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Target Type Tracking with Different Fusion Rules: A Comparative Analysis

Published in:

Florentin Smarandache & Jean Dezert (Editors)

Advances and Applications of DSmT for Information Fusion

(Collected works), Vol. II

American Research Press, Rehoboth, 2006

ISBN: 1-59973-000-6

Chapter XIII, pp. 323 - 342

Abstract: *We analyze the behavior of several combinational rules for temporal/sequential attribute data fusion for target type estimation. Our comparative analysis is based on: Dempster's fusion rule, Proportional Conflict Redistribution rule no. 5 (PCR5), Symmetric Adaptive Combination (SAC) rule and a new fusion rule, based on fuzzy T-conorm and T-norm operators (TCN). We show through very simple scenario and Monte-Carlo simulation, how PCR5, TCN and SAC rules allow a very efficient Target Type Tracking and reduce drastically the latency delay for correct Target Type decision with respect to Dempster's rule. For cases presenting some short Target Type switches, Dempster's rule is proved to be unable to detect the switches and thus to track correctly the Target Type changes. The approach proposed here is totally new, efficient and promising to be incorporated in real-time Generalized Data Association - Multi Target Tracking systems (GDA-MTT). The Matlab source code of simulations is freely available upon request to authors and part of this code can also be found in [5].*

This work is partially supported by the Bulgarian National Science Fund-grants MI-1506/05, EC FP6 funded project - BIS21++ (FP6-2004-ACC-SSA-2). This chapter is an extended version of [5].

13.1 Introduction

The main purpose of information fusion is to produce reasonably aggregated, refined and/or complete granule of data obtained from a single or multiple sources with consequent reasoning process, consisting in using evidence to choose the best hypothesis, supported by it. Data Association (DA) with its main goal to partitioning observations into available tracks becomes a key function of any surveillance system. An issue to improve track maintenance performances of modern Multi Target Trackers (MTT) [1, 2], is to incorporate Generalized Data¹ Association (GDA) in tracking algorithms [15]. At each time step, GDA consists in associating current (attribute and kinematics) measurements with predicted measurements (attributes and kinematics) for each target. GDA can be actually decomposed into two parts [15]: Attribute-based Data Association (ADA) and Kinematics-based Data Association (KDA). Once ADA is obtained, the estimation of the attribute/type of each target must be updated using a proper and an efficient fusion rule. This process is called *attribute tracking* and consists in combining information collected over time from one (or more) sensor to refine the knowledge about the possible changes of the attributes of the targets. We consider here the possibility that the attributes tracked by the system can change over time, like the color of a chameleon moving in a variable environment. In some military applications, target attribute can change since for example it can be declared as neutral at a given scan and can become a foe several scans later; or like in the example considered in this chapter, a tracker can become mistaken when tracking several closely-spaced targets and thus could eventually *track* sequentially different targets observing that way a true sequence of different types of targets. In such a case, although the attribute of each target is invariant over time, at the attribute-tracking level the type of the target committed to the (hidden unresolved) track varies with time and must be tracked efficiently to help to discriminate how many different targets are hidden in the same unresolved track. Our motivation for attribute fusion is inspired from the necessity to ascertain the targets' types, information, that in consequence has an important implication for enhancing the tracking performance. Combination rules are special types of aggregation methods. To be useful, one system has to provide a way to capture, analyze and utilize through the fusion process the new available data (evidence) in order to update the current state of knowledge about the problem under consideration.

Dempster-Shafer Theory (DST) [10] is one of widely used frameworks in target tracking when one wants to deal with uncertain information and take into account attribute data and/or human-based information into modern tracking systems. DST, thanks to belief functions, is well suited for representing uncertainty and combining information, especially in case of low conflicts between the sources (bodies of evidence) with high beliefs. When the conflict increases² and becomes very high (close to 1), Dempster's rule yields unfortunately unexpected, or what authors feel, counter-intuitive results [11, 17]. Dempster's rule also presents difficulties in its implementation/programming because of unavoidable numerical rounding errors due to the finite precision arithmetic of our computers.

To overcome the drawbacks of Dempster's fusion rule and in the meantime extend the domain of application of the belief functions, we have proposed recently a new mathematical framework, called Dezert-Smarandache Theory (DSmT) with a new set of combination rules, among them the Proportional Conflict Redistribution no. 5 which proposes a sophisticated and efficient so-

¹Data being kinematics and attribute.

²Which often occurs in Target Type Tracking problem as it will be shown in the sequel.

lution for information fusion as it will be shown further. The basic idea of DSMT is to work on Dedekind's lattice (called Hyper-Power Set) rather than on the classical power set of the frame as proposed in DST and, when needed, DSMT can also take into account the integrity constraints on elements of the frame, constraints which can also sometimes change over time with new knowledge. Hence DSMT deals with uncertain, imprecise and high conflicting information for static and dynamic fusion as well [3, 4, 11].

Recently in [16] the authors propose to connect the combination rules for information fusion with particular fuzzy operators. These rules take their source from the T-norm and T-conorm operators in fuzzy logics, where the AND logic operator corresponds in information fusion to the conjunctive rule and the OR logic operator corresponds to the disjunctive rule. While the logic operators deal with degrees of truth and false, the fusion rules deal with degrees of belief of hypotheses. In [16] the focus is on the T-norm based Conjunctive rule as an analog of the ordinary conjunctive rule of combination. It is appropriate for identification problems, restricting the set of hypotheses one is looking for. A new fusion rule, called Symmetric Adaptive Combination (SAC) rule, has been recently proposed in [7] which is an adaptive mixing between the disjunctive and conjunctive rule. This rule acts more like the disjunctive rule whenever at least one source is unreliable, while it acts more like the conjunctive rule, when both sources are reliable. In the next section we present briefly the basics of DST and DSMT. In section 13.3, we present the Target Type Tracking problem and examine four solutions to solve it; the first solution being based on Dempster's rule and the next ones based on PCR5, TCN and SAC rules. In section 13.4, we evaluate all the solutions on a very simple academic but checkable³ example and provide a comparative analysis on Target Type Tracking performances obtained by Dempster's, PCR5, TCN and SAC rules. Concluding remarks are given in section 13.5.

13.2 Fusion Rules proposed for Target Type Tracking

13.2.1 Basics on DST and DSMT

Shafer's model, denoted here $\mathcal{M}^0(\Theta)$, in DST [10] considers $\Theta = \{\theta_1, \dots, \theta_n\}$ as a finite set of n exhaustive and exclusive elements representing the possible states of the world, i.e. solutions of the problem under consideration. Θ is called the *frame of discernment* by Shafer. In DSMT framework [11], one starts with the free DSMT model $\mathcal{M}^f(\Theta)$ where $\Theta = \{\theta_1, \dots, \theta_n\}$ (called simply frame) is only assumed to be a finite set of n exhaustive elements⁴. If one includes some integrity constraints in $\mathcal{M}^f(\Theta)$, say by considering θ_1 and θ_2 truly exclusive (i.e. $\theta_1 \cap \theta_2 = \emptyset$), then the model is said *hybrid*. When we include all exclusivity constraints on elements of Θ , $\mathcal{M}^f(\Theta)$ reduces to Shafer's model $\mathcal{M}^0(\Theta)$ which can be viewed actually as a particular case of DSMT hybrid model. Between the free-DSMT model and the Shafer's model, there exists a wide class of fusion problems represented in term of DSMT hybrid models where Θ involves both fuzzy continuous hypothesis and discrete hypothesis.

Based on Θ and Shafer's model, the *power set* of Θ , denoted 2^Θ , is defined as follows:

³Our Matlab source code is available upon request to help the reader to check by him/herself the validity of our results. Part of this code can be also found [5].

⁴The exclusivity assumption is not fundamental in DSMT because one wants to deal with elements which cannot be refined into precise finer exclusive elements - see [11] for discussion.

- 1) $\emptyset, \theta_1, \dots, \theta_n \in 2^\Theta$.
- 2) If $X, Y \in 2^\Theta$, then $X \cup Y$ belong to 2^Θ .
- 3) No other elements belong to 2^Θ , except those obtained by using rules 1) or 2).

In DSMT and without additional assumption on Θ but the exhaustivity of its elements (which is not a crucial assumption), we define the *hyper-power set*, i.e. Dedekind's lattice, D^Θ as follows:

- 1') $\emptyset, \theta_1, \dots, \theta_n \in D^\Theta$.
- 2') If $X, Y \in D^\Theta$, then $X \cap Y$ and $X \cup Y$ belong to D^Θ .
- 3') No other elements belong to D^Θ , except those obtained by using rules 1') or 2').

When Shafer's model $\mathcal{M}^0(\Theta)$ holds, D^Θ reduces to the classical power set 2^Θ . Without loss of generality, we denotes G^Θ the general set on which will be defined the basic belief assignments (or masses), i.e. $G^\Theta = 2^\Theta$ if Shafer's model is adopted whereas $G^\Theta = D^\Theta$ if some other (free or hybrid) DSm models are preferred depending on the nature of the problem.

From a frame Θ , we define a (general) basic belief assignment (bba) as a mapping $m(\cdot) : G^\Theta \rightarrow [0, 1]$ associated to a given source, say s , of evidence as

$$m_s(\emptyset) = 0 \quad \text{and} \quad \sum_{X \in G^\Theta} m_s(X) = 1 \quad (13.1)$$

$m_s(X)$ is the gbba of X committed by the source s . The elements of G having a strictly positive mass are called *focal elements* of source s . The set \mathcal{F} of all focal elements is the *core* (or *kernel*) of the belief function of the source s .

The belief and plausibility of any proposition $X \in G^\Theta$ are defined⁵ as:

$$\text{Bel}(X) \triangleq \sum_{\substack{Y \subseteq X \\ Y \in G^\Theta}} m(Y) \quad \text{and} \quad \text{Pl}(X) \triangleq \sum_{\substack{Y \cap X \neq \emptyset \\ Y \in G^\Theta}} m(Y) \quad (13.2)$$

These definitions remain compatible with the classical $\text{Bel}(\cdot)$ and $\text{Pl}(\cdot)$ functions proposed by Shafer in [10] whenever Shafer's model is adopted for the problem under consideration since G^Θ reduces to 2^Θ .

13.2.2 Fusion rules

A wide variety of rules exists for combining basic belief assignments [9, 12, 14] and the purpose of this chapter is not to browse in details all fusion rules but only to analyze and compare the main ruels used with DST and DSMT approaches (Dempster's, PCR5, SAC rules) and the TCN fusion rule. Since these rules have already been presented in details in chapters 1 and 12, they will not be repeated in this chapter. Our main goal is to show their performance on a very simple Target Type Tracking example.

⁵The index of the source has been omitted for simplicity.

13.3 The Target Type Tracking Problem

13.3.1 Formulation of the problem

The Target Type Tracking Problem can be simply stated as follows:

- Let $k = 1, 2, \dots, k_{max}$ be the time index and consider M possible target types $T_i \in \Theta = \{\theta_1, \dots, \theta_M\}$ in the environment; for example $\Theta = \{Fighter, Cargo\}$ and $T_1 \triangleq Fighter$, $T_2 \triangleq Cargo$; or $\Theta = \{Friend, Foe, Neutral\}$, etc.
- at each instant k , a target of true type $T(k) \in \Theta$ (not necessarily the same target) is observed by an attribute-sensor (we assume a perfect target detection probability here).
- the attribute measurement of the sensor (say noisy Radar Cross Section for example) is then processed through a classifier which provides a decision $T_d(k)$ on the type of the observed target at each instant k .
- The sensor is in general not totally reliable and is characterized by a $M \times M$ confusion matrix

$$\mathbf{C} = [c_{ij} = P(T_d = T_j | \text{True Target Type} = T_i)]$$

Question: How to estimate $T(k)$ from the sequence of declarations obtained from the unreliable classifier up to time k , i.e. how to build an estimator $\hat{T}(k) = f(T_d(1), \dots, T_d(k))$ of $T(k)$?

13.3.2 Proposed issues

We propose in this work four methods for solving the Target Type Tracking Problem. All methods assume the same Shafer's model for the frame of Target Types Θ and also use the same information (vacuous belief assignment as prior belief and same sequence of *measurements*, i.e. same set of classifier declarations to get a fair comparative analysis). Three of proposed issues are based on the ordinary combination of belief functions and the fourth - on a new class of fusion rules, based on particular fuzzy operations.

The principle of our estimators is based on the sequential combination of the current basic belief assignment (drawn from classifier decision, i.e. our *measurements*) with the prior bba estimated up to current time from all past classifier declarations. In the first approach, the Demspter's rule is used for estimating the current Target type, while in the next three approaches we use PCR5, TCN and SAC rules.

Here is how our Target Type Tracker (TTT) works:

- a) Initialization step (i.e. $k = 0$). Select the target type frame $\Theta = \{\theta_1, \dots, \theta_M\}$ and set the prior bba $m^-(.)$ as vacuous belief assignment, i.e. $m^-(\theta_1 \cup \dots \cup \theta_M) = 1$ since one has no information about the first target type that will be observed.
- b) Generation of the current bba $m_{obs}(.)$ from the current classifier declaration $T_d(k)$ based on attribute measurement. At this step, one takes $m_{obs}(T_d(k)) = c_{T_d(k)T_d(k)}$ and all the unassigned mass $1 - m_{obs}(T_d(k))$ is then committed to total ignorance $\theta_1 \cup \dots \cup \theta_M$.

- c) Combination of current bba $m_{obs}(\cdot)$ with prior bba $m^-(\cdot)$ to get the estimation of the current bba $m(\cdot)$. Symbolically we will write the generic fusion operator as \oplus , so that $m(\cdot) = [m_{obs} \oplus m^-](\cdot) = [m^- \oplus m_{obs}](\cdot)$. The combination \oplus is done according either Dempster's rule (i.e. $m(\cdot) = m_D(\cdot)$) or PCR5, SAC and TCN rules (i.e. $m(\cdot) = m_{PCR5}(\cdot)$, $m(\cdot) = m_{SACR}(\cdot)$ and $\tilde{m}(\cdot) = m_{TCN}(\cdot)$).
- d) Estimation of True Target Type is obtained from $m(\cdot)$ by taking the singleton of Θ , i.e. a Target Type, having the maximum of belief (or eventually the maximum Pignistic Probability⁶ [11]).
- e) set $m^-(\cdot) = m(\cdot)$; do $k = k + 1$ and go back to step b).

13.4 Simulation results

In order to evaluate the performances of all considered estimators and to have a fair comparative analysis of all fusion rules (Dempster's, PCR5, TCN and SAC), we did a set of Monte-Carlo simulations on a very simple scenario for a 2D Target Type frame, i.e. $\Theta = \{(F)ighter, (C)argo\}$ for two classifiers, a good one C_1 and a poor one C_2 corresponding to the following confusion matrices:

$$\mathbf{C}_1 = \begin{bmatrix} 0.995 & 0.005 \\ 0.005 & 0.995 \end{bmatrix} \quad \text{and} \quad \mathbf{C}_2 = \begin{bmatrix} 0.65 & 0.35 \\ 0.35 & 0.65 \end{bmatrix}$$

In our scenario we consider that there are two closely-spaced targets: one Cargo (C) and one Fighter(F). Due to circumstances, attribute measurements received are predominately from one or another, and both target generates actually one single (unresolved kinematics) track. In the real world, the tracking system should in this case maintain two separate tracks: one for cargo and one for fighter, and based on the classification, allocate the measurement to the proper track. But in difficult scenario like this one, there is no way in advance to know the true number of targets because they are unresolved and that's why only a single track is maintained. Of course, the single track can further be split into two separate tracks as soon as two different targets are declared based on the attribute tracking. This is not the purpose of our work however since we only want to examine how work PCR5, TCN, SAC and Dempster's rules for Target Type Tracking. To simulate such scenario, a true Target Type sequence (the groundtruth) over 100 scans was generated according figures 13.1, 13.2, 13.3 and 13.4 below. The sequence starts with the observation of a Cargo Type (i.e. we call it Type 2) and then the observation of the Target Type switches onto Fighter Type (we call it Type 1) with different time step $T[scans]$ as follows: (Fig.13.1 - T has a variable number of scans, Fig.13.2 - $T = 10$ scans, Fig.13.3 - $T = 5$ scans and Fig.13.4 - $T = 3$ scans). Our goal is to investigate what is the behavior of different fusion rules in case of variable switches' time step and also in cases of equal switches' time step, when target type changes appear to be more frequent, or in other words, to test until which point the proposed fusion rules are able to detect and to adapt to the occurring type's changes. As a simple analogy, tracking the target type changes committed to the same (hidden unresolved) track can be interpreted as tracking color changes of a chameleon moving in a tree on its leaves and on its trunk.

⁶We don't provide here the results based on Pignistic Probabilities since in our simulations the conclusions are unchanged when working with max. of belief or max. of Pign. Proba.

Our simulation consists of 1000 Monte-Carlo runs and we compute and show in the sequel the averaged performances of the four fusion rules. At each time step k the decision $T_d(k)$ is randomly generated according to the corresponding row of the confusion matrix of the classifier given the true Target Type (known in simulations). Then the algorithm presented in the previous section is applied. The complete Matlab source code of our simulation is freely available upon request to authors.

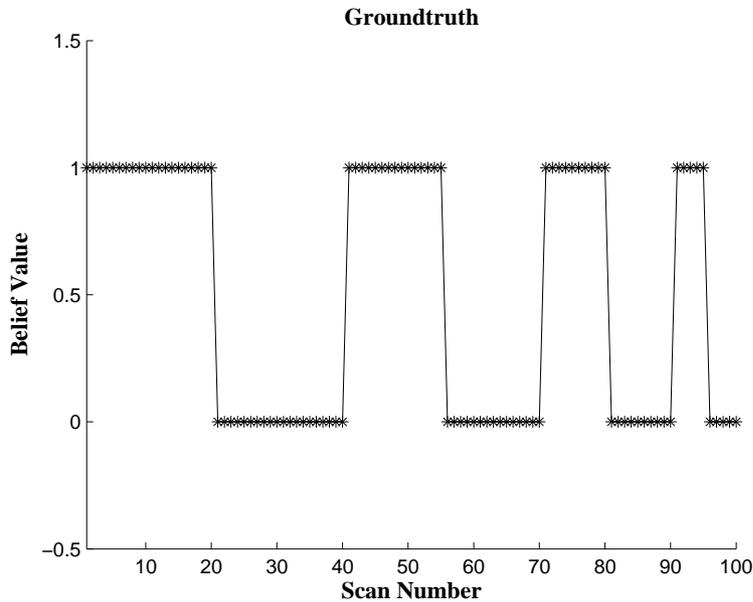


Figure 13.1: Sequence of True Target Type, T -variable number of scans

13.4.1 Results for classifier 1

Figures 13.5 - 13.8 show the belief masses, committed to Cargo type, obtained by our Target Type Trackers based on Dempster's rule (red curves -x-), PCR5 rule (blue curves -pentagram-), TCN rule (green curves -diamond-), SAC rule (magenta curves -o-). Figures 13.9 - 13.12 show the belief masses, committed to Fighter type. The investigations are for periods of target type switches respectively: figures 13.5 and 13.9 for T -variable time step; figures 13.6 and 13.10 for $T = 10$ scans; figures 13.7 and 13.11 for $T = 5$ scans; figures 13.8 and 13.12 for $T = 3$ scans. The target type classifier is $C1$.

It can be seen that the TTT based on Dempster's rule and for a very good classifier is unable to track properly the quick changes of target type. This phenomenon is due to the too long integration time necessary to the Dempster's rule for recovering the true belief estimation.

Dempster's rule presents a very long latency delay (about 8 scans in case of $T = 10$ scans) as we can see during the first type switch when almost all the basic belief mass is committed onto only one element of the frame. This rule does not provide a symmetric target type estimation - it is evident that graphics representing the estimated probability masses before and after the switching points are not settled in interval around the expected average value of mass

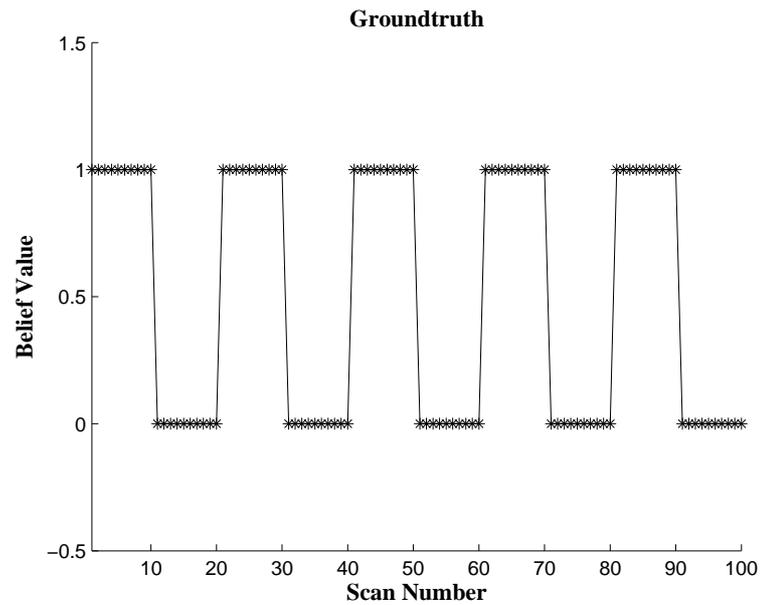


Figure 13.2: Sequence of True Target Type, $T = 10$ scans

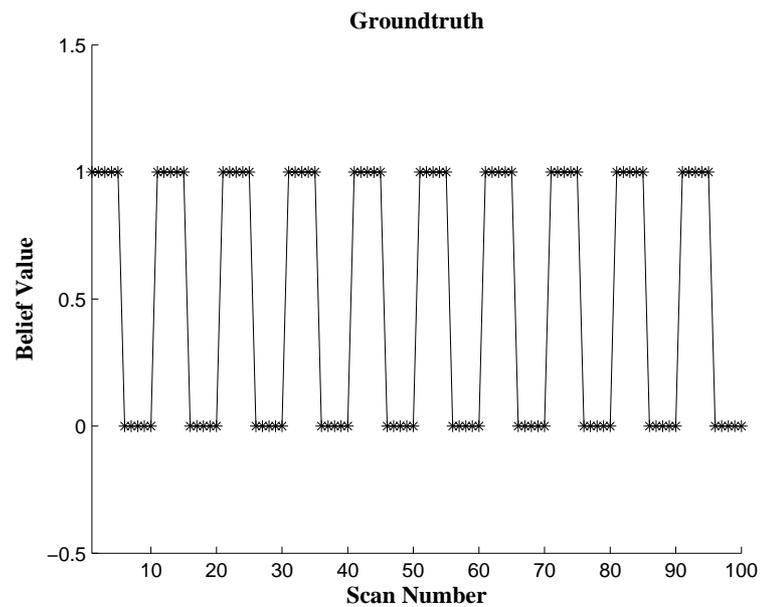


Figure 13.3: Sequence of True Target Type, $T = 5$ scans

$m(C) = 0.5$. In this case of very good target type classifier SAC rule, followed by PCR5 and TCN rules can quickly detect the type changes. They properly re-estimate the belief masses, providing a symmetric type estimation contrariwise to Dempster's rule. So in this configuration the TTT based on Dempster's rule works almost blindly since it is unable to detect the fighter in most of scans where the true target type is a Fighter.

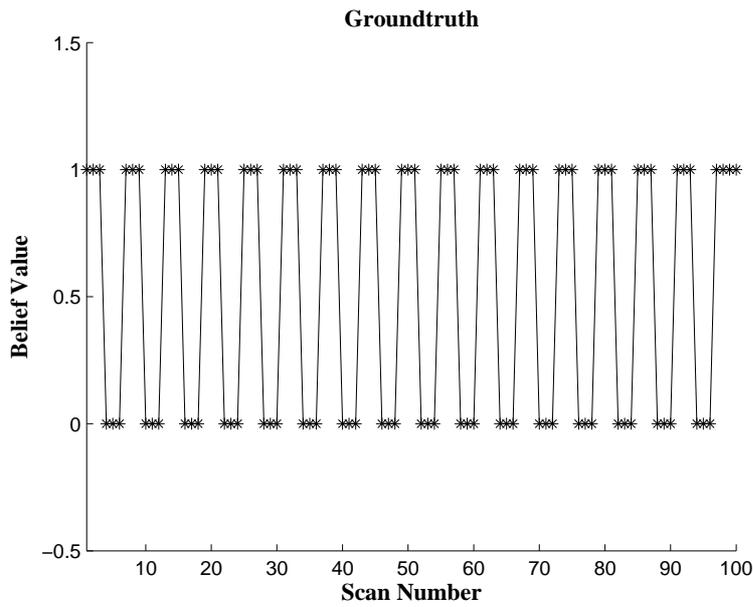
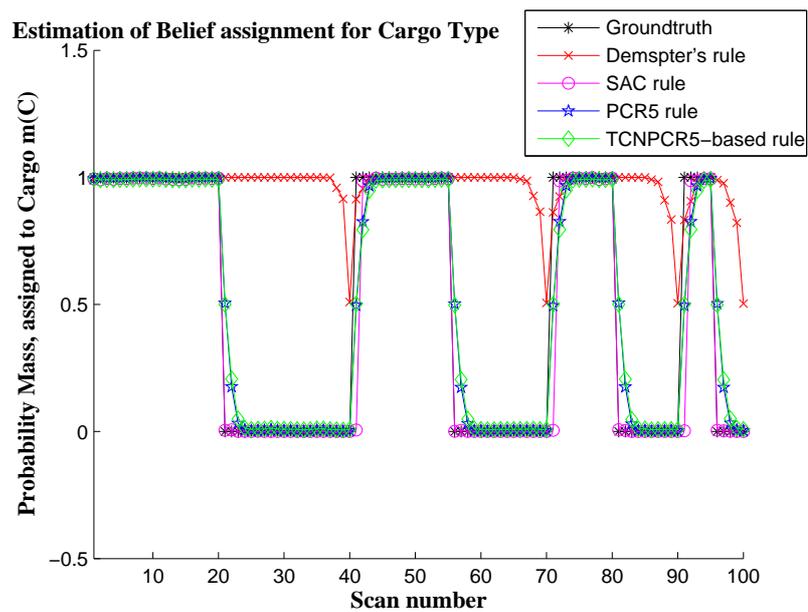
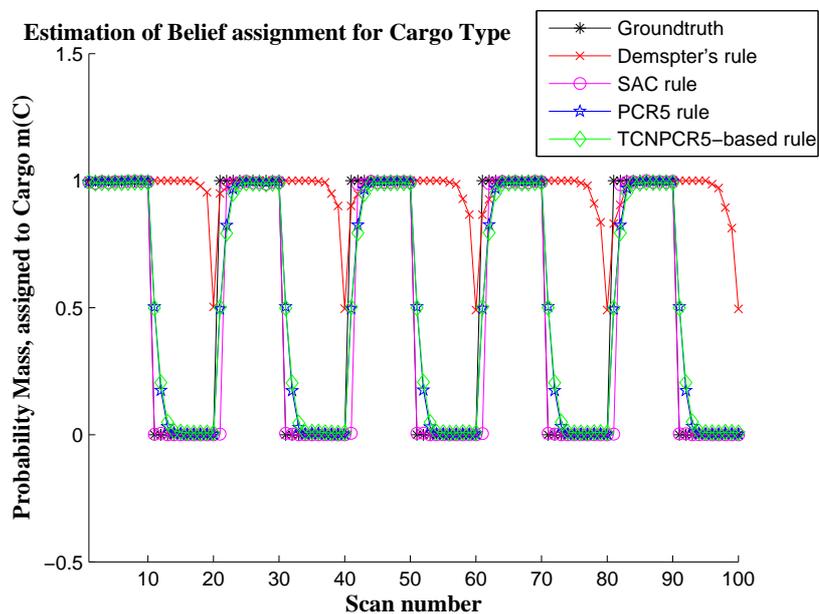


Figure 13.4: Sequence of True Target Type, $T = 3$ scans

Figures 13.5-13.12 show clearly the efficiency of PCR5, SAC and TCN rules with respect to Dempster's rule. Comparing the results obtained for T with variable time step, $T = 10scans$, $T = 5scans$ and $T = 3scans$, one can make the conclusion, that the processes of reacting and adapting to the type changes for PCR5, TCN and SAC rules do not depend on the duration of switching interval. Their behavior is quite stable and effective.

Figure 13.5: Belief mass for Cargo Type, T -variable step, case 1Figure 13.6: Belief mass for Cargo Type, $T = 10$ scans, case 1

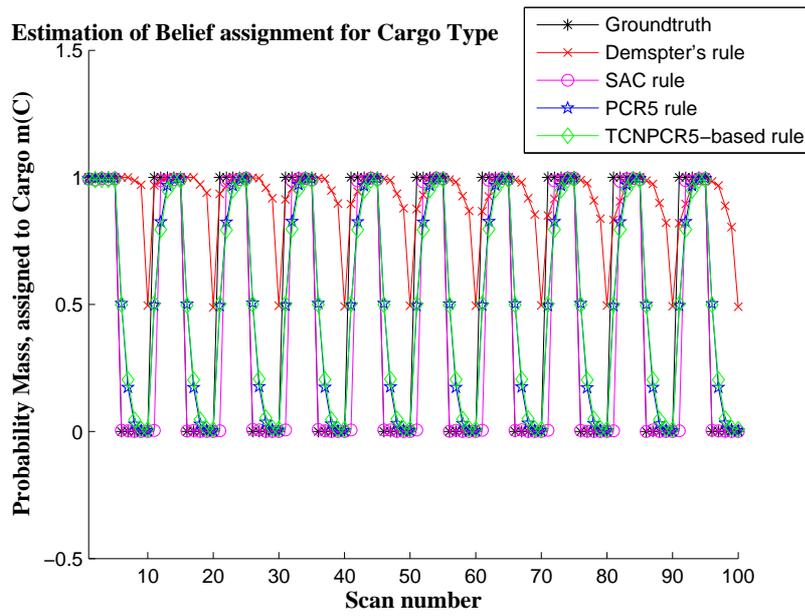


Figure 13.7: Belief mass for Cargo Type, $T = 5$ scans, case 1

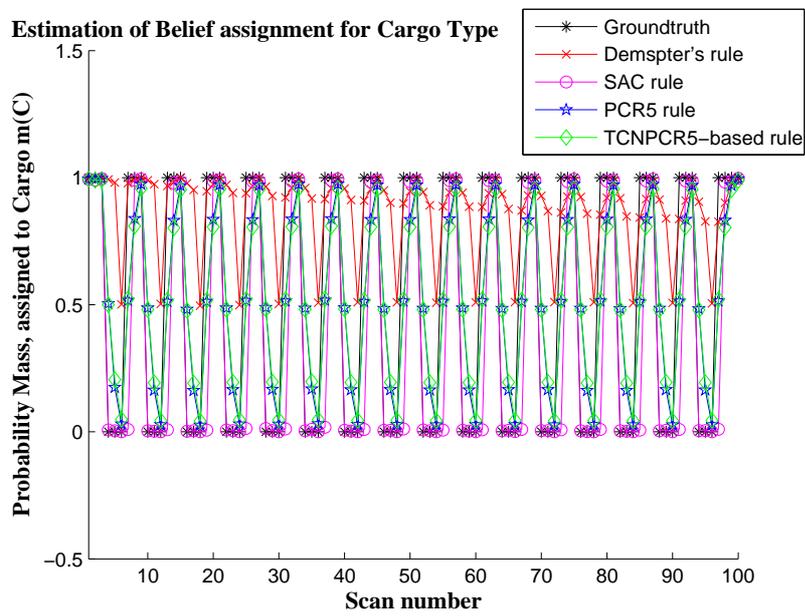


Figure 13.8: Belief mass for Cargo Type, $T = 3$ scans, case 1

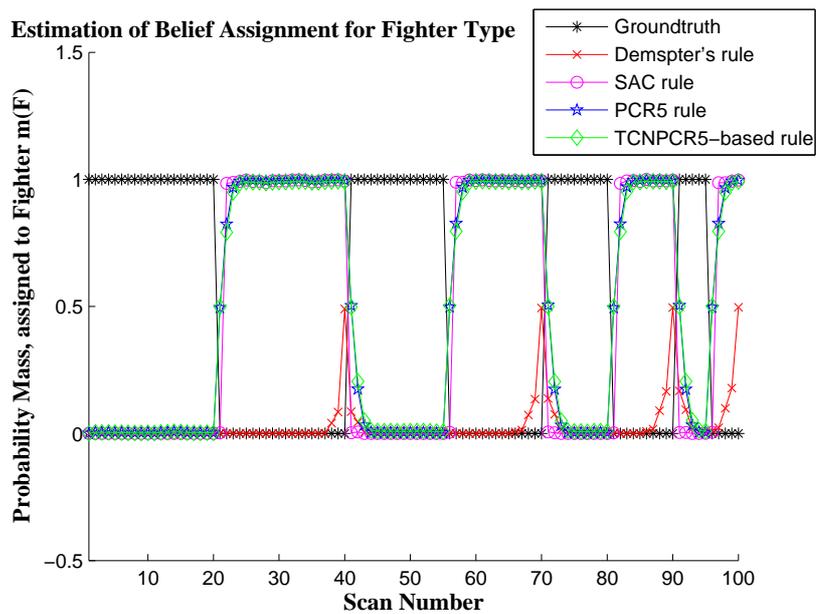


Figure 13.9: Belief mass for Fighter Type, T -variable step, case 1

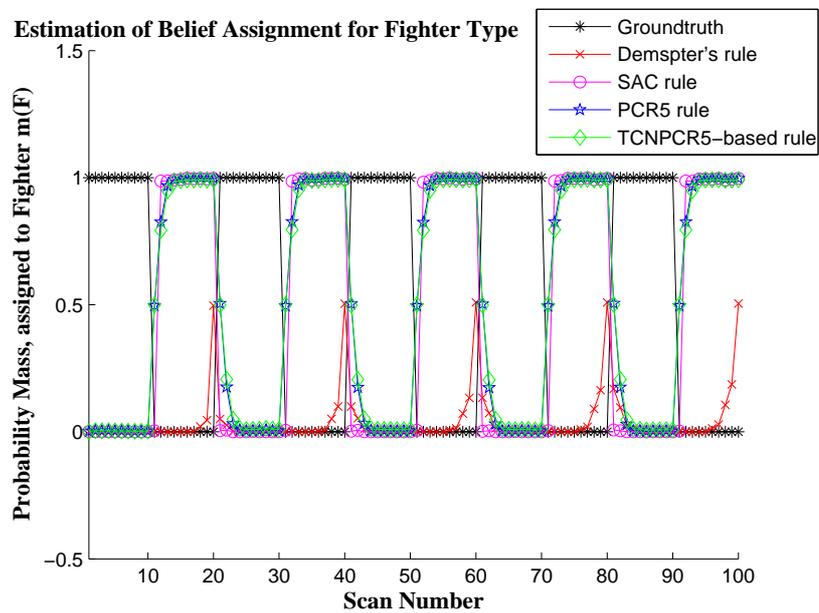


Figure 13.10: Belief mass for Fighter Type, $T = 10$ scans, case 1

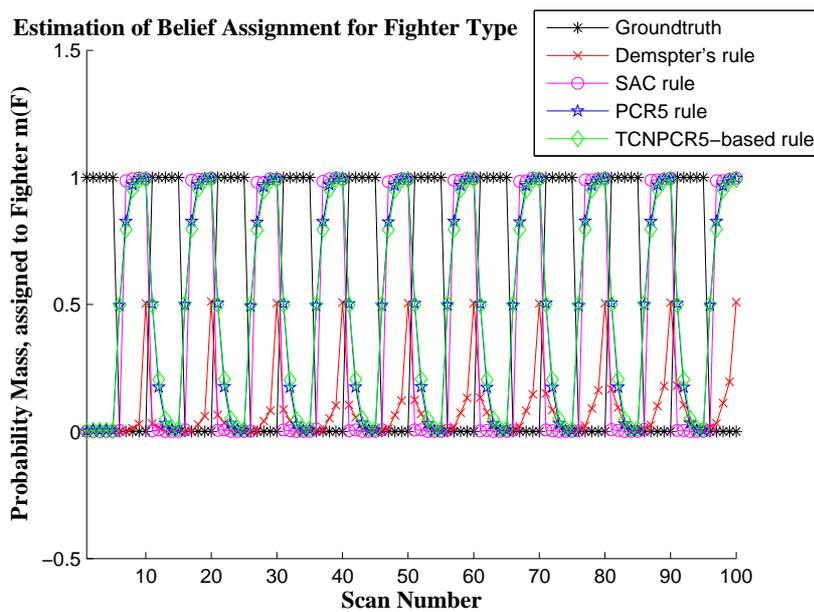


Figure 13.11: Belief mass for Fighter Type, $T = 5$ scans, case 1

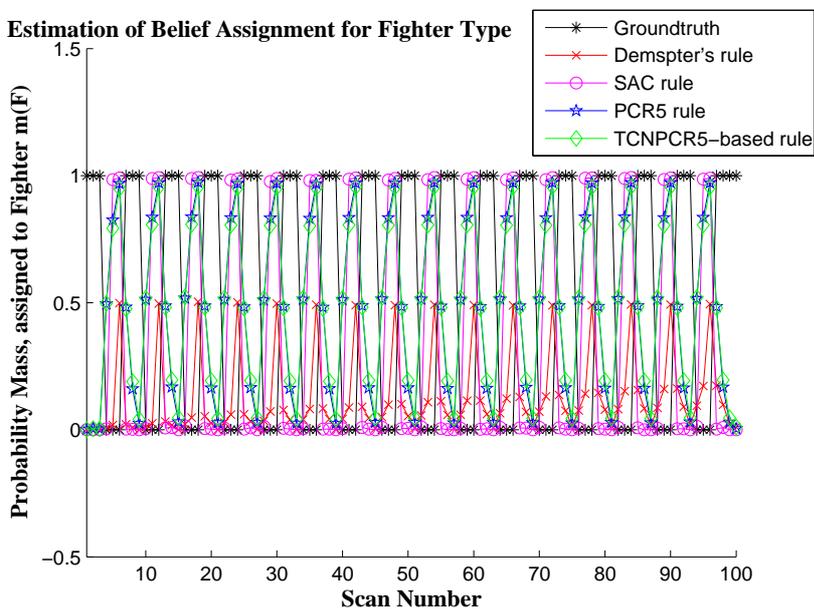


Figure 13.12: Belief mass for Fighter Type, $T = 3$ scans, case 1

13.4.2 Results for classifier 2

Figures 13.13 - 13.16 show the belief masses, committed to Cargo type, obtained by our Target Type Trackers based on Dempster's rule (red curves -x-), PCR5 rule (blue curves -pentagram-), TCN rule (green curves -diamond-), SAC rule (magenta curves -o-). Figures 13.17 - 13.20 show the belief masses, committed to Fighter type. The investigations are for periods of target type switches respectively: figures 13.13 and 13.17 - for T with variable time step, figures 13.14 and 13.18 - for $T = 10$ scans, figures 13.15 and 13.19 - for $T = 5$ scans, figures 13.16 and 13.20 - for $T = 3$ scans. The target type classifier is $C2$.

Paradoxically, we can observe that Dempster's rule seems to work better with a poor classifier than with a good one, because we can see from the red curves that Dempster's rule in that case produces small change detection peaks (with always an important latency delay although). This phenomenon is actually not so surprising and comes from the fact that the belief mass of the true type has not well been estimated by Dempster's rule (since the mass is not so close to its extreme value) and thus the bad estimation of Target Type facilitates the ability of Dempster's rule to react to new incoming information and detect changes. An asymmetric Target type estimation is detected as in the case of a very good classifier. When from Dempster's rule, one obtains an over-confidence onto only one focal element of the power-set, it then becomes very difficult for the Dempster's rule to readapt automatically, efficiently and quickly to any changes of the state of the nature which varies with the time and this behavior is very easy to check either analytically or through simple simulations. The major reason for this unsatisfactory behavior of Dempster's rule can be explained with its main weakness: counterintuitive averaging of strongly biased evidence, which in the case of poor classifier is not valid.

What is important according to the performances of PCR5, TCN and SAC rule is that in this case of the poor classifier PCR5 provides the best adaptation to the type changes and quick re-estimation of probability mass, assigned to corresponding target type. It is followed by TCN rule. Both of the rules (PCR5 and TCN) provide a symmetric type estimation in term of probability mass. In the same time SAC rule reacts more slowly than PCR5 and TCN and demonstrates the bad behavior of Dempster's rule, providing an asymmetric target type estimation. The process of reacting and adapting to the type changes for PCR5, TCN and SAC rules do not depend on the duration of switching interval even in the case of considered poor classifier.

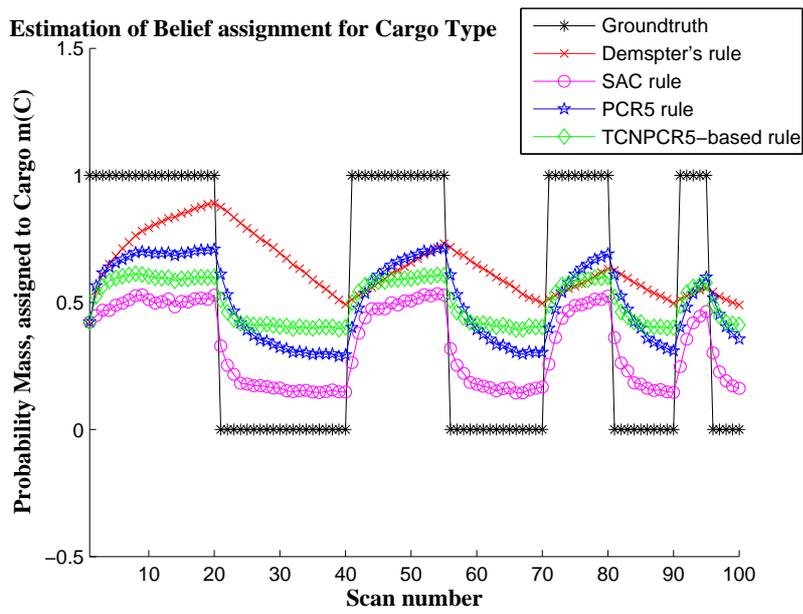


Figure 13.13: Belief mass for Cargo Type, T -variable step, case 2

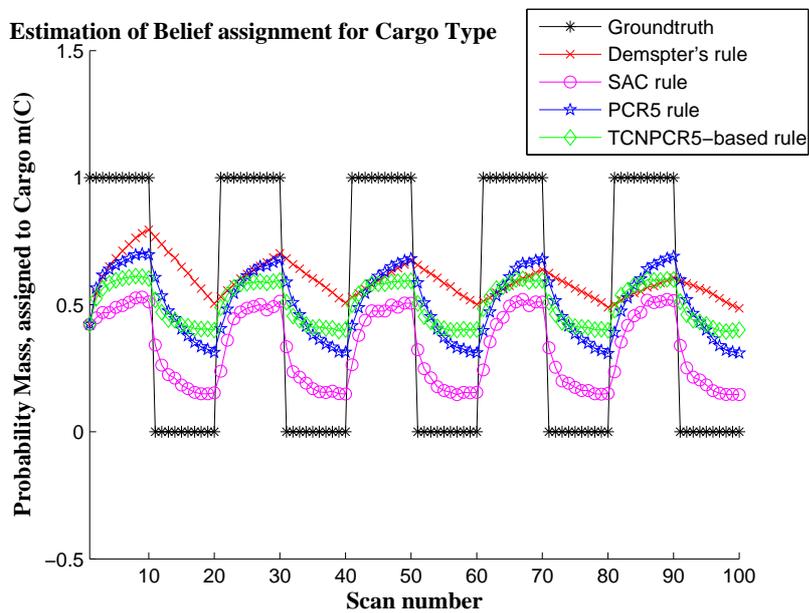


Figure 13.14: Belief mass for Cargo Type, $T = 10$ scans, case 2

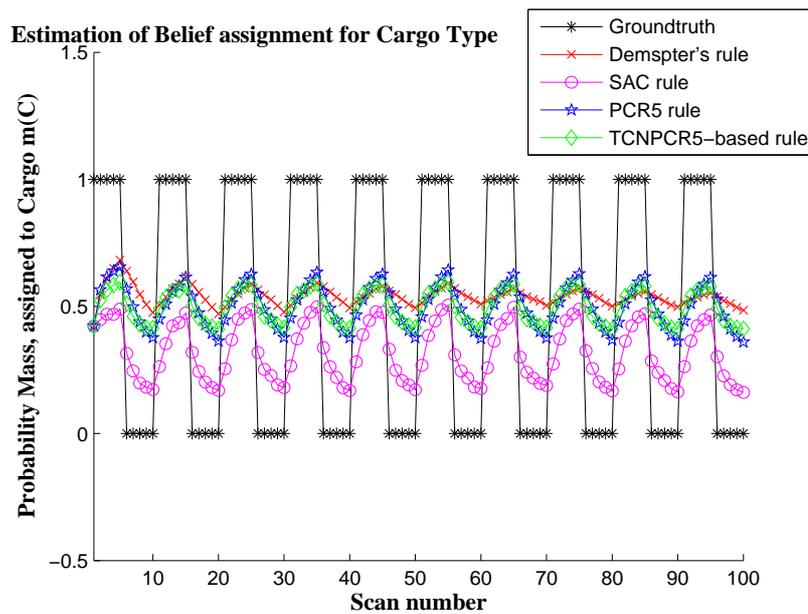


Figure 13.15: Belief mass for Cargo Type, $T = 5$ scans, case 2

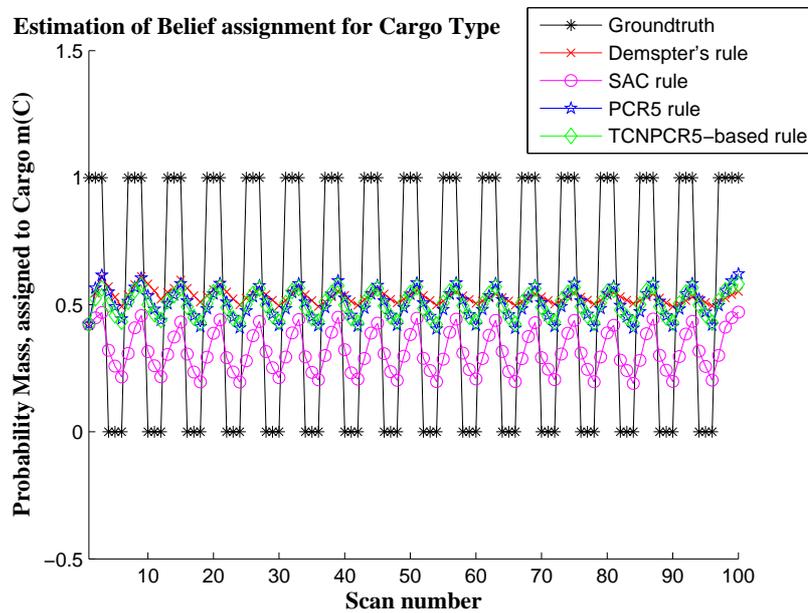


Figure 13.16: Belief mass for Cargo Type, $T = 3$ scans, case 2

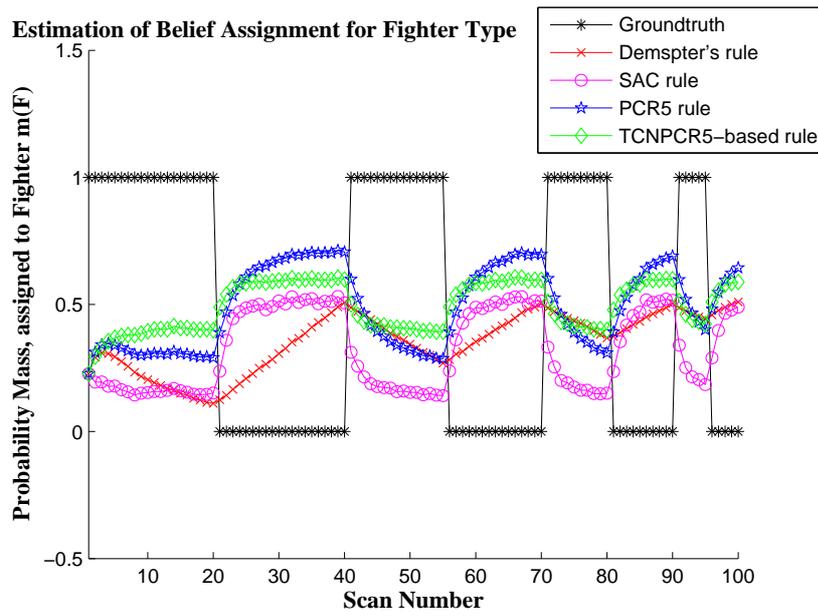


Figure 13.17: Belief mass for Fighter Type, variable step, case 2

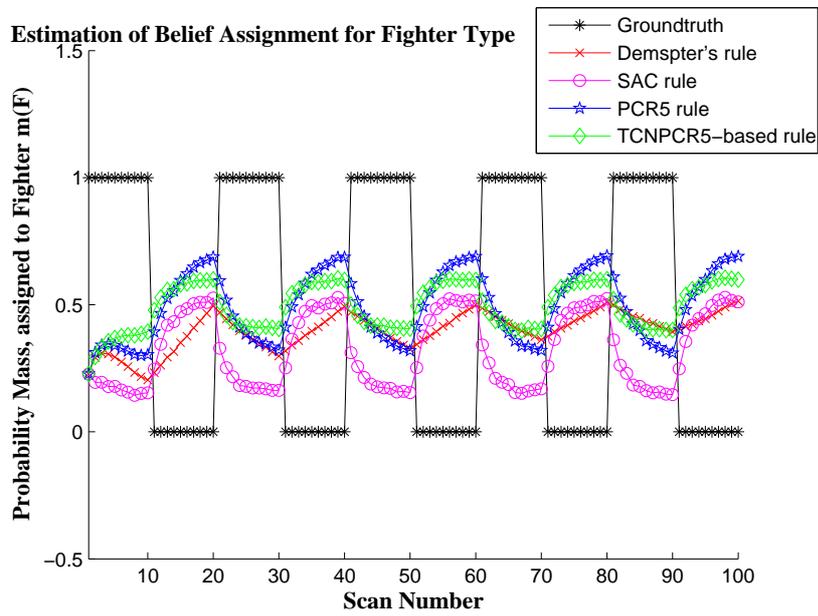


Figure 13.18: Belief mass for Fighter Type, $T = 10$ scans, case 2

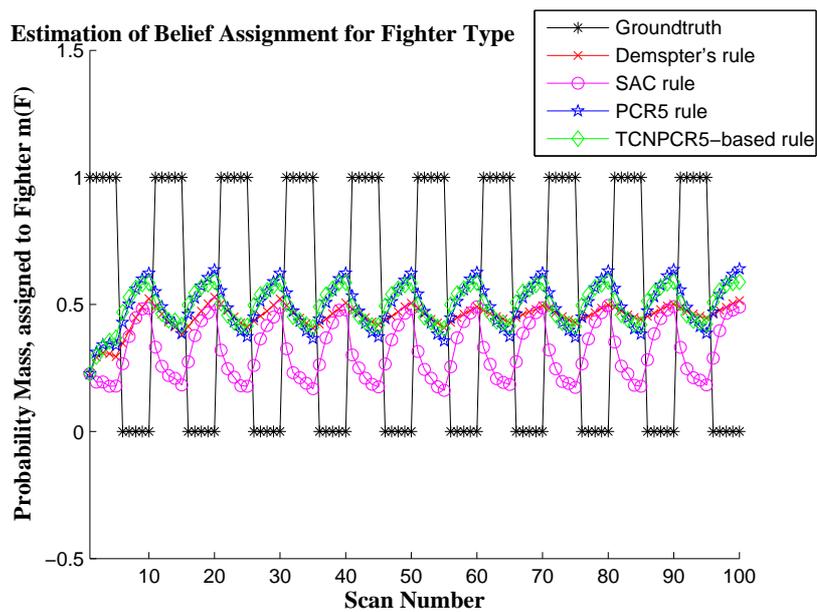


Figure 13.19: Belief mass for Fighter Type, $T = 5$ scans, case 2

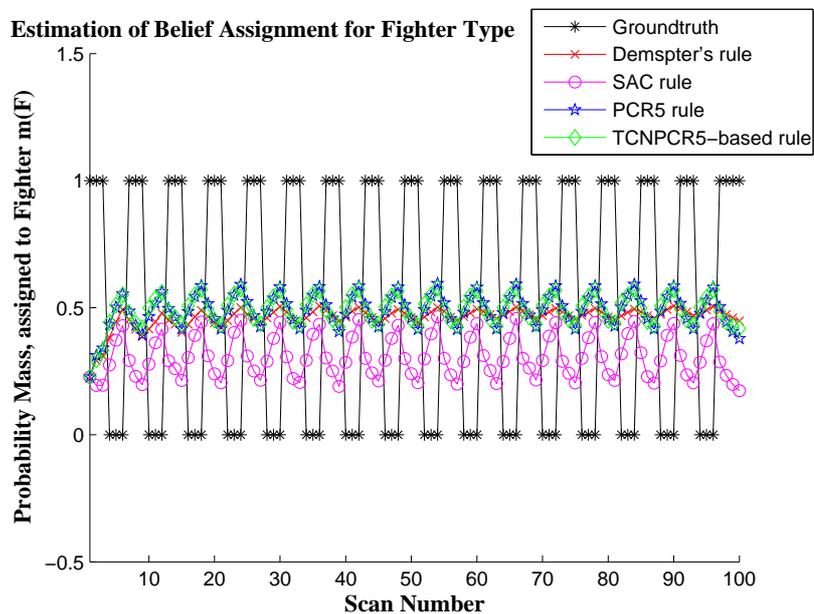


Figure 13.20: Belief mass for Fighter Type, $T = 3$ scans, case 2

13.5 Conclusions

Four Target Type Trackers (TTT) have been proposed and compared in this chapter. Our trackers are based on four combinational rules for temporal attribute data fusion for target type estimation: 1) Dempster's rule drawn from Dempster-Shafer Theory (DST); 2) Proportional Conflict Redistribution rule no. 5, PCR5 rule drawn from Dezert-Smarandache Theory (DSmT); 3) new class fusion rule, based on fuzzy T-Conorm and T-Norm operators (TCN); 4) new Symmetric Adaptive Combination (SAC) rule, drawn as a particular mixture of disjunctive and conjunctive rules. Our comparative analysis shows through a very simple scenario and Monte-Carlo simulation that PCR5, TCN and SAC rules allow a very efficient Target Type Tracking, reducing drastically the latency delay for correct Target Type decision, while Dempster's rule demonstrates risky behavior, keeping indifference to the detected target type changes. The temporal fusion process utilizes the new knowledge in an incremental manner and hides the possibility for arising bigger conflicts between the new incoming and the previous updated evidence. Dempster's rule cannot detect quickly and efficiently target type changes, and thus to track them correctly. It hides the risk to produce counter-intuitive and non adequate results. Dempster's rule and the SAC rule do not provide a symmetric target type estimation. Our PCR5/TCN/SAC-based Target Type Trackers are totally new, efficient and promising to be incorporated in real-time Generalized Data Association - Multi Target Tracking systems (GDA-MTT). The process of reacting and adapting to the type changes for PCR5, TCN and SAC rules do not depend on the duration of switching interval in both cases - of well defined and of poor classifier. It provides an important result on the behavior of these three rules with respect to Dempster's rule.

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