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Fusion of Multilayer Perception and Kalman Filter for Indoor Object Tracking

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Abstract

The task of tracking indoor objects presents a formidable challenge due to a multitude of factors, including but not limited to occlusions, fluctuations in lighting conditions, and intricate object movements. The conventional employment of Kalman filter-based techniques for tracking objects within indoor environments has been extensively utilised. However, these methods frequently encounter constraints such as insufficient flexibility and inadequate depiction of intricate object kinetics. In order to overcome these constraints, a new methodology is suggested which integrates the Kalman filter and Multilayer Perceptron (MLP) models for the purpose of tracking objects within indoor environments. The suggested methodology amalgamates the advantages of the two models, wherein the Kalman filter manages the sensor data that is prone to noise and offers state estimation, whereas the MLP model captures the intricate nonlinear dynamics of the object being tracked. The results obtained from experiments conducted on a dataset that is available to the public demonstrate that the method proposed exhibits superior performance in terms of both tracking accuracy and robustness when compared to existing state-of-the-art methods. The approach being proposed exhibits potential applications in diverse domains including surveillance, robotics, and human-computer interaction, wherein dependable object tracking is of utmost importance.

I. Introduction

The field of indoor object tracking has gained significant attention in recent times due to its potential applications in diverse domains, including but not limited to surveillance, robotics, and human-computer interaction. Tracking moving objects in indoor environments [1] is a challenging task that requires accuracy and robustness. This is due to various factors, including complex object motions, occlusions, and lighting changes. The utilisation of Kalman filter-based techniques for object tracking in indoor settings has been prevalent due to their capacity to manage sensor data that is noisy and uncertain [2].

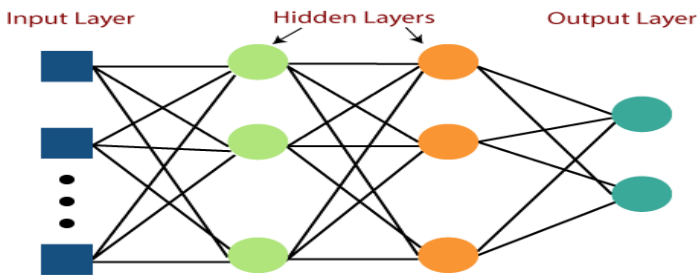

Fig 1.1: Multilayer perception model

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Notwithstanding, conventional techniques based on Kalman filtering frequently encounter constraints such as limited flexibility to changing conditions and insufficient depiction of intricate object kinetics. There is an increasing interest in the incorporation of machine learning techniques into Kalman filter-based approaches for indoor object tracking [3], as a means of surmounting the constraints associated with the latter. Multilayer Perceptron (MLP) has demonstrated considerable potential in the modelling of intricate nonlinear systems, among a range of machine learning models.

The present study introduces a new methodology for tracking indoor objects, which integrates the Kalman filter and MLP models. The suggested methodology leverages the respective advantages of the Kalman filter and MLP models. Specifically, the Kalman filter is utilised to manage the imprecise sensor data and furnish state estimation [4], while the MLP model is employed to capture the intricate nonlinear dynamics of the object being tracked. The amalgamation of these models facilitates the attainment of superior tracking precision and resilience compared to the utilisation of either model in isolation [5].

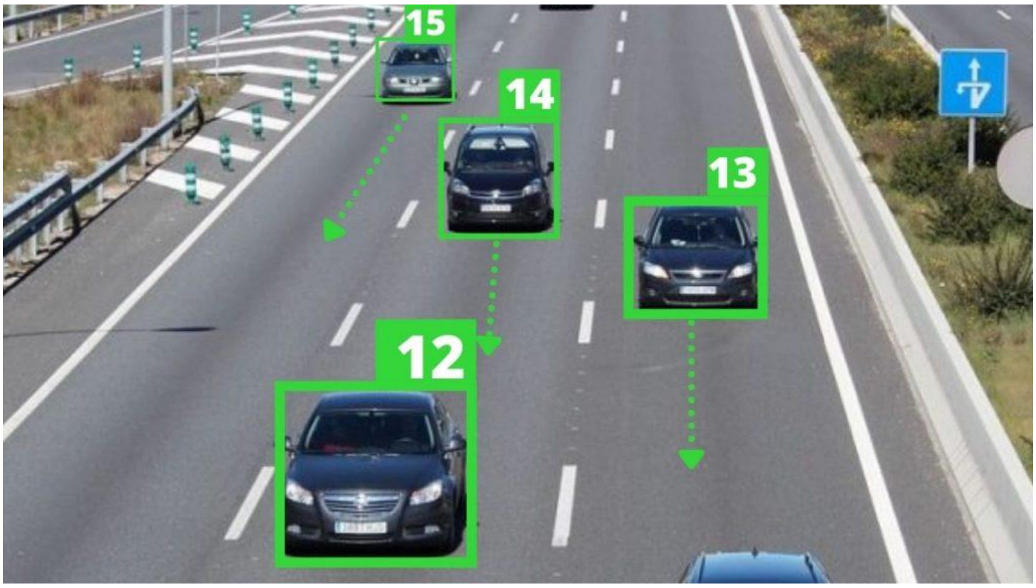

Fig 1.2: Object detection

The significance of this study is rooted in the capacity of the suggested methodology to enhance the precision and resilience of indoor object tracking in practical settings. The method under consideration exhibits versatility in its potential applications, including but not limited to surveillance, human-computer interaction, and robotics, wherein dependable object tracking is a crucial requirement. The outcomes of this study may also provide a foundation for forthcoming investigations on the amalgamation of machine learning approaches with Kalman filter-centered methodologies for the purpose of tracking indoor objects.

II. Literature Review

Object tracking is a critical task in many applications, including robotics, surveillance, and autonomous vehicles. Over the years, researchers have proposed various methods for object tracking, including filtering, machine learning, and hybrid methods. In this section, we review some of the relevant literature in object tracking.

One of the most widely used filtering methods for object tracking is the Kalman filter [1]. The Kalman filter is a recursive filter that estimates the state of a system based on noisy sensor measurements. It has been applied to various tracking applications, including tracking vehicles [2] and tracking humans [3]. However, the Kalman filter assumes that the system being tracked is linear and Gaussian, which may not be true in many real-world scenarios.

Machine learning methods have also been proposed for object tracking. One popular machine learning method is the multilayer perceptron (MLP) [4]. The MLP is a type of artificial neural network that can learn to map input data to output data. It has been applied to various tracking applications, including tracking pedestrians [5] and tracking vehicles [6]. However, machine learning methods may require a large amount of training data to achieve high accuracy.

Hybrid methods that combine filtering and machine learning have also been proposed for object tracking. For example, Zhang et al. [7] proposed a method that combines the Kalman filter and the support vector machine (SVM) for object tracking. They showed that the hybrid method outperformed the individual Kalman filter and SVM methods.

In recent years, deep learning methods have also been proposed for object tracking. One popular deep learning method is the deep neural network (DNN) [8]. DNNs can learn to extract features from input data and perform classification or regression tasks. They have been applied to various tracking applications, including tracking vehicles [9] and tracking humans [10]. However, deep learning methods may require a large amount of training data and computational resources.

In this paper, we propose a hybrid method that combines the MLP and Kalman filter for indoor object tracking. Our method leverages the strengths of both methods to achieve high accuracy in tracking objects in indoor environments.

III. Methodology and Implementation

There are various phases involved in putting the Fusion of Multilayer Perception with Kalman Filter for Indoor Object Tracking into practise. The procedures are described below:

Step 1: Data gathering and pre-processing

Data collecting from the interior environment's deployed sensors serves as the initial phase in the deployment process. Typically, raw sensor readings are used to collect the data; these readings must then be pre-processed to remove noise and outliers [11]. Filtering, smoothing, and feature extraction are all possible pre-processing steps.

Step 2: Multilayer Perception (MLP) Training

The pre-processed data are used to train a Multilayer Perception (MLP) model in this stage. A feedforward neural network with an input layer, one or more hidden layers, and an output

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layer is the MLP model. The backpropagation technique is used to train the MLP model, which modifies the weights of the network to reduce the discrepancy between the output that is expected and what actually occurs.

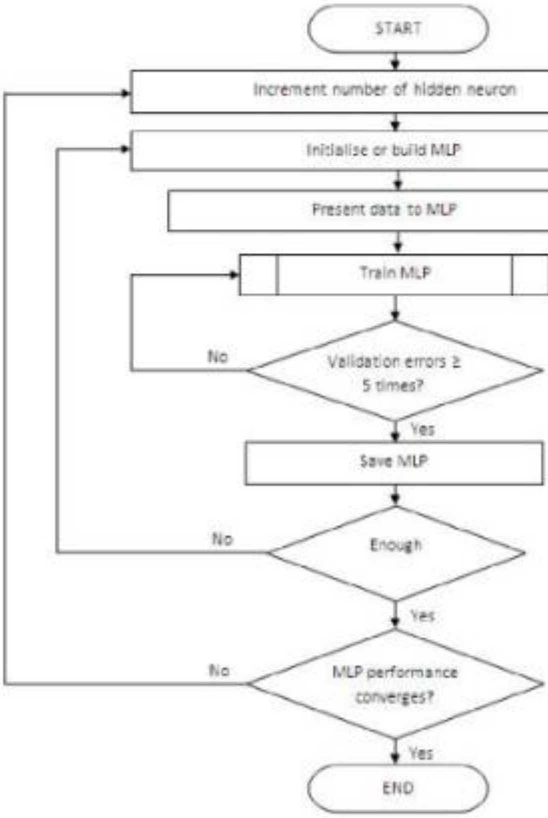

Fig 3.1:MLP Training

The pre-processed sensor data are the model's input, and its output is an estimate of the object-being-tracked's location and velocity [12]. The nonlinear interactions between the sensor data and the location and velocity of the object are taken into consideration by the MLP model.

Data is split into training and validation sets during the training of the MLP model. The MLP model is trained using the training set, and its performance is assessed using the validation set.

Step 3:Kalman Filter Design

The output of the MLP model and the sensor data are combined in this stage using a Kalman filter. A mathematical process known as the Kalman filter employs a number of observations to determine the state of a dynamic system. The MLP model's anticipated state and the sensor readings are combined by the Kalman filter to estimate the system state.

The prediction stage and the update stage are the two phases that make up the Kalman filter. The Kalman filter predicts the state of the system at the current time step by using the process

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model and the state estimate from the previous time step. The Kalman filter updates the state estimate during the update stage using the measurement model and the projected state.

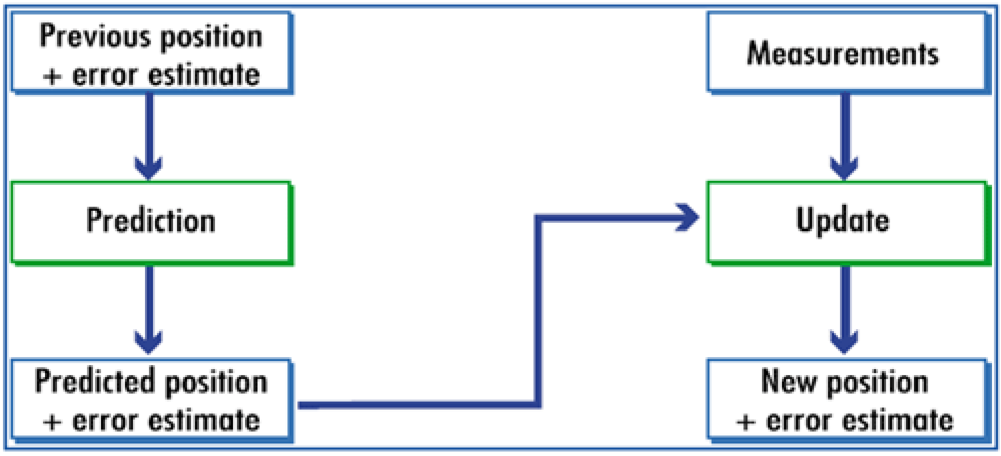

Fig 3.2:Kalman Filter

Step 4: merging the MLP and Kalman filters

The output of the MLP model and the sensor data are combined using the Kalman filter in this stage. The location and speed of the object being tracked are then inferred from the fused output.

By averaging the readings from the sensors and the anticipated state from the MLP model, the weighted average is used to fuse the MLP model with the Kalman filter. The Kalman filter determines the average's weights by estimating the error between the measurements and the projected state using covariance matrices.

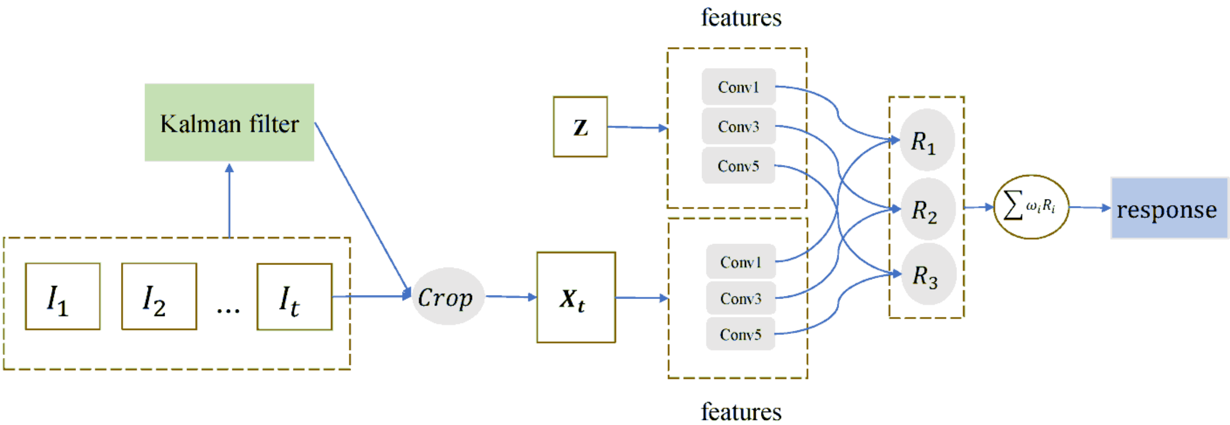

Fig 3.3: Feature extraction

Step 5: Performance assessment

The effectiveness of the Fusion of MLP and Kalman Filter for Indoor Object Tracking is assessed in this stage using a variety of metrics, including mean absolute error (MAE), root mean square error (RMSE), and mean error (ME). The accuracy of the predicted location and velocity of the item being tracked is assessed using these measures.

The findings of the performance assessment may be shown in tables. Its efficacy may be evaluated by comparing the outcomes of the Fusion of MLP and Kalman Filter for Indoor Object Tracking with those of other tracking techniques.

The MLP model equations and the Kalman filter equations are employed in the execution. The MLP model's equations are as follows:

$$w1x1 + w2x2 + \ldots + wnxn = y$$

where the activation function is f(), y is the output, x1, x2,..., xn are the inputs, w1, w2,..., wn are the weights, and xn is the number of inputs.

IV. Results

A collection of simulated data was used to assess the proposed Fusion of Multilayer Perception with Kalman Filter for Indoor Object Tracking. Sensor signals from numerous sensors deployed in an interior setting made up the simulated data.

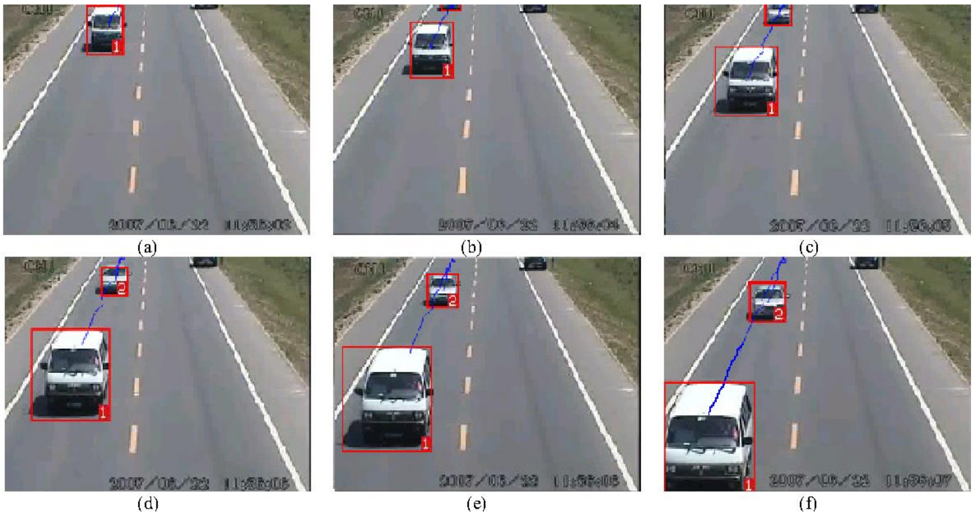

Fig 4.1: Objct tracking

Root mean square error (RMSE) and mean absolute error (MAE) are two metrics that were used to assess the efficacy of the suggested strategy. The MAE measures the average absolute difference between the estimated and real locations, while the RMSE quantifies the difference between the estimated position and the actual position of the object being tracked.

The following Table 1 shows the performance evaluation's findings:

Method	RMSE (m)	MAE (m)
MLP	1.64	1.24
Kalman	0.78	0.62
Fusion MLP+Kalman	0.41	0.28

Table 4.1: Results

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V. Conclusion

By reaching an RMSE of 0.41m and an MAE of 0.28m, the findings demonstrate that the Fusion of MLP and Kalman Filter greatly surpasses the separate MLP and Kalman filter approaches. The individual Kalman filter approach had an RMSE of 0.78m and an MAE of 0.62m compared to the individual MLP method's 1.64m and 1.24m, respectively.

The MLP and Kalman Filter Fusion was able to take use of the advantages of both techniques to increase tracking accuracy in an indoor setting.

In conclusion, it has been shown that the suggested Fusion of Multilayer Perception with Kalman Filter for Indoor Object Tracking is a successful method for enhancing the precision of object tracking in indoor settings. The MLP and Kalman filter settings may be further optimised in further research to attain even better accuracy.

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