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A Fuzzy-Logic-Based Approach for Soft Data Constrained Multiple-Model PHD Filter

Sepideh Seifzadeh, Bahador Khaleghi and Fakhri Karray
Electrical and Computer Engineering Department
University of Waterloo
sseifzad, bkhalegh, karray@uwaterloo.ca

***Abstract*—**
Tracking multiple targets with non-linear dynamics is a challenging problem. One of the popular solutions, Sequential Monte Carlo-Probability Hypothesis Density (SMC-PHD) filter, deploys a Random Set (RS) theoretic formulation along with the Sequential Monte Carlo approximation, which is a variant of Bayes filtering. The performance of Bayesian filtering-based methods can be enhanced by using extra information incorporated as specific constraints into the filtering process. Following the same principle, this paper proposes a constrained variant of the SMC-PHD filter, in which the inherently vague human-generated data are transformed into a set of constraints using a fuzzy logic approach. These constraints are enforced to the filtering process by applying coefficients to the particles' weights. The Soft Data (SD) reports on target agility level; wherein, the agility refers to the case in which the observed dynamics of the targets deviates from its given probabilistic characterization. Consequently, the proposed constrained filtering approach enables dealing with multitarget tracking scenarios in presence of target agility, as demonstrated by the experimental results presented in this paper.

I. Introduction

In the literature, a large number of methods has been proposed to tackle the problem of tracking multiple targets [10]. The Probability Hypothesis Density (PHD) filter [5] is one of the most popular multiple target tracking approaches. The sampling-based moment approximation methods, in particular the Sequential Monte Carlo (SMC) approach, have also been widely deployed to extend PHD filter to deal with non-linear tracking scenarios [7]. On the other hand , the problem of tracking targets whose dynamics include multiple-switching regimes, also known as maneuvering target tracking, has been studied extensively as reflected in the review paper series by Li & Jilkov [22], [23], [24]. The uncertainty regarding target mode and its transitions are typically characterized in a Markovian manner, using the so-called transition probability matrix (TPM), denoted by π [25]. The Interacting Multiple Model (IMM) is one of the most commonly used approaches to tackle this problem, which is deployed to develop the IMM SMC-PHD filter proposed in [1].

In this paper, we consider the problem in which dynamics of the maneuvering multiple-targets might deviate from the probabilistic characterization represented by TPM. We refer to this problem as agile multitarget tracking, and consider agility level to be directly associated with the likelihood of unpredictable target maneuvers. Agile multiple target tracking is an important and challenging problem; which, to the best of our knowledge, has been rarely addressed in the literature. This lack of interest is partly due to the difficulty of obtaining data regarding the agility level of targets using the conventional sensory mechanisms.

On the other hand, a relatively recent trend in the data fusion community aims at exploiting data provided by humans [26], [27], [9]. The conventional data provided by calibrated sensors, also referred to as hard data, is typically well characterized. In comparison, human-generated data, known as soft data [20] is typically unstructured, vague, and subjective. However, humans can provide high level information regarding targets that could be very difficult or impossible to obtain using hard conventional sensors. A tremendous amount of research has been studied on data fusion using conventional sensors. In contrast, limited work has been done to enable incorporating soft data into the fusion process. Humans have advanced cognitive abilities, which allow them to provide valuable information regarding intricate target behaviors, including the agility. Accordingly, the proposed approach in this paper deploys soft human-generated data regarding targets' agility level to improve the performance of the IMM SMC-PHD filter by incorporating soft data as constraints.

This paper is organized as follows. Section II summarizes the background and an overview of the related literature work. The proposed soft-data-constrained IMM SMC-PHD filter is described in section III. In Section IV, a multitarget tracking example is presented with simulation results. Finally, conclusions are given in Section V.

II. Background

A. Related Work

Early work to exploit external knowledge as constraints in order to improve tracking performance can be traced back to the early 1990s [12]. The constrained Bayesian filtering literature contains a wide spectrum of techniques, including pseudo-measurement [13], clipping [14], projection [15], and optimization-based methodologies [16]. The enforced constraints themselves are also diverse: linear, non-linear, soft, hard, equality, and inequality [17]. Variants of the constrained particle filtering methods have also been proposed in the literature, assuming a variety of domain-specific constraints [18], [19]. As discussed by Simon [11], for the case of linear systems with linear constraints, all of the existing approaches lead to the same optimal state estimate; whereas, for non-linear cases, the number of state estimation techniques can be overwhelming. This is because the constrained non-linear filtering problem can be viewed from many vantage points.

In the literature, limited work has studied the fusion of data produced by human and non-human sensors. Hall *et al.* [20] provide a brief review of ongoing work on dynamic fusion of hard/soft data, identifying its motivation and advantages, challenges, and requirements. A recent preliminary research in this area is the work on generating a dataset for hard/soft data fusion intended to serve as a foundation and a verification/validation resource for future research [32]. Very recently, a Dempster-Shafer theoretic framework for soft/hard data fusion was proposed that relies on a novel conditional approach for updating, as well as a new model to convert propositional logic statements from text into forms usable by Dempster-Shafer theory [31]. Another trend of work along this area is focused on the so-called *human centered data fusion* paradigm and puts emphasis on the human role in data fusion process [30], [29]. This new paradigm considers humans as active participants in the data fusion process and not merely as soft sensors but also as hybrid computers and *ad-hoc* teams (hive mind). It relies on emerging technologies such as virtual worlds and social network software to support humans in their new fusion roles. In spite of these accomplishments, research on hard/soft data fusion, as well as human-centered fusion is still in its fledging stage and should provide rich opportunities for further theoretical advancement and practical demonstrations in the future [28].

B. IMM SMC-PHD

The Probability Hypothesis Density (PHD) filter proposed by Mahler [5] is a well-known multitarget tracking approach. It relies on propagation of a first-order statistical moment of the multitarget posterior derived using the random set theory. The PHD filter can be implemented via the Gaussian Mixtures (GM) [6] or the Sequential Monte Carlo techniques [7]. SMC approaches have the advantage of computational tractability [3] and provable convergence properties [7], [4]. In addition, there is no need for the assumptions to be made on the form of the underlying probability density; therefore, they are applicable under the most general circumstances. The SMC approximation of the IMM PHD filter is applicable to track multiple maneuvering targets with nonlinear, non-Gaussian dynamics. In particular, the SMC-PHD filter [21] has been extended using the interacting multiple-model principle (IMM SMC-PHD) to enable tracking of multiple maneuvering targets[2].

Algorithm 1 shows the steps of the IMM SMC-PHD filter. As shown in the first step of the Algorithm 1, there is an initialization of an augmented particle set $[\{x_t^n, w_t^n\}_{n=1}^N]$; in which, each particle consists of a state x^n, weight w^n and a mode r^n, and N is the total number of particles. After the particles' mode is predicted as shown in *step 2.1*; it is followed by a mode-dependant state prediction of the targets. For the target with state x_{t-1} at time step $t-1$, the probability that it will survive at time t is given by $e_{t|t-1}(x_{t-1})$. The prediction step is as defined in *step 2.2*, where the Density $D_{t|t-1}(.)$ is similar to probability density except that it does not integrate to unity, $\delta(.)$ is the Dirac Delta function, and w_{t-1} is the weight of the n^{th} particle at time $t-1$. The function $f_{t|t-1}(.)$ in this equation characterizes the Markov target transition density.

Algorithm 1: IMM SMC-PHD

$[\{x_t^n\}_{n=1}^N]$ =IMM SMC-PHD $[\{x_{t-1}^n\}_{n=1}^N, z_t]$

Step 1: Initialization: $\{x_t^n, r_t^n, w_t^n\}_{n=1}^N$

Step 2: Prediction

Step 2.1: Mode prediction

$$p(r_t|z_{1:t-1}) = \sum_{m,m' \in \mathbb{N}} \sum_{n=1}^{N_t^P} h_{mm'}(x_{t-1}^n) w_{t-1}^n \delta(m - r_{t-1}^n)$$

Step 2.2: Mode-dependant state prediction

$$D_{t|t-1}(x_t, r_t|z_{1:t-1}) = \sum_{n=1}^{N_t^P} w_{t|t-1}^n \delta(x_t - x_{t|t-1}^n, r_t - r_{t|t-1}^n)$$

$$w_{t|t-1}^n = e_{t|t-1}(x_{t|t-1}^n) f_{t|t-1}(x_{t|t-1}^n | x_{t-1}^n, r_{t|t-1}^n)$$

Step 3: Correction (Updating)

$$w_t^n = (1 - P_D(x_{t|t-1}^n)) + \sum_{i=1}^{N_t^Z} \frac{P_D(x_{t|t-1}^n) f_{t|t}(z_t^i | x_{t|t-1}^n, r_{t|t-1}^n)}{\lambda_t c_t(z_t^i) + \psi_t(z_t^i)}$$

with the likelihood function,

$$\psi_t(z_t^i) = \sum_{n=1}^{N_t^P} P_D(x_{t|t-1}^n) f_{t|t}(z_t^i | x_{t|t-1}^n, r_{t|t-1}^n) w_{t|t-1}^n$$

Step 4: Evaluate number of targets

$$\hat{T}_t = \sum_{n=1}^{N_t^P} w_t^n$$

Step 5: Grouping & clustering estimations

Step 6: Go to step 2

The predicted PHD can be corrected with the availability of measurements $z_{1:t}$ at time step t to get the updated PHD. We assume that the number of false alarms is Poisson distributed with the average rate of λ_t, and that the probability density of the spatial distribution of false alarms is $c_t(z_t)$. Let the detection probability of a target with state x_t at time step t be $P_D(x_t)$, updating or correction step based on measurement data is defined in *step 3*, where N_t^Z indicates the number of measurements at time t. The single-target/single-sensor measurement likelihood function is defined by $f_{t|t}(.)$ in this equation.

In contrast to the Particle filter, in PHD filter the summation of the particles' weights is not equal to one, rather it is equal to the total number of targets at that moment. In other words, the expected number of targets at time step t is the summation of the weights of all the particles at that moment. In *step 4*, the total number of targets is estimated, where $\hat{T}_t$ and N_t^p indicate the number of estimated targets and the number of particles at time t, respectively. In the next step, particles are clustered to provide final targets' estimations.

Report=<Target ID> is <qualifier> <level of agility> agile	
Expression	Expression=<Target ID> is <RCL> <RAL> agile <Target ID> ∈ {robot} <RCL> ∈ {certainly, almost, perhaps} <RAL> ∈ {extremely, highly, marginally/not}

Fig. 1: The syntax considered for soft data reports

III. SD-Constrained IMM PHD Filter

This section presents the proposed soft-data-constrained IMM SMC-PHD filter used to tackle the problem of agile multitarget tacking. The filter uses a Fuzzy logic approach [8], [34] to model and incorporate the soft data.

A. Soft Data Modeling Using Fuzzy Logic

Fuzzy inference systems can be used to capture the uncertainty arising from the soft data vagueness. One could argue in favor of probabilistic approaches as an alternative to fuzzy inference systems for soft data processing. However, the probabilistic measures are most appropriate when dealing with ill-defined (random) variables hitting well-defined sets; whereas, fuzzy measures enable calculating the membership of well-known variables in ill-defined (vague) sets [28]. There has been rapid growth of research in fuzzy control and fuzzy modeling since Zade [34] first gave a mathematical foundation of fuzzy systems. Mamdani's fuzzy inference method [33], the most commonly used fuzzy methodology, is used in this paper, and the defuzzification method used is Centroid.

Soft data reports are supplied by a human observer and are assumed to comply with a specific syntax and semantics, both predefined by an ontology. Please note that, an appropriate Natural Language Processing (NLP) model can be used to format raw soft data according to the specified syntax. The syntax for the soft data report is shown in Figure 1, in which, each report is a natural language expression that reports on the agility level of the target along with the certainty level presumed by the reporter. In other words, each report is an expression comprised of a target-identification term, target ID, a qualifier term to express the level of certainty presented by the report, and a term to represent the perceived agility level of the target.

The semantics used to interpret given soft data can be explained as follows, with three different categories for the Reported Agility Level (RAL) and three different categories for the Reported Certainty Level (RCL). For RAL, the report can be extremely, highly, or marginally/not, and for RCL, it can be considered as certainly, almost, or perhaps; i.e., RCL∈{"certainly", "almost", "perhaps"} and RAL∈{"extremely", "highly", "marginally/not"}. Therefore, a set of FISs are defined based on the soft data report; i.e., the rules are defined based on the reported RAL, and fuzzy membership functions are defined using RCL. As a result, nine different FISs that have different rules and different membership functions are modeled (step 1 in Algorithm 2).

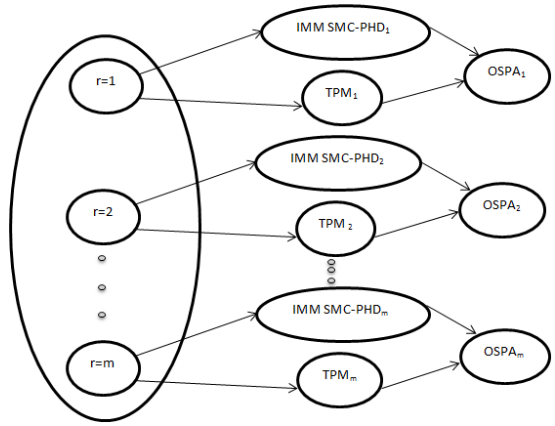


Fig. 2: OSPA distance calculation procedure including predicting clusters using both IMM SMC-PHD & TPM followed by computing the distance between two predicted densities

For a given soft data, one of the FISs is selected based on the corresponding RCL and RAL inputs (step2 in Algorithm 2).

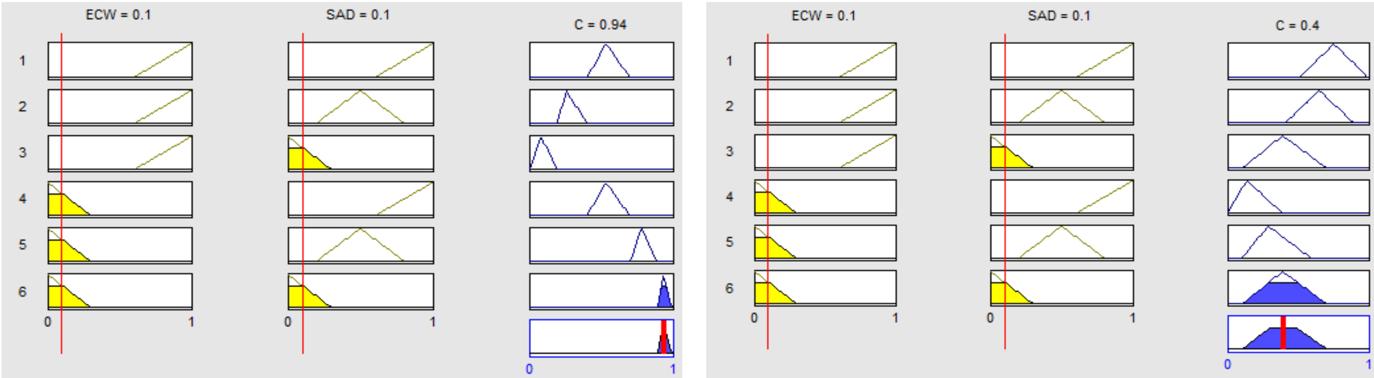
In the mode prediction step, early in SDC IMM SMC-PHD method, the same number of particles ($\frac{N}{M}$) is transferred to each mode, where N is the total number of particles and M is the total number of modes (step 4.1 in Algorithm 2). For particles with their current mode defined by m, the next mode (m') is predicted using the TPM. That is, respective value is extracted from the transition matrix, $\pi_{mm'}$. The value of $\pi_{mm'}$ is also assigned to a variable called the Stochastic Agility Discount (SAD). For each particle, the next mode is also predicted using the IMM SMC-PHD filter. Then the prediction step is performed using the predicted mode for each case, and the difference of the resulting clouds is evaluated using the Optimal Sub-Pattern Assignment (OSPA) [35], in order to compare the distance of these two density clouds (Figure 2). The OSPA is defined as follows:

$$\bar{d}_p^{(c)}(X,Y) = \Big(\frac{1}{\beta}\big(min_{\pi\in\prod_\beta}\sum_{i=1}^{\alpha} d^{(c)}(x_i,y_{\pi(i)})\big)^p + c^p(\beta-\alpha)\Big)^{\frac{1}{p}} \tag{1}$$

where $X=\{x_1,...,x_\alpha\}$ and $Y=\{y_1,...y_\beta\}$ are finite subsets, α and $\beta \in N_o=\{0,1,2,...\}$, $1\le p<\infty$ and $c>0$; in our simulations, $p=1$ and $c=50$. The output of this step is called the Expected Cluster Weight (ECW), and shows the estimated target's agility with respect to the maneuvering characteristics defined by the TPM (step 4.2 in Algorithm 2).

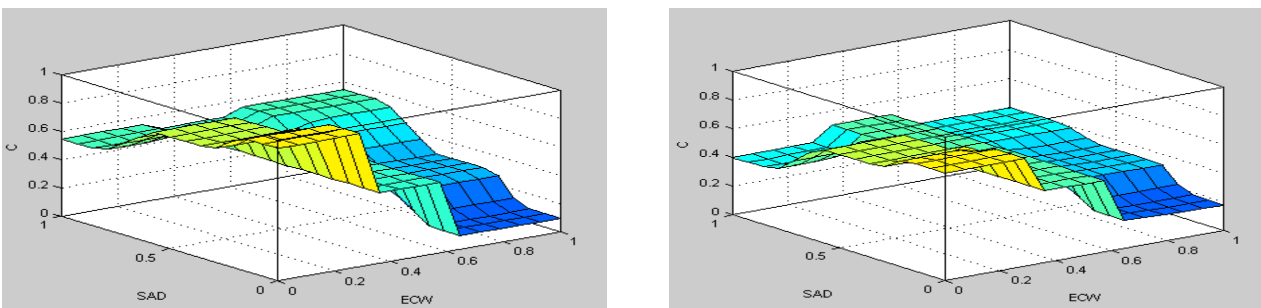
After choosing the FIS, the value ECW, which represents the divergency of the target behaviour with respect to the TPM, along with the SAD are the inputs to the FIS. The output of the FIS is the set of constraints $[\{C_t\}_{1=n}^N]$ used to reweigth the particles (step 5 in Algorithm 2), in order to incorporate the external knowledge in the estimation process (step 6 in Algorithm 2).

Figure 3 shows the fuzzy inference systems for two cases in



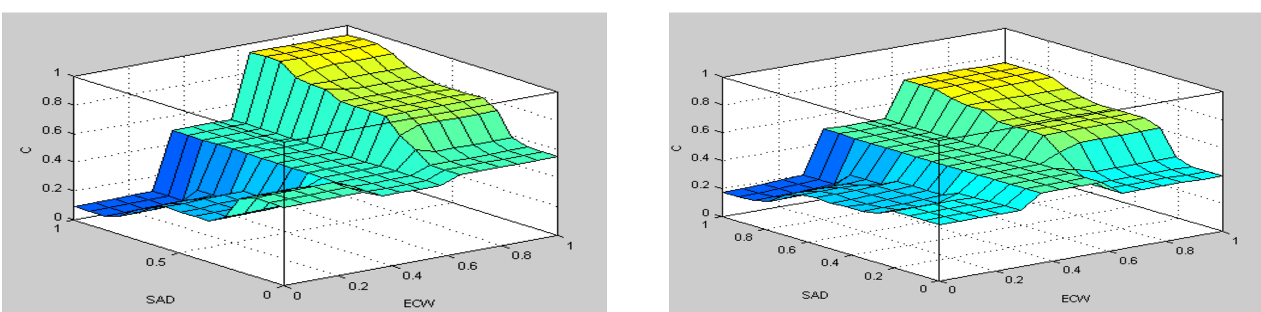
(a) (b)

Figure 3. Exemplary fuzzy inference systems for soft data report as: (a) “target is certainly extremely agile” and (b) “target is perhaps marginally/not agile”



(a) (b)

Figure 4. The effect of soft data report’s certainty level on fuzzy inference system, with soft data report as: (a) “target is certainly extremely agile” and (b) “target is perhaps extremely agile”



(a) (b)

Figure 5. The effect of soft data report’s certainty level on fuzzy inference system, with soft data report as: (a) “target is certainly marginally agile” and (b) “target is perhaps marginally agile”

TABLE I: Fuzzy rules for the case of: RCL="certainly" &RAL="extremely"

if (ECW is high) & (SAD is high) then ($C$is med)
if (ECW is high) & (SAD is med) then (C is low)
if (ECW is high) & (SAD is low) then (C is vlow)
if (ECW is low) & (SAD is high) then (C is med)
if (ECW is low) & (SAD is med) then (C is high)
if (ECW is low) & (SAD is low) then (C is vhigh)

TABLE II: Fuzzy rules for the case of: RCL="perhaps" &RAL="marginally/not"

if (ECW is high) & (SAD is high) then (C is vhigh)
if (ECW is high) & (SAD is med) then (C is high)
if (ECW is high) & (SAD is low) then (C is med)
if (ECW is low) & (SAD is high) then (C is vlow)
if (ECW is low) & (SAD is med) then (C is low)
if (ECW is low) & (SAD is low) then (C is med)

which the soft data is reported as "target is certainly extremely agile" (Figure 3(a)) and "target is perhaps marginally/not agile" (Figure 3(b)). The membership functions of the output are defined based on the value reported for the RCL. As shown in Figure 3(a), the membership functions are narrower and have less overlap to reflect a higher certainty level of the report; whereas, in the case of a less certain report, they are wider and have more overlap.

The rules of the FIS are adapted based on the value reported for the RAL. Table I (which corresponds to Figure 4(a)) and Table II (which corresponds to Figure 5(b)) demonstrate a set of rules defined for two different RALs. Table I shows the rules defined when the RAL is "extremely", and Table II depicts a case in which the reported RAL is "marginally/not". In these tables, the terms "vlow", "med" and "vhigh" represent very low, medium and very high, respectively. Please note that, Figures 3(a) and 3(b) correspond to the fuzzy rules presented in Table I and II, respectively, with the inputs (ECW is low) and (SAD is low). The discussion presented in Section III.B elaborates on how the fuzzy rules for each FIS are adapted to achieve the desired constrained filtering behaviour.

B. Incorporating Soft Data as Dynamic Constraints

As discussed in the previous section, the FIS is modeled based on the inputs RAL and RCL. After that, divergency of the target behaviour with respect to the TPM is evaluated (ECW) and is the first input to the FIS. For each particle, based on its previous mode (m) and its predicted mode (m'), the respective value of TPM is selected (SAD) and is the other input to the FIS. Then, constraints are calculated based on the fuzzy rules and are incorporated into the particles' weights.

Figures 4 and 5 show the effect of the inputs on the fuzzy inference output for two different fuzzy models selected based on the soft data report. These two figures are deployed to show how variation in the soft data report affects the constraints produced by FIS. To make the figures clearer and to briefly explain how the fuzzy rules are modeled to infer the constraints based on the report, some of the cases are explained as follows:

Algorithm 2: SDC IMM SMC-PHD

$[\{x_t^n, C_t^n\}_{n=1}^N]$ =SDC IMM SMC-PHD $[\{x_{t-1}\}_{n=1}^N, z_t, SD]$

Step 1: Define a set of FIS

Step 1.1: Define rules based on RAL

Step 1.2: Define membership functions based on RCL

Step 2: Interpret SD: {RCL & RAL}

Selecet FIS based on given RCL & RAL

Step 3: Particle Initialization

Step 4: Mode Prediction

Step 4.1: Cluster Particle cloud into M particle clouds

$PC_m : m = 1, ...M$

Step 4.2: For $PC_m : 1, ..., M$ (Figure 2)

Predict next mode (m') using TPM

Predict m' using generic IMM PHD

ECW α Distance of the two clouds using OSPA

SAD α The respective element of TPM based on m and m'

Step 5: Compute constraints:

For n=1:N

$ECW \ \alpha \ OSPA$ & $SAD_t^n \ \alpha \ \pi_{mm'}$

$C_t^n = FIS(SAD_t^n, ECW_t)$

Step 6: Apply constraints to particles' weights

For n=1:N

$w_t^n = w_t^n \times C_t^n$

Step 7: Resampling

Step 8: Mode-dependant state prediction

Step 9: Correction (Updating)

Step 10: Evaluating number of targets

Step 11: Grouping & clustering the estimates

Step 12: Go to Step 4

Let us consider the case in which the target is agile; therefore, the ECW is high, since the distance between the density predicted by IMM SMC-PHD filter and TPM is large. If the report is "target is certainly extremely agile", the FIS shown in Figure 4.a is selected for the inference process based on the RAL="extremely" and RCL="certainly". If the SAD is low for the n^{th} particle, then the constraint coefficient applied to the weight of the respective particle should be very high, Table I and Figure 3(a) depict the same situation, and vice versa.

That is, for particles with a high SAD value, indicating that the particle is behaving based on the behaviour characterized by TPM, the constraint should be low to decrease the weight of the respective particle, since in reality the target is agile and its trajectory is not based on the behaviour characterized by TPM. Based on the similarity of these two estimations calculated by TPM and IMM SMC-PHD, and the agility reported, the constraints are evaluated and are then applied to the respective particles. If the report indicates the existence of agility and the target is agile, i.e. it does not behave in a similar fashion to the TPM, the particles in dominant mode should get lower weights and the rest of the particles should be assigned higher weights in order to survive and to re-generate more. After incorporating the constraints into particles' weights, a resampling step is performed. If the target's agility level, which is input by the user, is high and the target is not agile, then the particles that follow the behavior defined by TPM should get low weights to gradually disappear. On the other hand, the rest of the particles should get higher weights in order to survive.

The soft-data-inspired dynamic constraints affect the particles' weights before the resampling step; therefore, the weighting of the particles is as follows:

$$w_t^n = w_{t-1}^n p(z_t|x_t, r = m')C_t^n \tag{2}$$

$$C_t^n = FIS(SAD_t^n, ECW_t) \qquad n = 1, ..., N \tag{3}$$

in which the constraints (C_t^n) are calculated in *step 5* of Algorithm 2. Algorithm 2 has many steps similar to those in Algorithm 1, and it also adds a number of additional steps to accomplish the mode prediction. The same concept of Soft data modeling and incorporating the constraints to the filtering process is presented and detailed in our previous work [9]; in which, a soft-data-constrained multi-model Particle filtering approach was proposed.

IV. Simulation Results

A two dimensional tracking example is used to compare the impact of the soft data in the case of agility in target dynamics. There are five targets that can appear and disappear successively, with initial positions of $(3\times10^2, 4\times10^2)m, (4\times10^2, 3\times10^2)m, (6\times10^2, 8\times10^2)m, (6\times10^2, 10\times10^2)m,$ and $(7\times10^2, 5\times10^2)m$. Figures 6 and 7 show target trajectories with no agility and high agility, respectively. There are three modes: a constant velocity model and two coordinated turn models. The Markovian transition probability matrix indicating the transition probability between different modes is shown below:

$$[h_{mm'}] = \begin{bmatrix} 0.1 & 0.45 & 0.45 \\ 0.7 & 0.1 & 0.2 \\ 0.7 & 0.2 & 0.1 \end{bmatrix} \tag{4}$$

The TPM represents the state transition probability from the m^{th} mode to the m'^{th} mode. Constant velocity and coordinated turn models are described as follows, respectively:

$$x_t = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} + x_{t-1} + \sigma_t \tag{5}$$

$$x_t = \begin{bmatrix} 1 & sin(\frac{\Omega_{t-1}T}{\Omega_{t-1}}) & 0 & -\frac{1-cos(\Omega_{t-1}T)}{\Omega_{t-1}} \\ 0 & cos(\Omega_{t-1}T) & 0 & 1-sin(\Omega_{t-1}T) \\ 0 & \frac{1-cos(\Omega_{t-1}T)}{\Omega_{t-1}} & 1 & \frac{sin(\Omega_{t-1}T)}{\Omega_{t-1}} \\ 0 & sin(\Omega_{t-1}T) & 0 & cos(\Omega_{t-1}T) \end{bmatrix} + x_{t-1} + \sigma_t \tag{6}$$

where Ω_t is the turning rate at time step t, and T, which is the sample time, is equal to one. σ is an i.i.d sequence of zero-mean Gaussian vectors with a covariance Q.

$$Q = \begin{bmatrix} \frac{T^4}{4} & \frac{T^2}{2} & 0 & 0 \\ \frac{T^2}{2} & T & 0 & 0 \\ 0 & 0 & \frac{T^4}{4} & \frac{T^2}{2} \\ 0 & 0 & \frac{T^2}{2} & T \end{bmatrix} q \tag{7}$$

The level of the power spectral density of the corresponding continuous process noise (q) is equal to 1×10^{-3}. Performance evaluation of multitarget tracking algorithms is of great practical importance in the design and comparison of tracking systems. In order to evaluate the performance of the proposed method, a consistent metric, recently proposed, called OSPA, is used as defined in the Section III.A.

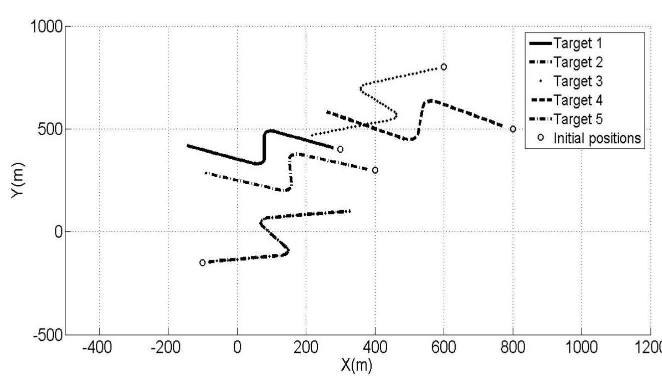


Figure 6. Targets trajectory without agility

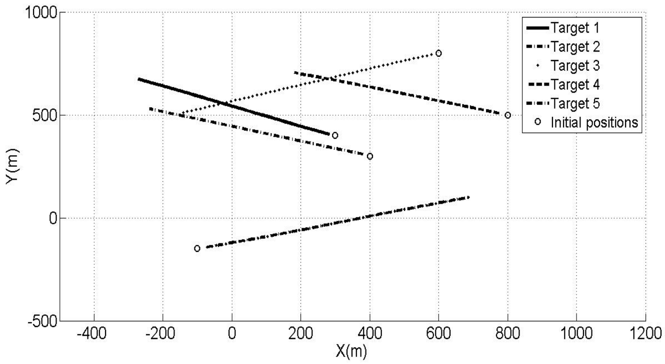


Figure 7. Targets trajectory with agility

A. Scenario I: Impact of Incorporating Soft Data

In this scenario, targets are highly agile, i.e, targets are expected to make turns based on TMP; however, they travel only in a straight line during the simulation. Figure 8 demonstrates a comparison of the OSPA for the case with no soft data provided, i.e., the generic IMM SMC-PHD filter, and the proposed SDC IMM SMC-PHD filter with the soft-data report "target is certainly extremely agile".

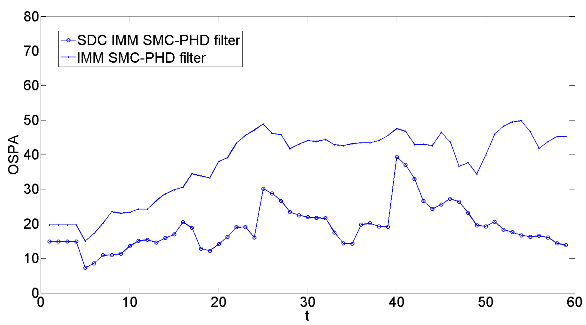


Figure 8. Soft-data effect in case of agility

The OSPA distances for both filters are shown in Figure 8. As shown in this figure, the proposed method, SDC IMM SMC-PHD filter, has less OSPA distance during the simulation time, which shows more accurate tracking performance. It is clear that when the targets do not switch their modes, there are no obvious differences between them; however, when maneuvers occur, the OSPA distances increase, i.e. at simulation times $t = 25$ and $t = 40$. This result occurs because when the conditional model probabilities and switching rates have small values, there may be very few particles for one or more models in the IMMSMC-PHD filter, especially if there is agility in the target dynamics. Then the empirical density spanned by all particles with such a mode does not perform an accurate approximation of the corresponding exact conditional density. Such problems have been solved by the proposed algorithm, since the exact conditional density is approximated by incorporating the external knowledge.

B. Scenario II: Impact of Soft Data Certainty Level

In this set of experiments, the effect of the soft data's certainty level of the soft data is examined and compared (Figure 9), for a case in which the target is agile and the reports are "target is certainly highly agile" and "target is perhaps highly agile". In both cases, the reported soft data provides a correct information regarding the targets' agility level; however, the certainty levels of the reports are different. The effect of the constraints on the particles' weights and therefore the filters' performance can be observed in this figure.

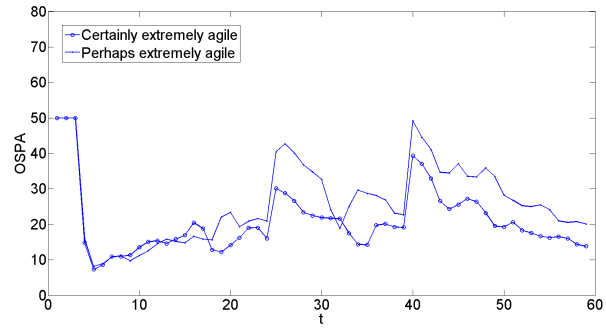


Figure 9. Impact of the soft data report's certainty level

As shown, when correct soft data is reported regarding the agility level of the target, the report with the higher certainty provides better approximation, i.e., a lower OSPA distances are observed. When the certainty level decreases, since the constraints are not that effective anymore, they have less effect on the particles' weights and therefore the approximation is not as accurate.

C. Impact of Number of Particles

Different number of particles are used in order to evaluate the resulting effects. As shown in Table III, in SMC-based methods, the number of particles used is very important. The accuracy of the approximation is directly proportional to the size of the particle set (N); increasing the total number of particles increases the accuracy of the approximation, but also increases the computational cost. In other words, choosing the number of particles is a trade-off between the accuracy and the computational resources.

TABLE III: Impact of number of particles

Number of Particles	Average simulation time(s)	Average OSPA distance(m)
100	10	40.01
500	70	30.84
1000	180	23.59

V. Conclusion

In this paper, we considered maneuvering multitarget tracking situations, wherein target maneuvers may deviate from their stochastic characterization represented by the jump

Markovian matrix. We refer to this phenomenon as agile multitarget tracking and propose a constrained variant of the IMM SMC-PHD filter that can leverage soft human-generated data regarding target agility using a fuzzy logic approach. The constraints are enforced by applying coefficients to particles' weights. These coefficients are produced by a fuzzy inference system, which is developed to enable inference using vague human-generated soft data. Three categories of experiments were performed in order to evaluate the effect of incorporating the soft data, the impact of the certainty level of the reported soft data, and the obtained tracking performance with respect to the size of the deployed particle set. The results of the first two categories of experiments demonstrate the ability of the proposed fuzzy inference system to successfully capture the vagueness of soft human-generated data regarding target agility. The last category of experiments shows the anticipated trade-off between the computational complexity and the overall performance of the proposed approach with respect to the number of particles.

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