Paper

Aggregation methods of multi-layered information about an environmental perception sensor

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This paper focuses on the fusion algorithms of multi-layer information, in which the environment quantities of temperature, humidity and brightness are to be sequentially aggregated. The fusion result is to give an overall illustration about the environment as comfort, which has been defined as one kind of high-level information. Three multi-layer fusion methods are totally proposed in this paper; i) probability criterion, ii) rule based fuzzy strategy and iii) multi-layer creditability tactics. Different from the popular fusion strategies, the presented approach works in a step-by-step framework, and proves to be more practical and more effective especially when more variables are in calculation. The applications to a multi-functional sensor have proved that the proposed algorithms deserve the advantages of multi-layer sensing. In the light of applications, these methods are compared each other in terms of efficiency and limitations. The extension of the fusion mechanisms to multi-sensors is also briefly discussed.

Keywords: multi-layer sensing, sensor fusion

1. Introduction

In recent years, the processing of high-level information (such as shape, danger, etc.) that is related to many conventional physical or other kinds of quantities has rapidly evolved[1-3]. Environment comfort can also be considered as such a type of information that comprises temperature, humidity and other variables. High-level information processing is of great importance to intelligent systems or to robotics, in which it needs to extract (or to fuse) data from multi-sensor systems to acquire more accurate information about the external environment and to decrease the uncertainties that hinder their manipulation. The processing of high-level information consists in aggregating the multi-sensor observations with adaptable algorithms, which are well known as the techniques of sensing fusion. Such a technique is also expected to increase the reliability of measurement (that is fairly immune to noise and to sensor failures).

On the other hand, multi-functional sensing technique has been approached in the last decade[4-6], while one multi-functional sensor takes charge of monitoring more than two quantities. The evaluation of the quantities consists in the reconstruction criteria on the multi-functional outputs of the sensor. However, when there are more than three quantities being measured, the reconstruction mechanism spans its calculation in a multi-dimensional space, and often leads to impractical solution. Multi-layer sensing idea has been developed for this case[7], which intends to decouple the reconstruction problem by resolving the group functions into lower degree ones, thus the quantities will be possibly evaluated step by step.

Almost all the existing researches deal with the sensing of poly-sensors, and fuse the data in parallel. This kind of fusion criteria may be entitled as compound fusion that has gained great popularity in many fields[8]. Most applications involve only a small number of inputs, which allows them to perform the entire fusion in one step. Supposing a system with N sensors aggregated by way of fuzzy description, and with each output of the sensor i described by M_i fuzzy sets, a different rule for the fusion may be written for every intersection of membership set that describes these sensors. The exhaustive methods then yield a rule set of size $\prod_{i=1}^{N} M_i$, and it is obvious that the number of evaluations exponentially increases as more inputs are added. Therefore, it results in an impractical computational load for system that is anything like mobile robots with typical high input dimensionality of sensing information[9].

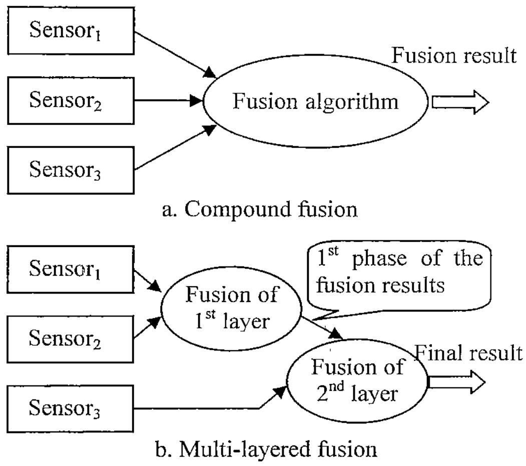


Fig.1 Schematic diagrams of sensor fusion

The multi-layered fusion techniques presented in this paper are expected to keep the fusion work manageable when more information exists in consideration. Different from the popular strategy, the new method attempts to fuse the sensor data asynchronously as shown in Fig.1 (with its comparison to compound fusion). The fusion work now is decomposed into frameworks of multi-layers in order to make the computation less complicated and more practical for operation. For simplicity, assuming that each sensor is described by M fuzzy subsets, the compound fusion and the multi-layer one now seem to yield a rule set of size about $\prod_{i=1}^{N} M = M^N = M^3$ and $\sum_{i=1}^{N-1} M^2 = (N-1)M^2$, respectively.

Where, N indicates the numbers of sensors and (N –1) equals the number of layers in the multi-layer fusion framework. If N=3 and M=4, then M^3=64 > $2M^2$=32. The decrease of calculations is more outstanding when N is much larger.

Multi-layer fusion method provides a computational efficient means of processing the entire sensing data with no initial data reductions. Moreover, it may possess other following advantages. (1) In its different layers, it provides the fusion results corresponding to special behaviors of the system, for which the sensor serves. (2) Weights of the counterparts can be adjusted more freely to highlight some quantities. (3) For the case of recursive or periodical fusion, effects of past data or fusion results might be easily recognized or confined within necessary limits.

Multi-layer information fusion idea is also something like a study of bionics, of which technique is applied to imitating the behavior of human being. When someone is trying to make commentary on an object, main factors are generally synthesized in the first place. Other secondary aspects will be gradually considered if higher or more meticulous demand is put forward.

This paper attempts to give a tentative setup on high-level information processing subject by making further advances on the past developed compound fusion methods. Three algorithms, those are, probability criterion, rule based fuzzy strategy and quantity creditability tactics with application to a multi-functional sensor are presented and compared each other in terms of efficiency and limitations. The application of the proposed algorithms to the case of multi-sensors is also briefly discussed.

2. Multi-layer fusion methods

In general, two situations could be considered in a multi-sensor fusion system. A first aspect concerns cases where each sensor provides information on the same entity, thus raising the problem of the fusion on redundant measurements. Conventional numerical techniques have been explored for many years to solve this problem[6][10]. Another aspect concerns the obtaining of abstract information, which is high-level one as we have described in the introduction section.

In the view of the latter situation, this paper focuses its attention on one kind of high-level information as environment comfort, which is linked to several heterogeneous physical values (temperature, humidity and brightness) measured by a multi-functional sensor as will be introduced in the next section. In this case, the sub-quantities being aggregated are not relevant before data pretreatment. Each quantity could only provide a linguistic opinion (such as low, middle, high and very_high) on hypotheses put forward in advance; thus the fusion task will not work in numerical domain but in a non-analytical way.

Probability estimation method is commonly considered as a classical criterion for the article of sensing fusion, especially in radar signal processing field. However, the method is originally developed for one entity measurement, that is, the first aspect of the two situations in multi-sensor system. Our research here is to extend this criterion to the field of high-level information fusion, as will be introduced in section 2.1.

Compared with precise mathematics, fuzzy theory is more useful to form the sensor opinions as for high-level information reasoning, and to fuse the linguistic hypotheses returned by each quantity.

For situations where a set of rules is available in describing the link between basic data and the aggregated entity, the rule based fuzzy strategy introduced in section 2.2 will give a fuzzy representation of these rules enabling a linguistic description of the high-level entity to be drawn.

Quantity creditability tactics proposed in section 2.3 intends to simplify the fuzzy algorithm, with the relationships among the fusion factors being monitored by control operators instead of rules.

All the three methods proposed in this paper work in a multi-layered way, thusly the perception of the environment is proceeded in order and advanced step by step.

2.1 Probability criterion At first, consider the binary hypothesis of the testing problem with N sensors, in which each sensor employs a predetermined rule. The final information is to be deduced depending on the fusion result of the N sensors.

2.1.1 Principle of the method If the two hypotheses have *a priori* probabilities $P(H_0)$ and $P(H_1)$, respectively, then the likelihood ratio can be expressed as[11]

$$\begin{aligned}\Lambda(u_1,u_2,\ldots,u_N) &= \frac{p(u_1,u_2,\ldots,u_N/H_1)}{p(u_1,u_2,\ldots,u_N/H_0)}\\ &= \frac{p_1(u_1)p_1(u_2/u_1)\ldots p_1(u_N/u_1,u_2,\ldots,u_{N-1})}{p_0(u_1)p_0(u_2/u_1)\ldots p_0(u_N/u_1,u_2,\ldots,u_{N-1})}\end{aligned} \tag{1}$$

Where, $p_i(u_k/u_1,u_2,\ldots,u_{k-1})=p_i(u_k/u_1,u_2,\ldots,u_{k-1},H_i)$, $i=0, 1$, are conditional probabilities and $u_1,u_2,\ldots,u_N$ are local decisions that are binary variables measured by N sensors, respectively. H_0 and H_1 represent the binary results of the environment being evaluated, and

$$u_k = \begin{cases} -1, & \text{If } H_0 \text{ is declared} \\ +1, & \text{If } H_1 \text{ is declared} \end{cases} \tag{2}$$

The MAP(maximum acceding probability) or minimum error probability detection rule is given by

$$\Lambda(u_1,u_2,\cdots,u_N) = \frac{p_1(u_1,u_2,\cdots,u_N)}{p_0(u_1,u_2,\cdots,u_N)} \underset{H_0}{\overset{H_1}{\gtrless}} \frac{p(H_0)}{P(H_1)} \tag{3}$$

In accordance with multi-layer fusion, some modifications on (3) are necessary.

Let
$$p_k = \frac{p_1(u_1,u_2,\cdots,u_{k-1},u_k=-1)}{p_1(u_1,u_2,\cdots,u_{k-1},u_k=+1)}$$
$$q_k = \frac{p_0(u_1,u_2,\cdots,u_{k-1},u_k=-1)}{p_0(u_1,u_2,\cdots,u_{k-1},u_k=+1)} \tag{4}$$

Then

$$p_1(u_k/u_1,u_2,\cdots,u_{k-1}) = \begin{cases} \dfrac{1}{1+p_k}, & \text{if } u_k=+1 \\ \dfrac{p_k}{1+p_k}, & \text{if } u_k=-1 \end{cases} \tag{5}$$

$$p_0(u_k/u_1,u_2,\cdots,u_{k-1})=\begin{cases}\dfrac{1}{1+q_k}, \text{if } u_k=+1\\ \dfrac{q_k}{1+q_k}, \text{if } u_k=-1\end{cases} \qquad (6)$$

By defining the weight w_k for $k=0,1,\ldots,N$ as

$$w_k=\begin{cases}\ln\dfrac{P(H_1)}{P(H_0)}, \text{for } k=0\\ \ln\dfrac{P_1(u_1)}{P_0(u_1)}, \text{if } u_1=1\\ \ln\dfrac{P_0(u_1)}{P_1(u_1)}, \text{if } u_1=-1\\ \ln\dfrac{1+q_k}{1+p_k}, \text{if } u_k=+1 \text{ and } k>1\\ \ln\dfrac{q_k(1+p_k)}{p_k(1+q_k)}, \text{if } u_k=-1 \text{ and } k>1\end{cases} \qquad (7)$$

Take the logarithm of (3) and substitute the equations from (4) to (7) for (3), the optimal fusion rule is equivalent to a recurrence one:

$$\begin{aligned}F(u_1,u_2,\cdots,u_N)&=\ln(\Lambda(u_1,u_2,\cdots,u_N))+\ln\frac{p(H_1)}{p(H_0)}\\ &=\sum_{i=0}^{N} w_i\cdot u_i \underset{H_0}{\overset{H_1}{\gtrless}} 0\end{aligned} \qquad (8)$$

Equation (8) indicates that the fusion results given in each layer are to be modified simply by adding the latest information of u_N as $w_N u_N$ to the existed values, that is

$$F(u_1,u_2,\cdots,u_N)=F(u_1,u_2,\cdots,u_{N-1})+w_N\cdot u_N \qquad (9)$$

If the calculation result is positive, it leads to the fusion result as H_1. Otherwise, H_0 is declared.

2.1.2 Data pretreatment of sensors To apply the equation (8) to the data processing of the general sensors that may output analogue values other than binary ones, the output figures of sensors have to be formalized as either -1 or 1. The principle way of data pretreatment has been shown in Fig.2. Here we assume that the results of the fusion are comfort (H_0) and uncomfortable (H_1). If the output data of sensor is within H_0 band, then its formalized value (u_k) will be considered as "-1", otherwise "1" is confirmed.

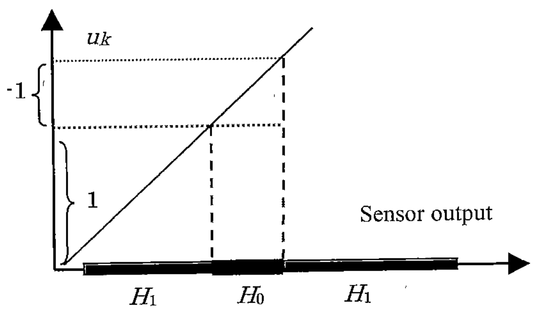


Fig.2 Data formalization of the sensor

By the way of highlighting the particular period of the sensor data, the probability criterion is naturally extended to the fusion of non-binary variables. The mapping range for H_0 or H_1 in abscissa varies with the different items concerning the fusion objective. Application results of this method are shown in section 3.

2.2 Rule based fuzzy strategy The purpose of this approach is to replace the numerical values by a rule based formalism working on linguistic descriptions. This method is particularly efficient when the basic features are of a linguistic type, as is often the case at high-level reasoning.

2.2.1 Theoretical basis of fuzzy sensors Information from sensors is basically numerical, of which the representation is precise, not redundant, complete, and provides a lot of arithmetical relations. Nevertheless, in poly-entity fusion cases, it is not relevant to use a numerical description.

As we have discussed in preceding sections, one is led to make a qualitative description of three observed quantities with words of natural language, if these quantities could be evaluated by sensors of fuzzy type[2]. The fuzzy meaning of a lexical value is defined by an injective mapping (τ) from linguistic domain E to the set of fuzzy subsets of the numerical domain $F(N)$. In the same manner, the fuzzy description of a numerical value x is now defined by a mapping (Θ) from N to the set of fuzzy subsets of the lexical domain $F(E)$. The two kinds of mappings could be expressed and linked by

$$\begin{aligned}&\tau: E\rightarrow F(N);\\ &\Theta: N\rightarrow F(E)\\ &\forall L\in E, \forall x\in N, \mu_{\Theta(x)}(L)=\mu_{\tau(L)}(x)\end{aligned} \qquad (10)$$

For an example, the fuzzy description of a temperature sensor is given here, as shown in Fig.3.

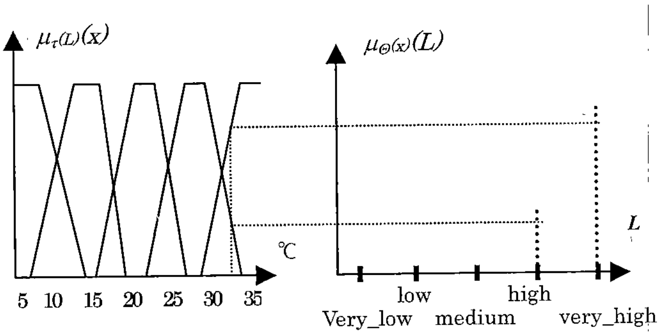


Fig.3 Fuzzy descriptions of a temperature sensor

Assuming the value of temperature is measured as 32.5℃, then we have

$\mu_{\Theta(32.5)}(\text{very\_low})=\mu_{\Theta(32.5)}(\text{low})=\mu_{\Theta(32.5)}(\text{medium})=0$, $\mu_{\Theta(32.5)}(\text{high})=0.25$, and $\mu_{\Theta(32.5)}(\text{very\_high})=0.75$.

2.2.2 Rule-based aggregation method Consider a fuzzy rule:

If X_1 is L_1 and X_2 is L_2, then Y is a.

Where X_1, X_2 and Y are fuzzy variables with L_1, L_2 and a being their linguistic values. By defining Γ as a fuzzy area on the Cartesian product $X_1\times X_2\times Y$, and E_1, E_2, as the domain of L_1 and L_2, respectively, and according to the combination/projection principle (also referred as the generalized modus ponens), we have[13]

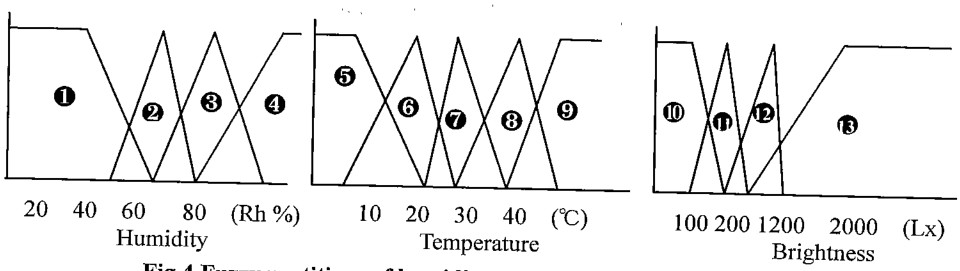


Fig.4 Fuzzy partitions of humidity, temperature and brightness

$$\mu_\Gamma(a) = \bigvee_{(L_1,L_2)\in X_1\times X_2} (\mu_{(E_1,E_2)}(L_1,L_2) \wedge \mu_\Gamma(L_1,L_2,a)) \tag{11}$$

Where, $\vee$ and $\wedge$ are co-norm and norm operators, respectively, and are usually substituted by logic ones like *OR*, *AND*, and *NOT* in fuzzy algorithm. If X_1, X_2 are independent, $\mu_{(E_1,E_2)}(L_1,L_2)$ is decomposable, then we get:

$$\mu_{(E_1,E_2)}(L_1,L_2) = \mu_{E_1}(L_1) \wedge \mu_{E_2}(L_2) \tag{12}$$

Assuming x_1 and x_2 are numerical outputs of the sensors (in this paper, equal to the first two layers of the measurement), and $\Theta(x_i)=X_i$, i=1,2, are their projection functions from numerical domain to linguistic one. Thus, (11) can be rewritten as

$$\begin{aligned}\mu_\Gamma(a) = \bigvee_{(x_1,x_2)} &((\mu_{\Theta(x_1)}(L_1) \wedge \mu_{\Theta(x_2)}(L_2)) \\ &\wedge \mu_\Gamma(L_1,L_2,a))\end{aligned} \tag{13}$$

The computation of equation (13) leads to a description of (x_1, x_2) on Y. It gives the result of the first layer fusion that is the aggregation of the primary outcomes from the first two multi-layer measurements. When the third quantity (at the third layer of multi-layer sensing) is added, the second layer of the fusion works, that is:

Rule: *If Y is a and* X_3 *is* L_3, *then P is b.*

Where, P is the further perception of high-level information with b being the second layer fusion result. Similar as (13), by defining Ξ as the fuzzy domain of (a, L_3), we have

$$\mu_\Xi(b) = \bigvee_{(a,\Theta(x_3))} ((\mu_\Gamma(a) \wedge \mu_{\Theta(x_3)}(L_3)) \wedge \mu_\Xi(a,L_3,b)) \tag{14}$$

2.2.3 Fuzzy description of the sensors To compute (13) and (14), we must know $\mu_\Gamma(L_1,L_2,a)$, $\mu_\Xi(a,L_3,b)$ and $\mu_{\Theta(x_i)}(L_i), i=1,2,3$. The first two are decided by the corresponding rules, while the latter is determined by experience. Here we describe humidity by terms in set X_1={low, medium, high, very_high} with labels 1~4, temperature in set X_2={cold, cool, mild, warm, hot} with labels 5~9, and brightness in set X_3={dark, dim, bright, dazzle} with labels 10~13. Their memberships are defined in Fig. 4. The terms in fuzzy domain Γ and Ξ are defined as: {uncomfortable, acceptable, comfortable}.

2.2.4 Fusion procedures There are totally two layers of fusion. The first layer is the aggregation of humidity and temperature from calculation of $\mu_\Gamma(a)$ for every a terms, which are {uncomfortable, acceptable, comfortable}. For example, the meaning "comfortable" can be defined by:

$$\begin{aligned}\mu_\Gamma(comfortable)|(h,t) = &(\mu_{\tau(high)}(h).AND.\mu_{\tau(coal)}(t)).OR \\ &.(\mu_{\tau(high)}(h).AND.\mu_{\tau(mild)}(t)).OR.(\mu_{\tau(medium)}(h) \\ &.AND.\mu_{\tau(cool)}(t))\cdot(\mu_{\tau(high)}(h).AND.\mu_{\tau(warm)}(t)) \\ &.OR.((\mu_{\tau(medum)}(h).AND.(\mu_{\tau(warm)}(t))\end{aligned} \tag{15}$$

Where, h is humidity, t is temperature and τ is the inverse projection operator of Θ in equation (13) with $\mu_{\tau(L_i)}(x_i) = \mu_{\Theta(x_i)}(L_i)$. For simplicity, we define here $\mu_\Gamma(\ )$ as 0 or 1.

The second layer is the aggregation of brightness and $\mu_\Gamma(a)\,|\,(humidity, temperature)$ to obtain $\mu_\Xi(b)$ for every b terms. For example, the meaning of comfortable can be defined as follows,

$$\begin{aligned}\mu_\Xi(comfortable)|(a,brightness) = &((\mu_\Gamma(acceptable)|(h,t)) \\ &.AND.\mu_{\tau(bright)}(bri)).OR.(\mu_{\Gamma(acceptable)}(h,t).AND \\ &.\mu_{\tau(\mathrm{dim})}(bri)).OR.(\mu_{\Gamma(comfortable)}(h,t) \\ &.AND.\mu_{\tau(bright)}(bri))\end{aligned} \tag{16}$$

Where, bri is brightness. For every b terms, the perception of environment is given on the maximum value of $\mu_\Xi(b)$.

In both layers, other terms (acceptable and uncomfortable) could be defined in the similar forms like (15) and (16).

2.3 Quantity creditability tactics The purpose of this approach is to replace the numerical values of the sensor by passing judgement formalism on creditable descriptions. The perception of environment will finally be given in creditability.

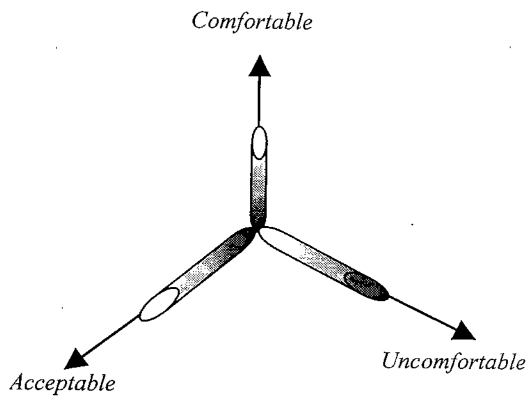


Fig.5 Quantities are spanned into vectors

2.3.1 Creditability division of three variables Similar as shown in Fig.4, assuming that every variable is defined as comfortable, acceptable and uncomfortable with degrees of confidence within [0,1], three quantities (humidity, temperature and brightness) may determine their own creditable values off line. It means that each of the quantity has a three-dimensional vector as shown in Fig.5, on which the exact values should be adjusted depending upon the request, as well as the shapes of the curves.

2.3.2 Multi-layer fusion criteria In accordance with the multi-functional sensor (as will be introduced later), the aggregation of humidity and temperature might be chosen as the first fusion layer. In [comfortable, acceptable, uncomfortable] domain of fusion descriptions, supposing that the confident degrees of the given two variables are $v_H \Rightarrow [H_c \quad H_a \quad H_u]$ and $v_T \Rightarrow [T_c \quad T_a \quad T_u]$. Thus, we get the observing vector as

$$Q=\begin{bmatrix} H_c & H_a & H_u \\ T_c & T_a & T_u \end{bmatrix} \tag{17}$$

Further more, we define the weight operator of humidity and temperature as

$$A_1=[a_H \quad a_T]. \tag{18}$$

The factors in (18) perform the competence of humidity and temperature, respectively. Then the fusion result in the first layer is given by

$$\begin{aligned} F_1 &= A_1 \circ Q = [a_H \ a_T] \circ \begin{bmatrix} H_c & H_a & H_u \\ T_c & T_a & T_u \end{bmatrix} \\ &= [(a_H \wedge H_c) \vee (a_T \wedge T_c) \quad (a_H \wedge H_a) \vee (a_T \wedge T_a) \\ &\quad (a_H \wedge H_u) \vee (a_T \wedge T_u)] \end{aligned} \tag{19}$$

The operator "$\circ$" in (19) has a broad sense for $\wedge$ and $\vee$, and here in this research is defined as *Einstein* operator:

$$a \wedge b \equiv \frac{ab}{1+(1-a)(1-b)}; \quad a \vee b \equiv \frac{a+b}{1+ab} \tag{20}$$

In the second layer of the fusion, the value of brightness is considered. Supposing that the confident degree vector is $v_B \Rightarrow [B_c \quad B_a \quad B_u]$, and the new weight vector is $A_2=[(a_H+a_T), a_B]$, then the fusion result in the second layer is given by

$$F_2 = A_2 \circ \begin{bmatrix} F_1 \\ v_B \end{bmatrix} = A_2 \circ \begin{bmatrix} F_{1c} & F_{1a} & F_{1u} \\ B_c & B_a & B_u \end{bmatrix} \tag{21}$$

F_2 is also the final result if there are only three quantities in line for fusion.

For N inputs case, the fusion result is

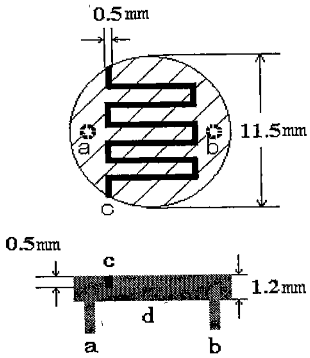
$$F_N = A_N \circ \begin{bmatrix} F_{N-1} \\ v_N \end{bmatrix} = A_N \circ \begin{bmatrix} F_{(N-1)c} & F_{(N-1)a} & F_{(N-1)u} \\ v_{N_c} & v_{N_a} & v_{N_u} \end{bmatrix} \tag{22}$$

Where, $F_{N\text{-}1}$ is the fusion results of the previous N-1 inputs (or sensors), and A_N is the weight operator (always 1×2 matrix size) of the N^{th} fusion layer. v_N is the N^{th} variable, which spans its values into a three-dimension confident vector ($v_{N_c}, v_{N_a}, v_{N_u}$).

3. Applications of the proposed methods

In this section, three proposed methods are applied to the fusion work on a multi-functional sensor, by which three quantities in environment has been sequentially evaluated. The application aims to give the environment an illustration with high-level information form: comfort, uncomfortable, acceptable, etc. Short introduction to the sensor is given in 3.1, and the detailed discussion can be referred to [7].

3.1 Principle of the multi-functional sensor The structure of a multifunctional sensor incorporating Fe_3O_4 and CdS for measurement of humidity, temperature and brightness is shown in Fig.6. CdS and Fe_3O_4 have been found to be sensitive to brightness and humidity, respectively, and also to temperature, as well as other semi-conductive materials. Their conductivity and dielectric characteristics may change with the variation of three above-mentioned physical quantities.



a,b- copper electrodes, connected by part c;
c- sensing materials, mixed with Fe_3O_4 and CdS;
d- insulate substrate;

Fig. 6 Structure of the multifunctional sensor

The equivalent circuit of sensor is shown in Fig.7, of which the output dimensions can be specified by resistance and capacitance:

$$\begin{aligned} R &= f(v_H, v_T, v_B) \\ C &= g(v_H, v_T, v_B) \end{aligned} \tag{23}$$

Where, v_H, v_T, v_B are the input values of humidity, temperature and brightness, respectively, and f and g are general forward functions.

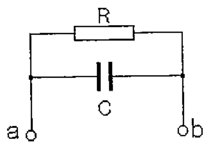


Fig.7 Equivalent circuit of the sensor

Further more, by adjusting the instrument frequency to be ω_1 and ω_2, we may get two kinds of capacitance outputs; And by modulating the light accessed to the sensor, two kinds of resistance are to be totally examined instead of only one. The modified measurement equations totally are

$$\begin{aligned} C_{\omega_1} &= g_1(v_H, v_T, v_B^*) \\ C_{\omega_2} &= g_2(v_H, v_T, v_B^*) \\ R_0 &= f(v_H, v_T, v_B^*)\big|_{\omega=\omega_1} \\ R &= f(v_H, v_T, v_B)\big|_{\omega=\omega_1} \end{aligned} \tag{24}$$

Where, g_1 and g_2 are forward functions with the instrument frequency set to be ω_1 and ω_2, respectively. Brightness intensity is modulated to make v_B^* a dark input value to the sensor.

The multi-layer sensing procedure is carried out in three layers according to the data reconstruction of equation (24). At the first layer, placing the sensor in dark environment, measuring its capacitance and resistance, humidity value is then evaluated. The reconstruction is based on the specimen data of C_{ω_1}, C_{ω_2} and R_0 (dark resistance). At the second layer, with the known humidity value in the same condition above, the temperature value is estimated. Finally at the third layer, exposing the sensor to the real circumstance, and with the influences on resistance by humidity and temperature having been eliminated, the value of brightness is assessed. To use a multi-functional sensor instead of poly sensors considers the topic of system compact structure.

3.2 Experimental setup of the methods

The experimental setup is shown in Fig. 8.

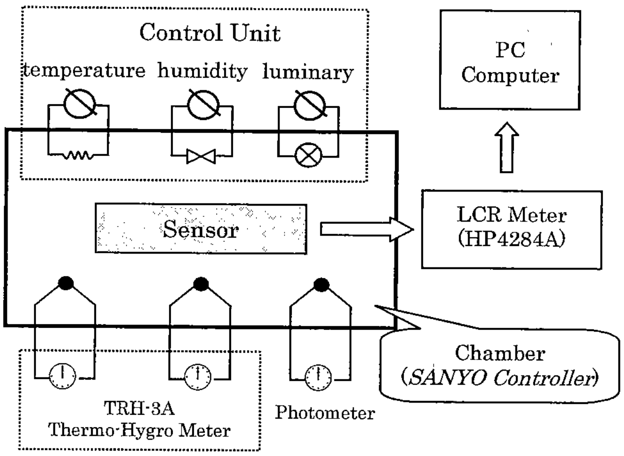


Fig.8 Experimental setup of the fusion methods

Where inside the enclosure, temperature value could be controlled from −10℃ to 60℃ (with the resolution being 0.1℃), and humidity could be adjusted from 20%Rh to 100%Rh (resolution is 1%Rh). Luminary control unit is attached to make the brightness varies from 0 to 1500Lx (only rough variation could be given). To get the precise information about the quantities that affect the sensor, the calibration meters are also set up. The resistance and capacitance values (outputs of the sensor) were measured by a LCR meter, from which the values of measurand are estimated in a way of multi-layer sensing[7].

Further more, the proposed multi-layer fusion algorithms are carried out with programming Matlab (software tools) on the personal computer.

3.3 Applications of the probability criteria Define u_1, u_2, and u_3 as the measured values of humidity, temperature and brightness, respectively, and the fusion results have also to be supposed to have duality values: H_0 − comfort (<0) and H_1 − uncomfortable (>0). Thus, if all of three sensors are added for the fusion calculation, the equation (8) can be rewritten as

$$F(u_1,u_2,u_3) = \ln(\Lambda(u_1,u_2,u_3)) + \ln\frac{P(H_1)}{P(H_0)} = \sum_{i=0}^{3} w_i \cdot u_i \tag{25}$$

Supposing three quantities (humidity, temperature and brightness) are independent and have the same even probability distribution. And their values are measured to be 85.4%, 21.6℃, 450Lx, we get u_1=1, u_2= -1, u_3=1. Set the initial value w_0=0 ($P(H_1)$=$P(H_0)$) and denote the fusion result of the ith layer as F_i, then we have

$$\begin{cases} F_1 = \sum_{i=0}^{1} w_i \cdot u_i = \ln\frac{P(H_1)}{P(H_0)} + u_1 \ln\frac{P(u_1/H_1)}{P(u_1/H_0)} \\ \quad = 0 + \ln\frac{P(H_0)}{P(H_1)}\cdot\frac{P(H_1/u_1)}{P(H_0/u_1)} = \ln\frac{0.66}{0.33} = 0.7 \\ F_2 = \sum_{i=0}^{2} w_i \cdot u_i = F_1 + u_2 \ln\frac{q_2(1+p_2)}{p_2(1+q_2)} \\ \quad = 0.7 - \ln\frac{1+0.66/0.50}{1+0.33/0.50} = 0.34 \\ F_3 = \sum_{i=0}^{3} w_i \cdot u_i = F_1 + F_2 + u_3 \ln\frac{q_3(1+p_3)}{p_3(1+q_3)} \\ \quad = 0.34 + \ln\frac{1+0.66/0.33}{1+0.33/0.66} = 1.03 \Rightarrow \text{uncomfort} \end{cases} \tag{26}$$

If F_i>0, the result in the ith layer could be considered as uncomfortable, otherwise "comfort" is given.

This method requires the data of the sensor to be mapped into two crisp fields (H_0 and H_1) so as to provide the algorithm with binary values. In this case, the description of the sub-quantities is abrupt and may lead to discontinuity in the acquired fusion information.

The method itself needs modification because it also requires the knowledge of *a priori* probabilities and conditional probabilities, which are sometimes either difficult to acquire or time varying.

However, the probability criterion has good feature of recurrence that has deserved the advantages of multi-layer information fusion.

3.4 Application of rule-based fuzzy strategy In the case that humidity is measured as 65% and temperature is 25°C. Checking data in Fig.4, and applying equation (15), then we have $\mu_\Gamma(comfortable)|(65\%,25^\circ C) = 1$. The environment is explained to be comfortable. For other situations within alteration range of the variables, "comfort" meaning in the first layer of fusion is evaluated and expressed in Fig.9.

$\mu_\Gamma(acceptable)$ and $\mu_\Gamma(uncomfortable)$ are also to be evaluated in the first layer.

For brightness luminance value of 1450(Lx), we have $\mu_\Xi(comfortable)\,|\,(a, brightness) = 1$; and for brightness of 300(Lx), in Fig.4, we can find that

$\mu_{\tau(dark)}(300) = 0$; $\mu_{\tau(\mathrm{dim})}(300) = 0.8$,

$\mu_{\tau(bright)}(300)$ =0.2;and $\mu_{\tau(dazzle)}(300)$ = 0 .

Accordingly, depending on equation (16), we have

$\mu_\Xi(comfortable)\,|\,(a,300) = 0.2$.

"Comfort" meaning in the second layer of fusion is shown in Fig.10. $\mu_\Xi(acceptable)$ and $\mu_\Xi(uncomfortable)$ are also to be evaluated in the second layer.

The presented strategy is mainly calculated for the membership functions of the quantities being aggregated. It is particularly efficient when the basic features are of a linguistic type, as it is often the case at high-level information reasoning.

If the value of $\mu_\Gamma(\ )$ is defined within [0, 1], more meticulous results of the fusion with believable degrees could be obtained. However, the programming of the algorithm is still complicated, and it also lacks the characteristic of recurrence.

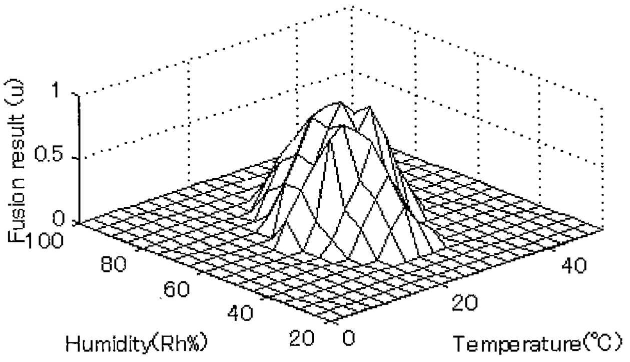


Fig.9 Fusion as "comfort" in the first layer

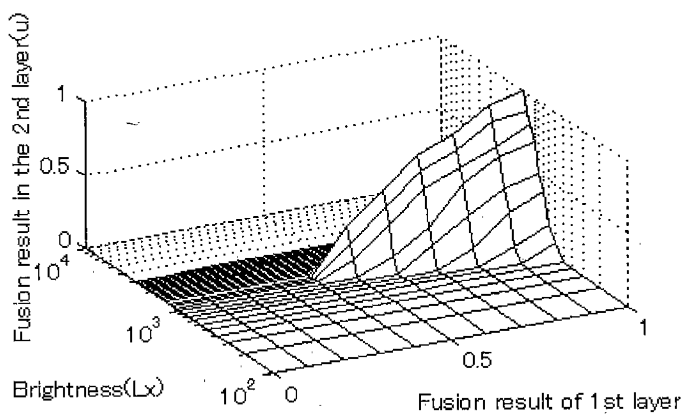


Fig.10 Fusion as "comfort" in the second layer

3.5 Fusion examples of quantity creditability tactics

Assuming that humidity, temperature and brightness values are examined as [85.4, 21.6, 450], and checking the creditability of the variables in Fig. 4, we get v_H=[0.10 0.20 0.70], v_T=[0.80 0.20 0.0] and v_B=[0.20 0.60 0.20].

Suppose A_1=[0.30 0.30] and A_2=[0.60 0.30], then from (19) and (21), we have

$$F_1 = [0.30 \quad 0.30] \circ \begin{bmatrix} 0.10 & 0.20 & 0.70 \\ 0.80 & 0.20 & 0.0 \end{bmatrix} \approx [0.23 \quad 0.08 \quad 0.17] \tag{27}$$

$$F_2 = [0.60 \quad 0.30] \circ \begin{bmatrix} 0.23 & 0.08 & 0.17 \\ 0.20 & 0.60 & 0.20 \end{bmatrix} \approx [0.15 \quad 0.18 \quad 0.12] \tag{28}$$

Finally, we get the perception of the environment as "acceptable" with the relative degree of 0.18 superior to 0.15 and 0.12.

The absolute value of factors in F_1 or F_2 is usually meaningless, and the fusion result is drawn from their relative values. Temporary result may give out contradict meaning like the case in (27), where the creditable degrees of "comfortable" and "uncomfortable" are much bigger than that of "acceptable". The reason results from the extreme values among the original variables. The final result can be more reasonable and stable with more fusion layer added.

Now keep the (under test) environment with constant quantities. Those are humidity (85.4%Rh), temperature (21.6℃) and brightness (450 Lx). Then process the fusion work continuously as follows:

(1) At the 1st layer, aggregate humidity and temperature, we get

$$F_1\text{=}[0.23 \ \ 0.08 \ \ 0.17] \tag{29}$$

(2) At the 2nd layer, add the brightness value for fusion, we get

$$F_2\text{=}[0.15 \ \ 0.18 \ \ 0.12] \tag{30}$$

(3) From the 3rd layer, measure and fuse the brightness value again and again. (It is necessary when we pay more attention to the variation of one quantity that influences our perception of the environment). Then we get

$$\begin{aligned} F_3 &= [0.75 \quad 0.25] \circ \begin{bmatrix} 0.15 & 0.18 & 0.12 \\ 0.20 & 0.60 & 0.20 \end{bmatrix} \\ &= [0.12 \quad 0.23 \quad 0.10] \\ F_4 &= [0.11 \quad 0.25 \quad 0.09] \\ F_5 &= [0.10 \quad 0.26 \quad 0.08] \\ F_6 &= [0.10 \quad 0.26 \quad 0.08]; \\ \cdots & \quad \cdots \end{aligned} \tag{31}$$

Physical meanings of the experiment results are shown in Fig. 11.

The results have shown that when we highlight brightness for perception (fuse brightness only after the 3rd layer), "Acceptable" is stressed and it does conform to real mankind feelings. The results have also shown that the method exhibits a good property of convergence because the fusion value converges to a constant as [0.10 0.26 0.08] after the 5th layer.

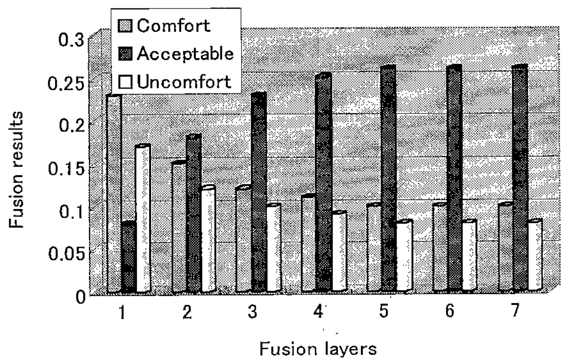


Fig. 11 Fusion results with more layers

The fusion result at every layer is given with the three-dimensional vector as shown in Fig.5. However, the length of the vector at each direction accordingly changes. The method calculates recurrence formulas, in which new variable vector is "added" to revise the original fusion result. As a consequence, the computation cost is much lower than that of the fuzzy rule based algorithm.

3.6 Evaluation of the proposed methods

To examine the fusion results, an empirical test is carried out in the environment-controlled enclosure.

The experimental results compared with mankind judg-

Table 1. Evaluation of the proposed methods as perception of "comfort"

Measured values			Fusion results on comfort (fusion values / yes or no)			Mankind feelings (number of persons who said yes for three kind of feelings)			Ratios on comfort
Humidity	Temperature	Brightness	PC	RFS	CT	Comfort	Un-comfort	Acceptable	
60%	25℃	1200Lx	-1.03/y	1.0/y	0.59/y	10	0	0	100%
85.4%	21.6℃	450Lx	-0.13/y	0.3/n	0.15 /y	7	0	3	70%
65%	25℃	300Lx	1.13/n	0.2/n	0.12/n	4	3	3	40%
40%	15℃	1200Lx	2.13/n	0.4/n	0.08/n	2	6	2	20%

ments (feelings) are shown in Table.1.

Where inside the tables, we have used the abbreviations PC, RFS and CT to indicate the proposed three methods: Probability Criterion, Rule Based Fuzzy Strategy and Creditability Tactics, respectively. The test results might have shown that the methods worked well as we have expected.

As we have analyzed in previous sections, the fusion values just have relative meanings. Perception of the under test environment is got by the comparison between the calculated values and the appointed thresholds.

On the other hand, the proposed methods themselves could be modified depending on the concrete requests. For example, the degree of control factors could be adjusted in the last proposed algorithm.

Probability criterion considers the quantities as random variables; it is theoretically applied to duality perceptions (e.g. comfortable or uncomfortable). The appropriate pretreatment of data is necessary when normal sensors are of consideration. On the other hand, the other two strategies regard the quantities as fuzzy variables, and present the fusion results more meticulously in fuzzy membership functions or vectors. The main characteristics of the three algorithms are compared in Table 2.

We have empirically established the fuzzy membership functions in Fig.4. For general applications, we propose to compute these multi-membership functions by linear interpolations between a few characteristic points given by experts. As for interpolation of arbitrary functions, an effective solution has been already proposed [12].

3.7 Considering the fusion that is in *N*-sensor case

In fact, the methods themselves could be theoretically extended to the application of fusion on N sensors, especially for Probability Criterion and Creditability Tactics. (For the Fuzzy Rule-based method, it will be a little difficult since the relationship fuzzy membership functions should be decided in advance). The reason is that their fusion equations (For example, (9) and (22) in the paper, respectively) originally open to N inputs (or N sensors).

To a great extent, fusion algorithms that can recognize a large number of data inputs could be cited as the proof on "the methods can recognize a large number of sensors", because the outputs of each sensor should have been normalized before fusion work is processed, it inherently does not indicate its original physical meaning but the "vote" on a particular decision. Even though sensors might give a variety of outputs, they are mapped into the same and specified fusion space with several confident vectors. (comfort, acceptable and un-comfort have constructed a 3-dimensional space in this paper). How many and what kind of vectors are selected in the particular fusion space depends on the concrete requests of particular fusion task. Therefore, the reactive performance of the fusion algorithm accounting for multi-sensors could be examined by way of providing multi-inputs to the fusion methods.

Experiment to examine Creditability Tactics in multi-inputs case is carried out. Humidity and brightness are kept constantly but the temperature value is changed into several discrete points inside the chamber. Then, take the measurement and fusion of the changeable temperature values. Fusion results are shown in the Fig.12.

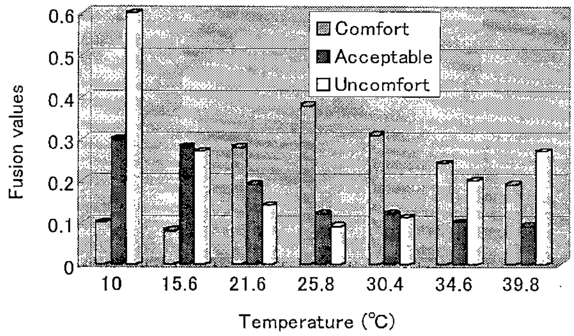


Fig.12 Fusion results of multi-inputs

The fusion values at each temperature point indicate the fusion result among present temperature values and the previous ones. For example, the final result [0.19 0.09 0.27] at 39.8℃ indicates the multi-layer fusion outcome of 10℃, 15.6℃, 21.6℃, 25.8℃, … , 34.6℃ and 39.8℃.

To fuse the N sensors for recognition of high dimensional shape with the original methods, we can design a maximum space that may include all cases that we concerned. For example, to apply the Creditability Tactics, the number of vectors in the fusion space is decided as M. Then, the confident vector of each sensor could be evaluated and spanned into M dimensions:

$$\begin{array}{ll} \text{Sensor1:} & [S_{11}, S_{12}, S_{13}, \dots \dots, S_{1(M-1)}, S_{1M}] \\ \text{Sensor2:} & [S_{21}, S_{22}, S_{23}, \dots \dots, S_{2(M-1)}, S_{2M}] \\ \dots & \dots \\ \text{Sensor } N\text{-1:} & [S_{(N-1)1}, S_{(N-1)2}, S_{(N-1)3}, \dots \dots, S_{(N-1)(M-1)}, S_{(N-1)M}] \\ \text{Sensor } N\text{:} & [S_{N1}, S_{N2}, S_{N3}, \dots \dots, S_{N(M-1)}, S_{NM}] \end{array} \tag{32}$$

Where, the values of factors (S_{ij}, $i = 1 \sim N$, $j = 1 \sim M$) of each vector are decided before fusion process is programmed. Some of the factors are definitely zero, since M is a maximum value designed to recognize the maximum dimensional shape in N sensor value space. M could be made larger and larger until the fusion method could entirely recognize the maximum (even larger than N) dimensional shape in N sensor value space. The fusion equations now becomes:

Table.2

	Pretreatment of inputs	Output illustration	Calculation complexion	Recursive ability	Adaptive extension
Probability criterion	Binary coded	Threshold	Normal	Good	Good
Rule based fuzzy strategy	Fuzzy classified	Membership functions	Large	Poor	No
Multi-layer creditability tactics	Fuzzy credits	Relative values	Small	Normal	Normal

$$F_1 = A_1 \circ \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1(M-1)} & S_{1M} \\ S_{21} & S_{22} & \cdots & S_{2(M-1)} & S_{2M} \end{bmatrix} \tag{33}$$

$$F_2 = A_2 \circ \begin{bmatrix} F_{11} & F_{12} & \cdots & F_{1(M-1)} & F_{1M} \\ S_{31} & S_{32} & \cdots & S_{3(M-1)} & S_{3M} \end{bmatrix} \tag{34}$$

$$\cdots \qquad \cdots$$

$$F_N = A_N \circ \begin{bmatrix} F_{N-1} \\ v_N \end{bmatrix}$$

$$= A_N \circ \begin{bmatrix} F_{(N-1)1} & F_{(N-1)2} & \cdots & F_{(N-1)(M-1)} & F_{(N-1)M} \\ S_{N1} & S_{N2} & \cdots & S_{N(M-1)} & S_{NM} \end{bmatrix} \tag{35}$$

Where, the control operator (matrix) A_N is decided on the significant degree of the Nth sensor that affects the fusion result. However, it keeps the 1×2 space vector.

Other two methods can extend their applications in the similar way. Further modifications might also be necessary. For example, appending "forgetting factors" in each fusion layer to place restrictions on old fusion results (pay more attention to new information), and so on.

4. Conclusions

In this paper, we have proposed three algorithms to solve the fusion problem of a multi-functional sensor. In a multi-layer way, general perception of the environment concerned temperature, humidity and brightness is given.

In fact, multi-layer fusion approach is also necessary even for the data fusion of poly-sensors, especially in robotic behavior inference system in which parallel criteria sometimes lose efficacy due to the calculation time cost. Though the methods had only been examined with the data of a multi-functional sensor, they theoretically could be extended their applications to the multi sensors cases. Modifications of the original methods are easy especially for Probability Criterion and Creditability Tactics.

Multi-layer fusion, however, lacks processing speed and precision compared with compound fusion. Combined scheme should be studied considering their respective advantages. We wish we had offered a few commonplace remarks on multi-layer fusion subjects in this paper so that others may come up with more fruitful developments. The experimental applications to more common sensors are also expected.

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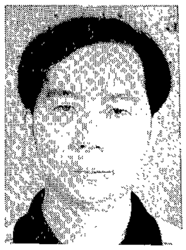

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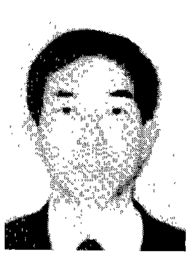

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