Exploitation of Track Accuracy Information in fusion Technologies for Radar Target Classification using Dempster-Shafer Rules

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Abstract - The surveillance of the littoral is required by applications in the defence, protection and security area. One might think about anti asymmetric warfare, harbour and coastal surveillance or the prevention of smuggling, illegal fishing, illegal immigration or acts of piracy.

To establish situation awareness ground, sea and air targets must be detected and tracked in the littoral simultaneously. Also the detailed classification of targets is of extraordinary importance, e.g. persons vs. vehicles, helicopters vs. planes or buoys vs. ships. This classification can be overtaken by an operator, who listens to the Doppler sound of a target. Unfortunately, obligated to the classification issue an operator gets distracted from the tactical surveillance task. Further, an operator is only able to classify a limited number of targets. Hence, automatic target recognition is an important issue for radar systems applied to the littoral surveillance. Finally, automatic target recognition offers also a synergy with the multi target tracking of such a radar system.

In this paper 2 Dempster-Shafer (DS) based fusion methods will be described. Both use tracks and track accuracy information to fuse with Doppler based classified targets, in order to provide a robust classification technique for distinguishes between different kinds of targets.

The first classification technique uses a hierarchical tree structured decision method, integrated in a track-based classifier.

The second classification technique uses a non-hierarchical decision method also integrated in a track based classifier.

In this paper both kinds of DS methods will be compared. The results will be discussed especially with respect to the following performance criteria: track accuracy, classification confusion matrix, targets hit rate, targets rejection probabilities, DS topology requirements, convergence reliability, training duration and generalization efficiency.

1 Introduction

A pulse Doppler radar system (PDRS) is used to process backscattered radar echo signals from different ground, air and maritime target classes, like persons, wheeled and tracked vehicles, helicopters and fixed wing aircrafts, buoys, small and large ships. These echo signals contain information about the Doppler shift from different moving parts of the target, like the rotor blades of a helicopter.

Using signal processing and pattern recognition methods, it is possible to classify targets on the basis of the Doppler sound, if the signal contains the characteristics, [12, 13].

Figure 1: Simplified diagram of a radar signal processing and fusion process

But there are scenarios, where the characteristical Doppler shifts can not be extracted, e.g. if the target moves tangential to the radar. In these cases the classification should not be done alone with a Doppler based classifier, but other information, like track information, should also be considered and the outputs should be fused to get a more
precise classification result (c.f. Figure 1). The Doppler sound classifier works with Hidden Markov Models and Neural Networks. These models are known for their application in temporal pattern recognition such as speech, sounds, image recognition and bioinformatics, c.f. [5, 6, 8, 10, 12, 13].

In the track based classifier two methods based on Dempster-Shafer theory of evidence, one using a hierarchical, the other using a non-hierarchical structure for the construction of the evidences are considered. Other possibilities for track based classification are based on fuzzy logic and fuzzy sets, [3].

One of the advantages of the Dempster-Shafer theory over Bayesian networks lies in the possibility of modeling inaccuracy. The inaccuracy can be extracted from the estimated covariance matrix which will be available from the tracking system of the radar. The fusion of the classifiers is done by Dempster's Rule of Combination using the accumulation of evidences, [4, 7].

2 Method 1: Hierarchical Exploitation of Track-Based Information in DS-Classifier

The Dempster-Shafer theory of evidences can be considered as an expanded theory of probabilities. The basic of this theory is a so called mass function m. This function assigns subsets of the frame of discernment to values in the interval [0; 1], provided that the sum of the masses over all elements of the power set is one and that exactly one element of the frame of discernment is true. The hypotheses are the elements of the power set. There are two functions in the Dempster-Shafer theory describing the belief and the plausibility of a hypothesis. The belief-function of a hypothesis X is defined as:

\[ b_m(X) = \sum_{Y \subseteq X} m(Y) \] 

(1)

The corresponding plausibility-function is defined as follows:

\[ b^*_m(X) = 1 - b_m(X^C) \] 

(2)

So it can be seen that the belief-function is a probability function if and only if the belief and the plausibility are equal for every subset of the frame of discernment. An advantage of the Dempster-Shafer theory is the possibility of considering the uncertainty of a hypothesis. The uncertainty of a element of the power set is defined as:

\[ u_m(X) = b^*_m(X) - b_m(X) \] 

(3)

Let the frame of discernment be the set containing the following elements:

\[ J = \{ \text{person, wheeled vehicle, tracked vehicle, helicopter}, \text{propeller aircraft, buoy, boat, nomatch} \} \]

This definition corresponds to a littoral scenario. Analog considerations can be done with land, air or sea scenarios. The element nomatch denotes everything not belonging to one of the defined classes, e.g. animals, windmills, etc.

For the track based classification the following physical parameters are considered:

\[ I = \{ \text{velocity, acceleration, RCS} \} \]

These values can be estimated from measured radar data. A possible hierarchical approach for the Dempster-Shafer theory of evidences is to design a tree-structure containing several subsets of the frame of discernment. For each considered physical parameter a separate structure should be designed. Exemplary a possible construction of evidences for the physical parameter velocity can be seen in Figure 2.

![Figure 2: Exemplary simple tree structure for the velocity in a typical littoral environment scenario](image)

Furthermore a knowledge data base with limit values, \( lv(I) < \ldots < lv(J) \), where \( J \) is the cardinal number of \( J \), in this case upper bounds for the maximum velocity, are used. The tracking system of the radar outputs a vector containing an estimated position and velocity together with the corresponding estimated covariance matrix. A confidence interval for the velocity \( \hat{v}_v = [\hat{v}_v, \ldots, \hat{v}_v] \) can be derived from these values as exemplary described in section 3. A possible determination of the uncertainty can then be done as follows:

\[ u_m(\{j_1, \ldots, j_k\}) = \min \left\{ 1, \max \left\{ 0, \frac{\hat{v}_v - lv(k)}{\hat{v}_v - \hat{v}_v} \right\} \right\}, \quad \forall k = 1, \ldots, N \] 

(4)

whereas \( j_k \) is the target class corresponding to the limit value \( lv(k) \). Due to formula (3) the belief and the plausibility can be derived from the uncertainty, if one of these is given. But neither the belief nor the plausibility of these subsets are known, so we make the following assumption:

\[ b_m(\{j_1, \ldots, j_k\}) = 0 \quad \forall k = 1, \ldots, N \] 

(5)

Therefore the plausibility function for these subsets is given by:
formula 2 yields
\[ b_m(J \setminus \{j_1, \ldots, j_k\}) = u_m(J \setminus \{j_1, \ldots, j_k\}) \quad \forall k = 1, \ldots, N \]  
(6)

Now the mass function of these sets can be set successively as follows:
\[ m(J \setminus \{j_1, \ldots, j_N\}) = b_m(J \setminus \{j_1, \ldots, j_N\}) \]

for \( k = 1, \ldots, N-1 \):
\[ m(J \setminus \{j_1, \ldots, j_k\}) = b_m(J \setminus \{j_1, \ldots, j_k\}) - b_m(J \setminus \{j_1, \ldots, j_{k-1}\}) \]

The membership value is then given by:
\[ m(J \setminus \{j_1, \ldots, j_k\}) = \begin{cases} 
\lambda_1 & \text{if } w_h < 0 \text{ or } j = \text{rest of the world} \\
\lambda_2 & \text{if } w_h > 0 \text{ or } j = \text{rest of the world} \\
\lambda_3 & \text{otherwise}
\end{cases} 
\]

\[ \hat{\lambda} = \frac{\lambda_1 + \lambda_2}{2} \]

\[ \lambda = \frac{\lambda_1 + \lambda_2}{2} \]

The position of the target is not of interest to the classification, so only the last two entries of the vector are relevant. Using the Euclidean Norm of the two-dimensional vector one gets an estimated velocity of the target:
\[ \hat{\mathbf{v}} = \sqrt{\hat{v}_x^2 + \hat{v}_y^2} \]

(10)

The covariance matrix of the velocity vector is given by the partial covariance matrix:
\[ \hat{\Sigma}_v = \text{Cov}(\hat{v}_x, \hat{v}_y) \]

(11)

An upper bound for the standard deviation can then be found with the principal components analysis, taking the maximum of the square root of the eigenvalues, which is the length of the semi-major axis of the ellipse described by the positive definite covariance matrix. This value is taken as the estimated standard deviation of the velocity:
\[ \hat{\sigma}_v = \sqrt{\hat{\lambda}_1 \hat{\lambda}_2} \]

(12)

where \( \hat{\lambda}_1 \) and \( \hat{\lambda}_2 \) are the eigenvalues of \( \hat{\Sigma}_v \). Now the confidence interval for the velocity can be taken as:
\[ \hat{I}_v = [\hat{\mathbf{v}} - \hat{\sigma}_v \mathbf{v}, \hat{\mathbf{v}} + \hat{\sigma}_v \mathbf{v}] \]

(13)

The other parameters are considered similarly. So we get the estimated values \( \hat{w}_- \) and \( \hat{w}_+ \).

As mentioned before, we want to consider in this case only singletons and the so called "rest of the world". For each class and each physical parameter a fuzzy membership function is considered. The trapezoidal functions are given by two supporting points, \( h_1 \) and \( h_2 \). The membership values are then calculated as follows:

\[ m_+(i, j) = \begin{cases} 
1 & \text{if } w_x \leq h_1 \text{ or } j = \text{rest of the world} \\
\frac{w_x - h_1}{h_2 - h_1} & \text{if } h_1 \leq w_x \leq h_2 \\
0 & \text{if } w_x > h_2
\end{cases} \]

(14)

\[ m_+(i, j) = \begin{cases} 
1 & \text{if } w_x \leq h_1 \text{ or } j = \text{rest of the world} \\
\frac{w_x - h_1}{h_2 - h_1} & \text{if } h_1 \leq w_x \leq h_2 \\
0 & \text{if } w_x > h_2
\end{cases} \]

(15)

The membership value is then given by:
The definition of evidence requires that the sum over all focal elements has to be 1, so a normalization is necessary. The evidences are then given by:

\[
m(i, j) = \sum_{j \in J} \hat{m}(i, j)
\] (17)

These are the evidences for each class and each parameter. The fusion of the mass functions is described in section 5.

4 Fusion of the Doppler Sound Classifier with Track-Based Classifier Using DS-Method 1

The result of the method described in section 2 consists of \( M = |I| \) mass functions defined on the elements of \( \mathcal{P}(J) \).

The intuitional approach would be to combine at first these mass functions to receive a track based classification result. The fusion can be done with Dempster's rule of combination using the accumulation of mass functions. The joint mass of two masses is then defined as follows:

\[
m_1(X) \oplus m_2(X) := \frac{1}{1 - K} \sum_{Y \cap Z = X} m_1(Y) \cdot m_2(Z)
\] (18)

whereas \( K \) can be interpreted as a measure of conflict between the two masses, because it is defined as follows:

\[
K := \sum_{Y \cap Z = \emptyset} m_1(Y) \cdot m_2(Y)
\] (19)

The summation has to be done over all subsets of \( J \) and can therefore be very time consuming. Looking on the result of the Doppler sound classifier it can be noticed that the output of this classifier is a vector containing a probability for each target class. Using the following lemma, we will treat the probability function as a mass function where the focal elements are singletons.

\[
\text{Lemma: Let } (A, \mathcal{P}(A), P) \text{ be a probability space. Then the mapping defined by}
\]

\[
m([a]) := P([a]) \quad \forall a \in A
m(X) := 0 \quad \forall X \subseteq A : |X| > 1
\] (20)

is a mass function in terms of the theory of evidences.

The accumulation of evidences is associative as well as commutative, so we first combine the probability vector of the Doppler sound classifier with one of the mass functions of the track based classifier e.g. the mass function related to velocity. One of the advantages of this proceeding lies in the reduction of the computational efforts, because the focal elements of an accumulated mass function of a probability function with another mass are only singletons.

5 Fusion of the Doppler Sound Classifier with Track-Based Classifier Using DS-Method 2

To receive the combined evidence for each class, the accumulation of evidences is used.

\[
m(j) = m(\text{vel}, j) \oplus m(\text{acc}, j) \oplus m(\text{RCS}, j)
\] (21)

The accumulation is defined as follows:

\[
m(i_l, j) \oplus m(i_{l+1}, j) := \frac{1}{1 - k_l} \sum_{Y \cap Z = j} m(i_l, Y) \cdot m(i_{l+1}, Z)
\] (22)

with

\[
k_l := \sum_{Y \cap Z = \emptyset} m(i_l, Y) \cdot m(i_{l+1}, Z)
\] (23)

Because only singletons and nomatch, regarded as additional target class, are focal elements in this case, the mass function can be totally described by a matrix. In this case first the results of the track based classifier given for each physical parameter are combined then the fusion with the Doppler sound classifier is done.

6 Experiments

Several experiments are performed in order to compare the classification performance of the two described Dempster-Shafer methods. The data for training and testing the classifiers was obtained from simulated radar measurements of moving targets using a stationary X-band low PRF pulse Doppler radar with horizontal polarization. The data sets used for this paper are simulated, due to company restrictions concerning publishing results based on real radar data. Experiments with such data sets are performed in-house. For the investigation, the eight following target classes were considered: person, wheeled vehicle, tracked vehicle, helicopter, propeller aircraft, buoy, boat and no match (animal). In the considered scenarios the ground and sea targets move tangential to the radar, the flying air targets...
perform weaving maneuvers. A simplified illustration of the scenarios can be seen in Figure 4. Each data set was generated using a total time on target of a few seconds with a measurement interval of 1 second and each measurement of some 100 milliseconds.

![Simplified illustration of a tangential littoral scenario](image)

Figure 4: Simplified illustration of a tangential littoral scenario

Taking a stand-alone Doppler based classifier with good results, based on the given data, an investigation focusing at the influence of training this classifier with an increasing number of false data sets was performed. One exemplary Markov based Doppler classifier was trained and tested with 100 data sets for each class. The false label ratio in the training sets was gradually increasing from 0% to 30%. The track based classifier was used both with a hierarchical Dempster-Shafer method and a non-hierarchical Dempster-Shafer method. Both methods were using Dempster's Rule of Combination for combining the track based classifier with the Doppler sound classifier.

### Results Comparison

The classification results are given in confusion matrices. Table 1 - Table 3 show the matrices for a 10% ratio of false data sets, Table 4 - Table 6 show the matrices for a 30% ratio.

As further criteria the false classification rate as well as the correct classification rate are given in Figure 5 and Figure 6. For the sake of completeness the rejection rate is shown in Figure 7.
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<th>Confusion Matrix for stand-alone Doppler based classifier with 30% false training ratio</th>
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Table 4: Confusion Matrix for Non-Hierarchical DS with 30% false training ratio

<table>
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Table 5: Confusion Matrix for Hierarchical DS with 30% false training ratio

Figure 5: False classification rate, the dashed curve of the Doppler based classifier, the solid one of the nonhierarchical DS classifier, the dotted one of the hierarchical DS classifier

Figure 6: Correct classification rate, the dashed curve of the Doppler based classifier, the solid one of the nonhierarchical DS classifier, the dotted one of the hierarchical DS classifier

Figure 7: Rejection rate, the dashed curve of the Doppler based classifier, the solid one of the non-hierarchical DS classifier, the dotted one of the hierarchical DS classifier
8 Conclusions

In this paper, two hybrid classifiers each consisting of a Doppler based classifier combined with a track based nonhierarchical Dempster-Shafer classifier on the one hand and a track based hierarchical Dempster-Shafer classifier on the other hand have been introduced for radar target classification in an environment with ground, sea and air targets. The results show an improvement of a radar target classifier by using fusion technologies. Considering the false classification rate shown in Figure 5, it could be seen that the performances of both Dempster-Shafer methods are better than the stand-alone classifier. Considering the correct classification rate shown in Figure 6, the Dempster-Shafer based fusion methods also give the better results in this comparison than the stand-alone classifier. Regarding the rejection rate as can be seen in Figure 7, the two fusion methods show similarly results.

In future works it would be interesting to discuss the investigation of comparison the Dempster-Shafer methods shown in this paper with other approaches like Bayesian Networks, introduced in [11], or knowledge based approaches, introduced in [15]. Also information of other sensor systems like IFF, Infrared Cameras and so on can be integrated.

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References