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Research of Localization Optimization Based on Multi-information Fusion for Housework Robot Positioning System

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Abstract:Against to the presence of high complexity, low accuracy and a smaller range of positioning in traditional positioning technologies, A single positioning technology can not completely cover the environment and lead to the problem of inaccurate positioning results,it presents the multi-information fusion positioning technology for housework robot positioning system. Uncertainties among the acquired data and mutually exclusive and compatibility of evidence for each channel, the technology takes full advantage of WLAN, RFID and odometer sensor and ultrasonic for fusion location,It proposes the secondary adjusting weighted DS evidence theory. Experimental results show that: Compared with classic DS evidence theory fusion results, the technology can improves positional accuracy and better meets the positioned requirements of home robots.

Keywords: Indoor positioning; Housework robots;Data fusion; DS evidence theory

1 INTRODUCTION

In the last few years,the definition of smart home has been formed[1] and many learners have been studying this direction.One of the top vital studies considers location of housework robots, in which localization technologies play an indispensable role. The key issue is how to maintain accuracy and precision in complex and changeable indoor environments.

Many localization technologies and methods have been proposed for indoor environments. Among the most widely used technologies are GPS, RFID, WIFI,odometer sensor and ultrasonic sensor, and so forth[2-3].A single positioning technology can not completely cover the environment and lead to the problem of inaccurate positioning results.For example, WIFI positioning is only suitable for user localization with low precision because of its accuracy varying from few meters to tens of meters;RFID,a proximity scheme, is limited in a small range since RFID readers cannot be installed at every location. It will be seen that the combination of these positioning technology,which may use fusion ways,is the research orientation to deal with Indoor positioning accuracy and precision.

To overcome the limitations in each technology and provide better results in both precision and availability characteristics. Combining multiple localization technologies have been proposed by a number of researches. It [4] introduced a design to extract results from localization technologies as useful information in real time. However, it lacked ideas and algorithms about how those results should be fused and analysed to produce better results. It [5] combined GPS, WIFI, and ZIBGEE into a system which can notably improve localization results in indoor areas. It [6] used WIFI and a pedometer in smart phones for high-precision localization applications. Other few hybrid systems showed improvements in precision, but these systems depended on specific technologies and lacked availability characteristics, such as RFID, WIFI, and camera [7-10]. None of those researches proposed a fusing algorithm to combine highly heterogeneous technologies.

Facing uncertainties among the acquired data and mutually exclusive and compatibility of evidence for each channel,this text proposes the secondary adjusting weighted DS evidence theory， while we can choose WLAN, RFID and odometer sensor and ultrasonic for fusion location.

2 DS EVIDENCE THEORY

2.1Basic Concepts

The theory DSTheory (DST), is a general framework for reasoning with uncertainty, with understood connections to other frameworks such as probability, possibility and imprecise probability theories. First introduced by Arthur P. Dempster[11] in the context of statistical inference, the theory was later developed by Glenn Shafer into a general framework for modeling epistemic uncertainty a mathematical theory of evidence.[12][13]The theory allows one to combine evidence from different sources and arrive at a degree of belief (represented by a mathematical object called belief function) that takes into account all the available evidence.

Often used as a method of sensor fusion, DST is based on two ideas: obtaining degrees of belief for one question from subjective probabilities for a related question, and Dempster'srule[14] for combining such degrees of belief when they are based on independent items of evidence. Belief functions base degrees of belief (or confidence, or trust) for one question on the probabilities for a related question. The degrees of belief itself may or may not have the mathematical properties of probabilities; how much they differ depends on how closely the two questions are related.Put another way, it is a way of representing epistemic plausibilities but it can yield answers that contradict those arrived at using probability theory.

2.2Formal Definition

Definition 1 Let U be the universe: the set representing all possible states of a system under consideration. The power set 2^u is the set of all subsets of U , including the empty set φ .The theory of evidence assigns a belief mass to each element of the power set. Formally, a

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function $\mathrm{m}:2^{\mathrm{u}} \longrightarrow [0,1]$ is called a basic belief assignment (BBA), when it has two properties. First, the mass of the empty set is zero:

$$\mathrm{m}(\varphi)=0 \quad (1)$$

Second, the masses of the remaining members of the power set add up to a total of 1:

$$\sum_{\mathrm{A}\subseteq \mathrm{U}} \mathrm{m}(\mathrm{A})=1 \quad (2)$$

Definition 2 From the mass assignments, the upper and lower bounds of a probability interval can be defined. This interval contains the precise probability of a set of interest (in the classical sense), and is bounded by two non-additive continuous measures called belief (or support) and plausibility:

for $\forall \mathrm{A} \subseteq \Theta$, The belief bel(A) for a set A is defined as the sum of all the masses of subsets of the set of interest,and The plausibility pl(A) is the sum of all the masses of the sets B that intersect the set of interest A:

$$\begin{cases} \mathrm{Bel}(\mathrm{A}) = \sum_{B\subseteq A} \mathrm{m}(B) \\ Pl(A) = \sum_{B\cap A\neq \phi} \mathrm{m}(B) \end{cases} \quad (3)$$

Definition 3 then Dempster's rule of combination is the appropriate fusion operator. This rule derives common shared belief between multiple sources and ignores all the conflicting (non-shared) belief through a normalization factor. Use of that rule in other situations than that of combining belief constraints has come under serious criticism, such as in case of fusing separate beliefs estimates from multiple sources that are to be integrated in a cumulative manner, and not as constraints. Cumulative fusion means that all probability masses from the different sources are reflected in the derived belief, so no probability mass is ignored.Specifically, the combination (called the joint mass) is calculated from the two sets of masses m1 and m2 in the following manner:

$$m(C)=\begin{cases} 0, & \forall C \subset U,\, C \neq \phi \\ \dfrac{1}{1-k_{i,j}} \sum_{A_i \cap B_i = C}^{n} m_1(A_i) m_2(B_i), & C = \phi \end{cases} \quad (4)$$

While $\mathrm{k}=\sum_{\mathrm{A_i}\cap \mathrm{B_i}=\varphi} \mathrm{m}_1(\mathrm{A_i})\mathrm{m}_2(\mathrm{B_i})$ is a measure of the amount of conflict between the two mass sets.

2.3 Advantage and Disadvantage of the DST

DS evidence theory has been done a lot of researches at home and abroad. According to DS theory of evidence distinguishes between uncertainty and ignorance by introducing belief functions ,then probability functions can be looked at as a subclass of belief functions, and the theory of evidence reduces to probability theory when the probability values are known. In addition, the theory of evidence provides appropriate method, Dempster rule for evidence combination, for computing belief functions for combinations of evidence. [15] It summarized the advantages of the DS theory as follows:

1. To model information in a flexible way without requiring a probability to be assigned to each element in a set.
2. Support for combining two or more pieces of evidence under certain conditions.
3. Rejection of the law of additivity for belief in disjoint propositions.

It also listed the disadvantages of the DS theory as follows:

1. The theory assumes that pieces of evidence are independent which is not always reasonable to assume independent evidence.
2. The computational complexity of reasoning within the DS theory could be one of the major points of criticism if the combination rule is not used properly.
3.DS theory only works on exclusive and exhaustive sets of hypotheses.

For the first disadvantage assuming pieces of evidence are independent, that is, uncertainties among the acquired data and mutually exclusive and compatibility of evidence for each channel. This text proposes the secondary adjusting weighted DS evidence theory to handle fusion location.

3 THE SECONDARY ADJUSTING WEIGHTED DS EVIDENCE THEORY

For the acquired data from each channel, It is inevitable to show conflict between the evidences. Special positioning environment for household robots, there are different levels of their own performance factors for each channel, and these problems will affect the positioning accuracy. Information Fusion data phase of each channel leading to another conflict between information, which cannot guarantee the reasonable of information processing ,It may lead to erroneous results .

3.1The Adjusting Weighted DS Evidence Theory

Supposing probability assignment of data m is $\mathrm{m}=(\mathrm{m}(\mathrm{A}_1),\mathrm{m}(\mathrm{A}_2),\cdots \mathrm{m}(\mathrm{A}_\mathrm{n}))$, confidence probability is $\mathrm{U}=\{\mathrm{u}_1,\mathrm{u}_2 \cdots \mathrm{u}_\mathrm{n}\}$,the conflict between the evidences $\mathrm{C_{ij}}$ is :

$$\mathrm{C_{ij}} = \sum_{\substack{p=1,q=1 \\ p\neq q}}^{n} \mathrm{m_i}(A_p)\mathrm{m_j}(A_q) \quad (5)$$

And similarity between the evidences $\mathrm{E_{ij}}$ is

$$\mathrm{E_{ij}} = \sum_{p=1,q=1}^{n} \mathrm{m_i}(A_p)\mathrm{m_j}(A_q) \quad (6)$$

During data acquisition and training sample, the less of difference in between data acquisition and the desired result ,the higher weight value should be assigned .According to euclidean distance, the difference between optimum solution and suboptimal solution is :

$$\begin{cases} d_i^+ = \left| s_i - s_i^+ \right| \\ d_i^- = \left| s_i - s_i^- \right| \end{cases} \quad (7)$$

while s_i^+ is data optimum solution, s_i^- is data suboptimal solution. Let suppose the membership of channel s_i is u_i for s_i^+,the membership is $1-u_i$ for s_i^-.And the distance difference is:

$$wd_i = \left[u_i d_i^+\right]^2 + \left[(1-u_i)d_i^-\right]^2 \quad (8)$$

It is idealization that acquired data from channels is similar to the result of data fusion if the distance difference is minimum, and that is:

$$\frac{dw(d_i)}{d(d_i)} = 0 \quad (9)$$

And it would be can be calculated u_i^* :

$$u_i^* = \frac{s_i^2}{(s_i-1)^2 + s_i^2} \quad (10)$$

In the end, acquired data from channels is similar to the result of data fusion, while u_i^* is more and more bigger.

Normalization weighted value of channels u_i,which based on acquired data from channels and formula（10）,It would be can be calculated.

$$u_i = u_i^* \Big/ \sum_{i=1}^{m} u_i^* \quad (11)$$

3.2 The secondary adjusting weighted DS evidence theory

In housework robot positioning system, the higher of similarity among the evidence ,the higher lower weighted value given .It is opposite to the evidence conflict ,that is ,the higher of conflict among the evidences, the lower weighted value given. Therefore, It is advisable to adjust the similarity to reduce the conflict among evidences, and improve positioning accuracy.

The proportion of conflict factor：

$$k_i = \frac{\sum_{j=1,\ i\neq j}^{m} C_{ij} - \sum_{j=1,\ i\neq j}^{m} E_{ij}}{\sum_{j=1,\ i\neq j}^{m} C_{ij} + \sum_{j=1,\ i\neq j}^{m} E_{ij}} \quad (12)$$

It gets the coefficient of conflict k^* based on the proportion of conflict factor k_i :

$$k^* = \frac{1 + \frac{1}{m}\sum_{i=1}^{m} k_i}{2} \quad (13)$$

It gets the weighted factor of the whole u' based on evidences conflict while α is the adjusted coefficient：

$$u' = m \times (k^*)^{\alpha} \times \min\{u_1, u_2, \cdots u_n\} \quad (14)$$

When u_{i1} , u_{i2} will be calculated based on the conflict and similarity among evidences.

$$\begin{cases} u_{i1} = \dfrac{E_i}{\sum_{i=1}^{m} E_i} \\ u_{i2} = \dfrac{C_i}{\sum_{i=1}^{m} C_i} \end{cases} \quad (15)$$

The secondary adjusting weighted of the positioning data obtained from all routes U :

$$U = \left\{u_1 - \frac{1}{m}u' + u_{11} - u_{12}, u_2 - \frac{1}{m}u' + u_{21} - u_{22}, \cdots u_n - \frac{1}{m}u' + u_{n1} - u_{n2}\right\} \quad (16)$$

while u_{n1} is proportion allocated by the similarity among the evidence, u_{n2} is proportion allocated by the conflict among the evidence.

The secondary adjusting weighted factor based on adjustment, It is obviously reduce the evidence conflict ,and can still use the adjusted evidence of DS rules synthetic, the positioning results calculated by the proposed algorithm are significantly more accurate than that of the classical DS evidence theory data fusion positioning method.

4 APPLICATIONS OF IMPROVED DS IN THEINDOOR LOCATION

4.1 Data Acquisition

In housework robot positioning system， based on each channel acquired data , the secondary adjusting weighted DS evidence theory fusion algorithm targeting optimization can be described as the following steps:

Step1 : Let U be the universe : while $U = \{A_1, A_2, \cdots A_n\}$, A_i the set representing all possible states of a system under consideration.

Step2：Initialization value to be recognized framework.

Step3 : Strike probability assignment m according to the definition 3.

Step4 : Normalization of new probability assignment , which based on formula（16）obtaining weighted factor ,It would be evidence combination.

According to the above described steps , the positioning data which obtain from the positioning result WIFI , RFID, ultrasonic sensor and odometer sensor, makes as data sources of making decision evidence to location. And the data acquisition flowchart in Figure 1.

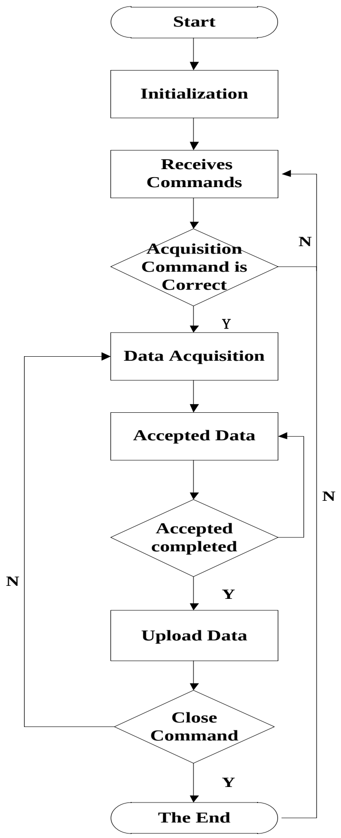

Fig.1 The flow chart of data collection

4.2Experiment Results

The text proposed method the second adjustment weighted DS evidence theory is adopted, in order to data of each channel acquired fusion (each channel are involved in integration, that is flag = 0). In the end, the experimental simulation with 30 subgroup data of the robot positioning results in different locations, then compared with the data fusion method of classical evidence theory, the fusion error results and the actual position shown in Figure 2.

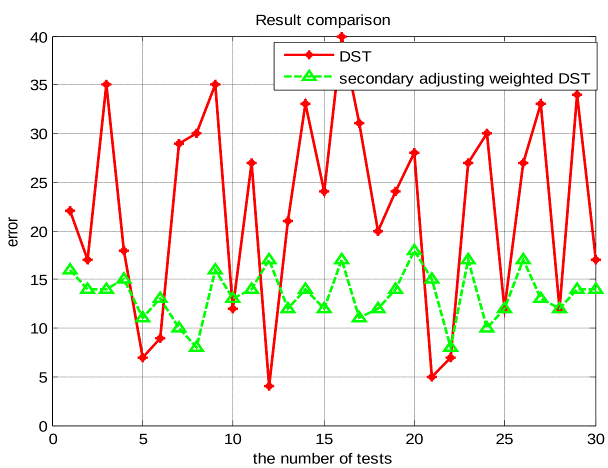

Fig.2 The fusion results of error

As you can see from Figure 2, The error of this text proposed positioning method is small, averaging about 13.46cm, while classical DS evidence theory data fusion average localization error is about 23.43cm, and it much higher than the proposed method. It means that adaptively adjusting weights according to conflict and similarity of a plurality of data, high positioning accuracy will be come true. Obviously, the positioning results calculated by the proposed algorithm are significantly better than that of the only use of classical DS evidence theory data fusion positioning method.

5 CONCLUTION

Positioning problem is should be an important consideration during the navigation and obstacle avoidance for household robots. However, a single positioning technology can not completely cover the indoor, or get inaccurate positioning results. In this paper, it presents the multi-information fusion positioning technology for Housework robot positioning system. Uncertainties among the acquired data and mutually exclusive and compatibility of evidence for each channel, The technology takes full advantage of WLAN, RFID and odometer sensor and ultrasonic sensor for fusion location, It proposes the secondary adjusting weighted DS evidence theory. Setting a flag in the program, and according to the obtained flag data sources, Experimental results show that: Compared with classic DS evidence theory fusion results. This technology can improves positional accuracy and better meets the positioned requirements of home robots.

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