UDK: 681.5.017:623.746.3
COSATI: 17-11

Determination of the Transition Probabilities for the Interacting Multiple Model Probabilistic Data Association Estimator

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The problem of state estimation for Markovian switching systems with an unknown transition probability matrix (TPM) of the embedded Markov chain governing the switching is presented in this paper. Under the assumption of constant TPM, an approximate recursion of the TPM's posterior probability density function is obtained. The exponential distribution of TPM is proposed and tested with the recursive algorithm for the Minimum Mean-Square Error (MMSE) estimation. The calculated initial TPM is incorporable into a typical Interacting Multiple Model with Probabilistic Data Association (IMMPDA) estimation scheme. Moreover, simulation results of TMP-adaptive algorithms for a maneuvering target tracking is shown. The results obtained test the scenario with two aircraft: military and civilian. The simulation shows that the proposed computation method increases the target tracking efficiency. The drawback of the simulation is that only one single target is assumed. The paper reports the preliminary results of an ongoing study and further investigation is under way.

Key words: **target tracking, maneuvering target, hybrid system, state estimator, transition probability, probability determination, Markov chain.**

Introduction

TARGET tracking is a very rapidly developing area. It is a complex procedure, containing many algorithms. For tracking a single maneuvering target in clatter, the IMMPDA algorithm is proposed in this paper. Maneuvering *target tracking* refers to the problem of state estimation of the target trajectory subjected to abrupt changes [1]. The standard Kalman filter (KF) with a single motion model is limited in performance for such problems due to ineffective responding in dynamics changes as the target maneuvers. Recently the adaptive estimation techniques approaches in maneuvering motion are categorized as state augmentation approaches, adaptive adjustment of filter parameters and *multiple models* (*MM*) approaches [2]. Designing a best set of filters requires prior knowledge about target motion. This is earlier, maximum acceleration and sojourn times in motion modes. The IMM estimate algorithm is the most efficient and cost-effective tool for tracking highly maneuvering targets [3, 4]. The results of simulations cited in many papers, reveal a very good performance of this algorithm in terms of track confirmation and maintenance. In the *Multiple Model* (MM) estimation the Transition Probability Marix (TPM) is almost always assumed to be known. Thus it is highly desirable to have algorithms which can identify the *TPM* recursively during the course of processing measurement data so as to allow on-line adaptation of the *MM* state estimation. A new generation of *MM* estimators assumes that the *TPM* governing the mode jumps is known. However, it is practically unknown. It is very difficult to determine appropriate *TPM* quantities and identify a Markov transition law that optimally fits the unknown target motion. Fortunately, the performance of MM estimation is not very sensitive to the choice of the *TPM* [5]. Also, Li discuss how to establish attribute association probabilities, which are possible to fuse with the association probabilities computed by the IMMPDA [6].

The paper is organized as follows. Section 2 provides a brief description of the *IMMPDA* algorithm. It gives the basic relationship and expressions between the variable and the parameters. A proposed algorithm which commutates transition probabilities in a new manner is presented in Section 3. The simulation results, referring to the target maintenance problem are presented in Section 4. Finally, the concluding remarks are presented in Section 5.

IMM estimator with the probabilistic data association filter

The *IMMPDA* filter is an algorithm for target tracking and association, which supports simultaneously track initiation, confirmation and deletion. A brief description of *IMMPDA* filter is has been presented in this section [7]. The case of two objects is considered: the single target and the clatter flying at the same altitude. The problem considered is that of tracking a single target in the clutter, which retrieves two measurements fall in the validation gate. The linear hybrid dynamical target state model is given by the following [8]:

$$\mathbf{x}^j(k+1) = \mathbf{F}^j\mathbf{x}^j(k) + \mathbf{G}^j v^j(k) \quad j = 1,2,...,n \tag{1}$$

$$y(k) = \mathbf{H}\mathbf{x}(k) + w(k) \tag{2}$$

where j is the ordinal number of the model, n is the total number of the model, $\mathbf{x}$ is the state, $\mathbf{y}$ is the measurement, $\mathbf{n}$ is the total number of the filter models, $\mathbf{F}$, $\mathbf{G}$ and $\mathbf{H}$ are known matrices, $v(k)$ and $w(k)$ are the independent zero-

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mean white Gaussian noise processes with covariance $Q(k)$ and $R(k)$ respectively. At the time k a set of $m(k)$ measurements $Y(k)=\left\{y_i(k)\right\}_{i=1}^{m(k)}$ is detected, where each measurement either originates from one of the n known linear measurement models or is a false detection. The sequences *v(k)* are mutually independent and uncorrelated with the process noise *w(k)*. The *Interacting Multiple Model* (*IMM*) estimator is used to predict the current state of the target using two or more different models. A *Markov* chain transition matrix is used to specify the probability that the target is one of the models of operations. However, the *IMM* algorithm runs filters in parallel, each with an appropriately weighted combination of state estimates as mixed initial conditions. The *Probabilistic Data Association Filter* (*PDA)* is a suboptimal Bayesian algorithm that associates probabilistically all the validated measurements to the target of interest [7]. The *PDA* method associates each validated measurement probabilistic to the estimated track. The case with two measurements in each radar scan is considered. The prediction computation is necessary for each target-originated measurement, but only one measurement is the target. The *PDA* method assumes that there is only one target of interest the track of which has already been initialized. The basic assumption is that the *PDA* filter state is normally distributed according to the latest estimates and the covariance matrix. The *PDA* uses a weighted average of all the measurements falling inside the validation gate of the target. Next, consider that the *modal state* $M(k)\in\mathbf{M}=\{M_1,M_2,...,M_n\}$, $M_i=M_i(k)$ is a Markov chain with initial and transition probabilities respectively:

$$P\left\{M_j(0)\right\}=\mu_j(0) \tag{3}$$

$$P\left\{M_j(k+1)\middle|M_i(k)\right\}=\pi_{ij},i,j=1,2,...,N \tag{4}$$

where $M_i(k)$ stands for the target obeying the *i*-th state model *a* the time *k*: $M_i(k)=i, i=1,2,...,n$. The procedure of *IMMPDA* consists of the following five steps.

Step* 1*: The initial state estimation on condition that the target moves according to the *q*-th model is given by:

$$\hat{x}^{0q}(k-1|k-1)=\sum_{\xi=1}^{n}\hat{x}^{\xi}(k-1|k-1)\pi_{\xi q}(k-1|k-1),\ q=1,2,...,n \tag{5}$$

$$P^{0q}\left(k-1|k-1\right)=\sum_{\xi=1}^{n}\pi_{\xi q}\left(k-1|k-1\rangle\right)\begin{Bmatrix}P^{\xi}(k-1|k-1)+[\hat{x}^{\xi}(k-1|k-1)-\hat{x}^{0q}(k-1|k-1)]\\ [\hat{x}^{\xi}(k-1|k-1)-\hat{x}^{0q}(k-1|k-1)]'\end{Bmatrix} \tag{6}$$

where $\hat{x}^{0q}(k-1|k-1)$, $P^{0q}(k-1|k-1)$ is the mixed initial state and its covariance, respectively, for the filter matched to the mode $m_q(k), q=1,2,...,n.$, $\hat{x}^{\xi}(k-1|k-1)$, $P^{\xi}(k-1|k-1)$ are the state and the covariance, respectively, for the filter matched to the model ξ, $\xi=1,2,...,n$.

$$\pi_{\xi q}(k-1|k-1)=\frac{p_{\xi q}\mu_{\xi}(k-1)}{\sum_{\xi=1}^{n}p_{\xi q}\mu_{\xi}(k-1)} \tag{7}$$

$p_{\xi q}$ is the Markov chain *Transition Probabilities Matrix* and $\mu_{\xi}(k-1)$ are the model probabilities computed at the time $k-1$.

Step* 2*: Next, the likelihood function is calculated as a joint probability density function of the innovations:

$$f_q(k)=[b(k)+\sum_{j=1}^{m(k)}e_j(k)]\frac{P_D P_G}{m(k)}V(k)^{-m(k)+1} \tag{8}$$

where

$$e_j(k)=\frac{1}{P_G}N[r_j;0;S(k)],\quad b(k)=\frac{m(k)(1-P_D P_G)}{P_D P_G V(k)} \tag{9}$$

and $N[\,.\,;\,.\,,.]$ Gaussian distributed process, P_D -probability of detection, P_G -probability that all measurements falling in the validation region, $V(k)$ -validation region, $m(k)$ - number of measurements falling in the validation region, $S(k)$ - innovation covariance.

Step* 3*: The association probabilities are to be calculated, by the following expression:

$$\beta_j(k)=\frac{e_j(k)}{b(k)+\sum_{j=1}^{m(k)}e_j(k)},\ j=1,...,m(k) \tag{10}$$

$$\beta_0(k)=\frac{b(k)}{b(k)+\sum_{j=1}^{m(k)}e_j(k)} \tag{11}$$

The combined innovation is defined as a weighted sum of the $m(k)$ measurements innovations:

$$r(k)=\sum_{j=1}^{m(k)}\beta_j(k)r_j(k) \tag{12}$$

***Step* 4:** It is the IMM step. The model probability is updated as:

$$\mu_q(k)=\frac{f_q(k)\sum_{\xi=1}^{n}p_{\xi q}\mu_{\xi}(k-1)}{\sum_{q=1}^{n}f_q(k)\sum_{\xi=1}^{n}p_{\xi q}\mu_{\xi}(k-1)} \tag{13}$$

***Step* 5:** The combined model-conditioned state estimate and the covariance are obtained according to the following expression:

$$\hat{x}(k)=\sum_{q=1}^{n}\hat{x}^q(k)\mu_q(k) \tag{14}$$

$$P(k)=\sum_{q=1}^{n}\mu_q(k)\left\{P^q(k)+[\hat{x}^q(k)-\hat{x}(k)][\hat{x}^q(k)-\hat{x}(k)]'\right\} \tag{15}$$

Appropriation of the Markov chain transition probability matrix

The *IMMPDA* algorithm consists of N filters - one for each state model. During the tracking process, which is a discrete time process, the number of filters is kept constant. In practice, the *IMMPDA* method usually uses three *Kalman* filters. A homogeneous *Markov* chain matrix $\prod$ represents conditional model probabilities of transition from the model i to the model j. Let us consider now the state estimation problem for the above hybrid system model without the presumed knowledge of the transition probability matrix, given by the following equations [10, 11]:

$$\Pi = [\pi_1 \quad \pi_2 \quad \cdots \quad \pi_n]' \tag{16}$$

where $\pi_i = [\pi_{i1} \quad \cdots \quad \pi_{i1}]'$, $i = 1,2,...,n$. The sum of elements of each row equals one $\sum_{j=1}^{n} \pi_{ij}(k) = 1$. Next, it is assumed that $\prod$ is an *unknown random constant matrix* with some given prior distribution defined over the simplex of valid TPMs. In such a Bayesian framework we formulate the following. The estimation objective: For $k = 0,1,2,...$ find recursively the posterior MMSE estimate $\bar{\Pi}(k) = E[\Pi | z^k]$ from: the previous time-step model probabilities

$$\boldsymbol{\mu}(k-1) = [\mu_1(k-1),...,\mu_N(k-1)]' \tag{17}$$

$$\mu_i(k-1) = P\{m_i(k-1) | Y^{k-1}\} \tag{18}$$

Assuming that it is most likely that the target keeps the current state model (does not change the way it moves), the diagonal elements of *Markov* chain matrix are the largest. Again, when the target exerts maneuver, accuracy of the position estimation is decreased. The observation of the *IMM* operational parameters which affects the maneuver is required. Generally, the transition probability depends on the expected sojourn time. The diagonal elements of the TPM may be approximated with the following expression [8]:

$$p_{ii}(\tau_i / T) = 1 - \frac{1}{\tau_i / T}, \quad \tau_i / T \geq 1 \tag{19}$$

where τ_i is the expected sojourn time of the $i-th$ mode, p_{ii} is the probability of transition from $i-th$ mode to the same mode and T is the sampling interval. Let us denominate this function inverse function of the ratio $\frac{\tau_i}{T} \geq 1$. The non-diagonal elements, are calculated as:

$$p_{ii}(\tau_i / T) = \min\left\{u_i, \max(l_i, 1 - \frac{1}{\tau_i / T})\right\} \tag{20}$$

where $l_i = 0.1$ and $u_i = 0.9$ are the lower and upper limits respectively for the i^{th} model transition probability.

The proposed method

Actually, (19) is the first order Taylor polynomial expansion of the following function:

$$p_{ii}(\tau_i / T) = e^{-\frac{1}{(\tau_i / T)}}, \quad \tau_i / T \geq 1 \tag{21}$$

The comparative graph of the inverse and exponential approximation of the *transition probability function* is given in Fig.1.

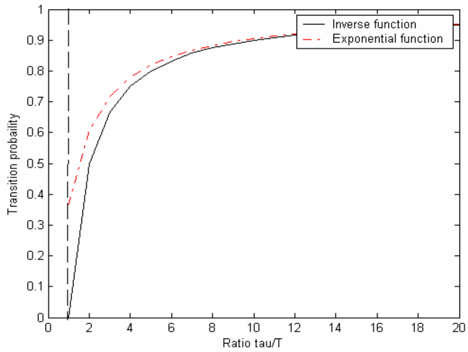


Figure 1. Inverse and exponential approximation of the transition probability function

The model of transition probability may be written as

$$p(a) = e^{-\frac{1}{a}}, \quad 1 \leq a < +\infty \tag{22}$$

where $a = \tau_i / T$. The probability density function is computed by the total probability theorem. From the conditions

$$\int_{-\infty}^{+\infty} pdf(x)dx = 1$$

and

$$\lim_{a \to \infty} (\int_0^a pdf(x)dx) = 1$$

it follows:

$$\int_0^a pdf(x)dx = p(a) = e^{-\frac{1}{a}} \tag{23}$$

Next, from the previous conditions and after developing the exponential function, we obtain:

$$p_{ii}(\tau_i / T) = 1 - \frac{1}{\tau_i / T} - \frac{1}{(\tau_i / T)^2} - \frac{1}{(\tau_i / T)^3} - \cdots, \quad \tau_i / T \geq 1 \tag{24}$$

Finally, if we stay at the third component, the diagonal elements of the *TPM* function are given by the:

$$p_{ii}(\tau_i / T) = 1 - \frac{1}{\tau_i / T} - (\frac{1}{\tau_i / T})^2 \tag{25}$$

Thus, from the total probability theorem it follows

$$\sum_{j=1}^{n} p_{ij} = 1, \; j = 1,2,...,n.$$

and finally,

$$\sum_{i=1}^{n} p_{ij}(k) = \sum_{i=1}^{n} [1 - \frac{1}{\tau_{i/T}} - (\frac{1}{\tau_i / T})^2] \\ = n - T \cdot \sum_{i=1}^{n} \frac{1}{\tau_i} - T^2 \cdot \sum_{i=1}^{n} \frac{1}{\tau_i^2} = 1 \tag{26}$$

An upper overall equation (19) has a real positive solution; the discriminate of square equation (26) satisfies the following condition:

$$\sum_{i=1}^{n} \frac{1}{\tau_i} \geq 2 \cdot \sqrt{n-1} \cdot \sqrt{\sum_{i=1}^{n} \frac{1}{\tau_i^2}} \tag{27}$$

If τ_i satisfies $\tau_i > T, i = 1,2,...,n$, the expected sojourn time of all n modes is assumed to be known and satisfies the condition given by (15).

The convergence

The hybrid estimation algorithm converges exponentially under several conditions. The exponential convergence refers to an algorithm which correctly identifies the model probabilities in finite time and has a base-state estimate sequence with a unique mean and convergent covariance, and an estimation-error mean converging exponentially to a bounded set with a guaranteed rate. Consider the problem of mode-sequence identification, where it is defined [11]:

$$\tilde{\mu}_j(k) = \frac{1}{c} \sum_{i=1}^{N} \Pi_{i,j}^{L} \tilde{\mu}_i\,(k-1) \exp[-A_{sj}] \\ A_{sj} = \lim_{L \to \infty} \frac{\left\| Z_s^k - Z_j^k \right\|^2}{L\sigma^2} \tag{28}$$

where $Z_j^k = \{z_{j'}[(k-1)\cdot L+1], z_{j'}[(k-1)\cdot L+2],...,z_{j'}(k \cdot L)\}$ are the measurements at the L discrete times, $(k-1)\cdot L+1, (k-1)\cdot L+2,...,k\cdot L$, m_j - is the correct model over the block, s - stands for the true model, $\Pi_{i,j}^{L}$ stands for the $(i,j)-$th element of the L-th power of the transition probability matrix, c - is the sum of the numerators over $i=1,2,...,N$. For a hybrid system the weights $\tilde{\mu}_j(k)$ will converge and the true model s- has the largest steady-state value $\lim_{k\to\infty} \tilde{\mu}_s(k)$ on condition that all mode transitions are possible but infrequent and the current model has the best fit to the data. Note that $\tilde{\mu}_j(k)$ is an approximation of the following de facto mode probability in the Gaussian case:

$$\mu_j(k) = \frac{1}{c} \sum_{i=1}^{N} \Pi_{i,j}^{L} \mu_i\,(k-1) \exp\left[-\frac{\left\| Z_s^k - Z_j^k \right\|^2}{L\sigma^2} \right] \tag{29}$$

assuming no mode transition within the block, by replacing the exponential factor with its steady-state value as the block size increases. As such, the above results for $\tilde{\mu}_j(k)$ hold approximately true for $\tilde{\mu}_j(k)$ which is meaningful if $\mu_j(k)$ is used as a fitness measure for an MM estimator.

Simulation results

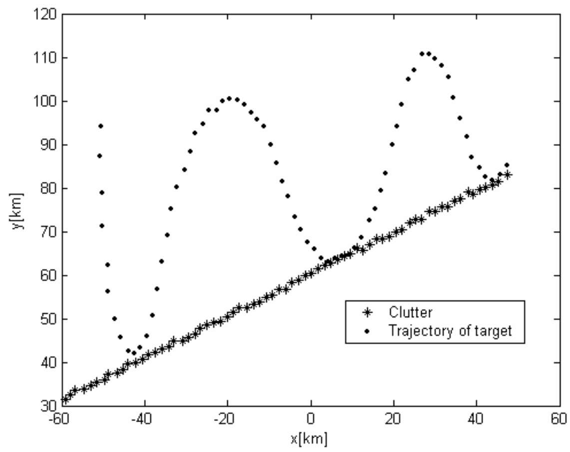
The simulation results of the three *IMMPDA* models, in nearly constant velocity, gentle maneuvers and closely maneuvers are presented in this section. The performances of the implemented tracking filters and the corresponding neural network method are evaluated by *Monte Carlo* (*MC*) simulations over several representative test trajectories. The measure of performance is done using the Root Mean Square Error [12]:

$$RMSE(k) = \\ \sqrt{\frac{1}{N_{MC}} \sum_{i=1}^{N_{MC}} (\hat{\xi}^i(k) - \xi^i(k))^2 + (\hat{\eta}^i(k) - \eta^i(k))^2} \tag{30}$$

where $\hat{\xi}^i(k), \hat{\eta}^i(k)$ are the position estimates (Cartesian coordinates) at the discrete time k, in MC run i and $\xi^i(k), \eta^i(k)$ are the measurement results.

The target motion scenario

The proposed algorithm was tested on an actual scenario which consisted of 80 frames of *Track While Scan (TWS)* radar data collection. Thesampling time interval is $T = 5\,\text{s}$. In order to test the efficiency of the proposed algorithm, two types of aircraft trajectories are formed. The first trajectory is with maneuver, and the second trajectory has no maneuver. The test trajectories are given in Fig.2.



Figue 2. The target and clatter trajectories

The first trajectory-target is a fast moving military fighter $v = 371\,\text{m/s}$. The target performs four turn maneuvers with intensities of g, $2g$, $5g$, $2g$ during the scans 10-28, 37-45, 55-58, and 65-73, respectively. *The second trajectory-clatter* is a civil aircraft with a constant velocity of v=240 m/s, and the rectilinear trajectory. Both trajectories are in clatter accident. It has been found that the following two models: the constant velocity (*CV*) model and the coordinated turn model, provide an adequate and self-contained model set for tracking purpose. If the state space vector is given by $\mathbf{x} = [x\ \dot{x}\ y\ \dot{y}]$ then the state transition matrix, for the *CV* and for CT model, is given by :

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

$$F_{CT}=\begin{bmatrix}1 & \dfrac{\sin\omega T}{\omega} & 0 & -\dfrac{1-\cos\omega T}{\omega}\\ 0 & \cos\omega T & 0 & -\sin\omega T\\ 0 & \dfrac{1-\cos\omega T}{\omega} & 1 & \dfrac{\sin\omega T}{\omega}\\ 0 & \sin\omega T & 0 & \cos\omega T\end{bmatrix}$$

The random sequences $\{v(k),\varpi(k)\}$ are assumed to be white, zero-mean, Gaussian, and mutually independent with:

$$E\left\{v(k),v^T(k)\right\}=Q(k) \tag{31}$$

$$E\left\{w(k),w^T(k)\right\}=R(k)\,. \tag{32}$$

Thus, we can specify the parameter of models as:

$$Q=q_i\cdot\begin{bmatrix}\dfrac{T^4}{4} & \dfrac{T^3}{2} & 0 & 0\\ \dfrac{T^3}{2} & T^2 & 0 & 0\\ 0 & 0 & \dfrac{T^4}{4} & \dfrac{T^3}{2}\\ 0 & 0 & \dfrac{T^3}{2} & T^2\end{bmatrix} \tag{33}$$

where $q_i, i=1,2.$ is the process noise covariance factor for both models $\left(q_1=0.005^2, q_2=0.05^2\right)$. The measurement model is given by $H=\begin{bmatrix}1&0&0&0\\0&0&1&0\end{bmatrix}$ and $R=\begin{bmatrix}\sigma_x^2 & 0\\ 0 & \sigma_y^2\end{bmatrix}$ where σ_x,σ_y are the denoted standard deviations for the Cartesian coordinates, which both have a value of 200m. The detection probability is $P_D=0.9$. The expected sojourn times in the proposed scenario of aircraft motion of 90 and 40 s, are assumed for M_1 and M_2 modes, respectively. The corresponding probabilities are p_{11}=0.941, p_{22}=0.875, p_{33}=0.666. The choice of the non-diagonal elements of the Markov transition matrix depends on the switching characteristics among the various modes and is calculated according to the following:

$$\begin{aligned}&p_{12}=0.1(1-p_{11})=0.0059,\ p_{13}=0.9(1-p_{11})=0.0941\\ &p_{21}=0.1(1-p_{22})=0.0125,\ p_{23}=0.9(1-p_{22})=0.1125\\ &p_{31}=0.3(1-p_{33})=0.0999,\ p_{32}=0.7(1-p_{33})=0.2331\end{aligned}$$

The expected sojourn time in the maneuver and the sampling interval, is assumed to be known and we calculated the diagonal elements of the *TPM* [10]. The *RMSE* position versus the transition probability is given in Fig.3. Furthermore, the table of the transition of probabilities (interval 0.1-0.99) with two models, is given in Table 1.

Table 1.

P_{11}	P_{22}									
0.99	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1	
0.99	359	452	505	545	580	613	645	677	710	752
0.9	316	397	436	461	481	497	512	527	543	562
0.8	294	359	386	403	415	425	435	445	457	471
0.7	272	321	339	350	359	366	374	383	392	403
0.6	245	280	293	302	310	318	326	334	343	352
0.5	212	239	252	262	272	280	289	297	306	315
0.4	178	204	220	233	243	252	261	270	279	288
0.3	154	182	199	212	223	232	242	250	259	267
0.2	150	171	186	199	209	218	227	236	244	252
0.1	148	165	178	189	199	208	216	225	233	240

The parallel diagrams of a proposed and of transition probability distribution are given in Fig.4. Finally, the overall *RMSE Position* for the inverse approximation of the transition probabilities function is 0.477, whence for the proposed exponential function it gives 0.462.

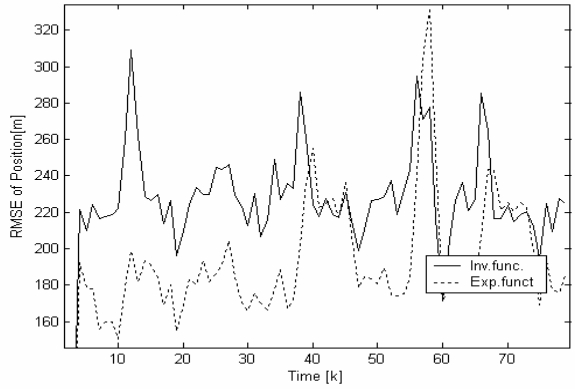


Figure 3. *RMSE* of position for the inverse and exponential function of transition probabilities

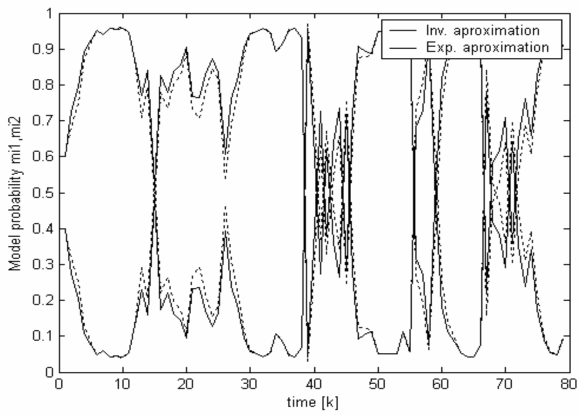


Figure 4. Distribution of the transition probability for the tested IMMPDA algorithm.

Conclusion

The *IMMPDA* state estimation method for a Markovian switching system with a unknown and exponential distributed transition probability matrix (*TPM*) is presented in this paper. Under the assumption of a constant but random *TPM*, an approximate recursion of the *TPM's* new exponential posterior probability density function is obtained. Based on the multiple model, the *IMM* estimation methodology associated with the *PDA* filter, is designed and tested. The performance of the *IMMPDA* algorithms with the new *TPM* coefficient is evaluated and compared over different flight scenarios. The simulation results have shown that during maneuvers, the proposed new initial probabilities method, *IMMPDA,* provided substantially better tracking characteristics. In this paper we have briefly illustrated the target tracking and data association procedure with the *IMMPDA* filter, for one target in the surrounding clatter. Data association is one of the most critical phases of the target tracking process. The simulations showed that computing the attribute association probabilities is important to increase efficiency of the target tracking.

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Received: 28.03.2007.

Određivanje verovatnoća prelaza za estimator stanja sa interaktivnim višestrukim modelom i pridruživanjem podataka po verovatnoći

U radu je predstavljen estimator stanja sa Markovljevim lancem i nepoznatom matricom verovatnoće prelaza (TPM). Polazeći od pretpostavke konstantne ali slučajne TPM i koristeći rekurzivni postupak ažuriranja istih, dato je izraćunavanje elemenata TPM matrice na osnovu funkcije gustine raspodele. Predložena je eksponencijalna raspodela verovatnoće i testirana na rekurzivnom MMSE (Minimum Mean-Square Error) algoritmu za estimaciju. Izračunate inicijalne vrednosti TPM su uključene u Probabilistic Data Association (IMMPDA) estimator. Rezultati simulacija sa praćenjem manevrišućih vojnih i civilnih aviona su pokazali smanjenje greške praćenja.
Pored toga, pokazan je značaj asocijativnih verovatnoća modela za tačnost predložene metode praćenja. U radu su dati preliminarni rezultati, a dalja istraživanja su u toku.

Ključne reči: **praćenje pokretnih ciljeva, hibridni sistemi, interaktivni višestruki model sa pridruživanjem podataka po verovatnoći, verovatnoće prelaza.**

Определение вероятностей переходов для оценки состояния со взаимодействующей многократной моделью и с присоединением данных по вероятности

В настоящей работе представлена оценка состояния со цепью Маркова и со неизвестной матрицей вероятности переходов (TPM). Исходя из предположения, что постоянная но случайная TPM и пользуясь рекурсивным поступком и способом привести их в порядок, произведён расчёт элементов TPM матрицы на основе функции плотности распределения. Предложено экспоненциальное распределение вероятности и испытано на рекурсивном ММСЕ (Минимум Меан-Съуаре Еррор) алгорифма для оценки. Расчисленные исходные величины TPM включены в Пробабилистиц Дата Ассоциатион (ИММПДА) оценку. Результаты имитационного моделирования со сопровождением военных и гражданских самолётов в маневре показали уменьшение ошибки сопровождения.
Кроме того, показано и значение соединимых вероятностей моделей для точности предложенного метода сопровождения. В работе приведены предварительные результаты, а дальнейшие исследования проводятся на днях.

Ключевые слова: сопровождение цели, подвижная цель, гибридная система, оценка состояния, вероятность перехода, определение вероятности, цепь Маркова.

Détermination des probabilités de la transition pour l’estimateur de l’état avec le modèle multiple interactif et l’association des données de probabilité

L’estimateur de l’état avec la chaîne de Markov et la matrice inconnue de la probabilité de transition (TPM) font l’objet de ce travail. Partant de la supposition que la TPM est constante mais aléatoire et en utilisant le procédé recursif pour leur mise au point, on a donné l’estimation des éléments de la matrice, à la base de la fonction de la densité de distribution. On a proposé la distribution exponentielle de la probabilité qui a été testée pour l’algorithme recursif de l’estimation MMSE. Les valeurs initiales obtenues sont incorporées à Probabilistic Data Association (IMMPDA) estimator. Les résultats des simulations avec la poursuite des avions militaires et civils ont démontré la diminution de l’erreur de poursuite. A part cela, on a souligné l’importance des probabilités associatives du modèle quant à l’exactitude de la méthode proposée de poursuite. Ce travail contient les résultats préliminaires alors que les recherches continuent.

Mots clés: **poursuite de la cible, cible mobile, système hybride, estimateur de l’état, probabilité de la transition, détermination de la probabilité,chaîne de Markov.**