Mathematical Methods for Information Technology of Biometric Identification in Conditions of Incomplete Data

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Abstract

The purpose of this research is to develop mathematical methods for information technology of biometric identification which will allow to recognize person's face in conditions of incomplete data such as wearing a medical face masks during the pandemic. During the ongoing pandemic researchers focus on quick and effective solutions to develop technologies that handle this problem. This research concentrates on the analysis of the already existing solutions and proposes a mathematical method of face identification for information technology based on wavelet transform under the condition of wearing masks by people. During this research, the experiments with face detection and recognition have been performed with the constraint information of covered face. There is no database of face images with masks, therefore a new database was created. This database contains 820 images of 40 people, whose faces was limited only by top part of the face (forehead, eyes). First experimental part was performed with the use of standard Python library face_recognition, which allows to perform face recognition from Python or from the command line with one of the simplest face recognition libraries. It built based on dlib face recognition toolkit with deep learning – it is a ResNet network that contains 29 conv layers. In the second set of experiments FaceNet system was used. It is a system that after high-quality features extracting from the face containing image creates a face embedding and predicts these features representation in a form of 128-element vector. Third part of experiments was performed to analyze the efficiency of three well-known face recognition methods: Eigenfaces, Fisherfaces and LBPH. Eigenfaces algorithm considers that different face parts are not identically significant in a face recognition process. It processes all the training images of all the people as a whole and extracts the components which are relevant and useful. Fisherfaces algorithm extracts principal components that differentiate one person from the others, so an individual's components become more useful over the others. The of LBPH algorithm is to find face local structure by comparing each pixel to its neighboring pixel, forming a list of local binary patterns, that can be converted into a decimal number.

Mathematical methods proposed in this research based on wavelet transform, that is widely used in the image processing tasks. Wavelet transform provides processing of patterns hidden in the data performing data analysis in general as well as in the detail. To compare the results of the commonly used algorithms with wavelet transform there was developed algorithm with the use of Daubechies wavelets and reverse biorthogonal wavelets. The results of experimentation analysis indicate that the popular and commonly used methods of face identification do not demonstrate high efficiency results. Proposed mathematical methods for information technology based on wavelet transform improves the face recognition and identification process under the condition of faces covered with mask. Specifically, the most accurate identification rate of 77,5% was obtained with the use of Daubechies wavelets.

Keywords

Biometric identification, face recognition, wavelet transform [1]

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1. Introduction

COVID-19 is an unprecedented crisis that has caused a huge number of casualties and security concerns. One of the methods which are using to reduce the spread of the coronavirus, is to wear masks in all public places to protect yourself and the others from being infected. So protective masks in these conditions have become an attribute of everyday life. It makes face recognition very challenging because some parts of the face are hidden. But face is the most common pattern that people use to identify each other in everyday life. Also, governmental identity documents, such as passport or driver's license, contains face image. Even in ideal conditions, face recognition technologies often struggle with accuracy.

Nowadays wearing medical masks caused increasing of the probability of false identification results of recognition systems, as the US National Institute of Standards and Technology (NIST) concluded. The National Institute of Standards and Technology conducted the research in which 89 face recognition algorithms with error rate of 0.3% were tested. And researchers found, after applying of those algorithms on images of persons with face masks, that the error rate increased from 5% to 50% [1].

Mask-wearing is now recommended as a measure to provide the spread of COVID-19. Therefore, the government, that uses face recognition algorithms to track and identify people across the US, conducted the research performed by the NIST in collaboration with the US Customs and Border Protection and Department of Homeland Security, both of which apply face recognition methods in their work. The research suggests that face mask wearing would decrease a person identification rate by face recognition. The result of a face recognition depends on mathematical models of the relative positions of face features. Anything that reduces the visibility of key characteristics of a face (such as the nose, mouth and chin) obstructs the positive outcome of face recognition. Findings also suggest that dark masks make it more difficult to recognize a face than blue surgical masks, and that wide masks that cover a person's entire face prevent the recognition more than round N95-style masks [2].

Notably, the report only lists a type of face recognition known as one-to-one matching. This is a procedure used at border crossings and at passport control, where an algorithm checks if a person matches their ID. However, facial recognition systems of mass surveillance scan the crowd to find matches with faces in the database, which is called a one-to-many system. And while the NIST report does not cover one-to-many systems, they are generally considered the most error-prone. The process of identifying a face in a crowd is more difficult, because of the different image scaling, angle of face position and lightning. Thus, wearing masks is likely to seriously interfere with one-to-many algorithms as well. Many companies that work on face recognition technologies have claimed they can identify people with high accuracy rate even in conditions of face masks wearing, but the latest research results show that the face coverings significantly increase face recognition error rates [3, 4].

During the ongoing pandemic researchers focus on quick and effective solutions to develop technologies that handle problem of face identification accuracy decreasing. This paper concentrates on the analysis of the already existing solutions and proposes a method of face identification based on wavelet transform under the condition of wearing masks by people, considering different image scaling, angle of face position and lightning. Experiments with face detection and recognition have been performed during the research with the incomplete data such as covered with mask face. Since there is no database which contains face images with masks, a new database was created. This database contains 9 images of 80 people, whose faces was limited only by top part of the face (forehead, eyes). These images prepared with different image scaling, angle and lightning.

2. Task solution methods

2.1. Face_recognition method

Python face_recognition library allows to perform face recognition and manipulation on images from Python or from the command line with one of the simplest face recognition libraries, built based on dlib face recognition toolkit with the use of deep learning. Applying of this model on the Labeled Faces in the Wild database indicated an accuracy rate of 99.38% [5].

Dlib's face recognition library performs conversion of a face image to a 128-dimensional vector space where images of the same person have a small Euclidean distance between them and images of different persons are, on the contrary, long-distance by Euclidean distance metric calculation.

Dlib model is based on the ResNet network that contains 29 conv layers. It is a version of the ResNet-34 network from the research study [6] with an exclusion of a few layers and filters per layer reduction by half. The network training was performed on a 3 million face images dataset, that includes several datasets (the VGG dataset [7], face scrub dataset [8]) and a large amount number of images derived from the internet. The total number of face images in the dataset is 7485 images.

Also, the face_recognition library method is using the k-nearest-neighbors (KNN) algorithm for face recognition [9]. It is useful when it is needed to recognize a large set of people, whose face images are stored in the database, and make a prediction for an unknown person in a feasible computation time. KNN algorithm provided by Python data science library - scikit-learn.

Neighbors-based classification based on prediction of a class labels using majority rule voting for the nearest neighbors of each point: the data class that has the most representatives within the nearest neighbors of the point defines as the query point.

Scikit-learn provides two different nearest neighbors classifiers: KNeighborsClassifier and RadiusNeighborsClassifier. The most used method in KNeighborsClassifier is k-neighbors classification. Each query point can be obtained with the use of k nearest neighbors learning, where k is an integer value specified by the user. The determination of k value depends on the data meaning that a larger k reduces the noise effects but, at the same time, makes the classification boundaries less distinct.

For the classification based on nearest neighbors there are commonly used uniform weights. But some conditions require to use the neighbors weighting so that nearer neighbors contribute more to the fit. For the purpose of this research it is better to use distance weights which are proportional to the inverse of the distance from the query point.

The KNN classifier is initially trained on a set of face images stored in the database that were labeled. Then it can identify the person in an input image by finding the k most similar faces by calculation of the closet face-features under Euclidean distance in its training set, and performing a majority vote (possibly weighted) on their label. For example, if k=3, and the three closest face images to the inputed image in the training set are one image of class1 and two images of class2, the result would be class2.

2.2. FaceNet method

FaceNet is a face recognition system that was presented in the paper [10]. It creates a mapping from face images to Euclidean space where, on the basis of a deep convolutional network computation, calculated distances correspond to a measure of face similarity.

System extracts high-quality features from the face image, given as an input, and transform they to a 128-element vector representation, performing a face embedding. This compact 128-D embedding uses a LMNN based triplet loss function [11]. Triplet loss function uses to determine similarity of the vectors, that can be defined by the calculation of the distance between vectors. Vectors for image of the same person is more similar (distance between those vectors is smaller) and vectors for the images of different persons is less similar (distance between those vectors is larger). It means that an embedding $f(x)$, from an image x into a feature space R^d, such that, independently of image quality, the squared distance between all face images of the same person is small, and the squared distance between face images of different persons is large.

Triplet loss function can be described as following. Image embedding representation expression is:

$$f(x) \in R^d. \quad (1)$$

It means that an image x is being converted into a d-dimensional Euclidean space. Then it is necessary to determine that an input image $x_i{}^a$ of a person is closer to other images of the same person $x_i{}^p$ than all images of different persons $x_i{}^n$. It can be expressed with the next:

$$\|f(x_i{}^a) - f(x_i{}^p)\|_2^2 + \alpha < \|f(x_i{}^a) - f(x_i{}^n)\|_2^2, \quad (2)$$

$$\forall(f(x_i{}^a),(fx_i{}^\rho),f(x_i{}^n)) \in T, \tag{3}$$

where α – is a limited space between images of the same person and all images of any other person; T represents the training set of all possible triplets with N cardinality.

The loss is needed to minimize, that can be described with the following:

$$\sum_i^N [\|f(x_i{}^a) - f(x_i{}^\rho)\|_2^2 - \|f(x_i{}^a) - f(x_i{}^n)\|_2^2 + \alpha]. \tag{4}$$

As the basis for classifier training system uses obtained face embeddings.

FaceNet model is provided by the Python deep learning API – Keras, that contains the pretrained Inception ResNet v1 model. This model has certain restrictions concerning input data. Expected input images must be colored, with pixel values standardized, and to have a square shape with the size of 160×160 pixels.

Face detection process is based on the use of Multi-Task Cascaded Convolutional Neural Network (MTCNN) [12]. It performs face finding and extracting from images with solution of 3 tasks: face classification, bounding box regression and facial landmark localization. For each sample of classification x_i the cross-entropy loss can be calculated:

$$L_i^{det} = -(y_i^{det}\log(\rho_i) + (1 - y_i^{det})(1 - \log(\rho_i))), \tag{5}$$

where p_i is the network probability of a sample being a face; $y_i^{det} \in \{0, 1\}$ is the correct label.

For each window, that possibly contains face, the offset between it and the nearest correct label can be predicted. Therefore, the research objective can be expressed as a regression problem, so the Euclidean loss for each sample x_i can be applied:

$$L_i^{box} = \left\|\hat{y}_i^{box} - y_i^{box}\right\|_2^2, \tag{6}$$

where $\hat{y}_i^{box}$ regression target obtained from the network and y_i^{box} is the correct coordinate. There are 4 coordinates, including left top, height and width, and thus $y_i^{box} \in R^4$.

After face detection and feature vector extraction, face classification takes part. For this purpose, Linear Support Vector Machine [13] can be used. The SVM algorithm is implemented using a kernel. Linear SVM can be presented with the use of the inner product between any two observations, rather than the observations themselves. The inner product between two vectors is the sum of the multiplication of each pair of input values.

A prediction for an input can be expressed with the following equation that uses the dot product between the input (x) and each support vector x_i:

$$f(x) = B_0 + sum(a_i * (x, x_i)), \tag{7}$$

where the coefficients B_0 and a_i (for each input) must be obtained after applying of the learning algorithm to the training data.

Thereby, this face classification system uses 3 methods: an MTCNN model for face detection, FaceNet model to create a feature vectors for each detected face and Linear Support Vector Machine (SVM) classifier model to predict the identity of a given face.

2.3. OpenCV methods: Eigenfaces, Fisherfaces, and LBPH

OpenCV (Open Source Computer Vision Library) is a computer vision and machine learning library, that provides commonly used tools for computer vision software. It contains well-known face recognition methods, such as Eigenfaces method, Fisherfaces method, and Local Binary Patterns method.

The Eigenfaces method [14] can be described with the following. Let $X = \{x_1, x_2, \ldots, x_n\}$ be a random vector with observations $x_i \in R^d$. First step is to compute the mean value μ of these observations:

$$\mu = \frac{1}{n}\sum_{i=1}^n x_i. \tag{8}$$

Then the covariance matrix S can be obtained:

$$S = \frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)(x_i - \mu)^T. \quad (9)$$

With the values of covariance matrix S the eigenvalues λ_i and eigenvectors v_i can be expressed with the next formula:

$$Sv_i = \lambda_i v_i, i = 1,2,\dots,n. \quad (10)$$

After that it is needed to order the eigenvectors descending by their eigenvalue. The core of the Eigenfaces method is Principal Component Analysis (PCA) [15]. It computes a features linear combination that maximizes the total variance in data. The k principal components are the eigenvectors corresponding to the k largest eigenvalues. The k principal components of the observed vector x are:

$$y = W^T(x - \mu), \quad (11)$$

where $W = (v_1, v_2, \dots, v_k)$.

The reconstruction with the use of the PCA basis is provided by:

$$x = W_{y+\mu}, \quad (12)$$

where $W = (v_1, v_2, \dots, v_k)$.

Mathematical description of the Fisherfaces [16] method is provided with the following. Let X be a random vector with samples drawn from c classes:

$$X = \{X_1, X_2, \dots, X_c\}, \quad (13)$$

$$X_i = \{x_1, x_2, \dots, x_n\}. \quad (14)$$

From this representation the scatter matrices S_B and S_w can be calculated as:

$$S_B = \sum_{i=1}^{c} N_i(\mu_i - \mu)(\mu_i - \mu)^T, \quad (15)$$

$$S_W = \sum_{i=1}^{c}\sum_{x_j \in X_i}(x_j - \mu_i)(x_j - \mu_i)^T, \quad (16)$$

where μ is the total mean, that expresses as:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i. \quad (17)$$

Mean value μ_i of class $i \in \{1, \dots, c\}$ is:

$$\mu_i = \frac{1}{|X_i|}\sum_{x_j \in X_i}(x_j). \quad (18)$$

Fisherfaces algorithm performs search of a projection W, that maximizes the class separability criterion:

$$W_{opt} = arg\,max_W \frac{|W^T S_B W|}{|W^T S_W W|}. \quad (19)$$

Following [17], this optimization problem can be solved by finding a solution of the general eigenvalue problem:

$$S_B v_i = \lambda_i S_w v_i, \quad (20)$$

$$S_w{}^{-1} S_B v_i = \lambda_i v_i. \quad (21)$$

Eigenfaces and Fisherfaces methods based on a holistic approach to face recognition that involves more efficient concentrating on extracting image local features. The basic idea of Local Binary Patterns (LBP) method [18] is to summarize the local structure in an image by comparing each pixel with its neighbors. Description of the LBP operator expressed with the following:

$$LBP(x_c, y_c) = \sum_{p=0}^{P-1} 2^p s(i_p - i_c), \quad (22)$$

where (x_c, y_c) is a central pixel with intensity i_c; i_n is intensity of the neighbor pixel; s is the sign function defined as:

$$s(x) = \begin{cases} 1\ if\ x \geq 0 \\ 0\ else \end{cases}, \tag{23}$$

Position of the neighbor (x_p, y_p), $p \in P$ for a pixel point (x_c, y_c) can be calculated by:

$$x_p = x_c + Rcos(\frac{2\pi p}{P}), \tag{24}$$

$$y_p = y_c - Rsin(\frac{2\pi p}{P}), \tag{25}$$

where R is the radius of the circle and P is the number of sample points.

2.4. Daubechies wavelets transform

The technology proposed in this research based on wavelet transform, that is widely used in the image processing tasks. Wavelet transform provides processing of patterns hidden in the data performing data analysis in general as well as in the detail. Wavelets apply in image processing when it is necessary for the result of analysis to contain information about location of characteristic frequencies and scales.

Daubechies wavelets [19] are the type of basic wavelets, that orthonormal basis defined as:

$$\phi_{r,j,k}(x) = 2^{\frac{j}{2}}\phi_r(2^j x - k), j, k \in Z, \tag{26}$$

where function $\{\phi_r(x-k)|k \in Z\}$, j is the scaling index, k is the displacement index, and r is the filter index.

To analyze these equations in more detail at a certain scale, it is necessary to define an orthonormal basis $\psi_r(x)$ with similar properties of $\phi_r(x)$

$$\phi(x) = \sqrt{2}\sum_k h_k\, \phi(2x - k), \tag{27}$$

$$\psi(x) = \sqrt{2}\sum_k g_k\, \phi(2x - k), \tag{28}$$

where $\sum_k |h_k|^2 < \infty$. Property of the scaled functions orthogonality allows to determine the coefficients:

$$\sum_k h_k g_{k+2m} = \delta_{0m}. \tag{29}$$

Wavelets are orthogonal to scalable functions, thus wavelet coefficients g_k are depend on the scaling function coefficients h_k:

$$g_k = (-1)^k h_{2M-1-k}. \tag{30}$$

Due to these properties, Daubechies wavelets provide good results of the image processing.

2.5. Reverse biorthogonal wavelets transform

Linear phase of the biorthogonal wavelets [20] allows to use them in image processing as well. It is maintained by the filter coefficients symmetry. Comparing to the orthogonal wavelets, biorthogonal wavelets involve higher degree of freedom and contain a symmetrical compact support.

Let's denote through $\bar{f}(x)$ and $\bar{y}(x)$ bases double to $f(x)$ and $y(x)$., expressing it with the formula:

$$[\langle\phi(x)|\bar{\phi}(x)\rangle] = I, \tag{31}$$

$$[\langle\psi(x)|\bar{\psi}(x)\rangle] = I, \tag{32}$$

Basic scaling functions in biorthogonal wavelet basis are orthogonal to double wavelets and scaling functions. This can be expressed with the following:

$$[\langle\phi(x)|\bar{\psi}(x)\rangle] = 0. \tag{33}$$

Reverse biorthogonal system uses wavelet and scaling functions separately for signal analysis and design both time and frequency domains. Problem of time and frequency resolution in reverse biorthogonal wavelet function solves with the property that it is always equal to the viewport range.

3. Experimental research and analysis

First set of experiments was performed with the use of standard Python library face_recognition. The training of KNN classifier was performed on the set of the images of 80 people, who are wearing masks, 8 images for each person. Images are not stable in scaling, position of a face and contain different levels of lightning. The total number of training set – 640 images. The dataset for the identification experiment was prepared with other images of same people. Obtained results indicate accuracy rate of identification of 55%.

In the second set of experiments FaceNet system was used. The dataset for the identification is the same. In this case system output provides an information of the predicted class of the input image and probability with which input image belongs to the class. FaceNet method performance on the set of masked face images indicated the identification accuracy rate of 72,5%.

Third part of experiments was performed to analyze the efficiency of three popular facial recognition methods: eigenface, fisherfaces, and LBPH. The accuracy of identification by eigenface method on the set of masked face images is 12,5%. Accuracy rate of the fisherfaces method is 25%. LBPH method provided accuracy rate of 5% of correctly identified images.

Results of performed experiments are presented in the Table 1 and Table 2.

Table 1

Results of experiments performed with face_recognition and FaceNet methods on the dataset of masked images

	Face_recognition library		FaceNet	
	Correctly identified images	Incorrectly identified images	Correctly identified images	Incorrectly identified images
Total number of images	80		80	
Number	44	36	58	22
Percentage	55%	45%	72,5%	27,5%

Table 2

Results of experiments performed with Eigenfaces, Fisherfaces and LBPH methods on the dataset of masked images

	Eigenfaces		Fisherfaces		LBPH	
	Correctly identified images	Incorrectly identified images	Correctly identified images	Incorrectly identified images	Correctly identified images	Incorrectly identified images
Total number of images	80		80		80	
Number	10	70	20	60	4	76
Percentage	12,5%	87,5%	25%	75%	5%	95%

As can be seen in a Figure 1, Eigenface, Fisherface and LBPH algorithms performed identification with a small part of a dataset, therefore percentage of incorrectly identified images is much greater than identification accuracy rate.

On the other hand, face_recognition and FaceNet methods do not tend to have such an issue, but still the difference between correctly and incorrectly identified images is decreasing.

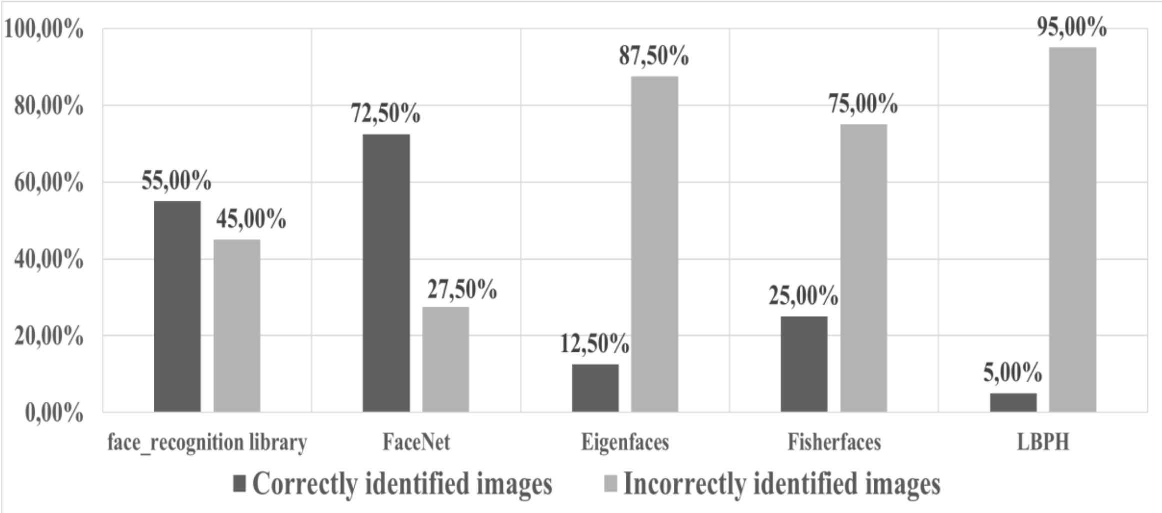

Figure 1: Results of identification with the use of face_recognition, FaceNet, Eigenfaces, Fisherfaces and LBPH methods on the dataset of masked images

Results of the experimentation with the same methods on the dataset of unmasked face images are presented in Table 3 and Table 4.

Table 3
Results of experiments performed with face_recognition and FaceNet methods on the dataset of unmasked images

	Face_recognition library		FaceNet	
	Correctly identified images	Incorrectly identified images	Correctly identified images	Incorrectly identified images
Total number of images	80		80	
Number	78	2	79	1
Percentage	97,5%	2,5%	98,75%	1,25%

Table 4
Results of experiments performed with Eigenfaces, Fisherfaces and LBPH methods on the dataset of unmasked images

	Eigenfaces		Fisherfaces		LBPH	
	Correctly identified images	Incorrectly identified images	Correctly identified images	Incorrectly identified images	Correctly identified images	Incorrectly identified images
Total number of images	80		80		80	
Number	60	20	74	6	48	32
Percentage	75%	25%	92,5%	7,5%	60%	40%

Figure 2 depicts percentage of correctly and incorrectly identified images.

Comparative diagram of the results between methods applied to the dataset of unmasked face images and to the dataset of masked face images is depicted on Figure 3. As can be seen, presence of the mask on the images considerably decrease identification accuracy rate from 26% to 67%.

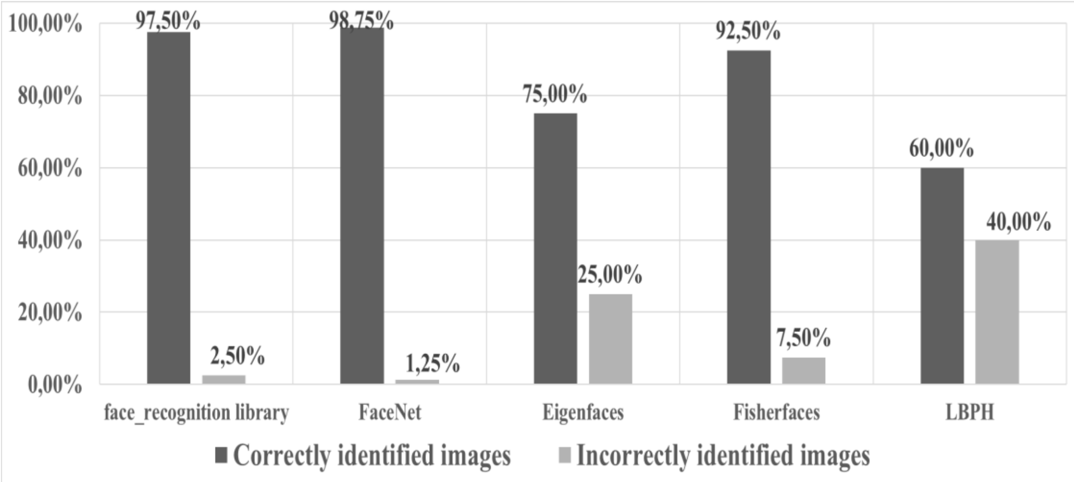

Figure 2: Results of identification with the use of face_recognition, FaceNet, Eigenfaces, Fisherfaces and LBPH methods on the dataset of unmasked images

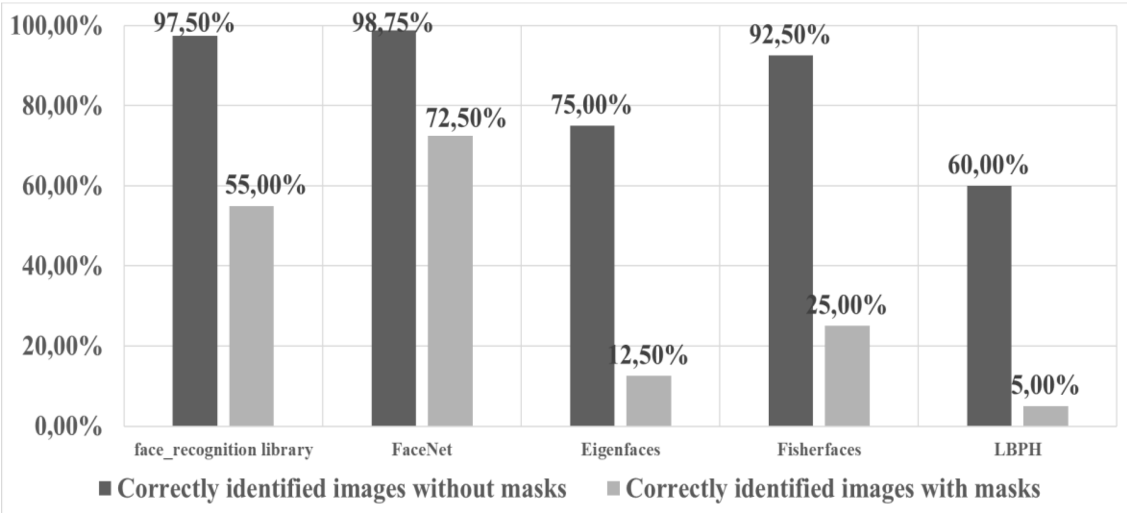

Figure 3: Comparative diagram of the results between face_recognition, FaceNet, Eigenfaces, Fisherfaces and LBPH methods applied to the dataset of unmasked face images and to the dataset of masked face images

During the analysis of experimentation results of the research [21] it was found that the system provided the highest accuracy of identification (92,5%) on unmasked face images with the use of Daubechies wavelet transform for image processing, standard deviation and variance methods for feature extraction stage and image classification by this vector by calculating distance with Euclidean, quadratic Euclidean and Canberra metrics [22]. Therefore, in this research it was decided to use the same methods for the dataset of face images with protective masks.

Results of experiments performed with Daubechies wavelet transform, standard deviation and variance calculation, and Euclidean, quadratic Euclidean, Canberra metrics presented in Tables 5 and 6.

Figure 4 depicts results of the Daubechies wavelet transform and standard deviation calculation on the dataset of masked images.

Figure 5 depicts results of the Daubechies wavelet transform and variance calculation on the dataset of masked images.

Analyzing the results of Daubechies wavelet transform, the highest identification accuracy rate result was obtained with the use of standard deviation calculation and Euclidean distance metric (77,5%). Accuracy rates for Daubechies wavelets and other methods are following: standard deviation calculation and Canberra metric (65%), standard deviation calculation and quadratic Euclidean metric (70%), standard deviation calculation and quadratic Euclidean metric (57,5%), variance calculation and Canberra metric (65%), variance calculation and quadratic Euclidean metric (57,5%).

Table 5
Results of experiments performed with Daubechies wavelet transform and standard deviation calculation methods on the dataset of masked images

	Standard deviation					
	Euclidean distance		Canberra distance		Squared Euclidean distance	
	Correctly identified images	Incorrectly identified images	Correctly identified images	Incorrectly identified images	Correctly identified images	Incorrectly identified images
Total number of images	80		80		80	
Number	62	18	52	28	56	24
Percentage	77,5%	22,5%	65%	35%	70%	30%

Table 6
Results of experiments performed with Daubechies wavelet transform and variance calculation methods on the dataset of masked images

	Variance					
	Euclidean distance		Canberra distance		Squared Euclidean distance	
	Correctly identified images	Incorrectly identified images	Correctly identified images	Incorrectly identified images	Correctly identified images	Incorrectly identified images
Total number of images	80		80		80	
Number	46	34	52	46	34	52
Percentage	57,5%	42,5%	65%	57,5%	42,5%	65%

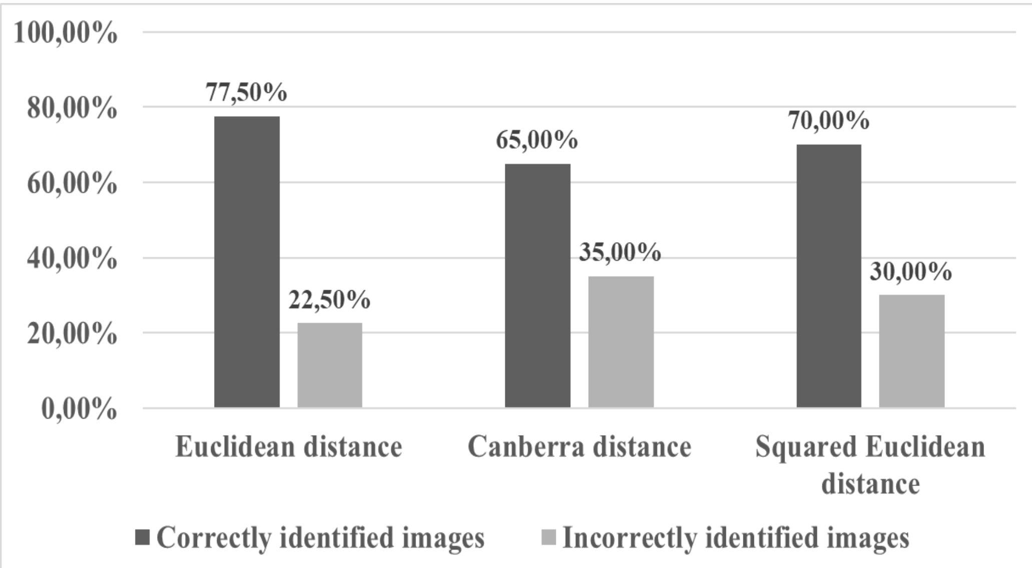

Figure 4: Results of the Daubechies wavelet transform and standard deviation calculation on the dataset of masked images

In the research [23] it was experimentally obtained the identification accuracy rate of 97,5% on face images without wearing mask.

This result was provided by the method of image processing based on reverse biorthogonal wavelets, standard deviation calculation and variance methods of feature vector extraction and Bray-Curtis, Canberra, and Manhattan distance metrics of image feature vector classification. Experimentation results of the same methods on the face images with mask dataset are provided next.

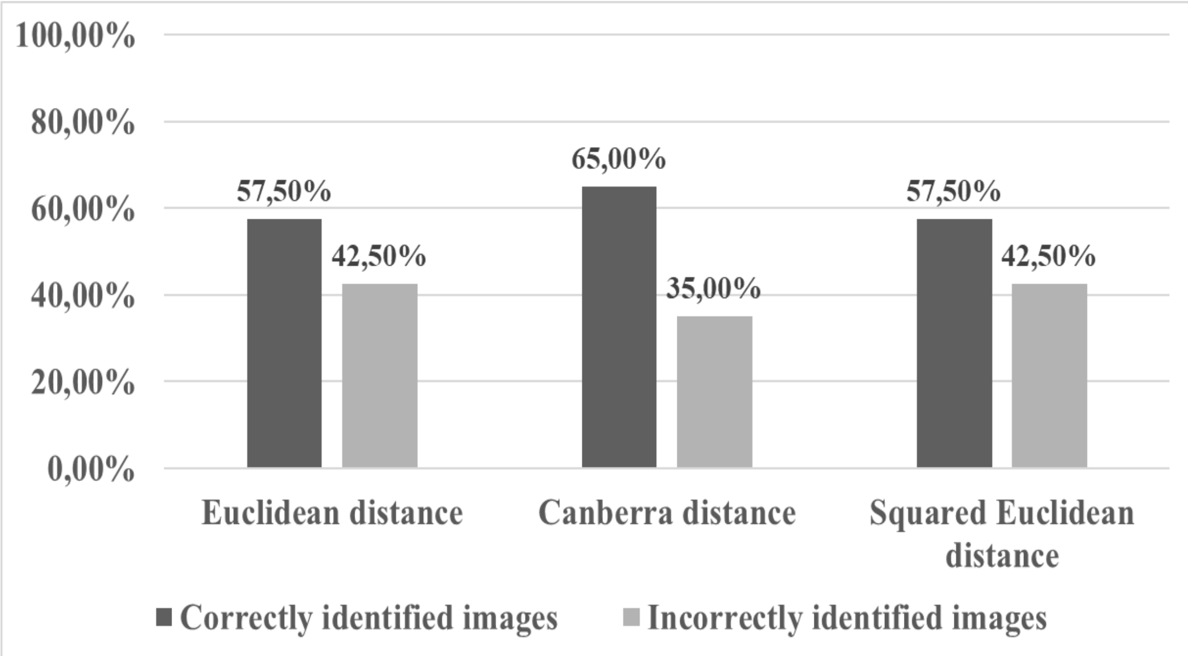

Figure 5: Results of the Daubechies wavelet transform and variance calculation on the dataset of masked images

Results of experiments performed with reverse biorthogonal wavelets, standard deviation and variance calculation and Bray-Curtis, Canberra, Manhattan distance metrics are presented in Table 7 and Table 8, accordingly.

Table 7
Results of experiments performed with reverse biorthogonal wavelet transform and standard calculation methods on the dataset of masked images

	Standard deviation					
	Bray-Curtis distance		Canberra distance		Manhattan distance	
	Correctly identified images	Incorrectly identified images	Correctly identified images	Incorrectly identified images	Correctly identified images	Incorrectly identified images
Total number of images	80		80		80	
Number	52	28	52	52	28	52
Percentage	60%	40%	60%	60%	40%	60%

Reverse biorthogonal wavelets transform based experiments provided the highest identification accuracy rate of 65% with combination of the following methods: standard deviation calculation and Bray-Curtis distance metric, standard deviation calculation and Bray-Curtis distance metric, variance calculation and Manhattan distance metric.

The results of other methods are next: variance calculation and Bray-Curtis metric – 52.5%, standard deviation calculation and Manhattan metric – 55%, variance calculation and Canberra distance metric – 55%.

Figure 6 depicts results of the reverse biorthogonal wavelet transform and standard deviation.

Analysis between standard deviation and variance calculation methods for feature vector extraction indicated that the use of the first method is more effective during the experiments on both wavelet transforms.

Table 8
Results of experiments performed with reverse biorthogonal wavelet transform and standard calculation methods on the dataset of masked images

	Variance					
	Bray-Curtis distance		Canberra distance		Manhattan distance	
	Correctly identified images	Incorrectly identified images	Correctly identified images	Incorrectly identified images	Correctly identified images	Incorrectly identified images
Total number of images	80		80		80	
Number	42	38	44	36	44	36
Percentage	52,5%	47,5%	55%	45%	55%	45%

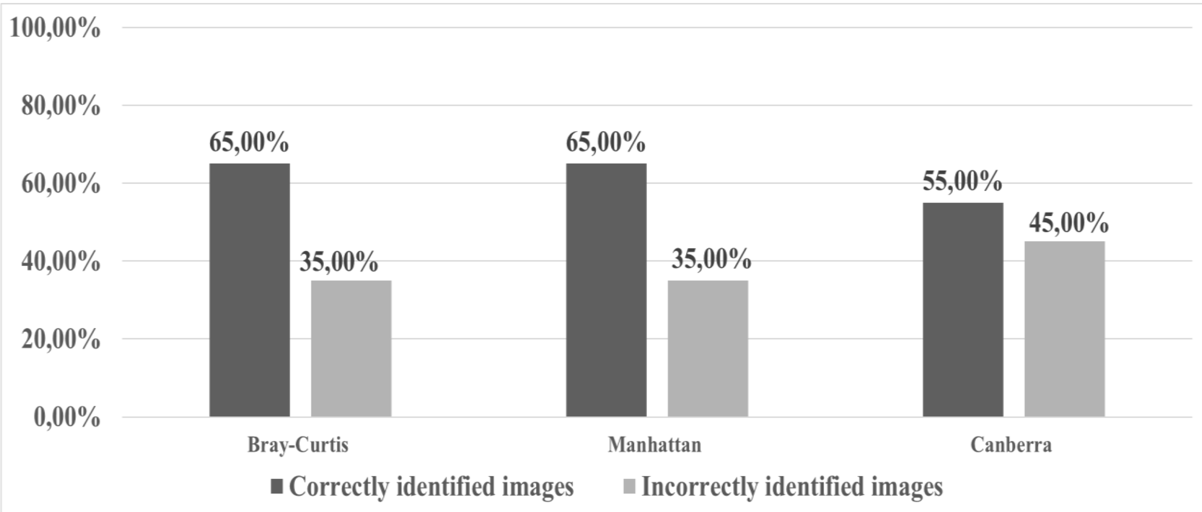

Figure 6: Results of the reverse biorthogonal wavelet transform and standard deviation calculation on the dataset of masked images

Figure 7 depicts results of the reverse biorthogonal wavelet transform and variance calculation.

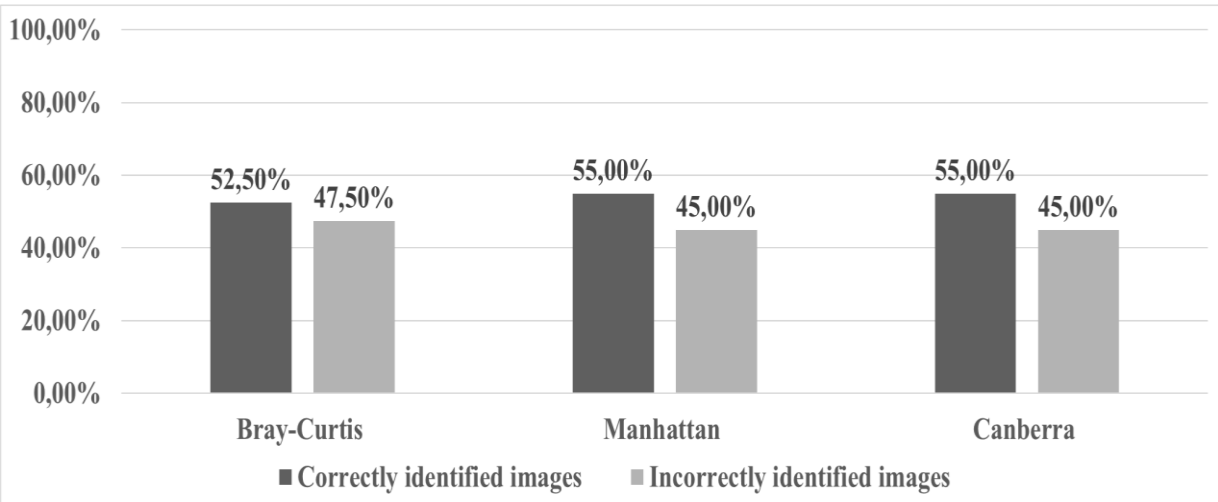

Figure 7: Results of the reverse biorthogonal wavelet transform and variance calculation on the dataset of masked images

4. Conclusion

During the research experiments were performed on the dataset of faces covered with mask in a conditions of different image scaling, face position and level of lightning with the use of face_recognition, FaceNet, Eigenfaces, Fisherfaces and LBPH methods. Results of the experimentation research are the following: face_recognition method – 55% of correctly identified images, FaceNet method – 72,5% of correctly identified images, Eigenfaces method – 12,5%, Fisherfaces method – 25% of correctly identified images, LBPH method – 5% of correctly identified images.

The obtained results indicate that commonly used face recognition methods identification rates are decreasing in a range from 26% to 67% in conditions of incomplete data, such as face covered with protective masks, and different image scaling, face position and level of lightning.

Appliance of Daubechies wavelet transform method indicated the highest identification accuracy rate result with the use of standard deviation calculation and Euclidean distance metric - 77,5% of correctly identified images, that was obtained on the same dataset of faces covered with mask in a conditions of different image scaling, face position and level of lightning. Accuracy rates for Daubechies wavelets and other methods are following: standard deviation calculation and Canberra metric - 65% of correctly identified images, standard deviation calculation and quadratic Euclidean metric - 70% of correctly identified images, standard deviation calculation and quadratic Euclidean metric - 57,5% of correctly identified images, variance calculation and Canberra metric - 65% of correctly identified images, variance calculation and quadratic Euclidean metric - 57,5% of correctly identified images.

Appliance of reverse biorthogonal wavelet transform method indicated the highest identification accuracy rate of 65% on the dataset of faces covered with mask in a conditions of different image scaling, face position and level of lightning. This result was obtained with combination of the following methods: standard deviation calculation and Bray-Curtis distance metric, standard deviation calculation and Bray-Curtis distance metric, variance calculation and Manhattan distance metric. Results of the other methods are the following: variance calculation and Bray-Curtis metric – 52.5% of correctly identified images, standard deviation calculation and Manhattan metric – 55% of correctly identified images, variance calculation and Canberra distance metric – 55% of correctly identified images.

Summarizing the foregoing conclusions, mathematical methods for information technology of biometric identification, proposed in this research, can be applied for face recognition in conditions of masked face images. The highest accuracy rate (77,5% of correctly identified images) of the identification performed on the dataset of masked face images was obtained during the experiments based on Daubechies wavelet transform as image processing method, standard deviation calculation as feature extraction method and Euclidean distance metric as image vector classification method.

5. References

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