Fusion For Multi-functional Perception Using Entropy-based Weighted Dempster-Shafer Theory

Feng Jiang, Hongxun Yao, Wen Gao
Computer Science and Technology, Harbin Institute of Technology, China
e-mail: fjiang@hit.edu.cn

***Abstract*-Sensor fusion which is a pivotal step for multi-functional perception challenges the traditional fusion methods with dynamic sensor configuration and measurement requirements commensurate with human perception. The Dempster-Shafer theory of evidence has uncertainty management and inference mechanisms analogous to our human reasoning process. In the practical application, the changeable circumstance makes the trust of channel confidence different, thus we can not confirm the value on trust. By combining concept of entropy with D-S evidence theory, an algorithm based on the fusion of multi-functional perception is presented. This paper describes our sensor fusion research work using Entropy-based Dempster-Shafer theory in comparison with the weighted sum of probability method. Our experiments show promising, thought-provoking results encouraging further research.**

Keywords: sensor fusion, Dempster-Shafer Theory, Entropy, multi-functional perception

I INTRODUCTION

Multi-functional perception is the comprehensive advanced man-machine interface technology of incorporating tendency of the pronunciation, body, emotion into an organic whole to perceive technology multi-functionally; it is the important means that the computing technology permeates all side to the human society. The multi-functional perception machine is to collect the natural language - the pronunciation, character in the intelligence interface system. The Chinese sign language recognition system based on data glove is a comprehensive application system which perceives intellectively, it is possible to exchange with normal person and offered with the sign language for the deaf person. According to the research work, independent biological characteristic recognition system have weak points in the present stage objectively. Even the sign language recognition system has bottlenecks in a certain degree. Sign language, people's face, expression, lip reading, impetus, body tendency, etc. these channels are integrative and merging channels that carry on different biological characteristic is an effective way of improving result[1]-[3]. Lip reading make for vision information, can be utilized to combine with the sign language channel. Lip reading work as assist of biological characteristic recognition system have respect that utilizing information of vision to supplement the lost information of the sign language, improve the accuracy and the robustness of the recognition of the sign. Different recognition systems of biological characteristic with large vocabulary base have the general limitation, which is close word. The set of the close word has nothing in common with each other in different recognition system, because close words in different channels general have obvious difference, so fusion of channels can get better result.

II FUSION APPROACH

A. Sensor Fusion Architecture

Information fusion or data fusion is the process of acquisition, filtering, correlation and integration of relevant information from various sources, like sensors, databases, knowledge bases and humans, into one representational format that is appropriate for deriving decisions regarding the interpretation of the information, system goals, and sensor management. Though have many kinds of forms to merge the systematic structure, its principle and function are often the same[4]. The fusion of redundant information from different sources can reduce overall uncertainty and thus increase the accuracy of the system. Multiple sensors providing redundant information can also increase the robustness of the system. Such a system usually has one central context data repository for each major entity to collect all the relevant information about that entity. The data repository usually collects several aspects of context information; each aspect of context information has its own. After collecting of context information, a process of combining information from multiple sensors and data sources will be made to get a more accurate solution. Such a process similitude the way humans and animals use multiple senses and experience and then reasoning to improve their chances of survival.

B. Demspter-Shafer Sensor Fusion Algorithm

The Bayesian theory is the canonical method for statistical inference problems. The Dempster-Shafer decision theory is considered a generalized Bayesian theory. The Bayesian theory follows the premise of probability and addition is the principle that theory generally follows .For example, if we believe one proposition with the confidence degree s then we really believe a topic against the proposition with $1-s$. Under many circumstances, this is unreasonable. As to confidence, evidence theory can give up this principle of adding etc., and replace with half add principle. In a Dempster-Shafer reasoning system, all possible mutually exclusive facts are enumerated.

We denote Θ the space of hypotheses, Dempster-Shafer theory allows to consider any subset of Θ. It contains not only single classes (also called singletons or simple hypotheses) but also any union of classes (also called compound hypotheses). Moreover, the notations of the set theory, inclusion, intersection, and union are extended to the set of hypotheses. The Dempster-Shafer evidence theory provides a representation of both imprecision and uncertainty through the definition of two functions: plausibility and belief, which are both derived from a mass function (m) . For any hypothesis A of 2^{θ}, $m(A) \in [0,1]$ .and:

$$\begin{cases} m(\phi) = 0 \\ \sum_{A \in 2^{\theta}} m(A) = 1 \end{cases} \quad (1)$$

In the case of Bayes theory, uncertainty about an event is measured by a single value (probability), and imprecision about uncertainty measurement is assumed to be null. In the case of Dempster-Shafer theory, the belief value of hypothesis A may be interpreted as the minimum uncertainty value about A, and its plausibility value, which is also the "unbelief" value of the complementary hypothesis A : Pls(A)=1-Bel(A), may be interpreted as the maximum uncertainty value of A . Thus, uncertainty about A is represented by the values of the interval [Bel(A), Pls(A)] and the length of this belief interval provides a The previous measurements of evidence and in particular the mass functions can be defined for each data set separately. They are then combined in the data fusion process according to the Dempster's combination rule, also called orthogonal sum[5]-[8]:

$$m(A) = m_1 \oplus m_2(A) = \frac{\sum_{A_i \cap B_j = A} [m_1(A_i) m_2(B_j)]}{1 - \sum_{A_i \cap B_j = \Phi} [m_1(A_i) m_2(B_j)]} \quad (2)$$

where m_i is the basic probability assignment and $m(A)$ the result of the combination. $\sum_{A_i \cap B_j = \Phi} [m_1(A_i) m_2(B_j)]$ represents the mass which would be assigned to the empty set, after combination, in the absence of normalization by $1 - \sum_{A_i \cap B_j = \Phi} [m_1(A_i) m_2(B_j)]$, and it is often interpreted as a measure of con- collision between the different sources. The larger the value is, the more the sources are conflicting and the less sense has their combination. One may suggest as in that the conflict comes from the fact that the "true" assumption has been forgotten (in the set of hypotheses). In particular, it is shown that the Dempster's rule of combination is commutative and associative. Having computed the mass, plausibility and belief values for each simple and compound hypothesis of the multi-source data set, the decision is made among the different hypotheses according to the "decision rule" chosen. The choice of this rule remains dependent of the considered problem or application. The three most popular decision rules are: (i) maximum of plausibility, (ii) maximum of belief, and (iii) maximum of belief without overlapping of belief intervals. Other rules can also be found depending on the considered specific application.

C. Entropy-Based Weighted Dempster-Shafer Theory

Implementation of the Dempster-Shafer combination rule implies that we trust different sensor equally. The "equally trusting" approach in Dempster-Shafer evidence combination is suitable only for situations when both observations have the same accuracy estimates or in situations where their probability distribution can quantitatively reflect the ignorance going with their observations. Because Dempster-Shafer theory are often used to deal with problems that the classical Bayesian method cannot deal with, due to lack of proved probability distribution model or due to unavailability of accurate mathematical analysis, in many systems using Dempster-Shafer theory, the "probability" numbers are in fact simply assigned by expert opinion. In the process of building a generalizable sensor fusion architecture working with sensors of different accuracy, it is often difficult to require all sensor widgets correctly to report their observation accuracy along with appropriate ignorance estimation. To approach this problem, a concept for a "*weighted Dempster-Shafer evidence combining rule*"[9][10] was proposed. The basic idea is this: suppose we know how a sensor performs historically in similar situations; we can then use the historically-estimated correctness rate as the reference to decide how much we trust the sensor's current estimation from its current observation.

$$m(A) = m_1 \oplus m_2(A) = \frac{\sum_{A_i \cap B_j = A} [w_i . m_1(A_i) . w_j . m_2(B_j)]}{1 - \sum_{A_i \cap B_j = \Phi} [w_i . m_1(A_i) . w_j . m_2(B_j)]} \quad (3)$$

It is a good idea to use WDS to solve the integration of every channel information in "not equally trusting" cases, but it is needed to confirm the accurate degree that every channel is observed of the past in advance. While in the practical application, the circumstance is changeable and thus, different channel will have different confidence value, so it is very difficult to confirm appropriate right value.

To solve this problem, this paper proposes a new concept for an "Entropy-based weighted Dempster-Shafer evidence combining rule". Let $\{\lambda_1, \lambda_2 \cdots \lambda_C\}$ be the finite set of C classes of nature and let $P(\lambda_i \mid O)$ be the posterior for each classes given the observation sequence. In case of extreme, if the posterior of all classes have the same value. In other words, $P(\omega_i \mid O) = \frac{1}{c}$ and the uncertain degree proposed by O so great then to discriminate the category conventionally is impossible. If the ambiguous decision is not permitted then it has to discriminate arbitrarily then the probability of error by deciding gets most. In another opposite case, if the information given by the observation sequence could make one posterior 1, in other words the uncertain degree get least and no error by deciding occur. By the above analysis, the posterior distribution of all classes gives suggest about the dependability in one channel. The method proposed in this paper calculates the distribution of different channels separately and get the entropy measure:

$$H_i(O) = -\sum_{j=1}^{c} P(\lambda_i \mid O) \log P(\lambda_i \mid O) \quad (4)$$

then we write formula of EWDS as

$$m(A) = m_1 \oplus m_2(A) = \frac{\sum\limits_{A_i \cap B_j = A} [v_i.m_1(A_i).v_j.m_2(B_j)]}{1 - \sum\limits_{A_i \cap B_j = \Phi} [v_i.m_1(A_i).v_j.m_2(B_j)]} \tag{5}$$

where the const $v_i = \overline{H}_i^{-1}$ and $\overline{H}_i^{-1}$ represents the unitary value of H_i^{-1}.

III. EXPERIMENTS AND DATA ANALYSIS

For a system with sign language input only, the whole process is as follows. The aim of sign language recognition is to provide an efficient and accurate mechanism to transcribe sign language into text so that communication between deaf and gearing society becomes more convenient. State of the art sign language recognition should be able to solve the signer independent problem for practical applications. In this paper, the SOFM/HMM model is used in the recognition system. It combines the powerful feature extraction

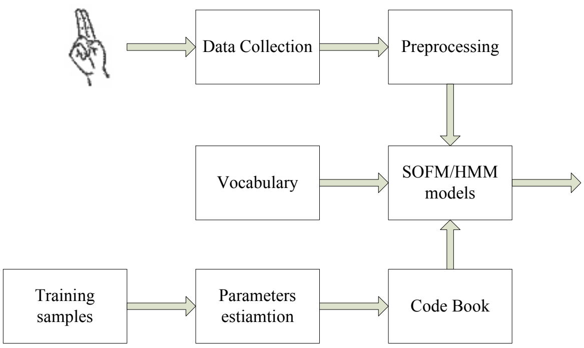

figure 1 sign language recognition system

performances of self-organizing feature maps with excellent temporal processing properties of hidden Markov models with in a novel scheme. Each SOFM[11] eigenvector centered is regarded as one of the components in the state of HMM which construct the state probability density function in terms of the weighted sum.

The essential of the recognition process is to choose one model in the code book which can describe the observation sequence best. Given a preprocessed observation sequence $O = O_1 O_2 O_3 \cdots\cdots O_T$, for each unknown word to be recognized, measurement of the observation sequence $O = O_1 O_2 O_3 \cdots\cdots O_T$, via a feature analysis of the speech corresponding to the word; following by calculation of model likelihoods for all possible models, $P(O / \lambda_v)$, $1 \le v \le V$; followed by selection of the word whose model likelihood is highest. The define of the basic probability assignment:

$$m_i(v) = \frac{P\ (O \mid \lambda_v)}{\sum\limits_v P\ (O \mid \lambda_v) + C(1 - \frac{P(O \mid \lambda_v)}{\sum\limits_v P(O \mid \lambda_v)})} \tag{6}$$

C is an controllable constant.

IV. EXPERIMENTAL RESULTS

In the baseline work, a weighted linear sum method is used to combine probabilities as: $P(word = w) = (1-a)P(word = w / O_{sign}) + aP(word = w / O_{lip})$, $a < 0.5$. Here four more experiments' data with the baseline method, the weighted Dempster-Shafer method sensor fusion results are shown in Table 1. The "Sign correct" and "Lip-reading correct" columns show percentages of correct estimations with sign channel' and lip-reading channel' contribution respectively. The "linear sum correct" column shows the estimation correctness rate with the sensor fusion algorithm that uses weighted probability linear combination method. The "WDS" column in Table 1 shows the estimation correctness rate resulting from using weighted Dempster-Shafer evidence combination rule to fuse the lip-reading and sign inputs. Finally, the"EWDS" column in Table 1 shows the estimation correctness rate resulting from using Entropy-based Weighted Dempster-Shafer Theory.

Table.1 experimental results

	Singer Independent	Lip-reading correct	Sign correct	linear sum correct	WDS	EWDS
Data processing	#1	62.1%	66.0%	86.8%	86.8%	89.3%
	#2	61.5%	76.2%	89.9%	90.3%	93.2.9%
	#3	62.3%	82.4%	92.9%	93.4%	95.4%
	#4	62.0%	84.6%	93.4%	94.3%	95.4%
summary		62.0%	76.3%	90.7%	91.2%	93.8%

V. CONCLUSION

Weighted probability linear combination method and WDS both need priori knowledge, that is, the proper confidence value. So the chosen value of confidence will influence the final fusion result directly. Further more, if we experiment under different circumstance the accuracy of different channels will change which makes it difficult to decide the proper confidence value. With the application of EWDS, it laid the foundation for the recognition in complex circumstance and on-line system. In continuing research, we are experimenting with integrating a larger number of sensors in a dynamic configuration. We expect the Dempster-Shafer theory of evidence algorithm, especially our proposed implementation of Entroy-based weighted Dempster-Shafer evidence combination rule, to demonstrate performance enhancement with such situations.

REFERENCE

[1] Anind K. Dey, "ProvidingArchitecture Support for Building Context-AwareApplications", PhD thesis, November 2000, Georgia Institute of Technology

[2] Enrique H. Ruspini, John D. Lowrance, Thomas M. Strat, "Understanding Evidence Reasoning", Technical Note 501, December 1990,Artificial Intelligent Center, Computer and Engineering Sciences Division, SRI International, Menlo Park, California 94025, USA

[3] Jie Yang andAlexWaibel, "AReal-Time Face Tracker", Proceedings of WACV, Page 142-147, 1996.

[4] A. Bendjebbour, Y. Delignon, et al., "Multisensor Image Segmentation Using Dempster-Shafer Fusion in Markov Fields Context", IEEE Transaction on GeoScience and Remote Sensing, Volume 39 Issue 8,August 2001.

[5]. Rainer Stiefelhagen, Jie Yang, Alex Waibel, "Estimating Focus of Attention Based on Gaze and Sound", Proceedings of Workshop on Perceptive User Interfaces PUI 2001, Orlando, Florida, USA

[6]. Lawrence A. Klein, "Sensor and Data Fusion Concepts and Applications" (second edition), SPIE Optical Engineering Press, 1999, ISBN 0-8194-3231-8.

[7]. Glenn Shafer, *A Mathematical Theory of Evidence*, Princeton University Press, 1976.

[8]. *Advances in the Dempster-Shafer Theory of Evidence*, edited by Ronald R. Yager, Janusz Kacprzyk, and Mario Fedrizzi. Wiley, 1993.

[9]. H. Wu, M. Siegel, and S. Ablay, "Sensor Fusion for Context Understanding," presented at IEEE International Measurement Technology Conference (IMTC) 2002, Anchorage AK USA, 2002.

[10]. H. Wu, M. Siegel, R. Stiefelhagen, and J. Yang, "Sensor Fusion Using Dempster-Shafer Theory," presented at IEEE International Measurement Technology Conference (IMTC) 2002, Anchorage AK USA, 2002.

[11] Fang Gao-lin, GAO Wen Et Al., "A Singer-Independent Sign Language Recognition System Based on SOFM/HMM", Chinese J.Computers, Jan 2002