RIGA TECHNICAL UNIVERSITY

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EFFECTIVE ALGORITHMS FOR OPTICAL IMAGE PROCESSING AND THEIR IMPLEMENTATION IN MICROELECTRONIC SYSTEMS FOR USAGE IN BIOMETRICS

Summary of doctoral thesis

Riga 2013

RIGA TECHNICAL UNIVERSITY
Faculty of Electronics and Telecommunications
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Summary of doctoral thesis

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Thesis developed in the
Institute of Electronics and Computer Science

Riga 2013

UDK 004.93(043.2)
Ņi 758 e

Ņikišins O. Effective algorithms for optical image processing and their implementation in microelectronic systems for usage in biometrics. Summary of the thesis.-R.:RTU, 2013.-30 lpp.

Printed in accordance to ETF doctoral committee „RTU P-08" decision, 27 June 2013, protocol Nr. 16.

This work has been supported by a funding from the following projects:

- Nr. 2DP/2.1.1.1.0/APIA/VIAA/098 - Multimodal biometric technology for safe and easy person authentication - managed by Dr.sc.comp. Modris Greitans,
- Nr. 2009/0219/1DP/1.1.1.2.0/09/APIA/VIAA/020 - R & D Center for Smart Sensors and Networked Embedded Systems - managed by Dr.sc.comp. Leo Selavo (2010-2012),
- State Research Program: Scientific Foundations of Information Technology,
- State Research Program: Development of innovative multi-functional material, signal processing and information technologies for competitive and research intensive products,
- Nr. 2004/0002/VPD1/ESF/PIAA/04/NP/3.2.3.1/0001/0002/0007 - Support for the development of doctoral studies at Riga Technical University.

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ISBN

DOCTORAL THESIS
IS NOMINATED FOR DOCTORAL DEGREE IN ENGINEERING SCIENCE IN RIGA TECHNICAL UNIVERSITY

Doctoral thesis which is nominated for doctoral degree in engineering science will be publicly defended in 31 October 2013 at 16.30 in the Institute of Electronics and Computer Science, 14 Dzerbenes street, room Nr. 101B.

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APPROVAL

I confirm that this doctoral thesis, which is nominated for doctoral degree in engineering science in Riga Technical university, has been developed by me. Doctoral thesis is not submitted to any other university for obtaining the doctoral degree.

Oļegs Ņikišins .... (Signature)

Date: ....

Doctoral thesis is written in English, consists of introduction, 5 chapters, conclusions, bibliography, 99 figures, 169 pages in total. Bibliography contains 135 references.

Contents

List of Abbreviations

ANN - Artificial Neural Network
EFW - Empirical Feature-level Weighting
IBW - Iterative Block-level Weighting
LBP - Local Binary Patterns
MB-DFW - Mini-Batch Discriminative Feature Weighting algorithm
MF - Median Filter
MSLBP - Multi - scale Local Binary Patterns
NNC - Nearest Neighbor Classifier PCA - Principal Component Analysis
SVM - Support Vector Machines
WNNC - Weighted Nearest Neighbor Classifier

List of Mathematical Symbols

$\boldsymbol{I}_L$ - LBP image / labeled image
P - number of sampling points in LBP label
R - radius of LBP label
$\boldsymbol{X}$ - matrix notation
$\boldsymbol{x}$ - vector notation
x - element of a vector
n_R - number of radii utilized in the MSLBP operator
$\boldsymbol{h}$ - histogram of the image
$f(x)$ - function notation
K - numbers of columns / rows in the LBP regioning grid
N - number of elements in the feature vector / dimensionality of the feature space
M - number of training examples
$\equiv$ - assignment symbol
s_j - number of neurons in layer j *without* a bias unit
L - total number of layers in ANN
N^{SV} - number of support vectors
L_{MSLBP} - size of the MSLBP label

1. GENERAL DESCRIPTION OF THE DOCTORAL THESIS

1.1. Theme topicality

The term *biometrics* refers to the recognition of humans by their physiological or behavioral characteristics or traits. In physiological biometric the individuals are identified by face, finger prints, palm geometry, DNA, voice and other parameters. Behavioral biometrics are related to the behavior of a person, for example typing rhythm or gait. Compared to other biometrics *face recognition* is considered to be more natural, non-intrusive, user-friendly due to its non destructive essence and can be used without the cooperation of the subject, thus the scope of this research is limited to the task of automatic face recognition. The first automatic face recognition system was introduced by Takeo Kanade in 1973 [13] and has contributed to an increasing attention to this scientific field. Due to increasing computational power of modern computers and successes in pattern recognition, face recognition systems can now operate in real time with high performance under controlled imaging conditions. That results in a wide range of real life applications, such as access control systems, border control, forensics, banking sector, human computer interaction, patient monitoring, image database investigations, video indexing and others.

Biometrics is gaining an increasing popularity and importance both in private and public sectors and even in the international cooperation. Biometrics related organizations are established in major countries, which is an incontrovertible proof of the importance of this scientific direction. Some of the main users of facial biometrics are USA visa department, which utilize the largest facial database in the world, London video surveillance center, automatic border control in Frankfurt airport, German police, Australian border control, Indian database of citizens.

The gaining popularity of biometrics over traditional security methods can be explained by a number of advantages: the biometric data can not be lost, forgotten, transmitted to other individuals and it is difficult to steal.

The task of automatic face recognition is an important scientific direction with significant progress achieved over the past decades, however this problem is still can not be considered as resolved. The ongoing research in this field is needed in algorithmic, system a user-related levels. The algorithmic part of automatic face identification system is based on three main modules (Figure 1.1):

- *Face detection* module determines the presence of faces in the input image (or video sequence) and returns their positions and dimensions. The system in Figure 1.1 is often designed to process a single user at a time. In this scenario the term face localization is employed. The scope of this research is limited to the task of face localization, however it can easily be extended for detection problems.

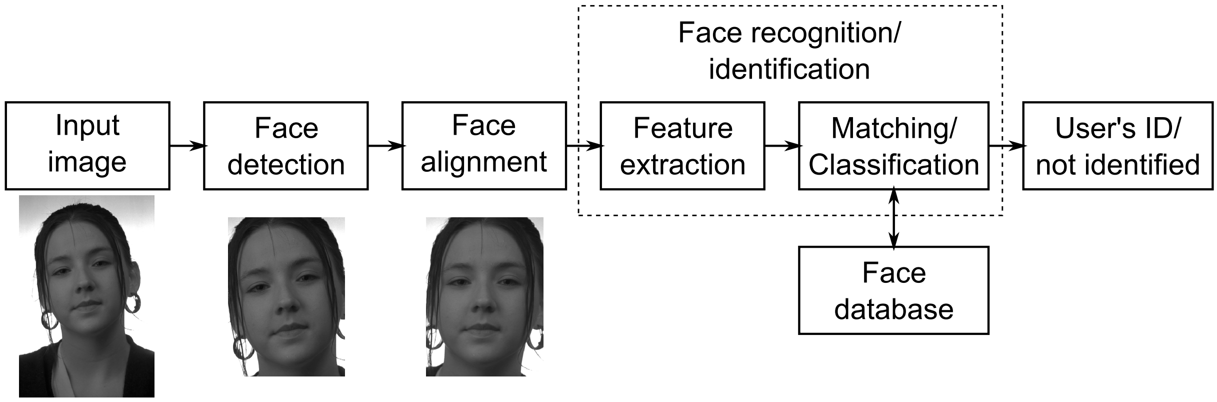

Figure 1.1: The block diagram of automatic face identification system

- *Face alignment* allows to define facial parameters more accurately based on the locations of such facial features as eyes, nose, mouth and chin. This information is then utilized in geometrical normalization of the face region. It is shown in literature that face alignment has a large impact on the recognition accuracy [15], [24], [5]. Most of the high performance face recognition techniques assume that face has been localized perfectly, thus face detection and alignment are important research areas in the field of computer vision.

- *Face identification* module consists of two main blocks: feature extraction and matching or classification. The design of feature extraction block is a field of extensive research, where a plethora of both empirical and analytically well-founded techniques have been developed. Ideal features should have high discriminative power to segregate different persons and should be stable to intra-class variability. Intra-class deviations may be caused by unstable illumination, expression changes, off-plane rotations of the face or partial occlusions. Another important aspects in real life applications are dimensionality of the feature space and the complexity of the feature computation process. The comparison of the face representation to face models that are stored in the database is performed after feature extraction. This stage is called classification or matching. At this step either the identity of the person is determined or an identification attempt is rejected. Ideal classifier should take into consideration the statistical information about the addressed problem and generalize well on previously unseen data.

Each block of automatic face recognition system is a field of extensive research and a plethora of various algorithms are designed for each step during last decades [32], [30], [33], [5], [11], [28]. The first two stages can be viewed as a special cases of the object detection task. The detectable object in the first step is face, while the second stage is often based on the detection of the eyes as a reference points for face alignment. Face and eye detection tasks have both common and unique issues to be resolved. Both objects have a large variance in their appearance, due to multiple factors such as skin color and texture, head pose and shape, facial expressions, lighting conditions, partial occlusions (glasses) and other features (hairstyle, beard, make-up). However eye detection task can be considered as more complicated problem due to reduced resolution of the eye image if compared to the resolution of the input facial image. This aspect degrades the amount of available statistical data about the detectable object and yields the degraded performance of the detector. Additionally, the presence of glasses in the face may significantly distort the eye region.

The above issues are also true for the face recognition stage: large variance in face appearance affects face recognition significantly. It has been observed that "the variations between the images of the same face due to illumination and viewing direction are almost always larger than image variations due to change in face identity" [2]. Illumination aspect makes the face recognition task really complicated and requires either to control the lighting conditions or to apply special techniques to compensate the negative impact of the illumination. In contrast to detection tasks, another issue in face recognition comes from the lack of training images for each person. Small amount of training data does not cover possible intra-class variations and degrades the usability of advanced classifiers such as ANN or SVM. The inability to build reliable models of each individual is called the generalization problem. The recognition performance is also highly dependent from the precision of the localization stage.

Nowadays embedded face recognition systems are gaining increasing attention due to their portability, low power consumption and cost. However embedded solutions places additional requirements on the algorithmic basics of the system. The computational complexity and dimensionality of the feature space become critical issue for all stages of automatic face recognition algorithm, which is determined by limited computational power and memory of embedded solutions.

The popularity of face recognition in many fields and the significant amount of unresolved issues determines the need of further research in this scientific direction.

1.2. Goals of the research

The main purpose of this research is to develop an effective automatic face recognition system which is based on innovative image processing and machine learning algorithms. The main requirement for the system is high recognition precision under semi-controlled lighting conditions, however the computational speed and the simplicity of the algorithms are also important aspects especially when dealing with embedded solutions. The following tasks are covered in the thesis:

- *Face detection*. The development of novel detection principle, which allows to adjust the trade-off between the dimensionality of the feature space, computational performance and precision of the detector.

- *Face alignment*. Eye pupils are selected as the reference points for the face alignment algorithm. The development of high precision eye and pupil detectors is planned. Both statistical information about the facial region and empirical knowledge about the face should be considered.

- *Face recognition*. Two directions should be enhanced in this field: the development of novel parameters for the description of the face; the design of novel classification / recognition principles. Facial parameters should be stable against intra-class variances and be informative in terms of identity representation. Face recognition task in general can be considered as a multi-class classification problem. Additionally, the amount of intra-class training data usually is very small. The usability of popular classifiers (ANN, SVM) in this case is limited, thus the development of novel recognition principles is needed.

- Automatic face recognition process should be merged by similar algorithmic principles in the feature extraction modules, which are based on Local Binary Patterns [22] and their extensions [6].

- *Performance evaluation*. Significant attention should be given to a unified principle of performance evaluation. The evaluation process should be based on informative criteria and popular databases, which are accepted by many researchers in the corresponding fields. In this case the results are accessible for the research community.

- *The demonstrator of automatic face recognition system*, which is based on the proposed algorithms, should be implemented in order to demonstrate the feasibility of the algorithms in the embedded solutions.

1.3. Scientific novelty and main results

The main innovations of the thesis are related to the algorithmic basics of the automatic face recognition system. The contributions of this research are briefly summarized here:

- *Frontal face localization* [18] (Nikisins et al.), [20] (Nikisins et al.). A novel face detection principle, which is based on the combination of Local Binary Pattern histograms with simple classifiers, namely Artificial Neural Network or Support Vector Machine, is proposed in this research. The advantage of this setup is the flexibility of the algorithm, which allows to adjust the trade-off between the dimensionality of the feature space and the complexity of the classifier. As the result, the performance which is comparable to state-of-the-art algorithms is obtained in low-dimensional feature space (several hundreds of features) and with simple classifier (Artificial Neural Network with 10 Neurons in the hidden layer or Support Vector Machine (SVM) with 100-200 Support Vectors). Another advantage is the absence of the down-sampling stage, which is often incorporated in the detection algorithms in order to localize object of various scales. The scope of the experiments with the proposed method is limited to the task of frontal face localization in images taken under semi-controlled lighting conditions. However these limitation can be overcome by incorporating more diversity in the training data. Instead of localization, the detection task can also be performed if thresholding of the output value of the classifier is added to the system. All classified sub-windows of the input image which exceed the threshold value are considered to be faces.

- *Eye localization based face alignment* [18] (Nikisins et al.), [20] (Nikisins et al.). The above mentioned principle can also be applied to detection of other objects. Same algorithm is utilized for the localization of eye regions in the input face image. For further gain in the localization precision the algorithm is supplemented with the second stage, namely detection of eye pupils. The performance of the whole system is highly dependent on the localization accuracy, thus the second stage is needed. The experiments clearly show that the proposed method outperforms many state-of-the-art eye localization approaches. Similar to face detection, the scope of the experiments is limited to the task of eye localization in frontal face images taken under semi-controlled lighting conditions. Partial occlusions are presented in the test images in the form of glasses.

- *Effective histogram based sliding window* [18] (Nikisins et al.). Proposed algorithms for object detection utilize the histogram-based sliding window principle. Moreover, the spatially enhanced histograms must be calculated at each scanning position. This is the most time-consuming operation in the introduced detection approaches. In order to resolve this issue an effective algorithm for recalculation of spatially enhanced LBP histograms at each scanning position of the sliding window is introduced in this research. The algorithm is optimized for a single pixel step of the sliding window.

- *Face recognition* [19] (Nikisins et al.), [20] (Nikisins et al.). A novel face recognition approach is introduced in this research. It is based on the combination of various preprocessing steps, modified Multi-Scale Local Binary Pattern histograms [7] and Weighted Nearest Neighbor Classifier. The experiments with color FERET [1] database show an equivalent or even improved performance of the proposed algorithm compared to state-of-the-art face recognition techniques.

- *Discriminative feature weighting* [19] (Nikisins et al.). Identification approaches are usually based on various Nearest Neighbor Classifiers. The Discriminative Feature Weighting (DFW) algorithm is developed in this research in order to compensate the statistical incompleteness of Nearest Neighbor Classifier by utilizing the information from all classes. The information obtained in the process of weights learning is incorporated in the recognition process by the use of Weighted Nearest Neighbor Classifier (WNNC). The DFW principles are utilized in two levels: block-level and feature-level weighting [19] (Nikisins et al.). In contrast to other weighting approaches [8] and [29], proposed methodology requires only *two* training examples per class. An algorithm also incorporates special procedure of learning data selection which makes it stable, predictable and provides better recognition results. The reduction of the learning time is another challenging aspect. This issue is very important in the cases of massive training data sets and highly dimensional feature vectors. Both of these aspects are usually true for biometric applications. This problem is resolved by the introduction of mini-batch principle, which accelerates the proposed training methodology.

- *Demonstrator of embedded face recognition system*. A fully automatic face recognition algorithm is implemented on TMS320C6416 DSK development board that contains a TMS320C6416 fixed-point digital signal processor operating at 600 MHz and an external non-volatile Flash memory of the size 512 Kbytes. The algorithmic base of the system is similar to the one described in [20] (Nikisins et al.), but a few simplifications are introduced in order to speedup the system. Proposed LBP and NNC based automatic face recognition algorithm is feasible in embedded systems and requires less than 2.3×10^9 CPU cycles to process a single 0.3 Mpixel image.

1.4. Theses to be defended

The following theses are nominated for the defending process:

- Proposed object detection algorithm, which is based on the combination of Local Binary Patterns (LBP) histograms with simple classifiers, such as Artificial Neural Network with 20 Neurons in the hidden layer and Support Vector Machine (SVM) with 100-200 Support Vectors (SV), is an effective solution for the design of robust face and eye detectors, which in addition operate in low dimensional feature space.

- Proposed Mini-Batch Discriminative Feature Weighting (MB-DFW) algorithm improves the recognition precision of Nearest Neighbour Classifier (NNC) in multi-class classification problems even if *only two* training examples per class are available. This principle can also be utilized for data compression.

- The application of MB-DFW and PCA learning algorithms to Multi - scale Local Binary Patterns – based face recognition process reduces the dimensionality of the feature space more than 20 times while the recognition precision on FERET database exceeds the boundary of 99 %.

- Proposed LBP and NNC based automatic face recognition algorithm is feasible in embedded systems and requires less than $2.3x10^9$ CPU cycles to process a single 0.3 Mpixel image.

1.5. Methodology of the research

The following criteria are established to the research methodology in order to make the results accessible to the scientific community:

- The standardization of evaluation criteria. The main research directions of the thesis are face detection, eye localization based face alignment and face recognition. The number of evaluation criteria in these fields are significant, however the most popular and informative approaches are selected.
- Requirements to the evaluation process: informativeness and conformity to the selected problem. The main purpose of the thesis is to develop the automatic face recognition system, which places specific demands on the evaluation principles. For example, face detection and face alignment blocks are optimized and tested in terms of minimization of the positioning offset, since this aspect has a significant impact on the precision of the face recognition module.
- The use of publicly available face databases. The evaluation results are reported for color FERET [1] database, which is one of the most popular datasets among face recognition researchers.

The algorithms are evaluated in the form of simulations in Matlab programming environment. Automatic face recognition algorithm is also implemented in the embedded solution in order to test the operation of the system in real life.

1.6. Practical applications

The proposed face recognition system consists of three main blocks: face detection, eye localization based face alignment and face recognition (Figure 1.1). Each module separately or a complete system has a wide range of applications. The proposed face recognition system can be used in access control systems, border control, forensics, banking sector, human computer interaction, patient monitoring, image database investigations, video indexing and others.

1.7. Approbation of the results

The main scientific achievements of the thesis have been presented in the following conferences:

- IEEE International Conference of the Biometrics Special Interest Group (BIOSIG 2012, Darmstadt, Germany), September 2012,
- IEEE International Conference on Imaging Systems and Techniques (IST 2012, Manchester, United Kingdom), July 2012

- 19th International Conference on Systems, Signals and Image Processing (IWSSIP 2012, Vienna, Austria), April 2012,
- International Conference of the Biometrics Special Interest Group (BIOSIG 2010, Darmstadt, Germany), September 2010,
- Conference ELEKTRONIKA 2010 (Kaunas, Lithuania), May 2010.

The main results of the thesis are discussed in the following scientific papers:

1. O. Nikisins and M. Greitans. Local binary patterns and neural network based technique for robust face detection and localization. *Proceedings of the Special Interest Group on Biometrics and Electronic Signatures (BIOSIG 2012)*, pages 147--158, September 2012
2. O. Nikisins and M. Greitans. A mini-batch discriminative feature weighting algorithm for lbp - based face recognition. *Peoceedings of IEEE International Conference on Imaging Systems and Techniques (IST 2012)*, pages 170--175, July 2012
3. O. Nikisins and M. Greitans. Reduced complexity automatic face recognition algorithm based on local binary patterns. *Peoceedings of 19th International Conference on Systems, Signals and Image Processing (IWSSIP 2012)*, pages 447--450, April 2012
4. Olegs Nikisins, Modris Greitans, Rihards Fuksis, Mihails Pudzs, and Zanda Serzane. Increasing the reliability of biometric verification by using 3d face information and palm vein patterns. In Arslan Brömme and Christoph Busch, editors, *BIOSIG*, volume 164 of *LNI*, pages 133--138. GI, 2010
5. O. Nikisins, R. Fuksis, M. Greitans, and M. Pudzs. Infrared imaging system for analysis of blood vessel structure. *Elektronika ir Elektrotechnika*, (1):45--48, 2010

Three publications [18], [19], [20] are indexed in IEEEXplore Digital Library. All publications are indexed in Scopus database.

The results are utilized in the following research projects:

- Nr. 2DP/2.1.1.1.0/APIA/VIAA/098 - Multimodal biometric technology for safe and easy person authentication - managed by Dr.sc.comp. Modris Greitans,
- Nr. 2009/0219/1DP/1.1.1.2.0/09/APIA/VIAA/020 - R & D Center for Smart Sensors and Networked Embedded Systems - managed by Dr.sc.comp. Leo Selavo (2010-2012).

1.8. Organization of the thesis

The main body of the thesis is organized in introduction (Chapter 1) and 5 chapters as follows:

Chapter 2 introduces the theoretical preliminaries of the thesis. The basics of Local Binary Patterns and their extension namely Multi-scale Local Binary Patterns are discussed in the first part of the chapter. These operators underlie the feature extraction modules in all blocks of automatic face recognition system. The dimensionality of the feature space affects the computational speed of the algorithms and memory requirements to store the data, thus the techniques for dimensionality reduction are also covered in Chapter 2. A brief overview of popular classifiers concludes the chapter.

Chapter 3 is dedicated to the problem of frontal face detection in digital still images. The main face detection approaches, including previous LBP-based detection techniques, are reviewed and a novel cluster of LBP-based face detection techniques is introduced. Significant attention is given to a unified principle of performance evaluation. The description of experimental setup and overall analysis of the performance of the detector is given in the conclusion.

Chapter 4 covers a second stage of automatic face recognition process, namely eye localization. The prior work in the field of eye localization, including previous LBP-based eye localization techniques, are briefly discussed at the beginning. A novel eye localization approach is introduced next. It consists of two main blocks: localization of eye regions and detection of eye pupils in the eye images. The first block is an extension of previously described face detection technique to another task. The second atypical stage complements the algorithm in order to raise the localization precision. The evaluation methodology, experimental setup and performance analysis concludes the chapter.

Chapter 5 addresses the problem of face recognition. Significant papers in the field of face recognition, including LBP-based techniques, are observed first. Proposed LBP and MSLBP-based face recognition approaches are described in details next. Significant attention is given to a novel mini-batch discriminative feature weighting algorithm both in feature and block levels. The mathematical and visual interpretation of the algorithm is presented. Experimental evaluation of the proposed face recognition methodologies is provided at the end of the chapter.

Chapter 6 describes the embedded implementation of automatic face recognition system in the TMS320C6416 DSP. The algorithmic part of the system is proposed first. The local face database is collected in order to test the system and analyze the performance of the algorithms. The structure of the system, implementational details and timing analysis are covered in the conclusion of the chapter.

2. THEORETICAL PRELIMINARIES

Chapter 2 introduces the theoretical preliminaries of the thesis. One of the most fundamental tasks in computer vision and pattern recognition is feature extraction [10]. The input signal of any computer vision system is usually a digital image or a video stream, which in turn is the set of pixels. Pixel value can potentially be considered as the simplest feature for object description, however such feature selection is very inefficient due to low robustness of the descriptor to various transformations and possibly very high dimensionality of the feature space. Therefore the design of feature extraction block is a field of extensive research, where a plethora of both hand-crafted and analytically well-founded techniques have been developed. The proposed algorithms are based on Local Binary Patterns transformation, therefore the details about LBP are introduced below.

LBP operator for the first time was introduced in [22] as a texture descriptor. In the input image each pixel is labelled by thresholding its 3×3 - neighborhood with the center value and representing the result as a binary number. An example of the labeling procedure for 3×3 region of an input image is illustrated in Figure 2.1. The histogram of labels is used as the descriptor of the image. Later extensions of LBP operator [23] use neighborhoods of different sizes.

The notation (P, R) is usually used for neighborhoods description [23] , where P is the number of sampling points on a circle of radius R. A histogram $\boldsymbol{h}$ of the labelled (LBP) image $\boldsymbol{I}_L(x, y)$ can be calculated:

$$h_i = \sum_{x,y} f(\boldsymbol{I}_L(x, y) = i - 1), i = 1, \ldots, n, \tag{2.1}$$

where $n = 2^P$ is the number of different labels and

$$f(A) = \begin{cases} 1, & A \text{ is true} \\ 0, & A \text{ is false.} \end{cases} \tag{2.2}$$

Histogram in the Equation (2.1) effectively represents the distribution of the gray-scale values in the digital input image [26], but the spatial information about the object is lost. In order to save spatial information about the object the division of the LBP transformed image into small regions $R_1, R_2, \ldots, R_m$ is required, where m is the number of regions. The regioning process has a lot of possible variations: regions could be of arbitrary shapes and dimensions, in different locations and with mutual overlapping. In order to simplify the regioning procedure the devision of the LBP image into $K \times K$ regions is selected, where K is the number of columns and rows in the regioning grid, in Figure 2.2 $K = 6$.

A spatially enhanced histogram is calculated by the substitution of region histograms into a

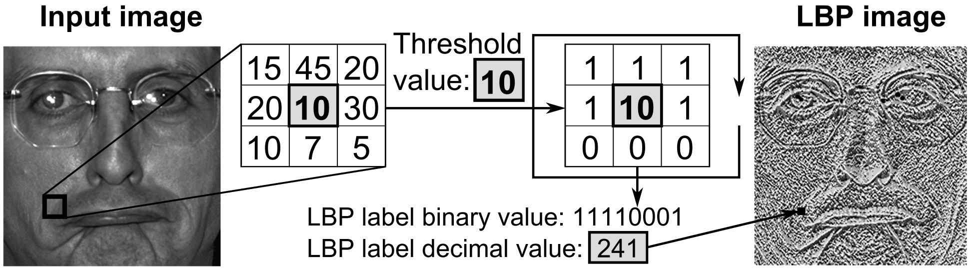

Figure 2.1: An example of labelling process of 3×3 neighborhood, $(P = 8, R = 1)$

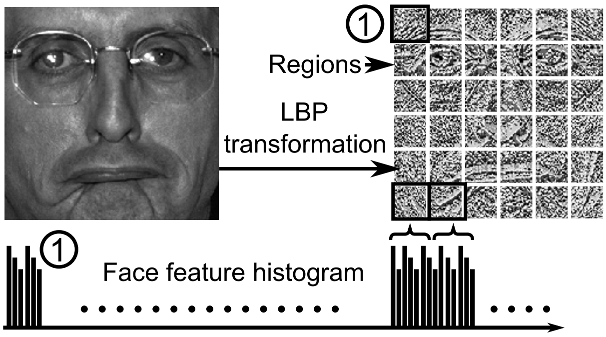

Figure 2.2: The process of spatial LBP histogram calculation, the regioning grid is 6×6

single feature histogram:

$$h_{i+n\cdot(j-1)} = \sum_{x,y} f(\boldsymbol{I}_L(x,y) = i-1) \cdot f((x,y) \in R_j), i = 1,\ldots,n, j = 1,\ldots,m. \tag{2.3}$$

The process of spatial LBP histogram calculation is schematically displayed in Figure 2.2. The vector $\boldsymbol{h}$ is now effectively represents both local and global features of the object.

In real life systems the scales of captured objects are different. The normalization of the spatially enhanced histogram $\boldsymbol{h}$ is needed before the classification step in order to get a coherent description:

$$h_i \equiv h_i / \sum_{j=1}^{N} h_j, i = 1,\ldots,N, \tag{2.4}$$

where N is the number of the elements in the vector $\boldsymbol{h}$. In general N is equal to $N = 2^P \cdot K^2$.

Another aspect which affects the performance of the system and memory requirements is the dimensionality of the feature space. Thus, the dimensionality reduction techniques are discussed next in the thesis. The simplified approach of dimensionality adjustment is based on varying the parameter P of LBP operator. A more sophisticated methodology incorporates the Principal Component Analysis.

Each block of face recognition system contains a classifier. Therefore the description of popular classifiers (Artificial Neural Network, Support Vector Machines, Nearest Neighbor Classifier) concludes the second chapter.

3. FACE DETECTION

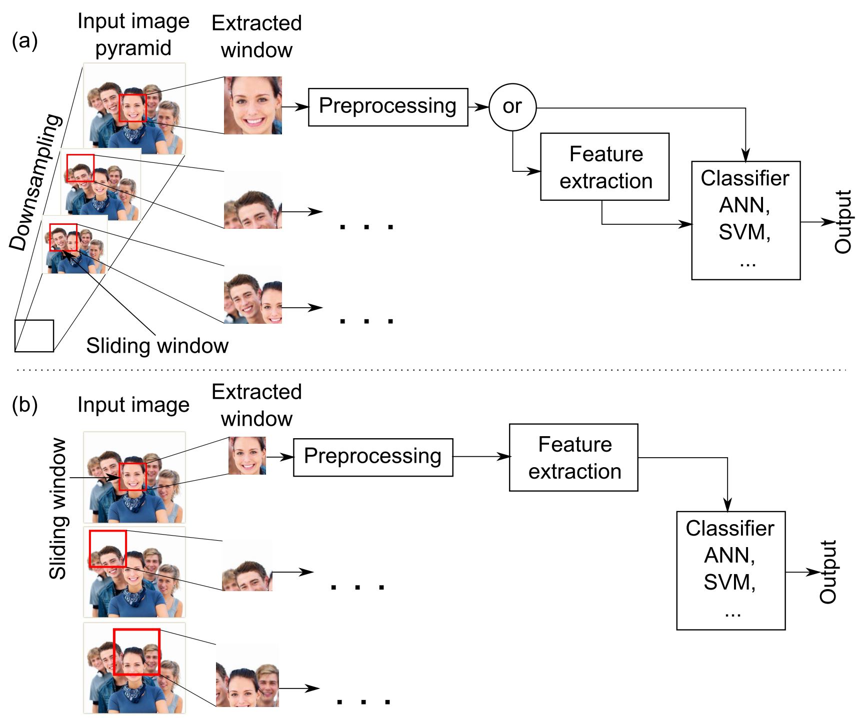

Figure 3.1: The block-diagram of appearance-based face detection system with two sliding window concepts: (a) - constant size of the sliding window, and (b) - variable size of the sliding window

Third chapter of the thesis is dedicated to the face detection problem. The significant results in the field are discussed first, including the LBP - based approaches. According to the taxonomy of [32] these methods can be divided into three main categories: *feature-based*, *template-based* and *appearance-based* face detectors.

Appearance-based approaches perform scanning of the input image with a small overlapping windows with the purpose of searching the most likely face candidates. Appearance-based methods are the most popular in object detection tasks. Most of the modern appearance based approaches rely on statistical classifiers, which are optimized using the sets of labeled face and non-face training examples. The block-diagram of the appearance-based face detection system is displayed in Figure 3.1. The proposed face detection algorithms belong to the concept (b), which in general is more effective due to the absence of the down-sampling stage.

The proposed face detection approaches are based on the LBP transformation and various classifiers.

The general structure of the LBP - based face detection algorithms is schematically displayed in the Figure 3.2. The first step of the algorithm is to calculate the LBP transformation of the input image, Figure 3.2 (2). The LBP transformed image is scanned with the sliding window of

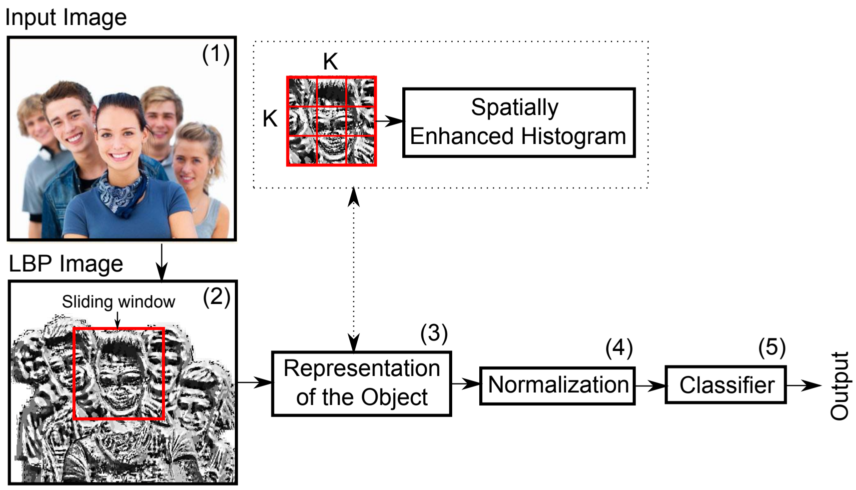

Figure 3.2: The block-scheme of proposed LBP based face detection algorithms

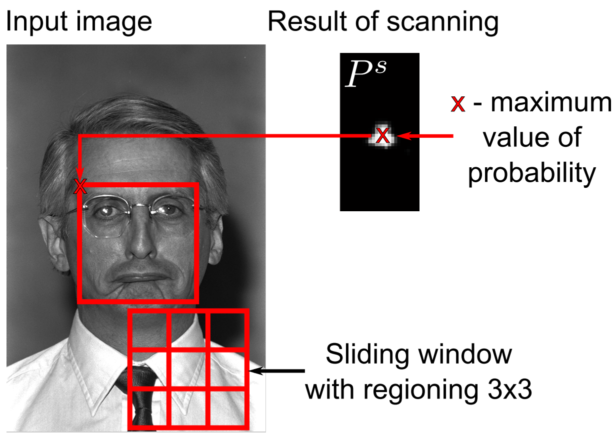

Figure 3.3: An example of the probability matrix $\boldsymbol{P}^s$ for ANN classifier with following scanning parameters: regioning grid $K = 3$, step of the sliding window is equal to 5 pixels, size of the sliding window is equal to the expected size of the face

variable size. At each position of the sliding window the representation of the object is calculated. The spatially enhanced histogram is selected as the representative feature vector in order to introduce the spatial information about the face in the feature vector. The length of the feature vector is: $N = K \cdot 2^P$. The normalization of the feature vector is needed at each scanning position due to variable size of the sliding window in order to get a coherent description of the face, Equation (2.4). The last block of the face detector is classifier, which determines the class of the object inside the sliding window. The result of scanning and classification is the probability matrix $\boldsymbol{P}^s$. The position of the maximal value in the probability matrix determines the position of the face in the input image, see Figure 3.3 for details.

The proposed face detection algorithms are tested on the color FERET face database [1]. Each image in the database contains a single face, which is a realistic scenario in biometric solutions. The correct face detection is determined with two main parameters: the displacement of face region from the expected (ground-truth) face position; the deviation between the detected and actual sizes of the face.

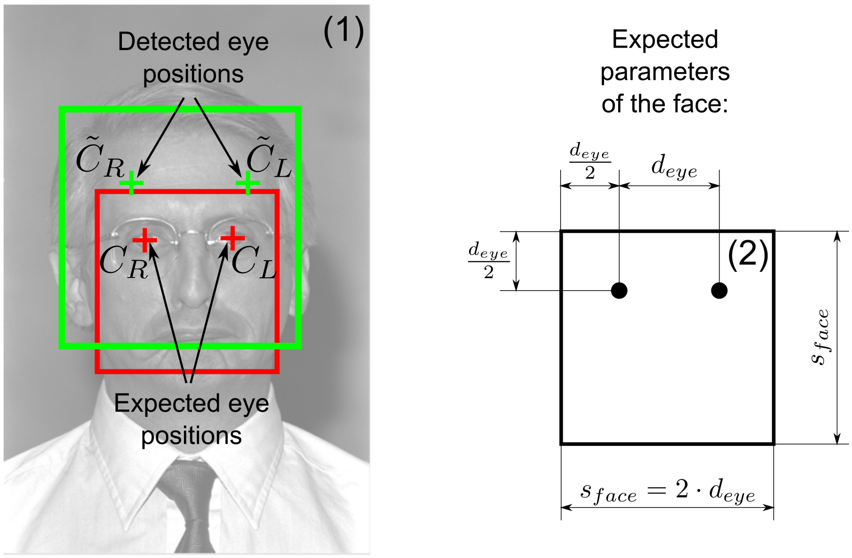

Figure 3.4: The displacement of the detected eye positions from the expected coordinates (1); the expected parameters of the face (2)

Both of the above parameters may be encoded into a single restrictive criteria. Authors in [12] introduced a relative error measure based on the distance between the detected and the expected eye center positions. The criteria for the evaluation of the detector performance can be written as follows:

$$\eta_{face} = \frac{\max(d(C_L, \tilde{C}_L), d(C_R, \tilde{C}_R))}{d(C_L, C_R)}, \tag{3.1}$$

where the notation $d(a, b)$ stands for the value of Euclidean distance between points a and b. The meaning of the corresponding points is explained in Figure 3.4.

In literature a successful detection is often accounted if $\eta_{face} \leq 0.25$, which corresponds to a quarter of an interocular distance [25]. The distribution of the proposed errors η_{face} for all faces in the test set is converted into empirical cumulative form. Such representation is called Empirical Cumulative Distribution Function (ECDF).

Significant part of the chapter presents the description of the simulation process and analysis of the results. Simulations are performed with various parameters of the system and for different classifiers. The proposed methods slightly outperform the Haar-like face detector [31], which is one of the most popular face detectors nowadays, see 3.1 Table for details.

Table 3.1:
Comparison of face detection algorithms

Method:	Parameters:	P($\eta_{face} \leq 0.25$)
LBP+SVM	$K = 5$, $N^{SV} = 144$	99.7%
Haar-like features [31]		99.5%
LBP+SVM	$K = 4$, $N^{SV} = 124$	98.2%
LBP+ANN	$K = 4$, $s_{L-1} = 10$	86.9%

4. EYE LOCALIZATION - BASED FACE ALIGNMENT

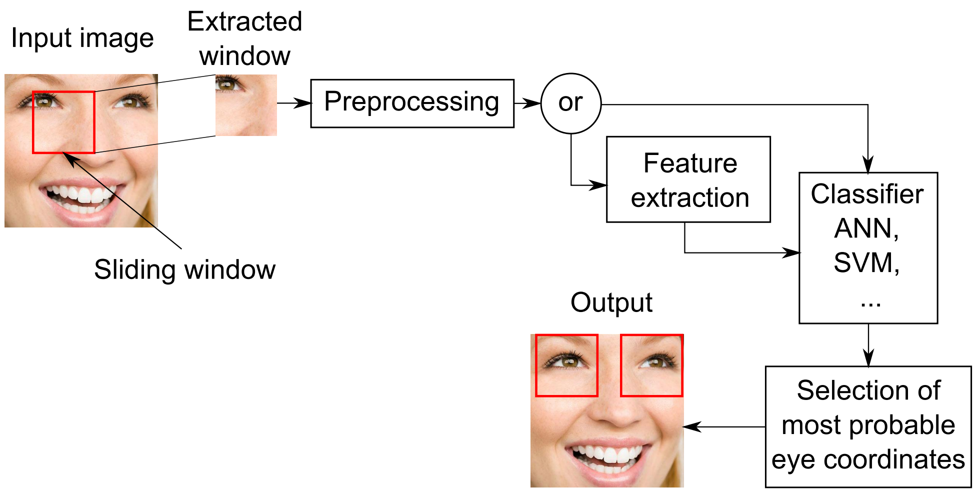

Figure 4.1: The block-diagram of appearance-based eye localization system with a sliding window concepts

Chapter 4 of the thesis is dedicated to the problem of face alignment. Face alignment allows to define facial parameters more accurately based on the locations of such facial features as eyes, nose, mouth and chin. Eye pupils are selected as the reference points for the face alignment algorithm.

The significant results in the eye localization field are discussed first, including the LBP - based approaches. Similar to the face detection taxonomy of [32] the eye localization methods can be divided into two main categories: *template-based* and *appearance-based* eye detectors.

Template-based approaches are robust in a wide range of pose and expression variability. Probably most widely-used techniques in the field of template based eye localization are *deformable face models* [16].

The proposed eye localization algorithms belong to the second group: *appearance-based* methods. Appearance-based approaches perform scanning of the input image with a small overlapping windows with the purpose of searching the most likely eye candidates. The block-diagram of the appearance-based eye detection system is displayed in Figure 4.1.

The proposed LBP - based face alignment algorithms can be divided into two steps:

- *Localization of eye regions* - in this stage the squared eye regions are detected in the face image. The center of the squared region is an approximate position of the eye.
- *Localization of eye pupils* in the eye images - in this step the centers of eye pupils are detected. Eye pupils are considered to be a good reference points in the face.

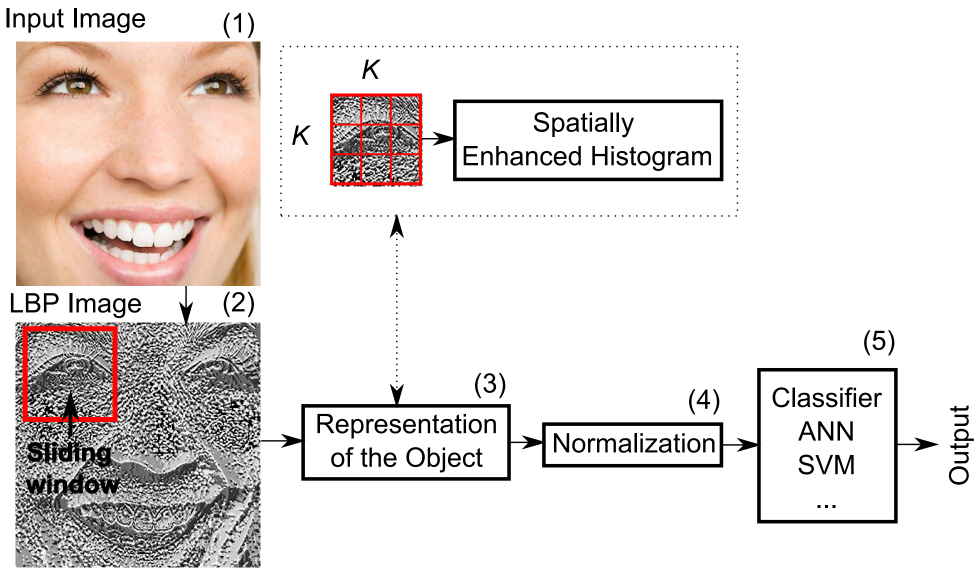

Figure 4.2: The block scheme of the proposed LBP - based eye localization algorithm

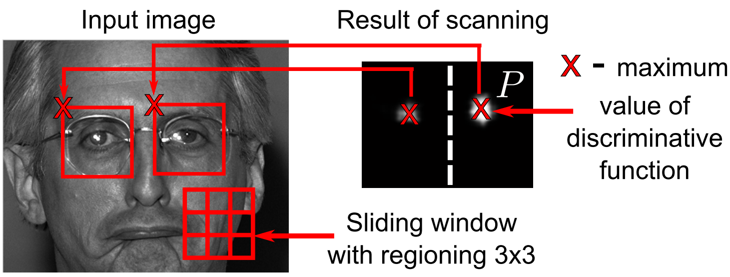

Figure 4.3: An example of the probability matrix $\boldsymbol{P}$ with following scanning parameters: $K = 3$, step of the sliding window is 2 pixels, size of the sliding window is equal to the size of detectable object

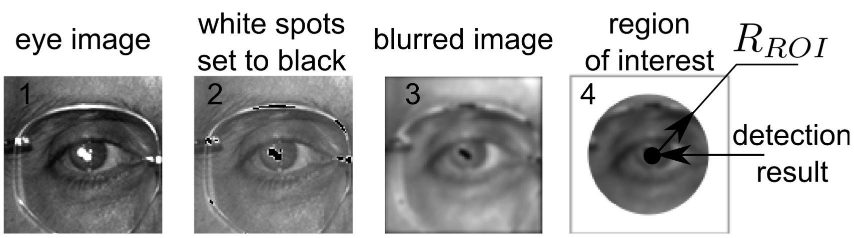

Figure 4.4: The process of eye pupil detection in the eye image

Localization of eye regions, which is the first step of face alignment algorithm, is based on the LBP transformation. The general structure of the LBP - based localization of eye regions is schematically displayed in the Figure 4.2. The principle of operation is similar to the face detection task and is discussed in the previous chapter. An example of the scanning result in the case of ANN classifier is displayed in the Figure 4.3, where $\boldsymbol{P}$ is the probability matrix. The coordinates of maximums in the probability matrix refer to the most likely positions of the eyes in the facial image.

Localization of eye pupils is the second part of face alignment algorithm. Previously de-

Table 4.1:
Comparison of eye localization algorithms

Method:	Parameters:	P($\eta_{eye} \leq 0.1$)
LBP+ANN (our)	$K = 3$, $s_{L-1} = 10$	96.7%
LBP+SVM (our)	$K = 3$, $N^{SV} = 216$	96.3%
PSEF [27]		83.0%
ASEF [4]		66.1%
Haar-like features [27], [31]		44.7%

scribed methodology for the detection of eye regions is quite insensitive to small detection offsets, a few more steps are needed to achieve the desired localization performance. These steps are based on the detection of eye pupils in the segmented eye images and are schematically displayed in Figure 4.4.

First, bright spots in the eye image are set to black, which is needed to reduce the effect of light - striking, Figure 4.4, image 2. The resulting image is blurred with Gaussian low-pass filter. Next, the disc shaped region of interest (ROI) is selected. The radius of the ROI R_{ROI} is selected according to the localization precision of the proposed eye region detector. Coordinates of the minimum (Figure 4.4, image 4) define the position of the eye pupil center in the eye image. Facial region can be precisely extracted from the input image based on the positions of eye pupils. This is the final step of face alignment procedure.

The proposed face alignment algorithms are tested on the color FERET database [1]. The measure of localization error is similar to the one described in Chapter 3, Equation (3.1). The acceptable value for η_{eye} lies in the range $\eta_{eye} \leq 0.1$, which is a more strict criteria than in the face detection task.

Significant part of the chapter presents the description of the simulation process and analysis of the results. Simulations are performed with various parameters of the system and for different classifiers. The main results are conducted in Table 3.1.

The proposed methods (LBP+ANN un LBP+SVM) significantly outperform other observed eye localization principles in terms of localization precision, see 3.1 Table for details.

While the Haar-like features are effective in face detection task (Table 3.1), this method significantly inferior in accuracy to our eye localization algorithm. Thus the cluster of proposed detection principles has a better generalization to various tasks. The correlation filters (PSEF and ASEF) for object detection are very effective in terms of computational time both for learning and detection stages, however the localization accuracy is still not high enough (see Table 4.1 for details).

5. FACE RECOGNITION

Chapter 5 of the thesis is dedicated to the face recognition problem, which is the last module of automatic face recognition system, Figure 1.1. All biometric systems perform recognition, but the recognition task can be divided in two groups: verification and identification. Identification occurs when the system attempts to determine the identity of an individual. A biometric data is collected and compared to all the templates in the database. The scope of this research is limited to *identification* task, which in general is more complicated than the verification problem.

The significant results in the field of face recognition are discussed first, including LBP-based approaches. To have a clear and high-level categorization, authors in [34] introduced the idea to follow a guideline suggested by the psychological study of how humans use holistic and local features. Specifically, the following categorization was offered:

- *Holistic matching methods.* Holistic methods use the whole face region as the raw input to a recognition system. One of the most widely used representations of the face region is eigenpictures [14] which are based on Principal Component Analysis.

- *Feature-based (structural) matching methods.* These methods typically utilize local features of the face, their locations and local statistics. Popular facial features are eyes, nose, and mouth. One of the first face recognition systems utilized feature-based approach [13].

- *Hybrid methods.* In this approach both local features and the whole face region are used to recognize a face. These methods could potentially offer the best of the two types of the above methods. The idea of hybrid approach is the most similar to the human perception system. The proposed face recognition methods belong to this group.

Proposed face recognition algorithms are based on the LBP transformation of the input face image. The spatially enhanced histogram of the labeled image $\boldsymbol{I}_L$ (Equation (2.3)) effectively represents both global and regional features of the face, however some advanced optimization and preprocessing steps are needed in order to get high performance face recognition system. The first phase of the proposed face recognition algorithm is the preprocessing of the input gray-scale image, which consists of two steps:

- input image rotation. This stage performs upright rotation of the input facial image in order to make the eye line horizontal.

- face region extraction. The region of the face in the input image is limited by the bounding box, which is determined by four coordinates: X_{start} and Y_{start} horizontal and vertical coordinates of the starting point of facial region, X_{end} and Y_{end} horizontal and vertical coordinates of the end point of facial region. These coordinates are defined as follows:

Figure 5.1: An example of face images used in the face recognition algorithms

$$
\begin{aligned}
X_{start} &= \text{max}\left(\{1, \text{round}\left(X(C_R) - 0.9 \cdot d_{eye}\right)\}\right), \\
X_{end} &= \text{min}\left(\{X_{max}, \text{round}\left(X(C_L) + 0.9 \cdot d_{eye}\right)\}\right), \\
Y_{start} &= \text{max}\left(\left\{1, \text{round}\left(\frac{Y(C_R) + Y(C_L)}{2} - 1.4 \cdot d_{eye}\right)\right\}\right), \\
Y_{end} &= \text{min}\left(\left\{Y_{max}, \text{round}\left(\frac{Y(C_R) + Y(C_L)}{2} + 1.9 \cdot d_{eye}\right)\right\}\right),
\end{aligned}
\tag{5.1}
$$

where the notations $X(C_R)$ and $X(C_L)$ stand for the X coordinates of the left and right eye pupils in the *rotated* input image and $Y(C_R)$, $Y(C_L)$ are the corresponding Y coordinates. X_{max} and Y_{max} are the width and hight of the input image in pixels. The examples of enhanced facial images that are utilized in the recognition process are displayed in the Figure 5.1.

Once preprocessing steps are completed the LBP or MSLBP transformation is performed as illustrated in Figure 2.2. The transformed image is divided into $K \times K$ regions to save the spatial information about the object. The spatially enhanced LBP histogram of the length $N = K^2 \cdot 2^P$ is calculated next according to the Equation (2.3). The normalization of spatially enhanced LBP histogram is performed according to the Equation (2.4) in order to get a coherent description.

For pattern classification in the face recognition tasks a nearest neighbor classifier is usually used [3]. Among the most popular approaches for similarity/dissimilarity measures are Histogram intersection, Chi-square statistics and Squared Euclidean distance. A usual problem in face recognition is having plenty of classes and only a small number, possibly even one, training sample per class [3]. This fact degrades the usability of complicated classifiers, such as Neural Networks or SVM, in face recognition. For this reason, we have developed a new learning algorithm, which iteratively adjusts the weights in the wighted nearest neighbor classifier. The combination of the the proposed weighting technique with WNNC is an effective solution for multi-class classification problems with poor intra-class training data.

The weighting principle is enhanced for the optimization in two levels: block-level weighting and feature-level weighting, see Figure 5.2 for details. The NNC classifier can be transformed to WNNC form by utilizing weighted distances. For example, the histogram intersection can be written as follows:

$$
d^{fw}(\boldsymbol{h}^{(1)}, \boldsymbol{h}^{(2)}) = \sum_{i=1}^{N} \min(w_i h_i^{(1)}, w_i h_i^{(2)}), \tag{5.2}
$$

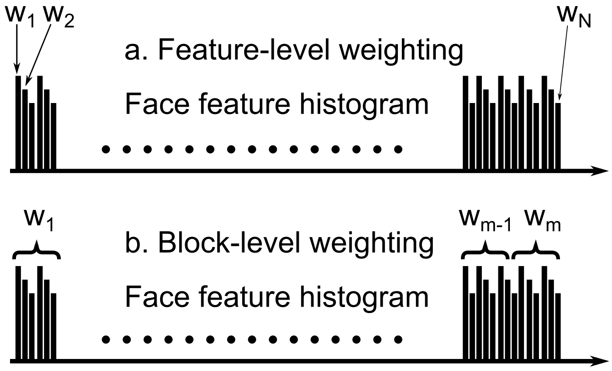

Figure 5.2: Approaches for weighting in the feature (a) and block (b) levels

where d^{fw} is the value of the distance with feature level weighting, w_i is the weight of the parameter h_i.

$$d^{bw}(\boldsymbol{h}^{(1)}, \boldsymbol{h}^{(2)}) = \sum_j \sum_i \min(w_j h_{i,j}^{(1)}, w_j h_{i,j}^{(2)}), \tag{5.3}$$

where d^{bw} is the value of the distance with block level weighting, i - is the number of the parameter in block j. According to our experiments histogram intersection is the most robust method for similarity measure and constantly provides the best recognition results.

The purpose of discriminative feature weighting algorithm is to place the intra-class (same class) training examples as close as possible along with keeping the inter-class (different classes) feature vectors as far as possible. From the user point of view the algorithm performs two useful functions:

- Compresses unstable features / data,
- Improves the classification precision of the WNNC approach by adjusting the feature weights.

An intuitive explanation of above principles is discussed next. Let's consider a very simple classification example with only three classes and each feature vector has only two parameters/coordinates, thus $M = 3$ and $N = 2$. Each feature vector can be represented as a point in 2D space, see Figure 5.3 for details (points with "o" and "+" markers). For each class only two training examples are given: $\boldsymbol{x}_i^{(1)}$ and $\boldsymbol{x}_i^{(2)}$, where $i = (1, 2, \ldots, M)$ is the number of the class.

The introduced mini-batch discriminative feature weighting algorithm is applied next in the feature-level, which iteratively adjusts the weights (w_1, w_2) of each parameter $(x_{i,1}, x_{i,2})$ in the feature vectors. The *initial* intra-class (same class) training examples in the Figure 5.3 are scattered from each other *mostly* in the vertical direction (along $x_{i,2}$ coordinate axis; the class-bounding ellipses are stretched vertically). Thus, the main classification error is incorporated by parameter $x_{i,2}$. The initial weights in the example (Figure 5.3) were $(w_1 = 1, w_2 = 1)$, and after 50 iterations of the weights adjustment algorithm the new values are $(w_1 = 1.43, w_2 = 0)$. The algorithm projected all feature vectors on the horizontal axis $x_{i,1}$ and the error-prone parameter

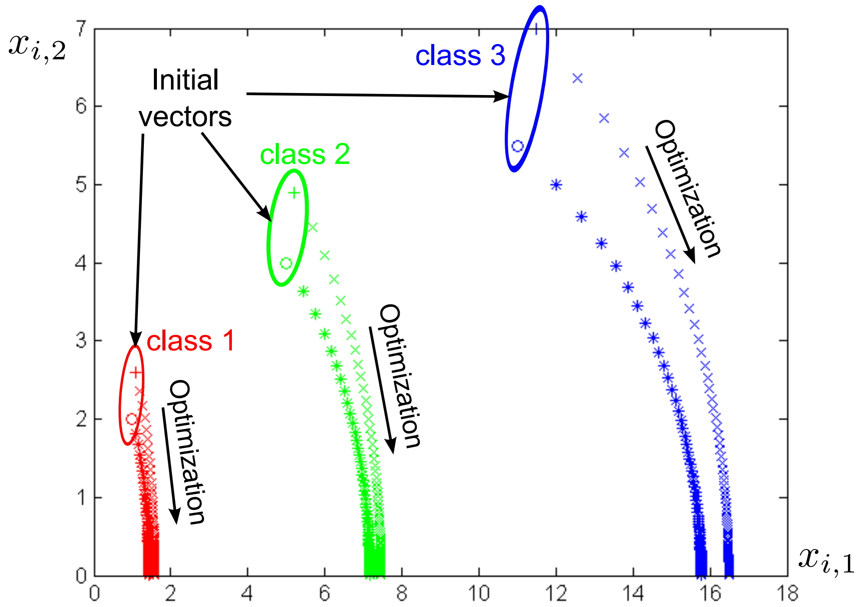

Figure 5.3: Visualization of optimization path of discriminative feature weighting algorithm for 3-class example in 2D feature space

$x_{i,2}$ is excluded from the recognition process (the weight w_2 is set to zero). The optimization path in the Figure 5.3 is displayed with "*" and "x" markers. The recognition precision both before and after optimization is on 100% level, but in this case the algorithm compressed unstable parameter.

Let's consider a more complicated classification example with five classes and 2D feature vectors, thus $M = 5$ and $N = 2$. Still only two training examples are given for each class: $\boldsymbol{x}_i^{(1)}$ and $\boldsymbol{x}_i^{(2)}$, where $i = (1, 2, \ldots, 5)$ is the number of the class. Additionally, the *initial* intra-class (same class) training examples in the Figure 5.4 (points with "o" and "+" markers) are now scattered from each other both in vertical and horizontal directions (the class-bounding ellipses are stretched vertically for classes 1,2,3 and horizontally for classes 4,5). Thus, the trivial solution with one of the weights equal to zero is not possible.

Again, a mini-batch discriminative feature weighting algorithm is applied in the feature-level. The initial weights in the example (Figure 5.4) were $(w_1 = 1, w_2 = 1)$, and after 200 iterations of the weights adjustment algorithm the new values are $(w_1 = 1.67, w_2 = 5.51)$. The result of optimization is displayed in the Figure 5.4. Suppose, that in the *initial state* samples which are marked with "+" symbol are stored in the database (*gallery* set) and "o"-marked samples are unknown feature vectors that are presented to the classification algorithm (*probe* set). If NNC classifier is used then the *initial* classification/recognition precision equals $P(w_1 = 1, w_2 = 1) = 3/5 = 60\%$. The patterns in the classes 4 and 5 were classified incorrectly. After the weighting is completed the *gallery* set is marked with "x" symbols and the *probe* set is marked with "*". In this case the classification precision becomes $P(w_1 = 1.67, w_2 = 5.51) = 5/5 = 100\%$. The feature vectors in classes 1,2 and 3 are now more scattered, while the opposite statement is true for classes 4 and 5. The gain in the performance of the classification

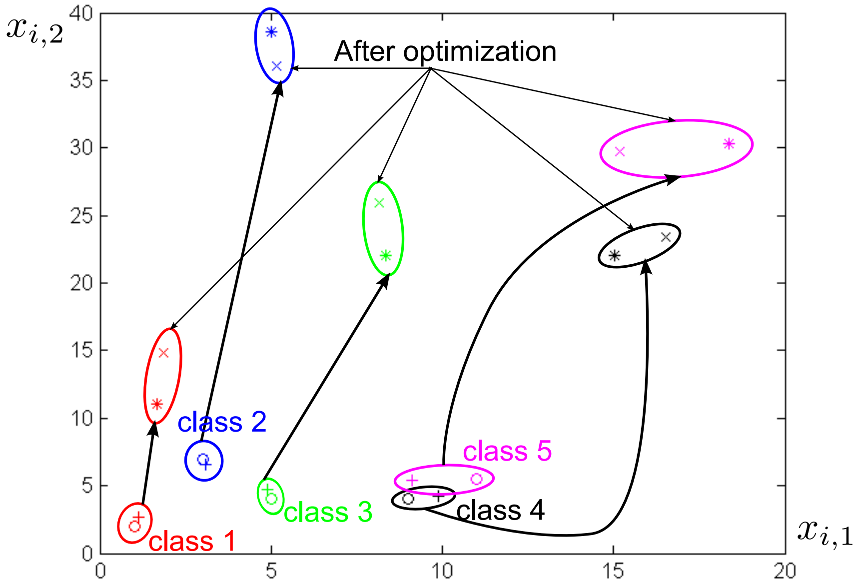

Figure 5.4: Visualization of the result of discriminative feature weighting algorithm for 5-class example in 2D feature space

Table 5.1:
Comparison of face recognition algorithms (**fa** and **fb** subsets of a color FERET)

Method:	Parameters:	$P_I(r=1)(\%)$
MSLBP + MF + EFW + IBW + PCA (our)	$N = 731$ Histogram intersection	99.1
MSLBP + MF + EFW + IBW (our)	$N = 16384$ Histogram intersection	**99.2**
MSLBP, our implementation of [6]	$L_{MSLBP} = 11$, $K = 8$, $P = 8$, $n_R = 3$, histogram intersection	96.8
MSLBP + LDA [6] (tested on **FERET**)		98.9
MSLBP [6] (tested on **FERET**)	Histogram intersection	95.6
LBP + EFW + IBW	Histogram intersection	98.9
LBP, our implementation of [3]	$K = 8$, $P = 8$, $R = 3$ Histogram intersection	95.8
LBP + EBW [3] (tested on **FERET**)		97.0
LBP [3] (tested on **FERET**)		93.0
PCA [9]	L1-metric	82.3
ICA [9]	L2-metric	81.5
LDA [9]	L2-metric	82.8

process is obvious: $P(\text{NNC}) = 60\%$ and $P(\text{WNNC}) = 100\%$.

Evaluation of the proposed face recognition methodology is performed on a **color FERET** database [1]. The standard subsets **fa** and **fb** (frontal face images) are selected from the color FERET database. Usually two separate datasets, namely *gallery set* and *probe set* are needed for performance evaluation. The *gallery set* contains the data of known individuals. An image of an unknown face presented to the algorithm is called a *probe*, and the collection of probes is called the *probe set*. The subset **fa** is used as a *gallery set* and **fb** as a *probe set* [24]. The total number of classes / persons in the database is $M = 993$, and individuals were asked for a different facial expressions in **fa** and **fb** sets.

In our case a **closed universe model** is selected for the evaluation of the algorithm performance [24]. In a closed universe identification every probe image has a corresponding matching template in the database. This assumption allows to determine the ability of the algorithm to identify a probe image. The probability of correct identification at rank one $P_I(r = 1)$ is the parameter, which is often used in the literature to compare the performance of different algorithms [24].

The significant part of the chapter is dedicated to the description of simulation processes and analysis of the results. The comparative study of the introduced face identification methodology has shown an equivalent or even improved performance compared to state-of-the-art recognition techniques, see Table 5.1 for details.

6. IMPLEMENTATION OF AUTOMATIC FACE RECOGNITION ALGORITHM IN DIGITAL SIGNAL PROCESSOR

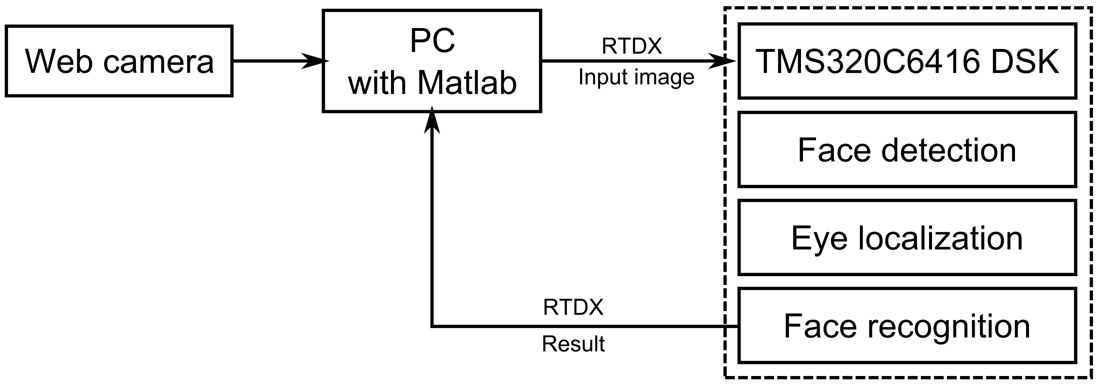

Figure 6.1: A block-scheme of the DSP based automatic face recognition setup

Chapter 6 is dedicated to the description of implementation of automatic face recognition system in digital signal processor (DSP). Face recognition systems is a significant part of todays video surveillance and biometrics markets [11]. The transition of biometric algorithms from research laboratories to real world products places new demands on the system: power consumption and cost become critical issues. An embedded implementations become attractive. One of possible approaches is to design the DSP-based system. The goal of this research is to evaluate the performance of face recognition system on the TMS320C6416 platform and to determine the feasibility of DSP-based implementation. The results show that LBP-based automatic face recognition algorithm is potentially a good choice for the design of embedded system.

At the beginning of the chapter on overview of embedded face recognition systems is given. Both laboratory and commercial solutions are described.

Significant part of the chapter covers the description of algorithmic basis of the system, which consists of three main stages: face detection, face alignment and face recognition. All functional blocks of the system are based on the LBP transformation and are covered in [20].

A fully automatic face recognition algorithm is implemented on TMS320C6416 DSK development board, which contains a TMS320C6416 fixed-point digital signal processor operating at 600 MHz and an external non-volatile Flash memory of size 512 Kbytes. Introduced implementation follows the the block diagram shown in the Figure 6.1. The experimental setup consists of three main blocks: *web camera*, *PC with installed Matlab software* and *TMS320C6416 DSK*. The functionality of these blocks is as follows:

Web camera - is a capturing device. A still input image of the face is obtained from this device by a computer. The Prestigion 2.0 Mega-pixels camera PWC2 is selected for experiments.

Table 6.1:
Performance profile of DSP based automatic face recognition algorithm

	CPU cycles ($\times 10^6$)	Computation time (CPU at 600 MHz)
LBP transformation	658	1.10 seconds
Face detection	314	0.52 seconds
Eye localization	1137	1.90 seconds
Face recognition	167	0.28 seconds

PC with Matlab software. One of the primary functions of the PC is a user-computer interface. It displays video from the web camera on the screen as a reference information for the user. When the face is in the desired position (70 to 90 centimeters from the camera, frontal view) a frame is captured by a single button press on the keyboard. The image is then preprocessed to a gray-scale format of the resolution 460×614 pixels and is transfered to the DSP via RTDX (real-time data exchange) interface. The TI C6000 DSP toolbox is needed for Matlab in order to use this interface. Once the processing of the input image is completed on the DSP the coordinates of eye pupils and the recognition result are transfered to the PC via RTDX. The information about eye pupils is utilized as a reference data that guarantees the correct operation of face detection and eye localization blocks. The recognition result is represented in the form of image number in the face database that is most similar to the input face image. An image of the identified individual from facial dataset is then displayed on the screen.

TMS320C6416 DSK is the main processing unit in the system. All stages of automatic face recognition process are implemented in the DSP: face detection, eye detection and face recognition. Since TMS320C6416 signal-processor is a fixed-point device the C code is optimized to operate with integer data. This optimization has both positive and negative impact on the performance of the system. Obviously, the calculations are executed faster in the DSP, however the gain in the computation time is not known due to the absence of floating-point C implementation of the algorithms. While the precision of face and eye detection stages is not affected much by fixed-point simplifications, the error of face recognition stage slightly increased.

The execution times for each block of the system are displayed in Table 6.1. The size of the input image in this case is 460×614 pixels, the number of face patterns in the database is 100.

The resulting timing analysis confirms the feasibility of the proposed LBP and NNC based automatic face recognition algorithm in embedded systems. The recognition process requires less than 2.3×10^9 CPU cycles to process a single 0.3 Mpixel image. The proposed detection and recognition methodologies are histogram-based, thus the effective parallelization of the process is possible. Therefore, modern FPGA and multi-core DSP are potentially a better choice for embedded system design.

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