Information systems research

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Olesia Barkovska[1], Andriy Kovalenko[1], Dmytro Oliinyk[1], Oleksandr Ruskikh[1], Peter Sedlacek[2]

[1] Kharkiv National University of Radio Electronics, Kharkiv, Ukraine
[2] University of Zilina, Zilina, Slovakia

STUDY OF METHODS FOR DETECTING OPTICAL MARKERS IN THE SYSTEM OF HUMAN GAIT AND POSTURE ANALYSIS

Abstract. The study is **dedicated** to the relevant topic of automated detection of muscle imbalance and postural deformities, which is particularly in demand among patients with orthopedic prostheses and in pediatric orthopedics. The authors **propose** a portable monitoring system that uses computer vision methods to assess the level of the pelvis, shoulders, and shoulder blades, ensuring the storage of photogrammetric data for subsequent analysis of rehabilitation results. **The purpose of the work** is to study methods for detecting optical markers on the human body when analyzing gait. **The research tasks** included conducting an analysis with a justification of the need to study computer graphics methods in the context of photogrammetric systems used in rehabilitation orthopedics; studying the impact of color characteristics of markers on detection accuracy; studying the impact of marker shape on detection accuracy; and analyzing the obtained results. The subject of the study is computer graphics and machine vision methods for detecting markers on the subject's body. The object of the study is photogrammetric technologies in orthopedics. **As a result of the study,** it was established that the use of the HSV color format for marker detection demonstrates high accuracy and low error even under changing lighting conditions. It was found that the shape of the marker affects detection accuracy, with the best results shown by the square shape. The research results confirmed the feasibility of using photogrammetry methods to assess joint asymmetry and muscle imbalance. **Further research** will focus on increasing the speed and accuracy of marker detection with non-stationary camera placement and a complicated background.

Keywords: system; model; method; monitoring; rehabilitation; image; spine; analysis; anthropometry; baropodometry; curvature.

Introduction

It is impossible to overestimate the role of computer graphics and computer vision methods in modern life for many fields. In the modern world, computer graphics and computer vision methods are increasingly used in various fields of life, significantly changing and improving their functioning. From medicine to entertainment, from industry to education, these technologies affect various aspects of our daily lives, contributing to efficiency, accuracy, and safety (Fig. 1). The importance of these methods lies in their ability to automate and improve processes that previously required significant human resources and were prone to high levels of errors.

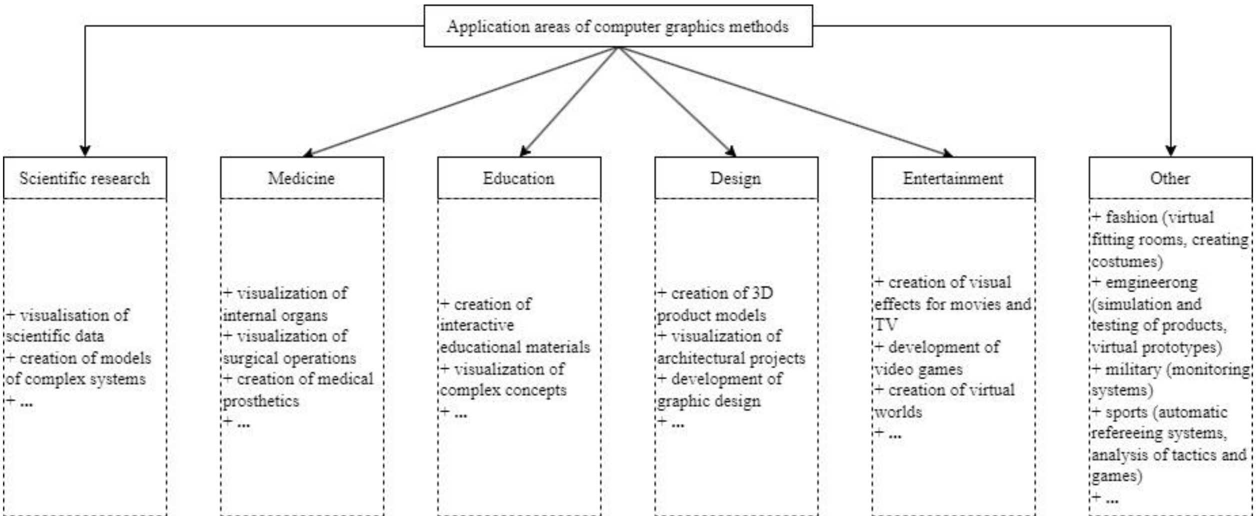

Fig. 1. Spread of computer graphics methods

Thus, computer graphics and computer vision methods are key technologies that significantly affect various aspects of our lives, improving its quality, increasing efficiency and safety, and opening new opportunities for innovation and development. These technologies provide the following capabilities:

– visualization (of scientific data, anatomical structures, educational materials, engineering prototypes, production processes, virtual worlds, etc.);

– analysis (of medical images, defects in production processes, people in security systems, biometric data in access control systems, etc.);

– understanding information (interactive educational materials, process simulations, augmented reality, etc.).

Overall, computer graphics can help people better understand information by making it more visual, interactive, dynamic, personalized, and contextual.

Research task rationale

The medical field is one of the most striking examples of the impact of computer graphics and computer vision. The use of these technologies in medical diagnostics improves the accuracy of disease detection and treatment planning [1, 2]. For example, research shows that machine learning algorithms can successfully detect tumors at early stages by analyzing medical images with accuracy that exceeds the capabilities of traditional methods.

Table 1 – **Medical directions and tasks solved by using computer graphics methods**

Medical direction	**Tasks solved by using optical systems**
Orthopedics	3D reconstruction of bones and joints, surgery planning, implant modeling, trauma and disease diagnosis, photogrammetry, creation of 3D motion models [3, 4]
Cardiology	Visualization of the heart and blood vessels, blood flow analysis, anomaly diagnostics, post-surgery condition assessment
Pulmonology	CT image analysis of the lungs, node and tumor detection, lung tissue volume assessment [5]
Otolaryngology	3D reconstruction of the ear and nasal sinuses, diagnostics of ENT diseases, surgery preparation
Surgery	Surgical planning, navigation during operations, creation of virtual simulations for surgeon training
Neurosurgery	Brain visualization, neurosurgical operation planning, intervention navigation
Ophthalmology	Eye structure visualization, retina disease diagnostics, eye surgery planning
Dermatology	Skin image analysis for cancer diagnosis, neoplasm detection, skin condition monitoring
Oncology	Tumor visualization, radiotherapy planning, image analysis to evaluate treatment effectiveness [6]
Dentistry	3D tooth scanning, orthodontic procedure planning, model creation for implants and prostheses
Gynecology	Ultrasound visualization for pregnancy diagnostics and monitoring, pelvic organ surgery planning
Urology	Visualization of kidneys and urinary tract, stone and tumor diagnostics, urological surgery planning

Computer graphics revolutionizes medicine by offering new and innovative methods for diagnostics, treatment, and medical education (Table 1).

Among the key applications of computer graphics in the medical field, we can highlight visualization of medical images (such as X-rays, MRI, CT, etc.), simulation of surgical interventions, development of personalized medical devices based on the creation of 3D models (e.g., for subsequent 3D printing), medical education and training (interactive educational materials for studying anatomy, physiology, and surgical techniques, creating virtual patients, etc.), and anatomy visualization [7, 8].

The last point mentioned, namely anatomy visualization, is the focus of this study. Anatomy visualization involves creating 2D and 3D models of anatomical structures such as organs, bones, and muscles using optical diagnostic and computer graphics methods. Currently, the direction of orthopedics and functional rehabilitation of those injured during and because of military actions, as well as pediatric orthopedics, is relevant for Ukraine.

The demand for functional rehabilitation of patients with orthopedic prostheses in Ukraine is driven by:

– an increase in the number of people requiring prosthetics due to the war in Ukraine;

– the imperfection of prostheses and the risks of complications (even the most modern prostheses can be heavy, uncomfortable, and not always meet all the user's needs);

– improving the quality of life by helping people return to work, study, sports, and other activities that were available to them before the injury;

– economic benefits by ensuring people return to working capacity.

The demand for pediatric orthopedics is driven by:

– changes in lifestyle (reduced physical activity in children due to a sedentary lifestyle, fascination with gadgets and computer games, increasing weight of children);

– increased load on the spine (due to prolonged sitting at a desk and carrying heavy backpacks);

– genetic predisposition (e.g., flat feet or hip dysplasia may have a hereditary nature);

– insufficient prevention (failure to comply with recommendations for preventive examinations of children by an orthopedist, ignoring the first signs of orthopedic problems).

Traditional examinations of children are conducted by an orthopedist, while the progress of rehabilitation of patients with orthopedic prostheses is assessed by an orthopedist, physical therapist, and rehabilitation specialist [7]. During physical examination and assessment of the functionality of the spine and joints, doctors assess movement limitations, pain and discomfort during palpation, joint stability and steadiness, motor abilities, the condition of the spine, the level of the shoulder blades, shoulders, and pelvis, which may be displaced from the norm due to various physiological and biomechanical reasons (Fig. 2) [9].

Asymmetry of the pelvis, shoulder blades, shoulders, and spinal curvature can have various physiological and biomechanical causes, including but not limited to muscle imbalance, postural disorders, injuries or diseases, uneven load, and genetic factors. In the case of patients with orthopedic prostheses, additional reasons related to adaptation to the prosthesis may arise, such as uneven load on the prosthesis and changes in posture to compensate for its features. These changes can lead to uneven positioning and functioning of the shoulder blades, shoulders, and pelvis, complicating the rehabilitation process and requiring an individualized approach to each patient.

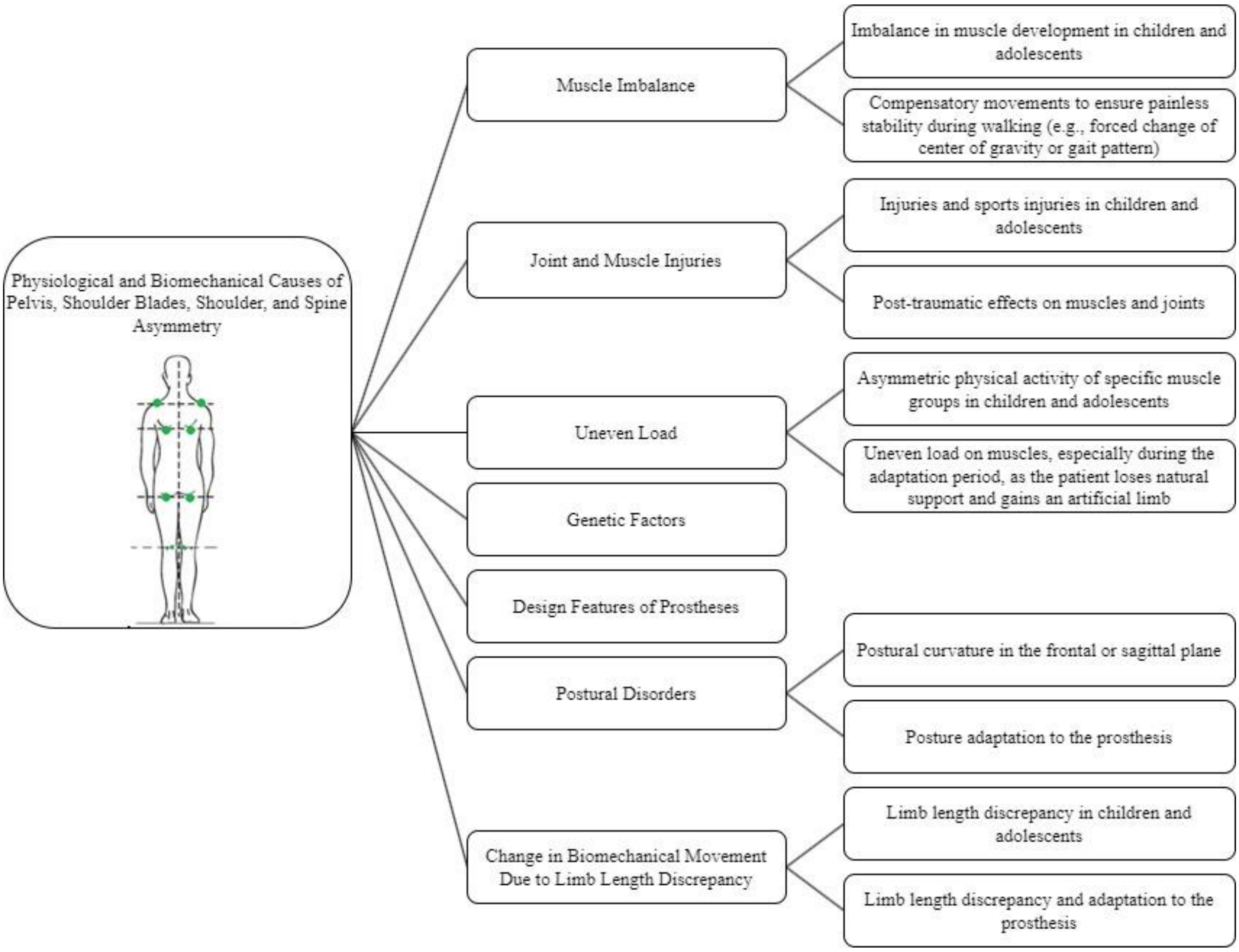

Fig. 2. Causes of asymmetry of upper trunk and pelvis joints

Assessment of shoulder, pelvis, and shoulder blade asymmetry, the degree of spinal curvature, and muscle imbalance can be performed using automated methods, namely [10, 11]:

– computer tomography (CT);
– magnetic resonance imaging (MRI);
– X-ray;
– Photogrammetry etc.

Changes in the anatomical structure of the spine can be examined by computer-optical video recording of human movements, a characteristic feature of which is the presence of only an optical communication channel between the recording equipment and the subject (Fig. 3).

This is the basic principle of photogrammetric systems.

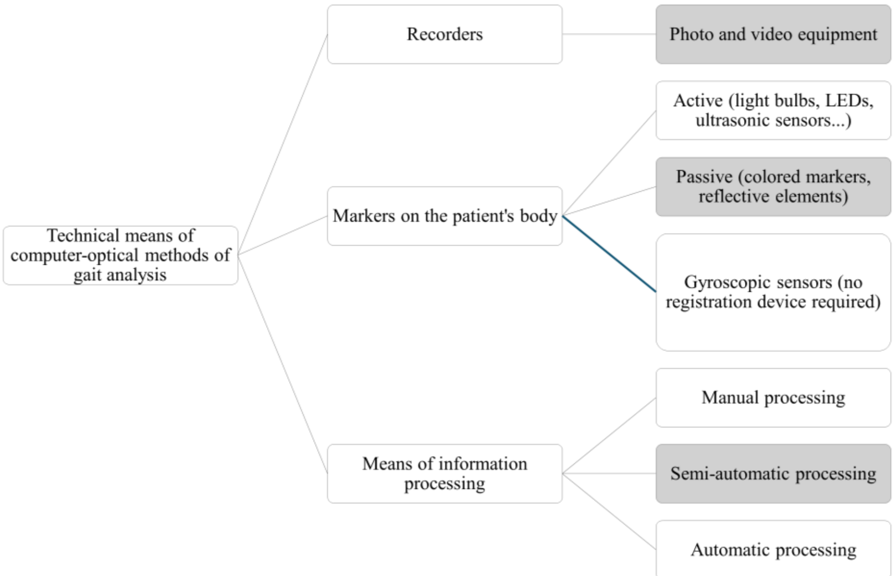

Fig. 3. Overview of computer-optical analysis of the subject's gait

Detection of muscle imbalance [12–14] even before the vertebrae are displaced from their natural position in the frontal and sagittal planes is possible by assessing dynamic baropodometry, as well as other indicators of muscle activity [15, 16]. Early detection of a possible cause of spinal curvature can have favorable prognosis and prevent complications in the patient's health. If we talk about the use of such platforms in the rehabilitation of military men with orthopedic prostheses, clinical examinations of the patient's gait help to identify relevant symptoms and specific compensatory reactions, the understanding of which is important for further rehabilitation. An example is the detection of osteoarthritis of the joints of a healthy limb, which can develop in the case of unilateral amputation of the lower leg.

Due to advantages such as low cost, portability (possible use of regular cameras or smartphones), safety (does not use ionizing radiation, unlike CT and X-ray), speed, detail, and a number of additional capabilities (generating not only 3D models but also texture maps, depth maps, and other data), this study focuses on photogrammetry. Artificial intelligence methods are a modern mathematical apparatus used for analyzing photogrammetric images and their preliminary processing [17–20].

A generalized representation of the mechanism for creating a clinical report [21] that supports various image modalities with subsequent analysis, including model-based analysis with artificial intelligence, is shown in Fig. 4.

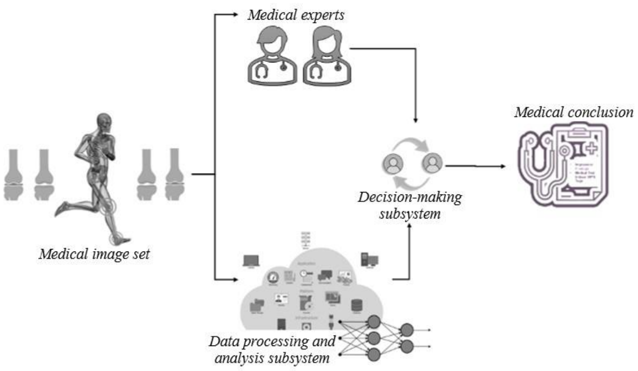

Fig. 4. Mechanism for creating a clinical report based on the analysis of medical images of various modalities

The disadvantage of photogrammetric systems is lower accuracy compared to CT or MRI, so increasing the accuracy of detecting and assessing the position of the spine, shoulders, pelvis, and shoulder blades is a relevant task.

The problem formulation

The purpose of the work is to develop an algorithm for detecting markers on the body of the subject.

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

– conduct an analysis with the justification of the need to study computer graphics methods in the context of photogrammetric systems used in rehabilitation orthopedics;

– study the impact of color characteristics of markers on detection accuracy;

– study the impact of the shape of markers on detection accuracy;

– analyze the obtained results.

Further research will focus on increasing the speed and accuracy of marker detection under the condition of non-stationary camera placement and a complicated background, making the system autonomous through calculations [22], for example, on programmable microchips [23, 24].

Results and Discussion

Research #1. Analysis of the color characteristics of markers.

The accuracy of determining the angle of inclination of the pelvis, shoulders, and shoulder blades depends on the accuracy of marker detection on the body of the subject, which necessitates the following studies (Fig. 5):

– the impact of choosing a color model representation of the marker on detection accuracy;

– the impact of the shape of the marker on detection accuracy;

– the impact of lighting quality in the room on detection accuracy.

Fig. 5. Example of an image included in the control dataset

Detection based solely on color is based on the operation of thresholding, using a certain color range. After thresholding, a binary image is obtained, where contours are found. For each obtained contour, its image moments are calculated, through which the center of mass and the center of the contour are obtained. If the thresholding was not perfect, i.e., more contours were found than expected, the most suitable ones are selected depending on the task, for example, the largest by area.

In this study, two color representation formats are used: RGB and HSV. The HSV color space can be graphically represented as a cylinder in three-dimensional Euclidean space in a polar coordinate system, where Hue is the polar angle, and Saturation and Value are radial coordinates forming the height and width of the cylinder.

The algorithm (Fig. 6) begins with obtaining an image with its subsequent conversion to the required color format. Then, thresholding is performed within predefined color ranges, followed by the application of morphological operations to suppress residual noise (Erosion operation) and restore remaining areas

(Dilation operation). The image is segmented by contours, which are then processed. If the necessary number of contour centers is found, the angle between them is calculated.

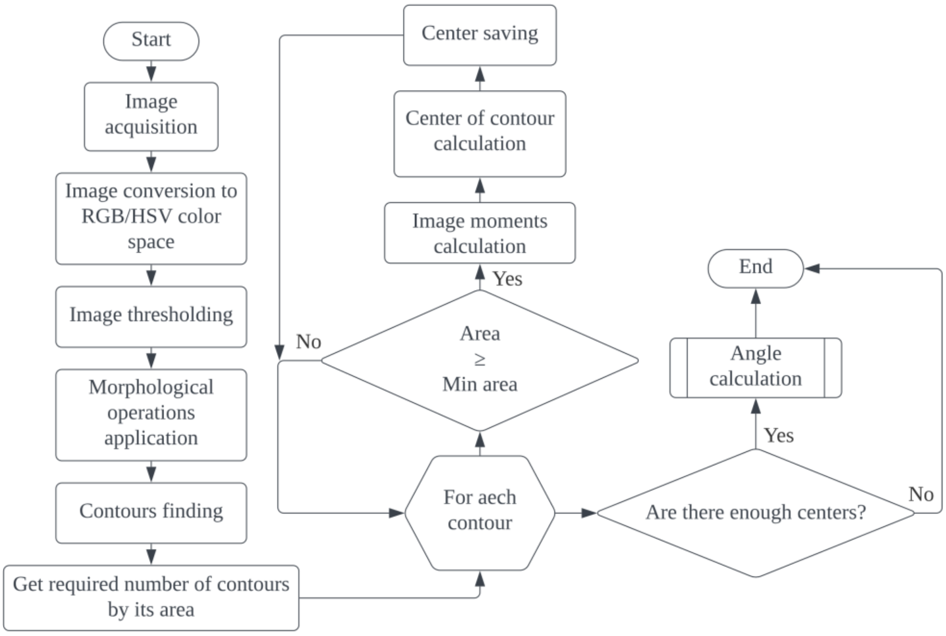

Fig. 6. Algorithm for color detection

Research #2. Analysis of marker shape characteristics.

For detection based solely on shape, the Canny edge detector is used, which is defined by two thresholding parameters that help filter out most edges that are not marker edges. After obtaining a binary image as a result of the detector, contours are found. Next, for each contour, its approximation is calculated, and the number of vertices remaining is checked, based on which a conclusion is made about which figure was found; for circle detection, the Hough Circle Transform method can be used, which is a special case of Hough Transforms, but this algorithm is not efficient enough in this case because it requires quite a lot of computations but still does not effectively identify ellipses, so a more heuristic algorithm was chosen.

To eliminate any potential overlap, the principles laid out in [25] were adhered to.

The detection algorithm (Fig. 7) begins with obtaining an image with its subsequent conversion to a gray color format. The next step is applying the Canny algorithm to highlight contours in the image. Next, morphological operations are applied to enhance the contours and close possible gaps in them (Dilation operation). Shape contours are identified (algorithm in Fig. 8). When contours with the desired shape are found, their centers are located, and the angle between them is calculated.

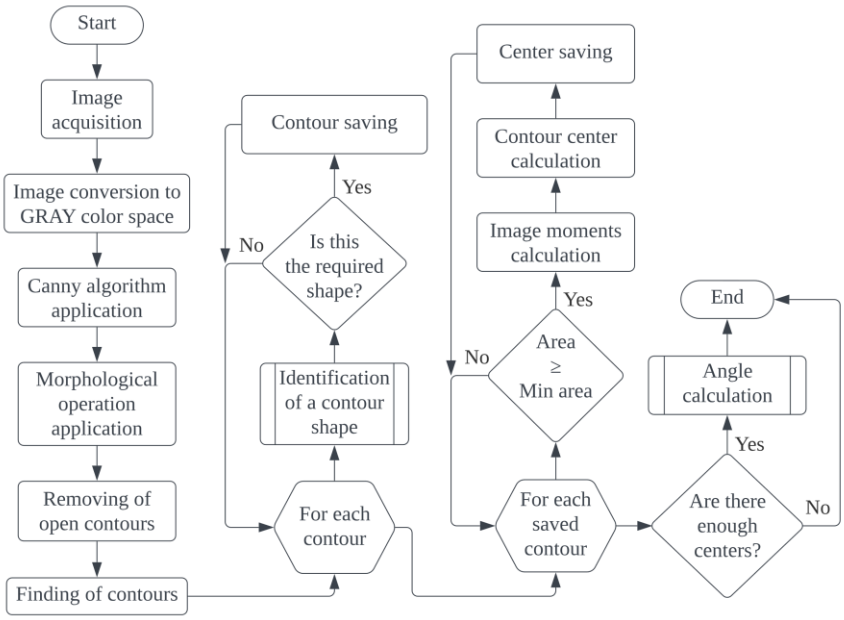

Fig. 7. Algorithm for shape detection

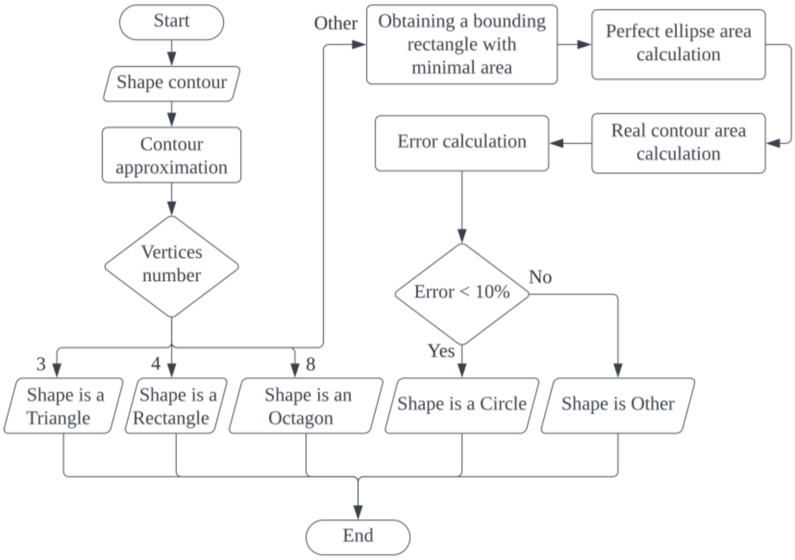

Fig. 8. Algorithm for shape identification

The evaluation criteria for the research results were accuracy and detection error, which are calculated according to formulas (1) and (2) respectively:

$$a\_d = f\_d / f\_t * 100\%; \quad (1)$$

$$e\_r = f\_md / f\_d * 100\%, \quad (2)$$

where *a_d* is the effectiveness or accuracy of detection, *f_d* is the number of frames correctly detected, *f_t* is total number of frames in the video, *f_md* is number of frames detected incorrectly, *e_r* is detection error.

The results are presented in the layout displayed in Table 2.

Table 2 – **Format of presenting results**

Marker detection accuracy without additional lighting, %
Marker detection accuracy with additional lighting, %
Marker detection error without additional lighting, %
Marker detection error with additional lighting, %

Analyzing the results of Tables 3 and 4, which present the results of experiments on marker color analysis, it is evident that detection accuracy using the HSV format under any lighting conditions is over 98% with an error of less than 0.6%, demonstrating detection stability and invariance to lighting conditions.

Table 3 – **Results of marker detection on a simple scene, RGB**

Color/Shape	Octagon		Rectangle		Circle		Triangle	
Blue	53.25%	17.50%	42.74%	46.22%	22.66%	38.44%	41.95%	11.96%
	62.34%	56.35%	37.46%	89.74%	25.81%	69.55%	50.39%	48.75%
Orange	72.93%	82.69%	62.57%	82.65%	66.67%	76.22%	47.15%	88.83%
	6.64%	18.68%	1.85%	11.13%	1.75%	24.11%	1.38%	11.77%
Green	35.38%	85.79%	70.77%	98.74%	51.11%	66.72%	49.48%	75.34%
	0.39%	0.00%	1.42%	0.00%	2.98%	0.46%	1.49%	0.60%
Yellow	95.84%	100.00%	93.04%	100.00%	95.92%	100.00%	91.71%	100.00%
	0.28%	0.13%	0.16%	0.16%	0.33%	0.46%	0.00%	0.00%

Table 4 – **Results of marker detection on a simple scene, HSV**

Color/Shape	Octagon		Rectangle		Circle		Triangle	
Blue	87.97%	95.42%	100.00%	99.85%	95.91%	100.00%	89.11%	81.32%
	0.00%	0.00%	0.00%	0.00%	2.90%	2.02%	0.00%	0.00%
Orange	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
	0.57%	0.00%	0.43%	0.00%	2.18%	0.41%	0.00%	0.00%
Green	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
	0.28%	0.00%	0.00%	0.00%	1.39%	0.31%	0.00%	0.00%
Yellow	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
	0.27%	0.53%	0.15%	0.00%	0.31%	1.08%	0.00%	0.00%

The results also showed that both the accuracy (62.07% without additional lighting, 73.19% with it) and the error (12.17% and 20.74% respectively) when using the RGB format are somewhat worse under any lighting conditions, which may be due to the complexity of selecting a suitable color range simultaneously for the scene with and without additional lighting. Analyzing the results of Tables 5 and 6, it can be seen that the use of the HSV color format for a complex scene still demonstrates quite high detection accuracy (67.05%), especially with additional lighting (86.54%), and relatively low detection error (5.57% and 0.21% respectively). Detection results using the RGB format show a fairly high error on the scene without additional lighting (11.06%), given the low detection accuracy (5.90%) and below-average accuracy (42.21%) with relatively low error (1.44%).

In both cases, the reduction in accuracy is expected because background objects in a complex scene have a wide color palette, requiring narrowing the color range for detection. Thus, using the HSV color format, as in the case of a simple scene, shows better results than the RGB format. From the summary graphs in Fig. 9, in all cases, the HSV color format shows better results, and in the case of a simple scene, the detection accuracy is almost 100% with almost no false detections.

Table 5 – **Results of marker detection on a complex scene, RGB**

Color/Shape	Octagon		Rectangle		Circle		Triangle	
Blue	0.00%	32.34%	1.90%	41.23%	37.64%	47.11%	3.85%	7.59%
	0.00%	0.00%	16.67%	2.76%	3.00%	0.50%	30.00%	3.51%
Orange	0.00%	78.03%	0.00%	64.04%	8.99%	24.67%	0.00%	52.22%
	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Green	0.00%	52.83%	1.40%	47.05%	40.24%	64.28%	0.00%	11.03%
	0.00%	0.26%	25.00%	0.49%	2.24%	0.16%	0.00%	0.00%
Yellow	0.38%	75.88%	0.00%	38.16%	0.00%	10.24%	0.00%	28.74%
	100.00%	0.49%	0.00%	1.88%	0.00%	12.90%	0.00%	0.00%

Table 6 – **Results of marker detection on a complex scene, HSV**

Color/Shape	Octagon		Rectangle		Circle		Triangle	
Blue	52.12%	95.54%	98.73%	100.00%	87.24%	94.21%	73.59%	84.02%
	0.00%	0.00%	1.12%	0.00%	2.59%	0.00%	0.70%	0.00%
Orange	46.63%	96.76%	92.89%	99.15%	88.92%	95.70%	72.47%	80.03%
	0.00%	0.00%	0.00%	0.00%	0.36%	0.00%	0.00%	0.00%
Green	69.21%	93.10%	98.43%	76.25%	90.84%	92.21%	50.32%	23.04%
	0.22%	0.00%	0.00%	0.30%	1.65%	0.00%	1.03%	0.00%
Yellow	18.64%	87.50%	54.12%	99.40%	74.24%	93.06%	4.37%	74.71%
	72.73%	2.71%	4.13%	0.00%	4.26%	0.00%	3.13%	0.34%

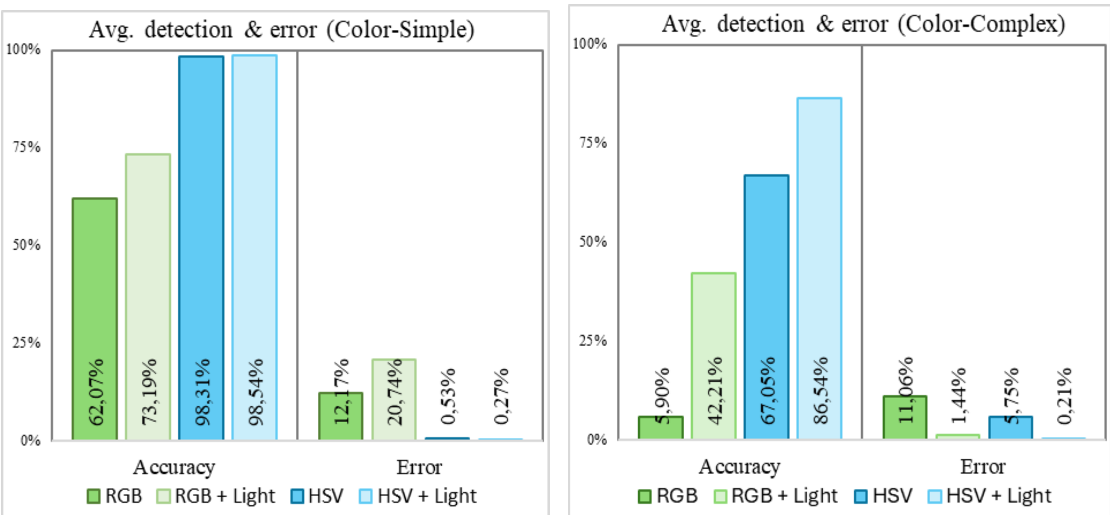

Fig. 9. Average detection accuracy and error by color format

Analyzing the results of Tables 7 and 8, which present the results of experiments on marker shape analysis, the octagon shape has the worst performance in all cases. This can be explained by the fact that at a distance from the camera, the edges of the octagon are not very clear, making it look like a circle.

The results also showed that the square shape has the highest detection accuracy among all shapes. This may be due to the simplicity of the shape, making it easier to identify. It is also noteworthy that blue and orange markers show better results in both scenes.

Thus, analyzing the difference between RGB and

HSV formats when using the color detection algorithm, even when considering a simple scene, the average detection accuracy using the RGB format is 67.63% with an error of 16.46%, while the average detection accuracy using the HSV format is 98.42% with an error of 0.40% (+30.79% and -16.06% respectively).

Table 7 – **Results of marker detection on a simple scene**

Color/Shape	Octagon		Rectangle		Circle		Triangle	
Blue	8.99%	20.28%	87.92%	100.00%	82.89%	93.21%	88.78%	100.00%
	1.54%	8.90%	0.00%	0.00%	2.12%	2.17%	0.18%	3.44%
Orange	5.13%	14.96%	59.10%	96.83%	47.74%	86.89%	74.71%	97.28%
	13.89%	2.48%	0.00%	0.00%	3.05%	0.00%	3.93%	0.59%
Green	3.34%	10.69%	21.35%	62.78%	36.43%	43.25%	17.58%	60.99%
	0.00%	10.13%	6.71%	0.89%	0.76%	0.35%	19.33%	8.09%
Yellow	0.00%	0.00%	6.51%	90.64%	0.00%	0.00%	0.31%	0.15%
	0.00%	0.00%	2.33%	0.00%	0.00%	0.00%	100.00%	100.00%

Table 8 – **Results of marker detection on a complex scene**

Color/Shape	Octagon		Rectangle		Circle		Triangle	
Blue	8.14%	19.21%	37.18%	77.22%	24.56%	65.64%	32.05%	55.39%
	4.00%	0.00%	1.28%	0.00%	1.97%	0.00%	1.20%	0.96%
Orange	6.00%	11.51%	33.60%	65.25%	25.04%	71.37%	38.09%	51.78%
	0.00%	3.64%	0.00%	0.00%	0.00%	0.00%	0.00%	1.14%
Green	0.00%	0.14%	39.79%	72.54%	0.30%	26.38%	0.13%	3.63%
	0.00%	0.00%	0.00%	0.32%	0.00%	0.00%	0.00%	3.85%
Yellow	0.00%	0.00%	58.08%	98.68%	0.00%	0.00%	0.00%	0.00%
	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

This can be explained by the structure of each format: the RGB format has 3 channels, each of which is responsible for all color characteristics at once; HSV, in turn, has 3 channels, each of which is responsible for a separate color characteristic, making such color representation invariant to lighting changes, provided the range is well chosen. Thus, the HSV format is better suited for color marker detection. When analyzing shape recognition results, the octagon shape has the worst performance in all cases (Fig. 10).

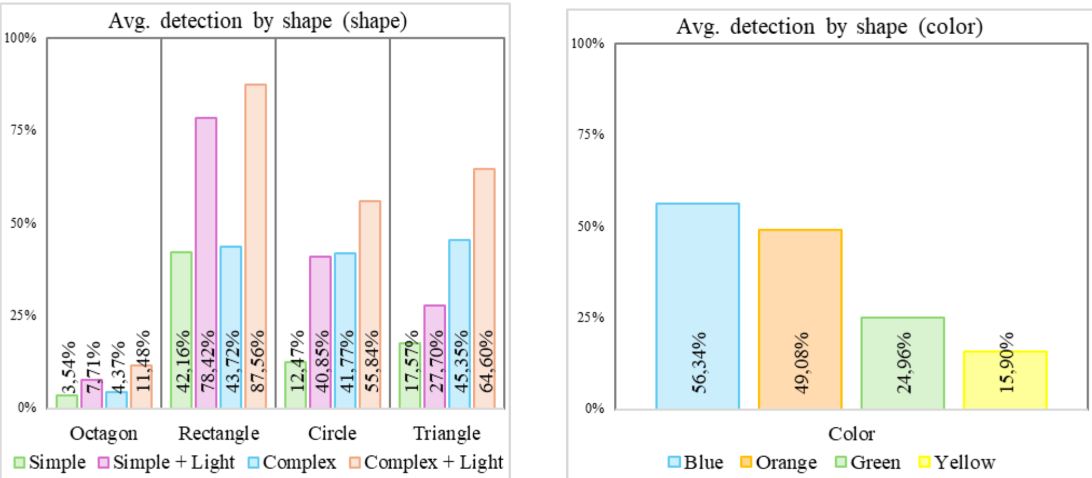

Fig. 10. Average detection accuracy by shape

This can be explained by the fact that at a distance from the camera, the edges of the octagon are not very clear, making it look like a circle. Higher video quality and closer proximity to the camera might hypothetically solve this problem, but with constant zooming in and out, it is better to avoid using markers of such shape. Among different shapes, the square shape shows the highest recognition efficiency. This may be due to the simplicity of the shape, making it easier to detect. It can also be seen that the color of the marker also affects detection accuracy. For example, blue markers have better results in both scenes. Therefore, when using the shape recognition algorithm, it is desirable to choose the marker color so that it stands out as much as possible against the background, i.e., to have a clear transition line. When comparing the two algorithms, in all cases, color detection using the HSV color format has higher accuracy.

Conclusions

The authors propose a portable monitoring system that uses computer vision methods to assess the level of the pelvis, shoulders, and shoulder blades, ensuring the storage of photogrammetric data for subsequent analysis of rehabilitation results. The work achieved its objectives: an analysis with a justification of the need to study computer graphics methods in the context of photogrammetric systems used in rehabilitation orthopedics was conducted; the impact of color characteristics of markers on detection accuracy was studied; the impact of marker shape on detection accuracy was studied; an analysis of the obtained results was performed. The study established that the use of the HSV color format for marker detection demonstrates high accuracy and low error even under changing lighting conditions. It was found that the shape of the marker affects detection accuracy, with the best results shown by the square shape. The research results confirmed the feasibility of using photogrammetry methods to assess joint asymmetry and muscle imbalance.

Further research will focus on increasing the speed and accuracy of marker detection with non-stationary camera placement and a complicated background.

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References

1. Anwar, S.M., Majid, M., Qayyum, A., Awais, M., Alnowami, M. and Khan, M. K. (2018), “Medical Image Analysis using Convolutional Neural Networks: A Review”, *J Med Syst*, vol. 42, art. no. 226, https://doi.org/10.1007/s10916-018-1088-1
2. Shen, D., Wu, G. and Suk, H.I. (2017), “Deep Learning in Medical Image Analysis”, *Annu Rev Biomed Eng*, vol. 19, pp. 221–248, doi: https://doi.org/10.1146/annurev-bioeng-071516-044442
3. Barrios-Muriel, J., Romero-Sánchez, F., Alonso-Sánchez, F.J. and Rodríguez Salgado, D. (2020), “Advances in Orthotic and Prosthetic Manufacturing: A Technology Review”, *Materials (Basel)*, vol. 13(2), doi: https://doi.org/10.3390/ma13020295
4. Hesham A. B. (2021), “The effect of poor posture on the cervical range of motion in young subjects”, *Egyptian Journal of Physical Therapy*, vol. 5, no. 1, pp. 5–12, doi: https://doi.org/10.21608/ejpt.2020.35919.1010
5. Hlavcheva, D., Yaloveha, V., Podorozhniak, A. and Kuchuk, H. (2021), “Comparison of CNNs for Lung Biopsy Images Classification”, *2021 IEEE 3rd Ukraine Conference on Electrical and Computer Engineering*, UKRCON 2021 – Proceedings, pp. 1–5, doi: https://doi.org/10.1109/UKRCON53503.2021.9575305
6. Hlavcheva, D., Yaloveha, V., Podorozhniak, A., and Kuchuk, H. (2020), “Tumor nuclei detection in histopathology images using R – CNN”, CEUR Workshop Proceedings, 2740, pp. 63–74, available at: https://www.scopus.com/record/display.uri?eid=2-s2.0-85096413380&origin=resultslist
7. Kim, G.U., Park, W.T., Chang, M.C. and Lee, G.W. (2022), “Diagnostic Technology for Spine Pathology”, *Asian Spine J.*, vol. 16(5), pp. 764–775, doi: https://doi.org/10.31616/asj.2022.0374
8. Harada, G.K., Siyaji, Z.K., Younis, S., Louie, P.K., Samartzis, D. and An H.S. (2019), “Imaging in Spine Surgery: Current Concepts and Future Directions”, *Spine Surg Relat Res.*, vol. 4(2), pp. 99–110, doi: https://doi.org/10.22603/ssrr.2020-0011
9. Vutan, A. M., Olariu, K. P., Jurjiu, N. A. and Pantea, C. (2022), “The influence of the visual analyzer on posture and balance–review type study”, *Studia Universitatis Babeș-Bolyai Educatio Artis Gymnasticae*, pp. 217–224, doi: https://doi.org/10.24193/subbeag.67(4).50
10. Saboor, A., Kask, T., Kuusik, A., Alam, M. M., Le Moullec, Y., Niazi, I. K. and Ahmad, R. (2020), “Latest research trends in gait analysis using wearable sensors and machine learning: A systematic review”, Ieee Access, vol. 8, pp. 167830-167864, doi: https://doi.org/10f.1109/ACCESS.2020.3022818
11. Dashkov, D. and Liashenko, O. (2023), “Motion capture with mems sensors”, *Advanced Information Systems*, vol. 7, no. 2, pp. 57–62, doi: https://doi.org/10.20998/2522-9052.2023.2.08
12. Wu, H.D. and Wong, M.S. (2020), “Assessment of Maximum Spinal Deformity in Scoliosis: A Literature Review”, *J. Med. Biol. Eng*., vol. 40, pp. 621–629, doi: https://doi.org/10.1007/s40846-020-00558-z
13. Cheng, F., Lu, L., Sun, M., Wang, X. and Wang, Y. (2024), “Non-invasive Scoliosis Assessment in Adolescents”, Wang, B., Hu, Z., Jiang, X., Zhang, YD. (eds) Multimedia Technology and Enhanced Learning, ICMTEL 2023, *Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications, Engineering*, vol 535, pp. 221–230, Springer, Cham, doi: https://doi.org/10.1007/978-3-031-50580-5_18
14. Amran, N.N., Basaruddin, K.S., Ijaz, M.F., Yazid, H., Basah, S.N., Muhayudin, N.A. and Sulaiman, A.R. (2023), “Spine Deformity Assessment for Scoliosis Diagnostics Utilizing Image Processing Techniques: A Systematic Review”, *Applied Sciences*, vol. 13(20), 11555, doi: https://doi.org/10.3390/app132011555
15. Yeroshenko, O. and Prasol, I. (2022), “Simulation of the electrical signal of the muscles to obtain the electromiosignal spectrum”, *Technology audit and production reserves*, vol. 2, no. 2 (64), pp. 38–43, doi: https://doi.org/10.15587/2706-5448.2022.254566
16. Yeroshenko, O., Prasol, I. and Suknov, M. (2022), “Modeling of electrostimulation characteristics to determine the optimal amplitude of current stimuli”, *Radioelectronic and computer systems*, no. 2, pp. 191–199, doi: https://doi.org/10.32620/reks.2022.2.15
17. Zaitseva, E, Levashenko, V, Rabcan, J. and Kvassay, M. (2023), “A New Fuzzy-Based Classification Method for Use in Smart/Precision Medicine”, *Bioengineering*, vol. 10(7), 838, doi: https://doi.org/10.3390/bioengineering10070838
18. Levashenko, V., Zaitseva, E., Kvassay, M. and Deserno, T. (2016), “Reliability estimation of healthcare systems using Fuzzy Decision Trees”, *Proc. of the 2016 Federated Conference on Computer Science and Information Systems* (FedCSIS 2016), Gdansk, Poland, September 11-14, 2016, pp. 331–340, doi: https://doi.org/10.15439/2016F150
19. Yaloveha, V., Hlavcheva, D., Podorozhniak, A. and Kuchuk, H. (2019), “Fire hazard research of forest areas based on the use of convolutional and capsule neural networks”, *2019 IEEE 2nd Ukraine Conference on Electrical and Computer Engineering, UKRCON 2019 – Proceedings*, doi: http://dx.doi.org/10.1109/UKRCON.2019.8879867

20. Zaitseva, E., Rabcan, J., Levashenko, V. and Kvassay, M. (2023), "Importance analysis of decision making factors based on fuzzy decision trees", *Applied Soft Computing*, vol. 134, 109988, https://doi.org/10.1016/j.asoc.2023.109988
21. Parvaiz, A., Khalid, M. A., Zafar, R., Ameer, H., Ali, M., and Fraz, M. M. (2023), "Vision transformers in medical computer vision—A contemplative retrospection", *Engineering Applications of Artificial Intelligence*, vol. 122, pp. 106–126, doi: https://doi.org/10.1016/j.engappai.2023.106126
22. Kuchuk, N., Mozhaiev, O., Semenov, S., Haichenko, A., Kuchuk, H., Tiulieniev, S., Mozhaiev, M., Davydov, V., Brusakova, O. and Gnusov, Y. (2023), "Devising a method for balancing the load on a territorially distributed foggy environment", *Eastern-European Journal of Enterprise Technologies*, vol. 1(4 (121), pp. 48–55, doi: https://doi.org/10.15587/1729-4061.2023.274177
23. Barkovska, O., Filippenko, I., Semenenko, I., Korniienko, V. and Sedlaček, P. (2023), "Adaptation of FPGA architecture for accelerated image preprocessing", *Radioelectronic and Computer Systems*, vol. 2, pp. 94–106, doi: https://doi.org/10.32620/reks.2023.2.08
24. Barkovska, O., Bilichenko, O., Uvarov, G. and Makushenko T. (2024), "Improved rendering method of skeletal animation on control points base", *Computer systems and information technologies*, no. 1, pp. 71–81, doi: https://doi.org/10.31891/csit-2024-1-9
25. Goyushova, U. (2023), "Algorithms for finding non-intersecting roads on images", *Advanced Information Systems*, vol. 7, no. 2, pp. 5–8, 2023, doi: https://doi.org/10.20998/2522-9052.2023.2.01

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ABOUT THE AUTHORS / ВІДОМОСТІ ПРО АВТОРІВ

Барковська Олеся Юріївна – кандидат технічних наук, доцент, доцент кафедри електронних обчислювальних машин, Харківський національний університет радіоелектроніки, Харків, Україна;
Olesia Barkovska – Candidate of Technical Sciences, Associate Professor, Associate Professor of Department of Electronic Computers, Kharkiv National University of Radio Electronics, Kharkiv, Ukraine;
e-mail: olesia.barkovska@nure.ua; ORCID Author ID: http://orcid.org/0000-0001-7496-4353;
Scopus ID: https://www.scopus.com/authid/detail.uri?authorId=24482907700.

Коваленко Андрій Анатолійович – доктор технічних наук, професор, завідувач кафедри електронних обчислювальних машин, Харківський національний університет радіоелектроніки, Харків, Україна;
Andriy Kovalenko – Doctor of Technical Sciences, Professor, Head of the Department of Electronic Computers, Kharkiv National University of Radio Electronics, Kharkiv, Ukraine;
e-mail: andriy.kovalenko@nure.ua; ORCID Author ID: https://orcid.org/0000-0002-2817-9036;
Scopus ID: https://www.scopus.com/authid/detail.uri?authorId=56423229200.

Олійник Дмитро Геннадійович– магістрант, Харківський національний університет радіоелектроніки, Харків, Україна;
Dmytro Oliinyk – master student, Kharkiv National University of Radio Electronics, Kharkiv, Ukraine;
e-mail: dmytro.oliinyk1@nure.ua; ORCID Author ID: https://orcid.org/0009-0004-0262-2716.

Рускіх Олександр Валерійович – магістрант, Харківський національний університет радіоелектроніки, Харків, Україна;
Oleksandr Ruskikh - master student, Kharkiv National University of Radio Electronics, Kharkiv, Ukraine;
e-mail: oleksandr.ruskikh1@nure.ua; ORCID Author ID: https://orcid.org/0009-0000-0277-1595

Седлачек Петер – доктор філософії (комп'ютерні науки), доцент кафедри інформатики, факультет управлінських наук та інформатики, Жилінський університет, Жиліна, Словаччина;
Peter Sedlaček – PhD in Computer Sciences, Assistant Professor of the Department of Informatics, Faculty of Management Science and Informatics, University of Žilina, Žilina, Slovakia;
e-mail: Peter.Sedlacek@fri.uniza.sk; ORCID Author ID: https://orcid.org/0000-0002-7481-6905;
Scopus ID: https://www.scopus.com/authid/detail.uri?authorId=57210661864.

Дослідження методів виявлення оптичних маркерів в системі аналізу ходи та постави людини

О. Ю. Барковська, А. А. Коваленко, Д. Г. Олійник, О. В. Рускіх, P. Sedlacek

Анотація. Робота **присвячена** актуальній темі автоматизованого виявлення м'язового дисбалансу та викривлення постави, що є особливо затребуваним серед ортопротезованих пацієнтів та в дитячій ортопедії. Авторами **запропонована** портативна моніторингова система, яка використовує методи комп'ютерного зору для оцінки рівня тазу, плечей та лопаток, забезпечує зберігання фотограмметричних даних для подальшого аналізу результатів реабілітації. **Метою роботи** є дослідження методів виявлення оптичних маркерів на тілі людини при аналізу ходи. **Задачами дослідження** було проведення аналізу із обгрунтуванням затребуваності дослідження методів комп'ютерної графіки в контексті фотограмметричних систем, що використовуються в реабілітаційній ортопедії; дослідження впливу колірних характеристик маркерів на точність їх детектування; дослідження впливу форми маркерів на точність їх детектування; аналіз отриманих результатів. Предметом дослідження є методи комп'ютерної графіки та машинного зору для детектування маркерів на тілі обстежуваного. Об'єктом дослідження є фотограмметричні технології в ортопедії. **В результаті дослідження** було встановлено, що використання колірного формату HSV для детектування маркерів демонструє високу точність і низьку похибку навіть в умовах змінного освітлення. Було виявлено, що форма маркеру впливає на точність детектування, причому найкращі результати демонструє форма квадрату. Результати досліджень підтвердили доцільність використання методів фотограмметрії для оцінки асиметрії суглобів та м'язового дисбалансу. **Подальші дослідження** будуть зосереджені на збільшенні швидкості та точності детекції маркерів за умови нестаціонарного розташування камер та ускладненим фоном..

Ключові слова: система; модель; метод; моніторинг; реабілітація; зображення; хребет; аналіз; антропометрія; бароподометрія; викривлення.