Sensor Fusion: A Review of Methods and Applications

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Abstract: This paper aims to present a brief overview of the development of sensor fusion in various application in recent years, and to understand the challenges and ability of sensor fusion. Various algorithms that are typically employed are covered to comprehend the complexity of usage in different scenarios.

Key Words: Multi-sensor fusion; fusion algorithm; fusion applications

1. INTRODUCTION

Sensor fusion had been a fast developing area of research in recent years. With the increase of the availability of the numbers and types of sensors, the need to manage the increasing quantity of information has produced the need to fuse such data for human to perceive. The ability to combine information and integrate them allows for new capability in myriads of areas. Some examples where sensor fusion is now widely engaged in different methods, are automotive automation, mobile robot navigation, and target tracking.

Through the integration of multiple sensors, there are certain advantages we can achieve, compared with just a single input. The enhanced reliability, extended parameter coverage, improved resolution are all desirable in any system. While sensor fusion research has improved leaps and bounds in recent years, certainly we are still far away from achieving the competence to mimic the human mind in analyzing different data simultaneously. Due to the multiple sources and types of information being fed continuously, there are various problems that arises, such as data association, sensor uncertainty, and management of data. In most cases, these are usually associated with the inherent ambiguity of each sensors, with device noise and also ambiguities in the environment being measured. A robust system of sensor fusion should be able to handle such uncertainties, and at the end, provide consistent results of the environment.

2. SENSORS, ADVANTAGES/PROBLEMS

Sensors are used to detect certain attributes or changes of the environment, and provide feedback to the system based on its detection. Existing sensors that are available include camera, rangefinder, sonar and ultrasonic. In many cases such as mobile devices, they may include accelerometers, magnetometer, ambient air temperature sensors, pressure sensors, gyroscopes, and proximity sensors. The classification of sensors is usually dependent on the purpose, and different criteria can be designated. Some methods which are typically employed to define sensors are between active and passive sensors, absolute or relative, as well as the stimulus of various sensors.

2.1 Characteristics of Sensors

Most sensors do not directly generate a signal from an external phenomenon, but via several conversion steps. Thus, the output that is read by the user may deviate from the actual input, and these performance-related parameters, or specifications provides information about the deviation from the ideal behavior. There are static characteristics like accuracy, precision, resolution and sensitivity. Typically, these can be easily managed before fusion process. Dynamic characteristics however, varies between changes of input. The speed and frequency of response, settling time and lag of sensors are all inevitable, and these leads to several of the inherent errors face by sensor fusion.
Most sensors are not ideal, and there are deviations which may come into the information required. Some can be assumed to be caused by random noise, which requires signal processing to reduce the error. The other case is a systematic error which is correlated with time, and this can be improved through a defined filter if the error is known.

2.2 Advantages of Multi-sensor Fusion

In general, multi-sensor fusion data provides significant advantages as compared to using only a single source data. The improvement of performance is summarize in four general areas [1]:
Representation. Information obtained throughout the fusion process has an abstract level, or a granularity, higher than the original individual input data set. This allows for a richer semantic and higher resolution on the data compared to that of each initial source of information.
Certainty. We expect the probability of the data to increase after fusion process, increasing the confidence rate of the data in use. The improved signal to noise ratio is also part of the reason of better confidence in the fused data. These are associated with redundant information from group of sensors surveying the same environment. The reliability of the system thus is improved as well in cases of sensor error or failure.
Accuracy. If at first data is noisy or have errors, the fusion process should try to reduce or eliminate noise and errors. Usually, the gain in certainty and the gain in accuracy are correlated. The accuracy can be in the timing as well, from

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the parallel processing of different information from multiple sensors.

Completeness. Through bringing new information to the current knowledge of the environment allows for a more thorough view. If individual sensors only provide information that is independent of other sensors, bringing them into a coherent space will give an overarching view of the whole. Usually, if the information is redundant and concordant, the accuracy will improve. The discrimination power of the information is also increased with more comprehensive coverage from multiple sensors.

The numbers of sensors which is employed is also a factor in the cost analysis of whether a multi-sensor system is better than a single sensor system [2]. A criterion has to be set up to assess the reliability of the whole system. However, as different applications require different numbers and types of sensor, it is difficult to define an overarching optimal number of sensors for any given system.

2.3 Possible Problems and Issues

Certainly, sensor fusion comes with its own inherent problems. Several key issues have to be considered for sensor fusion techniques [3, 4]:

Registration. Individual sensors have its own local reference frame from which it provides data. For fusion to occur, the different data sets have to be converted into a common reference frame, and aligned together. Calibration error of individual sensors should be addressed during this stage. This problem is critical in determining whether the process of fusion is successful or not.

Uncertainty in Sensor data. Diverse formats of data may possibly create noise and ambiguity in the fusion process. Competitive or conflicting data may thus be results from such errors. The redundancy of the data from multiple sensors have to be engaged to reduce uncertainty, and learning to reject outliers if conflicting data is encountered.

Incomplete, Inconsistent, Spurious data. Data is considered to be incomplete if the observed data remains the same regardless of the number of interpretations. Some methods to make data complete is by either collecting more data features, or through the usage of more sensors. Inconsistent sensors is defined to be two complete data sets but having different interpretations. This is the consequences of bad sensor registration or sensors observing different things. If data contains features that is not related to the observed environment, it is defined to be spurious. Just like uncertainty, the redundancy data have to be exploited to help in fusing the incomplete, inconsistent, and spurious data [5].

Correspondence / Data Association [6, 7]. One aspect of sensor fusion is establishing whether the two tracks from each sensor represent the same object (Track-to track). This is required to know how the data features matches each other from different sensors, and knowing whether there are data features that are outliers. The other forms of data association problem is measurement-to-track association, which refers to the problem of recognizing from which target each measurement originates [8].

Granularity. The level of details from different sensors is rarely similar. The data may be sparse or dense, relative to other sensors. The level of data may be different, and this has to be addressed in the process of fusion.

Time Scales. In different aspects, sensors may be measuring the same environment at different rates. Another case is two identical sensors measuring at different frequency due to manufacturing defects. The arrival timing at the fusion node may also not coincide due to propagation delays in the system. Especially for spatial distribution of sensors, with variation in the data rate, real-time sensor fusion has to be based on a precise time-scale setting to ensure all data are synchronized properly. In cases where fusion algorithm requires a history of data, how fast the sensor is able to provide data is directly related to the validity of results.

3. ALGORITMS FOR SENSOR FUSION

Due to the various natures of fusion process, different algorithms are engaged for different level of fusion. These are usually probability theory, classification methods, and artificial intelligence [9].

3.1 Kalman Filtering

The Kalman filter is an ideal statistical recursive data processing algorithm which continuously calculates an estimate of a continuous valued state based on periodic observations of the state. It uses an explicit statistical model of how x(t) changes over time and an explicit statistical model of how observations z(t) which are made are related [10, 11].

The explicit description of process and observations lets many models of sensor to be easily incorporated in the algorithm. Not only so, we can constantly assess the role of each sensor in the system.

As every iteration requires almost the same effort, the Kalman filter is well adapted for real-time usage.

We first define a model for the states to be estimated in the standard space-time form:

$$\dot{x}(t) = \mathrm{A}(t)x(t) + B(t)u(t) + n(t)$$

where x(t) is the state vector of interest, A(t) is the transition matrix, B(t) is the control matrix, u(t) is a known control input. The observations equation defined in standard space-time model:

$$z(t) = H(t)x(t) + v(t)$$

where z(t) is the observation vector, H(t) is the measurement matrix. n(t) and v(t) are random zero-mean Gaussian variable describing uncertainty as the state evolves, with covariance matrices Q(t) and R(t) respectively.

From this, the Kalman filter proceeds recursively in two stages, prediction and update [12].

A prediction $\hat{x}(k|k-1)$ of the state at time k is given as

$$\hat{x}(k|k-1) = A(k)x(k-1|k-1) + B(k)u(k)$$

The covariance P(k|k-1) is also computed as

$$P(k|k-1) = A(k)P(k-1|k-1)A^T(k) + Q(k)$$

At time k, and observation z(k) is made and the estimate $\hat{x}(k|k)$ is the update of state x(k). Together with the updated state estimate covariance matrix P(k|k), are computed from the state prediction and observation by

$$\hat{x}(k|k) = \hat{x}(k|k-1) + K(k)[z(k) - H(k)\hat{x}(k|k-1)]$$

$$P(k|k) = [I - K(k)H(k)]P(k|k-1)$$

K(k) is the Kalman gain matrix that is a measure of the relative confidence of the past estimates and the latest observation. The Kalman gain is chosen to minimize the *a posteriori* state estimate covariance.

The main advantage of Kalman Filter is that it has high computational efficiency since entire sequence of old observations is not reprocessed with every new observations. All these are condensed through the information in the current state and error correlation matrix. However, it is restricted to linear system dynamics, and that the initial uncertainty which is Gaussian [13, 14]. In such cases, extended Kalman Filter is employed. Using first-order Taylor series expansion, the system is linearize [15]. The EKF is a frequently employed methods for data fusion in robotic applications today. However, the linearization can be unstable if the time intervals are not small enough, with a tradeoff of higher requirement of computations with fine time intervals [16, 17]. In sensor network where each sensor is able to process information and move to the target, a distributed algorithm [18] can be used to estimate the average-consensus, and this is a form of distributed Kalman filtering (DKF) in scalable sensor fusion. Mobile sensor network has better mobility and performance compared to static network, making it of interest to take advantage of [19, 20]. Another algorithm that is gaining popularity is the unscented Kalman filter (UKF), which is based on a relatively low complexity in approximating a known statistical distribution [9]. It determines the minimum set of points around the mean, which is enough to describe the true mean and covariance completely. From there, it calculates the estimates without the need to linearize. This makes the UKF simple to implement on a complex process compared to the EKF. Also, the UKF can be employed in parallel implementations. Recent research have being done for robot navigation using the extended Kalman filter [21] and the unscented Kalman filter [22, 23].

3.2 Support Vector Machine (SVM)

Support Vector Machine was proposed in 1963, and the current standard in 1993 [24]. It is a learning model that analyses data, and extract patterns for classification and regression analysis. Taking a set of training examples, each belonging to one of two classes, SVM assign new examples into either category. It is thus a non-probabilistic binary linear classifier. The optimized hyperplane should minimize structural errors and maximize the margins between the hyperplane and the closest points – the support vectors [25, 26] summary of SVM method is stated here.

Taking a binary classification problem in a m-dimensional feature space $\Re^m$, consider a set of points $\{x_i, y_i\}_{i=1}^{N}$ which are the training data, where $x_i \in \Re^m$, $i = 1,2, \dots, N$ and $y_i \in \{-1, +1\}$ are corresponding class labels. The objective of SVM is to try to construct a hyperplane to allocate any new point into either classes through the linear classifier function

$$f(x_i; w, b) = \langle w \cdot x_i \rangle + b$$

where w and b are the normal vector and the bias respectively. The labeled points are then sorted, with the support vectors lying on two hyperplanes,

$$y_i(\langle w \cdot x_i \rangle + b) = \pm 1$$

which are parallel to the optimal linear separating hyperplane. The aim now is to minimize $\|\omega\|^2/2$ to obtain the maximum margin. However, if data is non-linear, they have to be mapped into a higher-dimensional feature space using a function $\Phi: \Re^m \to H$, and then linearly separated in this space using kernel functions. Some frequently used kernel functions include polynomial and Gaussian radial basis function.

SVM attempts to find the maximum margin is very suitable in cases of path planning, where safety margin is vital. Collision avoidance path planning and navigation, simultaneous localization and mapping (SLAM) frequently apply SVM [27, 28].

SVM is also used to compress information in sensor fusion system that may have limited bandwidth, and large set of data samples are not feasible for real-time processing [29]. A two-layer SVM scheme was also purposed and significantly improves the results of a single SVM [30].

3.3 Bayesian Inference Technique

Baye's rule provides a means of combining observed data with past beliefs about the state of the environment. It requires that the state of an object or environment described as x, and an observation z, be determined as a joint probability or joint probability distribution P(x,z) for discrete and continuous variables respectively. Expanding the joint probability by the chain-rule of conditional probabilities:

$$P(x, z) = P(x|z)P(z) = P(z|x)P(x)$$

And upon arriving in terms of P(x|z), we obtain Baye's rule:

$$P(x|z) = \frac{P(Z|X)P(x)}{P(z)}$$

$$posterior = \frac{likelihood \cdot prior}{evidence}$$

Bayesian inference is a statistical data fusion algorithm based on Baye's theorem, with a recursive predict-update process [31]. In sensor fusion however, the system state is most of the time time-dependent, which means that the system state changes over time even though no new observation has been taken. Not only so, but the prior changes with every new observations, and thus Baye's rule have to be applied recursively. We can conclude that the prior is dependent on time, and on the history of observations taken beforehand.

The multi-sensor form of Baye's rule requires conditional independence,

$$P(z_1, \dots, z_n|x) = P(z_1|x)..P(z_n|x) = \prod_{i=1}^{n} P(z_i|x)$$

So that

$$P(x|Z^n) = P(x)\prod_{i=1}^{n} P(z_i|x)$$

This states that the posterior probability of x, given all observation of Z^n, is proportional to the product of all the individual likelihoods from each sensor source. The recursive form of Baye's rule is then given by,

$$P(x|Z^k) = \frac{P(z_k|x)P(x|Z^{k-1})}{P(z_k|Z^{k-1})}$$

$P(x|Z^{k-1})$ include a complete summary of all past information at k-1 instant. At the next instant k, with next piece of information $P(z_k|x)$, the previous posterior acts as the current prior information, and provide the new posterior density. Thus, the computation is much less demanding.

3.4 Sequential Monte Carlo methods (Particle filter)

Particle Filters are a class of modern sequential Monte Carlo methods [32]. It is based on building a posterior density function using several random samples call particles. The advantage of particle filtering is its ability to represent arbitrary probability densities, when systems are non-Gaussian or nonlinear. Also, the error in calculation is usually an unknown or non-Gaussian, and a probability density function is mandatory.

Particle filter works by approximating the probability of the state as weighted sum of random samples, which are predicted, with their weights updated from the likelihood of measurement. This is called sequential importance sampling (SIS). A resampling step is introduced in newer iteration to prevent filter divergence, and this is done by removing particles with the lowest weights, and creating new particles at points with the highest weight [33]. This is called sequential importance resampling. Particle filter have being proven to be effective in distributed sensing environment [34]. A number of different types of particle filter exist, and the performance of different one varies when used for certain applications. The choice of importance density is the important factor that determines the performance [35].

3.5 Dempster-Shafer Theory of Evidence

The Dempster-Shafer (D-S) evidence theory was proposed by Dempster [36] and later extended mathematically by Shafer [37]. D-S theory is based on two ideas: obtaining degrees of belief for one question from subjective probabilities for a related question, and using Dempster's rule to combine the degrees of belief when they are based on independent items of evidence [38].

The evidence theory operates on a frame of discernment, Θ. Let 2^{Θ} denotes the power set of all subsets of Θ, including the null set Ø and Θ itself. For example, if Θ = {a,b}, then

$$2^{\Theta} = \{\emptyset, \{a\}, \{b\}, \Theta\}$$

In D-S inference, each element is assign a basic probability assignment,

$$m: 2^{\Theta} \rightarrow [0,1]$$

There are two properties, first the mass of the empty set is 0:

$$m(\emptyset) = 0$$

Remaining mass terms of the power set add up to 1:

$$\sum_{A\subseteq\Theta} m(A) = 1$$

For any proposition A, m(A) expresses the proportion of available evidence that supports the claim that the actual system state belongs to A. The belief and plausibility functions are then derevied from the value of m(A), where the belief is the lower bound of the probability P(A), and the plausibility is the upper bound:

$$bel(A) \leq P(A) \leq pl(A)$$

The belief of A is defined as the sum of all the masses of subsets of the set of interest A:

$$bel(A) = \sum_{B|B\subseteq A} m(B)$$

The plausibility of A is defined as the sum of all the masses of sets B that intersect the set of interest A:

$$pl(A) = \sum_{B|B\cap A\neq\emptyset} m(B)$$

From Dempster's rule of combination, evidence from sensors is fused. Taking two sources of information with belief mass functions m_1 and m_2, the joint belief mass function $m_{1,2}$ is then calculated as follows:

$$m_{1,2}(A) = (m_1 \oplus m_2)(A) = \frac{1}{1-K}\sum_{B\cap C=A\neq\emptyset} m_1(B)m_2(C)$$

$$m_{1,2}(\emptyset) = 0$$

where K represents the amount of conflict between the two sources sets, and is given as:

$$K = \sum_{B\cap C=\emptyset} m_1(B)m_2(C)$$

Unlike Bayesian inference, D-S theory allows each source to contribute information in its own levels of detail. For example, one sensor can give information to separate individual entities, while another provide information to separate classes of entities. We are able to represent partial knowledge, updated beliefs, together with a combination of evidence and to model the ambiguity explicitly [39].

To determine when to use Bayesian or Dempster-Shafer method, one have to decide whether a higher level of accuracy from the former is required, or the flexibility of the latter method is preferred [40]. Studies have been done to compare between Bayesian inference method and Shafer-Dempster method [41, 42]. A recent application presenting human-autonomy sensor fusion in object detection compares the performance between Bayesian, Dempster-Shafer, Dynamic Dempster-Shafer fusion method [43]. Certainly, there are issues with the D-S Theory, like the complexity of computations [44] and also counterintuitive results from conflicting data [45]. Some common approaches is to use D-S theory with other algorithms to enhance the accuracy and speed [46, 47].

3.6 Artificial Neural Networks (ANN)

ANNs are mathematical models composed of nonlinear computational elements (neurons), operating in parallel and connected as a graph topography characterized by different weighted links. ANNs have proven to be more powerful, and more adaptable method, compared to traditional linear or non-linear analyses [48, 49]. The layers of processing neurons can be connected in different ways. The neurons can be trained to learn behavior of any system, using sets of training data and learning algorithms to tune the individual weight of the links. Weights are altered to improve the robustness of the system. Once the errors for the training data have being minimized, the ANNs can remember the functions, and be engaged in further estimations. The data is closely linked with the processing. One major problems currently is determining the best topology for any given problem. Some factors which determines this are the problem itself, the prospective approach to the problem, and the neural network characteristics. Recent research in robot navigation have successfully used neural networks in sensor fusion [50].

3.7 Fuzzy Logic

Fuzzy logic is finding wide-spread popularity as a method to represent uncertainty in high-level fusion. Essentially, it is a type of multi-value logic that allows the uncertainty in multi-sensor fusion to be categorized in the inference process by assigning each proposition a degree of membership from 0 to 1 [51]. Fuzzy sensor fusion approach has shown a high degree of certainty and accuracy, although the tradeoff is the complex computations required [52].

In most application of sensor fusion, a combination of methods are used to exploit the advantages of artificial intelligence method and traditional method. [53] merges neural network and linearly constrained least squares method, which is shown to be stable and fast. [54] is able to take different information sources with different noise characteristics and achieve optimized results through the use of fuzzy logic. [55] integrate Kalman filter with fuzzy logic techniques, and is able to achieve the optimality of Kalman Filter, and the competence of fuzzy systems to handle inconsistent information.

4. APPLICATIONS / IMPLEMENTATION

Multi-sensor fusion systems have already being applied to different problems, but there are areas of which research is still being carried out, and being developed. Overlap may occur in the following cases, but this is a general attempt to covering the board aspects.

4.1 Internet of Things

In the last decade, the Internet of Things (IoT) has attracted attention from academia [56, 57] and industry, due to its potential to create a smart world where every objects are connected to the Internet and communicate with each other with minimum human intervention [58]. The IoT requires large amounts of real-time data to offer materials for analysis and action, and sensors are available everywhere, from smart devices (smartphones, tablets), wearables (smartwatches, camera glasses) and healthcare (RFIDs). Approaches to improve this allow IoT to work efficiently [59, 60]. Sensor fusion helps to enable context awareness, a cornerstone for the IoT. By knowing the circumstances or facts that form an event, we can use this information to understand why a situation is as it is, and form suitable action. With about 50 to 100 billion devices projected to connect to the internet by 2020 [61], and able to generate data constantly, this present an enormous amount of data to present. Some areas which is expected to see applications are building automation like smart energy consumption control [62], power grid [63], environment, industrial [64] and consumer home automation [65]. With cars being equipped with sensors, as well as camera feed on road, information can be generated to keep track of traffic anywhere in the city [66], and this can be provided back to the users [67].

4.2 Automotive and Navigation

With cars becoming more sophisticated, developments ae focused on improving performance, safety, comfort, environmentally friendliness and assistance to driver. In the area of autonomous driving, various sensors are being featured like GPS (Global Positioning System), LiDAR and ultrasound. Many of these are used to create object representation of both the car and its surrounding [68], and these data can be fused to provide a complete view of the driving condition. With the reliance on so many types of sensors, a multi-level fusion process is required, where low level sensor fusion process the massive amount of input data and high-level fusion process provides the real-time decision. With the recent development of RADAR and LiDAR, there is now a smaller demand of on-board camera, as these two produce richer and more accurate 3D representation which helps detect and classify objects better [69]. However, LiDAR sensors while provides a better field of coverage, it does not provide speed information, and RADAR gives accurate speed data but is not effective in lanes with curves. Many of these are related to mobile robotics, with path planning and obstacles avoidance [70] being scaled up to facilitate the real world application. The design of complementary sensors is essential to provide better 3D map [71], or allowing the system to recognize different bodies in the environment [72], and also the scalability of electronic systems to ensure that no bottle-necking occur during real-time processing [73], with the expected increases in information feed.

For safety and collision avoidance, sensor fusion research is being done to improve the quality of detection, especially in preventing false positive cases [74].

4.3 Quadrotors and Drone

Drones and quadrotors are also an emerging field for developing new technologies and methods to ensure the safe operation as well as reliable maneuver [75]. The navigation system of such quadrotor usually consist of three-axis gyroscope, three-axis accelerometer and magnetometer in the navigation system, with a complementary sensor group of pressure altimeter, ultrasonic sensors and GPS [76]. Autonomous flight [77] is one aspect of which new progress have allow quadrotor to work independently in places where human may be unable to reach. The cost of implementing fusion is relatively low, but still maintaining a satisfactory performance [78], allows for the wide availability of consumer level drones. Not only so, due to the robustness of sensor fusion, drones can hover in one fixed position without the need of GPS, through the usage of other sensors [79, 80]. It is important to show the reliability of fusion method, that operation will not be compromised despite one sensor input missing.

4.4 Computer Vision [81]

Computer vision, started off as trying to mimic the human vision, though using competing sensors [82]. As the understanding of the complexity of perception developed, new sensors, like 3D cameras, have help to augment the ability of computer vision. It had become an essential part in many applications, for example medical imaging, vision of intelligent robots [83], and nondestructive testing.

In recent years, the need to improve the security of the general public, as well as public assets had grown. One big hurdle is the detection of concealed weapons underneath person's clothing. Several fusion methods have being worked on, for example, multiple images with different exposure, together with infrared images [84], and combined detection for automatic bag screening at venues like stadium or museums [85].

4.5 Virtual reality / Augmented reality

A recent development, virtual reality (VR) is an emerging technology that is attracting attention from consumers as an entertainment or educational tool. Some of the current models available are HTC Vive and the Oculus Rift. One of the key challenges of virtual environment is the tracking of head movement. As a user change his viewpoints, the virtual elements must keep their alignment with the observed 3D position and the orientation to real world objects. In addition to the accuracy, the ability to provide stable motions is vital as well. The last challenge is to reduce the latency, defined here as the time between head movement and producing corresponding images to the user's retina. This had being an early problem which causes VR simulator sickness. A single gyroscope does not give information about the user's location, while accelerometers' reading tends to be noisy, and yaw reading cannot be read. A magnetometer can act like a compass, allowing an orientation estimate, however, this is easily affected by any ferromagnetic metals [86]. The current method of sensor fusion uses a weighted filter to determine the information to take from the different sensors, taking the long term accuracy of the accelerometer, while using the gyroscope to do reduction of the noise signal in the short term [87]. Predictive tracking methods have also been implemented from the angular speed of the gyroscope, to reduce latency to a rate of 30ms.

4.6 Healthcare

With aging population becoming a common trend in well developed country, it is important to have ways to monitor or track their health condition without the need to have people monitoring them around the clock [88]. Fall detection is an area being researched on, and that is especially helpful for elderly who live alone, with no supervision [89]. Not only does sensor fusion method benefits the elderly, we are able to monitor the development of infant motor functions, with new ability to assessment body postures in infants [90]. General research using body sensors and wireless sensor networks are common, with tracking [91] and identification [92] of human, tracking mental state of patients and attempting to classify individual's state of the mind by fusing data from various physiological sensors, for example, heart rate, respiration rate, carbon dioxide and oxygen level is being worked on [93]. Some of the main problems are software side, like reliability of measurement, and network status to prevent false positive from healthcare unit [94].

4.7 Micro-scale sensors fusion

Wearable electronics is a big opportunity for sensors, with them able to track user's activity, healthcare, and sports applications. The microelectromechanical systems (MEMS) is the technology which enables them. They are now everywhere, from tablets to smartwatch to smartphones. Besides MEMS, System on Chip (SoC) solutions are getting more common with the need to incorporate multiple sensors on a single hardware platform. To achieve this, the miniaturization of sensors is an active research area, as the number of sensors in a system will keep increasing.

5. CONCLUSION

This paper provide a review of sensor fusion theories, from the models of different application of sensor fusion, to some of the common algorithms being used to enable sensor fusion, as well as recent researches that is being carried out. New application areas like Internet of Things, automotive and healthcare applications show benefits when sensor fusion is applied, and there are still a wide range of potential applications that is unable to be covered fully. Certainly there are still areas of development and research that can help to further advance current level of knowledge. Algorithm fusion is still being debated, to try to focus on the advantages each method have, and using new methods to cover up the weakness of other. New approaches to combine the different level of sensor fusion and different approaches have to be developed, and a general framework to assess different sensor fusion technique will be essential to benchmark clearly the different techniques, and to allow us to determine precisely the constraints required for certain system. The accuracy, computational speed and cost of sensor fusion are the three basic requirements, but in most cases today, only two of them are usually fulfilled for every method.

REFERENCES

[1] H. B. Mitchell, *Multi-sensor data fusion: An introduction*. Springer, 2007.

[2] J. K. Hackett and M. Shah, "Multi-sensor fusion: A perspective," *Proceedings, International Conference on Robotics and Automation,* pp. 1324-1330, 1990.

[3] B. Khaleghi, A. Khamis, F. O. Karray, and S. N. Razavi, "Multisensor data fusion: A review of the state-of-the-art," *Information Fusion,* vol. 14, no. 1, pp. 28-44, 2013.

[4] R. Joshi and A. C. Sanderson, *Multisensor fusion: A minimal representation framework*. World Scientific, 1999.

[5] R. C. Luo and M. G. Kay, "A tutorial on multisensor integration and fusion," in *Industrial Electronics Society, 1990. IECON'90., 16th Annual Conference of IEEE*, 1990, pp. 707-722: IEEE.

[6] F. Castanedo, "A review of data fusion techniques," *Scientific World Journal,* vol. 2013, p. 704504, 2013.

[7] S. S. Blackman, "Theoretical approaches to data association and fusion," *Orlando Technical Symposium,* pp. 50-55, 1988.

[8] D. Smith and S. Singh, "Approaches to multisensor data fusion in target tracking: A survey," *IEEE Transactions on Knowledge and Data Engineering,* vol. 18, no. 12, pp. 1696-1710, Dec 2006.

[9] R. C. Luo, C. C. Chang, and C. C. Lai, "Multisensor fusion and integration: Theories, applications, and its perspectives," *IEEE Sensors Journal,* vol. 11, no. 12, pp. 3122-3138, Dec 2011.

[10] R. E. Kalman, "A new approach to linear filtering and prediciton problems," *Transactions of the ASME-Journal of Basic Engineering,* vol. 82, no. 1, pp. 35-45, 1960.

[11] J. Z. Sasiadek, "Sensor fusion," *Annual Reviews in Control,* vol. 26, pp. 203-228, 2002.

[12] H. Durrant-Whyte and T. C. Henderson, "Multisensor data fusion," in *Springer Handbook of Robotics*, B. Siciliano and O. Khatib, Eds.: Springer International Publishing, 2016, pp. 867-896.

[13] S. Julier and J. Uhlmann, "A non-divergent estimation algorithm in the presence of unknown correlations,," *American Control Conference, 1997. Proceedings of the 1997,* vol. 4, pp. 2369-2373, Jun 1997.

[14] J. Uhlmann, "Covariance consistency methods for fault-tolerant distributed data fusion," *Information Fusion,* vol. 4, no. 3, pp. 201-215, Sep 2003.

[15] D. Fox, J. Hightower, L. Liao, D. Schulz, and G. Borriello, "Bayesian filtering for location estimation," *IEEE Pervasive Computing,* vol. 2, no. 3, pp. 24-33, Jul-Sep 2003.

[16] S. Julier, J. Uhlmann, and H. F. Durrant-Whyte, "A new method for the nonlinear transformation of means and covariances in filters and estimators," *IEEE Transactions on Automatic Control,* vol. 45, no. 3, pp. 477-482, Mar 2000.

[17] S. Julier and J. Uhlmann, "A new extension of the kalman filter to nonlinear systems," *Proceedings of the Adaptive Systems for Signal Processing, Communications, and Control Symposium,* pp. 153-158, 2000.

[18] D. P. Spanos, R. Olfati-Saber, and R. M. Murray, "Approximate distributed Kalman filtering in sensor networks with quantifiable

performance," in *Information Processing in Sensor Networks, 2005. IPSN 2005. Fourth International Symposium on*, 2005, pp. 133-139: Ieee.

[19] H. Su, X. Chen, M. Z. Q. Chen, and L. Wang, "Distributed estimation and control for mobile sensor networks with coupling delays," *ISA transactions,* vol. 64, pp. 141-150, 2016.

[20] H. Su, Z. Li, and M. Z. Q. Chen, "Distributed estimation and control for two-target tracking mobile sensor networks," *Journal of the Franklin Institute,* 2017.

[21] S. Lynen, M. W. Achtelik, S. Weiss, M. Chli, and R. Siegwart, "A robust and modular multi-sensor fusion approach applied to mav navigation," *International Conference on Intelligent Robots and Systems (IROS),* pp. 3923-3929, Nov 2013.

[22] I. Ashokaraj, A. Tsourdos, P. Silson, and B. A. White, "Sensor based robot localisation and navigation: Using interval analysis and unscented kalman filter," *Proceedings of International Conference on Intelligent Robots and System,* vol. 1, pp. 7-12, 2004.

[23] M. L. Anjum, J. Park, W. Hwang, H. I. Kwon, J. H. Kim, C. Lee, K. S. Kim, and D. Cho, "Sensor data fusion using unscented kalman filter for accurate localization of mobile robots," *International Conference on Control Automation and Systems,* pp. 947-952, OCt 2010.

[24] C. Cortes and V. Vapnik, "Support-vector networks," *Machine Learning,* vol. 20, no. 3, pp. 273-297, Sep 1995.

[25] C. J. C. Burges, "A tutorial on support vector machines for pattern recognition," *Data Mining and Knowledge Discovery,* vol. 2, no. 2, pp. 121-167, Jun 1998.

[26] V. Vapnik, *Statistical learning theory*. Wiley, 1998.

[27] K. Tanaka, K. Yamano, E. Kondo, and Y. Kimuro, "A vision system for detecting mobile robots in office environments," *IEEE International Conference on Robotics and Automation,* vol. 3, pp. 2279-2284, 2004.

[28] J. Shen and H. Hu, "SVM based SLAM algorithm for autonomous mobile robots," *International Conference on Mechatronics and Automation,* pp. 337-342, Aug 2007.

[29] S. Challa, M. Palaniswami, and A. Shilton, "Distributed data fusion using support vector machines," *Proceedings of the Fifth International Conference on Information Fusion,* vol. 2, pp. 881-885, July 2002.

[30] B. Waske and J. A. Benediktsson, "Fusion of support vector machines for classification of multisensor data," *IEEE Transactions on Geoscience and Remote Sensing,* vol. 45, no. 12, pp. 3858-3866, Dec 2007.

[31] W. A. Abdulhafiz and A. Khamis, "Bayesian approach to multisensor data fusion with pre-and post-filtering," *10th IEEE International Conference on Networking, Sensing and Control,* pp. 373-378, 2013.

[32] D. Crisan and A. Doucet, "A survey of convergence results on particle filtering methods for practitioners," *IEEE Transactions on Signal Processing,* vol. 50, no. 3, pp. 736-746, Mar 2002.

[33] N. J. Gordon, D. J. Salmond, and A. F. Smith, "Novel approach to nonlinear/non-Gaussian Bayesian state estimation," *Radar and Signal Processing, Proceedings F,* vol. 140, no. 2, pp. 107-113, 1993.

[34] J. Liu, M. Chu, J. Liu, J. Reich, and F. Zhao, "Distributed state representation for tracking problems in sensor networks," *Third International Symposium on Information Processing in Sensor Networks,* pp. 234-242.

[35] M. S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, "A tutorial on particle filters for online nonlinear/non-gaussian bayesian tracking," *IEEE Transactions on Signal Processing,* vol. 50, no. 2, pp. 174-188, Feb 2002.

[36] A. P. Dempster, "A generalization of bayesian inference," *Journal of the Royal Statistical Society,* no. Series B (Methodlogical), pp. 205-247, 1968.

[37] G. Shafer, *A Mathematical Theory of Evidence*. Princeton University Press, 1976.

[38] R. C. Luo and C. C. Chang, "Multisensor fusion and integration: A review on approaches and its applications in mechatronics," *IEEE Transactions on Industrial Informatics,* vol. 8, no. 1, pp. 49-60, Feb 2012.

[39] G. Provan, "The validity of Dempster-Shafer belief functions," *International Journal of Approximate Reasoning,* vol. 6, no. 3, pp. 389-399, May 1992.

[40] B. R. Bracio, W. Horn, and D. P. F. Moller, "Sensor fusion in biomedical systems," *Proceedings of the 19th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* vol. 3, pp. 1387-1390, Nov 1997.

[41] Y. Cheng and R. L. Kashyap, "Comparision of bayesian and dempster's rules in evidence combination," in *Maximum-Entropy and Bayesian Methods in Science and Engineering*: Springer Netherlands, 1988, pp. 427-433.

[42] B. R. Cobb and P. P. Shenoy, "A comparison of bayesian and belief function reasoning," *Information Systems Frontiers,* vol. 5, no. 4, pp. 345-358, Dec 2003.

[43] R. M. Robinson, H. Lee, M. J. McCourt, A. R. Marathe, H. Kwon, C. Ton, and W. D. Nothwang, "Human-autonomy sensor fusion for rapid object detection," *Intelligent Robots and Systems (IROS), 2015 IEEE/RSJ International Conference on,* pp. 305-312, 2015.

[44] J. A. Barnett, "Computational methods for a mathematical theory of evidence," *Proceedings of the 7th international joint conference on Artificial Intelligence,* vol. 2, pp. 868-875, 1981.

[45] L. A. Zadeh, "Review of "a mathematics theory of evidence"," *AI Magazine,* vol. 5, no. 3, pp. 81-83, 1984.

[46] T. Denoeux, "A neural network classifier based on Dempster-Shafer theory," *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions,* vol. 30, no. 2, pp. 131-150, 2000.

[47] Y. Zhan, H. Leung, K. C. Kwak, and H. Yoon, "Automated speaker recognition for home service robots using genetic algorithm and Dempster–Shafer fusion technique," *Instrumentation and Measurement, IEEE Transactions on,* vol. 58, no. 9, pp. 3058-3068, 2009.

[48] D. Jiang, X. Yang, N. Clinton, and N. Wang, "An artificial neural network model for estimating crop yields using remotely sensed information," *International Journal of Remote Sensing,* vol. 25, no. 9, pp. 1723-1732, May 2004.

[49] J. Dong, D. Zhuang, Y. Huang, and J. Fu, "Advances in multi-sensor data fusion: Algorithms and applications," *Sensors (Basel),* vol. 9, no. 10, pp. 7771-84, 2009.

[50] H. Guanshan, "Neural network applications in sensor fusion for a mobile robot motion," *WASE International Conference on Information Engineering (ICIE,* vol. 1, pp. 46-49, Aug 2010.

[51] R. E. Gibson , D. L. Hall, and J. A. Stover, "An autonomous fuzzy logic architecture for multisensor data fusion," *International Conference on Multisensor Fusion and Integration for Intelligent Systems,* pp. 143-150, 1994.

[52] M. A. A. Akhoundi and E. Valavi, "Multi-sensor fuzzy data fusion using sensors with different characteristics," *arXiv preprint arXiv:1010.6096,* 2010.

[53] Y. Xia, H. Leung, and E. Bosse, "Neural data fusion algorithms based on a linearly constrained least square method," *IEEE Trans Neural Netw,* vol. 13, no. 2, pp. 320-9, 2002.

[54] K. Goebel and W. Yan, "Hybrid data fusion for correction of sensor drift faults," *IMACS Multiconference on Computational Engineering in Systems Applications,* vol. 1, pp. 456-462, Oct 2006.

[55] P. J. Escamilla-Ambrosio and N. Mort, "Hybrid kalman filter-fuzzy logic adaptive multisensor data fusion architectures," *Proceedings 42nd IEEE Conference on Decision and Control,* pp. 5215-5220, Dec 2003.

[56] K. S. Yeo, M. C. Chian, T. C. W. Ng, and D. A. Tuan, "Internet of things: Trends, challenges and applications," *2014 14th International Symposium on Integrated Circuits (Isic),* pp. 568-571, 2014.

[57] D. Singh, G. Tripathi, and A. J. Jara, "A survey of internet-of-things: Future vision, architecture, challenges and services," *2014 IEEE World Forum on Internet of Things (Wf-Iot),* pp. 287-292, 2014.

[58] H. Sundmaeker, P. Guillemin, P. Friess, and S. Woelfflé, "Vision and challenges for realizing the internet of things," European Commission Information Society and Media2010.

[59] F. H. Bijarbooneh, W. Du, E. C. H. Ngai, X. M. Fu, and J. C. Liu, "Cloud-assisted data fusion and sensor selection for internet of things," *IEEE Internet of Things Journal,* vol. 3, no. 3, pp. 257-268, Jun 2016.

[60] S. Din, H. Ghayvat, A. Paul, A. Ahmad, M. M. Rathore, and I. Shafi, "An architecture to analyze big data in the internet of things," in *Sensing Technology (ICST), 2015 9th International Conference on*, 2015, pp. 677-682.

[61] A. Zaslavsky, C. Perera, and D. Georgakopoulos, "Sensing as a service and big data," *arXiv preprint arXiv:1301.0159,* 2013.

[62] K. Akkaya, I. Guvenc, R. Aygun, N. Pala, and A. Kadri, "IoT-based occupancy monitoring techniques for energy-efficient smart buildings," *2015 IEEE Wireless Communications and Networking Conference Workshops (Wcncw),* pp. 58-63, 2015.

[63] N. Ouerhani, N. Pazos, M. Aeberli, and M. Muller, "IoT-based dynamic street light control for smart cities use cases," *Networks, Computers and Communications (ISNCC), 2016 International Symposium on,* pp. 1-5, 2016.
[64] F. Kirsch, R. Miesen, and M. Vossiek, "Precise local-positioning for autonomous situation awareness in the internet of things," *2014 IEEE Mtt-S International Microwave Symposium (Ims),* pp. 1-4, 2014.
[65] C.-L. Wu, Y. Xie, S. K. Pradhan, L.-C. Fu, and Y.-C. Zeng, "Unsupervised context discovery based on hierarchical fusion of heterogeneous features in real smart living environments," *Automation Science and Engineering (CASE), 2016 IEEE International Conference on,* pp. 1106-1111, 2016.
[66] S. K. Datta, R. P. F. Da Costa, J. Hyrri, and C. Bonnet, "Integrating connected vehicles in internet of things ecosystems: Challenges and solutions," *World of Wireless, Mobile and Multimedia Networks (WoWMoM), 2016 IEEE 17th International Symposium on A,* pp. 1-6, 2016.
[67] S. Wildstrom. (2012). *Better living through big data.* Available: http://newsroom.cisco.com/feature/778800/Better
[68] P. Bonnifait, P. Bouron, P. Crubillé, and D. Meizel, "Data fusion of four ABS sensors and GPS for an enhanced localization of car-like vehicles.," *Robotics and Automation, 2001. Proceedings 2001 ICRA. IEEE International Conference on,* pp. 1597-1602, 2001.
[69] F. Mujica, "Scalable electronics driving autonomous vehicle technologies," Texas Instruments2014.
[70] I. Ulrich and J. Borenstein, "VFH^*: Local obstacle avoidance with look-ahead verification.," *Robotics and Automation, 2000. Proceedings. ICRA '00. IEEE International Conference on,* pp. 2505-2511, 2000.
[71] M. Renato, E. Fernandez-Moral, and P. Rives, "Dense accurate urban mapping from spherical rgb-d images.," *Intelligent Robots and Systems (IROS), 2015 IEEE/RSJ International Conference on,* pp. 6259-6264, 2015.
[72] M. Caterina, H. H. Bülthoff, and P. Stegagno, "Autonomous vegetation identification for outdoor aerial navigation," *Intelligent Robots and Systems (IROS), 2015 IEEE/RSJ International Conference on,* pp. 3105-3110, 2015.
[73] E. Cardarelli, L. Sabattini, C. Secchi, and C. Fantuzzi, "Cloud robotics paradigm for enhanced navigation of autonomous vehicles in real world industrial applications," *2015 IEEE/Rsj International Conference on Intelligent Robots and Systems (Iros),* pp. 4518-4523, 2015.
[74] A. Westenberger, M. Muntzinger, M. Gabb, M. Fritzsche, and K. Dietmayer, "Time-to-collision estimation in automotive multi-sensor fusion with delayed measurements," *Advanced Microsystems for Automotive Applications,* pp. 13-20, 2013.
[75] S. Roelofsen, D. Gillet, and A. Martinoli, "Reciprocal collision avoidance for quadrotors using on-board visual detection," *2015 IEEE/Rsj International Conference on Intelligent Robots and Systems (Iros),* pp. 4810-4817, 2015.
[76] X. J. Wei, "Autonomous control system for the quadrotor unmanned aerial vehicle," *2016 13th International Conference on Ubiquitous Robots and Ambient Intelligence (Urai),* pp. 796-799, 2016.
[77] M. Tailanian, S. Paternain, R. Rosa, and R. Canetti, "Design and implementation of sensor data fusion for an autonomous quadrotor," *2014 IEEE International Instrumentation and Measurement Technology Conference (I2mtc) Proceedings,* pp. 1431-1436, 2014.
[78] A.-L. Chan, S.-L. Tan, and C.-L. Kwek, "Sensor data fusion for attitude stabilization in a low cost quadrotor system," *Consumer Electronics (ISCE), 2011 IEEE 15th International Symposium on,* pp. 34-39, 2011.
[79] Y. Ling, T. Liu, and S. Shen, "Aggressive quadrotor flight using dense visual-inertial fusion," *Robotics and Automation (ICRA), 2016 IEEE International Conference on,* pp. 1499-1506, 2016.
[80] W. Zheng, J. Wang, and Z. F. Wang, "Multi-sensor fusion based real-time hovering for a quadrotor without GPS in assigned position," *Proceedings of the 28th Chinese Control and Decision Conference (2016 Ccdc),* pp. 3605-3610, 2016.
[81] A. Yilmaz, "Sensor fusion in computer vision," *Urban Remote Sensing Joint Event,* pp. 1-5, 2007.
[82] H. Longuet-Higgins, "A computer algorithm for reconstructing a scene from two projections," *Readings in Computer Vision: Issues, Problems, Principles, and Paradigms,* pp. 61-62, 1987.
[83] A. Eitel, J. T. Springenberg, L. Spinello, M. Riedmiller, and W. Burgard, "Multimodal deep learning for robust RGB-d object recognition," *2015 IEEE/Rsj International Conference on Intelligent Robots and Systems (Iros),* pp. 681-687, 2015.
[84] E. M. Upadhyay and N. K. Rana, "Exposure fusion for concealed weapon detection," *2014 2nd International Conference on Devices, Circuits and Systems (Icdcs),* pp. 1-6, Mar 2014.
[85] A. M. Sagi-Dolev, "Multi-threat detection system," U.S. Patent 8171810, 2012.
[86] D. Gebre-Egziabher, G. H. Elkaim, J. D. Powel, and B. W. Parkinson, "Calibration of strapdown magnetometers in magnetic field domain," *Journal of Aerospace Engineering,* vol. 19, no. 2, pp. 87-102, Apr 2006.
[87] J. Favre, B. M. Jolles, O. Siegrist, and K. Aminian, "Quaternion-based fusion of gyroscopes and accelerometers to improve 3d angle measurement," *Electronics Letters,* vol. 42, no. 11, pp. 612-614, May 25 2006.
[88] H. Medjahed, D. Istrate, J. Boudy, J. L. Baldinger, and B. Dorizzi, "A pervasive multi-sensor data fusion for smart home healthcare monitoring," *IEEE International Conference on Fuzzy Systems (Fuzz 2011),* pp. 1466-1473, Jun 2011.
[89] G. Koshmak, A. Loutfi, and M. Linden, "Challenges and issues in multisensor fusion approach for fall detection: Review paper," *Journal of Sensors 2016,* 2015.
[90] A. Rihar, M. Mihelj, J. Pašič, J. Kolar, and M. Munih, "Using sensory data fusion methods for infant body posture assessment.," *Intelligent Robots and Systems (IROS), 2015 IEEE/RSJ International Conference on,* pp. 292-297, 2015.
[91] S. Knoop, S. Vacek, and R. Dillmann, "Sensor fusion for 3D human body tracking with an articulated 3d body model.," *Robotics and Automation, 2006. ICRA 2006. Proceedings 2006 IEEE International Conference on,* pp. 1686-1691, 2006.
[92] M. T. Yang and S. Y. Huang, "Appearance-based multimodal human tracking and identification for healthcare in the digital home," *Sensors (Basel),* vol. 14, no. 8, pp. 14253-77, Aug 05 2014.
[93] S. Begum, S. Barua, and M. U. Ahmed, "Physiological sensor signals classification for healthcare using sensor data fusion and case-based reasoning," *Sensors (Basel),* vol. 14, no. 7, pp. 11770-85, Jul 03 2014.
[94] H. Lee, K. Park, B. Lee, J. Choi, and R. Elmasri, "Issues in data fusion for healthcare monitoring," *Proceedings of the 1st international conference on Pervasive Technologies Related to Assistive Environments* 2008.