Multi-layered sensing approach for environment perception with one multi-functional sensor

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This paper presents a novel environment perception approach based on multi-layer sensing technique using one multifunctional sensor to measure temperature, humidity and brightness. It focuses on the processing of the multi-functional information in a multi-layer framework, which is more attractive in terms of both system simplicity and performance, and is proved to be effective to solve the problem of more than three quantities being reconstructed. A CdS and Fe_3O_4 material based multi-function sensor has been developed and the multi-layer data fusion idea has also been proposed for the use.

Keywords: multi-functional sensor, multi-layer sensing, measurement equations

1. Introduction

As a common sense, different sensors are used when there are different variables to be sensed^{[1],[2]}. Different from the popular technique, known as the compound sensing, multi-functional sensors have been developed in the last decade in case the quantities being measured affect more than one single sensor's input or compact structure of the sensing component is forcibly requested. The schematic structure of multi-functional sensor is shown in Fig.1, x_1 and x_2 are two quantities under test, with the sensor outputs

Fig. 1 A multifunctional sensor with two quantities

$\hat{x}_1$ and $\hat{x}_2$ being their estimations. We have acquired considerable achievements in this field. For example, with a metal spirals based sensor, many kinds of metals can be distinguished from the analysis of the measurement results as impedance, capacitance and inductance^[3]; and also by adding piezo-resistance rubber device, more non-metal materials will be recognized further^[4]. Moreover, the concentration of electrolyte had been precisely demarcated by using a non-destructive multi-functional sensor^[5].

Multifunctional sensing strategy consists in the algorithm to solve the measurement equations that result from the inputs and outputs of the multi-functions, on which quantities are mixed to exert their effects. The functions of the sensor are usually nonlinear ones, they are

$$\begin{aligned} y_1 &= f(x_1, x_2) \\ y_2 &= g(x_1, x_2) \end{aligned} \quad (1)$$

Where, $f(\cdot)$ and $g(\cdot)$ are general nonlinear functions.

Almost all the multi-functional sensors that had been developed examine no more than two variables, because only in this case could the least mean square method (LMS)

or database technique be possibly applied to the reconstruction of measurand (quantities being measured). For more than three variables, the number of measurement equations may go up to three, as a consequence, the solution algorithm must be performed in 4D space, in which arbitrary choice may more frequently be imposed, and leads to the estimation ceasing to be effective.

Four methods for measurand reconstruction have been introduced by Tomasz Szafranski^[6], but those techniques were practical only for single input/output pair. In the case of multi-functional converse problems, the identical study called "measurement equations" had been mathematically approached by Prof. Kobayashi^[7] early in 80s, and the solution to the nonlinear situation that accounts for a special case ($y = f(x_1, x_2, \dots, x_N) = x_1 f_1(x_2, \dots, x_N)$) was briefly discussed. However, algorithms suitable for general nonlinear functions have by far never appeared. Some researchers are trying to employ ANN (Artificial Neural Network) to map the nonlinear functions of sensors, but training problems certainly existed while serving for recognition of complex objects^[8].

Fig. 2 Multi-layer sensing to measure three quantities

In this paper, a novel multi-functional sensor is developed for measuring three environment quantities: humidity, temperature and brightness. The measurand reconstruction problem of the proposed sensor is solved by a new approach called multi-layer sensing, which acquires high-level information in a multi-layered architecture. The physical quantities are evaluated one by one according to the requirements, thus decoupling the reconstruction of 3-variables into 2-variables or 1-variable subjects, as shown

in Fig.2. This method is valid under the circumstance that two of the variables (e.g. x_1 and x_2) could be considered in the measurement equations but with others (e.g. x_3) available for being ignorable. The proposed approach itself has not satisfied the universal cases yet. However, the technique idea is effective not only for the proposed sensor, but also for many other measurement occasions.

The similar idea named hierarchical understanding has been broadly applied in pattern recognition field^[9]. A simple example is shown in Fig.3, which is required to classify the figures into several groups. Different factors (layers) must be detected for the classification, which may be area, linearity and confinement. Fig.4 denotes the flow chart of one possible classification strategy.

Another resemble research in sensing field has been approached as adaptive measuring system^{[10],[11]}. For example, a study on "Zooming Functional Measurement" was proposed to measure the two-dimension position more and more precisely by adjustment of the system parameters^[10]. Their main interests lie in controlling the system in its optimum condition to make the measurement of one physical variable more reasonable (e.g. precise), other than process multi-variables for high-level information as we do. However, the common strategy is to get the final solution gradually.

Fig.3 Figures under classification.

Fig.4 Flowing chart of the classification procedure.

Besides avoiding the calculation of reconstruction in 4D spaces, multi-layer sensing may possess other advantages: (a) Compared with conventional sensing, multi-layer sensing is often more efficient, in terms of both performance and system structure simplicity. (b) At any given time, information about an external world object may only reveal finite aspects, that may make the compound sensing impractical. (c) Complex information usually consists of high dimensional variables, processing too many of them simultaneously will result in a significant increase of time and cost^{[12],[13]}.

2. Measurement of temperature, humidity, and brightness by way of multi-layer sensing

2.1 Principle of the sensor A new multifunctional sensor incorporating Fe_3O_4 with CdS for the measurement of humidity, temperature and brightness has been developed, which structure is shown in Fig.5. The electrical characteristics of CdS and Fe_3O_4 had been found to be sensitive to brightness and humidity, respectively, and also to temperature as well as other semi-conductive materials^[9].

Consider the equivalent circuit of the sensor shown in

a,b- copper electrodes
c- sensing materials, mixed with Fe_3O_4 and CdS
d- insulated substrate

Fig. 5 Structure of the sensor.

Fig.6 Equivalent circuit of the sensor.

Fig.6, there is a two-dimensional pair as the sensor outputs specified by resistance R and capacitance C :

$$\begin{aligned} R &= f(v_H, v_T, v_B) \\ C &= g(v_H, v_T, v_B) \end{aligned} \quad (2)$$

Where, v_H, v_T, v_B are the sensor input values of humidity, temperature and brightness, respectively; Like equation (1), f and g are general forward functions denoting the relationships between the inputs and outputs of the sensor. However, there is one more quantity that is under measured in equation (2) than in equation (1).

Resistance effect of the sensor comes from energy transition of the particles inside the sensitive materials. When the particles get stimulation from ray radiation or the affinity from water molecules, and if the energy they each received is more enough, they could be resolved as electrons (jumping to transmit zone) and holes (jumping to valence zone). Thus, the electrical conductivity of the

sensor varies with the environment quantities. Capacitance effect generates from dielectric characteristic variation of the sensing device caused by the quantities.

2.2 Experimental setup of the sensor All experiments are carried out within a lounge, in which both temperature and humidity can be appointed. The experimental setup of the sensor is shown in Fig.7.

Where inside the lounge, temperature value could be controlled from -10°C to 60°C (with the resolution being 0.1°C), and humidity could be adjusted from 20%Rh to 100%Rh (the 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 to measure the three variables, respectively. The resistance and capacitance values (outputs of the sensor) were measured by a LCR meter, from which the signal is interfaced with the computer for data processing

Fig.7 Experimental setup of the sensor

2.3 Selection of the measurement equations It is impossible to estimate the whole three measurand values from (2) only, because its inverse function is obviously ill posed. (For ill posed measurement equations, the evaluation of few variables could be available at some special occasions^[6].) By adjusting the working frequency of the LCR meter used in the measurement, we may get the output results in two groups with the different frequency values:

$$\begin{cases} R_1 = f(v_H, v_T, v_B, \omega_1) = f_1(v_H, v_T, v_B) \Big|_{\omega=\omega_1} \\ C_1 = g(v_H, v_T, v_B, \omega_1) = g_1(v_H, v_T, v_B) \Big|_{\omega=\omega_1} \end{cases} \quad (3)$$

$$\begin{cases} R_2 = f(v_H, v_T, v_B, \omega_2) = f_2(v_H, v_T, v_B) \Big|_{\omega=\omega_2} \\ C_2 = g(v_H, v_T, v_B, \omega_2) = g_2(v_H, v_T, v_B) \Big|_{\omega=\omega_2} \end{cases} \quad (4)$$

Then considering the final impedance Z_{ab} in Fig.6, we have

$$Z_{ab} = \frac{R}{1 + \omega^2 C^2 R^2} - j \frac{\omega C R^2}{1 + \omega^2 C^2 R^2} \quad (5)$$

The Equation (5) implies that the real part of the

impedance (resistance) is much inert to frequency ω , compared with the imaginary part (capacitance). Relevantly we can select the measurement equations as below,

$$\begin{cases} R = f(v_H, v_T, v_B) \Big|_{\omega=\omega_1 \text{ or } \omega_2} \\ C_1 = g_1(v_H, v_T, v_B) \Big|_{\omega=\omega_1} \\ C_2 = g_2(v_H, v_T, v_B) \Big|_{\omega=\omega_2} \end{cases} \quad (6)$$

If g_1 and g_2 are independent, or $g_1/g_2 \neq \omega_1/\omega_2$, then (6) can be theoretically used for the evaluation of the quantities being measured, that is, the values of v_H, v_T and v_B may be estimated from the actual measurement results of R, C_1 and C_2 , as follows:

$$\begin{cases} v_H = \Gamma_1(R, C_1, C_2) \\ v_T = \Gamma_2(R, C_1, C_2) \\ v_B = \Gamma_3(R, C_1, C_2) \end{cases} \quad (7)$$

Where, $\Gamma_1, \Gamma_2, \Gamma_3$ are inverse group functions of (7).

Then we propose to lower the rank of (6) according to the gyroscopic effects of the sensor, and try to ascertain the variables (v_H, v_T, v_B) asynchronously to avoid reconstructing the quantities in high dimension space.

Fig.8 The relationships between resistance and temperature while brightness changes

It has been proved that the change of brightness or humidity can only stimulate the amount of free ions or holes on the surface of sensing material, while temperature also impacts the inside. Experiment data in Fig.8 shows that the change of the resistance value of the sensor for temperature also varies with the different brightness conditions. If the dark surrounding condition serves (among the three quantities, only brightness can be modulated to satisfy the measurement request without annoying the three quantities themselves), temperature value can influence the resistance of the sensor. Thus, two kinds of resistance are to be totally examined instead of only one:

$$R_0 = f(v_H, v_T, v_B^*) \quad (8)$$

$$R = f(v_H, v_T, v_B)$$

v_B^* , denoting the value of darkness, can be realized by periodically assessing the sensor to a closed and absolute dark lounge during the measurement. By using the measurement data of R_0 and C_1 (or C_2), temperature and

Fig.9 The relationships between resistance and humidity while temperature changes.

humidity values are to be reconstructed, and finally brightness value can be evaluated on the measurement of R in equation (8).

3. Experimental Results and Discussions.

3.1 Reconstruction of quantities The experiment of humidity effects to resistance (R_0) are shown in Fig. 9.

In fact, the value of the measured capacitance can be deduced from the imaginary part of (5):

$$C_x = \frac{1}{\omega^2 C R^2} + C \quad (9)$$

When the instrument frequencies are set to be ω_1 and ω_2 ($\omega_2 > \omega_1$), respectively, the capacitances C_1 and C_2 in (6) of the sensor are measured as

$$C_1 \equiv C_{x1} = \frac{1}{\omega_1^2 C R^2} + C \quad (10)$$

$$C_2 \equiv C_{x2} = \frac{1}{\omega_2^2 C R^2} + C \quad (11)$$

To estimate the value of humidity, instead of using the function C_1 (or C_2), C is selected in the reconstruction calculation, so as to improve the measurement dynamical characteristics. Compared with the resistance being influenced by both humidity and temperature, humidity variation affects the surface of sensing material more quickly because of the change of its dielectric nature. The

Fig.10 Relationships between humidity and C

value of C can be calculated by (10) and (11):

$$C = C_2 - \frac{1}{(\omega_2 / \omega_1)^2 - 1} (C_1 - C_2) \quad (12)$$

Based on (12) and with the dark condition of surrounding serving, the result of the humidity measurement is shown as Fig.10, on which the impact of temperature can be seen to be effectively restrained. Thus, humidity value can be evaluated principally based on the capacitance value with the measurement of resistance being considered as the calibration term.

In accordance with the preceding discussion, three kinds of outputs are measured in the process:

$$C = C_2 - \frac{1}{(\omega_2 / \omega_1)^2 - 1} (C_1 - C_2) = g(v_H, v_T, v_B^*)$$

$$R_0 = f(v_H, v_T, v_B^*) \quad (13)$$

$$R = f(v_H, v_T, v_B)$$

Where, R_0 is the resistance in dark condition, and R is the resistance when sensor is exposed in the radiance of environment. To get the exact values of humidity, temperature and brightness, practical measures are carried out in the following three layers.

(1). At first layer, placing the sensor in dark environment, measuring its capacitance and resistance, then evaluating the humidity value based on the data shown in Fig.11. Least mean squares (LMS) algorithm is used here to approach the converse solutions of the nonlinear functions. The reconstruction is based on the specimen data of C and R_0 , which are specified by the partial equations of (13):

$$\begin{cases} C = C_2 - \frac{1}{(\omega_2 / \omega_1)^2 - 1} (C_1 - C_2) = g(v_H, v_T, v_B^*); \\ R_0 = f(v_H, v_T, v_B^*). \end{cases} \quad (14)$$

Fig. 11 Humidity value reconstruction

(2). At the second layer with the humidity value known in the same condition above, the temperature value based on the data shown in Fig.12 is estimated, which is reconstructed on the equation, $R_0 = f(v_H, v_T, v_B^*)$.

Temperature can also be reconstructed on the measurement of C and R_0 , as well as in the first layer. The

reasons of using known humidity value instead of R_0 and C here to evaluate temperature might be:

- a. Convenient for the computation of reconstruction. As we now have described in the paper, Least Mean Square (LMS) method was used for the estimation of humidity by the interpolation of 1st order polynomial segments to connect the particular measured samples. The method works in 3D space, and could be considered as two-dimensional signal processing. However, for estimation of temperature, algorithm could be simplified since the processing now can be performed as one-dimensional processing.

Consider a nonlinear equation as $y = f(x_1, x_2)$. If x_1 is already known, then y is actually a mono function of x_2 , that is

$$y = f(x_1, x_2) = g_1(x_2) \Big|_{x_1=k_1} = g_2(x_2) \Big|_{x_1=k_2} = \dots \dots (15)$$

Thusly the inverse function of $g_1, g_2, \dots$ could simply be computed by way of mono mean square regression.

- b. The curved surface of the solution is relatively smooth compared using C and R_0 . In this case, the length of stages in the computation of LMS method could be bigger to approximate the nonlinear functions under same accuracy request.

Fig.12 Temperature value reconstruction

- (3). Finally at the third layer, exposing the sensor to the real surroundings (let the rays come in), and with the influences on resistance by humidity and temperature having been eliminated, the brightness value is assessed. Example data is shown in Fig.13 in the case that

Fig.13 Brightness value reconstruction

temperature and humidity are 20 °C and 65%Rh, respectively.

Example measurement results for the controlled small lounge are given in Tab. 1. Where, "Appointed value" is appointed by the control unit of the lunge and is calibrated by several meters. "Measured value" generated from the proposed sensor.

3.2 Uncertainty of the measurement The difference between "Appointed value" and "Measured value" denoted the measurement uncertainty of the proposed sensor.

For the case of humidity evaluation in this research, it can be considered that the nonlinear two-dimensional functions $y_1 = f(x_1, x_2)$ and $y_2 = g(x_1, x_2)$ were substituted by multi-1st polynomial ones (It means to separate both y_1 and y_2 with smaller regions). For example, the variation range of y_1 is considered as $[y_{11}, y_{12}], [y_{12}, y_{13}], \dots, [y_{1(N-1)}, y_N]$.

And within each smaller region, we have

$$y_1 = ax_1 + bx_2 + 1. \quad (16)$$

In the same way for y_2 , we have

$$y_2 = cx_1 + dx_2 + 1. \quad (17)$$

The parameters (a, b, c and d) of (16) and (17) are estimated by applying LMS algorithm on the sensing data within each smaller regions. Thus, the values of x_1 and x_2 could be calculated out by the solutions of (16) and (17) as below

$$\hat{x}_1 = \frac{dy_1 - by_2 + b - d}{ad - bc} \quad (18)$$

$$\hat{x}_2 = \frac{cy_1 - ay_2 + a - c}{bc - ad}. \quad (19)$$

Either $\hat{x}_1$ or $\hat{x}_2$ is actually a square plane in three-dimensional space (the coordinates are on the independent variables y_1 and y_2 , respectively). The whole regression solution plane is composed of such smaller inclined ones, of which the number depends on the amount of the divided regions of both y_1 and y_2 .

Define the uncertainty error of x_1 as $d\hat{x}_1/\hat{x}_1$, then from (18), we have

$$\Delta\hat{x}_1/\hat{x}_1 \approx \frac{(d \cdot \Delta y_1 + \Delta d \cdot y_1) + (b \cdot \Delta y_2 + \Delta b \cdot y_2) + \Delta b - \Delta d}{\frac{dy_1 - by_2 + b - d}{ad - bc}} + \frac{(a \cdot \Delta d + \Delta a \cdot d) - (b \cdot \Delta c + \Delta b \cdot c)}{bc - ad} \quad (20)$$

Where, $\Delta y_1, \Delta y_2$ —system error;

$\Delta a \sim \Delta d$ —LMS algorithm error.

System error resulted from the accuracy of instruments, calibration error of the meters that were used for monitoring the measurand, the stability of the sensor itself and the controlling performance of the lunge. LMS error existed in the reconstruction process where we approximated groups of linear equations to the nonlinear functions of the sensor. Electrical-magnetic noise may also influence the accuracy of the sensor.

System error is to be restrained by improving the experiment conditions and the technological manufacture

Tab.1 Measurement results

	Appointed value			Measured value		
	Humidity(%)	Temperature (°C)	Brightness (Lx)	Humidity(%)	Temperature (°C)	Brightness(Lx)
1	40.0	5.0	0	47.6	12.8	50
2	40.0	5.0	1350	45.2	7.8	1300
3	40.0	45.0	1450	50.8	37.9	1400
4	90.0	25.0	350	85.4	21.6	450
5	65.0	25.0	1450	59.3	22.4	1400
6	90.0	40.0	0	92.2	43.5	100
7	90.0	40.0	350	95.7	46.4	450
8	65.0	25.0	1150	70.6	29.8	1200

levels of the sensor; Introducing of other interpolation functions (e.g. spline function) is expected to reduce the LMS algorithm error.

3.3 Sensitivity of the sensor The sensitivity of the sensor is mainly decided by the values of local (partial) derivative of the forward measurement functions. For example, considering the humidity measurement, from (14) we have

$$\begin{cases} \frac{\partial R_0}{\partial v_H} = \frac{\partial f(v_H, v_T, v_B)}{\partial v_H} \\ \frac{\partial C}{\partial v_H} = \frac{\partial g(v_H, v_T, v_B)}{\partial v_H} \end{cases} \quad (21)$$

The values of the two derivatives obviously had determined the gradient of the camber shown of Fig.11, on which the sensitivity on humidity measurement of the sensor is given. Generally, the bigger the derivatives are, the higher the sensitivity is. Although the measurement results were finally from the reconstruction computations, the (LMS) algorithm could not change the characteristics of sensitivity in essence.

Since the measurement equations are non-linear ones, the sensitivity of the sensor is therefore not constant within the whole measurement range. Furthermore, the sensitivity of one quantity was also influenced by the value of other quantities. For example, when humidity and temperature are 65%Rh and 20°C, respectively, the sensitivity of brightness sensing changed from 2.5(Lx/kΩ) to 32.5 (Lx/kΩ).

To improve the sensitivity of the sensor, modification on the technological design of the sensor is needed.

4. Conclusions

In this approach, we use only one multi-functional sensor to measure three environment variables in a step by step way, of which the technique deserves the tactics of the multi-layer sensing.

Our proposed multi-layer sensing technique provides a possible strategy for the solution to measurement equations for multi-functional sensor, especially when the sensor processes more than three quantities that cannot be reconstructed in parallel by the input/outputs data of the sensor. The variables being measured could probably be classified into different layers or groups considering their

instinctive nature to the output of the sensor, for example, the non-linear sensitivity, frequency characteristics, and so on. Thus, the multivariate equations were lowered to avoid computing the data in high dimension space. However, both the sensing device and the reconstruction algorithm need modification to reduce the measurement uncertainty and enlarge the sensitivity. Attempts at modifying the sensor will be made in the follow-up research.

Furthermore, the universal solutions to measurement equations of nonlinear form are still far from realization, more fruitful approaches in this field are under expectation.

On other hand, the processing of high-level information that is related to many conventional physical or other kinds of quantities has rapidly evolved recently^{[1],[2],[14]}. Environment "comfort" can be considered as such a type of information that comprises temperature, humidity and other variables. High-level information is of great importance to intelligent systems (like robotics), in which it is needed to extract and fuse data from multi-sensor systems to acquire more accurate information about the external environment. Multi-layer information fusion that sequentially aggregates information is proposed here. Unlike traditional fusion methods, multi-layer fusion might probably be possessed of the advantage of high efficiency and dependency. Further explorations now still wait for making dependant on [15].

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