'92 KACC 1992. 10. 19～21

Special Session 5

Future Trends in Multisensor Integration and Fusion

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Abstract

The need for intelligent systems that can operate in an unstructured, dynamic environment has created a growing demand for the use of multiple, distributed sensors. While most research in multisensor fusion has revolved around applications in object recognition—including military applications for automatic target recognition—developments in microsensor technology are encouraging more research in affordable, highly-redundant sensor networks. Three trends that are described at length are the increasing use of microsensors, the techniques that are used in the handling of partial or uncertain data, and the application of neural network techniques for sensor fusion.

1. INTRODUCTION

The use of multiple sensors to gather information about an unstructured, time-varying environment presents various problems, and there may be many options available for each particular situation. The potential advantages in integrating and/or fusing information from multiple sensors are that the information can be obtained more accurately, concerning features that are impossible to perceive with individual sensors, in less time, and at a lesser cost. These advantages correspond, respectively, to the notions of the redundancy, complementarity, timeliness, and cost of the information provided to the machine or system. Many of the possible problems associated with creating a general methodology for multisensor integration and fusion, as well as developing the actual systems that use multiple sensors, center on the methods used for modeling the error or uncertainty in the integration and fusion process, the sensory information, and the operation of the overall system including the sensors. For the potential advantages in integrating multiple sensors to be realized, solutions to these problems have to be found that are both practical and theoretically sound.

A detailed description of many of the current issues involved in integrating and fusing the information from multiple sensors is provided in Luo and Kay [12] [11], while the trend towards the development of microsensors may lead to additional issues related to, for example, the need for more effective methods to abstract information from the sensor data when a large number of sensors are used. These microsensors may allow sensory systems to be modeled upon biological systems that incorporate large networks of highly redundant sensors.

While there are many approaches to multisensor fusion and integration, there are some basic operations that are common to most implementations. The diagram in Fig. 1 illustrates these basic operations. In the diagram, the family of n sensors provide the raw sensory data to create the abstract sensor models. The *sensor models* are required in order to supply some measure of the uncertainty or error that always accompanies actual sensor data to the remainder of the system. If low-level fusion of the sensor data is required, the data must be processed for *sensor registration* to make sure that all sensors that are involved in supplying the data are referring to the same location in the environment and at the same moment in time. If the information provided by a particular sensor is significantly different from other sensors in the system, a *separate operation*, which would be specific to the particular system, may be the path by which the information is integrated with the remaining sensors. The *guiding or cueing* refers to the process whereby a sensor uses information furnished by another sensor as input to determine the area or object that is to be observed. A common example would be a robot manipulator controller that uses video input in order to determine the location of a surface or object that will then be examined with tactile sensors.

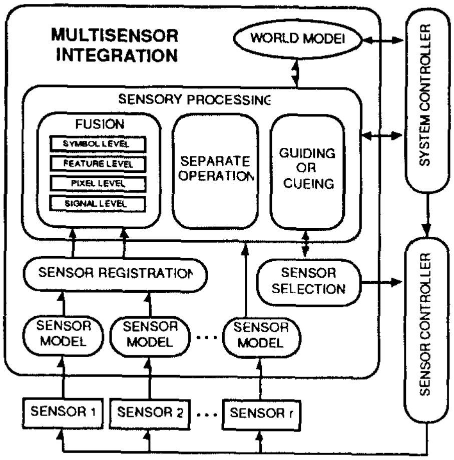

Fig. 1 -. Functional diagram of multisensor integration and fusion in the operation of a system. (from Luo and Kay, 1992; fig. 4).

The *world model* is where information about the environment is stored. Although it may be initiated with *a priori* information about the environment, this is likely to be a dynamic component which is continuously updated as the system continues to gain more information about the surroundings. Higher level processes can use the information supplied by the world model to make the assessment for which the system is designed. For example, in object recognition systems, the world model might contain information regarding the classification of an object that has been observed or it may contain the result that the system was unable to classify the object.

Research in multisensor integration and fusion will most likely continue to focus on adaptive systems which are able to more closely model the natural world, and models which allow the highly parallel collection and processing of sensor data. In the search for effective models of intelligent systems, hybrid systems that accommodate the most useful characteristics of knowledge-based systems, along with neural networks and techniques which incorporate uncertainty reasoning, appear to have the most promise for future useful results. They also offer the greatest challenge in establishing a mathematically rigorous foundation for the fusion process. The following sections will discuss the roles of microsensors, neural networks, and uncertainty calculus in the continuing evolution of multisensor fusion and integration.

1.1. Multisensor Fusion in Automatic Target Recognition

For over a decade, research in multisensor systems has focused primarily on applications related to automatic object recognition (AOR)—a more specific category of which is automatic target recognition (ATR) for military applications. AOR systems must be robust with respect to problems in occlusion, scaling, and the viewing angle of the object being scrutinized. ATR systems face these problems and they must also assume that they are dealing with adversarial objects that will use every means available in order to camouflage their presence. Often there are many targets present and there may be some friendly objects mixed in among the adversaries. In these battlefield situations, it is critical to gather as much information as can be processed within a crucial time-frame, and with a high degree of confidence. The time-frame within which the value of ATR data perishes is a factor that has contributed to the delay in the development of effective ATRs until the advent of faster computers and parallel processing.

Even with faster computers and parallel processing, researchers are still faced with problems that are not easily solved. Uncertainty in the physical sensors themselves, and the uncertainty due to changes in target signature because of fluctuations in the state of the natural environment have created problems whose solutions are often beyond the scope of statistical pattern recognition methods. To overcome these problems, researchers have turned to artificial intelligence techniques, neural networks, and evidential logic techniques such as fuzzy membership functions and Dempster-Shafer uncertainty reasoning.

Uncertainty due to a lack of data concerning target silhouettes and target features is also a problem and it can be reduced by increasing the number and types of sensors that are used to gather the data. This need for more data from multiple angles of view has created a need for the evolution of ATR systems from single-level architectures of similar or disparate sensors to distributed clusters of sensors, where each cluster may then be connected to a local processing element. These distributed clusters of sensors are the basic components of distributed sensor networks and they have a greater capacity to resolve the uncertainty that is common to platforms that contain multiple sensors at a single location. Figure 2 demonstrates the use of distributed multisensor platforms in a battlefield scenario.

The predilection for ATR applications is the reason that most research in multisensor integration and fusion has revolved around the use of military-type sensors such as MMW radar, LADAR, and FLIR [11]. While the theory and applications for multisensor fusion were being developed in ATR systems, progress was also being made in parallel systems architecture and algorithms, and in the miniaturization of electronic components. The 1970s and 1980s brought many improvements in micromachining techniques. This in turn helped make the manufacturing of microactuators (such as microvalves and resonant microstructures) and microsensors economically feasible [21].

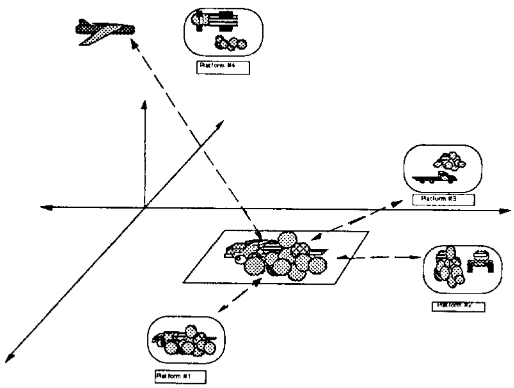

Fig. 2 - A network of distributed multisensor platforms.

1.2 Highly Redundant Sensors and Multisensor Fusion

The miniaturization of electronic components is currently making it possible to use multiple milli-scale sensors in consumer electronics. The same principles of system architecture, sensor fusion, and decision-making that have been developed for ATR systems can be applied to these consumer products. This convergence of developments in parallel-system architectures and in the manufacture of microsensors, coupled with the demand for improvements in intelligent systems for consumer products as well as for manufacturing, presents a strong motivation for continued research in multisensor integration and fusion for machine intelligence and automated manufacturing.

Advances in the manufacture of silicon chips which are able to integrate sensing devices and signal-processing electronics have opened the world to the development of microsensors on a scale approaching three orders of magnitude smaller than the diameter of a human hair [13]. A combination of microsensors and multisensor fusion will make possible a new range of applications. Continuing developments in microsensor technology demonstrate that it may soon be practical to consider using very dense populations of highly redundant sensors, in much the same way that they appear in biological systems.

The human olfactory sensors cover an area of about five square centimeters and have on the order of 10^6 chemoreceptors; the tongue has over 10 000 taste receptors; in the inner ear, the organ of corti has 20 000 hair cells that vibrate in response to sound [6]. Clearly, nature has adapted to a need for highly redundant sensory data. In the same way that biological systems are looked to for inspiration when modeling intelligent systems, evidence is easily found in nature for the benefits of using sensor redundancy. Martin Brooks [3] demonstrates the function of redundant sensors in biological systems that use lateral inhibition to resolve closely spaced applications of pressure on the skin, and he relates this action to competitive learning in self-organizing neural networks.

2. MICROSENSORS IN MULTISENSOR INTEGRATION AND FUSION

Future trends in multisensor fusion and integration must invariably include systems designed to incorporate the use of microsensors. Microsensors are sensors that are created on silicon chips using the process known as "micromachining," which is similar to the photolithographic process used in IC manufacturing. The main difference between the two processes is that micromachining is a deep-etching process which gives the microstructures of the sensor more of a three-dimensional quality than is found in ICs.

An example of a micro-sensor is shown in Figure 3. The microsensor shown in the figure is a "multichannel multiplexed recording array for studies of information processing in neural structures" ([21], fig. 6). Ken Wise developed this smart microsensor which has a multichannel micromachined recording array. The microsensor probe was designed to function as a neuro-electronic interface for the study of signal processing techniques in biological neural nets and for applications in neural prostheses. It incorporates on-chip amplifiers which provide a per-channel gain of 300 and bandlimit the recorded signals to 10 Hz to 10 KHz, and require no off-chip components. A three-lead interface connects it to the external world.

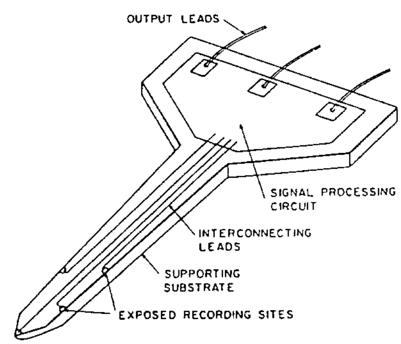

Fig. 3-. An example of a microsensor (fig. 6 in Wise, 1991b).

2.1 Advantages of microsensors

The advantages that microsensors have to offer over conventional sensors are due to their smaller size and to the potential for developing families of "smart" sensors. The advantages due to size include the following: the ability to use them in spaces that are too small for the use of conventional sensors; increased durability due to an enhanced resistance to damage from impact; and a better signal-to-noise ratio.

Smart sensors are sensors that have signal-processing electronics and sensing elements on the same chip. This improves the signal-to-noise ratio by preventing the attenuation of the signal due to connectors and cables that can be affected by electromagnetic interference. Also, since micromachining can be performed as a batch process, manufacturers will have the opportunity to recover development costs in much the same as they have with ICs. Thus, microsensors will tend to be less costly than conventional sensors and therefore more accessible for experimental research in multisensor integration and fusion.

2.2 Problems with microsensors

One of the major obstacles faced by smart microsensors is the lack of selectivity when exposing the sensors to severe environments. Unlike an IC, whose packaging is designed to protect the circuitry from the elements, a sensor must be exposed to what could be a severe environment if it is to supply the correct information. This can adversely affect the electronic signal processing components on smart sensors. Packaging sensors so that the electronics are protected while the sensor is exposed is a problem that must be addressed individually for each application. The microsensor and its packaging must be designed simultaneously [16].

The integration of sensors and processing elements on the same chip creates a need for simpler fusion schemes. Using a local processing element prohibits extensive access to large data bases that are available to conventional sensors. This is the same type of communication bandwidth problem that is encountered in ATR when, for example, groups of radar stations must contend for limited interprocessor communication links.

2.3 Applications of microsensors

Multisensor arrays are currently used in automotive monitoring and control systems, biomedical applications, instrumentation, and in many consumer products such as microwaves, dishwashers, cameras, and washing machines. These are but a few of the possibilities for microsensor applications.

Speculative applications for the near future include the use of multiple microsensors in robot manipulators and in environmental monitors. Their utilization in robot manipulators will allow the employment of robots in areas that currently require a high degree of dexterity, and the ability to work in tight spaces.

Autonomous microminiature robots, such as those found in the Artificial Intelligence Laboratory at MIT [4], might someday be used to deploy multisensor platforms to form untethered and highly mobile distributed sensor networks. They could be used as a way to inexpensively gather information in such applications as the environmental monitoring of contaminated reactor vessels, the development of miniature landrovers for planetary exploration, and for the non-destructive inspection of small enclosures such as pipes.

Biomedical applications of microsensors can be broadly divided into two categories: diagnostic applications and monitoring applications [19].

Diagnostic applications: Microsensor arrays are used to perform broad diagnostics such as screening for a variety of drugs simultaneously and performing the "cardiology panel" for cholesterol, triglyceride, sodium, and potassium. Catheter-based sonic imaging sensors are used by radiologists and vascular surgeons to examine the internal surfaces of blood vessels.

Monitoring applications: Multiple microsensors are used for on-line monitoring of patients' blood in operating rooms and intensive care units, and as a way to check for the presence of important blood electrolytes. Optoelectronic sensors have been used to measure vibrational amplitudes of the middle ear to a resolution of 0.005 microns [23]. Sensor arrays have been implanted in the respiratory tract of exercising patients and have shown a substantial difference between the temperature profiles of normal subjects and asthmatic patients [5]. The monitoring of multiple variables is implicit in most biomedical applications, making this a rich field for the exploration of multisensor fusion applications with microsensors.

3. NEURAL NETWORKS IN MULTISENSOR FUSION

Intelligent systems must have the capability to gather data, assimilate the data into abstract information, and formulate some decision based on that information. Fusion processing centers that are used in multisensor systems may need to perform these operations at one or more levels. System qualities that are necessary to ensure that these operations can be performed effectively include: that the system be adaptive—that is, have the potential for learning; that it be robust so that failure of some system components is expected and can occur without causing an abrupt degradation in overall system performance; and that it have the ability to handle uncertainty in sensory data.

3.1 Types of neural networks

There are many different types of neural network models. They are distinguishable by their network topology, node characteristics, and the learning rules under which they adapt. Two broad categories of neural network models that are often used for pattern classification applications and multisensor fusion are the supervised-learning type and the unsupervised-learning type. Specific models include: multi-layer perceptrons and Hopfield associative memories in the supervised-learning category; and Kohonen self-organizing feature maps in the unsupervised category.

In supervised learning, the system trainer must have *a priori* knowledge about the classification of the information in the training set. Patterns, whose classification is known by the trainer, are entered into the network along with their proper class label. The network then uses its appropriate training algorithm to correctly classify the training data. Once trained, the network will be able to classify new incoming data with varying degrees of success. One of the networks—the associative memory—has been successfully adapted for use in a fuzzy classifier [9],[17]. While these supervised-training models have found heavy use in the development of intelligent systems, they are hampered by some inherent problems.

Multi-layer Perceptron: The multi-layer perceptron uses a back-propagation learning algorithm that is computationally intensive and, when learning a large number of pattern classes, must often be trained off-line rather than in real time. It also lacks plasticity, in that, after having learned group classifications, if the modeler wishes the system to be trained for a new group classification, the system must repeat the learning process. The training time increases as the number of classifications increases. The system may become unstable so that training is never achieved.

Hopfield Associative Memory: The Hopfield associative memory is based on the Kohonen content addressable memory model. Hopfield [8] has demonstrated that the associative memory will always reach a stable state but that the number of classes that are separable in memory is directly proportional to the maximum number of nodes that are present in any of the network's layers.

In unsupervised learning, a neural network that is often used is the Kohonen self-organizing feature map. With this model, the output class of the input feature vector is not known ahead of time. Input vectors are presented to the network and the network will cluster the feature vectors. The clusters will be centered on the point that approximates the probability density function of the input vectors. Lippmann [10] presents an introduction to several types of neural networks, including a thorough discussion of Kohonen's algorithm that is used to form these feature maps. Ajjimarangsee and Huntsberger [2] use multi-stage self-organizing feature maps to model the fusion of visual and thermal data that occurs in the optic tectum of the rattlesnake. Pearson, et al. [15] use self-organizing feature maps to perform a computer simulation of the visual/acoustic sensor fusion techniques of the target-localization system of the barn owl.

3.2 Advantages of neural networks

Some potential advantages that neural network models offer in systems used for the integration and fusion of data are the following: *adaptive learning*—they are capable of learning how to do a task, based on training data, without the need to incorporate *a priori* error data; *self-organization*—they are able to create their own categories for classification of incoming data; *parallel architecture*—their basic architecture is parallel in nature, making them easily adaptable to macro-parallelism at the logic-gate hardware level as well as micro-parallelism at the chip level;*noise filtering*—back-propagation and autoassociative networks have shown a natural ability to reduce the noise in an input signal; *fault tolerance*—neural network architecture is inherently distributed, parallel, and highly interconnected, all of which are qualities that promote non-localized data storage, thus dampening the effects of partial system failure. These and other qualities make neural networks a good choice for sensor fusion.

4. HANDLING UNCERTAINTY IN MULTISENSOR FUSION

It is often the rule, rather than the exception, that sensory systems are able to supply only partial or uncertain information about their environment. In object recognition, occluded objects or insufficient lighting may be the reason that only partial information is available. Uncertainty may be caused by such things as noise corruption, an imperfect degree of sensor-measurement reliability, and sensor malfunction. Although the use of multiple sensors helps to reduce the amount of uncertainty, it will always be present in real-world environments. Research in uncertainty calculus examines techniques that can be used to improve the quality of information that can be extracted from the incomplete data that is collected about real-world situations.

Some of the more common techniques that are currently employed are the probabilistic methods of Bayesian estimation, the evidential reasoning of Dempster-Shafer theory, fuzzy set theory, and rule-based expert systems. Henkind and Harrison [7] present an introduction to these four types of uncertainty calculi and describe the advantages and disadvantages associated with each.

While there continues to be disagreement among experts as to which technique is the most effective in handling uncertainty, the Dempster-Shafer and fuzzy set techniques require the least *a priori* knowledge of statistics about the environment. A disadvantage of the Bayesian approach is that it may difficult, if not impossible, to gather the appropriate statistics for a given situation.

Another of the primary differences between the Dempster-Shafer approach and the Bayesian approach is that, with Dempster-Shafer, an interval of uncertainty is associated with the hypothesis that a proposition is true, whereas the Bayesian method uses a single value to represent the probability that a proposition is true. This may lead the users of the Bayesian technique to assign values to probability measures without associating it with an appropriate quantity to designate the uncertainty or ignorance that is inherent in the assignment.

Fuzzy set theory was presented initially by Zadeh in 1965 [22] as a technique in which uncertainty can be quantified as a degree of set membership. For example, a fuzzy set might be a set whose members are *reasonably tall* as opposed to the crisp set whose members are of height *greater than 6'2" and shorter than 7' tall.* Since many recognition and classification problems in the real-world are of a fuzzy nature, fuzzy set theory has been—and will continue to be—very useful in multisensor fusion.

Rule-based systems are often most effective when used for top-level control of systems rather than for low-level multisensor fusion, and are therefore not likely to be used for low-level fusion in systems that are based on large numbers of redundant sensors. Noble [14] and Adelman [1] note that problems in rule-based systems may arise due to difficulties regarding the subjective nature of: knowledge-elicitation techniques that are used to develop the data base for a rule-based system; problem domain descriptions; and the level of expertise that qualifies the knowledge experts to be "expert enough" to develop the system properly.

5. CONCLUSION

Research in the near future will continue to be aimed at developing integration and fusion techniques that will allow multisensory systems to operate in unknown and dynamic environments. Systems based on neural network architecture will be implemented on highly parallel computer architectures to take full advantage of the parallelism inherent in these models. Research in the areas of artificial intelligence, uncertainty reasoning, and fuzzy sets will continue to provide both theoretical and practical insights. AI-based research may prove especially useful in areas like sensor selection, automatic task error detection and recovery, and the development of high-level representations; research based on neural networks may have a large impact in areas like object recognition through the development of distributed representations suitable for the associative recall of multisensory information, and in the development of robust multisensor systems that are able to self-organize and adapt to changing conditions (e.g., sensor failure).

The development of integrated solid-state chips containing multiple sensors will continue to be the focus of much research [20]. As current progress in VLSI technology continues, "smart sensors" [13] will be developed that contain many of their low-level signal and fusion processing algorithms in circuits on the same chip as the sensor.

The availability of cheap integrated multisensors may enable some recent ideas concerning "highly redundant sensing" [18] to be incorporated into the design of intelligent multisensor systems. The lateral inhibition of competitive-learning neural networks may be especially useful—when combined with dense populations of microsensors—in the design of intelligent man-made systems that are inspired by biological systems.

In the same way that sensory information precluded intelligence in biological life forms, the availability of sensors on the microscopic scale is likely to lead to new understandings that are currently difficult to imagine.

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