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# Latent Lip Print Identification Using Fast Normalized Cross-Correlation

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*Abstract* — **This paper presents a method of latent lip print identification. Lip prints, among other latent traces, can be found at a crime scene. They are captured by police technicians and after further analysis provide a valuable evidence. In the proposed method image standardization and lip print pattern extraction are performed. Then analyzed lip print is identified using image matching based on Fast Normalized Cross-Correlation. Tests were conducted on 300 lip print images acquired from 50 individuals. The results obtained show promising identification performance and suggest further research.**

***Keywords – image processing; criminal identification; lip print; cross-correlation***

## I. Introduction

In modern crime scene investigation not only body fluids, fingerprints and DNA can be treated as criminal identifiers. Also other expressions of human biometric traits like lip, ear, palm, foot, nose or forehead impressions provide valuable evidence. If properly recovered and examined, lip prints left at a crime scene can contain useful data leading to criminal identification [2,3,5,16]. Lip prints are usually latent and has to be developed by means of latent powders or chemical methods (depending on surface type and condition of latent print). After development latent lip prints become visible and can be digitalized for further analysis by means of a scanner or a digital camera.

Lip prints are the impressions of human lips left on objects such as cups, bottles, cutlery, food or cigarettes. In 1932, Edmond Locard, the French criminologist, first recommended the use of lip prints for criminal identification [5]. The serious study of human lips as a means of personal identification was publicized in the 1970's by two Japanese scientists, Yasuo Tsuchihasi and Kazuo Suzuki [6]. According to those research lip prints are unique and stable throughout the life of a human being. Personal identification based on lip prints is possible due to a fact that lip prints, similar to fingerprints, possess the following specific properties: permanence, indestructibility and uniqueness [1,2,4].

It should be mentioned here that a literature review shows a small number of works in which lip print recognition have been mathematically described or practically utilized. First computer lip print recognition method was introduced by Smacki et al. in 2010 [9]. It extracted line segments from lip print image using Hough transform and compared them using similarity measure based on Euclidean distance. After further improvements [10,11] EER error rate of 21.2% was obtained for a test set of 120 lip prints coming from 30 individuals. In 2012 another lip print recognition method was published by Bhattacharjee et al. [8]. It was based on statistical analysis of average direction of lip print furrows. EER of this method was about 15% but tests were conducted on a small set (50 lip prints from 10 individuals) so results of both methods cannot be directly compared.

The above lip print recognition methods are not suitable for real-life criminal identification systems as they work in verification mode and require high quality images of both upper and lower lips. To overcome these limitations a new method of lip print identification based on Fast Normalized Cross-Correlation is proposed. In this paper an early version of the method is presented that utilizes an improved lip print segmentation algorithm invited by the author in [11]. The purpose of research presented in this paper is to check whether the proposed lip print identification method gives promising results and is worth further research. If yes, the method will be improved (including a new lip print segmentation algorithm) allowing identification of partial, blurred and distorted lip prints which will make is suitable for real-life criminal identification systems.

## II. Lip Print Segmentation

Latent lip prints are developed by different forensic techniques can have different color, brightness, contrast and contain unwanted artifacts (e.g. elements of background). Automatic comparison of this kind of images is very difficult. That is why a lip print segmentation has to be performed first.

The proposed segmentation algorithm includes a sequence involving image standardization and lip print pattern extraction. Input images has to be 300 dpi. The standardization procedure involves background removal, splitting of upper and lower lip and horizontal alignment. Lip print pattern extraction procedure smoothes lip print pattern, separates it from its background and reduce noise.

### A. Image Standardization

The image standardization algorithm consists of a sequence of steps:

1. Background removal,
2. Splitting,
3. Horizontal alignment.

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The process of lip print background removal itself consists of several stages. In the first stage pixels values of the original lip image (Fig. 1a) greater than global threshold level $t$ [17] are converted into the color white, while the remaining pixels remain unchanged (Fig. 1b):

$$f_{new}(x,y) = \begin{cases} 0 \; for \; f(x,y) > t \\ f(x,y) \; otherwise \end{cases} \qquad (1)$$

The $t$ parameter is calculated automatically for each image. Then, a median filter with a $7 \times 7$ mask is used to blur the image (Fig. 1c). In the last stage a binary image is generated by converting all non-white pixels to color black (Fig. 1d).

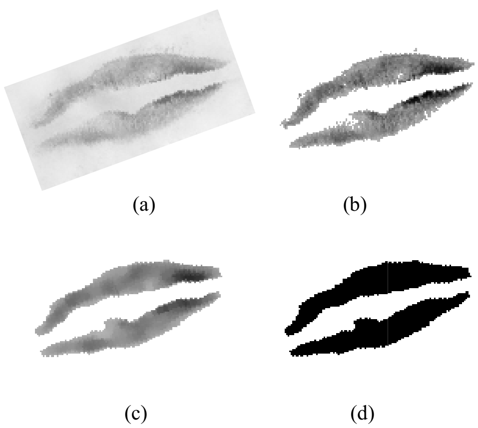



Figure 1. Steps of background removal: (a) the original image with background, (b) result of thresholding, (c) result of blurring, (d) the final lip print area.

The splitting of upper and lower lip is the next step of image standardization. The dividing line is determined by a curve that runs through the center of the space between the lips (Fig. 2). The split curve is determined from the average value of the corresponding coordinates of the upper and lower lip edges.

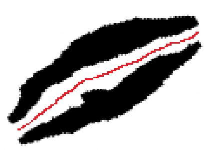


Figure 2. Upper and lower lip split line.

Last step of image standardization is horizontal alignment of the lip print. Initially, the curve obtained in previous step is approximated by a straight line (Fig. 3a). The straight line is established by means of a simple linear regression [13]. Finally, from the straight line equation a rotation angle $\alpha$ towards the Cartesian $OX$ axis is determined. Lip print image is then rotated by the angle $\alpha$ so the split straight line becomes horizontal (Fig. 3b).

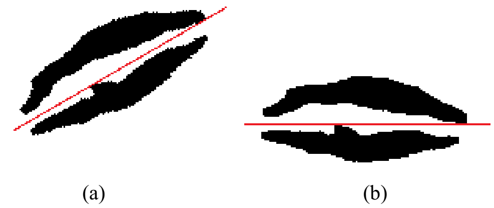



Figure 3. The principle of horizontal alignment: (a) the split curve approximated by a straight line, (b) the image after rotation .

Utilizing the data obtained from steps 1-3, an original lip print image can now be rotated, cropped and split into upper and lower lip areas (Fig. 4).

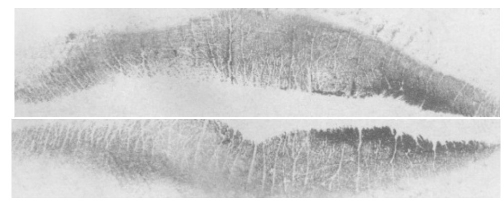


Figure 4. The original lip print image after image standardization.

*B. Lip Print Pattern Extraction*

The process of lip print pattern extraction involves a number of steps:

1. Smoothing,
2. Top-hat transform,
3. Thresholding,
4. Noise reduction.

The lip print smoothing process aims to improve the quality level of the lines forming a lip print pattern. In the proposed solution 8 masks of size 5×5 have been designed (containing lines at an angle of 45 degrees and multiples).

Masks are applied to the lip print image via convolution filtering and the resulting values are registered. The highest value obtained replace the appropriate value of the image pixel. To compare the results lip print smoothing, fragments of the selected images are shown in Fig. 5.

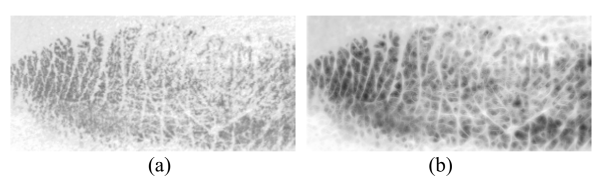
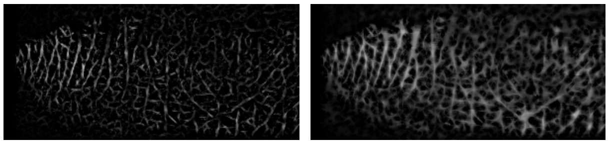



Figure 5. The result of lip print smoothing: (a) a fragment of a lip print before smoothing, (b) the same fragment after smoothing.

Top-hat transform [7,14] is the second step of lip print pattern extraction. The purpose of this procedure is to highlight the lines of the lip print pattern and to separate them from their background. To increase the effectiveness of this algorithm, transformation is applied twice using two different sizes of disk-shaped structural elements: $5 \times 5$ to highlight thin lines (of up to 3 pixels width) and $11 \times 11$ to highlight thick lines (of more than 3 pixels width). As a result two images are generated ( Fig. 6).



(a) (b)

Figure 6. Fragment of a lip print after the top-hat transformation: (a) thin lines highlighted, (b) thick lines highlighted.

After the top-hat transform the thresholding takes place. This procedure involves the application of a formula (2) to each of the two images resulting from the top-hat transform.

$$f_{new}(x,y) = \begin{cases} 1\ for\ f(x,y) > t \\ 0\ for\ f(x,y) \leq t \end{cases} \tag{2}$$

The $t$ parameter is the global threshold level of the analyzed image [17]. The effect of formula (2) is shown in Fig. 7.

(a) (b)

Figure 7. Fragment of the lip print after thresholding: (a) the thin lines highlighted, (b) the thick lines highlighted.

In the last stage of lip print pattern extraction the subimages of the thin and thick lines are combined into one single image, and this unified image is subjected to noise reduction. For this purpose 20 appropriate $7 \times 7$ dimensional masks have been designed (containing lines at an angle of 18 degrees and multiples). The masks are applied to the lip print pattern image via convolution filtering and the resulting values are registered. If the highest value obtained is less than 0.5 (les then half) then the analyzed pixel of the image is converted to white. Otherwise the value of the pixel remains unchanged. Fig. 8 shows the final effect of lip print pattern extraction.

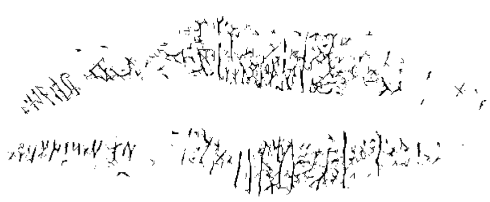


Figure 8. Example result of the lip print pattern extraction process (upper and lower lip).

## III. IDENTIFICATION

Criminal identification systems operate in the identification mode. Identification occurs when the biometric system attempts to determine the identity of an individual by comparing test sample with templates stored in a database [12]. Although the FBI's Integrated Automated Fingerprint Identification System (IAFIS) operates as a an open-set identification task (person is not guaranteed to exist in the database) we choose a close-set mode (person is assumed to exist in the database) as it is used in real life by lip print experts. Result of close-set identification is a ranking list containing individuals and their similarity scores sorted from the most similar one.

In the first step of lip print identification, as some parts of the test image can be low quality (e.g. blurred), test image is divided into multiple subimages. Size of the subimage was determined experimentally to $80 \times 80$ pixels. First subimage is created in the center of the source image, next ones are added on both sides. Every subimage is aligned vertically to a position where it covers the maximum number of black pixels. Subimage is created when black pixels cover at least 10% of the selected area. Fig. 9 shows test lip print image with subimages outlined.

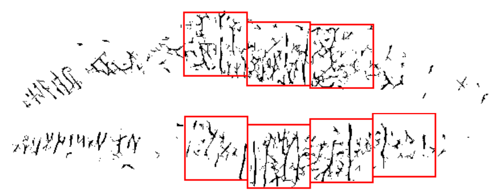


Figure 9. An upper and lower lip print with the subimages outlined.

Every generated subimage is matched to all lip print images in the database. In the first step, template lip print is subjected to image segmentation described in section III. Then, matching of a subimage and a lip print from the database is performed by means of Fast Normalized Cross-Correlation (FNCC) [15]. For every subimage a correlation matrix $\gamma$ is generated. It contains correlation coefficients calculated according to the formula [15]:

$$\gamma(u,v) = \frac{\sum_{x,y}\left[f(x,y) - \bar{f}_{u,v}\right]\left[s(x-u,y-v) - \bar{s}\right]}{\left\{\sum_{x,y}\left[f(x,y) - \bar{f}_{u,v}\right]^2 \sum_{x,y}\left[s(x-u,y-v) - \bar{s}\right]^2\right\}^{0.5}} \tag{3}$$

where

- f is the lip print pattern image from the database,
- $s$ is the subimage,
- sum is over $x,y$ under the window containing the subimage s positioned at $u,v$,
- $\bar{f}_{u,v}$ is the mean value of pixels in the region under the subimage,
- $\bar{s}$ is the mean value of pixels in the subimage.

The resulting matrix $\gamma$ contains the correlation coefficients. Maximum value found in $\gamma$ is the similarity score of subimage and lip print image from a database. Similarity between test and template lip print images is calculated by averaging component similarities for all subimages.

## IV. RESULTS

The study was conducted on set of 300 lip prints (100 test images and 200 database images) belonging to 50 individuals. Both types of lip prints were acquired in the same way as lip prints collected from suspects in police laboratories. As database images 200 lip prints of the highest quality were selected. The remaining 100 lip prints (lower quality, usually partially blurred or distorted) became test images. Lip prints were digitalized using a scanner (grayscale, 300 dpi) and saved as PNG image files.

Test were conducted in close-set identification. Similarity score of a test and database images was calculated using Standard FNCC (full lip pattern image compared) and FNCC with subimages (lip pattern image divided into subimages and then compared). From such investigations, a cumulative match characteristic (CMC) was determined (Fig. 10).

CMC curve shows the probability of identification for numerous ranks. Rank 1 shows probability that owner of the test lip print is on the first place in the ranking list, rank 2 on 2nd place, rank 3 on 3rd place, etc.

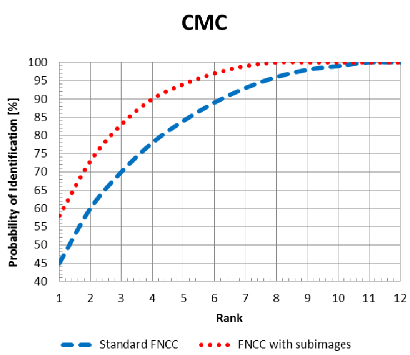



Figure 10. The CMC curves of lip print identification based on fast normalized cross-correlation (FNCC)

Table 1 show detailed results of the tests for the top 11 ranks. FNCC with subimages gets identification rate at rank 1 of 58% while standard version gets 45%. To acquire 100% probability of correct identification ranking list has to contain 8 positions for FNCC with subimages and 11 – for standard version.

TABLE I. DETAILED COMPARISON

| Rank | Probability of Identification [%] | |
|---|---|---|
| | ***Standard FNCC*** | ***FNCC with subimages*** |
| Rank 1 | 45 | 58 |
| Rank 2 | 60 | 73 |
| Rank 3 | 70 | 83 |
| Rank 4 | 78 | 90 |
| Rank 5 | 84 | 94 |
| Rank 6 | 89 | 97 |
| Rank 7 | 93 | 99 |
| Rank 8 | 96 | 100 |
| Rank 9 | 98 | 100 |
| Rank 10 | 99 | 100 |
| Rank 11 | 100 | 100 |

## V. CONCLUSIONS

The results obtained demonstrate that the performance of the presented lip print identification method is higher after dividing lip print pattern image into subimages. This stands from the fact that low quality lip print pattern areas are not converted to subimages which has a positive effect on identification performance.

Overall results of the proposed latent lip print identification method are promising and suggest further research in this area. Results cannot be directly compared with concurrent methods as they were tested on a much larger database and provide results for identification tests.

Future work will include improvements in the presented method allowing identification of partial, blurred and distorted lip prints. This will make the proposed approach more suitable for real-life criminal identification purposes.

## REFERENCES


[1] M. Choras, "The lip as a biometric", Pattern Analysis and Applications. Vol. 13, No. 1, 2010, pp. 105-112.

[2] J. Kasprzak, B. Leczynska, "Cheiloscopy. Human identification on the basis of a lip trace", 2001, pp. 11-29 (in Polish).

[3] M. Newton, "The Encyclopedia of Crime Scene Investigation", 2008, pp. 42.

[4] P. Sharma, S. Saxwna, V. Rathod, "Comparative reliability of cheiloscopy and palatoscopy in human identification", Indian Journal of Dental Research, Vol. 20, Issue 4, 2009, pp. 453-457.

[5] J. Siegel, P. Saukko, G. Knupfer, "Encyclopedia of Forensic Science", 2000, pp. 358-362.

[6] Y. Tsuchihashi, "Studies on personal identification by means of lip prints", Forensic Science, 1974, pp. 127-231.

[7] E. Dougherty, "An introduction to morphological image processing", 1992.

[8] S. Bhattacharjee, S. Arunkumar, S. K. Bandyopadhyay, "Personal Identification from Lip-Print Features using a Statistical Model", Int. Journal of Computer Applications, Vol. 55, No. 13, 2012.

[9] L. Smacki, P. Porwik, K. Tomaszycki, S. Kwarcinska, "Lip print recognition using the Hough transform", Journal of Medical Informatics and Technologies. Vol. 14, 2010, pp. 31–38.

[10] L. Smacki, K. Wrobel, "Lip Print Recognition Based on Mean Differences Similarity Measure", Advances in Intelligent and Soft Computing (AISC), Vol. 95, 2011, pp. 41–50.

[11] L. Smacki, K. Wrobel, P. Porwik, "Lip print recognition based on the DTW algorithm". Proc.of the Nature and Biologically Inspired Computing, Conf. Salamanca, Spain, 2011, pp. 601–606.

[12] P. Philips, A. Martin, C. L. Wilson, M. Przybocki, "An Introduction to Evaluating Biometric Systems", 2000.

[13] J. F. Keney, E.S. Keeping, S. "Linear Regression and Correlation". Mathematics of Statistics, 3rd edition, 1962.

[14] R. van den Boomgard, R. van Balen, "Methods for Fast Morphological Image Transforms Using Bitmapped Images". Computer Vision, Graphics, and Image Processing: Graphical Models and Image Processing. Vol. 54, No.3, 1992, pp. 252–254.

[15] K. Briechle, U. D. Hanebeck, "Template matching using fast normalized cross-correlation", Proceedings of SPIE, Vol. 4387, Optical Pattern Recognition XII, 2001.

[16] A. Castello, et al., "Luminous lip-prints as criminal evidence", Forensic Science International, Vol. 155, 2005, pp. 185-187.

[17] N. Otsu, "A Threshold Selection Method from Gray-Level Histograms", IEEE Transactions on Systems, Man, and Cybernetics, Vol. 9, No. 1, 1979, pp. 62-66.