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Automatic Detection and Classification of Permanent and Non-Permanent Skin Marks

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Sammanfattning

När forensiker försöker identifiera förövaren av ett brott använder de individuella märken när de jämför den misstänkta med förövaren. Ansiktsmärken används ofta vid identifikation och de hittas idag manuellt. För att skynda på denna process, är det önskvärt att detektera ansiktsmärken automatiskt. Detta examensarbete beskriver en metod för att automatisk detektera och separera permanenta och icke-permanenta märken. Den använder en snabb radial symmetri algoritm som ett huvud element i detektorn och en stödvektormaskin för märkes klassificeraren. Under arbetets gång har det uppmärksammats svårigheter med det stora antal feldetektioner. Detta kan dock åtgärdas i framtiden genom att ta bort falska detektioner.

Abstract

When forensic examiners try to identify the perpetrator of a felony, they use individual marks when comparing the suspect with the perpetrator. Facial marks are often used for identification and they are nowadays found manually. To speed up this process, it is desired to detect interesting facial marks automatically. This master thesis describes a method to automatically detect and separate permanent and non-permanent marks. It uses a fast radial symmetry algorithm as a core element in the mark detector and a support vector machine for the classifier of the marks. During this work it has been found that there exists an obstacle in the great number of false detections. This can however be solved in the future by further enhancement of the false detection eliminators.

Acknowledgments

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Linköping, November 16, 2016
Armand Moulis

Contents

1
Introduction

1.1 Motivation

The amount of video surveillance cameras, security cameras and cellphone cameras increases rapidly and today there exist millions of devises capable of catching perpetrators in the act. The videos and still images can be used as evidence for identification during trials where forensic experts evaluate the strength of evidence whether 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 [23] by the forensic examiners, and in order to evaluate the strength of the results, a likelihood ratio [14] from Bayes rule is calculated. The likelihood ratio is estimated from two hypotheses, where the numerator gives the probability to achieve the results if the perpetrator and the suspect are the same person and the denominator the probability to achieve the results if the perpetrator is another man.

NFC is currently running a project where an automatic facial recognition system can be used to extract statistics from a database of facial images. The main advantages of using such a method are that the likelihood ratio can be calculated based on statistics, and that the risk for human bias in the decision process is diminished.

This master thesis was motivated by the need of combining the automatically calculated likelihood ratio value with the evidential value derived from the frequency of facial marks in certain regions of the face. The National Forensic Centre (NFC) in Sweden is supporting this work by providing guidance and practical help.

1.2 Aim

The aim of thie master thesis is to create a algorithm to automatically create a large data base with facial images and their features. By using this algorithm, the evidential value in forensic facial image comparison examinations can be better grounded.

1.3 Problem specification

The problem of this master thesis is to find possible method to automatically detect and locate facial marks and classify them as permanent or non-permanent marks. The frequency, location and size of the permanent marks are stored such that they can be used to combine these values to the previously calculated likelihood ratio

1.4 Scope

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 assumes images which are high resolute, well illuminated, taken en face and in RGB-colours.

1.5 Thesis outline

This chapter describes the aim and problem specification of this master thesis. In Chapter 2, gives an insight in related work the methods used by other researchers. Chapter 3 describes the methods used in the algorithm developed during this master thesis. The results from the algorithm can be studied in Chapter 4 and an discussion about the result and methods used is found in Chapter 5. Finally, Chapter 6 consist of a conclusion of the master thesis and ideas for future work within the same scope.

2 Related work

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 Vorder Bruegge et al. [13] helped the development of an automatic and semi-automatic facial mark detector. 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. [21]. The study concluded that the facial marks can be used as features for distinguishing between identical twins even if there seems to exist a correlations between the twins set of marks.

Nurhudatiana et al. [16] 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 [6] 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 Laplacian of Gaussian-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 [13]. Skin marks which can be used for identification are called RPPVSM and they have to be relatively permanent, common and also be observable without any special equipment. [16]

3
Method

This thesis report present a algorithm to detect facial marks automatically. This Chapter 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 algorithm is presented in figure 3.1. The algorithm consist of several submodules which has it own functionality. Each image, I, is processed and go through each of these subsystems.

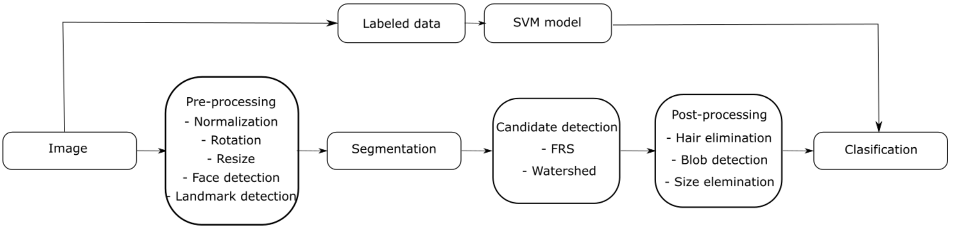

Figure 3.1: *Overview of the algorithm*

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 OpenCV implementation of object detection by Paul Viola et al. [24]. This face detection algorithm was chosen since it has equivalent positive result as other methods [20, 22]. In addition, it is much faster the the other detector. The algorithm from Paul Viola et. al. 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. A simple classifier is used to determine if the bounding boxes are promising candidates before a more complex classifier is engaged. This is repeated until all 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

To process a facial image, it would be good to know where different parts of the face i located, e.g. mouth and eyes. These parts can be pinpointed with points called landmarks. With these landmark, 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 implementation based on Vahid Kazemi et al. [8]. 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, mouth, nose and chin are marked. From these, a mask generated where the nostrils, eyes, throat and background is cut out.

3.1.3 Facial grid

The landmarks are also used to produce a grid over the face. The grid consist of 16 regions which are defined the supervisors at NFC. This grid is needed to calculate the number of facial marks within these predefined regions. This is necessary to improve the evidential value of the likelihood ration.

Figure 3.2: Image over the landmarks (blue points) and facial grid (black lines)

3.1.4 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 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)[17]. All tone mapping operator transform pixel intensities depending on its surrounding. 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 the intensity image of each RGB colour channels.

The geometric normalization consist of rotation of the image such that the line between the pupils is 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.

Figure 3.3: *Image after photometric and geometric normalization*

3.1.5 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. Since interactive segmentation methods are more and more popular [3], it should be beneficial to chose a interactive segmentation method. Carsten Rother et al.[18] compared several popular interactive segmentation methods and also presented their own method, GrabCut. They concluded that GrabCut performs as well as GraphCut [3] with fewer user interactions.

Thus, the segmentation method used for the algorithm is GrabCut which uses Gaussian Mixture Model (GMM) for a colour image. GrabCut needs a GMM for a know foreground and one for a known background. The known foreground used e.g. is the cheeks and forehead, is extracted with the help of 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 be searched for facial marks. This image will henceforth be called I_{pre}

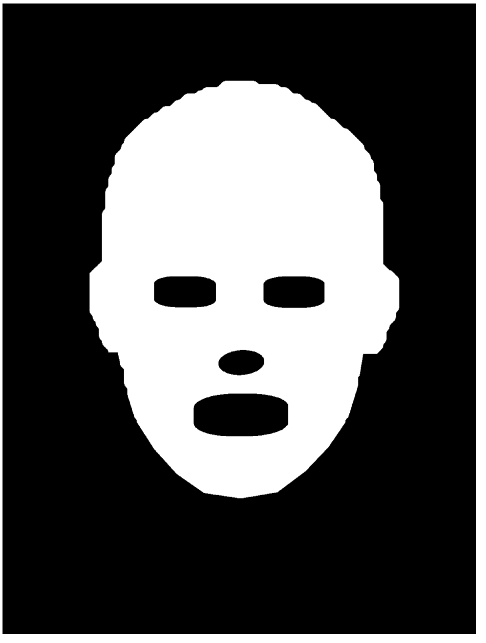

Figure 3.4: *Image of the facial mask*

3.1.6 Fast Radial Symmetry Detector

There are many ways to extract interesting points or marks. One way is to look at the radial symmetry in the image. This method has been used by several researcher [21, 11, 13, 19]. It seems to be a reliable method since the point is to detect small circular shapes, which is what Jan Schier et. al.[19] did whey they tried to count yeast colonies. This is why the actual mark detector uses an algorithm called Fast Radial Symmetry (FRS) and it was created by Gareth Loy et al.[11].

For each point, p, in the I_{pre}, the contribution of radial symmetry at radius r is calculated by producing an 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.

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

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

To retrieve the nearest integer the operation *round* is used. 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 calculated

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

This was a calculation for radius n and it desirables to use multiple radii to detect point larger than 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, an FRS-image with points of interest has been acquired. From this image, a binary threshold was applied with the threshold h_{FRS} to extract sinks. The sinks are needed for the watershed algorithm described by Fernand Meyer [12]. The use of watershed is good since it can find the contour of uneven marks as long as the pixels approximately have the same intensity value. The watershed algorithm with the sinks are applied on a grey image of the face. The output from this is a set of bonding boxes containing facial marks. This set is henceforth called candidates and the module used to detect the facial marks is called FRS-detector.

3.1.7 Candidate elimination

Since many facial mark candidates may be false positives, they have to be discovered and excluded. Vorder Bruegge et al. [13] used three elimination methods which seemed intuitive. Size, shape and presence of hair should be good indicators if the candidate is a false detection or not. Each detected candidate is given a 30x30 area which is processed through three eliminators.

Facial marks are often blob-shaped which is why the first eliminator uses a simple blob detector from OpenCV. It creates a thresholded images with connective pixels and does this with different threshold values. If the union of all the different images does not contain a blob-shaped object, the area is excluded from the candidates.

The second eliminator uses a hair removal algorithm by Tim Lee et. al. [10]. 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 larger than the one used in this implementation since their hair-structures where wider. Thus, the smaller structuring elements T_0, T_{45} and T_{90} were used.

$$T_0 = \begin{bmatrix} 0 & 1 & 1 & 1 & 0 \end{bmatrix} \quad T_{45} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad T_{90} = (T_0)^T$$

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. This means that M_c is a gray image of a mark where the structuring elements detect thin and small edges.

$$G_c = |M_c - \max_x(M_c * T_x)| \qquad (3.11)$$

$\max_x(M_c * T_x)$ means that the largest pixel value from the structuring elements are pick for that colour channel. 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.

The third eliminator removes candidates depending on their size. If the candidate has an area smaller than 5 pixels or an area larger than 1000 pixels, it is eliminated. The thresholds were chosen because since all annotated marks is within this interval, see fig. 3.5.

3.2 Classification

When choosing the suitable classifying method for the mark classifier, there are many methods to chose from. Kotsiantis et. al. [9] concludes that the best ma-

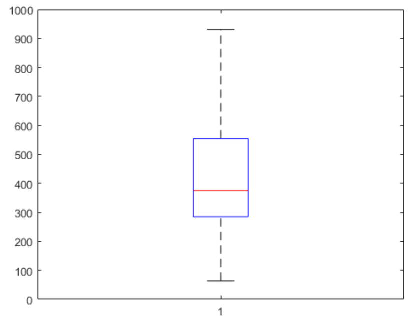

Figure 3.5: The distribution of areas from the annotated facial marks.

chine learning method depends greatly on the conditions the classifier are going to work in. Generally, support vector machine (SVM) tend to perform better with continuous and multidimensional features and with a large amount of samples. The features used in this case fulfill the continuity and multi dimension. Chih-Wei et. al. [5] also describes a good way to optimize the use of SVM and recommend to use radial basis function (RBF) as kernel. This is why a SVM with RBF kernel is chosen for the mark classifier.

The goal with a SVM is to separate different classes by finding the best hyperplane which divides them. The hyperplane is moved such that a loss-function is minimized. RBF kernel nonlinearly maps samples into a higher dimensional space which allows the classifier to handle non-linearly separable classes. This kernel also has fewer numerical difficulties. The parameters needed for a RBF kernel i C which determines the penalty parameter for the error and γ which defines how far the influence of a single training sample reaches. [5]

The training data consists of the labelled facial marks provided by the supervisors at NFC. To get a good classifier, a set of discriminative features are required.

3.2.1 Features

The most common color space in use is the RGB system, one channel each for the red, green and blue colors. Arfika Nurhudatiana et al. [15] used, among others, the minimum, maximum, and average from the RGB-channels as discriminative featuress. By using 11 more colour channels, presented by Joost van de Weijer et al.[7], it is possible to improve the classifier. The colour transformation is a trained colour mapping. It is trained on real world images from Google Image and has shown to out perform colour chips. The 11 colours consist of black, blue, brown, grey, green, orange, pink, purpale, red, white and yellow.

The features extracted from the facial marks are the mean and the standard deviation from the three RGB channels and the 11 colours from the work of Joost van de Weijer et al. This results in 28 features which is used to train the classifier.

To not let some feature with greater numeric rang dominate over features with smaller range, the features need to be scaled [5]. This is very important which is why the features are linearly scaled to a range from 0 to 1. The same scaling factor has to be used when the test data is scaled.

4

Result

This Chapter first describes the experiment to evaluate the algorithm and then presents the results.

4.1 Experiment

To evaluate the algorithm, a set of 106 images of faces en face were acquired from SCface database [4]. Facial marks of interest were marked and labeled as a permanent or a non-permanent by the supervisors at NFC. This resulted in 506 marks where 353 were permanent and 153 were non-permanent.

The experiment was set such that the image set was processed by the algorithm with 11 different thresholds values, h_{FRS}, for the FRS-image. The h_{FRS} ranged from 0.05 to 0.15. The output was compared to the ground truth. A correct detection was defined as all detections which had a union with an annotated mark. This definition has been chosen since some of the detections can be very small. Also, since candidates larger than 1000 pixels has been eliminated, no over large candidates can give correct detections.

The evaluation measurement for the detector is the precision (4.1) and recall (4.2) value. Precision tells how well the detector is to avoid false detections while recall tells how well it finds the annotated marks. The result from the different h_{FRS}-values can be seen in fig. 4.1.

$$Precision = \frac{\text{Number of correct detections}}{\text{Number of detections}} \tag{4.1}$$

$$Recall = \frac{\text{Number of correct detections}}{\text{Number of annotated marks}} \tag{4.2}$$

The h_{FRS}-value which gives the best recall value was used to evaluate the elimination process of the candidates. This was done by calculating the precision and recall values before the different elimination steps. The results is displayed in fig. 4.1.

To evaluate the facial mark classifier, a cross validation of the 506 annotated mark were performed. 25 marks was chosen at random to be used as test marks while the remaining marks was used for training the SVM. This was repeated until all the marks had been used as test marks.

In order to find the best C-value and γ-value for the mark classifier, the parameters are varied over a rough interval to narrow down the search. Afterwards, a more fin interval is used to find the best parameters. This has been shown by Chih-Wei et. al. [5] to be an effective method compared to a more random selection of parameters which is often used by people unfamiliar to SVM.

4.2 Results from experiment

In the fig. 4.1, the precision and recall for different h_{FRS}-value can be examined. The precision corresponds to the white bar and the recall corresponds to the black bar. Note that this is only the detections of facial mark and no classification between permanent and non-permanent marks.

As one can see, the precision increases with higher h_{FRS}-value without affecting the recall substantially. This is means that the number of candidates decreases with a growing h_{FRS}-value. Thus, a small h_{FRS}-value results in a large amount of candidates while a larger value gives fewer candidates.

In fig. 4.2, it is possible to see the effects of the different elimination steps. As before, the white bar represent the precision and the black bar represent the recall. The first pair is the result just after the candidate detection and the second pair is the result after the blob detector. Furthermore, the third pair is after the hair eliminator and the last pair is after the size eliminator.

It is obvious that the different eliminators are essential for the algorithm. The hair eliminator improves the precision the most while the blob detector worsen the recall the most.

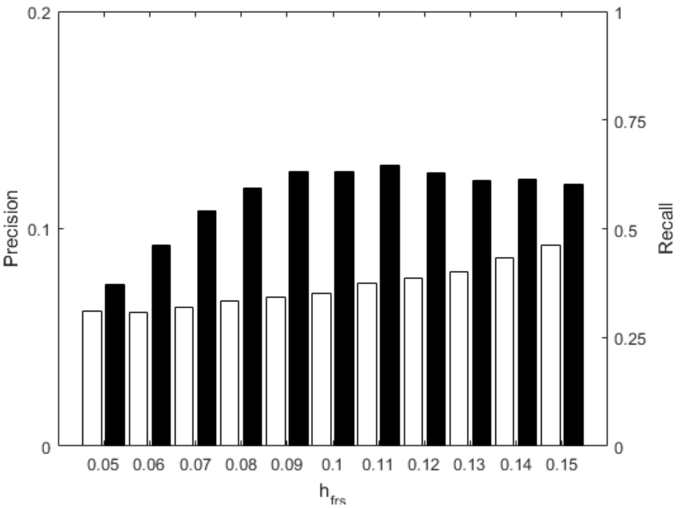

Figure 4.1: *Detection results from the algorithm with different h_{frs}-values. The white bars represent the precision value and the black bars represent recall value.*

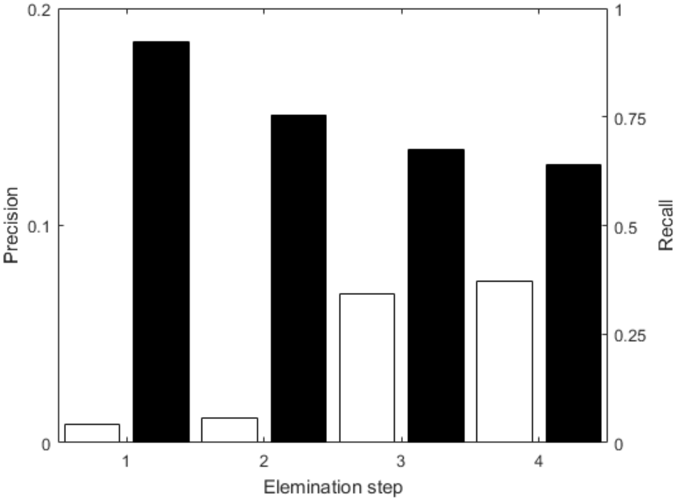

Figure 4.2: *Detection results from the algorithm after different candidate elimination steps. 1 = before elimination, 2 = after blob-elimination, 3 = after hair-elimination, 4 = after size-elimination. The white bars represent the precision value and the black bars represent recall value.*

The result from the mark classifier is presented as accuracy matrix with varying

C-value and γ-value. The accuracy is calculated as in (4.3). In fig. 4.3, the C-value ranges from 1 to 100 while the γ-value ranges from 10^{-2} to 1.

$$Accuracy[\%] = \frac{\text{True positive} + \text{True negative}}{\text{Number of annotated marks}} \tag{4.3}$$

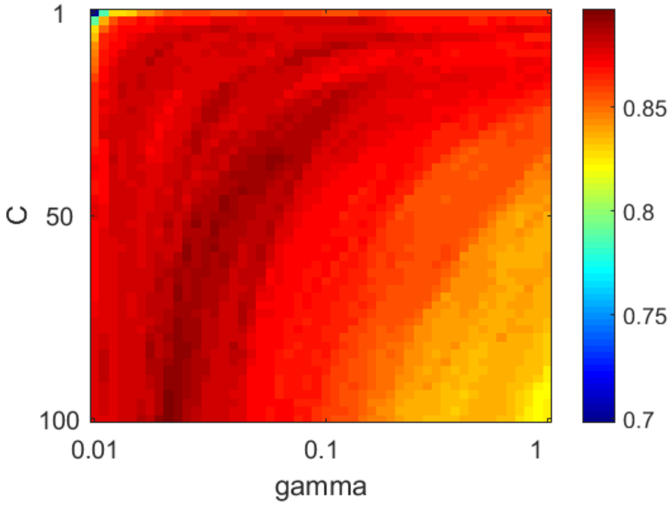

Figure 4.3: *Crude accuracy matrix where* $1 \leq \gamma \leq 100$ *and* $10^{-2} \leq \gamma \leq 1$.

As show, the best accuracy is when $C \approx 95$ and $\gamma \approx 5 * 10^{-2}$. Therefore, with a finer interval for the two parameters, fig. 4.4 was generated. Here, the C-value ranges from 90 to 115 while the γ-value ranges from $5 * 10^{-2}$ to $2 * 10^{-1}$.

Form fig. 4.4 it is possible to conclude that the best accuracy is acquired with several pair of parameters and results in the accuracy 90%. $C = 100$ and $\gamma = 0,14$ is one of those pairs. Therefore, the mark classifier is given these values as parameters for the SVM.

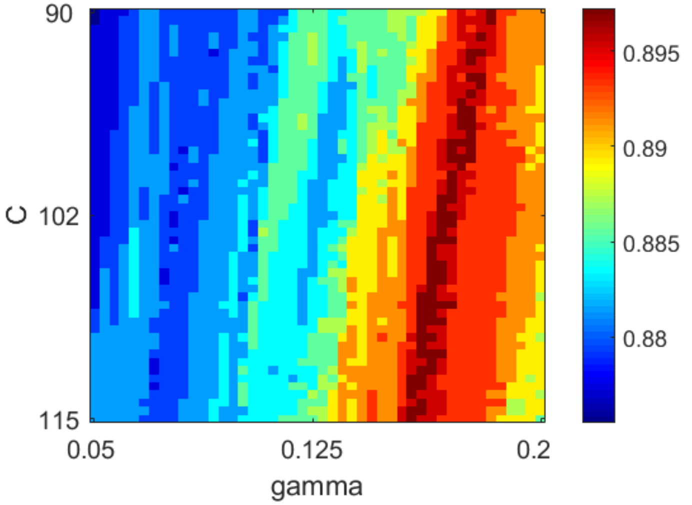

Figure 4.4: *Fine accuracy matrix where* $90 \leq \gamma \leq 115$ *and* $5 * 10^{-2} \leq \gamma \leq 2 * 10^{-1}$.

5 Discussion

This section will discuss the results from the algorithm and the methods used to implement it.

5.1 Result

As seen, the detector has problem with false detections which is a huge problem. The precision is not very good, not even over 10%, due to the many false detections. The precision does not increase faster than the decline of the recall with an increasing h_{frs}-value. This indicates that there are margins for improvement when it comes to the candidate detector. The elimination method used does improve the precession well enough which means that they also can be improved.

When looking at the accuracy of the mark classifier, with an accuracy of 90%, the result is pretty satisfactory.

5.2 Method

There are a lot to say about the methods used in the algorithm. The major problem with the algorithm is the elimination of candidates. The blob detector works well in not eliminating true detections which the hair removal algorithm does not. It eliminates candidates which are true facial marks. This is because it indicates that the facial marks are hair which makes it hard to separate the true candidates and the hair intensive candidates. Tim et Lee al. describes their algorithm well except when they are explaining how to calculate the hair mask for each colour channel. It is not clear what the maximum from refers to. The algorithm in this work used the maximal pixel value between the different structuring elements.

The mark detector used in the algorithm was good at indicating the potential facial marks but the simple thresholding method to pin point them out was not optimal. It kept the pixels larger than a certain percent of the maximal value in the FRS image. This resulted in many unnecessary candidates which of course contributed to the high false detection rate.

The blob-detector used is hardly improving the precision at the cost of recall loss. This means that the blob-detector is not contributing to the algorithm in a positive way. The hair-eliminator on the other hand does improve the precision which is the whole point with the candidate eliminators.

When it comes to the mark classifier, it could have performed better if the number of features was larger and more explored. Now the features are very simple and there is overweight of permanent marks among the annotated facial marks which is not ideal.

Regarding the references used in these thesis, several of them uses FRS to detect point of interest which shows the actuality of the method. Many of the papers trying to detect facial marks uses a crude segmentation mask which does not follow the hairline and chin well. This algorithm uses a more precise segmentation method which reduces the areas which is not processed.

5.3 Ethical perspective

As with all applications which can be used for surveillance of people, the integrity is at stake. Facial recognition algorithms using facial marks can be misused for malicious intent. They can also help the legal system to catch and convict criminals which is desirable outcome of this paper.

When it comes to the facial images, they are taken from a open source database which should only be used for academical research. There are no personal information attached to the images which makes them as anonymous as possible without corrupting the images.

6 Conclusion

This master thesis has examined the possibilities to develop an algorithm which could detect facial marks and separate them into permanent and non-permanent. The result from the experiments shows that the detector can initially find the facial mark with high recall but with a low precision. The precision increases as the false detections are eliminated. The mark classifier demonstrates good result with its accuracy of 90%.

A proposed remedy for the low precision on the detector is to improve the elimination of the false candidates. The hair-detector is to crude and may be combined with or replaced by a module which looks at the Fourier Transform of the candidates. The mark classifier could perform better with better discriminative features. By finding better features through examination of the differences between permanent and non-permanent marks.

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