LRTS Laboratoire de Télécommunications et de Traitement du signal

APPROXIMATION IN DSm THEORY FOR FUSING ESM REPORTS

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Introduction

- Electronic Support Measures consist of passive receivers which can identify emitters which, in turn, can be related to platforms that belong to 3 classes: Friend, Neutral, or Hostile. Decision makers prefer results presented in STANAG 1241 allegiance form, which adds 2 new classes: Assumed Friend, and Suspect.
- Dezert-Smarandache (DSm) theory is particularly suited to this problem, since it allows for intersections between the original 3 classes. However, as we know, the DSm hybrid combination rule is highly complex to execute and requires high amounts of resources.
- We have applied and studied a Matlab implementation of Tessem's klx approximation technique in the DSm theory for the fusion of ESM reports. Results are presented showing that we can improve on the time of execution while maintaining the similar rate of good decisions.

Theory & System Model

✓Hyperpower set

$$D^{\Theta}=\{\varnothing,\{\theta_1\},\{\theta_2\},\{\theta_1\cap\theta_2\},\{\theta_1\cup\theta_2\}\}\quad \Theta=\{\theta_1,\theta_2\}$$

✓Dezert-Smarandache Hybrid Combining rule

$$m_{M(\Theta)}(A)=\phi(A)\left[S_1(A)+S_2(A)+S_3(A)\right]$$

$$S_1(A)=\sum_{X_1\cap X_2=A} m_1(X_1)m_2(X_2)\quad \forall X_1,X_2\in D^{\Theta}$$

$$S_2(A)=\sum_{\substack{[(u(X_1)\cup u(X_2))=A]\vee\\ [((u(X_1)\cup u(X_2))\in\varnothing)\wedge(A=I_t)]}} m_1(X_1)m_2(X_2)\quad \forall X_1,X_2\in\varnothing$$

$$S_3(A)=\sum_{\substack{X_1\cup X_2=A\\ X_1\cap X_2=\varnothing}} m_1(X_1)m_2(X_2)\quad \forall X_1,X_2\in D^{\Theta}$$

✓Generalized Pignistic Transformation

$$\Pr\{A\}=\sum_{X\in D^{\Theta}}\frac{C_{\mathcal{M}}(X\cap A)}{C_{\mathcal{M}}(X)}m(X)\quad \forall A\in D^{\Theta}$$

✓Tessem's klx approximation method involves three parameters: k the minimum number of focal elements to be kept, l the maximum number of focal elements to be kept and x the maximum threshold on the sum of the lost masses. It can be summarized as follows:

- 1. Select the k focal elements with highest masses;
- 2. While the sum of their masses is less than 1-x, and while their number is less than l, add the next focal element with highest mass.
- 3. Normalize the values of the approximated belief function

✓For an ESM sensor that gives us Friend ($F=\theta_1$), Neutral ($N=\theta_2$) or Hostile ($H=\theta_3$) Figure 1 has the interpretation of the five classes:

- Friend = $\{\theta_1 - \theta_1\cap\theta_2\}$, Hostile = $\{\theta_3 - \theta_3\cap\theta_2\}$
- Assumed Friend = $\{\theta_1\cap\theta_2\}$, Suspect = $\{\theta_2\cap\theta_3\}$
- Neutral = $\{\theta_2 - \theta_1\cap\theta_2 - \theta_3\cap\theta_2\}$

✓We call the pignistic probability for those classes STANAG probability.

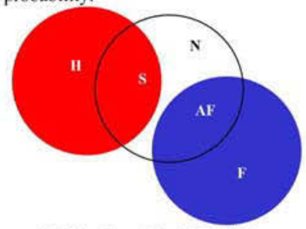

Fig. 1: Venn diagram for the STANAG allegiances.

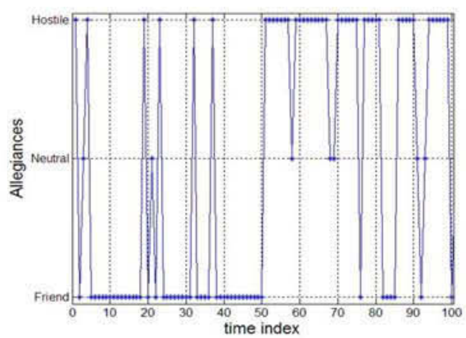

Fig. 2: Occurrences of singletons/allegiances from ESM.

✓Figure 2 shows us a sequence of sensor's information that was used in a single Monte Carlo run. As we can see,

- each run is composed of a hundred combinations
- the target's allegiance is identified with an accuracy of 80% and 80% of uncertainty.
- the allegiance switches from friend to hostile at midpoint

Results and Decision

✓The evaluation of the impact of the klx approximation technique is done on two aspects

- With the 'good decision rate' which is evaluated by comparing the set having the highest stanag probability with the ground truth (friend the first 50 time index, hostile the last 50) for the 100 Monte Carlo runs, with and without approximation, on the same generated dataset.
- With the time of execution evaluated for the whole simulation and specifically for the combination and approximation steps of the simulation.

Effects of varying the klx parameters

✓Our results, and figures 3 to 7, shows that for our scenario

- the impact of the **x** and **l** parameter is minimal
- the parameter **k** is the one that has the most significant impact, especially on time of execution, while maintaining a high 'good decision rate', close to the un-approximated version
- at some point, proceeding with the approximation consumes more time than the gained time

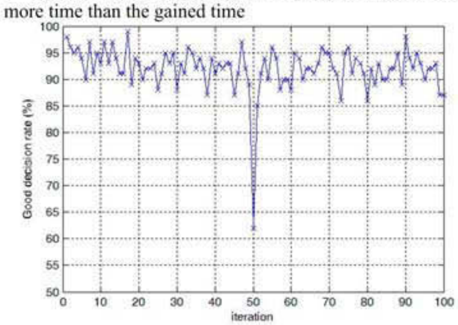

Fig. 3: DSmH result after 100 Monte-Carlo runs.

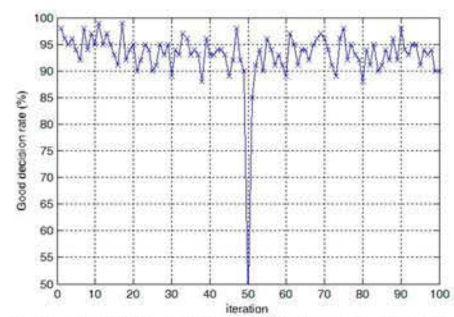

Fig. 4: Approximated DSmH result with klx = (5, 8, 0.2) for the same Monte Carlo simulation.

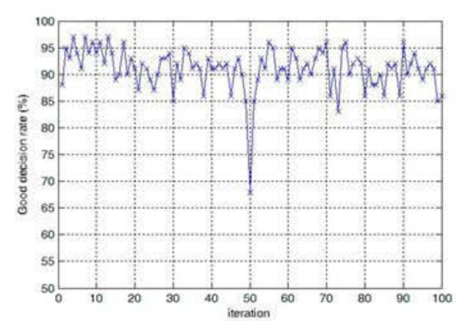

Fig. 5: Approximated DSmH result with klx = (3, 8, 0.2) for the same Monte Carlo simulation.

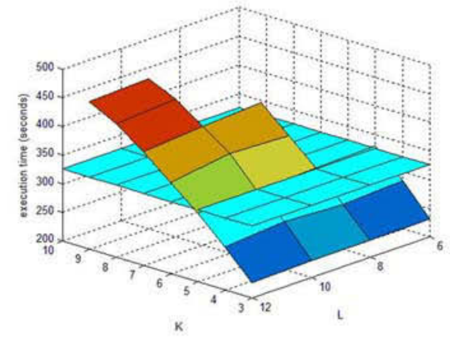

Fig. 6: Execution time for the combination and approximation processes.

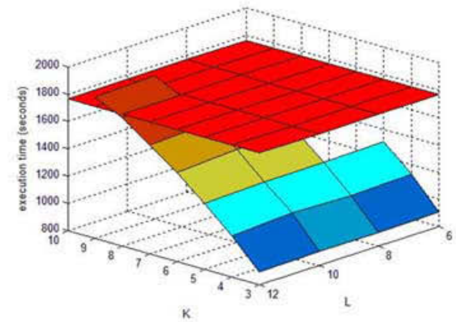

Fig. 7: Execution time for the whole simulation.

Conclusion

✓We have been able to acheive the same good decision rate with DSmH as with an approximated DSmH for the chosen realistic scenario, while achieving lower times of execution including the time to approximate when we reach a certain level of approximation

References

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