

A Framework for Recognizing a Facial Image from a Police Sketch

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Abstract

We present a theory and practical computations for automatically matching a police artist sketch to a set of true photographs. We locate facial features in both the sketch as well as the set of photograph images. Then, the sketch is photometrically standardized to facilitate comparison with a photo and then both the sketch and the photos are geometrically standardized. Finally, for matching, eigenanalysis is employed. Results using real police sketches and arrest photos are presented.

1 Introduction

When a crime is committed, invariably the major clue leading to apprehension of the perpetrators is verbal description of the criminals by witnesses. Police departments then release composite drawings from the descriptions in hopes of identifying the criminals.

Identifying composites normally consists of witnesses looking through books of true mugshot photographs. However, some departments (eg., the Osceola County Sheriff's Office in Florida), utilize a computer to assist in the search. The identification officer inputs the height, weight, and race of the suspect into a program, which searches the database and outputs a long list of possible candidates. The officer then calls up the image of each person on this list and compares it with the sketch obtained from witness descriptions. The images are obtained from databases of real photographs maintained by police and other governmental agencies. An automated comparison process would save many person-hours by eliminating the officer's manual search, and it might reduce the dependence on the public.

The problem we address is amongst the most difficult instances of the face identification problem. It takes as input a police artist sketch of a suspect and matches it to a database of photographs. The sketch is first transformed photometrically to resemble an actual digitized photograph. The transformed sketch is then compared to the database images to obtain a set of candidates.

Next, we review previous work, describe our algorithm, and present results and a discussion.

2 Previous Work

Two previous proposals have dealt with face retrieval for law enforcement. [6] retrieved faces by matching linguistic descriptions, obtained from human experts. [3] proposed three different methods to retrieve faces: one was to utilize computer vision, while

the other two relied heavily on human expert intervention. This system was not implemented at the time of publication [3], and it is our understanding that it has yet to be implemented. Hence, our work is the first concrete computational framework for automatically matching a police sketch to true photographs.

3 Overview of algorithm

Figure 1 depicts our police sketch recognition system.

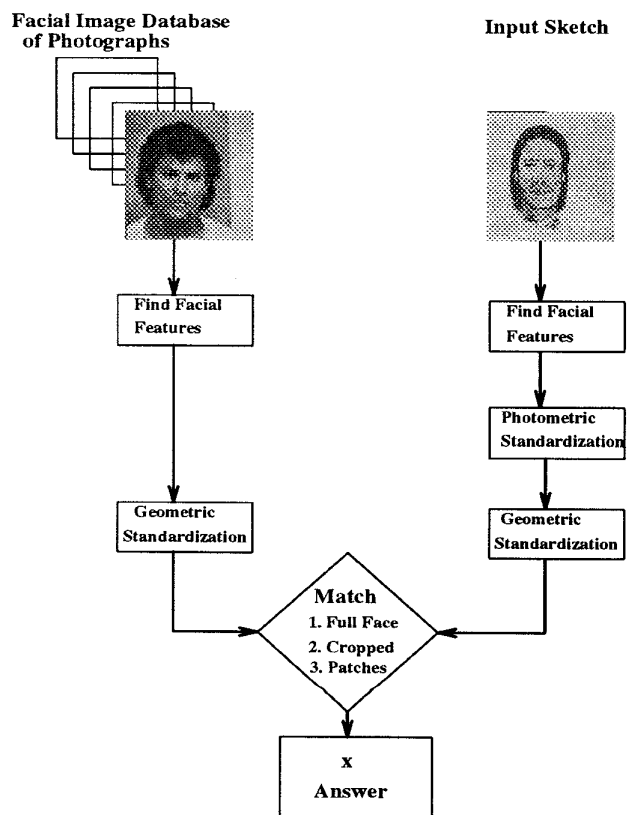


Figure 1: Police Sketch Recognition System

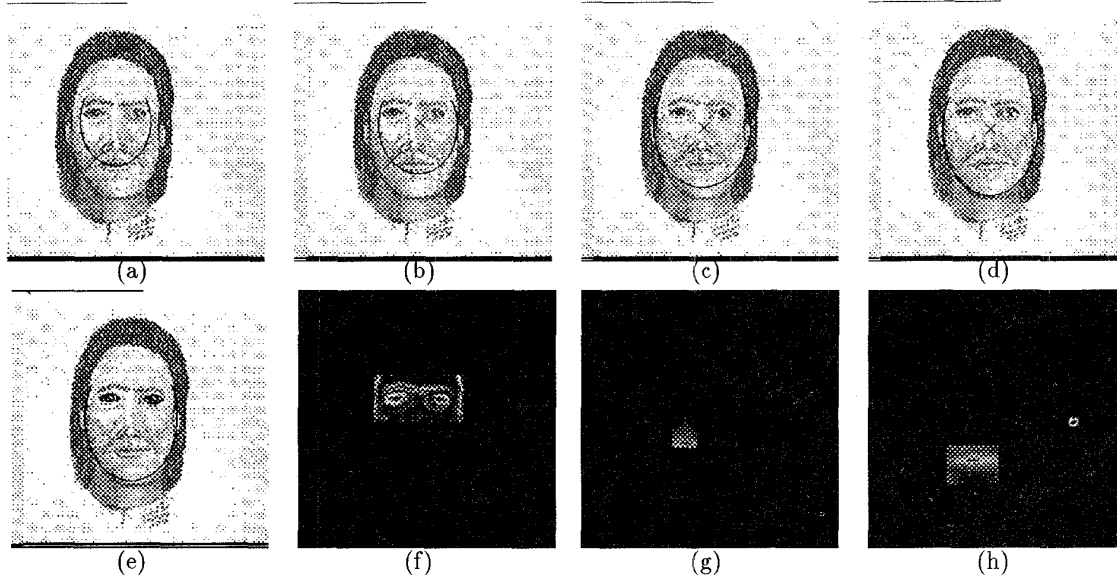


Figure 2: Various stages in the feature finding step. (a), (b), (c) and (d) are stages in finding the oval. (e) and (f) find the eyes, (g) finds the nose and (h) finds the mouth.

A high level description of the steps is:

- (1) Find facial features
 - a. Find initial rough oval
 - b. Find chin
 - c. Find sides of face
 - d. Improve face oval
 - e. Find eyes
 - f. Find mouth
 - g. Find nose
- (2) Photometric standardization
 - a. Remove high intensity regions
 - b. Blur within face oval
 - c. Create new pseudo-photograph
- (3) Geometric standardization
 - a. Tessellate image.
 - b. Mapping of image to CANDIDE model
 1. Facial image database photographs
 2. Pseudo-photographs
- (4) Match sketch pseudo-photograph to photographs in facial image database
 - a. Input to the matching algorithm (3 alternatives)
 1. Full face
 2. Cropped face
 3. Patches
 - b. Match
 1. Compute eigenfaces for photographs
 2. Compute each photograph's coefficient vector Ω_k
 3. Project pseudo-photograph to face space vector Ω
 4. Compute Euclidean distance between Ω and Ω_k

The module Find Facial Features finds the face oval, chin, eyes, nose and mouth. Our approach to finding the initial oval, and the eyes follows that of [9] and [5]. Finding the chin and the sides of the face, involves dropping a population of *snakelets* (small snakes [1])

around the boundaries of the initial oval, in three rectangular regions. The nose and mouth are found by convolution with dark-bar detectors.

A sketch then undergoes Photometric Standardization, involving controlled blurring, to give a "pseudo-photograph". Both the photographs and the pseudo-photographs undergo Geometric Standardization, using triangular tessellation [4] and re-projection.

Matching is then accomplished by eigenanalysis [7]. Three different inputs to matching are explored. The first utilizes the full face as input to the matching algorithm. The second uses images with cropped foreheads. The third uses individual triangles, as separate patches, thus, for example, only comparing all mouths. The training set is composed of geometrically standardized images of actual arrest photographs of those in the sketches plus photographs of other individuals. The geometrically standardized pseudo-photographs compose the recognition set.

4 Algorithm

4.1 Facial Feature Detection/Localization

The localization of the facial features is performed in stages, described in further detail in [8] and summarized here. At each stage, a particular facial feature parameter is found. The initial face-oval-finding stage finds an oval that best fits the face/head. The chin-finding stage finds the best chin in the rectangular area specified by the oval parameters. The face sides-finding stage finds the left and right sides of the face

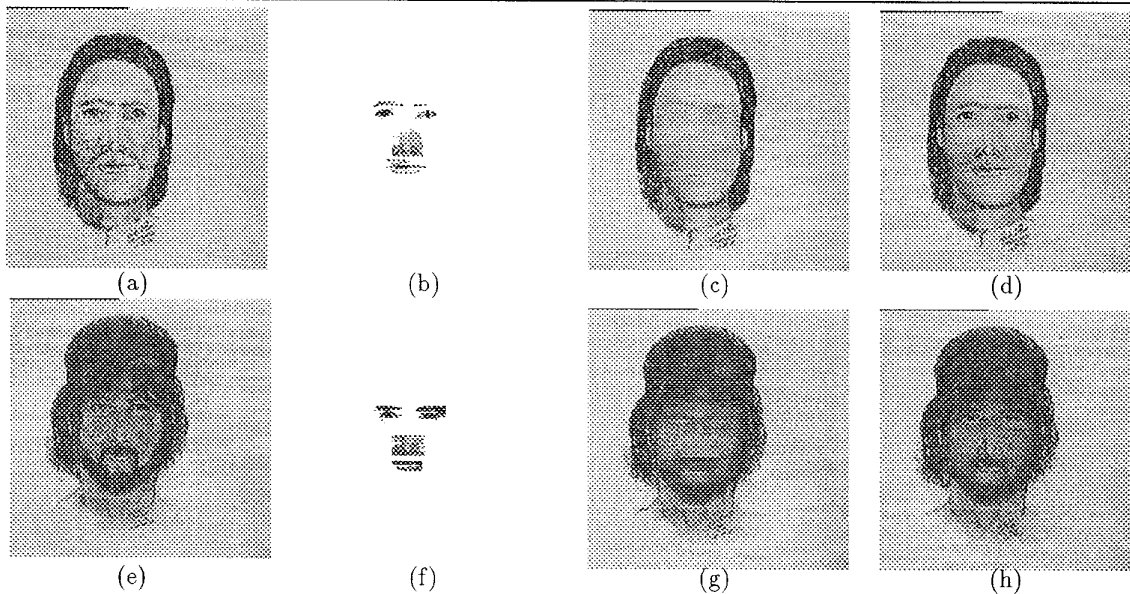


Figure 3: This shows various stages in the Photometric Standardization step of our algorithm. (a) and (e) original sketches. (b) and (f) removed features. (c) and (g) blurred oval. (d) and (h) Pseudo-photographs.

in the area specified by the chin and oval parameters. The chin parameter, if found robustly, is then used to refine the initial oval. Otherwise, the initial oval is used for the remaining stages. The iris-attracting stage places both the left and the right iris center of the template near the respective iris centers in the image specified by the oval parameter. The iris-fitting stage tries to fit more accurately the iris contour by estimating the iris radius and simultaneously improving estimates of both iris center positions. The mouth-finding stage finds the position of the center of the mouth and finally the nose-finding stage finds the position of the bottom of the nose. Figure 2 shows the intermediate stages at which facial features are found.

4.2 Photometric Standardization

Figure 7 includes the input sketches to our system. In these sketches it can be seen that the artist has added texture to convey 3D shading information of the suspect. Photometric-standardization blends this texture into the background, transforming the sketch into a "pseudo-photograph".

Remove High Intensity Regions. Care is needed to not lose important information around the facial features, as they uniquely define the person. Thus, we temporarily remove the high intensity variation in the regions around the features. The location of the features is known from Section 4.1. So, we scan an area around the feature and identify all high intensity-variation. These sub-regions are removed temporarily to be added back into the standardized sketch later. The removed pixel is replaced with a value of the aver-

age skin color in the local area of each feature. This is done for each of the two eyes, the nose and the mouth. Parts b and f of Figure 3 show the regions removed.

Blur Within the Face Oval. Once the high intensity sub-regions have been removed (temporarily) and replaced with the average skin intensity values, the image within the face oval is blurred with a Gaussian mask, $e^{-\frac{(x^2+y^2)}{2\sigma^2}}$, with $\sigma=1$. Parts c and g of Figure 3 show two typical sketch images after the blurring described above.

Create Pseudo-Photograph. Once the image has been blurred, the high intensity-variation pixels that were removed are replaced into the new blurred image at their original intensity values. Parts d and h of Figure 3 show the resulting pseudo-photographs.

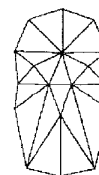


Figure 4: Simplified triangulated face model

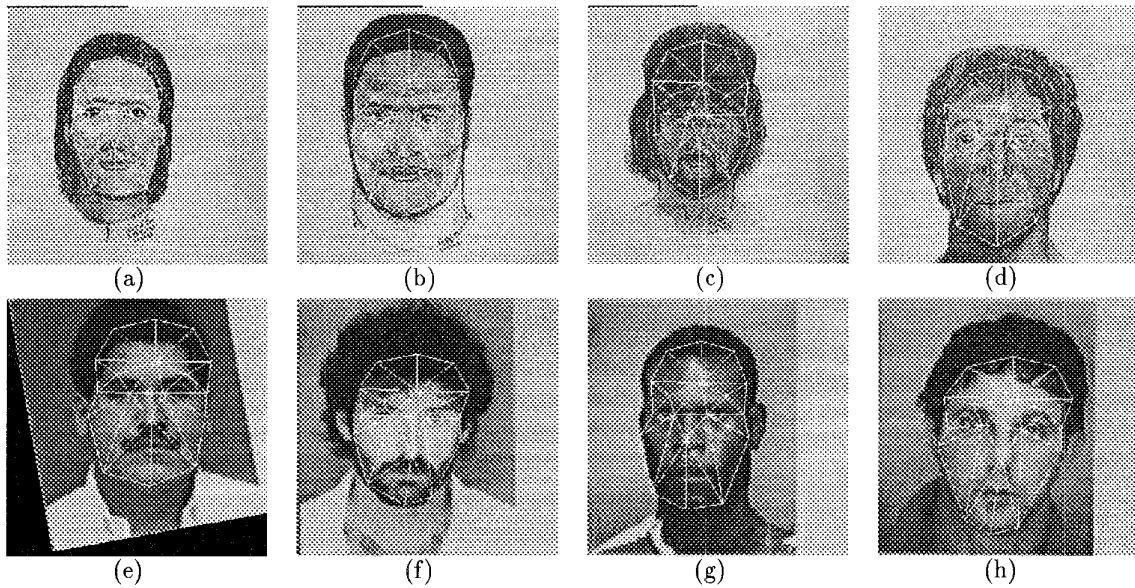


Figure 5: Typical sketches and photographs with the wireframe superimposed

4.3 Geometric Standardization

There are several reasons to perform Geometric Standardization. The height and width in the sketches were determined from witnesses descriptions of the suspect. The police artist would then sketch what she determined to be a “long thin face”. Obviously, this description could mean different things to different people and thus, not be accurately drawn in a manner that would match a photograph. There were also difficulties with photographs of people. The subjects were to be a uniform distance from the camera and looking directly at it. However, in practice, this is not exact. Thus, the faces would appear larger or smaller than they actually were. Figure 7 shows original photographs along with sketches of the subjects, showing the variety of sizes and orientations of faces.

To address this, we normalize the geometry of the face for both pseudo-photographs and photographs. [5] found in eye-recognition that the geometric normalization of the eye did not mask the identity of the eye, and indeed facilitated recognition. Our normalization uses the simplified CANDIDE model [4], shown in Figure 4. Figure 5 shows examples of the outcome of this process. Next, image intensities are interpolated according to the triangulation mapping from image to the CANDIDE model. Figure 6 shows results for both pseudo-photographs and photographs.

4.4 Match Pseudo-Photograph to Photos

Lastly, the sketch is matched to the database of images. Three approaches to the composition of the

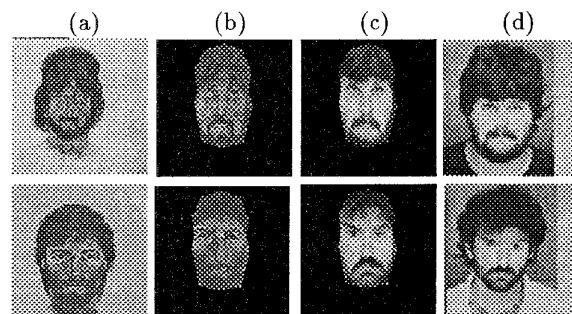


Figure 6: (a) are original sketches, (b) are mapped pseudo-photographs, (c) are original photographs and (d) are mapped photographs

images are explored to examine which yields improved results. All approaches utilize both the Photometric Standardization and the Geometric Standardization steps outlined above. In the first approach (match-method 1), the complete face was input to the matching algorithm. The second approach (match-method 2) cropped the image at the forehead prior to being input to the matching algorithm. In the third approach (match-method 3), after Photometric and Geometric Standardization, each individual triangular patch is

input to the matching algorithm, so that comparison occurs exclusively for the counterpart triangles in the database, independent of the rest of the face.

A database of photograph images is processed according to the method outlined in [7] and [2], sketched here for completeness. The average face image is denoted as $\Gamma = \frac{1}{J} \sum_{i=1}^J \Phi_i$, where J is the number of images in the database. Each face image (Φ_i) differs from the average face image by the vector $\Psi_i = \Phi_i - \Gamma$. Principle component analysis is performed on the resulting set of vectors. The J' most significant eigen-vectors are chosen, each being an eigen-face. Each original face k is a linear sum of the J' eigen-vectors and can be described by the weight vector Ω_k .

A new test image (a processed sketch) is matched as follows. The test image Ξ is projected into face space by the following operation, $\omega_m = v_m^T (\Xi - \Gamma)$ for $m = 1, \dots, J'$. The resulting weights form a vector $\Omega^T = [\omega_1 \omega_2 \dots \omega_{J'}]$ which corresponds to the contribution of each eigen-face in the set to the test image. This vector, Ω , is then compared with the face classes defined from the original set to find the one that matches best. The comparison is computed as the Euclidean distance between Ω and each Ω_k .

5 Results

In our experiments we used seven sketches and the corresponding actual photographs from the Osceola County Sheriff's Office, in addition to nine other photographs. Thus, our database has 16 photos.

The face feature finding algorithm is run on all 7 sketches and 16 photos. Then the 16 photos are all geometrically standardized and used to produce the eigen-faces from which the Ω_k vectors are then computed. When each of the sketches is presented, after its features are found, it is photometrically standardized and then geometrically standardized. Then its Ω vector is computed and its Euclidean distance from each of the Ω_k vectors are ordered. This distance is a measure of the success of the complete algorithm; it also provides a measure for comparison of how well the actual correct photo performs in matching relative to the other 15 photos.

We first matched the original 7 sketches to the original 16 photographs in a raw (non-Standardized) manner. This was done using the raw 256×256 images of sketches and photos to compute the Ω and Ω_k vectors. Table 1, lines 2, 3 and 4, show the raw results. Line 2 shows the distance measure that Sketch n matched with its counterpart photo n . Line 3 shows how photo n 's distance measure ranked relative to other photos, in serving as a match for sketch n . Line 4 shows the winning photo that matched sketch n , as well as the winning photo's matching distance from sketch n . Beneath, on lines 5, 6 and 7, for comparison, we show the counterpart results after applying photometric and geometric standardization using our system and match-method 1. We can see that due to our algorithm, the Euclidean distance between the sketch and the correct photographic match was reduced (compare lines 2 and 5). Also, the rank of the photo that should have won,

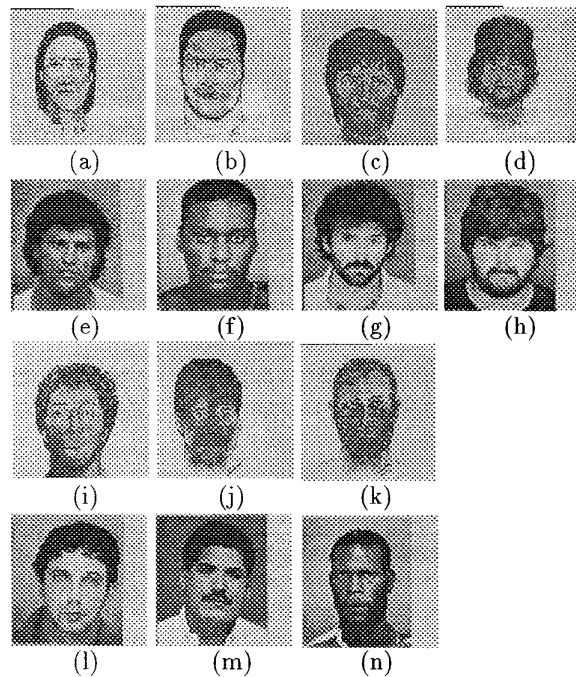


Figure 7: Original sketches with original photographs.

either improved or remained the same for all but 1 of the sketches (compare lines 3 and 6). The one exception (sketch 7) deserves some discussion. Firstly, note that even though the rank of photo 7 worsened (going from first to second place), its matching distance decreased (from 4063 to 2852). Secondly, the reason photo 7 did so well in the Raw experiment, was that it was fortuitously of the same size as the sketches (thus, it won as best match to most of the sketches). Figure 7 shows the original sketch images and corresponding photographs that were input to our system, while Figure 9 shows the Pseudo-photographs output from our algorithm and the corresponding geometrically standardized photographs output from our algorithm. The reason photo 7 (Figure 7n) loses ranking is due to the fact that for photograph 2, Figure 9f, its overall intensity is closer to that of sketch 7, Figure 9k.

Table 2 shows the results of the complete algorithm (using match-method 1) as previously shown, but also includes the results produced when our Photometric Standardization step was skipped for the sketches. From this table it can be seen that the addition of our Photometric Standardization step does lessen the Euclidean distance of the sketch from the corresponding photograph. Figure 8 has the images that were only geometrically standardized (i.e., without photometric standardization).

Table 3 demonstrates that Geometric Standardization is beneficial to the matching process and again

Sketch No.	1	2	3	4	5	6	7
Raw Match	9917.9	7646.2	9299.3	10853.7	7771.9	10298.0	4063.6
Rank	5th	2nd	5th	7th	2nd	7th	1st
Best Match	(7, 5133.2)	(3, 6771.8)	(7, 4618.0)	(7, 5220.3)	(7, 4977.8)	(7, 5285.3)	(7, 4063.6)
Pseudo Photo after Photom. and Geom. Standardization	5936.4	3717.1	3532.9	3781.5	1989.9	2760.0	2852.5
Rank	4th	2nd	5th	5th	1st	2nd	2nd
Best Match	(4, 1520.5)	(4, 1342.7)	(1, 1456.5)	(1, 1416.9)	(5, 1989.9)	(1, 2229.7)	(2, 2083.5)

Table 1: Similarity distance: Rows 2, 3 and 4 are Original sketch matched to original photo. Rows 5, 6 and 7 are Photometric and Geometric Standardized sketch matched to Geometric Standardized photo. Also shown is the rank of the sketch out of the 16 images in the database and the best match (n) with the distance from the sketch to photograph n for each test.

Sketch No.	1	2	3	4	5	6	7
Pseudo Photo After Photom. and Geom. Standardization	5936.4	3717.1	3532.9	3781.5	1989.9	2760.0	2852.5
Best Match	(4, 1520.5)	(4, 1342.7)	(1, 1456.5)	(1, 1416.9)	(5, 1989.9)	(1, 2229.7)	(2, 2083.5)
Sketch After Geom. Standard. only	7418.2	4220.1	3858.0	4294.0	3001.8	3881.7	3611.0
Best Match	(4, 4444.8)	(4, 2407.3)	(1, 2728.0)	(1, 3426.9)	(5, 3001.8)	(1, 3524.4)	(2, 3607.7)

Table 2: Similarity distance: Rows 2 and 3 are Photometric and Geometric Standardized sketch matched to Geometric Standardized photo. Rows 4 and 5 are Geometric Standardized sketch matched to Geometric Standardized photo.

Sk EP	1	2	3	4	5	6	7
0	10,16,5	10,8,16	2,12,7	12,1,2	2,5,12	2,12,6	12,1,7
1	5,10,11	5,10,11	7,2,12	2,15,7	2,5,15	7,12,2	7,12,2
2	3,4,11	5,3,4	12,7,2	12,7,2	2,5,12	12,7,1	12,7,2
3	8,5,10	8,5,10	3,2,15	15,3,2	2,1,3	10,2,1	2,7,3
4	8,9,16	8,10,5	3,2,15	2,3,1	5,6,11	6,10,5	3,2,7
5	5,8,10	5,11,8	12,1,7	2,1,5	5,10,4	6,12,1	12,1,6
6	5,10,8	5,10,16	12,2,7	12,2,7	5,16,4	5,6,10	6,2,1
7	16,15,12	8,10,9	2,5,16	7,12,2	16,3,10	5,15,16	7,2,5
8	8,3,16	11,9,3	15,5,3	2,7,1	9,11,3	3,15,14	8,3,16
9	3,5,15	3,7,2	7,2,3	1,12,2	5,3,16	4,6,2	2,7,3
10	13,14,15	2,5,10	12,7,10	6,1,12	5,2,10	12,7,6	10,9,13
11	11,13,15	9,8,13	16,10,5	6,12,7	10,16,8	10,16,5	13,10,9
12	16,15,8	2,7,14	9,4,6	4,9,6	10,2,14	4,9,6	10,15,14
13	11,15,16	2,13,10	4,2,3	12,7,1	2,10,13	4,6,2	10,14,15
14	11,15,16	2,7,12	4,9,12	4,9,3	9,12,10	4,9,6	12,9,10
15	15,13,10	2,5,12	3,9,4	3,4,9	2,14,13	3,7,4	2,12,7
16	13,16,15	13,3,5	7,6,1	7,12,1	16,5,3	2,6,5	13,16,15
17	13,8,10	7,12,2	7,12,6	1,7,12	5,2,13	3,2,4	7,2,13
18	3,10,16	3,7,2	3,7,2	4,1,12	3,6,10	3,6,4	3,5,7
19	3,16,9	3,4,5	10,5,3	2,5,7	6,11,9	5,10,4	8,16,3
20	5,3,8	3,4,8	5,2,16	2,16,7	5,16,3	2,5,7	2,5,16
21	3,10,16	3,2,12	4,6,5	1,2,12	3,5,10	1,2,6	3,10,2

Table 5: Votes of each eigen patch, EP, (from 0 to 21) for each sketch, Sk

this experiment utilized match-method 1. To show this point, we compare its performance to when instead of Geometric Standardization, only alignment of the face borders is used. Lines 2 and 3 show results for Geometric Standardization, and lines 4 and 5 show results for border alignment only.

As an alternative, we examined match-method 2. Prior to computing the Ω and Ω_k vectors we eliminated the forehead portions of all pseudo-photographs and photographs, to obtain cropped images. These were then input to the matching step and the Ω and Ω_k vectors were computed. (See Figure 10 and Table 4 for details.) In the six that improved all the forehead

regions differed between the pseudo-photographs and the photographs. In the one that did not improve the forehead regions were similar.

Using match-method 3, we input each of the 22 triangles to the matching algorithm, i.e., the input was a triangle from the sketch and the set it was matched with was the same counterpart triangle from the 16 photographs. Table 5 shows the top three "votes" for each of the 22 triangles and the seven sketches. The rows, 0 through 21, represent the 22 individual triangles (eigen-patches) making up the image. The columns, 1 through 7, represent the 7 sketches input to the system. The triple at the position given by the rows and columns represents the best match for the counterpart eigen-patch from the database of images. For example, row 10 and column 4 of Table 5 means: eigen-patch 10 of sketch 4 matches best with eigen-patch 10 of database photograph 6, followed in second place by eigen-patch 10 of database photograph 1 and in third place by eigen-patch 10 of database photograph 12. Tables 6, 7 and 8 tally these votes using three "weighting" values.

In Table 6 the votes were counted as all being equal. Any photograph which was voted into first, second or third place by a eigen-patch (see Table 5) received 1 point.

The points were tallied for all 22 triangles and all seven sketches. The results from this "election" are outlined in Table 6. The rows represent the order in which the database photographs ranked. The columns represent the input sketches. The double at the position of the rows and columns yields the place in which the database photograph ranked followed by the number of votes it received. The last line, marked "Correct", tallies up the total votes for the correct match. For example, row 1 and column 1 tells us that the best

Sketch No.	1	2	3	4	5	6	7
Sketch After Geom. Stand.	7418.2	4220.1	3858.0	4294.0	3001.8	3881.7	3611.0
Best Match	(4, 4444.8)	(4, 2407.3)	(1, 2728.0)	(1, 3426.9)	(5, 3001.8)	(1, 3524.4)	(2, 3607.7)
Sketch After Border Registration Only	8041.8	4817.1	5149.6	5458.1	3234.1	3952.6	3792.4
Best Match	(4, 5020.5)	(4, 3356.7)	(1, 2789.1)	(1, 3774.0)	(5, 3234.1)	(1, 3562.9)	(2, 3699.8)

Table 3: Similarity distance: Geometric Standardized sketch to Geometric Standardized photo. Border registered sketch to border registered photo. The best match (n) with the distance from the sketch to photograph n for each test is also shown.

Sketch No.	1	2	3	4	5	6	7
Pseudo Photo After Photom. and Geom. Standardization	3679.6	3544.5	3485.6	4052.0	1693.9	2282.3	2816.0
Rank	2nd	5th	5th	5th	1st	2nd	3rd
Best Match	(5, 1746.2)	(5, 1748.1)	(1, 1487.0)	(1, 2276.6)	(5, 1693.9)	(1, 1862.8)	(1, 1871.2)

Table 4: Similarity distance: Photometric and cropped Geometric Standardization. The best match (n) with the distance from the sketch to photograph n is also shown.

Skch No.	1	2	3	4	5	6	7
1st	16(10)	5(9)	2(11)	2(13)	5(12)	6(12)	7(10)
2nd	10(9)	3(8)	7(9)	12(12)	2(9)	2(9)	2(8)
3rd	8(8)	10(8)	12(8)	1(11)	10(9)	4(8)	3(7)
4th	3(7)	2(7)	3(7)	7(10)	3(8)	5(7)	10(6)
5th	5(7)	8(6)	5(6)	4(4)	16(6)	7(5)	12(5)
Correct	0	7	7	4	6	12	10

Table 6: Results of unweighted voting, i.e. 1st,2nd & 3rd=1 point.

Skch No.	1	2	3	4	5	6	7
1st	3(19)	5(22)	2(22)	2(26)	5(31)	6(21)	2(23)
2nd	16(18)	2(20)	7(21)	12(22)	2(24)	2(18)	7(19)
3rd	5(17)	3(20)	12(18)	7(21)	10(15)	4(16)	3(14)
4th	8(15)	10(14)	3(17)	1(18)	3(14)	5(14)	10(14)
5th	15(15)	8(13)	5(10)	4(11)	16(13)	12(12)	12(14)
Correct	0	20	17	11	31	21	19

Table 7: Results of simple weighted voting, i.e. 1st = 3 points, 2nd = 2 points and 3rd = 1 point.

match for sketch 1 was database photograph 16 and it receive a total of 10 votes. From the last line in Table 6 we see that sketch 1 received 0 votes. As with the rankings in previous tables, only the top five are shown. In this experiment six of the seven sketches correct match were within the top five. However, this performance was less than the full face input or the cropped face input.

Based on these results, Table 7 shows the tallies of using a weighted election scheme. Here, photographs

Skch No.	1	2	3	4	5	6	7
1st	8(12)	8(12)	2(11)	2(20)	5(11)	5(8)	2(11)
2nd	5(10)	5(8)	5(9)	7(8)	2(6)	6(6)	7(9)
3rd	16(7)	3(7)	3(8)	15(5)	11(5)	10(6)	3(7)
4th	3(7)	10(7)	15(5)	1(4)	6(5)	2(5)	8(6)
5th	10(4)	11(6)	7(4)	3(4)	9(4)	15(4)	12(5)
Correct	0	0	8	0	6	6	9

Table 8: Results of only using eigenfeature pieces, i.e. pieces (1,3,4,5,7,8,19,20) and using the weighted voting system of 3,2,1 points.

voted first received 3 points, second received 2 points and third received 1 point. Again, the points were tallied for all 22 triangles and all seven sketches. The results from this “election” are outlined in Table 6. The rows, columns and corresponding double have the same representation as in Table 6. Using this weighted method we had three correct matches, sketches 5, 6, and 7. Once again only six of the seven sketches were within the top five. This was consistent with the simple weighted voting system and worse than the full face (match-method 1) and the cropped face (match-method 2) approaches.

In this experiment only triangles containing all or part of a facial feature were input to the matching algorithm. These were triangles 1, 3, 4, 5, 7, 8, 19 and 20. Again the weighted voting system was employed (see Table 8, organized similarly to Table 6). This test gave 1 correct match and only four of seven within the top five. This was clearly the worst of any of the three weighting choices used in match-method 3.

Finally, we note that the rankings were all among the top 1/3 of the database for both the full face (match-method 1) and the cropped (match-method 2) face using photometric and geometric standardization. Performance using the eigen-patch approach (match-method 3) was poor for all three voting systems.

6 Discussion and Conclusion

Experimental results show that our framework is promising. In all cases the matching of the sketch to the photograph improved due to our algorithm.

In cases where the best match was not the correct photo, the correct photo is still in the top third of the database of photos. Reasons for missing matches are varied. Some poor matches are due to failures of our algorithm to process the sketch appropriately, and many poor matches are due to poor drawings from the artist. This is the nature of police sketches, and so law enforcement authorities compensate for this by taking a large set of candidate matches which then need to be manually pruned. Thus, even when our system

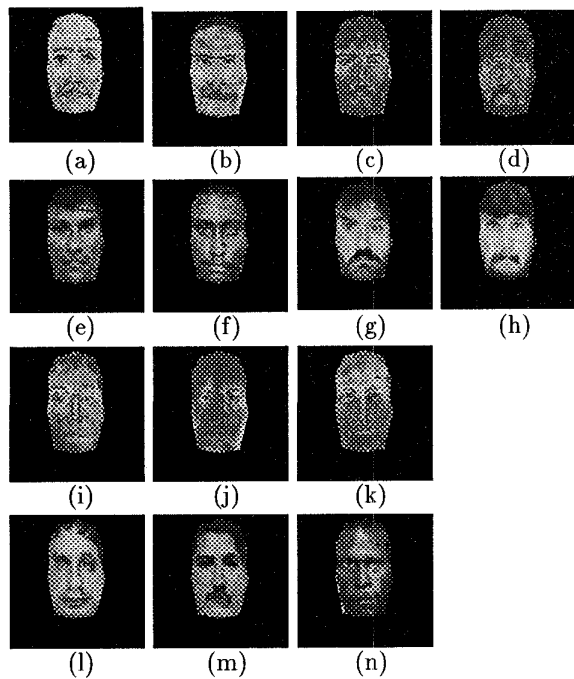


Figure 8: Geometrically Standardized sketches (not Photometrically Standardized) with Geometrically Standardized photographs.

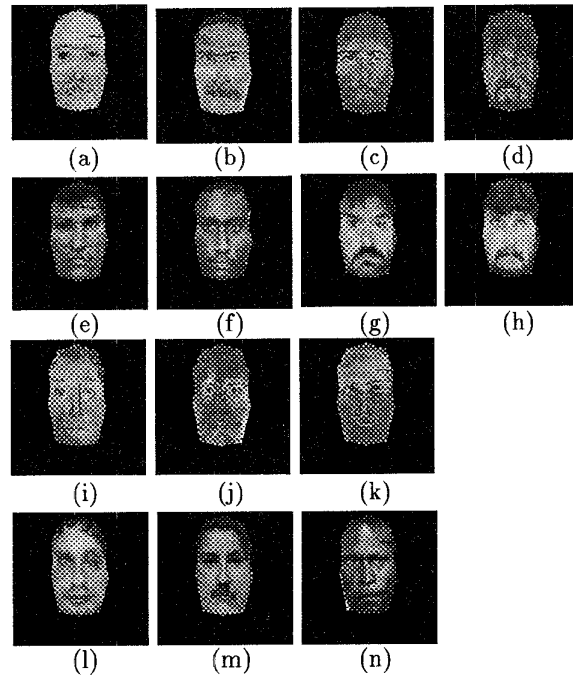


Figure 9: Photometric and Geometric Standardized sketches with Geometric Standardized photos.

performs poorly, it can still offer a means to obtain an initial set of matches.

Further improvements to our system could arise from better tessellation of the faces, and an improvement over the CANDIDE model. An important avenue for research is the processing of faces that are non-standard, eg., with eye-patches, or disfigurement, scars, uncommon hair-styles, etc. Our framework is the first concrete computational proposal for automatically matching a police sketch to true photographs. It offers the possibility of extension to other sketch matching problems in vision. Other avenues of police application work are now available for investigation. We expect to continue exploring these avenues in future research.

Acknowledgments

The first author was at UCF during this work. We wish to thank Officer Lucy Ross of the Osceola Sheriff's department for the sketches and photographs.

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Figure 10: Cropped sample of a sketch and its photo.