Towards a Social-Sense Enabled Military Decision Making Process

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ABSTRACT

With the emergence of advanced computational methods, enhanced insights into the social dynamics of complex operational environments, such as mega-cities, are now within reach. We contend the utilization of the standard Political, Military, Economic, Social, Information, Infrastructure, Physical Environment, and Time (PMESII-PT) framework to assess the operational environments within the Military Decision Making Process (MDMP) do not sufficiently address the subjectivity within the state space required to understand the target population or how their social landscapes interact with military operations. To close this gap, objective measures can be supplemented with new methods that utilize social-sense enabled informatics. Towards this end, we introduce the Pulse of the Population (POP) concept that augments the MDMP process. POP serves as a computational social science framework that enables on-going assessments of the population state space within varying military operational context. We postulate that conditions for desired end state in these complex landscapes are often shaped by social sensing demands which interact with a myriad of environmental factors. In this paper we describe how the POP concept would improve mission planning analysis, course of action development, and enable ongoing running estimates of the population state space within the area of operations.

Introduction

> *The human dimension is the very essence of irregular warfare environments. Understanding local culture, political, social, economic, and religious factors is crucial to successful counter-insurgency and stability operations, and ultimately, to success in the war on terror.*
>
> \- Human Terrain Team Handbook, p. 3

Human Terrain Teams (HTTs) were introduced in 2006 into Army operations to fill the gap of cultural knowledge in the operating environment and provide "cultural interpretations of events occurring within [the military's] area of operations" (Human Terrain Team, 2008, p.2). After several years of irregular fighting in Afghanistan and Iraq, it became clear to U.S forces that understanding the local population was a critical component for operational success. While conceptually ingenious, HTTs were difficult to operate, controversial, and required large amounts of time to gather relevant intelligence. Though HTT implementation was not optimal, the idea of understanding the local populous is important for future military success. To this end, the application of new methods capable of systematically capturing socio-cultural insights within the Military Decision Making Process (MDMP) will provide an improved understanding of social terrain. When used in concert, several emerging social-sense tools and techniques would serve to provide a Pulse of the Population (POP) to military commanders before, during and after operations; particularly in mega-city environments. POP will serve as a framework for applicable social-sense tools and methods meant to augment the MDMP. Mission planning that incorporates an improved understanding of the needs, necessities, perceptions, and concerns of the local population will greatly contribute to battlefield success.

In Section I, we provide an overview of the Military Decision Making Process (MDMP) as current military doctrine. Section II provides a broad taxonomy of social sensing tools as they exist in academia and the military today. Section III details the POP framework and provides an analysis of relevant areas within the MDMP where social sensing tools are best applied to improve mission outcomes.

Section I: Military Decision Making Process Overview

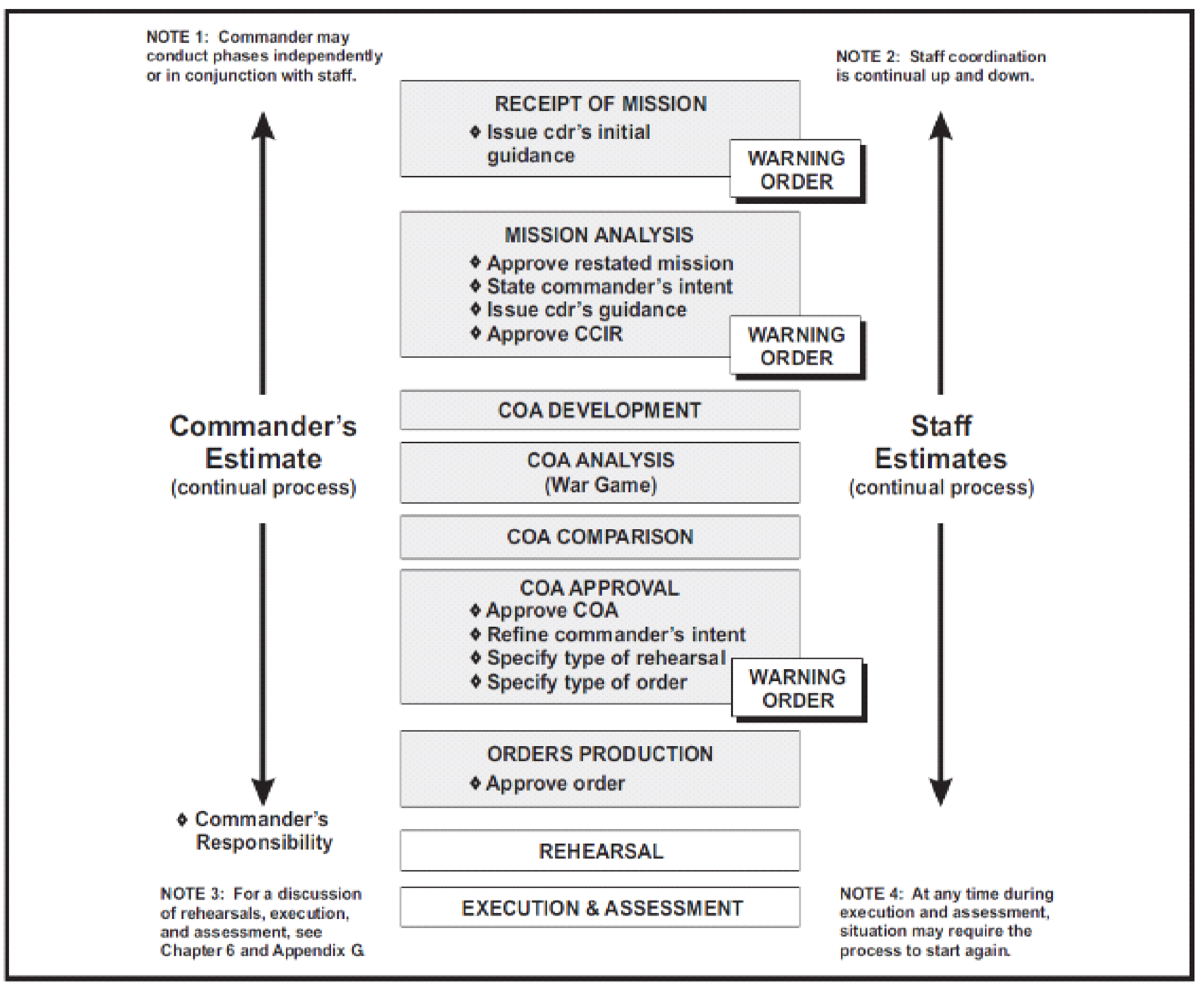

Figure 1: The MDMP

The Military Decision Making Process (MDMP) is an established and proven analytical process that provides a methodology for determining if, when, and how decisions are made within military contexts (Department of the Army (DoA), 1997). The MDMP has been the Army's decision-making model for more than three decades and, when exercised under the right conditions, enables commanders to produce tactically sound battle plans. Towards this end, the MDMP process relies on a subtle balance of quantitative and qualitative reasoning to understand, visualize, and describe complex, ill-structured problems and develop approaches to solve them (DoA, 2009).

As outlined in Figure 1 the MDMP is a seven-step analytical procedure with over 100 sub-steps:

- In the initial step, the commander receives a mission from a superior command and must breakdown the unit's part of that plan. Commander's guidance is developed from a unit-centric understanding of the mission and issued to the unit staff for development into an executable plan. The commander will continue to participate throughout the MDMP process as a guide and final decision authority.
- The second step is an analysis of the commander's guidance within the contextual situation, using the Intelligence Preparation of the Battlefield (IPB) process. The IPB products depict the commander's guidance directly within the realities of the situation and feature terrain analysis, threat elements, and the development of a general conditional understanding within the area of interest for the mission. Consideration of operational descriptive factors such as political, military, economic, social, information, infrastructure, physical environment, and time (PMESII-PT) are combined with more tactically relevant factors such as mission, enemy, terrain and weather, troops and support available, time available, and civil (METT-TC) considerations.
- Within the analytical framework of steps 1 and 2, MDMP steps 3-5 concentrate on the development of courses of actions (COAs) that the units can support. Given enough time, unit staffs will develop 3 or more COAs that the unit can both support and that have the best chance of success.
- In step 6, these COAs are presented to the commander who will choose one as the basis for the operation and offer adjustment and guidance on the development of the COA into the unit's operational plan.
- In step 7, the staff puts together the refined COA into an operational order (OPORD) for execution by the unit and, once approval is given by the commander, will distribute the OPORD to all subordinate units for execution as their next mission.

During mission execution, the staff will use unit feedback to maintain running estimates of internal unit mission progress and actions as well as external factors such as threats encountered and battlefield effects. As changes in conditions are noted through the running estimates, the commander may adjust unit activities using the OPORD as the foundational understanding. Overall, the foremost strength of the MDMP is its design as an inclusive, but flexible system for military operations. However, it is a time-consuming process to thoroughly accomplish. When faced with a time-constrained environment, the commander's guidance is emphasized, the acceptance of risk is carefully noted, the staff analysis is curtailed, and fewer COAs are developed for consideration.

Section II: Taxonomy of Relevant Social-Sense Tools and Modeling Methods

Social-sense technology has grown in popularity over the last few decades. Since the first Gulf War, conflicts in Afghanistan and Iraq have necessitated the development of cultural tools to understand the population of interest. An improved understanding of the population via the employment of several social-sense tools and methods will assist in reducing negative interactions with the local population and thus reduce operational risk within the time-constrained environment of the MDMP process. The purposes of an initial discussion of the POP framework, the following tools and methods are considered: 1) Sentiment Analysis and Event Extraction, 2) Spatial Mapping of Socio-Cultural Variables, 3) Social Network Analysis, and 4) Agent-based Simulation.

Sentiment Analysis and Event Extraction

The Network Science Collaborative Technology Alliance (NS-CTA) is a research initiative between U.S Army, industry, and university research organizations that serves to improve military capabilities through the advancement of network science, developing several projects focused on event extraction and sentiment. Work conducted as part of the ten-year project shows promise for the future deployment of social sensing tools with several teams focused on constructing new techniques for bringing contextual knowledge into automated entity recognition and event mapping (see DoA; NS-CTA B.P.P Context Aware, Multi-Genre Knowledge Networks, 2017). Methods for the disaggregation of social media data to form event timelines, link event information with Tweets, and develop knowledge structures that aid automated classification are all areas of concentration within the NS-CTA. Part of this work identifies protest sentiments in social media and how sentiment might translate through online communities. As outlined in Task 6.5, a summary of the final year for NS-CTA, current network and knowledge extraction technologies can become useful "information search tools for real-time monitoring of local population sentiment." (see DoA; NS-CTA B.P.P, 2018; p. 6-4) NS-CTA research focuses on social media networks because these are becoming a critical component through which social unrest begins and organization follows.

Work by Moojiman et al. (2018) within the NS-CTA, uncovered an association between moralization of issues and propensity to engage in violent protest. Utilizing publicly available Twitter data, researchers trained a deep neural network to classify tweets into moral and non-moral loadings. Online moral rhetoric correlated with days that violent protest occurred as well as hour by hour estimates for arrest-rates on protesters. They conclude that moralization of protests combined with moral convergence (the perception that others surrounding the user have the same moral concerns) leads to violence, providing a nuanced and socially-valid method to track citizen unrest.

The field of Natural Language Processing (NLP) has contributed a variety of tools for making meaning out of large amounts of collected text. Linguistic Inquiry Word Count (LIWC) (Pennebaker, Francis, & Booth, 2010;) has proven itself surprisingly useful in a wide array of speaker attributes such as simple sentiment analysis (Tausczik & Pennebaker, 2010), while more intricate methods attempt to identify the subject of sentiment (Wilson, Wiebe & Hoffman, 2005). Other work in NLP has attempted to capture the power, or social influence, (Biran et al. 2012) of a speaker via an examination of language use. Further work, again through the use of natural language, tackles personality detection (Kwantes et al., 2016; Park et al. 2014) and mental health issues (Resnik et al. 2015; Coppersmith et al. 2015).

Perhaps the most interesting findings with respect to understanding a population are the methods developed to capture moral concerns and values. Graham, Haidt, and Nosek (2009) developed the Moral Foundations Dictionary (MFD) for text analysis with LIWC - identifying morally loaded words that can capture content related to both vice and virtue within each of the five moral foundations. With the help of the MFD, text analysis experts have extended these analyses to natural language using LIWC-style word counts. Graham, Haidt, and Nosek (2009) started foundational moral rhetoric analysis on sermon transcripts during the Iraq war to gauge moral content in liberal versus conservative churches. Sagi, Dehghani (2014) extended Latent Semantic Analysis methods to moral foundations research to illustrate how concerns manifest in debates about the World Trade Center, Ground Zero Mosque, and abortion. In all three studies, the methods used were able to accurately identify moral attitudes and underpinnings, and confirm earlier results regarding the discrepancy in moral language between conservatives and liberals.

Most recently, the Distributed Dictionary Representations (DDR) (Garten et al., 2018) method was developed, which compares word2vec values of a document to the topic space of interest, in this case, a moral foundations dimension. Documents have been analyzed for moral rhetoric using the MFD and DDR in contexts ranging from Twitter to congressional debate with high accuracy when compared to human annotations (Garten et al., 2016).

Spatial mapping of Socio-cultural variables

Populated geographic regions are better visualized through the social characteristics of the people within them. Recent work that leverages social media data and geotagging has the potential to reshape how we see urban terrain. Gebru et al. (2017) used deep learning methods to accurately identify the model, make, and year of cars as seen on Google Street View. At first glance, this information doesn't seem important or applicable to a military context, but once combined with demographic variables, researchers were able to predict the income, race, education level, and voting patterns of populations within 200 cities across the United States. Moving beyond demographic indicators, data collected from YourMorals.org has been mapped to county-level specificity by Joe Hoover at the University of Southern California. To accomplish this, Hoover draws on methods from political science and spatial modeling in order to derive county-level estimates that are adjusted for sample biases, such as non-uniform demographic and geographical response rates. This approach is particularly useful for data with pockets of geographical sparsity, as it treats counties as a Gaussian random field and, thus, a given county's estimates are modeled as a function of its neighbors' estimates.

Jokela et al. (2015) utilized the Big 5 Personality index to identify regional differences in personality and life satisfaction across the London metropolitan area. More than 50,000 residents took part in the self-report survey, a rarity for most computational social science work. Paired with improved NLP methods like the ones described in Section II.1, this method will continue to identify how personal attributes interact with the environment. Even simple regional Google searches can provide insight to dynamics within the population. Research conducted by Chae et al. (2015) organized regions by their designated market area (DMA) and established area racism by calculating the proportion of total Internet searches containing the "N-word." Their work demonstrated a positive relationship between this observable measure of area racism and black mortality rates, shedding light on how observable socio-cultural factors can provide some insight into quality of life or disparities between people within a population. In equally pertinent work, Eichstaedt and colleagues (2015) used publicly available data from 1,347 U.S counties on Twitter to uncover language patterns that captured community-level psychological characteristics. Holding income and education constant across counties, negative language patterns predicted atherosclerotic heart disease rates better than typical demographic and health variables.

NS-CTA and its predecessor IPAN (Information Processing Across Networks) have produced the APOLLO social sensing tool which filters through large amounts of event-based social media data to summarize relevant and accurate sources, giving timely visualization of actual regions that an event takes place in. APOLLO serves two purposes: a) determine the veracity of content of a tweet and b) understand polarization in online communities. APOLLO filters out less credible sources in a Twitter stream while simultaneously providing a more accurate visualization of problem areas. When assessing polarization, APOLLO identifies clusters from retweet and interaction behavior using queries to guide content. Currently, APOLLO only addresses the kinetic components of a network without understanding the social underpinnings and other trait characteristics of the user, but this work has the potential to layer socio-cultural variables over events in real-time to explore how these two interact or predict problem areas.

Social Network Analysis

Social Network Analysis (SNA) is not a recent development and has seen application across a variety of domains (e.g. sociology, political science, biology, social psychology) to identify relationships between people, places, and things. Only in recent years, with the popularity of social media and ease of data access, has social network analysis begun to reach its potential. Moreover, as this technology rapidly evolves, military utilization remains far behind, particularly in socio-cultural variables of interest.

Research conducted by Barbera et al. (2015) examines how Twitter users communicate about political and non-political issues online, examining polarization in retweeting behavior. The authors take advantage of publicly available voting data to validate a social network approach (e.g. looking at neighboring nodes) for political ideology estimates of each user (for methods, see Barbera, 2013). In their analysis of political and non-political events as discussed on Twitter, Barbera and colleagues were able to identify when issues were polarized in network versus exhibiting mere information diffusion. While some events such as the 2012 U.S Presidential election were polarized from the beginning of discussion, other issues (e.g. Sandy Hook Elementary School shooting) started as a national conversation before descending into a politically polarized issue.

Social network analysis has also provided ISIS sentiment information across meta-communities in the Arab world. The RAND Corporation released a report in 2016 that documents ISIS support and opposition through social media networks (Bodine-Baron, Helmus, Magnuson, & Winkelman, 2016). Using lexical and network analysis methods, they constructed the relevant ideological "meta-communities" across the Arab world and their sentiments towards ISIS. Drawing on the language that each community uses when discussing ISIS, RAND makes recommendations for the virtual battlefield and how to combat sympathetic attitudes towards ISIS supporters while simultaneously amplifying existing anti-ISIS sentiment.

In similar work, one team within NS-CTA has focused on the spread of social contagion and the identification of relevant actors that propagate agitation. As the researchers state, "The ability to find the optimal influencers...allows us to design effective information spreading campaigns" (NS-CTA A.P.P, p. 82). Effective information contagion has continued to look at the moralization of messages as they propagate through Twitter networks. Brady et al. (2017) has identified the role of emotion in moral contagion online by using dictionary methods to account for moral and emotional words in tweets. The researchers identified the role that emotional vocabulary played in the diffusion of moral content surrounding U.S political issues, as measured in retweeting.

Agent-based Simulation

Agent-based, simulation as a method, has substantial promise for future military planning, particularly when enhanced by computational social science research. Agent-based modelling (ABM), in a military context, is a form of simulation and analysis that takes defined agents of an environment and models how they independently interact with each other, their environment, and actions taken during a mission. A modeler gives agents a set of parameters, goals, and thresholds for behavior before placement into an environment. Researchers at the Army Research Lab (ARL) have proposed an ABM approach to war-gaming that takes into account the social components of a mission territory, posing the question of how to accurately operationalize social attitudes (James et al. 2016). The authors note that "success of upcoming deployments in populated areas is likely to depend on social rather than combat considerations" (p. 66). Over the past twenty years, researchers have developed a number of tools designed to address mission analysis and war-gaming as well as assist operations planning.

A collaborative team of researchers from academic institutions and military research labs developed the Cultural Geography model in 2006 to assist in Stability Operations, aimed at understanding how agents interact with each other in zones of operation. Cultural variables for agents are guided by survey metrics and experts familiar with the subject matter. As an extension to this project, TRAC Irregular Warfare Tactical Wargame (IW TWG) was developed to focus on civilian attitudes as determined by the socio-cultural factors of a civilian population and their leadership as they interact with specified courses of action. IW-TWG can host a variety of granular variables about the population, but satisfying these data demands may take as long as nine months (James et al. 2016). Similar, but lower in granularity, Athena was developed by the National Aeronautics and Space Administration's Jet Propulsion Labs in 2009 and revised 2012, to model the impacts of operations on civilian populations by taking pre-defined parameters for modelling the interactions between social and economic variables of the population of interest. Athena includes a number of interesting parameters such as attrition as measured by non-combatant deaths and serves to "represent the interaction of PMESII and [diplomacy, information, military and economics] DIME effects on the operational environment over time" (James et al. 2016, p. 104). Like other models discussed above, Athena's methods are based on hypothetical, best-guesses of attitudes and behaviors of target populations to fulfill an agent's social parameters.

Other tools developed in more recent years attempt to take the influx of available data and make educated interpretations and predictions about the observed behavior. One such tool is the Worldwide-Integrated Crisis Early Warning System (W-ICEWS) as described to be a "social radar capability" (James et al. 2016, p. 109). W-ICEWS uses NLP methods to capture sentiment and identify key events and attributes to model possible future outcomes for a country in crisis. However, even this method requires important speculation from analysts for key inputs on human behavior.

Section III: Pulse of the Population: What a social-sense enabled MDMP looks like

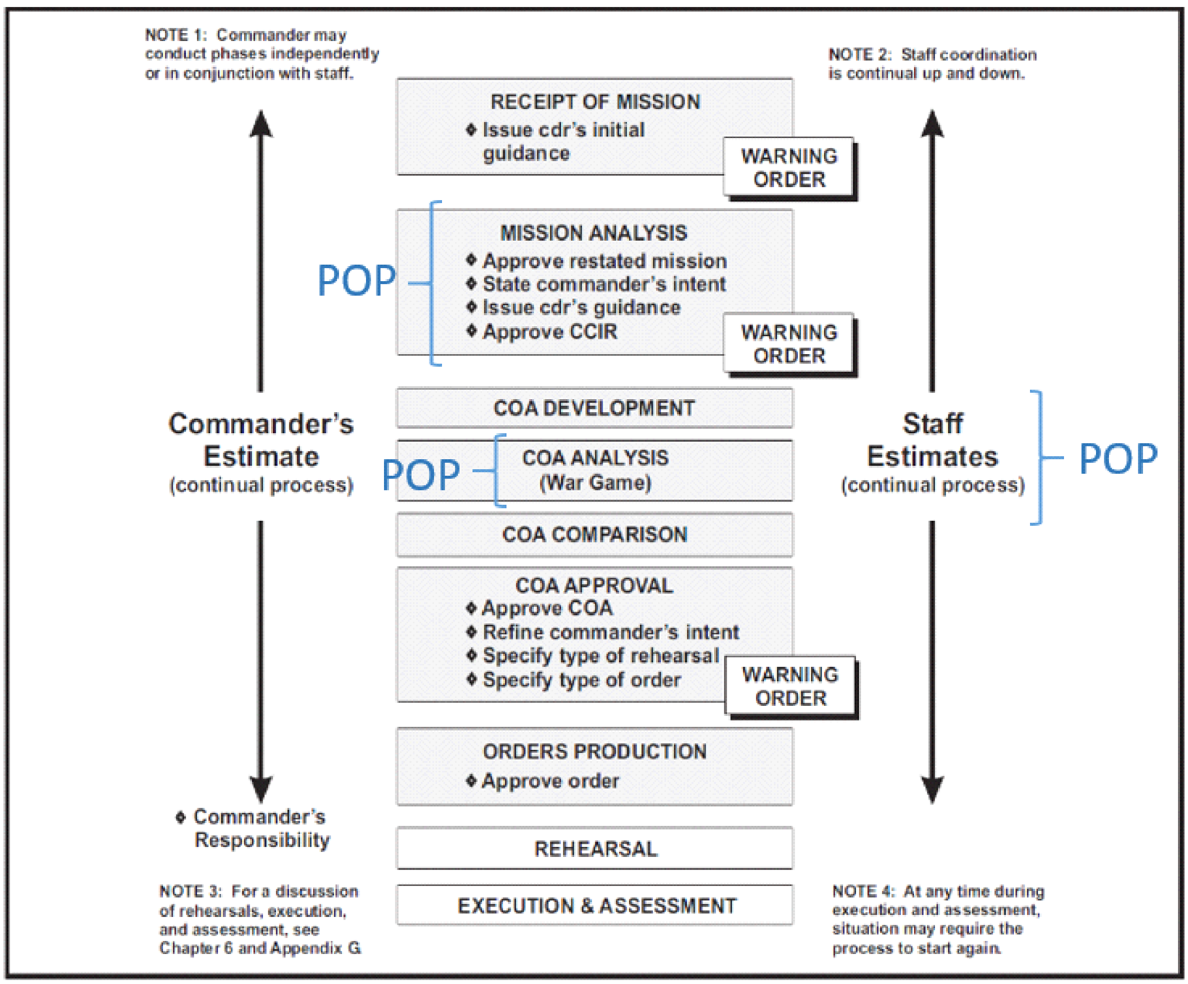

Figure 2: The MDMP as augmented by POP

Pulse of the Population (POP) serves as an overarching concept for social-sense tools to augment the MDMP as shown in Figure 2. POP variables are defined as a summary of relevant social and cultural variables, as gathered through computational social science methods (e.g. social sensing tools). In this section, we focus on the key areas of the MDMP where POP can best be applied as well as areas that should be considered for future development. In our assessment of the MDMP the importance of cultural fluency is paramount. Cultural fluency in this context is the ability of an analyst to make culturally informed interpretations of operation variables, and develop COAs from the perspective of the target population's culture. Context and the underlying cultural biases of analysts sometimes impact their abilities to provide culturally congruent mission analyses and COAs in a foreign environment.

When handling large amounts of information in a short time span, cultural expertise is a substantial challenge. POP serves to inform MDMP by providing an understanding of the population's subjective perspectives through the disaggregation of large amounts of social data; helping commanders make well-informed civil decisions. A discussion of MDMP augmentation will cover three pertinent steps: 1) Mission Analysis, 2) COA Development/Analysis, and 3) Running Estimates.

Mission Analysis

Often regarded as the most important part of the entire MDMP, the Intelligence Preparation of the Battlefield (IPB) process gathers all relevant information about the operation area utilizing PMESII-PT, ASCOPE (Area, Structures, Capabilities, Organizations, People, and Events), DIME, and METT-TC. Although the military provides some automated content, there is little work on a streamlined automation for civilian considerations within the analysis step. In fact, the MDMP manual recognizes the limitations of IPB stating that it "neglects to adequately describe all the characteristics of the 'threat'" (DoA 2009, p.13). POP will serve to help commanders prevent unintended agitation of the civilian population and thereby mitigate rates of civilian to non-state actor conversions. Drawing from research discussed above, social sense tools give us a more accurate reading of current civil stability (e.g. protest behaviors), the contentious issues governing the civilian population (e.g. moral outrage), and the subjective experiences of the population (needs/necessities).

Analysis models such as PMESII-PT have been a cornerstone of the IPB and MDMP for several decades as the means to establish the operational context with which COAs are developed. Today, operations often encounter non-state actors in the mission environment that make traditional models difficult to apply. Prior inquiry conducted by Ducote (2010) proposed a solution to this issue by urging Army operatives to adopt a new, identity-based approach to "ascertain the ‘why’ and not just the ‘what’ of [the mission] environment" (Ducote, 2010, p. 1).

Reviews of evidence and the decisions made in accordance with that evidence are inevitably guided by principles such as prior experiences, implicit biases, moral attitudes, and context. Taking this into consideration, it is not a great leap to postulate that PMESII-PT variables are often influence by these same guiding principles, despite a well-intentioned analyst's desire to decide variable importance from an "objective” point of view. As Ducote argues, "A military commander can certainly ascertain a better understanding of a complex environment using PMESII-PT; however, one must now determine the depth and utility [as well as] whether such a model is holistically complete to understand complex social systems" (Ducote, 2010, p. 21). In real world operations, PMESII-PT attributes are in a constant state of flux fueled by changes occurring in the physical environment and in the minds of the population as they interact with their surrounding social environment. Though PMESII-PT allows for the systematic categorization of people, terrain, events, and everything in between, it fails to capture how these systems interact with each other beyond linear relationships. Ducote (2010) suggests that a more holistic approach, through identity-based narratives, will better reveal the hidden forces that dictate living systems, but unfortunately, Ducote's tools rest mainly in abstractions that have little temporal consistency or guidelines. The tools and methods described within the POP concept are a closer answer to more flexible environmental models (e.g. PMESII-PT), leading to a more complete IPB, and therefore MDMP, even when operating the limited bandwidth of a military operational environment.

Only in the last decade was METT-T revised to include civil considerations as METT-TC (C for Civil Considerations). Even with this addition, civil considerations largely boil down to activities that the population participates in rather than beliefs or common held moral concerns. When handling missions in low-resource environments, our latest intelligence may be as old as ten years. Depending on a myriad of factors such as the length of conflict in the area to the local population's fears of retribution, data may be sparse. Low resource spatial analysis in conjunction with emerging text analysis methods described above for a variety of socio-cultural variables (e.g. personality, mental health, moral values, sentiment) can contribute valuable social mapping to regions of interest. Even simple search queries paired with known attributes of a region could be useful for identifying contention, apprehension, and regional differences. Paired with existing intelligence methods for gathered physical characteristics of the environment, we can begin to provide socio-cultural variables of interest in a mega-city environment. This type of analysis can be both practical and timely using POP to paint a city socio-cultural landscape, supplemented by other forms of traditional observable data like PMESII-PT, DIME, and METT-TC. Similarly, ASCOPE focuses on the *objective* experience from the analyst. With social media information, we can gather valuable insight into the population's perceptions of each component and how they interact with one's personal profile.

In the direction of POP concept, we suggest the development of social-sense tools that provide objective measures for the following areas:

- **Cultural Underpinnings:** Beliefs, Practices, Attitudes that shape the functions of the society, city, village, or neighborhood.

- **Moral Virtues, Concerns and Sacred Values:** Common-held or prominent attitudes on morality, present issues in operation environment that provoke or could provoke moral outrage or concerns (e.g. social unrest), sacred areas or sanctified rituals, struggles, identities.

- **Known needs/necessities:** Ordinal needs as perceived by the population of interest. Unlike facts about infrastructure or the physical environment that may outline the landscape, establishing the hierarchy of needs/values of the population will promote cooperation with and stability of the population in mission territory.

- **Relevant Identities**: Identities related to state, nation, religion, or community that are activated prior to or during operation that impact behavior and perception of actions taken by US forces.

This collection of human-domain areas are a subsample of where POP can benefit mission analysis, but serve our most immediate goals for the environments and conditions that we see U.S forces operating in.

COA Development and Analysis (War Game)

In addition to supplementing the current conditions ("the what") of the operational environment, POP would serve to capture the subjective experience ("the why") of the people. This would inform us of how their place in the social landscape interacts with our operations to predict sentiment and behavioral response. As an example, SNA and sentiment analysis can enable the identification of actors in a mission environment that have the highest sensitivity to force operations, interactions, and where collateral damages (e.g. sacred sites, sympathetic/neutral population neighborhoods) would shift the perceptions of the people to become hostile. The variables discussed in mission analysis section, also contribute to simulated estimates of the PMESII-PT's Political, Social, and Economic domains during the war-gaming process.

Equally important, mission analysis of at-risk populations can influence the COAs for stability operations (e.g. constructing command posts, pathways through the cityscape, anticipated collateral damage during mission, priority of reconstruction/stabilization operations). SNA work, like that of Barbera et al. (2016), can give us insight into the fractures within the community based on their interpretations of past events. With basic demographic data, we can use online communities to guide expected perceptions of U.S presence or events and superimpose them to the demographics of the known population of interest. These variables would answer the call to socially-sound variables for agent-based modelling techniques in war-gaming.

With the availability of social-sense tools and accumulated data, ABM will add civilian perception to simulated war-gaming outcomes. Current models provide inputs for simulation of attitudes or behaviors as they are subjected to environmental changes, but lack ground truth in their current form. Future work will address the integration of social attributes into fine-tuned, updatable parameters for ABM simulations. Our ability to simulate the interaction between human domain components and military COAs will greatly improve diagnostic capabilities of commanders and analysts. One of the difficult assumptions of many ABM models reviewed by the authors is the needs and necessities of the target population being modeled. These important variables guide how a population responds to simulate events, but are naturally biased through a cultural lens that does not capture the nuances of foreign population needs with respect to environmental, cultural, and moral concerns. Needs and necessities modelling exists, but remain in their infancy (Yang & Li, 2013). Especially in Stability Operations, the needs and necessities of a population may not readily be apparent to an outside observer, though accuracy of these variables is imperative to mission success.

It is difficult to recognize the threshold where perceived agitation turns destructive or shifts a population's cooperation against friendly endeavors, but POP metrics show great promise in their utility to ABM within war-gaming. With the emergence of higher computational ability in machines and methods for data disaggregation, fulfilling social parameters of the target population in a timely manner will greatly enhance the conduct war-gaming simulations.

Running Estimates

During execution of a MDMP-developed mission, POP methods and tools would enable real-time corrections via running estimates of social-sensing metrics. Available data and disaggregation tools are not far from the capability to extract meaning from social expressions as they occur. Within social networks, the use of political, religious, or community accounts to determine where a user falls on an attitude spectrum towards U.S forces and operations. Research conducted with the NS-CTA could be important in establishing running estimates of the known neighborhood sentiment as a mission is underway within a Mega-city. Inevitably, the disagreements about events occurring on the ground between civilian actor nodes will be reflected in online community interaction so long as the data is available. Moving beyond sentiment, the application of methods will predict population behaviors such as those used by Barbera et al. (2016) to recognize when our actions in mission territory lead to contentious debates within the population of interest, unanimous outrage, or neutral response as measured by interactions in social networks. Most importantly, POP will track when the actions taken during COA execution on the ground go from information diffusion to an amplification of community tensions or disagreement about U.S and Allied involvement in events.

Furthermore, POP will enable an examination of information and moral contagion related to mission activities, honing in on what information permeates through which citizen networks. In the case of negative information contagion, tools will focus on early identification and mitigation. Civil stability is an important goal long after a mission has been completed, but remains difficult to assess on an ongoing basis. POP provides a window into the future consequence of current missions via civilian sentiment, assisting with running estimates, especially in times of social unrest.

Conclusion

This paper provided a brief overview of the current Military Decision Making Process and existing research areas of computational social sciences. The Pulse of the Population was introduced to apply the budding area of social sense tools to the MDMP. The use of POP will establish a richer variable set for military operations that provide insights into how these operations will affect the complex social systems within the mission environment and enable COA developed with improved civilian considerations.

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