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ORIGINAL ARTICLE

Multi-sensor data fusion for an efficient object tracking in Internet of Things (IoT)

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Abstract
The IoT aims at creating a world that connects physical and virtual objects and integrates them. The IoT generates a range of large, multi-sourcing, heterogeneous, and sparse data sets with the participation of numerous wireless sensor devices. Fusion of data is mainly used to minimize data size and to optimize data traffic volume and extract significant raw data from which IoT services can be improved and intelligent services delivered. The Internet of Things (IoT) is a type of multi-source data preparation that seeks to provide a complete, perfect, and accurate inspection and input comparing actual data. Usually, a combination of multi-sensor information can manage a similar type. Nonetheless, as new qualities arise in IoT, interoperable innovations arranged to assist in the division and combination of certified information between heterogeneous IoT-related gadgets will be necessary. A design which can provide guidance to improve the IoT data combination is required to solve these problems. There is a lot of information in the literature, as well as IoT data fusion studies. This paper aims to provide certain possible aspects to address the above-mentioned challenges. This paper aims at data fusion techniques applied to overcome problems faced by IoT enabled autonomous systems and also addresses traditional data fusion algorithms and advanced data fusion algorithms. Two models were presented. One is a single filter and the second one is a multi-filer model. In the IMM combination stage, a model's weight is proportional to its likelihood, and as projected in results, there is a variation in error rate. With the single object detection method, the error rate generated is 30%, but with the use of the multi filter model, the error rate generated is reduced to 25% and became 5%.

Keywords Data fusion · IoT · Sensors · Data integration · Fusion algorithm

Introduction

Autonomous systems independently execute tasks in a complex and uncertain environment. It has recognition, assessment and judgment capabilities. Via this, any independent system may be added to all autonomous systems. Information is gathered from a variety of sensors. External climate and self-states for acceptance and self-recognition systems Decision-making. Smart robots are autonomous, traditional structures. The Internet of Things is often referred to as the Internet of Objects, as the new age in the history of the Internet, the objects or things here are fitted with certain information networks. The convergence of different technologies is the Internet of Things. Sensor fusion is the process of merging sensory input with data from other sources to obtain information with less uncertainty than if these sources were used separately. The Internet is the worldwide network for the storage and distribution of information. In almost all situations, the Internet is fully secure for people to get information. The Internet has several bytes of data generated only by humans. Our culture is focused on items from which knowledge is not obtained, computers and information technology are now accurate on ideas or information but not on stuff. IoT is an enhanced technology to make things smart (Shafique et al. 2020). The quantity of objects connected to IoT is anticipated to succeed in billions in the future because of the huge flow of numerous objects increasing more and more (Schermann et al. 2014). Internet of Things (IoT) devices create a huge amount of data (Taherkordi et al. 2017). Sharing and collaboration of information and

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alternative resources would be the key for facultative property omnipresent environments, like good cities and societies (Matos et al. 2020). The Internet of Things (IoT) allows smart objects to connect, fostering the ubiquitous presence around us of a number of things or objects that can interact and work together to achieve shared objectives (Hwang 2015). IoT objects, such as the home, workplace, industry or body, may obtain data from their context (Meneghello et al. 2019). The Internet of Things (IoT) generates tremendous amounts of data from its close setting (Sengupta et al. 2020). Wireless detector networks that type an area of IoT sense the environmental conditions and relay the data to the server (https:, , doi.org, 10.1016, j.jnca.2019.102481. xxxx). This data is then processed victimization data processing algorithms at the server aspect to induce associate degree overall image of however the conditions square measure so management actions square measure taken (Fahmy 2020). Usually, the info provided by the detector nodes is raw. Vital computation must be done on the info before significant extraction of knowledge will manifest itself (Wong and Yeo 2001). The computation ought to be performed before the info mining will manifest itself. The info mining is the final step of knowledge extraction (Chung and Gray 1999). However, before information is fed for mining, it must be within the correct format so the prognosticative pattern or anomalies within the data is found (Alam et al. 2017). This processing technique which mixes and integrates knowledge from totally different sources is termed as knowledge fusion (Alasadi and Bhaya 2017). With knowledge fusion, it becomes easier to require choices-supported high-level inferences from the info extraction. Also, less time associated degree process capability is exhausted to induce an abstract thought if the info is significant (Bleiholder and Naumann 2009). Knowledge fusion is not a replacement idea and has been enforced in several domains like image process for knowledge extraction. There are tons of analysis on IoT knowledge fusion techniques that study the fusion of information in wireless detector networks (Li et al. 2020). These strategies use mature knowledge fusion algorithms such as theorem, classical abstract thought, Dempster – Shafer, and symbolic logic approach for implementing it to Internet of Things (Rodger, 2012). However, analysis ought to conjointly travel into the hierarchy of information fusion implementation (Xu et al. 2018). The sublayers of design within which the info fusion techniques square measure enforced square measure vital (Zhang et al. 2020). This domain is not well explored, and therefore the analysis intends to place light weight on postulating design for knowledge fusion (Hajjaji et al. 2021). During this analysis, these implementations of information fusion techniques are studied thoroughly. Their hierarchical data structure is explained and compared with customary parameters (Ismael et al. 2021). On victimization of the information gained during this study, another class-conscious resolution is provided and will be compared with the present techniques (Kathidjiotis et al. 2020). This analysis can extend the class-conscious implementation of IoT and canopy all levels of information abstraction, i.e., from a detector to server (Kiruthika and Ponnuswamy 2021). To acquire new and more complex knowledge applying data fusion methods, these data can be merged (Ha et al. 2020). However, the complete architecture must address distributed nodes and decentralized communication and endorse scalability and node dynamicity, among other constraints, to implement data fusion algorithms in IoT environments (Souissi et al. 2019). Timely decision making in autonomous systems is still a challenging task (Liu 2019). Procedure intelligence would play a key role during this challenge (Alam et al. 2017). Sensor fusion combines two or more data sources to improve the consistency, accuracy, and dependability of dynamic system measurement. This is preferable to calculating the various sensors. Sensor fusion aims to reduce and increase confidence in device costs, complexity, number, and sensors. Data fusion methods can be classified into the following categories:

1. Probabilistic (Bayesian networks), (Kalman filter).
2. Statistical, (cross and covariance).
3. Knowledge based, (artificial neural networks).
4. Inference and reasoning methods (Kalman filter).

Some of the noted and very popular sensor data fusion algorithms for object detection are listed below:

1. Bayesian networks.
2. Extended Kalman filter algorithm.
3. Dempster–Shafer.

Major sensors used for fusing data:

- Accelerometers.
- Electronic support measures (ESM).
- flash LiDAR.
- Global positioning system (GPS).
- Infrared/thermal imaging camera.
- Magnetic sensors.
- MEMS.
- Phased array.

This paper addresses Kalman filter algorithm for single model filter estimation (SMFE) and interacting multiple model filter (IMMF) to detect object location as an example for multi-sensor data fusion.

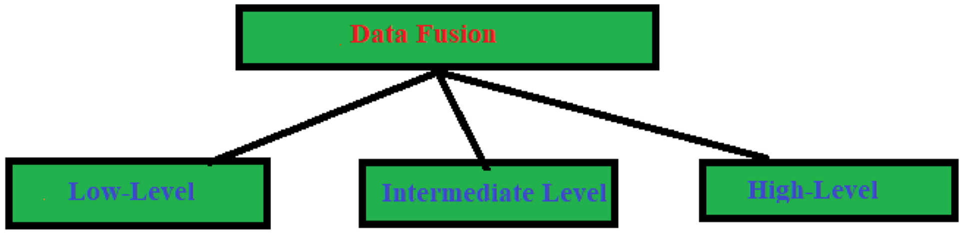


Fig. 1 Data fusion

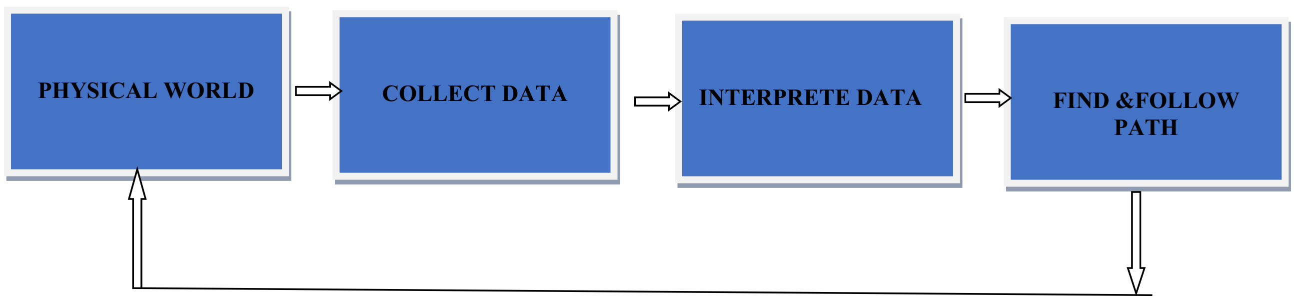


Fig. 2 Sensor data fusion scenario

Terminology and data fusion techniques

Data fusion

To generate more reliable, accurate, and useful information than that given by any individual data source, data fusion is the process of combining multiple data sources (Fig. 1).

Sensor fusion makes it possible to sensitize the context and the Internet of Things has tremendous potential (IoT). Advances in sensor fusion (emotion sensing and processing) for remote emotional computing could in the future also lead to exciting new applications, including intelligent healthcare. These capabilities, however, create essential privacy issues to be resolved by IoT management. If the use of sensor fusion and REC technologies grows, vast quantities of context-aware data will become available (Fig. 2).

Data association

A user-defined community of associated groups and elements constitutes a data association. Data associations are important, as they provide a structured way to establish data-level permissions in a single visibility rule for several data elements that have a common connection (Figs. 3, 4).

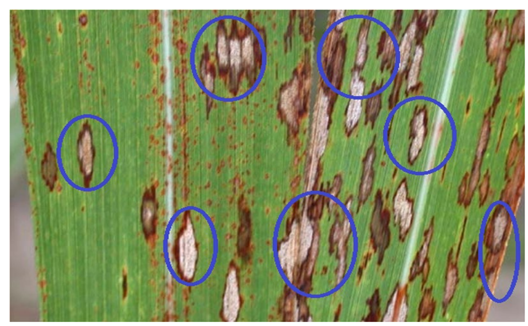


Fig. 3 Data association scenario-1

State estimation

State estimation is a method to determine the network's electric status by eliminating calculation data inaccuracies and errors. The state estimator output is thus a number of absolute voltage and voltage angles for all network buses.

Some of the examples of state estimations are:

Traffic state estimation.
Vehicle speed estimation.
Flying bird speed estimation.
Moving object state estimation.
Connected car (Fig. 5).

Decision fusion and classification

It will be useful for object classification. The efficiency of the classification for each design classification assignment

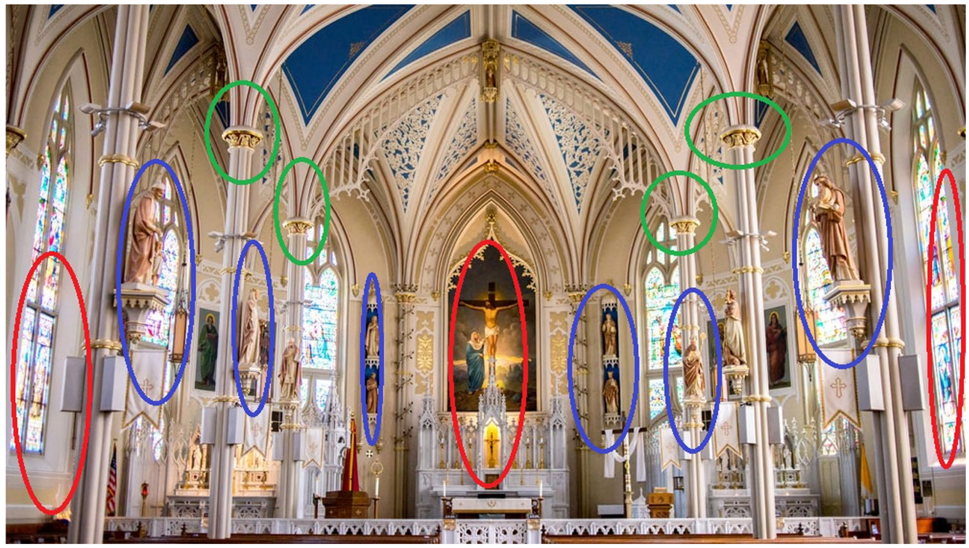


Fig. 4 Data association scenario-2

Fig. 5 Connected car

is affected by the increase in the size of the data, the class number, the spatial dimension and the interclass separability. In general, the wide range and scalability of data in any problem area cannot be solved by a single classifier. A combination of classifiers is used by many modern pattern classification techniques and blends judgments, often using a handful of functions. The problem of selecting and discarding a useful set of functions that does not give class separability is addressed in the task of selecting and merging functions.

Prediction or regression

"Prediction" refers to an algorithm's output following training on a historical data set, the likelihood of a certain outcome and the application to new data (Fig. 6).

Goal of data fusion

Sensors are now available in many different applications for smart mobile devices, automotive systems, industrial control systems, healthcare, oil exploration and climate monitoring. Sensors are used in close proximity to the world, and sensor technology closely resembles the ultimate sensor. The fusion sensor technology is used to merge data from various sensors using a microcontact (a brain) to allow for more accurate and reliable viewing of the data than with

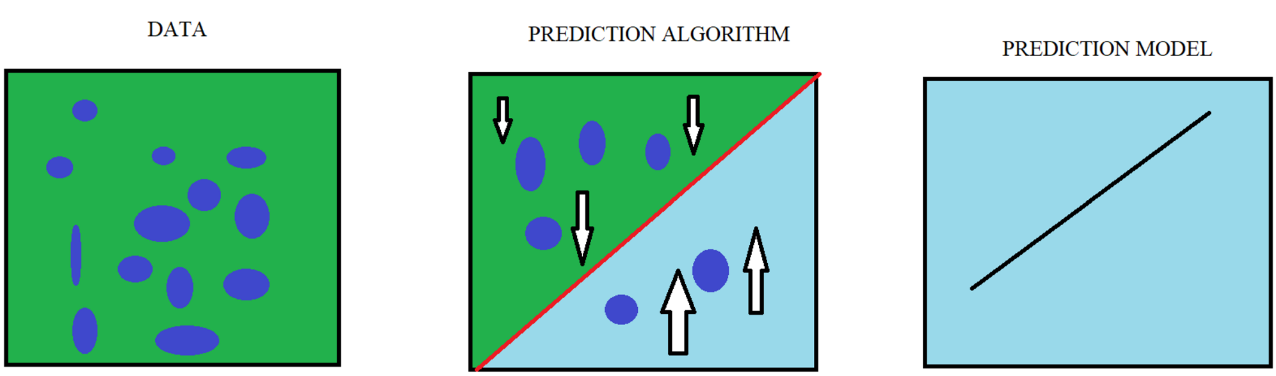


Fig. 6 Data prediction

the application of data from each sensor alone. The fusion of the sensor led to a rise. The act of merging many forms of data into a single model is known as data fusion. Multi-block approaches are a viable alternative among the different methods for merging data from multiple sources.

- Data resolution problem.
- Enhance the reliability of data.
- Extraction of higher levels of information.
- Enhance the integrity of data.

This knowledge and IoT access to the "global neural network in the sky" and tools for cloud-based computing would help to expand the delivery of context-oriented services. Services can be based on what a user does or does in different combinations, what computers do, what infrastructure does and what nature does. Data fusion would fulfill the dream of humans to make things smarter and faster.

Proposed method and experimental results

The basic architecture of the proposed model is shown in Fig. 7 and all its stages are described.

IoT sensors and actuator

IoT is sensors/activators/networks physical object (Internet). Sensors are created for sensing the environment and controlling the signals of the actuators according to the necessary action. The Internet of Things makes a significant contribution to the new economy of databases. In automation, for example, the value of an IoT system exceeds the original case of use. An IoT system is created for a different intelligence. The sensors are the IoT data source. In addition, industrial automation can be supported by IoT sensors and actuators. The company will have valuable insights over time from analyzing data generated with the sensors and actuators.

Data generated from IoT sensors:

An equipment monitors and may collect information from the environment using a sensor. A sensor measures physical quantity and transforms it into a signal. Real-world measurements are translated to digital domain data by sensors. By connecting an IoT sensor, any physical object can be transformed into an IoT. This collected data can be transformed to data preprocessing.

Data pre-processing

The Internet of Things gathers data from sensors and connected equipment (IoT). Therefore, the re-examination of irregular data from time series to a consistent regular frequency is an important pre-processing step for IoT. The IoT sensor networks frequently use wireless communication protocols for sharing information. These protocols are used as non-registered frequency bands to enhance sensor flexibility and scalability. However, uncontrollable interference results in the use of WSN communication protocols in non-licensed frequency ranges. Inappropriate noise, missing values,

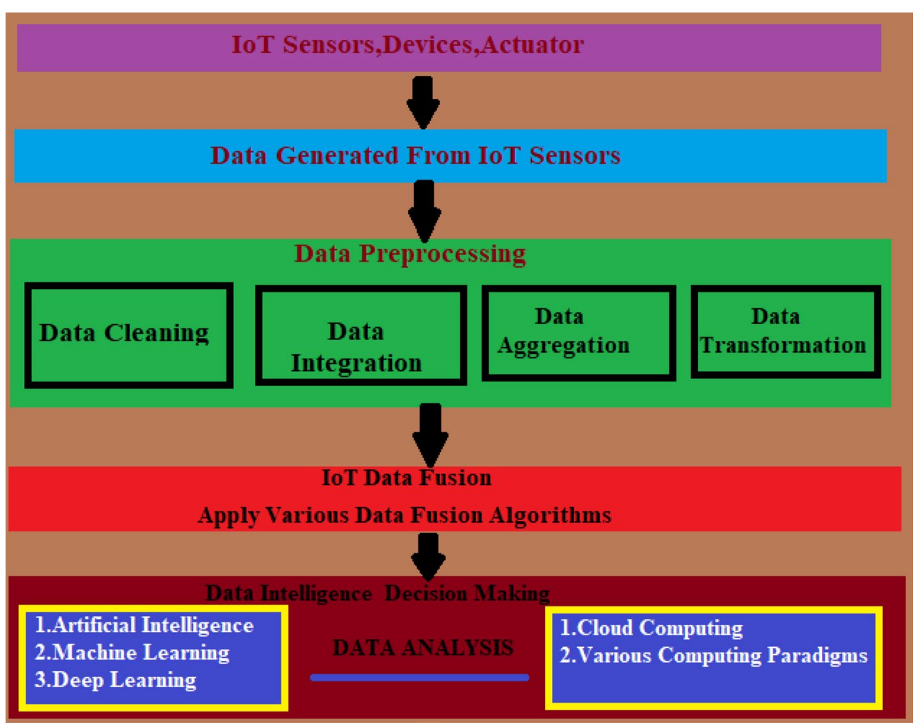


Fig. 7 Basic architecture

outlets and redundancy transmission for data and sensor data can lead to interference signals. This section discusses different analyses of IoT data sensors such as data clean, lack of imputation, detection of data contours and the aggregation of data. Noise is an unrelated portion of the signal that causes change and change in the original signal vectors. The noise function enables cheap data management resources to be processed and employed. The method of wavelet transformation can represent the signal and efficiently address the problem of signal estimation. The wavelet transformation maintains the original signal coefficients by removing the signal noise. The noise signal coefficient can be reduced and thus a perfect threshold control system is essential.

Data cleaning

The process of data clearance or processing includes the identification, replacement, change, deletion or removal of unmet, incorrect or inaccurate data parts or parts that are not relevant and can be found in a set, table or database to detect and correct corrupted or erroneous records. Since IoT data collected from heterogeneous sources have lots of irregularities and unmeaningful data, it needs some cleaning by the use of data mining cleaning techniques.

Data integration

To improve precision in various applications, the integrated data or fusion of multiple sensors is necessary. This could be used, for example, for monitoring and tracking the vehicle, for identifying a blockage in human body veins, etc. Data integration is a combination of technological and business processes which combines information from different sources and valuable and meaningful information. To support a prepared company pipeline, a comprehensive data integration solution offers reliable data from different sources. Data integration is continued in data fusion section.

Data aggregation

The method of aggregation is the collection and summary of information. For statistical analyses, this is appropriate. Heterogeneous data are gathered from different nodes by IoT. Separated from every node, data communication generates a high energy usage which requires a high network range to reduce network durability. Synthesis of data avoids data aggregation and reduces data transmission, increases the life of networks and reduces traffic. Processes of data aggregation avoid problems of this kind. The aggregation of data via the Internet of Things (IoT) helps to reduce the transmittal number. On one device most of the data is aggregated. The technique proposed includes the reconstruction of subspace data samples. Next, there must be a dominant subspace. For the low-ranking approximation, the rugged dominant subspace is also monitored fully for reliable sensor data. The method proposed increases precision and efficiency in the removal of insecurities and data collection from experimental results for sensor data.

Data transformation

Data transformation is the process by which data is converted in the required target system format from one format to another, usually from the source system format. Most data management and integration tasks such as data exchange and data storage are components of transformation data. To transform IoT DATA into useful real-world data, some of the transformation methods can be used.

IoT data fusion

Single filter model

As mentioned in the introduction, this paper proposes two methods: single model filter estimation (SMFE) and interacting multiple model filter (IMMF). Precise tracking of moving objects is needed for remote monitoring systems for automobiles, designs and robots. Kalman's filters are representative algorithms, such as extended/non-scented Kalman and particulate filters, for their variants. These can track movement accurately using an adaptive state space model filtering system. Figure 10 describes single object (plane) location using Kalman filter algorithms with multiple sensors. This model works like the predict and correct model. The first state is a predict state and the model gives us the predicted state. This predicted state can be compared with the measured state, so the result is the corrected state. To achieve it two or more sensors data can be fused. Let us consider two sensors, radar and camera sensors. Kalman filtering is a time measurement algorithm that includes statistical noise and other inaccurate measures, and produces an estimate of unknown, more accurate variables than the ones based on a single measure. There are numerous technological applications in the Kalman filter—including IoT. SFMs are particularly used in the concept of sensor fusion. It helps you to identify the status (or overall context) of the IoT system using several sensors to identify a combined meaning. Figure 8 describes the single path object tracking using Kalman filter algorithm. Any object path can be traced out with three models shown in Fig. 9.

The object path can be identified by constructing a model with the following:

1. The dynamic and kinematics of the system.
2. The commanded and known inputs.
3. The unknown and random inputs.

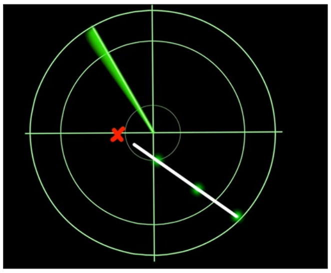


Fig. 8 Object path tracking with single Model (velocity)

At the risk of some paths, the sense of "state" for Kalman filters needs to be understood. The status of dynamic systems is generally predicted with Kalman filters. Dynamic systems are systems that, according to the fixed rule, change or evolve in time. In many physical systems, this rule can be defined as a set of first-class differential equations. The set is related to the first differential equation order input, output and state parameters, and is called a physical system state space depiction. We describe systems with linear and time invariant characteristics to make it easy to use.

Dynamic systems give an overview and reaction to certain minimum variables called state variables. To predict future system conditions and outputs in each case, minimum quantities of the variables (xi(t), I = 1, n) and the systems inputs t0 and t0-to-tax system are t > t0. A large range of engineering, biological, social, and economic systems can be covered by national models. Internet of Things apps have been included.

Kalman and IoT filters are therefore synergistic. Through time series, for example, data is used and input values are not complete. In more general terms, IoT systems should understand and interpret the context. Noise and project readings must be filtered to deduce the entire context is reflected in a host nation. A new state requires a combination of readings from different sources and their relative importance. As a result, Kalman filters are used for sensor fusion. There are a number of techniques including sensory fusion, radar, robots, wearables, etc. A user or system is important for mobility and computing in many fields. The interaction between user experience and reaction in digital contexts is the physical framework. Context-based design: examples of Kalman IoT health filter application is an adapted Kalman cardiovascular technique. Context information components which can be measured in a different confidence in the general state context can be generated by the sensors. Often, sensor outputs overlap and conflict with sensors, and the performance varies greatly. The sensed data contain the confidence level and the time stamp of the sensor from different sensors. The Kalman filter delivers a new measurement for a weighted average system status forecast. Written values are given greater faith with less estimated insecurity. The relative weights between input and sensor impact are measured using covariate. Therefore, the system is in a new position. The new evaluation and its covariances are always repeated and the prediction used in the next iteration is informed. As above, this can be achieved by Kalman filters. Sensor fusion can also be used with Shafer theory, but other methods are available, such as Dempster.

We differentiate between two models used here: single object detection and multi-model object Detection is shown in Fig. 11. Object tracking is shown in Fig. 11, where two constant velocities and turns are considered. The path of the object is not same in these two constant considerations, while the error rate is also reduced, as shown in results section.

Multi Filter Model

The Kalman filter is the ideal assessor for linear Gaussian noise in the minimum average sense of square error. There may be noise, but there are a lot of nonlinear interest systems. The optimal nonlinear filter for a particular system can be difficult or impossible to find, which often results in compromise. Nonlinear under-the-line filters can be produced as

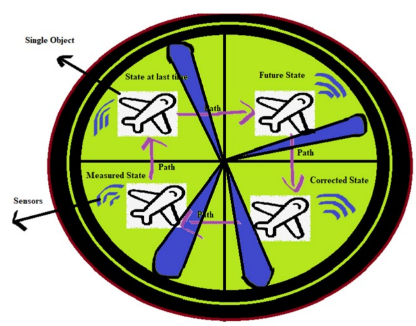


Fig. 10 :10 Object path tracking

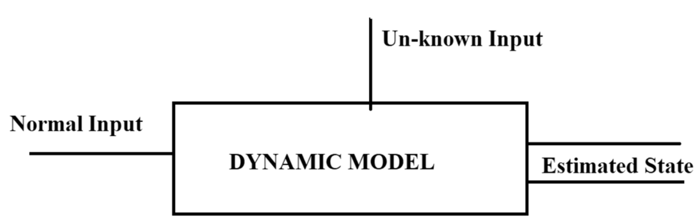


Fig. 9 Model for path identification

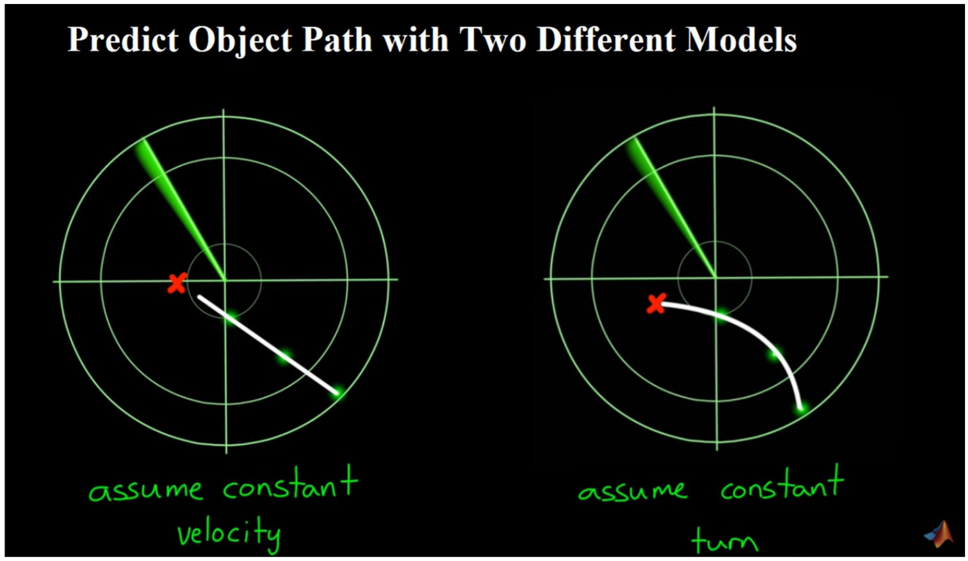


Fig. 11 Object path tracking with two models (velocity) and (turn)

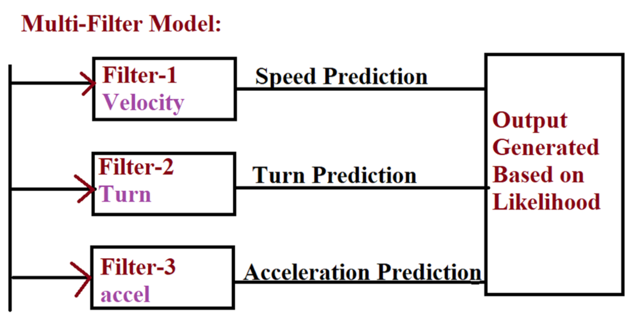


Fig. 12 Multi-filter model with velocity, turn and acceleration

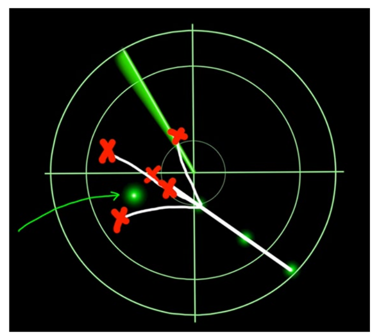


Fig. 13 Variations in object path

an extension to the Kalman filter, as a linear approximation from the Taylor series, or a Kalman filter bank can be used for an interaction model.

As shown in Fig. 12, the multi-filter model has three constants: velocity, turn and acceleration. Each predicts its outcomes and later will be fused to get optimized results. Algorithms for the implementation of IMM radio frequency, scan rates, pulse repetition range, radar data pulse width of the rumbling remarks compare moving and moving variance filter performance.

As projected in Fig. 13, variations in object path are indicated in red color. It is believed that the data sets simulated in the MATLAB, containing various noise, frequency hopping and short data runs, accurately mimic the spectrum of features observed in radar parametric data.

The properties of a system can change over time, making it challenging to capture this new behavior using a dynamic state model. The creation of a Kalman filter bank with a different state transition matrix or process noise is easy to imagine. Each filter runs parallel to each new observation in an ideal Kalman filter bank, but this could be prohibitively expensive. Figure 14 shows the process of low and high noise.

The continuous status and rapid changes of a random process in a typical IMM implementation are described in a small number of models. Depending on the probability of a finite, discrete Markov chain, the filter alternates between models in one finite collection. A final updated estimate is provided by the filter for each step in a linear combination of multiple model updates. There is only a difference between models in the size of the noise variances in the process. For stable or slow variations in data, a low-process noise model is weighed more, while a high-process noise model is adopted for major change. As already mentioned, both models are mixed in a weighted average. The IMM filter is similar to the one in this section we designed and used. The difference between IMM and KF filters is apparent in the root medium square error (Fig. 15, 16). The IMM algorithm maintains track of the goal when it abruptly deviates, but the KF algorithm overshoots. This example shows how an IMM can improve a nonlinear system by using a modest collection

Fig. 14 Low and high noise

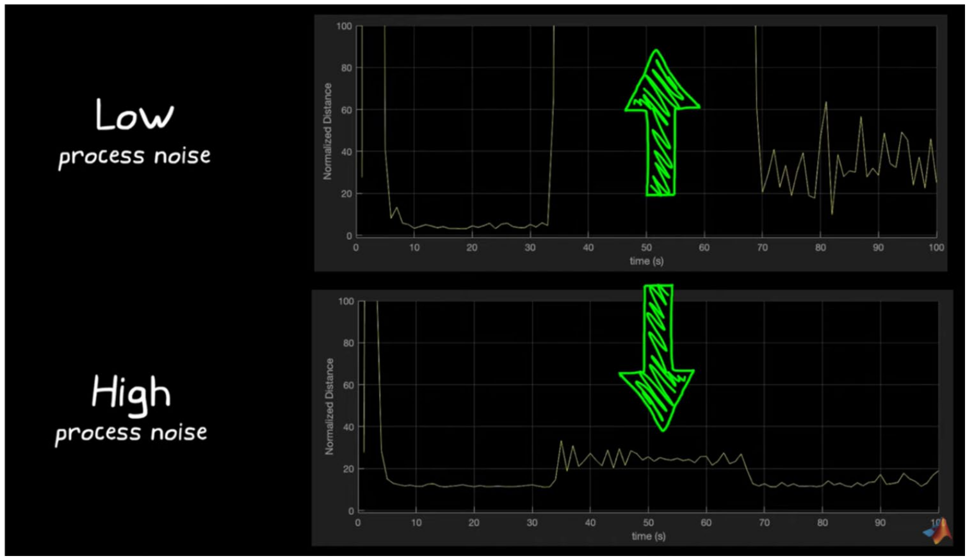
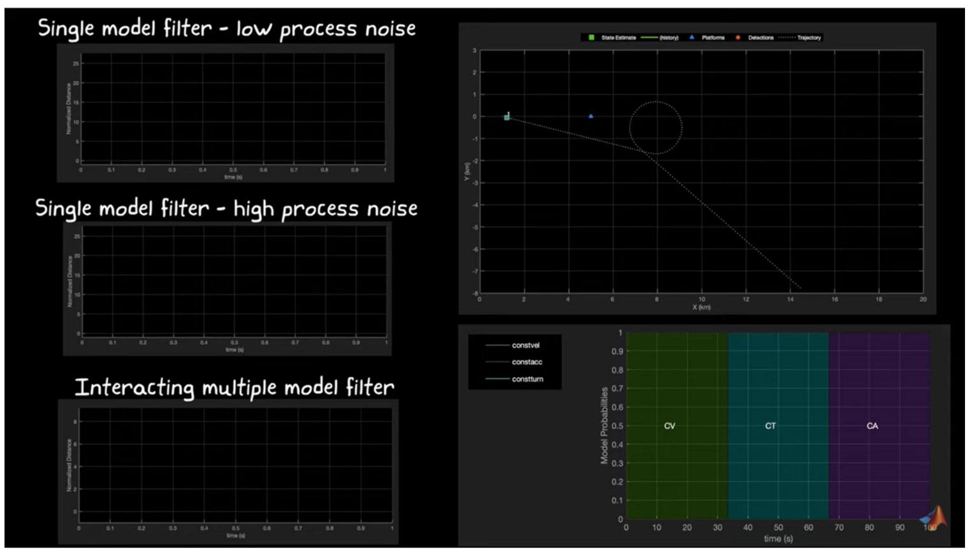


Fig. 15 Low and high noise with single and multi-filter model



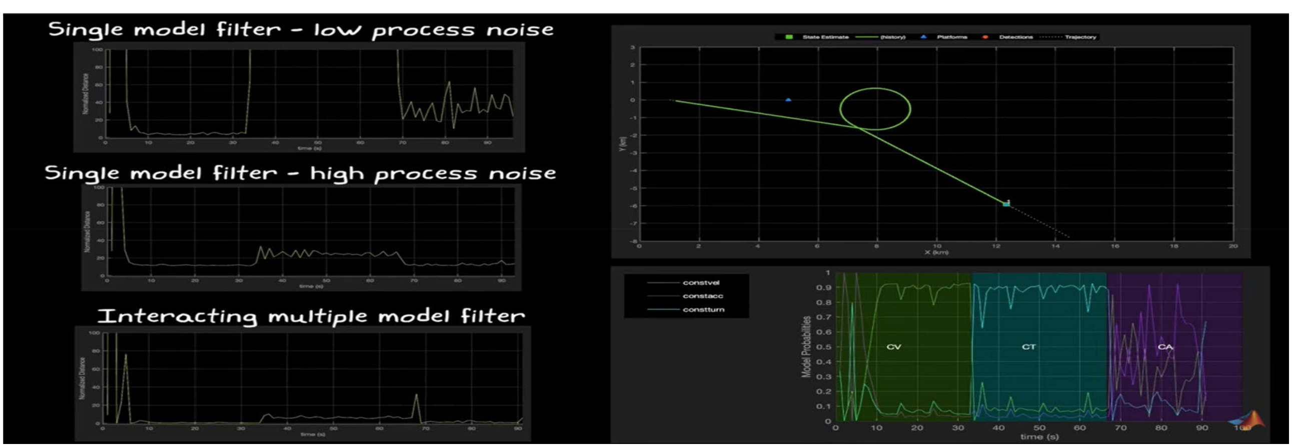


Fig. 16 Low and high noise with single and multi-filter model with varied noise rate

of simple linear Kalman filters. It can track the probability vector's evolution over time. The process noise variances of both IMM models are considerably different, despite the fact that they are both linear Kalman filters.

The development of models has given sound results, but it may increase the computational cost and result in more transitions.

Data intelligence and decision making

The Internet of Things (IoT) has had a significant impact on all aspects of life, but the rise of artificial intelligence (AI) has drawn the attention of experts to a new living standard paradigm in particular. As part of this revolution, smart sensors, actuators, and a range of other gadgets have been warmly adopted for their ability to make life easier. Artificial intelligence (AI)-enabled devices are more complex and capable of completing a task, saving time and money. In the literature, there are several ways based on AI and IoT systems that can be used to manage a variety of real-world circumstances. The relevance of decision-making in AI-enabled and IoT systems cannot be overstated. The research community urgently needs in-depth understanding of existing literature so that practitioners and researchers can benefit from existing proofs and offer new methods for solving a specific challenge of AI-enabled sensing and decision-making for IoT devices. AI, ML and DL techniques can be used for data intelligence and decision making.

Data analysis

Cloud analytics is a marketing term for companies that undertake analysis using cloud computing. It uses a number of analytical tools and approaches to help businesses extract information from large amounts of data and provide it in a format that is easy to categorize and access through a web browser. Various cloud and edge computing techniques can be applied at the last step. The IoT Analytics Platform module focuses on delivering tangible business value through better big data processing and real-time data analytics for M2M/IoT business purposes. It provides detailed data on how customers engage with your IoT devices. It also aids operational QoS concerns by detecting which device (or type of device) is generating issues, exhibiting data patterns and trends, and producing reports and abnormality analysis.

Conclusion and future scope

Data processing, data fusion, and sensor data analytics have all improved as a result of the IoT sensor network's paradigm shift to future technologies such as cloud, fog, and edge computing. Temperature, pollution, and humidity levels, as well as electricity usage, may all be monitored and responded to using IoT sensor networks in a building's environment. The wireless sensor network is a network of many sensors with a sensor that recognizes the phenomena of light, heat, and pressure. The sensor system contains a wide range of sensors. With the rapid technological development of sensors, WSNs will become the IoT's key technology. In this paper, section I introduce the significance of data fusion and discusses IoT. In Section II, terminology and data fusion techniques have been discussed. In section III, the goal of data fusion has been discussed. Finally, in section IV, the proposed method and experimental results have been provided with two models. One is the single filter model (SFM) and the other is the multi-filter Model (MFM). It has been shown that the multi-filter model has given noise removal in a good manner compared with the single-filter model. The future scope of this paper is to work with multi-filter model (MFM) by adding a greater number of inputs.

Declarations

Conflict of interest Author declared as there is no conflict of credit author statement.

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