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Data Fusion Research for Collaborative Robots-Manipulators within Industry 5.0

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Abstract: The article examines methods of data fusion (Data Fusion) for collaborative manipulator robots in the context of Industry 5.0. Three approaches are considered: Kalman filter, Bayesian estimation and Dempster-Shafer theory. The Kalman filter has proven to be effective for linear systems, but requires modification for nonlinear problems. Bayesian estimation provides accuracy for complex systems, although it requires more resources. The Dempster-Shafer theory is effective under data uncertainty, but has a high computational complexity. The conclusions indicate the importance of choosing a data fusion method depending on the requirements for accuracy and adaptability of robots in the production conditions of Industry 5.0.

Key words: Industry 5.0, Collaborative Robot, Work Area, Computer Vision, Sensor, Data, Data Fusion.

Introduction

In today's world, where production processes are becoming increasingly automated, the concept of Industry 5.0 emphasizes human-robot collaboration to achieve a high level of integration, personalization and flexibility [1]-[16].

Collaborative robot manipulators are central to this development, as they can directly interact with humans in real time to perform complex tasks [17]-[19]. However, to ensure effective cooperation and reliable functioning of such robots, accurate and prompt decision-making regarding their behavior in a dynamic environment is necessary. In this context, Data Fusion becomes a key tool for increasing the accuracy and reliability of managing collaborative manipulator robots.

Data Fusion allows you to combine information from different sources, such as sensors, video cameras, lidar and other systems that provide information about the external environment and internal states of the robot.

This is critically important for decision-making, since no single sensor can provide complete and reliable information about all aspects of the surrounding space and task conditions. For example, optical sensors can provide highly accurate data about the location of objects, but their effectiveness decreases in poor lighting or in the case of partial obstacles.

On the other hand, inertial sensors can provide information about the robot's movements even in difficult conditions, but on their own they are not accurate enough to make decisions at the micro level. Data fusion allows you to combine these sources to get a more accurate picture of the situation.

In the framework of Industry 5.0, this research is of particular importance due to the need for adaptive and safe solutions in conditions where a robot works side by side with a person [20]-[22]. Making decisions based on integrated data allows you to significantly reduce the risks of errors in the operation of the manipulator, improve the accuracy and stability of task performance, and also ensure a high level of safety for the operator.

Various methods and approaches can be used here [23]-[40].

The importance of such research lies in the creation of new methods and algorithms capable of efficiently processing large volumes of heterogeneous data in real time, which will allow the robot to quickly respond to changes in the environment and make the right decisions.

Related works

The use of data fusion is widely used to process data obtained from mobile robot sensors. Naturally, many scientific works are devoted to this technology. Let us look at some of these recent works.

Nascimento, H., & et al. in [41] consider the problem ensuring co-existence and space sharing between human and robot. Here collision avoidance is one of the main strategies for interaction between them without contact.

The authors in [42] analyze the detection process of intelligent detection robots for massage chairs, theoretical research is carried out from two aspects of decision-level fusion and data-level fusion.

The study [43] considers the problem hand gesture recognition. It is noted that the accuracy and reliability of hand gesture recognition are the keys to gesture-based human–robot interaction tasks. To solve this problem, a method based on multimodal data fusion and multiscale parallel convolutional neural network is proposed in this paper to improve the accuracy and reliability of hand gesture recognition.

Researchers in [44] presents a survey of simultaneous localization and mapping and data fusion techniques for object detection and environmental scene perception in unmanned aerial vehicles.

In [45] a comprehensive study on devices/sensors and prevalent sensor fusion techniques developed for tackling issues like localization, estimation and navigation in mobile robot are presented as well in which they are organized according to relevance, strengths and weaknesses.

The paper [46] focuses on data fusion, which is fundamental to one of the most important modules in any autonomous system: perception. There are presented various types of sensors, their data, and the need for fusion of the data with each other to output the best data for the task at hand, which in this case is autonomous navigation.

Qi, W., and co-authors in [47] designed a multi-sensor data fusion model for performing interference in the presence of occlusions. A multilayer Recurrent Neural Network consisting of a Long Short-Term Memory module and a dropout layer is proposed for multiple hand gestures classification. Detected hand gestures are used to perform a set of human-robot collaboration tasks on a surgical robot platform.

In the work [48] a complementary multi-modal sensor fusion approach is presented that improves the reliability of the pose estimation process for aerial robots by fusing visual-inertial and thermal-inertial odometry estimates with a LiDAR odometry and mapping solution.

Thus, we see that fusion technology is widely used in modern science. Next, we will consider our approach to using data fusion for a robot-manipulator.

Study of methods used for the data fusion process for collaborative robots.

Data Fusion for collaborative robots-manipulators within Industry 5.0 is the process of integrating and harmonizing information from various sensors and sources to obtain more accurate, complete and reliable information about the state of the system, environment or objects. This allows robots to work more efficiently in complex and dynamic environments.

For the mathematical representation of the data fusion process for collaborative robots different methods are used:

- Kalman filter for linear systems;
- Extended Kalman Filter for nonlinear systems;

- Bayesian estimation for probabilistic representation of uncertainty;
- Dempster-Shafer Theory of trust for combining evidence from different sources.

Within the framework of this study, we will indicate the following parameters: x_t - the state vector of the collaborative robot (positions of the manipulator joints, speed); u_t - control signals (commands for drives or motors); z_t - data from sensors (cameras, lidars, inertial sensors); w_t and v_t - process and measurement noise (sensor errors); $P_{t|t}$ - covariance matrix (determines uncertainty in the state); K_t - Kalman matrix (balance between measurement and prediction).

Let the collaborative robot system be described by the following state and observation equations:

- the state of the system can be described by the following model:

$$x_t = f(x_{t-1}, u_t) + w_t \tag{1}$$

x_t – system state vector in time t (e.g., positions, speeds, manipulator angles);

$f(x_{t-1}, u_t)$ - state transition function (describes system dynamics, robot control);

u_t - vector of control actions (for example, signals to drives);

w_t - process noise assumed to be normal with covariance Q.

- the observation model can be presented as follows:

$$z_t = h(x_t) + v_t \tag{2}$$

z_t - vector of measurements from sensors (e.g., data from cameras, lidars, accelerometers);

$h(x_t)$ - an observation function that describes how the state of a system is transformed into a measurement;

v_t - measurement noise, which is also assumed to be normal with covariance R.

In the context of collaborative manipulator robots, the covariance (Q,R) allows to evaluate the dependence between various sensors collecting data about the environment and the state of the robot itself.

For example, if one sensor measures the tilt angle of a manipulator, and another measures its position in space, the covariance of these two variables can help to understand how related they are. If the covariance is high, it means that changes in one parameter are accompanied by changes in another.

If the covariance is low or negative, then these variables may be independent or moving in opposite directions.

From a mathematical point of view, covariance is defined as the average product of the deviations of two variables from their average values:

$$Cov(X,Y) = \frac{1}{n}\sum_{i=1}^{n}(X_i - \mu_x)(Y_i - \mu_y) \tag{3}$$

X and Y - are the variables for which the covariance is calculated, X_i and Y_i are individual observations of these variables, μ_x and μ_y are their mean values.

In Data Fusion research for robots, covariance helps improve decision-making accuracy.

For example, when combining data from different sensors in a Kalman filter, a covariance matrix is used to model how errors are propagated between measurements. This allows the robot to adjust its actions based on the data fusion, reducing inaccuracies in measurements and predictions.

For data fusion in the case of a linear system, the Kalman filter can be used. It is a recursive algorithm that combines current measurements with state predictions.

It can be represented by the following expressions based on 1-2:

- updating the predicted state:

$$x_{t|t-1}=f(x_{t-1|t-1},u_t) \tag{4}$$

$x_{t|t-1}$ - predicted state for time t, based on the previous state $x_{t-1|t-1}$.

- updating the predicted covariance:

$$P_{t|t-1}=F_tP_{t-1|t-1}F_t^T+Q_t \tag{5}$$

F_t - matrix of partial derivatives of the state transition function.

- status updates based on measurements:

$$K_t=P_{t|t-1}\, H_t^T\, (H_tP_{t-1|t-1}H_t^T+R)^{-1} \tag{6}$$

$$x_{t|t}=x_{t|t-1}+K_t(z_t-h(x_{t-1|t-1})) \tag{7}$$

K_t - the Kalman matrix, which determines how much to trust measurements versus predictions.

If the system is nonlinear, the extended Kalman filter (EKF) is used, which linearizes the system using derivatives:

- linearization of the transition function:

$$\boldsymbol{F}_t = \frac{\partial f(\boldsymbol{x}, \boldsymbol{u})}{\partial \boldsymbol{x}}\bigg|_{\hat{\boldsymbol{x}}_{t-1|t-1}, \boldsymbol{u}_t} \tag{8}$$

- linearization of the observation function:

$$\boldsymbol{H}_t = \frac{\partial h(\boldsymbol{x})}{\partial \boldsymbol{x}}\bigg|_{\hat{\boldsymbol{x}}_{t|t-1}} \tag{9}$$

A Bayesian approach to data fusion uses a probabilistic representation of uncertainty. The state of the system is modeled as a probability distribution $p(x_t|z_{1:t})$, where $z_{1:t}$ - all received measurements up to time t.

- estimation of a priori probability:

$$\rho(\boldsymbol{x}_t|\boldsymbol{z}_{1:t-1}) = \int \rho\,(\boldsymbol{x}_t|\boldsymbol{x}_{t-1})\rho(\boldsymbol{x}_{t-1}|\boldsymbol{z}_{1:t-1})d\boldsymbol{x}_{t-1} \tag{10}$$

- update by measurements:

$$\rho(\boldsymbol{x}_t|\boldsymbol{z}_{1:t}) \propto \rho(\boldsymbol{z}_t|\boldsymbol{x}_t)\rho(\boldsymbol{x}_t|\boldsymbol{z}_{1:t-1}) \tag{11}$$

Dempster-Shafer theory, this method of data fusion allows working with uncertain and partially contradictory data. It generates confidence masses that represent the degree of support for various hypotheses about the state of the system. It can be represented as follows:

$$m(A) = \frac{1}{1-K}\sum_{B \cap C = A} m_1(B)m_2(C) \tag{12}$$

m(A) - the confidence level for a hypothesis *A* represents the confidence that the hypothesis is true;

K - conflict ratio between different data sources.

Table 1 shows a comparison of the main advantages and disadvantages of three methods of data fusion: the Kalman filter, Bayesian estimation and Dempster-Shafer theory in the context of application for collaborative robots-manipulators within the framework of Industry 5.0.

Table 1: Comparison of advantages and disadvantages of using data fusion methods: Kalman filter, Bayesian estimation and Dempster-Shafer theory in the context of application for collaborative manipulator robots within Industry 5.0.

Method	Advantages	Disadvantages
Kalman filter	- High accuracy in real time, especially in the presence of small Gaussian noises - Optimal for linear systems - Ease of implementation	- Difficult to use for non-linear systems without adaptation (extended or Unscented Kalman filter) - Sensitivity to incorrect initial conditions
Bayesian estimation	- The possibility of using complex a priori knowledge - Well suited for non-linear systems - Flexible in cases where the probabilities are not Gaussian	- High computational complexity - Requires accurate determination of a priori probabilities, which can be difficult with limited information
Dempster-Shafer theory	- Can handle uncertainty and conflicting data - Does not require an exact setting of a priori probabilities - Handles incomplete data well	- High computational cost for large sets of hypotheses - Difficulty in interpreting the results in case of a high degree of uncertainty or inconsistency

Analyzing Table 1, the following conclusions can be drawn:

- the Kalman filter is effective for real-time problems where the system has Gaussian noise and linear models, which makes it particularly convenient for controlling the position and movement of the manipulator. However, for non-linear problems, it needs to be modified, which complicates the implementation;

- Bayesian estimation provides flexibility in considering complex probabilities and non-linear models. This is important for complex Industry 5.0 work environments, but this approach requires significant computing resources and accurate a priori data;

- the Dempster-Shafer theory is well suited for working with uncertain or incomplete data, which can be useful for unstable sensors or in difficult production conditions. However, the complexity of this method makes it difficult to apply it to large data sets.

Conclusion

During the study Data Fusion for collaborative manipulator robots within Industry 5.0, three main mathematical models were considered: the Kalman filter, Bayesian estimation and the Dempster-Shafer theory. Each of these methods has its strengths and limitations in solving the tasks of data integration from different sources to improve the accuracy, reliability and adaptability of robots in the dynamic conditions of modern production. The Kalman filter demonstrates efficiency in real-time problems for linear systems with predictable noise, making it an optimal choice for systems where fast decision-making based on sensory information is required. However, for nonlinear environments, this approach needs to be extended through the use of nonlinear modifications. Bayesian estimation provides flexibility and accuracy in complex and nonlinear environments, allowing efficient use of a priori information, but requires significant computational resources and accurate a priori data. The Dempster-Shafer theory, in turn, is useful in conditions of high uncertainty and when working with incomplete or contradictory data, which allows to expand the possibilities of managing collaborative works, but this method is characterized by complexity and high computational cost when processing large arrays of information. In conclusion, each of the considered methods has the potential to be used in Industry 5.0 depending on the requirements for the data fusion system, but their effectiveness depends on the specifics of the environment, the nature of the data, and the complexity of the tasks faced by manipulator robots.

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