

A REVIEW OF FACE SKETCH RECOGNITION SYSTEMS

¹SALAH EDDINE LAHLALI, ²ABDELALIM SADIQ, ³SAMIR MBARKI

^{1,2,3}Department of Computing, Faculty of sciences, IbnTofail University, Kenitra, Morocco

E-mail: ¹lahlali_s@yahoo.fr, ²sadiq.alim@gmail.com, ³mbarkisamir@hotmail.com

ABSTRACT

Police sketching techniques are nevertheless a routine part of law enforcement investigation and often used to identify suspects from an eye witness memory. This classic technique of identifying is generally slow and fastidious and may not conduct to arrest the right offender. Therefore an automatic face sketch recognition systems that determine efficiently the perpetrator's appearance from gallery of face images is required. Such technology design is open challenging research because faces and sketches are generated from distinct sources and have different gaps to overcome in low and high levels. Although many methods have been proposed, we are unaware of any surveys on this particular topic. For this reason we wrote this paper for reviewing the different researches on recognizing face from forensic sketch by analyzing their approaches and identifying their limitations. We also discuss relevant issues such as benchmarking datasets and evaluation protocols. After, we conclude with several promising directions for future research.

+

Keywords: *Face Sketch Recognition, Gap, Feature Extraction, Matching Methods, Machine Learning, Evaluation Protocol, Datasets.*

1. INTRODUCTION

Police uses many automated biometric engineering to identify potential suspects. The technologies such as DNA, fingerprint, CCTV (closed circuit TV) face recognition are used when physical evidences are found at crime scene. However for many crimes the only available information is an eye witness. In this case, Investigators perform two following steps: first they build with a witness a suspect's face called forensic sketch by using skilled artists [41] or software composite[33][34]. Second, they identify a sketch by sending it to public appeals for information or to a forensic examiner who compare the sketch with images in mug shot database. These last methods of identifying suspects are generally manual, slow and fastidious and may not conduct to arrest the right offender. Therefore, an automatic solution of identifying a face sketch to a database of photographs is significant.

The main **Error! Reference source not found.** **Error! Reference source not found.** **Error! Reference source not found.** challenge that researchers encountered in building face sketch recognition system is how to reduce gap [20] between face image and forensic sketch. This question is closely related to many important factors such as visual characteristics, the quality of sketch, the face image database and the matching technologies.



Figure 1 : Examples of face sketches and their correspondent mugshots. The difference between sketch and photo are shown concerning visual characteristic.

One of the apparent factors that influence on comparison between face image and forensic sketch is their visual characteristics. For example, as shown in Figure1, the face image is a dense collection of colored pixels captured by digital camera however sketch is a black lines drawings on a flat white ground made up by artist.

The second factor is the sketch quality. This factor refers to the sketch generation process. Many psychological studies[39][41][42],[43],[44] have argued that oral portraiture techniques involving both the artist’s drawing skill and the witness description ability have a direct effect on the resulting face sketch. Therefore the gap between face image and forensic sketch is affected.

Another third potentially factor that challenges the comparison is the nature of face images gallery. This factor depends on several variables such as size of facial image collection or database, Presence or absence of Facial features (beards, mustaches, age and glasses.etc), Facial expression and Imaging conditions (lighting, camera characteristics.etc).

The last important factor that affects also the comparison is matching methods **Error! Reference source not found.**[19]. These methods aim to compare photo and sketch by their visual features. In last decade, great efforts have been devoted to the study of the computerization of face sketch recognition. For example, Uhl and lobo [1] proposed the first automatic retrieval of photos using a query sketch based on face recognition algorithm and more recently Klare and jain [14] suggests an effective method of matching sketch photo using many technique such as local descriptors [19], similarities algorithm [24]. However, although these attempts, there are no satisfying general solutions that make a task of face sketch recognition more accurate and fast to resolve several crimes.

This paper is organized in the following way. The second section gives **Error! Reference source not found.** a generic architecture of face sketch recognition system by introducing their basic concepts, describing their essential components and enumerating their core techniques. The third section reviews the most known studies that have focused on this challenging problem. In section four we examine the concepts of the test databases using to evaluate these typical systems. We conclude this paper with a discussion of several promising directions for our future research.

2. OVERVIEW OF THE SYSTEM

Face Sketch Recognition system or briefly FSR is a query by sketch image system that can be viewed in two different ways: as process or as techniques.

2.1 Face Sketch Recognition Processes

FSR processes are used to show the relationships and interactions among the user and the FSRs components.

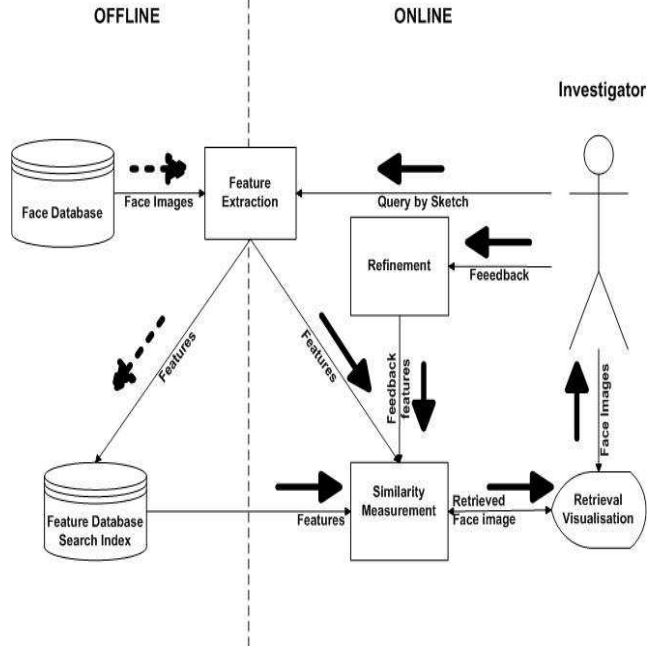


Figure 2: A Generic FSR Architecture. . The Dashed Line Divides The Offline And Online Processes The Dashed Arrows Show The Offline Creation Of The Feature Database From Face Database. The Solid Arrows Show The Online Query By Sketch Process. Note That Feature Extraction Module Participates In Both The Offline And Online Processes

As can be seen from the figure 2, FSR is divided into offline and online processes. The dashed arrows show the off-line process, while the solid arrows indicate the online process. During the offline process, FSR extract visual feature (color, shape, texture, and spatial information) of each face image in the database. As a result, a computational description called image’s signature[19] stored and indexed in a different database called a feature database. In the online process, the investigator can search and find the face images similar to query sketch image. This interactive retrieval process can be achieved in two stages, first by performing the same feature extraction above on the query sketch and subsequently by comparing using a defined similarity algorithm the features of indexed images and sketch feature. The value of the similarity algorithm can then be used to rank the retrieval images in order of similarity or to classify the

images as similar or not similar. This ranking result is then displayed to the investigator. In many cases, the investigator can interact with FSR by giving a form of weights or similarity indication to further refine the search results. The feedback and retrieval process is repeated until the Investigator is satisfied with the retrieved results.

2.2 Face Sketch Recognition Core Techniques

Research [19] identifies four broad classes of techniques that can influence on FSR image retrieval purposes. As shown in figure 3, FSR have techniques for features extraction, for the storage of these features, for distance measurements or similarity calculation between these features, and other techniques like relevance feedback with querying and browsing in a kind of graphical user interface.

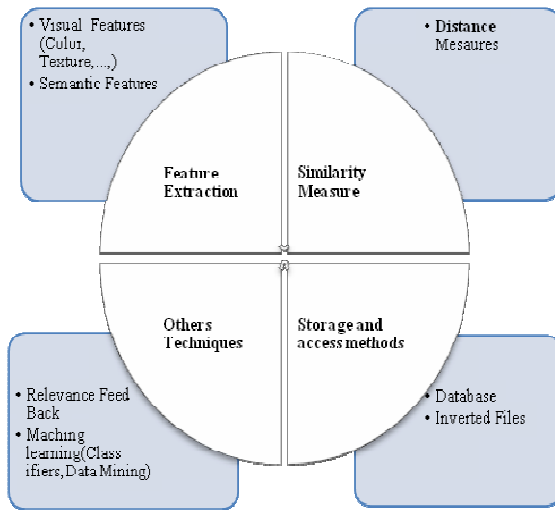


Figure 3: the main techniques of generic FSR

2.2.1 Feature extraction

As mentioned above, FSR use the concept of image descriptor to extract relevant features from forensic images (face and sketch). According to the research[19], feature descriptors were classified into visual and semantic. On the one hand, visual features can be common or domain specific. Common or low level feature include the most used visual feature such as color, texture, shape, spatial relationship, etc. while domain specific visual content, dependent on reserved domain

knowledge like human faces, medicine diagnosis, architectural and engineering design...etc. Visual features can be either global or local. A global descriptor uses the visual features of the whole image, whereas a local descriptor uses the visual features of regions or objects to describe the image content. Table 1 gives an example of the most widely descriptor proposed for FSR approaches. On other hand the semantic features or high level are done by textual annotation[19]or by complex inference procedures based on visual content. The difference between digital image and her extracted representation is called the semantic gap[20].

Table 1: Descriptors popular and proposed for FSR approaches.

Feature Descriptors	Description
PCA (Principal Component Analysis) [9],[27]	Eigen analysis global descriptor
SIFT(Scale Invariant Feature Transform)[23],[46][46]	Local descriptor robust to scale, orientation, and speed Based on interest points or specific pixels in digital images using gradient and orientation of neighboring points
MLBP(variant of Local Binary Patterns)[22]	A Wide Local descriptor used for Texture features (gray levels intensities)

2.2.2 Similarity measure

FSR achieved the comparison of extracted features of the query sketch to those of the face images in the database by an appropriate distance metric called also similarity measure[19],[28]. This distance value to the query sketch is used to rank face images according to its similarity. Often the choice of this particular distance affects significantly the performance of FSR. Table 2 show some common distances used in FSR.

Table 2: some common similarity measures used in FSR.

Distance Measure	Computation
Euclidian Distance	$d_e = \sqrt{\sum_{i=1}^n (x_i - y_i)^2}$ (1)
Mahalanobis Distance	$d_m(x) = \sqrt{(x - \mu)^T \Sigma^{-1} (x - \mu)}$ (2)
Manhattan Distance	$d_M = \sum_{i=1}^n x_i - y_i $ (3)
Weighted Euclidean Distance	$d_w = \sqrt{\sum_{i=1}^n w_i (x_i - y_i)^2}$ (4)



2.2.3

2.2.4 Storage and Access Methods

In order to allow an efficient and quick access to large amounts of forensic Images, FSR needs storage and access methods. Various technologies such as databases management, inverted files, indexing techniques, dimension reduction algorithms, pruning methods...etc can be used to enhance retrieval process.

2.2.5 Others Techniques

There are several other important techniques that can improve the performance of FSR. One of the most salient techniques is users' relevance feedback[19]. With this interactive technique, it is possible to establish the link between high-level concepts and low-level features of image by introducing the forensic expert during the retrieval process. The main idea is to control the pertinence of the retrieval results by controlling relevant and irrelevant face images. Other techniques from the artificial intelligence community [19] such as data mining and pattern recognition can improve FSR systems by applying learning and classifying strategies on face image data.

3 RELATED WORKS

Face Sketch Recognition is studied in three research team: cognitive psychology, forensic science and computer vision.

3.1 Cognitive Psychology

Psychologists and neuroscientists are often interested in artist and witness perception ability, specifically how artist sketch the appearance of suspect based upon the witness' description and how witness perceive human face and sketches drawn by forensic artists, this knowledge can help to design a robust FSR inspired from human vision system. One of the first examples of these studies is carried out by Zhang et al.[9], [42] in which they compared the performance of humans and PCA matching sketch-photo algorithm with variations in gender, age, ethnicity and inter-artist variations. They investigated the quality of sketches in terms of artist's skills, experience, exposure time, and distinctiveness of features. In another major study, Nizami et al. [37] analyzed the intrapersonal variation that occur in sketches drawn by different

artists. In more recent works, Frowd et al.[39] [39],[44],[45] have been developed a face composite system called EVOFIT based on both psychological parameters such as witness cognitive behaviors, facial distinctiveness and holistic features algorithms.

3.2 Forensic Science

The reliability of biometric system in general and FSR in particular is a continuing concern within forensic community. Law enforcement experts always investigate the admissibility of these systems in judicial decision. For this reason, it is agreed by researchers[19]that such system must be validated by a human expert using standards processes established by the forensic community. One of the best effort toward developing standards and guidelines for forensic facial identification is currently carried out by Facial Identification Scientific Working Group (FISWG)[38]. It works under Federal Bureau of Investigation(FBI)Biometric Center of Excellence (BCOE).

3.2 Computer Vision

The research in computer vision is focalized on developing efficient algorithms that match sketches to mug-shot photos. To date, several methods have been proposed for face sketch recognition which can be grouped into two categories: generative and discriminative approaches.

3.2.1 Generative approaches

Generative or intra-modality approach attempts to synthesize photo from input sketch for matching sketches and photos in a same modality or vice versa. Tang and Wang [2] have given the first generative algorithm that transform the face photos to pseudo-sketches using geometrical measures and Eigen face analysis. Then they perform matching techniques by projecting the resulting pseudo sketch into query sketch Eigen space. In the other way around, the authors could also metamorphose sketch into a pseudo-photo, and then compared the outcome with photo. The algorithm has been tested successfully on a gallery of faces and sketches called CUHK [31]. In [3], Liu et al. synthesized sketches based on locally linear embedding method. The nonlinear discriminate analysis is used to match the sketch from the synthesized pseudo-sketches. Experimental tests are conducted over 600 photo-

sketch pairs. In [8], Tang and Wang developed an alternate approach synthesizing local face structures at different scales using a learning Markov Random Fields model. A random sampling LDA classifier is utilized to match the pseudo photo synthesized from a sketch with photos under different conditions of lightings, expressions, and occlusions. In their experimental stage, they build a face photo-sketch datasets called CUFS. In another approach presented in [7], Gao et al.[6] proposed Embedded Hidden Markov Model to synthesis a sketch from photo. For matching purpose they use the classical Eigen face analyses.

Other schemes for face sketch synthesis from photos are proposed like sparse representation [10][10], multi-dictionary sparse representation[12]and local regression models[15].

3.2.2 Discriminative approaches

Discriminative or inter modality approaches directly compare the face photos and sketches using feature descriptors. Preliminary work on this kind of approach was undertaken by Uhl and Lobo[1]. They proposed an algorithm called photometric standardization method. It first geometrically normalized both the sketches and the photos, and then uses the Eigen analysis for matching. The algorithm was tested on a small datasets containing 16 subjects. Yuen and Man[5] used local and global feature measurements to bridge the gap between the sketches composed by the software AI- CAMS-FIT and mug-shot images. Zhang et al. [9] studied the performance of humans and PCA matching sketch-photo algorithm with different parameters such as gender, age, ethnicity, and inter-artist variations. They analyzed the quality of sketches in terms of artist's skills, experience, exposure time, and distinctiveness of features. In[4], Lin and Tang presented a general algorithm that reduce modality gap between the sketch and photo. They use Common Discriminant Feature Extraction (CDFE) method to match sketches and photos. They conducted their experiment on the set of 700 sketches composed by artists and 350 images from FERET [32] face database. Wang et al. [13] proposed a coupled information theoretic encoding descriptor which aims to calculate both face and sketch features using an information theoretic projection tree (CITP). The resulting hierarchical features are compared by using combined classifiers PCA and LDA. This approach was tested on CUFS DATABASE. Bhatt et al.[11] build a multi-resolution Laplacian pyramid to encode sketches

and photos. Then they perform feature extraction by using a variant of LBP descriptor. Matching is achieved via an application of genetic optimization based on weighted Chi square distance measure. Experimental results are given on a combined database of CUHK Database and IIT DATABASE. Klare et al. [14] proposed a local feature approach using Scale Invariant Feature Transform (SIFT) to describe faces and sketches. The comparison is provided using Local Feature Discriminant Analysis (LFDA). In[16], Bhatt et al. present a modification of [11], with two major two innovations that relate to the feature extraction and optimization stages. To extract features discriminating information from both sketches and digital face images, they encode local facial regions using multiscale circular Weber's local descriptor. In optimization, an evolutionary memetic algorithm is proposed to assign optimal weights to every local facial region to boost the identification performance. Han et al.[17] proposed a component based representation method to measure the similarity between a software generated composites and mugshot photograph. They first automatically detect facial landmarks in composite sketches and face photos using an active shape model (ASM) and multiscale local binary patterns MLBP for extraction and matching. They used for experiments a larger database with 10,000 mug shots. Another recent approach by Klum and al. [18] proposed a Facial composite to mugshot matching algorithms deployed in their FaceSketchID System. They combine together two different approaches proposed in[14][17]to boost the matching performance. They conduct their evaluation tests on private and more realistic datasets with more than 100,000 forensic images (sketches and photos).

Table 3 summarizes the representative works for face sketch recognition field classified by kind of approach, taking into account the method of forensic image description, type of experimental dataset, recognition rate and characteristics involving strengths and faults.

3.2.3 Discussion

The data in table 3 reveal many significant and interesting things. In the first place we can see that FSR topic still in its earliest stages and few studies have been published on this particular field. All of them have only focused on developing efficient proprietary algorithms that match sketches to mug-shot photos. Secondly, it is readily seen that researchers access their approaches on different databases with the recognition rate as a primary



dimension of performance comparisons. In addition don't follow a normalized design methodology that and to the best of our knowledge, these approaches

Table 3: Overview on FSR approaches with their Strengths and weakness.

FSR Approches	Publication /DATE	Image descriptor	DATABASE	DATAB ASE DIMENSION	RELEV ANCE	Recogni tion Rate	Strengths and Weakness
DISCRIMINATIVE	Uhl and Lobo[1], 1996	Photometric standardization	Hand-Drawn Composites ¹	16	Not Reported	N/A	+They provide a model that characterizes the relevant features in forensic image not all images so they perform fast than Generative approaches. +They are robust to many variations like scale, orientation, and speed...etc. +These methods are tested and experimented on more real datasets. -the datasets are private due to the security issues -These approaches need learning stage in order to perform better.
	Yuen and Man[5], 2002	Point distribution model and geometrical relationship	Software Generated Composites ²	300	Not Reported	100%	
	Lin and Tang[4] 2006	Common discriminant feature extraction	Viewed Hand-Drawn Composites CUHK ³	350	Not Reported	96%	
	Bhatt et al.[11] 2010	Extended uniform circular local binary pattern descriptor and Genetic Algorithm	Hand-Drawn Composites+CUHK	7,063	Not Reported	87 ,89%	
	Zhang et al. Error! Reference source not found.	Principle Component Analysis (PCA) based algorithm	Hand-Drawn Composites	100	Not Reported	N/A	
	Wang et al[13]. 2011	Coupled Information-Theoretic Encoding	Viewed Hand-Drawn Composites CUHK+CUFS	1, 194	Not Reported	98 ,70%	
	Klare et al. [14]	SIFT and MBLP feature descriptors with local-feature based discriminant analysis	Hand-Drawn Composites	10,159	Not Reported	32 ,6% (rank-50)	
	Bhatt et al. [16] 2012	Multi-scale circular Weber's local descriptor and Genetic Algorithm	Hand-Drawn Composites+CUFS	7,063	Not Reported	28 ,5% (rank-50)	
	Han et al. Error! Reference source not found. 2013	Component based representation using MLBP descriptors	Software Generated Composites	10,159	Not Reported	10 ,6% (Rank-1) 65% (Rank-100) 73 ,2% (Rank-200)	
	Klum et al.[18] 2014	FaceSketchID System(Feature+ Component approaches)	Viewed Hand-Drawn Composites CUFS, Hand-Drawn	100,000 +	Not Reported	14%(Rank -200)	

¹For Klum et al.[18], Hand Drawn Composite refers to facial sketches drawn by forensic artists based on the eyewitness testimony.

²Klum et al[18]. have provided a definition of Software Generated Composite: it means facial sketches created by forensic investigator using software composite such as IDENTI-KIT [33] and E-FIT[34] based on the witness description.

³In the website of Multimedia laboratory of Chinese University of Hong Kong[31], the terms Viewed Hand-Drawn Composite refer to the facial sketches drawn by hand while viewing the photograph. In his laboratory, researchers created for their evaluation test a dataset called CUKH which contains a number of viewed sketch photo pairs.



						Composites, Software Generated Composites	
GENERATIVE	Tang and Wang [2] 2004	Photo-to-composite conversion using eigentransform	Viewed Hand-Drawn Composites CUHK	100	Not Reported	90%	+These methods have the capability to synthesize face from sketch and vice versa and use the classical Face recognition algorithms.
	Liu et al. [3] 2005	Photo-to-composite conversion using locally linear embedding	Viewed Hand-Drawn CompositesCUHK	300	Not Reported	87,7%	-Their performance is unsatisfied due to the large dimensionality of training data from photo and sketch.
	Wang and Tang[8] 2009	Photo-to-composite conversion using multiscale Markov random field model	Viewed Hand-Drawn Composites CUHK	300	Not Reported	96,3%	-They are sensitive to variations on poses, lightings, expressions, and occlusions...etc.
	Gao et al. [6] 2010	Photo-to-composite conversion using embedded hidden Markov model	Viewed Hand-Drawn CompositesCUHK	Not reported	Not Reported	95,24%	-These methods are learned and evaluated on ideal datasets such CUHK and CUFS databases.

adequately covers all aspects of the issue such as forensic expert interaction with FSR system (Relevance feedback), standards benchmarking and so on.

Finally, table 3 provides also the strengths and faults of all mentioned FSR approaches regarding to the following features: image descriptor, sensitivity to variations[19][24], evaluation purposes involving experimental datasets.

Despite of its capability to synthesize face photo from sketch and vice versa, which can then be compared using existing face recognition algorithms [24],[27], Generative methods suffers from well knows limitations:

- Their performance is unsatisfied due to the large dimensionality of training data from photo and sketch.
- They are sensitive to variations on poses, lightings, expressions, and occlusions...etc.
- These methods are learned and evaluated on ideal datasets such CUHK and CUFS databases.

Compared with generative approaches, discriminative approaches typically have the following pros and cons:

- They provide a model that characterizes the relevant features in forensic image not all images so they perform fast than Generative approaches.

- They are robust to many variations like scale, orientation, and speed...etc.
- These methods are tested and experimented on more real private datasets.
- These approaches need learning stage in order to perform better.

4 FSR DATABASE AND PERFORMANCE EVALUATION

In order to measure and compare the performance of competing FSR approaches researchers should build face sketch databases. Although many FSR methods have been proposed, only a few face sketch databases have been designed for experimental tests. In this section we review the characteristics of the existing databases and their relevance to FSR approaches.

4.1 FSR Database

CUFS database has been widely used to assess the strengths and weaknesses of many proposed FSR approaches. it include a set of sketch-photo pairs in which sketches are drawn by an artist based on a photo taken in a frontal pose, under normal lighting condition, and with a neutral expression. The first version of this dataset contains 606 pairs of face sketch, 188 faces from the Chinese University of Hong Kong (CUHK) student database[31], 123 faces from the AR database[29], and 295 faces from the XM2VTS database[30]. Further, it has been released by adding 1,194 more sketch-photo pairs from the FERET dataset (called CUFSS)[32], giving a total result of 1800 pairs face

sketch. In order to evaluate their memetically optimized matching sketch algorithm, Bhatt and al.[16] created The IIT database[16]. It is the first public database that use three varied sketches and contain over than 6000 digital forensic images. It include 311 viewed sketches from CUHK , 6514 forensic sketches from lois Gibson [25], Karen taylor [26], law enforcement agencies and different source on internet and 140 semi forensic sketches drawn based on the memory of artist that remember a set of sketch from CUKH database. More recently, Klare and al. [18] build a big database as a test bed for their FaceSketchID System[18]. It contains more than 100000 forensic digital photos (face and sketch). The many digital images fall into four categories: hand-drawn composites sketches, software-generated composites sketches, surveillance composites sketches and forensic

mugshots photos. The sketches in Hand-drawn composites are the most widely used in criminal investigations since 19th century and drawn by forensic artists based on the witness description. In contrast, sketches in Software-generated composites are produced using software kits which allow an operator to select various facial components. The Surveillance composites sketches are drawn by forensic artists and are used when software surveillance systems generate bad quality surveillance images (due to poor lighting, off-pose faces, occlusion, etc.). The rest of digital images is a set of mugshots from Pinellas County Sheriff's Office[18]. This last more realistic face-sketch datasets is private due to security issues. Table 4 summarizes the characteristics of the abovementioned face sketch databases.

Table4: Some FSR Databases used for evaluation.

Data Set	Location	USED BY WORKS	Description
CUHK – CUFS Database	http://mmlab.ie.cuhk.edu.hk/archive/facesketch.html	[2][3][8][11][12][13][14][16][18][17]	1800 face-sketch pairs under normal lighting condition, and with a neutral expression. +available and benchmarks datasets, useful in training stage. - not realistic sketches.
IIT-D Sketch Database	https://research.iiitd.edu.in/groups/iab/sketchDatabase.html	[11][16][18]	311 viewed sketches from CUHK ,92 forensic sketches from lois Gibson and Karen taylor, 61 face sketch pairs from different source on internet , 140 semi forensic sketches and 6324 mugshots from law enforcement agencies. +available not a standars, varied set of sketch. - medium size for training and test.
FaceSketchID Database	[43]Not all available	[14][17][18]	A large collection of varied sketches from different sources (Hand-drawn composites, Software-generated composites, Surveillance composites sketches)and real criminal mugshots images from Pinellas County Sheriff's Office. +big size, more realistic sketches - Not all Available only few sketch

4.2 Discussion

From Table 4 we can see that most reviewed FSR approaches have been assessed on CUFS database. However, the major drawback of this evaluation is that provide biased results not applicable in real forensic world scenario; Due to the pitfalls that have been discussed in [43][35], [36],[43]. The problem arises, however, when the evaluation results are reported using different

training datasets with different tuning parameters. So, more researchers should design a standard protocol for evaluation or benchmarks, involving the following aspects:

- An Adequate dataset for evaluation: In their experimental tests, researchers should use representative dataset that encompass forensic domain knowledge.



- Relevance feedback by forensic expert: researchers must involve forensic expert in order to validate experimental test on FSR systems.
- A suitable Metric for evaluating Competing Approaches: researchers should use an appropriate metrics[19] in order to compare different approaches.

5 CONCLUSION

In this review, we have presented recent researches in face sketch recognition by providing the main approaches described in over 20 papers. We are aware that FSR field are immature and there is a lack of uniformity in how methods are evaluated and, so, it is imprudent to explicitly declare which methods indeed perform better. As mentioned above in the discussions, we conclude that future work should concentrate on adopting common methodology like CBIR[47] technology on designing and developing FSR systems approaches by taking account standardized evaluation protocol that would allow forensic experts to validate face sketch technology in their domain. So, there is still work to be done, and we believe that a powerful FSR system will see the light.

REFERENCES:

- [1] R. Uhl and N. Lobo, "A framework for recognizing a facial image from a police sketch," in Proc. Int. Conf. Computer Vision and Pattern Recognition, 1996, pp.586 -593.
- [2] X. Tang and X. Wang, "Face sketch recognition," IEEE Trans. on Circuits and Systems for Video Technology (CSVT), vol. 14 , no. 1, 2004, pp. 50–57.
- [3] Q. Liu, X. Tang, H. Jin, H. Lu, and S. Ma, "A nonlinear approach for face sketch synthesis and recognition," in Proc. Computer Vision and Pattern Recognition (CVPR), 2005, pp. 1005–1010.
- [4] Lin, Dahua, and Xiaou Tang, "Inter-modality face recognition," in Computer Vision–ECCV. Springer Berlin Heidelberg, 2006, pp. 13-26.
- [5] P. Yuen and C. Man, "Human face image searching system using sketches," IEEE Transactions on SMC Part A: Systems and Humans, vol. 37, no. 4, 2007, pp. 493 –504.
- [6] X. Gao , J. Zhong , J. Li and C. Tian "Face sketch synthesis algorithm based on E-HMM and selective ensemble", IEEE Trans. Circuits Syst. Video Technol, vol. 18, no. 4, 2008, pp.487-496.
- [7] B. Xiao, X. Gao, D. Tao, and X. Li, "A new approach for face recognition by sketches in photos," Signal Processing, vol. 89, no. 8, 2009, pp. 1576–1588.
- [8] X. Wang and X. Tang, "Face photo-sketch synthesis and recognition," IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 31, no. 11, 2009, pp. 1955–1967.
- [9] Y. Zhang , C. McCullough , J. Sullins and C. Ross, "Hand-drawn face sketch recognition by humans and a PCA-based algorithm for forensic applications", IEEE Trans. Syst., Man, Cybern. A, Syst., Humans, vol. 40, no. 3, 2010, pp. 475 -485.
- [10] L. Chang, M. Zhou, Y. Han, and X. Deng, "Face sketch synthesis via sparse representation," in Proc. International Conference on Pattern Recognition (ICPR), 2010, pp. 2146–2149.
- [11] H. Bhatt, S. Bharadwaj , R. Singh and M. Vatsa "On matching sketches with digital face images," in Proc. Int. Conf. Biometrics: Theory Applications and Systems, 2010.
- [12] N. Wang, X. Gao, D. Tao, and X. Li, "Face sketch-photo synthesis under multi-dictionary sparse representation framework," in International Conference on Image and Graphics (ICIG), 2011, pp. 82–87.
- [13] W. Zhang, X. Wang, and X. Tang, "Coupled information-theoretic encoding for face photo-sketch recognition," in Proc. Computer Vision and Pattern Recognition (CVPR), 2011, pp. 513–520.
- [14] B. Klare, Z. Li, and A. K. Jain, "Matching forensic sketches to mug shot photos," IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 33, no. 3, 2011, pp. 639–646.
- [15] N. Ji, X. Chai, S. Shan, and X. Chen, "Local regression model for automatic face sketch generation," in Int. Conf. on Image and Graphics (ICIG), 2011, pp. 412–417.
- [16] H. Bhatt, S. Bharadwaj, R. Singh, and M. Vatsa, "Memetically optimized MCWLD for matching sketches with digital face images," IEEE Trans. In Forensics Security, vol. 7, no. 5, October 2012, pp. 1522–1535.
- [17] H. Han, B. Klare, K. Bonnen, and A. Jain, "Matching composite sketches to face photos: A component based approach," IEEE Trans. Inf.



- Forensics Security, vol. 8, no. 1, January 2013, pp. 191–204.
- [18] Klum, Scott J., et al. "The FaceSketchID System: Matching Facial Composites to Mugshots.", 2014.
- [19] Ritendra Datta, Dhiraj Joshi, Jia Li and James Z. Wang, "Image Retrieval: Ideas, Influences, and Trends of the New Age," ACM Computing Surveys, vol. 40, no. 2, article 5, 2008, pp. 1-60.
- [20] Deserno, Thomas M., Sameer Antani, and Rodney Long. "Gaps in content-based image retrieval." Medical Imaging. International Society for Optics and Photonics, 2007.
- [21] G. L. Wells and L. E. Hasel, "Facial composite production by eyewitnesses," Current Directions Psychol. Sci., vol. 16, no. 1, Feb. 2007, pp. 6–10.
- [22] T. Ahonen, A. Hadid and M. Pietikainen "Face description with local binary patterns: Application to face recognition", IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 12, 2006, pp.2037 -2041.
- [23] D. Lowe "Distinctive image features from scale-invariant keypoints", Int. J. Comput. Vis., vol. 60, no. 2, 2004, pp.91 -110.
- [24] Ion Marqués, "Face recognition algorithms." Master's thesis in Computer Science, Universidad Euskal Herriko, Jun. 2010.
- [25] GIBSON, Lois. Forensic art essentials: a manual for law enforcement artists. Academic Press, 2010.
- [26] Taylor, Karen T. Forensic art and illustration. CRC Press, 2000.
- [27] S. Li and A. Jain (eds.), Handbook of Face Recognition, 2nd ed. Springer, 2011.
- [28] Aksoy, Selim, and Robert M. Haralick. "Probabilistic vs. geometric similarity measures for image retrieval," Computer Vision and Pattern Recognition, 2000. Proceedings. IEEE Conference on. Vol. 2. IEEE, 2000.
- [29] M. Martinez, and R. Benavente, "The AR Face Database," CVC Technical Report #24, June 1998.
- [30] K. Messer, J. Matas, J. Kittler, J. Luetin, and G. Maitre, "XM2VTSDB: the Extended of M2VTS Database," in Proceedings of International Conference on Audio- and Video-Based Person Authentication, 1999, pp. 72-77.
- [31] The Chinese University of Hong Kong. "CUHK Face Sketch Database (CUFS)," <http://mmlab.ie.cuhk.edu.hk/datasets.html>. [Online]. Available: <http://mmlab.ie.cuhk.edu.hk/archive/facesketch.html>. [Accessed: Sep. 12, 2009].
- [32] PHILLIPS, P. Jonathon, MOON, Hyeonjoon, RIZVI, Syed A., et al. "The FERET evaluation methodology for face-recognition algorithms," IEEE Transactions. On Pattern Analysis and Machine Intelligence, , vol. 22, no 10, p. 1090-1104, 2000.
- [33] Identi-Kit, Identi-Kit Solutions, [Online]. Available: <http://www.identikit.net/>.
- [34] E-FIT, VisionMetric Ltd., [Online]. Available: <http://www.vision-metric.com>
- [35] KUKHAREV, G., BUDA, K., & NADEGDA, S. Sketch generation from photo to create test databases. Przegląd Elektrotechniczny, vol. 90, 2014.
- [36] Choi, J., Sharma, A., Jacobs, D. W., & Davis, L. S. Data insufficiency in sketch versus photo face recognition. In: Computer Vision and Pattern Recognition Workshops (CVPRW), IEEE Computer Society Conference on. IEEE, 2012, p. 1-8.
- [37] H. Nizami , Adkins-Hill , P. Jeremy , Y. Zhang , J. Sullins , C. McCullough , S. Canavan and L. Yin "A biometric database with rotating head videos and hand-drawn face sketches", Proc. Int. Conf. Biometrics: Theory, Applications and Systems, 2009, pp.38 -43.
- [38] ALI, Tauseef, SPREEUWERS, L. J., et VELDHUIS, R. N. J. Forensic face recognition: A survey. 2012.
- [39] C. D. Frowd, D. Carson, H. Ness, J. Richardson, L. Morrison, S. McLanaghan, and P. J. B. Hancock, "A forensically valid comparison of facial composite systems," Psychol., Crime Law, vol. 11, no. 1, Mar. 2005, pp. 33–52.
- [40] H. Nejadi and T. Sim, "A study on recognizing non-artistic face sketches," in Proc. IEEE Workshop on Applications of Computer Vision (WACV), 2011, pp. 240–247.
- [41] R. Geiselman, R. Fisher, D. MacKinnon, and H. Holland, "Eyewitness memory enhancement with the cognitive interview," American Journal of Psychology, vol. 99, 1986, pp. 385–401.
- [42] Y. Zhang, S. Ellyson, A. Zone, P. Gangam, J. Sullins, C. McCullough, S. Canavan, and L. Yin, "Recognizing face sketches by a large number of human subjects: A perception-based study for facial distinctiveness," in IEEE International Conference on Automatic Face Gesture Recognition and Workshops, march 2011, pp. 707–712.



- [43] Nejati, H., Zhang, L., & Sim, T "Eyewitness Face Sketch Recognition Based on Two-Step Bias Modeling." in Computer Analysis of Images and Patterns Springer Berlin Heidelberg, Jan. 2013, pp. 26-33.
- [44] C. Frowd, D. Carson, H. Ness, D. McQuiston, J. Richardson, H. Baldwin, and P. Hancock, "Contemporary composite techniques: The impact of a forensically-relevant target delay," *Legal and Criminological Psychology*, vol. 10, no. 1, February 2005, pp. 63–81.
- [45] C. Frowd, P. Hancock, and D. Carson, "EvoFIT: A holistic, evolutionary facial imaging technique for creating composites," *ACM Trans. Appl.Percept.*, vol. 1, no. 1, July 2004, pp. 19–39.
- [46] C. Geng and X. Jiang "Face recognition using SIFT features", *Proc. Int. Conf. Image Processing*, 2009, pp.3313 -3316.
- [47] LONG, Fuhui, ZHANG, Hongjiang, et FENG, David Dagan. Fundamentals of content-based image retrieval. In : *Multimedia Information Retrieval and Management*. Springer Berlin Heidelberg, 2003. p. 1-26.