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Tag-Based Measurement and Calibration†

— Another Cooperative Framework Based on Sensor-Object Duality —

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We propose a system of networked sensors that improves the measurement accuracy and sensor calibration every time a sensor meets an object. We assume all objects are tagged by unique IDs. Hence any sensor can identify the object by the ID, and can access the corresponding database of it. When a sensor meets an object, it obtains a pair of the measurement value and its error variance estimate, which is transmitted to the shared database indicated by the unique ID. Using those values and the database, the system obtains improved estimates and transmits them back to the sensor and updates the database. Comparing the estimates and the original measurement, the sensor can calibrate its internal parameters more accurately. The procedure converges into consistent sensors and objects. Experimental results show that a system of networked scales successfully improved the precision of measurements and calibration.

Key Words: Networked sensors, Calibration, RFID-tag, Bayes estimation

1. Introduction

Sensor networks are useful for obtaining rich information on the physical world [1]. The obtained information is useful when it provides consistent descriptions of the physical world. Here, the word consistent means that there is no contradiction between the descriptions and that no contradiction between the physical world and the descriptions.

In order to obtain such consistent information, each sensor should output a measurement value that is identical to the true physical quantity of a measured object. This is the reason why each sensor should be calibrated. If some true physical quantities of some objects are known in advance, then we can calibrate sensors using the objects. But, in many cases, the true quantities are unknown before the measurement. In such cases, we must calibrate sensors with estimating the true quantities of objects based on the measurement values obtained by the un-calibrated sensors.

In this article, we consider a system that consists of uncalibrated sensors that are networked, and a set of objects whose physical quantities are unknown in advance. The objective is to propose a method for improving the precision of the calibration of each sensor, and of the estimates of the quantities of each object.

Every time a sensor in the system meets an object, the sensor estimates the physical quantity of the object based on the measurement value. In order to improve the precision of estimates, we make the estimates shared by all sensors. Assuming that the measurement values obtained by different (un-calibrated) sensors obey the normal distribution of which average is identical to the true quantity, we improve the precision. For this improvement, the system manages not only the estimates of the measurement values but also the estimates of the error variances of the values in a shared database.

In addition, every time a sensor measures an object, the sensor calibrates itself based on the shared estimates and on the newly obtained measurement value. For this purpose, each sensor manages by itself the estimates of its internal parameters and the estimates of their error variances. In order to manage the shared data, we attach an ID-tag onto every object. Using an ID-tag, a sensor can identify an object that is measured, and can access automatically the corresponding estimates in a shared database that are needed for updating the estimates.

2. Measurement and Calibration

In this section, we show the framework of measurement

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and calibration of the proposed system. We present a new tag-based sensor network for this framework in the next section.

2.1 Problem Statement

There are N objects to be measured. Each of them has a stable physical quantity x_i $(i = 1, 2, \cdots, N)$, which is unknown. Each object has a unique ID. In a shared database, the estimate $\bar{x}_i^k$ and the estimate of error variance σ_i^k are stored. Here, k shows that these estimates are obtained after the object i was measured k times. Those values can be accessed and updated at any time when necessary.

There are M sensors. Each of them has internal parameters a_j and b_j $(j = 1, 2, \cdots, M)$, which are unknown. Each sensor maintains the estimates of those parameters $\bar{a}_j^k$ and $\bar{b}_j^k$, and the estimates of their error variances $\bar{\sigma}_{aj}^k$ and $\bar{\sigma}_{bj}^k$. Let the measurement value obtained when the sensor j measures object i denoted as y_{ij}. We assume that each sensor can be modeled as follows.

$$y_{ij} = a_j x_i + b_j + \xi_j, \tag{1}$$

where x_i is the physical quantity of the measured object, and ξ_j is a measurement noise. The ideal (or designed) values of a_j and b_j are 1 and 0, respectively. The measured value y is always coupled with an estimate of error variance.

$$\sigma_{yj}^2 = (a_j x_i + b_j - x_i)^2 + < \xi_j^2 > . \tag{2}$$

In (2), the first term of the right side represents the variance of components of systematic error (reproducible instrumental deviation), and the second term the variance of components of measurement noise (random irreproducible error).

If the sensor maintains the parameter estimates $\tilde{a}_j$ and $\tilde{b}_j$, it can correct a measurement value as follows by using the parameters.

$$\tilde{y}_j = \frac{y_j - \tilde{b}_j}{\tilde{a}_j} \simeq \frac{a_j}{\tilde{a}_j} x + \frac{b_j - \tilde{b}_j}{\tilde{a}_j} + \xi_j. \tag{3}$$

For simplicity, we express $a_j/\tilde{a}_j$ and $(b_j - \tilde{b}_j)/\tilde{a}_j$ as a_j and b_j, respectively. Since the sensor maintains the error variance of its internal parameters, it can produce the error variance of the measurement as

$$\begin{aligned} \sigma_{yj} &= \{(a_j - 1)x + b_j\}^2 + < \xi_j^2 > \\ &= < (a_j - 1)^2 > x^2 + < b_j^2 > + < \xi_j^2 > . \end{aligned} \tag{4}$$

In the following, we express $< (a_j - 1)^2 >$ as σ_{aj}, $< b_j^2$ as σ_{bj}, and $< \xi_j^2 >$ as $\bar{\sigma}_j$. Then, we obtain next expression:

$$\bar{b}_{yj} = \sigma_{aj} \bar{x}_i^2 + \sigma_{bj} + \bar{\sigma}_j \tag{5}$$

2.2 Method of Measurement and Calibration

In this subsection, we describe a method for computing the estimates of measurement values, their error variances, the internal parameters of each sensor, and their error variances. Using the method, the system improves the precision of estimates of measurement values and the precision of estimates of the internal parameters.

At first, we describe a method for estimating the quantities x_i and their error variances. Every time the system measures an object i with arbitrary sensor, the system updates those estimates. As mentioned, we denote the estimate of the quantity x_i obtained after the k-th measurement as $\bar{x}_i^k$, and the estimate of the corresponding error variance as σ_i^k.

Assuming that the estimates $\bar{x}_i^k$ and the measurement values y obey normal distributions [2], we obtain next equations that are used for updating $\bar{x}_i^k$ and σ_i^k. These equations represent Bayesian inference on normal distribution [3].

$$\bar{x}_i^k = \frac{\frac{\bar{x}_i^{k-1}}{\sigma_i^{k-1}} + \frac{y_{ij}}{\bar{\sigma}_{yj}}}{\frac{1}{\sigma_i^{k-1}} + \frac{1}{\bar{\sigma}_{yj}}}, \tag{6}$$

$$\sigma_i^k = \frac{1}{\frac{1}{\sigma_i^{k-1}} + \frac{1}{\bar{\sigma}_{yj}}}. \tag{7}$$

The system maintains those estimates of objects in a shared database, so that any sensor in the system can use and update the data of the estimates.

Next, we describe a method for estimating the internal parameters and their error variances. Without loss of generality, we assume that two objects x_0 and x_1 are the latest ones that a sensor j has measured, consecutively. Each sensor maintains the estimates of its internal parameters and the estimates of their error variances:

$$(\bar{a}_j, \sigma_{aj}), \quad (\bar{b}_j, \sigma_{bj}). \tag{8}$$

When the sensor measures those objects, it obtains following values:

$$y_{0j} = a_j x_0 + b_j + \xi_j, \quad \sigma_{yj}^2 = \sigma_{aj}^2 x_0^2 + \sigma_{bj}^2 + \bar{\sigma}_{yj}^2, \tag{9}$$

$$y_{1j} = a_j x_1 + b_j + \xi_j, \quad \sigma_{yj}^2 = \sigma_{aj}^2 x_1^2 + \sigma_{bj}^2 + \bar{\sigma}_{yj}^2. \tag{10}$$

Then, the sensor estimates of its internal parameters as

$$\tilde{a}_j = \frac{y_{0j} - y_{1j}}{\bar{x}_0 - \bar{x}_1}, \text{ and } \tilde{b}_j = \frac{\bar{x}_0 y_{1j} - \bar{x}_1 y_{0j}}{\bar{x}_0 - \bar{x}_1}. \tag{11}$$

In addition, the sensor estimates the error variances $\tilde{\sigma}_{aj}$ and $\tilde{\sigma}_{bj}$ as follows.

$$\begin{aligned} \tilde{\sigma}_{aj} &= V\left[\frac{y_{0j} - y_{1j}}{\bar{x}_0 - \bar{x}_1}\right] \\ &= \frac{(\bar{x}_0^2 + \bar{x}_1^2)\sigma_{aj} + 2\sigma_{bj} + 2\bar{\sigma}_{yj}}{(\bar{x}_0 - \bar{x}_1)^2} + \frac{(y_{0j} - y_{1j})^2(\sigma_0 + \sigma_1)}{(\bar{x}_0 - \bar{x}_1)^4} \end{aligned} \tag{12}$$

$$\tilde{\sigma}_{bj} = V\left[\frac{\bar{x}_0 y_{1j} - \bar{x}_1 y_{0j}}{\bar{x}_0 - \bar{x}_1}\right] = \frac{2\bar{x}_0^2\bar{x}_1^2\sigma_{aj} + (\bar{x}_0^2 + \bar{x}_1^2)(\sigma_{bj} + \bar{\sigma}_y j) + y_{1j}^2\sigma_0 + y_{0j}^2\sigma_1}{(\bar{x}_0 - \bar{x}_1)^2} + \frac{(\bar{x}_0 y_{1j} - \bar{x}_1 y_{0j})^2(\sigma_0 + \sigma_1)}{(\bar{x}_0 - \bar{x}_1)^4}. \quad (13)$$

Here, V denotes the variance. In the process of deriving (12) and (13), we assume that and $\sigma_x << x^2$, $\sigma_y << y^2$ and that the variance of the ratio x / y is expressed as follows.

$$V\left[\frac{x}{y}\right] = \frac{1}{\bar{y}^2}V[x] + \frac{\bar{x}^2}{\bar{y}^4}V[y].$$

Redefining $(\bar{a}_j, \sigma_{aj})$ and $(\bar{b}_j, \sigma_{bj})$ as $(\bar{a}_j^k, \sigma_{aj}^k)$ and $(\bar{b}_j^k, \sigma_{bj^k})$, respectively, to indicate that they are the values after k-th learning calibration, we obtain

$$\bar{a}_j^k = \frac{\frac{\bar{a}_j^{k-1}}{\sigma_{aj}^{k-1}} + \frac{\tilde{a}_j}{\tilde{\sigma}_{aj}}}{\frac{1}{\sigma_{aj}^{k-1}} + \frac{1}{\tilde{\sigma}_{aj}}}, \quad (14)$$

$$\sigma_{aj}^k = \frac{1}{\frac{1}{\sigma_{aj}^{k-1}} + \frac{1}{\tilde{\sigma}_{aj}}}, \quad (15)$$

$$\bar{b}_j^k = \frac{\frac{\bar{b}_j^{k-1}}{\sigma_{bj}^{k-1}} + \frac{\tilde{b}_j}{\tilde{\sigma}_{bj}}}{\frac{1}{\sigma_{bj}^{k-1}} + \frac{1}{\tilde{\sigma}_{bj}}}, \quad (16)$$

and

$$\sigma_{bj}^k = \frac{1}{\frac{1}{\sigma_{bj}^{k-1}} + \frac{1}{\tilde{\sigma}_{bj}}}, \quad (17)$$

as the equations for updating the parameters and their error variances.

3. Architecture of the System

Figure 1 shows the architecture of the proposed system. A set of sensors are connected to the network via a computer. The computer maintains the internal parameters of the corresponding sensor. There is a shared database in the network, and maintains estimates of each objects. Each object has a unique ID, and is attached an RFID-tag that represents the object's ID.

3.1 Sensing of ID

In order to implement the method described in the previous section, each object should be identified when it is measured by the sensor. As mentioned, we attach an RFID-tag onto each object in order to realize stable and automatic identification. Each sensor has an RFID-tag reader, so that can identify an object that the sensor is measuring.

3.2 Flow of Knowledge

Each sensor maintains the estimates of its internal parameters, and the estimates of their variances. In addition, each sensor records the latest measurements of each object obtained by the sensor itself. On the other hand, the shared database maintains, for each object, estimates of the quantities, and estimates of their error variances. Any sensor can download the estimates in the database, and can upload the newly estimated values to the database.

When a sensor measures an object, the sensor identifies the object, downloads the latest estimates of the object via the network, and computes (6) and (7) in order to update the estimate of the quantity of the object and its error variance. When the sensor computes (6) and (7), the values of y_{ij}, $\bar{x}_i^{k-1}$, σ_i^{k-1}, and σ_{yj} are needed. The value y_{ij} is the measurement value newly obtained by the sensor. The values of $\bar{x}_i^{k-1}$ and σ_i^{k-1} are downloaded via the network. The value of σ_{yj} is computed as (5) using the estimates of the internal parameters recorded in the sensor.

After the sensor estimates the quantity and the error variance, the sensor estimates its internal parameters, and their error variances. For this estimation, the sensor computes (14)-(17). The resulted estimates are maintained by the sensor itself. In order to compute the equations (14)-(17), the sensor refers to the latest measurements y_{0j} and y_{1j} for computing (11).

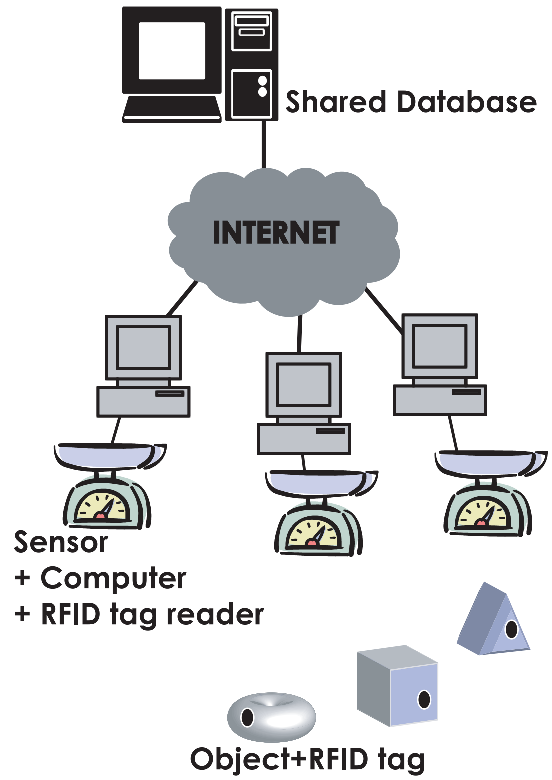

Fig. 1 The architecture of the proposed system.

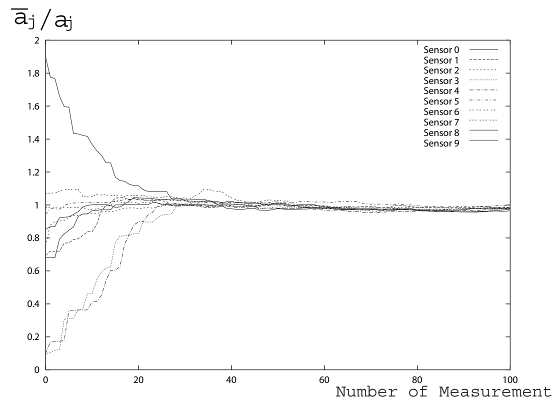

Fig. 2 An example of result. The estimate of the internal parameter of each sensor converged to the true value, as the sensors measured the objects iteratively.

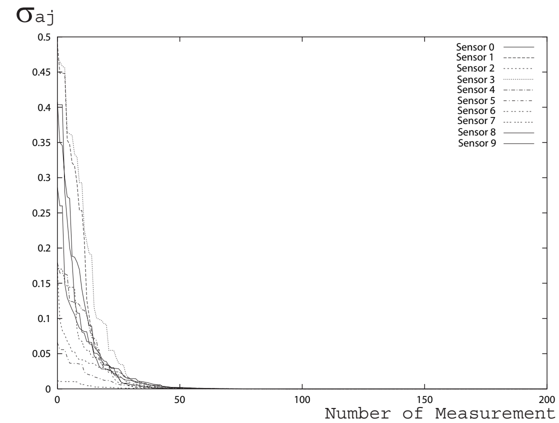

Fig. 3 An example of result. The estimates of error variance of a_j converged to zero.

4. Numerical Simulation

Setting the number of objects $N = 20$, and the number of sensors $M = 10$, we made a numerical simulation. In the simulation, each sensor selected one of the objects randomly, and measured its quantity. Each sensor measured objects iteratively, and every time the sensors measured the objects, the sets of estimates $(\bar{a}_j, \sigma_{aj})$, $(\bar{b}_j, \sigma_{bj})$ and $(\bar{x}_i, \sigma_i)$ were updated by means of the proposed method. We set the distribution of the initial values of $\bar{a}_j$ a Gaussian, of which average was 1.0, and set b_j a Gaussian of which average zero. We set the value σ_i of to ten percent of the average value of x_i.

Figure 2 shows the result of the change of $\bar{a}_j/a_j$. If the estimate is identical to the true value, then $\bar{a}_j/a_j$ is equal to one. As shown in Fig.2, as the sensors measured objects iteratively, the estimates of the internal parameter a_j converged to the true values.

Figure 3 shows the result of the change of σ_{aj} that corresponds to Fig.2. As shown in Fig.3, the estimates of error variance converged to zero. The change of the value $\bar{x}_j/x_j$ is shown in Fig.4. Because the number of the objects was twice of the sensors, the speed of change was slower than that of $\bar{a}_j/a_j$. The each estimate converged to the true value, and as shown in Fig.5, the estimates of their error variances converged to zero.

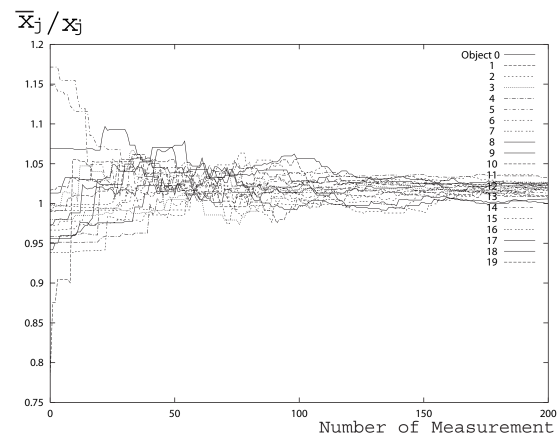

Fig. 4 The change of the estimates of the physical quantities. There were twenty objects. The estimates converged to the true values.

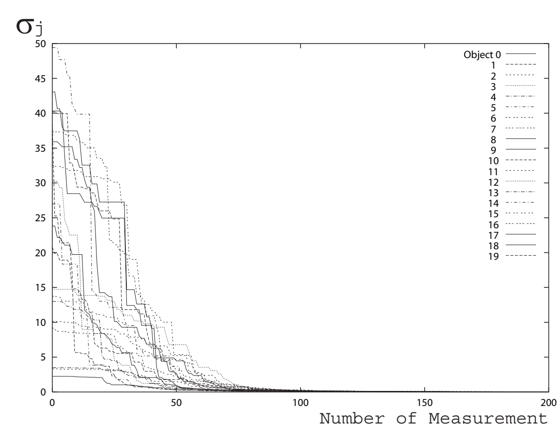

Fig. 5 The change of the estimates of the error variance. The estimates converged to zero as the objects were measured iteratively.

5. Experimental Result

In this section, we show some experimental results of a small system that consists of networked scales and a glove that has an antenna for recognizing the RFID-tag. We attached an RFID-tag (Mu-chip of HITACHI Corp.) onto each object, and incorporated an antenna of its RFID-tag reader into a glove. When a user picks an object up with the glove to put the object on the scale, the system identifies the object.

The system consists of two scales. One is a commercial

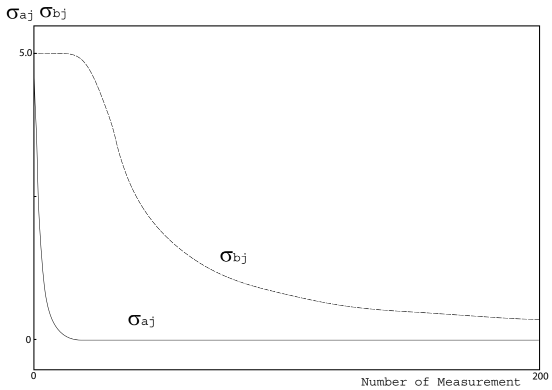

Fig. 6 Experimental results. As the objects were measured iteratively, the estimated error variances of the internal parameters decreased.

digital scale, and the other is an analog one. The latter is made of a thin plastic plate, on which face a strain gauge is attached. When we put an object onto the plate, the object strains the plate. The heavier object strains the plate more, and changes the resistance of the gauge more. Using the Wheatstone bridge, we convert the change in the resistance to the change in the voltage. A computer reads the change in the voltage via an A/D interface.

At initial state, the latter scale was not calibrated, and the internal parameters were unknown. We measured the weights of three objects with the two sensors, iteratively. Every time one of the sensors measured the weight, each sensor estimated the weight of each object, and calibrated the internal parameters.

Figure 6 shows the experimental results. The graph shows the change of the estimates of the error variances σ_{aj}^k and σ_{bj}^k of the analog scale. As shown in the figure, the estimates of the error variances decreased to zero as the sensor measures those objects, iteratively. By measuring the objects iteratively, the system calibrated the scales, and estimated the weights of the objects, successfully.

6. Summary

We proposed a system of networked sensors that improves the estimates of physical quantities of each object, and the estimates of the internal parameters of each sensor, consecutively.

The system has a shared database, which maintains the estimates of the quantities and the estimates of the error variances of the estimates for each object. When a sensor measures an object, the sensor downloads the shared estimates of the corresponding object from the database, and updates these estimates using the value newly measured. In addition, the sensor updates the estimates of internal parameters and estimates of the error variances of them, which are maintained in the sensor. It should be noted that, in the system, an RFID-tag that is attached onto every object plays an important role: the RFID-tag enables each sensor to identify the object and to access the corresponding data in the database, automatically.

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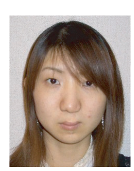

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