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Multisensor Data Fusion Algorithms for Estimation of a Walking Person Position

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Abstract: This paper presents the problem of sensor fusion to estimate a walking person position. Simple walking person moving model is introduced. We propose two filtering algorithms to solve the present problem. The first algorithm represents an extended Kalman filter (EKF) model which is based on the principle of the state transition matrix and observation matrix linearization under Taylor series expansions. During walking, several various "walking modes" differ from each other in terms of moving model parameters. This fact is addressed to the second sensor fusion algorithm, namely, the interacting multiple model (IMM) algorithm, which also employes a single EKF for each considered mode, combines the state estimates and covariance matrices.

Keywords: Data fusion, extended Kalman filter, interacting multiple model, multisensor model.

1. INTRODUCTION

Data fusion techniques combine data from multiple sensors and related information from associated databases to improve accuracy and specific inference in compassion with the case when we implement a single sensor [1] and [2]. The concept of data fusion is not new. The emergence of new sensors, advanced signal processing techniques, and improved signal processing hardware make possible a real-time fusion of data [3] and [4]. Currently, data fusion systems are employed extensively for target tracking, automated identification of targets, and limited automated reasoning applications. In principle, a fusion of multisensor data provides significant advantages over single source data. In addition to the statistical advantage gained by combining the same source data (e.g., to obtain an improved estimate of a physical phenomena via redundant observations), the use of multiple types of sensors may increase a performance accuracy.

Global Positioning System (GPS) is a satellite-based navigation system equipped with the receiver that provides the user with appropriate and accurate positioning information anywhere on the globe [5]. However, several errors are associated with the GPS measurement. It has superior long-term error performance but poor short-term accuracy. For many navigation systems, GPS is insufficient as a stand-alone positioning system. The integration of GPS and Inertial Navigation System (INS) is ideal procedure for navigational systems.

Kalman filtering is a form of optimal estimation characterized by recursive evaluation using an estimated internal model of system dynamic. The system dynamic weighting of incoming evidence with ongoing expectation produces estimates of the observed system state [6]. The extended Kalman filter (EKF) has been used extensively in the field of sensor fusion and navigation [7]–[9]. The EKF can be employed to fuse measurements from GPS and INS. In EKF circuitry, the INS data are used as a reference trajectory, and GPS data are considered to update and estimate the error states of trajectory. The Kalman filter requires that all the plant dynamics and noise processes are exactly known, and the noise processes are zero mean white Gaussian noise. If the theoretical performance and actual performance of the Kalman filter are differed, the problems of divergence are arises. There are two kinds of divergence: the apparent divergence [10] and the true divergence [11]. In the case of apparent divergence, the actual estimate error covariance matrix remains bounded but it approaches a higher bound than the predicted error covariance one. In the true divergence, the actual estimation covariance matrix becomes eventually infinite. For example, to track different phases of aircraft moving, a number of multiple-model algorithms have been developed for which interacting multiple model (IMM) estimator is widely used [12].

In this paper, we propose the multisensor data fusion algorithms for walking person position estimation. To solve this problem we investigate two filtering algorithms. The first algorithm is based on the extended Kalman filter model and the second one is based on interacting multiple model algorithm. Computer simulation results show a superiority in performance of the proposed algorithms under estimation of the moving object position over the modern algorithms used, in particularly, to identify the location and distance to the moving object.

The remainder of this paper is organized as follows. Section 2 describes the system model that is based on EKF and IMM algorithm with EKFs. In Section 3, we discuss the simulation results obtained for the proposed algorithms and confirmed our theoretical study. Finally, the conclusions are discussed in Section 4.

2. SYSTEM MODEL

2.1 Covariance matrix evaluation

The covariance is a measure of the extent to which corresponding elements from two sets of ordered data move in the same direction. Let X and Y represent the two random variables. Then the covariance of X and Y, can be mathematically represent by the following equation

$$\mathrm{cov}(X,Y)=\sum_{i=1}^{N}\frac{(x_i-\overline{x})(y_i-\overline{y})}{N}, \qquad (1)$$

where $\overline{x}$ is the mean of the random variables X and $\overline{y}$ is the mean of the random variables Y. The covariance matrix is the matrix with elements $c_{i,j}$. Considering the columns of the data matrix **A** as the sample vectors, we can write the elements of the covariance matrix **C** as:

$$c_{i,j}=\frac{1}{N}\sum_{i=1}^{N}a_{ij}a_{ji}, \qquad (2)$$

or in the matrix form

$$\mathbf{C}=\frac{1}{N}\mathbf{A}\mathbf{A}^T. \qquad (3)$$

The Singular Value Decomposition (SVD) is a technique for decomposing a matrix into a set of rotation and scale. SVD technique can be used to evaluate the covariance matrix of the clustering GPS data set, and can be expressed by the following matrix form

$$\mathbf{A}=\mathbf{U}\mathbf{S}\mathbf{V}^T, \qquad (4)$$

where **U** and **V** are the normalized eigenvectors of matrix $\mathbf{AA}^T$ and matrix $\mathbf{A}^T\mathbf{A}$, respectively. The columns of **U** and **V** are called the left- and right-singular vectors of **A**, respectively. **S** is the diagonal matrix, elements of which are the square-roots of eigenvalues of matrices $\mathbf{A}^T\mathbf{A}$ and $\mathbf{AA}^T$ and are the singular values along the diagonal of the **S** matrix [13]. Because of this **U** can be calculated as the eigenvectors of $\mathbf{AA}^T$. So, the elements of the **U** matrix are the eigenvectors of covariance matrix which are the axes of maximum variance. The **S** matrix takes in scalar factor.

2.2 System State Equation

Consider the object moving from B to B' as shown in Fig.1. The distance traveled is denoted by $\mathbf{\Delta}D(k)$ and the angle changed is denoted by $\mathbf{\Delta}\theta(k)$. Let $\mathbf{\Delta}D_r(k)$ and $\mathbf{\Delta}D_l(k)$ denote the covered distances of the right and left side of the reference point B, respectively. Therefore, based on Fig.1 we can write the following equations:

$$\mathbf{\Delta}D_r(k)=(R+L)\mathbf{\Delta}\theta(k) \qquad (5)$$

and

$$\mathbf{\Delta}D_l(k)=R\mathbf{\Delta}\theta(k). \qquad (6)$$

Now, we can derive the increments of distance denoted by $\mathbf{\Delta}D(k)$ and angle or orientation denoted by $\Delta\theta(k)$ as follows:

$$\mathbf{\Delta}D(k)=\frac{\mathbf{\Delta}D_l(k)+\mathbf{\Delta}D_r(k)}{2} \qquad (7)$$

and

$$\mathbf{\Delta}\theta(k)=\frac{\mathbf{\Delta}D_r(k)-\mathbf{\Delta}D_l(k)}{L}. \qquad (8)$$

From (7) and (8) it follows that $\mathbf{\Delta}D(k)$ is the average of the outer and inner arcs and $\mathbf{\Delta}\theta(k)$ is proportional to the difference between the outer and inner arcs.

The position and orientation of the moving object after relocation from the point B to the point B' through a circular arc is shown in Fig.2. Reference to Fig.2 allows us to obtain the following relations:

$$\mathbf{\Delta}D(\mathrm{k})=\widehat{BB'}; \qquad (9)$$

$$\mathbf{\Delta}\theta(k)=\angle B'OB=\angle BGG'; \qquad (10)$$

$$\Delta OB'G\cong\Delta OBG, \qquad (11)$$

where $\widehat{BB'}$ stands for the length of the circular arc BB', the symbol $\angle$ denotes the angle between two lines, Δ is the symbol of triangle, the symbol $\cong$ is used to indicate congruent triangles. From (11), we can get the following relations:

$$\angle B'GO=\angle BGO, \qquad (12)$$

$$\overline{B'G}=\overline{BG}. \qquad (13)$$

Here $\overline{B'G}$ and $\overline{BG}$ stand for the length of the line segment $B'G$ and BG, respectively. Reference to (12) and (13) allows us to define the following associated relations:

$$\Delta B'GE\cong\Delta BGE; \qquad (14)$$

$$\Delta BGE\sim\Delta BGO; \qquad (15)$$

$$\angle EBG\cong\angle GOB=\mathbf{\Delta}\theta(k)/2; \qquad (16)$$

$$\angle B'BC=\theta(k-1)+\mathbf{\Delta}\theta(k)/2. \qquad (17)$$

Here, the symbol ~ is used for similar triangles. Based on Fig.2 we can also derive the following equation:

$$\frac{\widehat{BB'}}{\overline{BB'}}=\frac{(R+L/2)\mathbf{\Delta}\theta(k)}{2(R+L/2)\sin[\mathbf{\Delta}\theta(k)/2]}=\frac{\mathbf{\Delta}\theta(k)}{2\sin[\mathbf{\Delta}\theta(k)/2]}. \qquad (18)$$

Using (18) the length of the line BB' can be derived finally in the following form:

$$\overline{BB'} = \frac{\sin[\boldsymbol{\Delta}\theta(k)/2]}{\boldsymbol{\Delta}\theta(k)}\widehat{BB'} = \frac{\sin[\boldsymbol{\Delta}\theta(k)/2]}{\boldsymbol{\Delta}\theta(k)}\boldsymbol{\Delta}D(k)\,. \quad (19)$$

The state vector of the moving object at kth reading is given by

$$\mathbf{X}(k) = [x(k), y(k), \theta(k)]^T\,, \quad (20)$$

where, $x(k)$, $y(k)$ and $\theta(k)$ represent the initial position of object at the center of rear axle and the heading angle of the moving object in the reference frame (X_{ref}, Y_{ref}), respectively, given by

$$\mathbf{X}(k) = \begin{bmatrix} x(k) \\ y(k) \\ \theta(k) \end{bmatrix} = \begin{bmatrix} x(k-1) + \Delta x(k) \\ y(k-1) + \Delta y(k) \\ \theta(k-1) + \Delta\theta(k) \end{bmatrix} + w(k)\,, \quad (21)$$

where $w(k)$ is the Gaussian noise.

Assuming that the position and orientation of the moving object at the (k–1)th reading is known, then we can obtain the state vector $\mathbf{X}(k)$ of the moving object at the kth reading as follows:

$$\mathbf{X}(k) = \begin{bmatrix} x(k-1) + \overline{BB'}\cos[\theta(k-1) + \Delta\theta(k)/2] \\ y(k-1) + \overline{BB'}\sin[\theta(k-1) + \Delta\theta(k)/2] \\ \theta(k-1) + \Delta\theta(k) \end{bmatrix} + w(k)\,. \quad (22)$$

Therefore,

$$\mathbf{X}(k) = \begin{bmatrix} x(k-1) + \dfrac{\sin[\Delta\theta(k)/2]}{\Delta\theta(k)/2}\Delta D(k) \\ \times\cos[\theta(k-1) + \Delta\theta(k)/2] \\ \\ y(k-1) + \dfrac{\sin[\Delta\theta(k)/2]}{\Delta\theta(k)/2}\Delta D(k) \\ \times\sin[\theta(k-1) + \Delta\theta(k)/2] \\ \\ \theta(k-1) + \Delta\theta(k) \end{bmatrix} + w(k)\,. \quad (23)$$

As $\theta(k) \to 0$, we think that $\dfrac{\sin[\Delta\theta(k)/2]}{\Delta\theta(k)/2} \to 1$. Thus we can conclude if the sampling interval is small enough, the state equation of the moving object can be also written as follows:

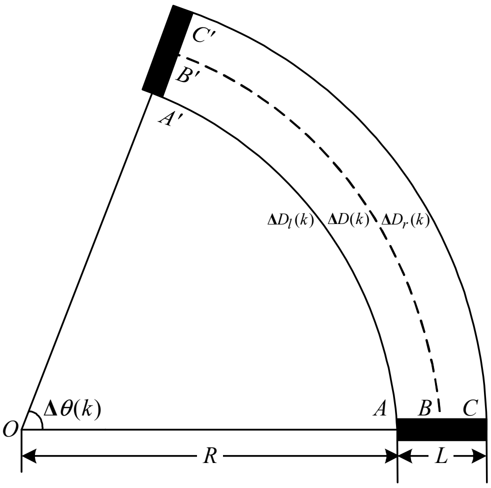


Fig. 1 Arc movement of the moving object.

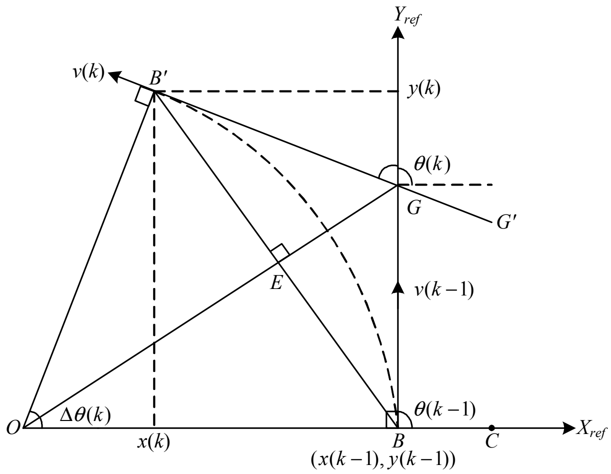


Fig. 2 The position and orientation changes after relocation.

$$\mathbf{X}(k) = \begin{bmatrix} x(k-1) + \boldsymbol{\Delta}D(k)\cos[\theta(k-1) \\ + \boldsymbol{\Delta}\theta(k)/2] \\ \\ y(k-1) + \boldsymbol{\Delta}D(k)\sin[\theta(k-1) \\ + \boldsymbol{\Delta}\theta(k)/2] \\ \\ \theta(k-1) + \boldsymbol{\Delta}\theta(k) \end{bmatrix} + w(k)\,. \quad (24)$$

Equation (24) will be used as the system state equation for determining the position and orientation of the moving object.

2.3 GPS Measurement Model

The position x_g, y_g and the heading angle θ_g measurement provided by GPS receiver is related with the state vector as given by

$$z_p = \begin{bmatrix} x_g(k) \\ y_g(k) \\ \theta_g(k) \end{bmatrix} = \begin{bmatrix} x(k) \\ y(k) \\ \theta(k) \end{bmatrix} + v_g(k) , \tag{25}$$

where $v_g(k)$ is the GPS measurement noise, which is assumed to be the additive white Gaussian noise (AWGN).

2.4 EKF Solution

The state transition and observation models equations must be linear for the extended Kalman filter application as given by

$$\mathbf{X}(k) = \mathbf{f}[\mathbf{X}(k-1), \mathbf{u}(k)] + \mathbf{W}\mathbf{w}(k-1) , \tag{26}$$

$$\mathbf{z}(k) = \mathbf{h}[\mathbf{X}(k) + \mathbf{V}\mathbf{v}(k)] , \tag{27}$$

where $\mathbf{z}(k)$ is the observed vector, $\mathbf{u}(k) = [\mathbf{v}(k), \varphi(k)]^T$ is the input of the system, $\mathbf{f}$ and $\mathbf{W}$ denote the Jacobian matrices of partial derivatives of the system state with respect to X and $\mathbf{w}$; $\mathbf{h}$ and $\mathbf{V}$ are the Jacobian matrices of partial derivatives of the observed equation with respect to X and $\mathbf{v}$.

2.5 IMM Algorithm with EKF

Let us consider the problem of distinguishing the various "walking modes" when the object is moving. These modes differ by parameters of movement models. This phenomenon is addressed to the second sensor fusion algorithm, namely, the IMM algorithm [14] and [15], which uses a specific and differed from mode to mode EKF for each considered mode and combines their state estimates and covariance matrices according to probabilities of current movement mode.

Let $\mu_i(k \mid k)$ be the probability of the event that mode i is valid in time step k. Let π_{ij} be the probability of the event that the mode i is switched to the mode j.

At the beginning of each time step k, the estimates from the previous step are mixed to determine the initialization estimates for the current time step. First, the predicted probability of mode is computed for each mode from set M ($1 \le j \le M$)

$$\mu_j(k \mid k-1) = \sum_i \pi_{ij} . \tag{28}$$

The mixing probability $\mu_{i|j}(k)$ denotes an influence of mode i from time step $k-1$ on initialization estimates of mode j at time step k

$$\mu_{i|j}(k) = \frac{\pi_{ij}\mu_i(k-1 \mid k-1)}{\mu_j(k \mid k-1)} . \tag{29}$$

The initialization estimate $\hat{p}_{0j}(k-1)$ and its corresponding covariance matrix $\mathbf{P}_{0j}(k-1)$ are computed as follows

$$\hat{p}_{0j}(k-1) = \sum_i \hat{p}_i(k-1 \mid k-1)\mu_{i|j}(k) ; \tag{30}$$

$$\begin{aligned} \mathbf{P}_{0j}(k-1) = \sum_i \Big(& P_i(k-1 \mid k-1) + [\hat{p}_i(k-1 \mid k-1) \\ & - \hat{p}_{0j}(k-1)] \times [\hat{p}_i(k-1 \mid k-1) \\ & - \hat{p}_{0j}(k-1)]^T \Big) \mu_{i|j}(k) . \end{aligned} \tag{31}$$

Each of the pairs $\hat{p}_{0j}(k-1)$ and $\mathbf{P}_{0j}(k-1)$ is then used as an input to the filter of mode j, instead of $\hat{p}_j(k-1 \mid k-1)$ and $P_j(k-1 \mid k-1)$. The estimate vector $\hat{p}_j(k \mid k)$ with covariance matrix $\mathbf{P}_j(k \mid k)$ and the innovation vector $\mathbf{s}_j(k)$ with covariance matrix $\mathbf{S}_j(k)$ are the filter output.

Next the likelihood function $\Lambda_j(k)$ and the new probability $\mu_i(k \mid k)$ of each mode are computed

$$\begin{aligned} \Lambda_j(k) = & \left(2\pi \det \mathbf{S}_j(k)\right)^{-0.5} \\ & \times \exp\left(-0.5\mathbf{s}_j^T(k)\mathbf{S}_j^{-1}(k)\mathbf{s}_j(k)\right) , \end{aligned} \tag{32}$$

$$\mu_{i|j}(k \mid k) = \frac{\mu_j(k \mid k-1)\Lambda_j(k)}{\sum_i \mu_i(k \mid k-1)\Lambda_i(k)} . \tag{33}$$

In the final step the estimates $\hat{p}_j(k \mid k)$ and covariance matrices $\mathbf{P}_j(k \mid k)$ from each filter are combined into single estimate $\hat{p}(k \mid k)$ and its covariance matrix $\mathbf{P}(k \mid k)$, namely,

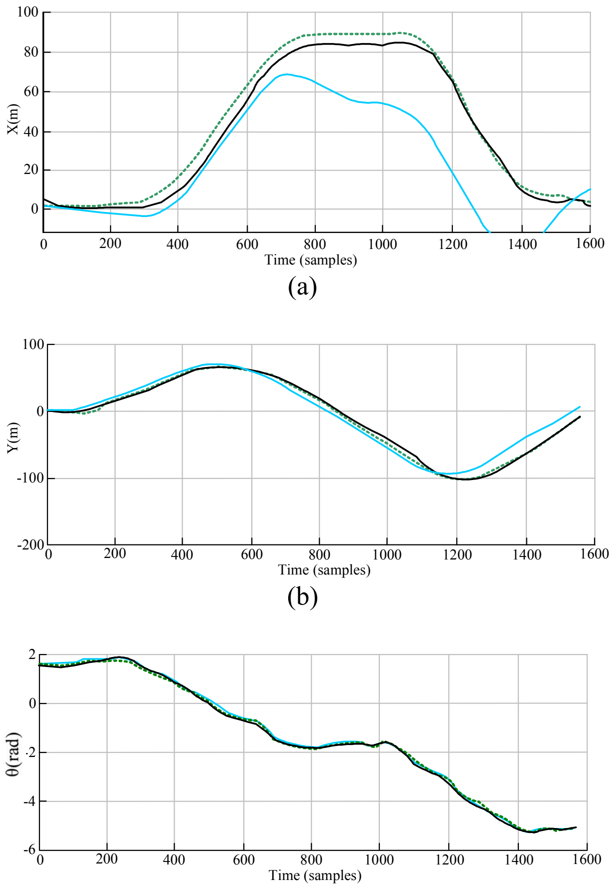
$$\hat{p}(k \mid k) = \sum_j \hat{p}_j(k \mid k)\mu_j(k) , \tag{34}$$

$$\begin{aligned} \mathbf{P}(k \mid k) = \sum_j \Big(& P_j(k \mid k) + [\hat{p}_j(k \mid k) - \hat{p}(k \mid k)] \\ & \times [\hat{p}_j(k \mid k) - \hat{p}(k \mid k)]^T \Big) \mu_j(k) . \end{aligned} \tag{35}$$

3. SIMULATION RESULTS

Fig. 3 presents the state in the X and Y directions and orientation of the moving object with the time step. The proposed algorithms to obtain estimation are compared with GPS data and the odometry estimation [12]. From Fig.3 (a) it is observed that EKF and GPS response are superior between the time step 0-250 and 750-1150. In the long term, GPS data provides time-invariant errors that are smaller in comparison with odometry and vice versa. Additionally, we can see that the response of the proposed algorithms is superior in comparison with odometry estimation but less superior in comparison with GPS response.

In Fig.3 (b) the moving object positions on the Y axis for three cases are almost the same up to time step 1200 but after time step 1200 a small variance is observed



(a)

(b)

(c)

Fig. 3 Position measurements (X (m)-a, Y(m)-b) and angle measurements (c) versus time step for EKF, GPS and odometry.

between EKF, GPS and odometry estimation data. In the location, where GPS variance is high, the estimation will decrease the reliability in GPS data to update state. The orientations of the moving object position for three cases are the same and this phenomenon is presented in Fig.3(c).

4. CONCLUSION

In this paper, the multisensor data fusion algorithms are derived for estimation of a walking person position. We propose two filtering algorithms to identify the location and distance to the moving object. The first algorithm is based on the extended Kalman filter model and the second one is based on the IMM algorithm. Simulation results demonstrate superiority of the proposed algorithms in estimation of moving object position. Further research requires an accurate analysis and definition of the factors acting on the performance of individual filters in order to improve the precision of moving object position estimation.

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