

## A Simultaneous Localization and Tracking Algorithm Based on Compressing Kalman Filter

<sup>1</sup> Zhao Yafeng, <sup>2</sup> Ren Hong'e, <sup>1</sup> Hu Junfeng

<sup>1</sup> College of Mechanical and Electrical Engineering, Northeast Forest University,  
Harbin, 150040, China

<sup>2</sup> College of Information and Computer Engineering, Northeast Forest University,  
Harbin, 150040, China

<sup>1</sup> Tel.: 86-13633610309

<sup>1</sup> E-mail: nefuzyf@126.com

*Received: 14 January 2014 / Accepted: 28 February 2014 / Published: 31 August 2014*

---

**Abstract:** Simultaneous Localization and tracking was studied to solve the problem of tracking a moving target in a sensor network while simultaneously localizing and calibrating the nodes of the network. RSSI is used for measuring the distance between the nodes pairs, multidimensional scaling techniques are used for the initial position of wireless sensor network based on the distance matrix. Then the compression Kalman filter is used to estimate and update the sensor node position and the target position. Simulation results show that the algorithm has high accuracy and real-time performance under low network, especially for long distance tracking. Copyright © 2014 IFSA Publishing, S. L.

**Keywords:** Wireless Sensor Network, Target Tracking, Simultaneous Localization and Tracking.

---

### 1. Introduction

The application of wireless sensor network is originated from the military practice, and until today one of its important applications is the detecting and tracking of enemy military target. Besides, it is widely applied in other civilian fields in tracking and localization such as bio-environmental monitoring, intelligent traffic control, infrastructural security, minimally invasive medical devices, etc. In these applications, it is necessary to establish a wireless sensor network constituted of a number of randomly allocated wireless sensor nodes in a predetermined area to realize the real-time tracking of a target position.

Precise location is required as a reference when it comes to the tracking of moving target, the changing of position or the recalibrating of the sensor

parameters in network reorganization. As for the larger demand in scale of wireless sensors network localization, it is impractical to adopt artificial deployment or GPS to reach the accuracy of position. Therefore, the best solution is an accurately tracking method with low cost, high precision and identification of a sensor network nodes position at the same time.

Recently, related algorithms have been proposed by some authors to solve the problem of localization and tracking of a moving target in sensor networks. It was pointed out that it was a good solution to locate the wireless sensor network by using a moving target (or a robot) [1-4], since it is not required to configure additional hardware resources in the node. However, the necessity to provide real-time position of moving objects fails to meet the needs of target tracking. Some authors use

a sensor network to track the moving target [5], assuming that the location of sensor network nodes is determined, which only suits small-scale sensor networks and raises higher requirements for network positioning capability.

We make a research on simultaneous localization and tracking algorithm to track the position of moving objects, localize and calibrate the information of sensor network nodes based on the theory of simultaneous localization and mapping (SLAM).

## 2. Simultaneous Localization and Tracking

The most common sensor network node positioning algorithm relies on the relative distance measurement of node pairs. Initial localization of sensor network nodes can be started when the measurement information is available. Moving target position can be determined in a rough environmental map the same time be rechecked according to the new measurement information. SLAM method has been confirmed effective in dealing with such issues in the past ten years. We estimate and update the position of moving objects online and update the location of sensor network nodes based on the idea of SLAM.

It is assumed that the target can move freely, the sensor nodes are fixed and the moving target and nodes can communicate with each other. The received signal strength indicator (RSSI) positioning technology does not require specialized hardware, the distance between nodes can be calculated directly by measuring the energy, and the RF signal can pass through people, furniture even walls without the common obstacles of sight vision sensor, RSSI ranging is adopted in this paper. On the other hand, the distance estimation based on RSSI is not so reliable due to the fluctuation resulted from environmental factors such as temperature, quantity, humidity, metal barriers, even self-interfering caused by multiple reflections. Whereas RSSI has great advantages in device cost and size balanced with the disadvantages in the large errors in distance estimation. In the preliminary estimate, the distance of every adjacent node in WSN is tolerated with some extent of error. Therefore, RSSI measurement is adopted to determine the relative distance between both the node pairs and the target and the node.

We use the multidimensional scaling (MDS) ideas to acquire relative coordinate diagram of the hop neighbors of each node according to the classic multidimensional measurement technology, and then obtain the relative coordinate diagram one by one through transmitting, that is to determine the unknown node coordinates according to the correlating information of nodes. Nevertheless, the RSSI value is in a nonlinear relationship with the distance oriented from

the reconstruction of the node coordinates by measuring the distance between nodes. Besides, it increases the algorithm complexity and generates errors because of the conversion between strength and distance and the omission of high-order terms directly. In order to improve the algorithm, non-value measurement multidimensional scaling algorithm is used by directly locating nodes on the wireless signal strength, where positioning errors are effectively reduced while complexity of the algorithm is decreased.

The core technology of realizing simultaneous localization and tracking lies in the repetition of estimating - updating process. First of all, we roughly localize the sensor network by using the distance of sensor network nodes. However, this positioning information typically includes a large error, which cannot be used as an absolute reference in target tracking and requires to update the node locations the same time track the target according to the relative distance of the nodes in moving. To achieve this goal, it has been extensively studied on the theory based on Kalman filtering. But with the target moving on, the measuring information increases and the dimension of filter state equation rises, which will generates a large amount of calculation, not suiting the distributed computing of wireless sensor network nodes. We utilize the desirability of Kalman filtering to take compressing Kalman filter estimation and updated response state into practice. Basic structure and principles of the algorithm is shown in Fig. 1.

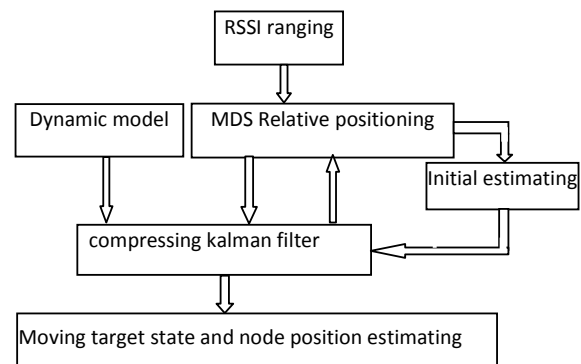


Fig. 1. Basic principles and structures of simultaneous localization and tracking.

## 3. Algorithm Analysis

### 3.1. Coarse Positioning Through MDS Sensor Networks

A solution without error can be given by classic MDS algorithm if geometric distances of all nodes are correct. However, almost no all-network nodes can be precisely measured due to the nodes' limitation in communication range [6]. In practical application, only the distance between adjacent nodes

can be measured, whereas for the distance of the multi-hops, the geometric distance is replaced by the product of hop numbers and communication distance in this paper.

Step 1: Calculate the distance of all the nodes and establish the distance matrix  $D(X)$  that MDS requires.

Step 2: Double centralize the matrix  $D2(X)$  composed of the squared distance and conduct Singular Value decomposition on it.

Step 3: Calculate the relative coordinates  $X$  of all points and generate relative coordinates diagram.

Step 4: Use a small number of beacon nodes to convert global relative coordinates into absolute coordinates. By coordinate rotation, translation:

$$\begin{cases} X = a_{11}x + a_{12}y + b_1 \\ Y = a_{21}x + a_{22}y + b_2 \end{cases} \quad (1)$$

We need to know the two-dimensional coordinates before and after conversion of three pairs, use linear transfer function  $T(x,y)$  determined as the constraint  $\min\|T(x,y) - (X,Y)\|^2$  to realize optimal linear transformation.

### 3.2. System Dynamic Model and Observation Model

The location information of nodes in the network can be obtained by using MDS algorithm. Considering all the nodes are stationary, the  $i$ -th position is described as  $p_i = (x_i, y_i)$ . The  $i$ -node state transition equation is:

$$p_i(k) = p_i(k-1) = p_i \quad (2)$$

Assuming that the number of valid nodes in the system is  $N$ , expressing it in vector as:

$$p = [p_1^T \dots p_N^T]^T \quad (3)$$

Assuming that the status of a moving target constituted of position and orientation is given as  $x_v(k)$ , then at time  $k$ , it can be described as  $x_v(k) = [x(k), y(k), \theta(k)]$ , where,  $x(k)$ ,  $y(k)$  are the positions of absolute coordinates,  $\theta$  is the orientation from the origin.

The system state is constituted of moving target state and sensor nodes locating state, the so called expanded state vector is expressed as:

$$X(k) = [x_v^T(k) \quad p_1^T \quad \dots \quad p_N^T]^T \quad (4)$$

The expanded state transition model can be completely described as:

$$X(k) = A(k)X(k-1) + v(k-1), \quad (5)$$

where  $A(k)$  is the state matrix,  $v(k)$  is the system dynamic noise. Moving target dynamic model is:

$$x_v(k) = \begin{bmatrix} x(k-1) + \Delta D(k-1)\cos\theta(k-1) \\ y(k-1) + \Delta D(k-1)\sin\theta(k-1) \\ \theta(k-1) + \Delta\theta(k-1) \end{bmatrix} + v(k-1), \quad (6)$$

where  $\Delta D(k)$  and  $\theta(k)$  are the distance and angle of two measurements. Target state matrix  $A(k)$  can be obtained by using the Jacobian matrix with the dimension expanded to  $n \times N$ , where  $n$  is a state variable associated with each node,  $N$  is the number of nodes forming the map. In a large environment, the measurement data of the external sensors, the number of signs in an environmental map and the dimension of matrix increase in an exponential way, imposing a heavy burden on the computer.

Moving target and sensor nodes use the same configuration. The relative positioning between nodes and the target is obtained by using RSSI technology. The  $i$ -th node observation model can be written as:

$$z_i(k) = H_i(k)x_i(k) + w_i(k), \quad (7)$$

where  $w_i(k)$  denotes to systematic measurement error, and the vector is a random white Gauss noise with its mean zero.  $H_i(k)$  is the observation matrix of the  $i$ -th observed node with respect to the system state  $x_i(k)$ :

$$x_i(k) = \sqrt{[x(k) - x_n]^2 + [y(k) - y_n]^2}, \quad (8)$$

Then  $H_i(k)$  is obtained through linearization by Jacobian matrix.

### 3.3. Filtering Algorithm Analysis

Kalman filter consists of two stages: estimation and updates. In estimation phase, the filter uses the previous state to estimate the current state. In updates phase, the filter uses the observed value of the current state to optimize the values of prediction state and obtain a more accurate estimation of the current state.

In classical SLAM algorithm, the dimension of state vector is the sum of twice the amount of the node number and moving target state, i.e.  $M = 2N + 3$ . But in the actual target tracking, only the nodes within one hop around the target are meaningful. Location of numerous nodes is meaningless [7]. With the increase of node numbers in classic algorithm, the calculation of standard filter increases significantly, which therefore is not suitable for real-time target tracking. The authors suggest a way to lower the real-time calculation through compressing filter, thus the complexity is reduced to the  $O(2Na^2)$ , where  $Na$  represents the number of local area signs.

In compressing EKF filtering, the state is divided into two parts:

$$X = \begin{bmatrix} X_A \\ X_B \end{bmatrix} \quad (9)$$

$$X_A \in R^{2N_A+3}, X_B \in R^{2N_B}, N = N_A + N_B,$$

where  $X_A$  is defined as the node state within a hop around the moving target. The mobile target state is also included in the  $X_A$ . Assuming that the observation points obtained within a period of time correlate only with  $X_A$ , namely:  $h(x) = h(X_A)$ .

At a given time  $k$ , the Jacobian matrix  $H$  is:

$$H = \frac{\partial h}{\partial X} \Big|_{x=x(k)} = \frac{\partial h}{\partial (X_A, X_B)} \Big|_{x=x(k)} = \begin{bmatrix} \frac{\partial h}{\partial X_A} & \frac{\partial h}{\partial X_B} \end{bmatrix} = [H_A \quad 0] \quad (10)$$

Obviously, Jacobian matrix  $H$  is independent of state  $X_B$ .

According to two different states, the error covariance matrix  $P$  is written as

$$P = \begin{bmatrix} P_{AA} & P_{AB} \\ P_{BA} & P_{BB} \end{bmatrix} \quad (11)$$

$$S = H \cdot P \cdot H^T + R = H_A \cdot P_{AA} \cdot H_A^T + R$$

Considering the zero in matrix  $H$ , the estimated Kalman gain matrix  $W$  is as follows:

$$W = P \cdot H^T \cdot S^{-1} = \begin{bmatrix} P_{AA} \cdot H_A^T \cdot S^{-1} \\ P_{BA} \cdot H_A^T \cdot S^{-1} \end{bmatrix} = \begin{bmatrix} W_a \\ W_b \end{bmatrix} \quad (12)$$

Matrix  $S$  and Kalman gain matrix  $W_A$  are the functions of  $P_{AA}$  and  $H_A$ , which are independent of  $P_{BB}$ ,  $P_{AB}$ ,  $P_{BA}$ ,  $V_B$ .

For simplicity, the previous formula ignores time beacon. Now considering time  $k$ , the updated covariance matrix is:

$$P(k|k) = P(k|k-1) - \Delta P, \quad \Delta P = \begin{bmatrix} P_{AA}(k|k-1) \cdot \mu(k-1) \cdot P_{AA}(k|k-1) & \xi(k-1) \cdot P_{AB}(k|k-1) \\ (\xi(k-1) \cdot P_{AB}(k|k-1))^T & P_{BB}(k|k-1) \cdot \eta(k-1) \cdot P_{BB}(k|k-1) \end{bmatrix} \quad (13)$$

where  $\mu = H_A^T \cdot S^{-1} \cdot H_A$ ,  $\xi = P_{AA} \cdot \mu$ .

The covariance after  $t$  times consecutive updates is:

$$P_{AB}(k+t|k+t) = \prod_{i=k}^{k+t} [I - \xi(i)] \cdot P_{AB}(k|k),$$

$$P_{BB}(k+t|k+t) = P_{BB}(k|k) - P_{BA}(k|k) \cdot \Psi(k+t) \cdot P_{AB}(k|k),$$

if

$$\Phi(k+t) = \prod_{i=k}^{k+t} [I - \xi(i)], \quad (14)$$

if

$$\Phi(k-1) = I,$$

if

$$\Psi(k+t) = \sum_{i=k}^{k+t} [\Phi^T(i-1) \cdot \mu(i) \cdot \Phi(i-1)],$$

$$\Psi(k-1) = 0,$$

where  $\Phi(k), \Psi(k), \mu(k), \xi(k) \in R^{2N_A \times 2N_A}$ .

In target tracking tasks, the dimension of  $X_A$  state will usually be smaller than the total dimension of a global map, namely,  $N_A \ll N_B \ll M$ , Matrix  $\mu(k)$ ,  $\xi(k)$  is sparse. To achieve a complete global map update, the following equations must be added after the partial forecast state and update stage.

Forecast phase:

$$\begin{aligned} \Phi(k) &= A_{AA}(k|k-1) \cdot \Phi(k-1) \\ \Psi(k) &= \Psi(k-1) \end{aligned} \quad (15)$$

Update phase:

$$\begin{aligned} \Phi(k) &= (I - \xi(k)) \cdot \Phi(k-1), \\ \Psi(k) &= \Psi(k-1) + \Phi^T(k-1) \cdot \mu(k) \cdot \Phi(k-1), \end{aligned} \quad (16)$$

where  $\Phi(0) = I, \Psi(0) = 0$ .

## 4. Experiments

Analysis shows that in order to keep the distance information of the moving objects in local area, the complexity of the algorithm should depends on the number of nodes in local area. Therefore, we need to select a suitable local area to ensure accuracy and reduce the complexity of the algorithm. When positioning distance is over 20 m, RSSI can be fairly erroneous. So we set 20 m as the maximum measuring distance of the sensors. We arrange 80 nodes randomly and set 3 anchor nodes with GPS in the area whose both length and width are 180 m. The error rate of initial position of the nodes in the network is 5 % by using MDS algorithm. In Fig. 2, the blue circles represent the estimated position, the red dots represent the actual position, the black boxes represent the anchor nodes, the lines between circles and dots are the size of errors.

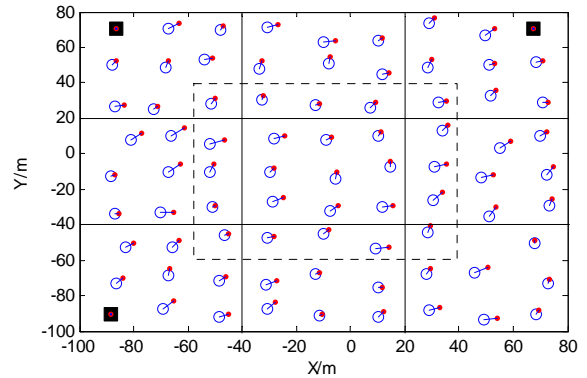


Fig. 2. The map processing of compressing filter algorithm.

The authors divide the global map into 9 squares with the same side length 60 m in a simple method. The local area can also be divided into 9 little squares. The side length of each little square is the distance of sensors. As few nodes we set, the number of nodes in each little square is only 1. We can not guarantee the accuracy of fixed position, so we treat the square whose side length is 60 m as a local area.

If the moving targets and probed nodes belong to the same closed area, it will not generate a large error. But when we probe the nodes from adjacent area, it will make the estimated position error large and change the node fixing errors due to the lost information of previous nodes. The authors set a hysteresis area in local area to prevent the positioning error by switching multiple maps, which means these maps are overlapping in some degree. The size of overlapping area is set 20 m. Fig. 2 shows an example of the hysteresis area in the central region, as shown in broken lines.

In the layout of the sensor nodes in Fig. 2, the moving targets start randomly from the origin whose moving velocity, the standard deviation of the linear velocity, angle velocity is 1 m/s, 0.1 m/s, 3.00 rad/s respectively. In the experiment we set some observation parameters. The maximum viewing distance is 20 m; the interval of observation is 0.2 s; the standard deviation of observing distance is 0.1 m. Target tracking and the fixing position of sensor nodes are shown in Fig. 3:

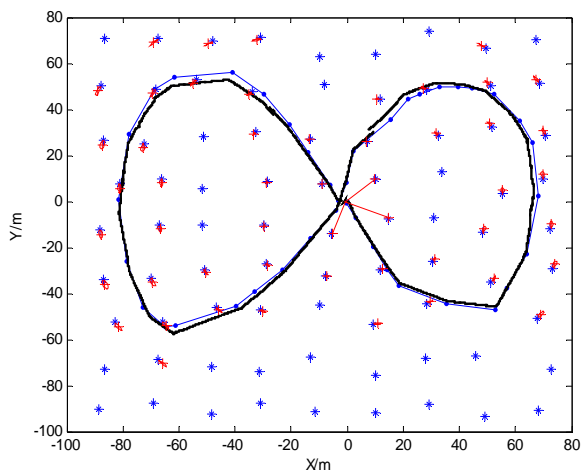


Fig. 3. WSN localization and target tracking.

In Fig. 3, "\*" describes the actual node position, "+" indicates the estimated node position, ellipse indicates the estimated error, black "-" indicates the estimated moving path, blue "-" refers to the actual moving path.

In classic EKF filtering algorithms, the computational complexity increases dramatically with the measurement nodes increasing. In 80 reference node target tracking, the algorithm complexity is  $o(812)$ . As used herein, the calculated amount of compressing filter algorithm is  $o(Na^2)$ ,

when leaving the local area, the updated complexity is  $o(Na^2Nb^2)$ . When a moving target moves in the region, the state vector  $XA$  in compressing filter is all state of moving target and regional neighbors, the number of nodes in each region is less than 10, the maximum complexity of the algorithm within the region is  $o(10^2)$ . When moving into a new area, the state vector  $XA$  changes to the node status that belongs to the new region, it would do a global update at the same time, the overall complexity of the algorithm is much smaller than the classic EKF, too. The estimate of the carrier location and the landmarks in local map is completed at the cost of a local SLAM algorithm, reflecting the superiority of the algorithm executed in a large area for a long time. The network energy consumption is shown in Fig. 4.

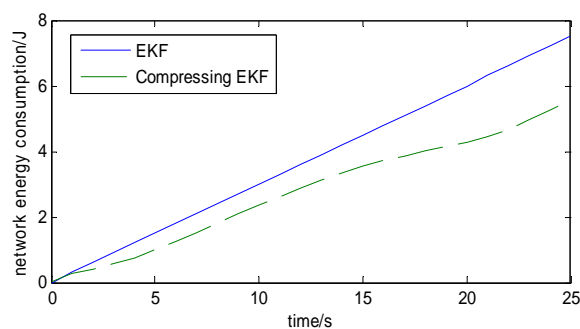


Fig. 4. Network energy consumption.

In classical target tracking, node position error was depended on the initial position. In this paper the node position error is decreased as the number of path increase, mainly because of the association of some certain node positions. The node position error varies with time as shown in Fig. 5. Solid line represents the node position mean error by MDS, dotted line represents the error in this paper.

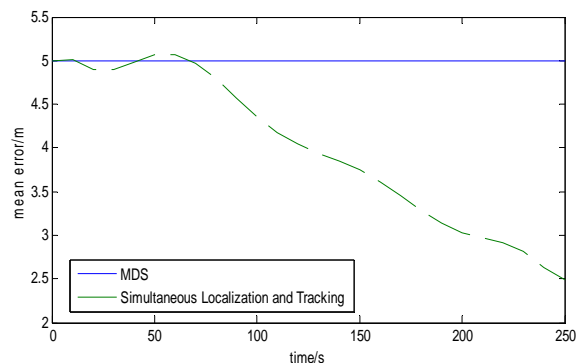


Fig. 5. Node location error comparison.

## 5. Conclusions

This paper presents the moving target tracking and node position updates when the wireless sensor network node position is uncertain. Firstly,

multidimensional scaling techniques is used to generate relative coordinate diagram, and a small amount of beacon nodes to transform global relative coordinates into absolute coordinates, an initial sensor network node positioning is completed. Then a sensor networks with certain error is used as a reference for online estimation and updating. According to the compression EKF filter, correcting sensor node locations and track moving targets. Simulation results show that the algorithm can reduce wireless sensor network node position error and greatly lower complexity of the algorithm, especially in the long-distance tracking task. The classical EKF filtering algorithm complexity is too high to meet the real-time requirements, however, in this algorithm the complexity of the algorithm can be fixed in a small range to meet the real-time tracking.


## Acknowledgements

This work is supported by the Natural Science Foundation of Heilongjiang Province of China (Grant No. QC2012C101) and the Fundamental Research Funds for the Central Universities of China (Grant No. DL10AB06).

## References

- [1]. P. Pathirana, N. Bulusu, S. Jha, *et al.*, Node localization using mobile robots in delay-tolerant sensor networks, *IEEE Transactions on Mobile Computing*, 4, 4, 2005, pp. 285-296.
- [2]. Galstyan A., Krishnamaehari B., Lerman K., *et al.*, Distributed Online localization in sensor networks using a moving target, in *Proceedings of the 3<sup>rd</sup> International Symposium on Information*, 2004, pp. 61-70.
- [3]. Menegatti E., Zanella A., Zilli S., *et al.*, Range-only SLAM with a mobile robot and a wireless sensor networks, in *Proceedings of the IEEE International Conference on Robotics and Automation*, 2009, pp. 1699-1705.
- [4]. Joseph Djugash, Sanjiv Singh, George A. Kantor, *et al.*, Range-Only SLAM for Robots Operating Cooperatively with Sensor Networks, in *Proceedings of the IEEE International Conference on Robotics and Automation*, 2006, pp. 2078-2084.
- [5]. Yao Xianlian, Hu Zhen, Lv Xiaoling, Kalman Filtering Research in the Tracking of Moving Target in WSN, *Journal of Changchun University of Science and Technology (Natural Science Edition)*, 34, 3, 2011, pp. 88-92.
- [6]. Wang Jian, Zhao Yafeng, Liu Jinfeng, A Localization Algorithm for Large-Scale Wireless Sensor Network, *Journal of Northeast University*, 37, 8, 2009, pp. 84-89.
- [7]. Nebot E., Simultaneous localization and mapping 2002 summer school [EB/OL], <http://acfr.usyd.edu.au/homepages/academic/enebot/>, 2002.

2014 Copyright ©, International Frequency Sensor Association (IFSA) Publishing, S. L. All rights reserved. (<http://www.sensorsportal.com>)



## Handbook of Laboratory Measurements and Instrumentation

Maria Teresa Restivo  
Fernando Gomes de Almeida  
Maria de Fátima Chouzal  
Joaquim Gabriel Mendes  
António Mendes Lopes

The Handbook of Laboratory Measurements and Instrumentation presents experimental and laboratory activities with an approach as close as possible to reality, even offering remote access to experiments, providing to the reader an excellent tool for learning laboratory techniques and methodologies. Book includes dozens videos, animations and simulations following each of chapters. It makes the title very valued and different from existing books on measurements and instrumentation.

**IFSA**  
International Frequency Sensor Association Publishing

Order online:  
[http://www.sensorsportal.com/HTML/BOOKSTORE/Handbook\\_of\\_Measurements.htm](http://www.sensorsportal.com/HTML/BOOKSTORE/Handbook_of_Measurements.htm)