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

Ren C. Luo and Chih-Chen Yih
Intelligent Automation Laboratory
Department of Electrical Engineering, National Chung Cheng University
160 Shang-Shing, Ming-Hsiung, Chia-Yi, Taiwan 621

Abstract

In recent years, benefits of multisensor fusion have motivated research in a variety of application areas. Redundant and complementary sensor data can be fused and integrated using multisensor fusion techniques to enhance system capability and reliability. This paper provides an overview of the paradigm of multisensor integration and fusion. Applications of multisensor fusion in robotics and other areas such as biomedical system, equipment monitoring, remote sensing, and transportation system are presented. Finally, future research directions of multisensor fusion technology including microsensors, smart sensors, and adaptive fusion techniques are addressed.

I. Introduction

Sensors are used to provide a system with useful information concerning some features of interest in the system's environment. Multisensor integration and fusion refers to the synergistic combination of sensory data from multiple sensors to provide more reliable and accurate information. The potential advantages of multisensor integration and fusion 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 integration and fusion 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 integration and fusion.

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 the paradigm of multisensor integration and fusion. Applications of multisensor integration and fusion are also presented in the area of robotics, biomedical system, equipment monitoring, remote sensing, and transportation system. This paper is organized as follows. Section II presents the paradigm of multisensor integration and fusion. Section III presents applications of multisensor integration and fusion in robotics and a variety of other areas. Section IV discusses future directions of multisensor integration and fusion including microsensors, smart sensors, and adaptive fusion techniques. Finally, Section V presents brief concluding comments.

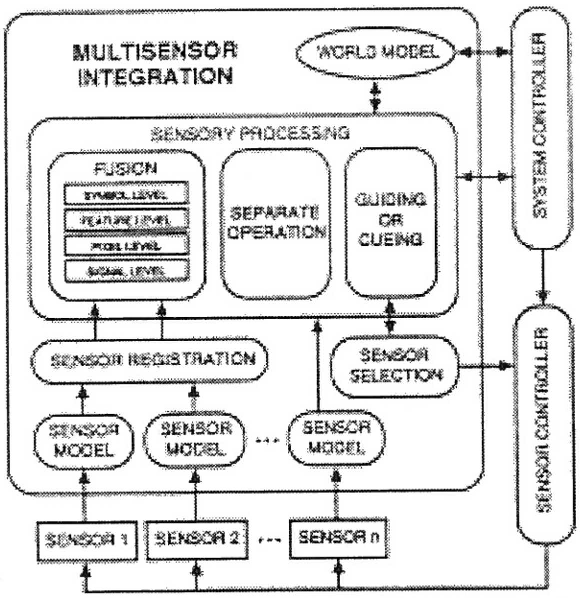
II. Paradigm of Multisensor Integration and Fusion

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. Mutlisensor 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 NBS sensory and control hierarchy [2], logical sensor network [2], and JDL model [3], [11], [12]. 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 Figure 1 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. Sensor registration refers to any of the means used to make the data from each sensor



commensurate in both its spatial and temporal dimensions.

Figure 1. Functional diagram of multisensor integration and fusion [1].

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 Figure 1, 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].

III. Emerging Applications of Multisensor Fusion and Integration

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 sensory capabilities are required in many industrial applications to enhance their flexibility and productivity. Multisensor integration and fusion techniques are suitable for application areas of industrial robots such as material handling, part fabrication, inspection, and assembly [1], [13], [14]. Recent advances in robotics include multirobot cooperative system, dexterous hands, underactuated and nonholonomic systems, interaction between the robot and the environment, teleoperation, visual servoing, etc [15], [16].

Mobile robot is one of the most important application areas for multisensor fusion and integration [17]. Considering the operation in an uncertain or unknown dynamic environment, integrating and fusing data from multiple sensors enable mobile robots to achieve quick perception for navigation and obstacle avoidance. 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 Figure 2, the contact data obtained from the tactile sensors mounted on the fingertips is fused with the processed image data obtained from the camera, to estimate the position and orientation of the object [14]. Multisensor fusion and integration of vision, tactile, thermal, range, laser radar, and forward looking infrared sensors plays a very important role for the above-mentioned 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. 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 [18] used fusion of imageries from a multispectral camera and an infrared sensor to reduce false-alarm rate and improve the surface land-mine detection. Carson et al. [19] proposed the 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. [20] studied the position and attribute fusion of surveillance radar, Electronics Support Measure (ESM), IFF and a tactical data link. The fuzzy logic and pruning rules were used to enhance system capabilities for the Dempster-Shafter evidential reasoning over attribute data [20].

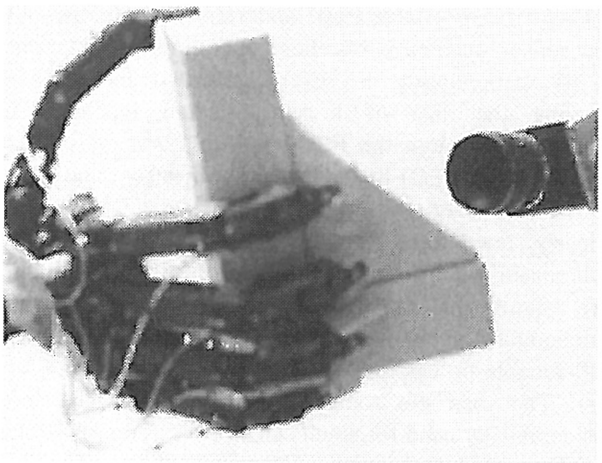


Figure 2. The *Anthrobot* five-fingered robotic hand holding an object in the field-of-view of a fixed camera [14].

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 [21]. 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 [22] 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 [23] 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 [24] to unsupervised classification in multisource 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 the land environment [25], the sea-ice [26] and algae blooms in the Baltic Sea [27]. Solaiman et al. [28] proposed an information fusion method for multispectral image classification postprocessing.

D. Equipment Monitoring and Diagnostics

Condition-based monitoring of complex equipment such as automated manufacturing systems, turbomachinery, and drivetrains 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 artificial neural network to fuse measurement data such as force signal, acoustic emission, accelerometer data and power signal to predict tool wear [29]-[33]. 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.

E. Biomedical Applications

Multisensor fusion has been applied to critical care monitoring [34] and medical images. In October 1999, IEEE Transactions on Biomedical Engineering had a special topic section on biomedical data fusion.

Hernandez et al. [35] 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. [36] 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 area for multisensor fusion.

Solaiman et al. [37] 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 of good quality detection were shown.

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 [38] discussed sensor fusion for train speed and position measurement using different combination of GPS (Global Positioning by Satellite), INS (Inertia Navigation Systems), tachometers, Doppler radar, etc. A Kalman filter based sensor architecture was proposed in [39] for fault detection and isolation in multisensor train navigation systems. Kobayashi et al. [40] investigated the problem of improving accurate positioning of vehicles by fusing measurement data from differential GPS, wheel speedometer, optical fiber rate gyro via Kalman filtering. Robust vision sensing techniques for a multisensor transportation system were proposed by Smith et al. [41] 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 [42] 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.

IV. Future Research Directions

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

A. Multilevel Sensor Fusion

A system only with single level sensor fusion has its inherent limit of capability. Due to the possible weakness of uncertainty, missing observation, and incompleteness of single sensor, there is a growing need to integrate and fuse multisensor data for advanced systems with high robustness and flexibility. Therefore, the multilevel sensor fusion system is necessary for advanced systems [28]. The general architecture is according to the four levels of Luo and Kay's taxonomy [44] and is designed for decision making from the fusion levels of the time-varying data, features and decisions. Low level fusion methods can be fuse the multisensor data, and medium level fusion methods can fuse data/feature to obtain fused feature or decision. Finally, high level fusion methods can fuse feature/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 a risk will take place. Many innovative methods have been proposed to accomplish effective fault detection in the literature. Fernandez and Durrant-Whyte [44] investigated a Kalman filter algorithm in a decentralized multisensor system and implemented the method on the pilot process plant. Aitouche and Maquin [45] proposed a multiple sensor fault detection algorithm for applications in heat exchanger system. Balle and Fussel [46] developed a reliable fault detection and isolation (FDI) scheme for nonlinear processes. Mirabadi et al. [47] used FDI method on train navigation system. Long et al. [48] proposed a virtual sensor approach, instead of hardware structures, for effective sensor failure detection. In addition, the fault detection methods include Kalman filtering, neural fuzzy network, Bayesian method, and polynomial $H\infty$ formulation.

C. Microsensors and Smart Sensors

Sensors play an important role in our everyday lives 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. 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, 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.

The smart sensor integrates the main processing, hardware, and software. According to the definition proposed by Breckenbridge and Husson [49], a smart sensor must possess three features: 1) perform a logical computable function, 2) communicate with one or more other devices, 3) make a decision using logic or fuzzy sensor data.

D. Adaptive Multisensor Fusion

In general, the multisensor fusion algorithm requires exact information about the sensed environment. However, in the real world, little certain information (a priori information) about the sensed environment is known and the sensors are not always perfectly functional. Therefore, a robust fusion algorithm in the presence of all kinds of uncertainties is necessary. Researchers have developed adaptive multisensor fusion algorithms to address the uncertainties associated with imperfect sensors. Hong [50] extended the correlation method using an innovation process, which can estimate the optimal Kalman gain for the filtering of the single measurement sequence.

V. Conclusions

In this research, the paradigm of multisensor integration and fusion was presented. In addition, multisensor-based applications in robotics, military, remote sensing, equipment monitoring, biomedical and transportation systems were discussed. Further research is required for future directions of multisensor integration and fusion such as microsensors, smart sensors, 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 integration and fusion.

References

[1] R. C. Luo and M.G. Kay, "A tutorial on multisensor integration and fusion," in *Proc. 16th Annual Conference of IEEE on Industrial Electronics*, vol. 1, pp. 707 –722, 1990.

[2] R. C. Luo and M.G. Kay, "Multisensor integration and fusion in intelligent systems," *IEEE Transactions on Systems, Man and Cybernetics*, vol. 19, no. 5, pp. 901 –931, Sept.-Oct. 1989.

[3] D. L Hall and J. Llinas, "An introduction to multisensor data fusion," in *Proceedings of the IEEE*, vol. 85, no. 1, pp. 6-23, Jan. 1997.

[4] D. Hall, *Mathematical Techniques in Multisensor Data Fusion*. Boston, MA: Artech House, 1992.

[5] J. Llinas and E. Waltz, *Multisensor Data Fusion*. Boston, MA: Artech House, 1990.

[6] P. K. Varshney, "Scanning the special issue on the data fusion," in *Proc. IEEE*, January 1997, 85, pp. 6-23.

[7] B. V. Dasarathy, *Decision Fusion*. Los Alamitos, CA: IEEE Computer Society, 1994.

[8] M. Kokar and K. Kim, "Review of Multisensor Data Fusion Architectures and Techniques," in *Proceeding of the 1993 International Symposium on Intelligent Control*, Chicago, Illinois.

[9]B. V. Dasarathy, "Sensor fusion potential exploitation-innovative architectures and illustrative applications," in *Proceedings of the IEEE*, vol. 85, no. 1, pp. 24 –38, 1997.

[10] P. K. Varshney, "Multisensor data fusion," *Electronics & Communication Engineering Journal*, vol. 9, no. 6, pp. 245 – 253, 1997.

[11] E. Waltz, "Data Fusion for C3I: A Tutorial," *Command, Control, Communications Intelligence (C3I) Handbook*, EW Communications, Inc., Palo Alto, CA, pp. 217-226, 1986.

[12] L. A. Klein, *Sensor and Data Fusion Concepts and Applications*, SPIE Optical Engineering Press, Tutorial Texts, Vol. 14, 1993.

[13] Ren C. Luo, Min-Hsiung Lin, R. S. Scherp, "Dynamic Multi-sensor Data Fusion System for Intelligent Robots," *IEEE Journal of Robotics and Automation*, vol. 4, no. 4, August 1988.

[14] Rajive Joshi and Arthur C. Sanderson, "Minimal Representation Multisensor Fusion Using Differential Evolution," *IEEE Transactions on Systems, Man, and Cybernetics- Part A: Systems and Humans*, vol. 29, no. 1, January 1999.

[15] B. Siciliano, "Control in robotics: open problems and future directions," in *Proceedings of the 1998 IEEE International Conference on Control Applications*, vol. 1, pp. 81 –85, 1998.

[16] K. Hirai, M. Hirose, Y. Haikawa, T. Takenaka, "The development of Honda humanoid robot," in *Proceedings of IEEE International Conference on Robotics and Automation*, vol. 2, pp. 1321 –1326, 1998.

[17] M. Kam, X. Zhu, and P. Kalata, "Sensor Fusion for Mobile Robot Navigation," in *Proceedings of the IEEE*, vol. 85, no. 1, January 1997.

[18] A. Filippidis, L. C. Jain, N. Martin, "Multisensor data fusion for surface land-mine detection," *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, vol. 30, no. 1, pp. 145 –150, 2000.

[19] R. R. Jr. Carson, M. P. Meyer, D. J. Peters, "Fusion of IFF and radar data," in *Proc. 16th DASC AIAA/IEEE Digital Avionics Systems Conference*, vol. 1, pp.5.3-9-15, 1997.

[20] P. Valin, J. Couture, M. Simard, "Position and attribute fusion of radar, ESM, IFF and Datalink for AAW missions of the Canadian Patrol Frigate," in *Proceeding of the 1996 IEEE/SICE/RSJ International Conference on Multisensor Fusion and Integration for Intelligent Systems*, pp. 63 –71, 1996.

[21] T. E. Bell, "Remote sensing," *IEEE Spectrum*, vol. 32, no. 3, pp. 24-31, March 1995.

[22] B. Solaiman, L. E. Pierce and F. T. Ulaby, "Multisensor data fusion using fuzzy concepts: application to land-cover classification using ERS-1/JERS-1 SAR composites," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 37, no. 3, pp. 1316-1326, May 1999.

[23] A. Chiuderi, F. Stafano, V. Cappellini, "An application of data fusion to landcover classification of remote sensed imagery: a neural network approach," in *Proc. IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems*, pp. 756 –762, 1994.

[24] S. Le Hegarat-Mascle, I. Bloch, and D. Vidal-Madjar, "Application of Dempster-Shafer evidence theory to unsupervised classification in multisource remote sensing," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 35, no. 4, pp. 1018-1031, July 1997.

[25] D. G. Goodenough, P. Bhogal, D. Charlebois, S. Matwin, O. Niemann, "Intelligent data fusion for environmental monitoring," in *Proc. Geoscience and Remote Sensing Symposium*, vol. 3, pp. 2157 –2160, 1995.

[26] Partington,, M.-R. Keller, P. Seymour, C. Bertoia, "Data fusion for use of passive microwave data in operational sea-ice monitoring," *Geoscience and Remote Sensing Symposium*, vol. 3 , pp. 1579-1581, 1999.

[27] O. Rud, and M. Gade, "Monitoring algae blooms in the Baltic Sea: a multi sensor approach," in *Proc. OCEANS '99 MTS/IEEE*, vol. 3, pp. 1234 –1238, 1999.

[28] B. Solaiman, R. K. Koffi, M. -C. Mouchot, A. Hillion, "An information fusion method for multispectral image classification postprocessing," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 36, no. 2, pp. 395 –406, 1998.

[29] T. I. Liu and K. S. Anantharaman, " On-line sensing of drill wear using neural network approach," *IEEE International Conference on Neural Network*, vol. 2, pp. 690-694, 1993.

[30] Kang-Ning Lou and Cheng-Jen Lin, "An intelligent sensor fusion system for tool monitoring on a machining center," in *Proc. IEEE/SICE/RSJ International Conference on Multisensor Fusion and Integration for Intelligent Systems*, pp. 208 –214, 1996.

[31] G. Littlefair, M. A. Javed, and G. T. Smith, "Fusion of integrated multisensor data for tool wear monitoring," in *Proceedings of IEEE International Conference on Neural Networks*, vol. 2, pp. 734 -737, 1995.

[32] S. Kakade, L. Vijayaraghavan, and R. Krishnamurthy, "Monitoring of tool status using intelligent acoustic emission sensing and decision based neural network," in *Proc. IEEE/IAS International Conference on Industrial Automation and Control*, pp. 25-29, 1995.

[33] R. J. Hansen, D. L. Hall, and S. K. Kurtz, "A New approach to the challenge of machinery prognostics," *Trans. ASME, J. Engineering for Gas Turbines and Power*, pp. 320-325, Apr. 1995.

[34] F. A. Mora, G. Passariello, G. Carrault, and J.-P. Le Pichon, " Intelligent patient monitoring and management systems: a review," *IEEE Engineering in Medicine and Biology Magazine*, vol.12, no.4 , pp. 23-33, Dec. 1993.

[35] A. I Hernandez, G. Carrault,, F. Mora, L. Thoraval, G. Passariello, and J. M. Schleich, "Multisensor fusion for atrial and ventricular activity detection in coronary care monitoring," *IEEE Transactions on Biomedical Engineering*, vol. 46, no. 10, pp. 1186-1190, Oct. 1999.

[36] F. Azuaje, W. Dubitzky, N. Black, and K. Adamson, "Improving clinical decision support through case-based data fusion," *IEEE Transactions on Biomedical Engineering*, vol. 46, no. 10, pp. 1181 –1185, Oct. 1999.

[37] B. Solaiman, R. Debon, F. Pipelier, J.-M. Cauvin, and C. Roux, "Information fusion, application to data and model fusion for ultrasound image segmentation," *IEEE Transactions on Biomedical Engineering*, vol. 46, no. 10, pp. 1171-1175, Oct. 1999.

[38] A. Mirabadi, N. Mort and F. Schmid, "Application of sensor fusion to railway systems," in *Proc. IEEE/SICE/RSJ International Conference on Multisensor Fusion and Integration for Intelligent Systems*, pp. 185-192, 1996.

[39] A. Mirabadi, N. Mort, F. Schmid, "Fault detection and isolation in multisensor train navigation systems," in *Proc. UKACC International Conference on Control*, vol. 2, pp. 969-974, 1998.

[40] K. Kobayashi, F. Munekata, and K. Watanabe, "Accurate navigation via differential GPS and vehicle local sensors," in *Proc. IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems*, pp. 9 –16, 1994.

[41] C. E. Smith, S. A. Brandt, and N. P. Papanikolopoulos, "Vision sensing for intelligent vehicle and highway systems," in *Proc. IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems*, pp. 784 –791, 1994.

[42] Z. Korona and M. M. Kokar, "Multisensor integration in the tracking of landing aircraft," in *Proc. IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems*, pp. 771 –778, 1994.

[43] R. C. Luo and M. G. Kay, "Data Fusion and Sensor Integration: State-of-the-art 1990s," in *Data Fusion in Robotics and Machine Intelligence*, M. A. Gonzalez, Eds. San. Diego, CA: Academic, 1992.

[44] M. Fernandez and H. F. Durrant-Whyte, "A Failure Detection and Isolation Algorithm for a Decentralized Multisensor System," MFI 94, Las Vegas, NV. Oct. 2-5, 1994, PP.27-PP.33.

[45] A. Aitouche, D. Maguin and F. Busson, "Multiple Sensor Fault Detection in Heat Exchanger System," in *Proc. International Conference on Control Applications*, Trieste, Italy 1-4 Set. 1998, PP.741-PP.745.

[46] P. Balle. , D. Fussel and O. Hecker, "Detection and Isolation of Sensor Faults on Nonlinear Processes Based on Local Linear Models," in *Proceedings of the American Control Conference*, Albuquerque, Ne Mexico June 1997, PP. 468 - PP. 472.

[47] A. Mirabadi, N. Mort and F. Schmia, "Fault Detection and Isolation in Multisensor Train Navigation System," in *Proc. UKACC International Conference on Control '98*, 1-4. September 1998, PP. 909 - PP. 974.

[48] T. W. Long. L. Hanzevack and W. L. Bynum, "Sensor Fusion and Failure Detection Using Virtual Sensor," *Proceedings of the American Control Conference*, San Diego, California, June 1999, PP. 2417 – PP. 2420.

[49] Breckenbridge RA and Husson C , Smart sensor in spacecraft: the impact and trends *Proc. AIAA/NASA Conference on Smart Sensors*, Hamptom, USA, PP. 1 – PP. 5, 1978.

[50] L. Hong, "Adaptive Data Fusion," ISSN/IEEE 1991, PP. 767 – PP. 772.