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Multisensor Data Fusion and Integration for Mobile Robots: A Review

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Article Info	ABSTRACT
	One of the most important and useful feature of autonomous mobile robots is their ability to adopt themselves to operate in unstructured environment. Today robots are performing autonomously in industrial oor, oce environments, as well as in crowded public places.The basic requirement of an intelligent mobile robot is to develop and maintain localization and mapping parameters to complete the complex missions. In such situations, several diculties arise due to the inaccuracies and uncertainties in sensor measurements. Various techniques are there to handle such noises where the multisensor data fusion is not the exceptional one. During the last two decades, multisensor data fusions in mobile robots become a dominant paradigm due to its potential advantages like reduction in uncertainty, increase in accuracy, and reduction of cost.This paper presents the detail review of multisenosr data fusion and its applications for autonomous mobile.

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1.   INTRODUCTION

Robotics is an extremely challenging research area which deals with various issues like structural design, mobility, control, localization and mapping, etc. In the last two decades, several new technologies have been explored to improve the above issues. Today robots are able to navigate autonomously in different environments such as dynamic or static, indoor or outdoor, etc. But still there are several open challenges that need to be considered for further developments. Multisensor data sensor fusion technique is an essential process to improve the autonomous capabilities of the modern robots. There is a considerable contribution in this research area that shows how measurements from different sensors can be combined together to make the system more reliable and accurate.In the view of this, the literature survey in this paper is divided into different sections. The initial section deals with an overview of autonomous mobile robots and role of multisenosr data fusion. In this section, multisenosr data fusion and integration is differentiated and reviewed in detail. second part of the paper deals with the literature showing various advantages of multisenosr data fusion in mobile robots. The last section of the paper explodes various sensor fusion algorithms.

2.   AUTONOMOUS MOBILE ROBOTS AN OVERVIEW

Today Robotic technology has moved from the industrial manufacturing plants to the unpredictable complex environment. Due to high demand of service robots, the traditional industrial robots are being

replaced by the emerging autonomous intelligent mobile robots. Such intelligent robots have the ability to adjust their behavior autonomously, according to the environment. High degree of autonomy is desired in various mobile robot applications such as: space exploration, floors cleaning, mowing lawns, and material transportation, etc. In these applications, the workplaces are highly challenging and often contain untidy and unpredicted physical environment. In such unpredicted environment, the necessary processes that must be coordinated to perform the desired tasks are sensor-based exploration, motion planning, localization and mapping [1, 2, 3, 4, 5, 6, 7]. The literature shows that intelligent autonomous robots are capable of dealing with uncertainties encountered in its environment in an independent fashion [8, 9, 10, 11, 12, 13, 14, 4, 15]. A fully autonomous robot has the power to gain information about the environment that can work for an extended period without human intervention [16, 17, 18, 19, 20]. Such mobile robots act autonomously in different ways such as an autonomous robot `URMAD' provides assistance to the patients in hospitals and an autonomous mobile robot `MOVAID' is in service to assist the disabled and elderly people [21] . Robots like `ABIO' are capable of self docking to charge their batteries [22]. The robot like `Khepera' is performing autonomous services in case of a partially known environment where hybrid method is used to explore the advantages of global and local navigation tasks. The coordination of these strategies are based on a fuzzy inference system that involves on-line comparison between the real scene and a prior memorized one [2, 23]. The `Seekur' and `MDARS' robots demonstrate their autonomous navigation and security capabilities at an airbase [24]. Prototype urban robot has been developed for urban reconnaissance mission scenario at Fort Sam Houston, with autonomous navigation capabilities like stereo vision-based obstacle avoidance, visual servoing to user-designated goals, and autonomous stair climbing [19]. Today autonomous robots are on high demand for laborious jobs like domestic chores, laundry handling, cleaning and attending elderly persons, etc. [15, 25, 26, 27, 28, 29, 30]. Interestingly, the most demanding mobile robots are required for indoor applications. In order to see the high demand of service robots the review is intended to explore more state-of-the-art technology on mobile robots emphasizing on the emerging area of multisensor data fusion.

3.   MULTI SENSOR DATA FUSION AND INTEGRATION

To explore the unknown or partially known environment, mobile robot needs to map the environment and to maintain the localization parameters. For mobile robot mapping, the rst significant assignment is to access the range information and second leading assignment is to convert the range reading into internal representation. The robot requires the internal information to update its state as it moves around. It helps the mobile robot to attain full autonomy so that it may operate without human intervene. It is an extremely difault task for mobile robot to take the decision without updating the previous status of the environment as the environment may be highly dynamic. In such situations, the mobile robot system accumulates the local environmental information and *update* recursively by fusion process.

3.1. Multisensor Fusion

During the last decade, significant research has made to solve the problems concerning how to combine or fuse data from multiple sources in order to support decision-making [1, 31, 32]. The term `information fusion' becomes well established for engineering, medical and military and robotics applications, etc. we have presented here some important definitions of multisensor data fusion available in the literature as given below: Joint Directors of Laboratories (1987), defined data fusion as a process dealing with the association, correlation, combination of data and information from single and multiple sources to achieve refined position and identity estimates, and complete and timely assessments of situations and threats, and their significance. The process is characterized by continuous refinements of its estimates and assessments, and evaluation of the need for additional sources, or modification of the process itself, to achieve improved results [16]. In (1987), Durrant-Whyte defined fusion as "The basic problem in multi-sensor systems is to integrate a sequence of observations from a number of different sensors into a single best-estimate of the state of the environment" [33]. Luo in (1990), defined "Multisensor fusion, refers to any stage in an integration process where there is an actual combination (or fusion) of different sources of sensory information into one representational format" [34]. Hall et al., (1997), defined the "Data fusion techniques combine data from multiple sensors, and related information from associated databases, to achieve improved accuracy and more specific inferences than could be achieved by the use of a single sensor alone" [35]. later Steinberg (1999), defined that "Data fusion is the process of combining data to refine state estimates and predictions" [36]. In (2001), Dasarathy defined the "Information fusion encompasses the theory, techniques, and tools conceived and employed for exploiting the synergy in the information acquired from multiple sources (sensor, databases, information gathered by humans etc.) Such that the resulting decision or action is some sense better (qualitatively and quantitatively, in terms of accuracy, robustness and etc.) than would be possible, if these sources were used individually without such synergy exploitation" [37].

Das (2008), defined the sensor fusion in to different levels such as `high level fusion'. "high level fusion is the study of relationships among objects and events of interest within a dynamic environment" [38]. Llinas in 2009 modified the definition of information given as "Information fusion is an information process dealing with the association, correlation, and combination of data and information from single and multiple sensors or sources to achieve refined estimates of parameters, characteristics, events, and behaviours for observed entities in an observed field of view. It is sometimes implemented as a Fully Automatic process or as a Human-Aiding process for Analysis and/or Decision Support" [16].

For mobile robot applications, fusion refers to any stage in the integration process where an actual combination of different sources of information takes place. The combination depends upon the nature of information to be fused at different levels of hierarchical model as shown in Figure 1 the di erent levels of information fusion are classified as:

- **Signal-Level Fusion**: It includes signal enhancement technique such as beam forming using microphone arrays. The resulting signal from multiple sensors is usually of the same form as the original signal but with a greater quality.
- **Pixel-Level Fusion**: It refers to fusion of the information in the form of pixels. The sensors produce such information in CMOS or CCD cameras. The fused image can be created either by the fusion of pixel-by-pixel or by the fusion of associated local neighborhoods of pixels in each of the images.
- **Feature-Level Fusion**: It is applicable in different areas such as mobile robot mapping, person tracking and automatic speech recognition. In this process, the features are extracted from scene and fused with other sensory information such as microphones, etc.
- **Symbol-Level Fusion**: The statistical inference can be used for symbol level fusion where fusion of symbols is represented in the form of conditional probability.
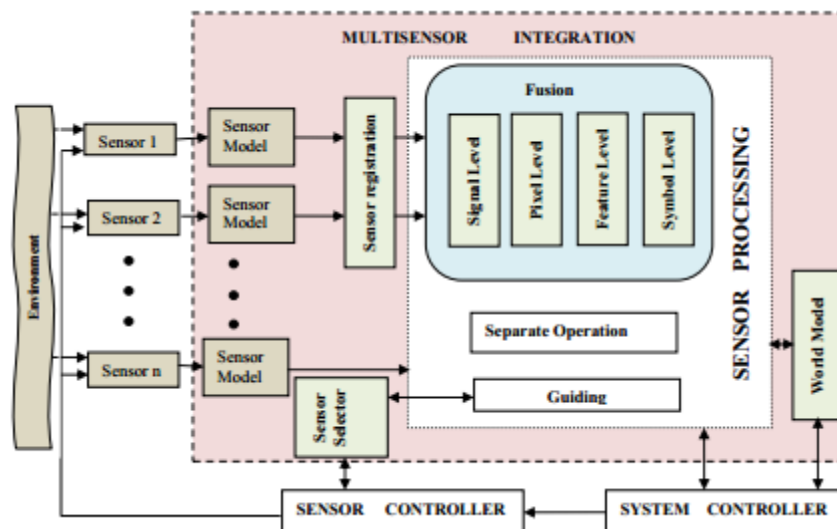

Figure 1. Functional Diagram of Multisensor Integration and Fusion (Figure redrawn from [39])

3.2. Multisensor Integration

Multisensor integration is the synergistic use of the information provided by multiple sensing devices to assist in the accomplishment of a task by a system. The distinction between integration and fusion serves to separate general issues involved in the integration of multiple sensory devices at the system architecture [40, 41]. Hierarchical structures of integration are useful for an efficient representation of different levels and fusion nodes in the architecture. Examples are National Bureau of Standards (NBS) sensory and control hierarchy [42]. Figure 1 represents multisensor integration as a composite of basic functions. Elements of multisensor integration are explained as follows:

- **Sensors**: A group of sensors (Homogeneous or Heterogeneous) providing input to the integration process. Raw data filtering and signal enhancement can be part of sensors.

- **Sensor Model**: The function of sensor model is to convert the range information from the sensor of different modalities into common representation. The range information provided by the sensor can be in the form of voltage, current, pulse width modulated signal or signal in the form of an image [43].
- **Sensor Registration**: It is significant to proportionate the unique and temporal dimensions of sensor information before the actual fusion process.
- **Sensor Processing**: Fusion is done at the symbol, feature, pixel level, and signal level. If the data from the sensor is significantly different from other sensors, it can be separated from the fusion process.
- **World Model**: During navigation, a mobile robot extracts the information from the sensors and generates the local map with respect to the current position. The information is updated with prior information that generates the world model. The world model is usually defined in terms of high level representation for multisensor fusion in mobile robot navigation.
- **Sensor Selection**: It enables the multisensor system to select the most appropriate configuration of sensor [44]. The sensor selection can be classified as: a) **Pre-Selection**: It is the primary step towards a general methodology to select a suitable sensor in respect to environmental conditions. Pre-selection depends upon geometric location of sensors and static/dynamic conditions of mobile robot (Hovland et al., 1997). b) **Real Time**: [45] presented the approach of sensor selection in real time by evaluating the performance value of each sensor [45]. If the performance value of a particular sensor is low, then the algorithm rejects that sensor to participate for integration.
- **System Controller**: System controller executes the commands to the mobile robot actuators. The algorithm like path planning, collision avoidance, and navigation rely upon the feedback signal of sensors.

3.3. Advantages of Multisensor Data Fusion
For mobile robot applications Potential advantages of multisensor data fusion are given as:

- **Reduction of Uncertainty**: Sensors provide only the estimation of range which may be uncertain. Multisensor data fusion reduces the uncertainty as the fusion process is redundant. Hence, it increases the accuracy which the system perceives from the environment [41, 43].
    a. Uncertainty in Sensory Information: Uncertainty in the sensory information can be caused by limited resolution of the sensor, random measurement of noise, systematic errors and due to incompleteness of the information e.g. Single fixed camera cannot sense the entire information of the environment due to limited view. To complete the information multiple views are needed to form the complete local view [46].
    b. Uncertainty in the Environment: The mobile robot environment becomes uncertain, when no prior information is available or the environment is highly dynamic. The robots operate in underwater and space explorations are highly uncertain about the environment [28, 47, 48, 49].
    c. Uncertainty in Robot Localization: For accurate mapping robot needs accurate localization parameters such as, mobile robot `position' and `orientation'. Odometric errors due to wheel slip, inclination of robot can cause position and orientation errors [50].
- **Complementary**: Multisensor data fusion is a complementary process because it allows perceiving the information of different parts of the environment by different sensors [7].
- **Well-Timed**: Multisensor data fusion increases the processing speed due to the process of parallelism [37].
- **Less Costly**: Single sensor needs several electronic modules to process the signal, whereas commonprocessing module of multisensor data fusion process reduces the overall cost of the system [51].
- **Increased Confidence and Reduced Ambiguity**: If several sensors contribute to a measurement result, the level of confidence of the fused value become higher [52]
- **Increased Reliability**: A system relying on different sensors is less susceptible to disturbance caused by human actions or natural phenomena [53].
- **Enhanced Spatial Resolution**: Multiple sensors data fusion enables the system to enhance and increase the map resolution [54].

3.4. Multi Sensor Data Fusion Algorithms
In this section our review is intended to find various methods used to fuse the information for mapping and localization.The data fusion methods can be classified as Estimation Method (that includes recursive and non-recursive method), Classification Method, Inference Method, and Artificial Method.

Weighted Average Method of multisensor data fusion is the responsive and simple method in which a weighted average of redundant information provided by a group of sensors is used as the fused value

[16]. A weighted average is used in various mobile robots such as "HILARE" in which the information from multiple sensors is fused by using weighted average method [52]. This method is not suitable for dynamic environment as compared to the static environments.

Kalman Filter is a set of mathematical equations that provides an efficient computational means to estimate the state of a process in a way, that, it minimizes the mean of the squared error [55]. Jetto (1999) in his research used an extended Kalman filter to fuse information of encoders and sonar sensors [56]. An extended Kalman filter is used to solve the concurrent mapping and localization (CML) of the mobile robot [57]. Recently, extended Kalman filter is used to combine ultrasonic and stereo camera information to increase the robustness of the map [58]. **'Extended Kalman Filter'** (EKF) served as the primary approach to map dynamic environment for the last several years but it suffers from two well known shortcomings. These two problems are the quadratic complexity, and the sensitivity to failures in data association [51]. The EKF has become widely known in terms of growth of complexity due to the update step that requires large computation time proportional to the square of the number of landmarks in the environment.

Dempster-Shafer, (DS) theory of multisensor data fusion is used to reduce the uncertainty in the grid caused due to the sensory information where the weight of conflict metric and the enlargement of the frame of discernment are the two components used to measure the amount of consensus between di erent sensors. Lack of consensus leads the robot to either compensate within certain limits or investigate the problem further; with this it helps in adding robustness to the robot's operation [27, 59].

Artificial Neural Networks used to map the occupancy grid has proven to be robust and adaptive to the environmental changes [60, 61, 62, 63, 64]. [65] proposed back-propagation training of multi-layer perception [65]. The neural network is trained to perform the correct conversion of range information in to occupancy grid. In the work of Thrun, the robot obtains the training samples by driving around in a calibration environment [28]. Dam (1996) in his paper proposed a neural network method to learn the probabilistic sonar sensor model. The conversion of the sensor data remains adaptive to change in either the sensor or its environment [66]. Kam (1997) presents a hierarchical neural network for mobile robot control. The network receives input from the sensors and transmits on/off commands to the motors. But major drawback is that large time is required to train the network [67] Later large work is done on NN by di erent researchers [68, 69, 64].

Histogrammic in Motion Mapping, (HIMM) algorithm developed by Borenstein and Koren in 1991 at the University of Michigan which provides a different approach to score whether a particular element in an occupancy grid is occupied or empty [70, 43]. The main objective of HIMM was to improve obstacle avoidance for mobile robot.

Bayesian Method allows multisensory information to be combined according to the rules of probability theory. Bayes' rule of combination allows the combining of a priori probability of a hypothesis with the conditional probability of given hypothesis [71, 72, 73, 74]. Moravec (1985) at Carnegie Mellon University pioneered the probabilistic approach. Later Moravec turned into a form of Bayes' Rule which uses probabilities expressed as likelihoods and odds [57].

Fuzzy Logic based sensor fusion relates to the artificial intelligence class of multisensor data fusion. This method can also be considered as a possibilistic approach in the sense that the method does not assign probabilities to the propositions but it assigns the membership values to proposition [39]. There is tremendous flexibility to perform fusion of multisensory information under the special rule of combination of fuzzy values.

4. CONCLUSION

In mobile robots there are challenges to develop better and effient system to to work in complex environments. Literature shows that there is ample scope for devising implementations in existing multisensor data fusion frameworks. Bayesian is the oldest approach and one with strongest foundation. Bayesian and DS methods have some fundamental problems like information uncertainty, conflicts and incompleteness. Sensor fusion using NN requires long time to train the mobile robot for a particular environment and it is considered as difficult for complex environment with large variations exists. HIMM is limited to sonar, but it has significant computational advantage. In practice Bayesian method of information fusion is found to be more straightforward to adopt for indoor and outdoor environment.To make the mapping and localization robust there is need of preprocessing and post processing of the sensory information and resultant internal representation in the form of map.

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