Multi-Sensor Data Fusion for Target Tracking Using Machine Learning Techniques

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Abstract

Target detection using multi fusion data is one of the common techniques used in military as well as defence units. The usage of a wide variety of sensors is now possible due to modern data fusion technology. The major problem is the existing multi-sensor fusion technique is loss of data and delay is message transfer. To overcome the existing problems, proposed work includes optimization, machine learning, and soft computing techniques. Multi Sensor Data Fusion (MSDF) is becoming an increasingly significant field of study and is being explored by a broad range of individuals. Data defects, outliers, misleading data, conflicting data, and data association are some data fusion concerns. In addition to the statistical advantages of more independent observations, the precision of an observation may be improved by using a variety of different types of sensors. Target tracking has earned a lot of attention in recent years in the realm of surveillance and measurement systems, particularly those in which the state of a target is approximated based on measurements. Academics as well as implementers in the fields of radar, sonar, and satellite surveillance are interested in the bearings-only tracking (BOT) problem. The BOT is the sole option available in many surveillance systems, such as those found aboard submarines. Significant difficulties arise because of the constrained observability of target states based only on bearing measurements. The work that is suggested tackles the limitations of EKF and its derivatives in controlling MSDF within the context of BOT. Specifically, the study identifies divergence as a primary challenge and works to devise solutions for it. It is recommended that two key methods of fusion, data level and feature level (or state level), be investigated in depth. This is in recognition of the fact that the MSDF may increase observability, thereby reducing the tendency of the tracking algorithm to diverge and realizing a better estimate of the states. The Information Filter, which is a casting of the Kalman Filter, and its expansions are employed via extensive simulation to lessen the influence of initial assumptions on the convergence of MSDF tracking algorithms. This is accomplished by using the Kalman Filter.

Keywords: Tree-Based Fusion Technique; Potential Energy Efficient Data Fusion; LEACH; Wireless Sensor Network.

1. Introduction

The human body is equipped with five senses, each of which handles bringing a significant amount of data into the brain. Following the integration of this information, the human brain will next develop perceptions and reactions. Each of the five senses—sight, hearing, touch, taste, and smell—contributes to the generation of information in a unique band, and this information [1] may perceived on a spectrum of intensities. There are several types of sensory data that are moderated by the human thought process as they are processed in phases, either one at a time or collectively in groups.

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This term encompasses all the facets of combining information from a variety of sources to supply a cohesive picture of an environment or process of interest, and it is also the name of the solution to the problem [2]. The solution to the problem called multi-sensor data fusion, or MSDF for short. When information gathered from different sensors at the same time, it is possible to draw conclusions that are more specific than those that might reached from the information supplied by a single, self-contained sensor. The present level of technology makes it possible to install a substantial number of sensors [3], each of which may perform its own set of capabilities in a manner that is entirely distinct from the others. Now accessible for deployment are sensors that equipped with a diverse set of capabilities. These sensors might be as simple as microscopic objects or as complex as radar networks.

A network of extremely tiny geo sensors spread out over a large area in the landscape to collect data that might use for seismic assessments. This network ramified to get data. Most battlegrounds gave a broad array of radars [4], guns, and armoured personal carriers, all which aid in finding contacts in the air and on the ground. (Fig. 1).

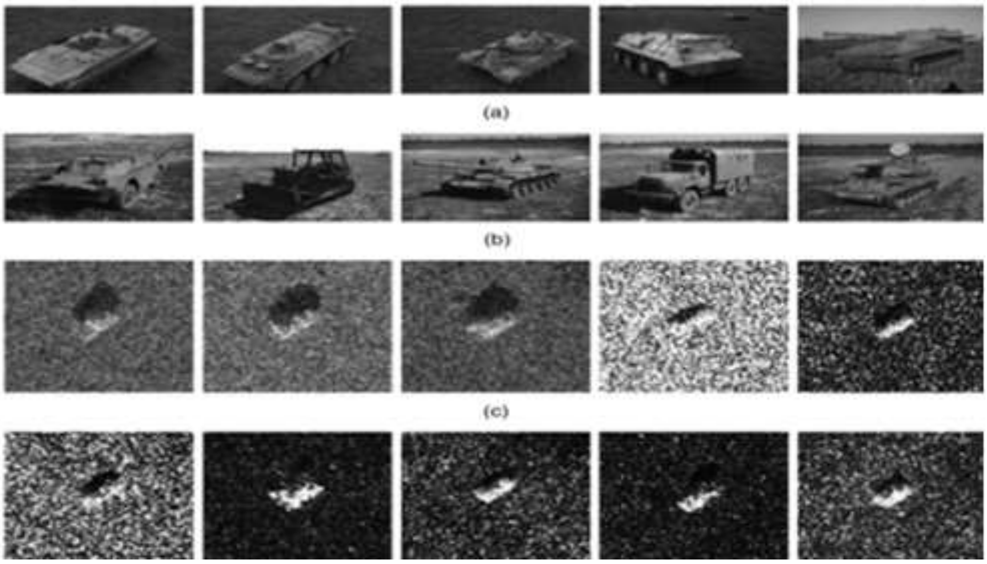

Figure 1: Target detection in battlefield

The Generation and Evaluation of Composite Data Using Information Collected from Sensors technical upgrades as well as innovative approaches to the processing of data. The fusion of novel ideas for data fusion [5] has supported by recent advances in areas such as optimization, machine learning, and soft computing, and the results have been encouraging. As a direct result of this, the MSDF has reached an extremely elevated level of relevance, and the research community all over the world is examining it in detail. As a direct result of this, the data fusion technique is gaining increasing popularity for use in a broad range of robotics, civilian surveillance, and military systems.

In addition, throughout the course of a considerable number of years, MSDF has been of aid in enhancing the monitoring of interactions. Continuous tracking of a contact is needed because it is necessary to keep a record of a moving system. This is necessary in order to continuously record the data from the sensors that are kept on board the system, capture the status of the system, which may include position, velocity, acceleration, [6] and other state variables such as spectral components, expected values of parameters such as temperature, pressure, and salinity and their correlations, and device control strategies to combat the molecular motion. Monitoring a contact in a constant manner. Target tracking is one of the topics that discussed in this piece of work. Target tracking is the process of estimating the status of one or more objects over a period by utilising measurements collected from one or more sources. This can be done for a single object or for multiple objects simultaneously. One set of equations used to predict the state of the target [7], while the second set of equations is used to correct the expected state based on observations from a variety of sensors. In most situations, the algorithms for tracking the target are made up of two distinct sets of equations. If there are several targets that need to be tracked, it is the responsibility of the tracking algorithm to manage the data association operations as well.

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1.1 Evaluation and Monitoring of Progress

Estimation is the process of finding the value of a quantity of interest by drawing conclusions about it from facts that are indirect, imperfect, and uncertain. This approach may traced all the way back to the time of Laplace, when he was working on the so-called "Sunrise problem." [8] Laplace, Legendre, and Gauss were the first people to investigate the difficulty of estimating the parameters of planetary orbits.

Estimation methods are used to a great extent for statistical inference, tracking for the purpose of deciding the position and velocity of a target, and control systems for the purpose of estimating the state variables to control a plant in the presence of uncertainty. All these applications require a great deal of data collection and analysis, which is conducted through the utilisation of estimation methods. The use of estimate methods in statistical inference is among the most prominent uses of these methods. Other common applications of estimation include system identification for the purpose of determining the model parameters necessary for predicting the states, such as in the case of weather forecasting; economic analysis for the purpose of market prediction; communication theory for the purpose of determining the message that was received through a noisy corrupted channel; and signal and image processing for the purpose of determining some parameters or characteristics of an object. Estimation refers to the overarching principle, while tracking is a particular use of that principle. Target tracking is the process of making educated guesses about the whereabouts of one or more targets based on observations made over a period [9]. This procedure may be carried either for a single item or for a large number of objects. The word "states" may be used to refer to any information that was gleaned from an observation. This information can include geometric statuses such as position and velocity, as well as spectrum components, average values, and correlations, among other things. Two examples of unique issues linked with target tracking are "measurement to track association" and "sensor registration." [10] It is vital to take into consideration the computational needs that come along with the distributed processing of target tracks to discover solutions to these issues. There is a possibility that some of the objects include targets on the ground, in the air, or in the sea, in addition to ships and aircrafts. Most of the methods used for tracking targets may be grouped together under the heading of state estimation.

The process of tracking may be conducted by using the readings from a single sensor or from a large number of sensors in concert with one another. When referring to a dynamic system, the word "filtering" refers to the process of estimating the current state [11] of the system based on noisy data. Computational algorithms often arrive at a best solution with reference to a set of criteria to get the best possible result when processing measurements to produce an estimate of a variable of interest. This is done to obtain the most correct result possible.

The repeated calculation of the probability that the state X_k occurs at any time k, given the measurements $Z_k = z_k$ up to time k, is represented in Eqn 1 as the Bayesian approach to solving the generic tracking problem from a Bayesian perspective.

$$Z_k = \{z_k\}\ up\ to\ time\ k. i. e. P(X_N/Z_k). \quad (1)$$

The Kalman filter, which minimises the prediction error in the observation] is a well-known example of a best estimator that has garnered broad notoriety because of its effectiveness. [12] The fact that a best estimator makes the most effective use of the data at their disposal, in addition to one's knowledge of the system and any disruptions, is the major advantage of using such an estimate [13]. The disadvantage of this approach is that it is prone to mistakes in the modelling, and there is also the risk that it will be computationally expensive.

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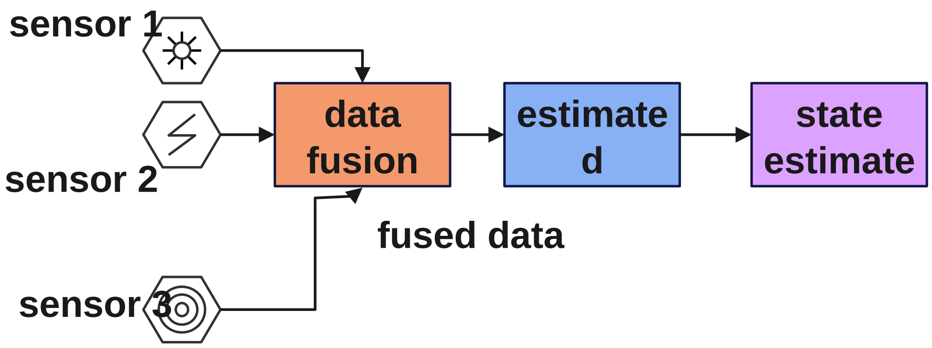

Figure 2 :Sensor Data collection

Academics have been devoting a significant amount of their attention, throughout the course of the course of the last few years, to the problems of how best to integrate information that has been collected from a range of sources to enhance the quality of decision-making. In this setting, the term "decision making" can be understood in a broad sense, and it may be used to refer to both the process of making judgments automatically as well as the process of making decisions by humans based on the outputs of the fusion system. This is because the phrase "decision making" has a broad sense in this setting. To undertake a literature review on the subjects that are relevant to this domain and to encourage exploratory research in data fusion, it is essential to develop a clear definition for the concept of data fusion.

Data fusion refers to the act of merging information or data from various sources for the purpose of estimating or predicting the condition of an object [14]. The identity, qualities, movements, position, and actions of an entity at a certain point in time in the past, in the present, or in the future may all be referred to as that entity's state during that time. The data fusion model, which was developed in 1985 by the US Joint Directors of Laboratory (JDL) Data fusion group, is the method for finding data fusion functions that has garnered the greatest amount of support from the scientific community [15]. According to their explanation, data fusion is "A multi-level process dealing with the association, correlation, and combination of data and information from, single and multiple sources to achieve refined position, identity estimates, and complete and timely assessment of situations, threat, and the significance of their relationship."

The fundamental emphasis of both Level 1 and Level 2 is placed on various methods of numerical fusion that are based on probability theory. These levels are split down into the following categories: The themes that are addressed in these levels include the building of a track, the identification or estimation of information, and the integration of this information received from multiple sources.

They are concerned with both the direct fusing of sensor information (shown in Figure 2) and the indirect fusing of estimates obtained from regional fusion centres (Fig. 3). When it comes to fusing data, these levels supply a variety of obstacles, some of which include multi-target tracking, track-to-track fusion, and distributed data fusion systems.

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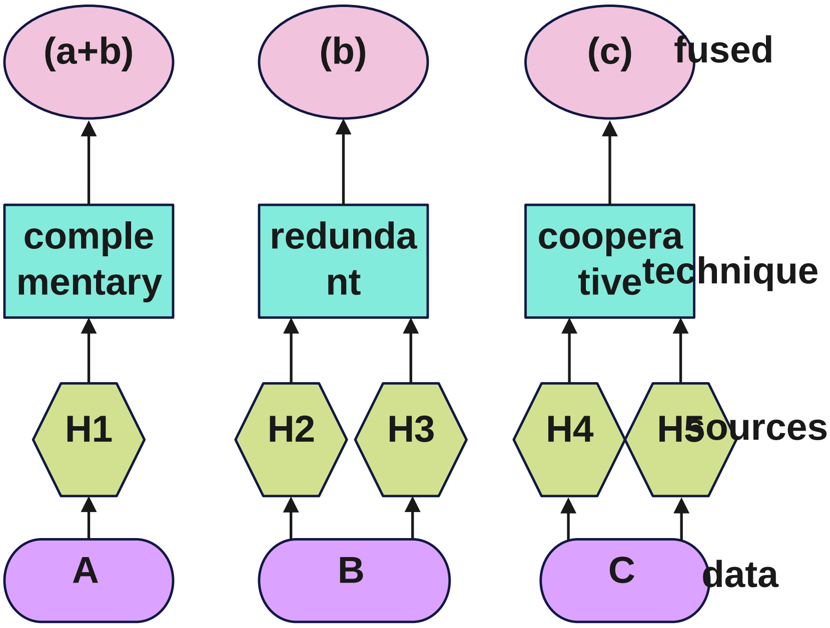

Figure 3: Data Fusion Methods

The process of integrating data from several sensors is a challenging one, and some of the issues that occur as a direct consequence are described in the paragraphs that follow [16].

This happens because of imprecision in the positioning of the sensors as well as ambiguity in the measurements obtained by the sensors themselves. Both factors contribute to the issue. To properly fuse the data, it is needed to manage the large variations in the data that are the consequence of the restrictions showed above [17]. Only then can the fusing of the data be successful.

Outliers and misleading data may be traced back to the environment's inherent ambiguities and inconsistencies, which are the fundamental cause of the problem [18]. The Bayesian modelling approach may be used to find discrepancies in sensor data. This can help reduce the amount of mistaken data that is produced because of the fusion process, which eventually leads to a more correct estimate of the state variable that is desired.

Data that are in direct opposition to one another: The combining of facts that conflict with one another has the potential to supply very deceptive results, when the system that combines the data employs evidential belief reasoning, as it does in Dempster's rule of combination [19].

Data corruption due to the presence of associated noise: It is usual for some nodes in wireless sensor networks to be exposed to external correlated noise. Therefore, the measurements that are acquired from these nodes are likely to be mistaken. For such systems to function properly, the algorithms that are used to combine the data must take into consideration the connections that exist between the data.

Prior to beginning the fusion process, the first stage is called "data alignment," which is also known as "data registration." This phase entails converting data from the local frame of a sensor into a common frame. When radiographic and geometric modifications are made to frames that have been received in a satellite image, for instance, here is an illustration of the kind of corrections that are included in this category.

This problem often arises in multi-target tracking systems or while tracking single targets in environments with a lot of clutter, both of which are common scenarios. The association problem may be split down into two distinct categories: track-to-track association and measurement-to-track connection. The former method finds from which target, if any, a measurement was collected, while the later method concentrates on discriminating and combining many tracks [20].

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Both centralised and decentralised systems are used extensively throughout the data fusion procedure. These are the two primary types of frameworks. Even though centralised systems are more often preferred for surveillance in general, decentralised solutions are better suited for usage in wireless sensor networks. This is the case because of the nature of the networks themselves. It is necessary to have an elevated level of computer and data processing skills to perform centralised introduction, development, and evaluation of multi sensor data fusion systems, but decentralised systems may work effectively with a decreased ability for processing data if they are designed properly.

It is possible that the data will be received in an order that is not consecutive because of the varying operating frequencies of the sensors, as well as the asynchronous nature of the sensors themselves. Because of this, it is essential to make use of a number of different time scales and to conduct reliable resampling.

It is possible for the pre-processing of measurement data to take place either locally at each sensor node or globally at the fusion centre. Either way, the pre-processing of measurement data contributes to the compression of the data into data with smaller dimensions, with the understanding that some data is lost in compression. By lowering the amount of communication bandwidth and power that is needed for data transmission, this pre-processing helps to save money [20].

When compared to the data from a single sensor, the information obtained via the fusion of data from many sensors offers several benefits. The fusing of data from many sensors does, in fact, give these benefits, even though the process of data fusion requires a significant amount of processing resources and that it entails a number of problems. The ease and low cost of installing a large number of sensors is one of the things that inspired the development of MSDF. In addition to the statistical benefits gained from a better estimate of a physical phenomenon achieved via the accumulation of added independent observations, the use of a wide variety of sensors contributes to an improvement in the observation's level of precision. This improvement can also be attributed to the accumulation of added independent observations. Naturally, MSDF stands out as a technique that must be considered in a substantial number of practical applications, which increases the desire for added research and emphasises the significance of doing such research.

2. Related Work

The act of gathering observations of the world and drawing conclusions based on those observations is what is meant by the term "sensor data fusion" in a more general sense [21]. The term "data fusion" may be understood in a variety of ways, all of which can be discovered in the relevant academic literature. According to the Joint Directors of Laboratories, "data fusion" is a "multi-level, complex process managing the automated identification, association, correlation estimation, and integration of data and information from many sources" (JDL). [22] This term is included in the JDL's definition of data fusion, which you can find here. According to [23] who supplies a definition that is more all-encompassing, data may originate from a sole source, or they can originate from a number of diverse sources all at the same time. The authors of present a review and discussion of a large number of potential data fusion definitions in [24] may be found online. The following definition of information fusion was presented by [25] and it is as follows: "The study of efficient ways for automatically or semi-automatically converting information from several sources and different points in time into a representation that effectively supports human or automated decision making" is what "the study of information fusion" refers to.

The JDL categorization system was designed for use in the armed forces. It is predicated on the inputted data as well as the outputs that are produced by the system. The technique for fusion is split down into four more general steps in the first version of the JDL model. These stages are referred to as the object stage, the scenario stage, the impact stage, and the process refinement stage. The JDL model has a number of drawbacks, including the fact that it is excessively restrictive and is specifically tailored to the needs of military applications. Even though it has achieved a lot of popularity, it still has a lot of these issues. As a direct consequence of this, a number of different suggestions for enlargement [26] have been developed to alleviate them. Dasharatha’s framework [27] was a different approach to the JDL model, which views the fusion system, from the perspective of software engineering, as a data flow characterised by input/output as well as functionality or processes. Dasarathy's framework was an alternative to the JDL model. The Dasarathy model is a framework that was set up as a reaction to the JDL model.

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Another generalisation of fusion was presented by [28], and this one is based on the concept of random sets as its foundation.

Because the inherent imperfection of the data is the most challenging problem that may occur with data fusion systems, a significant amount of research effort has been focused on the development of potential solutions to this issue. It is possible for a number of distinct mathematical theories, such as the probability theory [29], to be used to express the imperfection of data. These conceptual frameworks or scientific approaches reflect certain aspects of the flawed data. For instance, uncertainty may be modelled as a probabilistic distribution; ambiguity of data can be modelled using fuzzy set theory; and evidential belief theory can describe both uncertain data as well as ambiguous data at the same time.

Since the dawn of time, anytime humans have needed to deal with any kind of flawed information, they have resorted to probability theory. Fuzzy set theory and evidential reasoning are two alternative methodologies that have been proposed in the literature to deal with perceived restrictions in probabilistic approaches. These limits include, but are not limited to, complexity and accuracy of models, to name just a few examples [30]. The following are some of the negatives, however the list is not exhaustive: Together, the data fusion algorithm and its many different iterations are working toward the same aim of developing an approach to the imperfection of the data that is more comprehensive and all-encompassing.

Two examples of hybrid frameworks that have been constructed are fuzzy Rough Set theory and fuzzy Dempster Shafer theory [31] respectively. As an alternate approach, the author of this proposed work suggests using a probabilistic fusion technique in conjunction with fuzzy set theory. As a result, we will now go on to conduct an in-depth analysis of the theoretical foundations supporting both methods.

Table 1: Survey of Background Work

Framework	Characteristics	Capabilities
[32]	Represents sensory data using probability distributions fused together within Bayesian framework	Well established approach to treat data uncertainty.
[34]	Relies on probability mass to characterize data using belief and plausibility and fuses uses Dempster's combination rule.	Enables fusion of uncertain and ambiguous data
[35]	Allows vague representation using fuzzy membership, fusion based on fuzzy rules	Intuitive approach to deal with vague data
[36]	Similar in data representation to probabilistic and evidential framework and fusion to fuzzy framework.	Handles incomplete data, common in poorly informed environment.
[37]	Deals with ambiguous data using classical set theory operators.	Does not require any preliminary or additional information

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When checking targets with a probability of detection that is lower than one, connecting the data is a fundamental need to account for the possibility of false alarms. To discover an answer to this problem, a number of distinct algorithms have been developed. The SNF and the NNF are both basic ways that may be used to solve this problem. You can choose any one of them. Among the measures that have been checked, the signal that has been proven to have the highest strength is the one that is used for track updating in the SNF. The other signals are disregarded as invalid. The measurement that is used in NNF is the one that is determined to be the one that is closest to the one that was expected. As it comes to tracking targets, these algorithms work very well in surroundings with little distractions; nevertheless, when the number of false alarms increases or when dealing with low-observable items that are moving, they start to fail. An alternative approach is the Probabilistic Data Association Filter, which is both highly efficient at tracking a single target even when there is a lot of clutter present and quite correct in its results (PDAF). Instead of using just one measurement out of the ones that were received and discarding the others, the PDAF method uses all the confirmed measurements with varied weights. This is done rather than selecting just one measurement to use out of the ones that were received. In contrast to this, conventional methods only make use of a single measurement out of all the ones they get. In the statistical technique known as Fuzzy Recursive Least Squares-Probabilistic Data Association, PDA is the part that is used to generate the merged measurement (FRLS-PDA). After that, FRLS is used to make an estimation of the current condition of the aim. This approach has been shown to be superior to both the PDAF and the IMM-PDA filter. It is more difficult to correlate data together when there are numerous targets since a measurement in and of itself may be confirmed by many tracks. This makes it more difficult to decide which measurements are relevant. By analysing the measurement to check association probabilities and combining the results to obtain the state estimate, the Joint Probabilistic Data Association (JPDA) method may be used to track numerous targets. This may be achieved by assessing the measurement to keep track of the association probabilities.

3. Proposed Work

It presents an original concept known as membership in just portion of a collection. A fuzzy set denoted by the notation FX that is defined using the generic gradual membership function _F (x) in the interval [0,1] and written as _F (x) [0,1]. The higher the membership degree, the greater the amount of x's affiliation with F. Fuzzy rules are used to integrate fuzzy data to generate fuzzy fusion output. Categories for conjunctive and disjunctive relationships are included inside the fuzzy fusion rules. The standard intersection and product of two fuzzy sets are both examples of the conjunctive category. These examples are provided by Equations 2 and 3, respectively.

$$\mu_1^{\cap}(x) = m \quad [\mu_{F1}(x)\mu_{F2}(x)]\forall x \tag{2}$$

$$\mu_2(x) = \mu_{F1}(x)\mu_{F2}(x)\forall x \in X \tag{3}$$

Examples of disjunctive fusion category are standard union and algebraic sum of two fuzzy sets given by Eq. 4 and Eq. 5 respectively.

$$\mu_1^{\cup}(x) = m \quad [\mu_F(x)\mu_{F2}(x)]\forall x \in X \tag{4}$$

$$\mu_2^{\cup}(x) = \mu_F(x) + \mu_{F2}(x) - \mu_{F1}(x) \cdot \mu_{F2}(x)\forall x \in X \tag{5}$$

The use of conjunctive fuzzy rules is seen as being acceptable for the process of fusing data that was obtained from sources that were both equally dependable and homogenous. Disjunctive fusion rules are used on the other hand when combining data that is extremely contradictory or when one of the sources is considered credible even though it is unknown which of the sources is reliable. In addition to this, there are certain fuzzy fusion rules that were designed as a middle ground between the two groups. In a manner like that of probability theory, which requires previous knowledge of probability distributions, fuzzy set theory necessitates prior knowledge of membership functions for various fuzzy sets. Experts in linguist data that was provided by humans may be linked with probabilistic get better outcomes if fuzzy set theory is used. This is because fuzzy set theory is a strong tool that can represent imprecise data.

The Shannon information (entropy) H p (x), which relates to a probability distribution P(x), is calculated based on the random variable x

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$$H_p(x) ≜ -E\{log\, P(x)\} \qquad (6)$$

For continuous distribution, $H_p(x) = -\int_{-\infty}^{\infty} P(x) log\, P(x) dx$
For discrete distribution, $H_p(x) = -\sum_{x \in X} P(x) log\, P(x)$
Fisher information is defined as second derivative of log likelihood.

$$J(x) = \frac{d^2}{dx^2} log\, P(x) \qquad (7)$$

When dealing with estimation problems that include several sensors, the IF performs much better than the more conventional KF. It was said that the information that was produced from each given sensor might be found in the following, in the form of kik and its co-variance: As demonstrated by Equations 7 and 8, respectively, it is feasible to add kik to the information state as well as the information matrix. The information that is acquired from the different sensors is integrated in a linear way to decide the update estimate of the information state and the information matrix, as showed in equations 8 and 9. This is the consequence of extending the principles to a large number of sensors.

$$y_{kik} = y_{kik-1} + \sum_{k=1}^{N} \quad i_k^s \qquad (8)$$

$$Y_{k/k} = Y_{k/k-1} + \sum_{t=1}^{N} \quad I_k \qquad (9)$$

where, N refers to the number of sensors. Finally, the estimated state of the target is given by

$$X_{k/k} = Y_{k/k}^{-1} y_{k/k} \qquad (10)$$

The $X_{k/k}$ estimated value may be compared to the estimate in the case of PDA, which uses the EKF for the purpose of fusing the inputs from a number of different sensors. In the case of PDA, an estimate cannot be generated by just adding together the contributions provided by each sensor to obtain a cumulative total. The estimate is obtained from a weighted aggregate of the contributions made by each individual sensor in the form of innovations rather than directly from the sensors themselves (where the weights are likelihood functions). In KF-based fusion, the input from each sensor is not associated, but the innovations that were made by the sensors are correlated. Because the IF combines the data bought from a variety of various sensors, the filter in question is referred to as an information fusion filter. This moniker came about because the IF integrates the data.

At the event that all the information is made available to the sensor suites, the fusion may be conducted in a single centralised location, or it may be conducted independently by each of the sensor suites. Because of this, the IFF can execute a decentralised fusion algorithm.

As was said previously, the information measurements that are derived by each sensor are broadcast to all the other sensors to allow for an estimate to be produced on the state of the target. During a normal BOT problem, the information that different sensor suites that are in various locations buy from the bearing observation is often exchanged across those sensor suites. The measurement that is used in Equation 10 is represented as a vector with a single dimension. In a typical scenario, there would be four different fixed sensor suites, each of which would be situated in a different area geographically speaking, and they would all be tracking the same moving target (Fig. 4). Each sensor will only get the bearing update, which is represented by the symbol $X_{k/k}$that is pertinent to its location at any given time k. It is believed that the sensors are associated with unique differences in the measurements that they provide

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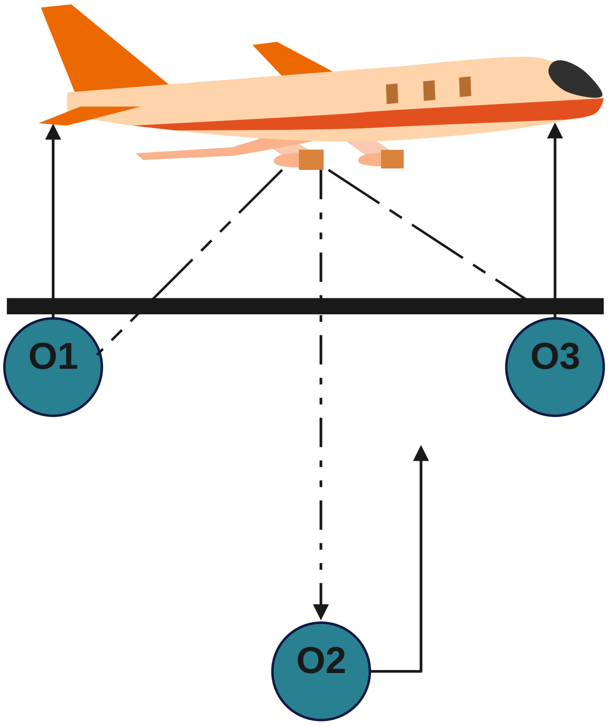

Figure 4: Target Detection

The simulations that are presented below for the situation that is depicted in Figure 4 demonstrate the fusion of measurements from multiple sensors. These simulations also give interesting leads regarding the dependence on initial assumptions on target positions, errors in plant and measurement, to obtain sustained tracking by utilizing the IFF.
We will assume that the target state X at time k, denoted by Xk, is a four-dimensional vector that represents the x and y positions of the target as well as the velocities in both the x and y directions. The definition of the state vector at any given time k is as follows:

$$X_k = [x_k, y_k, v_{xk}, v_{yk}] \tag{11}$$

where, x_k, y_k, v_{xk}, v_{yk} are the x position, y position, x velocity, y velocity respectively at time k. It is assumed that the target follows a CV model, and the state evolves in time according to

$$X_k = A_{k-1}X_{k-1} + Gw_k \tag{12}$$

G is defined as shown below:

$$G = [T^2/2\ 0\ 0\ T^2/2\ T\ 0\ 0\ T\ ] \tag{13}$$

where T is the duration between samples. The readings of the bearing angle at any given time k are represented by the equation Z ki, where i=1,23 and 4 refer to the four sensors. According to the non-linear observation model established in earlier proposed works, the sensors perform their observations of the target in accordance with the formula Z k=h (k, X k) +v k. The covariance of the measurement error, denoted by R, as well as the covariance of the plant, denoted by Q, are shown in the following table.

$$R = E[v(k)v(k)] \tag{14}$$

$$Q = E[\{Gw(k)\}\{Gw(k)\}] \tag{15}$$

4. Experimental Results and Analysis

The situation that is being analysed is the same as the one in Case 1, with the exception that it is assumed that the starting state of the target (for all sensors) is [7700 m, 9700 m, 4.9 m, 2.9 m], which is a less ideal starting state than the one that was assumed in Case 1. The situation that is being analysed is the same as the one in Case 1. The actual and estimated track of the target, as well as the mean squared error (MSE) in both the location estimate and the velocity estimate, are displayed in Fig. after the filter was run for 850 iterations. Additionally, the mean squared error (MSE) in both the location estimate and the velocity estimate is shown.

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In this case, the same thing that was seen in Case1 was observed: the filter was proved to follow the target for a time, but it finally started to display a predisposition to diverge from the target. This was the same thing that was seen in Case1. It is plainly clear, as shown by the scenario diagram in Fig. 3.

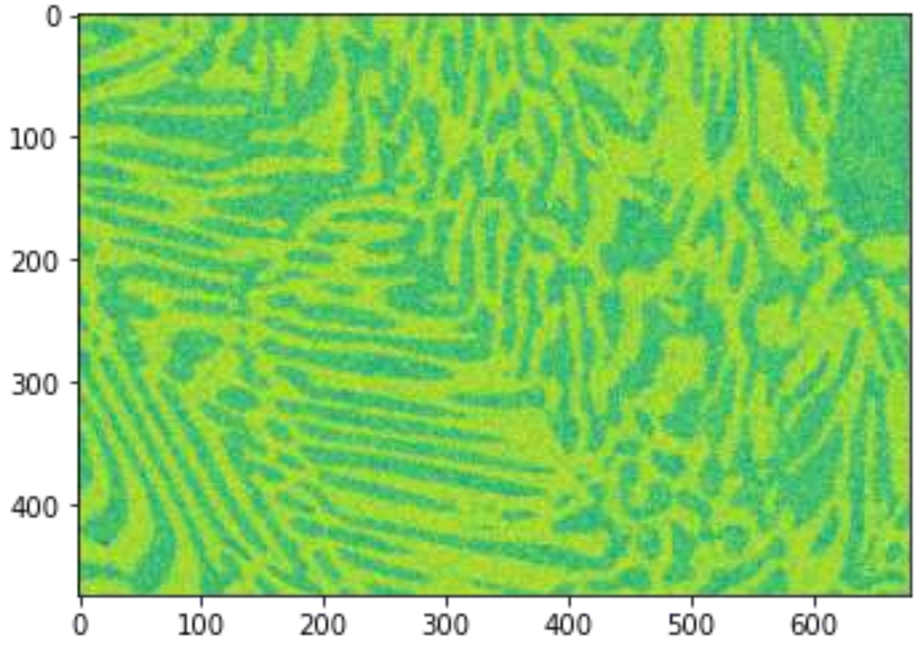

Figure 5: Example of simulation

It manages the problem of information filter divergence, which arises while trying to track an object based merely on its bearing. The FIFF that has been described in this proposed work has been proved to enable effective control over the divergence problem. This is conducted by altering the standard deviation of the measurement error, which is denoted by the letter R. Even though the measurement variance has an impact on the total length of time it takes, both the position estimate and the velocity estimate have a propensity to converge. This is the case even though both estimates tend to converge. This proposed work presents a comparison between the IFF that was reported in the literature and the FIFF that was suggested in this proposed work. The results of the comparison are described in this proposed work. During the comparison, the actual track and the anticipated track, as well as the mean squared error in the location of the track, and the velocity in both the x and y directions, are taken into consideration.

The study also shows that the FIFF has a stronger tracking capability than the FIF, illustrating the advantages of using many sensors to check a target.

Table 2: Parameters and the distance captured

Parameter		Distances (in cm)				
Correct Distance (TMD)	10.00	80.00	290.00	300.00	400.00	
US Sensor reading	10.23	77.86	284.00	293.90	392.20	
The output of the	Tri MF	8.08	77.47	290.76	300.96	400.47

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neuro-fuzzy system based on	Trap MF	9.61	79.30	290.13	300.23	399.84
	Gauss MF	9.57	79.32	290.09	300.20	399.77
	Gauss2 MF	9.60	79.29	290.09	300.17	399.75
	P Sig MF	9.27	79.11	290.09	300.25	399.87
	Pi MF	9.27	79.11	290.09	300.25	399.87
	dSig MF	9.13	79.01	290.18	300.29	400.05

After 650 iterations, the mean square error in the estimate decreases from 140 metres to 50 metres, which leads to better tracking in comparison to Case 3. When compared to Case 3, it is possible to draw the conclusion that the MSE in position estimation decreases to a greater degree when the Information Fusion Filter is used in target tracking Development and Evaluation of Multi sensor Data Fusion sensors that have significantly larger measurement variances. In IFF, it has been discovered that when R has a value that is quite high, the MSE in estimating decreases significantly before the filter starts to diverge for the same first estimate as when R has a value that is exceptionally low. This occurs for the same reason that when R has a value that is exceptionally low, the filter starts to diverge. In contrast to this, when R has a value that is exceedingly low, this outcome occurs. When compared to exceptionally low values of R, it is seen that when R is quite big (Case 4), the filter requires a longer amount of time to reach its minimal MSE value. This contrasts with when R is relatively small, which only requires a short amount of time for the filter to reach its minimal MSE value (Case 3). An added point to keep in mind is that an information filter is still capable of following a target even if it does not have a particularly good first estimate; nevertheless, the mean squared error (MSE) in position estimation will not be as low as it is when there is a relatively accurate estimate. Research has been done into the influence of R and the assumption of starting state X on the performance of the information fusion filter. This research was done for each scenario that was analysed for the purpose of this proposed work. The value of Q was assumed to be somewhat low in each of these scenarios.

The MSE in tracking may be reduced to some degree, albeit not entirely, by the process of fine-tuning the state process error covariance matrix, Q. This procedure, however, will not cut the MSE entirely. The information filter is not too sensitive to changes in Q that are just marginally significant. The filter will only be sensitive to Q in the case that the procedure has been misrepresented in some way. The literature does not concentrate on the divergence of information filters even though a large number of researchers have investigated the divergence of the EKF. The tendency of the filter to diverge after the error has been reduced to a low value is a topic that needs more investigation.

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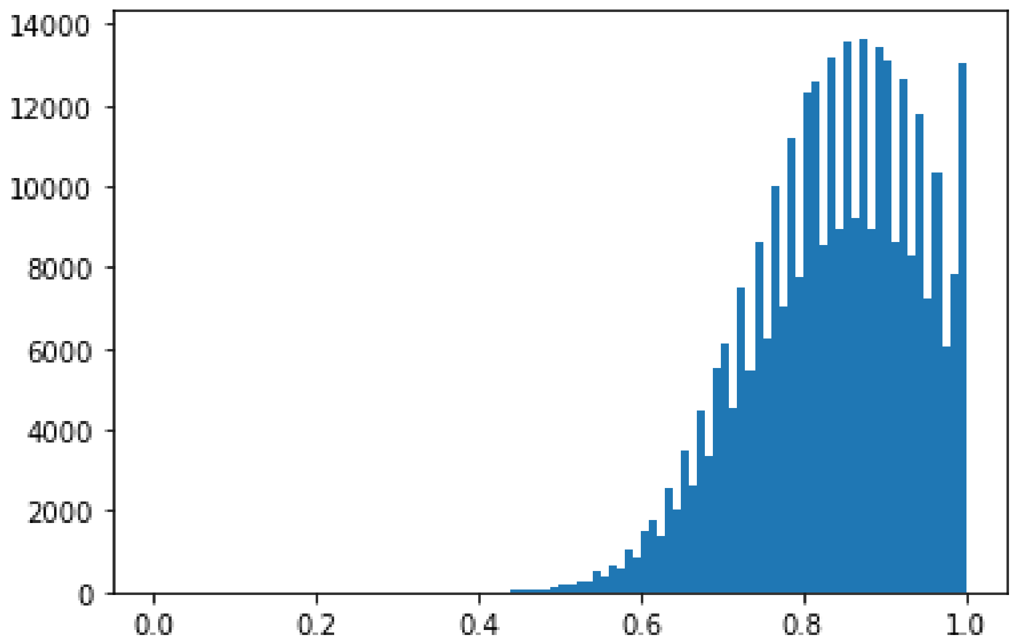

Figure 6: range of the object detected

The following values were used for the parameters of the input membership functions mf1, mf2, and mf3 in the system that was based on the D-Sigmoidal membership function: [0.07986 -80.43 0.05998 107.7], [0.04181 107.7 0.1021 295.8], and [0.1051 295.8 0.07995 483.9]. [1.027 -1.428], [1.015 1.854], and [1.015 2.142] were the values that were used for the parameters of the output membership functions mf1, mf2, and mf3, respectively. It is essential to take notice that the calculated range of input MF using the MATLAB® toolbox is found to be [9, 400], and the kind of MF that is produced is linear. This information is very crucial. This is something that must be considered, so keep that in mind. Table 6.4 displays the findings of an investigation of the efficiency of the different forms of membership function, which was conducted. The neuro-fuzzy system that is based on Gaussian MF yields 79.32 cm, even though the real distance value (TMD) is 80 cm. In contrast to this, the reading that was obtained from the sensor found in the United States was 77.86 cm. After doing research on the whole dataset, it was found that the Gaussian membership function delivers the lowest RMSE when compared to the other membership functions. This was decided because of the study that was conducted. The proper distance for this collection of data varied from 10 centimetres to 400 centimetres.

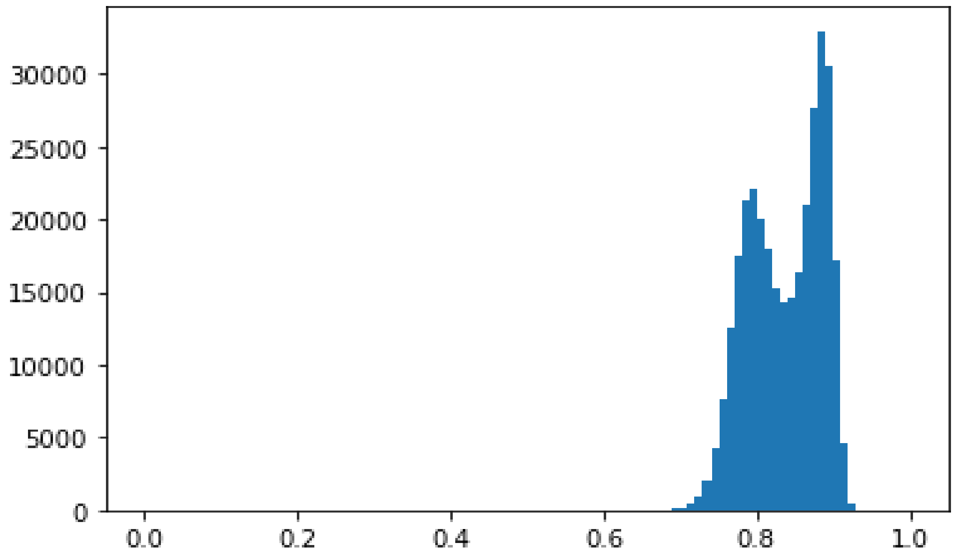

Figure 7: Range of The Input Detected

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Figure 7 is a visual representation of the Homogenous Ranking Factor tolerance, and it also supplies information on the data dependability score in relation to the distance that separates the fusion node from the sink. Figure 7 illustrates that despite a rise in the value of the Immediacy Factor (IF), the Homogenous Ranking Factor tolerance is best for curves with CPF=3000 and TX=30m when compared to curves with CPF=6000 and TX=60m. This is the case even though the value of the Immediacy Factor (IF) has increased. This is since curves whose CPF values are 3000 and whose TX values are 30 metres have a lower value of the Immediacy Factor (IF) than curves whose CPF values are 6000 and whose TX values are 30 metres. The fact that the IF values are climbing to greater levels does not change the reality that this is still the case. It would seem from the occurrence of this event that PEE-DF is using an optimization strategy that is more effective than others.

It is possible to see that the heterogeneous ranking factor reaches its maximum value simultaneously with the expansion in the total number of nodes when the number of fusion nodes is increased from 30 to 40 and then to 50. This can be seen when the number of fusion nodes is increased from 30 to 50. In both cases, this is the situation. This is clear from the remark that was made before the one that is being considered here. Therefore, it is a plausible argument to suggest that the possibility of unique incoming data being indexed grows in proportion to the number of heterogeneous ranking components that are already present in the system. This is something that may be described as "the possibility of one-of-a-kind incoming data being indexed".

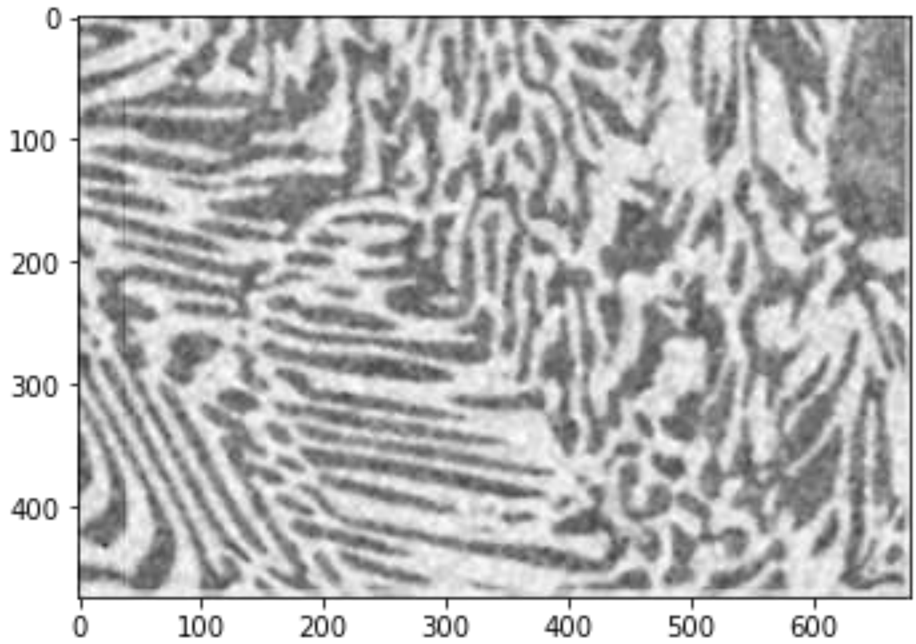

Figure 8: grey scale images

According to Fig. 8, the performance of the suggested algorithm resulted in an increase in the percentage accuracy of the ultrasonic sensor from 97% to 99%. In Figure 8, the labels US1, US2, US3, and US4 correspond to the percentage of accuracy of the sensors with respect to TMD. On the other hand, the labels FIS1, FIS2, FIS3, and FIS4 correspond to the percentage of accuracy of the output of a neuro-fuzzy system based on a Gaussian membership function with respect to TMD in three different experiment trials.

According to the TMD and SMD data that was gathered from a total of four sensor modules (S1, S2, S3, and S4) over a total of four separate trials (T1, T2, T3 and T4) To begin validating the importance of the suggested neuro-fuzzy model, linear regression and non-linear regression models were originally created and tested. A parametric model with one or more coefficients is required for the regression process that is based on the Ordinary Least Square (OLS) approach. This model must tie the TMD to the SMD and the output of ANFIS (which is related to the SMD). The technique of least squares looks to find the estimated coefficients of variables by minimising the sum of the squares of the residuals.

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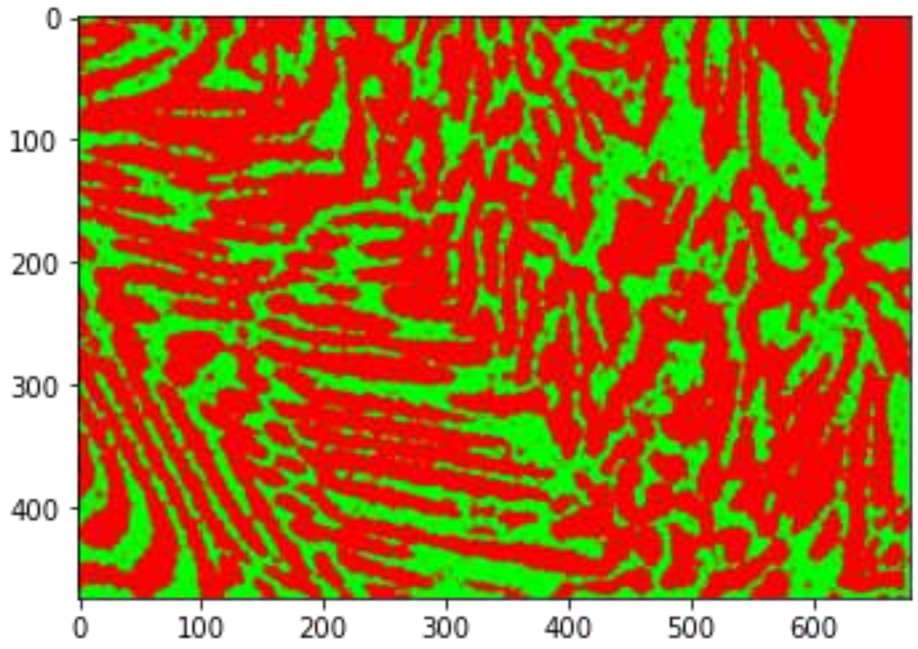

Figure 9: Iteration 1 Segmented Region

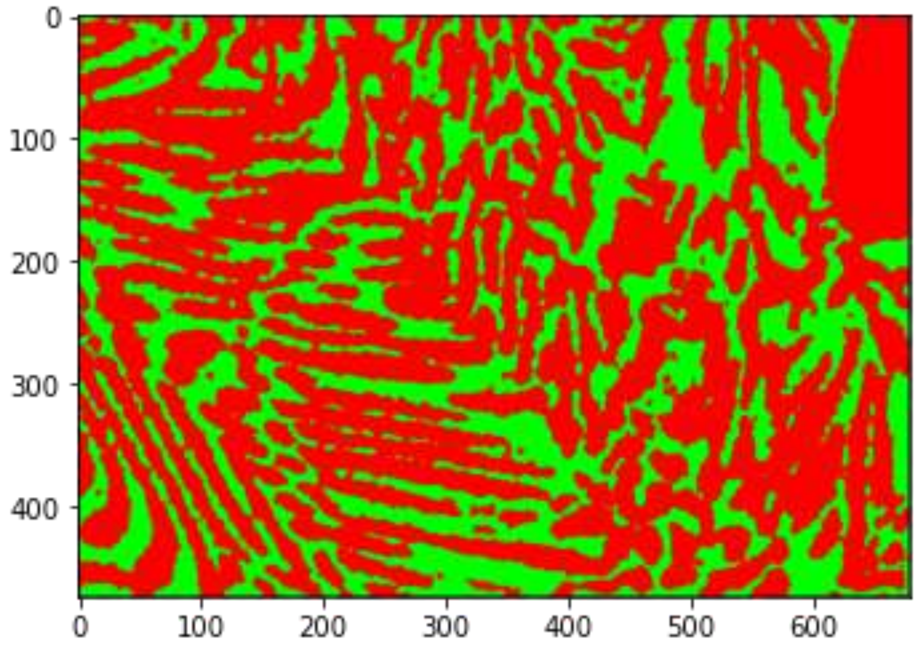

Fig 10: Iteration 2 Segmented Region

The benefit of using such a model is that it produces less errors (in comparison to conventional regression models) and reduces the amount of unnecessary processing (in contrast to a neuro-fuzzy system), in addition to being simpler to put into practise.

The correct distance was 80 cm. Both the linear and non-linear regression expressions, which are constructed based on the neuro-fuzzy system (Eqn. 10, Eqn 11), have the potential to offer a 98 value of 79.39 cm and 79.32 cm, respectively. It is important to note that the performance of the neuro-fuzzy system and regression based on the neuro-fuzzy systems was much better than that of the traditional regression models at the greater distance values. This is something that can be seen. The results of the algorithm were compared to those obtained by an ultrasonic rangefinder model CP-3007 that is available for purchase.

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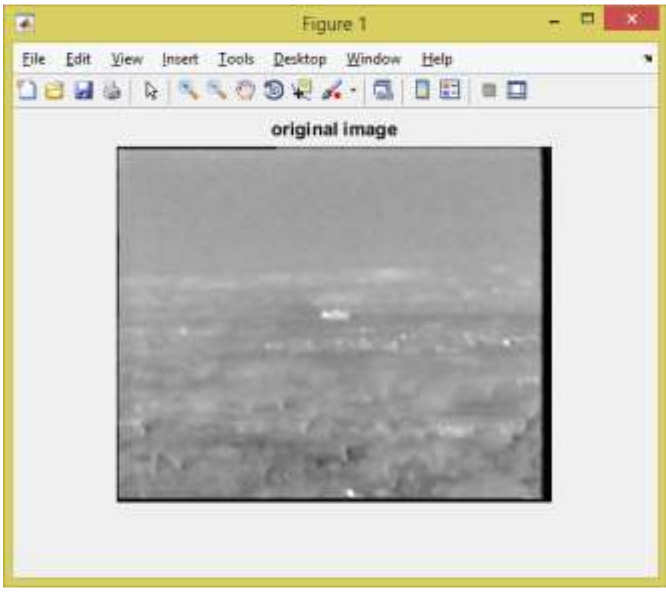
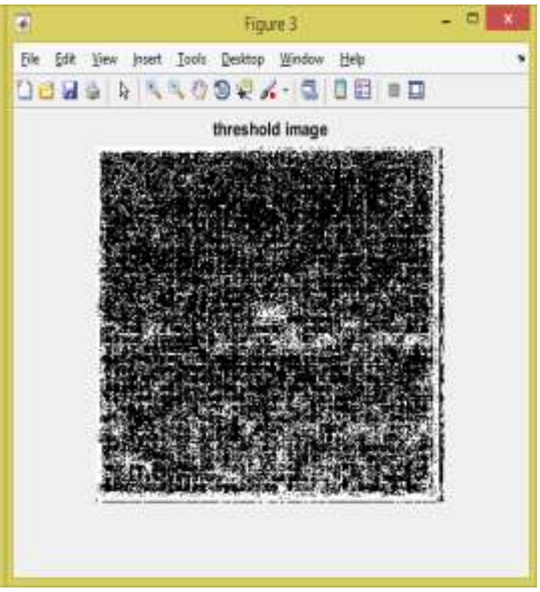
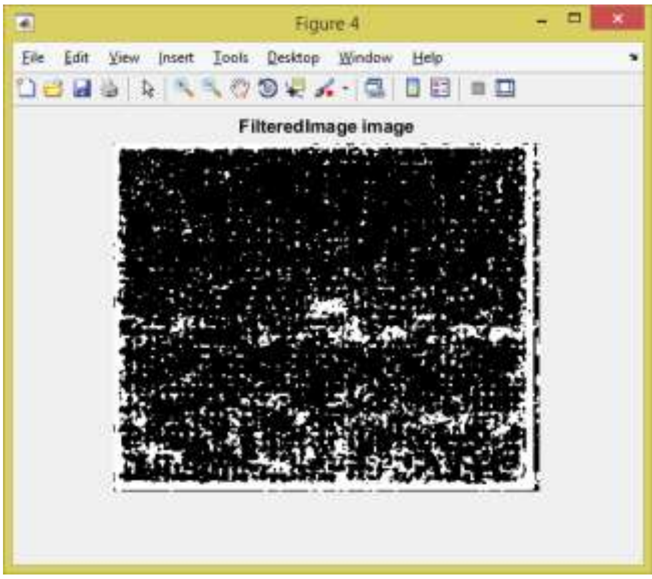
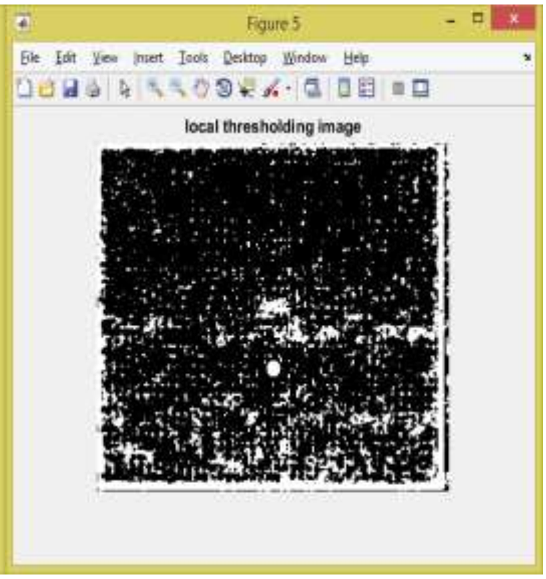




(a) (b)





(c) (d)

Figure 11: Detection of Targets at Each Stage of Processing

The accuracy of the sensor is going to be improved over its whole measurement range because of the work that is going to be done. The percentage of accuracy of the sensor, denoted by US, was found to be 97.14 percent, while the output of the neuro-fuzzy, denoted by G MF, was found to be 99.42 percent. The regression model (LR G) yielded an accuracy percentage of 98.93% when it was applied to the data. When performing a reading on the sensor's full scale, it is possible to see that the suggested approach results in an accuracy that is 2% more precise than the earlier one (i.e., from 2 cm to 4 m). The greater measuring range of the sensor is mostly affected by the 2% gain in precision that has been achieved. To confirm the same, three independent boxplots were constructed at the proper distance (TMD) of 10, 200, and 400 cm. The minimum error was found at 10 cm, while the moderate error was found at 200 cm, and the maximum error was found at 400 cm (max. error)

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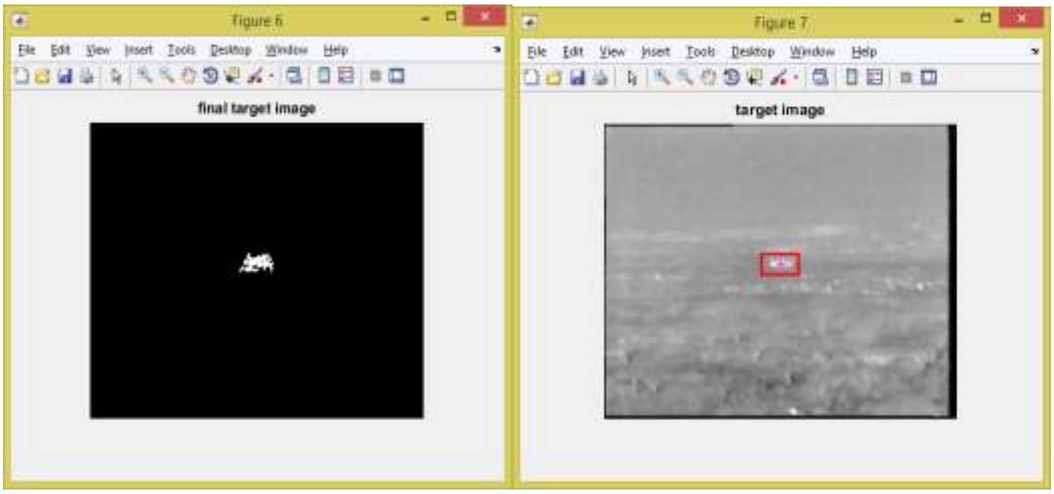

(a)   (b)

Figure 1: Detected target from radar images

The mobile robot was stationed up against an obstacle in the form of a concrete wall and was given permission to move for every 10 centimetres over the whole of the sensor's measuring range. Figure presents an analysis of the suggested method's absolute error in comparison to the correct distance (TMD). The proposed approach is based on a regression model, a Gaussian-based neuro-fuzzy system, and the data from a commercial range finder. The terms "error of ultrasonic sensor," "output of corresponding Gaussian-based neuro-fuzzy system," "output for linear/non-linear regression models based on neuro-fuzzy system," and "output from the commercial sensor based on ultrasonic sensor" are referred to by the abbreviations "US," "G MF," "LR(G)," and "NLR(G)," respectively.

The root means square error (RMSE) of the SMD compared to the TMD, the outputs of the Gaussian system, linear regression, non-linear regression, and the commercial sensors were, respectively, 6.45 centimetres, 0.89 centimetres, 1.77 centimetres, 1.72 centimetres, and 1.03 centimetres.

5. Conclusion

The purpose of this proposed work was to create and evaluate multi-sensor data fusion algorithms for bearing-only target tracking, and those methods are presented here (BOT problem). The research community has created a number of methods for fusing data from numerous sensors, and they are all based on the EKF algorithm or one of its modifications. These methods have been used to investigate a range of questions, including Both the PDAF algorithm and the variance-based fusion algorithm are examples of practical applications of computational techniques that are often put into action. The variance-based fusion approach was examined in this body of work, and it started with the proposed work that the availability of states predicted by independent EKF, in addition to its variance for each sensor suite, was a given. This supposition was evaluated using the variance-based fusion method. After that, the variance-based fusion technique was used so that the states of the target that were being checked and evaluated could be combined. To do this, it was necessary to take a number of different situations into consideration, each of which began with a unique set of assumptions and had varying degrees of measurement inaccuracy. The mean squared error in the position estimate of the target was another measure that was used in assessing the performance of MSDF. It was inferred that sensors with strong first assumptions of states create excellent predictions of the target state. This conclusion was reached based on the results of variance-based fusion tracking. While it was also saw that the fused estimate was always better than the poor estimates, it was discovered that the fused estimate was not as excellent as the best estimate that could be derived from the combination of all the inputs that were considered for the fusion. This discovery was made even though it was seen that the fused estimate was always better than the poor estimates. The results of the simulation tests have shown that the use of variance-based fusion in target tracking is an approach that is successful. Although fusion was used, it was intriguing to see that first estimates were insufficient, and measurement variances were exceptionally large, which often resulted in the ultimate loss of track.

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Because of this, a more in-depth investigation of the topic of divergence was conducted later while writing my proposed work.

The PDAF approach of fusing data to generate the track has showed excellent performance in a number of different simulation environments. However, each one of these algorithms had to work around the problem of divergence to function properly. According to the study that has been done so far, divergence is one of the most significant characteristics that plays a role in deciding success in all BOT competitions.

The effective algorithm known as the filter for the merging of information, IFF, which is a casting of EKF, is based on a decentralised approach that fuses the information that is acquired from a variety of sensors. This method is a casting of EKF. The information matrix is what is used to extract the states from the information that has been combined. The author of this proposed work made the decision to study how effectively IFF functioned in a variety of different target tracking settings, even though IFF is amazingly simple to compute. In a common configuration, there may be four unique sensors that are kept at great geographical distance from one another and that collaborate with one another to detect the movement of the thing that is being followed.

It was concluded that IFF was a beneficial alternative to EKF-based fusion filters in target tracking after looking at a number of different situations with changing values of Q, R, and beginning estimate X. This conclusion was reached after looking at a variety of different scenarios. On the other hand, IFF tends to go in different directions.

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References

[1] D. L. Hall and J. Llinas, “An introduction to multisensor data fusion,” Proceedings of the IEEE, vol. 85, no. 1, pp. 6-23, 1997. DOI: 10.1109/5.554205.
[2] B. Khaleghi, A. Khamis, F. O. Karray, and S. N. Razavi, “Multisensory data fusion: a review of the state-of-the-art,” Inform. Fuss., vol. 14, no. 1, pp. 28-44, 2013. DOI: https://doi.org/10.1016/j.inffus.2011.08.001.
[3] S.-L. Sun and Z.-L. Deng, “Multi-sensor optimal information fusion Kalman filter,” Automatica, vol. 40, no. 6, pp. 1017–1023, 2004. DOI: https://doi.org/10.1016/j.automatica.2004.01.014.
[4] P. Vadakkepat and L. Jing, “Improved particle filter in sensor fusion for tracking randomly moving object,” IEEE Trans. Instrum. Meas., vol. 55, no. 5, pp. 1823-1832, Oct. 2006. DOI: 10.1109/TIM.2006.881569.
[5] J. Yuan, H. Chen, F. Sun, and Y. Huang, “Multisensor information fusion for people tracking with a mobile robot: A particle filtering approach,” IEEE Trans. Instrum. Meas., vol. 64, no. 9, pp. 2427-2442, Sep. 2015. DOI: 10.1109/TIM.2015.2407512.
[6] R. C. Luo, Y. T. Chou, C. T. Liao, C. C. Lai, and A. C. Tsai, “NCCU security warrior: An intelligent security robot system,” in Proc. 33rd Annu. Conf. IEEE Ind. Electron. Soc., Nov. 2007, pp. 2960–2965. DOI: 10.1109/IECON.2007.4460380.
[7] M. Kam, X. Zhu, and P. Kalata, “Sensor fusion for mobile robot navigation,” Proceedings of the IEEE, vol. 85, no. 1, pp. 108-119, Jan. 1997. DOI: 10.1109/JPROC.1997.554212.
[8] E. Waltz and J. Llinas, Multisensor Data Fusion. Norwood, MA, USA: Artech House, 1990 ISBN: 978-0890-06277-7.
[9] M. Markin, C. Harris, M. Bernhardt, J. Austin, M. Bedworth, P. Greenway, R. Johnston, A. Little, and D. Lowe, “Technology foresight on data fusion and data processing,” Publication of The Royal Aeronautical Society, 1997.
[10] R. C. Luo and M. G. Kay, “A tutorial on multisensor integration and fusion,” in Proc. 16th Annu. Conf. IEEE Ind. Electron. Soc., 1990, vol. 1, pp. 707–722. DOI: 10.1109/IECON.1990.149228.
[11] R. Alami, R. Chatila, S. Fleury, M. Ghallab, and F. Ingrand, “An architecture for autonomy,” Int. Journ. Robot. Res., vol. 17, no. 4, pp. 315–337, Apr. 1998.
[12] M. D. Bedworth and J. O’Brien, “The omnibus model: A new architecture for data fusion?” in Proc. 2nd Int. Conf. Inform. Fus. (FUSION’99), Helsinki, Finland, Jul. 1999. DOI: https://doi.org/10.1177/027836499801700402.

Doi : https://doi.org/10.54216/FPA.080205
Received: May 05, 2022 Accepted: September 14, 2022

[13] R. C. Luo and C.-C. Chang, "Multisensor fusion and integration: A review on approaches and its applications in mechatronics," IEEE Trans. Ind. Informat., vol. 8, no. 1, pp. 1385- 1393, Mar. 2008. DOI: 10.1109/TII.2011.2173942.

[14] A. Agah, "Human interactions with intelligent systems: Research taxonomy," Comput. Electric. Eng., vol. 27, no. 1, pp. 71-107, Nov. 2000. DOI: https://doi.org/10.1016/S0045-7906(00)00009-4.

[15] A. Grau, M. Indri, L. Lo Bello, T. Sauter "Industrial robotics in factory automation: From the early stage to the Internet of Things," in Proc. 43rd Annu. Conf. IEEE Ind. Electron. Soc., Beijing, China, Nov. 2017, pp. 6159–6164. DOI: 10.1109/IECON.2017.8217070.

[16] S. Y. Lee, K. Y. Lee, S. H. Lee, J. W. Kim, and C. S. Han, "Human–robot cooperation control for installing heavy construction materials," Autonom. Robots, vol. 22, no. 3, pp. 305–319, Mar. 2007. DOI: 10.1007/s10514-006-9722-z.

[17] H. Wang and X. Liu, "Haptic interaction for mobile assistive robots," IEEE Trans. Instrum. Meas., vol. 60, no. 11, pp. 3501–3509, Nov. 2011. DOI: 10.1109/TIM.2011.2161141.

[18] K. Kosuge and Y. Hirata, "Human–robot interaction," in Proc. IEEE Int. Conf. ROBIO, Shenyang, China, Aug. 2004, pp. 8–11. DOI: 10.1109/ROBIO.2004.1521743.

[19] L. Iocchi, J. Ruiz-del-Solar, and T. van der Zant, "Domestic service robots in the real world," J. Intell. Robot. Syst., vol. 66, no. 1/2, pp. 183–186, Apr. 2012. DOI: https://doi.org/10.1007/s10846-011-9628-7.

[20] P. Vaddakkepat, P. Lim, L. C. De Silva, L. Jing, and L. L. Ling, "Multimodal approach to human-face detection and tracking," IEEE Trans. Ind. Electron., vol. 55, no. 3, pp. 1385- 1393, Mar. 2008. DOI: 10.1109/TIE.2007.903993.

[21] C. Micheloni, G. L. Foresti, C. Piciarelli, and L. Cinque, "An autonomous vehicle for video surveillance of indoor environments," IEEE Trans. Veh. Technol., vol. 56, no. 2, pp. 487–498, Mar. 2007. DOI: 10.1109/TVT.2007.891478.

[22] O. Zoidi, A. Tefas, and I. Pitas, "Visual object tracking based on local steering kernels and color histograms," IEEE Trans. Circuits Syst. Video Technol., vol. 23, no. 5, pp. 870–882, May 2013. DOI: 10.1109/TCSVT.2012.2226527.

[23] W. Choi, C. Pantofaru, and S. Savarese, "A general framework for tracking multiple people from a moving Camera," IEEE Trans. Patt. Anal. Mach. Intell., vol. 35, no. 7, pp. 487–498, Jul. 2013. DOI: 10.1109/TPAMI.2012.248.

[24] Z. Wang, L. Zheng, and H. Ye, "Design and implementation of a following robot system based on monocular vision," in Proc. IEEE 2nd Adv. Inform. Tech., Electron. Automat. Cont. Conf. (IAEAC), Chongqing, China, Mar. 2017, pp. 1360–1363. DOI: 10.1109/IAEAC.2017.8054236.

[25] C.-S. Fahn, C.-P. Lee, and Y.-S. Yeh, "A real-time pedestrian legs detection and tracking system used for autonomous mobile robots," in Proc. Int. Conf. Appl. Sys. Innov. (ICASI), Sapporo, Japan, May 2017, pp. 1122–1125. DOI: 10.1109/ICASI.2017.7988208.

[26] P. Kondaxakis, H. Baltzakis, and P. Trahanias, "Learning moving objects in a multi-target tracking scenario for mobile robots that use laser range measurements," in Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst., St. Louis, MO, USA, Oct. 2009, pp. 1667–1672. DOI: 10.1109/IROS.2009.5353913.

[27] C. T. Chou, J.-Y. Li, M.-F. Chang, and L. C. Fu, "Multi-robot cooperation based human tracking system using laser range finder," in Proc. IEEE Int. Conf. Robot. Autom., Shanghai, China, May 2011, pp. 532–537. DOI: 10.1109/ICRA.2011.5980484.

[28] H. T. Duong and Y. S. Suh, "Human gait tracking for normal people and walker users using a 2D LiDAR," IEEE Sens. Journ., vol. 20, no. 11, pp. 6191-6199, Jun. 2020. DOI: 10.1109/JSEN.2020.2975129.

[29] N. Kawarazaki, L. T. Kuwae, and T. Yoshidome, "Development of human following mobile robot system using laser range scanner," Proced. Comp. Sci., vol. 76, pp. 455-460, 2015. DOI: https://doi.org/10.1016/j.procs.2015.12.310.

[30] D. Li, L. Li, Y. Li, F. Yang, and X. Zuo, "A multi-type features method for leg detection in 2-D laser range data," IEEE Sens. Journ., vol. 18, no. 4, pp. 1675-1684, Feb. 2018. DOI: 10.1109/JSEN.2017.2784900.

[31] N. Bellotto and H. Hu, "Multisensor-based human detection and tracking for mobile service robots," IEEE Trans. Syst., Man, Cybern. B, Cybern., vol. 39, no. 1, pp. 167-181, Feb. 2009. DOI: 10.1109/TSMCB.2008.2004050

[32] C.-C. Wang, C. Thorpe, M. Hebert, S. Thrun, and H. Durrant-Whyte, "Simultaneous localization, mapping and moving object tracking," Int. J. Robot. Res., vol. 26, no. 9, pp. 889-916, Sep. 2007. DOI: https://doi.org/10.1177/0278364907081229.

Doi : https://doi.org/10.54216/FPA.080205
Received: May 05, 2022 Accepted: September 14, 2022

[33] K. Rebai, A. Benabderrahmane, O. Azouaoui, and N. Ouadah, “Moving obstacles detection and tracking with laser range finder,” in’Proc. Int. Conf. Adv. Robot., Munich, Germany, Jun. 2009, pp. 1–6, ISBN: 978-3839-60035-1.

[34] M. Montemerlo, S. Thun, and W. Whittaker, “Conditional particle filters for simultaneous mobile robot localization and people-tracking,” in Proc. IEEE Int. Conf. Robot. Autom., Washington, DC, USA, May 2002, pp. 695–701. DOI: 10.1109/ROBOT.2002.1013439.

[35] Z. Xu, R. Fitch, and S. Sukkarieh, “Decentralised coordination of mobile robots for target tracking with learnt utility models,” in Proc. IEEE Int. Conf. Robot. Autom., Karlsruhe, Germany, May 2013, pp. 2014–2020. DOI: 10.1109/ICRA.2013.6630846.

[36] D. Schulz, W. Burgard, and D. Fox, “People tracking with mobile robots using samplebased joint probabilistic data association filters,” Int. J. Robot. Res., vol. 22, no. 2, pp. 99- 116, Feb. 2003. DOI: https://doi.org/10.1177/0278364903022002002.

[37] R. C. Luo, Y. J. Chen, C. T. Liao, and A. C. Tsai, “Mobile robot based human detection and tracking using range and intensity data fusion,” in Proc. IEEE Workshop Adv. Robot. Social Impacts, Hsinchu, Taiwan, Dec. 2007, pp. 1–6. DOI: 10.1109/ARSO.2007.4531416.

[38] M. Kleinehagenbrock, S. Lang, J. Fritsch, F. Lomker, G. A. Fink, and G. Sagerer, “Person tracking with a mobile robot based on multi-modal anchoring,” in Proc. 11th IEEE Int. Workshop Robot Human Interact. Commun., Berlin, Germany, Sep. 2002, pp. 423-429. DOI: 10.1109/ROMAN.2002.1045659.

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