

O. Barkovska, A. Shapiro, O. Mavrynskyi, P. Zhebin

Kharkiv National University of Radio Electronics, Kharkiv, Ukraine

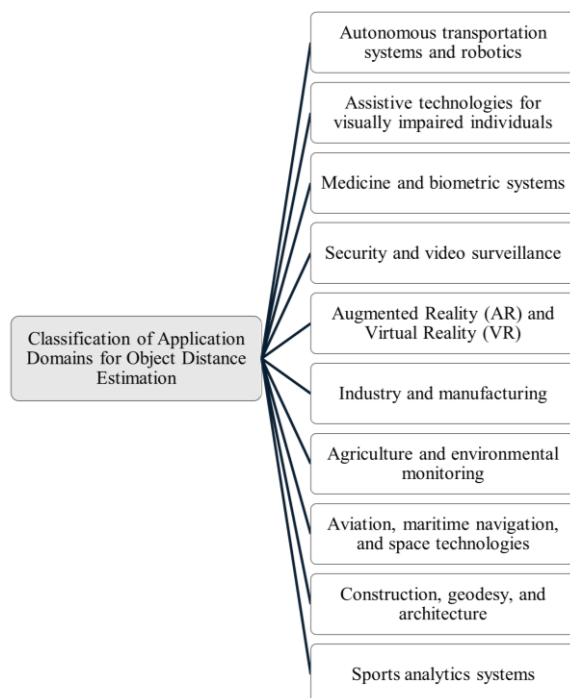
## RESEARCH ON THE SENSITIVITY OF THE DISTANCE MEASUREMENT METHOD BASED ON THE FACEMESH ALGORITHM

**Abstract. Relevance.** The article explores a method for estimating the distance to a user's face under varying lighting conditions, camera resolution, and head tilt angles. This method is significant for developing adaptive computer vision systems in medical, educational, and navigational applications. **The goal** of the research is to analyze the accuracy of distance measurement to an indoor object using a geometric approach based on the FaceMesh algorithm under variable external factors. The tasks include determining the impact of lighting quality, head position, and camera resolution on measurement accuracy; implementing a distance estimation algorithm using facial landmarks; conducting experiments; and formulating recommendations for the proposed method. The following methods were used: monocular geometry with the FaceMesh algorithm and real-time video processing techniques. **As a result** of the experimental studies, it was confirmed that the optimal conditions for accurate distance measurement are a frontal face position relative to the camera, a resolution of 640×480, and lighting above 200 lux. The error increases at tilt angles exceeding 15° and under low lighting. Under these conditions, the FaceMesh algorithm demonstrates an error of less than 3% at distances up to 90 cm. **Conclusions.** The method is suitable for use in real-time mobile systems with limited resources and has potential for further integration into multimodal recognition systems and adaptive navigation platforms.

**Keywords:** distance measurement, FaceMesh, computer vision, monocular geometry, resolution, lighting, head tilt.

### Introduction

**Problem Statement.** Distance measurement to objects has broad applications in autonomous systems, security, medicine, military technology, and the entertainment industry [1, 2]. Further advancements in this field will improve the adaptability of recognition systems and reduce errors under variable environmental conditions. To understand the importance and impact of distance measurement methods on practical problem-solving, examples of their applications can be analyzed (Fig. 1).



**Fig. 1.** Classification of distance measurement applications

Accurate distance measurements enhance safety, automate processes, optimize management, and improve human-technology interaction.

In autonomous vehicles, drones, and industrial robots, precise distance measurement is essential for obstacle avoidance, navigation, and trajectory adjustments. For example, autopilot systems in cars use LiDAR, cameras, and radars to estimate distances to other vehicles, pedestrians, and infrastructure, thereby improving road safety [3].

Intelligent orientation systems, such as smart glasses or mobile apps, help visually impaired individuals avoid collisions by using computer vision technologies to detect obstacles along their path.

In medical technologies, distance measurement methods are applied in systems monitoring patients' vital parameters, medical imaging (MRI, CT) for assessing tissue damage depth, and non-contact temperature measurement or remote patient monitoring [4].

In smart video surveillance systems, distance analysis helps assess threat levels, track object movements in critical zones, and identify potentially dangerous situations. For instance, real-time detection of aggressive actions or unauthorized proximity to certain objects.

In AR/VR technologies, distance measurement aids in creating realistic virtual environments and correctly positioning objects in space. This is used in video games, educational simulators, engineering modeling, and even surgical training.

Distance control in industrial applications is employed in production lines for automated part inspection, precise machinery positioning, and assembly tolerance checks, reducing errors and improving product quality.

Drones and satellite technologies enable distance measurement to plants, soil terrain features, and field condition assessments, optimizing resource use such as

water and fertilizers with the help of artificial intelligence.

In aerospace, maritime transport, and space exploration, precise distance measurement is crucial for safe landings, navigation, and terrain analysis. For example, NASA uses depth estimation methods for spacecraft landings on other planets.

Laser rangefinders and 3D scanning help measure distances between objects in construction, verify design accuracy, and create digital infrastructure models.

In sports analytics, distance measurement methods analyze athletes' movement trajectories, speed, and motion precision, enhancing training processes [5].

Thus, distance measurement methods significantly impact automation and safety across various fields. Accurate distance measurement improves the adaptability of machine vision systems used in autonomous transport, medicine, industry, and other sectors. These technologies reduce the risk of accidents and errors in critical systems, enhance monitoring and diagnostic accuracy, and enable

more realistic digital models and simulations. Combining deep neural networks with classical computer vision methods improves scene depth estimation efficiency even under challenging lighting and obstacle conditions. Additionally, integrating these methods into resource-limited devices, such as mobile phones or embedded systems, opens new possibilities for developing accessible technologies for a broad user base.

However, it should be noted that distance measurement methods for indoor and outdoor applications differ significantly due to environmental conditions, typical obstacles, and accuracy requirements. The main differences concern the technologies used, sensitivity to external factors, and measurement accuracy and range.

**Analysis of Recent Research and Publications.** Sensitivity to external conditions depends on the characteristics of photo and video sensors and their adaptability to varying lighting, atmospheric obstacles, measurement ranges, etc. The analysis of differences between indoor and outdoor methods is presented in Table 1.

Table 1 – Key Differences Between Indoor and Outdoor Distance Measurement Methods

Parameter	Indoor (Enclosed Spaces)	Outdoor (Open Environments)
Typical Conditions	Stable lighting, absence of atmospheric obstacles, limited space	Variable lighting (sun, shade), atmospheric factors (rain, fog), large distances
Measurement Range	0.1 m – 10 m	10 m – Several kilometers
Main Obstacles	Signal reflections from walls, furniture, objects	Weather changes, large spaces, complex terrain
Light Sensitivity	Minimal (lighting can be controlled)	High (depends on time of day, presence of direct sunlight)
Typical Technologies	Ultrasonic, LiDAR, stereo vision, structured light, ToF sensors	LiDAR, satellite data, radar technologies, aerial photography

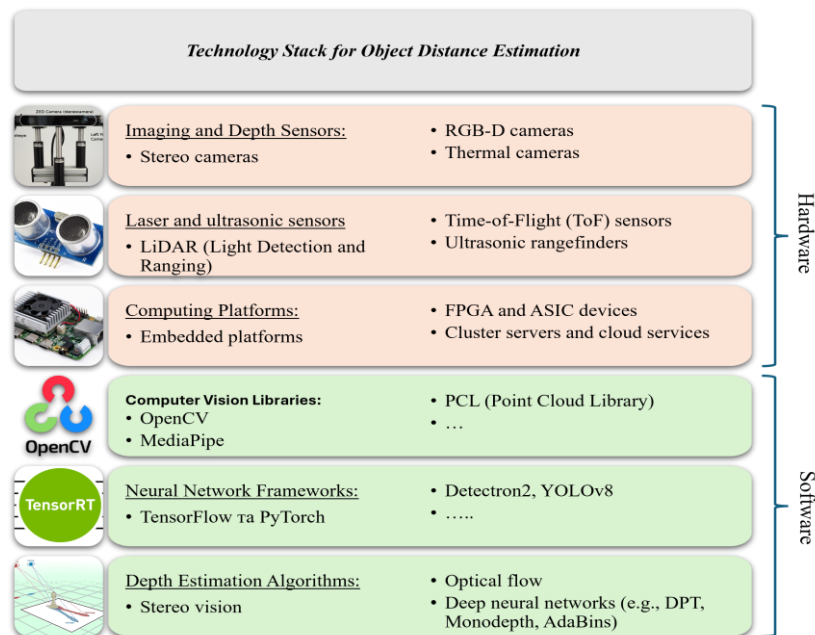


Fig. 2. Technological stack for distance measurement to objects

External factors affecting distance measurement accuracy differ between indoor and outdoor detection systems. Thus, for accurate distance measurement, it is essential to consider the environment's specifics (indoor or outdoor) and its characteristics. Indoors, lighting, reflections, and limited space have the most significant impact, while outdoors, variable weather, natural lighting,

long distances, and moving objects are key factors. The choice of methods depends on these factors, so effective solutions often combine various technologies (stereo vision, LiDAR, neural network approaches) to compensate for individual method limitations.

Distance measurement systems use various software and hardware tools tailored to specific tasks and

environments. The technological stack includes hardware for data collection and software for processing this data to obtain accurate results (Fig. 2)

Considering individual software and hardware tools in the context of indoor and outdoor applications, ultrasonic sensors (Sonar) are used for short distances (in robotics, orientation systems for visually impaired individuals). They are sensitive to signal reflections from smooth surfaces, making them suitable for indoor use. For outdoor applications, they are less practical due to signal loss in the air and wind or rain interference.

Laser sensors (LiDAR) are popular in autonomous transport, geodesy, and environmental monitoring [6–8]. They can operate over long distances but require high power, making them more suitable for outdoor use than ultrasonic sensors. Indoors, LiDAR sensors are used for space mapping (robots, drones, VR/AR), but issues may arise with laser reflections from mirror-like surfaces.

Stereo vision methods work well in controlled environments and are widely used in robotics and motion capture systems but lose effectiveness outdoors due to lighting variability.

Computational methods for distance measurement based on Time-of-Flight (ToF) are effectively used in smartphones and VR systems for scene depth estimation. They offer high accuracy within a few meters but are sensitive to lighting changes and atmospheric conditions. Radar technologies are rarely used for indoor distance measurements but are effective for long distances (automotive safety systems, satellite navigation, meteorology). Thus, the technological stack for distance measurement includes a wide range of hardware (LiDAR, cameras, ToF sensors) and software (OpenCV, TensorFlow, PyTorch). The choice of technologies depends on the application: robotics and navigation use LiDAR and deep neural networks, mobile devices use ToF cameras and neural depth estimation models, and engineering applications use stereo vision and PCL.

Research and optimization of software and hardware improve distance estimation accuracy and make these technologies more accessible for widespread use.

This underscores the relevance of the chosen research topic, namely the analysis of external factors' impact on the accuracy of distance measurement to a human face during indoor filming.

For the experimental part of the project, the Python programming language, PyCharm development environment, and OpenCV and FaceMesh libraries [9] were used.

**The goal** of the research is to analyze the impact of external factors on the accuracy of distance calculation to a filmed object indoors using geometric characteristics.

To achieve this goal, the following tasks must be solved:

- determine the specifics of variable external factors (lighting, camera resolution, head position) on distance measurement accuracy;
- justify the choice of distance estimation method based on facial landmarks (FaceMesh), considering speed and hardware limitations;
- implement a software module based on OpenCV for distance measurement using monocular geometry;

- conduct a series of experiments to evaluate the method's accuracy under various conditions (distance, resolution, lighting, object position);

- analyze the experimental results to determine the conditions for using the proposed method.

Further research directions include improving the distance measurement method by combining geometric approaches with neural network depth estimation models (e.g., Monodepth or DPT), enhancing accuracy under challenging conditions such as noise, glare, or partial face occlusion. Another promising direction is extending the algorithm for real-time video processing on mobile platforms using optimized libraries (TensorRT, MediaPipe) and incorporating individual biometric features to improve system personalization and adaptability. Integration into multisensory smart environments or navigation solutions for visually impaired individuals could also be explored.

## Materials and Research Methods

The main physical principles of image depth determination are:

- geometric properties of light rays;
- optical effects (e.g., blur, motion);
- material properties (e.g., texture).

Given that camera parameters are known before the study, interpretability of results is required, and a solution must be obtained in the shortest time for objects like a human face, geometric methods are optimal for this task.

The FaceMesh method (or similar approaches using predefined scales) is based on geometric calculations, where distance is computed using known object dimensions (e.g., average distance between human eyes) and their pixel projection. This approach has several advantages over modern deep learning methods, especially in specific scenarios:

- minimal data dependency (geometric methods like FaceMesh do not require training on large datasets. Knowing the physical dimensions of the object (e.g., 6.5 cm between human eyes) and camera parameters (focal length) is sufficient. Deep learning, in contrast, requires massive labeled datasets for training. For example, models like Monodepth [10] depend on thousands of images with known depths, which are often unavailable for niche tasks);

- low energy consumption (algorithms based on OpenCV (e.g., keypoint detection) operate in real-time on weak devices (smartphones, Raspberry Pi). Deep learning involves complex architectures (e.g., DepthNet) and requires GPUs for inference, increasing cost and energy consumption);

- interpretability and control (in terms of interpretability and control, formulas based on projective geometry, which underlie FaceMesh, are transparent and allow precise error analysis. Deep learning often acts as a "black box," making it difficult to determine why the model incorrectly estimated distance for non-standard faces) [11];

- avoidance of potential ethical issues (geometric methods do not store biometric data, as FaceMesh operates locally and anonymously. In deep learning, models trained on user data may violate GDPR due to personal information collection (e.g., face scans) [12].

A detailed model of the face capture process for distance measurement from the recorder to the object (face) is shown in Fig. 3. The model includes five interdependent functional modules:

- video capture from the camera (a video stream from the camera provides continuous data updates);
- face detection (the frame is analyzed to identify the region of interest containing the target object);
- region of interest detection (detectors locate keypoints on the object for depth calculation);
- depth calculation (based on known object and camera parameters using the formula:

$$D = (W \times f)/w,$$

where  $D$  – is the distance to the object,  $W$  – is the physical width of the object,  $f$  – is the camera's focal length,  $w$  – is the measured object width in pixels;

- result output (displays the distance between the camera and the object).

The system begins by capturing video using `cv2.VideoCapture`, providing a real-time video stream. Next, face detection is performed using `FaceMeshDetector`, which identifies keypoints on the user's face. The program checks if a face is detected. If not, the process repeats until a face is captured. If a face is detected, the algorithm proceeds to extract the coordinates of the left and right eyes.

Using these points, the distance between the eyes is calculated with the `findDistance` function, determining the relative head position. Then, using the camera's focal length, the depth (distance to the camera) is calculated. This calculation is performed twice for higher accuracy. After depth calculation, the program displays the results using `cvzone.putTextRect`.

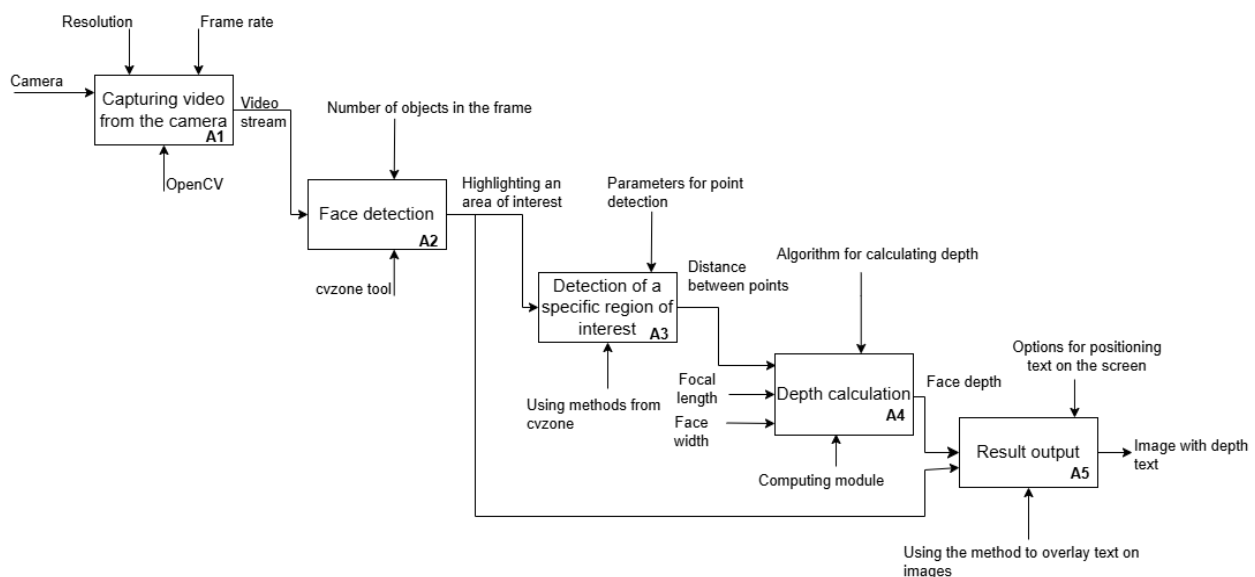


Fig. 3. Functional model of the distance measurement system based on the FaceMesh method

## Research Results

The experimental procedure is as follows: fix the actual distance (using a ruler or laser rangefinder), position the camera stably (on a tripod or fixed surface), run the FaceMesh/OpenCV distance measurement algorithm, compare the calculated distance with the actual distance, and record the error.

Experiment №1. Investigates the accuracy of distance measurement at different camera resolutions (640×480, 1280×720, 1920×1080 (if supported)) for

various actual distances to the object (30 cm, 60 cm, 90 cm, 120 cm).

The hypothesis is that the farther the object is from the camera, the less accurate the pixel scale determination will be. Lower resolutions make it harder to recognize fine details, reducing accuracy (higher resolutions increase the number of pixels per keypoint (eyes, nose), improving accuracy).

Experiment 1 results show that camera resolution has minimal impact on distance measurement accuracy (Fig. 4).

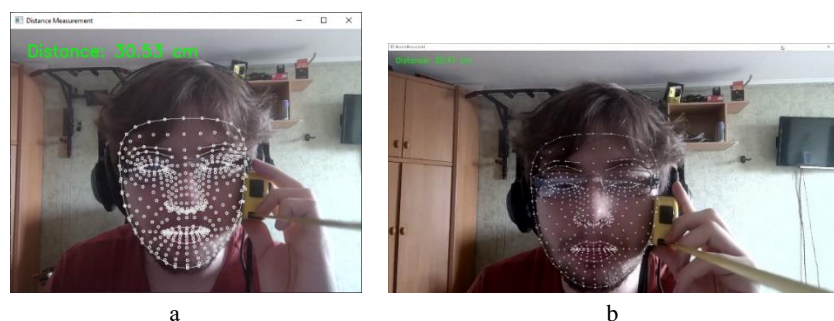


Fig. 4. Display of the results of experiment 1 with: a – separate building 640x480, b – separate building 1920x1080



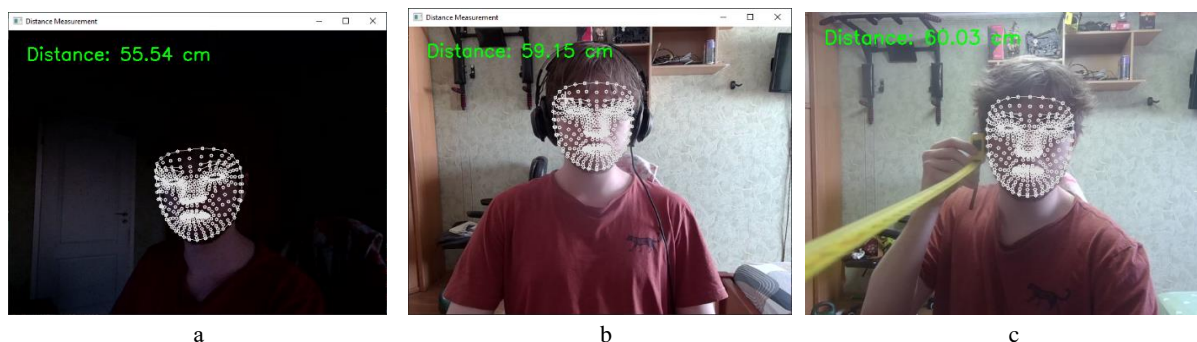
The most stable and accurate results are observed at 640×480 resolution, where errors are minimal or absent. At higher resolutions (1280×720 and 1920×1080), errors increase, particularly at distances of 90 cm and 120 cm, where accuracy drops below 99%. Thus, higher resolution does not always guarantee better distance measurement accuracy. This may be due to image processing specifics, optics quality, or distance measurement algorithms. Given that a human face is not entirely static, higher resolutions increase sensitivity to minor head movements, which does not occur at 640×480. Therefore, the optimal resolution in this experiment is 640×480, providing high accuracy with lower computational costs (Fig. 5).

Experiment №2 (Fig. 6) investigates the accuracy of distance measurement under varying lighting conditions (near 0 lux, ~50 lux – low lighting, ~200 lux –

normal lighting, ~500 lux – excessive lighting) for various actual distances to the object (30, 60, 90, 120 cm).



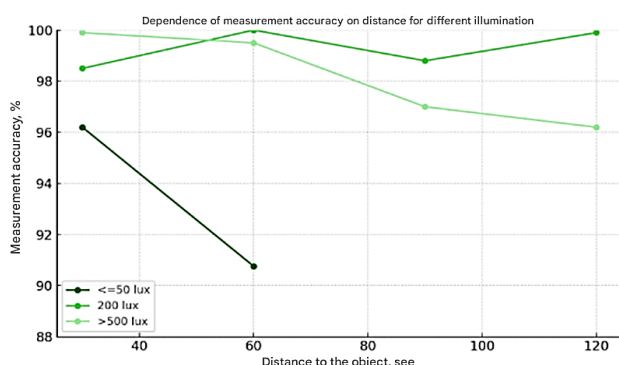
**Fig. 5.** Evaluation of resolution impact on distance measurement accuracy



**Fig. 6.** Representation of the results of experiment 2 with lighting: a ~ 0 lux, b ~50 lux, c ~ 500 lux

The hypothesis is that under low lighting, FaceMesh keypoint detection accuracy significantly decreases, while excessive lighting may cause glare, affecting contour recognition

Experiment 2 results show that lighting level significantly impacts distance measurement accuracy—under high lighting, accuracy remains highest across all distances (Fig. 7).



**Fig. 7.** Assessment of the influx of lighting intensity for the accuracy of the determined position of the object in front of the camera

Under low lighting (< 50 lux), accuracy noticeably decreases, especially at longer distances (e.g., at D = 90 cm and 120 cm, the error exceeds 3%). Beyond 60 cm, when lighting is below 50 lux, the camera cannot capture the face, making the method ineffective for long distances in dark conditions.

Under moderate (200 lux) and high lighting (>500 lux), accuracy significantly improves, reaching nearly 100% regardless of distance. Specifically, lighting above 500 lux yields the most stable results. Thus, optimal conditions for accurate system performance are well or moderately lit environments (200 lux and above). Low lighting significantly reduces measurement accuracy, especially as distance to the object increases.

Experiment №3 (Fig. 8) investigates the accuracy of distance measurement depending on head tilt angle (in frontal and sagittal planes at 0°, 15°, 30° tilt) for various actual distances to the object (30, 60, 90, 120 cm).

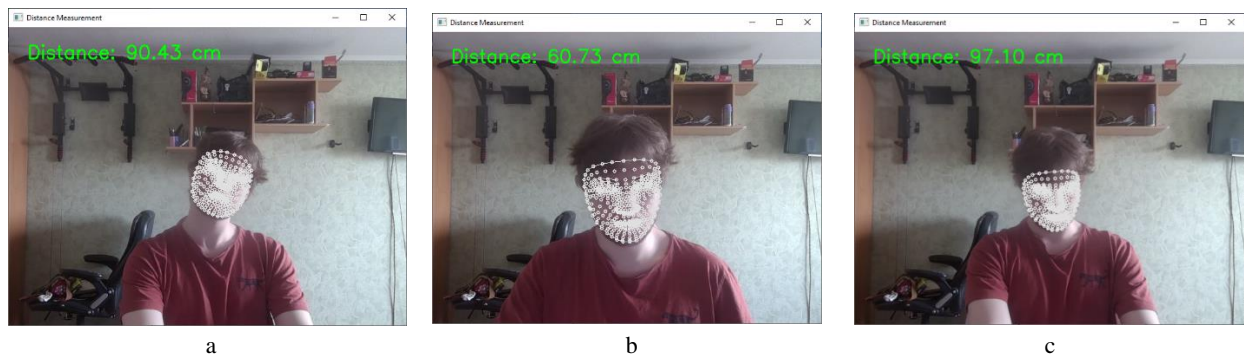
The hypothesis is that head tilt in different planes reduces algorithm accuracy. Experiment 3 results show that head tilt, both in frontal and sagittal planes, significantly impacts distance measurement accuracy. The highest accuracy is observed at 0° tilt, i.e., when the object is directly facing the camera without deviations. Here, measurement accuracy is nearly 100% regardless of distance under normal lighting. At 15° and 30° frontal tilt, accuracy drops to 95–96%, especially at closer distances. A more noticeable accuracy decrease occurs at 30° sagittal tilt—e.g., at 30 cm distance and 30° tilt, accuracy drops to 84%. This is because tilt changes the object's projection in the camera's field of view, making it harder for algorithms to determine distance accurately.

Thus, for best results, the object should face the camera directly without tilts in any direction.

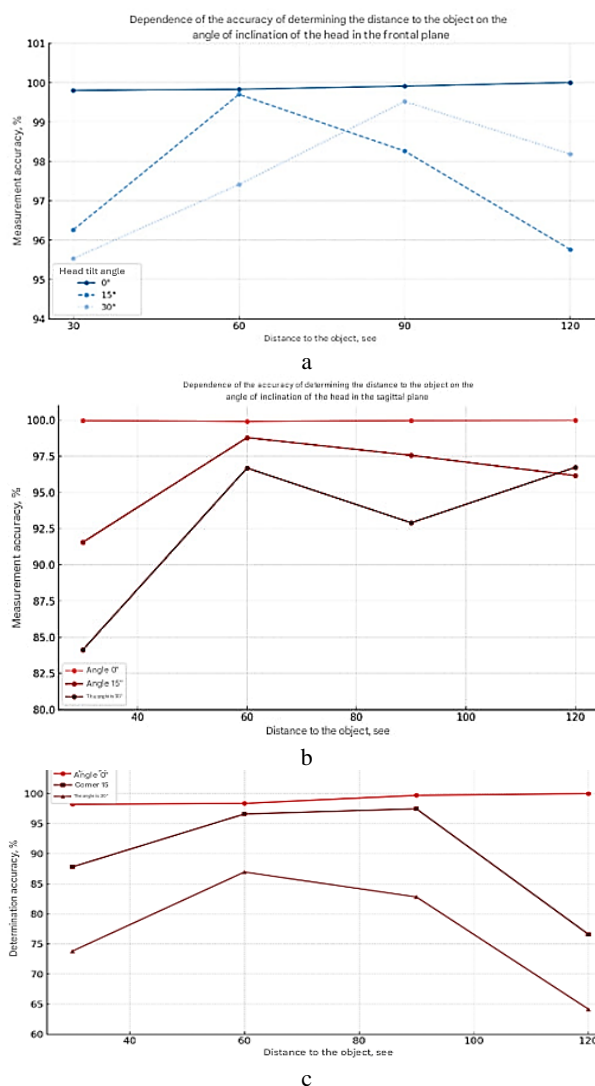
Analysis of the experimental results forms the basis for practical recommendations on using the studied distance measurement method: the most accurate distance

measurement is achievable with a camera resolution of at least  $640 \times 480$  and indoor lighting  $>200$  lux. Distances beyond 120 cm require additional sensors to compensate

for accuracy loss. Face tilt partially or fully occludes key facial landmarks, necessitating additional keypoint detectors (Fig. 9).



**Fig. 8.** Representation of the results of experiment 3 with head tilt at: a – frontal area at  $30^\circ$ , b – sagittal area at  $15^\circ$ , c – sagittal area at  $30^\circ$



**Fig. 9.** Evaluation of the head angle for the accuracy of the designated object position in front of the camera: a – at the frontal plane, b – at the sagittal plane, c – when turning the head

Thus, the FaceMesh/OpenCV algorithm provides sufficiently high distance detection accuracy only under the following conditions: the object faces the camera directly without tilts, the camera operates under sufficient lighting (200 lux and above), and optimal resolution ensuring stable algorithm performance (in this study,  $640 \times 480$ ).

Deviations from these conditions noticeably reduce accuracy, which must be considered in practical applications.

## Conclusions

The scientific novelty. For the first time, the impact of external factors (lighting, resolution, tilt angle) on the accuracy of a geometric distance measurement method to a user's face indoors based on the FaceMesh algorithm has been systematically analyzed. Conclusions regarding permissible application conditions and method limitations have been drawn.

The practical significance. The research results enable developers to use inexpensive and computationally lightweight algorithms for distance estimation in resource-constrained environments, particularly in mobile apps, IoT devices, and adaptive access interfaces for visually impaired individuals.

A set of operational recommendations for minimizing errors has been proposed.

Prospects for further research. Future research will evaluate neural network distance measurement methods for further integration into more complex adaptive models that automatically account for human position and adjust parameters based on predefined distance.

Deployment of systems incorporating the studied method on IoT devices or low-power systems, where standardized objects with known dimensions (e.g., human faces, road signs) are considered and algorithm transparency is critical (e.g., medical diagnostics), is also possible.

## REFERENCES

1. Dietrich, O., et al. (2025). An Open-Source Tool for Mapping War Destruction at Scale in Ukraine Using Sentinel-1 Time Series. arXiv:2406.02506, arXiv, 20 Feb. 2025. arXiv.org. <https://doi.org/10.48550/arXiv.2406.02506>.
2. Barkovska, O., Oliynyk, D., Sorokin, A., Zabroda, I., & Sedlaček, P. (2024). A system for monitoring the progress of rehabilitation of patients with musculoskeletal disorder. Advanced Information Systems, 8(3), 13-24.

3. Barkovska, O., & Serdechnyi, V. (2024). Intelligent Assistance System for People with Visual Impairments. INNOVATIVE TECHNOLOGIES AND SCIENTIFIC SOLUTIONS FOR INDUSTRIES, (2)28, 6–16. DOI.org (Crossref). <https://doi.org/10.30837/2522-9818.2024.28.006>.
4. Kunczik, J., et al. (2022). Breathing pattern monitoring by using remote sensors. Sensors, 22(22), 8854.
5. Deng, Z., et al. (2023). Smart Wearable Systems for Health Monitoring. Sensors, 23(5), 2479. <https://doi.org/10.3390/s23052479>.
6. Kaur, B., et al. (2023). Novel Wearable Optical Sensors for Vital Health Monitoring Systems—A Review. Biosensors, 13(2), 181. <https://doi.org/10.3390/bios13020181>.
7. Olmedo-Aguirre, J. O., et al. (2022). Remote Healthcare for Elderly People Using Wearables: A Review. Biosensors, 12(2), 73. <https://doi.org/10.3390/bios12020073>.
8. Adeghe, E. P., et al. (2024). A Review of Wearable Technology in Healthcare: Monitoring Patient Health and Enhancing Outcomes. Open Access Research Journal of Multidisciplinary Studies, 7(1), 142–148. <https://doi.org/10.53022/oarjms.2024.7.1.0019>.
9. Wang, W., et al. (2016). Algorithmic principles of remote PPG. IEEE Transactions on Biomedical Engineering, 64(7), 1479–1491.
10. Tirink, C., et al. (2023). Estimation of body weight based on biometric measurements by using random forest regression, support vector regression and CART algorithms. Animals, 13(5), 798.
11. Di, H., Shafiq, M., & AlRegib, G. (2018). Patch-level MLP classification for improved fault detection. SEG technical program expanded abstracts 2018. Society of Exploration Geophysicists, 2211–2215.

Received (Надійшла) 11.03.2025

Accepted for publication (Прийнята до друку) 21.05.2025

#### ВІДОМОСТІ ПРО АВТОРІВ / ABOUT THE AUTHORS

**Барковська Оlesia Юрійвна** – кандидат технічних наук, доцент кафедри електронних обчислювальних машин, Харківський національний університет радіоелектроніки, Харків, Україна;

**Olesia Barkovska** – Candidate of Technical Sciences, Associate Professor at the Department of Electronic Computers, Kharkiv National University of Radio Electronics, Kharkiv, Ukraine;

e-mail: [olesia.barkovska@nure.ua](mailto:olesia.barkovska@nure.ua); ORCID Author ID: <http://orcid.org/0000-0001-7496-4353>;

Scopus Author ID: <https://www.scopus.com/authid/detail.uri?authorId=24482907700>

**Шапіро Анатолій Сергійович** – магістрант кафедри електронних обчислювальних машин, Харківський національний університет радіоелектроніки, Харків, Україна;

**Shapiro Anatoliy Serhiyovych** – master's student of the Department of Electronic Computers, Kharkiv National University of Radio Electronics, Kharkiv, Ukraine;

e-mail: [anatoliy.shapiro@nure.ua](mailto:anatoliy.shapiro@nure.ua); ORCID Author ID: <https://orcid.org/0009-0000-7244-8232>.

**Мавринський Олександр Денисович** – магістрант кафедри електронних обчислювальних машин, Харківський національний університет радіоелектроніки, Харків, Україна;

**Mavrynskyi Oleksandr Denysovych** – master's student of the Department of Electronic Computers, Kharkiv National University of Radio Electronics, Kharkiv, Ukraine;

e-mail: [oleksandr.mavrynskyi@nure.ua](mailto:oleksandr.mavrynskyi@nure.ua); ORCID Author ID: <https://orcid.org/0009-0002-0596-1559>.

**Жебін Павло Дмитрович** – магістрант кафедри електронних обчислювальних машин, Харківський національний університет радіоелектроніки, Харків, Україна;

**Zhebin Pavlo Dmytrovych** – master's student of the Department of Electronic Computers, Kharkiv National University of Radio Electronics, Kharkiv, Ukraine;

e-mail: [pavlo.zhebin@nure.ua](mailto:pavlo.zhebin@nure.ua); ORCID Author ID: <https://orcid.org/0009-0002-2271-8016>.

#### Дослідження чутливості методу визначення відстані до об'єктів на основі алгоритму FaceMesh

О. Ю. Барковська, А. С. Шапіро, О. Д. Мавринський, П. Д. Жебін

**Анотація. Актуальність.** У статті розглянуто метод оцінки відстані до обличчя користувача в умовах змінного освітлення, роздільної здатності камери та кута нахилу голови, що має велике значення для побудови адаптивних систем комп'ютерного зору в медичних, освітніх та навігаційних задачах. **Метою** дослідження є аналіз точності визначення відстані до об'єкта в приміщенні за допомогою геометричного підходу на базі алгоритму FaceMesh в умовах змінних зовнішніх факторів. Задачами дослідження є визначення впливу якості освітлення, положення голови та роздільної здатності камери на точність вимірювання; реалізація алгоритму оцінки відстані за допомогою контрольних точок обличчя, проведення експериментів та формування рекомендації щодо використання запропонованого методу. В роботі використано наступні методи: метод монокулярної геометрії з використанням алгоритму FaceMesh, методи обробки відео в реальному часі. **В результаті** експериментальних досліджень було підтверджено, що оптимальними умовами для точного визначення відстані є розташування обличчя фронтально до камери, роздільна здатність 640×480, освітлення вище 200 лк. Визначено, що похибка зростає при кутах нахилу понад 15° та при слабкому освітленні. За таких умов алгоритм FaceMesh демонструє похибку менше 3% на відстані до 90 см. **Висновки.** Метод є придатним для використання в мобільних системах реального часу з обмеженими ресурсами, має потенціал до подальшої інтеграції в багатомодальні системи розпізнавання та адаптивні навігаційні платформи.

**Ключові слова:** визначення відстані, FaceMesh, комп'ютерний зір, монокулярна геометрія, роздільна здатність, освітлення, нахил голови.