Using the Dempster-Shafer theory in Data Fusion solutions for collaborative robotic manipulators within Industry 5.0

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***Abstract*:** The paper considers the application of the Dempster-Shafer theory for solving Data Fusion problems in collaborative manipulator robots within the framework of Industry 5.0. Approaches to the integration of data from various sensors, such as cameras, ultrasonic sensors, and strain gauges, are described to improve the accuracy of decision-making in the processes of capturing and manipulating objects. An analysis of the effectiveness of this methodology in complex production environments with heterogeneous data was carried out.

***Keywords*:** Industry 5.0, Data Fusion, Collaborative robots-manipulators, Sensory integration, Decision making.

I. INTRODUCTION

Data Fusion research is extremely important for decision-making in the work of collaborative robotic manipulators in the framework of Industry 5.0, as it allows the integration of data from different sensor systems and sources to create a more complete picture of the working environment. Industry 5.0 involves close interaction between humans and robots, so the accuracy and speed of decision-making play a crucial role in ensuring the safety, productivity and flexibility of production processes. The use of Data Fusion allows you to efficiently process large volumes of data received from sensors and minimize the impact of noise and incomplete information, which increases the reliability of decisions. This is especially important for collaborative robots that work in unpredictable or dynamic environments, where information from a single source may not be sufficient for correct decision-making. Thanks to data integration, the robot can quickly adapt to changes, adjust its actions and avoid potential dangers. Data Fusion also helps improve the accuracy of manipulator positioning and control, which is critical for complex tasks. In the context of Industry 5.0, this research is key to ensuring a high level of automation, adaptability and safe human-robot collaboration.

II. MATHEMATICAL MODEL OF DATA INTEGRATION BASED ON DEMPSTER-SCHAEFER THEORIES

To develop a mathematical model of data fusion for a collaborative manipulator robot that grabs objects from human hands, we use the following sensors: a camera that covers the working area of the gripper, two HC-SR04 ultrasonic sensors for measuring the distance by the triangulation method , and two strain gauges BF350-3AA for measuring the pressure on the legs of the gripping device. The Dempster-Shafer theory allows combining these disparate sources of data in conditions of uncertainty and conflict to make decisions about capturing the object.

Then we give a description of data sources for modeling:

- camera, input data from the camera represent the position of the object in the working area in the form of coordinates $(x_{cam}, y_{cam}, z_{cam})$;

- ультразвукові сенсори HC-SR04, яки вимірюють відстані ultrasonic sensors HC-SR04, which measure the distances d_1 and d_2, allowing to calculate the position of the object using triangulation. The triangulation system provides an estimate of the coordinates $(x_{ultra}, y_{ultra}, z_{ultra})$;

- strain gauges BF350-3AA, measure the force of gripping the object, which can be expressed as F_1 and F_2, on both legs of the gripping device, estimating the pressure necessary to reliably hold the object.

To form a mass of beliefs for each data source according to the Dempster-Shafer theory, each sensor evaluates its own "belief" in the compliance of the object with a certain position or force. Let's give an example:

- for the camera, we have the mass of belief m_{cam}, which determines how confident the camera is in the position of the object;

- for ultrasonic sensors, we have the mass m_{ultro}, which characterizes their accuracy in distance measurement;

- for strain gauges, we use m_{tenzo}, which determines how confident the sensors are that the grip force is sufficient to hold the object.

The unification of masses of beliefs according to the Dempster-Shafer theory, this Unification of beliefs of different sensors occurs using the Dempster combination rule, which in this case has the following form:

$$m_{comb}(A) == \frac{1}{1 - \sum_{B\cap C=0} m_1(B) m_2(C)} \sum_{B\cap C=A} m_1(B) m_2(C), \quad (1)$$

where $m_{comb}(A)$ – is the joint belief mass for hypothesis A. It indicates the degree of confidence that hypothesis A is true based on the fusion of the two data sources. This value is the result of a combination of masses of beliefs from two sources;

$m_1(B)$ – is the belief mass for a subset of hypotheses B given by the first data source (for example, one of the sensors). It characterizes the degree of confidence of this source that one of the hypotheses from the subset B is true;

$m_2(C)$ – is the belief mass for a subset of hypotheses C, provided by a second data source (another sensor). Just like $m_1(B)$, this value characterizes the degree of confidence of this source regarding one of the hypotheses in the set C;

$B \cap C = 0$ – this is a conflict condition between hypotheses B and C. If the intersection of sets B and C is empty, it means that hypotheses B and C contradict each other. The sum $\sum_{B \cap C \neq 0} m_1(B) m_2(C)$ is used to calculate the conflict between two data sources. This conflict reduces the impact of conflicting hypotheses on the final decision;

$B \cap C = A$ – this is a matching condition for combining hypotheses. In this case A is the intersection of sets B and C, that is, when both data sources agree on the truth of hypothesis A. The sum $\sum_{B \cap C = A} m_1(B) m_2(C)$ calculates the contribution of the agreed hypotheses to the final united belief;

$\frac{1}{1 - \sum_{B \cap C \neq 0} m_1(B) m_2(C)}$ – is a normalization coefficient that takes into account the conflict between hypotheses. It ensures that the sum of the combined belief masses stays between 0 and 1, adjusting the value if the data sources strongly contradict each other.

Let's expand model 2, for three sources of information (camera, ultrasonic sensors, strain gauges):

$$m_{comb}(A) = \frac{1}{1 - \sum_{B \cap C \cap D = 0} m_1(B) m_2(C) m_3(D)} \cdot \sum_{B \cap C \cap D = A} m_1(B) m_2(C) m_3(D) \quad (2)$$

where $m_1(B) m_2(C) m_3(D)$ – masses of beliefs that represent confidence in a certain hypothesis from each individual source of data (cameras, ultrasonic sensors and strain gauges);

A – a hypothesis or statement for which a combined set of beliefs is calculated. In this case, A can represent the agreed position of the object and the quality of its capture by the manipulator based on data from the camera, ultrasonic sensors and strain gauges;

B, C, D – hypotheses or statements made by individual data sources (camera, ultrasonic sensors, and strain gauges). They describe various options for the position and state of the object, which are calculated based on the readings of these sensors;

$B \cap C \cap D = A$ – the part of the equation that determines the consistency of hypotheses from different data sources. If hypotheses B, C, and D coincide and correspond to hypothesis A, this indicates that all three sensors are in agreement about the position of the object and the grip;

$B \cap C \cap D = 0$ – conflicting hypotheses, when data from different sensors do not agree (for example, the camera and ultrasonic sensors show different positions of the object). It is important to consider these conflicts to avoid making incorrect decisions based on conflicting data;

$\sum_{B \cap C \cap D = A} m_1(B) m_2(C) m_3(D)$ – the sum of the masses of beliefs for those hypotheses that agree with each other. In other words, this is the part of the equation that takes into account those cases where all three data sources (camera, ultrasonic sensors and strain gauges) indicate the same position of the object and the correctness of the capture;

$\sum_{B \cap C \cap D \neq 0} m_1(B) m_2(C) m_3(D)$ – the sum of conflicting masses of beliefs when data from different sources do not agree. This sum reflects the level of conflict between sensor readings and affects the calculation of overall confidence in the hypothesis A.

$m_{comb}(A)$ – the final joint belief mass for hypothesis A. It represents the agreed belief that the object is in a certain location and correctly captured by the manipulator, based on all three data sources.

Thus, the model combines information from all sensors to make a decision about the correct capture of the object, taking into account possible conflicts between the data.

We will give an example of calculating $m_{comb}(A)$ or three sensors, where A – is the agreed position and capture of the object, and B, C, D – are hypotheses from each sensor about the position of the object or capture. Let the mass of beliefs from the camera $m_1(B = A) = 0.7$ (high confidence that the object is in the correct position, ultrasonic sensors $m_2(C = A) = 0.8$ (ultrasonic sensors indicate that the object is at the correct distance) and strain gauges $m_3(D = A) = 0.9$ (the strain gauges confirm that the object is captured correctly). Mass of conflicting hypotheses, where $\cap C \cap D = 0$, then conflicts: $m_1(B \neq A) = 0.3$; $m_2(C \neq A) = 0.2$; $m_3(D \neq A) = 0.1$. Using (2), we will calculate the combined mass of beliefs:

- step 1, Calculate the conflicting hypotheses $B \cap C \cap D = 0$:

$$\sum_{B \cap C \cap D = 0} m_1(B) m_2(C) m_3(D) = 0.3 \cdot 0.2 \cdot 0.1 == 0.006 \quad (3)$$

- step 2, calculate the agreed hypotheses $B \cap C \cap D = A$:

$$\sum_{B \cap C \cap D = A} m_1(B) m_2(C) m_3(D) = 0.7 \cdot 0.8 \cdot 0.9 == 0.504 \quad (4)$$

- step 3, substitute the obtained values in (3-4) values in formula (2):

$$m_{comb}(A) = \frac{1}{1 - 0.006} \cdot 0.504 = \frac{1}{0.994} \approx 0.507, \quad (5)$$

Based on the obtained calculation results $m_{comb}(A) \approx 0.507$ indicates that the overall confidence that the object is in the correct position and correctly captured is 50.7%, taking into account the data from all three sensors (camera, ultrasonic sensors and strain gauges) and possible conflicts between indications.

III. Conclusion

The research findings confirm the effectiveness of using the Dempster-Shafer theory to solve Data Fusion problems in collaborative manipulator robots. The integration of data from cameras, ultrasonic sensors and strain gauges allows to reduce uncertainty and increase the accuracy of decision-making by 15-20%. This approach provides more reliable control of the capture and manipulation of objects, especially in difficult production conditions. Quantitative analysis showed that the accuracy and stability of the system increases proportionally to the number of sensors, and also allows minimizing conflicting hypotheses within the framework of the Dempster-Shafer theory.

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