BACHELOR THESIS

Artificial Intelligence
Radboud University Nijmegen

Biometric authentication based on face and gesture recognition

"Wink twice if it's you!"

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December 20, 2012

Abstract

It is possible to fool an authentication system based on face recognition with a picture of a person's face. This can be made impossible by introducing gesture recognition to the authentication process. In this thesis an authentication system is investigated that combines face and gesture recognition by instructing a user to perform a sequence of randomly determined gestures. In this system, every image in a stream of camera images is inspected to see if it contains a face. This is done by using the Viola-Jones object detection algorithm, which also looks for other regions of interest (the eyes and mouth in a face) if a face is found. After that, face and gesture recognition takes place based on the results of the Viola-Jones cascades along with the principal component analysis algorithm. If the recognised gestures correspond with the given instructions and face recognition is successful, authentication will succeed. Experiments showed that the Viola-Jones cascades performed their task well. In contrast, the performance of the gesture recognition process was poor and unreliable, as its performance was dependent on the subject using the system and different lighting conditions. This makes it difficult to use the proposed system and additional work is required to make the system suitable for real world usage.

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Chapter 1

Introduction

Digital security has become a prominent aspect of modern society and some form of authentication is required for activities that are of any importance. Such activities include online banking and submitting governmental forms online, but also customary actions like checking your e-mail or accessing a personal device like a smart-phone. Such personal devices are literally finding their way into the hands of people as they become part of managing everyday life by keeping track of an agenda or providing access to the internet and email (Google and MediaCT, 2011). The information that can be accessed with such a device is private and access to it must be regulated and/or protected lest it be obtained by an unauthorised person who could use it for malevolent purposes. Therefore some method of authenticating oneself to one's own devices has become mandatory.

The established way of authentication is "authentication by something you know" which means that you authenticate yourself by providing a password, a Personal Identification Number (PIN) or a chosen pattern. There are a number of risks to this way of authentication like forgetting/losing passwords or people watching over your shoulder as you enter your password. An additional risk is the use of a single password for multiple applications, because if someone else obtains this password they will be able to access all of the applications. All these dangers combined pose a great security threat to your personal data.

Another way of authentication that is much less susceptible to these dangers, if at all, is "authentication by something you are" which typically uses biometric data as a form of authentication. Examples of this form of authentication include fingerprint matching (Shihai and Xiangjiang, 2010), retinal scanning (Ortega, Mario, Penedo, Blanco, and Gonzlez, 2006), outer ear image matching (Moreno, Sanchez, and Velez, 1999) and face recognition (Turk and Pentland, 1991; Le, 2011).

From the above-mentioned methods, face recognition is easy to implement, user friendly and comes at no additional cost in equipment for smart-phones as those already have a built-in camera. This makes face recognition a great candidate to become an alternative method of authentication as opposed to the established password-based methods. Indeed, this type of authentication has already been extensively researched and various methods have been developed using *principal component analysis* (PCA) (Turk and Pentland, 1991; Yang, Zhang, Frangi, and Yang, 2004), *independent component analysis* (ICA) (Bartlett, Movellan, and Sejnowski, 2002) or *neural networks* (Lin, Kung, and Lin, 1997; Le, 2011). Also, its use in combination with a password for securing money transactions with a bank has been investigated (Kumar, Kumar, Kumar, and Karthick, 2012).

1.1 Extending Face Recognition

Unfortunately, face recognition has been proven to be insecure or at least the implementation in the smart-phone operating system Android, as this implementation also accepts the photo of a person's face (Newton, 2011). Obviously this is undesirable as it is not difficult to obtain a picture of someone's face. Because it is likely that this is not simply a flaw in the aforementioned implementation, but a more fundamental problem of this method of authentication, a solution to this problem has to be found.

Luckily a solution exists that is based on a simple principle. Photos are static images, which means that by introducing movement into the authentication process you can ensure that it is impossible for a person to authenticate as someone else with their picture. When thinking of introducing movement the use of intended facial gestures comes to mind in order to do this in a well-defined way. This results in a setting where a person is able to perform a number of facial gestures from a small set, which can be applied in various ways. The intended purpose for its use is as a security check, for which there are two options to achieve this goal.

The first option is to generate a random sequence of gestures which a person must perform while in the background a face recognition check is being performed. The second option is based on the established password-based methods and lets a user determine a sequence of gestures themselves which they must perform if they want to authenticate themselves. In such a setup, face recognition could be optional, as knowing the sequence of gestures would be sufficient. However, determining the sequence of gestures a person is using is probably a lot easier compared to determining a written password, so if face recognition would be turned off, none of the advantages of biometrics would be present. Unfortunately, in the case that face recognition would be turned on it would be possible to record a video of a person while they perform the required sequence of gestures. It would then be possible to display this video to the system and gain access in this manner. Of course this can also be done with the first option, but due to the fact that the sequence of gestures would be determined randomly, there would be too many possibilities to be feasible. It is because of these drawbacks that the first option is preferred

Also, such a system could be used for creating a hands free interface or as an additional way for entering input, as each possible gesture could be linked to a command. For example, in a web browser environment a wink with the left eye could stand for 'go to the previous page', a wink with the right eye for 'go to the next page' and tilting your head left or right could respectively stand for 'scroll up' or 'scroll down'. The idea to use facial gestures for interaction is not new, as it has been previously suggested, both seriously (Algorri and Escobar, 2004) and as a joke when Opera used the very idea of facial gestures for browser control (Opera, 2009). Clearly the idea has been around for a while and it is just a matter of time before it finds its way into an application.

1.2 Challenges

In order to create a system which combines face recognition and gesture recognition certain challenges have to be overcome. When the only task that needs to be performed is face recognition, two steps are sufficient to reach the goal. The first step is to locate a face in a presented image. After finding a face in the image, the second step will follow: comparing the found face to a database of faces and find the closest match. When adding gesture recognition to the process, there are a number of extra steps that have to be performed besides the two required steps for face recognition.

The first step is to locate any additional *regions of interest* (ROI). A ROI is an area in an image that contains information that must be further processed. For example, the ROIs that must be located for face recognition are the faces in an image.

An algorithm that performs these steps can be summarised in three phases:

1. Locate regions of interest - In the first phase the algorithm locates all relevant regions of interest (ROIs). First, the face-region must be located and once it has been found, other ROIs (like eyes) must be found within the face-region.

2. Perform face recognition - In the second phase a detected face must be matched with a saved face which must belong to a person that is authorized to access the device.

3. Perform gesture recognition - In the last phase the detected faces and their corresponding ROIs are compared and differences are measured in order to determine what gestures are made.

Now that the problem has been defined at a high level and the required steps have been determined, an implementational solution has to be found to solve it. For each of these steps a lot of research has already been performed and various algorithms exist for solving them. For face detection, various algorithms have been developed of which a selection has been surveyed by Degtyarev and Seredin (2010) and the recent advances in face detection algorithms by Zhanh and Zhang (2010). The most extensively discussed by far is the *Viola-Jones* face detection algorithm (Viola and Jones, 2004) which is based on their object detection algorithm (Viola and Jones, 2001).

Just like face detection, various algorithms have been developed for face recognition which use different approaches, including PCA features (also known as Eigenfaces) (Turk and Pentland, 1991)(Yang, Zhang, Frangi, and Yang, 2004), independent component analysis (ICA) features (Bartlett, Movellan, and Sejnowski, 2002) as well as neural networks (Lin, Kung, and Lin, 1997)(Le, 2011).

However, in the area of facial gesture recognition it seems that a lot less fundamental work has been done and a clear direction has yet to be found. Currently two major directions are being explored. The first utilises principal component analysis, which is borrowed from regular face recognition. The second direction investigates the use of *support vector machines* (SVMs) for classifying gestures.

There are two main methods possible for using PCA: the first one uses a face as a whole as input and tries to classify its corresponding Eigenface as displaying a certain gesture or emotion (Banerjee and Sanyal, 2012). The second method that has been explored uses subparts of the face like the eyes or mouth and calculates the corresponding Eigeneyes and Eigenmouths (Algorri and Escobar, 2004). The same method of looking at subparts of the face can be applied when using SVMs to classify images (Fazekas and Snta, 2005) after which the individual classifications are combined for recognising emotion. More recently SVMs have also been applied in order to recognise yes/no gestures as opposed to recognising expressions of emotion (Baltes, Seo, Cheng, Lau, and Anderson, 2011).

1.3 Research Questions

As described in Section 1.2, there are many different possibilities to build the different components of an authentication algorithm based on face and gesture recognition. However, when selecting the

components for such an algorithm there are certain constraints that must be met in order for it to be practical in use. Perhaps it is stating the obvious, but an authentication system has to be dependable in accepting the right and rejecting the wrong people. This means that any algorithm must have a high classification performance with a low amount of false positives and false negatives.

Keeping in mind that authentication by face recognition is already in use on smart-phones, it is desirable that an alternative authentication method should also be fit to run on such devices. There is one big constraint when running an application on such a device, which is its limited processing capabilities. Therefore it is important that potential algorithms have a low computational complexity, or at least one that can be scaled to manageable proportions for the available computational power. If this turns out to be a difficult constraint to satisfy, an acceptable alternative would be to use other methods to make the process as a whole more efficient. Such methods could be the clever combining of used algorithms so they complement each other or the construction of a cascade of classifiers could be used to reduce the computational requirements.

Lastly, an authentication system should be available for use straight away. This means that if any form of training is required, it should not take much time for users and they should not be required to keep training the algorithm. If this constraint is met, the result is that there will not be a lot of training data available for algorithms to train on, so the selected algorithms should be able to cope with this.

These constraints can be expressed in the following research questions:

1. For the suggested application, what algorithms for the three phases are suitable in terms of:
   - accuracy (few false positives and few false negatives)?
   - computational complexity?
   - sparse training data?
2. How can unrelated algorithms be combined in such a way that they complement each other and save unnecessary computations?
3. What techniques (for example, cascade classifiers) can be used to to improve the overall efficiency of the algorithm?

To answer these questions, a prototype program has been made which performs the required task by making use of the Viola-Jones object detection and principal component analysis algorithms. These algorithms will be explained in detail in Chapter 2, after which the proposed method will be discussed in Chapter 3. Then, the performed experiments and their results will be described in Chapter 4, followed by a discussion and conclusion in Chapter 5.

Chapter 2

Methods

This chapter serves to introduce the used algorithms and inform the reader about what they can be used for before they are referred to. First the *Viola-Jones object detection* algorithm will be introduced, followed by the *principal component analysis* algorithm.

2.1 Viola-Jones Object Detector

The Viola-Jones Object Detection algorithm was first described in the paper 'Rapid Object Detection using a Boosted Cascade of Simple Features' by P. Viola and M. Jones (Viola and Jones, 2001) and the goal of the algorithm is to detect the objects it is trained to recognize in a given input image. The authors demonstrated its use in the field of face detection where they achieved exceptionally low computation times while improving detection accuracy (Viola and Jones, 2004).

When given a grey-scale image, the algorithm will look at sub-images of the original image one by one until every sub-image of a certain size is considered. Then, the size of the sub-images that are considered is scaled up by a chosen factor and the process repeats until the sub-image is as large as the input image. For every sub-image a cascade of classifiers decides whether or not it contains the object it is trained for to detect. A cascade is a collection of classifiers placed in a certain order and one by one they accept or reject a sub-image as containing the object or not. Should a sub-image get rejected by any of the classifiers, it is immediately discarded and not considered further. On the other hand, if a sub-image gets accepted by every classifier in the cascade, it is classified as containing the object. This process is visualised in Figure 2.1.

Within such a cascade the order of classifiers is chosen carefully and the first few are weak classifiers (which means that they base their decision on very few features) which have a high true negative rate. By selecting the first few classifiers in this manner, a lot of uninteresting regions that definitely do not contain the object that is being searched for get rejected. Only images that pass the first few classifiers and therefore potentially contain the object will get processed further by more complex, and thus computationally more expensive, classifiers. This way a very high detection accuracy is achieved while maintaining a low computation time.

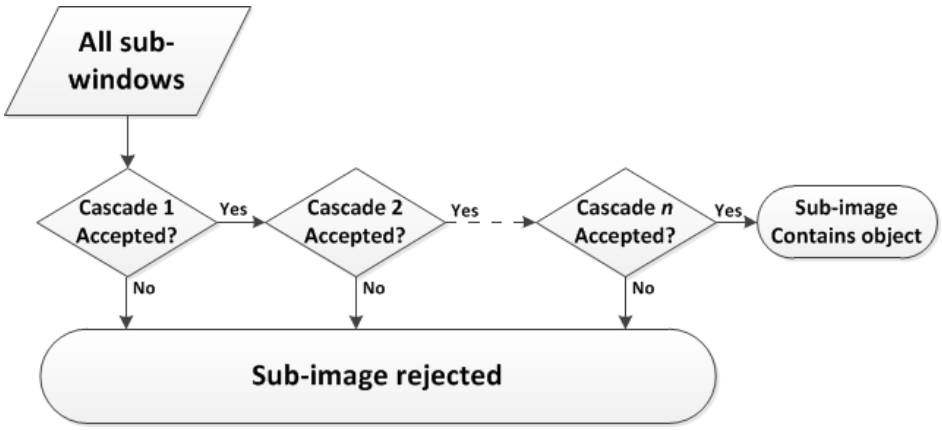


Figure 2.1: An abstract visualisation of a cascade of classifiers. Based on Viola and Jones (2004).

2.1.1 Integral Image and Rectangle-Features

To further understand the algorithm, it is important to be familiar with the kind of features the classifiers base their decision on and how these are calculated. The used features are called *two-*, *three-* and *four-rectangle* features. Each of these features consist of a number of rectangles that are equal in size and lie adjacent to each other at a position relative to the selected sub-image. For each feature, the sum of the pixel values within one or more rectangles is subtracted from the sum of the pixel values within the remaining rectangles. In Figure 2.2a these features are visualised and within this image the sum of the pixel values inside the white rectangles are subtracted from the sum of the pixel values inside the grey rectangles.

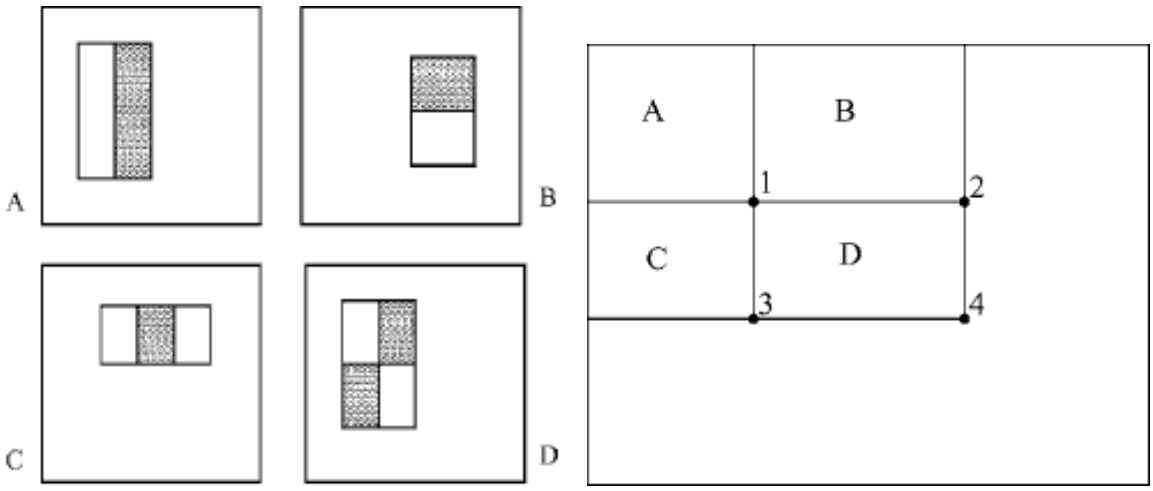
These features are calculated from an intermediate representation of the original image, called the *integral image* which is no more than a summed area table. This representation of the image makes computing the sum of pixel values within a rectangle a lot more efficient, as it is not required to sum up the pixel values in every rectangle, which would be the case if the original image were used. Instead using the values at the corners of the rectangles is sufficient. The integral image formula calculates the sum of all the pixel values above and to the left of every position in the original image. This formula is expressed as:

$$ii(x, y) = \sum_{x' \leq x, y' \leq y} i(x', y')$$

where *ii* is the integral image, *ii(x, y)* is a position in the integral image, *i* the original image and *i(x', y')* refers to a position in the original image. The integral image can also be computed more efficiently using a recursive formula:

$$ii(x, y) = ii(x - 1, y) + ii(x, y - 1) - ii(x - 1, y - 1) + i(x, y)$$

This integral image has to be computed only once per image, after which every feature for every sub-image can be efficiently calculated (as mentioned, one only has to use the integral image values at the corners of a rectangle). How this is done is best explained when considering Figure 2.2b. In this figure, four different locations and regions are marked. The question is how one can obtain the sum of the pixels within D as this region represents any random rectangle within the



(a) Example rectangle features. A and B show two-rectangle features, C shows a three rectangle feature and D shows a four rectangle feature.

(b) The integral image-value at position 1 is the sum of the pixels within A, the value at position 2 is A + B, the value at position 3 is A + C and the value at position 4 is A + B + C + D.

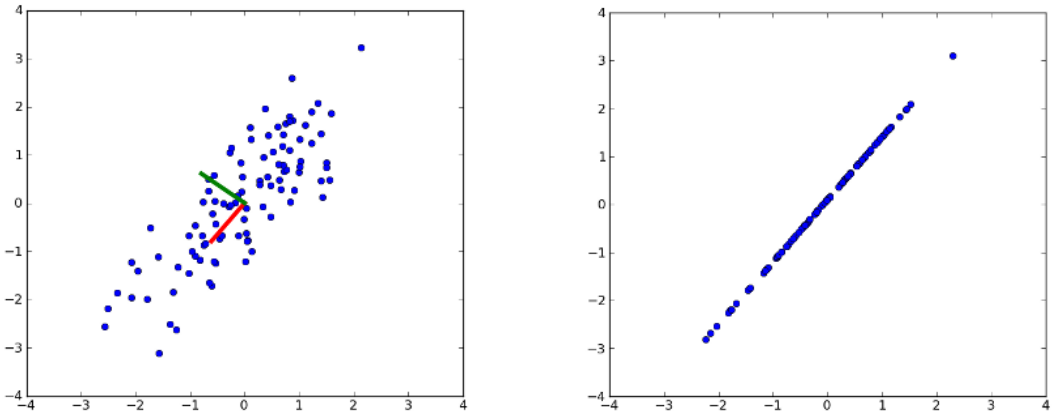
Figure 2.2: Taken from Viola and Jones (2004).

image (that is not against the border of the image). Expressed in the marked locations within the integral image, the answer is 4 + 1 - (2 + 3). It is this simplicity that makes calculating the features so efficient. One rectangle can be computed with just 4 references to the integral image by using simple additions and subtractions. A two-rectangle feature can be computed with 6 references, a three-rectangle feature with 8 references and a four-rectangle feature with 9 references. Thus, by computing the integral image a priori, a lot of computations on the original image that would otherwise be required are prevented.

2.1.2 Computational Costs

The computational cost of using the Viola-Jones algorithm is determined by three major factors. The first factor is the cascade itself. The higher the amount of classifiers in the cascade and the more features they use, the more calculations that need to be performed. Luckily this should not matter too much if the cascade has been constructed correctly, but it matters enough that it is worth mentioning. The second contributing factor is the image resolution. The larger the image, the more possible sub-images there are that need to be considered and thus more time is consumed by judging them. The last factor is the scaling factor of the size of the sub-images, as the smaller this factor is, the longer it will take before the size of the sub-images is as large as the image itself. This means that more sub-images will be considered by the algorithm before it stops, which consumes more time.

The last two factors can be directly influenced, the first one however can not as pre-trained classifiers are used (see Section 3.6 for more information on this) and unfortunately influencing the other two has a direct influence on the results of the algorithm. However, preliminary tests have shown that there is room to finetune the settings so that acceptable results can be achieved while maintaining reasonable computation times.



(a) **(b)**

Figure 2.3: Figure **(a)** shows sample data with a dimenstionality of two, along with the first and second principal components. The first principal component is the bottom line in the figure, the second principal component is the top line. In Figure **(b)** the data has been restructured according to the first principal component,which accounts for the most variability in the data. This data can now be displayed on a single axis. Taken from (Albanese, Visintainer, Merler, Riccadonna, Jurman, and Furlanello, 2012).

2.2 Principal Component Analysis

The foundation of principal component analysis (PCA), formerly known as the *Karhunen-Loève procedure*, was laid in 1901 by K. Pearson (Pearson, 1901). It was first applied in a facial context by M. Kirby and L. Sirovich in their paper 'Application of the Karhunen-Loève Procedure for the Characterization of Human Faces' (Kirby and Sirovich, 1990) in which they explained how PCA could be used to represent images of faces in a way that they could be further processed by a computer. Their approach is best summarised by quoting the authors directly: "The goal of the approach is to represent a picture of a face in terms of an optimal coordinate system. (...) The set of basis vectors which make up this coordinate system will be referred to as eigenpictures. They are simply the eigenfunctions of the covariance matrix of the ensemble of faces.". Their idea was then expanded upon by A. Turk and A. Pentland who expressed new images in terms of this new coordinate system and used this vector to compare it to the eigenvectors of sample pictures. The result of such a comparison is the Euclidian distance between two vectors, which can be seen as a measure of error. By determining which of the existing vectors has the lowest distance to a new vector, the image corresponding to this vector can be labeled as containing or displaying the person that is depicted in the picture of the closest existing vector.

Explained in just a few sentences, PCA is a technique for transforming data from one coordinate system into another that describes the variance in the data more optimally. During this process dimensionality reduction can take place for data compression or to make further processing easier. How this is done will be explained in the next section, Section 2.2.1 and a visualisation of example input for the algorithm and the corresponding result is shown in Figure 2.3a and 2.3b.

2.2.1 Mathematical Procedure for PCA

This section explains the mathematical procedure which performs PCA step by step in order to try and increase the understanding of the technique. The structure of this section and the explanation were based on the writings of Lindsay I. Smith (Smith, 2002).

The kind of data that is used in face recognition by PCA are grey-scale images of N by M pixels and one image can be seen as a point in an N*M dimensional space in which every pixel is a feature.

Step one: subtract the mean In order for PCA to function properly, for every variable (dimension) in the gathered data the mean of that variable must be subtracted. The mean of a set of numbers is calculated as:

$$\bar{X} = \frac{\sum_{i=1}^{n} X_i}{n}$$

Step two: calculate covariance matrix Step two is to calculate the covariance matrices between the features of the data. Covariance is a measure of how much features vary from their mean with respect to each other. The formula to calculate the covariance is

$$\text{cov}(X, Y) = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{(n-1)}$$

where X and Y are features (pixels in the images), X_i an element of X from training image i, $\bar{X}$ the mean of feature X (the mean of the pixel value over all the training images) and n is the total number of data samples.

Because a lot of features are involved with images (every pixel is a feature), there are also a lot of covariance matrices involved. The amount of covariance matrices can be calculated with $\frac{n!}{2*(n-2)!}$ where n is the number of features, which becomes an awful lot when dealing with a large number of features. However, these matrices can be put together in one big n * n matrix.

Step three: calculate the eigenvectors and eigenvalues of the covariance matrix For any square matrix of $n * n$ there are n eigenvectors and n eigenvalues. Every eigenvector has a corresponding eigenvalue, which can be seen as some sort of 'weight' for the eigenvector (see step four). All these eigenvectors are orthogonal to each other within the dimensions in which they are defined and they can be seen as a line within n-dimensional space. Making the jump back to the original data, an eigenvector can be seen as a new axis within the original space which can be used to express the data.

Step four: choosing features and forming a feature vector As previously mentioned, an eigenvalue can be seen as some sort of weight for its corresponding eigenvector and the eigenvector with the highest eigenvalue is called the principle component of a data set. This means that it best captures the variance between the data points in the data set on just one axis. Of course, if just one single eigenvector would be used to describe the data, a lot of information would be lost as only all eigenvectors together describe the data completely. Leaving out any eigenvector results in a loss of information.

This is where dimension reduction becomes possible. If you order all the eigenvectors based on their eigenvalues you could choose to discard the eigenvectors with lower eigenvalues, as they are of

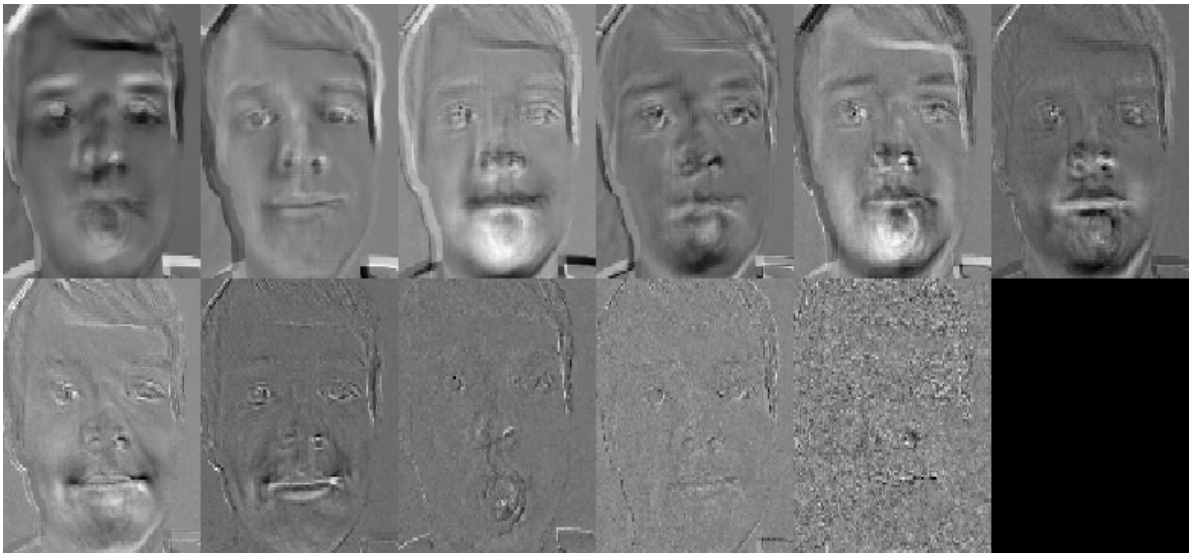


Figure 2.4: Visual representation of examples of eigenfaces (eigenvectors of faces). Notice that just as eigenvectors go from very descriptive to less descriptive the images become less expressive.

the least importance in describing the data. By doing this information is lost, but your new data set expressed in terms of the remaining eigenvectors has a lower dimensionality. The remaining eigenvectors become the new features of your data and they together form your new feature vector.

Step five: transforming the original data set into one based on the new feature vector The next step is to actually transform the original data into a new data set based on the selected features in the feature vector. This actually is the most simple step, as can be seen in the formula below:

$$\text{NewData} = \text{FeatureVector} \times \text{OriginalData}$$

This formula can also be applied on new data to transform it to the newly determined dimensions.

2.2.2 Computational Costs

The computational costs of the recognition part of the PCA algorithm is only dependent on two factors. The first factor is the length of the chosen feature vector, since the longer this vector is, the more computations have to be done when expressing an input image in these features and the longer it takes to calculate the distance between pictures (although this last point is negligible). The second factor is the image resolution since a higher resolution directly leads to more computations. The advantage here though, is that both these factors can be influenced if there is a need for it, which allows experimenting with different settings.

Chapter 3

Approach

Now that the selected algorithms have been explained, their role in the algorithm that solves the face and facial gesture recognition problem can be examined more closely. Previously in Section 1.2 the three phases or subproblems for such an algorithm were defined as:

1. Locate regions of interest (ROIs)
2. Perform face recognition
3. Perform gesture recognition

In the next sections these phases will be investigated in detail and for each phase, possible solutions will be explored.

3.1 Defining and Locating Regions of Interest

Defining the gestures and regions of interest for this application Before any ROI's are located it must first be defined what a ROI actually is and what regions qualify for being classified as interesting. A region of interest is a sub-image which contains something of importance. For this application it is clear that an area in an image containing a face is an interesting region, as within such a region the facial gestures will be performed. Also, in order to perform a face recognition algorithm the image of a face is required as input. However, it is still not clear what regions within the facial area must be monitored in order to recognize any performed gestures, as the gestures themselves have not yet been selected and defined yet. A list of gestures which are used in this application is listed below along with a short description (see Figure 3.1 for examples of some of the gestures).

- Eye winking - A wink-gesture is considered as being performed when an eye is closed. This gesture can be performed by both eyes individually. This means that two possibilities exist for performing this gesture, effectively making it two different gestures for the program.
- Smiling - A smile-gesture is a gesture when one simply uses his or her mouth to smile.
- Sticking tongue out - This gesture is considered as being performed when a person sticks their tongue out of their mouth so that it can be clearly observed.

Figure 3.1: Examples of possible gestures that can be performed.

- Head tilting - The head tilting gesture can be performed by either tilting the head to the left or to the right. Just as with the wink-gesture, this means that effectively there are two gestures that can be performed.

It is also useful to define the neutral state of a face when no gestures are performed. This neutral state is when both eyes are open, the mouth is closed in a relaxed state while the head is held straight.

Now that the gestures have been defined, it is easy to deduct from the first three gestures that the eyes and mouth are regions of interest. However, the head tilting gesture has no specific regions of interest, apart from the whole face perhaps. Because it might be difficult for an algorithm to determine from an image of a face whether a head is tilted or not, another option might be more suitable. One such option is to use the information that can be deducted from regions of interest that have already been defined, the eye regions. How this and each of the other gestures are recognised will be explained in detail in Section 3.3. In summary, the regions of interest that must be located are:

- The face region
- The eye regions
- The mouth region

Of these regions the last two can be found within the first region. Therefore, finding a face region is considered to be stage one and finding any other regions is considered stage two in the process of finding ROI's.

Finding the regions of interest After defining the relevant regions of interest, the problem of actually finding them has to be solved. This is not a trivial task as finding an object in an image is difficult for a computer. This is where the Viola-Jones object detector is utilised. The first step for finding all regions of interest is scanning every image in the camera stream for faces with a Viola-Jones classifier. Once a facial region has been found, other Viola-Jones object detectors will further process the selected sub-image in order to locate the eye and mouth regions. This process of finding the relevant ROIs is visualised in Figure 3.2.

3.2 Face Recognition

For the face recognition task the PCA algorithm is used. The input images the algorithm operates upon are the facial regions of interest that are found in the first stage in the process of finding the

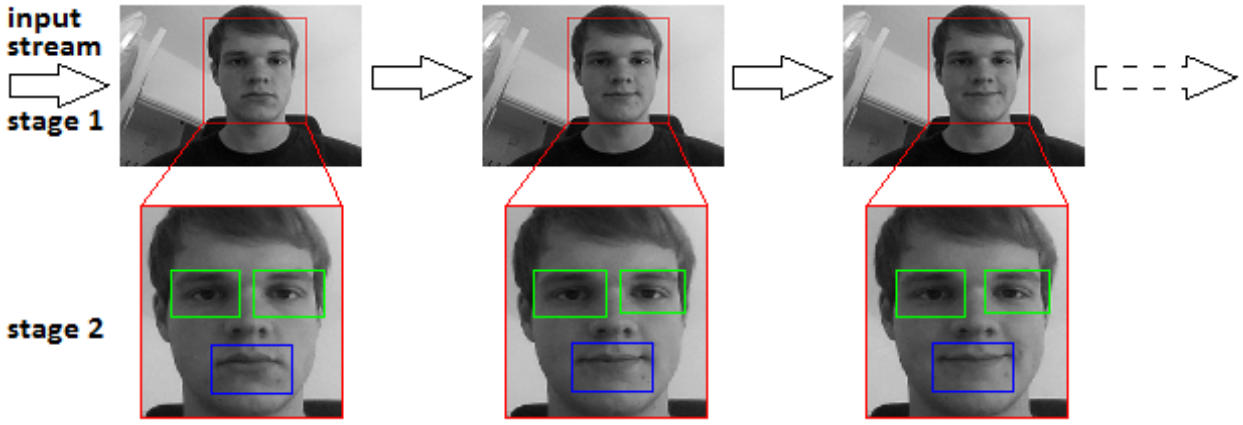


Figure 3.2: Process of locating the regions of interest.

ROIs (see Figure 3.2). Normally PCA classification gives the distance between an input image and the closest image and the corresponding label as output, thereby determining who is shown in the input image. However, in this setup the algorithm has been trained with images of just one person, so the decision whether the correct person is shown must be made differently. Instead the distance is transformed to a confidence score between [-1, 1] where a score of -1 means the distance is bigger than the default threshold of the implementation of the algorithm and a score of 1 means the input image is exactly the same as one of the input images. Using such a score, a threshold value can be picked and if the score for an input image is above this threshold, it is considered as being similar enough to the images of the faces it has been trained with in order to be accepted.

However, the determination of such a threshold requires careful consideration, as a program that is too lenient might result in someone getting unauthorised access to the program. On the other hand, a threshold that is too strict might lead to the denial of access to a person that actually is entitled to access, resulting in frustration, annoyance and a generally undesirable situation. In reality the chance of someone being wrongfully rejected is higher than the chance of someone being wrongfully accepted, due to the variance in conditions and the effect it has on the PCA algorithm. Therefore it is possible to choose a relatively lower threshold of 0.4. This is sufficiently low for a person to authenticate himself in different conditions, but high enough to prevent an unauthorised person from gaining access. See Section 4.2.3 for supporting numbers on why this threshold has been chosen.

3.3 Gesture Recognition

The used methods for determining if any gestures are performed differ per type of gesture. In the following paragraphs the methods that were used for each type will be explained shortly. The one factor that is constant between the used methods is that they all use the ROI's that were found in the second stage of the process of locating the ROI's (see Figure 3.2)

Mouth gestures Any of the possible mouth gestures (smiling and sticking the tongue out) are recognised by using the PCA algorithm. As this algorithm requires sample pictures for training, there is a training process during which those are gathered. For more information on the training

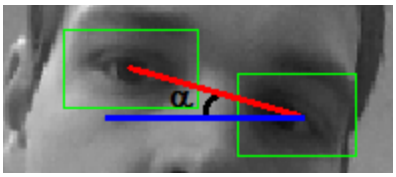


Figure 3.3: Calculating the angle α so it can be determined if a head is tilted to the left, to the right or not at all.

process, see Section 3.4. As opposed to how PCA is used in this application for face recognition (as described in Section 3.2), it is sufficient for the algorithm to find the closest training image and its corresponding label and classify the input image with this label. As the label corresponds directly to the performed gesture, no further processing is required.

Eye gestures For recognising eye gestures (winking with the left or right eye) two Viola-Jones object detectors are used. The first one is a detector that detects both open and closed eyes. The second detector only detects open eyes. Every frame serves as input for both detectors and from the difference between the output of these detectors it can be deducted whether or not a wink-gesture is performed. This is because if the first detector does detect an eye where the second detector does not detect an eye, it is likely that the eye is closed. The results of two Viola-Jones cascades are used here as opposed to the PCA algorithm is because preliminary tests showed a poor performance of the PCA algorithm when it was used to detect the different eye gestures. Experiment 5 as described in Section 4.1 aims to provide numbers to back up this claim.

Head gestures Instead of using an advanced recognition algorithm for detecting the head tilting gestures, a simple calculation which uses some of the information that is already available is sufficient. This calculation is based on the detected eye regions by the Viola-Jones detector that detects both open and closed eyes. First, the centers of the detected eye regions are calculated. Between these two centers you could hypothetically draw a line and then measure the angle between that line and the horizontal axis. See Figure 3.3 for an illustration of this concept. Below are the mathematical steps that must be performed in order to calculate the angle.

$$x' = C2.x - C1.x$$

$$y' = C1.y - C2.y$$

$$\alpha = \tan^{-1} \frac{x'}{y'}$$

where C1 is the center of the left eye region and C2 the center of the right eye region.

Once α has been calculated it can be determined how much it differentiates from the 0-degree mark, which is what you get if the center of the eye regions are at exactly the same height. Based on pilot studies it was concluded that a head can be classified as being tilted if the absolute difference is larger than 10 degrees. Whether it is tilted to the left or the right depends on whether or not the angle is positive or negative (of course an angle cannot be negative, but the result from the equation can be negative). If it is positive the head is tilted to the left (in the image) and if it is negative it is tilted to the right (in the image).

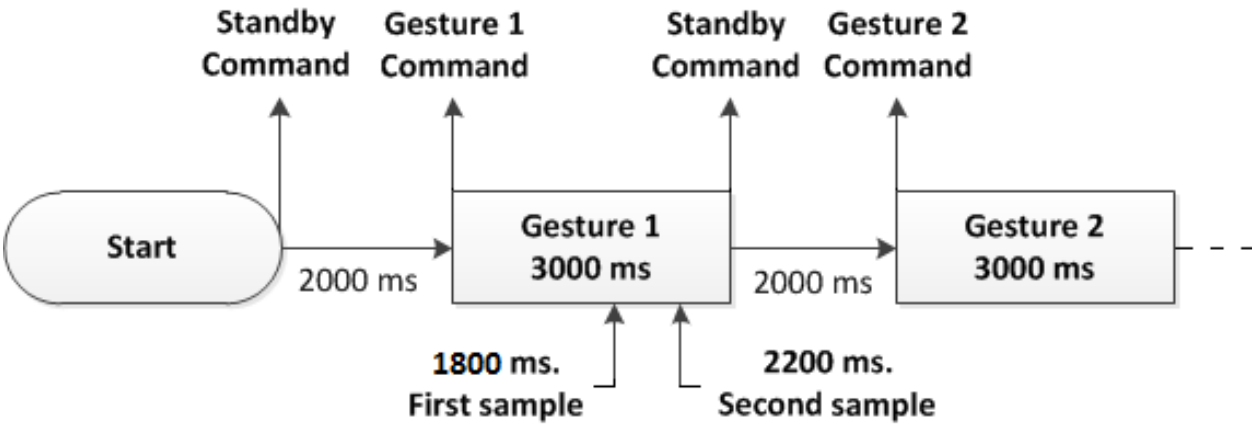


Figure 3.4: Visualisation of the training process during which data is gathered of the user performing gestures.

3.4 Training the Program and Gathering Data

In order for the system to work properly, personalised data must be gathered of all the possible gestures that are recognised with the PCA algorithm (the Viola-Jones object detectors also need to be trained, see Section 3.6 for information on how that is handled). As face recognition was also performed with PCA, sample faces also must be obtained. So in order for a user to be able to use this authentication method, they must first go through a training process during which the required samples are gathered. During this process, the user is asked to perform every relevant gesture (a gesture that is classified by PCA) twice. Every time a gesture is performed, two samples are taken which means that there are in total four samples per gesture. The reason that two samples are taken per time the user performs a gesture, is because the detected regions within which the gestures are performed are different for each input frame. This means that the exact same gesture is captured, but that the sample image is different which gives PCA extra data to train with. The whole training process can be described in the following steps, which are also visualised in Figure 3.4:

1: Give standby command - allow user to relax
2: Wait 2000 ms.
3: Give gesture command - instruct user to perform a gesture
4: Take sample pictures at 1800ms. and 2200 ms
5: After 3000 ms. repeat steps 1 through 4
6: Display end-of-training-message
7: Train classifiers on gathered data

It has not been explained yet why the sample pictures are taken at 1800 and 2200 ms. The reason for these times is that first and foremost the user must be able to react to the given command of what gesture to perform. Various research has shown for human reaction times to range from anywhere between 200 ms. to 600 ms. depending on the type of stimulus, the type of response that is required and if a person is primed for the stimulus or not (Kosinski, 2010). Instead of taking all these factors into account, simply rounding it up to 1000 ms. should be enough time for a person to react to a given command. Also, the correct estimation of a user's reaction time is of no importance

Figure 3.5: Sample training data that is obtained during the training process. The top two rows show faces performing the various gestures and are used to train the face recognition algorithm. The two middle rows show the left and right eye for the two possible gestures (note how in the second eye row a nose got classified as an eye by the Viola-Jones cascade). The last row shows the collected data for mouth gestures. The resolution of the obtained images have a resolution of respectively 130 x 180, 36 x 24 and 50 x 30 pixels.

whatsoever for this application, so it is not further investigated. This leaves 2000 ms. to pick two moments for gathering data and around halfway the remaining time is the logical choice. This is because if the picked moment is too early the user's face might not yet be perfectly still. On the other hand, if a picked moment is too late, the user might either get tired from performing the gesture or anticipate the end of the period during which they have to perform the gesture and relax their face. Also, these moments must not be too close together as the time it takes for the camera stream to supply a new image cannot be guaranteed. Because of these reasons the two chosen moments are at 1800 ms. and 2200 ms.: they are 400 ms. apart which should be enough for the camera to supply a new image and the moments are nicely around the 1000 (+1000) ms. mark, which is half of the remaining 2000 ms. After the user has completed the training process, the PCA algorithm will be trained on the gathered data so that it can be used for detection straight after. Sample data which is the result of the training process is displayed in Figure 3.5.

3.5 Authentication Process

Every time a user wants to authenticate himself, they must successfully complete the authentication process. This process is visualised in Figure 3.6. In order to complete the process, a sequence of randomly determined gestures must be correctly performed by the user. The number of gestures that needs to be performed is predetermined and is consistent between authentication attempts. A gesture is considered performed after it has been recognised for a period of 1000 ms. without interruption. Straight after a gesture has been performed the command is given for the next gesture (but only if the user has not yet performed the complete sequence of gestures). The program does not start monitoring for the new gesture start straight away, but instead it waits for 1000 ms. to allow the user to actually react to the command (see Section 3.4 for a short explanation about this). After this time the monitoring for the new gesture starts. Should the program detect the performance of any other gesture than the required one for a 1000 ms. or more, the authentication process fails immediately.

However, the correct performance of the required gestures is not the only criterion. In the

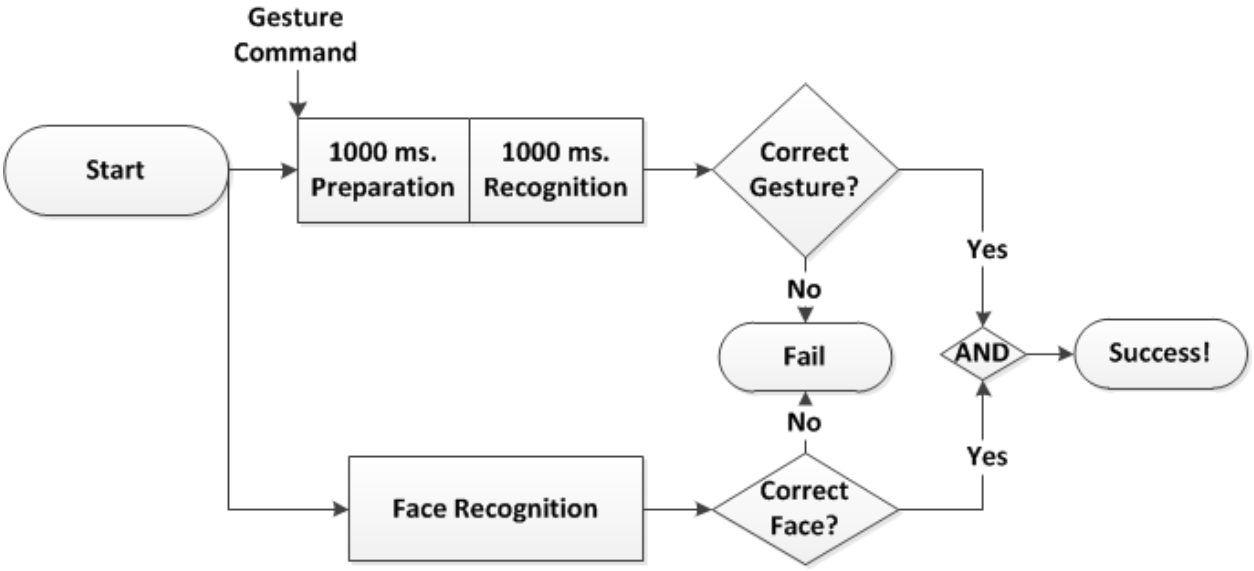


Figure 3.6: Visualisation of the authentication process.

background the face recognition algorithm is checking whether or not the face of the person that is trying to authenticate matches with the face of the person that trained the algorithm. Only if all gestures are performed correctly and the faces match will a person succeed in authenticating himself. This process can be summarised in the following steps, which have also been visualised in Figure 3.6:

1: Start face recognition process in background
2: Give first gesture command to user
3: Wait 1000 ms. to allow for reaction time
4: Monitor if any gesture is performed for at least 1000 ms.
5:
6: **if** gesture is detected and it is correct **then**
7: **if** more gestures **then**
8: repeat steps 2 through 6
9: **else**
10: continue with step 16
11: **end if**
12: **else**
13: abort authentication and inform user
14: **end if**
15:
16: **if** detected face similar enough to trained face **then**
17: continue with step 22
18: **else**
19: abort authentication and inform user
20: **end if**
21:

22: authentication successful and grant access

It is likely that not every input image of a face passes the threshold required in order for it to be classified as being the correct face. Because of this, it is not required that every image passes the threshold, but rather a percentage of the total amount of frames.

3.6 Implementation and Technical Details

This section describes the program that has been created according to the processes as described in Section 3.4 and 3.5. A screenshot along with an explanation of the different interface components can be found in Figure 3.7. It has been programmed in the programming language Java, which is the native language of the Android Operating System. The usage of the Java language facilitated the use of the JavaCV library, which is the wrapper of OpenCV library, an open source computer vision library. This library contains implementations of the Viola-Jones Object Detection algorithm as well as the Principal Component Analysis algorithm. Both these implementations where used in the program that was written. JavaCV version 0.2 and OpenCV version 2.4.2 were used which can be obtained respectively from `http://code.google.com/p/javacv/` and `http://opencv.org/`.

Instead of training my own Viola-Jones detectors, pretrained cascades were used. Two of the detectors, the face detector and the open eye detector, were included with the OpenCV library. Three other detectors that were used, a mouth detector and a left and a right eye detector for both open and closed eyes, were created by M. Castrillon et al. for their research (Castrillon-Santana, Deniz-Suarez, Anton-Canalis, and Lorenzo-Navarro, 2008) and are freely available.

This proof-of-concept program has been used mainly for experiments which could be better performed on a regular computer than a smart-phone. Therefore parts of the program, like the obtaining of images from the camera stream, are specifically designed for the Windows operating system. However, the algorithms themselves are platform independent. Any platform specific code has been coded for both the Windows and Android operating systems and a transition between these systems should not be a problem. The only expected difference between these platforms could be increased computation times due to the fact that the Android operating system typically is installed on devices with limited computing capabilities. This fact should have no impact on the accuarcy of the suggested application. The used laptop is equipped with a Amd Athlon II Dual-Core M300 2.0 Ghz CPU, 4096MB RAM and had the Windows 7 Professional 64 bit operating system installed.

Because of the low computing power of smart-phones everything must be run on a lower resolution in order for the algorithms to run at real-time. In order to get results when running the program on a computer with Windows OS that are comparable to the results you would get when running the program on a smart-phone with Android OS, the difference in resolution is taken into account. All obtained camera images are resized to to a resolution of 240 * 160 pixels, which is one of the possible resolution settings for camera's in a smart-phone. This image gets downsized with a factor of 4, resulting in an image of 60 * 40 pixels. It is in this small image that the Viola Jones algorithm searches for faces. When it has found a face region, the region is translated to the larger image. Then the region in the larger image is used to find the other ROI's. The advantage of scaling the original image down is to save the computing time which would be necessary for the full-scale image. The larger image is then used again because the Viola-Jones detectors are unable to find the other ROI's within the small region that would be left over from the 60 * 40 pixels.

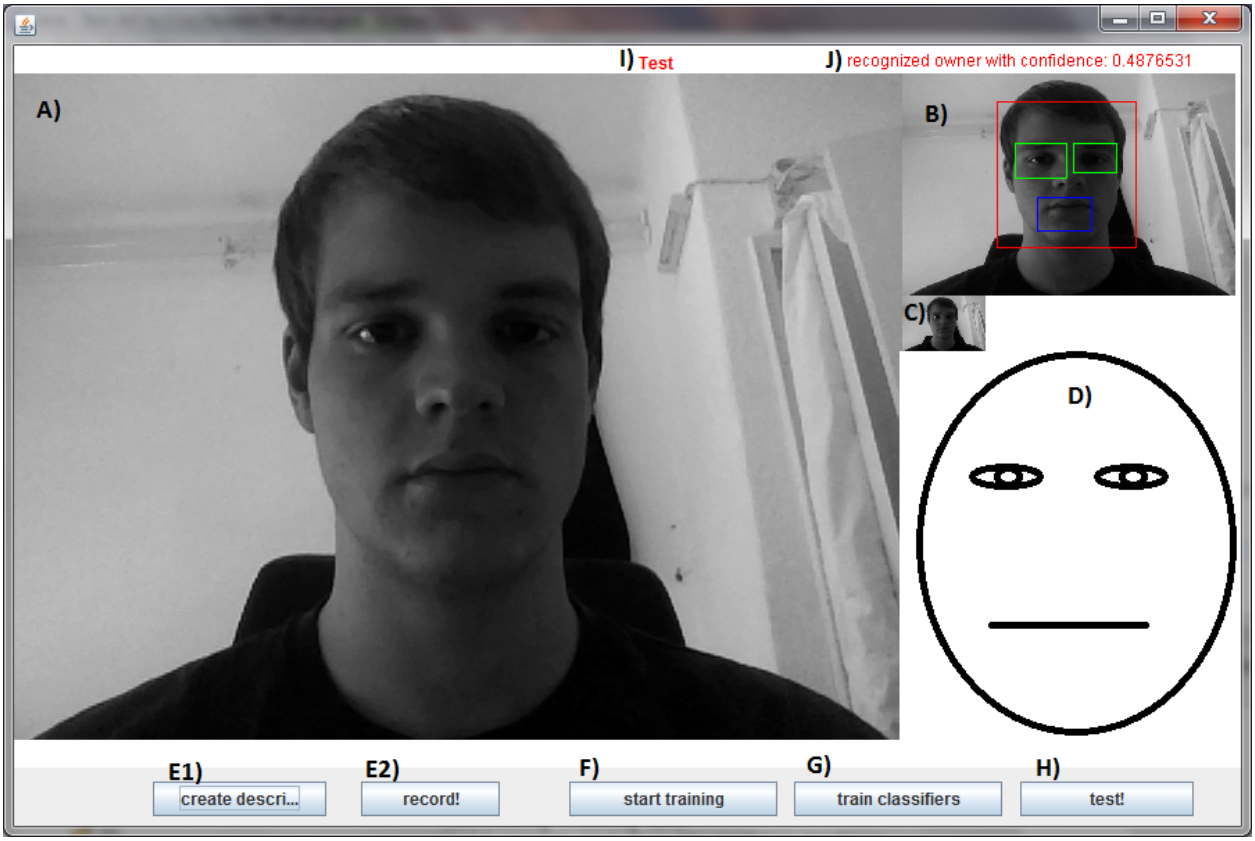


Figure 3.7: Interface of the program that was used to perform the experiments. A) shows the original camera input image from the input stream, which has a resolution of 640 x 480 pixels. B) shows the original image scaled down to the possible size of the images from a smartphone, a resolution of 240 x 160 pixels, and marks the found ROIs. C) shows the image of B) scaled down by factor 4, resulting in a resolution of 60 x 40 pixels, which is used for face detection. D) Is the gesture-feedback area and shows which gestures are performed. E1 & 2) are buttons that were useful in setting up the experiments and gathering illustrative pictures. F), G) and H) are buttons that respectively start the training process, train the classifier on the gathered data and start the authentication process. I) is the instruction area where the user can see what has to be done. J) shows the similarity value as result of the face recognition algorithm.

Chapter 4

Experiments & results

In order to be able to judge the chosen algorithms and the authentication method as a whole, various experiments have been performed. In the next Section, Section 4.1, every performed experiment and what it aims to investigate will be explained in detail. The results will be presented in Section 4.2 and shortly discussed in Section 4.3.

4.1 Experimental Setup

The performed experiments can be divided into three categories: experiments that determine the recognition rate of gestures, experiments that determine if the program can be used successfully for authentication and experiments that determine the generalisation capabilities of the classifiers. The order in which these categories are listed is also the order in which the experiments will be presented in the following sections.

4.1.1 Determining Recognition Rates of Gestures

The first thing that is interesting to determine is the recognition rate of all performable gestures in order to be able to evaluate the chosen algorithms. By doing this, both the ROI's that were found by the Viola-Jones cascades and the gesture recognition methods can be evaluated. When doing this, it is interesting to see how the different methods perform in different conditions compared to the standard conditions. The standard conditions of an experiment are defined as:

- The experiment is performed straight after training
- The resolution of the images in which is searched for the non-face ROI's is 240*160
- Two Viola-Jones cascades are used to determine the performed eye gestures

During such an experiment a subject is asked to perform all gestures in succession during which all detected ROI's are recorded and classified. From this data the relevant results can be derived.

Experiment 1: Baseline performance The first experiment aims to establish a baseline with the standard conditions so that the results from the other experiments can be compared to

the results from this experiment. Also, the average time it takes to process one frame is measured in order to be able to determine differences in computation time.

Experiment 2: Different lighting conditions Different conditions than the conditions a person trained to program in can affect the performance of the PCA algorithm. The goal of this experiment is to investigate the effect of different lighting conditions by training the program in conditions where the face is evenly and clearly lit. Testing then takes place in darker conditions with less uniform lighting. This was achieved by simply switching the lights on and off while a second source of lighting, sunlight coming in through a window in the roof of the room, remained unchanged.

Experiment 3: Data from two training sessions The amount of training data might influence the performance of the PCA algorithm, especially if the data is gathered in different lighting conditions. In this experiment data from two different lighting conditions is taken (the data of the first and second experiment) and the performance is measured. The average processing time per frame is also measured in order to determine the influence of extra data data samples on the processing time.

Experiment 4: Different resolution In this experiment a higher resolution than normal is used: a resolution of 360*240 pixels which increases the amount of pixels by a factor of 2.25. This means that the found ROI's are of a higher resolution as well and thus contain more information. This could be of effect for the Viola-Jones cascades and the trained PCA classifier, which is investigated in this experiment. This experiment also measures the average processing time per frame to determine the influence of higher resolutions.

Experiment 5: Using PCA for eye gestures In the final experiment it is investigated how a PCA classifier performs at the task of classifying eye gestures in comparison to the two Viola-Jones cascades. Undoubtedly this will also influence the average processing time per frame, which will be measured as well.

4.1.2 Authentication Success Rate

Of course it is important to measure the success rate of authentication and different experiments are performed to determine this rate. The starting point is the same as the standard conditions as previously defined in Section 4.1.1. For every experiment 20 attempts at authentication were performed and in order to succeed the subjects had to perform a random gesture sequence of 4 gestures. The similarity threshold for faces is set at 0.5 as it is expected to provide a high enough bar which is expected to be unreachable when another face is presented. The required percentage of faces of which the similairty value must exceed this threshold of the total amount of frames during an authentication attempt was set at 7.5%, because it is expected that different lighting conditions will make it difficult for the correct face to reach this threshold. These experiments were performed by three subjects.

Experiment 6: Straight after training This experiment aims to establish a baseline against which the other authentication experiments can be compared and it is performed straight after

training the program. The experiment is performed as described directly above: 20 authentication attempts are performed during which a sequence of 4 random gestures must be completed.

Experiment 7: Different conditions than training conditions In different lighting conditions this method of authentication should also be usable and this experiment aims to determine if this is possible. Again, a subject has to try and authenticate himself 20 times by completing a sequence of 4 random gestures. However, this time the experiment is performed in different lighting conditions than the algorithm was trained in.

Experiment 8: Using a classifier trained with data from two conditions As previously suggested in experiment 4, extra training data might be of influence on the performance of the algorithm. This algorithm investigates if there is an increase in the authentication success rate if training is performed with data gathered in two different lighting conditions.

4.1.3 A Classifier's Ability to Generalise

An important question to ask is whether or not a trained classifier generalises well and if it is able to classify the gestures of a person if it is trained to detect the gestures of another person? The answer to this question is of direct importance for the security of this authentication method. If the classifiers generalises well, it becomes more important that a face is properly recognised and the purpose of using gestures will be solely to make sure that no picture of a face is shown. However, should the classifiers not be able to generalise well and it cannot recognise the gestures of a person it is not trained for, it adds to the security value of the program and the face recognition itself becomes of less importance. These experiments were performed by two subjects, the same as those who performed experiment 1 through 5.

Experiment 9: Recognition of gestures between subjects This experiment aims to determine whether or not a classifier can recognise the gesture of one person when it is trained for recognising the gestures of another person. The conditions in which this is tested are the same as described in Section 4.1.1, however, the images that were used for training are the images of the other subject.

Experiment 10: Distance between faces in different settings and between persons Lastly, it is important to determine how much the face recognition classifier considers person to be the same in order to be able to determine a proper threshold for face recognition as described in Section 3.2. This experiment aims to determine a threshold by inspecting the obtained similarity values from the experiments 1, 2, 3 and 9. When these experiments where performed, the required data for this experiment automatically collected and it should provide insight what the influences of the different settings are. It should also become clear what happens if a person other than the person the program got trained to recognise is presented.

4.2 Experimental Results

The results of the performed experiments will be presented in this section. They are ordered in the same manner as they were listed in Section 4.1.

4.2.1 Recognition Rates of Gestures

The results of the experiments that determine the performance of the gesture recognition methods are described here. These experiments were performed by two subjects and the results of these experiments will be presented per gesture per subject. For every combination, two numbers will be reported: the *precision* value for the Viola-Jones cascades and the *recall* value of every gesture. Both precision and recall are measurements of performance. Precision is a measure for determining how many detections are actually correct. Recall measures how many instances of a class actually got detected. Precision is defined as:

$$\text{Precision} = \frac{\text{TruePositives}}{\text{nTruePositives} + \text{nFalsePositives}}$$

and recall is defined as:

$$\text{Recall} = \frac{\text{nTruePositives}}{\text{nTruePositives} + \text{nFalseNegatives}}$$

In Appendix A the confusion matrices are listed, which is the data on which the presented precision and recall values are based. Such a matrix displays how many times a gesture gets classified correctly or as another gesture. A row stands for the actual performed gesture and the columns are the gestures it is recognised as. In the cells the percentages are displayed as measure of how many times an event occurred. Within these matrices, there are also a row and a column labeled "v-j fault". The number in the cell where this row and column cross stands for the amount of times the viola-jones algorithm selected the wrong ROI as a percentage of the total number of frames. A Viola-Jones error always leads to the wrong classification of the supposedly displayed gesture as there is no right answer. These misclassifications are not taken into account in other cells, hence the extra cell to display this error.

When relevant, the mean and standard deviation of the processing time per frame will be reported (in ms.). Note that the processing time in the Viola-Jones tables also includes the detection time of the second eye cascade, which detects only open eyes (except for experiment 5). The processing times listed in the gesture recognition methods tables correspond to the time it takes for the PCA algorithm to classify mouth gestures (and in experiment 5 also eye gestures) and for determining the gestures of the other regions.

Experiment 1: Baseline performance In Table 4.1 and Table 4.2 the precision and recall values are listed for experiment 1 of which the purpose was to establish a baseline for performance. In these tables it can be observed that the Viola-Jones cascades perform their job adequately and achieve high precision values.

Where the gestures are concerned, the head gestures get recognised reasonably well, except for the 'Head: tilt right' gesture for subject s02. This is due to mistakes in the located eye regions by the Viola-Jones cascade, as no special classifier is in charge of classifying head gestures. Also, the 'Head: straight' and 'Head: left' are correctly classified and these are determined in the exact same manner as the 'Head: right' gesture and which have just as much chance of getting misclassified.

For the eye gestures, the 'Eye: wink' gesture poses a problem (especially for subject s02), while the 'Eye: open' gesture is classified reasonably fine. This could indicate that the second Viola-Jones cascade (the one that only recognises open eyes) might actually perform too well in the sense that

it also detects closed eyes which would lead to the 'E: wink' gesture being classified as an 'E: open' gesture.

The mouth gestures have mostly been classified correctly, with the exception of the 'Mouth: tongue' gesture for subject s01.

Table 4.1: Baseline precision values and computing times of the Viola-Jones cascades.

	Head	Eye	Mouth
s01	1.00	1.00	1.00
s02	1.00	0.97	0.99
avg. ms./frame	125.5		
std. dev.	16.3		

Table 4.2: Baseline recall values and computing times for the gesture recognition methods.

	Head: straight	Head: tilt left	Head: tilt right	Eye: open	Eye: wink	Mouth: normal	Mouth: smile	Mouth: tongue
s01	0.93	1.00	0.88	0.84	0.68	0.99	0.94	0.50
s02	0.95	1.00	0.27	0.90	0.32	0.89	1.00	1.00
avg. ms./frame	3.0							
std. dev.	0.5							

Experiment 2: Different lighting conditions For this experiment the corresponding precision values can be found in Tables 4.3 and 4.4. The Viola-Jones precision values only tell that different lighting conditions do not seem to influence the cascades.

There are some changes in the recall values of the gestures that can be observed. The change in conditions was expected to only have an influence on the performance of the PCA algorithm, but it seems that it is of influence on the second Viola-Jones cascade. The 'Eye: wink' gesture got a worse score for subject s01, while it improved for subject s02, which is in contrast with the improvement for the 'Eye: open' gesture for subject s02.

As expected, the change in conditions was of influence on the classification of mouth gestures as well, as can be observed by looking at the values of 'Mouth: tongue' for subject s01 and 'Mouth: normal' for subject s02.

Experiment 3: Data from two training sessions Using data from two training sessions is expected to only be of influence of the classification of mouth gestures, as the PCA algorithm is the only classification method that benefits from training data. This is why only mouth-related information is displayed. The results of this experiment are presented in Table 4.6. When comparing this table to Table 4.2 from the first experiment, it can be observed that the recall values of the

Table 4.3: Precision values of the Viola-Jones cascades in different conditions.

	Head	Eye	Mouth
s01	1.00	1.00	1.00
s02	1.00	1.00	1.00

Table 4.4: Recall values and for the gesture recognition methods in different conditions.

	Head: straight	Head: tilt left	Head: tilt right	Eye: open	Eye: wink	Mouth: normal	Mouth: smile	Mouth: tongue
s01	1.00	1.00	0.53	0.96	0.53	1.00	0.86	0.00
s02	0.97	0.75	0.00	0.29	0.95	0.64	0.89	1.00

'Mouth: smile' and 'Mouth: tongue' gestures improved, but that for subject s01 the value for the 'Mouth: normal' gesture decreased. Also, just like the amount of training images doubled, the processing time for classifying the gestures doubled.

Table 4.5 shows the corresponding Viola-Jones precision values and the processing time, which are not much different from the values presented in Table 4.1 from experiment one. Table 4.5 is only presented to validate the claim that extra training is not of influence for the Viola-Jones cascades (and thus not of influence on the classification of the other gestures that are not listed).

Table 4.5: Precision values and computing times of the Viola-Jones cascades with data from two training sessions.

	Mouth
s01	1.00
s02	1.00
avg. ms./frame	126.3
std. dev.	21.1

Experiment 4: Different resolution The use of higher resolution input images could influence the gesture recognition methods, as more information is available and this experiment investigates this.

In Table 4.7 the precision values and computing times are reported and when these are compared to the precision values in Table 4.1 from experiment 1, it can be observed that the eye cascades performed worse, if only slightly. Aalso apparent is the fact that the average computation time per frame more than doubled. This does not come as a surprise as the amount of pixels in the input images increased by a factor of 2.25.

When comparing the recall values from this experiment as displayed in Table 4.8 to the recall values from experiment 1 in Table 4.2, the lack of recognition of the 'Eye: wink' gesture can not

Table 4.6: Recall values and computing times for the mouth gesture recognition method trained with data from two training sessions.

	Mouth: normal	Mouth: smile	Mouth: tongue
s01	0.79	1.00	1.00
s02	0.92	1.00	1.00
avg. ms./frame	6.0		
std. dev.	0.8		

be missed. The recognition of mouth gestures seems to have improved for subject 1, while no 'M: tongue' gestures are recognised anymore for subject 2. Also the average computation time per frame doubled here, just like the time for the Viola-Jones cascades.

Table 4.7: Precision values and computing times of the Viola-Jones cascades with a base resolution of 360 x 240 pixels.

	Head	Eye	Mouth
s01	1.00	0.96	1.00
s02	1.00	0.98	1.00
avg. ms./frame	266.3		
std. dev.	42.8		

Table 4.8: Recall values and computing times for the gesture recognition methods with a base resolution of 360 x 240 pixels.

	Head: straight	Head: tilt left	Head: tilt right	Eye: open	Eye: wink	Mouth: normal	Mouth: smile	Mouth: tongue
s01	0.98	1.00	1.00	1.00	0.00	0.98	1.00	1.00
s02	1.00	1.00	0.29	1.00	0.00	0.89	1.00	0.00
avg. ms./frame	6.5							
std. dev.	1.0							

Experiment 5: Using PCA for eye gestures As this experiment determines whether there is a difference between using two Viola-Jones cascades or the PCA algorithm to classify eye gestures, only eye-related information is of relevance and will be displayed.

When comparing the precision values in Table 4.9 from this experiment to values in Table 4.1 from experiment 1 the difference in the average processing time per frame becomes clear. It

seems that the second Viola-Jones cascade for eye detection added roughly 25 ms. to the average computation time per frame to detect open eyes.

The recall values in table 4.10 show that the detection of winks has worsened when compared to the results displayed in Table 4.2 of experiment 1. Also, the average processing time per frame did increase by roughly 5 ms. which is no surprise as the PCA algorithm is now performing an additional task.

Table 4.9: Precision values and computing times of the Viola-Jones cascades when PCA was used to classify eye gestures.

	Eye
s01	0.99
s02	1.00
avg. ms./frame	101.4
std. dev.	14.9

Table 4.10: Recall values and computing times when PCA was used to classify eye gestures.

	Eye: open	Eye: wink
s01	0.89	0.43
s02	1.00	0.00
avg. ms./frame	8.2	
std. dev.	1.3	

4.2.2 Results of Authentication Experiments

In this section the results of the authentication experiments, experiments 6, 7 and 8, are shortly presented and are shown in Table 4.11. What is directly apparent is the fact that only subject s01 managed to authenticate successfully using the program. Using the training data from two training sessions did improve results somewhat, but only for subject s01 while subject s03 and s04 were still unable to authenticate themselves. For subject s03 this was due to the fact that only every eye gesture got classified as a wink, while for subject s04 only the smile-gesture got recognised in the mouth region. This means that authentication would fail the moment any other gestures would have to be performed, as gestures must be performed exclusively and not in combination with other gestures.

4.2.3 Results of Generalisation Experiments of Trained Classifiers

The results of the experiments that determine the generalisation capabilities of a trained classifier are described in this section.

Table 4.11: Results of the authentication experiments

	Straight after training	Different conditions	Combined data
s01 success rate	0.10	0	0.35
s03 success rate	0	0	0
s04 success rate	0	0	0

Experiment 9: Recognition of gestures between subjects The only relevant results for this experiment are the recall values of the mouth gestures, as the mouth region is the only region that is classified by the PCA algorithm, which is the only algorithm that is influenced by training. These recall values are presented in Table 4.12. When comparing these values to the recall values in Table 4.2 from experiment 1 the first noticeable fact is that the recognition of the 'Mouth: normal' gesture got a little bit worse. The recognition of the 'Mouth: tongue' gesture actually improved for subject s01, while classifying it correctly failed completely for subject s02.

Table 4.12: Recall values and for the mouth gesture recognition method of the between-subject gesture recognition experiment.

	Mouth: normal	Mouth: smile	Mouth: tongue
s01 vs s02	0.94	1.00	1.00
s02 vs s01	0.85	1.00	0.00

Experiment 10: Distance between faces in different settings and between persons The purpose of this experiment was to determine the similarity values of faces in different settings and of different persons. In Table 4.13 the obtained similarity values are reported in intervals of 0.05 and they are sorted per subject, per experiment. The last two columns display the obtained similarity values when the program was trained with the data from subject s02 (from experiment 1) and presented with subject s01 and the similarity values of the opposite setup respectively. The displayed values are percentages of the total amount of frames that were obtained in their respective experiments.

What can be observed is that in the settings from experiment 2 (different lighting conditions compared to training) the similarity values for both subjects is considerably lower, although there are a few outliers for subject s01. Also, the obtained similarity values are higher with the setup from experiment 3 (2 training sessions in different lighting conditions) compared to experiment 2, although this effect is pretty small for subject s02.

The last two columns that display the data from experiment 9 (between subject values) show that it is possible to obtain similarity values not much different from the values which were obtained with experiment 2. However, they are unmistakingly lower than the similarity values obtained with the settings from experiment 1 and 3.

Table 4.13: Similarity values of faces taken from data of different experiments.

experiment	1	2	3	1	2	3	9	9
Bin	*s01*	*s01*	*s01*	*s02*	*s02*	*s02*	*s01 vs s02*	*s02 vs s01*
<0.1	0	0	0	0	0	0	0	0
0.1 - 0.15	0	0	0	0	0	0	0	0
0.15 - 0.2	0	0	0	0	0	0.04	0.01	0
0.2 - 0.25	0.06	0.02	0	0	0.01	0.04	0.02	0.13
0.25 - 0.3	0.16	0.44	0	0	0.24	0.04	0.26	0.38
0.3 - 0.35	0.16	0.26	0	0	0.61	0.14	0.43	0.16
0.35 - 0.4	0.11	0.13	0.09	0	0.12	0.37	0.25	0.12
0.4 - 0.45	0.13	0.05	0.53	0.02	0.01	0.24	0.02	0.10
0.45 - 0.5	0.09	0.04	0.17	0.11	0	0.13	0	0.01
0.5 - 0.55	0.05	0.03	0.07	0.30	0	0	0	0.05
0.55 - 0.6	0.07	0.01	0.10	0.32	0	0	0	0.04
0.6 - 0.65	0.04	0	0.04	0.17	0	0	0	0
0.65 - 0.7	0.05	0.01	0	0.08	0	0	0	0
0.7 - 0.75	0.06	0	0	0	0	0	0	0
0.75 - 0.8	0	0	0	0	0	0	0	0
>0.8	0	0	0	0	0	0	0	0
mean	0.43	0.33	0.46	0.56	0.31	0.38	0.32	0.32
std dev	0.14	0.08	0.06	0.06	0.04	0.07	0.04	0.09

4.3 Discussion of Results

In this section the experimental results are discussed. However, before this is done it must be noted that no statistical tests have been performed to check for any significance of the results. This is because only two subjects performed the experiments (three subjects performed experiments 6, 7 and 8) and it is unlikely that any overwhelmingly convincing statistical significance would be found. However, as long as this is kept in mind the results are suitable for drawing rough conclusions.

4.3.1 Finding Regions of Interest

The Viola-Jones object detection algorithm was utilised to find all relevant regions of interest for the suggested application. Pre-trained cascades were used for every relevant ROI and they all performed well: the cascade for finding faces always achieved a precision value of 1.00 while the eye and mouth detection cascades never achieved lower precision values than 0.96 an 0.99 respectively. The only setting that had a (negative) effect on the precision values was the increasing of the resolution of the input images that were given to the algorithm.

However, these cascades require a significant amount of time to perform their task. Finding the bare regions of interest where only one cascade is used to find eye regions takes 101.4 ms. on average on the computer the experiments were performed on. Adding the second eye detection

cascade increases the required time to 125.5 ms. on average. These numbers are influenced linearly (by estimation) by the resolution of the input images: increasing the resolution by a factor of 2.25 increased the average computation time to 266.3 ms. Unfortunately these numbers will only worsen when the algorithm is run on a smart-phone, thereby reducing the amount of frames that can be processed per second.

4.3.2 Gesture Recognition

Eye gestures Two Viola-Jones cascades were used to recognise eye gestures and the experimental results were not encouraging. Winks were never reliably detected with recall values in normal conditions of 0.68 and 0.32 for the two subjects. Open eyes were detected more reliably, but the highest obtained recall value did not get above 0.90. In different conditions the cascades seemed to get a preference for either closed or open eyes, depending on the subject. This emphasizes that the current method for detecting winks is undependable. When higher resolutions were used no wink-gestures were recognised at all, so nothing can be gained by trying this.

An alternative possibility to detect eye gestures that was investigated was to use the PCA algorithm for eye gesture classification. However, this was to no avail as for subject s01 the recall value for winks was 0.43 while for subject s02 no wink gestures were recognised at all.

Mouth gestures For recognising mouth gestures the PCA algorithm was used. In normal conditions these gestures were recognised pretty well with an average recall value of 0.89 (averaged over both subjects and all gestures) , although in different conditions the average recall value dropped to 0.73. With extra training data from two different condition the average recall value increased to 0.95. When higher resolution images were used, there was a general improvement and for subject s01 almost perfect recall rates were obtained, although no tongue-gestures were recognised for subject s02. This led to an average recall value of 0.81.

Head gestures The recognition of head gestures is done by calculating the result of a simple mathematical formula on which the different -experimental setups had no influence. Therefore the only possible influence on the outcome of this formula is the input and if the input is wrong, the output will be wrong too. Any of the low recall values (for example, 0.27 for a 'tilt right' gesture for subject s02 in normal conditions) indicate that the found eye regions were not correct and that the cascades might have a problem finding tilted eyes.

4.3.3 Face Recognition

The PCA algorithm was used for face recognition and similarity values between the set of training faces and presented faces were used to determine if these faces belonged to the same person. The similarity values obtained with the experiments indicate that this method can be reliably used as long as data is used from two training sessions in different conditions. This yields average similarity values of 0.46 and 0.38 for both subjects. The necessity to use two training sessions becomes clear when comparing the similarity values obtained in Experiment 2: Different conditions and Experiment 9: Recognition of gestures between subjects. For Experiment 2 the average similarity values for both subjects were 0.33 and 0.31, which are very much like the obtained average similarity values of 0.32 for both subjects in Experiment 9. This shows that the training data from just one

condition is not sufficient for the algorithm to reliable distinguish between two subjects, but that the distinction can be made with training data from two different conditions.

4.3.4 Capability to Generalise

The PCA algorithm was able to generalise by recognising gestures from a subject while it was trained with the gestures of another surprisingly well. The average recall value was 0.80 for mouth gestures, which is worse than the baseline average of 0.89, but not far below. However, this is not well enough in order to be able to use another person's training data to recognise one's own gestures. This is a good thing though, as it adds to the security of the application because it must be trained for a person specifically in order to recognise gestures correctly. Even though this is true, the difference is not big enough to be able to be counted upon as a full-fledged security measure by itself.

Chapter 5

Discussion

5.1 Usability

The implementation of the proposed method of authentication which was used for the experiments is not usable for its intended purpose. This becomes evident from the results from Experiments 6, 7 and 8 as presented in Section 4.2.2. This is the result from the imperfect recognition of all possible gestures, as the chance on erroneous classifications of gestures increases with lower recall values and longer gesture sequences that need to be performed when authenticating. It also appears that subjects tend to have at least one gesture that the system would (almost) never classify correctly. This means that if such a gesture were to be included in the sequence of gestures that needs to be performed, the authentication process will fail. Possible solutions will be discussed in Section 5.2.

5.2 Future Research

As mentioned in Section 5.1 the current implementation is not fit for use, but there are various aspects that can be improved. The first aspect is the Viola-Jones cascades. Sometimes the eye and mouth cascades would make a mistake and classify a nose as an eye or a mouth region. Such mistakes can possibly be filtered out by inspecting where the found region is located relative to the face region, as eyes or mouths are not positioned in the middle of the face. Doing this could improve the precision values of the cascades, providing an opportunity for overall improvement.

Secondly, gesture recognition itself could possibly be improved by finding optimal parameters for the PCA algorithm in terms of the amount of training data that is used and the resolution of input images. Also, the results from experiment 1 and 2 show that the Viola-Jones cascades are not fit for detecting eye gestures, so the use of PCA for recognising eye gestures could be further and more thoroughly investigated.

Another method that could possibly improve the results of the PCA algorithm is the use of a different colourspace. Currently, the input images are defined in the *RGB* (Red, Green and Blue) colourspace before they are converted to greyscale images. However, these images could first be converted to the *HSL* colourspace, which stands for Hue, Saturation and Lightness. This would allow for the normalisation of images on the Lightness-axis relative to the training images. This could possibly reduce the influence of different lighting conditions and improve recognition rates.

After normalisation, the images could be converted to greyscale and serve as input just as before. Whether or not this has any effect, would have to be investigated.

Should the proposed efforts to improve the performance of the PCA algorithm fail, alternative algorithms for recognising gestures can be investigated. Examples of possible algorithms were previously listed in Section 1.2. An important consideration in choosing an alternative is that currently no actual movement-information is used as feature: input images are considered individually. It might be beneficial for performance as well as security to choose an algorithm that is able to use actual movement-information. The computational costs of algorithms that do this are high though and this factor should not be overlooked.

Should one of the proposed methods make the suggested authentication system fit for real world use, the possibilities of using it as a widespread method of authentication should be investigated. However, if this would be achieved attempts will be made to try and hack the system and find weaknesses to abuse it. To stay one step ahead, research would have to be performed to try and identify such weaknesses so the system can be improved and made more secure.

5.3 Conclusion

The precision of the Viola-Jones algorithm and the used cascades are more than sufficient for finding the regions of interest for this authentication method. The computational costs of the algorithm are high and the performance is good.

The used gesture recognition methods do not achieve sufficiently high recall values in order to be usable in this application. However, there is potential for improving these methods, which would be especially beneficial for the PCA algorithm. The current manner in which the PCA algorithm is utilised does not achieve sufficiently high recognition rates in order to be useful, but if it can be made to work reliably it definitely pays off as the required computational time is very low.

Overall, the current implementation of an authentication method based on face recognition combined with facial gesture recognition is unfit for use. However, there are enough possibilities for improvement and it has been shown that there definitely is potential.

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Appendix A

Experiment Confusion Matrixes

In a confusion matrix a row stands for the actual performed gesture and the columns are the gestures it is recognised as. In the cells the percentages are displayed as measure of how many times an event occurred. This is illustrated in Table A.1.

Table A.1: Example confusion matrix.

	observed class	
actual class		

Table A.2: Confusion matrix of experiment 1. Subject 1: Head gestures. 111 frames total.

	normal	tilt left	tilt right	v-j fault
normal	0.93	0.00	0.07	
tilt left	0.00	1.00	0.00	
tilt right	0.13	0.00	0.88	
v-j fault				0.00

Table A.3: Confusion matrix of experiment 1. Subject 1: Eye gestures. 222 frames total.

	open	wink	v-j fault
open	0.84	0.17	
wink	0.32	0.68	
v-j fault			0.00

Table A.4: Confusion matrix of experiment 1. Subject 1: Mouth gestures. 111 frames total.

	normal	smile	tongue	v-j fault
normal	0.99	0.01	0.00	
smile	0.06	0.94	0.00	
tongue	0.38	0.13	0.50	
v-j fault				0.00

Table A.5: Confusion matrix of experiment 1. Subject 2: Head gestures. 105 frames total.

	normal	tilt left	tilt right	v-j fault
normal	0.95	0.00	0.05	
tilt left	0.00	1.00	0.00	
tilt right	0.73	0.00	0.27	
v-j fault				0.00

Table A.6: Confusion matrix of experiment 1. Subject 2: Eye gestures. 210 frames total.

	open	wink	v-j fault
open	0.90	0.10	
wink	0.68	0.32	
v-j fault			0.00

Table A.7: Confusion matrix of experiment 1. Subject 2: Mouth gestures. 105 frames total.

	normal	smile	tongue	v-j fault
normal	0.89	0.02	0.08	
smile	0.00	1.00	0.00	
tongue	0.00	0.00	1.00	
v-j fault				0.01

Table A.8: Confusion matrix of experiment 2. Subject 1: Head gestures. 106 frames total.

	normal	tilt left	tilt right	v-j fault
normal	1.00	0.00	0.00	
tilt left	0.00	1.00	0.00	
tilt right	0.47	0.00	0.53	
v-j fault				0.00

Table A.9: Confusion matrix of experiment 2. Subject 1: Eye gestures. 212 frames total.

	open	wink	v-j fault
open	0.96	0.04	
wink	0.47	0.53	
v-j fault			0.00

Table A.10: Confusion matrix of experiment 2. Subject 1: Mouth gestures. 106 frames total.

	normal	smile	tongue	v-j fault
normal	1.00	0.00	0.00	
smile	0.14	0.86	0.00	
tongue	1.00	0.00	0.00	
v-j fault				0.00

Table A.11: Confusion matrix of experiment 2. Subject 2: Head gestures. 78 frames total.

	normal	tilt left	tilt right	v-j fault
normal	0.97	0.03	0.00	
tilt left	0.25	0.75	0.00	
tilt right	1.00	0.00	0.00	
v-j fault				0.00

Table A.12: Confusion matrix of experiment 2. Subject 2: Eye gestures. 156 frames total.

	open	wink	v-j fault
open	0.29	0.71	
wink	0.05	0.95	
v-j fault			0.00

Table A.13: Confusion matrix of experiment 2. Subject 2: Mouth gestures. 78 frames total.

	normal	smile	tongue	v-j fault
normal	0.64	0.30	0.06	
smile	0.00	0.89	0.11	
tongue	0.00	0.00	1.00	
v-j fault				0.00

Table A.14: Confusion matrix of experiment 3. Subject 1: Mouth gestures. 81 frames total.

	normal	smile	tongue	v-j fault
normal	0.79	0.19	0.01	
smile	0.00	1.00	0.00	
tongue	0.00	0.00	1.00	
v-j fault				0.00

Table A.15: Confusion matrix of experiment 3. Subject 2: Mouth gestures. 105 frames total.

mouth gestures:				
	normal	smile	tongue	v-j fault
normal	0.92	0.05	0.03	
smile	0.00	1.00	0.00	
tongue	0.00	0.00	1.00	
v-j fault				0.00

Table A.16: Confusion matrix of experiment 4. Subject 1: Head gestures. 64 frames total.

	normal	tilt left	tilt right	v-j fault
normal	0.98	0.00	0.02	
tilt left	0.00	1.00	0.00	
tilt right	0.00	0.00	1.00	
v-j fault				0.00

Table A.17: Confusion matrix of experiment 4. Subject 1: Eye gestures. 128 frames total.

	open	wink	v-j fault
open	1.00	0.00	
wink	1.00	0.00	
v-j fault			0.04

Table A.18: Confusion matrix of experiment 4. Subject 1: Mouth gestures. 64 frames total.

	normal	smile	tongue	v-j fault
normal	0.98	0.00	0.02	
smile	0.00	1.00	0.00	
tongue	0.00	0.00	1.00	
v-j fault				0.00

Table A.19: Confusion matrix of experiment 4. Subject 2: Head gestures. 77 frames total.

	normal	tilt left	tilt right	v-j fault
normal	1.00	0.00	0.00	
tilt left	0.00	1.00	0.00	
tilt right	0.43	0.29	0.29	
v-j fault				0.00

Table A.20: Confusion matrix of experiment 4. Subject 2: Eye gestures. 154 frames total.

	open	wink	v-j fault
open	1.00	0.00	
wink	1.00	0.00	
v-j fault			0.02

Table A.21: Confusion matrix of experiment 4. Subject 2: Mouth gestures. 77 frames total.

	normal	smile	tongue	v-j fault
normal	0.89	0.11	0.00	
smile	0.00	1.00	0.00	
tongue	1.00	0.00	0.00	
v-j fault				0.00

Table A.22: Confusion matrix of experiment 5. Subject 1: Eye gestures. 258 frames total.

	open	wink	v-j fault
open	0.89	0.11	
wink	0.57	0.43	
v-j fault			0.01

Table A.23: Confusion matrix of experiment 5. Subject 2: Eye gestures. 206 frames total.

	open	wink	v-j fault
open	1.00	0.00	
wink	1.00	0.00	
v-j fault			0.00

Table A.24: Confusion matrix of experiment 9. Subject 1: Mouth gestures. 81 frames total.

	normal	smile	tongue	v-j fault
normal	0.94	0.00	0.06	
smile	0.00	1.00	0.00	
tongue	0.00	0.00	1.00	
v-j fault				0

Table A.25: Confusion matrix of experiment 9. Subject 2: Mouth gestures. 99 frames total.

	normal	smile	tongue	v-j fault
normal	0.85	0.04	0.11	
smile	0.00	1.00	0.00	
tongue	1.00	0.00	0.00	
v-j fault				0