ДОДАТОК А

Лістинг програми

```
import cv2
from ultralytics import YOLO

# Завантажуємо YOLOv8
model_yolo = YOLO('yolov8n.pt')  # заміни на свій файл, якщо треба

# Класи COCO
coco_classes = [
    "person", "bicycle", "car", "motorcycle", "airplane", "bus", "train",
    "truck", "boat", "traffic light", "fire hydrant", "stop sign", "parking meter",
    "bench", "bird", "cat", "dog", "horse", "sheep", "cow", "elephant", "bear",
    "zebra", "giraffe", "backpack", "umbrella", "handbag", "tie", "suitcase",
    "frisbee", "skis", "snowboard", "sports ball", "kite", "baseball bat",
    "baseball glove", "skateboard", "surfboard", "tennis racket", "bottle",
    "wine glass", "cup", "fork", "knife", "spoon", "bowl", "banana", "apple",
    "sandwich", "orange", "broccoli", "carrot", "hot dog", "pizza", "donut",
    "cake", "chair", "couch", "potted plant", "bed", "dining table", "toilet",
    "tv", "laptop", "mouse", "remote", "keyboard", "cell phone", "microwave",
    "oven", "toaster", "sink", "refrigerator", "book", "clock", "vase",
    "scissors", "teddy bear", "hair drier", "toothbrush"
]

# Константа для приблизної оцінки відстані
K = 5000

# Відкриваємо камеру
```

```
cap = cv2.VideoCapture(0)

while True:
    ret, frame = cap.read()
    if not ret:
        break

    results_yolo = model_yolo(frame)
    operator_detected = False

    for result in results_yolo:
        for box in result.boxes:
            cls = int(box.cls[0])
            class_name = coco_classes[cls] if cls < len(coco_classes) else "unknown"

            x1, y1, x2, y2 = map(int, box.xyxy[0])
            bbox_height = y2 - y1

            distance_cm = K / (bbox_height + 1e-5)
            distance_cm = round(distance_cm, 1)
            distance_cm = min(max(distance_cm, 0), 999)

            label = f"{class_name}, {distance_cm} cm"

            # Вибір кольору підпису
            if distance_cm < 10:
                color = (0, 0, 255)  # червоний
            else:
                color = (0, 255, 0)  # зелений
```

```
            # Малюємо прямокутник і підпис
            cv2.rectangle(frame, (x1, y1), (x2, y2), color, 2)
            cv2.putText(frame, label, (x1, y1 - 10), cv2.FONT_HERSHEY_SIMPLEX,
0.7, color, 2)

            if class_name == "person":
                operator_detected = True

                # Логіка команд
                if distance_cm < 1:
                    command = "Stop"
                    print("Recognized command:", command)
                elif distance_cm < 8:
                    command = "Emergency stop"
                    print("Recognized command:", command)
                elif 11 <= distance_cm <= 15:
                    command = "Slow down"
                    print("Recognized command:", command)
                elif distance_cm > 15:
                    command = "Normal operation"
                    print("Recognized command:", command)
                else:
                    command = "No action"

                # Виводимо команду на кадр
                cv2.putText(frame, command, (x1, y1 - 40),
cv2.FONT_HERSHEY_SIMPLEX, 0.7, (255, 0, 255), 2)

    if not operator_detected:
```

```
        cv2.putText(frame, "Operator not found", (10, 50),
cv2.FONT_HERSHEY_SIMPLEX, 1, (0, 0, 255), 2)

    cv2.imshow("Work zone", frame)
    if cv2.waitKey(1) & 0xFF == 27:
        break

cap.release()
          cv2.destroyAllWindows()
```

ДОДАТОК Б

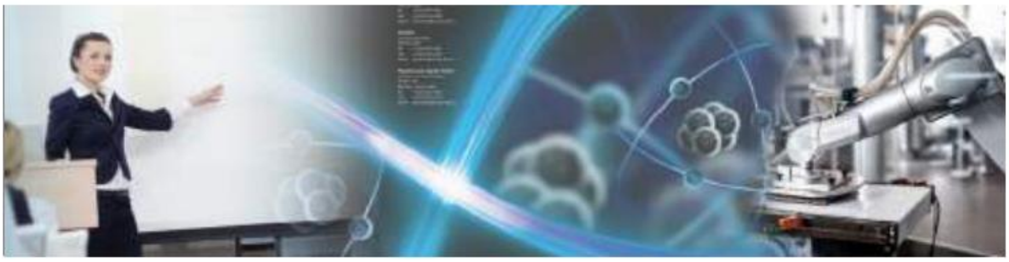
Апробація результатів кваліфікаційної роботи

Міністерство освіти і науки України

Харківський національний університет радіоелектроніки

Кафедра комп'ютерно-інтегрованих технологій, автоматизації та робототехніки

IX Міжнародна Конференція
ВИРОБНИЦТВО
&
МЕХАТРОННІ СИСТЕМИ 2025



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УДК: 005:004.896:62-65:338.3

Виробництво & Мехатронні Системи 2025: матеріали IX-ої Міжнародної конференції, Харків, 25-26 жовтня 2025 р.: тези доповідей / [редкол. І.Ш. Невлюдов (відповідальний редактор)].-Харків: [електронний друк], 2025. – 115 с.

У збірник включені тези доповідей, які присвячені сучасним тенденціям розвитку технологій та засобів виробництва та мехатронних систем, передовому досвіду та впровадженню їх в галузях систем промислової автоматизації та керування виробництвом; системній інженерії; CAD/CAM/CAE системах; мехатроніці (електро-механічних системах, електронних інструментах систем керування, механічних CAD системах); робототехніці та засобахм інтелектуалізації; MEMS (сучасних матеріалів та технологіях виготовлення MEMS) та компонентах і технологіях автоматизації видобутку, переробки та транспортування нафти та газу.

Manufacturing & Mechatronic Systems 2025: Proceedings of IX st International Conference, Kharkiv, October 25-26, 2025: Thesises of Reports / [Ed. I.Sh. Nevlyudov (chief editor).] .- Kharkiv .: [electronic version], 2025. - 115 p.

The collection includes the thesises of reports on modern trends in the development of technologies and means of production and mechatronic systems, top experience and implementation of them in fields of: industrial automation and production management systems; systems engineering; CAD/CAM/CAE systems; mechatronics (electrical and mechanical systems, electronic control tools, mechanical CAD systems); robotics and intellectual toolls; MEMS (modern materials and manufacturing technologies MEMS) and components and technologies for the automation of oil, gas and oil extraction, processing and transportation.

ЗМІСТ

Analysis of operator identification methods in the working area of a collaborative manipulator robot

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***Abstract*:** The paper presents the results of the analysis of modern methods of operator identification in the working area of a collaborative robot-manipulator, which is important in the context of safe and effective interaction between a person and a robotic system. Sensor approaches, computer vision methods, biometric technologies, algorithms based on deep neural networks, as well as integration solutions using data fusion and fuzzy logic are considered. It is shown that sensor methods provide basic security, but are limited in accuracy, while computer vision and deep learning allow achieving high detail in identification, although they require significant computing resources. Biometric approaches create conditions for personalization of interaction, but may lose effectiveness in a production environment with a high level of noise and the need to use personal protective equipment. Data integration methods increase the stability of the system and its ability to work in conditions of uncertainty, ensuring multi-level adaptability. The analysis confirms that optimal solutions should be based on a combination of several methods, which is consistent with the concept of Industry 5.0 and contributes to the development of new generation cognitive robotic systems.

***Keywords*:** operator identification, collaborative robot, manipulator, computer vision, sensor systems, neural networks, data fusion, biometrics, fuzzy logic, Industry 5.0.

I. INTRODUCTION

In modern production scenarios that correspond to the concept of Industry 5.0, the interaction of humans and collaborative robot manipulators plays a key role, where safety, reliability and efficiency are the determining factors. Identification of the operator in the robot's working area is one of the most important tasks, since it ensures not only the safe functioning of the system, but also creates the prerequisites for flexible adaptation of the robot to human actions. The uncertainty of the environment, various scenarios of operator behavior, as well as possible obstacles or limited sensor data complicate the task of timely detection and correct identification. Traditional approaches based on simple sensor triggers are no longer able to meet the growing requirements for accuracy and speed of system response. Modern methods, in particular computer vision, deep learning algorithms, sensor networks and data fusion systems, make it possible to form a complete picture of the operator's position and actions in the working area. This is especially important in cases where the robot has to perform complex manipulations in close proximity to a person, where even minimal errors can lead to emergency situations. Research into operator identification methods allows for the creation of safer and more intelligent control systems that are able to predict human actions and adapt the robot to individual interaction characteristics. The relevance of this issue is determined by the need to integrate new technologies into intelligent production processes, which will contribute to the development of collaborative robotics and increase the efficiency of human-machine collaboration.

II. ANALYSIS OF OPERATOR IDENTIFICATION METHODS IN THE WORKING AREA OF COLLABORATIVE WORK

Analysis of methods and models for operator identification in the working area of a collaborative robot-manipulator is one of the key areas of development of modern robotics, since the level of safety and quality of interaction in the conditions of Industry 5.0 depends on the correctness and speed of determining the presence of a person. The first group of methods are classical sensor systems based on the use of ultrasonic, infrared and laser sensors. They allow determining the presence of an object in the robot area by registering the reflected signal. Such methods are characterized by relative simplicity of implementation and low cost, but their accuracy is often limited by lighting conditions, the presence of noise and reflective surfaces. Their main purpose is to detect the fact that the operator is in a dangerous zone with the subsequent transmission of a signal to reduce the speed or stop the manipulator. However, they do not provide complete information about the identity of the person or his specific actions, therefore they are used mainly as a basic level of protection.

Another approach is to use computer vision methods based on the analysis of the video stream from cameras located in the working area. These methods allow to identify the operator by his contour, pose or biometric features. Algorithms for highlighting key points of the skeleton (for example, OpenPose) provide the ability to track movements and gestures in real time, which allows the robot to adapt its behavior in accordance with human actions. The main advantage of this approach is the ability to provide detailed information about the position and movement of the operator, but its effectiveness may decrease with changing lighting, partial overlaps or a complex background. The use of depth cameras (for example, Intel RealSense or Kinect) significantly expands the capabilities, as it allows to obtain three-dimensional information about the spatial position of the person, which is especially important when working in a dynamic environment.

Deep learning methods open up new prospects for operator identification in the robot zone. The use of convolutional neural networks allows for high accuracy in recognizing both the face and the human body, as well as detecting specific gestures or signals. Such systems are capable of self-learning on large data sets and gradually improving the quality of identification, which makes them particularly promising for use in production environments. The main purpose of this approach is to ensure stable identification even in complex scenarios, but its main drawback is the high requirements for computing resources and the need to train on a large amount of data, which can be a difficult task in practical implementation. An important place is occupied by methods based on the integration of data from several sensor systems, i.e. the concept of data fusion. The simultaneous use of cameras, ultrasonic sensors and inertial sensors allows for the formation of a more accurate and reliable picture of the working zone. This approach compensates for the weaknesses of individual sensors and increases the system's resistance to interference. For example, if a camera cannot provide reliable identification due to poor lighting, data from ultrasonic sensors can confirm the presence of a person. The purpose of this method is to create a robust multi-level protection system that can operate under conditions of uncertainty and with a minimum number of false positives. The main disadvantage of this approach is the increased complexity of integration and the need for complex synchronization and information processing algorithms.

Biometric identification methods, such as facial recognition, voice recognition, or even individual movement patterns, are also used in collaborative robotics. Their purpose is to identify the specific person working with the robot, which can be important in personalized interaction scenarios. For example, the robot can adapt its behavior depending on the level of experience of a particular operator. The advantage of this approach is the possibility of individualization and creating a more "intelligent" interaction, while the disadvantage is the difficulty in ensuring stable operation in conditions of noise, environmental changes, or the use of personal protective equipment that can obscure biometric features.

Of particular interest are methods based on fuzzy logic and probabilistic models. They allow you to work in conditions of incomplete or inaccurate data, which is typical for real-world production environments. The use of fuzzy rules allows the system to make decisions about the presence and identification of the operator based on partially contradictory or ambiguous information. Probabilistic models, such as hidden Markov processes or POMDP, allow you to predict human behavior based on previous observations. This opens up opportunities for creating systems that can not only detect a person, but also adapt their actions to their future intentions. The disadvantage of these methods is their complexity in setting up and the need for careful selection of parameters, but their flexibility and ability to work in real-world conditions make them extremely promising.

The general analysis shows that none of the methods is universal and each has its own advantages and limitations. Sensory approaches provide basic security, computer vision and deep learning allow for detailed information about the operator, biometric methods provide personalization, while data fusion and fuzzy logic increase the system's resilience under uncertainty. The most promising direction of development is the creation of hybrid systems that integrate different methods to achieve high accuracy, speed, and reliability in detecting and identifying the operator in the working area of a collaborative robot-manipulator.

III. COMPARATIVE ANALYSIS OF OPERATOR IDENTIFICATION METHODS IN THE WORKING AREA OF COLLABORATIVE WORK

A comparative analysis of operator identification methods in the working area of a collaborative robot-manipulator shows that each of them has its own strengths and weaknesses, which manifest themselves depending on the application conditions. Sensor methods based on ultrasonic or infrared sensors are reliable for basic detection of human presence and respond quickly to entering a dangerous zone, but they are not able to provide accurate identification or discrimination of specific actions, and are also often prone to false positives in complex environments. Computer vision methods provide more detailed information about the operator's posture, position, or even gestures, which makes them promising for adaptive interaction, but they are vulnerable to changes in lighting, overlapping objects, and require significant computing resources for stable real-time operation. Deep neural networks demonstrate high accuracy in human recognition, even in complex environments, and can learn new scenarios, which makes them universal, but high computational complexity and the need for large data sets limit their practical implementation in compact robotic systems. Data fusion methods allow for the integration of information from multiple sensors, which increases the stability and reliability of the system even under conditions of uncertainty, but they complicate the system structure and require special synchronization algorithms. Biometric methods provide the opportunity to personalize interaction and increase the intelligence of the system, but may lose effectiveness in cases where the operator uses protective helmets, gloves, or other personal protective equipment that distorts biometric features. Finally, methods based on fuzzy logic and probabilistic models provide high flexibility in working with incomplete or contradictory data and the ability to predict operator behavior, but their implementation requires complex tuning and precise selection of parameters to ensure reliable operation. In conclusion, it can be noted that sensor methods are best suited for the basic level of security, computer vision and neural networks for detailed identification, and data fusion and fuzzy logic are the most promising for building integrated systems that provide high reliability in real production conditions.

IV. CONCLUSION

As a result of the analysis of operator identification methods in the working area of a collaborative robot-manipulator, it was found that each of the approaches has its own strengths and limitations, which determine the scope of its practical application. Sensor methods remain the most accessible and provide a basic level of security, but their effectiveness is limited by insufficient accuracy and dependence on external factors. Computer vision methods and deep learning algorithms open up the possibility of highly accurate identification even in dynamic conditions, but they require significant computing resources and a stable environment. Biometric technologies demonstrate the potential for individualized recognition, but face challenges in production environments, where operators may use protective equipment that complicates access to biometric features. Integration methods based on data fusion and fuzzy logic have shown the highest level of reliability and the ability to adapt to uncertainty, which makes them especially promising for Industry 5.0 systems. Thus, the optimal solution to the operator identification problem is to combine several approaches, which allows taking into account various factors of the production environment, increasing the level of safety, and ensuring effective interaction between a person and a collaborative robot-manipulator.

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ДОДАТОК В

Демонстраційний матеріал

№ документа	Позначення	Найменування	Додаткові відомості
		<u>Текстові документи</u>	
1	ГЮИК. XXXXXX.008 ПЗ	Пояснювальна	А4, 73 с.
		записка	
		<u>Додаткові матеріали</u>	
2		Демонстраційний	А4, 14 с.
		матеріал у виляді	
		презентації	

Змін	Арк	№ документу	Підпис	Дата	ГЮИК. XXXXXX.008 ПЗ			
Розробив		Моложанов Л.М.			Розроблення програмного модуля ідентифікації оператора в робочій зоні колаборативного робота маніпулятора	Літер	Аркуш	Аркуш
Перевірив		Косенко В.В.				Н	1	1
						Кафедра КІТАР ХНУРЕ		
Норм. контроль		Стародубцев М.Г.						
Затвердив		Невлюдов І.Ш.						