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On A Notion of Sensor Modeling in Multisensor Data Fusion

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ABSTRACT

In this paper, we describe a notion of sensor modeling method in multisensor data fusion using fuzzy set theory. Each sensor module is characterized by its fuzzy constraints to specific features of environment. These sensor fuzzy constraints can be imposed on multisensory data to verify their degree of truth and compatibility toward the final decision making. In comparison with other sensor modeling methods, such as probabilistic models or rule-based models, the proposed method is very simple and can be easily implemented in intelligent robot systems.

1. INTRODUCTION

For many intelligent systems, the synergistic use of multisensory information is a crucial element to increase their capabilities. The efficient use of multisensory information is achieved by fusing the outputs of a given sensory module with those of other, dependent or independent, sensory modules. The key to efficient fusion is to employ an efficient model of a sensor ability and to characterize multisensory information appropriately.[1,2]

Sensor modeling is the process of describing how a sensor images the world. In other world, a sensor model is an abstraction of the physical sensing process whose purpose is to describe the ability of a sensor to extract descriptions of the environment in terms of the information available to the sensor itself. This model should provide an ability to analyze and reason with uncertain state of the environment and the state of the sensor itself.[3]

Various sensor modeling methods have been proposed over the years. They can be classified into two major categories: probabilistic models of sensor ability and rule-based models. Probabilistic models of sensor information have been realized by a number of researchers in robotics. Most notably, Durrant-Whyte has developed probabilistic models using the idea of an information structure which has been developed as an element of team decision theory.[4] Probabilistic models are well suited to describing the uncertainties in the sensor data and the quantitative representation of different sensor information in a common probability space. But they have modeling complexity and computation necessity and they need to have broad assumptions, simplifications, and generalizations such as Gaussian distribution(mean and variance).

Rule-based models have been proposed for integrating sensor information by heuristic rule or by input-output characteristics of a given sensor (device or algorithm). Henderson's logical sensor descriptions and Flynn's production rules are the most comprehensive rationalization of sensor abilities in the context of rule-based sensor models.[5,6] The advantages of this approach are that they lend to ideas of modularity, extensibility and qualitative representation. But rule-based approaches to sensor modeling cannot quantify sensor performance explicitly and they have only concentrated on the task-oriented or object-oriented models.

Clustering of consensus sensor data and fusion of them are the key elements in the realization of a multisensor system. And sensor failure check and cluster selection problem are the essential procedures of the multisensor data fusion. But the above approaches of sensor modeling (probabilistic models or rule-based models) are not possible to carry out this procedures or need to have much complex modeling sequence or computation necessity. To overcome these problems, we describe a notion of sensor modeling techniques by using fuzzy set theory in this paper. Each sensor module is characterized by its fuzzy constraints to specific features of environment. These sensor fuzzy constraints can be imposed on the consensus multisensory data to verify their degree of truth and compatibility toward the final decision making. Also they can be used to verify cluster validity and to check what sensor is in failure.[7]

2. SENSOR FUZZY MODELS

Exact mathematical models of real sensors are very often impossible or vague in a number of ways due to lack of the detailed characteristic descriptions or the interactions between components of sensor. But we can express sensor abilities in words or by semantic meaning without difficulty. For examples, infrared sensors are *good* at detecting *small* area objects or features, such as points or edges, while ultrasonic sensors are typically *poor* at such operation. However, ultrasonic sensors are *better* than infrared sensors at measuring depth. Sonar's usefulness is limited to *about* five meters. Stereo vision's range is limited by the triangulation geometry required and affected by the illumination *significantly*. Laser range finder(LRF) generally provide accuracy and *better* spatial resolution, but it is *very weak* in light source (especially sunlight). Above uncertain descriptions of the sensor characteristics in semantic meaning (in *italic* character), so called *fuzziness*, can be well expressed in fuzzy framework.

Ideas

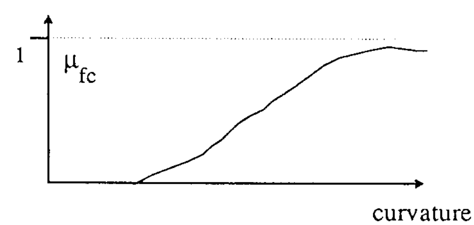
(1) Bellman and Zadeh introduce a fuzzy constraint of the fuzzy statement about fuzzy environment in fuzzy decision making area.[8] Using this idea we can describe sensor's constraints about sensor data as a membership function which represents the degree of compatibility about the data, that is, sensor fuzzy constraints.

(2) To calculate Sugeno's fuzzy integral and g_λ-fuzzy measure, fuzzy density value which represents the degree of importance about some data source must be known or assigned.[9] To apply sensor fusion, it means that the degree of importance of each sensors must be known before data fusion and we can describe it as a sensor fuzzy constraint about the final representative values.

(3) Weighted combination fusion method of the outputs of two or more sensory modules is a general fusion technique. The weighting of one information source with respect to another is derived from the relative importance of the two information sources. This implies that we can describe the weighting as a sensor fuzzy constraint.

Definition and Examples

A sensor fuzzy constraint is a set of sensor restrictions and is characterized by the membership function $\mu_{fc}(\cdot)$. For examples, the statement that 'ultrasonic sensor has different performance with respect to the reflected surface curvature' is described by sensor fuzzy constraint as shown in fig.1. Another statement that 'forward looking infrared(FLIR) sensor has good performance between 3[m] and 6[m]' is described as shown in fig.2. Also, the statement that 'LRF sensor has bad performance in daylight environment' can be described as shown in fig.3 using $\mu_{fc}(\cdot)$.



where fc : " good performance " ; a fuzzy set

fig. 1 ultrasonic sensor fuzzy constraint

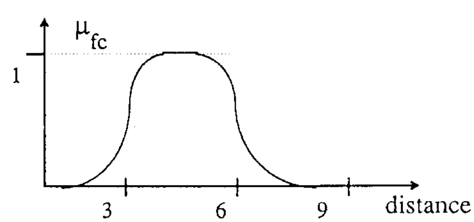


fig. 2 FLIR sensor fuzzy constraint

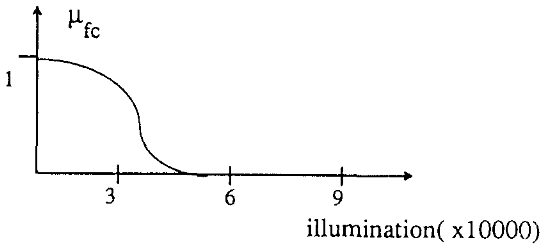


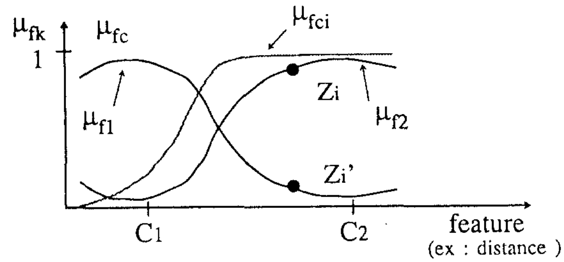
fig. 3 LRF sensor fuzzy constraint

3. APPLICATIONS

According to the fuzzy clustering procedure(typically fuzzy c-means algorithm), each consensus muitisensor data can be expressed in membership grade with respect to the cluster center. This allows that multisensor data construct a membership function about a feature of an object or environment. We can impose a sensor fuzzy constraint on this membership function to verify what cluster is selected or to check what sensor is in failure.

Using the fuzzy c-means algorithm, we can obtain two membership functions, μ_{f1} and μ_{f2}, about one feature of an object or environment as shown in fig.4. We assume that sensor i has its fuzzy constraint μ_{fci}. And its membership grade to the second cluster center C2 is Zi and to the first cluster center C1 is Zi' (Zi+Zi'=1). In this case, the sensor fuzzy constraint μ_{fci} and the sensor i data satisfy the compatibility with respect to the second cluster simultaneously. So we can postulate that the second cluster is more creditable than the first cluster and select the second cluster. In fig.5, sensor i data and μ_{fci} satisfy the compatibility with respect to the second cluster and sensor j data and μ_{fcj}, sensor j's fuzzy constraint, satisfy the compatibility with respect to the first cluster simultaneously. In this case we assume that both clusters are credit-able. If the sensor fuzzy constraint μ_{fci} and sensor i data shown in fig.6 are represented in opposite characteristic, we can treat sensor i to be in failure probably.

After the cluster selection and the sensor failure check, we can calculate a new cluster center excluding suspicuous sensor data and fuse a new representative value about a feature.. If both clusters are selected, new representative sensor data can be obtained from averaging the center values of two clusters.



Where

μ_{fk} : membership function of feature for cluster k (k=1,2)

μ_{fc} : membership function for sensor fuzzy constraints

μ_{fci} : membership function for sensor i fuzzy constraint

C1 : cluster 1 center

C2 : cluster 2 center

Zi : membership grade of sensor i w.r.t. C2

Zi' : membership grade of sensor i w.r.t. C1

fig. 4 one cluster selection

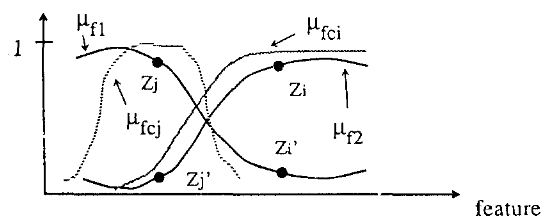


fig. 5 two clusters selection

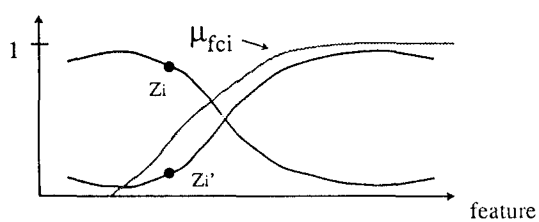


fig. 6 sensor failure check

4. CONCLUSION

In this short note, we described a notion of sensor modeling techniques using a simple *sensor fuzzy constraint* concept. The proposed method was very easily applicable to select valid cluster and to check sensor failure in fuzziness environment at robot workspaces. Sensor fuzzy constraint could be obtained from the sensor calibration procedure, sensor coordination, training phase, transfer function offered by the sensor manufacturing company, commonsense, heuristic, or experiences, etc. As a result, our sensor modeling method was very simple and could be easily implemented in intelligent robot systems. The proposed sensor modeling method constitutes a part of multisensor data fusion module for mobile robot navigation in our laboratory presently.

REFERENCES

[1] W. J. Kim, J. H. Ko, and M. J. Chung, "Multisensor Data Fusion for Intelligent Robot Systems," Proc. '91 KIEE Summer Conference, pp.787-794, Jul., 1991.

[2] R. C. Luo and M. G. Kay, "A Tutorial on Multisensor Integration and Fusion," Proc. '90 IECON, California, pp.707-722, Nov., 1990.

[3] H. F. Durrant-Whyte, *Integration, Coordination and Control of Multisensor Robot Systems*, Boston, MA: Kluwer Academic Publ., 1987.

[4] H. F. Durrant-Whyte, "Sensor Models and Multisensor Integration," Int. J. of Robotics Research, Vol.7, No.6, pp.97-113, Dec., 1988.

[5] T. Henderson, E. Weitz, and C. Hansen, "Multisensor Knowledge System: Integrating 3-D Structure," Int. J. of Robotics Research, Vol.7, No.6, pp.114-137, Dec., 1988.

[6] A. M. Flynn, "Combining Sonar and Infrared Sensor for Mobile Robot Navigation," Int. J. of Robotics Research, Vol.7, No.6, pp.5-14, Dec., 1988.

[7] W. J. Kim, J. H. Ko, and M. J. Chung, "Multisensor Data Fusion Using Fuzzy Techniques," Proc. '91 KIEE Summer Conference, pp.781-786, Jul., 1991.

[8] R. R. Yager et al., *Fuzzy Sets and Applications: Selected Papers by L. A. Zadeh*, John Wiley & Sons, pp.53-79, 1987.

[9] H. Tahani and J. M. Keller, "Information Fusion in Computer Vision Using the Fuzzy Integral," IEEE Trans. on SMC, Vol.20, No.3, pp.733-741, May/June, 1990.