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# Estimation of Target Behavior Tendencies using DSmT

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**Abstract:** *This chapter presents an approach for target behavior tendency estimation (Receding, Approaching). It is developed on the principles of Dezert-Smarandache theory (DSmT) of plausible and paradoxical reasoning applied to conventional sonar amplitude measurements, which serve as an evidence for corresponding decision-making procedures. In some real world situations it is difficult to finalize these procedures, because of discrepancies in measurements interpretation. In these cases the decision-making process leads to conflicts, which cannot be resolved using the well-known methods. The aim of the performed study is to present and to approve the ability of DSmT to finalize successfully the decision-making process and to assure awareness about the tendencies of target behavior in case of discrepancies in measurements interpretation. An example is provided to illustrate the benefit of the proposed approach application in comparison of fuzzy logic approach, and its ability to improve the overall tracking performance.*

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## 13.1 Introduction

Angle-only tracking systems based on sonars are poorly developed topic due to a number of complications. These systems tend to be less precise than those based on active sensors, but one important advantage is their vitality of being stealth. In a single sensor case only direction of the target as an axis is known, but the true target position and behavior (approaching or descending) remain unknown. Recently, the advances of computer technology lead to sophisticated data processing methods, which improve sonars capability. A number of developed tracking techniques operating on angle-only measurement data use additional information. In our case we utilize the measured emitter's amplitude values in consecutive time moments. This information can be used to assess tendencies in target's behavior and, consequently, to improve the overall angle-only tracking performance. The aim of the performed study is to present and to approve the ability of DSmT to finalize successfully the decision-making process and to assure awareness about the tendencies of target behavior in case of discrepancies of angle-only measurements interpretation. Results are presented and compared with the respective results, but drawn from the fuzzy logic approach.

## 13.2 Statement of the Problem

In order to track targets using angle-only measurements it is necessary to compensate the unknown ranges by using additional information received from the emitter. In our case we suppose that in parallel with measured local angle the observed target emits constant signal, which is perceived by the sensor with a non-constant, but a varying strength (referred as amplitude). The augmented measurement vector at the end of each time interval $k = 1, 2, \dots$ is $Z = \{Z_\theta, Z_A\}$, where: $Z_\theta = \theta + \nu_\theta$ denotes the measured local angle with zero-mean Gaussian noise $\nu_\theta = \mathcal{N}(0, \sigma_{\nu_\theta})$ and covariance $\sigma_{\nu_\theta}$; $Z_A = A + \nu_A$ denotes corresponding signal's amplitude value with zero-mean Gaussian noise $\nu_A = \mathcal{N}(0, \sigma_{\nu_A})$ and covariance $\sigma_{\nu_A}$. The variance of amplitude value is because of the cluttered environment and the varying unknown distance to the object, which is conditioned by possible different modes of target behavior (approaching or descending). Our goal is, utilizing received amplitude feature measurement, to predict and to estimate the possible target behavior tendencies.

Figure 13.1 represents a block diagram of the target's behavior tracking system. Regarding to the formulated problem, we maintain two single-model-based Kalman-like filters running in parallel using two models of possible target behavior - *Approaching* and *Receding*. At initial time moment $k$ the target is characterized by the fuzzified amplitude state estimates according to the models $A^{\text{App}}(k|k)$ and $A^{\text{Rec}}(k|k)$. The new observation $Z_A(k+1) = A(k+1) + \nu_A(k+1)$ is assumed to be the true value, corrupted by additive measurement noise. It is fuzzified according to the chosen fuzzification interface.

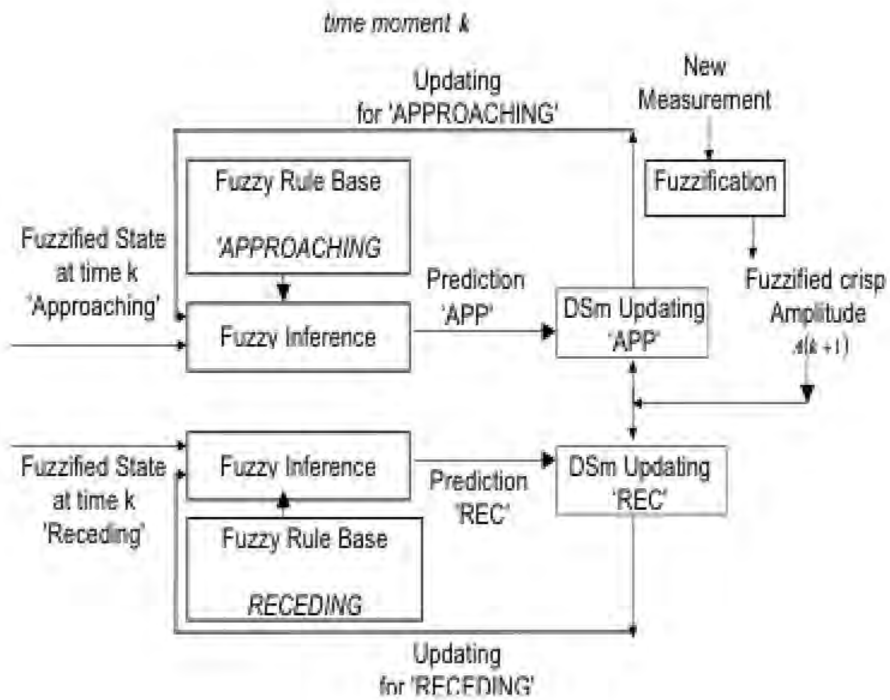


Figure 13.1: Block diagram of target's behavior tracking system

The tendency prediction approach is based on Zadeh compositional rule. The updating procedure uses Dezert-Smarandache classical combination rule based on the free DSm model to estimate target behavior states. Dezert-Smarandache Theory assures a particular framework where the frame of discernment is exhaustive but not necessarily exclusive and it deals successfully with rational, uncertain or paradoxical data. In general this diagram resembles the commonly used approaches in standard tracking systems [1, 2], but the peculiarity consists in the implemented particular approaches in the realizations of the main steps.

## 13.3 Approach for Behavior Tendency Estimation

There are a few particular basic components in the block diagram of target's behavior tracking system.

### 13.3.1 The fuzzification interface

A decisive variable in our task is the transmitted from the emitter amplitude value $A(k)$, received at consecutive time moments $k = 1, 2, \ldots$. We use the fuzzification interface (fig. 13.2), that maps it into two fuzzy sets defining two linguistic values in the frame of discernment $\Theta = \{S \triangleq \text{Small}, B \triangleq \text{Big}\}$. Their membership functions are not arbitrarily chosen, but rely on the inverse proportion dependency between the measured amplitude value and corresponding distance to target.

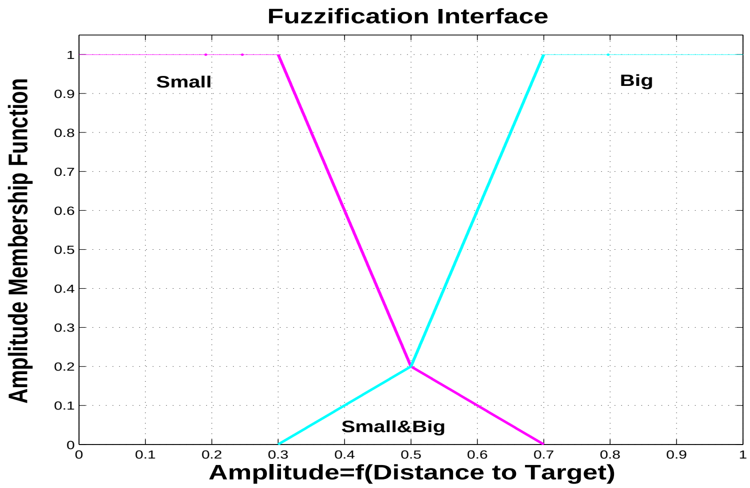


Figure 13.2: Fuzzification Interface

The length of fuzzy sets' bases provide design parameter that we calibrate for satisfactory performance. These functions are tuned in conformity with the particular dependency $A \approx f(1/\delta D)$ known as a priori information The degree of overlap between adjacent fuzzy sets reflects amplitude gradients in the boundary points of specified distance intervals.

### 13.3.2 The behavior model

In conformity with our task, fuzzy rules' definition is consistent with the tracking of amplitude changes tendency in consecutive time moments $k = 1, 2, \ldots$. With regard to this a particular feature is that considered fuzzy rules have one and the same antecedents and consequents. We define their meaning by using the prespecified in paragraph linguistic terms and associated membership functions (according to paragraph 13.3.1). We consider two essential models of possible target behavior:

**Approaching Target** - it's behavior is characterized as a stable process of gradually amplitude value increasing, i.e. the transition $S \to S \to B \to B$ is held in a timely manner;

**Receding Target** - it's behavior is characterized as a stable process of gradually amplitude value decreasing, i.e. the transition $B \to B \to S \to S$ is held in a timely manner.

To comprise appropriately these models the following rule bases have to be carried out:

**Behavior Model 1: Approaching Target:**

**Rule 1**: IF $A(k) = S$ THEN $A(k + 1) = S$

**Rule 2**: IF $A(k) = S$ THEN $A(k + 1) = B$

**Rule 3**: IF $A(k) = B$ THEN $A(k + 1) = B$

**Behavior Model 2: Receding Target:**

**Rule 1**: IF $A(k) = B$ THEN $A(k+1) = B$

**Rule 2**: IF $A(k) = B$ THEN $A(k+1) = S$

**Rule 3**: IF $A(k) = S$ THEN $A(k+1) = S$

The inference schemes for these particular fuzzy models are conditioned on the cornerstone principle of each modeling process. It is proven [4], that minimum and product inferences are the most widely used in engineering applications, because they preserve cause and effect. The models are derived as fuzzy graphs:

$$g = \max_i(\mu_{A_i \times B_i}(u, v)) = \max_i(\mu_{A_i}(u) \cdot \mu_{B_i}(v)) \tag{13.1}$$

in which $\mu_{A_i \times B_i}(u, v) = \mu_{A_i}(u) \cdot \mu_{B_i}(v)$ corresponds to the Larsen product operator for the fuzzy conjunction, $g = \max_i(\mu_{A_i \times B_i})$ is the maximum for fuzzy union operator and

$$\mu_{B'}(y) = \max_{x_i}(\min(\mu_{A'}(x_i), \mu_{A \times B}(x_i, y_i)))$$

is the *Zadeh max-min operator for the composition rule.*

The fuzzy graphs related to the two models are obtained in conformity with the above described mathematical interpretations, by using the specified membership functions for linguistic terms *Small*, *Big*, and taking for completeness into account all possible terms in the hyper-power set $D^\Theta = \{S, B, S \cap B, S \cup B\}$:

| $k \to k+1$ | $S$ | $S \cap B$ | $B$ | $S \cup B$ |
|---|---|---|---|---|
| $S$ | 1 | 0 | 1 | 0 |
| $S \cap B$ | 0 | 0 | 0 | 0 |
| $B$ | 0.2 | 0 | 1 | 0 |
| $S \cup B$ | 0 | 0 | 0 | 0 |

Relation 1: Approaching Target

| $k \to k+1$ | $S$ | $S \cap B$ | $B$ | $S \cup B$ |
|---|---|---|---|---|
| $S$ | 1 | 0 | 0.2 | 0 |
| $S \cap B$ | 0 | 0 | 0 | 0 |
| $B$ | 1 | 0 | 1 | 0 |
| $S \cup B$ | 0 | 0 | 0 | 0 |

Relation 2: Receding Target

### 13.3.3 The amplitude state prediction

At initial time moment $k$ the target is characterized by the fuzzified amplitude state estimates according to the models $\mu_{A^{\text{App}}}(k|k)$ and $\mu_{A^{\text{Rec}}}(k|k)$. Using these fuzzy sets and applying the *Zadeh max-min compositional rule* [4] to relation 1 and relation 2, we obtain models' conditioned amplitude state predictions for time $k+1$, i.e. $\mu_{A^{\text{App}}}(k+1|k)$ is given by $max(\min(\mu_{A^{\text{App}}}(k|k), \mu_{\text{App}}(k \rightarrow k+1)))$ and $\mu_{A^{\text{Rec}}}(k+1|k)$ by $max(\min(\mu_{A^{\text{Rec}}}(k|k), \mu_{\text{Rec}}(k \rightarrow k+1)))$.

### 13.3.4 State updating using DSmT

The classical DSm combinational rule is used here for state updating. This procedure is realized on the base of fusion between predicted states according to the considered models (Approaching, Receding) and the new measurement. Since $D^\Theta$ is closed under $\cup$ and $\cap$ operators, to obey the requirements to guarantee that $m(.) : D^\Theta \mapsto [0,1]$ is a proper general information granule, it is necessarily to transform fuzzy membership functions representing the predicted state and new measurement into mass functions. It is realized through their normalization with respect to the unity interval. Models' conditioned amplitude state prediction vector $\mu_{\text{pred}}^{\text{App/Rec}}(.)$ is obtained in the form:

$$[\mu_{\text{pred}}^{\text{A/R}}(S), \mu_{\text{pred}}^{\text{A/R}}(S \cap B), \mu_{\text{pred}}^{\text{A/R}}(B), \mu_{\text{pred}}^{\text{A/R}}(S \cup B)] \tag{13.2}$$

In general the terms, contained in $\mu_{\text{pred}}^{\text{App/Rec}}$ represent the possibilities that the predicted amplitude behavior belongs to the elements of hyper-power set $D^\Theta$ and there is no requirement to sum up to unity. In order to use the classical DSm combinational rule, it is necessary to make normalization over $\mu_{\text{pred}}^{\text{App/Rec}}$ to obtain respective generalized basic belief assigments (gbba) $\forall C \in D^\Theta = \{S, S \cap B, B, S \cup B\}$:

$$m_{\text{pred}}^{\text{App/Rec}}(C) = \frac{\mu_{\text{pred}}^{\text{App/Rec}}(C)}{\sum_{A \in D^\Theta} \mu_{\text{pred}}^{\text{App/Rec}}(A)} \tag{13.3}$$

The equivalent normalization has to be made for the received new measurement before being fused with the DSm rule of combination.

## Example

Let's consider at scan 3 the predicted vector for the model *Approaching* $\mu_{\text{pred}}^{\text{App/Rec}}(4|3)$ with components $\mu(S) = 0.6$, $\mu(S \cap B) = 0.15$, $\mu(B) = 0.05$ and $\mu(S \cup B) = 0.0$, then the normalization constant is $K = 0.6 + 0.15 + 0.05 + 0.0 = 0.8$ and after normalization, one gets the resulting gbba

$$m_{\text{pred}}^{\text{App/Rec}}(S) = \frac{0.6}{K} = 0.75 \qquad m_{\text{pred}}^{\text{App/Rec}}(S \cap B) = \frac{0.15}{K} = 0.1875$$

$$m_{\text{pred}}^{\text{App/Rec}}(B) = \frac{0.05}{K} = 0.0625 \qquad m_{\text{pred}}^{\text{App/Rec}}(S \cup B) = \frac{0.0}{K} = 0.0$$

That way one can obtain $m_{\text{pred}}^{\text{App/Rec}}(.)$ as a general (normalized) information granule for the prediction of the target's behavior.

The target behavior estimate $m_{\text{upd}}^{\text{App/Rec}}(.)$ at measurement time is then obtained from $m_{\text{pred}}^{\text{App/Rec}}(.)$ and the amplitude belief assignment $m_{\text{mes}}(B)$ (built from the normalization of the new fuzzyfied crisp amplitude measurement received) by the DSm rule of combination, i.e.

$$m_{\text{upd}}^{\text{App/Rec}}(C) = [m_{\text{pred}}^{\text{App/Rec}} \oplus m_{\text{mes}}](C) = \sum_{A,B \in D^{\Theta}, A\cap B=C} m_{\text{pred}}^{\text{App/Rec}}(A) m_{\text{mes}}(B) \tag{13.4}$$

Since in contrast to the DST, DSmT uses a frame of discernment, which is exhaustive, but in general case not exclusive (as it is in our case for $\Theta = \{S, B\}$), we are able to take into account and to utilize the paradoxical information $S \cap B$ although being not precisely defined. This information relates to the case, when the moving target resides in an overlapping intermediate region, when it is hard to predict properly the tendency in its behavior. Thus the conflict management, modeled that way contributes to a better understanding of the target motion and to assure awareness about the behavior tendencies in such cases.

## 13.4 The decision criterion

It is possible to build for each model M = (A)pproaching, (R)eceding a subjective probability measure $P_{\text{upd}}^{\text{M}}(.)$ from the bba $m_{\text{upd}}^{\text{M}}(.)$ with the generalized pignistic transformation (GPT) [3, 6] defined $\forall A \in D^{\Theta}$ by

$$P_{\text{upd}}^{\text{M}}\{A\} = \sum_{C \in D^{\Theta} | A\cap C \neq \emptyset} \frac{\mathcal{C}_{\mathcal{M}^f}(C \cap A)}{\mathcal{C}_{\mathcal{M}^f}(C)} m_{\text{upd}}^{\text{M}}(C) \tag{13.5}$$

where $\mathcal{C}_{\mathcal{M}^f}(X)$ denotes the DSm cardinal of proposition $X$ for the free DSm model $\mathcal{M}^f$ of the problem under consideration here. The decision criterion for the estimation of correct model $M$ is then based on the evolution of the Pignistic entropies, associated with updated amplitude states:

$$H_{pig}^{\text{M}}(P_{\text{upd}}^{\text{M}}) \triangleq -\sum_{A \in \mathcal{V}} P_{\text{upd}}^{\text{M}}\{A\} \ln(P_{\text{upd}}^{\text{M}}\{A\}) \tag{13.6}$$

where $\mathcal{V}$ denotes the parts of the Venn diagram of the free DSm model $\mathcal{M}^f$. The estimation $\hat{\text{M}}(k)$ of correct model at time $k$ is given by the most informative model corresponding to the smallest value of the pignistic entropy between $H_{pig}^{\text{A}}(P_{\text{upd}}^{\text{A}})$ and $H_{pig}^{\text{R}}(P_{\text{upd}}^{\text{R}})$.

## 13.5 Simulation study

A non-real time simulation scenario is developed for a single target trajectory (fig.13.3) in plane coordinates $X$,$Y$ and for constant velocity movement. The tracker is located at position $(0km, 0km)$. The target's starting point and velocities are: $(x_0 = 5km, y_0 = 10km)$, with following velocities during the two part of the trajectory $(\dot{x} = 100m/s, \dot{y} = 100m/s)$ and $(\dot{x} = -100m/s, \dot{y} = -100m/s)$.

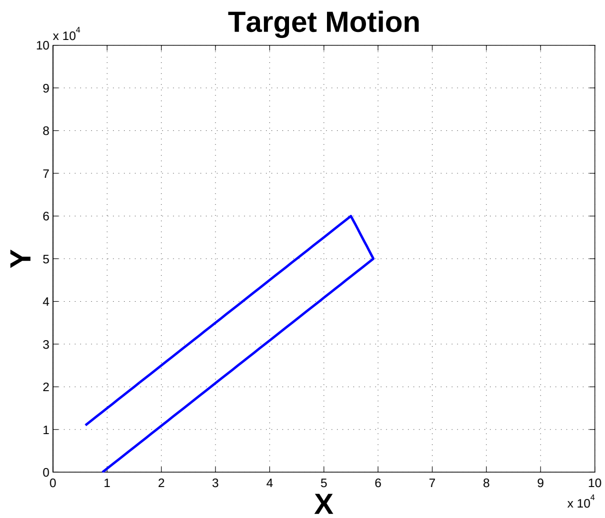


Figure 13.3: Target trajectory.

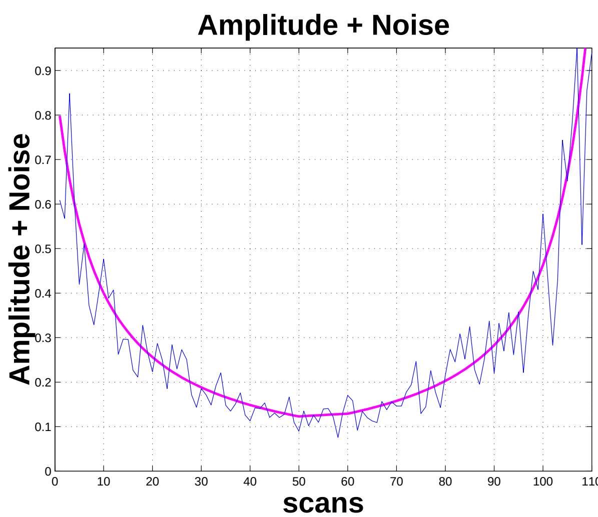


Figure 13.4: Measurements statistics.

The time sampling rate is $T = 10s$. The dynamics of target movement is modeled by equations:

$$x(k) = x(k-1) + \dot{x}T \quad \text{and} \quad y(k) = y(k-1) + \dot{y}T$$

The amplitude value $Z_A(k) = A(k) + \nu_A(k)$ measured by sonar is a random Gaussian distributed process with mean $A(k) = 1/D(k)$ and covariance $\sigma_A(k)$ (fig. 13.4). $D(k) = \sqrt{x^2(k) + y^2(k)}$ is the distance to the target, $(x(k), y(k))$ is the corresponding vector of coordinates, and $\nu_A(k)$ is the measurement noise. Each amplitude value (true one and the corresponding noisy one) received at each scan is processed according to the block diagram (figure 13.1).

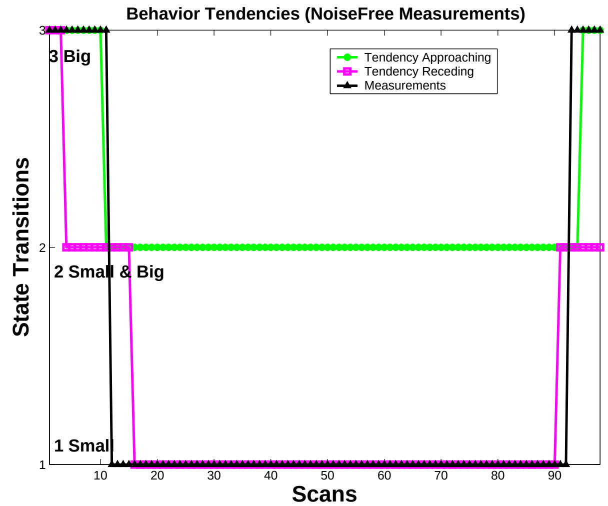


Figure 13.5: Behavior tendencies (Noise-free measurements).

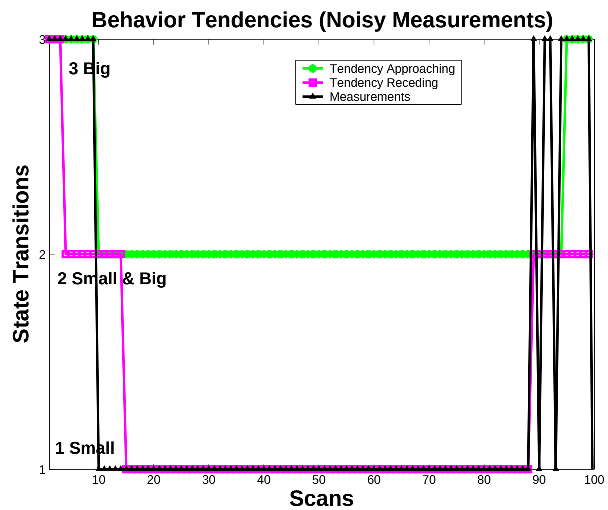


Figure 13.6: Behavior Tendencies (Noisy measurements).

Figures 13.5 and 13.6 show the results obtained during the whole motion of the observed target. Figure 13.5 represents the case when the measurements are without noise, i.e. $Z(k) = A(k)$. Figure 13.6 represents the case when measured amplitude values are corrupted by noise. In general the presented graphics show the estimated tendencies in target behavior, which are described via the scan consecutive transitions of the estimated amplitude states.

Figure 13.7 represents the evolution of pignistic entropies associated with updated amplitude states for the Approaching and Receding models in case of noisy measurements; the figure for the noise-free measurement is similar. It illustrates the decision criterion used to choose the correct model. If one takes a look at the figure 13.5 and figure 13.7, it can be seen that between scans 1st and 15th the target motion is supported by *Approaching* model, because that mode corresponds to the minimum entropies values, which means that it is the more informative one.

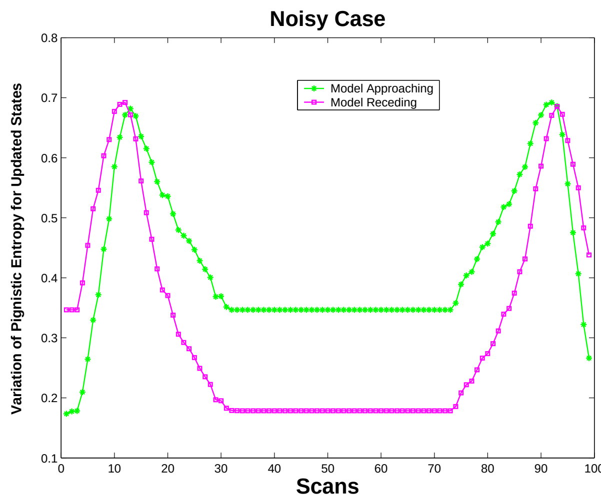


Figure 13.7: Evolution of the pignistic entropy for updated states.

The *Approaching* model is dominant, because the measured amplitude values during these scans stable reside in the state *Big*, as it is obvious from the fuzzification interface (fig.13.2). In the same time, *Receding* model supports the overlapping region $S \cap B$, which is transition towards the state *Small*. Between scans 16th and 90th the *Receding* model becomes dominant since the variations of amplitude changes are minimal and their amplitude values stable support the state *Small*. During these scans *Approaching* model has a small reaction to the measurement statistics, keeping paradoxical state $S \cap B$.What it is interesting and important to note is that between scans 16th and 30th the difference of entropies between *Approaching* and *Receding* models increases, a fact, that makes us to be increasingly sure that the *Receding* mode is becoming dominant. Then, between scans 75th and 90th the difference of these entropies is decreasing, which means that we are less and less sure, that *Receding* model remain still dominant. After switching scan 91th the *Approaching* model becomes dominant one, until scan 100th. In general the reaction of the considered models to the changes of target motion is not immediate, because the whole behavior estimation procedure deals with vague propositions *Small*, *Big*, and sequences of amplitude values at consecutive scans often reside stable in one and the same states.

Comparing the results in figure 13.6 with the results in figure 13.5, it is evident, that although some disorder in the estimated behavior tendencies, one can make approximately correct decision due to the possibility of DSmT to deal with conflicts and that way to contribute for a better understanding of target behavior and evaluation of the threat.

## 13.6 Comparison between DSm and Fuzzy Logic Approaches

The objective of this section is to compare the results received by using DSm theory and respective results but drawn from the Fuzzy Logic Approach (FLA) [4, 8, 9], applied on the same simulation scenario. The main differences between the two approaches consist in the domain of considered working propositions and in the updating procedure as well. In present work, we use DSm combination rule to fuse the predicted state and the new measurement to obtain the estimated behavior states, while in the fuzzy approach state estimates are obtained through a fuzzy set intersection between these entities. It is evident from the results, shown in figures 13.8 and 13.9, that here we deal with only two propositions $\Theta = \{\text{Small}, \text{Big}\}$. There is no way to examine the behavior tendencies in the overlapping region, keeping into considerations every one of possible target's movements: from $S \cap B$ to $B$ or from $S \cap B$ to $S$.

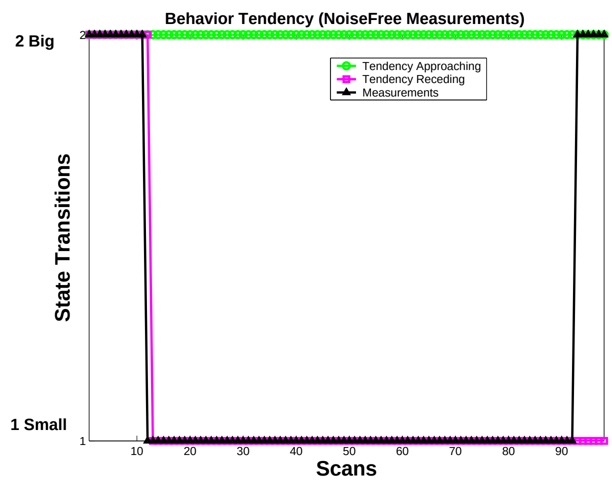


Figure 13.8: Behavior Tendencies drawn from FLA (NoisyFree Measurements).

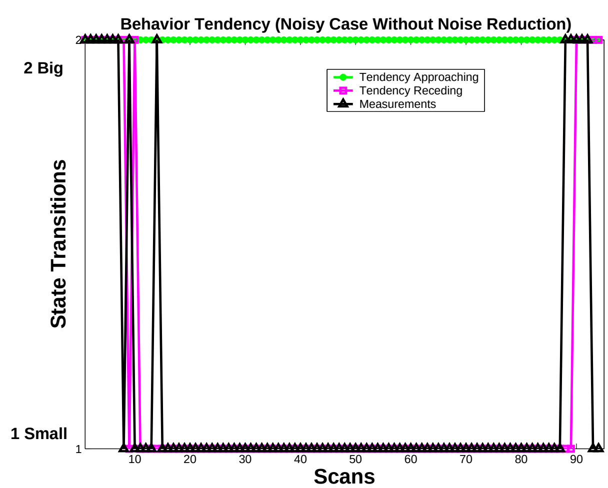


Figure 13.9: Behavior Tendencies without Noise Reduction drawn from FLA (Noisy Case).

Figure 13.8 shows the noise-free measurement case. It could be seen that between scan 10 and 90 target motion is supported by the correct for that case Receding model, while Approaching one has no reaction at all. If we compare corresponding figure 13.5 (DSm case) and present figure 13.8, we can see, that in the case of DSm approach Receding model reacts more adequately to the true target tendency , because there is a possibility to deal with the real situation – the tendency of the target to make a movement from $B$ to the overlapping region $B \cap S$. In the FLA case there is no such opportunity and because of that between scan 1st and 10th Receding model has no reaction to the real target movement towards the $B \cap S$. Figure 13.9 represents the case when the measured amplitude values are corrupted by noise. It is difficult to make proper decision about the behavior tendency, especially after scan 90th., because it is obvious, that here the model *Approaching* coincide with the model *Receding*. In order to reduce the influence of measurement noise over tendency estimation, an additional noise reduction procedure has to be applied to make the measurements more informative. Its application improves the overall process of behavior estimation. Taking in mind all the results drawn from DSmT and FLA application, we can make the following considerations:

- DSmT and FLA deal with a frame of discernment, based in general on imprecise/vague notions and concepts $\Theta = \{S, B\}$. But DSmT allows us to deal also with uncertain and/or paradoxical data, operating on the hyper-power set $D^\Theta = \{S, S \cap B, B, S \cup B\}$. In our particular application it gives us an opportunity for flexible tracking the changes of possible target behavior during the overlapping region $S \cap B$.

- DSmT based behavior estimates can be characterized as a noise resistant, while FLA uses an additional noise reduction procedure to produce 'smoothed' behavior estimates.

## 13.7 Conclusions

An approach for estimating the tendency of target behavior was proposed. It is based on Dezert-Smarandache theory applied to conventional sonar measurements. It was evaluated using computer simulation. The provided example illustrates the benefits of DSm approach in comparison of fuzzy logic one. Dealing simultaneously with uncertain and paradoxical data, an opportunity for flexible and robust reasoning is realized, overcoming the described limitations relative to the fuzzy logic approach. It is presented and approved the ability of DSmT to ensure reasonable and successful decision-making procedure about the tendencies of target behavior in case of discrepancies of angle-only measurements interpretation. The proposed approach yields confident picture for complex and ill-defined engineering problems.

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