UNDERSTANDING AND PROJECTING BATTLE STATES

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ABSTRACT

This paper presents an automated data analysis tool developed for processing battlespace data in order to provide the battle staff (or the nerve center of the Future Combat System) with current battle state information and to predict future battle outcomes. Some results obtained by applying some of these techniques to ONESAF combat simulation data are reported.

1. INTRODUCTION

To assist battle commanders in making better decisions, an automated data analysis toolbox is developed. The toolbox takes battlespace data as input and produces two pieces of information: what battle-state the force is in and which way the battle outcome is heading. The battlespace data could be gathered from a combat simulation, an exercise, or a real battle.

The toolbox currently has three major components: preprocessing, clustering, and time series prediction. The preprocessing module converts raw battlespace data into a form amicable for analysis. The clustering module is used to establish the concept of battle states based on the processed data. The time series prediction module uses the past battlespace data to predict the future battle state.

2. EXPERIMENTS AND DATA

Data are needed to test the effectiveness of our tool. To this end, we created a battle scenario using the ONESAF combat simulation [Heilman *et al.*, 2002]. A total of 225 experiments were run and data were collected using the Killer-Victim Scoreboard (KVS) method developed [O'May and Heilman, 2002].

The raw experimental data collected have to be preprocessed. Five indicators of battle states were selected, which includes:

- Relative territory ownership
- Relative firepower strength
- Relative logistic support strength including ammunitions and fuels
- Relative firing intensity

A time trace of all five indicators throughout the battle for each echelon level (vehicle, platoon, side, and all) was eventually obtained. Fig. 1 shows one run for the entire blue force. Note that the data points are not uniformly sampled.

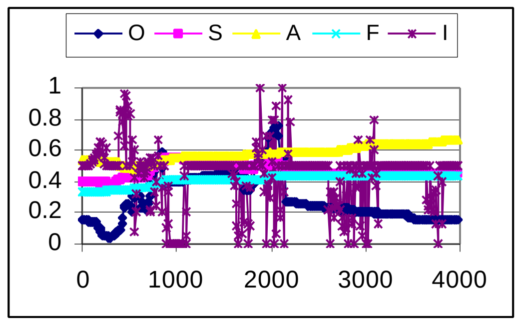

Figure 1. Sample run of 5 indicators for the blue force.

3. ANALYSES AND RESULTS

The interpolation operation is first performed to convert a non-uniform time series into a uniform one. Two programs were implemented for this particular task: simple interpolation and genetic-fuzzy modeling. Fig. 2 shows the three time series for the relative territory ownership for the blue force.

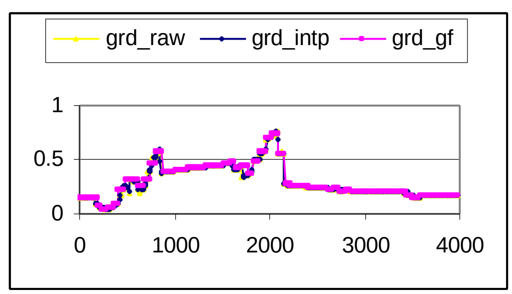

Figure 2. Interpolation results for the ownership.

To form the concept of battle states, all five indicators gathered from representative runs should all be considered together. Several clustering techniques were implemented for this task. They include the k means, genetic clustering, fuzzy c-means (FCM), and Gaussian c-means. The genetic clustering technique can be implemented in several ways depending upon how a chromosome is represented. Since the amount of data is relatively large, we chose to use the real coded representation of cluster centers. Regardless of the clustering technique used, an important question is how many battle states are sensible. Several indices have been developed as criteria to determine the optimum number of clusters (i.e., battle states here) based on the clustering results. However, their usefulness to this application is untested.

Three runs were chosen as the input data. Table 1 shows three and four centers of battle states found by the FCM algorithm. Similarly, other number of clusters could be determined. The algorithm arbitrarily labels the clusters. Cluster 0 for the 3-cluster set actually corresponds to Cluster 3 for the 4-cluster set. The 4-cluster set seems to be better than the 3-cluster set because it has a cluster portraying close to tie situation (Cluster 0). Further investigation is needed to firm up this idea of battle states. It should be noted that the selection of input data could have a large impact on the centers of battle states.

Table 1. Centers of battle-states found by FCM.

		own	str	ammo	fuel	ints
	0	0.955	0.827	0.645	0.502	0.550
3	1	0.286	0.466	0.575	0.401	0.461
	2	0.011	0.155	0.626	0.341	0.415
	0	0.476	0.525	0.559	0.412	0.408
4	1	0.003	0.131	0.639	0.341	0.415
	2	0.173	0.423	0.578	0.386	0.506
	3	0.974	0.844	0.649	0.506	0.545

As a result of the clustering operation, a time series of battle states could be derived for each simulation run. Fig. 3 shows all 3 runs used in forming the battle states given above.

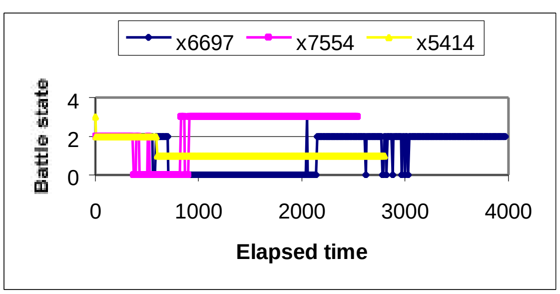

Figure 3. Traces of battle states for 3 OneSAF runs.

The x6687 series indicates that the blue force was struggling early (State 2) and got into "close to tie" situation (State 0) after 1000 seconds into the battle and lost it again past 2000 seconds. Despite of sporadic contentious moments, eventually the blue force lost and was stuck in State 2. The x7554 series is a "winning" one for the blue force whereas the x5414 series is a "losing" one.

Predicting future battle states based on what has happened so far is very desirable, but an extremely difficult task, especially at the early stages of the battle. To provide the commander with such information, the toolbox implemented an adaptive genetic-fuzzy modeling approach. This analysis assumes that no two battles are alike. Therefore, no data from other battles are used in the process of deriving a prediction. It relies solely on the data acquired from the battle to be predicted. The accuracy depends upon the amount of data available for model generation and how they resemble those being predicted. By adaptively revising the model, a better prediction accuracy is expected.

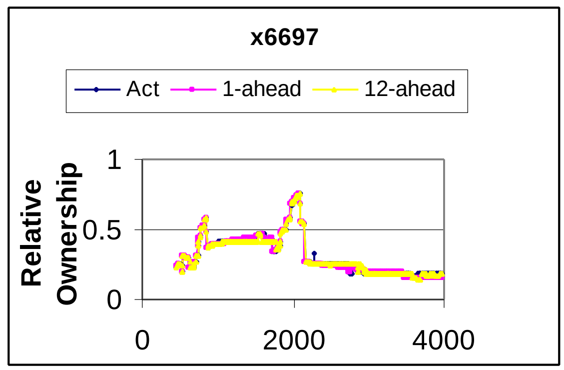

Figure 4. Prediction series of blue relative ownership.

The genetic-fuzzy method is first used to determine two near-optimum values: number of lags and number of fuzzy terms. The values of 13 and 11 were found for the x6697 ownership series. Using the above values, fuzzy models were constructed to predict x-period-ahead predictions and dynamically revised after the prediction period. Two prediction series were shown in Fig. 4. One would expect that the farther ahead the period to be predicted the lower the prediction accuracy would be. The RMSE accuracy is 0.02754 for 1-ahead predictions, 0.02929 for 12-ahead predictions, and 0.032473 for 24-ahead predictions.

ACKNOWLEDGMENT

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