

Multi-Sensor Blind Recalibration in mHealth Applications

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Abstract—This paper considers the problem of self-calibration of multi-sensor systems for health care cyber-biological systems, such as closed-loop glucose control. The recalibration method is performed periodically in the cloud resulted in significant advantages over traditional methods, including increased on-line accessibility and fast automated recovery from failures. Since the size of dataset has direct impact on the recalibration quality, we use cloud database which let us have a more complete recalibration dataset compared to limited on-board logging at different times and situations. Three methods are presented and evaluated in terms of accuracy and time. The proposed Minimum Mean Square Error (MMSE) recalibration method delivers the superior precision compared to other two techniques which are based on average and correlation. While all these approaches are generic and applicable to different medical multi-sensor systems, the experimental results are evaluated on temperature sensors due to their simple and reliable setup.

Keywords— *Sensors, recalibration, multi-sensor systems, Minimum Mean Square Error.*

I. INTRODUCTION

The last decade has witnessed vast biomedical applications for sensing and monitoring devices. The current medical sensing system specifications require high accuracies, as well as tolerance to sensors' declibration resulting from the prolonged use or aging [1]. Multi-sensor data fusion [2]-[3] is a common approach, which combines data from multiple sensors to achieve more accurate readouts compared to the case where a sensor is used alone [4]. In the cyber-biological systems due to inherent deficiency or aging, the sensors can suffer from large calibration shifts. Therefore, sensors self-calibration is critical for healthcare systems.

In particular, the current push for closed-loop insulin control (CLIC) systems must guarantee the continuous supply of insulin to the patient without causing the possibly dangerous state of hypoglycemia. Given the lack of the insulin sensing devices and the low reliability of continuous glucose monitoring systems (CGMs), this task is not possible to achieve without the multi-sensor platform. Meanwhile, for the recalibration of multi sensory systems, a patient will have no access to special calibration hardware or expert data analysis. Therefore, a blind sensor recalibration method is required which applies a comprehensive data set resulted in high accuracy with reasonable complexity. Manual calibration of every sensor in a multi-sensor platform is an unfeasible task, as a typical multi-sensor system can incorporate even tens of sensing devices [5]. Since health care applications need more accurate measurements than these provided by uncalibrated low-cost sensors, the need of automatic methods for jointly calibrating medical multi-sensor systems has to be considered.

This paper considers the problem of self-calibration of multi-sensory systems for mobile health applications. Since the applied recalibration data has direct impact on the accuracy, we use cloud database which let us have a complete recalibration dataset from data collected at different times. Three different methods for both single and multi-sensor recalibration are presented and evaluated in terms of accuracy and time.

In our system, the sensors are connected to a device such as PC or Smartphone, and communicate wirelessly via Bluetooth Low Energy (BLE) to send their real-time data. Then, the data is sent to our cloud to be periodically calibrated and used for further analysis. The recalibration period is determined by the physicians based on the criticality of the medical application. The overall view of the proposed self calibration is shown in Fig. 1. It is worth noting that, not only the data is used for the purpose of recalibration, also the physicians or hospital staffs could track the sensory data wherever they are with devices such as smartphones, tablets or the web regardless of their proximity to the patients.

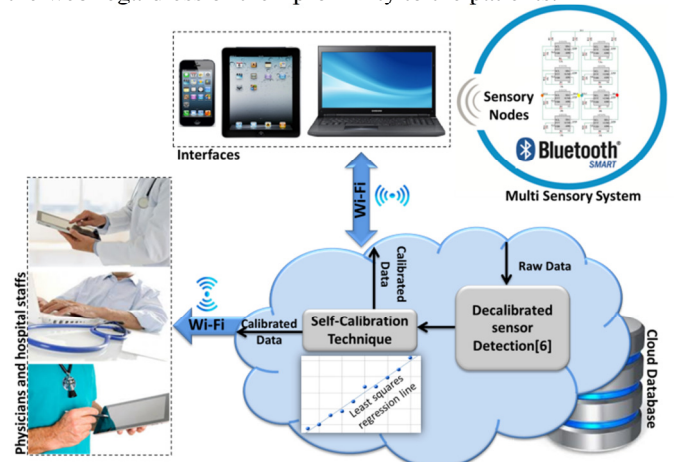


Fig. 1. Overall view of the proposed cloud-based recalibration procedure

In section II, three methods are presented for blind recalibration of multi sensory systems. Experimental results are presented and discussed in section III. Finally section IV concludes the paper.

II. BLIND CALIBRATION

The following notations are used through the rest of the paper:

$x_{readout,i}$: The i^{th} sensor readout ($i = 1, \dots, n$), where n is the total number of sensors,

$x_{est,i}$: Estimation of i^{th} sensor for recalibrating purpose,

$x_{ref,i}^{1:t}$: The reference readout of i^{th} sensor in the data set with t samples,

$x_{recalib,i}$: The recalibrated value of sensor i .

X : The set of all non-decalibrated (good) sensors,

f : The index of the decalibrated sensor,

A_f : The Minimum Mean Square Error (MMSE) coefficients of sensor f ,

a_i, b_i : The gain and offset values for recalibrating sensor i , respectively,

In the following sections we propose two schemes for the individual recalibration of the decalibrated sensors based on readouts of systems' remaining good sensors.

A. Average Method

The initial phase in the recalibration process performs a screening of all the sensors in the system in order to exclude faulty or decalibrated sensors. Towards this goal we apply the procedure presented in [6]. Further, in the proposed recalibration scheme we use a data set, which includes the pre-calibrated data (factory calibrated or after applying a non-blind calibration with exact references). The primary idea for blind calibration is to consider the average of sensors readouts as a reference to be fitted linearly using the method of least squares while excluding the decalibrated ones. The required gain and offset are to be used for further readouts. The algorithm for a calibration of a single decalibrated sensor is presented in Fig. 2. The method could be expanded for multiple faults.

Average Recalibration ($x_{readout,1:n}, f, a_f, b_f$) {
//Inputs: $x_{readout,1:n}, f$ **Output:** a_f, b_f
 1- $x_{Average} = \frac{\sum_{i=1, i \neq f}^n x_{readout,i}}{n-1}$;
 // excluding the decalibrated sensor
 2- $[a_f \ b_f] = \text{polyfit}(x_{readout,f}, x_{Average})$;
 // Linear polynomial curve fitting meaning $x_{recalib,f} = a_f \times x_{readout,f} + b_f$
 3- **Return** a_f, b_f ;

Fig. 2. The Average Recalibration Method

This solution has a low complexity, which makes it suitable for real-time blind calibration. However, the quality of recalibration suffers, and has to be improved especially in the critical areas such as health monitoring devices. For that purpose, in Fig. 3 we propose a second method of recalibration. For each sensor i , different combinations of other sensors are obtained. In each combination, the average of sensors readouts is compared with sensor readouts i using the correlation as a criteria. As an example in our experiment, sensor readouts 8 have the best correlation with the average of sensors readouts 1, 2, and 6. Therefore, the average of these three sensors is used to estimate the 8th sensor behavior for recalibration purpose. The correlation between two readouts m and n with t samples is calculated as follows:

$$R_{m,n} = \frac{t(\sum_{i=1}^t m_i n_i) - (\sum_{i=1}^t m_i)(\sum_{i=1}^t n_i)}{\sqrt{[t \sum_{i=1}^t m_i^2 - (\sum_{i=1}^t m_i)^2][N \sum_{i=1}^t n_i^2 - (\sum_{i=1}^t n_i)^2]}}$$

Correlation Recalibration ($x_{readout,1:n}, f, SS, a_f, b_f$) {
//Inputs: $x_{readout,1:n}, f, SS$ **Output:** a_f, b_f
 // SS is the Sensors Subset having the maximum correlation with sensor " f " obtained from offline procedure
 1- $x_{SS_Average} = \frac{\sum_{i \in SS} x_{readout,i}}{\text{size}(SS)}$;
 2- $[a_f \ b_f] = \text{polyfit}(x_{readout,f}, x_{SS_Average})$;
 3- **Return** a_f, b_f ;

Fig. 3. The average method based on correlation

This procedure is applied on individual sensor according to data set generated during the operation of the multi-sensor platform. This approach leverages the correlation in the subset of sensors without requiring a dense deployment. For each sensor, there are maximum $2^{n-1} - 1$ combinations which have to be checked in order to find the maximum correlation. As shown in Fig. 3, the average of sensors readouts of the best-correlated subset is used as the reference of our curve fitting to obtain the gain and offset. This procedure (see Fig.4) is performed offline and only once to compute the best correlations. This method improves the accuracy of the recalibration comparing to the simple average method.

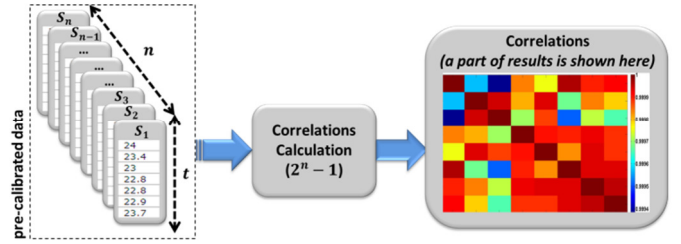


Fig. 4. The average method based on correlation overall view

B. MMSE Method

In this section, MMSE estimator [7] is used to linearly find the optimum reference for recalibration. The Mean Square (MS) estimator of $x_{ref,f}^{1:t}$ given the set of non-decalibrated sensors (X) is defined as:

$$x_{est,f} = E(x_{ref,f}^{1:t} | X).$$

We presented its formal definitions for a single error, which could be expanded for multiple errors, as well. The homogenous linear MS estimator of $x_{est,f}$ given $X = [x_{ref,1}^{1:t} \dots x_{ref,f-1}^{1:t} x_{ref,f+1}^{1:t} \dots x_{ref,n}^{1:t}]^T$ is:

$$x_{est,f} = A_f^T X = \sum_{i=1, i \neq f}^n \alpha_i \cdot x_{ref,i}^{1:t}$$

$$\text{Objective: Min } \{E(x_{est,f} - x_{ref,f}^{1:t})^2\}.$$

This means that the error must be orthogonal to each of the data in X . After solving this problem we obtain:

$$A_f = R^{-1}P \quad (1)$$

where:

$$R = \begin{bmatrix} r_{1,1} & \cdots & r_{f-1,1} & r_{f+1,1} & \cdots & r_{n,1} \\ & & \vdots & & & \\ r_{1,f-1} & \cdots & r_{f-1,f-1} & r_{f+1,f-1} & \cdots & r_{n,f-1} \\ r_{1,f+1} & \cdots & r_{f-1,f+1} & r_{f+1,f+1} & \cdots & r_{n,f+1} \\ & & \vdots & & & \\ r_{1,n} & \cdots & r_{f-1,n} & r_{f+1,n} & \cdots & r_{n,n} \end{bmatrix}_{n-1 \times n-1}$$

$$, r_{i,j} = E\{x_{ref,i}^{1:t} x_{ref,j}^{1:t}\}; i, j \neq f.$$

$$P = [p_1, \dots, p_{f-1}, p_{f+1}, \dots, p_n],$$

$$p_i = E\{x_{ref,f}^{1:t} x_{ref,i}^{1:t}\} \quad i \neq f$$

$$A_f = [\alpha_1, \dots, \alpha_{f-1}, \alpha_{f+1}, \dots, \alpha_n]^T$$

After calculating the coefficients in step 1, Fig. 5, the recalibration reference is generated in step 2. It is then used for calculating the appropriate gain and offset. The evaluation of each method is discussed on a real data set in details in section III.

MMSE_Recalibration ($x_{readout,1:n}, x_{ref,1:n}^{1:t}, f, X, a_f, b_f$) {
//Inputs: $x_{readout,1:n}, x_{ref,1:n}^{1:t}, f, X$ *Output:* a_f, b_f
 1- $A_f = \text{MMSE}(x_{ref,1:n}^{1:t}, f);$ *//procedures of equation(1)*
 2- $x_{est,f} = A_f \times X;$
 3- $[a_f \ b_f] = \text{polyfit}(x_{readout,f}, x_{est,f});$
 4- *Return* $a_f, b_f;$

Fig. 5. The MMSE recalibration method

III. EXPERIMENTAL RESULTS

The proposed methods have been applied on eight non-blind calibrated [8], digital temperature sensors. This case study uses temperature sensors due to simplicity and reliability of the setup. In the experimental setup a dual-slope temperature ramp was generated, where the temperatures are changed in 4° steps between 10°C and 30°C with the starting point of 10°C. In total, 7000 sample readouts were gathered. Almost half of the data ($t=3000$ samples) were used as the data set for the recalibration procedure, while the rest served as the validation set. Based on the uniform distributions of the original data, the sensor errors uniformly distributed in the interval $[-20 \ 20]$ have been injected to simulate the decalibrated behaviors of sensors. According to the results in [8], the noise of each sensor can be mapped to Gaussian distributions with a zero mean, but with different variances. This means that the sensors do not have identical statistical characteristics, and hence, the individually blind calibration method becomes very useful. The accuracy comparisons of three proposed method are depicted in Table I. As can be seen the correlated based average method improves sum of mean square error by 23.44% comparing to the simple average method. Further, the proposed MMSE recalibration method delivers the superior precision compared to the other methods.

The impact of the size of the data set has been also evaluated in Fig. 6. In particular, we have swept the number of samples (t) from 3000 to 9. As expected, experiments show that by decreasing the size of data set, the accuracy of the recalibration will suffer.

TABLE I. ERROR COMPARISON OF DIFFERENT RECALIBRATION METHODS ON 8 TEMPERATURE SENSORS

#of decalibrated sensors	Sum of Mean Square Errors		
	Average	Average based on correlation	MMSE
1	0.0319	0.0098	0.0094
2	0.4561	0.3681	0.1407
3	2.111	2.0401	0.7068
4	4.8859	4.9768	1.8748
<i>Average Improvement w.r.t. average</i>		23.44%	61.63%
<i>Average Improvement w.r.t. average based on correlation</i>			48.57%

The percentages on Fig. 6 show the accuracy reduction compared to the case, where 3000 samples are used. Note, that there are four decalibrated sensors in the system. Therefore, it is important to choose an appropriate data set size according to the required accuracy for given specific applications.

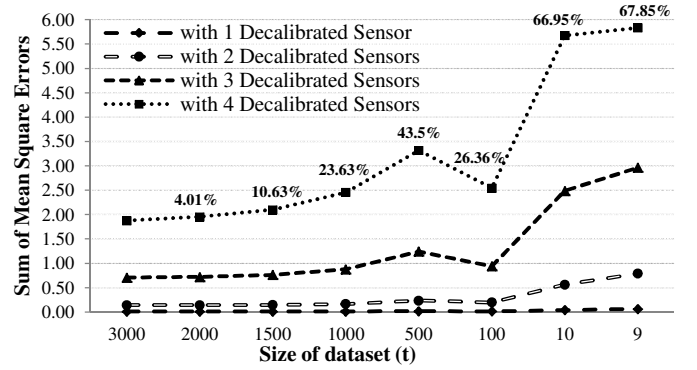


Fig. 6. Impact of the data set size (t) on errors in MMSE method

For example, when we reduce the number of samples (t) used in MMSE estimation, from 3000 to 1500, we need to tolerate the error of 10.63% for the case of having four decalibrated sensors (see Fig. 6). Hence, in this paper the cloud database allows us log the recalibration data in different times and conditions without limitations in memory or number of sensors. Thus, the blind calibration could be implemented on a comprehensive dataset which resulted in better accuracy compared to on-board logging. Besides, the computations are performed in the cloud and the results are available for physicians and hospital staffs regardless of their locations.

The presented methods make it possible to recalibrate multiple-sensor systems fast. The run time of either simple or correlated based average method is 0.7ms for single and multiple recalibrations. The MMSE method takes 1.8ms to estimate the reference, therefore, it is not only suitable to recalibrate sensors in real time, but also to provide high accuracy. The proposed algorithms can be applied to maintain the correct operability of other sensors such as CMS, which current frequent recalibrations from blood reference are a tedious task.

IV. CONCLUSION

In this paper, we addressed the problem of jointly calibrating medical multi-sensor systems. In fact, early identification of faulty sensors through such technique and timely recalibrating the sensors can decrease the risk and cost in applications that deal with high risks such as patients'

health. For instance, regarding closed-loop insulin control systems for managing glucose levels, sensor readouts should not only have a high accuracy, but also must be robust enough to blindly recalibrate the sensors in a reasonably short amount of time. In this work, the proposed generic recalibration approaches and the recalibration data set are done in cloud which brought significant advantages over traditional methods, including increased on-line accessibility and fast automated recovery from failures. Among three analyzed methods, the MMSE results in the best accuracy in reasonable short amount of time. The evaluation of accuracy with respect to size of the database demonstrates the need of using cloud computing instead of on-board logging and processing.

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