DSmT Applied to Seismic and Acoustic Sensor Fusion

Erik P. Blasch
Defence R&D Canada-Valcartier
2459 Pie-XI Blvd. North
Québec City, QC G3J 1X5
erik.blasch@drdc-rddc.gc.ca

Jean Dezert
ONERA DTIM/SIF
Chemin de la Hunière
91761 Palaiseau Cedex, France
jdezert@onera.fr

Pierre Valin
Defence R&D Canada-Valcartier
2459 Pie-XI Blvd. North
Québec City, QC G3J 1X5
Pierre.valin@drdc-rddc.gc.ca

Abstract – *In this paper, we explore the use of the Dezert-Smarandache Theory (DSmT) for seismic and acoustic sensor fusion. The seismic/acoustic data is noisy which leads to classification errors and conflicts in declarations. DSmT affords the redistribution of masses when there is a conflict. The goal of this paper is to present an application and comparison on DSmT with other classifier methods to include the support vector machine(SVM) and Dempster-Shafer (DS) methods. The work is based on two key references (1) Marco Duarte with the initial SVM classifier application of the seismic and acoustic sensor data and (2) Arnaud Martin in Vol. 3 with the Proportional Conflict Redistribution Rule 5/6 (PCR5/PCR6) developments. By using the developments of Duarte and Martin, we were able to explore the various aspects of DSmT in an unattended ground sensor scenario. Using the receiver operator curve (ROC), we compare the methods for individual classification as well as a measure of overall classification using the area under the curve(AUC). Conclusions of the work show that the DSmT results with a maximum forced choice are comparable to the SVM.*

Keywords: *Information Fusion, DSMT, PCR5, PCR6, Area Under the Curve(AUC), SVM.*

1 Introduction

The goal of this paper is to present an application and comparison on DSmT with other classifier methods. The work is based on two key references (1) Marco Duarte with the initial classifier application of the seismic and acoustic sensor data [1] and (2) Arnaud Martin in Vol. 3 for the implementation of the DSmT methods. [2] By using the developments of Duarte and Martin, we were able to explore the various aspects of DSmT in an unattended ground sensor scenario. In the exploration of information fusion metrics for classification, there is a need to develop metrics of effectiveness that support the user's utility needs [3] and can vary over the sensor types, environmental conditions, targets of interest, situational context, and users [4].

DSmT is an extension to the Dempster-Shafer method of evidential reasoning which has been detailed in numerous papers and texts: *Advances and applications of DSmT for information fusion (Collected works)*, Vols. 1-3 [5]. In 2002, Dezert [6] introduced the methods for the reasoning and in 2003, presented the hyper power-set notation for DSmT [7]. Recent applications include the DSmT Proportional Conflict Redistribution rule 5 (PCR5) applied to target tracking [8].

The key contributions of DSmT are the redistributions of masses such that no refinement of the frame Θ is possible unless a series of constraints are known. For example, Shafer's model [9] is the DSm hybrid model in DSmT. Since Shafer's model, authors have continued to refine the method to more precisely address the combination of conflicting beliefs [10, 11, 12] and generalization of the combination rules [13, 14]. An adaptive combination rule [15] and rules for quantitative and qualitative combinations [16] have been proposed. Recent examples for sensor applications include electronic support measures, [17, 18] and physiological monitoring sensors [19]. One application of DSmT that has not been fully explored is in seismic, magnetic, and acoustic classification fusion of moving targets. Kadambe conducted an information theory approach [20] and used DSmT as integrity constraints [21], but did not take advantage of the conflict redistribution.

Detecting moving vehicles in an urban area [22] is an example where DSmT conflicting mass redistribution could be helpful [8]. Detecting traffic can be completed by fixed ground cameras or on dynamic unattended ground vehicles (UGVs). If the sensors are on UGVS, path planning is needed to route the UGVs to observe the traffic [23, 24] and cooperation among UGVs is necessary[25]. The DARPA Grand Challenge featured sensors on mobile UGVs observing the environment [26]. Mobile sensing can be used to orient [27] or conduct simultaneous location and mapping (SLAM) [28].

Deployed ground sensors can observe the vehicles; however they are subject to noisy measurements from environmental conditions. One interesting question is how to deploy the fixed sensors that optimize the performance of a system. Issues for distributed wireless networks (WSNs) include distributed processing, communications, and data fusion [29]. In a dynamic scenario, resource coordination [30] is needed for both context assessment, but also the ability to be aware of impending situational threats [31, 32]. For distributed sensing systems, to combine sensors, data, and user analysis requires pragmatic approaches to metrics [33, 34, 35, 36]. For example, Zahedi [37] develops a QOI architecture for comparison of centralized versus distributed sensor network deployment planning.

Information fusion has been interested in the problems of databases for target trafficability (i.e. terrain information) [38], sensor management [39], and processing algorithms [40] from which to assess objects in the environment. Various techniques have incorporated grouping object movements [41], road information [42, 43], and updating the object states based on environmental constraints [44]. Detecting, classifying, identifying and tracking objects [45] has been important for a variety of sensors, including 2D visual, radar [46], and hyperspectral [47] data; however newer methods are of interest for ground sensors with 1D signals.

Seismic data provides passive sensing of ground vibrations which can be used for motion tracking. Passive magnetic sensing can detect hidden objects that might indicate intent. Finally, acoustic data can be used for signature detection from vehicle engines. [48] The DARPA SENSIT program investigated deploying a distributed set of wireless sensors along a road to classify vehicles as shown in **Figure 1**.

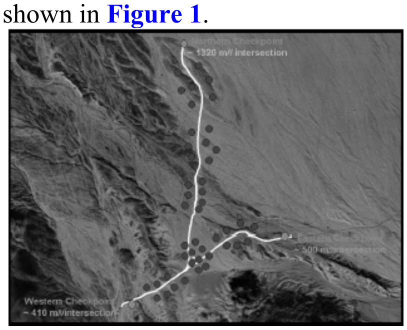

Figure 1. SENSIT Data from [M. F. Duarte and Y. H. Hu, "Vehicle Classification in Distributed Sensor Networks," 2004 [49]

The sensors include acoustic and seismic signals. Given the deployed set of sensors, feature vectors were used to classify signals based on the data from the seismic and acoustic signals. [49] Various approaches include combining the data with decision fusion [50], value fusion [51], and simultaneous track and identification methods [52, 53]. Information theoretical approaches including the KL method were applied to the data for sensor management [54] as shown in **Figure 2**. Processing sensor data for target classification using acoustic [55, 56] and seismic [57] results have been explored in support of information theoretical sensor placement [58].

Much work has been completed using imaging sensors and radar sensors for observing and tracking targets. Video sensors are limited in power and subject to day/night conditions. Likewise, radar line-of site precludes them from observing in the same plane. Together, both imaging and radar sensors do not have the advantage of UGSs which can power on and off, can work for a long time on battery power, and can be deployed to remote areas.

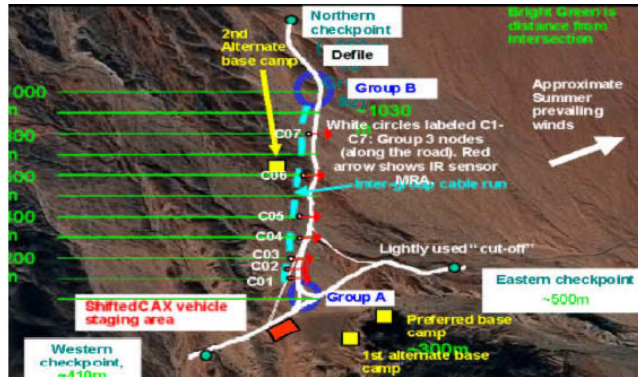

Figure 2. Deployed Sensors. From S. Kadambe and C. Daniell, "Theoretic Based Performance of Distributed Sensor Networks", *AFRL-IF-RS-TR-2003*, 231, October 2003. [54]

Track management situational awareness tools receive input from sensor feeds (examples include electro-optical, radar, electronic support measures (ESMs), and sonar) and display this information to a user. User inputs include: creation of new objects, such as tracks, contacts and targets. Methods to reduce data-to-decisions include: fusing multiple tracks into a single track, incorporating alerting mechanisms, or visualizing track data common operational picture (COP). Sensor and track data can grow rapidly as the user desires to keep historical data.

Our goal is to utilize the DSmT method for the fusion of information from seismic and acoustic data in which each sensor/classifier is in direct conflict with the other sensor. We address (1) intelligent use of the data based on value for classification, (2) DSMT sensor data fusion for detection, classification, and positional location, and (3) metrics to support the sensor and data management as supporting a user control.

2 Location / Detection

We desire to track and identify the targets based on the sensor reports. In this study, we concentrate on the classification of targets which can be used with the kinematic/position information for target identification.

2.1 Sensor Information Management

The goal is to utilize the UGSs sensors which may be acoustic, magnetic, seismic, and PIRoelectric (passive infrared for motion detection. With a variety of sensors, information fusion can (a) utilize the most appropriate sensor at the correct time, (b) combine information from both sensors on a single platform, (c) combine results from multiple platforms, and (d) cue other sensors in a hand-off fashion to effectively monitor the area. Sensor exploitation requires an analysis of feature generation, extraction, and selection or (construction, transformation, selection, and evaluation). To provide track and ID results, we develop method or target classification.

2.2 Sensor Classification

Sensor exploitation includes detection, recognition, classification, identification and characterization of some object. Individual classifiers can be deployed at each level to robustly determine the object information. Popular methods include voting, neural networks, fuzzy logic, neuro-dynamic programming, support vector machines, Bayesian and Dempster-Shafer methods. One way to ensure the accurate assessment is to look at a combination of classifiers. Combination of classifiers [59] could include different sensors with classifiers, different methods over a single or multiple sensors, and various hierarchies of coordinating the classifiers such as Bayes nets and distributed processing.

Issues in classifier combination methods need to be compared as related to decisions, feature sets, and user involvement. Selecting the optimal feature set is based on the situation and environmental context of which the sensors are deployed. An important question for sensor and data management is measures of effectiveness. For instance, what is the quantification of fusion/decision gain using a set of classification methods and placement methods? There is a need for a robust combination rule that includes the location and detection of the sensors subject to the target and environmental constraints. Typically, a mobile sensor needs to optimize its route and can be subject to interactive effects of pursuers and evaders with other targets [60] as well as active jamming of the signal [61].

Detecting targets from seismic and acoustic data in a distributed net centric fashion requires pragmatic approaches to sensor and data management. [62] To robustly track and ID a target requires both the structured data from the kinematic movements as well as the unstructured data for the feature analysis. [63]

3 DSMT

Here we use the *Proportional Conflict Redistribution* rule no. 5 (PCR5) and no. 6 (PCR6) and the *Dezert-Smarandache Probability* (DSmP) selections which are discussed below. We replace Smets' rule [10] by the more effective PCR5 or eventually the more simple PCR6 and replace the pignistic transformation by the more effective DSmP transformation to estimate target classification probabilities. All details, justifications with examples on PCR5 and PCR6 fusion rules and DSmP transformation can be found freely from the web in the DSmT compiled texts [5], Vols. 2 & 3..

3.1 PCR5 and PCR6 fusion rules

In DSmT (Dezert-Smarandache Theory) framework, the PCR5 is used generally to combine the basic belief assignment (bba)'s. PCR5 transfers the conflicting mass only to the elements involved in the conflict and proportionally to their individual masses, so that the specificity of the information is entirely preserved in this fusion process. Let $m_1(.)$ and $m_2(.)$ be two independent bba's, then the PCR5 rule is defined as follows (see [5], Vol. 2 for full justification and examples): $m_{PCR5}(\varnothing) = 0$ and $\forall X \in 2^\Theta \setminus \{\varnothing\}$, where $\varnothing$ is the null set and 2^Θ is the power set:

$$m_{PCR5}(X) = \sum_{\substack{X_1, X_2 \in 2^\Theta \\ X_1 \cap X_2 = X}} m_1(X_1) m_2(X_2) + \sum_{\substack{X_2 \in 2^\Theta \\ X_2 \cap X = \emptyset}} \left[\frac{m_1(X)^2 m_2(X_2)}{m_1(X) + m_2(X_2)} + \frac{m_2(X)^2 m_1(X_2)}{m_2(X) + m_1(X_2)}\right] \quad (1)$$

where $\cap$ is the interesting and all denominators in the equation above are different from zero. If a denominator is zero, that fraction is discarded. Additional properties of PCR5 can be found in [64]. Extension of PCR5 for combining qualitative bba's can be found in [5], Vol. 2 & 3. All propositions/sets are in a canonical form. A variant of PCR5, called *PCR6* has been proposed by Martin and Osswald in [5], Vol. 2, for combining more than 2 sources. PCR6 coincides with PCR5 when one combines two sources. The difference between PCR5 and PCR6 lies in the way the proportional conflict redistribution is done as soon as three or more sources are involved in the fusion. For example, let's consider three sources with bba's $m_1(.)$, $m_2(.)$, and $m_3(.)$, $A \cap B = \varnothing$ for the model of the frame Θ, and $m_1(A) = 0.6$, $m_2(B) = 0.3$, and $m_3(B) = 0.1$. With ***PCR5*** the partial conflicting mass $m_1(A)\, m_2(B)\, m_3(B) = (0.6)(0.3)(0.1) = 0.018$ is redistributed back to A and B only with respect to the following proportions respectively: $x_A^{PCR5} = 0.01714$ and $x_B^{PCR5} = 0.00086$ because the proportionalization is [8]:

$$\frac{x_A^{PCR5}}{m_1(A)} = \frac{x_B^{PCR5}}{m_2(B)\, m_3(B)} = \frac{m_1(A)\, m_2(B)\, m_3(B)}{m_1(A) + m_2(B)\, m_3(B)}$$

that is $$\frac{x_A^{PCR5}}{0.6} = \frac{x_B^{PCR5}}{(0.3)(0.1)} = \frac{0.018}{0.6 + 0.03} \approx 0.02857$$

thus $$x_A^{PCR5} = 0.60\ (0.02857) \approx 0.01714$$
$$x_B^{PCR5} = 0.03\ (0.02857) \approx 0.00086$$

With the ***PCR6*** fusion rule, the partial conflicting mass $m_1(A)\ m_2(B)\ m_3(B) = (0.6)(0.3)(0.1) = 0.018$ is redistributed back to A and B only with respect to the following proportions respectively: $x_A^{PCR6} = 0.0108$ and $x_B^{PCR6} = 0.0072$ because the PCR6 proportionalization is done as follows:

$$\frac{x_A^{PCR6}}{m_1(A)} = \frac{x_{B;2}^{PCR6}}{m_2(B)} = \frac{x_{B;3}^{PCR6}}{m_3(B)} = \frac{m_1(A)\, m_2(B)\, m_3(B)}{m_1(A) + m_2(B) + m_3(B)}$$

that is

$$\frac{x_A^{PCR6}}{0.6} = \frac{x_{B;2}^{PCR6}}{0.3} = \frac{x_{B;3}^{PCR6}}{0.1} = \frac{0.018}{0.6+0.3+0.1} \approx 0.018$$

thus

$$x_A^{PCR6} = (0.6)\,(0.018) = 0.0108$$
$$x_{B,2}^{PCR6} = (0.3)\,(0.018) = 0.0054$$
$$x_{B,3}^{PCR6} = (0.1)\,(0.018) = 0.0018$$

and therefore with PCR6, one gets finally the following redistributions to *A* and *B*:

$$x_A^{PCR6} = (0.6)\,(0.018) = 0.0108$$

$$x_B^{PCR6} = x_{B,2}^{PCR6} + x_{B,3}^{PCR6} = 0.0054 + 0.0018 = 0.0072$$

From the implementation point of view, PCR6 is simpler to implement than PCR5. For convenience, Matlab codes of PCR5 and PCR6 fusion rules can be found in [5].

3.2 The DSmP Transformation

The DSmP probabilistic transformation is an alternative to the classical pignistic transformation which allows us to increase the probabilistic information content (PIC), i.e. to minimize the Shannon entropy, of the approximated subjective probability measure drawn from any bba. Justification and comparisons of DSmP(.) with respect to BetP(.) and to other transformations can be found in details in [65, 5 Vol. 3, Chap. 3].

BetP: The pignistic transformation probability, denoted BetP, offers a compromise between maximum of credibility *Bel* and maximum of plausibility *Pl* for decision support. The *BetP* transformation is defined by BetP(∅) = 0 and $\forall X \in G^\Theta \setminus \{\emptyset\}$ by

$$BetP(X) = \sum_{Y \in G^\Theta} \frac{\mathcal{C}_\mathcal{M}(X \cap Y)}{\mathcal{C}_\mathcal{M}(Y)} m(Y) \tag{2}$$

where G^Θ corresponds to the hyper-power set including all the integrity constraints of the model (if any). $G^\Theta = 2^\Theta$ if one adopts Shafer's model for Θ and $G^\Theta = D^\Theta$ (Dedekind's lattice) if one adopts the free DSm model for Θ [5]. $C_M(Y)$ denotes the DSm cardinal of the set *Y*, which is the number of parts of *Y* in the Venn diagram of the model *M* of the frame Θ under consideration [5, Book 1, Chap. 7]. The BetP reduces to the Transferable Belief Model (TBM) when G^Θ reduces to classical power set 2^Θ when one adopts Shafer's model.

DSmP transformation is defined by $DSmP_\in(\emptyset) = 0$ and $\forall X \in G^\Theta \setminus \{\emptyset\}$ by

$$DSmP_\epsilon(X) = \sum_{Y \in G^\Theta} \frac{\sum_{\substack{Z \subseteq X \cap Y \\ \mathcal{C}(Z)=1}} m(Z) + \epsilon \cdot \mathcal{C}(X \cap Y)}{\sum_{\substack{Z \subseteq Y \\ \mathcal{C}(Z)=1}} m(Z) + \epsilon \cdot \mathcal{C}(Y)} m(Y) \tag{3}$$

where C($X \cap Y$) and C(Y) denote the cardinals of the sets $X \cap Y$ and Y respectively; $\varepsilon \geq 0$ is a small number which allows to reach a highest PIC value of the approximation of *m*(.) into a subjective probability measure, and *Z* is the new evidence. Usually ε = 0, but in some particular degenerate cases, when the $DSmP_{\varepsilon=0}(.)$ values cannot be derived, the $DSmP_{\varepsilon>0}$ values can however always be derived by choosing ε as a very small positive number, say ε = 1/1000 for example in order to be as close as we want to the highest value of the PIC. The smaller ε, the better/bigger PIC value one gets. When ε = 1 and when the masses of all elements *Z* having C(*Z*) = 1 are zero, $DSmP_{\varepsilon=1}(.) = BetP(.)$.

4 Seismic/Acoustic Exmaple

We use the SENSIT data which was described above. To perform the data analysis we use data mining [66] techniques such as a *support vector machine* (SVM) [67, 68] to process the unstructured data. Through analysis, we can determine the optimum use of the data given environmental conditions (i.e. obscurations) and sensor's capabilities to detect a moving target.

Figure 3 shows the methodology of comparison. A key comparison is made between combining all the acoustic and seismic data together for testing and training via the SVM versus using the outputs from the acoustic and seismic data separately from which conflicts in classification are detected and sent to DS and DSmT processing.

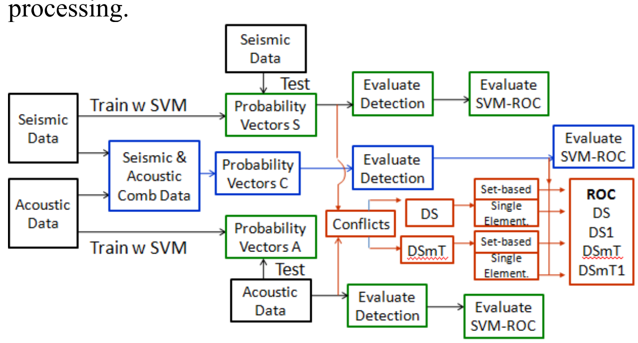

Figure 3. Experimentation Flow.

For the data, we have 50 seismic and 50 acoustic measurements at each time step for 10,000 time steps. We trained the SVM over the first 500 measurements and ran the study over a different 500 time steps. With limited explanation of the all the data, we note that contextual factors could vary the measurement quality over the different time intervals we chose to test and evaluate, but we are unable to verify differences over the intervals. The combined decision $m(\bullet)$ is from two sources with three target choices $m_1(\mathrm{A})$, $m_X(\mathrm{B})$, $m_X(\mathrm{C})$, where X is acoustic, seismic, or combined decisions. We implement as a probability vector (e.g. $[m_A(1), m_A(2), m_A(3)]$, for acoustic with target labels of 1, 2, 3). We then use the DSmP with a cardinality of 3. As per (1)-(3), the combined results use $[m_A(1), m_A(2), m_A(3)\ m_S(1), m_S(2), m_S(3)]$, where source A is acoustic and source S is for seismic and the outputs are x_1^{PCR6}, x_2^{PCR6}, and x_3^{PCR6}. It is noted that we have not used the raw measurements, but the aggregate decision trained from the SVM over the 50 measurements.

Using the results of the analysis, we compared the decisions versus the truth data over all decisions for 100 trails and plotted a receiver operator curve (ROC). The ROC plots the probability of detection (P_D) or true positive rate (TPR) versus probability of false alarm (P_{FA}) or False Positive Rate (FPR). To further gather a meaningful measure we plot the area under the curve (AUC) to compare the different cases.

4.1 Data Processing

We compare two cases of (1) processing the data separately and (2) jointly processing the acoustic and seismic results **Figure 4** shows the case of the acoustic results where the AUC for each target is calculated as an overall performance criterion.

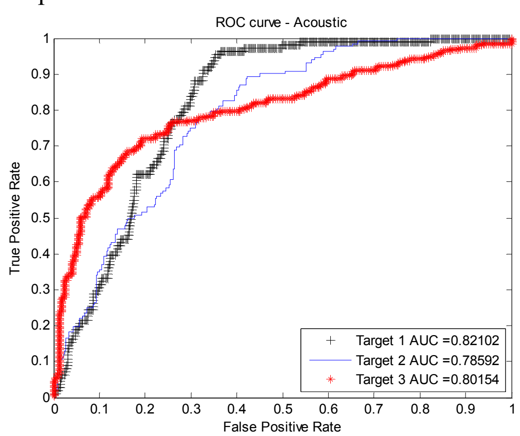

Figure 4. Acoustic Results.

Figure 5 plots the seismic results. Note that for the data set, the seismic results have a lower probability of false alarms for target 3 and target 2; however, target 2 exhibits more confusion.

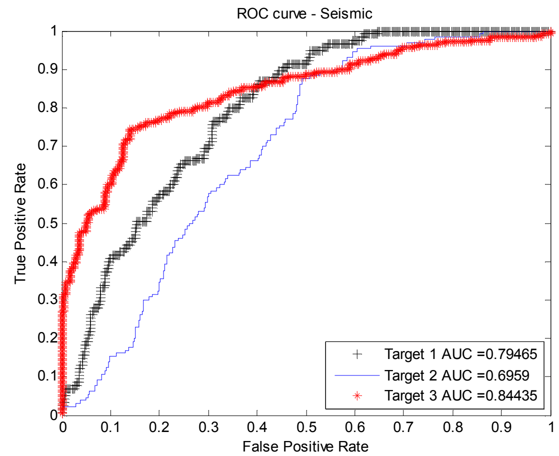

Figure 5. Seismic Results.

Next we explore the case of the joint seismic and acoustic data management and utilize SVM for classification, shown in **Figure 6**. Note the false alarm reduction which is desired by users.

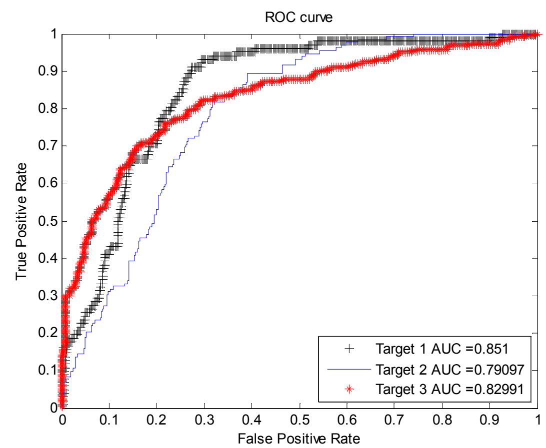

Figure 6. Combined Results

In general, the joint analysis supports better decision making as confidence was PD was improved for a constant false alarm rate, accuracy was improved as to the target location from joint spatial measurements, and timeliness in decision making as fewer measurements were needed to confirm the target ID (i.e. decision made with two modalities required fewer measurements than that of a single modality).

4.2 Application of DS

Below, we show the results of the application of DS methods. Given a training and prediction results in a combined probability, we have for target1, target2, and target3 a vector of $\mathbf{m} = [m_1\ m_2\ m_3]$. Based on the prediction results from the SVM, there are many conflicts of the sensor decision based on the maximum probability. When a conflict occurs, it would be better suited to acknowledge the conflict and then redistribute the probabilities based on a set notation. In this case, the focal elements are $\Phi = [\theta_1, \ldots, \theta_7] =$ [‘1’, ‘1⋂2’, ‘2’, ‘2⋂3’, ‘3’, '1⋂3', '1⋂2⋂3']. Using the analysis by Martin, we conduct an analysis over the set criterion. **Figure 7** shows that a significant reduction false alarms (at a low FPR the TPR remains high). The shift of the curve to the left (versus Figure 6 of the SVM) demonstrates that DS is better at low P_{FA}. However, if we compare the AUC for all results, then the SVM performs better. Thus, there is a trade off when for using DS for increasing the P_D at low P_{FA} versus the SVM for overall classification analysis.

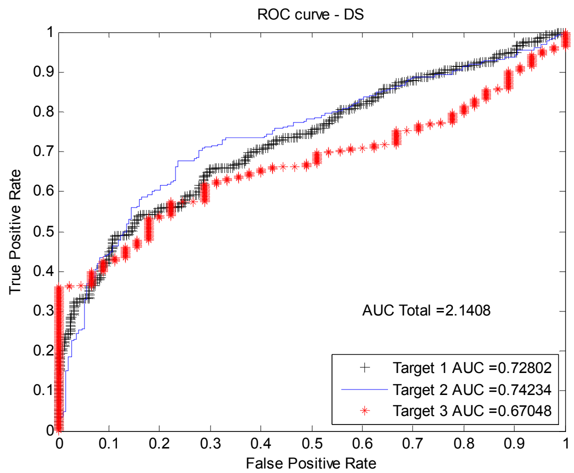

Figure 7. DS allowing for set declarations.

To explore a comparison of approaches, we utilized the bba and forced the evidential reasoned to choose a single target. From this analysis, the AUC improves in comparison to the SVM approaches which are a forced choice analysis. **Figure 8** plots the DS (for one target designation).

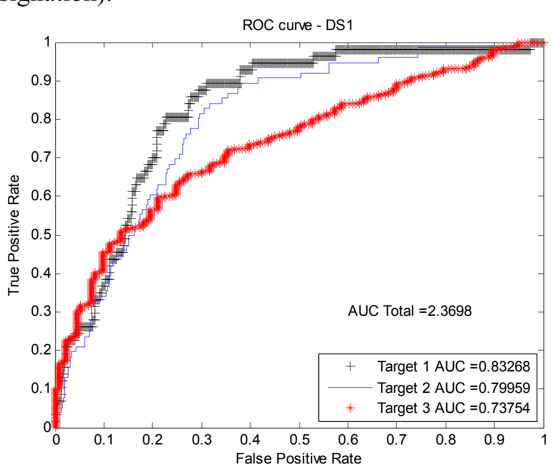

Figure 8. DS Single Target Detection.

4.3 Application of DSMT

DMST, as described above, improves on the methods of DS conflict redistribution. In this example, the bba were computed from the SVM and calculated with (1)-(3). DSmT classification was comparable to the complete SVM fusion analysis for the AUC, with improvements at the low P_{FA}.

Figure 9 presents the DSmT results for set declaration and **Figure 10** shows the case of a forced target choice from the DSmT. From Figure 9, we can see that the set-based approach improves the detection for low false alarm rates. At high false alarm rates or FPR (0.3 – 0.9), the detection probability for DSmT is lower than the SVM results. Using the maximum of the target bba, shown in Figure 10, provides an analysis threshold that renders the DSmT comparable to a SVM.

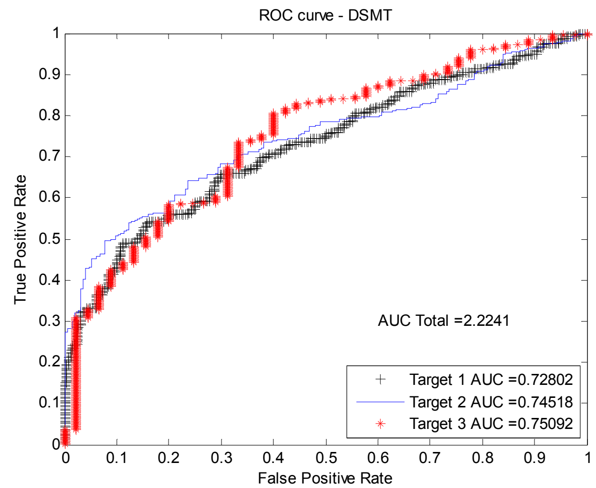

Figure 9. DSmT allowing for set declarations.

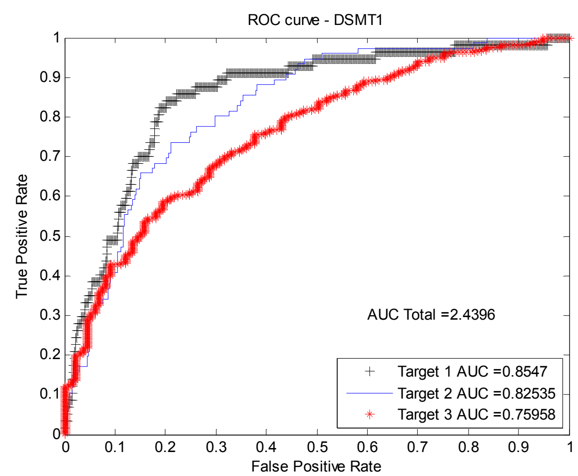

Figure 10. DSmT Single Target Detection.

In the table below, we look at the entire analysis using the area under the ROC (AUC) as a key metric in the analysis. There are cases in which the maximum AUC and minimum AUC are improved but the overall analysis (Total AUC) varies. We see from the comparison three results : (1) that the DSmT improves upon the DS methods, (2) information fusion improves the results, and (3) the DSmT without redistribution of the conflict for each measurement can obtain results similar to the SVM.

Table 1: AUC Comparisons of SVM, DS, and DSmT

Method	**Min AUC**	**Max AUC**	**Total AUC**
A-SVM	0.786	0.821	2.401
S-SVM	0.696	0.844	2.335
C-SVM	**0.791**	**0.851**	**2.472**
DS	0.671	0.742	2.141
DS1	0.738	0.833	2.371
DSMT	0.728	0.751	2.224
DSMT1	**0.760**	**0.855**	**2.440**

A – Acoustic, S-Seismic, C-Combination

Table 1 has three motivations. In the first look, for a single target detection; the SVM alone (run over all the data) does perform slightly better than the DSmT information fusion case. Second, from the results we advocate the use of DSmT over DS. Third, we see that while DSmT is more complex, it offers further capability to look at each measurement and redistribute the conflict versus using all of the data in a force SVM case.

If we compare Figure 6 (SVM combined) and Figure 10 (DSmT max choice), we see that all curves in the DSmT have better results at low at low P_{FA} rate over all targets; whereas the SVM has lower performance for target 1 and target 2 and a better classification of target 3. The aggregate AUC measure provides a global comparison; which advocates the SVM; however, DSmT is more conservative through the proportional conflict redistribution which improves the SVM analysis over the low P_{FA} rate results. The P_{FA} is important for decision support as operators are interested in the P_D at low P_{FA}.

5 Conclusions

We have explored DS and DSmT methods for seismic and acoustic information fusion. The goal of the paper wasto extend the existing techniques presented by Martin and Durate for further demonstration of how to deal with conflicting information. From the initial results, the use of DSmT can be tailored to the seismic and acoustic sensors for on-line high conflict mass redistribution of decision outputs as the sensors measure different target phenomenologies and might not always be globally optimized as with the SVM. We utilized a Bayesian basic belief assignment (bba) with only singleton as focal elements which from the *P* vectors of the target probabilities. Future work will use non-Bayesian approaches to get the bbas, further assessment of the conflict redistribution, and set-based decision logic.

Information theoretic measures [**69**] and tracking analysis [**70**] can support the sensor and data management as well as determine the Quality of Information and Quality of Service needs. Use of the *Area Under the Curve* (AUC) provides decision support for situational awareness for command and control from which we can extend to higher dimensions [**71**]. Various other sources of soft data (human reports) can be combined with the hard (physics-based sensing) [**72**] to update the sensor management, placement, and reporting of the situation based on the context and the needs of users such as measures of effectiveness for mission support.

Acknowledgement

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