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The description of some moving air target tracking algorithms

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A concept of moving target tracking is based on the estimation of the state of the target position, velocity and acceleration and data association. The paper is dedicated to description of two chosen algorithms, for estimation and data association, in order to generate a combined moving target tracking algorithm, that is the next step in the research. The algorithm for data association (PDA) and the algorithm for data estimation (IMM) are shown. The simulation steps in the system analysis for radar data processing are described. The results of simulation are shown in qualitative manner.

Key words: **target tracking, air target, state estimation, algorithm of prediction, Kalman's filter, IMM algorithm, PDA algorithm.**

Introduction

MULTIPLE-TARGET tracking (MTT) is an essential requirement for surveillance systems employing one or more sensors, along with computer subsystems, to interpret the environment. Primary sensors for the detection and target tracking are radars, as the active sensors, but they are increasingly supplemented with the passive sensors as infrared cameras and acoustic sensors. This is the way for data fusion of the systems with multiple sensors. The signals arriving from many sensors of same or different kind are processed in order to establish the estimation, prediction and tracking of air moving targets over the state territory or a region of interest. The multi-target tracking objective is to partition the sensor data into sets of observations, or tracks, produced by the same source. Once tracks are formed and confirmed, the number of targets can be estimated and quantities, such as target future predicted position, target velocity and target classification characteristics, can be computed for each track. The earliest and probably still the best known type of the MTT system is the TWS (Track While Scan) system. The TWS system is a special case of the MTT system in which the data are received at regular intervals as the radar regularly scans a predetermined search volume. For the conventional TWS system, search and track update functions are simultaneously performed [1].

The sophisticated tracking algorithms, based on the recursive linear and nonlinear filters, e.g. Kalman filters, and IMM (Interacting Multiple Model) algorithm, are developed. The base of these algorithms is the choice of appropriate mathematical model for data association, and the problem becomes complicated with the increasing of the actual number of targets. The algorithms based on the PDA (Probabilistic Data Association) algorithm consider the case of the single target tracking.

This paper includes a review of the known algorithms for estimation and data association in the target tracking problem. The air situation data are obtained with the reconnaissance radar. The picture on the radar indicator contains other background noise sources also (clutter, etc.) along with the actual targets. The concept of moving target tracking implies defining the target trajectory (track), i.e. the tracking can be defined as the process of partitioning the sensor data from the object into sets. The number of parts should be equal to the number of targets tracked simultaneously. The initial parameters of the target position are presented in the polar coordinate system, and the tracking process is performed in the Descartes rectangular coordinate system. The radar data arrive in the time intervals precisely defined by the radar scan period that is characteristic only for the TWS systems.

This article consists of five parts. After the introduction, the mathematical model of algorithm for state estimation (IMM) is given in the second part. In the third part, the probabilistic data association algorithm (PDA) is described. In the fourth and fifth parts, besides the description of the software module of algorithms, the simulation results as graphical presentation of the root mean square error in position are shown.

The mathematical model of the IMM algorithm

The interacting multiple model algorithm is used for solving the problems of the multiple target tracking including the modes of manoeuvring. The algorithm is based on using two or more filters, one for each mode of the target motion. In [2,3], the detailed overview of the IMM algorithm is given. Starting from the equations for

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stationary discrete linear system model with known parameters, the following is obtained [1]:

$$x(k+1) = Fx(k) + Q(k) \tag{1}$$

$$z(k) = H(k)x(k) + R(k) \tag{2}$$

and after the initiation of the parameters and the transition matrix, the noise covariance matrices of the process and measurement are calculated along with the conditional Bayesian probabilities. In the next step, the probability density function for the n – dimensional random variable, is calculated as [4, 5]:

$$P(k) = \frac{1}{(2\pi)^{n/2}\sqrt{\det S(k)}} \exp\left\{-\frac{1}{2} r(k)^T S(k)^{-1} r(k)\right\} \tag{3}$$

where

– the residuals are

$$r(k) = z(k) - H\hat{x}(k-1) \tag{4}$$

– the residual covariance matrix is

$$S(k) = HP(k-1)H^T + R(k) \tag{5}$$

that is calculated as the error of future state estimation of the target motion. In the references, the interacting multiple model is described in the following standard steps:

Step one: Kalman filters are formed, depending on the number of hypotheses for target motion. In this paper, the three hypotheses for most frequent models of target motion (the uniformly linear moving without acceleration, the accelerated moving with slight manoeuvre and the accelerated target moving with sharp manoeuvre), are used. In this step, the mathematical models for all (three) hypotheses have to be defined and the input estimations formed. The transition matrices for the Kalman filters that are used in the parallel work in the IMM algorithm can be presented as:

$$F_1 = \begin{bmatrix} 1 & T & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & T & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$F_2 = F_3 = \begin{bmatrix} 1 & T & T^2/2 & 0 & 0 & 0 \\ 0 & 1 & T & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & T & T^2/2 \\ 0 & 0 & 0 & 0 & 1 & T \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{6}$$

The cycle starts with combining the previous state estimates $\hat{x}_i(k-1)$ and covariance matrices $P_i(k-1)$, using the appropriate weighted coefficients p_{ij} and μ_i, in order to form the data $\left(\hat{x}_j^0(k-1), P_j^0(k-1)\right)$ for the filter that is composed from the N filter models $M_j(k), (1 \le j \le N)$:

$$\hat{x}_j^0(k-1) = \sum_{i=1}^{N} \hat{x}_i(k-1)\frac{p_{ij}\mu_i(k-1)}{c_j} \tag{7}$$

$$P_j^0(k-1) = \sum_{i=1}^{N} \frac{p_{ij}\mu_i(k-1)}{c_j}\left[P_i(k-1) + (\hat{x}_i(k-1) - \hat{x}_i^0(k-1))(\hat{x}_i(k-1) - \hat{x}_i^0(k-1))^T\right] \tag{8}$$

where

– $c_j = \sum_{i=1}^{N} p_{ij}\mu_i(k-1)$, is the constant of normalization,

– p_{ij} is the transition probability from the filter model describing the target moving M_i in the moment $(k-1)$, to the model M_j in the moment (k),

– $p_i(k-1)$ is the value of the weighted coefficient.

Step two: Setting the parameters of the appropriate Kalman filters used in this model. Each of the three parallel filters generates the new estimates $\hat{x}_i(k-1)$ and $P_i(k-1)$, according to the model of target motion $M_i (1 \le i \le N)$.

Step three: Calculating the weighted coefficients. The appropriate probability density is given as:

$$P_j(k) = \frac{1}{\left[(2\pi)^n \det\left(S_j(k)\right)\right]^{1/2}} \exp\left[-\frac{1}{2} r_j^T(k) S_j^{-1}(k) r_j(k)\right] \tag{9}$$

where

– $r_j(k)$ - is the residual,

– n - is the dimension of the measurement, and

– $S_j(k)$ - is the covariance matrix of the innovation sequence in the filter with the model M_j.

The weighted coefficients are presented as:

$$\mu_j(k) = \frac{P_j(k)c_j}{\sum_{j=1}^{N} p_j(k)c_j} \tag{10}$$

Step four: Calculating the final state estimate:

$$\hat{x}(k) = \sum_{j=1}^{N} \hat{x}_j(k)\mu_j(k) \tag{11}$$

and covariance matrix:

$$P(k) = \sum_{j=1}^{N} \mu_j(k)\left[P_j(k) + \left(\hat{x}_j(k) - \hat{x}(k)\right)\left(\hat{x}_j(k) - \hat{x}(k)\right)^T\right] \tag{12}$$

At the beginning, it is necessary to introduce the initial values of the weighted coefficients which are later updated in each period of the radar antenna rotating. Unlike MM (Multiple Model) algorithm, the IMM algorithm updates the values of the transition matrix elements M_i from one hypothesis into the others. The sum of the probabilities in the matrix rows is equal to one. The decreasing of the scan period causes the diagonal coefficients increase and the decreasing of the out-of-diagonal coefficients, which are equal to zero when the scan period is very small. That is understandable, due to the fact that with the decreasing of the period, the possibility of any manoeuvre change between two scans.

Measurement noise covariance matrix $\boldsymbol{R}$ is calculated by appropriate Jacobian, in the following manner [4,6]:

$$J_{12}(k) = \begin{bmatrix} \cos\theta(k) & -\sin\theta(k) \\ \sin\theta(k) & \cos\theta(k) \end{bmatrix}$$

$$\boldsymbol{R}_0 = \begin{bmatrix} \sigma_r^2 & 0 \\ 0 & \sigma_\theta^2 \end{bmatrix} \quad (13)$$

$$\boldsymbol{R}(k) = J_{12}(k) R_0 J_{12}{}^T(k)$$

where θ – is the azimuth, σ_r – is the standard deviation per range (1 km) and σ_θ – is the standard deviation in the azimuth (0.017 rad) [4].

Gating

In practice, the gate represents a validation region in the vicinity of the predicted value of the target position. All measurements within the gate are included into the process of the track updating. The manner, in which the observations (measurements) are actually chosen for the track update, depends on the method of data association [7, 1, 8]. Let it be assumed that the measurement size is of dimension M. The norm of the residual vector (or innovation) is defined by the value d_{ij}^2 as:

$$d_{ij}^2 = \tilde{z}_{ij}^T S^{-1} \tilde{z}_{ij} \quad (14)$$

which is also called the statistical function of the distance between the observation j and the track i or the normalised distance. The M - dimensional Gaussian probability density for the residual is calculated as:

$$g_{ij}(\tilde{y}) = \frac{e^{-d_{ij}^2/2}}{(2\pi)^{M/2}\sqrt{|S_i|}} \quad (15)$$

where $|S_i|$ is the determinant of S_i.

The threshold constant for the gate G, is defined so that the correlation is completely accomplished if the following equation for the norm of the residual vector is valid:

$$d_{ij}^2 = \tilde{z}_{ij}^T S^{-1} \tilde{z}_{ij} < G \quad (16)$$

The value d_{ij}^2 represents the sum of the squared M independent Gaussian random variables with the zero mean values and the standard deviations equal to one. Therefore, d_{ij}^2 are χ_M^2 – distributed for the correct observation-track joining with M degrees of freedom and allowed probability $P = 1 - P_d$ that the valid observation is out of the gate, where P_d is the detection probability. The threshold constant G, can be defined by the table of χ^2 distributions with M degrees of freedom and the allowed probability that the valid observation is out of the gate.

In this paper, the circular gate with defined radius around the predicted position is assumed. The choice of the constant threshold G represents simple but less adaptable method [1].

The differences between the predicted values and observations are the sources of the errors, which ought to be included into the covariance matrix of the Kalman filter.

The probabilistic data association algorithms

The data association problem is the first step in the detaching (extracting) of a single target from a clutter. For this purpose, a family of algorithms has been developed. In the beginning, the algorithms are based on the distance between the target and the prediction in the next scan (the nearest neighbour method). Those are the SNN (Suboptimal Nearest Neighbour) and the GNN (Global Nearest Neighbour) method [7], in which the decision as to which observation belongs to the track is made on the bases of the minimization of the distance between the track and the predicted target position from the previous scan, d_{ij}. These models of association are inefficient in cases of multiple targets and a clutter existing in one scan. Therefore, algorithms based on calculating the associated probabilities for each validated measurement at the current time step are developed. In case of one target, the probabilistic data association algorithm (PDA) is used. The example when during the scan two observations out of which only one is the track, is shown in Fig.1.

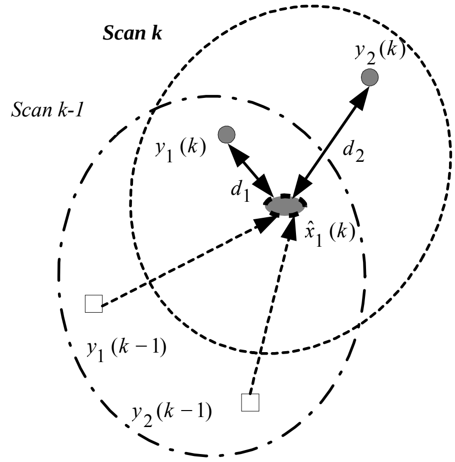

Figure 1. The PDA algorithm illustration, in the case of two observations existing in one scan

From the probabilistic point of view, there is one hypothesis more than the number of tracks in the current scan. In the case from the Fig.1, three hypotheses can exist:

- The first track is the target,
- The second track is the target, and
- None of the tracks is the target.

The clutter appears on the radar picture due to some kinds of noises from the individual objects in the scene, interference of signals, sensors, etc. The mentioned noises induce raise a false alarm.

Mathematical model of the PDA algorithm

Let there be M_t measurements (observations) in one scan [8]:

$$y_t^{(i)},\ i = 1,2,...,M_t \quad (17)$$

This set of measurements at a time t can be denoted as:

$$Y_t = \left\{ y_t^{(i)} \right\}_{i=1}^{M_t} \quad (18)$$

and the set of all cumulative measurements up to the time t as:

$$Y_t = \{Y_t, Y_{t-1}, Y_{t-2}, ...\} \quad (19)$$

In this method, the estimation is based on the latest set of measurements. In other words, the future states can be summarized approximately by the Gaussian probability distribution, by the relation:

$$p(x_t | Y_{t-1}) = N(x_t;\, \hat{x}_{t|t-1},\, P_{t|t-1}) \quad (20)$$

Let the following events be considered:

$H_t^{(0)} =$ {None of the measurements at the time t originates from the target}

$H_t^{(i)} =$ {target-originating measurement}

with probabilities:

$$p_t^{(i)} = P_r\left\{H_t^{(i)} | Y_t\right\}, i = 0,1,...,M_t \quad (21)$$

In the next step, the estimate is updated using the total probability theorem:

$$\hat{x}_{t|t} = E\left\{x_t | Y_t\right\} = \sum_{i=0}^{M_t} E\left\{x_t, H_t^{(i)}, Y_t\right\} p_t^{(i)} = \sum_{i=0}^{M_t} x_{t|t}^{(i)} p_t^{(i)} \quad (22)$$

where $x_{t|t}^{(i)}$ is the updated state conditioned by the event $H_t^{(i)}$, that $y_t^{(i)}$ is the correct measurement. In case when there are no correct measurements, pure prediction is taken as estimation $x_{t|t}^{(0)} = \hat{x}_{t|t-1}$.

From the Kalman filter for $i = 1,2,...,M_t$ the prediction and residual expressions are taken:

$$x_{t|t}^{(i)} = \hat{x}_{t|t-1} + K_t \varepsilon_t^{(i)} \quad (23)$$

$$\varepsilon_t^{(i)} = y_t^{(i)} - h(x_{t|t-1}^{(i)}) \quad (24)$$

where the Kalman gain has the value of one, with respect to the hypothesis condition $H_t^{(i)}$, that there is no measurement uncertainty. Combining the above equations results in the following:

$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t \varepsilon_t \quad (25)$$

where

$$\varepsilon_t = \sum_{i=0}^{M_t} p_t^{(i)} \varepsilon_t^{(i)} \quad (26)$$

The error covariance matrix is updated by relation:

$$P_{t|t} = p_t^{(0)} P_{t|t-1} + (1 - p_t^{(0)}) P_{t|t}^c + \tilde{P}_{t|t} \quad (27)$$

where

$$P_{t|t}^c = [I - K_t H_t] P_{t|t-1} \quad (28)$$

$$\tilde{P}_{t|t} = K_t [\sum_{i=1}^{M_t} p_t^{(i)} \varepsilon_t^{(i)} \left(\varepsilon_t^{(i)}\right)' - \varepsilon_t \varepsilon_t{}'] K_t' \quad (29)$$

Based on the fact that exist measurements M_t in the last measurement set, the following probability is obtained:

$$p_t^{(i)} = P_r\left\{H_t^{(i)} \middle| Y_t\right\} = P_r\left\{H_t^{(i)} \middle| Y_t, M_t, Y_t\right\}, i = 0,1,2,...,M_t \quad (30)$$

Applying Bayes' rule yields:

$$p_t^{(i)} \propto p\left(Y_t \middle| H_t^{(i)}, M_t, Y_{t-1}\right) P_r\left\{H_t^{(i)}, M_t | Y_{t-1}\right\} \quad (31)$$

The probability density for correct measurement is given by:

$$p(Y_t^{(i)} | H_t^{(i)}, M_t, Y_t) = P_G^{-1} N(y_t^{(i)};\, h_{t|t-1},\, S_t) = P_G^{-1} N(\varepsilon_t^{(i)};\, 0,\, S_t) \quad (32)$$

The first factor in (31) is:

$$p\left(Y_t \middle| H_t^{(i)}, M_t, Y_{t-1}\right) = \begin{cases} V_t^{1-M_t} P_G^{-1} N\left(\varepsilon_t^{(i)}; 0, S_t\right), & i = 1,2,...,M_t \\ V_t^{-M_t}, i = 0 \end{cases} \quad (33)$$

where V_t is the volume of the validation region. The second factor in (31) is calculated as:

$$P_r\left\{H_t^{(i)} | M_t, Y_{t-1}\right\} = P_r\left\{H_t^{(i)} | M_t\right\} = \begin{cases} \frac{1}{M_t} P_D P_G \left[P_D P_G + \left(1 - (P_D P_G) \frac{\mu_F(M_t)}{\mu_F(M_{t-1})}\right)^{-1} \right], \\ i = 1,2,...,M_t \\ (1 - P_D P_G) \frac{\mu_F(M_t)}{\mu_F(M_{t-1})} \left[P_D P_G + \left(1 - (P_D P_G) \frac{\mu_F(M_t)}{\mu_F(M_{t-1})}\right)^{-1} \right], \\ i = 0 \end{cases} \quad (34)$$

where

- $\mu_F(M_t)$ is the probability mass function for the number of false alarms.
- The gate probability P_G, is the probability that the correct measurement is within the validation gate.
- P_D is the detection probability.

In [9], two different assumptions are considered for $\mu_F(M_t)$, namely a parametric model with a Poisson density with parameter λV_t or non-parametric model using a diffuse operator. The mentioned cases can be marked as:

- Poisson density

$$\mu_F(M_t) \propto e^{-\lambda V_t \frac{\lambda V_t^{M_t}}{M_t!}}, \; M_t = 0,1,2,...$$

- Diffuse operator

$$\mu_F(M_t) = \frac{1}{\bar{M}}, \; M_t = 0,1,...,\bar{M} - 1,$$

where $\bar{M}$ is large enough.

The software module of the IMM algorithm

The software module for application of the IMM algorithm with three Kalman filters was developed. According to the manner of the target motion, the filter parameters are defined. The programme input data for the appropriate trajectory are taken from the observation data file. During the first circle, the initiation of the prediction for all three filters and an associated prediction is made, followed by entering the cycle of the IMM algorithm. On the basis of the deviation of the individual prediction with regard to the associated prediction, the covariance matrices are calculated. The observation is processed in all three filters separately, and the result is presented as three independent predictions. The weight coefficients of the filter participation in the prediction are calculated and the prediction for the following circle is created. The algorithm is tested on the noiseless trajectory [10], which is created so that it contains three modes of target motion: motion in a straight line without manoeuvre, motion with a slight manoeuvre and motion with a sharp manoeuvre. The results of the use of the IMM algorithm on the mentioned trajectory are shown in Fig.2, and the distribution of the probability of the weight coefficients are shown in Fig.3. The results presented in this paper are in good agreement with the published results in [10].

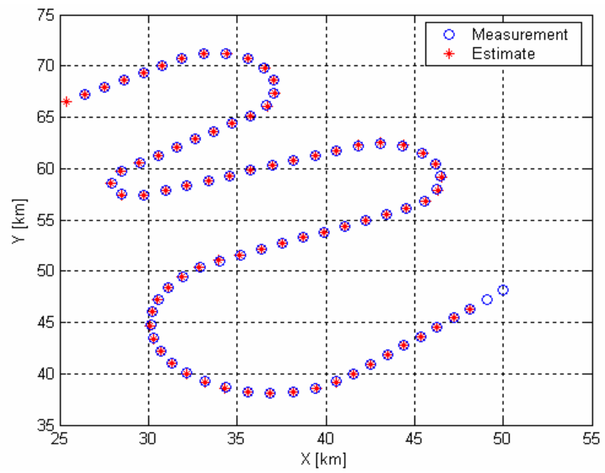

Figure 2. The test trajectory for **IMM** algorithm.

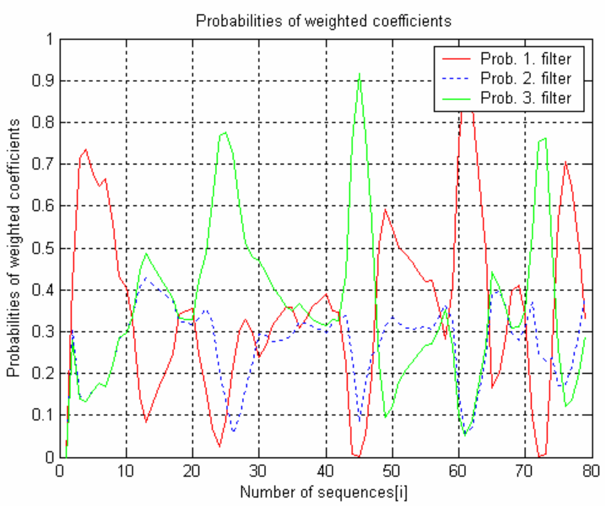

Figure 3. The distribution of the probability of the weight coefficients for **IMM** algorithm.

The Fig.4 shows a comparative root mean square error in the position for IMM algorithm with three Kalman filters and algorithm used for one Kalman filter. The figure presents the error rise that is proportional to the manoeuvre strength, so that the IMM algorithm can often be used as the manoeuvre detector and target type classifier. A small error when the IMM algorithm is used can also be noticed in the figure, as it is expected.

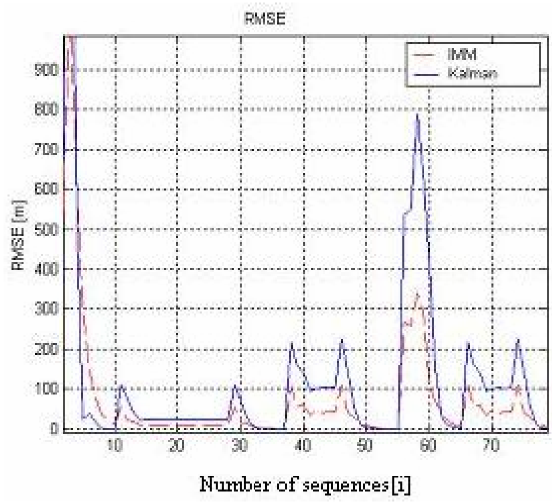

Figure 4. The root mean square error per position.

The software module of the PDA algorithm

When only one observation is found in the gate of a track, the observation-track association process is performed directly and uniformly. However, in the case of close targets, a conflict often occurs when multiple observations are in the same gate. The probabilistic data association algorithm (PDA) is based on calculating the probability of observation-track association and the detections from the track gate are used for track updating. The file with observations for two very close trajectories is used for testing the PDA algorithm. The trajectories are created in kinetic coordinate system.

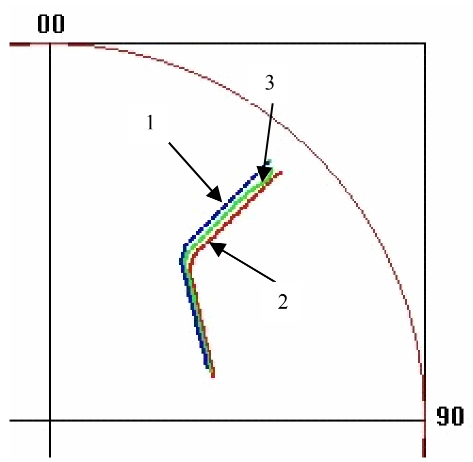

Figure 5. The graphical presentation of the test results for the **PDA** algorithm software module.

The PDA algorithm should ensure successful tracking of an established track with two very close observations from the same scan. The programme checks the remaining of the observations within the gate. By the PDA algorithm, the probabilities of the observation-track association for each observation in the gate are calculated, and also the weight factors in the vector state estimate update. Instead of residual from a single observation, the weighted sum of the residuals associated with all observations in the gate is used in the Kalman filter equation. The covariance matrix of the standard Kalman filter is modified taking into consideration the multiple reflections in the same gate. In the Fig.5, the test results in the polar coordinate system are shown. The tracked trajectory is marked with (1), the observations belonging to other trajectory with (2), and position prediction with (3).

Fig.6 shows the root mean square error per position on the target trajectory, obtained via the PDA algorithm for the scenario similar to that presented in Fig.5. The initial error growth is the consequence of the parametric initiation of the algorithm. Afterwards, the error uniformly decreases until manoeuvre of the target motion (from 34 to 42 scan) appears, when a slight increase is noticed. That can be explained by simultaneous manoeuvre of both airplanes, followed by the error decreasing, when the airplanes start moving in a straight line again.

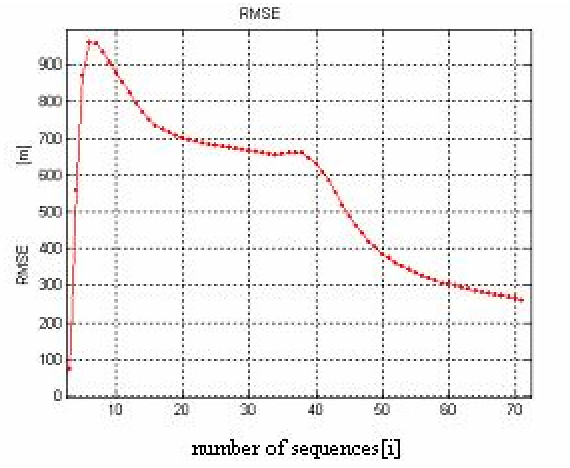

Figure 6. The root mean square error per position.

Conclusion

A brief overview of the selected methods for the data estimation and association, used for controlling the air space is given. These methods enable automatic multiple target tracking. The presented algorithms are constituent modules of the state-of-the-art technological devices for automatic traffic control and multiple target tracking. These algorithms have been tested on a simulation model and the simulation results are given as the root mean square error per position. The reconnaissance radar is used as the sensor, and in the future works, this sensor will be supplemented with the acoustic and infra-red sensors in order to form a multi-sensor system [11, 12]. The data association represents a classification of the measurements into groups containing only the observations from the same source, a condition for the track forming. If the classification is correct, the data can be used for the target vector state estimation by means of the Kalman filters or some other filters for data estimation. One of the problems yet to be solved is processing data in the real-time, in the presence of clutter, which results in the track loss, track overlapping, false track initiation and other errors. This paper can be seen as the introduction into more complicated real-time tracking process. The theoretical model of the data association algorithm (PDA) and two estimation algorithms (Kalman filter and IMM algorithm) are shown. The root mean square error per position, showing the advantage of the IMM algorithm as the state estimator, is calculated and shown. The steps in the simulation for the analysis of the system for the radar data processing are explained and the used algorithms in the multiple target tracking with the simulation results are presented.

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Prikaz nekih algoritama za praćenje pokretnih ciljeva u vazduhu

Proces praćenja pokretnih ciljeva zasnovan je na estimaciji narednih stanja položaja, brzine i ubrzanja cilja kao i procesu pridruživanja podataka. Rad je posvećen prikazu dva odabrana algoritma, za estimaciju i pridruživanje podataka u cilju generisanja kombinovanog algoritma za praćenje pokretnih ciljeva što predstavlja naredni korak u daljem istraživanju. Prikazan je algoritam za pridruživanje podataka (PDA algoritam) i algoritam za estimaciju podataka (IMM algoritam). Opisani su simulacioni koraci analize sistema za procesiranje radarskih podataka, a rezultati simulacije su predstavljeni u kvalitativnoj formi.

Ključne reči: **praćenje cilja, cilj u vazduhu, estimacija stanja, algoritam predikcije, Kalmanov filtar, IMM algoritam, PDA algoritam.**

Обзор некоторых алгорифмов для сопровождения подвижных целей во воздухе

Процесс сопровождения подвижных целей основывается на расчёте следующих состояний, положения, скорости и ускорения цели и на процессе соединения данных. В этой работе показан обзор двух выбранных алгорифмов для оценки (расчёта) и соединения данных со целью формирования объединённого алгорифма для сопровождения подвижных целей во воздухе, что представляет следующий шаг в будущих исследованиях. Здесь показан алгорифм для соединения (ПДА алгорифм) и алгорифм для оценки (расчёта) данных (ИММ алгорифм). Тоже описаны и моделирующие шаги анализа системы для обработки радиолокационных данных, а результаты моделирования показаны в качественной форме.

Ключевые слова: сопровождение цели, цель во воздухе, расчётное состояние, алгорифм прогнозирования, фильтр Калмана, ИММ алгорифм, ПДА алгорифм.

La description des algorithmes pour la poursuite des cibles mobiles en l'air

Le processus de la poursuite des cibles mobiles est basé sur l'estimation des états de positions suivantes, vitesse et accélération de cible ainsi que sur le processus de l'association des données. Ce travail est consacré à la description de deux algorithmes choisis pour l'estimation et l'association des données dans le but de créer l'algorithme combiné pour la poursuite des cibles mobiles, ce qui représente le pas suivant dans cette recherche. On a démontré l'algorithme pour l'association des données (algorithme PDA) et l'algorithme pour l'estimation des données (algorithme IMM). On a décrit les pas de simulation de l'analyse du système pour le traitement des données fournies par radar. Les résultats de la simulation sont présentés en forme qualitative.

Mots clés: **poursuite de cible, cible en l'air, estimation de l'état, algorithme de prédiction filtre de Kalman, algorithme IMM, algorithme PDA**