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Automatic Detection and Localization of Relatively Permanent Pigmented or Vascular Skin Marks

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Sammanfattning

Abstract

Acknowledgments

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Contents

Notation

1 Introduction

1.1 Motivation

The amount of technical tools available for forensic analysis in law enforcement increases rapidly and today there exist millions of devises capable of taking colour images. Video surveillance cameras, security cameras and cellphone cameras can all be used to catch perpetrators in the act. The videos and still images can be used as evidence for identification during trails which means that forensic technicians need tools to evaluate if the suspect is the same person as the one caught on camera.

One common method of evaluating whether the perpetrator and the suspect are the same person is to compare facial features such as eyes, nose, mouth, scars, and other facial marks. This is nowadays done manually [16] by the forensic examiners and in order to give a objective and comparable conclusion value a likelihood ratio [10] is calculated. The likelihood ratio expresses how strong the evidences against the suspect.

To calculate the likelihood ratio it is required to have enough observations of facial features and these are acquired manually by experts since facial recognition processes have not been found to be reliable enough [9]. To record all these observations manually is time consuming and there exist a interest in doing this automatically [14].

This master thesis was motivated by the need of large amount of data from facial marks. The National Forensic Centre (NFC) in Sweden is supporting this work by providing guidance and practical help.

1.2 Aim

The aim of this master thesis is to examine the possibilities of automatically detecting and locating facial marks and classifying them as permanent or non-permanent marks. The frequency, location and size of the permanent marks are stored such that it can be used to calculate the likelihood ratio. By automatically creating a large data base with face images and their features, the accuracy and speed in face recognition cases can be increased.

1.3 Problem specification

This master thesis is going to answers the following questions:

> Is it possible to implement a program which can automatically detect RPPVSM?
>
> How can the RPPVSM be given a location and size within a face?
>
> With which accuracy can the program detect and localize RPPVSM?

1.4 Boundary

In general, when working with image, the quality of the images are crucial for the results. Low resolution and badly illuminated images taken from different angles can cause analytical difficulties. Therefore, this thesis will us images which are high resolute, well illuminated, taken en face and in RGB-colours.

2

Related work/Background

The work of systematically recording physical measurements for law enforcement was introduced by Alphonse Bertillon as early as in the 19th century. He developed the Bertillonage system since he believed that each person could be uniquely identified by a set of measurements [1]. This system was however outdated quickly thanks to the explosion of technology.

Resent research by Srinivas et al. [9] have resulted in an automatic and semi-automatic facial recognition processes. It uses a multiscale automatic facial mark detector for the automatic detector and receive a equal error rate of 15.48%. This result was improved by introducing human knowledge in the semi-automatic detector.

When distinguishing identical twins it is useful to look at facial marks which has been examined in an other article by Srinivas et al. [15]. The study concluded that the facial marks can be uses as features for distinguishing between identical twins even if there seems to exist a correlations between the twins set of marks.

Nurhudatiana et al. [11] describes in their article the distribution of Relatively Permanent Pigmented or Vascular Skin Marks (RPPVSM) in Caucasians, Asians, and Latinos. They conclude that if the number of RPPVSM are few they are randomly distributed which can be used for personal identification in law enforcement.

Anil and Park found during their research [3] that facial mark can be used to increase the recall and precision for a state-of-the-art face matcher (FaceVACS). The facial mark detector used the 3x3 LoG-operator as blob detector. Adding these features to the algorithm improved the face matcher from 92.96% to 93.90% on the Facial Recognition Technology (FERET) database and from 91.88% to 93.14% on a Mugshot face database.

2.1 Facial marks

The skin in the face does not have a homogeneous colour and contains regions with different coloured facial marks. The most common facial marks are moles, pockmarks, freckles, scars, and acne. Some of these marks are not permanent, e.g. acne usually heals without leaving any marks, while scares and moles remain the whole life [9]. Skin marks which can be used for identification are called RP-PVSM and they have to be relatively permanent, common and also be observable without any special equipment. [11]

3

Method

This paper present a algorithm to detect facial marks automatically. This section will describe the methods briefly used to develop the algorithm. If more details are requested, they can be found in the referred works.

3.1 Detection

An overview of the detections system is presented in figure 3.1. The system consist of several subsystems which has it own functionality. Each image, I, is processed and go through each of these subsystems.

3.1.1 Face detection

An important component for further processing is the bounding box of the face in each image. It is found by using an implementation of object detection by Paul Viola et al. [17]. The algorithm take advantage of three different parts.

The first is part is a new image representation which allows Haar features from each image to be calculated rapidly. The speed is achieved by using integral images instead of the original image.

The second part is the extraction of the most important features through AdaBoosting. It creates a strong classifier by combining the strength of weaker classifiers. A weak classifier is the best threshold for a feature which separates the faces from the non-faces.

The third part is a cascade decision which reduces the computations costs by rejecting potential bounding boxes for the face. If the first weak classifier gives a positive result, the second classifier is engaged. This is repeated until all weak classifiers has been passed or if one of the returns a negative result. All bounding boxes which has returned a negative result is rejected immediately.

When a suitable bonding box as been found for I, the landmarks in the image can be extracted.

3.1.2 Landmark detection

With landmark in the face, it is possible to create a unique mask for each face and produce a grid with different regions in the face. The landmarks are extracted by using an implantation based on Vahid Kazemi et al.[5] It uses sate of the art algorithms for face alignment where cascade of regression functions are crucial for its success. The estimated shape of the face is updated by regressing the shape parameters based on normalized features from the image. The parameters are updated until they converges.

From this algorithm, 68 landmarks are extracted where the eyes, moth, nose and chin are marked. From these, a mask generated where the nostrils, eyes, throat and background is cut out. Also, a grid of 16 regions is generated according to the supervisors at NFC demands.

3.1.3 Normalization

In order to get a reliable and uniform result, the image has to be normalized. There are two kind of normalization applied on the image, geometric normalization and photometric normalization.

The geometric normalization consist of rotation of the image such that the eyes are aligned with the bottom of the image. The rotations angle is calculated with the help of the landmarks at the corners of the eyes. An angle is calculated by averaging an angle from the right and left eye. The geometric normalization also include a resize of the image such that the interpupillary distance is 500 pixels. A resizing factor is calculated by taking the fraction between 500 and the distance between the pupils.

The photometric normalization is performed by using tone mapping operator based on the work of Nikola Banic et al.[2]. It uses a Light Random Sprays Retinex (LRSR) which is an improvement of the Random Sprays Retinex (RSR)[12]. All tone mapping operator transform pixel intensities depending on its surrounding and the RSR uses a random selection of pixels around the the current pixel which decreases computations costs, sampling noise and dependency. The calculations are done on intensity image for LRSR while uses the RGB colour channels.

3.1.4 Segmentation

When searching for facial mark, hair lines and hair can cause false detection. Therefore the image has to be segmented so that only skin area is regarded in search for facial marks. The segmentation is done with GrabCut produced by Carsten Rother et al.[13]. It uses Gaussian Mixture Model (GMM) for a colour image. GrabCut needs a GMM for know foreground and one for known background. The known foreground used e.g. is the cheeks and forehead, which is extracted from the landmarks.

After creating GMM:s, a energy function is created so that its minimum correspond to a good segmentation which depends on the given foreground and background. The function is minimized iteratively until a converged segmentation is produced.

The segmentation mask is used to improve the mask created from the landmarks. Now using the improved mask, a well segmented image can searched for facial marks. This image will henceforth be called I_{pre}

3.1.5 Colour space

Facial marks tend to have a brown or red colour and thus would it be of interest to process these colours in the image. This is possible by converting the RGB image to red-channel and brown-channel images respectively. This is done by using a trained transformer from the work of Joost van de Weijer et al.[4]. It is trained on real world images from Google Image and has shown to out perform colour chips. The colour transformed images are used for the watershed algorithm to find the contours of the facial marks and to extract relevant features for the classifier.

3.1.6 Fast Radial Symmetry Detector

The actual mark detection uses local radial symmetry to detect interesting point in the I_{pre}. The algorithm used i called Fast Radial Symmetry and was created by Gareth Loy et al.[7]. For each point, p, in the I_{pre}, the contribution of radial symmetry at radius r is calculated by producing a orientation projection image O_n and a magnitude projection image M_n. These images are created by examining the positively-affected, $p_+(p)$, and negatively-affected, $p_-(p)$. To do this, the gradient, g, of the image is needed and it is calculated using a 3x3-Sobel kernel. Since the gradient computations are discrete, it is necessary to average I_{pre} with a 3x3 Gaussian kernel to remove sharp edges.

$$p_+(p) = g(p) + round\frac{g(p)}{\|g(p)\|}n \tag{3.1}$$

$$p_-(p) = g(p) - round\frac{g(p)}{\|g(p)\|}n \tag{3.2}$$

The O_n and M_n are then updated according to eqs. (3.3) to (3.5) and (3.10)

$$O_n(p_+) = O_n(p_+) + 1 \tag{3.3}$$

$$O_n(p_-) = O_n(p_-) - 1 \tag{3.4}$$

$$M_n(p_-) = M_n(p_+) + \|g(p)\| \tag{3.5}$$

$$M_n(p_-) = M_n(p_-) - \|g(p)\| \tag{3.6}$$

The radial symmetry contribution at radius n depends on F_n and A_n which is defined as

$$F_n = \frac{M_n(p)}{k_n}\left(\frac{|\tilde{O}_n(p)|}{k_n}\right)^{\alpha} \tag{3.7}$$

$$\tilde{O}_n(p) = \begin{cases} O_n(p) & \text{if } O_n(p) < k_n \\ 0 & \text{else} \end{cases} \tag{3.8}$$

A_n is a Gaussian kernel with different size depending on n, α is radial strictness parameter and k_n is a scaling factor. α is set to 2 and k_n to 9.9 since Gareth Loy et al. deemed suitable for most applications.

The final radial symmetry image S_n is calculate

$$S_n = F_n * A_n \tag{3.9}$$

This was a calculation for radius n and it desirables to use multiple radii to detect point larger then n. It is not necessary to use a continuous spectrum of radii, thus the radii used are $N = \{1, 3, 5, 7, 9, 11, 13, 15\}$

The average of radial symmetry images, S, are calculated as

$$S = \frac{1}{N}\sum_{n=1}^{N} S_n \tag{3.10}$$

At this point, a image with points of interest has been acquired. From this image, a binary threshold was applied with the threshold h_{FRS} to extract sinks for the watershed algorithm described by Fernand Meyer [8]. The output is now a set of bonding boxed containing facial mark candidates.

3.1.7 Candidate elimination

Since many facial mark candidates may be false positives, they have to be discovered and excluded. Each candidate is given a 25x25 area which is processed through two eliminators.

The first eliminator uses a simple blob detector. It searched thresholded binary images for connective pixels and returns true is the area contains a blob. If the mark does not contain a blob, it is excluded from the candidates.

The eliminator uses a hair removal algorithm by Tim Lee et. al.[6]. The algorithm smooth out hair pixels with closing operations using the three different structuring elements. The suggested structuring elements by Tim Lee et. al. is T_0, T_{45} and T_{90}.

$$T_0 = \begin{bmatrix} 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 \end{bmatrix}$$

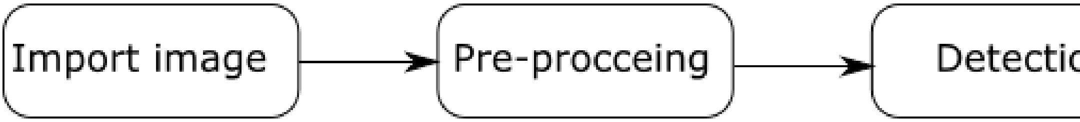

Figure 3.1

$$T_{45} = \begin{bmatrix} 0&0&0&0&0&0&0&0&0 \\ 0&1&0&0&0&0&0&0&0 \\ 0&0&1&0&0&0&0&0&0 \\ 0&0&0&1&0&0&0&0&0 \\ 0&0&0&0&1&0&0&0&0 \\ 0&0&0&0&0&1&0&0&0 \\ 0&0&0&0&0&0&1&0&0 \\ 0&0&0&0&0&0&0&1&0 \\ 0&0&0&0&0&0&0&0&0 \end{bmatrix}$$

$$T_{90} = (T_{90})^T$$

The closed image is generated by applying each structure element on each colour channel as 3.11, where G is the closed image, M is the image of a mark, $T_x = [T_0, T_{45}, T_{90}]$ and C the RGB-channels.

$$G_c = |M_c - max(M_c * T_x)| \tag{3.11}$$

If the number of hair pixels in the union of G_c is larger then a threshold h_{hair}, the mark is excluded from the candidates.

3.2 Classification

The algorithm should also separate RPPVSM from non-permanent marks. This is done by training a SVM-classifiers using radial basis function kernels and 1000 iteration. The training data consists of the labelled facial marks provided by the supervisors at NFC. To get a good classifier, a set of features are required.

3.2.1 Features

The features extracted from the facial marks can be looked up in the table below.

Feature	Description
Mean	Mena from RGB channels and red and brown channel
Standard deviation	Standard deviation from RGB channels and red and brown channel

3.3 Experiment

4

Result

5

Conclusion

Appendix

A

Trista saker

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