Tracking of a Rotating Object in a Wireless Sensor Network Using Fuzzy Based Adaptive IMM Filter

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***Abstract*—In this paper, a new fuzzy-logic based adaptive Interactive Multiple Model (IMM) filter is presented for tracking a vehicular rotating object in a Wireless Sensor Network (WSN). In this method, a Fuzzy-logic Inference System (FIS) is employed to adaptively tune the system noise covariance matrix associated with the Nearly Constant Velocity (NCV) model. By reducing the number of interacting models, our algorithm simplifies state-of-the-art IMM algorithms for tracking of a rotating object. Localization for data aggregation process is performed by means of the triangulation method in conjunction with dynamic grouping of sensors. Monte Carlo simulations show that this scheme achieves good tracking performance for both highly rotating and non-rotating objects compared to state-of-the-art IMM algorithms.**

I. Introduction

The capability to manufacture small-sized and low-cost sensor nodes, which include sensing, data processing, and communication components, makes it possible to set up so-called Wireless Sensor Networks (WSN). This emerging technology has been utilized for environmental measuring, monitoring, surveillance, audio enhancement, and many other applications. A WSN consists of many low cost, spatially dispersed position sensor nodes. Each node can process information and share data with the sensor nodes that are placed within its communication range or only with a leader node (cluster head). The advantages of WSNs over the traditional sensing methods are not only extending the spatial coverage and achieving higher resolution, but also increasing the fault tolerance and robustness of the whole system [1].

Among the WSN applications, object tracking has received great attention for commercial, public-safety, and military applications. The greatest challenge associated with this problem is the accuracy of the state estimation module. Since the nodes of a WSN are physically distributed, the computation and estimation procedure in object tracking should preferably also be distributed. For an object with nearly constant velocity, kinematics will be linear and the tracking problem could be performed using the standard Kalman Filter (KF). However, when rotation is to be taken into consideration, the single standard (linear) KF is not applicable anymore due to the fact that in this case the dynamics are nonlinear. This issue makes that the unknown acceleration appears as large process noise in the object model and since the model's noise level cannot cover it, filter divergence may occur. A first attempt to resolve this difficulty was made by Singer [2], who proposed an object localization model in which rotation was assumed to be a first-order Markov process with time correlation. Many approaches were proposed for increasing the performance of the filters with a single model. Some works also combined fuzzy logic with the KF [3], but still were not able to track a highly rotating object because of the hybrid nature of the problem. Later, various techniques were developed, where multiple models are used to describe the different potential modes of object motion where the final estimate is obtained by a weighted sum of the estimates from the sub-filters of the different models [4]. In this scheme, different levels of potential object movements are performed in parallel using distinct filters. To be more realistic, rotations are typically abrupt deviations from basically a straight-line object motion and therefore the problem can be treated as a hybrid problem. One of the most successful yet challenging hybrid state estimators is an Interactive Multiple Model (IMM) approach which has received a large amount of research attention on itself. However, this algorithm needs predefined sub-models with different dimensions or process noise levels, and may not guarantee good performance in the case where one of the models does not exactly match the object's motion. An approach to resolve this problem is estimating an unknown input simultaneously or using the adaptive IMM (AIMM) algorithm, where the input is estimated by a two-stage Kalman estimator and sub-

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models are determined based on the estimated input [11, 12]. On the other hand, the bank of models should incorporate all possible modes of motion [5] and therefore, the complexity of the system and computational burden increase considerably. In [6], the authors used fuzzy logic to enhance the performance of a radar-based tracking system, yet merely utilizing the linear constant velocity models that cannot track a rotating object. By taking the above limitations into consideration, this paper proposes a novel scheme to adjust the process noise covariance level based on a fuzzy inference module for an object which moves in a sensor field. The input of a nonlinear Nearly Coordinated Turn (NCT) model will be estimated and considered as a maneuver interval detector which is the input of the fuzzy module. By applying this modification to the IMM, the need for several models which are alike but different in noise level is relaxed and therefore this takes IMM hybrid estimator to the next level by removing the need of models for all possible modes. Consequently, beside increasing the performance of the object tracking system , which is the main objective of this paper, the computational burden and energy consumption of the sensor nodes decreases dramatically.

The outline of the paper is as follows: Section II presents the Nearly Constant Velocity (NCV) and NCT models. Moreover the IMM algorithm and fundamental topics of triangulation are also introduced in this part. The proposed Fuzzy-based adaptive IMM is explained in section III. Section IV shows the simulation results of the proposed algorithm. Conclusions are drawn in Section V.

II. Problem Statement

The problem of tracking a rotating object in a wireless sensor network will be considered. In addition to defining the problem, this section discusses the required models and approaches used in this paper. The main contribution of this paper is highly focused on fuzzy-logic based adjustment of the noise covariance matrix for the NCV model which is performed in parallel with the NCT model in an IMM framework. The entire block diagram of the proposed system is illustrated in figure 1. In the sequel, we will explain the different blocks of this system. We assume that the rotating object has a nearly constant velocity and angular rate, at least within a sensor sampling interval. This section introduces the kinematic models, IMM, and explains the details and the assumptions on the data association module of the tracker system which is performed by wireless sensor nodes.

A. Nearly Constant Velocity (NCV) Model

A Nearly Constant Velocity (NCV) model is given by the following state-space representation, in which the state vector is defined as $X_k = [x_k|v_{x_k}|y_k|v_{y_k}]^T$, where k is the sample time, x_k and y_k denote the 2D coordinates of the location of the object, and v_{x_k} and v_{y_k} denote the 2D coordinates of the velocity vector:

$$\begin{bmatrix} x_{k+1} \\ v_{x_{k+1}} \\ y_{k+1} \\ v_{y_{k+1}} \end{bmatrix} = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} X_k + \begin{bmatrix} \frac{1}{2}T^2 & 0 \\ T & 0 \\ 0 & \frac{1}{2}T^2 \\ 0 & T \end{bmatrix} V_k$$

where T is the sampling interval and $V_k \sim N(0, \sigma_v^2)$ is zero-mean Gaussian white noise used to model small accelerations and other possible imperfections [7]. The noise covariance matrix Q, which will be needed in the KF, can be calculated easily [4].
This model differs from the uniform motion models only in the considered white noise level. The most interesting point about this model is that it is linear, and therefore a standard KF can be applied [7].

B. Nearly Coordinated Turn (NCT) Model

In order to describe the object's more complex moving patterns, including rotation, we consider the following coordinated turn model similar to what is used in [8,17]:

$$\begin{bmatrix} x_{k+1} \\ v_{x_{k+1}} \\ y_{k+1} \\ v_{y_{k+1}} \\ \omega_{k+1} \end{bmatrix} = \begin{bmatrix} 1 & \frac{\sin \omega_k T}{\omega_k} & 0 & -\frac{1-\cos \omega_k T}{\omega_k} & 0 \\ 0 & \cos \omega_k T & 0 & -\sin \omega_k T & 0 \\ 0 & \frac{1-\cos \omega_k T}{\omega_k} & 1 & \frac{\sin \omega_k T}{\omega_k} & 0 \\ 0 & \sin \omega_k T & 0 & \cos \omega_k T & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} X_k + \begin{bmatrix} \frac{1}{2}T^2 & 0 & 0 \\ T & 0 & 0 \\ 0 & \frac{1}{2}T^2 & 0 \\ 0 & T & 0 \\ 0 & 0 & 1 \end{bmatrix} V_k$$

where in the system dynamics matrix above ω_k is the turn rate and $V_k \sim N(0, diag[\sigma_x^2, \sigma_y^2, \sigma_\omega^2]$ is a zero-mean Gaussian white noise used to model imperfections. It should be noticed that this model is nonlinear since the turn rate is included in both the state vector and the transition matrix. Because of this nonlinearity, the estimation of the state parameters will be done with an Extended Kalman Filter (EKF) within the IMM filtering framework [15,18].

C. IMM Filter

The IMM filter assumes that an object acts according to one of M modes (e.g. moving with constant velocity/acceleration, or rotating with a constant turn rate or even stopped). The mode (model) switching is considered as a Markov Chain and thus it can be fully characterized by the transition and initial probabilities. Estimation of these transition probabilities is the main goal of the IMM filter which, in turn, minimizes the tracking error. In each time step, the corresponding measured observations play an important role in the estimation update. The operation of the IMM algorithm can be explained as follows:
1) In this paper, IMM consists of two models and their associated filters: a linear NCV with standard KF covering uniform movements and small maneuvers, and a nonlinear NCT in conjunction with EKF covering rotating motions,

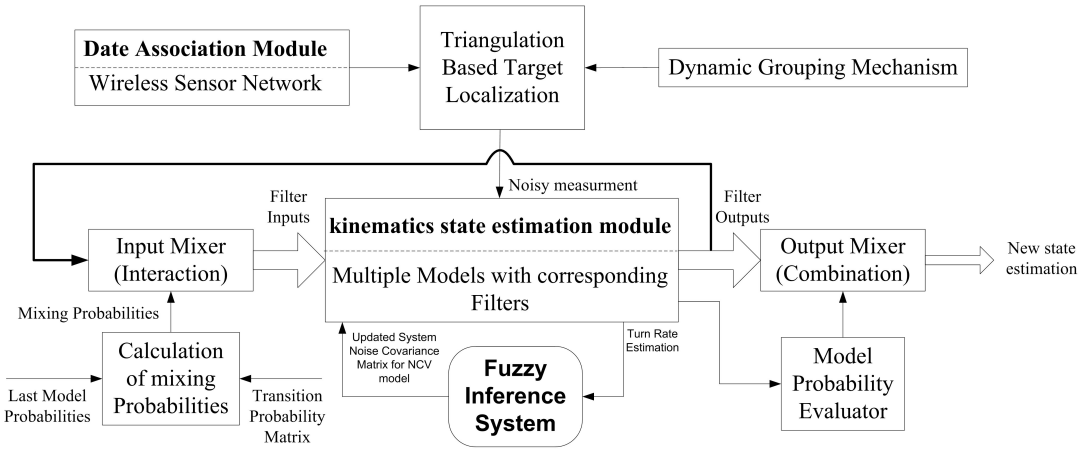

Fig. 1. Complete Block Diagram of the System

2) these filters interact (exchange information) with time-varying weights i.e. the mixing probabilities,
3) the final estimate is a combination (weighted average) of each filter's estimate, with the weights being the mode probabilities,
4) the weights for interaction and combination are based on which model fits best with the data (and other factors, such as the expected transition from one mode to another) [8].
In the sequel, we only provide a concise description of the IMM filter and for further details, refer to [4,9]. In general, we will use $\hat{X}$ to denote the estimation of X, where X is the state vector of the tracking system. Furthermore, we use superscripts "$+$" and "$-$" to denote the estimation *after* and *before* arrival of the measurement at the specific time step. One cycle of the algorithm at time step k consists of the following steps [4,10]:
Step1- Calculation of the mixing probabilities and interaction between models:

$$\mu_{i|j_{k-1}} = \frac{p_{ij}\mu_{i_{k-1}}}{\sum_{i=1}^{r} p_{ij}\mu_{i_{k-1}}} \tag{1}$$

where $\mu_{i|j_{k-1}}$ is the probability that the ith model was in effect at step $k-1$ given that the jth mode is in effect at step k, and p_{ij} is the assumed transition probability for switching from model i to model j. It is claimed in [4] that the final results are not very sensitive to the values of these transition probabilities. The mixed initial condition (denoted by superscript "^{0}"), which is obtained by means of the weighted sum of the individual filter outputs from the previous time step, is computed as:

$$\hat{X}^{+^0}_{j_{k-1}} = \sum_{i=1}^{r} \hat{X}^{+}_{i_{k-1}}\mu_{i|j_{k-1}} \qquad j = 1, \cdots, r \tag{2}$$

$$P^{+^0}_{j_{k-1}} = \sum_{i=1}^{r} \mu_{i|j_{k-1}}\{P^{+}_{i_{k-1}} + [D]\,[D]^T\} \tag{3}$$

$$D \triangleq \hat{X}^{+}_{i_{k-1}} - \hat{X}^{+^0}_{i_{k-1}}$$

where P is the covariance matrix associated with state estimate at each time step.
Step2- Filtering Updates: the updates for each sub-filter or model are performed using the standard KF or EKF equations. Both filters take $\hat{X}^{-}_{j_k}$, $P^{-}_{j_k}$ and a noisy measurement at step k as inputs, and compute the outputs $\hat{X}^{+}_{j_k}$ and $P^{+}_{j_k}$ [10].
Step3- Model probability evaluator: The data association module, which is responsible for gathering the measurements, performs a triangulation-based object localization [11]. The basic principle of triangulation is depicted in figure 2(a). The main advantage of this approach is that it considerably reduces the amount of system nonlinearity by making the observation model linear. Measuring the positions in 2D space will provide:

$$Z_{j_k} = H_{j_k}X_k + W_k = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} X_k + W_k \tag{4}$$

where $W_k \sim N(0, R)$ is a zero-mean Gaussian white noise used to model position imperfections where the noise covariance matrix R is assumed to be known, and note that the measurement model matrix H_{j_k} is identical for all time steps. Subsequently, filter measurement residuals $\tilde{Z}_{j_k}$ and their covariances S_{j_k} can be calculated as:

$$\tilde{Z}_{j_k} = Z_{j_k} - H_{j_k}\hat{X}^{-}_{j_k} \tag{5}$$

$$S_{j_k} = H_{j_k}P^{-}_{j_k}H^{T}_{j_k} + R \tag{6}$$

Assuming the Gaussian distribution, the likelihood of each model can then be obtained as follows:

$$\Lambda_{j_k} = \frac{1}{\sqrt{2\pi|S_{j_k}|}} \exp\left[-0.5(\tilde{Z}^{T}_{j_k}(S_{j_k})^{-1}\tilde{Z}_{j_k})\right] \tag{7}$$

Utilizing Λ_{j_k}, the mode probability μ_{j_k}, which is used as a weighting in the next step to form the final state estimation at time k, will be:

$$\mu_{j_k} = \frac{\Lambda_{j_k}\hat{c}_j}{\sum_{j=1}^{r}\Lambda_{j_k}\hat{c}_j} \qquad j = 1, \cdots, r \tag{8}$$

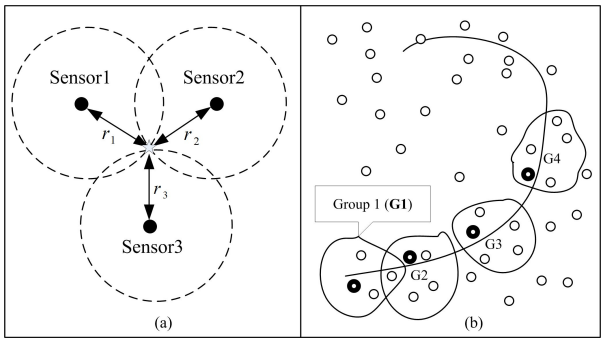

Fig. 2. (a) Triangulation in wireless sensor networks (b) Dynamic-Group Scheduling Scheme (DGSS)

where $\hat{c}_j$ is a normalizing constant that can be found in [4].
Step4- output mixer: the output mixer combines all the state estimates and covariances from individual filter outputs as follows:

$$\hat{X}_k^+ = \sum_{j=1}^{r} \hat{X}_{j_k}^+ \mu_{j_k} \tag{9}$$

$$P_k^+ = \sum_{j=1}^{r} \mu_{j_k} \{P_{j_k}^+ + [\hat{X}_{j_k}^+ - \hat{X}_k^+][\hat{X}_{j_k}^+ - \hat{X}_k^+]^T\} \tag{10}$$

D. Data Association Module and Sensor Node Selection

Considering that each of the wireless sensor nodes can range an object inside their sensing radius, a single range measurement, r, defines the locus of the object on a circle in which the center is located at the corresponding measuring sensor. Thus in order to obtain a unique position of the object in this 2D sensing field, we need to utilize at least 3 sensors. Figure 2(a) illustrates triangulation using three sensors. In order to exploit the potential of the network efficiently, it is needed to apply a mechanism for node selection so that other non-selected nodes can remain in the sleep mode and thus just few sensors are activated at a time. To achieve this goal, the Dynamic-Group Scheduling Scheme (DGSS) [12] is applied in addition to the triangulation process. This scheme includes three steps. First, it searches for the nearest node to the object- when the object is detected for the first time, the nearest node to the object is selected as the current tasking node and the first cluster head. It is shown as the bold circle inside the first group (G1) in figure 2(b). Second, the cluster head acts as a reference node and chooses M nodes to create a group. This task is done according to the shortest path distance between the cluster head and all other nodes. Third, while the object moves out the structured group, another cluster head is sought and the next group (G2) will be formed. The details about the DGSS algorithm can be found in [12]. With the help of DGSS, triangulation can be easily performed.

The assumptions being used for the sensors utilized in this work, which are highly aimed at decreasing the level of energy consumption to extend the network's lifetime, are the following: 1) Features and characteristics are equal for all the sensors and they are all synchronous, 2) Sensors are scattered without any prior node placement pattern, i.e. randomly, and with uniform density across the sensor field, 3) sensors have two modes regarding their sensing range, the normal beam r_{min} and the high beam R_{max}. In normal condition, the default operation uses the low beam and the high beam will be activated just in case of necessity (e.g. object recovery or the lack of availability of sufficient number of sensors detecting the object with low beam), 4) To save energy, communication and sensing components will be kept in sleep mode most of the time. In order to check any probable message from the cluster head, the communication channel will be activated regularly. The sensor starts the sensing process when it receives the command from its cluster head.

III. Fuzzy-logic Based Adaptive IMM filter

The major drawback of the conventional IMM is that, for each mode it should have a model that fits the condition to some extent, thus many models should be included to achieve the desirable performance. This means that, besides the NCT model, the filter needs several linear NCV models with different uncertainty (system noise covariance) levels (e.g. Low, Medium, High in the simplest form) in order to ensure having at least one suitable model for each mode. Nevertheless, taking the algorithm in the previous section into consideration, and due to the need of performing each model with its associated filter in parallel, it is obvious that, if we apply all potential uncertainties and different models, the complexity and computational burden of the filter would be increased dramatically. To overcome this difficulty, one solution could be auto-tuning of the covariance matrix level in the NCV (instead of applying many NCV models running in parallel with the NCT). In this paper, a Fuzzy Inference System (FIS) is proposed to adaptively revise the level of the system noise covariance matrix in order to increase precision with fewer models, i.e with just one NCT and one NCV. By applying the FIS, changing the process noise covariance of the NCV model according to the maneuver intensity in real-time is desired. Therefore, a mapping from the maneuver intensity level to the proper level of process noise covariance is needed. In order to employ the turn rate as a detector of the maneuver intensity level, and considering that it is an input of the NCT model, an approach to estimate this unknown input must be applied. In this paper, state vector augmentation using Modified Input Estimation proposed in [13] is utilized. The internal structure of the FIS is shown in figure 3. For an overview about fuzzy logic and its applications, one can refer to [14].

In this paper, Mamdani based [15] FIS is applied. The greatest advantage of such a system is that it is easily understandable, but on the other hand selecting the proper rules for knowledge base subsystem requires expertise. The fuzzifier converts the crisp input to a linguistic variable using the membership functions stored in the fuzzy knowledge base. The membership functions of the fuzzifier applied in this

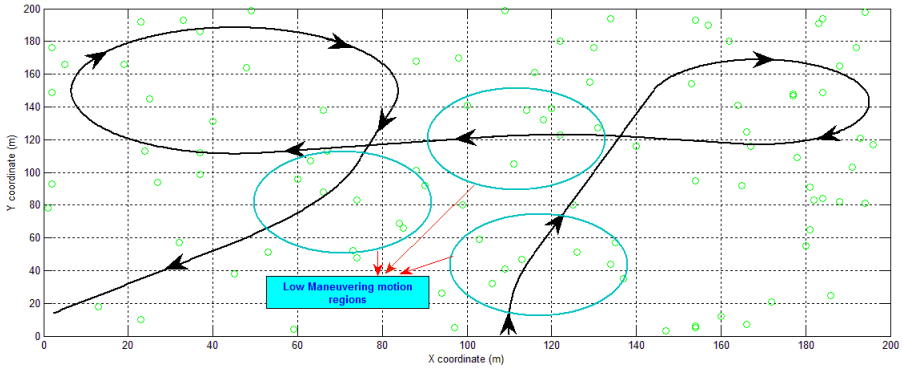

Fig. 6. Complete trajectory of the defined scenario

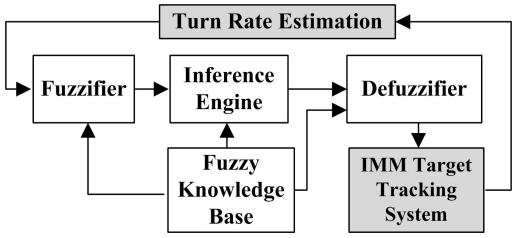

Fig. 3. Internal structure of the FIS

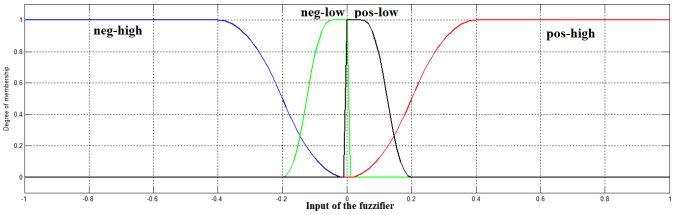

Fig. 4. Fuzzifier membership functions

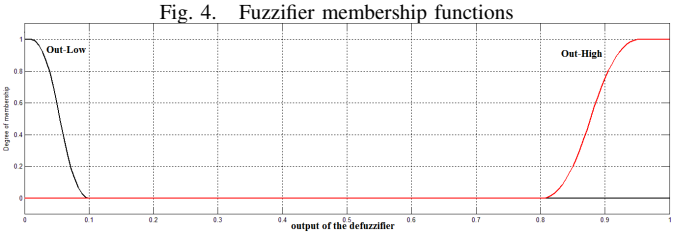

Fig. 5. Defuzzifier membership functions

paper are illustrated in figure 4. In figure 3, the Inference Engine is the core of FIS in which a control procedure is done using IF-THEN rules. In Mamdani FIS, the antecedents and the consequents of these IF-THEN rules are expressed as linguistic variables. If the turn rate increases, then it is likely that the object is rotating. In constant velocity or turn motion models, this will appear as a process noise covariance alteration. Consequently, by tuning the process noise covariance appropriately, the state vector with the minimum estimation error can be estimated. Therefore, to support this notion, and considering turn rate estimation as input and the NCV model noise covariance level as output, the fuzzy rules are proposed as follows:

Rule 1: If the input is neg-high Then the output is out-high.
Rule 2: If the input is pos-high Then the output is out-high.
Rule 3: If the input is neg-low Then the output is out-low.
Rule 4: If the input is pos-low Then the output is out-low.

The final stage in the Mamdani-based FIS is the defuzzifier which converts the fuzzy output of the inference engine to a crisp number using membership functions depicted in figure 5. The proposed method provides a simple method for adaptation of the conventional IMM filter. This adaptation enhances the ability of the IMM filter in tracking a rotating object by using a more accurate modeling of the object motion dynamics.

IV. Simulation Results

To show the effectiveness and to demonstrate the improvement of state estimation carried out by the proposed method, the method is compared with the conventional IMM. For this purpose, the comprehensive real trajectory is defined. The monitored field is $200m \times 200m$ and covered by 100 sensors randomly deployed. In this simulation we assume that the normal beam range of each sensor is $r_{min} = 35m$ and high beam range is $R_{max} = 55m$. Moreover, the locations of all the sensors placed randomly in the field are known.

Scenario: In this simulation, the sampling time is considered to be $T = 0.05$. The trajectory of the object is shown in figure 4. The initial conditions of the object are $[x_0, y_0] = [110, 0]$ and $[v_x(0), v_y(0)] = [0, 10]$. In the time steps $k \subset [20, 100]$ it starts to maneuver slowly with accelerations $[u_x, u_y] = [0.7, 0]$ and then it moves on a straight line up to $k = 300$. For $k \subset [301, 530]$ it carries out a high maneuver with turn rate $\omega = -0.4$ corresponding to a right turn. After moving on a straight line for a few steps, it again starts to maneuver tardily at $k \subset [581, 650]$ with $[u_x, u_y] = [0, -1]$. For $k \subset [751, 1130]$ it turns right with turn rate $\omega = -0.27$.

The IMM filter has two models: the NCT model with EKF filter and a system noise covariance matrix of $0.05 \times I$; and the NCV model with a KF and a system noise covariance matrix of $0.5 \times I$ (I is the identity matrix). Moreover, the

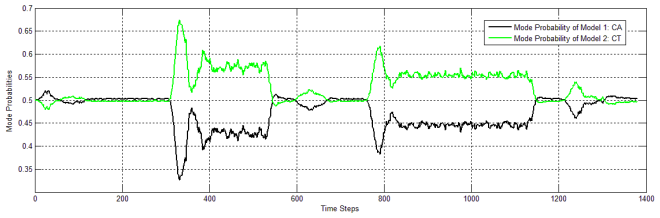

Fig. 7. Motion mode probabilities of the IMM filter

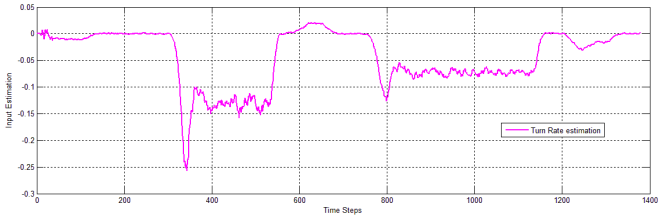

Fig. 8. Turn rate estimation using Augmented EKF for maneuver interval detection

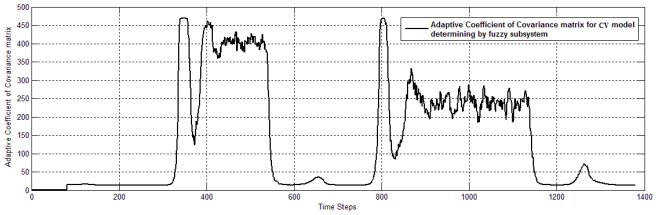

Fig. 9. Adaptive coefficient of covariance matrix for NCV model

covariance matrix of the measurement noise is assumed to be $R = 0.5 \times I$. Other simulation parameters of the IMM are as follows:

$$p_{ij} = \begin{bmatrix} 0.9 & 0.1 \\ 0.1 & 0.9 \end{bmatrix}, P_{1_0}^{+} = P_{2_0}^{+} = I, \mu_{1_0} = \mu_{2_0} = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}$$

These values are chosen based on emperical experiments, and it should be noted that the final results is not very sensitive to the choice of these values.

7 shows the evolution in time of the filter mode probabilities. This figure illustrates the soft switching that takes place when a maneuver is initiated: it takes a few samples to detect the maneuver. Moreover, the turn rate estimation which is done by the EKF filter is depicted in Figure 8. As it is obvious in this figure, though it is not thoroughly accurate, it can be a good indicator of the high rotating modes and can be used as measure for maneuver interval detection. By employing this value, the adaptive coefficient of the covariance matrix for the NCV model which results from the fuzzy block can be observed in Figure 9. This coefficient is increased with the amount of process noise of the NCT model where necessary, i.e, in high rotating motion modes. Table 1 shows the simulation results based on performing 50 independent runs. The results demonstrate the performance increase for the proposed approach.

V. Conclusion

In this paper, a Fuzzy-IMM filter was employed to track a rotating object in a wireless sensor network. The triangulation method along with dynamic grouping are utilized to gather measurements. With the proposed Fuzzy-IMM tracker, the distributed algorithm can properly track variations of the location estimate computed from the triangulation-based method and improve the location accuracy. This method considerably decreases the computational burden by eliminating the need of excess models. Simulation results demonstrated that the proposed Fuzzy IMM filter outperforms the conventional IMM filter in terms of accuracy and efficiency.

TABLE I
Results of 50 times Monte Carlo simulation

	Fuzzy-IMM	IMM	Improvement
Total X position error	224.31	557.64	148%
Total Y position error	252.62	643.87	154%
Total X speed error	657.29	1051.5	59.2%
Total Y speed error	721.4	1223.6	69.6%

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