A Visualization Approach for Group Behaviors, Beliefs and Intentions to Support Critical Decisions

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Abstract. During persistent surveillance of a given population in a conflict situation, data management can quickly become unwieldy due to the inundation of low-level information from many, disparate sources. Computational population models can easily fuse and aggregate information input, but there is still the challenge of providing effective data visualization which minimizes information overload and introduces misinterpretation by simplified visualization based on aggregations. Visualizations of the actionable knowledge to the analyst based on the population effects as evidenced by their stratagemical behaviors are needed. Five model classes that study the beliefs of groups and how their beliefs change as a result of events were evaluated for their potential for visualization based on an analyst's cognitive model of the conflict situation. A visualization approach was developed that can be used for all of the classes of models based on frames of reference for time and physical location within the environment.

Keywords: data visualization, group modeling, stratagemical behaviors, beliefs.

1 Introduction

Current low-intensity, theater military operations are multi-dimensional. In Iraq and Afghanistan, and before that, in Somalia and Bosnia, the desired geo-political outcome has required significantly more than applying military force to defeat an armed enemy. As a result, the importance of joint efforts in diplomacy, information distribution and economic interventions can be significant to the outcome of achieving military dominance [1]. During wartime, the US presence in a host nation (HN) can trigger conflicts beyond those of battle. Local conflicts can arise within the HN populace since our presence might be viewed as being part of a military conspiracy to disrupt their way of life.

Over the past few years, the US military has set the stage for moving away from a reactive, divisive approach, to one of local populace engagement manifested through multiple DIMEFIL (Diplomatic, Informational, Military, national Economic, personal Financial, Intelligence guided, and Law enforced) interventions [2]. Estimating the potential effects of these interventions involves persistent surveillance of populations within the operational area and the social, economic, informational and ideological

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forces within those populations. Models of the population and its PMESII-PT (Political, Military, Economic, Social, Informational, and Infrastructure with Physical and Time) elements need to be predictive with respect to DIMEFIL interventions and how these actions in the current situation will result in changes to the beliefs, desires and intentions of the members of the groups involved [3]. The visualization of actionable knowledge about the population's reactions to these interventions is necessary for the analyst to make a choice between the various DIMEFIL intervention options.

During persistent surveillance of the population and its PMESII-PT, data management can quickly become unwieldy due to the inundation of low-level information from many, disparate sources [4]. Computational population models can easily handle this data for input by aggregating and fusing, but there is still the challenge of visualizing all of the data and incurring information overload or inducing misinterpretation by simplified visualization based on aggregations [5]. Representing the actionable knowledge to the analyst based on the population effects are needed at the strategic (long-term), operational (near-term), and tactical (current) levels. Modeling population response to interventions is an important research topic with broad application to politics, marketing, advertising and education. As a result, there is a large, multidisciplinary literature of both research and practice in measuring and modeling the beliefs, desires and intentions of populations.

1.1 Analyst's Decision Cycle

An understanding of the PMESII-PT environment, the populations involved, and DIMEFIL interventions to take can be modelled in the Analyst's Decision Cycle for choosing interventions depicted in Figure 1 below [6]. Starting at the top of the diagram, monitoring the situational environment (the PMESII-PT and populations involved) is followed by assessing the situation, making plans to adjust the environment, directing the actions for these interventions, and continuing the cycle of persistent monitoring of the PMESII-PT and the populations.

This workflow is continuously iterated as the analyst continues to monitor a populations response to PMESII-PT effects.

There are three event horizons corresponding to how far ahead the planning occurs. The decision cycle iterates at the fastest rate in terms of traversing the stages during

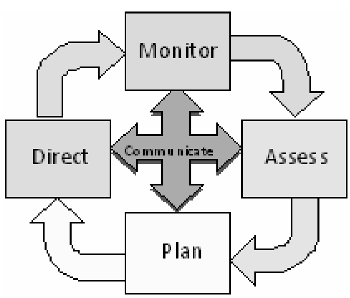


Fig. 1. Every intervention decision made by the analyst uses a similar cycle to assist in understanding the environment and focusing the resources to support their decisions

the tactical level planning/execution of interventions. The second planning horizon occurs near-term. These interventions may take months and the iteration rate through this horizon is slower than at the tactical level. The last event horizon is for strategic planning for the order of one to two years and the cycle iterates at the slowest rate.

1.2 Five Classes of Population Models

A trade study of computable social models was performed and the dozens of models found were organized into five classes by the authors for this paper. The five model classes that study the beliefs of groups and how their beliefs change as a result of events were categorized into the following models with pros and cons:

1. System Dynamics Models [7]: coarse grain data, large time scales O(years), validity of model parameters estimation is difficult, heavy footprint to deploy, explicit causal mechanisms, inherent representation of time,
2. Social Network Models [8]: lack of causality mechanisms, does not aggregate to larger social units, limited predictive ability, rich and detailed representation of population entities, sensitive to differences in populations,
3. State Transition Models [9]: behaviors described statistically, lack of explicit representation and reasoning about population's reactions, inherent representation of time, potential for prediction of long-term effects,
4. Group Ideology Models [10]: uses every day perceptions in terms of a large amount of unstructured data, has inherent mechanisms for representing causality, representation of differences in populations, needs continuous updating and maintenance, and
5. Group Dynamics Models [11]: richest representation of causal data with same challenges as the group ideology model, best for short term predictions, group intention understanding possible, and future states of a population can be predicted.

The set of challenges facing all models will need to be resolved in order to realize their full potential. The first challenge is fuzzy matching of observations to behavioral patterns. To be of value to the analyst, the visualization tool needs to be able to match attributes of a behavioral observation to a behavioral pattern and display that pattern in a meaningful way to enable actionable intelligence. The next challenge is handling uncertainty via a reasoning mechanism. The basis of the models is the perception of truth instead of truth itself. A mechanism is needed for distinguishing strong beliefs from weaker ones. The last challenge for population models is the negotiation of objectives. When dealing with multiple populations, there will be population expectations of differing needs and objectives. A capability to recognize opportunities for collaboration and alliances is needed which incorporates voting mechanisms and simulated outcomes.

2 Information Requirements for Persistent Surveillance

In order to understand the visualization design for supporting the analyst's decision-making cycle for various populations and the possible corresponding interventions based on predicting population reactions, an analysis of the human information processing

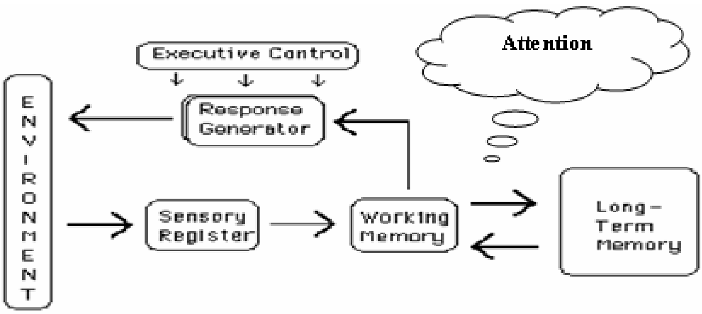


Fig. 2. The Human Information Processing Model as described by Wickens

requirements needs to be made. A simple model of how the human processes information and the model for the persistent surveillance of populations are described.

2.1 Human Information Processing Model

The human brain performs complex mental operations on information perceived from the environment. The widely accepted model that allows us to conceptualize these complex operations as a sequence of information processing stages is in Figure 2 and adapted from Wicken's model [12]. Sensory processing and storage is the first stage when information is coming from the environment. Of course, if we don't attend to it, we will not know it is occurring. Once perceived, we can place it into working memory and with the use of long-term memory we can ultimately make decisions. This is a useful framework for interpreting human performance in complex tasks such as deciding which intervention to take based on expected population reactions. Of course these stages will need to be mapped to the analyst's tasks described next.

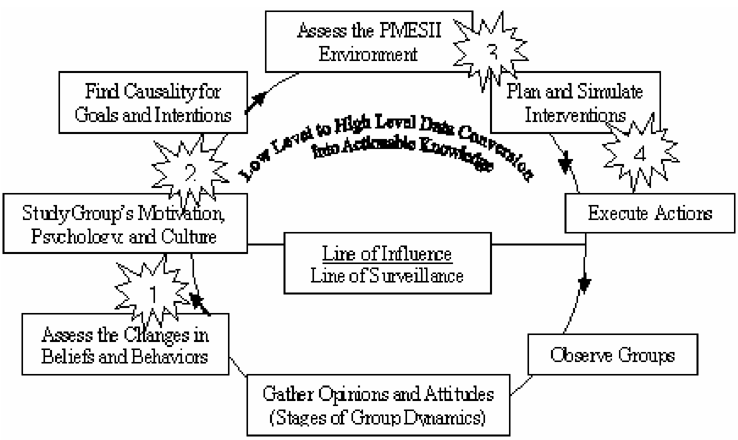


Fig. 3. Population Behavior Assessment Model showing labeled points 1-4 where visualization is needed to display the information required by the analyst

2.2 Behavior Assessment Model

Various sources of information are required in order to select a set of interventions that will have the desired population outcome. Based on current military documentation and many interviews with military analysts, the relevant situational information (seen in Figure 3) is required at the four points described in the assessment loop. Since it is a constant loop for persistent surveillance, there is no starting or stopping point. For visualization, we need 1) an assessment of the changes in beliefs, 2) low level data fused and aggregated into high level data (actionable knowledge), 3) an assessment of the PMESII-PT environment, and 4) a simulation of the expected population reactions based on DIMEFIL interventions which have been proposed. The remainder of the loop involves observation and study (below the line of influence) called the area of surveillance.

3 Visualization Methodology for Population Models

The last step to attaining visualization is the mapping of the human and task information requirements to the visualization design features. Then a relationship between the interface design features and the population model chosen can be defined. Based on the analyst's task requirements, there are four components that need to be visualized as shown (and numbered) in Figure 3. These components should directly support the analyst by adhering to the human processing model.

3.1 Mapping Information Needs to the Visualization Design

The visualization is triggered by changing population beliefs or behaviors. In order for the analyst to know this has occurred (because the visualization environment is one that persists), we need to get the analyst's attention when the state of the world has changed. This corresponds to the sensory register in Figure 2. Alerts and notifications within the interface should be utilized to increase the chance that the changing information is sensed and perceived. In Figure 4, a highlighted alert (that also flashes red) has been generated for the analyst in the lower left screen. The corresponding box at a location on the map also flashes red. The analyst is then visually notified when an event has occurred which requires their attention.

Next, the incoming low level data needs to be fused and aggregated. Since the human working memory (see Figure 2) has limited capacity, only high level data should be presented to the analyst on the top screen to prevent information overload and quickly convey the meaning of the alert to the analyst (See Figure 5a). In the top left side are the current PMESII-PT elements and the population beliefs that have reached a set threshold for an alert to be issued to the analyst.

However, to understand why the alert was issued, the analyst may need to look at more details (or drill down into the statistics) in order to make knowledgeable assessments. In the human long-term memory (see Figure 2), deep knowledge is stored and portions are placed into working memory to combine, manipulate, and hypothesize about decision variables and outcomes. Memory problems associated with information retrieval and recovery can be avoided by using tabs to display the low level data trends and changes (see Figure 5b).

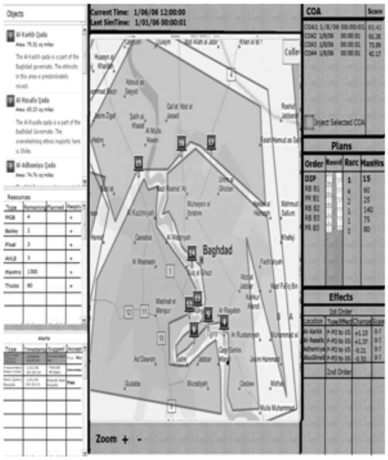
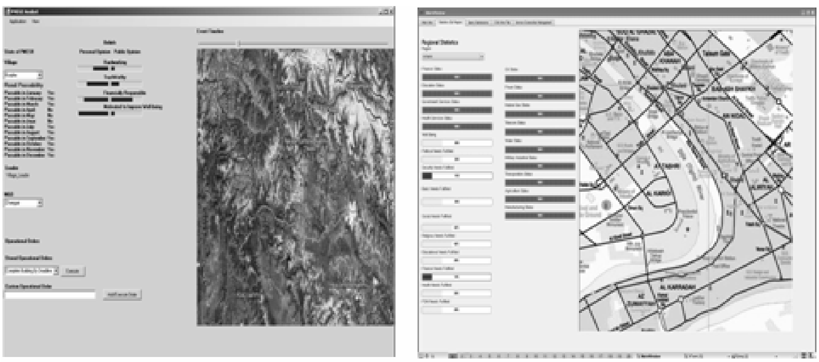


Fig. 4. Screenshot of the visualization interface showing the alert notification to the analyst



(a) (b)

Fig. 5. (a) (Left) The visualization interface showing high level details presented to the analyst. (b) (Right) Visualization is shown for low level trends in information bars of green (clear), yellow (caution), and red (alert) types of notification.

Lastly, since the working memory of the analyst can only consider a number of hypotheses at one time, and long-term memory may have trouble retrieving them, a capability to simulate various courses of actions (COAs), plans, and their ultimate population side effects need to be visually presented to the analyst (see Figure 6). The visualization capability should allow storing and retrieval of possible interventions that could be both analyst and/or computer generated.

Since the visualization is persistent, the display returns to the top level awaiting the next alert to the analyst and the visualization cycle continuously loops. This visualization approach can be applied to the population model classes previously defined.

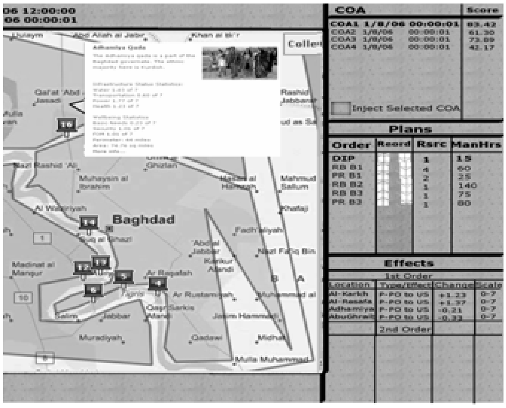


Fig. 6. Further drilling down the tabs gives us actionable knowledge needed for the analyst to make a sound decision for minimizing the 2nd and 3rd order effects seen in lower right corner

3.2 Information Requirements for the Five Classes of Population Models

Each of the five classes of population models has different information requirements. For the system dynamics models, the population belief trends are typically modeled over a long period of time. This model would be used in the strategic event horizon to look at long term effects covering months of interventions. This model would assist the analyst in developing plans for courses of actions and could hypothesize potential population side effects before courses of action were taken. The visualization of the model would come in the form of low level trends over a long period of time. This model could be incorporated by being one of the methods for simulating the possible interventions under “what if” circumstances.

The social network models have their place in the analyst’s visualization. By looking at how the network of people within a population, represented by nodes in the network, move and communicate, represented by links in the network, the analyst is able to add another layer of intelligent information to incorporate into their decision making. As the network adds and subtracts active members over time, the shape and distribution of the nodes and links change. As the situation changes and the network updates, the analyst can start linking actions to the network members. An example of how this would be visualized to the analyst is shown in Figure 7.

For a state transition model, there is a tremendous amount of statistics which would assist in the deeper drill down that may be required by the analyst. However, there would be no way of determining causality of a population’s behavioral reactions to a particular choice of intervention. An example of the visualization of state transition data is given in Figure 8 [13]. In this example, the conflict between the leader of Russia and the Leader of Georgia were modeled (each representing their population beliefs in terms of their military and diplomatic strengths. This diagram shows how the various countries beliefs about these strengths changed over time and differed from each other. Causality cannot be inferred from these data.

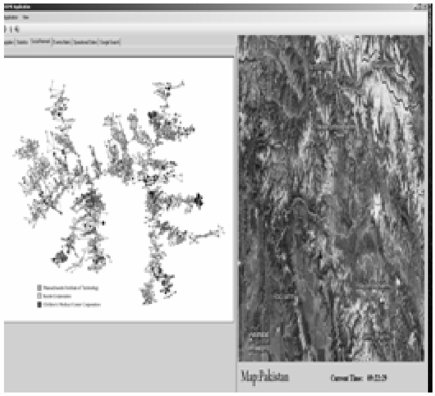


Fig. 7. A social network of the various religious factions within Pakistan

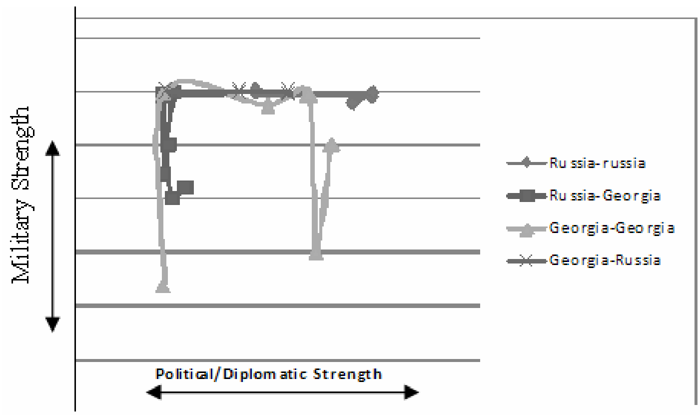


Fig. 8. Graph of the four perspectives of Military and Political Strengths

Group ideology models are best for use as inherent mechanisms for visualizing causality. The targeted populations can be represented at several levels and reflect sufficient differences in populations. These models are driven on every day perceptions as opposed to survey data. This generates a large volume of unstructured data. The groups, being goal-driven, define their actions by their adopted ideology, and may be in conflict with the goals of other groups. Each group has their beliefs which may be inaccurate, incomplete, and inconsistent. The model directly represents the qualities of a belief and uses those qualities to infer relationships to other beliefs, and thus derive corresponding interventions. This makes the model a good candidate for projecting short term population reactions and beliefs. This ideology model of causality could be used in combination with the social network model which does not have an explicit mechanism to show causality. This model would populate the belief statistics used for further drill down by the analyst.

Group dynamics models are very similar to the group ideology model in mechanizations; however, the knowledge within this class of model is focused on group

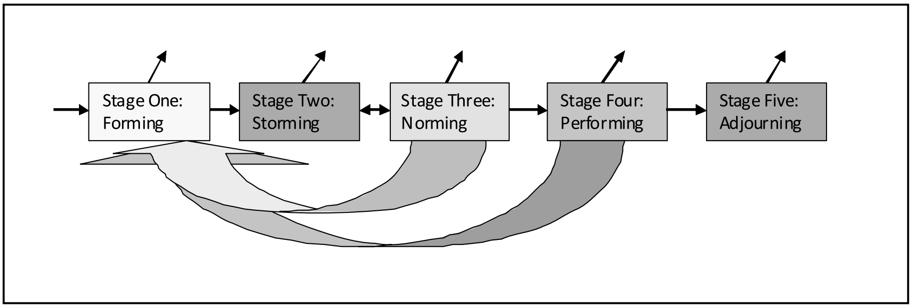


Fig. 9. The five stages of group development according to Tuckman's theory. The arrows show the possible transfer from state to state, to a previous state, or transitioning out.

dynamics rather than ideology. Based on Tuckman's model, there are five stages concerned with group behaviors: 1) Forming – initially, how groups orient and communicate, 2) Storming – how group members try to convey their individual perspectives and concerns, 3) Norming – turning individual perspectives into group goals and missions, 4) Performing – where the group takes action based on consensus, and 5) Adjourning – how groups disband (Figure 9)[14]. The group dynamics model studies information exchanges between the groups involved and identifies optimal strategies for influencing their behaviors [15]. This type of model represents the behaviors and intentions of groups within a population and suggests what actions the groups are likely to take in the future based on their internal and external dynamic relationships.

Of all five classes of models discussed, the group dynamics model extends all of the benefits of the other models, and additionally offers the richest representation of causal data and reactions to interventions.

4 Conclusions

Five classes of population models were evaluated for their potential for visualization based on an analyst's cognitive model of the persistent conflict situation. The conflict situation and its persistent surveillance can be viewed as a process model that 1) takes DIMEFIL actions, 2) collects population data on action effects, 3) analyzes data by classifying and aggregating, 4) generates hypotheses on why population reacted in that way, 5) develops strategies for mitigating the effects, 6) simulates intervention effects, 7) makes a decision, and 8) takes actions again to complete the cycle. The various stages were analyzed to exploit the visualization of actionable knowledge needed for persistent surveillance. It was found that each of the five model classes differ in their visualization requirements. A visualization approach was developed that can be used for all of the classes of models using the analyst's cognitive model of the conflict situation based on frames of reference for time and physical location within the PMESII-PT environment. The actionable knowledge found in common for all models included the PMESII-PT situational factors, population values and beliefs, the analyst's decision process and use of PMESII-PT elements, adversary motivations, and current capabilities to make decisions about population interventions.

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