings remember the familiar with the help of internal features and unfamiliar faces with the help of external features of the face. Since a culprit is essentially unfamiliar and you don't come across him in your every day life, the external features of the face region are very important and hence need not be removed.

2. Forensic Sketch artists not only draw the internal parts of the face, but also the external ones. More over, logically from the first point, it is clear that external features are more saliently remembered and hence drawn with a good accuracy. Also, Jain *et al.* [14] reported that when doing the matching of forensic sketches, using only the external features(Chin,hairline,ears) of the face gave better accuracies compared to using only the internal features(eyes,nose,mouth etc.,). Further in their experiments, they found out that using both internal and external features gave better accuracies compared to using only external features.

Since SURF is both rotation and scale invariant, we did not preprocess the images further. As present in [11], we did not scale up/down the images to be of same size or converted them into grid format taking patches. Also, the use of haar wavelet responses makes SURF invariant to a bias in illumination [12].

2.4 Speeded Up Robust Features

SURF stands for Speeded Up Robust Features. It is an approach which is generally used to construct a robust image detector and descriptor that can be used in computer vision tasks like object recognition and 3D reconstruction. Recent experiments by Du *et al.* [15] proved SURF to be the most robust detector and descriptor available for face recognition. Also, using SURF feature descriptors, the differences in image modalities between a sketch and a photo are mostly diminished.

The features calculated with SURF, are both rotation and scale invariant. In a typical face recognition experiment, there is always a need to scale up/down the images and also to rotate the subjects face so that both eye levels fall on a straight line. This overhead is completely removed with SURF.

As a detector, SURF locates the interest points in the image that produce major variation while the descriptor constructs feature vectors around each of these interest points. In the next few sections we describe how SURF can actually be used for recognition purposes.

2.4.1 Interest Point Detection

To detect the interest points, SURF uses the determinant of the approximate Hessian matrix. Blob like structures are detected in the image, where the local determinant is maximum (see Figure 2.2a). In the Hessian matrix approximation, we use integral images instead of the original ones reducing the time required for calculations.The Hessian matrix $H(x, \sigma)$ for a given point x= (x, y) of an image at a scale σ

$$H(\mathrm{x}, \sigma) = \begin{bmatrix} L_{xx}(\mathrm{x}, \sigma) & L_{xy}(\mathrm{x}, \sigma) \\ L_{xy}(\mathrm{x}, \sigma) & L_{yy}(\mathrm{x}, \sigma) \end{bmatrix}, \tag{2.1}$$

Where $L_{xx}(\mathrm{x}, \sigma)$, $L_{xy}(\mathrm{x}, \sigma)$ and $L_{yy}(\mathrm{x}, \sigma)$ are the convolutions of Gaussian second order partial derivatives of the image I at point x.

A set of 9 X 9 box filters are used as approximations of Gaussian second order derivatives with σ=1.2, to reduce the computation time. These filters represent the lowest scale(i.e. highest spatial resolution) for computing blob response maps and are denoted as $D_{xx}(x, \sigma)$, $D_{xy}(x, \sigma)$ and $D_{yy}(x, \sigma)$
. The weights applied to the rectangular region are kept simple for computational efficiency. These yield:

$$\det(H_{approx}) = D_{xx}D_{yy} - (\omega D_{xy})^2, \quad (2.2)$$

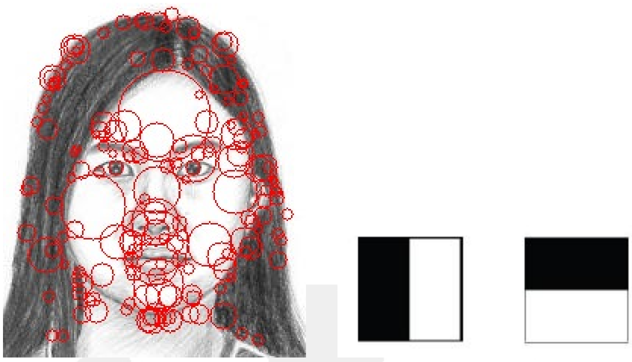
where ω is a weight for the energy conservation between Gaussian kernels and the approximated Gaussian kernels. To be scale invariant SURF implements scale spaces as image pyramids. In a general scenario, these images are repeatedly smoothed with a Gaussian and subsequently sub-sampled in order to achieve a higher level pyramid. But in SURF, since we use box filters and integral images, we can directly apply the filters of any size at exactly the same speed directly, on the original image.

2.4.2 Interest Point Description

SURF uses the sum of Haar wavelet responses to describe the features of an interest point, which make it invariant to rotation. Figure 2.2b shows the Haar wavelet filters, that are used to compute the responses at x and y directions. To extract the descriptors, we first construct a square region centered at the interest point and oriented along the orientation decided by a special selection method as described in [12].

Now the square region is split up equally into smaller 4 X 4 square sub-regions (as shown in Figure 2.3). This preserves important spatial information. For each sub-region, we compute Haar-wavelet responses at 5 X 5 equally spaced sample points. We denote d_x as the Haar Wavelet response in horizontal direction and d_y as the Haar wavelet response in vertical direction. For each sub-region, the d_x and d_y are calculated and these are weighted with a Gaussian centered at the interest point to increase the robustness towards geometric deformations and localization errors.

The wavelet responses d_x and d_y are summed up over each sub-region and these form a first set of entries to the feature vector. In order to bring in information about the polarity of intensity changes, we also extract the sum of the absolute values of responses, $|d_x|$ and $|d_y|$.



(a) (b)

Figure 2.2: (a) The interest points detected, when SURF is applied on a sketch, (b) The Haar Wavelet types used for SURF.

Now each sub-region has a four-dimensional descriptor vector v for its underlying intensity structure, where $\mathbf{v} = (\sum d_x, \sum d_y, \sum |d_x|, \sum |d_y|)$. Concatenating these vectors of all the 4 X 4 sub-regions, we get a descriptor vector of length 64. The wavelet responses are invariant to a bias in illumination (offset).

2.4.3 Speed Up the Matching

To speed up the matching, we used the sign of the Laplacian (i.e. the trace of the Hessian matrix) for the interest point. If two point pairs are of different sign, their features are not matched. Figure 2.4 gives the example blobs of the sign where they are different and hence are not matched. More detailed description of SURF matching can be found in [12]

2.4.4 Algorithm for matching

The images used for matching i.e, both sketches and photos were first preprocessed based on the guidelines in 2.3. After the preprocessing, the matching step is performed.

Algorithm for matching using Speeded Up Robust Features

When performing recognition, we categorize the images we use into one of the two below types:

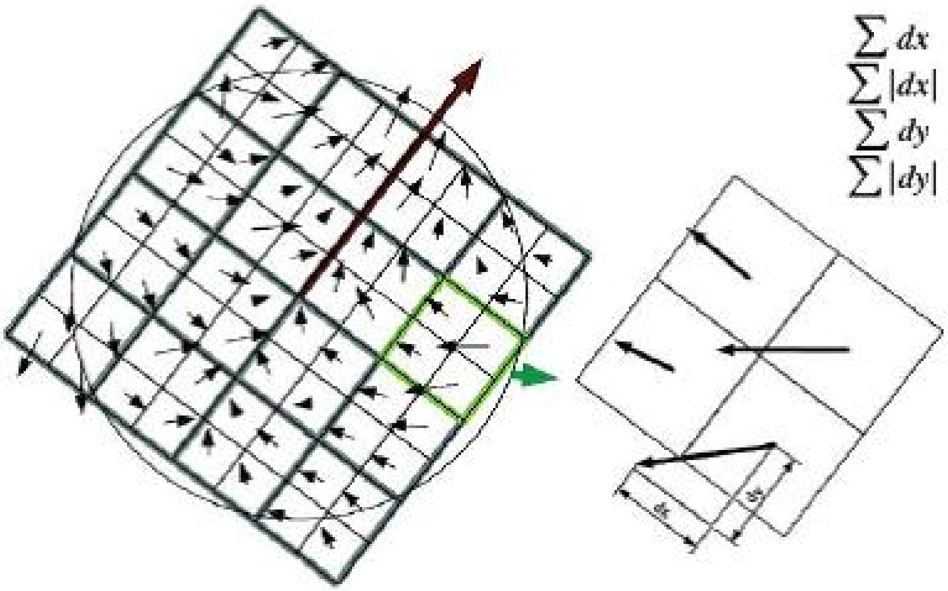


Figure 2.3: To build the descriptor, an oriented quadratic grid with 4 X 4 square sub-regions is laid over the interest point.

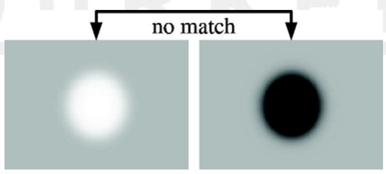


Figure 2.4: Figure showing the sign of the Laplacian (the trace of the Hessian matrix)

Probe images - These are the images for which we need to find a match for. Since we are trying to find the correct match for a sketch, the sketches will be probe images

Gallery images - These are the images that are used to match against. These include the photographs that we try to compare with sketches.

So, we have a set of sketches (Probe) and a set of gallery photographs to be matched against. The SURF algorithm we propose works as follows

1. For all the given images, find their corresponding descriptors and store them in text files, so that for every image (Gallery or Probe) a text file is associated with it. This text file contains all the descriptors and their values associated with the image that it represents.
2. For every Probe image, we do the following
   (a) Create a text file with the name of the probe image appended with .txt
   (b) Take a gallery image
   (c) Initialize a variable DIS to zero
   (d) Take a descriptor of the probe image and compare it with all the descriptors of the gallery image
   (e) The nearest descriptor distance is added to DIS
   (f) Take a descriptor of the probe image, which is not already taken and go to step-c. If all the descriptors are taken, go to next step
   (g) Divide the variable DIS with the total number of descriptors of probe image, so that we get an average distance (AVE_DIS) of descriptors between the probe and the gallery image
   (h) In the text file, append the name of the gallery image followed by a white space and then the AVE_DIS
   (i) For a gallery image not yet used, go to step-b
3. For every probe image, the corresponding match is the one that has the lowest AVE_DIS, among all the neighbours stored in the text file associated with it.

4. For every probe image, we rank the gallery images
5. For all the probe and gallery images combined, using ranking, we show the performance in the form of Cumulative Match Curves (CMC)

This is how the SURF algorithm operates. An example of the matching can be seen in Figure 2.5

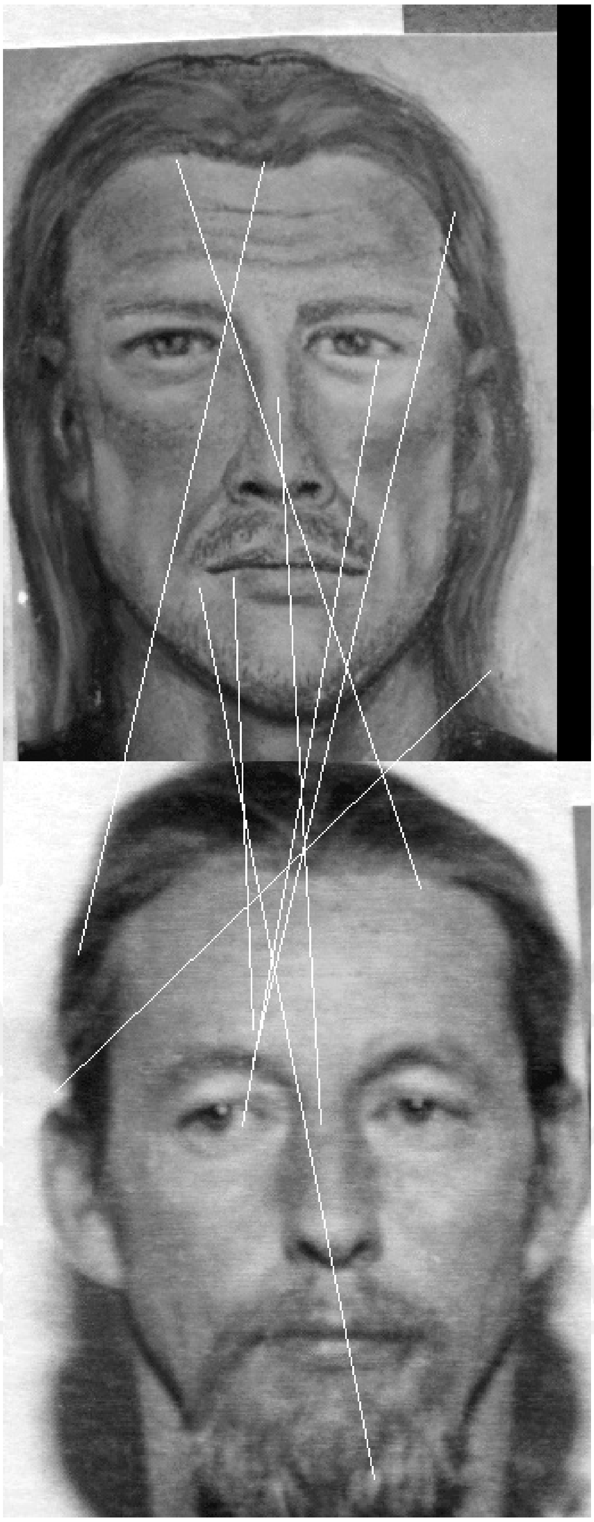


Figure 2.5: An example of forensic sketch matching. The lines show the corresponding features, as depicted by SURF in between the sketch and photo

Chapter 3

Experimental Results

This chapter is divided into two main sections. In the first section, we talk about the databases and technologies used. The second section gives the experimental results, using the set-up in first section

3.1 Experimental set-up

In this section, we talk about the databases and technologies used in the experiments conducted on sketch matching.

3.1.1 Databases used

As discussed in 1.1, there are two kinds of sketches that are dealt in this project - viewed and forensic.

Viewed sketches are present in a public repository (available free online), from where we downloaded and tested them. The viewed sketches, as a bunch of sketch-photographic pairs, were collected from two different sources:

- From AR face database [16], 123 pairs of sketches were collected
- 188 pairs were collected from CUHK face sketch database [6]

As a result, we had 311 pairs of viewed sketches that are available with us. Along with the sketches, we collected the photographic pairs of the corresponding sketches. Then we proceeded for acquiring the database of forensic sketches. Forensic sketches are not available in a public repository. The paper published in LFDA [11], which is considered as the first large scale experiment in forensic sketch matching could collect only 159 forensic sketches. These sketches were collected from various sources such as police department, Sheriff's office and two books from forensic sketch artists. The books were the only source, from which we could collect the photos. Although the two books combined have 116 pairs of forensic sketches, we could only get sample copies of the books and hence could collect only 64 sketches. The mug shot photographic pairs of the sketches, which were taken after their apprehension, were also collected from the book. The number of sketches collected book-wise were:

1. 54 pairs were collected from the book *Forensic Art Essentials* [17]
2. 10 pairs were collected from the book *Forensic Art Illustration* [18]

So before the start of experiments, 311 pairs of viewed sketches and 64 pairs of forensic sketches were available with us. But, in order to conduct a large scale experiment with forensic sketches, we need to populate the gallery of mug shot photos that we are matching against. Initially, only 64 photos in the mug shot database were with us, which were the corresponding photographic pairs of the 64 forensic sketches that we collected. So in order to populate the gallery of mug shot photos, we used the frontal images (called as *Fa type*), taken from the FERET color database [19]. These were 994 in number. These were converted into grey scale, before the start of the experiments. So, finally we had 1058 (994+64) photos available to us and we are ready for the experiments.

3.1.2 Technologies used

The technologies that were used for all the experiments stated in this thesis and the ones that were conducted as part of the research work are shown in Table 3.1

Operating System	Ubuntu 9.10
Libraries Used	OpenCV
Programming Language	ANSI C, Shell Scripting
Processor	2.1 GHZ, Core -2-duo
Compiler	GCC
Other Software	GNU plot, GIMP

Table 3.1: Table indicating the technologies that were used for conducting experiments

3.2 Results

Experiments were conducted on both viewed and forensic sketches. We will discuss them in the subsequent sections.

3.2.1 With viewed sketches

We first performed experiments on viewed sketches to test our SURF based system. 311 pairs of viewed sketches that were collected from CUHK face data set [6] and AR face database [16] were used. Taking a random sample of 100 pairs, we conducted the recognition experiments. There is no training required as in grid based methods since we are using the detector capabilities of SURF. The rank curve (Cumulative match curve) that was generated is as shown in Fig. 3.1

At rank-10, we achieved an accuracy rate of 78%. Although this result lags behind the viewed sketch matching results of [6] and [2], we have shown that without any training or higher level preprocessing, good accuracy results can be achieved using SURF. Also, the reason for a low accuracy is the fact that we preprocessed the images keeping in mind the cognitive research on forensic sketches, but not on viewed sketches.

3.2.2 With forensic sketches

A database consisting of 64 forensic sketches is made, before the start of the experiment as stated in 3.1.1. These images were collected from two different sources:

1. 54 images from the book *Forensic Art Essentials* [17]

2. 10 images from the book *Forensic Art Illustration* [18]

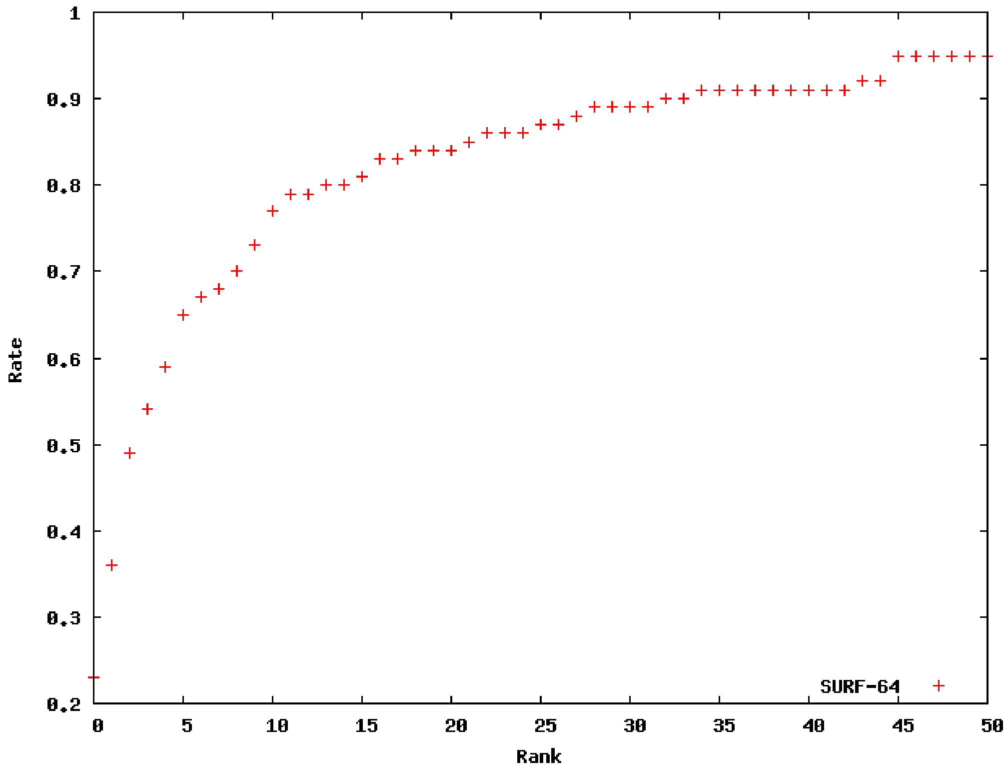


Figure 3.1: Rank curve showing the matching performance with Viewed Sketch Images.

Collection of mug shot database is a huge problem, since there is no publicly available database for them. Only 64 mug shot photos which were the pairs of the sketches we have collected were available. We could not collect any additional mug shot photos. So, in order to populate the gallery, we used the *Fa type* images(994 in number) of FERET color database [19]. As a result, we have a gallery 1058 photographs in the end. The next two paragraphs, give an overview of the results in the matching of forensic sketches.

When the matching the forensic sketches is being done, generally we are concerned with the accuracy at rank-50 i.e. whether or not the true subject is present within the top-50 images that were near (Euclidean distance between descriptors) or top-50 retrieved images. This is because forensic sketch matching significantly differs a lot from the conventional face recognition. In normal face recognition, human interaction is limited to the cases, only when there is some ambiguity. But in forensic sketch matching, we are matching a sketch to a photo, and that sketch too is drawn just based on the verbal description of an eye-witness; hence, there are a lot of chances for ambiguity. So the law enforcement officers are generally concerned with the top P retrieved results. Here, we take P to be 50.

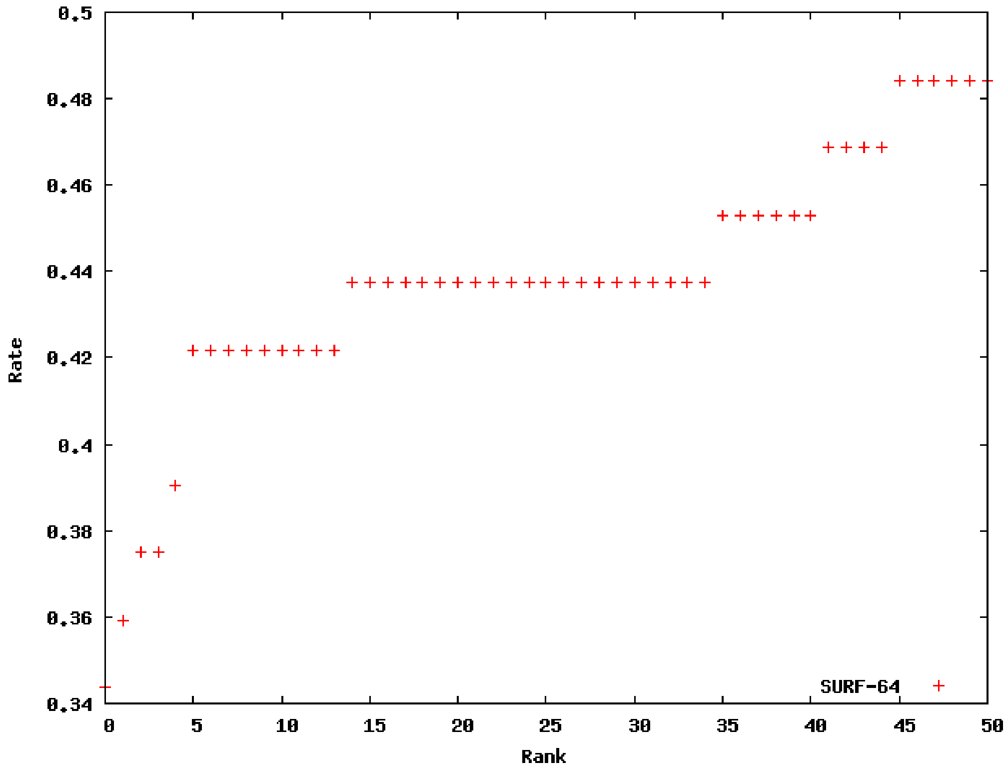


Figure 3.2: Figure showing the rank curve that was generated when 64 forensic sketches are matched against 1058 photographs

First, all the 64 forensic sketches available with us were used for matching. We achieved a very good accuracy rate of 46.87%. We believe, that this is by far, the best recognition rate achieved in forensic sketch matching. The rank curve or the Cumulative Match Curve (CMC) that was generated is shown in Fig. 3.2

In order to compare our result with the existing systems LFDA [11] and FaceVACS [20], we tried to perform the experiment in [11] under similar conditions. In [11], 49 good quality forensic sketches were taken from a lot of 159 forensic sketches (as stated in 3.1.1) available to them and showed their results with rank curves experimentally. From the lot of 64 forensic sketches that were available to us, we separated 49 sketches as good quality and performed matching on them. Reader should keep in mind that the 64 sketches we have, are a subset of the 159 sketches in [11]. The results were shown in Tab. 3.2. The outcome of our experiments as stated in Tab. 3.2 clearly show the SURF based method, along with the novel preprocessing technique we proposed as a clean winner. The CMC that was generated with 49 sketches is as shown in 3.3. Our results at rank-50 is clearly apparent from the

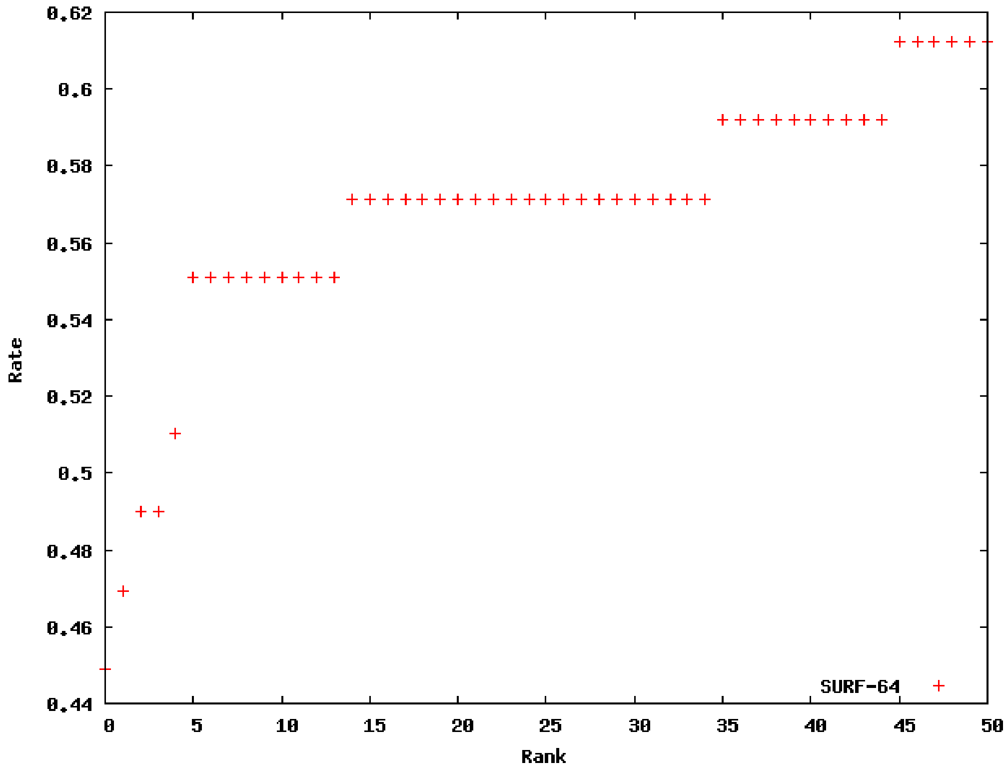
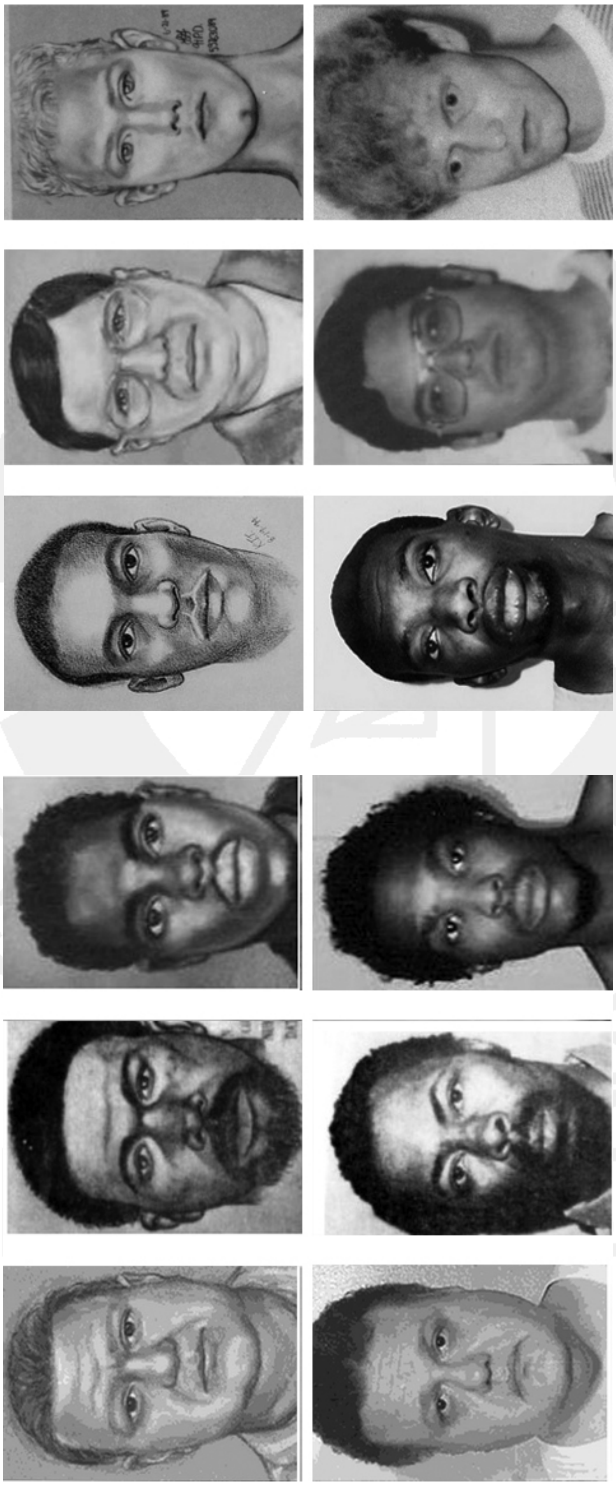


Figure 3.3: Figure showing the rank curve that was generated when 49 forensic sketches are matched against 1058 photographs

Method	Rank-50 accuracy
SURF with novel preprocessing	61.33%
LFDA	53%
FaceVACS	22.32%

Table 3.2: Comparison of rank-50 accuracies of our method (SURF) with LFDA and FaceVACS

graph. The accuracy can be further improved if race, gender and ancillary information are included. Fig. 3.4 shows some of the examples of matching with our proposed approach. The top retrieval may sometimes, look visually more similar to sketch rather than the true subject as shown in Fig. 3.5). This gives us another reason (along with the ones in previous paragraph) to explain why we consider top-50 retrieved images rather than one single image that appears at rank-1.



(a) Best matches

(b) Worst matches

Figure 3.4: Examples of matching when good quality forensic sketches are matched against 1058 photographs (a) Three of the best matches which were discovered at rank-1 and (b) Three of the worst matches discovered at ranks 320,217 and 287 (From left to right) successively.

(a) Forensic Sketch (b) Top Retrieval (c) True Subject

Figure 3.5: Example showing the failed retrieval for a good quality sketch. Even though the top retrieval is not true subject, it visually looks more similar to the forensic sketch.

Chapter 4

Conclusion

We presented a novel approach for the matching of forensic sketches to mug shot photographs. Although feature based descriptors are recently being used for sketch matching, this is the first time that SURF has been used for the same. As stated earlier in section 1.1 matching forensic sketches is a very tough problem. The reasons for it can be boiled down to two main points:

1. The sketch quality or the accuracy (of features between sketch and the subject)is directly proportional to the victims memory

2. There is a need to match across image modalities

The latter problem was solved with the help of SURF and with a special preprocessing technique we tried to solve the former one. Also, by removing the needs of training and other higher level preprocessing techniques (scaling and rotating of images), we reduced the time required for preprocessing drastically. Further, we provided an optimal approach for the matching of forensic sketches and proved it's superiority experimentally, compared to the existing methods (discussed in section 2.1). Future work can be extended by making enhancements to SURF.

There is a need for continual research on forensic sketch matching. This can help assist the law enforcement agencies to apprehend criminals quickly, before they commit another crime. Requests have been sent to various universities doing the research on forensic sketch matching to make their databases publicly available. A bigger database of forensic sketches is needed to further understand and dive into complexity of the problem.

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