Target Behaviour Tendency Estimation Using Fuzzy Logic ⋆

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Abstract. The objective of this paper is to present an approach for targets' behaviour tendency estimation. An algorithm for target behaviour tracking is developed and evaluated. It is based on Fuzzy Logic principles applied to conventional passive radar amplitude measurements. A set of fuzzy models is used to describe the tendencies of target behaviour. A noise reduction procedure is applied. The performance of the developed algorithm in the presence of noise is estimated on the base of computer simulations.

1 Introduction

The objective of this work is to present an approach for targets' behavior tendency estimation based on Fuzzy Logic principles applied to conventional passive radars. It utilizes the measured emitter's amplitude value in consecutive time moments and uses a set of developed particular filters with respective set of possible target behavior models.

2 Statement of the Problem

In order to track targets using passive sensors it is necessary to compensate the unknown ranges by using additional information received from the emitter. In our case we suppose that the observed target emits constant signal. It 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 $k = 1, 2, ...$ is $Z = \{Z_\Theta, Z_A\}$, where: Z_Θ denotes the measured local angle with zero-mean Gaussian noise ν_Θ,and $Z_A = A + \nu_A$ denotes corresponding amplitude value with zero-mean Gaussian noise $\nu_A = N(0, \sigma_{\nu_A})$ and covariance σ_{ν_A} . The variation of amplitude value is because of the cluttered environment and the varying unknown distance to the object. It is conditioned by modes of target behaviour (approaching or descending). Our goal is to utilize received

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amplitude feature measurement, for predicting and estimating the tendency of target behaviour. The block diagram of target's behavior tracking system is shown on Fig.1. Two single-model-based filters running in parallel and using two models for target behaviour (*Approaching* and *Receding*) are maintained. At initial time moment k the target is characterized by the fuzzified amplitude state estimates according to the two models $A^{App}(k/k)$ and $A^{Rec}(k/k)$. The new observation at time is assumed to be the true value, corrupted by additive measurement noise. It is fuzzified according to the chosen fuzzification interface. A weighting procedure for noise reduction is developed and applied. Particular

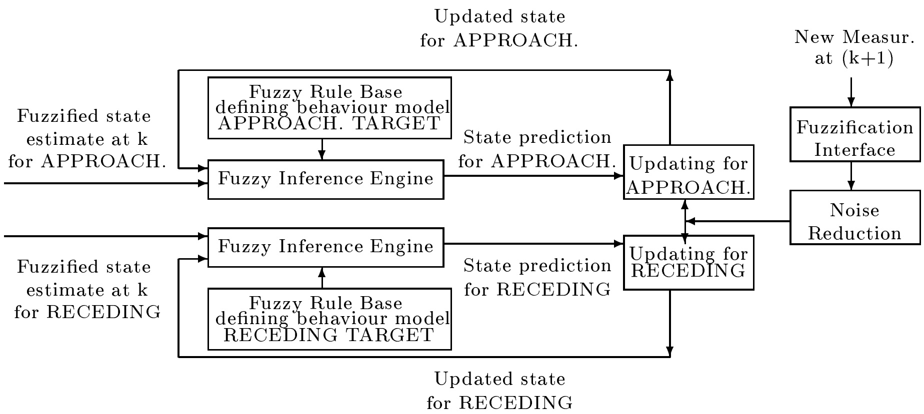

Fig. 1.

tendency prediction and updating methods are used to estimate present and future target behaviour states. In general this diagram resembles the commonly used approaches in standard tracking systems [1]. But the peculiarity consists in the implemented fuzzy logic approach [2] to realize the main steps.

3 Fuzzy Approach for Target Behaviour Tracking

3.1 Fuzzification Interface.

Fuzzification transforms each received from a sensor numerical measurement into fuzzy set in accordance to the a priori defined fuzzy partition of input space (the input frame Θ). It comprises all considered linguistic values related to particular important input variables and their associated membership functions. An important variable in our case is the transmitted from the emitter amplitude value $A(k)$, received at consecutive time moments $k = 1, 2, ...$ The fuzzification interface (Fig.2) maps $A(k)$ into four fuzzy sets, which define four linguistic values $\Theta = \{VerySmall(VS), Small(S), Big(B), VeryBig(VB)\}$ .Their membership functions are not arbitrarily chosen, but rely on the well-known inverse proportion dependency between the measured amplitude value and corresponding distance to target(Fig.3).

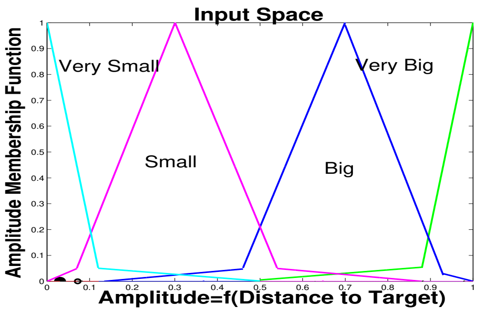

Fig. 2.

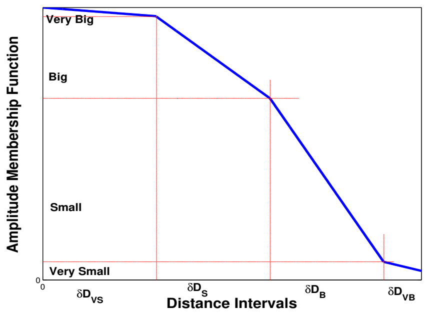

Fig. 3.

These functions are tuned in conformity with the particular dependency $A = f(1/\delta_D)$ which is a priori information. The degree of overlap between adjacent fuzzy sets reflects amplitude gradients in the boundary points of specified distance intervals δ_D .

3.2 Fuzzy Model Identification.

A set of fuzzy mapping IF-THEN rules forms our fuzzy models. The foundation of fuzzy mapping rules is the fuzzy graph g, which is an union of Cartesian products involving linguistic input-output associations. It is described by a set of i number fuzzy rules in the form of: 'IF x is A_i THEN y is B_i '. It is expressed mathematically as:

$$g = \bigcup_i A_i \times B_i \tag{1}$$

where A and B are the linguistic values, describing input and output variables. The Cartesian product of A and B is defined as:

$$\mu_{A \times B}(u, v) = \mu_A(u) \otimes \mu_B(v) \tag{2}$$

where $\otimes$ denotes a fuzzy conjunction (t-norm) operator; $\mu_{A \times B}(u, v)$ is a membership function, which measures the degree of truth of the implication relation between corresponding antecedents and consequents.

Relying on the cornerstone principle of modelling [2], our model is derived as a fuzzy graph, in which Larsen product operator is used for fuzzy conjunction and "maximum" for fuzzy union operator:

$$g = \max_i(\mu_{A_i \times B_i}(u, v)) = \max_i(\mu_{A_i}(u) \cdot \mu_{B_i}(v)) \tag{3}$$

The inference of such a collection is based on compositional rule of inference:

$$B' = A' \circ g = A' \circ \bigcup_i A_i \times B_i \tag{4}$$

We apply the most commonly used Zadeh max-min compositional rule [2, 3]. If input "x is A' " is given, the inferred output is:

$$\mu_{B'}(y) = \max_{x_i}(\min(\mu_{A'}(x_i), \mu_{A\times B}(x_i, y_i))) \tag{5}$$

Bearing in mind that our considered fuzzy rules have one and the same antecedents and consequents, we consider two essential models of possible target behaviour: (a) *Approaching Target* - which behaviour in time is characterized by an increase of the amplitude, described by a set of transitions: $VS \to VS \to S \to S \to B \to B \to VB \to VB$; (b) *Receding Target* - which behaviour in time is characterized by a decrease of the amplitude value, described by a set of transitions: $VB \to VB \to B \to B \to S \to S \to VS \to VS$. To comprise appropriately these models the following fuzzy rule bases have to be carried out:

Behaviour 1: APPROACHING TARGET	Behaviour 2: RECEDING TARGET
Rule1:IF $A(k)$ **is** VS **THEN** $A(k+1)$ **is** VS	**Rule1:IF** $A(k)$ **is** VB **THEN** $A(k+1)$ **is** VB
Rule2:IF $A(k)$ **is** VS **THEN** $A(k+1)$ **is** S	**Rule2:IF** $A(k)$ **is** VB **THEN** $A(k+1)$ **is** B
Rule3:IF $A(k)$ **is** S **THEN** $A(k+1)$ **is** S	**Rule3:IF** $A(k)$ **is** B **THEN** $A(k+1)$ **is** B
Rule4:IF $A(k)$ **is** S **THEN** $A(k+1)$ **is** B	**Rule4:IF** $A(k)$ **is** B **THEN** $A(k+1)$ **is** S
Rule5:IF $A(k)$ **is** B **THEN** $A(k+1)$ **is** B	**Rule5:IF** $A(k)$ **is** S **THEN** $A(k+1)$ **is** S
Rule6:IF $A(k)$ **is** B **THEN** $A(k+1)$ **is** VB	**Rule6:IF** $A(k)$ **is** S **THEN** $A(k+1)$ **is** VS
Rule7:IF $A(k)$ **is** VB **THEN** $A(k+1)$ **is** VB	**Rule7:IF** $A(k)$ **is** VS **THEN** $A(k+1)$ **is** VS

In conformity with equations (1-3) and by using the specified membership functions, we obtain the resulting fuzzy graphs as fuzzy relations:

Relation1:Approaching Target

$k \to k+1$	VS	S	B	VB
VS	1	1	0.15	0.02
S	0.15	1	1	0.15
B	0.02	0.15	1	1
VB	0	0.02	0.15	1

Relation1:Receding Target

$k \to k+1$	VS	S	B	VB
VS	1	0.15	0.02	0.0
S	1	1	0.15	0.02
B	0.15	1	1	0.15
VB	0.02	0.15	1	1

Then we are able to realize our models' based filters running in parallel.

3.3 Models' Conditioned Amplitude State Tendency Prediction

At initial time moment k the target is characterized by the fuzzified amplitude values according to the models $\mu_{A^A{}_{pp}}(k/k)$ and $\mu_{A^R{}_{ec}}(k/k)$. Using these fuzzified amplitudes and applying the described above Zadeh max-min compositional rule equation(5) to relation 1-$App(k \to k+1)$ and relation 2 - $Rec(k \to k+1)$, we obtain modes conditioned amplitude state tendency prediction for time moment $k+1$, i.e.:

$$\mu_{A^A{}_{pp}}(k+1/k) = \max(\min(\mu_{A^A{}_{pp}}(k/k), \mu_A pp(k \to k+1))) \tag{6}$$

$$\mu_{A^R{}_{ec}}(k+1/k) = \max(\min(\mu_{A^R{}_{ec}}(k/k), \mu_R ec(k \to k+1))) \tag{7}$$

3.4 Weighting Procedure for Noise Reduction

In order to reduce the influence of measurement noise over the amplitude tendency prediction, a weighting procedure is applied to make the measurement more informative. This procedure can be considered as an adaptive linear combiner as follows:

• we compute the degree to which the new fuzzified measurement intersects each of the linguistic terms in the frame $\Theta = \{VS, S, B, VB\}$. Actually that way we make considerations about the likelihoods of receiving particular observation on condition that it originates from each of these terms, i.e.:

$$L_i(A(k+1)/\Theta(i)) = hgt[A(k+1) \cap \Theta(i)] = \sup\{\min(\mu_{A(k+1)}, \mu_{\Theta(i)})\}, i = 1 \div 4 \tag{8}$$

where the operator hgt denotes the height of a resulting fuzzy sets, obtained after intersection between fuzzified new amplitude value and membership function of each of the linguistic terms in the frame Θ;

• using these likelihoods as respective weighting coefficients we form the convex combination of the linguistic terms. Thus we take into account the degree of their influence over the received measurement. A normalization procedure is applied. The new fuzzy set represents the weighted measurement with a following membership function:

$\mu_{A^W}(x) = \sum_i L_i^N \cdot \mu_{\Theta(i)}$, where $L_i^N = L_i/\Sigma L_i$; $L_i^N \geq 0$; $\sum_i L_i^N = 1$.

Example *At scan 4 the new crisp amplitude measurement is* $A = 0.7487$.

• *after applying fuzzification procedure one obtains:*

$\mu_{VS}(A) = 0.0$; $\mu_S(A) = 0.0189$; $\mu_B(A) = 0.7854$; $\mu_{VB}(A) = 0.0373$.

• *bearing in mind the a priori defined input feature frame* θ, *it is possible to define:* $L_1(A/VS) = hgt[A \cap VS] = \max\{\min(\mu_A, \mu_{VS})\} =$

$=\max\{\min(0, 1), \min(0.0189, 0.15), \min(0.7854, 0), \min(0.0373, 0)\} = 0.0189$

the application of the above procedure according to the other linguistic values yields: $L_2(A/S) = 0.15$; $L_3(A/B) = 0.7854$, $L_4(A/VB) = 0.15$.

• *a normalization procedure is applied to* L_i*:* $L_i^N = L_i/\Sigma L_i$, $i = 1 \div 4$. *It yields:* $L_1^N = 0.0172$; $L_2^N = 0.1358$; $L_3^N = 0.7112$; $L_4^N = 0.1358$.

• *the weighted measurement is formed as a convex combination:* $\mu_A^W = L_1^N * \mu_{VS} + L_2^N * \mu_S + L_3^N * \mu_B + L_4^N * \mu_{VB}$. *As a result it is obtained:* $\mu_{VS}(A^W) = 0.0499$; $\mu_S(A^W) = 0.3259$; $\mu_B(A^W) = 1.0$; $\mu_{VB}(A^W) = 0.3225$.

3.5 State Updating

The updated states are obtained through a fuzzy set intersection between the weighted new measurement and corresponding modes conditioned amplitude state predictions:

$$\mu_{A^A{}_{pp}}(k+1/k+1) = \min(\mu_{A^W}, \mu_{A^A{}_{pp}}(k+1/k)) \tag{9}$$

$$\mu_{A^R{}_{ec}}(k+1/k+1) = \min(\mu_{A^W}, \mu_{A^R{}_{ec}}(k+1/k)) \tag{10}$$

4 Simulation Study

A simulation scenario is developed for a simple target trajectory (fig.4) in plane coordinates (X, Y) and for constant velocity movement. The target's starting point and the velocities are: $(X_0 = 5km, Y_0 = 10km)$, $\dot{X} = 100m/s, \dot{Y} = 100m/s$ and $\dot{X} = -100m/s, \dot{Y} = -100m/s$. The time sampling rate is $T = 5s$. Target dynamic process is modeled by a simple equations:

$$x(k) = x(k-1) + \dot{x} \cdot T; \quad y(k) = y(k-1) + \dot{y} \cdot T \tag{11}$$

The measured by passive radar amplitude value $Z_A(k) = A(k)+\nu_A(k)$, is random Gaussian distributed process (fig.5), with $A(k) = 1/D(k)$ mean, and covariance $\sigma_A(k) = 0.3 \cdot rand(1,1)/D(k)$. $D(k) = \sqrt[2]{x(k)^2 + y(k)^2}$ is the distance to the target, $\{x(k), y(k)\}$ is the corresponding vector of coordinates, and $\nu_A(k)$is the measurement noisy. Each amplitude value (true one and corresponding noisy one) received at time (scan) $k = 1, 2, \ldots$ is processed according to the block diagram of our target's behavior tracking system (fig.1).

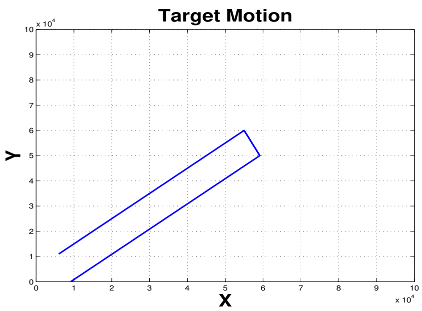

Fig. 4.

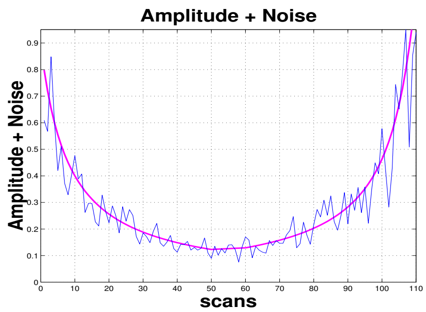

Fig. 5.

Figures 6-10 show the results obtained during the whole motion of the observed target (descending and approaching directions). They represent the tendency in target behavior, which is described via the time (scan) consecutive transitions of amplitude value $VB \to VB \to B \to B \to S \to S \to VS \to VS$ and respectively $VS \to VS \to S \to S \to B \to B \to VB \to VB$.

Fig. 6 represents the case when the measured amplitude values are without measurement's noise, i.e. $Z_A(k) = A(k)$.

Two models - *Approaching* and *Receding* are maintained in parallel. As a result of the developed algorithm (Fig.1) implementation, it becomes possible to make a correct decision about the considered models' plausibility. It could be seen that between scans 1 and 90 target motion is supported by the correct for that case *Descending* model. In the same time the *Approaching* model has no reaction to the measurements dynamics, because it does not match the real target behaviour *Receding*. Taking into account fig.5, the amplitude measurements

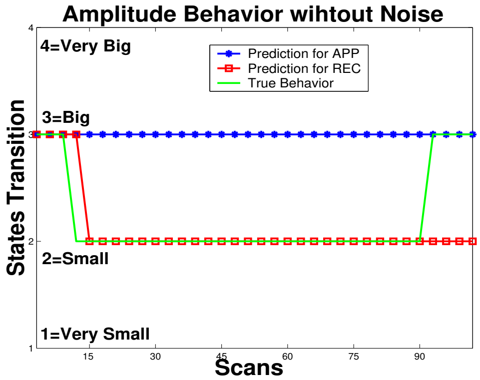

Fig. 6.

dynamics between scans 10 and 90 could be analized as relatively weak from the point of view of fuzzification interface (fig.2). Such a transition area is contingent on the assumed possibility for sojourning time, when the measured amplitude values during consecutive scans stable reside in one and the same regions of that interface. It is characterized with a latency delay before switching to the opposite behaviour mode. After scan 90 and until scan 115 it is obvious that the *Descending* model misses the amplitude changes, while the *Approaching* model becomes the plausible one. Fig.7 represents the case when the measured amplitude values are corrupted by noise with $\sigma_A = 0.2.rand(1,1)/D(k)$.Some disorder and discrepancy between predicted behaviour tendency and true amplitude behaviour take place, and it is difficult to make a firm decision about the target behaviour tendency. As it is shown in Fig.8 the application of noise reduction procedure produces a "smoothed" predicted behaviour tendency, and it becomes possible to make a robust decision about the target behaviour tendency.

Case 1: Amplitude Noise with $\sigma_A = 0.2.rand(1,1)/D(k)$

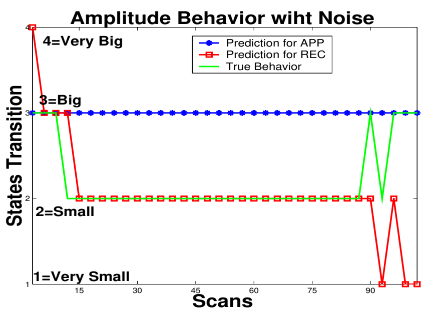

Fig. 7.

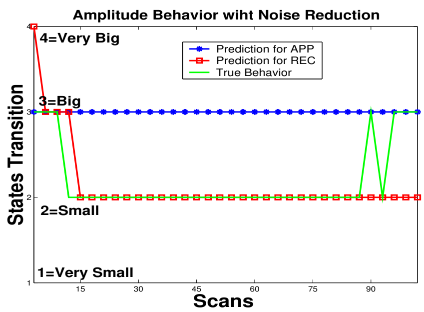

Fig. 8.

The effect of that procedure is more essential when input measurements are corrupted by a bigger noise - for example with $\sigma_A = 0.4.rand(1,1)/D(k)$ (Fig.9). In that case some chaotic behaviour is detected. In such a critical situation the noise reduction procedure assures a more consistent process of amplitude tendency prediction (Fig.10).

Case 2: Amplitude Noise with $\sigma_A = 0.4.rand(1,1)/D(k)$

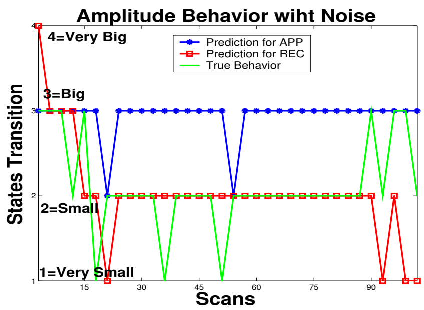

Fig. 9.

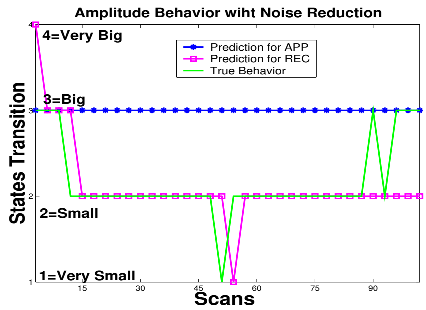

Fig. 10.

5 Conclusions

An approach for targets' behavior tendency estimation was proposed and evaluated. It is based on Fuzzy Logic principles applied to conventional passive radar measurements. A particular real-time running algorithm was developed. It was evaluated using computer simulation. Dealing simultaneously with numerical and linguistic data an opportunity for robust reasoning becomes possible. The additionally applied weighting procedure for noise reduction improves the overall process of target behavior tendency estimation. The developed algorithm is suitable and adapted for noisy amplitude measurements processing. It works with modest computational load and provides simple and robust decisions about target behavior tendency.

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