Multisensor Fusion and Integration: Approaches, Applications, and Future Research Directions

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***Abstract*—Multisensor fusion and integration is a rapidly evolving research area and requires interdisciplinary knowledge in control theory, signal processing, artificial intelligence, probability and statistics, etc. The advantages gained through the use of redundant, complementary, or more timely information in a system can provide more reliable and accurate information. This paper provides an overview of current sensor technologies and describes the paradigm of multisensor fusion and integration as well as fusion techniques at different fusion levels. Applications of multisensor fusion in robotics, biomedical system, equipment monitoring, remote sensing, and transportation system are also discussed. Finally, future research directions of multisensor fusion technology including microsensors, smart sensors, and adaptive fusion techniques are presented.**

***Index Terms*—Classification of sensors, fusion algorithms, multisensor fusion, multisensor integration, smart sensors.**

I. Introduction

SENSORS are used to provide a system with useful information concerning some features of interest in the system's environment. Multisensor fusion and integration refers to the synergistic combination of sensory data from multiple sensors to provide more reliable and accurate information. The potential advantages of multisensor fusion and integration are redundancy, complementarity, timeliness, and cost of the information. The integration or fusion of redundant information can reduce overall uncertainty and thus serve to increase the accuracy with which the features are perceived by the system. Multiple sensors providing redundant information can also serve to increase reliability in the case of sensor error or failure. Complementary information from multiple sensors allows features in the environment to be perceived that are impossible to perceive using just the information from each individual sensor operating separately. More timely information may be provided by multiple sensors due to either the actual speed of operation of each sensor, or the processing parallelism that may be possible to achieve as part of the integration process [1].

Multisensor fusion and integration is a rapidly evolving research area and requires interdisciplinary knowledge in control theory, signal processing, artificial intelligence, probability and statistics, etc. There has been much research on the subject of multisensor and fusion in recent years. A number of researchers have reviewed the multisensor fusion algorithms, architectures, and applications [2]–[8]. Luo and Kay [2] reviewed the general paradigms, fusion techniques, and specific sensor combination for multisensor integration and fusion. Multisensor-based mobile robots and applications in industrial, space, navigation, and *et al.* were surveyed. Hall and Llinas [3] conducted an overview of multisensor data fusion technology, JDL fusion process model, military, and nonmilitary applications. Dasarathy [9] reviewed various characterizations of sensor fusion in the literature and proposed the input/output representation of the fusion process. Vashney [10] presented an introduction to multisensor data fusion including conceptual framework, system architecture, and applications. The above-mentioned papers and references therein provide a framework for the study of multisensor fusion and integration.

However, there is little literature available regarding recent advances on multisensor technologies, advanced fusion techniques, and emerging applications. The object of this paper is to provide an overview of sensor technology and describes the paradigm of multisensor fusion and integration as well as fusion techniques at different fusion levels. Applications of multisensor fusion and integration are also presented in the area of robotics, biomedical systems, equipment monitoring, remote sensing, and transportation systems. In addition, this review presents future research directions including microsensors, smart sensors, adaptive fusion techniques, etc.

This paper is organized as follows. Section II discusses sensor technologies and related applications. Section III presents the paradigm of multisensor fusion and integration. In Section IV, fusion techniques at different fusion levels are addressed. Section V presents applications of multisensor fusion and integration in a variety of areas. Section VI discusses future research directions of multisensor fusion and integration including microsensors, smart sensors, and adaptive techniques. Finally, Section VII presents brief concluding comments.

II. Sensor Technologies and Applications

Intelligent system equipped with multiple sensors can interact with and operate in an unstructured environment without the complete control of a human operator. Due to the fact that the system is operating in a totally unknown environment, a system may lack of sufficient knowledge concerning the state of the outside world. Storing large amounts of this knowledge may not be feasible. Considering the dynamically changing world and unforeseen events, it is usually difficult to know the state of the world *a priori*. Sensors can allow a system to learn the state of the world as needed and to continuously update its own model of the world [1], [2].

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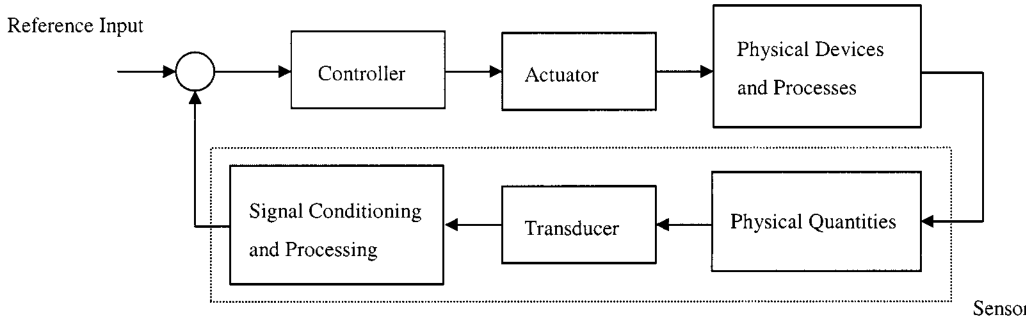

Fig. 1. Role of sensors in mechatronic systems.

Principle	Representative Examples
Mechanical Parameter Variation	• Capacitance (Electret microphones, pressure gauges) • Inductance (LVDTs) • Reluctance (Hall position sensors) • Magnetic coupling (Synchros, resolvers) • Optical coupling (Optical encoders)
Material Parameter Variation	• Temperature coefficient (resistance thermometers) • Piezoresistance (Diffused semiconductor strain gauges) • Magnetication (Fluxgate magnetometers) • Semiconductor field effect (ISFETS, CHEMFETS) • Dielectric constant changes (capacitive humidity sensors) • Rayleigh scattering temperature effects (optical thermometer) • Refractive index changes (Pockels and Faraday effect field sensors) • Photoelastic strain sensors
Direct Signal Generation	• Piezoelectric Effect (Microphones, Accelerometers) • Hall Effect (Proximity sensors) • Pyroelectric Effect (IR detectors) • Moving coil (Accelerometers, dynamic microphones)
Ionization based	• P-N junctions (Photodetectors) • Photoelectric effect (Photomultipliers) • Semiconductor radiation detectors Ge • Gas counters (Ion chambers, proportional counters) • Photoconductors
Quantum Mechanical	• SQUID magnetometers • Superconducting resistance H field meters • Quantum will photodetectors

Fig. 2. Classification of sensors.

A. Sensor Technologies

A transducer is a device that converts the change in some form of physical quantity such as temperature, pressure, flow rate, the intensity of sound, and light into an electrical signal. In general, the direct output of the measurable signal might be inconveniently small, or its impedance might be inconveniently high. Using an amplifier and signal-conditioning circuit to process the transducer signal is necessary. The complete package as a sensor indicated in the dashed line is shown in Fig. 1. Fig. 2 shows the grouping of sensors based on the transduction principles, namely, mechanical parameter variation, material parameter variation, direct signal generating, ionization based, and employing quantum mechanical phenomena [11].

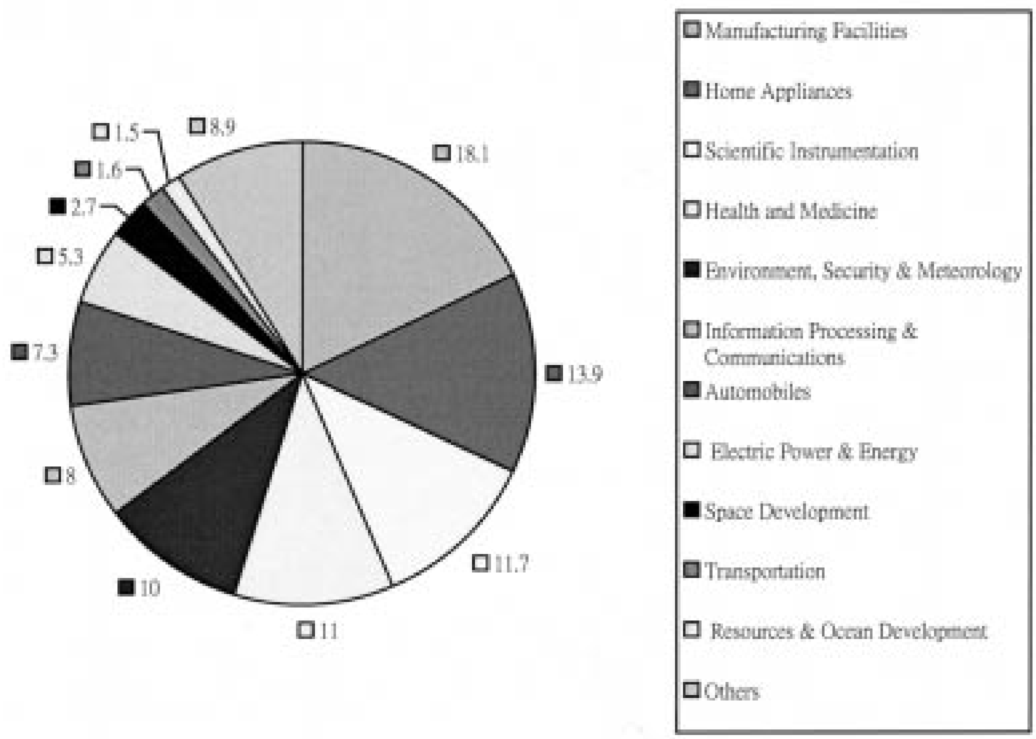

Fig. 3. Application areas of sensors.

B. Sensor Applications

The application of sensors is extremely widespread, as shown in Fig. 3. It is noteworthy that manufacturing is the largest application area where sophisticated sensing devices have been used to improve production quality and reliability. Home appliances such as air conditioner, washing machine, and microwave oven also play an important role for sensor applications.

A multisensor-based electrical wheelchair developed by Luo and Chen [12] is shown in Fig. 4 to illustrate the application of multiple sensors. An intelligent wheelchair, like a mobile robot, must operate in an uncertain or unknown dynamic environment. It is necessary to integrate or fuse the data from a variety of different sensors so that an adequate amount of information from the environment can be quickly perceived.

III. Paradigm of Multisensor Fusion and Integration

Multisensor integration is the synergistic use of the information provided by multiple sensory devices to assist in the accomplishment of a task by a system. Multisensor fusion refers to any stage in the integration process where there is an actual combination of different sources of sensory information into one representational format. The distinction between integration and fusion serves to separate the more general issues involved in the integration of multiple sensory devices at the system architecture and control level from the more specific issues involving the actual fusion of sensory information [2].

A. Multisensor Integration

Hierarchical structures are useful in allowing for the efficient representation of the different forms, levels, and resolutions of the information used for sensory processing and control. Examples are National Bureau of Standards (NBS) sensory and control hierarchy [2], logical sensor networks [2], and Joint Directors of Laboratories (JDL) models [3], [14], [15]. Modularity in the operation of integration functions enables much of the processing to be distributed across the system. The object-oriented programming paradigm and distributed blackboard control structure are two constructs that are especially useful in promoting modularity for multisensor integration. Adaptive integration can deal with the error and uncertainty inherent in the multisensor integration. The use of the artificial neural network formalism allows adaptability to be directly incorporated into the integration process [1].

The diagram shown in Fig. 5 represents multisensor integration as being a composite of basic functions. A group of n sensors provide input to the integration process. In order for the data from each sensor to be used for integration, it must first be effectively modeled. A sensor model represents the uncertainty and error in the data from each sensor and provides a measure of its quality that can be used by the subsequent integration functions. A common assumption is that the uncertainty in the sensory data can be adequately modeled as a Gaussian distribution. After the data from each sensor has been modeled, it can be integrated into the operation of the system in accord with three different types of sensory processing: fusion, separate operation, and guiding or cueing. The different types of sensor fusion will be discussed in Section IV. Sensor registration refers to any of the means used to make the data from each sensor commensurate in both its spatial and temporal dimensions. If the data provided by a sensor is significantly different from that provided by any other sensors in the system, its influence on the operation of the other sensors might be indirect. The separate operation of such a sensor will influence the other sensors indirectly through the effects

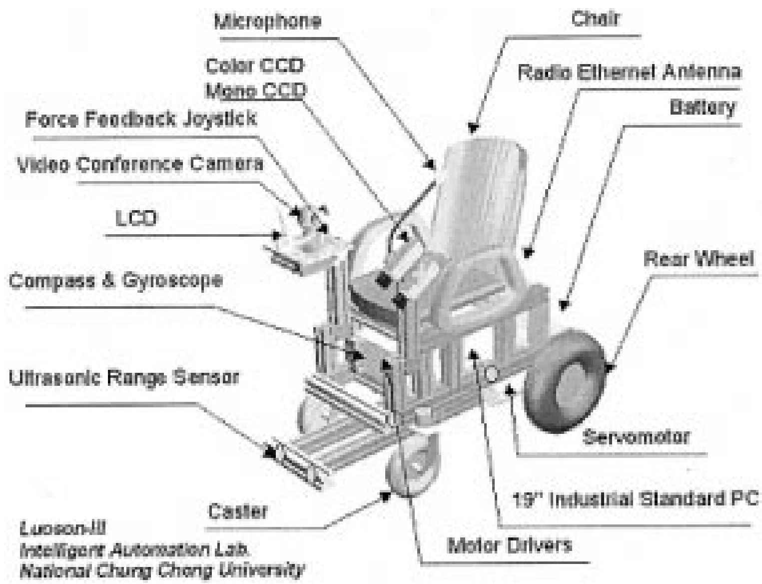

Fig. 4. Multisensor-based electrical wheelchair.

the sensor has on the system controller and the world model. A guiding or cuing type of sensory processing refers to the situation where the data from one sensor is used to guide or cue the operation of other sensors [1]. As shown in Fig. 14, there is no sensor registration for the last of the sensors because it can be part of the three types of sensory processing.

The results of the sensory processing function serve as inputs to the world model. A world model is used to store information concerning any possible state of the environment that the system is expected to be operating in. A world model can include both *a priori* information and recently acquired sensory information. High-level reasoning processes can use the world model to make inferences that can be used to direct the subsequent processing of the sensory information and the operation of the system controller.

Sensor selection refers to any means used to select the most appropriate configuration of sensors among the sensors available to the system. In order for selection to take place, some types of sensor performance criteria need to be established. In many cases the criteria require that the operation of the sensors be modeled adequately enough so that a cost value can be assigned to measure their performance. Two different approaches to the selection of the type, number, and configuration of sensors to be used in the system can be distinguished: "preselection" during design or initialization and "real-time selection" in response to changing environmental or system conditions [1].

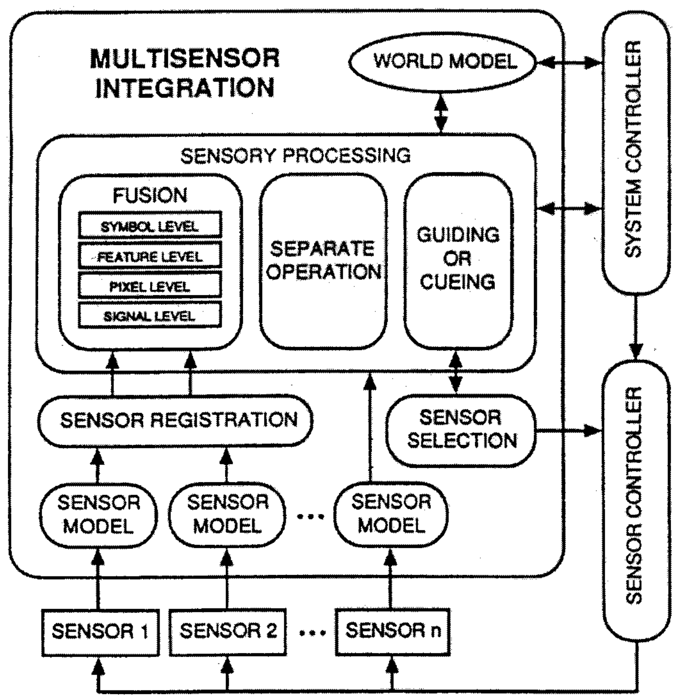

Fig. 5. Functional diagram of multisensor fusion and integration.

B. Multisensor Fusion

The fusion of data or information from multiple sensors or a single sensor over time can take place at different levels of representation. As shown in Fig. 5, a useful categorization is to consider multisensor fusion as taking place at the signal, pixel, feature, and symbol levels of representation. Most of the sensors typically used in practice provide data that can be used at one or more of these levels.

The different levels of multisensor fusion can be used to provide information to a system that can be used for a variety of purposes; e.g., signal-level fusion can be used in real-time applications and can be considered as just an additional step in the overall processing of the signals, pixel-level fusion can be used to improve the performance of many image processing tasks like segmentation, and feature- and symbol-level fusion can be used to provide an object recognition system with additional features that can be used to increase its recognition capabilities [1].

C. An Illustrated Example: Multilevel Multiagent Multisensor (M^3) Based Team Decision Fusion

Advanced multisensor based systems for some sets of goals or tasks always involve a team of local decision makers that cooperate to solve decision problems [16]. Each of local decision

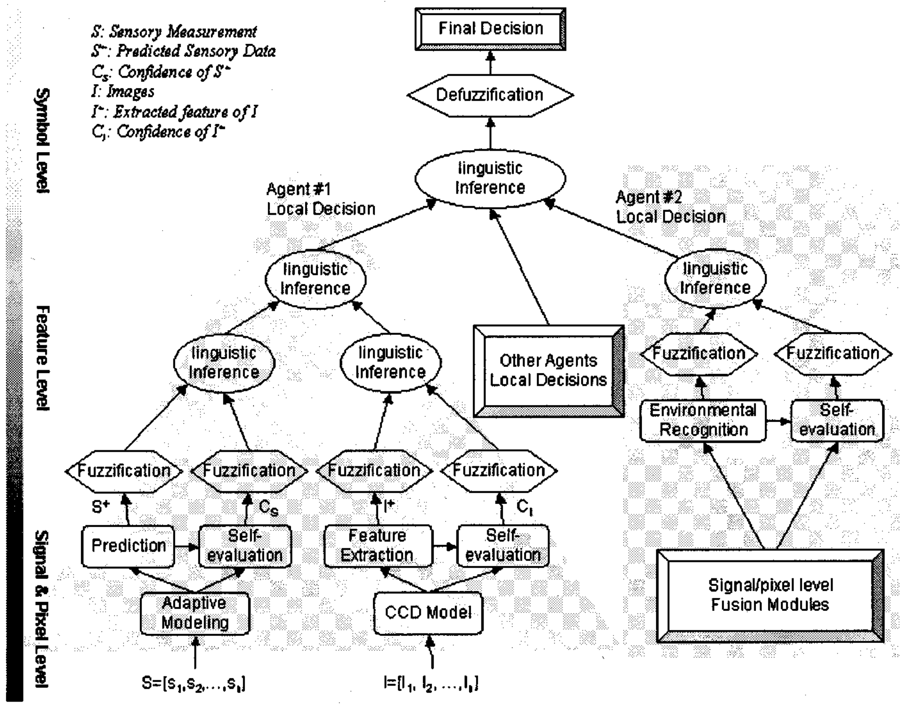

Fig. 6. Conceptual architecture for sensor fusion across multiple levels.

makers in the system can be treated as an agent who is an expert capable of lower level fusion to suggest a recommendation for the global decision maker [17]. The function of the global decision maker is to fuse the local decisions from the agents to derive the team decision using symbol-level fusion. Therefore, each agent needs to perform sensor fusion across levels and the global decision maker conducts high-level symbolic fusion. As shown in Fig. 6, the conceptual architecture for decision making from the multilevel fusion of the time-varying data, features, and symbols is based on the four levels of Luo and Kay's taxonomy [1]. In the lower-level fusion of time-sequential data fusion, we first assume that the parameters of detected target model are unknown *a priori*. Adaptive modeling modules are used for on-line estimation of dynamic parameters. Based on the estimated model parameters the proposed method can perform prediction on incoming sensory input data/measurements for higher-level fusion. The look-ahead method has the advantage of fast error convergence rate for high performance systems, and can perform data extrapolation when data loss problem occurs, but the confidence of prediction has to be evaluated to ensure the validity. To this purpose, the self-evaluation module calculates the confidence according to the modeling accuracy and timing parameters.

IV. Multisensor Fusion Algorithms

This section presents fusion algorithms for multisensor data. Overview of multisensor algorithms can be found in [2]–[5], [8]. As shown in Fig. 7, multisensor fusion algorithms can be broadly classified as follows: estimation methods, classification methods, inference methods, and artificial intelligence methods.

A. Estimation Methods

One of the simplest and most intuitive general methods of fusion is to take a weighted average of redundant information provided by a group of sensors and use this as the fused value. While this method allows for real-time processing of dynamic low-level data, Kalman filter is predominantly preferred because it provides a method that is nearly equal in processing requirements and, in contrast to a weighted average, results in estimates for the fused data that are optimal in a statistical sense.

The Kalman filter uses the statistical characteristics of the measurement model to determine estimates recursively for the fused data [13]. If the system can be described with a linear model and both the system and sensor error can be modeled as white Gaussian noise, a Kalman filter provides unique, statistically optimal, estimates for the data of interest. Consider a linear dynamic system and N sensors represented by the following state-space model:

$$x(k) = A(k)x(k-1) + B(k)u(k) + v(k) \quad (1)$$
$$y(k) = H(k)x(k) + w(k) \quad (2)$$

where k represents the discrete-time index, $x(k)$ is the state-vector, $u(k)$ the input vector, $y(k)$ measurement vectors, $H(k)$ the observation model of N sensors, $v(k)$ and $w(k)$ zero-mean white Gaussian noise with covariance matrices $Q(k)$ and $R(k)$, respectively. It is assumed that the measurement noise is independent.

The Kalman filter provides an unbiased and optimal estimate of the state-vector in the sense of minimum estimate covariance, which can be described by the following equations:

Prediction:

$$\hat{x}(k|k-1) = A(k)x(k-1|k-1) + B(k)u(k) \quad (3)$$
$$P(k|k-1) = A(k)P(k-1|k-1)A^T(k) + Q(k). \quad (4)$$

Estimation methods	Non-recursive: •Weighted Average •Least Squares Recursive: •Kalman Filtering •Extended Kalman Filtering
Classification methods	•Parametric Templates •Cluster Analysis •Learning Vector Quantization (LVQ) •K-means Clustering •Kohonen Feature Map •ART, ARTMAP, Fuzzy-ART Network
Inference methods	•Bayesian Inference •Dempster-Shafer Method •Generalized Evidence Processing
Artificial intelligence methods	•Expert System •Adaptive Neural Network •Fuzzy Logic

Fig. 7. Multisensor fusion algorithms classification.

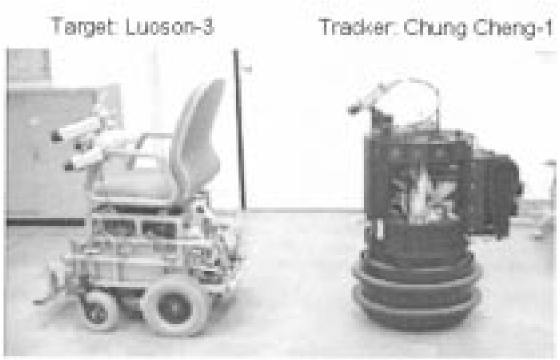

Fig. 8. Experimental setup for target tracking: Target—electrical wheelchair; tracker—autonomous mobile robot.

Estimate:

$$K(k) = P(k|k-1)H^T(k) \cdot [H(k)P(k|k-1)H^T(k) + R(k)]^{-1} \quad (5)$$

$$\hat{x}(k|k) = \hat{x}(k|k-1) + K(k)[y(k) - H(k)\hat{x}(k|k-1)] \quad (6)$$

$$P(k|k) = [I - K(k)H(k)]P(k|k-1) \quad (7)$$

where $\hat{x}(k|k)$ represents the estimate of the state-vector $x(k|k)$, $P(k|k)$ is the state estimate covariance matrix, and $K(k)$ is the Kalman gain matrix.

Extended Kalman filters (EKF) can be used where the model is nonlinear, but can be suitably linearized around a stable operating point. The nonlinear dynamic model and the observation model for the EKF can be expressed as follows.

$$y(k) = H(k, x(k)) + w(k) \quad (8)$$

$$x(k) = f(k, x(k-1), u(k)) + v(k). \quad (9)$$

B. Classification Methods

The multidimensional feature space can be partitioned into distinct regions, each representing an identification or identity class [3]. The location of a feature vector is compared to prespecified locations in feature space. A similarity measure must be computed, and each observation is compared to *a priori* classes. A feature space may be partitioned by geometrical or statistical boundaries. Therefore, the templating approach may declare a unique identity or an identity with an associated uncertainty. The implementation of parametric templates is computationally efficient for multisensor fusion systems.

Cluster analysis tries to establish geometrical relationships on a set of sample data in a training process [18]. Clustering methods include hierarchical agglomerative, hierarchical divisive, iterative partitioning methods, etc. The hierarchical agglomerative approach builds a class for each sample measurement, and then joins classes based on a distance measure until either a predefined number of classes is reached or a given distance is exceeded between two classes. The hierarchical divisive approach starts with one class and divides it into two or more classes also upon a distance measure until a predefined number of classes is reached or a certain value of the maximum distance between any two clusters is achieved. The iterative partitioning approach works on a fixed number of clusters, hence the sample measurements are distributed randomly over the clusters, and clusters are adjusted accordingly until each cluster's average over the inside distance is minimal. Cluster analysis is a powerful tool to classify multisensor data. Data scaling, selection of similarity metric, and clustering algorithms will affect the resulting clusters.

Unsupervised or self-organized learning algorithms such as learning vector quantization (LVQ), *K*-means clustering, Kohonen feature mp can be used for classification [19]. K-means clustering algorithm is one of the commonly used unsupervised

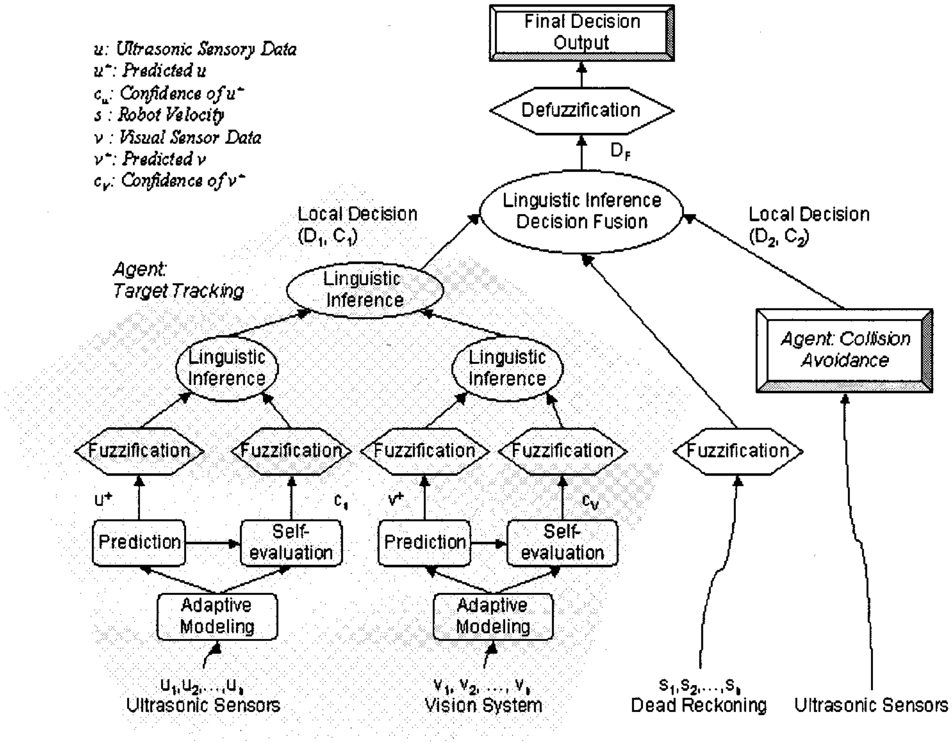

Fig. 9. Implementation of target tracking system to integrate the visual detection and ultrasonic sensory data.

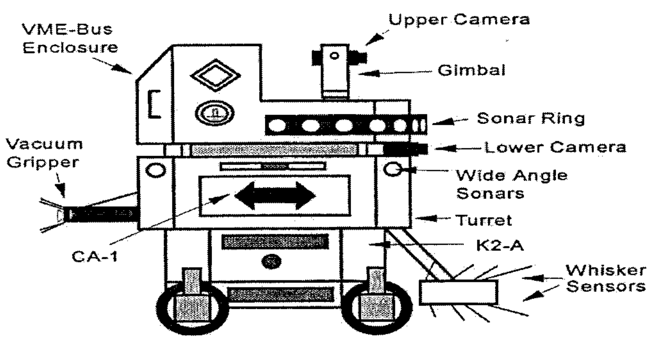

Fig. 10. MARGE mobile robot with a variety of sensors.

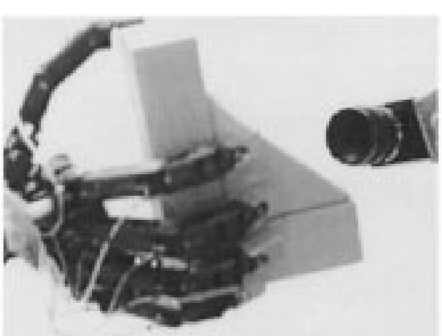

Fig. 11. *Anthrobot* five-fingered robotic hand holding an object in the field-of-view of a fixed camera [24].

learning algorithms. An adaptive K-means update rule forms the basis of the Kohonen feature Map. There are also ART, ARTMAP, and Fuzzy ART networks which do sensor fusion in adaptive manner and allow to automatically adjust the granularity of the classifier and are stable against category proliferation in the presence of drifting inputs and changing environments.

C. Inference Methods

Bayesian inference allows multisensor information to be combined according to the rules of probability theory. Bayes' formula provides a relationship between the *a priori* probability of a hypothesis, the conditional probability of an observation given a hypothesis, and the *a posteriori* probability of the hypothesis [4]. Bayesian inference updates the probabilities of alternative hypotheses, based on observational evidence. New information is used to update the *a priori* probability of the hypothesis.

Dempster–Shafter evidential reasoning is an extension to the Bayesian approach that makes explicit any lack of information concerning a proposition's probability by separating firm support for the proposition from just its plausibility. When additional information from a sensor becomes available and the number of unknown propositions is large relative to the number of known propositions, an intuitively unsatisfying result of the Bayesian approach is that the probabilities of known propositions become unstable. In the Dempster–Shafter approach, this is avoided by not assigning unknown propositions an *a priori* probability. Ignorance is reduced only when supporting information becomes available.

Thomopoulos [20] proposed a generic architecture and analytical framework to address sensor fusion problems at three different levels: the signal level, the level of evidence, and the level of dynamics. A generalized evidence processing theory that unifies Bayesian and Dempster–Shafer evidence processing is presented to perform sensor fusion at the level of evidence.

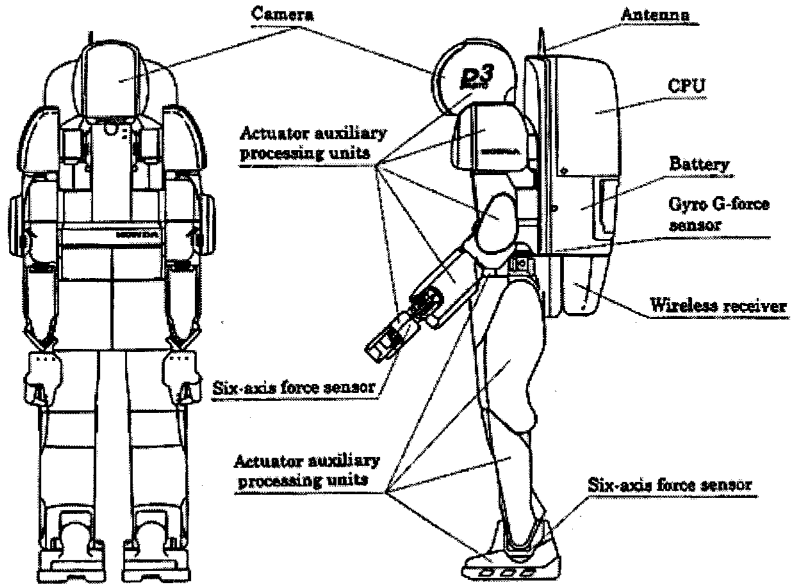

Fig. 12. Honda humanoid robot [26].

D. Artificial Intelligence Methods

High-level inferences require human reasoning such as pattern recognition, planning, induction, deduction, and learning. A large number of expert systems have been developed for industrial and military applications. The inference process utilized by expert system begins with an initial data set and the rule-based knowledge base comprising rules, frames, scripts, or semantic nets [4]. The inference process uses the *a priori* data set, and searches the complete set of rules to identify applicable rule. The rule selection strategies from among multiple applicable rules include refraction, actuation, rule ordering, recency, specificity, and random choice.

A neural network consists of layers of processing elements that may be interconnected in a variety of ways. Neurons can be trained to represent sensor information and, through associate recall, complex combinations of the neurons can be activated in response to different sensory stimuli. For example, simulated annealing is one of many different techniques that can be used to find a global optimal state in a network based on the local state of activation of each neuron in the network.

Fuzzy logic, a type of multiple-valued logic, allows the uncertainty in multisensor fusion to be directly represented in the inference process by allowing each proposition, as well as the actual implication operator, to be assigned a real number from 0.0 to 1.0 to indicate its degree of truth. Consistent logical inference can take place if the uncertainty of the fusion process is modeled in some systematic fashion [21], [22].

As shown in Fig. 5, multisensor fusion can be performed at the different levels: the signal level, the pixel level, the feature levels, and the symbol level. Appropriate fusion algorithms can be accordingly applied to fusing the sensory data from multiple sensors at different levels. In general, estimation methods have been successfully used for signal-level sensor fusion. Classification methods can be used to extract features and fuse data at the pixel and the feature level. Inference methods can be effective for symbol-level sensor fusion due to their capabilities of evidential reasoning. As for artificial intelligence methods, they can be seen as the advanced versions of the estimation, the classification, and the inference methods. Artificial intelligence methods can be model-free, rather than model-specific, and have sufficient degree of freedom to fit complex nonlinear relationships, with the necessary precautions to properly generalize. As a result, artificial intelligence methods can effectively conduct sensor fusion at different levels.

E. An Illustrated Example: Implementation of Fusion Algorithm for Mobile Robot Target Tracking

As shown in Fig. 8, the experimental setup consists of one autonomous mobile robot and a multisensor-based electrical wheelchair. The mobile robot "Chung Cheng-1" (Nomad 200 platform) is a three-wheel mobile platform equipped with a vertical sliding manipulating arm and other sensory modules. The experimental target is the multisensor-based electrical wheelchair named "Luoson-3" which is developed in our laboratory.

Fig. 9 illustrates the implementation structure of the autonomous target tracking system. It contains two major agents for local decisions, one is the target-tracking agent whose inputs are the target position measurements from ultrasonic and vision sensors and the other is the collision-avoidance agent whose inputs are the surrounding range measurements from 16 ultrasonic sensors. The target-tracking agent is shown in the shadowed area, where u_x is the sequential measurements of distance between robot and target from ultrasonic range sensor. Similarly, the v_x is the distance measurement from visual detection, and s_x is the robot driving velocity. The local decision relative to target position is made by fusion of the two sensory data, the error of predicted distance and the desired distance of 40 in, and the changes in error. Outputs are the local decision D_1 and the relative confidence C_1 of D_1, where C_1 is calculated from the fusion of the two prediction confidence levels and the difference of the two predictions. The local decision represents the relative velocity of target and tracker.

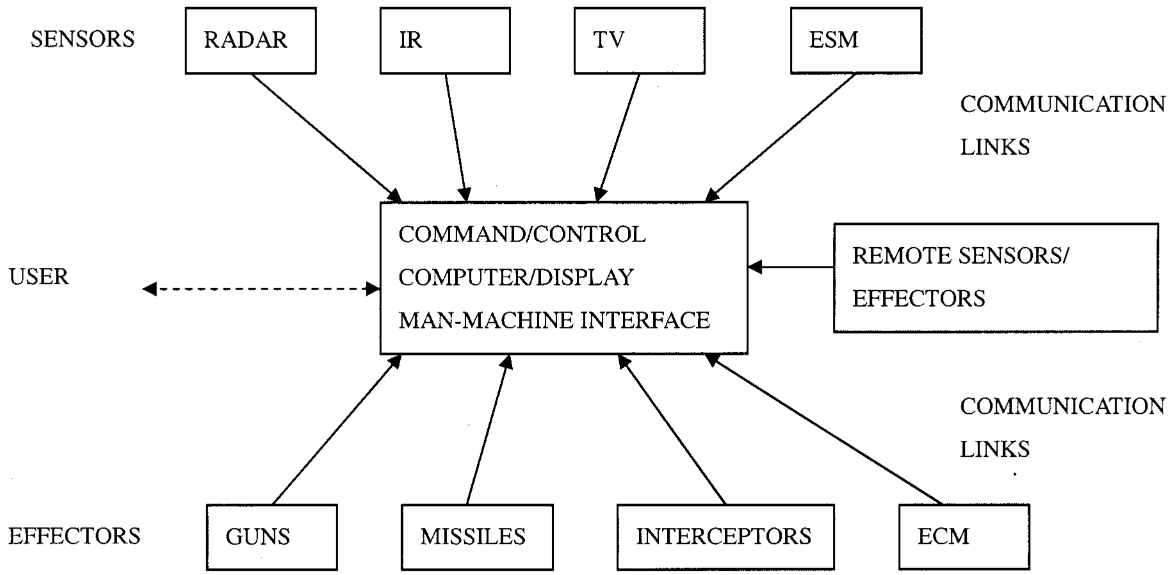

Fig. 13. Schematic representation of a complex air-defense system [30].

The collision avoidance agent integrates the ultrasonic range sensor array equipped on the mobile robot to detect obstacles and navigate accordingly. The confidence of the decision from the collision avoidance module is inversely proportional to the distance from robot to the closest obstacle. The final decision calculated by fusion of the two local decisions is the absolute driving velocity of the mobile robot.

V. Applications of Multisensor Fusion

Redundant and complementary sensor data can be fused and integrated using multisensor fusion techniques to enhance system capability and reliability. In recent years, benefits of multisensor fusion have motivated research in a variety of application areas as follows.

A. Robotics

Robots with multisensor integration and fusion capabilities enhance their flexibility and productivity in industrial applications such as material handling, part fabrication, inspection, and assembly [1], [23]. Recent advances in robotics include multi-robot cooperative system, dexterous hands, underactuated and nonholonomic systems, interaction between the robot and the environment, teleoperation, visual servoing, etc. [25].

Mobile robots present one of the most important application areas for multisensor fusion and integration [28], [29]. When operating in uncertain or unknown dynamic environments, integrating and fusing data from multiple sensors enable mobile robots to achieve quick perception for navigation and obstacle avoidance. As an example, the MARGE mobile robot equipped with multiple sensors is shown in Fig. 10. Perception, position location, obstacle avoidance, vehicle control, path planning, and learning are necessary functions for an autonomous mobile robot. Luo and Kay [1] reviewed some of multisensor-based mobile robots including Hilare, Crowley's mobile robot, ground surveillance robot, stanford mobile robot, CMU's autonomous land vehicles, and the DARPA autonomous land vehicle. As shown in Fig. 11, contact data obtained from tactile sensors mounted on the fingertips of a robotic hand is fused with the processed image data obtained from the camera, to estimate the position and orientation of an object being held [24]. As shown in Fig. 12, the body of the Honda humanoid robot is equipped with an inclination sensor that consists of three accelerometers and three angular rate sensors. Each foot and wrist is equipped with a six-axis force sensor and the robot head contains four video cameras [26]. Multisensor fusion and integration of vision, tactile, thermal, range, laser radar, and forward looking infrared sensors plays a very important role for robotic systems.

B. Military Applications

Military applications of multisensor integration and fusion are in the area of intelligence analysis, situation assessment, force command and control, avionics, and electronic warfare. Radar, optical, and sonar sensors with various filtering techniques have been employed for tracking targets such as missiles, aircrafts, and submarines. A schematic representation of a complex air-defense system is shown in Fig. 13 [30]. Hall and Llinas [4] pointed out some defense-related applications such as ocean surveillance, air-to-air and surface-to-air defense, battlefield intelligence, surveillance, target acquisition, and strategic warning and defense.

Filippidis and Martin [31] used fusion of imagery from a multispectral camera and an infrared sensor to reduce false-alarm rate and improve the surface land-mine detection. Carson *et al.* [32] proposed fusion algorithms to fuse radar data and identification friend or foe (IFF) data. The overall system tracking and target identification can be improved significantly by fusing different types of sensors. Vain *et al.* [33] studied the position and attribute fusion of surveillance radar, electronics support measure (ESM), IFF, and a tactical data link. Fuzzy logic and pruning rules were used to enhance system capabilities for the Dempster–Shafter evidential reasoning over attribute data [33].

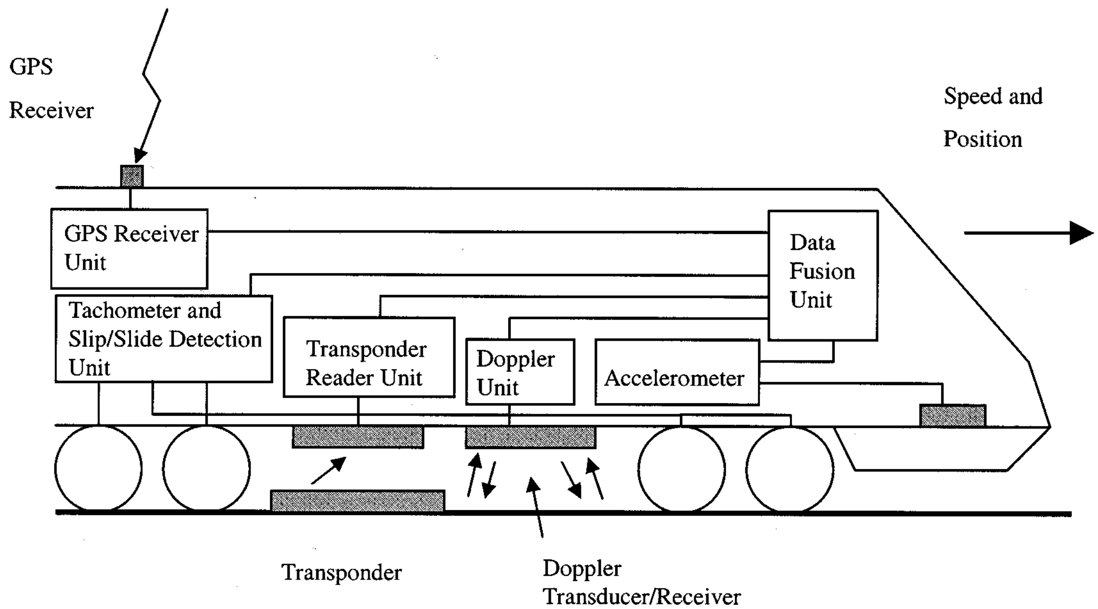

Fig. 14. Integration of different sensors in train position and speed measurement [50].

C. Remote Sensing

Applications of remote sensing include monitoring climate, environment, water sources, soil and agriculture as well as discovering natural sources and fighting the import of illegal drugs [34]. Fusing or integrating the data from passive multispectral sensors and active radar sensors is necessary for extracting useful information from satellite or airborne imagery.

Fuzzy logic and neural network based multisensor fusion techniques have been used for classification of remote sensed imagery. Solaiman [35] proposed a thematic class membership level between the data level and the decision level. Inspired by expert reasoning approach, the proposed fuzzy classifier is based on the multisensor data and contextual information associated with membership values. The class membership values can be updated by using the membership values assigned to the multisensor data and contextual information until predefined decision conditions are satisfied. The proposed scheme was successfully applied to land cover classification using ERS-1/JERS-1 SAR Composites. Chiuderi [36] used a neural network approach for data fusion of land cover classification of remote sensed images on an agricultural area. By using supervised and unsupervised neural network, the optical-infrared data and microwave data were fused for land cover classification.

Dempster–Shafer evidence theory was applied by Le Hegarat–Mascle [13] to unsupervised classification in multi-source remote sensing. Using different combinations of sensors or wavelengths, the proposed method can effectively identify the land cover types. Multisensor fusion of remote sensed data was also used for monitoring land environment [37], sea-ice [38], and algae blooms in the Baltic Sea [39]. Solaiman *et al.* [27] proposed an information fusion method for multispectral image classification postprocessing. Fusion of the thematic map and the edge map provided a series of closed contours corresponding to individual fields and containing a unique class.

D. Equipment Monitoring and Diagnostics

Condition-based monitoring of complex equipment such as automated manufacturing systems, turbomachinery, and drive-trains can improve safety and reliability as well as reduce the repair/maintenance costs [4].

For example, monitoring of tool condition plays an important role for manufacturing systems to ensure quality and efficient production. Researchers have applied multisensor fusion techniques via an artificial neural network to fuse measurement data, such as force signal, acoustic emission, accelerometer data and power signal to predict tool wear [40]–[44]. Collected data from multiple sensors and machine parameters can be used to train the multi-layer neural network to identify the tool wear. Experimental results indicate that neural-network-based schemes can successfully fuse multisensor data for the complicated manufacturing system and improve the accuracy of identification of tool wear conditions. A fusion process for condition-based equipment maintenance using JDL model was investigated in [45].

E. Biomedical Applications

Multisensor fusion has been applied to critical care monitoring [46] and medical images. In October 1999, IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING had a special topic section on biomedical data fusion.

Hernandez *et al.* [47] used multisensor fusion techniques to enhance automatic cardiac rhythm monitoring by integrating electrocardiogram (ECG) and hemodynamic signals. Redundant and complementary information from the fusion process can improve the performance and robustness for the detection of cardiac events including the ventricular activity and the atrial activity. Case-based data fusion methods were proposed by Azuaje *et al.* [48] to improve clinical decision support. Three different data fusion models were established for case-based decision support and reasoning. Evaluated results indicate that the proposed method can improve the fusion significantly at the retrieval level for heart disease risk assessment.

Medical image fusion is one of the most important biomedical application areas for multisensor fusion. Solaiman *et al.* [49] studied the problem of detecting the esophagus inner wall from ultrasound medical images. Fuzzy logic based fusion methods were used for feature extraction from the images. The proposed schemes were implemented on real medical images and the results show good quality detection.

F. Transportation Systems

Transportation systems, such as automatic train control systems, intelligent vehicle and highway systems, GSP-based vehicle navigation, and aircraft landing tracking systems, utilize multisensor fusion techniques to increase reliability, safety, and efficiency. Mirabadi and Schmid [50] discussed sensor fusion for train speed and position measurement using different combination of global positioning by satellite (GPS), inertia navigation systems (INS), tachometers, Doppler radar, etc. (see Fig. 14). A Kalman filter based sensor architecture was proposed in [51] for fault detection and isolation in multisensor train navigation systems. Kobayashi *et al.* [52] investigated the problem of improving accurate positioning of vehicles by fusing measurement data from differential GPS, wheel speedometer, and optical fiber rate gyro via Kalman filtering. Robust vision sensing techniques for a multisensor transportation system were proposed by Smith *et al.* [53] to increase safety in a variety of traffic situations. Applications for vehicle tracking and pedestrian tracking were used to demonstrate the effectiveness of the proposed schemes. Korona and Kokar [54] used an extended Kalman filter and learning algorithm to integrate passive sensor data from a laser range finder (LRF) and an infrared camera (FLIR) for tracking a landing aircraft.

G. Other Applications

Other application areas of multisensor fusion and integration include space, agricultural mechanization, drug interdiction, etc. The most important multisensor-based applications in space are the increasing use of autonomous systems for repair and maintenance of satellites, assembly of space structures and object sensing. Sato *et al.* [55] studied an automatic harvester that can operate in the rice field without human operator. The harvester was equipped with contact, revolution, level sensors and gyroscopes as well as actuators and on-board computer. Chong and Liggins [56] proposed a distributed architecture to fuse data such as radar, infrared, and database from different law enforcement agencies for drug detection, tracking, and interception.

VI. Future Research Directions

It is obvious from this survey that current state of the art in multisensor fusion is in continuous development. There are, therefore, promising future research areas that encompass multilevel sensor fusion, sensors fault detection, microsensors and smart sensors, and adaptive multisensor fusion as follows.

A. Multilevel Sensor Fusion

Single level sensor fusion limits the capacity and robustness of a system, due to the weaknesses in uncertainty, missing observation, and incompleteness of a single sensor. Therefore, there is a clear need to integrate and fuse multisensor data for advanced systems with high robustness and flexibility and the multilevel sensor fusion system is needed in advanced systems [57], [58]. A general architecture is designed according to the four levels of Luo and Kay's taxonomy [59] for decision making from fusion levels of the time-varying data, features and decisions. Low level fusion methods can fuse the multisensor data, and medium level fusion methods can fuse data and feature to obtain fused feature or decision. Finally, high level fusion methods can fuse feature and decision to obtain the final decision.

B. Fault Detection

Fault detection has become a critical aspect of advanced fusion system design. Failures normally produce a change in the system dynamics and pose a significant risk. Many innovative methods have been proposed to accomplish effective fault detection in the literature. Fernandez and Durrant-Whyte [60] investigated a Kalman filter algorithm in a decentralized multisensor system and implemented the method on a pilot process plant. Aitouche and Maquin [61] proposed a multiple sensor fault detection algorithm for applications in a heat exchanger system. Balle and Fussel [62] developed a reliable fault detection and isolation (FDI) scheme for nonlinear processes. Mirabadi *et al.* [63] applied the FDI method to a train navigation system. Long *et al.* [64] proposed a virtual sensor approach, instead of hardware, for effective sensor failure detection. In addition, the fault detection methods include Kalman filtering [65], neural fuzzy networks [66], Bayesian method [67], and polynomial $H\infty$ formulation [68].

C. Microsensors and Smart Sensors

Sensors play an important role in our everyday life because we have a need to gather information and process it for some tasks. Successful application of a sensor depends on sensor performance, cost, and reliability [69]. However, a large sensor may have excellent operating characteristics but its marketability is severely limited by its size. Reducing the size of a sensor often increases its applicability through the following: 1) lower weight and greater portability, 2) lower manufacturing cost and fewer materials, and 3) wider range of application.

Clearly, fewer materials are needed to manufacture a small sensor but the cost of material processing is often a more significant factor. The silicon revolution and semiconductor technology have enabled us to produce small reliable processors in the form of integrated circuits (ICs). The microelectronic applications have led to a considerable demand for small sensors or microsensors that can fully exploit the benefits of IC technology.

Smart sensors can integrate main processing, hardware, and software [70]. According to the definition proposed by Breckenbridge and Husson [71], a smart sensor must possess three features: the ability to 1) perform a logical computable function, 2) communicate with one or more other devices, and 3) make a decision using logic or fuzzy sensor data.

D. Adaptive Multisensor Fusion

In general, multisensor fusion requires exact information about the sensed environment. However, in the real world, precise information about the sensed environment is scarce and the sensors are not always perfectly functional. Therefore, a robust fusion algorithm in the presence of various forms of uncertainty is necessary. Researchers have developed adaptive multisensor fusion algorithms to address uncertainties associated with imperfect sensors. Hong [72] extended the correlation method using an innovation process, which can estimate the optimal Kalman gain for the filtering of a single measurement sequence [73]–[76].

VII. Conclusion

The paradigm of multisensor fusion and integration as well as fusion techniques and sensor technologies were presented, and multisensor-based applications in robotics, defense, remote sensing, equipment monitoring, biomedical engineering, and transportation systems were discussed. Some directions for future research in multisensor fusion and integration target microsensors and adaptive fusion techniques. The overview of this paper may be of interest to researchers and engineers attempting to study the rapidly evolving field of multisensor fusion and integration.

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