Research and Comparative Analysis of Person Identification Information Technology

Oleksii Bychkov, Yelyzaveta Zhabska, Kateryna Merkulova and Mykyta Merkulov

Taras Shevchenko National University of Kyiv, Volodymyrska str. 64/13, Kyiv, 01601, Ukraine

Abstract

Face recognition and person identification technologies are increasingly being used in sensitive areas where a false identification can lead to irreparable consequences. Therefore, the research of such technologies in order to improve their efficiency is relevant.

Today, most recognition and identification technologies are based on algorithms containing neural networks. However, the use of such approaches requires a large amount of data, high computing power of hardware, and time used for training, which does not allow them to be adapted to rapidly changing real-world conditions.

Methods based on local-texture descriptors in contradiction to neural networks based methods do not require a fulfillment of any of previously mentioned conditions. Furthermore, the efficiency of local-texture methods is close to the efficiency of methods based on neural networks under constrained conditions and even exceed its performance in some cases of unconstrained conditions.

This paper proposes the research of local-texture descriptors based methods in compare to methods based on neural networks. In this work an approach to person identification was proposed, that is based on local-texture descriptors of face images, eliminating the shortcomings of algorithms based on neural networks. As a result of the experimental study, it was found that the accuracy of identification of the proposed algorithm exceeds the accuracy of identification of algorithms based on neural networks under conditions of different positions of the subject's head by 13.75-16.25% and incomplete visibility of facial features on the image by 10.5-27.5%.

Keywords

Information technology, face recognition, biometric identification, local-texture descriptors

1. Introduction

At the present face recognition and identification technologies are one of the most important technologies used to ensure security in a variety of industries, such as border services, police, and military affairs.

The most common areas of face identification technologies appliance, according to the research [1], are the following: access control – confirmation of a person's identity by a facial image; identification of wanted persons – person identification using surveillance cameras in real time, that allows to quickly neutralize suspects and increases the level of security in public places; criminal investigations – confirmation of the suspect's identity at the scene of the crime based on the image from surveillance cameras.

Constant improvement of face identification technologies allows to use them on an even larger scale and in more complex conditions. In the future, such technologies may be implemented in unmanned aerial vehicles of special operations forces for perimeter protection, intelligence gathering, and rescue missions [2].

International Scientific Symposium «Intelligent Solutions» IntSol-2023, September 27–28, 2023, Kyiv-Uzhhorod, Ukraine
EMAIL: bos.knu@gmail.com (O. Bychkov); y.zhabska@gmail.com (Y. Zhabska); kate.don11@gmail.com (K. Merkulova); sodiguy@gmail.com (M. Merkulov)
ORCID: 0000-0002-9378-9535 (O. Bychkov); 0000-0002-9917-3723 (Y. Zhabska); 0000-0001-6347-5191 (K. Merkulova); 0009-0004-9517-6275 (M. Merkulov)

Government services of Ukraine and independent organizations use personal identification technologies during the Russian-Ukrainian war to increase security at checkpoints, identify and detain Russian criminals, expose military psychological information operations [3].

The use of such technologies in sensitive areas, where incorrect identification can lead to irreparable consequences, such as reputational damage, wrongful conviction, or even human death, leads to the need to improve identification technologies in order to reduce the probability of identification errors.

2. Related Works and Research Objective

Currently, most works devoted to the research of face recognition and identification technologies use approaches based on neural networks. According to the results of the analysis of several studies comparing different approaches to face recognition, it was found that deep convolutional neural networks provide high accuracy of face recognition by learning more discriminative functions on large datasets and outperform the recognition performance compared to holistic, geometric, and local-texture approaches. For example, in the paper [4] thirty-seven studies were analyzed for the period from 2014, which described algorithms based on such neural network architectures as CNN, VGGNet, GoogleNet, LeNet, ResNet. The overall recognition accuracy for all studied algorithms ranges from 97.35% to 99.86%. But effective training of neural networks requires large amounts of high-quality training data and requires improved hardware, such as GPUs.

However, approaches based on neural network methods are not sufficiently flexible and able to quickly adapt to the conditions of the real world, which can change rapidly. For example, after the beginning of the coronavirus pandemic, the National Institute of Standards and Technology conducted a study in July 2020 on the accuracy of recognition of the most common algorithms at that time on images containing medical masks [5]. According to the results of the study, in the conditions of the need for identification on images of faces partially covered by a mask, the most accurate algorithms were unable to identify a person in 20% to 50% of cases, which was caused by the inability of identification algorithms to distinguish facial features from the image. For the period of November 2020, the study was conducted again, as a result of which it was established that some widely used algorithms do not identify a person in 10-40% of cases [6]. Since algorithms based on neural networks require a large amount of high-quality data for training and are also expensive to maintain, most developers are unable to quickly adapt such algorithms to the fast-moving conditions of the real world.

An alternative to approaches to face recognition and identification based on neural networks can be a local-texture approach, which is characterized by such advantages as high efficiency of analysis time and recognition speed. Local-texture methods are easy to integrate, allowing real-time imaging in complex environments. In addition, these methods are invariant to scale and displacement [4]. There are several studies that compare the performance of algorithms based on these descriptors with algorithms that use neural network methods.

Paper [7] describes the comparison of the algorithm based on local binary patterns (LBP) and histogram of oriented gradients (HOG) with the algorithm based on the CNN neural network according to the data described in other works. According to the results of this study, the use of the neural network algorithm CNN allows to obtain an average recognition accuracy rate equal to 99%, in contrast to the LBPH algorithm with an average rate of 92%. The authors found that according to the data from the literature reviewed in the paper, the accuracy of the algorithms is affected by the position of the subject's head recorded in the image. After applying the LBPH algorithm, the obtained accuracy was 86% when the head is in a straight position, and 80% when the head is tilted. At the same time, for the CNN algorithm, the test results showed that the accuracy obtained when the head is straight is 81.25%, when the head is tilted – 75%, and when the subject is looking down – 43.75%. Thus, the LBPH-based algorithm is more resistant to the condition of the recognition subject's head rotation, while the efficiency of the neural network based algorithm may decrease on about 37.5% under the same condition. The authors also state that the main difficulty in using neural network algorithms is that they require many data sets to train them, and accordingly, an efficient way of collecting data sets is needed.

Besides, in [8] these above-mentioned methods were compared in terms of the computation time required for face recognition from the trained data set. As a result of the experiments, the following computation time was obtained: LBP – 01.065 ms, HOG – 02.330 ms, CNN – 13.743 ms. That is, local-texture descriptors demonstrate better detection and recognition speed, compared to the neural network based method. At the same time, according to the authors of the study, with the increase in the complexity of the images, all methods showed mostly the same rates of recognition accuracy.

In [9] experiments were conducted with the appliance of methods based on ResNet and FaceNet neural networks to images of faces covered by medical masks, as a result of which the recognition accuracy of these methods decreased on 42.5% and 26.25%, respectively, compared to the rates obtained as a result of appliance of methods to images where faces are fully visible.

The authors of the paper [10] also noted that methods, such as Gabor wavelet transform and LBP, have an advantage for extracting detailed features of face images, while methods based on neural networks have good reliability under unfavorable conditions for recognition. Although neural networks can be used to identify detailed facial features, the cost of face identification is also very high because a deeper network model and more training samples are required.

Thus, in contrast to neural networks, methods based on local-texture descriptors do not require a large amount of data, high computing power of hardware, and time used for training. Moreover, on images captured under controlled conditions, the efficiency of such methods is close to the efficiency of methods based on neural networks, and under some unconstrained conditions they even exceed it. Therefore, methods based on local-texture descriptors should be investigated and improved, in particular, in works devoted to solving the tasks of recognition and identification of a person based on a face image.

In the work [11] there was firstly proposed a person identification information technology, based on an algorithm containing local-texture descriptors. The purpose of this paper is to study the proposed information technology and compare the results of the algorithm, underlying in its basis, with the known results of algorithms based on neural networks that were presented in the reviewed literature.

3. Proposed Approach

The algorithm, on the basis of which the proposed information technology of person identification is built, contains such methods of the local-texture approach as local binary patterns in one-dimensional space (1DLBP) and histogram of oriented gradients (HOG).

As noted in [4], feature extraction strategies, that focused on texture knowledge, play a significant role in pattern recognition and computer vision. Local texture descriptors have attracted much attention and have been implemented in many applications designed for texture classification, face recognition, or image indexing. Algorithms for texture selection proposed in the literature are divided into statistical and structural methods. They are characteristic, resistant to monotonous changes in gray gradation, poor lighting, brightness dispersion and do not require segmentation. The purpose of the local descriptor is to transform information at the pixel level into the appropriate form that acquires the most compelling content, insensitive to various aspects caused by variations in the environment. In contrast to global descriptors, which compute features directly from the entire image, local descriptors, which are more effective in unconstrained situations, model features in small local fragments of the image.

The methods of the local-texture approach are characterized by such advantages as high efficiency of analysis time and recognition speed. They are easy to integrate, enabling real-time imaging in complex environments. In addition, these methods are invariant to changes in scale and displacement.

During the analysis of existing algorithms based on local-texture descriptors, it was found that combining several descriptors significantly increases the efficiency of face recognition algorithms [12, 13]. Therefore, to implement the algorithm described in this paper, that is the basis of the person identification information technology, it was decided to use a combination of two descriptors. The first of these methods is a modification of the local binary pattern (LBP) descriptor, that produces a binary code of a two-dimensional image in one-dimensional space (1DLBP). This descriptor allows to get fine details and relative relationships between all pixels, and also combines local and global features of the human face image. Several studies have proven the efficiency of the combination of descriptors based on LBP with histograms of oriented gradients (HOG) – the combination of these descriptors allows to obtain an increasement in the recognition accuracy rate. Therefore, to increase the performance of the 1DLBP descriptor, it was decided to combine it with the HOG descriptor.

The proposed algorithm consists of the following stages:

1. Localization of a person's face in the image. For this, the method of detecting objects in images is used – a classifier based on Haar features [14]. This approach is based on machine learning, where a cascade function is trained on sets of images in which a human face is captured and sets of images in which a human face is absent. As a result of learning features f_j, it is possible to obtain the limit value θ_j and the value of comparability modulo p_j. Simple classifier can be described as follows:

$$Haar(I(x,y)) = h_j(x) = \begin{cases} 1, if\ p_i f_i(I(x,y)) < p_j \theta_j; \\ 0\ else. \end{cases} \quad (1)$$

To improve the efficiency of a simple classifier the AdaBoost learning algorithm is used. It chooses the classifier h_t *(for t = 1, ..., T)* with the lowest error ε_t, where $\varepsilon_i = 0$ if example x_i is classified correctly, $\varepsilon_i = 1$ otherwise, and $\beta_t = \varepsilon_t / 1 - \varepsilon_t$. After applying this algorithm, the final strong classifier can be defined as follows with $\alpha_t = log\ 1 / \beta_t$:

$$Haar(I(x,y)) = h(x) = \begin{cases} 1\ if\ \sum_{t=1}^{T} \alpha_t h_t(x) \geq \frac{1}{2} \sum_{t=1}^{T} \alpha_t; \\ 0\ else. \end{cases} \quad (2)$$

The process of face localization and extracting from the image only the region containing the face is presented in Figure 1.

Figure 1: Example of result of face localization stage performance of the proposed algorithm

2. Processing of an image containing only a face by Gabor wavelet transform [15]. Gabor wavelets have a shape similar to the receptive fields of simple cells of the primary visual cortex, so the representation of images using Gabor wavelets is based on the principles of image representation in the human mind [16]. Due to its biological significance and technical characteristics, this method is effective for image processing to highlight object edges. The complex Gabor function in the spatial domain is defined as:

$$Gabor(I(x,y)) = s(x,y)\omega_\tau(x,y), \quad (3)$$

where $s(x, y)$ is a complex sine wave, or carrier, and $\omega_\tau(x, y)$ is a 2D Gaussian function, or envelope function.

Complex sine wave can be described with the following:

$$s(x,y) = \exp(j(2\pi(u_0 x + v_0 y) + P)), \quad (4)$$

where (u_0, v_0) and P define spatial frequency and sine wave phase, respectively.

Concerning the 2D Gaussian function, it can be written as follows:

$$\omega_\tau(x,y) = K\ exp\left(-\pi(a^2(x-x_0)_\tau^2 + b^2(y-y_0)_\tau^2)\right), \quad (5)$$

where (x_0, y_0) is the peak of the function, a and b are the Gaussian function scaling parameters, and the index τ denotes the rotation operation.

By changing the parameters of the wavelet, it is possible to obtain several wavelet-transformed images as a result, examples of which are presented in Figure 2.

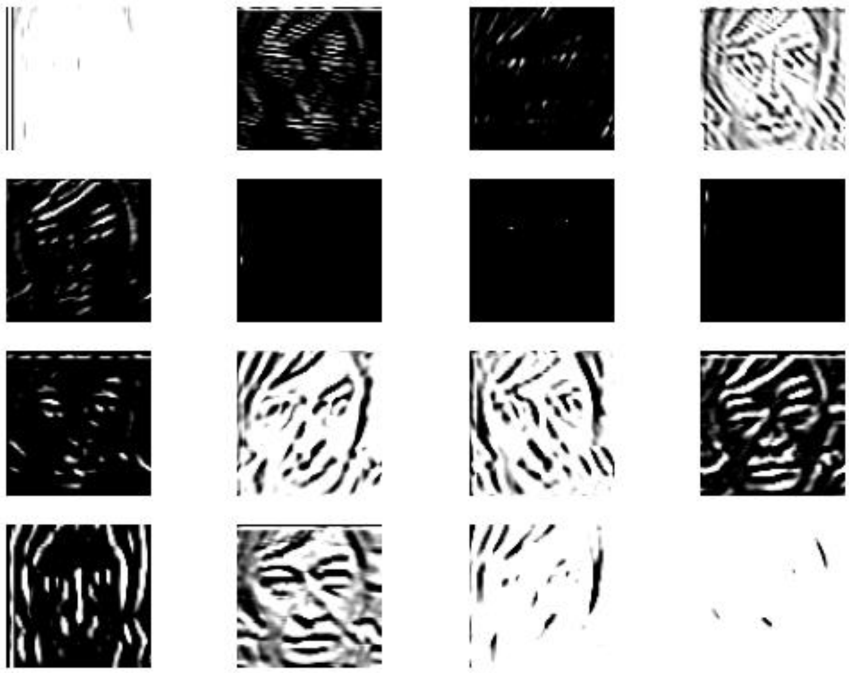

Figure 2: Example of result of image processing stage performance of the proposed algorithm

3. Extracting the vector of image features. The methods of the local-texture approach are consistently applied to the images formed as a results of Gabor wavelet transform processing.

The original LBP operator was used for texture discrimination, showing powerful and efficient performance under conditions of changing rotation angles and illumination. For example, there is a pixel $(x, y)_c$ in a gray image, its LBP texture is calculated by comparing this pixel with neighboring pixels P at a distance R from the given pixel. The value of $LBP((x, y)_c)$ is obtained as:

$$LBP^{P,R}(x,y)_c = \sum_{i=1}^{P} S\big((x,y)_i^{P,R} - (x,y)\big)\, 2^{i-1}, \quad (6)$$

where $S(x)$ can be described as:

$$S(x) = \begin{cases} 1\, if\ x \geq 0, \\ 0\ otherwise. \end{cases} \quad (7)$$

However, the main disadvantage of LBP is the size of the descriptor, that is the 3×3 pixel mask, that cannot capture the large-scale structures that can be considered the dominant structures in the image. The authors of the study [17] proposed an algorithm that eliminates this shortcoming and makes it possible to use local binary patterns for face recognition tasks in images. The main difference of this method is the use of a descriptor based on LBP in one-dimensional space (1DLBP). To provide an efficient way to better describe local and global patterns, the algorithm uses a one-dimensional row projection of each level of the image matrix. To form a binary code, the value of the central pixel is compared with the values of neighboring pixels. Neighboring pixels are replaced by 1 if they are greater than or equal to the current element, and 0 otherwise. Each element of the resulting vector is multiplied by the weight corresponding to its position. Finally, the current element is replaced by the sum of the resulting vector. This process can be described as follows:

$$1DLBP\big(I(x,y)\big) = \sum_{n=0}^{N-1} S((x,y)_n - (x,y)_0) \cdot 2^n, \quad (8)$$

where $(x,y)_n$ and $(x,y)_0$ are the values of the central element and its one-dimensional neighbors.

Examples of 1DLBP feature vectors are presented in Figure 3. It contains the output of 1DLBP method for each Gabor wavelet transformed image, presented in Figure 2, respectively. The x-axis represents the feature vector value, the y-axis represents the value index in the feature vector sequence. Each of these vectors contain 512 values, that further get summed up and normalized to form a first part of global feature vector of an input image.

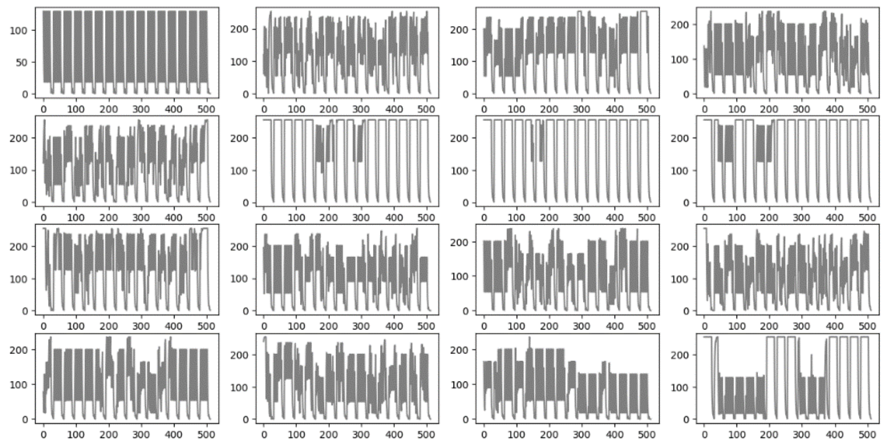

Figure 3: Examples of the feature vector extraction stage results obtained after 1DLBP descriptor appliance to Gabor wavelet transformed images (x-axis – the feature vector value, y-axis – the feature vector value index)

The HOG method is applied to wavelet-transformed images to extract image shape features. The number of edges of image objects that have an orientation with a certain range is represented by each interval within the histogram. Combining the computed histograms in all subranges of the images allows to form a HOG descriptor containing texture and shape information. To create a histogram of local gradients, orientation gradients are first calculated for each region of the normalized image. The gradient is calculated by first convolution filtering with one-dimensional horizontal D_x and vertical D_y discrete derivative masks. The resulting value is the sum of adjacent pixels, taking into account the weight of the mask [18]:

$$I(x, y) = \left(D_x \cdot I, D_y \cdot i\right), \tag{9}$$

$$I(x) = I \cdot D_x, I(y) = i \cdot D_y. \tag{10}$$

In Figure 4 the examples of HOG feature vector values are presented. It contains the output of HOG method for each Gabor wavelet transformed image, depicted in Figure 2, respectively, that are images HOG feature vectors. The x-axis represents the feature vector value, the y-axis represents the value index in the feature vector sequence. As well as the 1DLPB vectors, HOG vectors contain 512 values, that further get summed up and normalized to form a second part of global feature vector of an input image. Finally, the vectors formed as a result of applying the 1DLBP and HOG methods to the image are concatenated, forming a global feature vector of the face image.

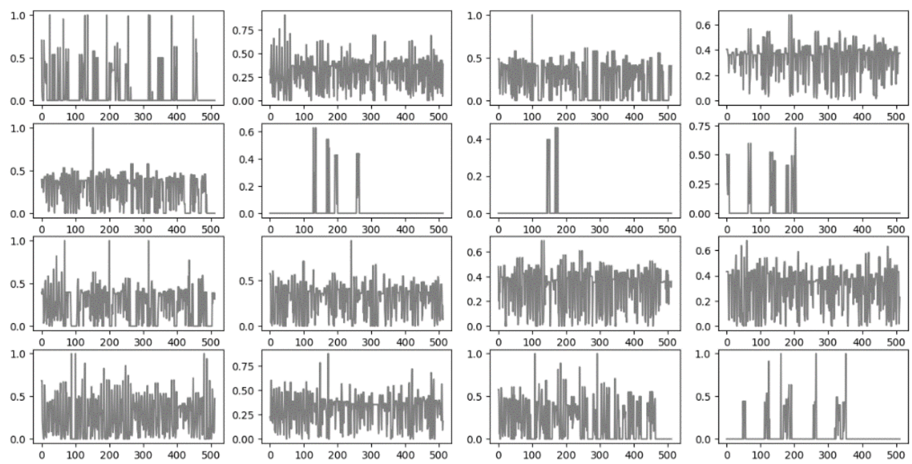

Figure 4: Examples of the feature vector extraction stage results obtained after HOG descriptor appliance to Gabor wavelet transformed images (x-axis – the feature vector value, y-axis – the feature vector value index)

4. Classification of the vector of image features.

The result of the algorithm performance is an identifier that can be used to identify the person captured in the image that was submitted to the algorithm input.

Above-described general process of the proposed algorithm performance is presented in Figure 5.

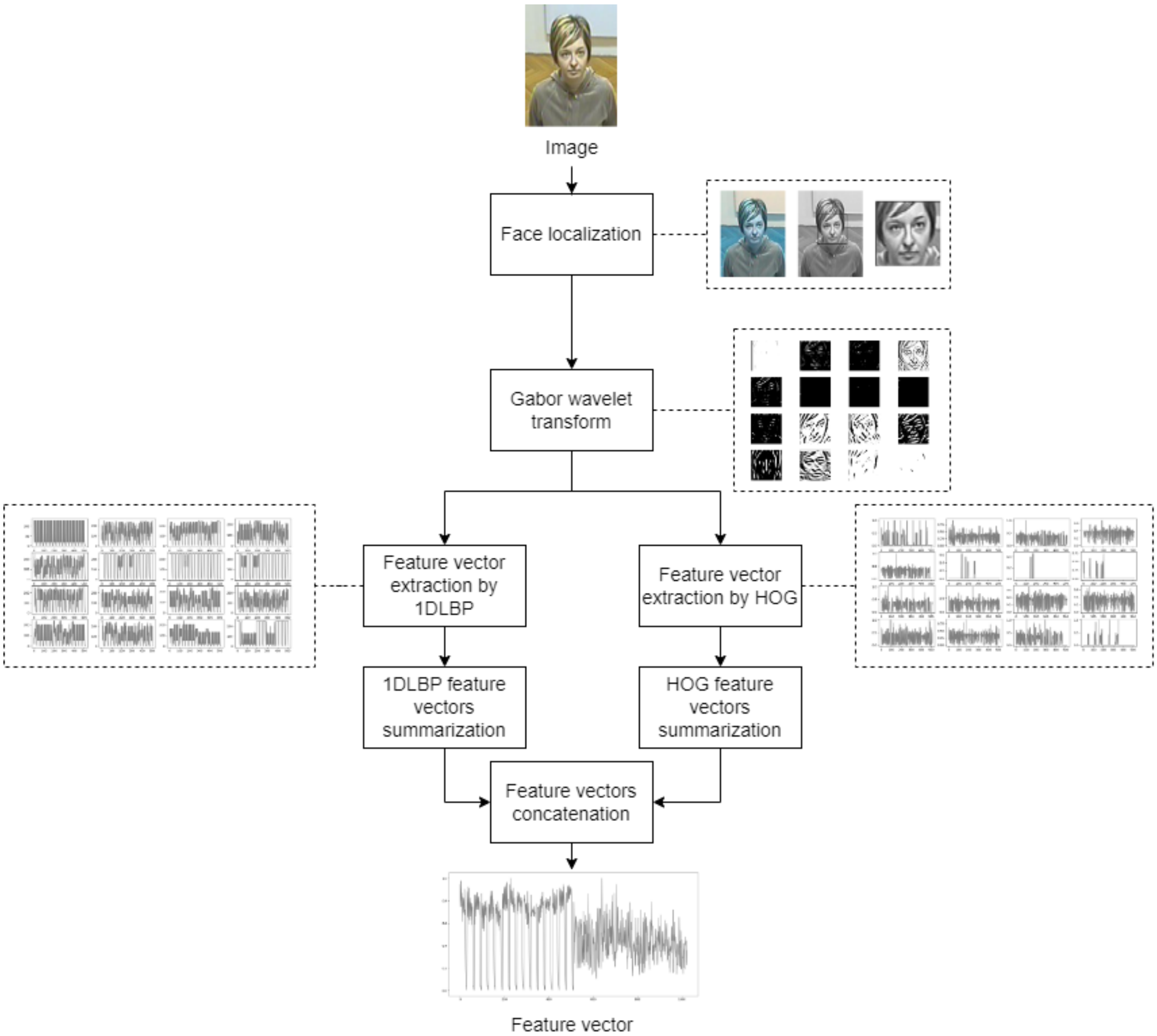

Figure 5: General process of the proposed algorithm performance

4. Experimental Research

Experimental research was conducted in order to establish the efficiency of the proposed algorithm on images with various parameters and to compare it with the most common algorithms based on neural networks.

During the experiments there was used a dataset of face images captured from different distances and angles of view of the camera on the subject, with various head positions (the subject looks directly into the camera, the camera is placed above the subject's head, or the subject look at different non-fixed points), with changes in lighting, facial expressions (unsmiling or smiling, closed or open eyes) and in the presence of some face details (such as glasses). Dataset was formed from 136 images of 40 individuals.

First, let's compare the result obtained during the experimental study of the proposed algorithm with the results of the most common algorithms based on neural networks, indicated in the literature review in [4]. The results of the experiments are presented in Table 1. For comparison, the highest identification accuracy rates among all sets of experiments were used.

Table 1
Algorithms identification accuracy rates

Approach	Method	Identification accuracy
Neural network	CNN	97.35-99.77%
Neural network	VGGNet	98.06-99.53%
Neural network	ResNet	99.12-99.86%
Local-texture	1DLBP + HOG	95%

As can be seen in Figure 6, the difference between the efficiency of the proposed algorithm and algorithms based on neural networks is 2.35-4.86%.

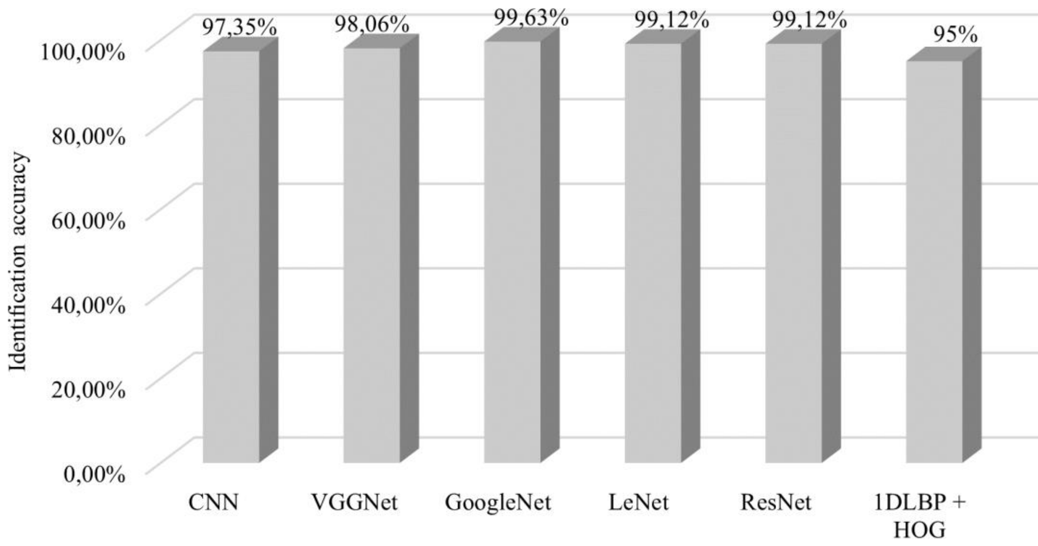

Figure 6: Comparative diagram of algorithms identification accuracy rates

At the second stage of the research, experiments were conducted on images with different positions of the subject's head. The dataset consisted of images of faces ranging from left to right profile in equal steps of 22.5 degrees. Thus, for one subject, the set contained several images with a viewing angle from -67.5 to +67.5 degrees. The experimental results shown in Table 2 are compared with the results of the algorithm based on the CNN neural network given in the paper [7].

Figure 7 shows a comparative diagram of the results of experiments on images with variability in the subject's head position. In this set of experiments, the proposed algorithm based on local-texture descriptors exceeds the results of the algorithm based on the neural network on 13.75% on images where the subject's face is located straight (the subject is looking at the camera) and on 16.25% in images where the subject's face is not completely visible (the subject is looking down).

Table 2
Results of experiments on face images with different head positions

Approach	Method	Subject's head position	Identification accuracy
Neural network	CNN	Straight	81.25%
Neural network	CNN	Sloping	75%
Neural network	CNN	Down	43.75%
Local-texture	1DLBP + HOG	Straight	95%
Local-texture	1DLBP + HOG	Sloping	75%
Local-texture	1DLBP + HOG	Down	60%

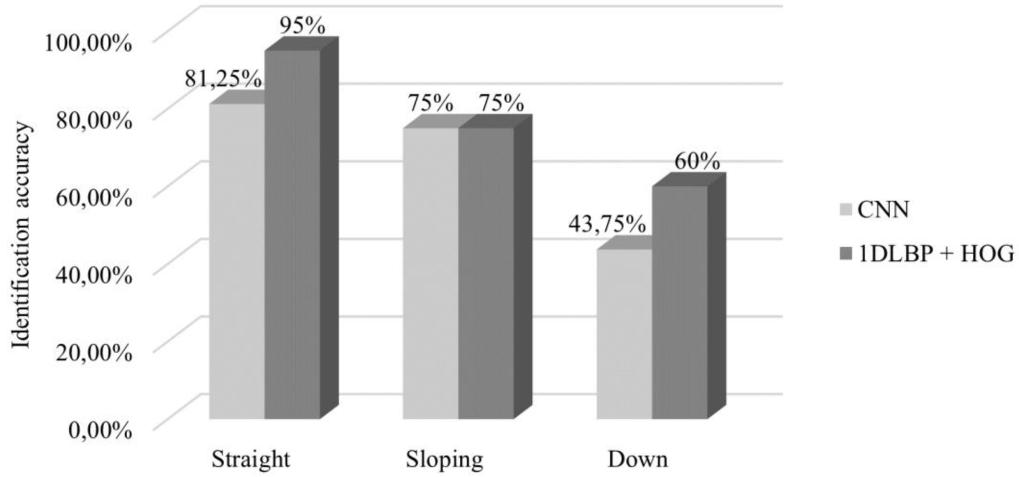

Figure 7: Comparative diagram of algorithms identification accuracy rates

The next set of experiments to study the proposed algorithm was performed on images of faces, the lower part of which is hidden from the observer, thus simulating the possibility of identifying a person wearing a medical mask or balaclava. The algorithm identification accuracy rates are compared with the results of algorithms based on ResNet and FaceNet neural networks, which were obtained in the course of a previous study [9]. The results of the experiments are presented in Table 3.

Table 3
Results of experiments on images of a partially hidden face

Approach	Method	Face visibility	Identification accuracy
Neural network	ResNet	Full	97.5%
		Partial	55%
Neural network	FaceNet	Full	98.75%
		Partial	72.5%
Local-texture	1DLBP + HOG	Full	95%
		Partial	82.5%

A comparative diagram of the results of experiments on partially hidden face images is shown in Figure 8. Even though on images, where the subject's face is fully visible, algorithms based on neural networks demonstrate higher results, during the appliance to images of a partially hidden face, the efficiency is significantly reduced: for the algorithm based on the ResNet neural network – on 42.5%, for the algorithm based on the FaceNet neural network – on 26.25%. In turn, identification accuracy rate of the proposed algorithm based on local-texture descriptors is the highest among all obtained and is 82.5%, compared to 55% and 72% obtained after appliance of neural network algorithms. Thus, in condition of partial visibility of face features, the proposed algorithm is more efficient on 10.5-27.5% in compare to FaceNet and ResNet based approaches, respectively. The percentage of reduction in efficiency compared to the result obtained on images of fully visible faces is 12.5%, which is the smallest rate among all experiments.

5. Conclusion

This paper is devoted to the research of the information technology of person identification by face image, the basis of which is an algorithm containing the methods of the local-texture approach, with the purpose of establishing its efficiency in comparison with algorithms based on neural networks.

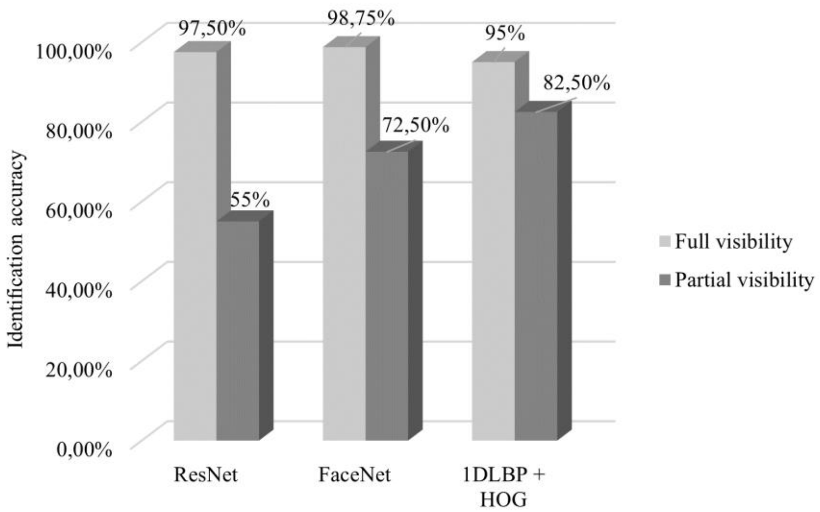

Figure 8: Comparative diagram of experiment results on partially hidden face images

Based on the analysis of the results of existing studies, it was established that algorithms based on neural networks, although the accuracy of identification is quite high, require a large amount of high-quality data, high computing power of hardware and time required for training. Because of this, quickly adapt such algorithms to the rapidly changing conditions of the real world is a rather difficult task that most developers are unable to perform. Therefore, there is a need to explore alternative approaches to the person recognition and identification, the efficiency of which will be close to the efficiency of algorithms based on neural networks, and which, at the same time, will provide better resistance to changes in environmental conditions.

The proposed algorithm consists of a classifier based on Haar features for face localization on the image; Gabor wavelet transform method for face image processing; local-texture descriptors, such as local binary patterns in one-dimensional space (1DLBP) and histogram of oriented gradients (HOG), to extract the face image feature vector.

Based on the results of an experimental research performed on 136 images of 40 individuals with variations in the position of the subject’s head relative to the camera, it was established that the proposed algorithm is more resistant to such recognition and identification conditions. On images where the subject looks directly into the camera, the identification accuracy of the proposed algorithm is 13.75% higher than that of the neural network based algorithm, and on images where the subject is looking down – on 16.25%.

During the analysis of the results obtained after conducting the experiments on the images of a partially hidden face, it was established that the algorithm based on local-texture methods is more resistant to the condition of recognition and identification, when the features of the human face are not fully visible. The identification accuracy of the proposed algorithm on 10.5-27.5% higher than the accuracy of neural network algorithms. At the same time, the percentage of reduction in identification accuracy for the proposed algorithm is 12.5%, while for algorithms based on neural networks – from 26.25% to 42.5%.

Thus, the main scientific contribution of this paper is the results of comparative analysis, based on which it can be concluded that the efficiency of the researched algorithm, which contains local-texture descriptors and underlies in the basis of the person identification information technology, exceeds the efficiency of algorithms based on neural networks under the conditions of different positions of the subject’s head and partial visibility of facial features in the image.

6. References

[1] Y. Zennayi, F. Bourzeix and Z. Guennoun, “Analyzing the Scientific Evolution of Face Recognition Research and Its Prominent Subfields,” in IEEE Access, vol. 10, pp. 68175-68201, 2022, doi: 10.1109/ACCESS.2022.3185137.

[2] S. Brodsky, "U.S. Air Force's Drones Can Now Recognize Faces: How It Works", Popular Mechanics, February 24, 2023. URL: https://www.popularmechanics.com/military/a43064899/air-force-drones-facial-recognition/

[3] "War in Ukraine", Clearview AI. URL: https://www.clearview.ai/ukraine

[4] I. Adjabi, A. Ouahabi, A. Benzaoui and A. Taleb-Ahmed, "Past, Present, and Future of Face Recognition: A Review," Electronics 2020, 9, 1188. doi: 10.3390/electronics9081188.

[5] M. Ngan, P. Grother and K. Hanaoka, "Ongoing Face Recognition Vendor Test (FRVT) Part 6A: Face recognition accuracy with masks using pre- COVID-19 algorithms," NIST Interagency/Internal Report (NISTIR), National Institute of Standards and Technology, Gaithersburg, MD, 2020. doi: 10.6028/NIST.IR.8311.

[6] M. Ngan, P. Grother and K. Hanaoka, "Ongoing Face Recognition Vendor Test (FRVT) Part 6B: Face recognition accuracy with face masks using post-COVID-19 algorithms," NIST Interagency/Internal Report (NISTIR), National Institute of Standards and Technology, Gaithersburg, MD, 2020. doi: 10.6028/NIST.IR.8331.

[7] A. Budiman, Fabian, R. A. Yaputera, S. Achmad and A. Kurniawan, "Student attendance with face recognition (LBPH or CNN): Systematic literature review," Procedia Computer Science 216, pp. 31-38, 2023. doi: 10.1016/j.procs.2022.12.108.

[8] A. P. Rajan and A. R. Mathew, "Evaluation and Applying Feature Extraction Techniques for Face Detection and Recognition," Indonesian Journal of Electrical Engineering and Informatics (IJEEI) 7 (4), pp. 742-749, 2019. doi: 10.52549/ijeei.v7i4.935.

[9] O. Bychkov, O. Ivanchenko, K. Merkulova and Y. Zhabska, "Mathematical Methods for Information Technology of Biometric Identification in Conditions of Incomplete Data," Proceedings of the 7th International Conference "Information Technology and Interactions" (IT&I-2020), CEUR Workshop Proceedings, pp. 336-349, 2020.

[10] C. Li, Y. Huang, W. Huang and F. Qin, "Learning features from covariance matrix of gabor wavelet for face recognition under adverse conditions". Pattern Recognition, Vol. 119, 2021. doi: 10.1016/j.patcog.2021.108085.

[11] O. Bychkov, K. Merkulova, Y. Zhabska and A. Shatyrko, "Development of information technology for person identification in video stream," Proceedings of the II International Scientific Symposium "Intelligent Solutions" (IntSol-2021), CEUR Workshop Proceedings, 3018, pp. 70-80, 2021. URL: https://ceur-ws.org/Vol-3018/Paper_7.pdf

[12] M. Ghorbani, A. T. Targhi and M. M. Dehshibi, "HOG and LBP: Towards a robust face recognition system," 2015 Tenth International Conference on Digital Information Management (ICDIM), Jeju, Korea (South), 2015, pp. 138-141, doi: 10.1109/ICDIM.2015.7381860.

[13] I. Chhabra and G. Singh, "Effective and Fast Face Recognition System Using Complementar OC-LBP and HOG Feature Descriptors With SVM Classifier", J. Inf. Technol. Res. 11 (1), pp. 91–110, 2018. doi: 10.4018/JITR.2018010106.

[14] T. Mantoro, M. A. Ayu and Suhendi, "Multi-Faces Recognition Process Using Haar Cascades and Eigenface Methods," 2018 6th International Conference on Multimedia Computing and Systems (ICMCS), Rabat, Morocco, 2018, pp. 1-5, doi: 10.1109/ICMCS.2018.8525935.

[15] T. Gong, "Expression Recognition Method of Fusion Gabor Filter and 2DPCA Algorithm," 2020 International Conference on Computer Information and Big Data Applications (CIBDA), Guiyang, China, 2020, pp. 515-518, doi: 10.1109/CIBDA50819.2020.00121.

[16] O. Bychkov, K. Merkulova and Y. Zhabska, "Improvement of Information Technology for Person Identification for Usage in Energy Smart Systems," 2022 IEEE 8th International Conference on Energy Smart Systems (ESS), Kyiv, Ukraine, 2022, pp. 199-203, doi: 10.1109/ESS57819.2022.9969307.

[17] A. Benzaoui, A. Boukrouche, H. Doghmane and H. Bourouba, "Face recognition using 1DLBP, DWT and SVM," 2015 3rd International Conference on Control, Engineering & Information Technology (CEIT), Tlemcen, Algeria, 2015, pp. 1-6, doi: 10.1109/CEIT.2015.7233002.

[18] B. Attallah, A. Serir, Y. Chahir and A. Boudjelal, "Histogram of gradient and binarized statistical image features of wavelet subband-based palmprint features extraction," J. Electron. Imag. 26(6), 2017. doi: 10.1117/1.JEI.26.6.063006.