UDC 004.932+004.023
https://doi.org/10.31891/csit-2022-1-7

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INFORMATION TECHNOLOGY OF FACIAL EMOTION RECOGNITION FOR VISUAL SAFETY SURVEILLANCE

Emotional expressions serve a crucial role in interpersonal communication between people while improving social life. In particular, information safety systems for visual surveillance that aim to recognize human emotional facial states are highly relevant today. In this regard, this study is devoted to the problem of identifying the main criteria for expressing the face of emotional manifestations for the possibility of recognizing without the use of specialized equipment, for example, security surveillance cameras with low resolution. In this work, we propose informational technology to define the face's areas that reproduce the face's emotional look. The input data from the proposed information technology is a set of videos with detected faces with the primary emotional states reproduced on them. At first, normalization of the faces of images is conducted to compare them in one base. It is executed by centering the face area and normalizing the distance between the eyes. Based on the analysis of point features moving in the set of input images, information points are then allocated (i.e., those points whose movement in the person's emotional expression is the most significant). At the final stage, the areas of the face (with different bias thresholds) are determined, the changes of which form a visual perception of emotions. For each selected region, a set of possible states is formed. In conclusion, the behavior of point-specific features of a person under the manifestation of specific emotions is explored experimentally, and high-quality indicators for these emotions are highlighted. According to the study results, it is preferable to create a software product based on qualitative criteria for assessing the main areas of the face to determine the mimic expression of emotions.

Keywords: information technology, emotion recognition, facial feature extraction, geometric features, visual safety surveillance, hyperplane classification

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ІНФОРМАЦІЙНА ТЕХНОЛОГІЯ ІДЕНТИФІКАЦІЇ ЗМІН ЕМОЦІЙНОГО СТАНУ ЛЮДИНИ ЗА МІМІЧНИМИ ПРОЯВАМИ ДЛЯ СИСТЕМ, ЩО ВІДПОВІДАЮТЬ ВИМОГАМ БЕЗПЕКИ

Емоційні прояви на сьогодні відіграють значну роль у міжособистісному спілкуванні та взаємодії між людьми в будь-якій галузі людської діяльності. Зокрема, вкрай актуальними є системи інформаційної безпеки для візуального спостереження, які спрямовані на розпізнавання змін емоційних станів за мімічними проявами на обличчі людини. Для розв'язання проблеми розпізнавання емоцій для систем візуального спостереження, що відповідають вимогам безпеки, у цій роботі запропоновано інформаційну технологію ідентифікації змін емоційного стану людини за мімічними проявами для розпізнавання емоцій без використання спеціалізованого обладнання (для камер відеоспостереження з низькою роздільною здатністю). У роботі запропоновано інформаційну технологію для визначення ділянок обличчя, які відтворюють емоційний стан людського обличчя. Вхідними даними запропонованої інформаційної технології є набір відеороликів з виявленими обличчями з відтвореними на них первинними емоційними станами. Спочатку проводиться нормування граней зображень для їхнього порівняння в одній площині. Нормалізування виконано через центрування зони обличчя і стандартизації відстані між очима. На основі аналізу точкових ознак, що рухаються в наборі вхідних зображень, виділено інформаційні точки (тобто ті точки, рух яких в емоційному вираженні людини є найбільш значущим). Далі визначено ділянки обличчя (з різними порогами зміщення), зміни яких формують візуальне сприйняття емоцій. Для кожного обраного регіону формується набір можливих станів. На завершальному етапі експериментально досліджено поведінку точкових особливостей людини при прояві конкретних емоцій та виділено якісні показники цих емоцій. За результатами експериментальних тестувань визначено вагові коефіцієнти, на основі якого побудовано лінійний класифікатор для ідентифікації змін емоційних станів.

Ключові слова: інформаційна технологія, розпізнавання емоційних станів, виявлення ознак мімічних проявів, геометричні ознаки, спостереження за безпекою, гіперплощинна класифікація

Introduction

Throughout the history of human civilization, facial expressions have been and remain a practical approach to establishing nonverbal interaction between people. Over the last decade, facial expressions have proved to be one of the simplest and most effective means of nonverbal interaction in various information systems [0]. Thus, methods of intellectual data processing by facial expressions to recognize changes in the emotional states are successfully employed in safety surveillance systems [0], intelligent gesture communication systems [0], and medical image analysis [0]. At the same time, the use of computer vision techniques in intellectual systems to identify changes in an emotional state in security-compliant systems seems critical. Undeterred by promising engineering advances in facial emotion recognition over the past decade [0], several issues that remain unresolved [0] consider improving the performance of real-time information systems for security-compliant visual surveillance systems.

There has been considerable interest among the scientific community in recognizing a person's emotional state through facial expressions based on images and videos. It is worth noting that research on new facial emotion recognition methods is conducted to detect changes in emotional manifestations in the real world [0] based on well-known benchmark datasets of facial expressions [0]. Such works are mainly based on the already traditional facial

coding system (FACS), developed by Paul Ekman et al. [0] in the 70s of the last century. In general, FACS is understood as a system of terms, symbols, and rules for categorizing human facial features and identifying changes in emotional states.

The standard classification system distinguishes six primary emotional states categories: anger, fear, joy, sadness, disgust, and surprise. FACS defines the human face through about a hundred so-called action units (AUs), each of which is responsible for the movement of a specific facial muscle. Nowadays, AUs are considered benchmarks for identifying changes in emotional states by facial expressions and are widely used in information systems for recognizing emotions. However, a considerable number of AUs and their superimposition on each other to describe emotional facial features usually lead to significant computational complexity and difficulty of computational models [0]. Such a shortcoming can lead to critical defects in operating information systems, especially regarding security and data leakage. Thus, it is essential to develop an information system for identifying changes in a human emotional state by facial expressions for systems that meet security conditions in real-time and with little computational complexity.

Related works

Computer vision techniques are generally utilized to detect facial expressions and recognize emotional facial expressions visually. Traditional approaches to the computer description of the human face are to divide the face into many small grids and combine facial expressions from all these grids to identify facial expressions [0]. However, even a slight displacement of a face in space impairs recognition accuracy because of the disproportionate displacement of the points superimposed on a face. As a result, traditional face recognition systems' computational complexity (in terms of computation time and allocated memory) increases proportionally the number of AUs. Several new approaches to combining and analyzing already known AUs have been proposed in [0] to solve the problem described above. Thus, the number of AU was set empirically from 10 to more than 200. It was also investigated that the number of AU and their location in the facial plane depend on the objective and requirements for recognizing emotions [0]. It is noteworthy that the question of the standard amount of AU to ensure efficient recognition of emotions remains open.

In recent years, the scientific community has considered and suggested dozens of improvements to existing means of formalizing the human face and identifying emotional changes. For example, in [0], the authors applied the method of geometric description of the face based on the area and perimeter selected from the eyes, mouth, and nose, and could achieve classification accuracy >93% on different reference data sets. Another study [0] proposed a triangular approach with fuzzy rules based on an emotion recognition system. The authors singled out fourteen AUs as sets of points, connecting each edge of the point to form eight triangles. As a result of this modification, the authors achieved a recognition accuracy of 89%. In [0], the authors proposed an angle and position of more than fifty AUs in the form of geometric characteristics for the emotion recognition system. The Euclidean distance and angle between each pair of landmarks were used for estimates within the boundary frame, which provided 90-93% recognition accuracy for different data sets. In [0], a multiclass ensemble model was proposed to detect extended feature vectors. The authors combined an active-looking model, a geometric approach, and a native binary pattern to recognize emotional facial expressions and achieved 95% accuracy in identifying changes in emotional states.

In parallel with static approaches to the recognition of emotions are also actively developing tools for determining the features of the human face in real-time [0]. For instance, the Delaunay triangular approach [0] joints sixty AUs to recognize several facial mimic expressions, which are anger, fear, happiness, surprise, sadness, disgust, and neutrality. This technique is devoted to define the spatial facial features with using support vector machine as a classifier, In [0], the maximum classification level was achieved by 93,7%. In [0], a few old-fashioned machine learning approaches were applied to determine slight mimic changes considering four emotions, i.e., happiness, sadness, anger, and fear. These traditional and solid techniques (decision tree, random forest, logistic regression) could reach the average maximum recognition accuracy of 95.47% on several facial emotion benchmarks. In study [0], the authors suggested a novel vectorized facial emotion recognition neural network model based on seventy vectors to recognize three primary human emotions: anger, happiness, and neutral. The model could achieve an average accuracy of 94.33%. Other recent studies focused primarily on spatial and temporal information from input images and video sequences to extract different facial features using long-term memory network [0], deep convolutional neural network (DCNN) [0], and multilevel ensemble DCNN [0].

Overall, based on the analysis of related works, a few common challenges of the up-to-date approaches in emotion recognition were established: poor quality of train and test benchmarks, the disproportion of statistical measurements in assessing approaches, high computational complexity, and the redundant amount of physical memory of the prepared models. Taking into consideration the above-mentioned factors, an urgent task appears to develop a new approach to describing the features of human facial expressions that will be computationally efficient and provide high recognition accuracy for real-time surveillance safety systems.

Problem statement

This study proposes information technology (IT) to identify changes in a human emotional state by facial expressions for systems that meet security requirements. The following tasks must be solved in order to achieve the

aim of the work:

1. To analyze various facial emotion recognition techniques for visual safety surveillance.

2. To develop an information technology based on the previously proposed model of the expressions of the facial emotions based on grouping classes of feature vectors [0], method of the geometric interpretation of facial expressions proposed in [0], and classification technology based on hyperplanes for visual analytics [0].

3. To conduct computational experiments with the proposed IT and its analogs to identify emotional facial states.

4. To validate the IT of facial emotion recognition on a reference benchmark.

The information technology

Developed IT is designed to identify abnormal manifestations of the emotional state of Fear in a crowd of people on video from surveillance cameras. The use of IT is the automated conversion of input information, presented in a video, into the resulting information in the number of identified people with an abnormal manifestation of Fear.

IT identification of changes in a human emotional state by facial expressions for systems that meet security requirements uses the model to recognize facial expressions of emotions, the geometric interpretation of facial expressions, and the hyperplane classification of emotional state. The use of the model and methods in the further application of IT is shown schematically in fig. 1.
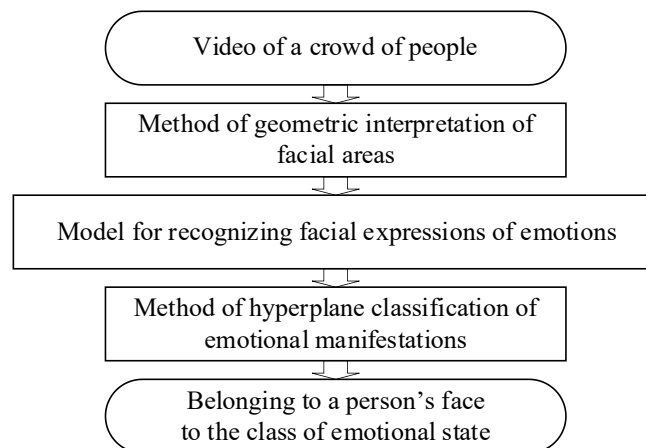

Fig. 1. The scheme of applying the model to recognize facial expressions, method of geometric interpretation, and hyperplane classification in the proposed information technology of facial emotion recognition for visual safety surveillance

According to fig. 1, the achievement of the IT goal occurs through the consistent application of the method of geometric interpretation and hyperplane classification. At the same time, the method of hyperplane classification is used once to calculate the weights of the hyperplane classifier W. Fig. 2 shows the scheme of the proposed IT.

IT inputs are two elements:

1) video of the crowd of people in the form of a matrix of numbers *P*;

2) weight coefficients of the hyperplane classifier (W), prepared according to the reference data set of changes in a human emotional state by facial expressions.

Block 1 (*method of the geometric interpretation of facial expressions*) is the first stage of IT. The result of the block is formed seven quantitative characteristics of areas of the human face, each of which corresponds to the facial features of a person's emotional states.

In *step 1.1*, the mechanism for determining specific points of the face using the open-source library [0] is applied to the input data. The face is described by points of 468, which is the basis for the geometric interpretation of facial expressions. A sample of superimposing mesh on a human's face is visualized in fig. 3. *Step 1.2* is designed to obtain a vector of features, which are the quantitative characteristics of seven face areas. After that, in *step 1.3*, the feature vector is normalized to bring the feature values to the range [0; 1].

As a result of block 1, *intermediate data* generated by the normalized vector of facial features $X' = (x_1', x_2', \ldots, x_7')$, are obtained and presented to the model for the recognition of facial expressions of emotions:

$$f: P \to \langle X, W \rangle, \qquad (1)$$

where P – pixel matrix of video input of a crowd of people; X – feature vector of facial expressions of emotions on a person's face, $X = (x_i)_{i=1}^{7}$, W – vector scales model identification of emotional state on a human face.
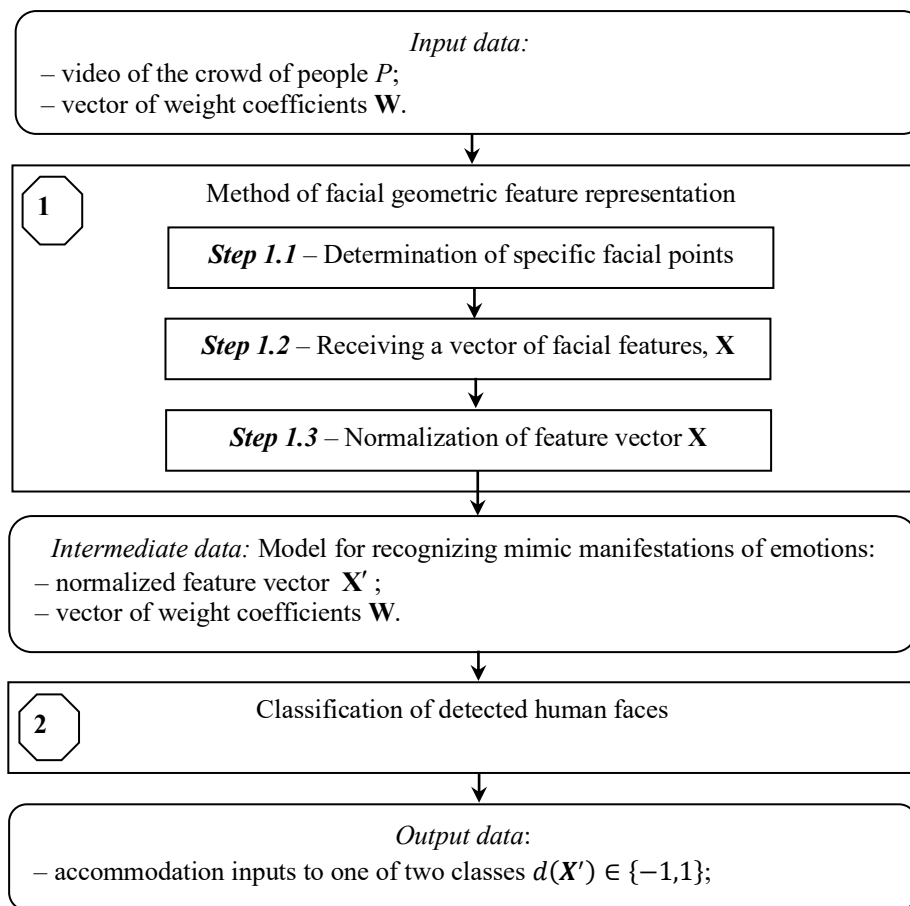
Fig. 2. Generalized scheme for the use of the proposed information technology

a) b)
Fig. 3. An example of the superimposed mesh on a human's face: a) – initial image; b) – face with landmarks

Empirically determined features that form the vector X are formally presented as follows:
– x_1 – facial feature expression of mouth.
– x_2 – facial feature expression of corners of the lips.
– x_3 – facial feature expression of eyes.
– x_4 – facial feature expression of nasal root.
– x_5 – facial feature expression of eyebrows.

– x_6 – facial feature expression of the outer corners of the eyebrows.

– x_7 – facial feature expression of the inner corners of the eyebrows.

The result of mapping (1) determines the normalized vector of features $X^{'}$, which together with the vector of weights W form the input data for block 2.

Intermediate data fall into *Block 2* (*classification of detected human faces*), the second stage of IT implementation. The result of this block is the belonging of the input data to one of the two classes $d(X^{'}) \in \{-1,1\}$, where –1 corresponds to the emotional state "Fear," 1 – to the emotional state "Not Fear."

The output data of IT is an assessment of the emotional state $d_j(X_j^{'})$, $j = \overline{1, n}$ of the j-th person whose face is found in a video of a crowd of people. The calculated n assessments serve to identify abnormal manifestations of Fear in the crowd of people on video.

Thus, the use of the model to recognize facial expressions of emotions in the proposed IT allows the input data in the form of a video of a crowd of people to obtain the resulting data in the form of assessments of emotional state to identify abnormal manifestations of emotional state Fear in crowds. The weights of the hyperplane classification W are determined once with subsequent use in IT.

Data preparation

A reference data set (ADFES) [29] obtained from the Amsterdam Interdisciplinary Center for Emotions of the University of Amsterdam (see fig. 3) was used to determine the weights of the hyperplane classifier W. The ADFES dataset contains videos of people's faces collected from 22 models. From the original set of ADFES, the author of the dissertation formed a subset with five emotions: Anger, Fear, Joy, Neutral, and Sadness. Each of the 22 models of the ADFES set depicts five different emotional states.

First, the method of the geometric interpretation of facial expressions was applied to the training data set. The input data of the method are 110 images of human faces of the ADFES data set, classified by five emotions. As a result of applying a method, the matrix of normalized values $X^{'} = (x_{ijk}^{'})$, $i = \overline{1,7}$ – facial features of a person $j = \overline{1,110}$ – objects of a training data set $k = \overline{1,5}$ – researched emotions is received. Preparation of weights was carried out according to the hyperplane classification of emotional state by facial expressions. The input data of the method is a matrix of normalized values $X^{'} = (x_{ijk}^{'})$, $i = \overline{1,7}$, $j = \overline{1,110}$, $k = \overline{1,5}$.
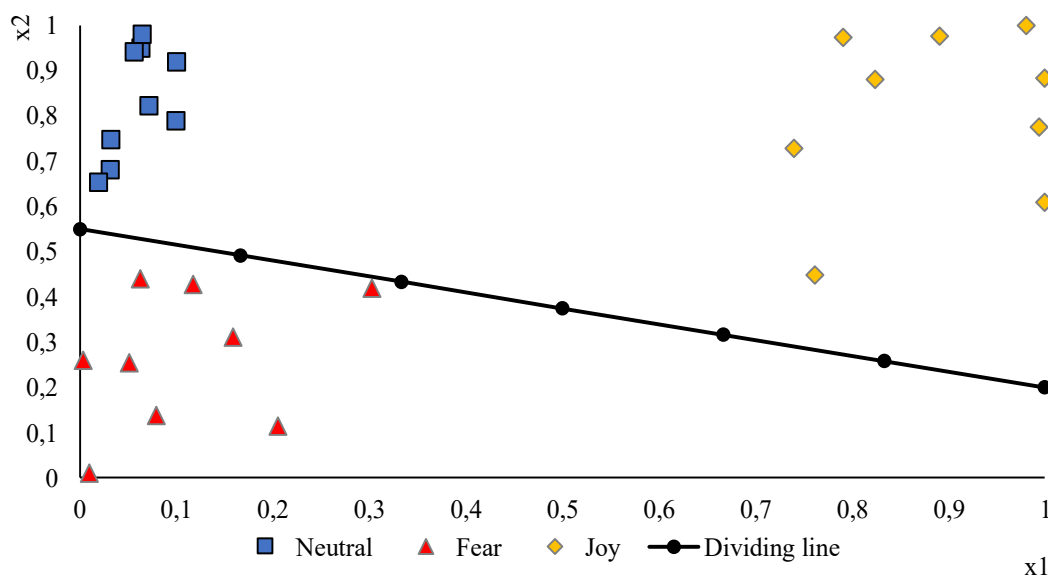

Fig. 4. The result of visualization of input data into space $\mathbf{R}^2$

The first step in applying the method of hyperplane classification is the mapping of the matrix is the visualization of normalized values $X^{'} = (x_{ijk}^{'}) \in \mathbf{R}^7$, $i = \overline{1,7}$, $j = \overline{1,110}$, $k = \overline{1,5}$ in two-dimensional space, i.e., $\mathbf{R}^7 \to \mathbf{R}^2$. To do this, the optimization problem was solved based on the evolutionary algorithm. While analyzing the results of the geometric interpretation of facial expressions, it was found that between changes in the emotional state of Anger, Neutral, and Sadness, there is a large intersection in space $\mathbf{R}^2$. This intersection may be due to the low resolution of ADFES images or the imperfection of the tool for overlapping specific feature points. However, the dissertation's purpose is to identify the emotional state of Fear among all other emotional states by facial expressions. Therefore, to effectively find the values of **W** weights, the ADFES training set of 110 human faces was reduced to a subset of 27 faces, i.e., nine models were left, each of which depicts three emotions: Fear, Joy, and Neutral. Here it is accepted that the emotion Neutral includes emotional states Anger and Sadness.

Experimental results

As a result of solving the optimization problem, the matrix $X' = (x'_{ijk}) \in R^7$, $i = \overline{1,7}$, $j = \overline{1,110}$, is mapped to the matrix $X^* = (x^*_{ijk}) \in R^2$, $i = \overline{1,2}$, $j = \overline{1,27}$, $k = \overline{1,3}$. Reflection $R^7 \rightarrow R^2$ is visualized in fig. 4.

From fig. 4, the synthesized values of the matrix $X^* = (x^*_{ijk}) \in R^2$, obtained by the method of the geometric interpretation of facial expressions, were grouped by different emotional states. This result confirms the ability of the proposed model (1) to be used to classify emotional states. Using the dividing line, the manual division into classes Fear and Not Fear is performed.

The next step of the method is inverse reflection $R^2 \rightarrow R^7$, which was conducted by the optimization problem based on the evolutionary algorithm. Here, matrix $X^{*L} = (x^{*L}_{1i}) \in R^7$, $i = \overline{1,7}$, was calculated for one dividing line built on seven points. As a result, dividing line $L^2 \in R^2$ is mapped to a hyperplane $L^7 \in R^7$ with coordinates X^{*L} (table 1).

Table 1

Coordinates of separating hyperplanes in space R^7

The points of the line	x_1^L	x_2^L	x_3^L	x_4^L	x_5^L	x_6^L	x_7^L
1	0.053	0.457	0.012	0.366	0.266	0.053	0.724
2	0.064	0.676	0.355	0.408	0.990	0.161	0.794
3	0.352	0.793	0.781	0.460	0.899	0.598	0.636
4	0.077	0.124	0.478	0.154	0.813	0.738	0.381
5	0.590	0.114	0.654	0.873	0.653	0.214	0.226
6	0.295	0.788	0.355	0.644	0.537	0.146	0.426
7	0.900	0.329	0.184	0.325	0.492	0.214	0.500

The resulting matrix from table 1 was used to construct a system of equations as follows:

$$\begin{cases} w_1 x_1^L(1,1) + w_2 x_2^L(1,1) + \ldots + w_m x_m^L(1,1) + b = 0; \\ w_1 x_1^L(1,2) + w_2 x_2^L(1,2) + \ldots + w_m x_m^L(1,2) + b = 0; \\ \ldots \\ w_1 x_1^L(1,m) + w_2 x_2^L(1,m) + \ldots + w_m x_m^L(1,m) + b = 0. \end{cases} \quad (2)$$

The constructed system (2) is laid out in the first line, according to block 5 of the method of hyperplane classification. Therefore, because of applying a method of hyperplane classification of an emotional state on facial expressions, weight coefficients of a separating hyperplane are received:

$$\begin{aligned} W = (&0{,}005565 \quad 0{,}002142 \quad 0{,}027011 \quad 0{,}004986 \\ &-0{,}0047 \quad -0{,}01164 \quad -0{,}03891 \quad 0{,}028614). \end{aligned} \quad (3)$$

Based on the determined weighting factors (3), a linear surface as a linear classifier was constructed. This linear surface (3) was used to allocate facial emotional manifestations. Also, the proposed IT of facial emotion recognition for visual safety surveillance was compared with FACS [0], traditional triangle method [0], and novel DCNN [0] in the classification task. The main objective is to identify emotional facial states by mimicking manifestations. Fig. 5 shows the classification results obtained on the test dataset.
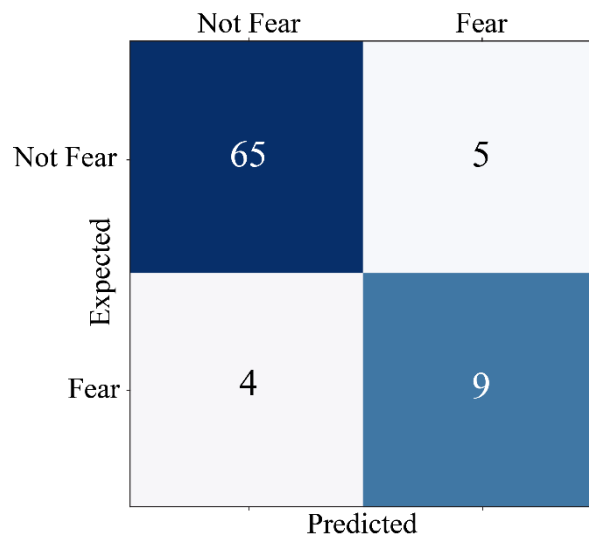

Fig. 5. The confusion matrix obtained by the proposed IT

In addition, the values of statistical estimates obtained by the IT and other approaches on the test dataset are presented in table 2.

From table 2 one may note that the proposed IT surpassed other techniques in F_1 score (76.12%) with over 0.62%. On the other hand, even though DCNN exceeded the analogs in classification accuracy (93.11%), the proposed IT achieved the competitive results in traditional (91.10%) and balanced (84.85%) accuracies. At the same time, utilizing straightforward mathematical operations in the method of facial geometric feature representation within our IT considerably reduced the computational cost (0.003 sec) over the analogs (the closest result is 0.012 sec).

Table 2

Classification results obtained by the considered approaches

Feature definition approach	Accuracy, %	Balanced Accuracy, %	F_1, %	Time, sec
FACS [9]	77.14	70.54	60.77	0.039
Triangle method [12]	92.89	85.01	72.95	0.012
DCNN [23]	93.12	85.27	75.50	0.180
The proposed IT	91.10	84.85	76.12	0.003

Conclusions

This study is devoted to the problem of identifying the main criteria for expressing the face of emotional manifestations for the possibility of recognizing without the use of specialized equipment (for visual safety surveillance cameras with low resolution). In this regard, informational technology to define the face's areas that reproduce the face's emotional look is proposed. The input data from the proposed information technology is a set of videos with detected faces with the primary emotional states reproduced on them. At first, normalization of the faces of images is conducted to compare them in one base. It is executed by centering the face area and normalizing the distance between the eyes. Based on the analysis of point features moving in the set of input images, information points are then allocated (i.e., those points whose movement in the person's emotional expression is the most significant). At the final stage, the areas of the face (with different bias thresholds) are determined, the changes of which form a visual perception of emotions. For each selected region, a set of possible states is formed. In conclusion, the behavior of point-specific features of a person under the manifestation of specific emotions is explored experimentally, and high-quality indicators for these emotions are highlighted. According to the study results, it is preferable to create a software product based on qualitative criteria for assessing the main areas of the face to determine the mimic expression of emotions.

Future work will be dedicated to developing an information system to detect human faces from low-resolution or long-distance video cameras and creating appropriate information systems to ensure efficient visual safety surveillance.

References

1. Sauer J., Schmutz S., Sonderegger A., Messerli N. Social stress and performance in human-machine interaction: a neglected research field. *Ergonomics*. 2019. Vol. 62, No. 11. P. 1377-1391. DOI: https://doi.org/10.1080/00140139.2019.1652353

2. Arunnehru J., Kalaiselvi Geetha M. Automatic human emotion recognition in surveillance video. *Intelligent Techniques in Signal Processing for Multimedia Security*. Vol. 660. Springer, Cham, 2016. P. 321-342. DOI: https://doi.org/10.1007/978-3-319-44790-2_15

3. Bahrii R., Krak I., Barmak O., Kasianiuk V. Implementing alternative communication using a limited number of simple sign language gestures. *2019 IEEE International Conference on Advanced Trends in Information Theory (ATIT)*, Kyiv, Ukraine, 18-20 December 2019. IEEE Inc., 2019. P. 435-438. DOI: https://doi.org/10.1109/atit49449.2019.9030496

4. Krak Iu., Barmak O., Radiuk P. Detection of early pneumonia on individual CT scans with dilated convolutions. *The 2nd International Workshop on Intelligent Information Technologies & Systems of Information Security (IntelITSIS-2021)* : Proceedings. Vol. 2853. (Khmelnytskyi, Ukraine, 24-26 March 2021). Khmelnytskyi, 2021. P. 214-227.

5. Kartali A., Roglić M., Barjaktarović M., Đurić-Jovičić M., Janković M. M. Real-time algorithms for facial emotion recognition: A comparison of different approaches. *2018 14th Symposium on Neural Networks and Applications (NEUREL)* : Proceedings. (Belgrade, Serbia 20-21 November 2018). Cham, IEEE Inc., 2018. P. 1-4. DOI: https://doi.org/10.1109/neurel.2018.8587011

6. Barrett L. F., Adolphs R., Marsella S., Martinez A. M., Pollak S. D. Emotional expressions reconsidered: challenges to inferring emotion from human facial movements. *Psychological Science in the Public Interest*. 2019. Vol. 20, No. 1. P. 1-68. DOI: https://doi.org/10.1177/1529100619832930

7. Martinez B., Valstar M. F., Jiang B., Pantic M. Automatic analysis of facial actions: A survey. *IEEE Transactions on Affective Computing*. 2019. Vol. 10, No. 3. P. 325-347. DOI: https://doi.org/10.1109/taffc.2017.2731763

8. Radiuk P. M., Hrypynska N. V. A framework for exploring and modelling neural architecture search methods. *The 4th International Conference on Computational Linguistics and Intelligent Systems (COLINS-2020)* : Proceedings. Vol. 2604. (Lviv, 23-24 April 2020). Lviv, 2020. P. 1060-1074.

9. Ekman P., Friesen W. V., Hager J. C. The facial action coding system: The manual. *UT Research Nexus eBook*. Salt Lake City, 2002. 527 p.

10. Lim J. Z., Mountstephens J., Teo J. Emotion recognition using eye-tracking: Taxonomy, review and current challenges. *Sensors*. 2020. Vol. 20, No. 8. P. 2384. DOI: https://doi.org/10.3390/s20082384

11. Perumal Ramalingam S., Chandra Mouli P. V. S. S. R. Modified dimensionality reduced local directional pattern for facial analysis. *Journal of Ambient Intelligence and Humanized Computing*. 2017. Vol. 9, No. 3. P. 725-737. DOI: https://doi.org/10.1007/s12652-017-0473-9

12. Xu Y., Pang Y., Jiang X. A facial expression recognition method based on improved HOG features and geometric features. *2019 IEEE 4th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)* : Proceedings. (Chengdu, China, 20-22

December 2019). IEEE Inc., 2019. P. 1118-1122. DOI:https://doi.org/10.1109/iaeac47372.2019.8997772

13. McDonnell R., Zibrek K., Carrigan E., Dahyot R. Model for predicting perception of facial action unit activation using virtual humans. *Computers & Graphics*. 2021. Vol. 100. P. 81-92. DOI: https://doi.org/10.1016/j.cag.2021.07.022

14. Lin J., Xiao L., Wu T. Face recognition for video surveillance with aligned facial landmarks learning. *Technology and Health Care*. 2018. Vol. 26. P. 169-178. DOI: https://doi.org/10.3233/thc-174534

15. Rutkowska D., Kurach D., Rakus-Andersson E. Face recognition with explanation by fuzzy rules and linguistic description. *Artificial Intelligence and Soft Computing*. Cham, 2020. P. 338-350. DOI: https://doi.org/10.1007/978-3-030-61401-0_32

16. Li R., Tian J., Chua M. C. H. Facial expression classification using salient pattern driven integrated geometric and textual features. *Multimedia Tools and Applications*. 2018. Vol. 78, No. 20. P. 28971-28983. DOI: https://doi.org/10.1007/s11042-018-6133-z

17. Iqtait M., Mohamad F. S., Mamat M. Feature extraction for face recognition via active shape model (ASM) and active appearance model (AAM). *IOP Conference Series: Materials Science and Engineering (IORA-ICOR-2017)* : Proceedings. Vol. 332. (Tangerang Selatan, Indonesia, 12 October 2017). Bristol, 2018. P. 012032. DOI: https://doi.org/10.1088/1757-899x/332/1/012032

18. Kunz M., Meixner D., Lautenbacher S. Facial muscle movements encoding pain–a systematic review. *PAIN*. 2019. Vol. 160, No. 3. P. 535-549. DOI: https://doi.org/10.1097/j.pain.0000000000001424

19. Valev H., Gallucci A., Leufkens T., Westerink J., Sas C. Applying Delaunay triangulation augmentation for deep learning facial expression generation and recognition. *Pattern Recognition. ICPR International Workshops and Challenges (ICPR-2021)* : Proceedings. Vol. 12663. (Switzerland, Cham, 10-11 January 2021). Cham, 2021. P. 730-740. DOI: https://doi.org/10.1007/978-3-030-68796-0_53

20. M. M., A. M. Facial geometric feature extraction based emotional expression classification using machine learning algorithms. *PLOS ONE*. 2021. Vol. 16, No. 2. P. e0247131. DOI: https://doi.org/10.1371/journal.pone.0247131

21. Sun X., Zheng S., Fu H. ROI-Attention vectorized CNN model for static facial expression recognition. *IEEE Access*. 2020. Vol. 8. P. 7183-7194. DOI: https://doi.org/10.1109/access.2020.2964298

22. Li C., Bao Z., Li L., Zhao Z. Exploring temporal representations by leveraging attention-based bidirectional LSTM-RNNs for multi-modal emotion recognition. *Information Processing & Management*. 2020. Vol. 57, No. 3. P. 102185. DOI: https://doi.org/10.1016/j.ipm.2019.102185

23. Akhand M. A. H., Roy S., Siddique N., Kamal M. A. S., Shimamura T. Facial emotion recognition using transfer learning in the deep CNN. *Electronics*. 2021. Vol. 10, No. 9. P. 1036. DOI: https://doi.org/10.3390/electronics10091036

24. Hao M., Cao W.-H., Liu Z.-T., Wu M., Xiao P. Visual-audio emotion recognition based on multi-task and ensemble learning with multiple features. *Neurocomputing*. 2020. Vol. 391. P. 42-51. DOI: https://doi.org/10.1016/j.neucom.2020.01.048

25. Barmak O., Kalyta O., Krak Iu., Manziuk E., Kuznetsov V. Model of the facial emotions expressions based on grouping classes of feature vectors. *Lecture Notes in Computational Intelligence and Decision Making (ISDMCI-2020)*. Advances in Intelligent Systems and Computing : Proceedings. Vol. 1246. Springer, Cham. 2021. P. 65-76. DOI: https://doi.org/10.1007/978-3-030-54215-3_5

26. Barmak O., Krak Iu., Manziuk E., Lytvynenko V., Kalyta O. Classification technology based on hyperplanes for visual analytics with implementations for different subject areas. *1st International Workshop on Intelligent Information Technologies & Systems of Information Security (IntelITSIS-2020)* : Proceedings. Vol. 2623. (Khmelnytskyi, Ukraine, 10-12 June 2020). Khmelnytskyi, 2020. P. 96-106.

27. Kalyta O. D. Method of geometric interpretation of facial expressions for emotions recognition. *Herald of Khmelnytskyi National University. Technical Sciences*. 2022. Vol. 305, No 1. P. 57-61.

28. MediaPipe: A framework for building perception pipelines / C. Lugaresi [et al.] // arXiv:1906.08172. 2019. P. 1-9.

29. Van der Schalk J., Hawk S. T., Fischer A. H., Doosje B. Moving faces, looking places: Validation of the Amsterdam dynamic facial expression set (ADFES). *Emotion*. 2011. Vol. 11, No. 4. P. 907-920. DOI: https://doi.org/10.1037/a0023853

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