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Comparative Analysis of methods for Predicting the Trajectory of Object Movement in a Collaborative Robot-Manipulator Working Area

Svitlana Maksymova[1], Amer Abu-Jassar[2], Dmytro Gurin[1], Vladyslav Yevsieiev[1]

[1]Department of Computer-Integrated Technologies, Automation and Robotics, Kharkiv National University of Radio Electronics, Ukraine

[2]Department of Computer Science, College of Computer Sciences and Informatics, Amman Arab University, Amman, Jordan

Abstract: This article presents a comparative analysis of methods for predicting object movement trajectories in a collaborative robots-manipulator working area. The following approaches are evaluated: linear method, Kalman filter, extended Kalman filter (EKF), behavioral models and LSTM models. A mathematical description of each method is accompanied by an analysis of their advantages and disadvantages, including prediction accuracy, implementation complexity, and resource requirements. The results show that the choice of the method depends on the specifics of the task and the robot's operating conditions, which allows for an optimal combination of efficiency and computational costs.

Key words: Industry 5.0, Collaborative Robot, Work Area, Computer Vision, Trajectory Prediction.

Introduction

In the modern conditions of the Industry 5.0development, where the emphasis is on the integration of advanced technologies to create more adaptive and efficient production systems, the importance of accurately predicting the trajectories of the movement of objects in a collaborative robots-manipulator working area cannot be overestimated [1]-[12]. Robotic manipulators working in close contact with people and performing complex tasks in dynamic environments require high accuracy in predicting the movements of objects to ensure the safety and efficiency of production processes [13]-[27]. Various methods and approaches can be used for analysis here [28]-[44]. Choosing the appropriate trajectory prediction method is critical to achieving optimal results, as different methods have different properties, advantages, and limitations. In this context, conducting a comparative analysis of forecasting methods, such as the linear method, the Kalman filter, the extended Kalman filter (EKF), behavioral models and LSTM models, is necessary to determine the most effective approaches to solving tasks within the concepts of Industry 5.0. Each of these methods has unique features that can affect the accuracy of forecasting and the efficiency of manipulator robots in various scenarios.

The analysis of these methods allows you to find out which approach best corresponds to specific working conditions, taking into account the dynamism of the environment, the complexity of the interaction of objects and the requirements for computing resources. This allows for the creation of more adaptive, accurate and safe systems that meet the modern requirements of industrial and research applications. Thus, this article is aimed at deepening the understanding and selection of optimal forecasting methods for increasing efficiency and safety within the framework of Industry 5.0.

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Related works

Collaborative robots are currently finding more and more application. Naturally, when a person and a robot work together, the task of detecting an object in the robot's work area and tracking this object becomes extremely relevant. This leads to the task of predicting the possible position of the object. Many works are devoted to solving this problem. Let's look at several recent scientific works.

Marchetti, F., and co-authors in [45] propose MANTRA, a model that exploits memory augmented networks to effectively predict multiple trajectories of other agents, observed from an egocentric perspective. Their model stores observations in memory and uses trained controllers to write meaningful pattern encodings and read trajectories that are most likely to occur in future.

A novel two-stage motion prediction framework, Trajectory Proposal Network (TPNet) is presented in [46]. TPNet first generates a candidate set of future trajectories as hypothesis proposals, and then makes the final predictions by classifying and refining the proposals which meets the physical constraints. By steering the proposal generation process, safe and multimodal predictions are realized.

Researchers in [47] present Goal-GAN, an interpretable and end-to-end trainable model for human trajectory prediction. They leverage information about the past trajectory and visual context of the scene to estimate a multi-modal probability distribution over the possible goal positions, which is used to sample a potential goal during the inference.

Quan, R., & et al. in [48] propose a novel Long Short-Term Memory (LSTM), namely, to incorporate multiple sources of information from pedestrians and vehicles adaptively. Different from LSTM, their one considers mutual interactions and explores intrinsic relations among multiple cues.

The paper [49] introduces a novel motion-based tracker, MotionTrack, centered around a learnable motion predictor that relies solely on object trajectory information. This predictor comprehensively integrates two levels of granularity in motion features to enhance the modeling of temporal dynamics and facilitate precise future motion prediction for individual objects.

Scientists in [50] propose their own method to predict objects moving. Their method predicts both current and past locations in the first stage, so that each object can be linked across frames and the comprehensive spatio-temporal information can be captured in the second stage.

So, we see that the task of predicting the movement of various objects occupies the minds of many scientists. Further in this article we will consider the most common ways of solving this problem and present their comparative characteristics.

Mathematical Representation of Methods for Predicting the Trajectory of Objects in a collaborative robots-manipulator workspace

Trajectory prediction is a key component in the development of a method for identifying and tracking objects in the workspace of a collaborative robot, especially in the context of cyber-physical manufacturing systems. Collaborative robots work in a dynamic environment where there are moving objects, including people, whose actions can be unpredictable. To ensure the safety and efficiency of interaction between a robot and a person, it is necessary not only to accurately determine its current position, but also to predict possible trajectories of its movement. This allows the robot to adapt its actions in advance, minimizing the risks of collisions or other dangerous situations. Trajectory prediction also helps optimize workflows by allowing workers to effectively

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plan their actions in real time. The use of this method increases the level of robot autonomy, which is an important aspect for the integration of such systems into modern production processes within the framework of the concept of Industry 5.0.

There are several basic methods of trajectory prediction that are widely used in computer vision tasks:

- linear methods, based on the assumption that the movement of the object is linear. They are easy to implement and fast, but have low accuracy for complex or variable trajectories.
- Kalman filter for linear systems, which allows to predict the trajectory taking into account noise and uncertainty. It works well for smooth trajectories, but has limited ability to adapt in complex dynamic environments.
- the extended Kalman filter (EKF), is an extension of the standard Kalman filter for nonlinear systems. It provides better accuracy in cases with complex trajectories, but requires more computing power.
- behavioral models, use previous data about the movements of objects to build behavioral models. They provide high accuracy, but depend on the availability of a large amount of training data.
- recurrent neural networks (RNN) and Long Short-Term Memory (LSTM), these models can take into account long-term dependencies in the data and are well suited for predicting complex trajectories. However, they require significant computing resources.

Let us analyze each method of predicting the trajectories of moving objects in a collaborative robots-manipulator working area and identify their advantages and disadvantages.

Linear methods are based on the assumption that the change in the position of the object in the working area of the robot can be described by linear functions. These methods are easy to implement and understand, but they have limitations when modeling nonlinear processes.

The simplest linear method is to use linear regression equations to predict an object's position based on its previous positions.

$$y(t)= \beta_0+\beta_1 x_1(t)+ \beta_2 x_2(t)+\ldots+ \beta_n x_n(t)+e(t) \tag{1}$$

$y(t)$ - the predicted position of the object at the moment of time t;

$x_1(t), x_2(t), \ldots, x_n(t)$ - values of independent variables (previous positions of the object);

$\beta_0, \beta_1, \ldots, \beta_n$ - coefficients of the model;

$e(t)$ - model error.

Linear forecasting methods for moving objects in a collaborative robot-manipulator working area are simple to implement and fast, which makes them attractive for tasks with low computational complexity. They are well suited for systems where object movements are linear or can be adequately approximated by linear models. However, their main disadvantage is limited accuracy in cases where object movements are non-linear, which is often observed in real production conditions. Linear methods may also not take into account complex dynamics or interactions between objects, which can lead to errors in prediction and reduce the efficiency of the robots-manipulator.

The Kalman filter is an optimal recursive filter that estimates the state of an object in noisy systems. It is able to predict the next state of the object based on previous observations, taking into account the existing noise in the measurements. From the point of view of mathematical

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description, this method includes two main phases: prediction and correction, which are represented in the following expressions:

- forecasting phase:

$$\tilde{x}_{(k|k-1)} = A\tilde{x}_{(k|k-1)} + Bu_k \tag{2}$$

$$P_{(k|k-1)} = AP^T_{(k|k-1)} + Q \tag{3}$$

- correction phase:

$$K_k = P^{\mathrm{T}}_{\mathrm{(k/k\text{-}1)H}}(HP^{\mathrm{T}}_{\mathrm{(k/k\text{-}1)H}} + R)^{-1} \tag{4}$$

$$\tilde{x}_{(k|k)} = \tilde{x}_{(k|k-1)} + K_k(z_k - H\tilde{x}_{(k|k-1)}) \tag{5}$$

$$P_{(k|k)} = (1 - K_k H)P_{(k|k-1)} \tag{6}$$

$\tilde{x}_{(k|k-1)}$ - predicted state;

$P_{(k|k-1)}$ - predicted error covariance;

K_k - matrix of Kalman coefficients;

z_k - measured value;

A - state transition matrix;

B – control matrix;

u_k - vector of controlling influences;

H - observation matrix;

Q - process noise covariance;

R - measurement noise covariance.

The Kalman filter is an effective tool for predicting the movement of objects in a collaborative robot-manipulator working area, as it provides an optimal assessment of the system state in conditions of noise and uncertainties. It performs well in real time, adapting to dynamic changes in the environment, which is important for accurate trajectory prediction. However, the main disadvantages are its limitations in application to linear systems and dependence on the correctness of process and measurement models. In conditions of significant nonlinearities or inaccuracies in modeling, the effectiveness of the Kalman filter may decrease, which leads to less accurate prediction of movement trajectories.

The extended Kalman filter (EKF) is a variant of the standard Kalman filter, but applies to nonlinear systems. It linearizes nonlinear equations of state and measurements by computing their derivatives. The EKF also has two main phases: prediction and correction, which are presented below:

- forecasting phase:

$$\tilde{x}_{(k|k-1)} = f(\tilde{x}_{(k-1|k-1)} * u_k) \tag{7}$$

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$$P_{(k|k-1)} = F_k P_{(k-1|k-1)F_k^T} + Q \tag{8}$$

- correction phase:

$$K_k = P^{\mathrm{T}}_{(\mathrm{k/k\text{-}1})\mathrm{H}_\mathrm{k}^\mathrm{E}} (HP^{\mathrm{T}}_{(\mathrm{k/k\text{-}1})\mathrm{H}_\mathrm{k}^\mathrm{T}} + R)^{-1} \tag{9}$$

$$\tilde{x}_{(k|k)} = \tilde{x}_{(k|k-1)} + K_k (z_k - h(\tilde{x}_{(k|k-1)})) \tag{10}$$

$$P_{(k|k)} = (1 - K_k H_k) P_{(k|k-1)} \tag{11}$$

f() - nonlinear state transition function;
h()-nonlinear observation function;
F_k - matrix of derivatives (Jacobian) of the state transition function;
H_k - matrix of derivatives (Jacobian) of the observation function.

The Extended Kalman Filter (EKF) is effective for predicting the movement of objects in a collaborative robots-manipulator working area, as it allows for the processing of nonlinear systems, which is common in such tasks. The EKF provides more accurate state estimation compared to the standard Kalman filter due to linearization around the current state, which allows it to adapt to complex dynamic changes. However, this approach has drawbacks: it requires large computational resources and can be sensitive to initial conditions and errors in the model, which can lead to accumulation of errors and inaccuracies in predictions under significant nonlinearities or strong perturbations.

Behavioral forecasting models are based on the analysis of behavioral patterns of the object. They can be based on rules, expert systems or machine learning. These models are often used to predict the movement of objects interacting with the environment or other objects. Behavioral models can use different mathematical approaches, including decision rules, finite state machines, or neural networks. For example, a neural network can be used to train a behavior model based on previous data:

$$y(t)=\sigma(W*x(t)+b) \tag{12}$$

y(t) - predicted position;
x(t) - input data (previous position, speed, direction);
W - weighting coefficients;
b – shift;
σ() - activation function.

Behavioral prediction models have the advantage of being able to take into account the complex interaction of objects and context, which allows the operation of the manipulator to adapt to various scenarios in the work area. They work effectively in environments with unpredictable or dynamic changes, which is important for tasks where the behavior of objects may differ significantly from standard trajectories. However, the main drawback is the dependence on high-quality training data and the high complexity of creating an adequate model, which can require

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significant resources for training. In addition, behavioral models may be less accurate when predicting new or rare scenarios that were not considered during training.

Long Short-Term Memory (LSTM) is a type of recurrent neural networks (RNN) specially designed to work with sequential data and solve the problem of "forgetting" long-term dependencies. LSTMs are used to predict the movement of objects when it is important to consider long-term dynamics. LSTM has special blocks consisting of three main gates: input, forget and output, which regulate the flow of information. The mathematical representation of the blocks is given below:

- input gate:

$$i_t=\sigma(W_i*[h_{t-1},x_t]+b_i) \tag{13}$$

- forgetting gate:

$$f_ft=\sigma(W_ff*[h_t(t-1),x_tt]+b_ff) \tag{14}$$

- candidate of new states:

$$C_1t=HTan(W_cC*[h_1(t-1),x_tt]+b_cC_t) \tag{15}$$

- state update:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{16}$$

- output gate:

$$o_1t=\sigma(W_oo*[h_1(t-1),x_1t]+b_oo) \tag{17}$$

- hidden state update:

$$h_t=o_t*HTan(C_t) \tag{18}$$

x_t - input vector at a time t;
h_t - hidden state at a time t;
C_t – memory state at a time t;
W_i, W_f, W_c, W_o - weight matrices for the corresponding gates;
b_i, b_f, b_c, b_o - shift for the corresponding gate;
$\sigma()$ - sigmoid function;
HTan - hyperbolic tangent.

LSTM prediction models have the advantage of being able to efficiently process sequential data and take into account long-term dependencies, which makes them ideal for predicting complex and non-linear object trajectories in a collaborative robots-manipulator working area. They work well in situations with changing conditions where historical data must be taken into account for accurate forecasting. However, LSTM models require large computing resources and a large amount of training data to achieve high accuracy, which can be a challenge in real-world settings. In addition, their complexity can lead to long training and tuning times, as well as the risk of overtraining with limited data.

Based on the analysis, we will build a table comparing the advantages and disadvantages of each method: linear method, Kalman filter, EKF, behavioral models and LSTM models, the comparison results are given in Table 1.

Table 1. Comparison of the advantages and disadvantages of the methods of predicting the trajectories of the objects movement in a collaborative robots-manipulator working area

Method	Advantages	Disadvantages
Linear methods	Simple to implement, fast to implement, suitable for linear or almost linear systems.	Limited accuracy in non-linear movements, do not take into account complex dynamics, may cause errors.
Kalman filter	Effective in real time, works well with noise and uncertainties, adapts to changes.	Only suitable for linear systems, depends on the accuracy of the process model and measurements.
Extended Kalman filter (EKF)	Works with nonlinear systems, more accurate than the usual Kalman filter.	Requires large computing resources, sensitive to initial conditions, possible accumulation of errors.
Behavioral models	They take into account the complex interaction of objects, adapt to various scenarios, and are effective in dynamic environments.	Dependence on qualitative data, complexity of modeling, less accurate in new or rare situations.
LSTM models	Take into account long-term dependencies, are effective for non-linear and complex trajectories, work well with sequential data.	Requires large resources and data for training, difficult to configure, risk of overtraining.

Conclusion

In this article, a comparative analysis of methods for predicting object movement trajectories in a collaborative robots-manipulator working area was conducted, including linear methods, Kalman filter, extended Kalman filter (EKF), behavioral models, and LSTM models. Each of these methods has its own advantages and disadvantages, which determine their effectiveness in specific conditions. Linear methods are simple to implement and fast, but are limited in accuracy when dealing with nonlinear systems. The Kalman filter shows high efficiency in linear systems and in noisy conditions, but requires modeling accuracy, which can be problematic in cases with complex systems. The EKF is a powerful tool for dealing with nonlinear systems, but it depends on the initial conditions and can be resource intensive. Behavioral models provide flexibility and the ability to adapt to a variety of scenarios, but they require high-quality data for training and are complex to develop. LSTM models, on the other hand, can efficiently handle sequential data and account for long-term dependencies, making them a powerful tool for predicting complex trajectories, although they require significant computing resources and training time. In conclusion, the choice of a specific method for predicting trajectories in a collaborative robot working area depends on the specifics of the task, the complexity of object dynamics, and available resources. Careful analysis of these factors is key to achieving the optimal balance between accuracy and efficiency in forecasting.

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