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FUZZY SETS AND FUSION OF MULTISENSOR DATA

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Since the notion of fuzzy sets was introduced by L. A. Zadeh in 1965, a great number of papers have been published about different aspects of this theory. However, it is difficult to find one which showed that a real problem, which might be solved by a probabilistic approach, had been solved by a possibilistic approach. In this paper, we present a comparative study of probabilistic and possibilistic approaches for solving the same problem: the fusion of multisensor data under uncertainty. It shows that both approaches can be used, but the resolutions are different.

1. INTRODUCTION

In the last several years, there has been an increasing interest in the development of multisensor systems for autonomous mobile robots. One of the main research topics in this field is the fusion of multisensor data, that is the process by which data derived from different sensors are used to yield an optimal estimation of the environment. However, different sensors have different characteristics of precision and different ranges of measurement. As a consequence of this, data provided by these sensors are always tainted with imprecision and uncertainty.

In artificial intelligence, the following distinction between uncertainty and imprecision is usually made [4]: A proposition is uncertain if its truth cannot be definitely established; a proposition, whose contents state the value of some variable, is imprecise if this value is not sufficiently determined with respect to a given scale. In the particular case of sensory data fusion, we distinguish between imprecision and uncertainty in the following way. Imprecision is due to intrinsical characteristics of each sensor, since there is not perfect sensor. Uncertainty exists in estimating a real value from data provided by different sensors. For example, if we make an arithmetical average of N data provided by N sensors to estimate a distance and obtain a value d_A, we can only conclude that the real distance is almost certainly between $[d_A - \max(3\sigma_i),\ d_A + \max(3\sigma_i)]$, where σ_i is the standard deviation of the ith sensor, with $i = 1, 2, \ldots, N$. Since imprecision is an inherent characteristic of sensors, the only thing that we can improve through fusion process is to reduce uncertainty.

In the remainder of this paper, we will present probabilistic and possibilistic approaches for the fusion of multisensor data and give a comparative study of these methods for dealing with some experimental data. Note that, in this paper, the fusion of multisensor data signifies especially the fusion of homogeneous sensory data.

2. PROBABILISTIC APPROACHES

2.1. Durrant–Whyte's multi-Bayesian approach

Bayesian method is the most formally mature technique for uncertainty management. Bayes' rule states that, given a set of exhaustive and mutually exclusive hypotheses, $H = \{h_1, \ldots, h_n\}$, and a set of observation, $\{e\}$, the posterior probability of each hypothesis (our belief about h_i after making an observation e) can be derived from:

$$P(h_i \mid e) = \frac{P(e|h_i)\,P(h_i)}{\sum_{j=1}^{n} P(e|h_j)\,P(h_j)}$$

where, $P(e \mid h_i)$ is the conditional probability of the observation given that hypothesis, and $P(h_i)$ the prior probability of the hypothesis before the observation. It is clear that, in order to use this approach, we need to determine the appropriate prior and conditional probabilities.

Durrant–Whyte [2] proposes to use Bayesian approach to combine multisensor observations: each sensor is considered as a Bayesian estimator. By choosing the prior probability to be jointly normal with mean m and variance σ^2, he describes that, if a consensus estimate d_D (the scale variable that we try to estimate from the observations d_i) can be found (for details about this condition see [2]), then it can be given by:

$$d_D = \frac{\sum_{i=1}^{n} d_i\,\sigma_i^{-2}}{\sum_{i=1}^{n} \sigma_i^{-2}}.$$

Durrant–Whyte's approach explains that we suppose each sensor reading to be the most probable value according to Gaussian distribution and we will make more belief on higher accuracy sensors (sensors with small variance σ^2). However, it is quite possible for all of the sensor readings to be greater (or smaller) than the real value, and, it is also possible that a sensor reading provided by a sensor with big variance be the nearest to the real value.

2.2. Luo's pre-selection approach

Another probabilistic approach is presented by Luo et al. [3]. Instead of integrating all of the sensor data, they have proposed to fuse data that are "correct" and reject those which are "incorrect". For doing this, they described that: If the sensor values are close to each other, we may fuse them together but if the values vary greatly from each other, some values may be suspected to be incorrect and therefore not to be considered for fusion. Then, by fixing a threshold, they defined a criterion called distance measure for detecting the correctness of sensory data.

Just like in Durrant–Whyte's approach, Luo et al. have also supposed each sensor reading to be the most probable value according to the Gaussian distribution. However, as we have mentioned above, this is not true. Therefore, we will be in danger of losing important information, because it is quite possible that a sensor reading which appears to be "incorrect" is in fact nearest to the real value.

3. FUZZY SETS APPROACH

Introduced by Zadeh [7] in 1965, fuzzy sets theory has been applied in many application fields. It is most relevant where the fuzzy relations denote extent on continuous variables (such as height, distance, age, etc.). Quantification is achieved by the identification of membership functions (or possibility functions), which are distributions of set membership $[0,1]$ over the relevant variable. A membership value of 1 indicates complete set membership, a value of 0 indicates set exclusion and the values between $(0,1)$ indicate degrees of partial set membership.

Just as there are difficulties in determining the relevant prior and conditional probabilities for a Bayesian approach and there are difficulties in justifying the rationality of data in Luo's approach, so the production of membership functions is no simple matter. They are often derived by empirical methods.

Based upon the possibility theory [1], our previous work [5] presented a possibilistic approach for dealing with uncertainty in the fusion of multisensor data. The original point of this apprach is that two aspects have been taken into account: (i) individual sensor measurement and relevant accuracy; (ii) whole effect of multiple measurement. This can only be achieved by using the fuzzy sets theory.

Table 1 gives a comparison of different approaches for coping with a set of eight experimental sensory data provided by four ultrasonic range finders, the standard deviations of which (for a distance of about 5 meters) are 95 mm, 54 mm, 68 mm and 60 mm respectively.

Table 1. Comparison of results estimates by different approaches.

	1	2	3	4	5	6	7	8
d_1	5.042	4.882	5.068	4.916	5.064	5.004	4.918	5.018
d_2	4.988	5.034	5.032	4.988	5.028	5.048	4.962	4.906
d_3	4.992	5.016	5.106	4.950	5.034	5.066	5.008	4.978
d_4	5.014	4.982	5.030	5.034	4.896	5.078	4.956	5.054
d_A	5.009	4.978	5.064	4.970	5.006	5.049	4.961	4.989
d_D	5.003	4.997	5.058	4.984	4.993	5.056	4.966	4.979
d_L	5.009	5.011	5.050	4.951	5.042	5.064	4.945	4.989
d_W	5.007	4.980	5.048	4.972	5.017	5.050	4.960	4.993

We can see that, in the light of Wang's estimate d_W, the real value is almost certainly between $[d_W - \min(\sigma_i),\ d_W + \min(\sigma_i)]$, with $i = 1, 2, \ldots, N$. This result cannot be certified by neither arithmetical average d_A, nor Durrant-Whyte's estimate d_D, nor Luo's estimate d_L. It should be noted that possibilistic approach does not always give a best result for each particular case, but it can guarantee a best resolution. Furthermore, it should also be noted that fuzzy sets approach is normally slower (in regard to computing time) than probabilistic approaches.

4. CONCLUSION

We have shown the advantageous point of fuzzy sets theory for dealing with uncertainty in the fusion of homogeneous sensory data. This theory is also profitable for the fusion of heterogeneous sensory data [6]. Generally speaking, fuzzy sets approaches are not always better than probabilistic approaches. The most appropriate technique for a particular application depends upon a number of facts: the nature of the domain, the number of data, the level of accuracy required, the function that the system is intended to support, etc.

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