Team 8: Combat Identification and Fratricide: A Human Affair

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INTRODUCTION

Over the past two years TNO and Dstl developed an Agent Based Combat ID Model to support the research on factors influencing the success and failure of Combat Identification processes. During the International Data farming Workshop (IDFW) 15 in Singapore, we evaluated this model by conducting the first data farming experiments. The model represents Situation Awareness (SA) and the cognitive processes to combine new sensor input with SA in order to make identification decisions. A description of the model and the results of the Singapore experiments can be found in [ref 1].

A more general treatment about an architecture for placing the human at the centre of a constructive simulation, which also contains a more extensive description of this agent based Combat ID model, can be found in the ICCRTS 2008 paper [ref 2]

This paper describes the progress we made with the model development since IDFW 15 and the results from the data farming experiments we conducted during IDFW 16 in Monterey. In a few paragraphs an overview will be given of the new features, the objectives, the design of the experiments and the results. We will conclude this paper with lessons learned, conclusions and future developments.

New Features

Based on our "development master plan" and the results of IDFW 15, we enhanced the Combat ID model with a number of new features that are described below.

1. The new Combat ID model incorporates a much richer set of Measures of Merit (MoM). Each MoM is characterized by three dimensions:
    - decision (3 values: blue, red or green)
    - ground truth (3 values: blue, red or green)
    - object type (3 values: tank, car or person)

    These three dimensions result in 27 MoM that give an accurate and detailed picture of the successes and failures of identification for each type, e.g. the combination (decision=red, ground truth=blue, type=car) gives the number of fratricide incidents where cars are involved.
2. The identifying agent(s) use(s) the more realistic ACQUIRE sensor model, developed by Night Vision Laboratory (NVL). This model takes into account characteristics on:
    - Terrain
    - Weather
    - Sensor
    - Object

    Although in principle, all parameters can be dynamic or can be "data farmed on," the first three are held constant during IDFW 16. The last one is dependent on the type of object encountered. Apart from the characteristics mentioned, the output of the sensor model is dependent on the distance of the identifying agent to the object. The relation between distance and probability of detection, classification and identification take the shape of an "S-curve" as shown in Figure 1.

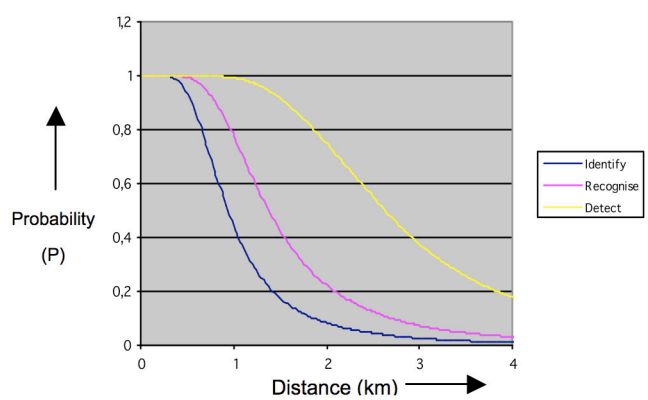

Figure 1: The probability curves for Detection, Recognition, and Identification.

3. The processing of sensor input has been changed. The following steps are involved.
    - The agent calls the ACQUIRE algorithm to get a probability of detection.
    - If the probability of detection is above a certain, data farmable threshold, a stochastic function determines whether the

agent indeed detects the object or "misses" it. This corresponds to the situation that the user does not pay attention to the sensor or simply overlooks the object. The probability for missing is inversely proportional to the probability of detection, but involves a "rolling the dice" mechanism.

- After detection, the agent makes a rough assessment how much closer it needs to go in order to make an identification. It makes a movement "on the safe side" of this assessment.
- After making the calculated movement, the agent uses the sensor data and the ACQUIRE algorithm to determine the probability distribution (blue, red, green) of the objects identity and combines this with its preconception distribution (situation awareness) in order to get the new belief distribution about the identity of the object. As in previous versions, it uses the information acceptance curves for this purpose. If the resulting value is below the decision threshold, the process starts again until either an identification decision can be made or the agent is as close as a hundred meters from the target. If the last condition is the case, the agent leaves the object alone and focuses on other objects.

As in previous versions of the model, the whole process also involves dynamic adaptations of the preconception grid of the agent and modification of the Measures of Merit if the agent takes a decision.

Objectives of IDFW 16

The objectives of the study during IDFW 16 are:

- Evaluate the new features described above
- Get insight on the effects and relative importance of influencing parameters and establish a foundation for further model improvements.

Design of Experiments

As the basis for our experiments, we use a Near Orthogonal Latin Hypercube (NOLH) with 16 parameters. These parameters deal with the number of objects for each type (3 parameters), the distribution of those objects on the screen (3 parameters), the distribution of the preconception (3 parameters), the shape of the information acceptance curves (2 parameters), the radius of the circle in which the agent tries to detect objects, the decision threshold, the size of the local SA grid, the size of global SA cells and finally the surprise level. Most of the parameters are explained in [ref 1], with the difference that we use different parameters for the distribution of preconceptions that make them relative to the ground truth.

In our current design we use data farmable parameters for the correlation between ground truth and perceived truth and for the mixture of objects. These parameters are not directly settable, but are derived from others like the centers of ground truth for red, green and blue and the parameters for the relative distance of perceived to ground truth. These dependent variables make sure that the results are based on variables that do not contain interdependencies anymore.

During IDFW 16, we performed three data farming runs with basically the same design, but with different data points in the hypercube of all possible design points. Also, we looked at the outcomes of the initial runs to fine tune the maximum delta of the perceived truth compared to the ground truth and to limit the maximum number of steps.

RESULTS

The description of the results in this paragraph is limited to two examples and is, by far, not exhaustive. Results are omitted because of limited space, the detailed nature of the results, and the lack of a clear graphical visualization of them. For those interested, more detailed analysis will be available later this year.

Figure 2 shows the relation between the fraction of samples and the percentage of objects that were correctly or incorrectly identified by the agent after 10.000 steps. The graph is based on results of the second experiment.

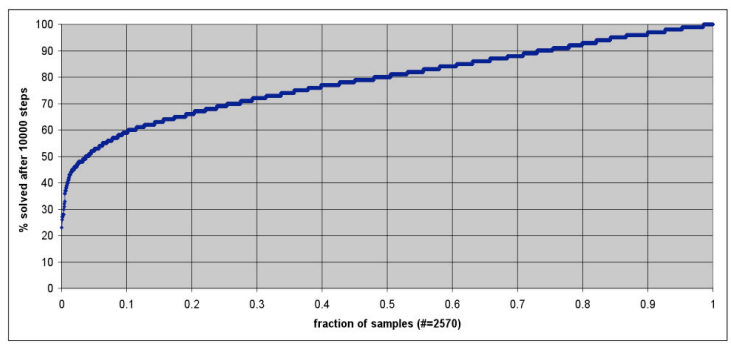

Figure 2: The fraction of samples related to the percentage of identified objects after 10000 steps.

The figure shows that for roughly half of the samples 80 percent or less of the total number of objects are identified. For the other half of the samples, 80 percent or more of the objects are identified. It also shows that the relation is almost linear. Regression analysis shows that the decision threshold is the most significant factor influencing the percentage of decisions. The second most important factor is the Y-intercept-indicator, a variable responsible for the shape of the information acceptance curve. A flatter curve caused more correct decisions. The flatter the curve the more the agent is open for new information in the case of extreme values of preconception (strong belief).

Figure 3 shows a regression tree for the third experiment, with the relationship between the importance of input parameters and the percentage of fratricide. The tree shows that the most important factor responsible for fratricide is the ratio by which an area with blue ground truth is misconceived as red (by the initial preconception).

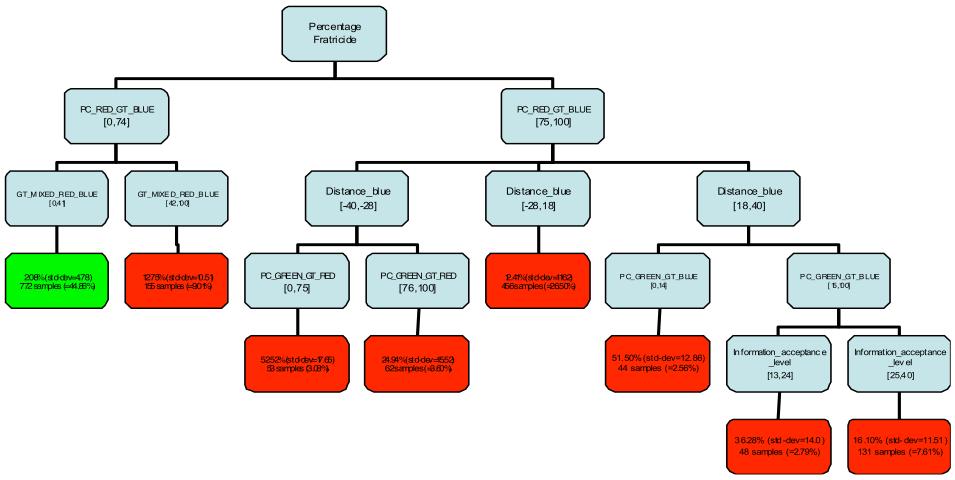

Figure 3: The regression tree for the fratricide measure of Merit. The R2 of this metamodel is 0.63.

LESSONS LEARNED AND CONCLUSIONS

IDFW brought us a step further towards a mature Combat ID agent based simulation model. Although the results still have to be analyzed in detail, our first impression is that our Combat ID model in combination with the data farming approach is a good method to get insight into the parameters that influence the success and failures in Combat ID processes. However, it is important to keep a close connection between the experiments and the customer questions and we feel that we need to take a number of measures to ensure this in the future. This is reflected in the lessons learned below:

The lessons learned from IDFW 16 are:

- Although data farming is a good approach to get quick results in an iterative way based on a large number of model runs, it is important to have a clear understanding of the questions that needs to be answered. In hindsight, we feel that we lacked a detailed enough and shared question to steer our process of discovery. Future workshops will need better preparation with respect to the questions to be answered.
- Good analysis tools are essential for data farming. Although we had tools available for data analysis, the lack of a good graphic representation of results made it hard to get quick insights in the meaning of the results. This hindered the depth of analysis during a workshop severely.

FUTURE DEVELOPMENT

During IDFW16 we started with the development of the next version of the Combat ID agent based model. Contrary to the current version, where an agent moves around in a world that is defined by parameters that determine, for example, the number of objects and their distribution, as well as the initial preconception, this new version will be scenario-driven and will focus on a limited number of data farmable parameters like decision threshold, situation awareness and information processing characteristics. The reasons to go to this model style are that a scenario driven model:

- is closer to the mental model of the customer,
- enables us to simulate historical incidents, and
- gives more control on the behavior of the model.

In the new version, the setup of the scenario will be handled in a separate "setup" application. The scenario can be stored and then imported into the "execute" application.

New features of this scenario driven version will be:

- Both the Ground Truth distribution and the Perceived Truth distribution can be defined manually in a separate "scenario" application.
- More than one identifying agent can be defined. Each agent will have its' own characteristics, SA and behavior. This includes levels of training and experience, and the consequences of this on the identification process.
- The route of agents and objects can be defined in terms of waypoints (instead of the current semi-random movement)
- The scenario can be written to a file with a specified name. This file can be imported by the Combat ID "execution" application.

We plan to develop and test this scenario driven version of our Combat ID model before September 2008 and use IDFW 17 in Garmish Partenkirchen to conduct data farming experiments with this model. We will develop two or three scenarios as the basis for our analysis.

References

[1] Scythe: Proceedings and Bulletin of the International Data Farming Community, Issue 3 - Workshop 15, pages 30 and 31. Publication Date: January 2008.

[2] 13th ICCRTS in 2008 "C2 for Complex Endeavors", paper "architecture for placing the human at the centre of the constructive wargame", David Dean, Alasdair Vincent, Beejal Mistry – Dstl, UK; Mink Spaans, Peter Petiet – TNO, NL.