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FACE RECOGNITION IN SECURITY APPLICATIONS

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Abstract: *During last two decades, the field of biometric person recognition has undergone significant progress. Next-generation human-communication system interfaces will incorporate biometric person recognition, using face, iris, speech, video and other behavior signals to provide more user friendly, efficient and safer communication operation, as well as secure communication. Biometric person recognition in all systems, like communication systems or automatic driving systems, especially represent a challenge for researchers because of difficulties posed by involvement methods and identification parameters of person under recognition process. In this article, we present an overview person recognition technologies. We also present that the levels of accuracy required for person recognition can be achieved only by fusing multiple modalities. In the paper we discuss also about possible methods and techniques for major biometric parameters recognition*

Keywords: Biometrics, face recognition, eigenspace, eigenface, fingerprints

1. INTRODUCTION

In recent years enhanced security systems were composed of image, video and voice recognition systems, but nowadays they are extended by identification systems of some additional biometric parameters, so that Biometrics Security Systems became very complex. The methods for face, iris, walking dynamics recognition, together with fingerprints, DNA and skin color analysis became a part of mentioned nowadays human's identification processes. Today we can also identify the research activities in the direction of automatic psychological and behavior analysis of inspected person. Therefore biometric methods for automated uniquely recognizing of humans would be extended on one or more intrinsic physical and

behavioral traits. In secure technology, biometric authentications refer to technologies that measure and analyze human
physical and behavioral characteristics, together with fingerprints, eye retinas and irises, facial patterns and hand measurements. Examples of behavioral characteristics mostly include signature, poise, walking dynamics and typing patterns. Voice is in most cases considered as a mixture of physical and behavioral characteristics.

In a typical biometric system, person identification is processed by a group of different numerical algorithms, and then compared with the data entered into a database in learning phase. Because only one of mentioned biometric parameters is generally not sufficient for exact identification of inspected human, we have to combine a set of recognition methods and algorithms. Such bundle of different algorithms creates more representative set of biometric parameters. Each attempt to use the biometric system for human authentication requires capturing of some parameters together with appropriate processing. That pattern of parameters is then compared with existing patterns in the system database and matched with the nearest set of patterns. The comparison process involves the use of a Hamming distance between data strings of two patterns. Mentioned single algorithm human identification have widely varying error rates, from as low as 60% to as high as 90.0%, but combination of methods used in biometric system error variation are much smaller and can be achieved from 95% to 99,9%. On a such base Yun [1] ranks biometric systems on the categories as being low, medium, or high. A low ranking indicates poor performance in the evaluation criterion whereas a high ranking indicates a very good performance.

In real-world of biometric systems one of the most common efficiency measure is the rate at which both accept and reject errors are equal. Despite mentioned misgivings, biometric systems have the potential to identify individuals with a very high degree of certainty.

2. MOST USED BIOMETRICS METHODS

With many interesting and powerful developments of biometrics methods, there is concern about technology efficiency in practice. A set of producers are trying to measure those user specific biological characteristics to create a unique *identifier*, which can be electronically stored in a subsequent identifiers. The levels of accuracy required for person identification can be achieved only by fusing multiple modalities, because if only one of them is build in the system for automatic identification of user, it would probably fail.

The biometric parameters can be obtained by the scan of user face, hand, etc., and from the set of live scanned images the biometric parameters can be evaluated by a set of identification procedures and matched to a pre-stored, static "matching identifiers database" created when the user was enrolled in the security system.

In this paper we are planning to present a short overview of algorithms and measures presented in papers and on congresses used in biometrics parameter definition, where the face recognition would be the main focus of this paper.

Face is not as unique as fingerprints and eye iris, so its recognition reliability is much lower compared to other two parameters. It can be used together with fingerprint recognition, iris identification or another biometrical method used in the system to ensure more reliable and secure application.

Therefore the multi-biometrical approach is important for reliable identification of user. Multi-biometrical approach also usually helps in situations where certain biometric feature is not practical for special groups. From these considerations we can conclude that facial recognition should be considered as a serious alternative in biometrical or multi-biometrical systems development.

2.1. FINGERPRINT IDENTIFICATION METHODS

Fingerprint-based identification is among all identification methods the oldest method, which has been successfully used in numerous applications. Over the last decade many novel techniques have been developed to acquire fingerprints with special scanners. The basic principle is to sense the ridges and valleys on a finger when the finger is in contact with the surface of the scanner.

The uniqueness of a fingerprint can be determined by the pattern of ridges and furrows as well as the *minutiae* - finer points. They are local ridge characteristics that occur at either a ridge bifurcation or a ridge ending (Fig. 1).

The main goal of the fingerprint authentication module is to report some sort of distance between two fingerprint feature sets accurately and reliably. The authenticate function has to compensate for (i) translation, (ii) rotation, (iii) missing features, (iii) additional features, (iv) spurious features and, more importantly, (v) elastic distortion between a pair of feature sets.

Fingerprint matching techniques can be placed into two categories: *finer points - minutiae - based* and *correlation based*. Finer points - based techniques first find fine points and then map their relative placement on the finger. However, there are some difficulties using this approach. It is difficult to extract the finer points accurately when the fingerprint is of low quality. The correlation-based method is able to overcome some of such difficulties of the finer point-based approach. Correlation-based techniques require the precise location of a registration point and are affected by image translation and rotation.

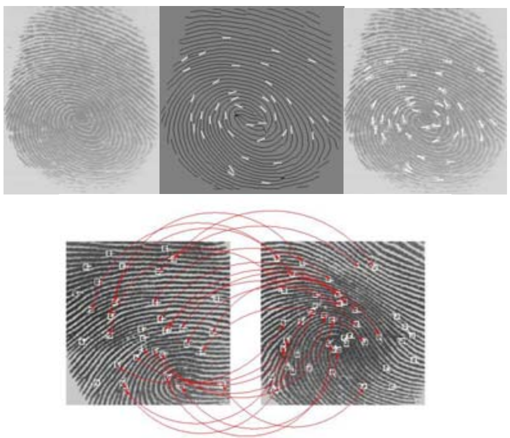


Fig. 1. Fingerprint matching based on *finer points /2/* has problems in matching different sized finer point's patterns.

Prabhakar and Jain [2] developed algorithms which are more robust to noise in fingerprint images and deliver increased accuracy in real-time. A commercial fingerprint-based authentication system requires a very low False Reject Rate (FAR)

Fingerprint images contain a large amount of data [31]. Because of the high level of data present in the image, it is possible to eliminate false matches and quickly reduce the number of possible matches to a small number, even with large database sizes. Because of the fact that Fingerprint Imaging Systems use more than one finger image in the match process, the match discrimination process is geometrically increased. Today the fingerprint identification process has a 98%+ identification rate and the false positive identification rate is less than 1%.

2.2. FACE RECOGNITION METHODS – BASIC PRINCIPLES

Face recognition [3, 4, 5] is the most means of biometric identification and distinguished one individual from another. It is also particularly compelling biometric method, because it is used every day by everyone during our visual and oral correspondence. For humans it is the most favorite and the acceptable than the majority of others biometric methods.

Despite mentioned natural attraction, face recognition is not sufficiently accurate to accomplish the large-population identification tasks compared with fingerprint or iris. One clear limit is the identity of two snapshots of the same person, which is followed by all of the following problems like:

- Physical changes: expression change; aging; personal appearance (make-up, glasses, facial hair, hairstyle, disguise).
- Acquisition geometry changes: change in scale, location and in-plane rotation of the face (facing the camera) as well as rotation in depth.
- Imaging changes: lighting variation; camera variations; channel characteristics.

Facial recognition technology has been recently developed into two areas of study; *facial metr*ics and *eigenfaces*. Facial metrics technology relies on the measurement of specific facial features e.g., the distance between the inside corners of the eyes, the distance between the outside corners of the eyes and the outside corners of the mouth, etc. and the relationship between these measurements.

A face recognition system is today a computer-driven system for automatic identification of a person from a digital image. It is typically used for security systems and can be integrated together with other biometrics such as fingerprint or eye iris recognition systems.
Popular face recognition algorithms include *eigenface,* the Hidden Markov model, and the facial metric neuronal motivated Dynamic Link Matching. A newly emerging trend is three-dimensional face recognition. Another emerging trend uses the visual details of the skin, as captured in standard digital images.

2.2.1. **LIST OF IMAGE-BASED FACE RECOGNITION METHODS** From usefully organized collection of face recognition literature [7] it is evident that the most popular recognition methods are based on decomposition methods like PCA, ICA, LDA, EP, on topological structures like EBGM, on linear and non-linear manifolds as Kernel Methods, on Radon transform like Trace Transform, on statistical modeling as AAM, on Morphable Face model like 3-D Morphable Model or 3-D Face Recognition, on based on Bayesian belief like Bayesian Framework, on Support Vector Machine as SVM, on Hidden Markov Models as HMM and also on classifiers like Boosting & Ensemble. In [7] researchers just started on the topic of face recognition can find the list of recent papers and literature about the Image-Based Face Recognition methods shortly listed in next section.

2.2.1.1 **PCA - Principal Component Analysis** is derived from Karhunen - Loeve's decomposition method and is a linear transformation that transforms the data from time being coordinate system to a new one, such that the greatest variance by any projection of the data comes to lie on the first coordinate - called the principal component, the second greatest variance on the second coordinate, and so on. PCA can be used for dimensionality reduction in a dataset while retaining those characteristics of the dataset that contribute most to its variance, by keeping lower-order principal components and ignoring higher-order ones. Such low-order components often contain the "most important" aspects of the data. PCA has the distinction of being the optimal linear transformation for keeping the subspace that has largest variance. Therefore the main objectives of principal component analysis are to:

- reduce the dimensionality of the data set and
- to identify new meaningful variables.

In the case of face recognition methods, each face image in a training set of images is presented as an *n*-dimensional vector. Principal Component Analysis tends to find an *r*-dimensional subspace whose basis vectors correspond to the maximum variance direction in the original image space. This new subspace is normally lowered dimensional *(r<<n)*. Image elements are considered as random variables; therefore the PCA basis vectors are defined as eigenvectors of the scatter image matrix.

Fig. 2. illustrates normalization, however, can remove noise and make the data less variant, which could affect the ability of PCA to capture data structure.

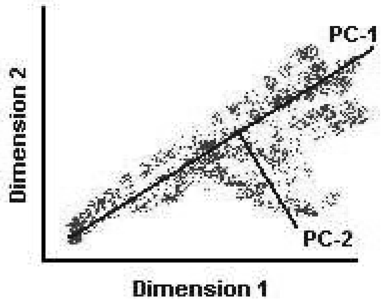


Fig. 2**.** The PC-i lines represent 2 consecutive principle components. Note that they are orthogonal to each other.

PCA can be imposed on datasets to capture the cluster structure prior to cluster analysis. Performing PCA is the equivalent of performing Singular Value Decomposition (SVD) on the *covariance matrix* of the data. For the sake of example, let **A** be a matrix that represents image content. The SVD of X is said to be the factorisation:

$$X = \mathbf{USV^T} \qquad (1)$$

In equation (1), matrices U and V are such that they are orthogonal. The columns of U are called *left singular* and the rows of V^T are called *right singular values*. To calculate the matrices U and V, one must calculate the eigenvectors and eigenvalues of $X.X^T$ and $X^T.X$. These multiplications of X by its transpose results in a *square* image.

The columns of V are made from the *eigenvectors* of $X^T.X$ and the columns of U are made from the *eigenvectors* of $X.X^T$. The *eigenvalues* obtained from the products of $X.X^T$ and $X^T.X$.

The *diagonal* of S is said to be the *singular values* of the original matrix. Each eigenvector represents a principle component **PC** (**P**rinciple **C**omponent), which is defined as the eigenvector with the highest corresponding eigenvalue. The individual eigenvalues are numerically related to the variance they capture via PC's - the higher the value, the more variance they have captured.

2.2.1.2 **ICA - Independent Component Analysis** is a statistical and computational technique for revealing hidden factors that underlie sets of random variables, measurements, or signals and minimizes both second-order and higher-order dependencies in the input data. Unlike PCA, which decorrelates the data, ICA searches for directions in data-space, which are independent across all statistical orders.
ICA defines a model for the observation of a large database of samples. In the model, the data variables are assumed to be linear mixtures of some unknown latent variables, where the mixing system is also unknown. The variables are assumed to be nongaussian and mutually independent and they are called the independent components of the observed data. These independent components, also called *basis subspaces*, called also *subimages***,** can be found by ICA. There are known two basic architectures of ICA for face recognition task: *Architecture I* - statistically independent basis images, and *Architecture II* - factorial code representation.
ICA is a much more powerful technique, capable of finding the underlying factors or sources when these classic methods fail completely. Typical algorithms for ICA use centering, whitening and dimensionality reduction as preprocessing steps in order to simplify and reduce the complexity of the problem for the actual iterative algorithm. The data analyzed by ICA could originate from many different kinds of application fields, including digital images, document databases, economic indicators and psychometric measurements. In many cases, the measurements are given as a set of parallel signals or time series; the term blind source separation is used to characterize this problem.

2.2.1.3. **Linear Discriminant Analysis (LDA)** is a statistical technique to classify objects into mutually exclusive groups based on a set of measurable object's features. Term discriminant analysis comes with many different names like *pattern recognition*, *supervised learning*, or *supervised classification*. If the number of classes is more than two, it is also sometimes called Multiple Discriminant Analysis (MDA). LDA finds the vectors in the underlying space that best discriminate among classes. For all samples of all classes the between-class *scatter matrix SB* and the within-class *scatter matrix SW* are defined.
Linear discriminant analysis is used in statistics to find the linear combination of features which best separate two or more classes of object or event. Linearly separable suggests that the groups can be separated by a linear combination of features that describe the objects. If only two features, the separators between objects group will become lines. If the features are three, the separator is a plane and the number of features (i.e. independent variables) is more than 3, the separators become a hyper-plane.
LDA is closely related to principal component analysis (PCA) and factor analysis in that both look for linear combinations of variables which best explains the data. LDA explicitly attempts to model the difference between the classes of data. PCA on the other hand does not take into account any difference in class, and factor analysis builds the feature combinations based on differences rather than similarities.

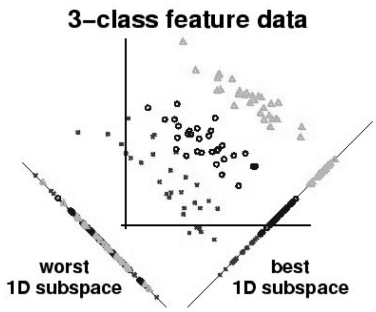


Fig. 3. LDA method transformation

In *face recognition*, each image and therefore also face, is represented by a large number of pixel values. Linear discriminant analysis is primarily used here to reduce the number of features to a more manageable number before classification. The linear combinations obtained using the related principal component analysis is called *eigenfaces*. *Eigenfaces* are a set of eigenvectors used in the computer vision problem of human face recognition. These eigenvectors are derived from the covariance matrix of the probability distribution of the high-dimensional vector space of *possible faces* of human beings.

Many authors prefer the term *eigenimage* rather than *eigenface*, as the technique has been used for handwriting, lip reading, voice recognition, and medical imaging.

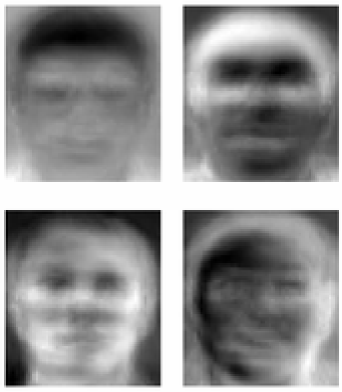


Fig. 4 Some eigenfaces from AT&T Laboratories Cambridge.

Eigenfaces are a set of "standardized face ingredients", derived from statistical analysis of many pictures of faces. Any human face can be considered to be a combination of these standard faces. This means that if you want to record someone's face for use by face recognition software you can use less space than would be taken up by a digitized photograph. To generate a set *of eigenfaces*, a large set of digitized images of human faces, taken under the same lighting conditions, are normalized to line up the eyes and mouths. They are then all resampled at the same pixel resolution and after that the eigenvectors of the *covariance matrix* of face image vectors are extracted.

Viewed in this way, the *principal eigenface* looks like an *average human face*. Some subsequent eigenfaces Fig. 4 can be seen to correspond to generalized features such as left-right and top-bottom asymmetry, or the presence or absence of a beard. Other eigenfaces are hard to categorize, and look rather strange. Properly weighted, eigenfaces can be summed together to create an approximate gray-scale rendering of a human face. Remarkably few eigenvector terms are needed to give a fair likeness of most people's faces, so eigenfaces provide a means of applying data compression to faces for identification purposes.

2.2.1.4 <u>Elastic Bunch Graph Matching - GM</u> All human faces share a similar topological structure. Faces are represented as graphs, with nodes positioned at fiducially points (eyes, nose...) and edges labeled with 2-D distance vectors. Graph nodes are labeled with *Jets* and graph edges are labeled as *distance vectors*. Jets are N dimensional vectors based on 2D Gabor wavelet transform. Each node contains a set of 40 complex Gabor wavelet coefficients at different scales and orientations (phase, amplitude). Complex Gabor wavelets are localized filters, each have a certain spatial frequency and orientation. Jets are presentation of local grey level value regions of image. If the faces are compared across pose, there should be a set of about 40 to 50 facial points – *fiducials* at which nodes are positioned. In the case of different poses the same points should be used. They have to be identical for all different poses. From Fig. 5 we can identify some important facial points like tip of the nose, the corners of the mouth, the chin, etc… The graph thus has an object-adapted grid with nodes. In the case of different views they can be compared wit each other. In the case of larger number faces, the identification method should consist of a graph structure based on the face bunch graph. This bunch graph is constructed from a representative set of model graphs having the same pose and the same structure. New faces can be encoded by taking jets from different models at each node. This takes the advantage of combinatorial possibilities of bunch graph and makes it possible to present and process faces not seen before. Recognition is based on labeled graphs where is labeled graph and set of nodes connected by edges are compared with bunch graph jets and edges which are selected as a minimal distance among all possible pairs from the bunch graph.

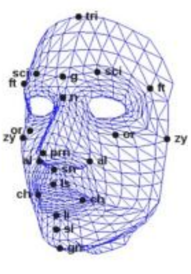


Fig. 5 Face as a graph

2.2.1.5 <u>An Active Appearance Model (AAM)</u> This is an integrated statistical model [11] which matches a model of shape variation with a model of the appearance variations in a shape-normalized frame. Matching to an image involves finding model parameters, which minimize the difference between the image and a synthesized model example projected into the image.

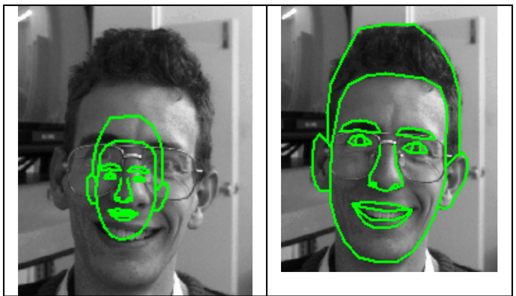
The associated search algorithm exploits the locally linear relationship between model parameter displacements and the residual errors between model instance and image. This relationship can be learnt during a training phase. To match to an image we measure the current residuals and use the model to predict changes to the current parameters. The algorithm converges in a few iterations. The algorithm uses the difference between the current estimate of appearance and the target image to drive an optimization process. By taking advantage of the least squares techniques, it can match to new images very swiftly. A good overall match is obtained in a few iterations, even from poor starting estimates.

Figure 6 shows frames from an AAM search for a new face, each starting with the mean model displaced from the true face centre.

2.2.1.6 <u>Active Shape Models – ASMs</u> Method [39,40,41] is closely related to the Active Appearance Models. This is statistical model of the shape of objects which are iteratively fitted to the object in a new image [38]. The shapes are constrained by a Statistical Shape Model to vary only in ways seen in a training set of labeled examples. The shape of an object is represented by a set of points, controlled by the shape model. The ASM algorithm aims to match the model to a new image. It works by alternating the following steps:

- Look in the image around each point for a better position for that point
- Update the model parameters to best match to these new found positions

To locate a better position for each point one can look for strong edges, or a match to a statistical model of what is expected at the point. Both techniques *<u>AMM, ASM</u>* had been widely used to analyze images of faces, mechanical assemblies and medical images.



Initial Position	Final iteration

Fig. 6. Multi-Resolution searches from displaced position

2.2.1.7 **3-D Morphable Model** This model is very convenient for a human face is a surface lying in the 3-D space. The 3-D model should be better for representing faces, especially to handle facial variations, such as pose, illumination etc. Blantz et al. [13] proposed a method based on a 3-D face model that encodes shape and texture in terms of model parameters, and algorithm that recovers these parameters from a single image of a face. 3D Morphable Models, as a means to generate images of a class of objects and to analyze them, have become increasingly popular. 3D faces can either be generated automatically from one or more photographs.

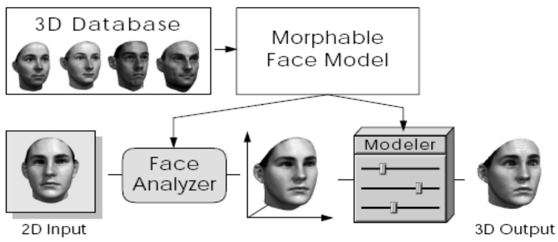


Fig. 7. Morphable face model derived from a dataset of prototypical 3D scans of faces
Starting from an example set of 3D face models, the authors derive a morphable face model by transforming the shape and texture of the examples into a vector space representation. *New faces and expressions* are modeled in modeler by forming linear combinations of the prototypes. Shape and texture constraints derived from the statistics of our example faces are used to guide manual modeling or automated matching algorithms.

Figure 7 shows 3D face reconstructions from single images and their applications for photo-realistic image manipulations. It demonstrates also face manipulations according to complex parameters such as gender, fullness of a face or its distinctiveness.

2.2.1.8 **3-D Face Recognition** Model plays the main novelty of this approach and represents the new ability to compare surfaces independent of natural deformations resulting from facial expressions, head orientation and makeup [14]. These are known limitations of 2D methods approaches. It became evident that the use of 3D data of the face can be of great help, as 3D information is viewpoint and lighting condition independent, that means that this method doesn't suffer of weakness of 2D approaches. An attempt to overcome mentioned 2D difficulties the bending invariant canonical forms are introduced. In this approach the facial surface is converted into a presentation, which is practically identical to different postures of the face.

First, the range image and the texture of the face are acquired. Next, the range image is preprocessed by removing certain parts such as hair, which can complicate the recognition process. Finally, a canonical form of the facial surface is computed. Such a representation is insensitive to head orientations and facial expressions, thus significantly simplifying the recognition procedure. The recognition itself is performed on the canonical surfaces.

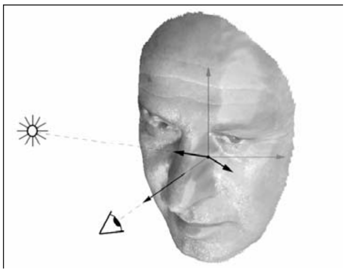


Fig. 8: 3D face models to robust automatic human face recognition

By applying 3D face models to robust automatic face recognition in [17, 18, 19] the focus was given to mention most critical factors limiting performance: illumination and pose variation. There was proposed a novel system for capturing the 3D shape of a human face from a sequence of sparse 2D silhouettes from multiple cameras (or video) at affordable cost and with no manual user interaction.

A multi-view face recognition system is developed [19, 20, 21, 22], which utilizes three-dimensional (3D) information about the face, along with facial texture, resulting in a multi-modal face matching system that is able to handle head pose changes (Fig. 9). A feature extractor is developed to locate facial anchor points, such as the nose tip, eye corners, and mouth corners, in the presence of large head pose changes, leading to a fully automatic 3D face matching system. The entire automatic 3D face recognition system is designed to handle large head pose and facial expression changes simultaneously.

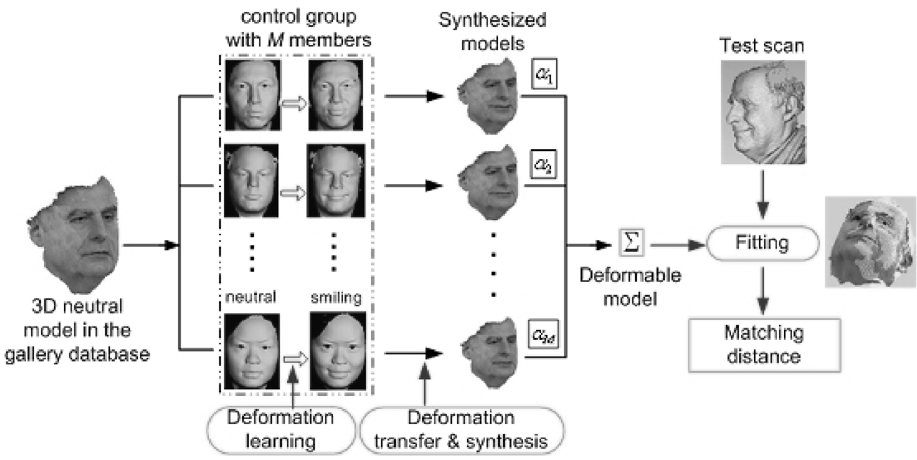


Fig. 9: A multi-view face recognition system

2.2.1.9 **<u>Support Vector Machines SVM</u>**'s are based on the concept of decision planes that define decision boundaries and present a set of related supervised learning methods used for classification and regression. They belong to a family of generalized linear classifiers. A special property of this family of classifiers is to simultaneously minimize the empirical classification error and maximize the geometric margin. Hence it is also known as maximum margin classifier. A decision classifier or plane is one that separates between a set of objects having different class memberships.

The example of a linear classifier, i.e., a classifier that separates a set of objects into their respective groups with a line is not common and so simple in real classification tasks. Generally the classifier based on drawing separating lines to distinguish between objects of different class memberships are known as hyperplane classifiers. Support Vector Machines are particularly suited to handle such tasks.

The illustration from Fig. 10 shows the basic idea behind Support Vector Machines. The original objects are mapped, i.e., rearranged, using a set of mathematical functions, known as kernels. The process of rearranging the objects is known as mapping. Note that in this new setting, the mapped objects is linearly separable and, thus, instead of constructing the complex curve, all we have to do is to find an optimal line that can separate the both group of objects.

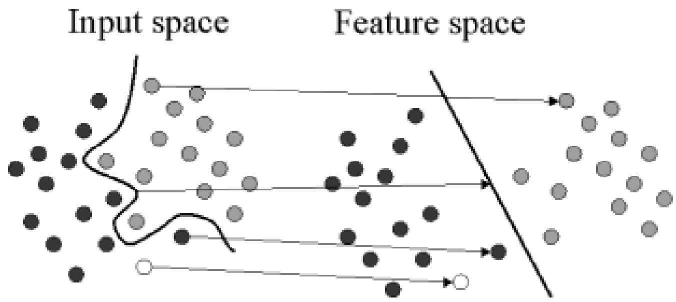


Fig. 10 Mapping of two nonlinearly separated groups of objects into linear separated groups of objects

Support Vector Machine (SVM) [24, 25] is primarily a classifier method that performs classification tasks by constructing hyperplanes in a multidimensional space that separates cases of different class labels. SVM supports both regression and classification tasks and can handle multiple continuous and categorical variables.

Maximum-margin hyperplanes for a SVM trained with samples from two classes. Samples along the hyperplanes are called the support vectors.
We consider data points of the form:
$$\{(\mathbf{x}_1, c_1), (\mathbf{x}_2, c_2), \ldots, (\mathbf{x}_n, c_n)\}$$
where the c_i is either 1 or −1 -- this constant denotes the class to which the point $\mathbf{x}_i$ belongs. Each $\mathbf{x}_i$ is a p − (statistics notation), or n − (computer science notation) dimensional vector of scaled [0,1] or [-1,1] values. The scaling is important to guard against variables (attributes) with larger variance that might otherwise dominate the classification. We can view this as *training data*, which denotes the correct classification, which we would like the SVM to eventually distinguish, by means of the dividing hyperplane, which takes the form $\mathbf{w} \cdot \mathbf{x} - b = 0.$

The vector $\mathbf{w}$ points perpendicular to the separating hyperplane. Adding the offset parameter **b** allows us to increase the margin. In its absence, the hyperplane is forced to pass through the origin, restricting the solution.

2.3. SUPPLEMENTAL METHODS

2.3.1. RETINA AND IRIS SCAN

Retina Scan technology is based on the blood vessel pattern in the retina of the eye. An infrared light is used to illuminate the retina and the infrared energy is absorbed faster by blood vessels than by surrounding tissue of the eye. The image of blood vessel pattern of the retina at the back of the eye has a unique pattern, from eye to eye and person to person and therefore represents the unique input image for accurate biometric analysis. The human retina is stable from birth to death; therefore these biometric parameters are the most accurate for biometric person identification.

Based on the fact that large number of data enables the system to a high discrimination rate, it became evident that retina scan may be also so efficient than fingerprint scan. This approach to retina scan is more susceptible to disease influence on blood vessel structures that change the characteristics of the eye, method uses a laser light, therefore is personally invasive and also the method of image capturing depends heavily on the skill of the operator.

Fig. 11 Retina scans for cattle identification

A retinal scan involves very accurate biometric data and enables the highest crossover accuracy of any other biometric approaches. It is estimated to be in the order of 1:10,000,000. Nowadays technology is capable of capturing a retinal scan in less than 1 second.

An iris scan represents the unique input image for very accurate biometric analysis. The iris recognition method uses the concentric circular outer boundaries of the iris and the pupil in a photo of an eye. The set of iris pixels is transformed into a bit pattern. The mathematical methods use lossy compression algorithms for photographic images. Gabor wavelet transform is used to extract from the spatial frequency range a set of complex numbers, which is a phase and amplitude function of the iris image. This fact contributes significantly to the long-term stability of the code. A practical problem of iris recognition is that the iris is usually partially covered by eyelids.

The advantages of the usage of iris based biometric identification of the human is in fact that iris is very good protected against damage, that iris is mostly flat and its geometric configuration is only controlled by a single muscle, that iris has a fine texture determined randomly during embryo growth and that iris scan is simple to realize and is based on digital photo technologies.
As a disadvantage of usage iris based biometric identification is that there exists a possibility of surgical procedures that can affect the color and overall shape of the iris. Also some photographic technologies are not good for iris capturing from the distance from more than 2 meters.
This technology should be more acceptable to user than retinal scans and it does not use an infrared light source to highlight the biometric pattern in the iris.

2.3.2. HAND GEOMETRY is based on person's hand shapes. The shape of a person's hand after mature years does not significantly change its form. Various methods are used to measure the hand parameters. From the literature [31, 32, 33] two methods of identification can be identified - *mechanical detection* and *hand image-edge detection*. Either method produces measurements of the hand parameters like length of fingers and thumb, widths of fingers, hand, etc. On the basis of these data the system can identify a person.

Hand geometry does not produce a large data set, compared to some other biometric identification methods. Hand geometry may not be able to distinguish one individual from another who has similar hand characteristics. Therefore there must be an increased number of biometric parameters of the used to narrow the number of identified candidates. With hand geometry, there is not enough data available to distinguish among different users.

However, it is possible to develop a method by combining various individual features to get robust verification. Therefore the number of biometric parameters should be extended probably by a photo image, which has to be added to the set of parameters needed in identification process. Such hand image acquisition system therefore must provide a live visual feedback of the top-view and the side-view of the hand.

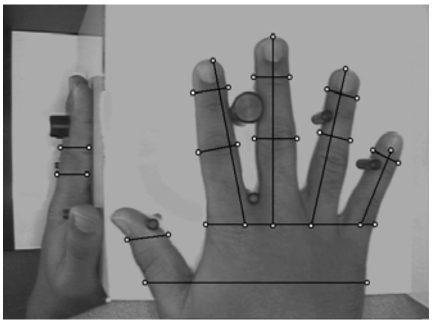


Fig. 12 Visualization of feature parameters

3. ENSEMBLE OF METHODS AND CONCLUSION

Biometrics technologies nowadays cover the recording and measurement of living beings and their characteristics. In the nowadays research and development activities *biometrics* refers to the measurement of an individual physical, physiological or behavioral features of an individual for the purpose of *biometric identification* and hence differentiation from other individuals. The idea behind such very accurate biometric analysis is to sequentially employ weak points of in the paper mentioned methods with other user friendly, but accurate vital strict methods. Among the producers of such biometric identification systems we can identify such trends that each of them plans to integrate few different biometric methods in a systems which enables, on the basis of a given training samples set of classifiers, the highest crossover accuracy than any other biometric approach, higher than is the order of 1:10,000,000.

The reliability of such integrated biometric identification depends on ensuring that the signal acquired and compared has actually been recorded from a live body part of the person to be identified. Many commercially available recognition systems are easily fooled by presenting a high-quality photograph of a face instead of a real face, which makes such devices unsuitable for unsupervised applications, such as door access-control systems therefore the of live tissue verification has to be integrated in all supervision applications Methods that have been suggested to provide some defense against the use of fake faces, fingerprints, eyes and irises and hand forms include:

- Changing ambient lighting during the identification
- Analysing the 2D spatial frequency spectrum of the image
- Analysing the dynamic frequency spectrum of the images
- Using spectral analysis instead of merely monochromatic cameras to distinguish retina and iris tissue from other material
- Observing the characteristic natural movement of body, face and eye
- Using 3D imaging to verify the position and shape of the face, iris and retina are relative to environment features.

From the practical viewpoint, the biometric techniques and systems working with these characteristics must be rapid, compatible with existing security elements, robust, accurate, safe, economic and reliable. None of the biometric characteristics currently used or available systems fully satisfies all requirements. Even so, there are numerous systems in operation worldwide in various application contexts, e.g. to check authorization of individuals in e-banking and e-commerce transactions, or for access controls for sensitive areas. Most frequently used is identification of fingerprint, hand geometry, face, voice, iris/retina and signature/handwriting, the physiological, technical, economic and user aspects of which are more and more important.
Conventional systems cannot check passwords or PIN chip cards to see if the user providing correct data is also the lawful owner. As biometric techniques work with person-linked characteristics, they promise a new dimension in quality, comfort and security in personal authentication.

However, there is as yet no generally recognised method for comparing the strengths and weaknesses of the various biometric systems. In addition, the varying level of maturity of the different biometric systems makes comparative evaluation difficult. Such an evaluation would have to include logical and informative data on for example reliability, accuracy, sensitivity, acceptance, robustness, compatibility, simplicity and costs. An exact assessment of the strengths and weaknesses of a technique can only be made in a specific application context, and must be empirically designed with logical individual steps.

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Sadržaj: *Biometrijsko personalno prepoznavanje je postalo značajno poslednje dve decenije. Nova generacija humano-komunikacionih sistema uključiće biometrijsko personalno prepoznavanje korišćenjem oblika lica, govora, videa, i drugih signala koji treba da obezbede efikasnu, bezbednu i sigurnu komunikaciju, orijentisanu ka korisniku. Biometrijsko personalno prepoznavanje predstavlja izazov za istraživače, zbog teškoća koje donose izabrani metodi i identifikacija parametara u procesu prepoznavanja. U ovom radu se razmatraju tehnologije personalnog prepoznavanja. Takođe se daju nivoi pouzdanosti koja se postiže kod personalnog prepoznavanja sa višestrukim modalitetima. Na kraju rada se diskutuje o mogućim metodama i tehnikama za prepoznavanje glavnih biometrijskih parametara.*

Ključne reči: *biometrika, prepoznavanje lica, sopstveni prostor, otisci prstiju*

PREPOZNAVANJE LICA U BEZBEDNOSNIM APLIKACIJAMA

Jurij Tasič