Exploring Image Unified Space for Improving Information Technology for Person Identification

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Abstract

This paper describes the study of conditions and parameter settings of the algorithm, that underlies in the basis of information technology of person recognition and identification, for creating a unified space for both low-quality and high-quality images with the purpose of developing the requirements to the input images, that will allow correctly identify images with different characteristics. For experimental research the algorithm was used that underlies in information technology of person identification in video stream. It includes the anisotropic diffusion as an image preprocessing method, Gabor wavelet transform as an image processing method, histogram of oriented gradients (HOG) and local binary patterns in 1-dimensional space (1DLBP) as the methods of feature vector extraction from the images. In this work anisotropic diffusion was applied with the parameter that preserves sharper boundaries than previous formulations and improves the automatic stopping of the diffusion. In the study three person images databases were used: The Database of Faces, Facial Recognition Technology (FERET) database and Surveillance Cameras Face Database (SCface). The algorithm performance provided various identification accuracy rate results with the difference, which amount to 20% in average. It arose the issue of input images space mismatching that significantly affected the algorithm performance. Therefore, it has been decided to perform the experimental research to search the possibility to create unified space of the requirements to the input images that will allow correctly identify images from different databases. So, there were performed the experiments with the image compression variety, difference of image resolutions and areas of face regions covering the images.

Keywords 1

Biometric identification, face recognition, wavelet transform

1. Introduction

Face recognition and identification is a technology that broadly uses nowadays within various scopes. It has evolved from simple applying such as people recognition on photos in social networks to the applying in police forces tasks of crime investigation and searching for missing kids. Several state governments have gained gigantic headway in applying this technology in different fields.

Nowadays it is often that images to be identified and image to identify with are belong to different image spaces due to the variety of image compression, resolution and area of face region covering the face. For example, an image containing the face of a person to be identified may be captured by surveillance cameras, which usually only provide low-quality images, i.e., with compressed format, low resolution, with different angles of a face, etc. On the other hand, to perform identification, this image is compared with images from databases that may belong to law enforcement agencies, which usually store high-quality frontal images of fully visible faces, that were captured during passport receiving or the arrest after committing an offense. Thus, if the images being compared are not unified, the failure

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of identification process may occur. So, it is important challenge in face recognition field that must be overcome.

1.1. Related works

For quite some time researchers of face recognition field of knowledge are trying to develop and explore methods of creating a common space between images with different features, such as resolution, alignment, scaling and others.

In study [1] authors described the development of a robust real-time face recognition approach that uses super-resolution to detect faces in the video and improve captured face images. The approach aims to improve descriptor count of the image based on the super-resolved faces and to mitigate the noise effect. Furthermore, it uses a parallel architecture to implement a super-resolution algorithm and overcomes the efficiency drawback increasing face recognition performance.

Authors of paper [2] proposed a model of face recognition and hallucination for case of low-resolution face images ground on feature-mapping. Proposed model includes a new loss function – identity-aware loss, that is combined with the feature loss and image-content loss to jointly train models.

Paper [3] provides an insight into the difference between down-sampled and real low-resolution images. Authors of this work found out that the degradation of face recognition performance does not depend on how much information a low-resolution image would contain. Incorrect alignment can be the main issue that could cause problems during the face recognition performance on low-resolution images in the absence of such conditions as pose and illumination variations.

In the work [4] the solution to the problem of unidentifiable face images in the training dataset is proposed. Due to the difference in recognition performance affected by image quality, authors of the paper were trying to solve the problem by using a feature norm as a proxy for the image quality and changing the margin function adaptively based on the feature norm to control the gradient scale assigned to different quality of images.

Authors of paper [5] proposed a method, that is designed to recognize faces using dictionaries with different levels of blurriness. The method was tested and proven to be more robust with respect to low-quality images.

For handling high-resolution and low-resolution images dimensional mismatch, in work [6] there was applied multidimensional scaling. The discriminative power of proposed model was improved by introducing an inter-class-constraint to enlarge the distances of different subjects in the subspace. This study was developed into paper [7], that is also proposed the same method in order to learn a mapping matrix, high-resolution and low-resolution images to a common subspace. It utilizes the information within image pairs and set an inter-class constraint is employed to enlarge the distances of different subjects in the subspace to ensure discriminability.

More computationally efficient method of multidimensional scaling was proposed in [8]. The method was improved by using a reference-based strategy. Instead of matching an incoming testing image with all database images, it only matches testing face images to selected reference images in the database. Authors constructed two orthogonal dictionaries in low-resolution and high-resolution domain and aligned them using bipartite graph matching.

In work [9] there was proposed an approach of Discriminant Correlation Analysis (DCA), that allows to highlight the differences between classes, and also has an advantages over Canonical Correlation Analysis.

Authors of [10] established that several works ignored the occlusions in the low-resolution testing images. To extract the global structures of images from both database and testing sets and to find if these images contain an occlusion, the method of double low-rank image representation was used.

In paper [11] a centerless regularization was presented to allows to localize the intra-class samples closer to one another in the learned representation space. On the other hand, work [12] presents an extra branch network on top of a trunk network and proposes a new coupled mapping loss performing supervision in the feature domain in the training process.

1.2. Research gaps and objectives

Global face recognition market is expected to grow till USD 11.62 billion in 2026 from USD 3.72 billion in 2020, as was stated in the report [13] made by analytical company Mordor Intelligence. According to other report made by forecasting company Grand View Research [14], it is possible that face recognition technology usage will be significantly adopted by security segment. Its compound annual growth rate will be significantly growing next few years.

Data obtained with the use of face recognition can also be helpful for crime prevention and enforcement of law and order on crowded festive events, person assessment during the process of employment or loan issuance by a bank, car accident prevention by analyzing health indicators of drivers, etc. Face recognition is biometric method that does not require any intervention in personal area, because face is the simplest biometric indicator that naturally people use to identify one another. Therefore, it can be used for the small IT projects as well as for major state security aims.

But it is common that law enforcement databases contain images of high quality such as passport image or mugshot image. On the other hand, surveillance cameras often provide images of lower quality. Such variety may create the situation when face images of a person to be identified compares with images from the database, and those images are not unified [15]. This problem can cause the failure of the identification process and the fact of it means the necessity to research the prerequisites of that process with the purpose to increase the identification accuracy rate.

At present, authors of most of the works devoted to the study of image unified space, such as [16] and [17], use approaches based on artificial intelligence techniques. However, such approaches are not sufficiently flexible and able to quickly adapt to the conditions of the real world, that can change rapidly, because they require a large amount of high-quality data for training, hardware improvements, and are also expensive to maintain, as indicated in [18-20]. In modern research, the issue of using local texture descriptors in the tasks of recognizing and identifying faces on images of different quality is insufficiently studied. Such methods, unlike artificial intelligence methods, do not require a large amount of data, high computing power of hardware, and time spent on training. Moreover, on images captured under unconstrained conditions, the effectiveness of such methods is close to the effectiveness of artificial intelligence methods, and under some constrained conditions even exceeds it [20, 21]. Therefore, in our opinion, methods based on local-textural descriptors should be investigated and improved, particularly in works devoted to solving the tasks of face recognition and identification on images of different quality.

This paper focuses on studying of conditions to create a unified space for both low-quality and high-quality images and selection of parameters of the algorithm, that underlies in the basis of information technology of person recognition and identification, in such way, so that if the images to be identified and database images are different in terms of quality they can still be compared obtaining as a result high accuracy rates.

2. Research methodology and design

In study [22] it was proposed the information technology for person identification on the basis of the algorithm that consists in the following methods: anisotropic diffusion as an image preprocessing method, Gabor wavelet transform as an image processing method, histogram of oriented gradients (HOG) and local binary patterns in 1-dimensional space (1DLBP) as the methods of feature vector extraction from the images, square Euclidean distance metric for vector classification. As an input data for the algorithm face image of a person is used.

2.1. Algorithm description

2.1.1. Face detection and localization

First step of the algorithm performance is image preprocessing. It aims to transform the original image to contribute to algorithm performance on the next steps and enhances the speed of face recognition [23]. If as an input a color image was used, it is been converted to a grayscale.

The next stage is detection and localization of a face region on the input image. With this purpose Haar features are used, which are a set of primitives - white and black blocks. As a result of image features f_j learning, it is possible to obtain the limit value θ_j and the value of comparability modulo p_j. The simple classifier can be described as:

$$h_j(x) = \begin{cases} 1, if\ p_j f_j(x) < p_j \theta_j, \\ 0, else. \end{cases} \quad (1)$$

Examples of the original image, image that is result of face localization on the original image and image of a face as a result of that process are presented on Figure 1.

2.1.2. Anisotropic diffusion

Then, the image that contains only face region is processed using the anisotropic diffusion method to determine the most significant features. As opposed to the original algorithm, presented in work [22], where during the image preprocessing high contrast edges were used over low contrast ones, the current paper describes the usage of anisotropic diffusion method with the parameter that preserves sharper boundaries [24] than previous formulations and improves the automatic stopping of the diffusion. This step of the algorithm can be expressed with the following formula [25]:

$$f(x)_t = div\big(c(x,y,t)\nabla f(x)\big) = c(x,y,t)\Delta f(x) + \nabla c \cdot \nabla f(x), \quad (2)$$

where $f_0(x, y)$ is the input image, div – divergence operator, ∇ – gradient operator, Δ – Laplacian operator, t – Gaussian kernel variance and $f(x, y, t)$ is a family of derived images obtained by convolving the original image with a Gaussian kernel $G(x, y, t_0)$.

In Figure 2 there is an example of the image processed by anisotropic diffusion.

2.1.3. Gabor wavelet transform

After applying of the anisotropic diffusion on image, Gabor wavelet transform [26, 27] was used for image processing. During the process different parameters values of the wavelet function were used, that allowed to obtain several transformed images that were summed in the global image. Gabor wavelet transform generally describes with the following [28]:

$$(x,y) = K \cdot exp(-\pi(\alpha^2 (x-x_0)_r{}^2 + b^2 (y-y_0)_r{}^2)) exp(j(2\pi(u_0 x + v_0 y) + P), \quad (3)$$

where K – parameter that scales Gaussian envelope value; (a, b) – parameters that scale two axes of the Gaussian envelope; (x_0, y_0) – Gaussian envelope peak coordinates; (u_0, v_0) – sinusoidal carrier spatial frequencies; P – sinusoidal carrier phase [29].

Figure 1: Examples of: a) original image; b) image with localized face; c) image that contains face only

Figure 2: Examples of images: a) face only image; b) face only image processed by anisotropic diffusion

Figure 3 presents the examples of the images proceed by Gabor wavelet transform.

Global image, that is a result of Gabor wavelet transform, further get processed by methods of histogram of oriented gradients and 1-dimensional local binary patterns.

2.1.4. Histogram of oriented gradients

It was decided to use a combination of two local-texture descriptors to extract the feature vector from the global image, because such approach allows to increase the recognition accuracy rate. In particular, several studies [30-34] have proven the effectiveness of combining LBP-based descriptors with histograms of oriented gradients (HOG).

Creation of histogram of oriented gradients [35] requires a calculation of the orientation gradients for each area of the image and normalization of histograms and separate groups of their plots. To calculate the gradient image firstly filtered with a 1-dimensional horizontal discrete derivative mask Dx and then forms a convolution with a 1-dimensional vertical discrete derivative mask Dy [36]:

$$I(x) = I \cdot D_x, \tag{4}$$

$$I(y) = i \cdot D_y. \tag{5}$$

Figure 4 contains the examples of histograms of oriented gradients after deriving it from single image with different parameters.

2.1.5. 1-Dimensional local binary patterns

Method of local binary patterns is the most widely used local-texture method, that is characterized by powerful and effective robustness to rotation and illumination fluctuations, as well as simplicity of calculation. However, its main drawback is the size of the extracted feature vector, which does not describe the global models that can be considered the dominant structures in the face image. In paper [37] there was proposed LBP-based descriptor, which creates a binary code of a two-dimensional image in one-dimensional space (1DLBP). This descriptor allows to get small details and relative relationships between all pixels, as well as combines local and global features of the human face image.

Figure 3: Examples of images processed by Gabor wavelet transform with various parameter settings

Figure 4: Examples of images with derived histogram of oriented gradients

As a result of LBP and 1DLBP comparing, the developers of the 1DLBP method found that the recognition accuracy rates for the LBP descriptor range from 85.2% to 94.3%, and for the 1DLBP descriptor from 92% to 98.3%; rates of false positive recognition for the studied descriptors are: LBP - from 3.1% to 3.62%, 1DLBP - from 1.1% to 2.36%. So, the 1DLBP descriptor shows better performance than the LBP descriptor, both in terms of recognition accuracy and the number of false positive recognition cases. Also, according to study [38], combination of 1DLBP and HOG increases identification rate on 5-20%. Therefore, the 1DLBP descriptor was preferred for feature vector extraction from face images.

To create 1-dimensional local binary patterns [39] firstly form a binary code that describes the local excitation of a segment in a 1-dimensional signal. Binary code can be calculated by comparing the value of the central pixel with the values of neighboring pixels. If neighboring pixel is less than the current element, it gets a value of 0, and vice versa, if it is greater than the current element or equals to it, it gets a value of 1. Each element of the resulting vector is multiplied by a weight according to its position. Then the sum of the resulting vector replaces the current element [40]. This process can be described with the following notion:

$$1DLBP = \sum_{n=0}^{N-1} S(g_n - g_0) \cdot 2^n, \tag{6}$$

where g_0 and g_n are the values of the central element and its one-dimensional neighbors.

2.2. Feature vector formation and its classification

After appliance of histogram of oriented gradients and 1-dimensional local binary patterns to the image, there are formed two 512-value feature vectors. For further use they are processed with min-max normalization [41]:

$$x' = \frac{x_i - Min(X)}{Max(X) - Min(X)}. \tag{7}$$

The HOG feature vector and 1DLBP feature vector concatenates to form a 1024-value global feature vector of a face image. The global feature vector of the image can be obtained by concatenating into a single feature vector the normalized feature vectors of 1DLBP and HOG features.

If the normalized 1DLBP feature vectors is $D = [d_1; d_2; d_3 ; ...; d_n]$ and normalized HOG feature vectors is $h = [h_1; h_2; h_3; ...; h_n]$, then global vector is [35]:

$$V_g = [d_1, d_2, d_3, \dots, d_n, h_1, h_2, h_3, \dots, h_n]. \tag{8}$$

1024-value feature vectors are stored in the database, one for each person. Classification and identification perform by calculating the distance between the feature vector of input image and feature vectors stored in the database. For described algorithm square Euclidean distance metric [42] is used:

$$D_{ij} = \left\| V_{di} - V_{gj} \right\|_2^2, \tag{9}$$

where V_d – is feature vector, stored in the database, V_g – is feature vector of an image to be identified.

Overall process of the proposed algorithm performance presented in Figure 5

3. Experimental research and analysis

3.1. Setup of experiments

Experimental research was conducted on three face image databases: The Database of Faces, Facial Recognition Technology (FERET) database and Surveillance Cameras Face Database (SCface). The requirements for the selection of face image databases were formed based on the numerous previous studies of the algorithm, under which it were obtained the best performance rates: databases must contain frontal images with different facial expressions, occlusions, variety in head poses and lighting, captured under constrained conditions.

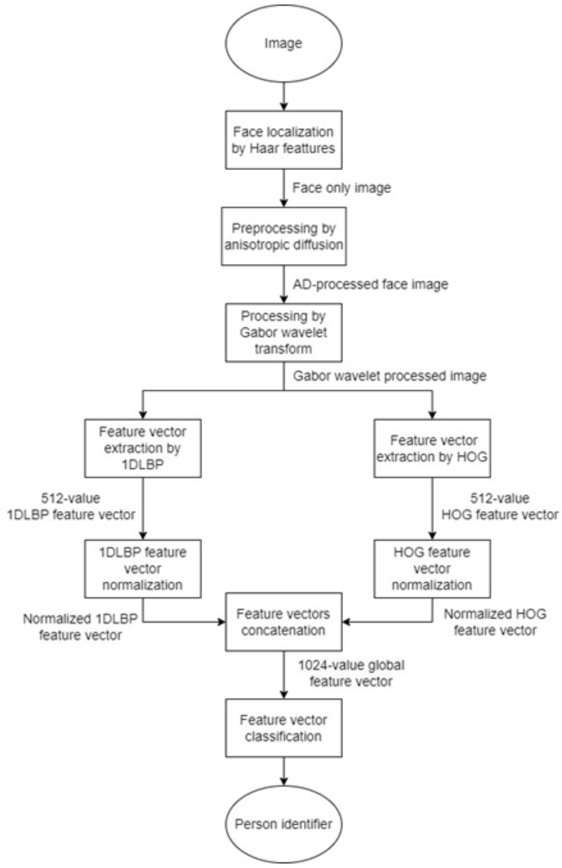

Figure 5: Overall process of proposed algorithm performance

The Database of Faces is the image database created by AT&T Laboratories Cambridge [43] that contains a set of face images of 40 different individuals. It is organized in 40 directories with 10 PGM format images in each directory. The size of each image is 92x112 pixels, with 256 grey levels per pixel. Images for experiments were selected on the basis of several requirements: they needed to be frontal images with variety of facial expression, details such as glasses, beard, different background, pose and lighting diversity.

The FERET Database [44] is owned by The National Institute of Standards and Technology (NIST). It is a part of the Face Recognition Technology program that researches automatic face recognition capabilities to develop new algorithms for the automatic recognition of human faces. Database contains 14126 high-resolution images of 1199 individuals with the resolution of 256x384.

SCface database was created by researchers from University of Zagreb [45] for testing face recognition algorithms in conditions of the real world. Database contains 4160 static images of 130 individuals. Images of the database were taken with the use of surveillance cameras, so they can be defined as low-quality images.

Since in The Database of Faces images for 40 people in total are stored, and it is the least amount among all described databases, it has been decided to select images of 40 people as well to perform the experiments on other databases.

3.2. Experiments with original images

Results of experiments on the original images from all above-described databases are presented in the Table 1.

The highest identification accuracy rate of 95% was obtained on the images from the SCface database. The images that were selected for experimentational reason, are low-quality video surveillance images.

Obtained result indicates that proposed algorithm provides better result on low-quality images in comparison to the images with more details. However, the results from the other databases are also promising and amounts to 72,5% and 75% for The Database of Faces and FERET database, respectfully.

Variation of the obtained results, that amounts from 20 to 22.5%, raises the following issue: if the algorithm provides the high identification accuracy rate on certain images, there must be some factors in the processed images that affect the efficiency of the algorithm.

Table 1

Results of the experiments on original images

	The Database of Faces	FERET	SCface
Total number of individuals / images	40 / 120	40 / 99	40 / 160
Number of identified / nonidentified individuals	29 / 11	30 / 10	38 / 2
Identification accuracy / error rate	72.5% / 27.5%	75% / 25%	95% / 5%

Therefore, it has been decided to perform the experimental research to search the possibility to create unified space of the requirements to the input images that will allow correctly identify images from different databases. The most obvious factors if variation could be image compression due to its format and image resolution.

3.3. Experiments with converted images

Face recognition and identification algorithms perform faultlessly in the conditions of high quality of database images and testing images to be identified and, also, when these two sets do not vary much. However, there are many situations, when database images and testing images do not share much similarity, so the performance of face recognition and identification algorithms can be failed [46]. In the context of this paper low-quality images define as small-sized, blurry, indistinct, pixelated, noised images, and high-quality images vice versa define as more distinct, low-compressed and noise-reduced.

For example, law enforcement database can store in the database a single high-resolution frontal face image per individual, which is passport photo. But there can be situation when it is needed to identify a person by the surveillance footage screenshots in the testing sample, that contain appearance variations due to changes in illumination, expression, pose, motion-blur, occlusion, focus, and varying resolutions. Testing images quality problems and the quality mismatch between the database and testing images are the main causes of the performance drop in deep face recognition models when they are tested under such conditions [47].

In general, tasks of low-quality face recognition have several issues [48]. One of them is blurriness of the images. Low quality images might contain blurriness as an effect of unstable camera focus or subject movement. The issues of blurriness and face aligning are solved by anisotropic diffusion method underlying in the basis of the proposed algorithm.

Image compression can affect the process of identification depending on file format. In biometric identification tasks compression rate can negatively affect the recognition and identification accuracy due to lack of details in the image.

The difference in resolution of face images of the same subject might influence the possibility of subject identification. During the surveillance camera footage, the target subject can move in different directions with various poses, locating closer or further relative to the camera. Consequently, it can cause the size variety of face images been captured [49].

Some images of the face that standard surveillance camera can capture are either low-resolution or taken from large distance. Therefore, such images do not provide information of enough amount to perform correct recognition. So, there is become an issue that the area of face region covering the image could be too small.

It has been decided to address issues of image compression variety and difference of resolution in this work by exploring the factors, such as, amount of information included in the images depending on its format and resolution matching between the database and testing images.

3.3.1. Image compression

Experiments for exploring the amount of information included in the images was performed with the conversion of original images from the previously mentioned databases to the different image formats: JPG, PNG and BMP. Results of these experiments are presented in the Table 2.

Identification accuracy rate for images from SCface database is equals to 95% in all sets of experiments, meaning that the format conversion did not affect the experimentational results for these images.

Result for the images from FERET database decreased up to 72.5% after images being converted to JPG format, but at the same time after conversion of images to PNG and BMP formats the result is equal to 75%, as well as for the original images. Conversion of the images from SCface database to the JPG format from PGM improved the obtained result from 70 to 75%.

For further experiments it has been decided to use PNG format, since the image conversion to it allowed to obtain the most stable results for all three databases.

3.3.2. Image resolution

In order to determine the dependence of the recognition rate on the image resolution, it was decided to experiment on different resolution values.

Table 2
Results of the experiments on original images

	The Database of Faces	FERET	SCface
Total number of individuals / images	40 / 120	40 / 99	40 / 160
		JPG	
Number of identified / nonidentified individuals	31 / 9	29 / 11	38 / 2
Identification accuracy / error rate	77.5% / 22.5%	72.5% / 27.5%	95% / 5%
		PNG	
Number of identified / nonidentified individuals	29 / 11	30 / 10	38 / 2
Identification accuracy / error rate	72.5% / 27.5%	75% / 25%	95% / 5%
		BMP	
Number of identified / nonidentified individuals	27 / 15	30 / 10	38 / 2
Identification accuracy / error rate	67.5% / 32.5%	75% / 25%	95% / 5%

It can be seen from the analysis of previous experimental studies that the algorithm is applied to the images in the SCface database, and the highest recognition accuracy is obtained, including images with resolutions of 75x100, 96x128 and 108x144 pixels. The same resolution value was chosen to perform resolution conversion experiments on other databases, and the SCface database converted all images to a uniform resolution.

The thumbnail feature is used to convert image resolutions in the early stages of research. During the experiment, it was found that the images in the face database cannot be converted to a size of 75x100 by the thumbnail function, but the images are converted to a resolution of 75x91 pixels.

When preparing for the experiment, it is important to convert the images to the same resolution value. However, since all databases used contain original images with different resolutions, the aspect ratio of the images may have changed. Therefore, image features may also be altered, including the facial features depicted in the image, which are essential in face recognition tasks. So, the image resolution has been transformed by a single height, keeping the aspect ratio the same, keeping the automatically defined value of the image width.

Therefore, experiments were carried out with the following resolution values: 75x91, 75x100, 96x128 and 108x144 - for The Database of Face; 61x91, 67x100, 85x128 and 96x144 - for the FERET database; 68x91, 75x100, 96x128 and 108x144 - for the SCface database. The format of the images was also changed according to the first set of experiments. The experimental results are shown in Table 3.

Applying the resolution conversion method to the images from The Database of Faces, the recognition accuracy improves from 72.5% of the original image to 80% of the image with a resolution of 75x91 pixels. The identification result increased by 2.5% relative to the result of the single format conversion. Compared to the results obtained before, the results for converting resolutions of 82x100, 105x128 and 118x144 dropped to 67.5-72.5%. After converting the image resolutions to 61x91 and 67x100 pixels, the recognition accuracy determined in the FERET database dropped significantly - from 75% to 55-62.5%. On the other hand, for images with resolutions of 85x128 and 96x144 pixels, the results agree with the previously obtained results of 75%.

Results for the SCface database images decreased after being converted to the resolution of 68x91, 75x100 and 96x128 pixels. Identification accuracy rate varies from 65% to 95%. On contrary, image resolution conversion to 108x144 pixels allowed to obtain the result of the initial 95%.

3.3.3. Face region area

In the next phase of experimental research, it was decided to define whether the recognition accuracy depends on the size of the facial region contained in the image. To this end, the experiments with the highest recognition accuracy in previous studies are analyzed, especially the experiments containing PNG images from the SCface database. The analysis results found that images with face areas of 47x47 and 78x78 pixels were correctly identified in most of the experiments. Since the initial etalon and test images are also of different sizes, the size of the face area on the images from the SCface database will vary. Therefore, it was decided to use the specified size for the purpose of the experimental research in this work. Also, to determine the variety of the identification rate beyond the selected sizes, it was decided to conduct the experiments on the images that contain face region below and beyond the threshold values (32x32 and 128x128), and between the selected values and threshold values (64x64).

Thereby, the experiments on the face image region were performed as follows: face detection on the image, conversion of the obtained face region to the selected size, input of the image containing only face region of the size of 32x32, 47x47, 64x64, 78x78 or 128x128 pixels to the algorithm. Table 4 contains the results of the described experiments.

The recognition accuracy does not depend on whether the database image and testing image samples contain any information except for the face region itself. The algorithm provides face detection and image resizing methods that can solve tasks independently, regardless of the quality of the input data.

Table 3
Results of the experiments on resolution-converted

	The Database of Faces	FERET	SCface
Total number of individuals / images	40 / 120	40 / 99	40 / 160
		width x 91	
Number of identified / nonidentified individuals	32 / 8	22 / 18	26 / 14
Identification accuracy / error rate	80% / 20%	55% / 45%	65% / 35%
		width x 100	
Number of identified / nonidentified individuals	27 / 13	25 / 15	28 / 12
Identification accuracy / error rate	67.5% / 32.5%	62.5% / 37.5%	70% / 30%
		width x 128	
Number of identified / nonidentified individuals	29 / 11	30 / 10	34 / 6
Identification accuracy / error rate	72.5% / 27.5%	75% / 25%	85% / 15%
		width x 144	
Number of identified / nonidentified individuals	29 / 11	30 / 10	38 / 2
Identification accuracy / error rate	72.5% / 27.5%	75% / 25%	95% / 5%

Table 4
Results of the experiments on face region conversion of images

	The Database of Faces	FERET	SCface
Total number of individuals / images	40 / 120	40 / 99	40 / 160
		32 x 32	
Number of identified / nonidentified individuals	2 / 38	2 / 38	2 / 38
Identification accuracy / error rate	5% / 95%	5% / 95%	5% / 95%
		47 x 47	
Number of identified / nonidentified individuals	2 / 38	14 / 26	27 / 13
Identification accuracy / error rate	5% / 95%	35% / 65%	67.5% / 32.5%
		64 x 64	
Number of identified / nonidentified individuals	19 / 21	28 / 14	35 / 5

Identification accuracy / error rate	47.5% / 52.5%	70% / 30%	87.5% / 12.5%
		78 x 78	
Number of identified / nonidentified individuals	19 / 21	29 / 11	34 / 6
Identification accuracy / error rate	47.5% / 52.5%	72.5% / 27.5%	85% / 15%
		128 x 128	
Number of identified / nonidentified individuals	29 / 11	29 / 11	35 / 5
Identification accuracy / error rate	72.5% / 27.5%	72.5% / 27.5%	87.5% / 12.5%

Comparative diagram of the results obtained in all sets of experiments presented in Figure 6.

3.3.4. Results analysis

In order to establish whether the algorithm described in the paper is technically reliable, it is worth to compare the obtained accuracy rates with other existing algorithms based on local texture descriptors. Based on the results of the analysis of modern papers on the topic of the research, experiments similar to those presented in this work were not conducted on algorithms based on local-texture descriptors and those artificial intelligence methods based algorithms considered before. Therefore, obtained results of the identification accuracy of similar algorithms can be only compared by face image databases, on which the accuracy rate was obtained, and such parameter of contained in these databases images as resolution.

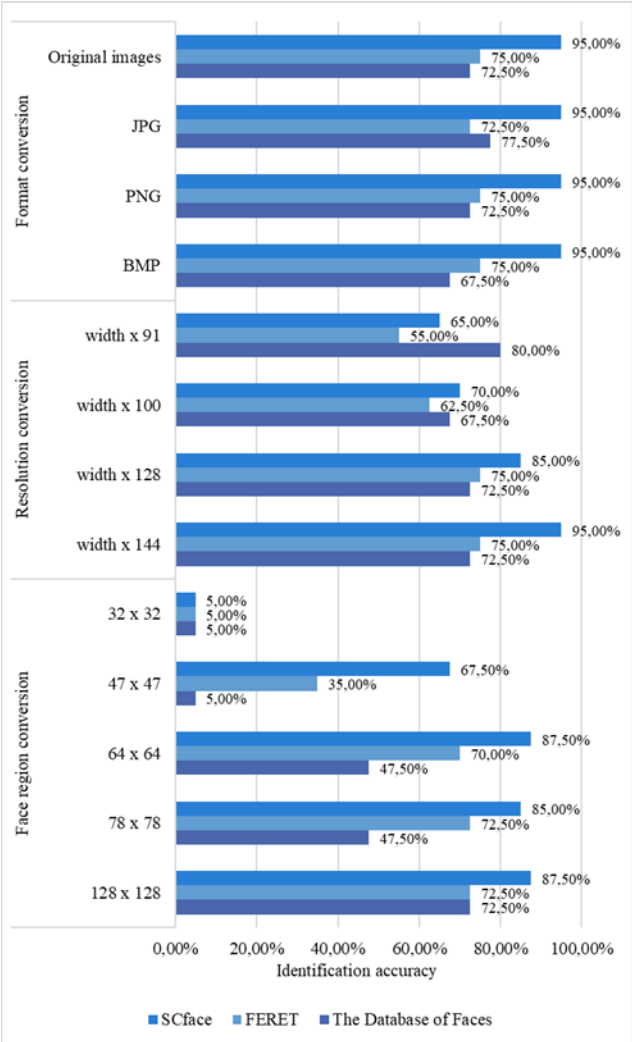

Figure 6: Comparative diagram of identification accuracy rates obtained in all sets of experiments

In Table 5 the comparative results of those descriptors and descriptors underlying in the basis of proposed algorithm are presented. As can be concluded from analysis of the local-texture descriptors overview results, the efficiency of the methods significantly varies depending on the database of face image they were applied to. The proposed combination of 1DBP and HOG descriptors surpasses the efficiency of performance of such methods as gradient directional pattern (GDP) on 16.2-40.22%, local directional texture pattern (LDTP) on 7.05-42.92%, local frequency descriptor (LFD) on 3.65-30.42%, local gradient pattern (LGP) on 9.1-35.36% and local transitional pattern (LTrP) on 19.9-41%. Concerning the rest of the methods, the identification accuracy rate proposed algorithm is close to the higher limit of their efficiency and exceeds its lower limit, which was obtained on images from ORL database (also known in this study as The Database of Faces) on 22.06% for local binary pattern (LBP), on 23.67% for median binary pattern (MBP), 1.97% for monogenic binary coding (MBC), 21.86% for local arc pattern (LAP), 24.31% for local directional number pattern (LDN), 4.78% for local phase quantization (LPQ), 17.42% for local gradient increasing pattern (LGIP), 15.83% for local monotonic pattern (LMP), 17.78% for local ternary pattern (LTP), 23.58% for gradient local ternary pattern (GLTP), 12.81% for median ternary pattern (MTP), 1.89% for pyramid of histogram of oriented gradients (PHOG) and 15.36% for Weber local descriptor (WLD).

Table 5
Local texture descriptors identification accuracy rates

Descriptor	Database	Resolution	Number of individuals / images	Accuracy
LBP	PUT	128 x 128	100 / 1000	87.22-98.4%
	ORL	92 x 112	40 / 400	50.44-83.35%
MBP	PUT	128 x 128	100 / 1000	78.92-96.6%
	ORL	92 x 112	40 / 400	48.83-80.85%
MBC	PUT	128 x 128	100 / 1000	93.44-99.8%
	ORL	92 x 112	40 / 400	70.53-96.25%
LAP	PUT	128 x 128	100 / 1000	80.92-97.7%
	ORL	92 x 112	40 / 400	50.64-84.4%
GDP	PUT	128 x 128	100 / 1000	57.9-78.8%
	ORL	92 x 112	40 / 400	32.28-52.5%
LDN	PUT	128 x 128	100 / 1000	81.61-97.1%
	ORL	92 x 112	40 / 400	48.19-78.8%
LDTP	PUT	128 x 128	100 / 1000	63.72-87.95%
	ORL	92 x 112	40 / 400	29.58-52.45%
LPQ	PUT	128 x 128	100 / 1000	86.75-98.55%
	ORL	92 x 112	40 / 400	67.72-94.25%
LFD	PUT	128 x 128	100 / 1000	70.89-91.35%,
	ORL	92 x 112	40 / 400	42.08-67.1%
LGIP	PUT	128 x 128	100 / 1000	87.25-98.45%
	ORL	92 x 112	40 / 400	55.08-88.5%
LGP	PUT	128 x 128	100 / 1000	64.36-85.9%
	ORL	92 x 112	40 / 400	37.14-62.4%
LMP	PUT	128 x 128	100 / 1000	89.78-99.25%
	ORL	92 x 112	40 / 400	56.67-87.85%
LTP	PUT	128 x 128	100 / 1000	96.58-99.55%
	ORL	92 x 112	40 / 400	54.72-88.55%
GLTP	PUT	128 x 128	100 / 1000	92.92-99.25%
	ORL	92 x 112	40 / 400	48.92-80.4%
MTP	PUT	128 x 128	100 / 1000	93.33-99.05%
	ORL	92 x 112	40 / 400	59.69-92.6%
LTrP	PUT	128 x 128	100 / 1000	56.89-75.1%
	ORL	92 x 112	40 / 400	31.5-50.75%
PHOG	PUT	128 x 128	100 / 1000	86.81-99.15%
	ORL	92 x 112	40 / 400	70.61-94.9%
WLD	PUT	128 x 128	100 / 1000	83.44-97.55%
	ORL	92 x 112	40 / 400	57.14-89.3%
1DLBP + HOG	DoF (ORL)	92 x 112	40 / 120	72.5%
	FERET	256 x 384	40 / 99	75%
	SCface	108 x 144	40 / 160	95%

Also, obtained results of the experimental research of can be compared with the results of the studies of similar algorithms that contain LBP-based and HOG descriptors, as far as appliance of 1DLBP and HOG descriptors combination to face images processed using the Gabor wavelet transform has not been previously studied in face recognition and identification tasks. Results of performance comparison of LBP-based and HOG descriptors are presented in Table 6. Analyzing the identification accuracy rates of considered methods, it can be concluded that efficiency of those methods also varies considerably after its appliance to images from different databases as well as within one database. Efficiency of the combination of methods proposed in this work exceeds the performance of algorithms based on original LBP and HOG on 1-12.5% and it is close to the performance of other combinations of LBP-based and HOG descriptors.

Identification accuracy rates of the algorithm under research in this paper are 72.5-95%, that exceeds the rates of some of the similar algorithms. Comparing with the recognition accuracy rates of algorithms based on other local texture descriptors, it can be concluded that proposed algorithm may not be the most efficient, but the results of its operation are superior to the results of some algorithms or close to these results. Obtained results varies in average on 20-22.5% depending on the image sample the algorithm was applied on, that shows the necessity of further research.

Table 6
Identification accuracy rates of combination of lbp-based and hog descriptors

Descriptor	Database	Resolution	Number of individuals / images	Accuracy
HOG + LBP [30]	LFW	58 x 50	N/A	75-94%
	AR		N/A	88-93%
	Yale		N/A	86-97%
HOG + LBP [34]	Yale	N/A	N/A	86.47-92%
OC-LBP + HOG [31]	ORL	64 x 64	N/A	91-96%
	Yale	64 x 64	N/A	85.4-100%
	FERET	64 x 64	N/A	82.3-100%
HOG + LBP + KNN [32]	N/A	N/A	10 / 100	82.5%
CS-NWALBP + HOG [33]	CMUPIE	112 x 112	40 / 240	72.8-94.2%
	Yale B	192 x 168	N/A	97-99%
	FERET	80 x 80	40 / 240	79.1-96.6%
1DLBP + HOG	DoF (ORL)	92 x 112	40 / 120	72.5%
	FERET	256 x 384	40 / 99	75%
	SCface	108 x 144	40 / 160	95%

Table 7
Identification accuracy rates of proposed algorithm compared to algorithms based on artificial intelligence methods

Method	Database	Resolution	Accuracy
AdaFace [16]	LFW	112x112	99.80-99.83%
	CFP-FP		98.49-99.17%
	CPLFW		93.53-94.63%
	AgeDB		97.90-98.17%
	CALFW		96.02-96.08%

	IJB-B		95.67-96.03%
	IJB-C		96.89-97.39%
	IJB-S		2.50-76.11%
	TinyFace		67.81-74.52%
MagFace [17]	LFW	112x112	99.83%
	CFP-FP		98.46%
	AgeDB		98.17%
	CALFW		96.15%
	CPLFW		92.87%
	IJB-B		40.91-94.51%
	IJB-C		89.26-95.97%
1DLBP + HOG	DoF (ORL)	from 47x47 to 118x144	5-72.5%
	FERET	from 47x47 to 128x128	5-75%
	SCface	from 47x47 to 128x128	5-95%

The performance of the algorithm can also be compared with works that investigate the problem of face recognition on images of varying quality in training and test sets. For example, in [16] and [17] approaches based on artificial intelligence methods are described and the recognition rates obtained as a result of these studies reach 2.5-99.83% and 40.91-99.83% verification accuracy, respectively, depending on the quality of the images to which algorithms were applied. The recognition accuracy rates of the algorithm proposed in this paper vary from 72.5% to 95% on original images from databases, 67.5% to 95% on format-converted images, from 55% to 95% on resolution-converted images, from 5 % to 87.5% on face region converted images. Identification accuracy rates obtained in compared studies are presented in Table 7. All the proposed algorithms are most efficient when applied to high-quality images, but the accuracy decreases significantly when applied to a set of low-quality images.

However, it is worth noting that approaches of face recognition based on artificial intelligence methods, in contrast to algorithms based on local texture descriptors, require a large amount of high-quality training data and are not efficient for face recognition tasks in conditions where the database only has one face image per person.

4. Conclusion

This paper is devoted to the study of both low-quality and high-quality images prerequisites with the purpose of defining conditions and parameters of the algorithm, that underlies in the bases of information technology for person recognition and identification, that would allow to create a unified space, so as if the images to be identified and database images are different in terms of quality they can still be compared obtaining as a result high accuracy rates.

To perform the experimental research the algorithm proposed in a previous work was used with modification in preprocessing method. Algorithm underlies in the information technology for person identification in video stream and consists of the following methods: anisotropic diffusion as an image preprocessing method, Gabor wavelet transform as an image processing method, histogram of oriented gradients (HOG) and local binary patterns in 1-dimensional space (1DLBP) as the methods of feature vector extraction from the images.

In this work anisotropic diffusion was applied with the parameter that preserves sharper boundaries than previous formulations and improves the automatic stopping of the diffusion.

Experimental research was conducted on three face image databases: The Database of Faces, Facial Recognition Technology (FERET) database and Surveillance Cameras Face Database (SCface).

The algorithm performance provided the following results: for the images from The Database of Faces identification accuracy rate of 72.5% was obtained, the appliance on the FERET database images indicated 75% of correctly identified images and the highest identification accuracy rate of 95% was provided by performance on the images that SCface database contains. So, the difference between all the results in average amount to 20-22.5%.

Such variety of identification accuracy rates have arisen the issue of input images space mismatching that significantly affects the algorithm performance. Therefore, it has been decided to perform the experimental research to search the possibility to create unified space of the requirements to the input images that will allow correctly identify images from different databases. For this purpose, it became necessary to study the image compression variety, difference of image resolutions and areas of face regions covering the images.

Analysis of obtained results have drawn the conclusion about the necessity of further studies in this scope in order to create unified image space.

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