A Survey of Multisensor Fusion Techniques, Architectures and Methodologies

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***Abstract*—In this paper, an overview of multi-sensor fusion is presented. Topics such as sensor fusion types, topologies and basic architectures used for multi-sensor fusion are reviewed. Also, fusion methods for signal level processing and decision level or symbol level are covered to provide the reader with basic understanding and techniques encountered in sensor fusion applications.**

Keywords—multi-sensor fusion classification; sensor topologies and configurations; signal fusion; track-to-track fusion; symbol level fusion; dempster-shafer evidential reasoning

I. INTRODUCTION

Sensor fusion involves combining data from several sensors to obtain better information for perception. Humans and animals process multiple sensory data to reason and act and the same principle is applied in multi-sensor data fusion. Multi-sensor fusion combines data from different sensors into a common representation format [1, 2]. In developing robotic systems, multi-sensor fusion plays a crucial role since interaction with the environment is instrumental in successful execution of the task. Significant applications of multi-sensor fusion can be found in applications such as mobile robots [2, 3, 4, 5], defense systems (such as target tracking [2, 6, 7, 8]), medicine [9, 10], transportation systems [11, 12] and industry [13, 14, 15].

The motivation for sensor fusion is discussed in section II. Section III describes the various types of sensor fusion proposed in literature. The various topologies and models for sensor fusion is covered in sections IV and V. Sections VI, VII provide an overview of signal and decision level fusion.

II. MOTIVATION

The main goal of multi-sensor fusion is to achieve better operation of the system using the collective information from all sensors. This is also referred to as the synergistic effect [16, 17, 18]. Combining the data from a single sensor at different time intervals can also produce this effect [18]. In order to have better spatial and temporal coverage multiple sensors can be used. Also, with multiple sensors there is increased estimation accuracy and fault-tolerance [18].

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III. SENSOR FUSION CATEGORIES

Depending upon the sensor configuration, there are three main categories of sensor fusion: Complementary, Competitive and Co-operative [19]. These are described below as follows:

A. Complementary

In this method, each sensor provides data about different aspects or attributes of the environment. By combining the data from each of the sensors we can arrive at a more global view of the environment or situation. Since there is no dependency between the sensors combining the data is relatively easy [19, 20].

B. Competitive

In this method, as the name suggests, several sensors measure the same or similar attributes. The data from several sensors is used to determine the overall value for the attribute under measurement. The measurements are taken independently and can also include measurements at different time instants for a single sensor. This method is useful in fault tolerant architectures to provide increased reliability of the measurement [19, 20].

C. Co-operative

When the data from two or more independent sensors in the system is required to derive information, then co-operative sensor networks are used since a sensor individually cannot give the required information regarding the environment. A common example is stereoscopic vision [19, 20].

Several other types of sensor networks exist such as corroborative, concordant, redundant etc [18]. Most of them are derived from the above mentioned sensor fusion categories.

Dasarthy [21, 22] classified sensor fusion types depending upon the input/output characteristics. Figure 1 [21], shows the various sensor fusion types. Only a few combinations are allowed in Dasarthy's scheme for the inputs and outputs.

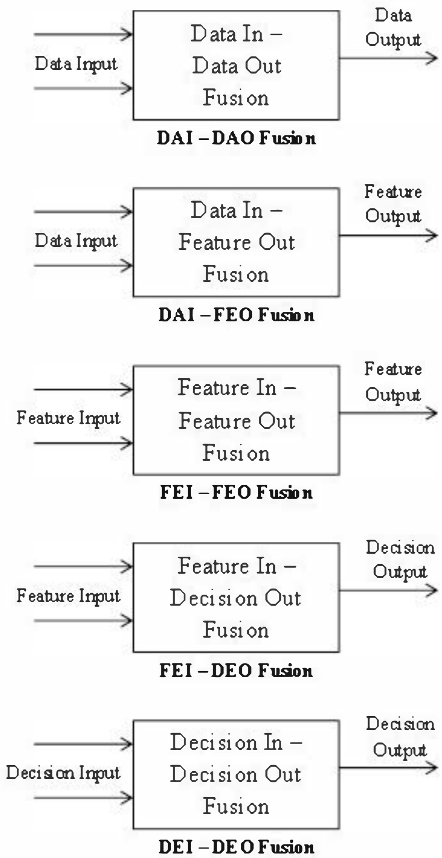

Fig. 1. Dasarthy's classification of multi-sensor fusion [21].

IV. Sensor Fusion Topologies

There are different topologies namely, Centralized, Decentralized and Hybrid [18, 20, 23, 24]. Each of these is described as follows:

A. Centralized Architecture

In this architecture, a single node handles the fusion process. The sensors undergo preprocessing before they are sent to the central node for the fusion process to take place. Figure 2 shows a typical centralized architecture [18, 20].

B. Decentralized Architecture

In this architecture, each of the sensor processes data at its node and there is no need for a global or central node. Since the information is processed individually at the node, it is used in applications that are large and widespread such as huge automated plants, spacecraft health monitoring etc. [20]. Figure 3 shows a typical decentralized architecture [18, 20].

C. Hierarchical Architecture

This architecture is a combination of both centralized and distributed type. When there are constraints on the system such as a requirement of less computational workload or limitations on the communication bandwidth, distributed scheme can be enabled. Centralized fusion can be used when higher accuracy is necessary [20, 23].

A simple comparison between the centralized and decentralized topologies is shown below in Table I [18, 20].

V. Multi Sensor Fusion Models

The application that uses the sensor fusion plays a vital role in determining the type of architecture. Hence there is no specific model or architecture that is definitive for all applications [25, 26, 27].

In this section, the two most widely used architectures namely, the JDL Fusion architecture and the Waterfall Fusion Process Model are discussed.

A. JDL Fusion Architecture

JDL stands for the US Joint Directors of Laboratories that was established under the guidance of Department of Defense and was proposed in 1985. The JDL model is functionality dependent and can be customized depending on the application. Varieties of applications from sensor networks to human robot interface can be implemented using this model [20].

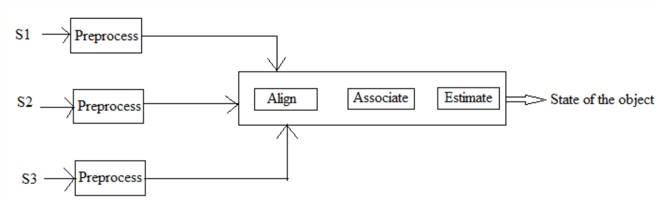

Fig. 2. Centralized Topology [23].

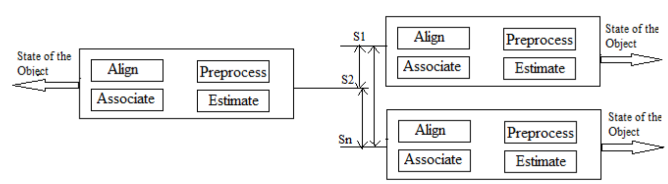

Fig. 3. Decentralized Topology [23].

TABLE I. CENTRALIZED AND DECENTRALIZED TOPOLOGIES [18, 20]

Parameter	Centralized	Distributed
Communication	Central node acts bottleneck	Data processing load distributed
Computation	Depends on the performance of central processor	Can be easily scaled
Modularity	Re-programming for new sensors	Modular in design
Fault-tolerance	Depends on the central computer	Distributed data processing

The model uses five levels for data processing and a database. These components can communicate through a bus interface [20, 24, 26]. The JDL model is shown in Figure 4 [24, 26]. These levels could be executed sequentially or concurrently during the application.

Sources, in the JDL model can consist of sensor data or data given by the user such as user input, reference data or geographical data. The Man-Machine Interaction block, as the name suggests, enables the user to interact with the system through user command, reports etc. Furthermore, this block helps in providing alert messages and could use multimedia tools such as displays, sounds etc. to achieve communication with the user.

The Source Pre-Processing also referred to as Level 0, performs pre-screening of data and then allocates it to the appropriate process [24, 26]. In the Object Refinement or Level 1, the following operations are performed namely, alignment of data using frame transformation, data association, tracking and estimation of the current and future position of the object. Also, Level 1 can be considered to be composed of kinematic and identity fusion [20]. In kinematic fusion, the velocity, acceleration of the object is determined. In identity fusion, the type of the object such as aircraft or missile is determined using parametric estimation [20, 24]. After processing the data from Level 1, based on the situation the contextual relationship is determined between the event and the object under observation. This process of refinement is called as Situation Refinement or Level 2. Depending on the a priori data and the future situation prediction inferences are drawn in Level 3 or Threat Refinement. The inferences are used to identify the vulnerabilities and the opportunities for the operation. This level uses game theoretic techniques [24].

Process Refinement or Level 4 deals with monitoring the system performance (handles real time constraints) and sensor allocation to satisfy mission objectives and goals. This level does not perform data processing operations and uses sensor management techniques [20, 24, 26]. The Database Management System helps monitor, update, add and provide information to the fusion process [20, 24, 26].

Although the JDL model helps in basic understanding of the sensor fusion process it is data centric and hence hard to extend or reuse the applications based on this model. It is abstract and interpretation could be difficult [24, 26].

Table II [24] highlights the summary of various components used in JDL model.

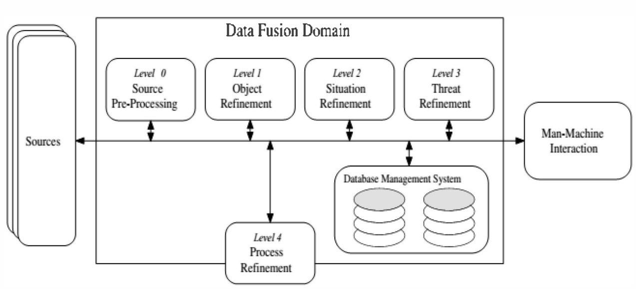

Fig. 4. JDL Fusion Model [24, 26].

TABLE II. SUMMARY OF JDL PROCESS COMPONENTS [24].

SOURCES	Can include data from sensors to a priori information from databases to human input.
PROCESS ASSIGNMENT	Enables the data fusion process to concentrate on the data most pertinent to the current situation as well as reducing the data fusion processing load. Involves data pre-screening and allocating data to appropriate processes.
OBJECT REFINEMENT I (Level 1)	Transforms data to a consistent reference frame and units and estimate or predict object position, kinematics, or attributes. Also, assigns data to objects to allow statistical estimation and refine estimates of the objects identity or classification.
SITUATION REFINEMENT (Level 2)	Describes of the relationship between objects and observed events. This processing determines the meaning of a collection of entities and accounts for environmental information, a priori knowledge, and observations.
THREAT REFINEMENT (Level 3)	Projects the current situation into the future and indicates possible threats, vulnerabilities, and opportunities for operations.
PROCESS REFINEMENT (Level 4)	Monitors real-time performance of data-fusion, identifies information required for data fusion improvement. Also, allocates and directs sensor and sources to achieve mission goals.
DATABASE MANAGEMENT SYSTEM	Most extensive ancillary function required to support data fusion. Also features data retrieval, storage, archiving, compression, relational queries, and data protection.
HUMAN-COMPUTER INTERACTION	Enables human input and communication of data fusion results to operators and users, and includes methods of alerting human as well as augmenting cognition.

B. *Waterfall Fusion Process Model*

The Waterfall fusion process model (WFFM) deals with the low level processing of data and is shown in Figure 5 [24, 28]. The Waterfall model has a lot of common features as the JDL model. The processing stages of the Waterfall models relate to the levels of the JDL model [24, 26, 28] and the comparison is shown in Table III.

However, similar to the JDL model the Waterfall fusion model is abstract and doesn't have feedback between the stages. It is an acyclic model. The modified WFFM is described in [20] that provides for some feedback between the stages. This modified model is action oriented and has the provision for control loop action or feedback loop as shown in Figure 6 [20]. Several other fusion models exist such as the Omnibus model [29], Boyd or OODA model [30], LAAS Architecture [31].

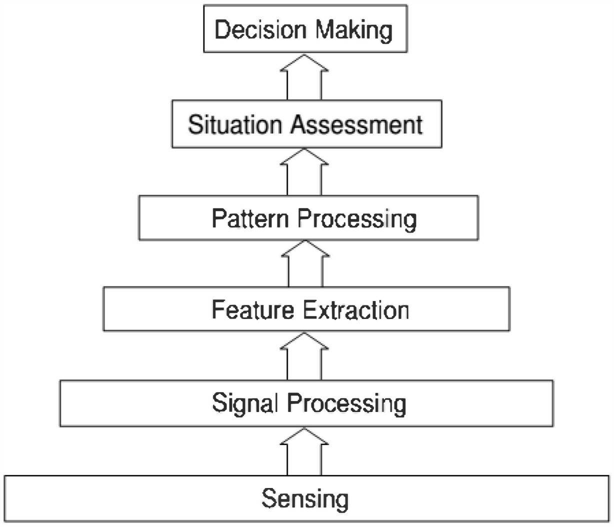

Fig. 5. Waterfall Fusion Process Model [28].

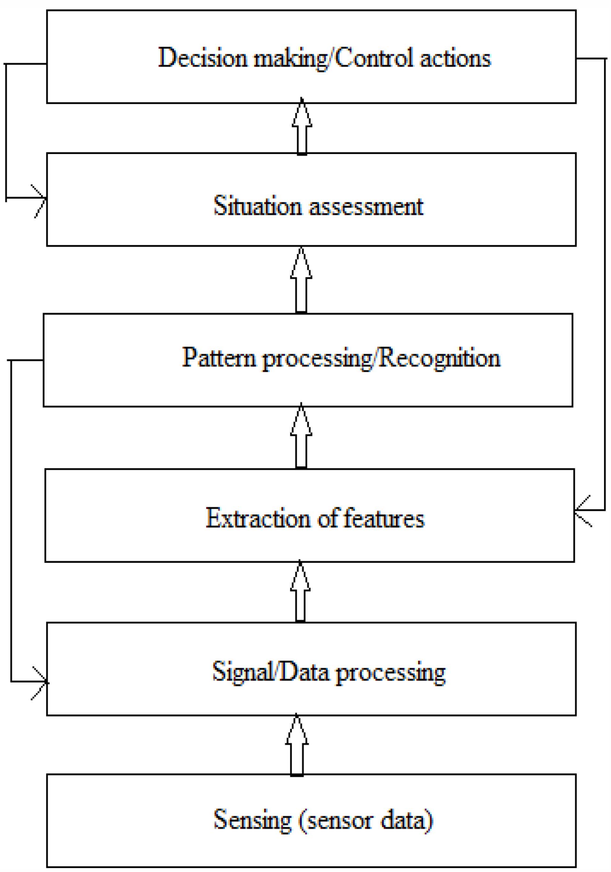

Fig. 6. Modified Waterfall Fusion Model [20].

TABLE III. JDL AND WATERFALL FUSION MODELS [24, 26, 28]

JDL levels	Waterfall stages
Level 0	Sensing and Signal Processing
Level 1	Feature Extraction and Pattern Processing
Level 2	Situation Assessment
Level 3	Decision Making

VI. SIGNAL LEVEL FUSION

In signal level fusion, data from multiple sources (sensors) are combined to obtain better quality data and higher understanding of the environment being observed. Signal level fusion often has either or both of the following goals:

- Obtain a higher quality version of the input signals i.e. higher signal to noise ratio [32]. Sensor measurements from several sensors which have same physical properties are combined to determine the parameter being measured, more accurately [18]. This minimizes and sometimes eliminates any uncertainty or inaccurate predictions caused by measurements from faulty sensors, measurement noise and state noise. For instance, readings from multiple temperature sensors in close proximity in a given space can be used for this kind of fusion.

- Obtain a feature or mid-level information about the system that a single measuring node cannot reveal. A feature is the first stage in understanding the state of the environment that helps the system in formulating a decision. Heterogeneous sensors are often employed for this process. For instance, signals from radar and images from camera are used in target recognition [24].

For sensor data to undergo signal level fusion, it is essential to condition the signals in the signal preprocessing phase. The signals have to be in a common representation format [18]. The stages involved in this process, as shown in Figure 7, include but not limited to: Signal alignment, normalization and scaling [18].

There are several methods by which signal level fusion can be achieved. The choice of method depends on various factors like the scenario and type of application, type of data or signal, relationship between the data or the state representation of the system.

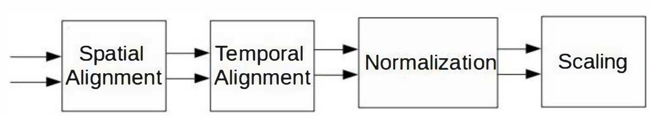

Fig. 7. Common representation format functions [18].

The following are some of the commonly used signal fusion methodologies:

A. Weighted Averaging

Signal fusion can be achieved by taking an average of the various sensor signals measuring a particular parameter of the environment. If signals from some sensors can be trusted more than the other, a higher weight is assigned to that sensor to increase its contribution towards the fused signal. The confidence level is a function of variance of the sensor signal. [32]

$$x_{fused} = \sum_{i=0}^{n} w_i x_i \tag{1}$$

where, w_i = f(variance)

B. Kalman Filter

The Kalman filter method is a common adaptive method of sensor fusion to remove redundancy in the system and to predict the state of the system. This is a linear model and the current state of the system is dependent on the previous state. The system is represented by the following state-space model:

$$x(k) = F\, x(k-1) + B\, u + G\, w$$
$$z(k) = H\, x(k) + v$$

where, x: state vector, F: state transition matrix, B: Input transition matrix, u: Input vector, G: Process noise transition matrix, w: process noise vector, H: Measurement matrix, v: measurement noise vector. The covariance matrices of w and v are Q(k) and R(k) respectively. There are two phases of state estimation with Kalman filter:

1) Predict phase:

$$\hat{x}_k = A\, \hat{x}_{k-1} + B\, u_k \tag{2}$$

$$P_k = A\, P_{k-1}\, A^T \tag{3}$$

2) Update phase:

$$K_k = P_k C^T (C P_k C^T + R)^{-1} \tag{4}$$

$$\hat{x}_k = \hat{x}_k + K_k (z_k - C\, \hat{x}_k) \tag{5}$$

$$P_k = (1 - K_k C) P_k \tag{6}$$

where, P: estimation covariance, K: Kalman gain

In the update or correction phase, the estimate from the predict phase is updated with the observation. If there are two sensors and both of them sending data simultaneously, then Z = [z1, z2]. If the sensors are sending data one after the other, then the reading from first sensor can be used as a priori information before observation from second sensor is used to update the prediction. [32]

C. Track to Track Fusion

Track to track fusion methodology has local tracks generated by distinct local sensors. Then at a central node the tracks are fused as shown in Figure 8 [33]. The local track can be individual Kalman filter nodes that provide state estimation at the local track level. These states are then fused into a state vector that has combined information from all the local sensor nodes. Sometimes, this new estimate is sent as feedback to the local sensor nodes. The new state estimate is obtained by the following formula [33].

$$\hat{x}_{k|k} = \hat{x}^1_{k|k} + \left[P^1_{k|k} - P^{12}_{k|k}\right]\left[P^1_{k|k} + P^2_{k|k} + P^{12}_{k|k} + P^{21}_{k|k}\right]^{-1} \left(\hat{x}^2_{k|k} - \hat{x}^1_{k|k}\right) \tag{7}$$

where, $P^m_{k|k}$ is the error covariance matrix of the corresponding state estimation $x^{\wedge m}_{k|k}$. $P^{12}_{k|k}$ is the cross covariance matrix of the two state vectors where $P^{12}_{k|k} = (P^{12}_{k|k})^T$.

$P^{12}_{k|k}$ is defined by the following equation:

$$P^{12}{}_{k|k} = \left(1 - K^1_k H^1_k\right) F_{k-1} P^{12}_{k-1|k-1} F^T_{k-1} \left(1 - K^2_k H^2_k\right)^T + \left(1 - K^1_k H^1_k\right) G_{k-1} Q_{k-1} G^T_{k-1} \left(1 - K^2_k H^2_k\right)^T \tag{8}$$

This configuration can be extended for multiple sensors. A modified track-to-track fusion and three fusion algorithm are explained in detail in [33].

There are other ways to define the track fusion algorithm such as taking confidence weighted averaging of the tracks based on variance [33].

D. Neural Networks

An artificial neural network consists of interconnection of processing nodes called neurons. There is a pattern of interconnection between the neuronal layers that are weighted and the learning process that updates these weights. Data fusion models can be established using neural networks such that neurons and interconnecting weights are assigned based on the relationship between the multi-sensor data input and the signal output. The neural networks can be multilayer feed-forward or recurrent type. [34]

Unlike Kalman filters, neural networks offer non-linear transfer functions and parallel processing capabilities. This can help in performing image fusion. Figure 9 shows a basic structure of three layer neural network with nonlinear mapping.

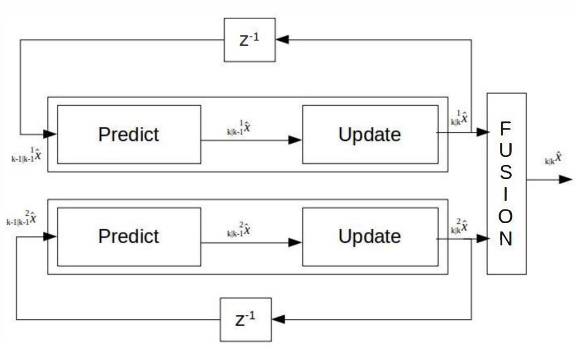

Fig. 8. Track to track fusion architecture [33].

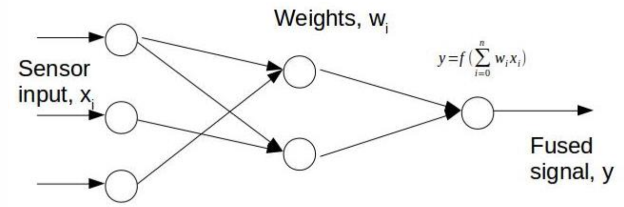

Fig. 9. Neural network structure for sensor fusion [34].

The fused output is a combination of input signal and corresponding weights calculated by the equation [34]:

$$y = \sum_{i=0}^{n} w_i x_i \tag{9}$$

where, w_i is the weight; x_i is the sensor data.

Several fusion methodologies are used and depending on the input and outputs required the stages in the model can perform either signal, feature or decision level fusion. These methods are either used as standalone or can be combined with aforementioned signal fusion methods.

The probabilistic approach for sensor fusion includes the use of joint probability distributions and Gaussian distributions [38]. Other fusion methods include Bayesian, least-squares for feature extraction [39] and some statistical approaches. [18, 32, 40]. In [35, 36, 37] the authors explain various approaches for modeling sensor fusion architecture using neural networks.

VII. Decision Level Fusion

Also known as Symbol level fusion, the decision level fusion combines several sub-decisions or features to yield a final or higher decision that can be used to take an action. Symbol could be an input decision. In this case, fusion of symbolic information insists the use of reasoning and inference while handling uncertainty. Symbol level fusion increases the confidence or truth value and is considered as decision fusion [41, 42]. Identity and Knowledge based methods form the two categories of decision fusion [20, 42]. Table IV [20, 42] lists few of the decision fusion methods or AI techniques for each category.

One of the most widely used decision or inference method is Dempster-Shafer theory (D-S theory). This method is very useful for human-robot interaction based applications [41, 42, 45, 46]. We describe in detail the D-S theory in the following sub-section followed by a comparison with Bayesian inference which is another widely used decision fusion technique.

A. Dempster-Shafer Theory of evidence

D-S theory is a generalization of the probability theory [41, 43, 44, 45]. In this method, a frame of discernment Ω is defined which is set of elementary hypotheses:

$$\Omega=\{a_i\}, i=1, ..., n \tag{10}$$

TABLE IV. Decision Fusion Models [20, 42]

Identity based	**Knowledge based**
Maximum a priori (MAP)	Syntax rule
Maximum Likelihood (ML)	Neural Network (NW)
Demspter-Shafer, etc	Fuzzy Logic , etc

The sum of the mass function of all hypotheses is one. Belief function is used to express inaccurate beliefs. Mass values are assigned to the elements of the power set 2^{Ω} of the frame of discernment which hold the following properties:

belief (null) = 0

belief (hypothesis) = Sum of all mass functions for all evidence to support the proposition.

The confidence interval is upper-bounded by the plausibility value to include all observations that don't rule out the proposition supported by the corresponding belief function. In order to combine two mass functions m1 and m2 the Dempster-Shafer theory defines the following rule [43, 44]:

$$m_1 \oplus m_2(\emptyset) = 0 \tag{11}$$

$$m_1 \oplus m_2(H) = \frac{\sum_{X \cap Y = H} m_1(X) m_2(Y)}{1 - \sum_{X \cap Y = \emptyset} m_1(X) m_2(Y)} \tag{12}$$

B. Dempster-Shafer and Bayesian fusion comparison

Although both these methods are widely used in inference engines there are few differences between them [42, 46]. The main difference being the concept of support and plausibility to define uncertainty limits in Dempster-Shafer [42, 43, 44] which is not found in Bayesian inference. D-S theory is an evidential reasoning method where belief masses can be assigned to elements and sets, and on sets of sets [42]. Capturing ignorance or uncertainty is another strong feature of evidential reasoning methods which is not achievable in probabilistic methods. It is not necessary to have a prori probabilities and data is provided only at the time when sensor reads them [42, 46] during observation. Dempster-Shafer theory of evidence finds widespread use in human-robot interactive (HRI) applications. A review of a few applications of HRI can be found in [47].

By using the power set as the frame of discernment beliefs can well represented. However, when the set is continuous the number of subsets cannot be measured and hence this is a significant limitation that is found in evidential reasoning methods [41, 42] that work well with discrete sets.

In our current research, we are working on a sensor fusion framework for robotic vehicle navigation in an unknown terrain. The framework is similar to waterfall fusion model and uses track to track fusion and Dempster-Shafer theory of evidence for signal and decision level fusions.

VIII. Conclusion

In this paper a brief overview of the various concepts of multi-sensor fusion was presented. The types of sensor fusion, the sensor fusion topologies and architectures were reviewed. Signal level and Decision level fusion was also covered highlighting the methods used to achieve each of them.

REFERENCES

[1] Iyengar, S. S., & Brooks, R. R. (Eds.). *Distributed sensor networks: sensor networking and applications*. CRC press, 2016

[2] Joshi, R., & Sanderson, A. C. *Multisensor fusion: A minimal representation framework* (Vol. 11). World Scientific, 1999

[3] Luo, R. C., & Lai, C. C. Multisensor fusion-based concurrent environment mapping and moving object detection for intelligent service robotics. *IEEE Transactions on Industrial Electronics*, *61*(8), 4043-4051, 2014

[4] Axenie, C., & Conradt, J. Cortically inspired sensor fusion network for mobile robot egomotion estimation. *Robotics and Autonomous Systems*, *71*, 69-82, 2015

[5] Matía, F., & Jiménez, A. Multisensor fusion: an autonomous mobile robot. *Journal of Intelligent and robotic systems*, *22*(2), 129-141, 1998

[6] Khaleghi, B., Khamis, A., Karray, F. O., & Razavi, S. N. Multisensor data fusion: A review of the state-of-the-art. *Information Fusion*, *14*(1), 28-44, 2013

[7] Dallil, A., Oussalah, M., & Ouldali, A. Sensor fusion and target tracking using evidential data association. *IEEE sensors journal*, *13*(1), 285-293, 2013

[8] Bar-Shalom, Y., Willett, P. K., & Tian, X. *Tracking and data fusion*. YBS publishing, 2011

[9] Banerjee, T. P., & Das, S. Multi-sensor data fusion using support vector machine for motor fault detection. *Information Sciences*, *217*, 96-107, 2012

[10] James, A. P., & Dasarathy, B. V. Medical image fusion: A survey of the state of the art. *Information Fusion*, *19*, 4-19, 2014

[11] El Faouzi, N. E., Leung, H., & Kurian, A. Data fusion in intelligent transportation systems: Progress and challenges–A survey. *Information Fusion*, *12*(1), 4-10, 2011

[12] Cho, H., Seo, Y. W., Kumar, B. V., & Rajkumar, R. R. A multi-sensor fusion system for moving object detection and tracking in urban driving environments. In *2014 IEEE International Conference on Robotics and Automation (ICRA)* (pp. 1836-1843). IEEE, 2014

[13] Cardarelli, E., Sabattini, L., Secchi, C., & Fantuzzi, C. Multisensor data fusion for obstacle detection in automated factory logistics. In *Intelligent Computer Communication and Processing (ICCP), 2014 IEEE International Conference on* (pp. 221-226). IEEE, 2014

[14] Wan, W., Lu, F., Wu, Z., & Harada, K. Teaching robots to do object assembly using multi-modal 3d vision. *arXiv preprint arXiv:1601.06473*, 2016

[15] Zhang, J., Song, C., Hu, Y., & Yu, B. Improving robustness of robotic grasping by fusing multi-sensor. In *Multisensor Fusion and Integration for Intelligent Systems (MFI), 2012 IEEE Conference on* (pp. 126-131). IEEE, 2012

[16] Luo, R. C., & Kay, M. G. Multisensor integration and fusion in intelligent systems. *IEEE Transactions on Systems, Man, and Cybernetics*, *19*(5), 901-931, 1989

[17] Xiong, N., & Svensson, P. Multi-sensor management for information fusion: issues and approaches. *Information fusion*, *3*(2), 163-186, 2002

[18] Mitchell, H. B. *Multi-sensor data fusion: an introduction*. Springer Science & Business Media, 2007

[19] Durrant-Whyte, H. F. Sensor models and multisensor integration. *The international journal of robotics research*, *7*(6), 97-113, 1988

[20] Raol, J. R. *Multi-Sensor Data Fusion with MATLAB®*. CRC Press, 2009

[21] Dasarathy, B. V. *Decision fusion* (Vol. 1994). Los Alamitos, CA: IEEE Computer Society Press, 1994

[22] Dasarathy, B. V. Sensor fusion potential exploitation-innovative architectures and illustrative applications. Proceedings of the IEEE, 85(1), 24-38, 1997

[23] Castanedo, F. A review of data fusion techniques. The Scientific World Journal, 2013.

[24] Hall, D. L., & Llinas, J. An introduction to multisensor data fusion. *Proceedings of the IEEE*, *85*(1), 6-23, 1997

[25] Elmenreich, W. A review on system architectures for sensor fusion applications. In *IFIP International Workshop on Software Technolgies for Embedded and Ubiquitous Systems* (pp. 547-559). Springer Berlin Heidelberg, 2007

[26] Elmenreich, W. An introduction to sensor fusion. *Vienna University of Technology, Austria*, 2002

[27] M. Kam, X. Zhu, and P. Kalata. Sensor fusion for mobile robot navigation. Proceedings of the IEEE, 85(1):108-119, Jan. 1997

[28] 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, The Royal Aeronautical Society, 1997

[29] M. D. Bedworth and J. O'Brien. The omnibus model: A new architecture for data fusion? In Proceedings of the 2nd International Conference on Information Fusion (FUSION'99), Helsinki, Finnland, July 1999

[30] Boyd, J. R. A discourse on winning and losing. Maxwell Air Force Base, AL: Air University. *Library Document No. MU*, *43947*, 79, 1987

[31] R. Alami, R. Chatila, S. Fleury, M. Ghallab, and F. Ingrand. An architecture for autonomy. International Journal of Robotics Research, 17(4):315{337, April 1998

[32] Abidi, M. A., & Gonzalez, R. C. *Data fusion in robotics and machine intelligence*. Academic Press Professional, Inc, 1992

[33] Jingwei, S., Yongjie, Z., Haiyun, Z., Tao, Z., Leigang, W., Wei, R. & Huifeng, L. A multi-MEMS sensors information fusion algorithm. In *The 26th Chinese Control and Decision Conference (2014 CCDC)* (pp. 4675-4680). IEEE, 2014

[34] Y. Wang, S.D. Goodman, Data Fusion with Neural Networks, *International Conference on Systems Man and Cybernetics IEEE 1994*, vol. 1, pp. 640-645, Oct 1994

[35] H. Chen, "Research on multi-sensor data fusion technology based on PSO-RBF neural network", Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), 2015 IEEE, Dec 2015

[36] Y. H. Liang and W. M. Tian, Multi-sensor Fusion Approach for Fire Alarm Using BP Neural Network, *2016 International Conference on Intelligent Networking and Collaborative Systems (INCoS)*, Ostrawva, 2016, pp. 99-102, 2016

[37] Q. Liu, X. Wang and N. S. V. Rao, "Artificial neural networks for estimation and fusion in long-haul sensor networks," *2015 18th International Conference on Information Fusion (Fusion)*, Washington, DC, 2015, pp. 460-467, 2015

[38] M. Kok, "Probabilistic modeling for sensor fusion with inertial measurements", Linköping studies in science and technology. Dissertations.No. 1814, ISBN 978-91-7685-621-5, 2016

[39] Kovvali, N., Prior, C., Cizek, K., Galik, M., Diaz, A., Forzani, E., ... Tsui, R. Least-squares based feature extraction and sensor fusion for explosive detection. In *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*. (pp. 2918-2921). [5496159] DOI: 10.1109/ICASSP.2010.5496159, 2010

[40] G. D. Hager, S. P. Engelson and S. Atiya, "On comparing statistical and set-based methods in sensor data fusion," *[1993] Proceedings IEEE International Conference on Robotics and Automation*, Atlanta, GA, 1993,pp.352-358vol.2.,1993

[41] Munz, M., Dietmayer, K., & Mählisch, M. Generalized fusion of heterogeneous sensor measurements for multi target tracking. In *Information Fusion (FUSION), 2010 13th Conference on* (pp. 1-8). IEEE, 2010

[42] Siciliano, B., & Khatib, O. (Eds.). *Springer handbook of robotics*. Springer Science & Business Media, 2008

[43] Dempster, P., "A Generalization of Bayesian Inference," Journal of the Royal Statistical Society B, vol. 30, no. 2, pp. 205–247, 1968.

[44] Shafer, A., MathematicalTheory of Evidence , Princeton University Press, Princeton, NJ, USA, 1976

[45] Wu, H., Siegel, M., Stiefelhagen, R., & Yang, J.. Sensor fusion using Dempster-Shafer theory [for context-aware HCI]. In Instumentation and Measurement Technology Conference, 2002. IMTC/2002. Proceedings of the 19th IEEE (Vol. 1, pp. 7-12). IEEE, 2002

[46] Challa, S., & Koks, D. Bayesian and dempster-shafer fusion. *Sadhana*, *29*(2), 145-174, 2004.

[47] Chandrasekaran, B., & Conrad, J. M. Human-robot collaboration: A survey. In SoutheastCon 2015 (pp. 1-8). IEEE, 2015