Automatic Tattoo Matching Technique For Suspect Identity

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Abstract

At the few years ago, the attention of drawing tattoo on a part of the body is more popular, especially in younger populations with age between 20 and 30 years old. Lawenforcement agencies tend to use the tattoo images as a biometric for the identificationof a suspect or victim and routinely catalog tattoo images for this process. So the need to development an automatic system for the verification process and matching tattoo sketch (that obtained from the description of the eyewitness) with a stored tattoo image became most important. The attempts in this scope are limited because of the challenges in matching sketch to image. In this work a set of features that are invariant against changes in (scale, change, mirroring, rotation and translation) are used. Moment Invariants features are extracted from tattoo images and combined with the eigenvalues to construct feature vector with 13 values. These vectors are used in the process of matching between sketch tattoo and image tattoo. A total number of images that used here is 120 for sketch tattoos and tattoo images, and the obtained results were 85 % of images correctly matched its sketch features.

Key words: Sketch-Image, Moment Invariants and Eigenvalues.

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تقنية مطابقة التاتو الاوتوماتيكية لتحديد هوية المشتبة بهم

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الخلاصة

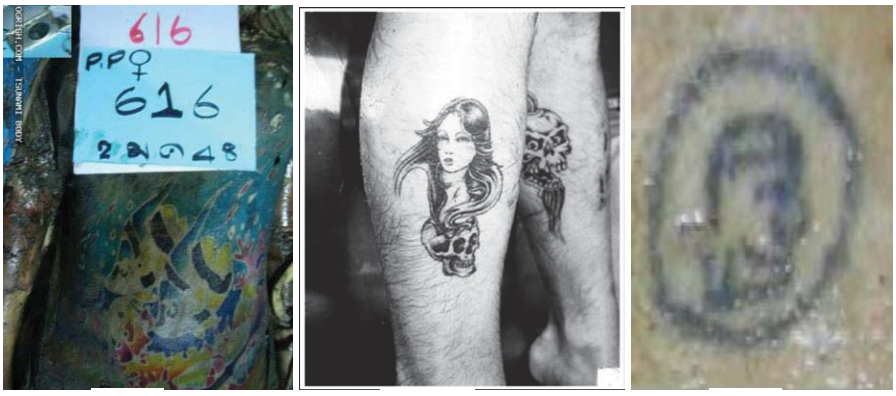
ظهرت في السنوات القليلة المنصرمة اهتمامات كثيرة بعملية النقش او ما يسمى التاتو على بعض اجزاء الجسم او ربما باكمله و خصوصا بين فئات الشباب الذين تتراوح اعمارهم مابين العشرين و الثلاثين.قامت بعض الوكالات الامنية باستخدام مثل هذه الصفات في عملية التحقق من المشتبة بهم او الضحايا و كانت بشكل مستمر تقوم بتجميع و حفظ هذه الصفات كوسيلة اضافية للتعرف على المشبوهين, لهذا السبب اصبح من الضروري وجود تقنيات الية تقوم بعملية التحقق و المطابقة مابين صورة النقش المخزونة لدى جهة معينة و بين الشكل المرسوم من قبل مختصيين بالاعتماد على وصف الشهود العيان. الابحاث في مثل هذا الحقل محدودة لاسباب منها صعوبة عملية المطابقة بين الصورة و الرسم الذي يشبه الصورة. في هذا البحث تم استخدام مجموعة من الصفات الثابتة ضد مجموعة من العوامل مثل (تغيير الحجم, تغيير شكل, الانعكاس, التدوير والنقل) و صفات القيم الذاتية وبالتالي تم الحصول على متجه للصفات يحوي ١٣ صفة استخدمت في عملية المطابقة.

1- Introduction

The classical methods for identification and verification tend to use images taken under controlled conditions; these methods may be failingwhen the images don't satisfy such conditions. So another metrics can be used to overcome these statessuch asscars, marks and tattooswhich called soft biometric, B. Heflin, et al.(2012).

Previously, counted number of people such as sailors, motor drivers and gangs' members,were used the tattoo as specializing property. Today, tattooing propertyisnot limitedon particular group, so size of this population is grown increasingly as a result. The most persons whose have a tattoo are from theyoung generation. In 2006 apaperin the American Academy of Dermatology Journal explained that about 36% of Americans with age between (eighteen and twenty nine years old) tend to have one tattoo on their body or more than one, Tattoo Facts and Statistics (٢٠٠٦).

The 9th of November in 2001 when worst attack occurred the use of Tattoos give best result in identification, also in the disaster the Asian tsunami that happened in 2004, H. Bay, et al. (2008), because pigments of tattoo are engraved on the body in some depth so that strong injuriesoften cannotcase distortionon it,fig. (1). Also identification of criminal is another important application of tattoos because it often contained hidden information related to a suspect's history (e.g., gang membership, previous convictions, years spent in jail, etc.), Hu Han and Anil K. Jain(2013).



(a) (b) (c)

Fig.1: Examples of Tattoo on (a) victim of tsunami disaster in 2004, (b) victim of (9/11) explosion and (c) part of human body found in a Florida state park, J. Lee, et al. (2008)

Inthe identification of both criminals and victims, for many years, law agencies have been used tattoos to assist lawin arrested these persons. A tattoo is an affective soft biometric that contained special

information about the suspectin addition to traditional soft biometrics such as genderand race, Mei Ngan, et al. (2015).

A tattoo is not unique feature that used to identifier someone, butit decreases the search area of the suspect identity. For this, images for tattoos have been collected by law enforcement agencies of the suspects at theinvestigation time. Only some attempts developed to construct an automatic system to matching a query tattoo image with a tattoo database to find the closest images. However, in mostsituations, the scene of criminal isnot presented, so the query will be a sketch of a tattoothat is drawn (based on the description provided by an eyewitness) corresponding to a tattoo image, Hu Han and Anil K. Jain (2013).

Jain and others, Anil K. Jain, et al. (2007) develop image retrieval system based on the image content called(content-based image retrieval -CBIR) to solving the weakness of keyword-based system, it use matching image-to-image tattoo. In 2008 S. Acton and A. Rossiproposed extraction of global features from tattoo images, S. Acton and A. Rossi (2008).

J. Lee, et al. (2012)presented an improvement system for the CBIR by suggestion a more strong measures of the similarity between probe tattoo and database image. After few years, in 2012, B. Heflin and others introduce detection and classification approach to recognize scar, mark and tattoo underuncontrolled conditions, B. Heflin, et al. (2012).

All system introduced above assume that the query tattoo image is available, so thattheydepending on the image-to- image matching process. Unfortunately, in many otherstates, there is no probe image for the suspect tattoo for example in a place without surveillance cameras. In these situations, like case of sketch recognition depends on the face image [B. Klare, etc. 2011], depending on the victim or eyewitness description the sketch of a tattoo can be drawn and used in the system, Hu Han and Anil K. Jain(2013).

The sketch- face recognition system has obtained some attention in the face recognition communitye.g. Klare, Z. Li, and A. K. Jain(2013), X. Tang and X. Wang (2004), X. Wang and X. Tang(2009)and others. In the sketch – tattoo recognition systems there are no morework has been reported.

The main challenging in the automated matching system between (sketch –image) is the great different in color, texture and scale, and there is another reasons is the eyewitness may cannot provide accurate tattoo description, this will casing fail of the matching process. Further, the losses in the small details of the tattoo sketch, Hu Han and Anil K. Jain(2013).

In this paper a method for automatic tattoo sketch - image matching system is proposed. Thispaper is ordered as follows: In section 2 Preliminaries that includes (database, moment invariants), section 3

introduce the proposed system (preprocessing, feature extraction, matching). In section4 we introduce the results and references in section5.

2. Preliminaries

2- 2.1Tattoo Sketch Database

The data set that used in this paper from a data set consisting of 60 tattoo sketches, each sketch corresponding to a tattoo image stored in the database. The drawing process of the tattoo sketch as follow as explained in (fig.2),the tattoo sketchesare drawn on a paper and then stored in the digital form using scanner device. Figure below (fig.3) shows some examples of sketch and the image that represent it, Hu Han and Anil K. Jain(2013).

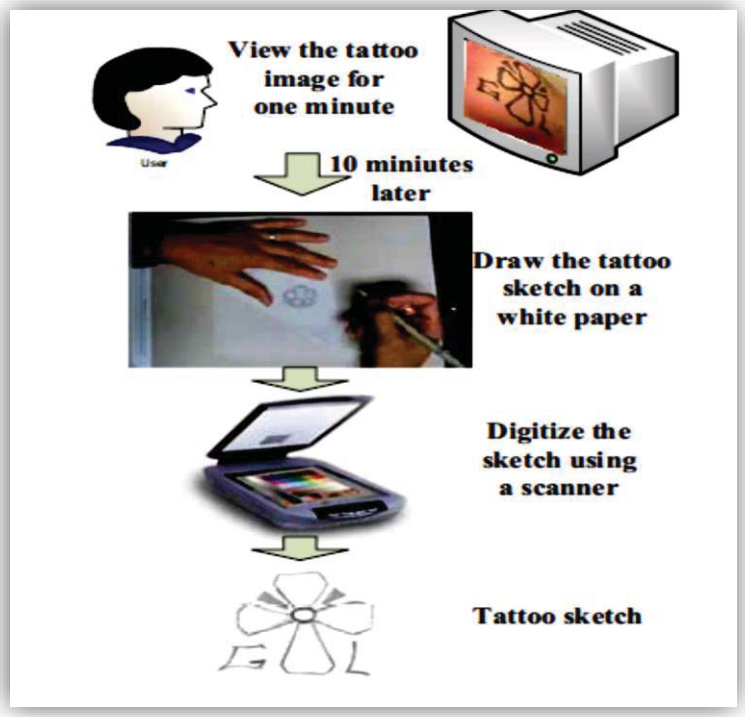


Fig. (2): The protocol for drawing the tattoo sketch, Hu Han and Anil K. Jain (2013).

3- 2.2 Moment Invariants

Before many years, before the appearance of first computers, in 19th century the moment invariants began depending on the theory of algebraic invariants. The algebraic invariants probably theory originates from famous German mathematician David Hilbert, D. Hilbert (1993) and was thoroughly studied also in G. B. Gurevich(1964), I. Schur(1968).

In image processing, Moment invariants have been frequently used as features. These moments can provide characteristics of an object that so near represent its shape, Laura Keyes, BAdamWinstanley(1998).

The moment invariants firstly introduced in 1962 by Hu, M. K. Hu (1962) to the pattern recognition community. Since that time, many attempts have been dedicated to some development of these moment invariants and its applications, Jan Flusser(2005).

4- The 2-D moment of order $(p + q)$ of a digital image f(x ,y) is defined as, Gonzalez R. C. and Woods R. E. (2012):

5- m L ^ ^ : Æ ; (1)

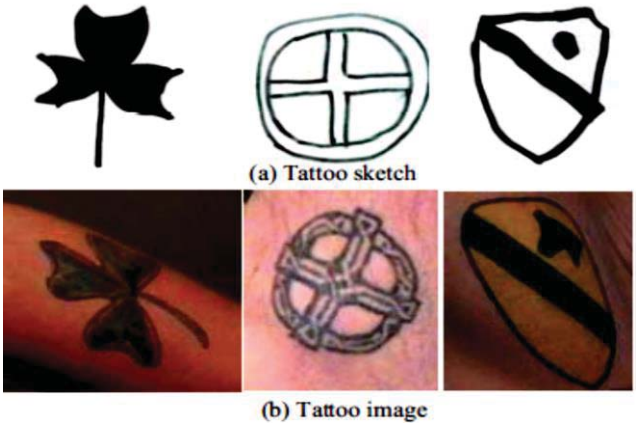


Fig. (3):(a) tattoo sketches, (b) corresponding tattoo images,
Hu Han and Anil K. Jain (2013)

Forp ,q = 0, 1, 2, …, where the summations are over the values of the spatial coordinates *x* and *y* spanning the image. The corresponding ***central moment*** is defined as

L ^ ^ :T F T$:U F U$; B:T ÆU; (2)

Where

T$L—and U$L—

The normalized central moment of order (p + q) is defined as

L— (3)

For p ,q = 0, 1, 2, … , where

» L— E

For p + q = 2, 3,….

A group of seven 2-D moment invariants that are insensitive toscale, change, mirroring, rotation and translation can be derived from these equations,Gonzalez R. C. and Woods R. E. (2012),They are

$$\emptyset_1 = \eta_{20} + \eta_{02} \quad (4)$$

$$\emptyset_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \quad (5)$$

$$\emptyset_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \quad (6)$$

$$\emptyset_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \quad (7)$$

$$\emptyset_5 = (\eta_{30} + 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} - \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} - \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \quad (8)$$

$$\emptyset_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \quad (9)$$

$$\emptyset_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{30})(\eta_{21} + \eta_{03})[3(\eta_{30} - \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \quad (10)$$

3- The proposed Sketch-Image Tattoo Matching

The most case of verification and authentication depend on the alignment between the query image and the corresponding image in the data base; in contrast, tattoo images not have a standard shape construction which make the matching more difficult.

In addition to this challenge, in the tattoo sketch to image matching we cannot depend on the texture information or the deformation of the image, sosketch image iscompared with image captured using digital camera.Another thing in the image, the small details may not present in the query sketch, so these details must be eliminated using some morphological operations, and the use of local feature descriptor for such scenarios in the matching step is very useful.

The proposed method solve the problem of automatic sketch-image matching for tattoo, the sketch used from database in Hu Han and Anil K. Jain(2013), which obtained from the suspect, and compared with the image in the database. The database images are with extension ' .jpeg '.A group of 60 sketch and the corresponding images are chosen in thiswork. The proposed method architected schematic is shown in the fig. 4.

6- 3.1 read the probe sketch

In this paper we use pictures from the used database.

7- 3 .2Preprocessing Steps

For both the sketch and images in the database the preprocessing steps are essential to eliminate unwanted details from the image. Enhancement methods are used to enhance the image quality to obtain a modified image. This step frequently referred to as preprocessing step, which include:

- Convert colored image into the gray image using a combination of the three color channels.
- Filtering step is performed using Gaussian filterwith disk size 10, chosen experimentally.
- A type oflinear filter (Adaptive Wiener filter) applied to an image. This filter often produces better results than linear filtering and more selective, keeping edges and other high-frequency parts of an image, Rafaed C. Gonzalez, Richard E. Woods(2002).

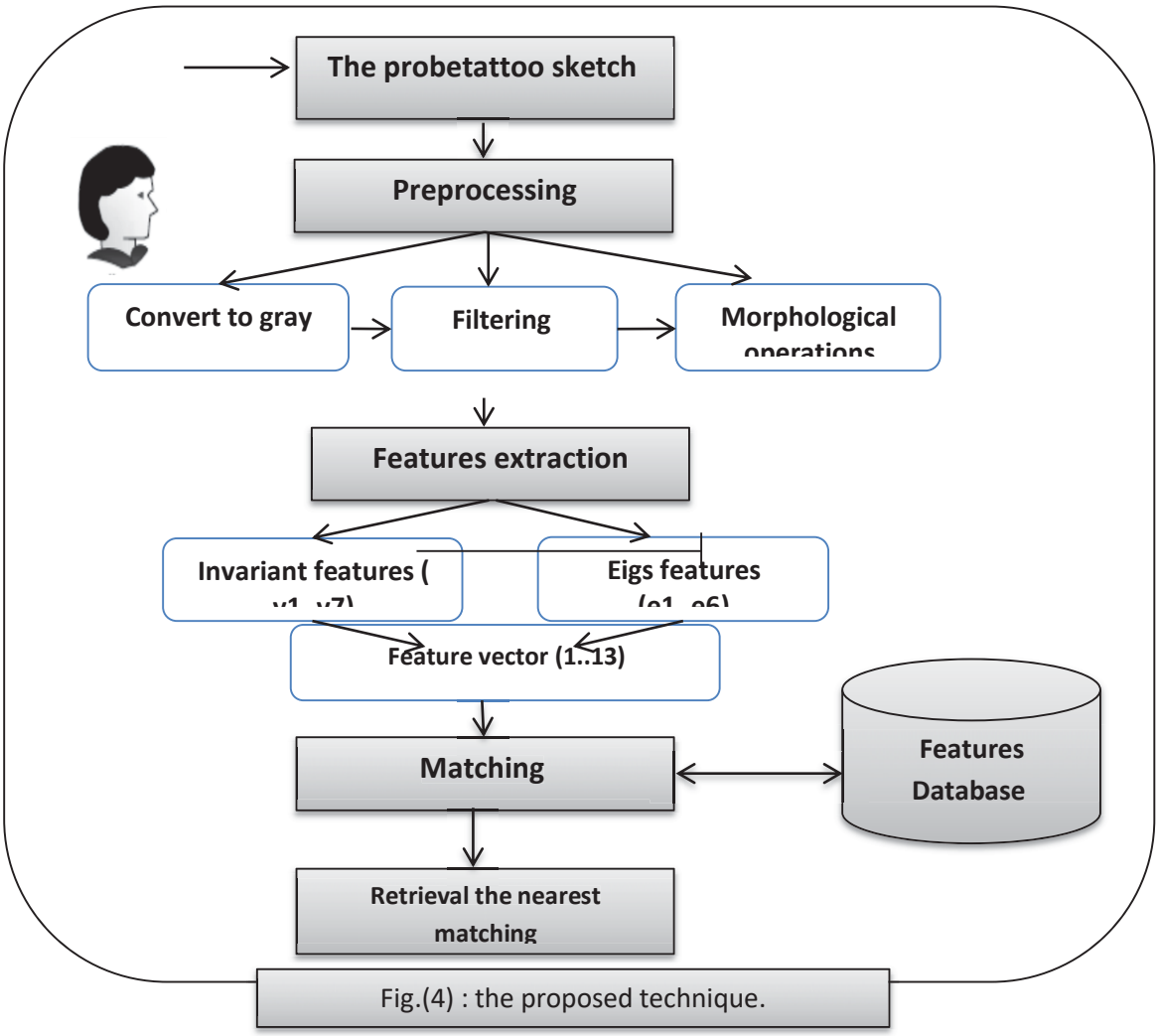


Fig.(4) : the proposed technique.

3.3 Feature Extraction

In this step the Moment Invariants algorithm is used to extract feature from probe sketch image. These features are invariant against variations in translation, scale, change, mirroring, and rotation; these features are extracted from images in the database and stored in vectors of features, these vectors are

stored as a features database that is used in matching with the feature vector extracted from the probe sketch image and find the closest match.

$$\begin{Bmatrix} v1 \\ v2 \\ \cdot \\ \cdot \\ \cdot \\ v7 \end{Bmatrix} \text{ matching with the stored vectors: } \begin{Bmatrix} v11 \\ v21 \\ \cdot \\ \cdot \\ \cdot \\ v71 \end{Bmatrix} \begin{Bmatrix} v12 \\ v22 \\ \cdot \\ \cdot \\ \cdot \\ v72 \end{Bmatrix} \begin{Bmatrix} v13 \\ v23 \\ \cdot \\ \cdot \\ \cdot \\ v73 \end{Bmatrix} \ldots\ldots \begin{Bmatrix} v1n \\ v2n \\ \cdot \\ \cdot \\ \cdot \\ v7n \end{Bmatrix}$$

Probe vector *Database feature vectors*

Another set of 6 features are extracted from the images in the database, these features are the eigenvalues from the images in the database and added to features database.

$$\begin{Bmatrix} e1 \\ e2 \\ \cdot \\ \cdot \\ \cdot \\ e7 \end{Bmatrix} \text{ matching with the stored vectors: } \begin{Bmatrix} e11 \\ e21 \\ \cdot \\ \cdot \\ \cdot \\ e71 \end{Bmatrix} \begin{Bmatrix} e12 \\ e22 \\ \cdot \\ \cdot \\ \cdot \\ e72 \end{Bmatrix} \begin{Bmatrix} e13 \\ e23 \\ \cdot \\ \cdot \\ \cdot \\ e73 \end{Bmatrix} \ldots\ldots \begin{Bmatrix} e1n \\ e2n \\ \cdot \\ \cdot \\ \cdot \\ e7n \end{Bmatrix}$$

Probe vector *Database feature vectors*

In this case we have 13 features to each image stored in a feature vector which is used to be compared with the feature vector extracted from the sketch tattoo image.

$$\begin{Bmatrix} f1 \\ f2 \\ \cdot \\ \cdot \\ \cdot \\ f13 \end{Bmatrix} \text{ matching with the stored vectors: } \begin{Bmatrix} f11 \\ f21 \\ \cdot \\ \cdot \\ \cdot \\ f131 \end{Bmatrix} \begin{Bmatrix} f12 \\ f22 \\ \cdot \\ \cdot \\ \cdot \\ f132 \end{Bmatrix} \begin{Bmatrix} f13 \\ f23 \\ \cdot \\ \cdot \\ \cdot \\ f133 \end{Bmatrix} \ldots\ldots \begin{Bmatrix} f1n \\ f2n \\ \cdot \\ \cdot \\ \cdot \\ f13n \end{Bmatrix}$$

Final Probevector *Database feature vectors*

8- 3.3 Matching

The nearest match represents the closet similarity between the input sketch and the image in the database.To do this we proposed theuse Euclidian distance to find the closest one in the stored features. Table.1 shows the feature vector for input probe sketch and the nearest vector in the features database.

Table (1): The probe feature vector and the nearest vector in the features database

Sketch 1	Invariant features							Eigen values					
	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13
Prob V.	.0007	.0019	.0021	.0021	.0042	.0030	.0046	1.4917	.0269	.0171	.0115	.0112	.0132

Matched V.	**.0007**	**.0017**	**.0019**	**.0019**	**.0039**	**.0028**	**.0041**	**1.2553**	**.0361**	**.0338**	**.0135**	**.0224**	**.0146**

The following table (**table2**) shows the algorithms for feature extraction and matching processes.

Table (2): The algorithms for feature extraction and matching processes.

Algorithm1	Algorithm2
1. Convert RGB image in to gray. 2. Filtering. 3. Morphological operation. 4. Extract invariant moments. 5- Extract eigs values. 6. Constructs feature vector.	1. Obtained the feature vectors from the feature database. 2. Using Euclidean Distance between the probe feature vector and stored images vectors. 3. Find the vector that has the index corresponding to the minimum distance. 4. Returen the resulting image.

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Now we show the results of interning another sketch and the closest two images feature vectors Table3.

Table (3): The probe feature vector and the closest two vectors in the features database

Sketch 1	**Invariant features**							**Eigen values**					
	F1	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**	**F8**	**F9**	**F10**	**F11**	**F12**	**F13**
Prob V.	**.0057**	**.0018**	**.0021**	**.0024**	**.0042**	**.0030**	**.0045**	**1.2917**	**.1089**	**.0471**	**.0315**	**.0212**	**.0192**
Matched V1.	**.0049**	**.0016**	**.0020**	**.0023**	**.0040**	**.0029**	**.0042**	**1.2085**	**.0848**	**.0427**	**.0356**	**.0250**	**.0246**
Matched V2.	**.0065**	**.0014**	**.0019**	**.0018**	**.0039**	**.0028**	**.0041**	**1.7315**	**.0661**	**.1286**	**.0926**	**.0284**	**.0285**

4-Results

In this paper the presented mothed is for matching the sketchwhich is obtained from a witnesswith the tattoo image. This sketch is used to extract some features from it and matched them with a database of 60 tattoo images, each image represented as feature vector in database of features. The vector with the nearest distance will be the features that are extracted from the image that represent this sketch. The obtained results were 85% of images correctly matched its sketch features and 15 % fail. We find that when the number of extracted features increase the verification system accuracy will increase accordingly, from this in the future steps to this system the main point will increasing the number of features to achieve higher accuracy.

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