Biometric Identification using Lip Imprint with Hybrid Feature Extraction Techniques

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Abstract: This paper is representing a hybrid feature extraction technique for biometric identification using lip imprint. This research work combined the shape and texture features of human lip imprint. Canny Edge Detection Algorithm is used here to extract the shape features and to extract texture features GLCM (Gray Level Co-occurrence Matrix) is calculated. The whole set of complied features are then inputted to the Support Vector Machine (SVM) classifier to identify and/or verify the corresponding person.

Keywords: Shape Features, Texture Features, Biometric Identification, Support Vector Machine (SVM), Canny Edge Detection, GLCM.

Introduction

Lip imprints are proven to be used for biometric identification and well accepted globally for this purpose. The science which includes the study of lip imprint and the use of lip imprint as biometric identification of human being is called “Chelioscopy” which is derived from the Greek word “Chelian” for English word “Lip”. There are many different biometric identification techniques adapted worldwide based on fingerprint, palm-imprint, DNA sequence, iris and retina pattern, signature etc. Among them Lip imprint based identification technique is having some specific advantages. In has been proven that, lip imprint of a person doesn’t change over age of a person. So this technique of biometric identification will get better result over fingerprint based or palm imprint based identification. Moreover, gender and blood group of a person also can be identified from lip imprint. So, the lip imprint based biometric detection has been adapted globally and also accepted as unique identifier of people legally as well as may be accepted as court room evidence. This technique is presently used in Criminal Forensics to identify criminals from their lip imprints collected from crime scene.

The fact of lip imprint to be used as biometric identification was first recommended by French Criminologist Edmond Locard in 1932. Then in 1950 in his book titled “Homicide Investigation”, LeMoyne Snyder mentioned the lip imprint as a potential biometric identifier. Afterwards many researchers, criminologists and dentists researched to prove acceptability of lip imprint as biometric identifier. Some of the researches even tried to extract other information, like sex, age, family, blood group etc, about the owner from lip imprints.

The research on lip imprint based identification system actually got a mileage when in 1970 Japanese doctor Suzuki [1] and in 1974 Tsuchihasi proved the claim of lip imprint to be used as biometric identification in their corresponding researches on different age grouped Japanese people. In 1975 Suzuki and Tsuchihasi identified five different kinds of groove patterns using which further lip imprints could be easily categorized and identified [2]. Grooves are the fine lines present in a lip imprint. These five groove patterns are known as Suzuki’s Classification. The five types of groove patterns are:

Type I: A clear-cut line or groove running vertically across the lip.

> Type I’: Straight grooves that disappear half way into the lip, instead of covering entire breadth of the lip, or partial-length groove of Type I

Type II: Grooves that fork in their course or a branched groove (like Y)

Type III: An intersected groove (crisscross pattern)

Type IV: A reticular groove

Type V: Grooves that doesn’t fall in any of the above categories and cannot be differentiated morphologically

Figure 1 is depicting all the above-mentioned types of groove patterns mentioned above.

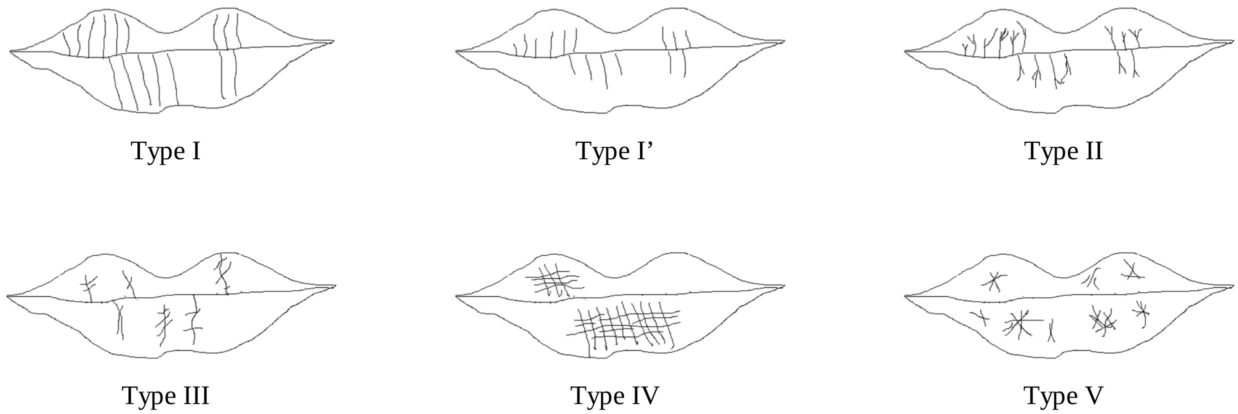


Figure 1: Suzuki Classification: different groove patterns

Lots of researches are carried out then after on lip imprint detection. Some of the researches are carried out manually, by registering the imprint on transparent sheet or glass using some sticky colouring agent like petroleum jelly or lipstick. The measurement and classification of grooves are also done manually using rulers and magnifying glasses. On the other hand some researchers took the computer algorithms for image processing and different classifiers to identify lip imprints in automated way. Automated techniques are advanced than the manual technique as the precision and accuracy of similarity measurement are more in case of automated techniques. There is no room for human error. Only the imprint taken on transparent sheets are to be converted as digital image and fed to the algorithm as input; the algorithm further analyze the imprint automatically.

The manual lip imprint identification techniques are generally based on Suzuki’s Classification. The study of grooves and presence of groove patterns are matched between different lip-imprints are similarity is measured between them. The study of lip imprint is done manually using high power magnifying glass. Besides finding matches between lip-imprints, in different research works, people tried to gather more information about the person using lip-imprint. In 2009 a group of researchers proved that in female lip imprints Type I and Type II grooves are majorly identified, whereas in male lip imprints Type III, Type IV and Type V type of grooves are majorly found [3]. In the same year, another group of scientists proved the power of lip imprint as biometric identifier in their research on 300 North Indian people aged between 18 – 65 years [4]. In 2010 another research tried to prove that, by studying groove patterns of lip imprint gender, blood group and family of human being can be identifies [5]. Later in the same year, another research proved that, by studying lip imprint, blood group and gender can be identified, but family of a person cannot be detected [6]. They decided from the result of their research that, there is no correlation between the lip imprints of siblings, parent and children and thus no correlation among the lip imprints of the people belonging to the same family.

The automated machine learning based approaches for lip imprint detection generally takes two different approaches: structural information oriented approaches where different structural measurements of the lip imprint are taken in account and statistical analysis based approaches where the presence of grooves are represented in terms of features and different statistical analysis are carried out on those set of features.

Some structural information oriented approaches

In 2009, Michał Choraś extracted different geometric patterns from lip imprint and used them to identify the imprint [7]. Thus he proved that besides lip imprint, lip structures also can be used to identify a human being. In 2010 another research used Variance Based Haar-like Features and Kalman Filter and further used SVM on those features to identify lip imprints [8]. In the same year another research adapted “Generalized Hough Transform” to identify lip imprint [9]. Here they have used GHT on the pre-processed image to form R table, Accumulator Array and Hyper-surface. Using these extracted features they computed the matching. Another research in 2013 adapted GHT to find out distances between groove-patters [10]. In this research, the GTH is used for extracting the grooves from lip imprint and further the imprints are matched based on linear distance and angle formation between neighbouring grooves. In 2011 another group of scientists extracted the local structural features like Lip’s Width to Perimeter ratio, Upper to Lower Lip height ratio, Upper Lip Height to Width ratio, Lower Lip Height to Width ratio, Inner to Outer Circle ratio, Width to Middle Height ratio, Left side Upper to Lower Lip Convexity ratio, Right side Upper to Lower Lip Convexity ratio, and Indent ratio to identify lip imprints [11]. Whereas in the same year another group applied “Brute Force Algorithm” to reduce False Acceptance Rate and False Rejection Rate in the lip imprint identification technique [12]. FAR and FRR are the measurement of inefficiency of any biometric identification system.

Some statistical analysis based approaches

The Mean Differences Similarity Measurement was adapted by a research [13] where the features were extracted by forming segments of lip patterns and afterwards by applying Hough Transformation on each segment. GLCM [14], Scale Invariant Feature Transform (SIFT) [15], Speeded Up Robust Features (SURF) [16] and combination of SIFT and SURF [11] was used by the researchers to extract the features of an image. On the extracted features the Mean Differences Similarity Measurement was applied to find out the match.

In 2011 a research implemented the lip imprint identification system using Dynamic Time Warping algorithm (DTW) [17]. In this research three steps were adapted to extract features: Image normalization, Lip pattern extraction, and Feature extraction. The feature extraction part is done here by DTW algorithm for both the upper and lower lip. This process detects the vertical, horizontal and diagonal projections of the lip imprint images. In 2012 another research divided the lip imprint into two segments: upper lip and lower lip imprint [18]. Further each of these segments is subdivided into four quadrants as shown in Figure2. They applied Gaussian Filter, Canny Edge Detection and four different Sobel filters to extract the groove patterns horizontally, vertically and both diagonally. The matching is performed as average match of groove patterns in all the eight segments. Another research applied Dynamic Time Wrapping Algorithm and Coperland Vote Counting Method to identify similarity between lip-imprints [19]. The first algorithm is used to compare between imprint features and the second one is used for detecting maximum similarity within a group. In 2015 another statistical analyses based research used Bi-function Analysis Method to detect lip imprint [20]. All these different lip imprint detection and identification techniques discussed above are carefully reviewed in a research paper [21] published in the year of 2015, where all the different approaches are discussed on a single platform.

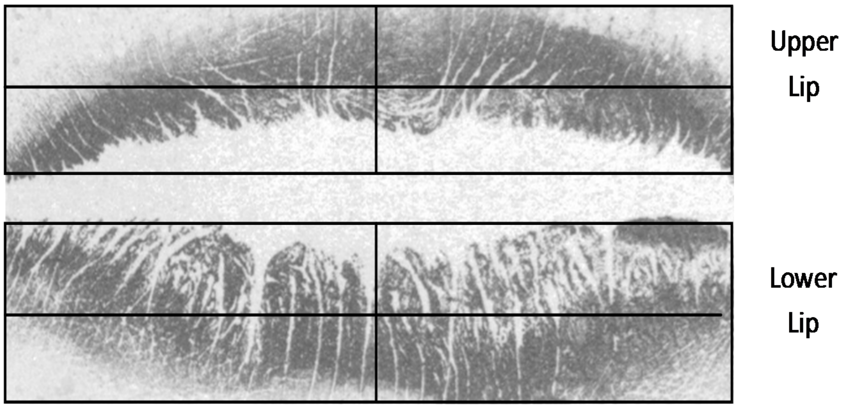


Figure 2: Lip-imprint segments

In this paper, different features are extracted in three levels namely local, global and shape. As described in the next sections, GLCM is used for both local and global level features and Canny edge detector is used for shape features.

Prerequisite

Canny Edge Detection

Canny Edge Detection Algorithm [22] results into providing optimal edge output based on three criteria namely: Flawless Edge Pixel Detection, Localization and Avoidance of False Responses. The basic aim of this algorithm was to increase the detection of actual edge pixels and reduction of false acceptance. Another aim of this algorithm is to provide seamless contour of the edge. Figure3 shows an input image and its corresponding output of Canny Edge Detection Algorithm as an example.

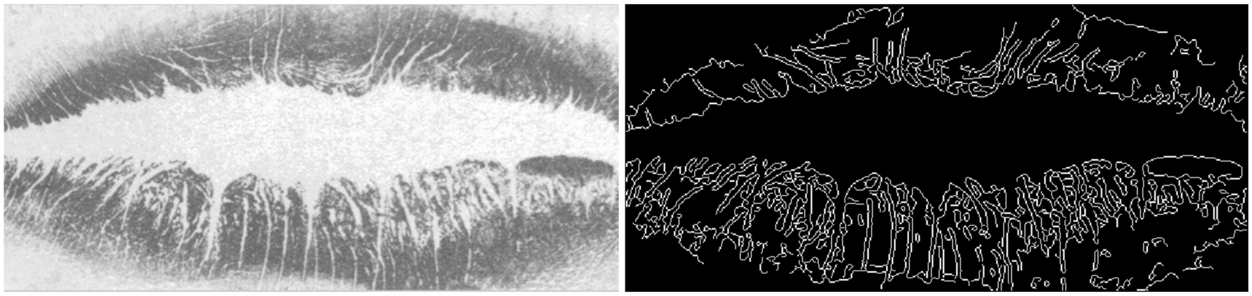


Figure 3: Source and Output of Canny Edge Detection Algorithm

The Canny Edge Detection Algorithm works in the following five steps:

Step 1: In the preliminary step any kind of noise gets filtered out from the source image by applying Gaussian Filter. In this step, a tactfully chosen Convolution Mask is applied to the image which imposes a blurring effect and thus helps to reduce noise and to detect edge more flawlessly.
Step 2: In the current step, the gradient of the image is computed as at the edge strength can be identified where gradient of the image is maximum. The gradient of the image is computed using the following formula:

$$|G| = |Gx| + |Gy|$$

[where Gx and Gy are gradient of the image in horizontal and vertical direction respectively. The Gx and Gy are shown in Figure4.]

-1	**0**	**+1**
-2	**0**	**+2**
-1	**0**	**+1**

Gx

-1	**-2**	**-1**
0	**0**	**0**
+1	**+2**	**+1**

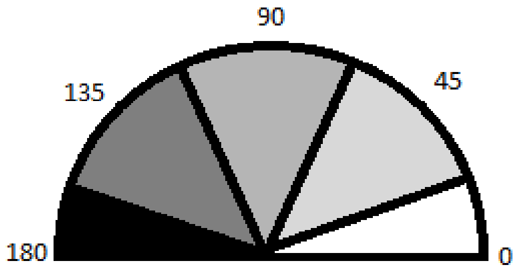
Gy

Figure 4: Gx and Gy gradients

Step 3: In this step, the edge direction gets computed using the following equation:

$$\theta = \tan^{-1} (Gy/Gx)$$

[where θ indicates direction of the edge, only 0, 45, 90, 135 and 180 degrees are considered. All other values are approximated to this set. The approximation is done as shown in Figure5.
In Figure5, different shaded regions are approximated as the values given in the index.]
If Gx becomes 0, decision gets based on value of Gy. If Gy is 0, θ is considered as 0 degree, otherwise θ is considered as 90 degree.
Step 4: To find out perfect this edge, after computing direction, candidature of all non-maximum pixels (a pixel for which gradient is not at local maxima) got involved into the detected edge, are suppressed.
Step 5: Finally at this last step, a unique feature of Canny Edge Detection, called Hysteresis, is applied. Generally by involving single threshold value the detected edge may have dashed line contour representation. To get rid of this, Canny Edge Detection uses double threshold values T1 and T2, one high and the other is low. The starting pixel is accepted based on T1, but the continuing pixel selection is dependent on both T1 and T2.



Region	Approximated Angle
	0 degree
	45 degree
	90 degree
	135 degree
	180 degree

Figure 5: Approximation of detected edge direction

Gray Level Co-occurrence Matrix (GLCM)

Statistical based features are describing the texture of an image. Gray Level Co-occurrence Matrix (GLCM) [23] is well known method to describe the texture of an image. The co-occurrence matrix provides spatial distribution of intensity or gray value of neighbor pixels in an image. GLCM could be calculated to consider one pixel, two neighbor pixels and three or more neighbor pixels, i.e. first order, second order and third order or higher order statistic of gray value of an image. GLCM find out the frequency of reference intensity of a pixel i, with the intensity of neighbor pixel j either in horizontal, vertical or diagonal direction with a defined radius. It has been proved by the researchers that large radius value is not suitable to detect fine texture information of an image.

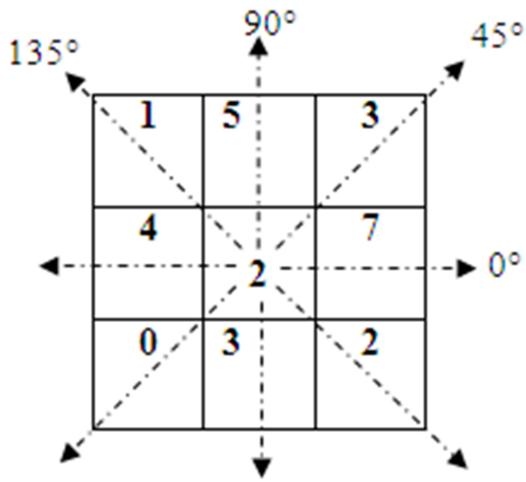


Figure 6: Angles for GLCM calculation

For extracting the fine texture, the value of radius is considered 1 or 2 for eight neighbors of reference pixel in angles of , 45°, 90°, 135°, 180°, 225°, 270° or 315°. The calculation of GLCM is similar in 0° and 180°, 45° and 225° and so for others. So, we consider the angles in 0°, 45°, 90°and 135° for calculation of GLCM as shown in Figure6.

GLCM Features

G(i, j) is the (i, j)th entry and G_n denotes the dimension of the normalized co-occurrence matrix. There are fourteen features defined by Haralick. Six of them are used in our propose work for classification of lip imprint images listed below:

i. $\text{Energy} = \sum_{i,j} G(i,j)^2$

ii. $\text{Homogeneity} = \sum_i \sum_j \frac{1}{1+(i-j)^2} G(i,j)$

iii. Entropy $= - \sum_{i,j} G(i,j)\log(G(i,j))$

iv. Inertia $= \sum_{i,j} (i-j)^2 G(i,j)$

v. Dissimilarity $= \sum_{i=0}\sum_{j=0} G(i,j)(i-j)$

vi. Correlation $= \sum_{i=0}\sum_{j=0} G(i,j)\dfrac{(i-\mu_x)(j-\mu_y)}{\sigma_x\sigma_y}$

Support Vector Machine (SVM)

Support vector machine (SVM) [24] [25] is a supervised learning classifier which creates a separating hyperplane that maximizes the margin between two data sets in a space. SVM minimizes the empirical classification error as well as maximize the geometric margin between two classes. In multiclass classification, the problems are divided into several binary classifications. There are two common approaches to design such binary classifier as (i) One-Versus-All and (ii) One-Versus-One. In One-Versus-All, the classification is done by "winner takes all strategy"; the highest output function assigns the class. The classification of one-versus-one approach is done by a max-wins voting strategy. We have used SVM tool "SVM^{light}" for classification [26].

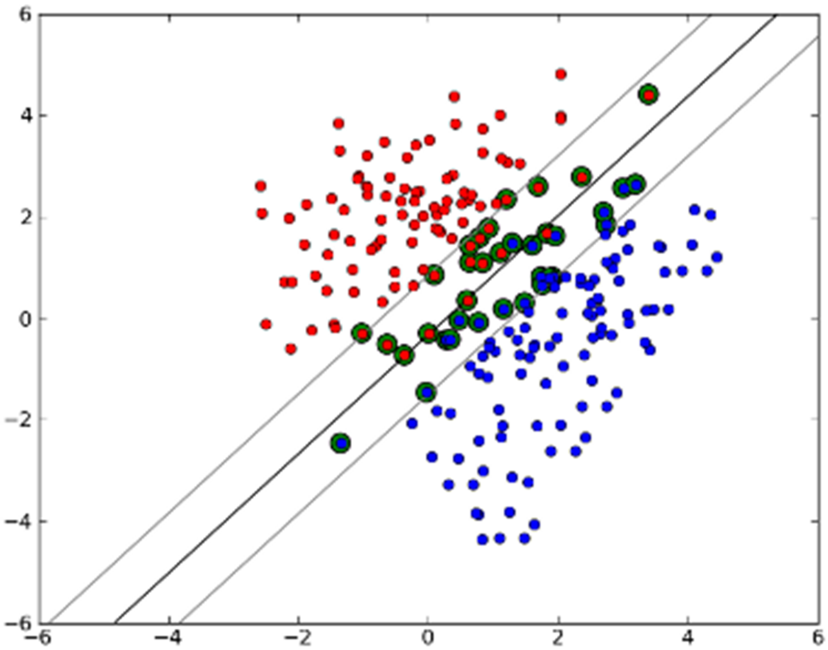


Figure 7: Support Vector Machine

Proposed Method

The proposed method can be divided into two parts: feature extraction and classification. The accuracy of lip imprint image classification depends on extracting discriminate features from the preprocessed image and the nature of classifier. In feature extraction part image features are extracted from three levels namely global, local and shape as depicted in Figure9. The texture features are extracted using GLCM in global and local level. The preprocessed lip imprint images are divided into four equal parts in local level as shown in Figure8. From each part we extract the features using GLCM to create feature vector at local level. Generally in global level whole lip imprint images are consider to extract the feature using GLCM. But the size of the images is scaled down to reduce the complexity of GLCM calculation. In the proposed method preprocessed lip imprint images are resized into 100 × 200. The Canny edge detection algorithm is used to extract the shape features.

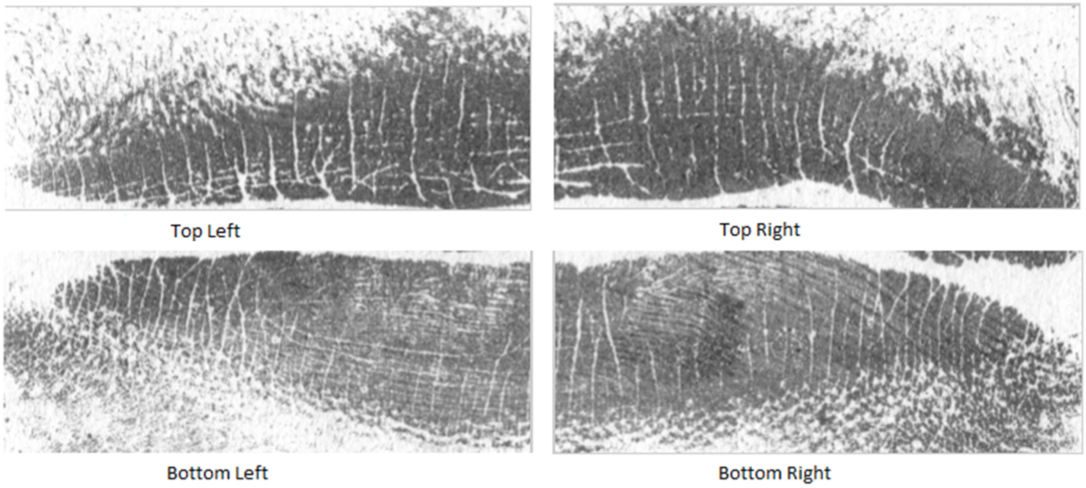


Figure 8: Four parts of lip imprint as used at local level feature extraction

For the lip imprint classification SVM is used. After extracting features, a feature vector is created which is passed to SVM for training. With help of the trained SVM we can identify or verify an unknown person. To do this we extract the features from the test image at three levels using GLCM for texture features and canny edge detector algorithm for shape features.

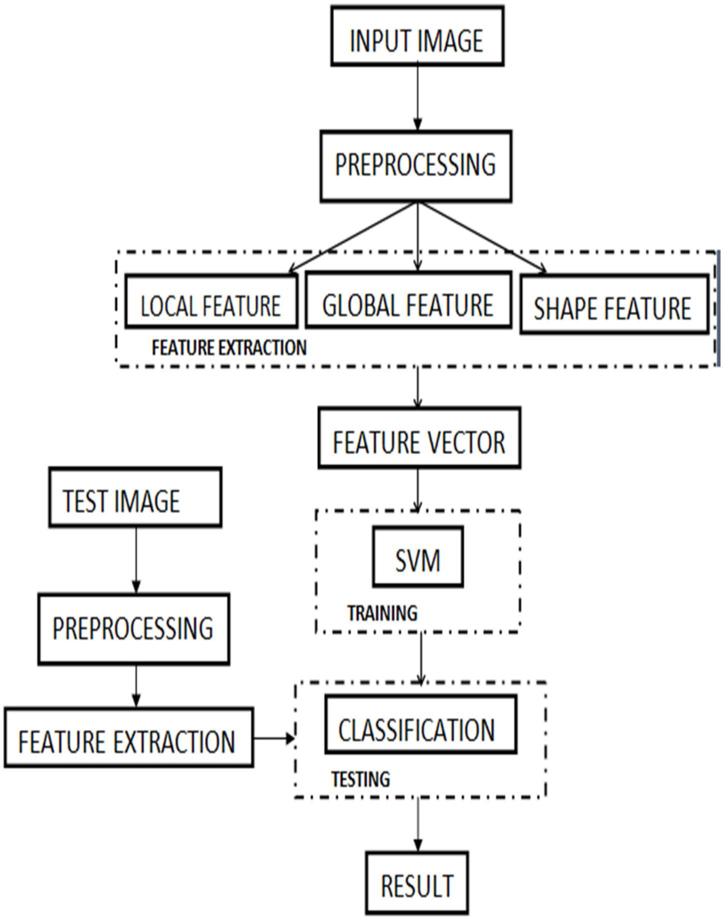


Figure 9: Flowchart of the proposed method

Result Analysis

To evaluate the performance of the proposed method, several experiments were performed on different lip images. We have performed different experiments on three lip-imprint image datasets – Lip-Print, Roller set 1 and Roller set 2 [http://biometrics.us.edu.pl (Lip imprint database from Biometric Research Centre, University of Silesia at Katowice, Poland)].

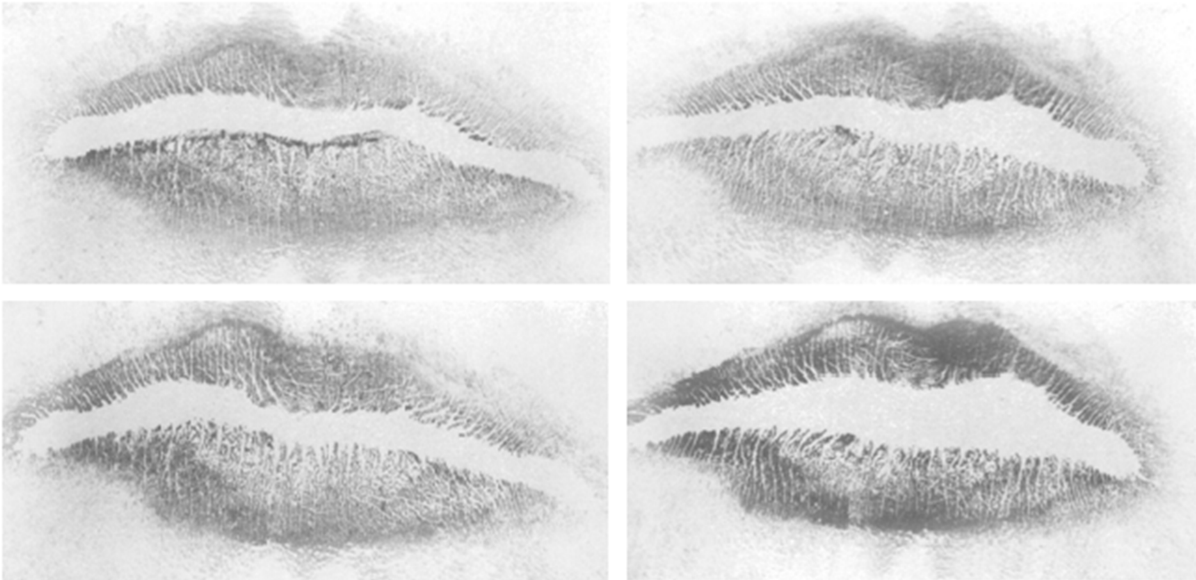


Figure 10: Data Set of Lip Imprint (Lip_print)

We have presented these three datasets as indicated in Figure10, Figure11 and Figure12 respectively. The first data set, Lip_print contains 4 lip imprint images of 15 people; hence all together 60 images. Further the second data set, Roller_set_1 represents the same 4 imprint images for 30 persons. So we applied this dataset to check the efficiency of the proposed method with more different types of images. Lastly Roller_Set_2 dataset provided us with more number of varied images. It contains the lip imprints of 40 people and for each of them 10 imprints are recorded. So totally 400 images are present in Roller_Set_2.

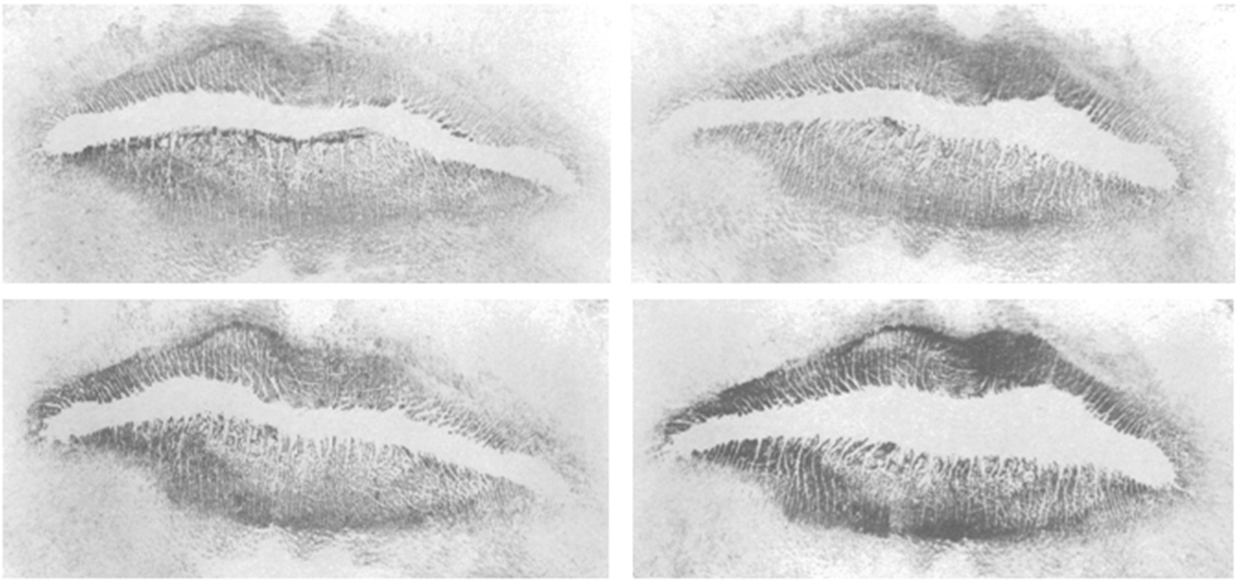


Figure 11: Data Set of Lip Imprint (Roller_Set_1)

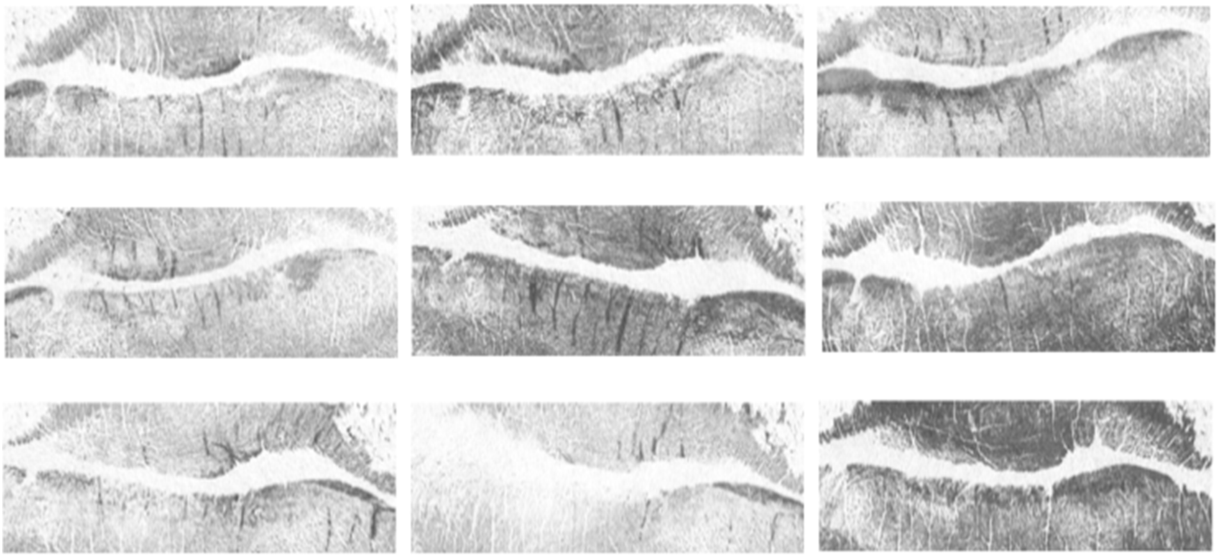


Figure 12: Dataset of Lip imprint (Roller_Set_2)

Experimental results of the proposed method on dataset given in Figure12 are given in Figure14. In this proposed method, we extracted features from three levels. In local level, lip-imprint images are equally partitioned into four parts namely Top Left, Top Right, Bottom Left and Bottom Right. From each part we calculated GLCM at angles of 0°, 45°, 90°and 135°. Six features i.e. Energy, Homogeneity, Entropy, Inertia, Dissimilarity and Correlation, are extracted from each GLCM. So, in total 24 features are extracted in every part. Images are resized into 100 x 200 in global level and resized images are considered to calculate GLCM. In global level 24 texture features are extracted. The proposed method 120 numbers of texture features are extracted from the lip-imprint images.

In this article, we also considered the shape features. Canny edge detection algorithm is used to find out the structural or shape information. We extracted shape information every 5° from lip-imprint images. Feature vector contained 120 texture features and 73 shape features as shown in Figure13. Total 193 features are used for classification the lip-imprint images.

In this paper we have applied two classifier – k-NN [27] and SVM. The result of our proposed algorithm is shown in Table1. The proposed method shows convincing results compared to both SURF [16] and SIFT [15] in respect to identify the owner of the lip imprint as tabulated in Table2.

Table 1: Result of the proposed method

Datasets	k-NN	SVM
Lip-Print (Figure9)	66.66%	86.67%
Roller set 1 (Figure10)	70%	79.92%
Roller set 2 (Figure11)	78.34%	91.67%

Table 2: Comparative Result Analysis

	Misclassification rate by SVM classifier
Proposed method	8.33%
SURF	16.66%
SIFT	11.11%

The proposed method shows convincing results compared to both SURF [16] and SIFT [15] in respect to identify the owner of the lip imprint.

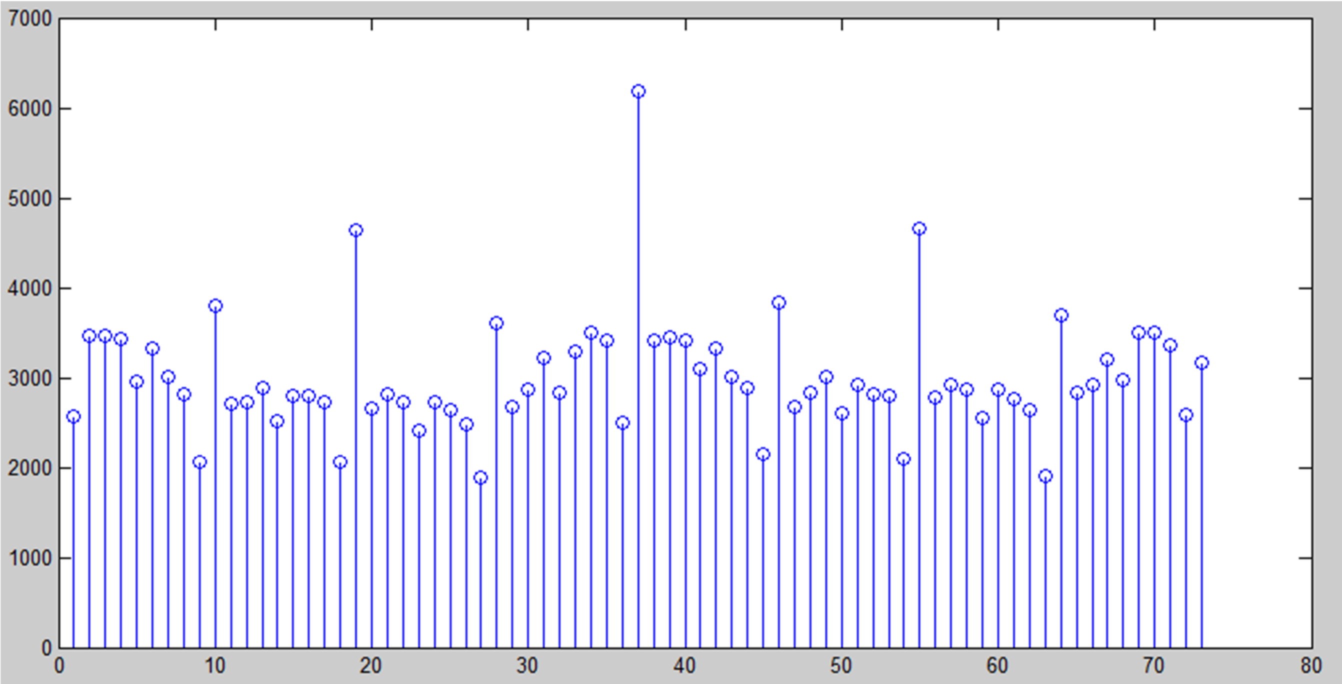


Figure 13: Features extracted using Canny Edge Detection Algorithm

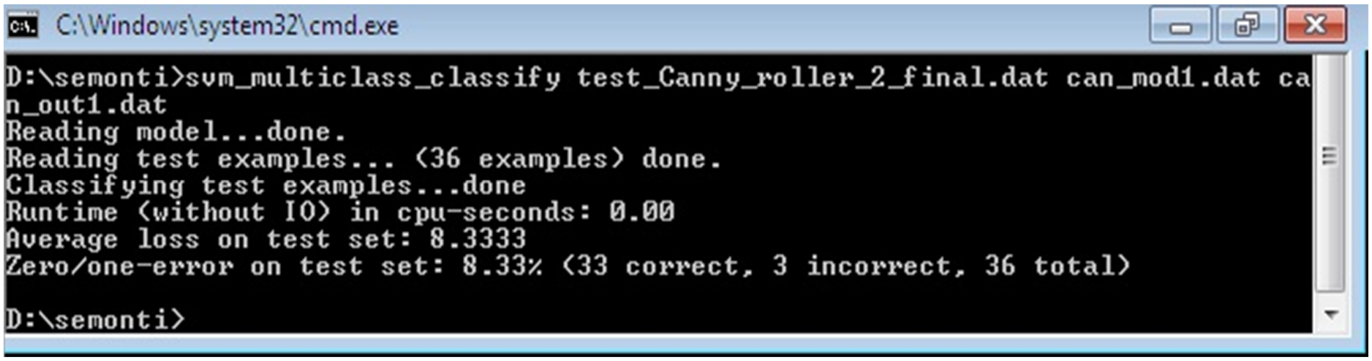


Figure 14: Result of proposed method

Conclusion

In this article, an effective technique is proposed to identify owner of the lip imprint using feature vector and SVM. GLCM and Canny edge detector method is used as feature extractors. Results of the proposed method show significant improvement over the existing algorithms with respect to identify owner of the lip imprint. The result generated by the proposed algorithm is compared with many other methods used for the same purpose and it has been identified that, relevant betterment is achieved with the newly proposed procedure.

The result has shown significant improvement in accuracy. As lip imprint is globally accepted as biometric identifier, accuracy of detecting the owner of the lip imprint has immense importance in criminology.

The proposed method has generated significantly less number of misclassifications compared with other globally acclaimed methods of classification as applied on lip-imprint data.

The proposed method is efficient to be used for biometric identification of human being by means of lip imprint using automated systems. In future we will further enhance the performance of the proposed algorithm in terms of accuracy.

Acknowledgement
We would like to thank University of Silesia at Katowice, Faculty of Computer Science and Material Science, Institute of Computer Science, Computer Systems Department for allowing us to use their datasets for the purpose of this research. We also thank T. Joachims for SVM^{light} which we have used as classifier in this research work.

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