OPTIMAL ALLOCATION AND DATA FUSION SCHEME IN WIRELESS SENSOR NETWORK FOR TARGET TRACKING

[1]YEE MING CHEN, [2]KAI-CHI CHUANG

[1,2]Department of Industrial Engineering and Management, YuanZe,
E-mail: [1]chenyeeming@saturn.yzu.edu.tw, [2]S1038901@mail.yzu.edu.tw

Abstract— Mobile objects location/tracking methods in wireless sensornetworks (WSN)have received significant attention in recent years.Among the network-based approaches, time of arrival (TOA) andtime difference of arrival (TDOA) are two major time-basedtechniques used for location/tracking estimation.InWSN, the geometric distribution of various sensor nodes has a significant influence on the positioningaccuracy. Geometric dilution of precision (GDOP) can be used to measure the positioning precision of the localization system.This paper presents a data fusion scheme for mobile objects location via the weighted least square (WLS) algorithm.Whenthe sensors present the optimal allocation and then the WLS algorithm achieves the optimal estimate. Simulation results verify the analysis of the optimal allocation form the data fusion framework, which can be used in multi-sensor passive localization and validate our analysis.

Index Terms— Geometric dilution of precision; Data Fusion; Extended Kalman filter.

I. INTRODUCTION

Wireless sensor networks (WSN) are collection of sensor nodes that can sense or observe physical orecological conditions cooperatively. Every wireless sensor nodeprovides certain sensing capability, computing and communication capacity. WSN is a networkcomposed of these sensor nodes, which is well used in mobile objects tracking.Once the density of sensor nodes ishigh enough, the sensed data is large amount data packets.Data fusion performs in-network fusion of data packets, coming from various sensors en routeto the master station, in an effort to diminish the number and size of data transmissions and thus savesensor energies [1]. Such fusion can be performed when the data from different sensors are highlyinterrelated.Conventional techniques used for datafusion include Kalman filter, Bayesian Networks and Dempter-Shafer method. Datafusionwhich seek performance gain by fusing data fromdifferent types of sensor nodes measurements. We classify data fusion methodsas three types: measurement fusion, estimate fusion andmixed fusion. In measurement fusion, only the raw locationpertainingmeasurements are fused. In estimate fusion, only the each sensor node estimates are fused. In mixed fusion, combinations ofraw measurements and sensor node estimates are fused.Concerning measurement fusion, has an angle-of-arrival(AOA) positioning system, time-difference-of-arrival(TDOA),received signal strength (RSS) and so forth.Besidesmeasurement fusion, estimate fusion is used in[2] to fuse two sensor node location estimates from TOA and TDOA estimators[n].

Mobile objects tracking has been widely applied in many fields of WSN, such as battle surveillance, environment monitoring, and fire warning control. The goal of tracking is to obtain trajectories of objects moving over the sensing field.Emerging WSN tracking systems feature in networks of a large number of small sensor nodes that can be densely deployed over the monitoring field. In this emerging WSN tracking systems using large-scale wireless sensor networks, sensor management is an essential task in order to balance the tracking performance and costs subject to limited network resources in terms of energy, communication bandwidth, and sensing range. The new paradigm results in new issues due to bandwidth and energy limitations of the network. Meanwhile, the limited sensing coverage of each sensor suggests that it is challenges for anobject to be tracked by a fixed subset of static sensors over the entire moving range.These sensor management issues are not considered in traditional tracking systems. Overall, the goal is to balance the WSN tracking quality against system resource constraints based on certain performance criterion.

Geometric Dilution of Precision (GDOP) is a measure of the performance criterion depending on the actual position of the mobile relative to the sensing nodes.Mathematically, it is defined as theratio between measured ranging error and estimated position error, and a smaller GDOP value indicates a higheraccuracy[3].For WSN tracking systems, GDOP has beenwidely used as the sensor nodes allocation performance metric. Since high localizationaccuracy always requires accurate distance measurement andgood geometric relationship between the target and thesensor nodes, it is necessary to analyzeGDOP in determiningthe performance of a WSNtracking system.To the best of the authors' knowledge, the proposed GDOP and Data fusion is an innovative idea for discussionwhen exploring the field of WSN tracking.Therefore,in this paper, we propose a data fusion scheme based on the weighted least square (WLS) algorithm for WSNtrackingproblem. The reminder of this report is organized as follows.The data fusion for WSN tracking system is presented in Section II. In Section III, we describe the optimal allocation analysis. The evaluation and experimental results are discussed in Section IV followed by conclusion in Section V.

II. DATA FUSION FOR WSN TRACKING SYSTEM

The track state vector of target j is defined as $u_j = [x_j(t), y_j(t), z_j(t), \dot{x}_j(t), \dot{y}_j(t), \dot{z}_j(t)]^T$, where $\dot{x}_j$、$\dot{y}_j$ and $\dot{z}_j$are the object velocity projected onto the$x$、y and $z$coordinates, respectively. At each time slot$t$，the mobile object obeys a linear discrete-time Markov process[4],modeled as

$u_j(t) = A_j(t)u_j(t-1) + C_J(t)v_j(t)$ (1)

Where $A_J(t)$ is the state transition matrix and $C_j(t)v_j(t)$ is process noise with $v_j(t)$ following Gaussiandistribution, i.e.,$v_j(t) \sim N(0, Q_j(t))$。

At each sensor i, its measurement vector z_{ij} for theobject$j$can be modeled as

$z_{ij}(t) = H_{ij}(t)u_j(t) + w_{ij}(t)$(2)

Where $H_{ij}(t)$is the measurement matrix, and$w_{ij}(t)$is the measurement noise of Gaussian distribution$w_{ij}(t) \sim N(0, R_{IJ}(t))$. If the equation (1) is adopted, then $z_{ij}(t) = [\widehat{x_{ij}}, \widehat{y_{ij}}, \widehat{z_{ij}},]^T$ and $H_{ij}(t)$ is simplified to

$$H_{i,t} = -\begin{bmatrix} \frac{x_0}{R_0} - \frac{x_1}{R_1} & \frac{y_0}{R_0} - \frac{y_1}{R_1} & \frac{z_0}{R_0} - \frac{z_1}{R_1} \\ \vdots & \vdots & \vdots \\ \frac{x_0}{R_0} - \frac{x_i}{R_i} & \frac{y_0}{R_0} - \frac{y_i}{R_i} & \frac{z_0}{R_0} - \frac{z_i}{R_i} \\ \vdots & \vdots & \vdots \\ \frac{x_0}{R_0} - \frac{x_n}{R_n} & \frac{y_0}{R_0} - \frac{y_n}{R_n} & \frac{z_0}{R_0} - \frac{z_n}{R_n} \end{bmatrix} \quad (3)$$

The sensor nodes allocation method developed in thispaper focuses on GDOP performance criterion, as the following:.

$$GDOP = \frac{\sqrt{Var_{(x)} + Var_{(y)} + Var_{(z)}}}{\sigma_R} = \frac{\sqrt{\sigma_R^2 trace(H^T Q^{-1} H)^{-1}}}{\sigma_R}$$
$$= \frac{\sigma_R \sqrt{(H^T Q^{-1} H)^{-1}}}{\sigma_R} = \sqrt{trace(H^T Q^{-1} H)^{-1}}$$

(4)

In equation (4), the process noisecovariance matrix $Q_j(t)$ depends on the target motionand is typically assumed to be time invariant andknown a priori.

After target-sensor allocation decisions$\{S_j(t)\}_{j=1}^{N_a}$have been made in the sensor management module, track fusion for each object$j$is performed viacooperation among all sensors in$S_j(t)$，$\forall j$. To do so, Extended Kalman filtering (EKF) can be applied based on theWSN dynamic model and themeasurement model in (2). Following the notational convention of EKF, we let $\hat{u}_j(t|t-1)$denote the predicted a priori statevector of object$j$at time tgiven all the availablemeasurements up to$t-1$, and $\hat{u}_j(t|t)$ denote theupdated a posteriori state estimate after incorporatingthe measurements $\{z_{ij}(t)\}_i$ from the allocated sensor nodes $i \in \hat{u}_j(t)$. Correspondingly, the prior and posteriorestimation errors for object$j$are $e_j(t|t-1) = u_j(t) - \hat{u}_j(t|t-1)$ and $e_j(t|t) = u_j(t) - \hat{u}_j(t|t)$, respectively, whose error covariance matrices are defined as$P_j(t|t-1) = E[e_j(t|t-1)e_j^T(t|t-1)]$ and $P_j(t|t) = E[e_j(t|t)e_j^T(t|t)]$,where $(\cdot)^T$ denotes transpose and$E[\cdot]$denotes expectation.

To facilitate sensor management, we adoptan information form of EKF for track fusion scheme(Figure 1), inwhich the state vector estimate $\hat{u}_j$ and the estimateerror covariance matrix P_j are transformed intothe information state vector$\hat{y}_j = P_j^{-1}\hat{u}_j$ and the information matrix$Y_j = P_j^{-1}$, respectively. Evidently, the updates $(\hat{u}_j, P_j)$, in the traditional EKFcan be equivalently obtained from ($\hat{y}_j, Y_j$), which aregiven by the transformed EKF updating rule, as follows:

State Prediction:

$\hat{y}_j(t|t-1) =$
$Y_j(t|t-1)A_j(t)Y_j^{-1}(t-1|t-1)\hat{y}_j(t-1|t-1)$(4)

$Y_j^{-1}(t|t-1) = A(t)Y_j^{-1}(t-1|t-1)A^T(t)$
$+ C(t)Q(t)C^T(t)$ (5)

State correction from neighbornodes (*Na*) of measurements:

$\hat{y}_j(t|t) = \hat{y}_j(t|t-1) + \sum_{i \in s_j(t)} H_{ij}^T(t)R_{ij}^{-1}(t)z_{ij}(t)$(6)

$Y_j(t|t) = Y_j(t|t-1) + \sum_{i \in s_j(t)} H_{ij}^T(t)R_{ij}^{-1}(t)H_{ij}(t)$ (7)

The above information form of EKF is equivalent tothe traditional EKF in terms of tracking performance,and provides computational advantages formulti-sensor nodes data fusion.

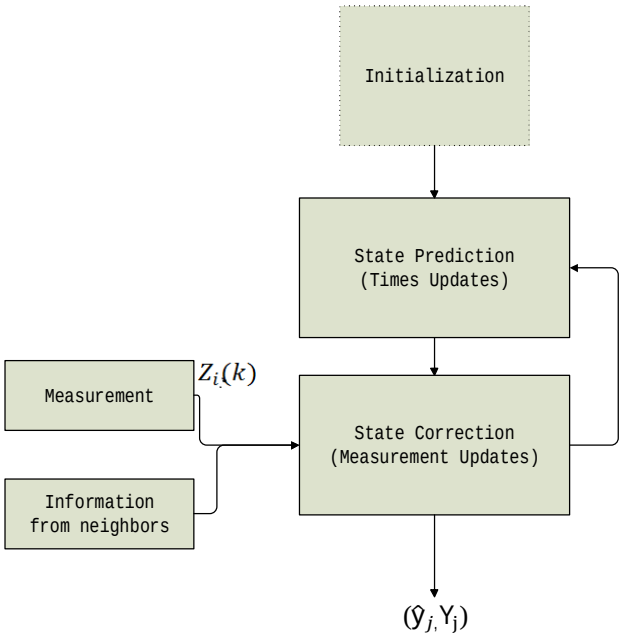


Figure 1. The data fusion scheme for WSN tracking system

The WLS solution for data fusion scheme[5], which weights are

$$\beta_i = \frac{\left[GDOP^i_{(t+1|t+1)}\right]^{-1}}{\left[\sum_{j=1}^{N} GDOP^j_{(t+1|t+1)}\right]^{-1}} \quad (8)$$

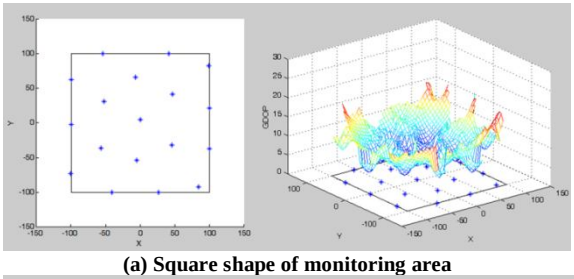
And master sensor node (i.e. cluster head) states is updated as the following

$$\hat{Y}^m_{(t+1|t+1)} = \sum_{i=1}^{Na} \beta_i \hat{X}^i_{(t+1|t+1)} (9)$$

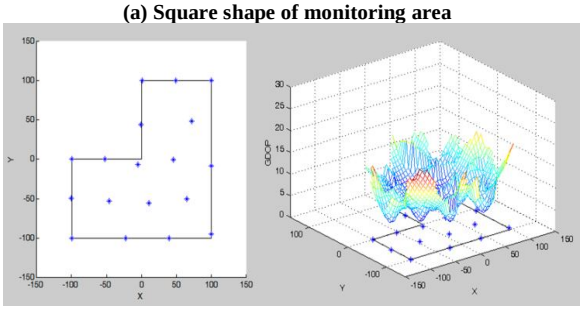
III. OPTIMAL ALLOCATION ANALYSIS

Passive location performance is usually measured in terms of theaccuracy of the position estimation. GDOP also describes theeffect of geometry on the relationship between measurementerror and position determination error. Thus, in general, theaccuracy of a position estimate can be expressed as the productof the GDOP at a point and the root-mean-square error(RMSE) of the ranging errors from stations to the moving object. When the time error is definite, the GDOP value ishigher resulting in poorer location performance while theGDOP value is lower resulting in higher location performance. For a WSN tracking system, if the location and number of sensor nodes in the monitoring area are not carefully allocated, theGDOP effect can become the dominant factor in limiting the tracking performance.

Through the above analysis of the location accuracy, theaccuracy depends on a number of factors, including the mobile object position and the geometry of allocation, TDOAtime measurement error standard deviation, and disposition patterns and so on.In this paper, we emphasize the optimal allocation influence on the location and discuss the3D curves of location error and GDOP contour maps of eighteen sensornodes allocation in the various monitor area as the Figure 2.



(a) Square shape of monitoring area



(b) L-shaped of monitoring area

Figure 2.The GDOP 3D curve and countour map of the location error distribution in two cases

In general, a larger GDOP value corresponds to a comparably worse geometric allocation, which consequently results in augmented errors for location estimation.The GDOP associated with the position error is utilized as an index for observing the location precision of the master node under different geometric location within the networks.

IV. EVALUATION AND EXPERIMENTAL RESULTS

In this section, we will present the simulation results of ourdata fusion scheme for WSN tracking system. All simulations are executed in Matlab 7.0.

At first, 18 sensor nodes (denoted by blue circle) are randomly allocation in the monitoring of square area, the red circle, mobile object, moving to thepredefined area. Figure 3 show the WSN tracking system in location/tracking working around. We can see that the sensor nodes initially andrandomly distributed over the monitoring area and dynamically allocation in the ring along with mobile object, which means the adaptive allocation is achieved.

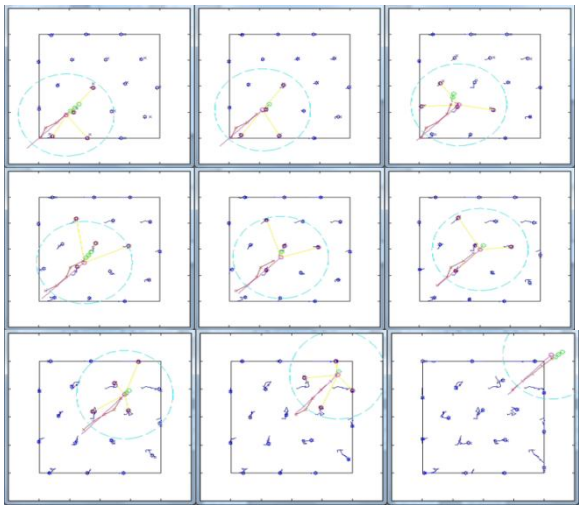


Figure 3 Illustration of WSN tracking system in different steps with dynamically allocation on a compact region

We next evaluate the performance of the proposed data fusion scheme in tracking multiple targets in three dimensions[6]. Figure 4 shows the results of five targets.As shown in the bottom of Figure 4, the proposed data fusion scheme provides very accurate estimation for WSN measurements. Clearly, the estimated trajectories match well the any trajectories of the ground truth.

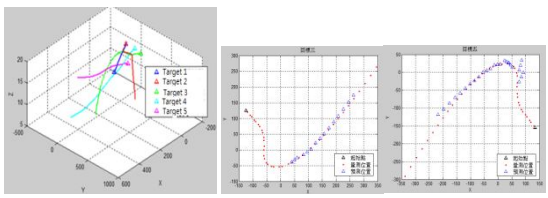


Figure4.Tracking motion of five targets. The red dots show the true measurements(Target 3 on the left bottom; Target 5 on the right bottom); the blue dots represent the estimated of targets

CONCLUSION

In this research, the data fusion scheme based on the weighted least square (WLS)for WSNtracking is proposed. The scheme obtained from the extendedKalman filtering formulation is exploited as theadditional measurement inputs for the sensor nodes optimal allocation. With this information, sufficient multi-sensor information became available for location and tracking of a mobile object. It is shown in the simulation results that the proposed data fusion scheme can provideconsistent accuracy for sensor nodes allocation and tracking even with multiple objects.

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