Biometric recognition through hand and face

Ivan Krevatin
Network Strategy and Service Planning Department
Hrvatski Telekom
Zagreb, Croatia
ivan.krevatin@t.ht.hr

***Abstract*—Hand and face provide a rich set of biometric data that can be used to build a biometric system. This paper gives an overview of the recognition techniques applied to hand and face biometrics. Detailed description of palmprint recognition systems is given, as well as the face recognition methods with some recent findings in age-invariant face recognition.**

Keywords: biometrics; palmprint recognition; hand shape; face recognition; principal component analysis; Fisher's linear discriminant; facial aging

I. INTRODUCTION

Establishing the proper connection between the physical and electronic identity is a major issue in the today's modern society. Biometrics uses physical, chemical or behavioural [1] attributes of the person in finding such connection and as such is one of the most powerful and reliable means of personal authentication [2]. In general, a biometric system captures the biometric data from an individual, extracts the relevant feature set from the data, compares this feature set against the feature set(s) previously stored in the database and based on the result of this comparison authenticates or not the individual.

The success of a biometric system depends in the first place on the proper choice of biometric data and then on the applied techniques that lead from raw data to the decision. Which biometric data will be used depends on the indented application domain of the system. The desirable characteristics of biometric data are [3]: (*i*) universality – every person should have this characteristic, (*ii*) uniqueness – no two persons should be identical in terms of the characteristic, (*iii*) permanence – the characteristic should be invariant over time and (*iv*) collectability – the characteristic can be measured quantitatively, (*v*) performance – refers to the identification accuracy depending on the resource requirements and environmental factors, (*vi*) acceptability – indicates the willingness of the people to provide this biometric characteristic, (*vii*) circumvention – refers to how easy is to fool the system by fraudulent techniques.

The human hand and face provide the source for a number of distinctive information suitable for building a biometric system. Facial dynamic features from which behavioral patterns are extracted include tracking the motion of skin pores on the face during a facial expression [4], smile recognition, eye blinking and lip movement which is typically used in multimodal biometric systems combined with speaker recognition [5]. Behavioral characteristic extracted from dynamic hand movements are: dynamic signature/handwriting recognition, gesture, handgrip, keystroke dynamics, tapping and mouse movements. Physiological characteristics commonly used in hand based biometrics are the fingerprint, hand geometry, palmprint and palm vein pattern using infrared imaging. When talking about face recognition, the term generally refers to the physiological part of face biometrics where 2D or 3D face images are used in recognition. Face recognition is the second most wide spread biometric technology after fingerprint [6] and the first selection for the machine readable travel document (MRTD) system [7] [8] based on the following criteria: enrollment, renewal, machine-assisted identity verification requirements, redundancy, public perception, and storage requirements and performance.

Biometrics have many advantages over traditional authentication systems, however when comparing passwords or identification numbers in traditional systems the only results of a comparison can be equal or not equal. In biometrics such comparison is performed based on a chosen similarity measure. Such approach is necessary because it is almost never the case that two biometric feature sets obtained from the same characteristic of a user are equal. The degree of similarity between the two feature sets defines a similarity match score. In biometric terms two feature sets are considered to be equal if the similarity score between them exceeds the predefined threshold value. Depending on the variability of the feature set of an individual (intra-class variation), the variability between the feature sets originating from two different individuals (inter-class variation) and the choice of the threshold the matching module of a biometric system generates two kind of error rates: (*i*) the False match rate (FMR) that indicates the rate the rate on which the module mistakes the feature sets originating from two different individuals to be from the same individual, and (*ii*) the False non match rate (FNMR) that indicates the rate on which the module mistakes the feature sets originating from the same individual to be from two different individuals. While the FMR and FNMR are the errors that indicate the performance of the matching module, in overall evaluation of the biometric system the False accept rate (FAR) and the False reject rate (FRR) are commonly used. The FAR and FRR are errors that are associated with verification and identification and are application dependant, i.e. depend on the type of identity claim made by the user [9], and are additionally influenced by errors of capture and feature extraction modules that can be commonly expressed with a Failure to acquire (FTA) measure. In literature [1] is often for simplicity FAR treated as synonymous with FMR and FRR as synonymous with FNMR. Details on the relationship between FAR and FMR, and FRR and FNMR can be found in [10].

The distribution of false accepts and false rejects is not evenly distributed across the users of the biometric system. The statistical testing procedures for detecting the users that have such characteristics that are increasing the errors of the system are analyzed by Doddington et al. [11]. Although the introduced classification of such subjects was proposed for speaker recognition systems it is applicable to other biometric modalities as well [1].

The performance of biometric systems is additionally measured with other types of parameters (e.g. failure to enroll, the average times of enrolment and recognition processes etc.). A deeper insight on the biometric system evaluation, performance measures and graphs can be found in [12]. For the purpose of the evaluation of biometric systems several biometric databases are made available [13] [14] [15] [16], as well as the reference systems and evaluation framework [17].

In this paper we give an overview of the research in the physiological biometric systems that use hand based and face characteristics. The rest of the paper is organized as follows. The Section II presents approaches in hand based biometrics focusing on palmprint recognition methods. Section III gives an overview of face biometrics including some findings in face recognition under temporal variations. Conclusions are given in Section IV.

II. HAND BASED BIOMETRICS

The human hand provides a rich set of biometric data that can be used in many ways, focusing on particular hand region such as the fingertip, finger, palm, dorsal hand and 3D hand models or combining the features extracted from multiple regions into a multimodal biometric system. The most prominent approaches are: (*i*) fingerprint, (*ii*) hand shape, (*iii*) palmprint, and (*iv*) hand vein biometrics. These approaches will be discussed in this section with detailed overview of the techniques applied in palmprint recognition.

A. Fingerprint

The fingerprint recognition systems are based on the characteristics of the structure of fingertip skin. The most evident characteristic is the pattern of ridges and valleys that form distinctive shapes classified as loops, deltas and whorls. The points where ridges become discontinuous are called minutiae. Beside that, at higher resolutions (e.g. 1000dpi) intra ridges details and sweat pores can be detected. Details on the methods applied for fingerprint recognition can be found in [9].

B. Hand vein biometrics

Infrared or near infrared imaging is used to capture dorsal [18], palmar [19] or finger [20] vein network structure. Systems use infrared light emitting diodes and CCD cameras with infrared filters and exploit the property of the deoxidized hemoglobin in the vein vessels to absorb the light with a wavelength of about 7.6 x 10^{-4} mm. The pattern of dark lines (veins) is visible on such images and further analyzed with suitable pattern recognition techniques.

C. Hand shape

The hand shape is widely exploited for extracting geometry features such as the widths, lengths and thickness of hand and fingers at various positions. Initial research systems [21] [22] and commercially available systems with patented capturing devices use the imaging system based on pegs, thus limiting the hand position on the sensor (Figure 1). Later research focuses on extracting hand geometry features from freely positioned hand on the sensor. Hand geometry features are combined with geometry features of principal lines of the palmprint [23], [24] and finger geometry features are combined with eigenfinger features [25].

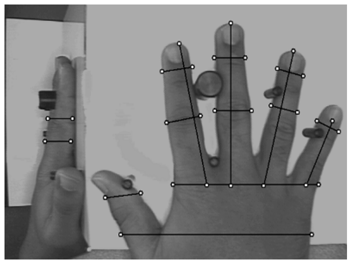


Figure 1. Hand geometry features [21]

All these approaches use image processing methods to localize and extract the hand contour and the characteristic points on it representing tops of the fingers and valleys between them. The contour and characteristic point are used in palmprint or finger recognition systems for localizing the region of interest of palm or fingers for further image processing and features extraction as well as for determination of hand position and orientation and its normalization.

Apart from measures expressed as widths and lengths, various other features can be extracted from the hand contour [26], like representing the contour with implicit polynomials or active shape models. In [27], Yörük et al. apply principal component analysis, independent component analysis, angular radial transform and distance transform both to hand shape and to palm texture features and present a comparative analysis of the methods.

D. Palmprint

1) Structure and acquisition methods

The palm is defined as the inner surface of the hand that extends from the wrist to the base of the fingers. Similar to fingerprints, the characteristic structure of the palm skin forms the palmprint. We can identify three types of lines in this structure [2]: flexure lines, tension lines, and papillary ridges. Figure 2 shows the palmar physiology with pointed out the types of lines and details that are found on the plamprint. Details on the palm texture genesis and forensic palmprint features can be found in [28].

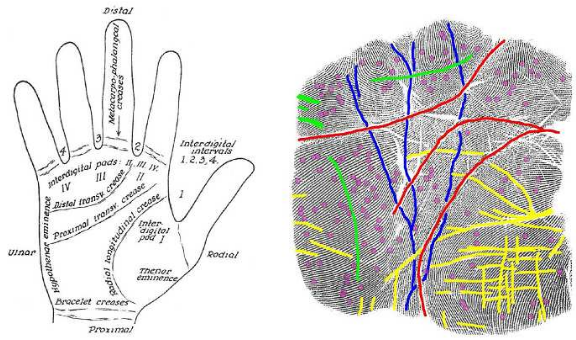


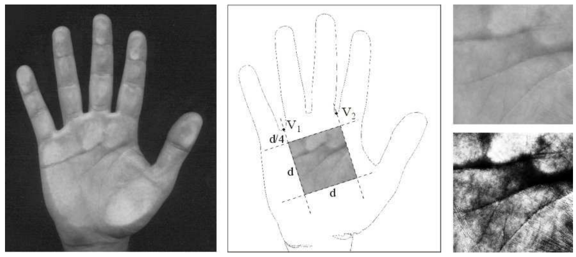
Figure 2. Palmar physiology: a) Anatomical landmarks for the palm; b) Main groups of palmar lines: principal lines (red), minor flexure lines (green), minor finger lines (blue), secondary lines (yellow) and papillary ridge details: minutiae (magenta) [28]

The palm region has a very rich texture and is much larger than the fingertip region therefore the research possibilities for palm features extraction are very extensive. From application point of view we can distinguish forensic and non-forensic plamprint recognition. Correspondingly the palmprint acquisition methods differ. The offline methods are more suitable for forensic applications where the palmprints, obtained by inking the palm surface and pressing it against the paper or collected as latent palmprints from the crime scene, are scanned at high resolutions (500 dpi or higher). For real-time applications like access control only online palmprint acquisition is applicable. Palmprints are scanned directly with a scanner or captured with a CCD camera. Using a camera results in much faster acquisition than using a conventional scanner, but the camera based acquisition devices are much larger due to the required palm camera distance depending on the camera lens angle and the need to position proper source of lighting. The description of the construction of various camera based palmprint acquisition devices can be found in [2] together with the description of the publicly available palmprint database [15] collected with such devices. The contact surface of such devices can cause users' discomfort due to hygienic reasons and dirty surface can deteriorate image quality. Recent researches focus on contactless plamprint acquisition [29].

2) Preprocessing

Before applying feature extraction techniques the preprocessing of acquired palmprint images needs to be performed. The role of preprocessing is to correct distortions by reducing noise and smoothing the images, and what is most important to put all palmprints under the same coordinate system. In that way the palmprint region of interest (ROI) can be extracted for further processing. The preprocessing is especially important in the systems that allow free placement of the hand on the sensor as the wrongly extracted ROI increases the system error rates.

Figure 3 illustrates the preprocessing steps applied in [30]. A square ROI is extracted from the centre of the palm. The ROI is defined on the basis of two stabile points on the contour of the hand: the first is located in the valley between the little finger and the ring finger, and the second is located between the index finger and the middle finger (marked with V_1 and V_2 on Figure 3 c). The preprocessing steps on a scanned palm image is shown, the same can be applied on camera images. The steps can be summarized as following: (i) global thresholding; (ii) border following; (iii) locating the region of interest (ROI); (iv) extracting the ROI and compensating for its rotation; (v) applying the Gaussian mask; (vi) resizing the ROI to a required size; and (vii) performing histogram equalization.



a b c

Figure 3. Illustration of preprocessing of palm images: a) input image, b) localization of the ROI, c) ROI before and after the histogram equalization [30]

The size and the shape of the ROI and which segmentation methods and how will they be applied in the preprocessing depends on the requirements of the palmprint recognition technique that is used. Beside square ROI, inscribed circle that meets the boundary of a palm [2] and polygonal [31] [32] approaches to ROI extraction are used. Edge detection operators (e.g. Sobel operator) are used to detect principal lines and datum points [33] for ROI definition.

3) Recognition techniques

Various recognition techniques have been used for palmprint recognition. We can distinguish the techniques that focus on image segmentation methods to directly extract features from palmprint lines and points, and techniques that apply different transformations to the whole palmprint ROI and extract features in the transformed space, also known as subspace or appearance based methods.

Palmprint features based on characteristic palm lines and point have been first analyzed by Shu and Zhang in [34] where they extract palmprint geometry features and principal lines features obtained from offline palmprint images. They further discuss the required image resolutions for extracting each type of characteristic, i.e. principal lines, wrinkle features, delta points and minutiae. This approach is further extended in [35] and [36] where the line features extraction and matching methods are presented and detection of singular and datum points is analyzed. Datum points are defined as the ending points of the principal lines and singular points are defined as core and delta points formed by skin ridges and are extracted from directional images.

Accurate extraction of wrinkles in online palmprint recognition when dealing with low resolution images is a difficult task. Still, wrinkles carry important and much more discriminating information than solely principal lines. In [37], Zhang et al. employ 2D Gabor filter to capture texture information from palmprint images at the resolution of 75 dpi. Gabor filter is widely applied in image processing and pattern recognition. Namely, the proposed Gabor phase coding scheme for palmprint representation has been previously used in iris recognition. Each sample point in the filtered image is coded with two bits representing the real and imaginary parts. Feature matching is performed using normalized Hamming distance modified in order to provide horizontal and vertical translation invariance. The success of Gabor phase coding depends on the selection of filter parameters. Performance tests on various filter sizes and parameters used is given in [2].

Palmprint recognition in frequency domain by applying Fourier transform is presented in [38]. Correspondences between palmprint features in spatial and frequency domains are exhibited in two ways: the stronger the principal lines are in spatial domain the less compact is the information in the frequency domain; and if a palmprint image has a strong line, in the frequency domain there will be more information in the line's perpendicular direction. Figure 4 shows different palmprints with their correspondence frequency images.

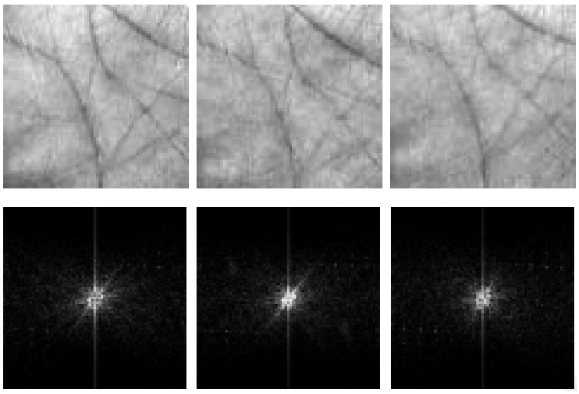


Figure 4. Different palmprints and their correspondence frequency images [38]

Principal component analysis (PCA), also known as the Karhunen-Lóeve transform, is a widely used technique in pattern recognition. The concept is in face recognition known as the eigenface method [39], correspondingly in palmprint recognition the same method is applied and extracted features are called eigenpalm features [40]. The PCA is used to approximate the original high dimensional data with a lower dimensional feature vector. For this purpose the palm image is represented as the column vector with the length equal to the total number of pixels (palm vector). This palm vector is then projected on the projection axes that define the feature space with lower dimensionality. The result of this projection is the feature vector. The PCA chooses the projection axes ($\mathbf{W}_{\mathrm{PCA}}$) in the way to maximize the determinant of the total scatter matrix of the projected samples (1).

$$\mathbf{W}_{\mathrm{PCA}} = \arg\max_{\mathbf{W}} \left| \mathbf{W}^{\mathrm{T}} \mathbf{S}_{\mathrm{T}} \mathbf{W} \right| \tag{1}$$

The matrix $\mathbf{W}_{\mathrm{PCA}}$ that satisfies this criterion is the one whose columns are formed from the set of eigenvectors of the total scatter matrix of the training samples $\mathbf{S}_{\mathrm{T}}$. Eigenvectors that correspond to the largest eigenvalues are used for recognition. The eigenvectors have the same dimensionality as the palm vector, and presented as pictures look like palms, therefore are called eigenpalms.

Figure 5 shows three eigenpalms corresponding to the largest eigenvalues from [41] that are calculated based on the set of 180 palm images.

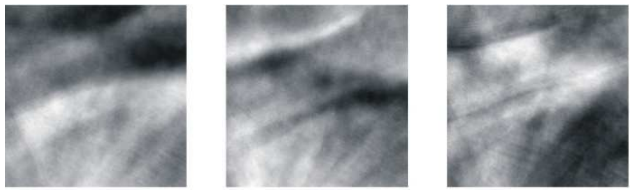


Figure 5. Eigenpalms from [41]

Fisher's linear discriminant (FLD), also known as linear discriminant analysis (LDA) exploits the fact that the training samples are labelled for building more reliable projection space in the sense of classification. The FLD selects the criterion in such way to maximize the ratio of the between-class scatter and the within-class scatter of the projected samples. The criterion is given with (2):

$$\mathbf{W}_{\mathrm{opt}} = \arg\max_{\mathbf{W}} \frac{\left| \mathbf{W}^{\mathrm{T}} \mathbf{S}_{\mathbf{B}} \mathbf{W} \right|}{\left| \mathbf{W}^{\mathrm{T}} \mathbf{S}_{\mathbf{W}} \mathbf{W} \right|} \tag{2}$$

where $\mathbf{S}_{\mathbf{B}}$ and $\mathbf{S}_{\mathbf{W}}$ are between-class scatter matrix and within-class scatter matrix respectively. The solution that satisfies this criterion is the set of generalized eigenvectors of $\mathbf{S}_{\mathbf{B}}$ and $\mathbf{S}_{\mathbf{W}}$. Due to the fact that the original image space is high-dimensional and the number of images in the training set is in practice much smaller than the dimensionality of the image space, the matrix $\mathbf{S}_{\mathbf{W}}$ is always singular. One way to overcome the singularity problem is to first apply PCA thereby reducing the dimensionality of the original image space and to apply FLD [42] [43] [44]. This approach is known as Fisherpalms approach. Figure 6 shows first three Fisherpalms from [41] calculated from the set 190 images belonging to 19 different persons. The maximal number of Fisherpalms that can be calculated from a set of training images is one less than the total number of persons whom those palmprints belong.

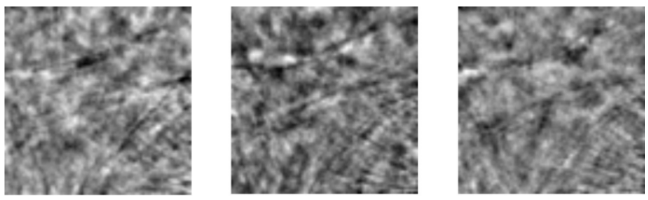


Figure 6. Fisherpalms from [41]

In independent component analysis (ICA) the palmprint image is observed as a composition of a set of linearly independent signals, i.e. images. ICA is a technique for calculating the separating matrix to recover the set of statistically independent basis images. Since there is no closed form expression to calculate this matrix, many iterative algorithms exist to approximate it. The obtained input signals are in fact an estimate of the true source. In [45], Bartlett et al. analyzed the applicability of the ICA technique on face recognition and compared it to PCA based face recognition. They use two Architectures (I and II) for performing ICA on images for recognition. Their goal is to find a set of spatially independent basis images, and to find a representation in which the coefficients used to code the images are statistically independent, respectively. Connie et. al. in [46] applied the same approach to palmprint recognition. Figure 7 shows some basis images obtained when ICA is applied to palmprint recognition (from [46]).

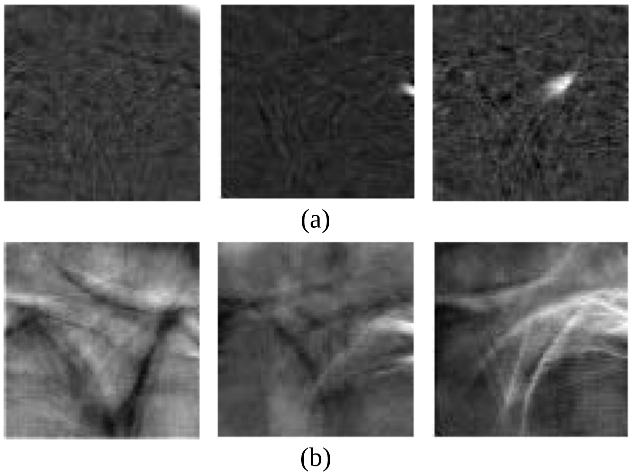


Figure 7. Basis images generated by ICA from [46]: (a) ICA Architecture I, (b) ICA Architecture II

Such approaches require that the entire set of training images of all the users of the system is available for calculating the projection axes of the system. This is hardly achievable in real life applications. Biometric systems are by their nature very dynamic, especially the ones used for access control. Initially, they start with very few users, then the number of users grows, in time some users need to be deleted from the systems, or their biometric data has to be renewed. These needs have been recognized and incremental approaches for eigenspace have been proposed [47] [48]. In [30] and [49] Krevatin and Ribarić propose and analyze a different approach to this problematic for PCA and FLD methods. In this approach the projection axes are calculated based on the training set of images that is large enough to approximate the targeted distribution of the samples of the users of the system. This training set doesn't contain images of the users of the targeted system therefore it is completely independent. The results of the experiments indicate that it is possible to construct an equally performing system with predefined projection axes that are independent on the users' database for specific application. With this approach it s possible to reduce computational costs in the system training phase and avoid introducing the complexity of incremental methods.

III. FACE BIOMETRICS

Face recognition is perhaps the most intuitive of all biometric modalities. People recognize known faces on every day basis in various situations and even in the cases when they haven't seen that face for years. It is the naturalness and unawareness of the complexity of this process that puts high demands and expectations on face recognition systems. This section will discuss methods and challenges in face recognition.

A. *Applications and tasks*

Various tasks and expectations from face recognition arise primarily from the intended application area. In this sense we can point out the applications in access control, video surveillance and travel documents verification. Probably the most common application is the access control which is performed in more or less controlled environment. The subject is enrolled in the system with an online capture device in a usual way for such type biometric systems and it is cooperative with minimal variations in facial expressions and with background and lighting conditions that can be adjusted to the satisfy the system minimal requirements. The travel document verification system can be observed as a special case of access control system where the verification is performed based on one, usually scanned, face image of a person. With the introduction of biometric documents, stricter rules are posed to the image quality and the format of photographs. The primary difference in this type of applications is the emphasized need for the verification of an individual based on one image that can be several years old. Over the years, the aging process changes not only the skin texture, but also the face shape. Such variations increase the difficulties in face recognition. This problem is recently gaining a lot of research interest [50] [51]. The video surveillance systems put high expectations on face recognition systems, apart from aging problems, extreme variations in pose and lightning are present. Faces have a notable 3D structure that under hard light conditions produces shadows that create partial face occlusions. It is also reasonable to assume that suspects will put some efforts in changing their appearance with some disguise at least in form of sun glasses. Face detection and recognition are applied in several other fields, like multimedia services or user interfaces. All these factors show the complexity of the face recognition task.

B. *Face detection and normalization*

Face detection and image normalization are the first steps in the face recognition process. Methods for face detection are based on the following parameters: motion (from video sequences), skin color, facial shape, characteristic elements (eyes, nose, lips etc.), facial appearance and various combinations of these parameters. Which face detection method to apply depends on the application, i.e. expected scene complexity. Generally, the appearance based face detection algorithms are considered to be most successful [52]. For the normalization step, facial components like eyes, nose and facial outline are accurately located and face images are geometrically normalized based on those location points. Further normalization is performed based on illumination variations. Figure 8 illustrates the preprocessing stage of a face recognition system, where face localization based on elliptic face shape and location points of eyes and nose is performed [53]. After the normalization, the images are used in face recognition experiments in [30].

a) b) c)

Figure 8. Illustration of face detection and normalization: a) input image, b) normalized image, c) extracted ROI before and after the histogram equalization

C. Face recognition methods

The continuous research in face recognition resulted with a wide variety of face recognition methods. Early methods were based on geometrical features of the face such as the distances and angles between eyes, eyebrows, nose, lips and other characteristic points. Typical number of extracted feature points was between 35 and 45 [54]. The performance of such approach highly depends on the accuracy of the feature location algorithm. The methods are very sensitive to errors in cases of partial facial occlusions.

Currently, the most popular face recognition methods are the appearance based approaches. The principles of such methods that are described in previous section on palmprint recognition systems are applicable in the same way on face images. The first reference in this field is the one of Turk and Pentland [39] that applied principal component analysis on face recognition problem and called this approach the eigenface method. Linear discriminant analysis has also been applied in face recognition by several researchers [43] [55]. Belhumeur et al. in [43] compared the two methods showing the better performance of LDA method under lighting variations. The results of PCA method are usually used as a reference to compare the performance of other appearance based methods like ICA [45]. Further research in this field includes extensions of these methods in the nonlinear space by using the techniques of kernel methods. The kernel approach takes in consideration the higher order correlations and in this way separates the data that is not linearly separable with conventional methods. Extensions of LDA, as well, focus on the fact that the small sample size problem reduces the classification ability of the LDA method. Applying PCA before LDA eliminates the null space which may contain discriminatory information. To avoid the loss of this information the direct LDA (D-LDA) method and other methods that exploit this fact have been proposed [56].

In [57], Gao and Leung proposed a face recognition method called Line edge map which is a combination of template matching and geometrical features matching. In this approach lines are extracted from face edge map as features. The motivation for the method was the fact that people recognize line drawings as quickly and almost as accurately as gray level pictures. The method is compared to eigenface method in various conditions, showing better performance under variations of lighting, pose and size. The line segment Hausdorff distance measure is used for matching.

Variations in facial expressions cause deformations of parts of the faces. Some parts deform more than other. To handle these changes, face recognition methods need to learn those deformations or have a built-in deformation models. In [58], Moghaddam et al. treat the face image as a 3D surface and apply a deformable 3D mesh in the XYI-space, using both spatial (XY) and grayscale (I) components. A set of training images is used to model two classes of variation in appearance: intrapersonal – between multiple expressions of the same individual and extrapersonal – between different individuals. A probabilistic similarity measure is used. The method is experimentally compared to intensity difference (template matching) and optical flow.

Wiskott et al. [59] use image graphs to represent faces in order to handle larger variations in pose. They tested the method in a scenario where recognition is performed based on a single image per person present in the gallery set. Faces are represented by labelled graphs where edges are labelled with distance information and nodes are labelled with wavelet responses locally bundled in jets. To achieve more accurate location of the nodes, the phase of the complex Gabor wavelet coefficients is used. The nodes are the fiducial points of the face like pupils, corners of the mouth, tip of the nose and chin etc. The class specific information is encoded in the form of bunch graphs in which for each fiducial point, a jet from a different sample face can be selected, forming in this way an adaptable model. In the recognition process the average similarity between pairs of corresponding jets is calculated. The method is known as Elastic bunch graph matching. Figure 9 shows the face representations using face bunch graphs from [59].

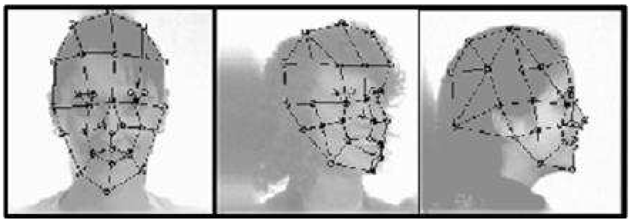


Figure 9. Grids for face recognition from [59]

Further improvements of the method, like morphological elastic graph matching and use of support vector machines have been proposed. The method requires large size images e.g. 128×128.

D. Facial aging

Age progression across different periods of life results in various aging effects on human faces. The changes in craniofacial size and shape are most evident in childhood, after the teenage the bones structure remains more or less stable, and in adulthood skin size and texture changes the most. Apart from the long-term aging effects, in short-term aging is noticeable in finer textural changes, growth of facial hair, deformations due to the loss or gain of the weight etc. All these variations pose a challenge to the automated face recognition. An estimated decrease in performance for each year of age difference is approximately 5% [51].

Unlike with variations in pose, expression and lightning, the problem of face recognition under the influence of aging has gained little attention until recently. The related fields are age estimation and age modeling, thus some researches tend to reduce age effect by transforming the photos in comparison to have the same age. In [7], Zhou et al. perform age estimation using a general technique of image based regression. For face recognition they have built a Bayesian age-difference classifier on a probabilistic eigenspace framework. Only the better illuminated half of the frontal face (called PointFive face) is used. The eigenspace method and the Bayesian model are applied to obtain the extra and intra-personal image differences. Park et al. [51] propose an aging simulation technique based on a 3D deformation model for craniofacial aging. The texture aging simulation is then applied on the model and age-adjusted image is rendered. In [60], Drygajlo et al. analyze the aging influence on the face classifiers. Age progression modelling is performed using local ternary patterns (LTP). The age factor is considered as a metadata quality measure since the age difference causes the degradation of accuracy. This quality measure is used for the Q-stack framework of classification. In the classification scenario LTP is used as a baseline classifier, and its result is used as input to the Q-stack together with the quality measure. In [50], Ortega et al. present a quantitative approach to facial aging focusing on the changes in the face appearance in the short time period. They compute a global face map on which they identify regions that are the most stable over time. The stable regions are identified by calculating the time evolution differences for the facial regions. In [61], Ling et al. analyze the aging face verification problem using discriminative methods. They propose the gradient orientation pyramid as the face descriptor for this purpose. Such representation is insensitive to illumination and skin colour changes. This representation is combined with support vector machine methods for face identification. In such way age estimation and simulation are avoided.

IV. CONCLUSIONS

In this paper we describe a number of approaches used in hand and face biometrics. As it can be seen, such biometric system can be built not only based on the variety of available biometric data, but also on the choice of different feature extraction and classification methods. The growing need for biometric in real life applications pushes the research in this field further. In this sense we can observe the face recognition under variations caused by aging as the unexplored field which is rapidly gaining attention.

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