Application of Artificial Intelligence for Dynamic Military Information Prioritization

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ABSTRACT

The U.S. military has recently emphasized the need to reduce vulnerabilities that result from large physical, electromagnetic, and power signatures of current command posts. A need for agile and on-the-move operations is driving conceptualization and implementation of portable networks which are moveable, wireless command post capabilities that enable secure wireless transmission of information. A limitation of emerging mobile command post solutions is the reduced computing capacity for the vast amounts of information exchanged across disparate assets during operations. Failure to support effective and fast information processing and prioritization can negatively impact situation awareness (SA), a core construct for effective decision making in military contexts. Advances in AI-driven data analytics are producing capabilities for effective information management and prioritization based on multiple interrelated factors associated with military intelligence. Analytical algorithms can be applied to dynamically evaluate operational parameters to determine the relevance and priority of data and battlefield assets that may be used as information sources. This paper presents AI approaches approach being explored in an ongoing research program that highlights the promise for automated and personalized information prioritization. The program is working toward a set of rule-based and AI-supported algorithms enabling the right data to be routed to the right commander at the right time given a mission and variable operational parameters, including network bandwidth. Initial AI model evaluations using simulated battlefield datasets produce 94% accuracy.

ABOUT THE AUTHORS

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INTRODUCTION

On January 8, 2020, an Iranian missile strike was launched in a precise attack on U.S. forces at Ain al-Assad Airbase in Iraq. This was the first time in decades that U.S. forces were targeted by traditional ballistic missiles. Though there were no casualties and early warning systems detected the ballistic missiles well in advance (Snow & Altman, 2020), the incident highlighted the vulnerabilities associated with the physical, electromagnetic, and power signatures of large, static command posts. It emphasized the criticality of recent military initiatives (e.g., Army Command Post Integrated Infrastructure (CPI_2); Clark, 2021) to increase defenses and survivability through agile, modernized, on-the-move operations. Several broad goals aim to migrate from a fixed structure to maneuver-oriented command post implementations, such as decreased logistics and manpower support, sustainable operational tempo, outperforming the enemy's command, and survivability of equipment and personnel. Agility goals are primarily being addressed through the reduction of footprint (e.g., personnel, tents, trailers, and generators) which substantially reduces physical and electronic visibility, speeds set up and tear down times, and maintains the cover and concealment necessary to avoid detection and targeting. Success in this area, however, results in challenges concerning connectivity due to fewer computing resources which can result in reduced and sporadic bandwidth. One solution comes in the form of portable servers/networks which are moveable, wireless command post server capabilities that enable secure transmission of information across wireless networks and can be hand maneuvered across disparate locations. This technology offers a new opportunity to maintain, if not increase, the network power achieved from the traditional wired command post setup that required physical stations and hours of wiring to establish. Another solution in active fielding is mobile command posts or vehicles which may allow units to pack up and relocate command on a few-minutes notice.

A major limitation of emerging mobile command post solutions is the reduced computing capacity for the vast amounts of information available to support effective decision-making cycles for the rapidly evolving battlefield. Battlefield decision making is dynamic; many factors interact within each new tactical engagement to influence the viability and efficacy of available courses of action. Success and superiority hinge on the capacity to provide timely and relevant, prioritized information in support of accurate situation awareness. Situation Awareness (SA) is defined as "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future" (Endsley, 1995). SA has been identified as critical to decision making, particularly in chaotic, uncertain, and dynamic, high-stakes environments such as battlefield operations. The development of SA – perception, comprehension, and projection - is essential to military commanders, as they must not only attend to information but integrate that information from multiple data sources to determine its value based on relevancy to overall goals and mission decisions (Riley, et al., 2007). As such, mission command systems must provide the right information, to the right people, at the right time for optimizing SA and mission success. This goal is not trivial when considering the multiple interrelated factors (mission constraints and goals, enemy capabilities and tactics, terrain characteristics, civilian patterns of life and associations, time, etc.), that must be considered, or the proliferating number of data sources. Distributed decision making, reduced manpower, and limiting computing resources in emerging command post implementations put even greater strain on this process due to smaller, distributed networks. As such, it is critical to facilitate effective management of information flow and prioritization to optimize resource and bandwidth usage and ensure the most relevant information is available for command decision makers in network-limited conditions.

Advances in AI-driven data analytics are producing capabilities for effective information management and prioritization based on multiple interrelated factors associated with military information and intelligence. Analytical algorithms can be applied to dynamically evaluate operational parameters to determine the relevance and priority of data and battlefield assets that may be used as information sources. Approaches such as priority queueing systems, job scheduling techniques, bandwidth management systems, information theory and coding theory methods facilitate rapid consideration of key factors such as battlefield sensing assets, system and network availability/health, information source, redundancy, timeliness, resilience, and critical information requirements to effectively manage information prioritization, distribution and routing, storage, and presentation. There are increasing opportunities to explore the application of these automated data analytics techniques for effective military information processing and management of battlefield intelligence such that methods can be applied toward the success of decision making in modernized and mobile command posts. This paper presents an approach and example application that highlights the promise of such approaches.

ARITIFICAL INTELLIGENCE APPROACHES FOR INFORMATION PRIORITIZATION

The authors have ongoing research toward evaluating AI approaches for military information prioritization. The research effort aims to identify AI and data analytics methods that can be integrated to effectively identify the highest priority data for a given role/position, time, and needs. The focus is on supporting SA for a specific decision maker. Called MISTec (Military Information Superiority Technology), the project has initially aimed at supporting military commanders who may have specific critical information requirements (CCIR) for achieving mission success. The program blends human factors engineering with the AI approaches to identify the relevant factors and to define measures of performance and effectiveness for resulting prioritization approaches. The MISTec method applies a customized, scalable AI algorithm to monitor data from multiple sources, evaluate the relevance of data, and prioritize the mass of relevant information from disparate sources so that a decision maker can complete his/her observe, orient, decide, and act (OODA) cycle faster than the adversary. Three components are being explored: an event classification module, an event prioritization algorithm, and an event queuing method. They are discussed here to describe how they can be applied to the information prioritization challenge.

Event and Topic Classification

Initial work on the event and topic classification method focused on identifying information needs, factors that should influence information prioritization, and where in the information and decision-making cycle an automated prioritization technology would provide the most benefit to decision makers. Using cognitive task analysis, specifically goal-directed task analysis (GDTA; Bolstad et al., 2002), the authors completed a systematic examination of goals, decisions, and information (SA) requirements for command post decision makers (Commanders and roles such as Digital Master Gunners, Intelligence Officers, and Operations Officers which support command decision making). The analysis included knowledge elicitation with domain experts (in house military subject matters experts and Digital Master Gunner training instructors) and review of past task analysis results for the relevant roles (Bolstad et al., 2002; Endsley & Riley, 2002; Riley et al., 2002). The results of the analysis provided a list of initial operational factors, mapped to military METT-TC (mission, enemy, terrain, troops, time, civilian) information considerations, including:

- Mission events, activities, constraints, goals,
- Information user,
- Information source,
- Information source location, reliability, sensing capabilities,
- “Size” of information / data packet,
- Available connectivity and bandwidth,
- Absolute and relative time of reported information/event,
- Absolute and relative location of reported information / event, and
- Certainty of reported information / event.

The factors identified in this initial work provide a foundation for classifying events and identifying topics and are also used later for the prioritization approach.

Input from domain experts was critical during the conceptual design of the event classifier as it is important to understand how military decision makers address issues regarding the quality and timeliness of information within the command post via training for decision making and during the ongoing modernization efforts. Key elements of the analysis results (the hierarchy of information needs based on battlefield decision making in context) were examined in conjunction with findings in various US Army Field Manuals (FM-6-02-43; FM-6-02.71) resulting in the identification of places in the command decision cycle where automated prioritization support, including consistent monitoring and strategic "filtering" of key information components based on critical information requirements would be most beneficial. Support needs identified were:

- Extracting and synthesizing information from potential data elements and sources,
- Filtering information based on relevance (influenced by time, space, situation, and information user),
- Ranking information priority (influenced by time, space, situation, and information user), and
- Dynamically queuing of information for delivery.

The results of the analyses also highlighted the influence of the operational concept of communication-based control loops, the top level being the commander critical information requirements (CCIRs). The CCIRs have the potential to influence information and SA behaviors of others in the command post and in the field. As such, the approach considered the need to sample and route information to various communication control loops connecting the people and systems based on identified CCIRs. In this way, CCIRs influence event classification and identification of key "topics" that are important to information managers and decision makers supporting the military commander and directly relevant to CCIRs. Topics, in this use case, can be described as a characteristic or constituent of data relevant to CCIRs that can be gleaned from information provided by a given source. It is not a specific discourse but a feature of the information that may influence relevance to information user, for example, how closely a message relates to each CCIR and thus how close the message's priority should be to each of the pre-defined information priority. Potential topics may include, but are not limited to:

- Source or asset (unattended ground sensor (UGS)),
- Location or position,
- Friendly unit or US forces.
- Enemy unit,
- Civilian,
- Fires or engagement,
- Casualty (injury or death),
- Damage to equipment / infrastructure,
- Type of event (IED, helicopter down),
- Weapons or stockpile, and
- Critical infrastructure or asset.

In the current approach, CCIRs are used as the initial way of grounding the classification. These requirements are currently set manually (via input), but in the future can be automatically extracted from common documents and reports (e.g., operational orders).

A two-step process for event and topic classification is used to distill data into information from multiple sources. The first step includes a simple, rules-based system. The rules are used to identify concrete topics that are in information about an event or topics that may be about an event. For example, data provided by an unattended ground sensor should be labeled as "UGS" (a potential topic), to concretely identify the source. As another example, a radio transmission that explicitly includes information on enemy fires should be labeled as "fires" (a potential topic). This system also automatically parses metadata to determine topics such as the sender of the information or its location.

The second step in the event and topic classification involves application of a natural language processing approach to determine if a message relates to various aspects of a military operation. Traditional text classification models require a good deal of data labeling which can be difficult and requires substantial effort for collection and processing. However, emerging zero-shot learning approaches sidestep this requirement, using models pretrained on large datasets that can be repurposed to perform tasks without any training data related to the specific use case – here, zero-shot text classification (Alcoforado et al., 2022). With zero-shot classification, a model takes an incoming message with a set of potential topics and outputs the probability that the message is related to one or more of these topics, even if the model has never been explicitly trained on these topics previously. These probabilities can then be thresholded to determine binary topic classifications. The authors have applied the Bidirectional and Auto-Regressive Transformers (BART) transformer neural network model for this purpose. BART is a denoising autoencoder built with a sequence-to-sequence model that can be applicable to a large variety of language-based tasks (Lewis et al., 2019) and is applied here to automatically classify text into topics. For example, the event "non-combatant in minefield at location XYZ" is distilled into the below topics with descending confidence.

Table 1. Example of a single message topic classification.

Topic	**True**	**Predicted**
Civilian	1	1
Position	1	1
Mine	1	1
Injury	0	1

*True indicates the SME-determined topic classification of the message; Predicted indicates the topic classification determined by BART with a 0.65 probability threshold. All other topics not listed in this table were 0 for both True and Predicted.

The authors tested the approach using a synthetic dataset vetted with support of a domain expert. This validation set demonstrated model performance with 0.94 accuracy, 0.78 precision, and 0.89 recall using a pre-set 0.65 probability threshold, and 0.92 area under the ROC curve (AUC ROC; Bradley, 2007) which indicates model performance agnostic to the threshold (0.5 indicating chance and 1 indicating perfect performance at all thresholds).

Information Prioritization

Classification of topics sets the stage for prioritization of events or information. As stated earlier, the event prioritization in the military context is mapped directly to CCIRs. As such, the approach can use CCIRs and commander-provided priorities for these CCIRs as training for appropriate prioritization of novel messages and information thereafter. As CCIRs change and/or as the level of relevance and importance change over an evolving mission, new prioritization can be computed.

The relevance of an event increases as the number of CCIRs that depend on that event increases and as the importance (or priority) of those CCIRs increases. Mathematically the event relevance is defined as:

$$\eta = \vec{p}\hat{C}\overrightarrow{\epsilon^{T}} + \alpha \quad \text{(Eqn. 1)}$$

Where:

- η is the computed event relevance (a single number or vector if multiple events are considered),
- $\vec{p}$ is the vector of CCIR priorities authored by the user (each element is a priority for a particular CCIR),
- $\hat{C}$ is the CCIR topic matrix,
- $\overrightarrow{\epsilon^{T}}$ is the event topic vector, or matrix for multiple events, and
- α is the relevance intercept used as a free parameter for updating priorities based on user feedback and is normally set to zero.

The relevance of an event is defined as the number of CCIRs depending on that event and the priority of the CCIR (Table 2). The example includes CCIRs with their associated priorities (5, 2, 5) given by the commander. CCIRs are automatically distilled into their constituent topics. The topic matrix, then, associates CCIRs (examples in the rows in table) with relevant military topics (examples in the columns in table) using a Boolean (0 = False, 1 = True). Only a subset of potential topics is illustrated here.

Table 2. Example CCIR priorities and classification into topics.

CCIR	**PRIORITY**	**TOPIC**

		Combat	Casualty	Within Town	Helicopter
Combat within town limits	5	1	0	1	0
Friendly helicopter enters town limit	2	0	0	1	1
U.S. and friendly casualties	5	0	1	0	0

The CCIR priority vector is important because it allows the priority of events to change as the CCIR priority changes. For example, a CCIR that is no longer relevant can have its corresponding elements in the priority vector set to zero or removed from the training set altogether. Table 3 shows the same topics as in the CCIR table but mapped to a novel event.

Table 3. Example event distillation into topics

EVENT	Combat	Casualty	Within Town	Helicopter
Enemy sniper fire taken by U.S within town limits	1	1	1	0

The next step in the process is compute event relevance. Computing the product of CCIR priority vector, the CCIR topic matrix, and the event topic matrix provides prioritizations for a novel event or information. In other words, the novel event prioritization is based on two factors: the dot-product similarity between an event and each CCIR (given by the CCIR and event topic matrices), and the commander-provided priority of that CCIR (given by the CCIR priority vector). The relevance is a single number (illustrated by the green notional number line in Figure 1) which captures the high-dimensional information contained in the topic matrices and the priority vector. The two dots on the notional number line represent the relevance values of the two events (rows in the event topic matrix). Using three CCIRs as training data, this illustrates the event prioritization computation for two novel events (showing only a subset of the topics).

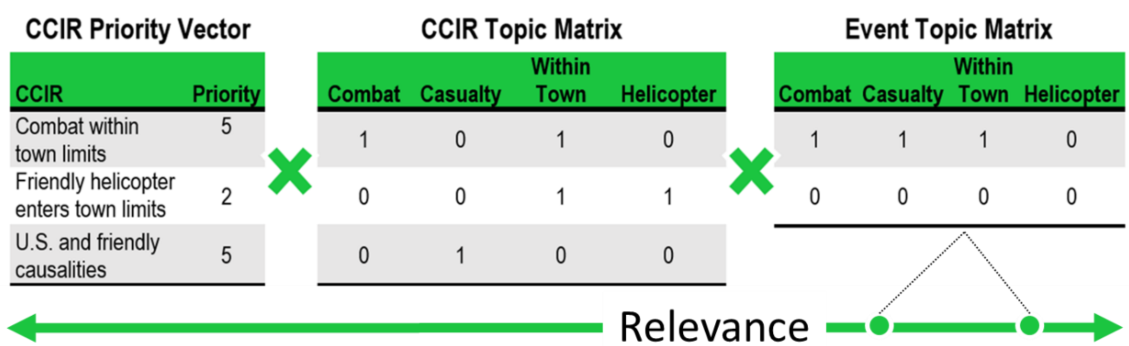

Figure 1. Illustration of the prioritization algorithm backbone.

These steps outline how topics function within the theory to measure the similarity or relationship between each event and the CCIRs to produce a final prioritization score based on these similarities. This mathematical formulation serves as a backbone for event prioritization computation through a linear similarity metric. Additional preprocessing steps can be used to refine predictions, such as normalization of topic matrices, scaling of user-provided CCIR priorities, alternative non-binary transformations of topic probabilities in the topic matrices, and the automated creation of composite topics (e.g., casualty *and* within town, helicopter *and not* combat) to identify nonlinear similarities across events and CCIRS.

Queueing Algorithm

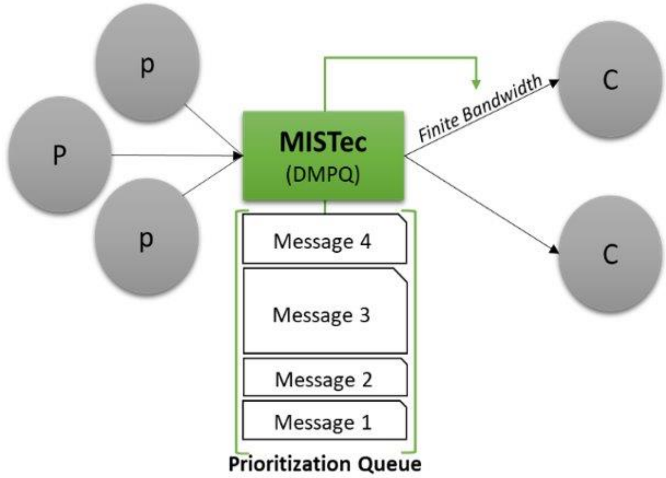

Figure 2. Illustration of Message Queueing.

Once event priorities are determined, the event messages or data must be sent to recipients for whom it is important and/or displayed to a screen. Unfortunately, technical constraints, like bandwidth and connectivity limitations in modernized and mobile command posts influence capacity for all event messages to be sent or displayed at once, particularly if data packets are large. A queuing algorithm applies approaches for the selection of specific event messages to be provided to the information consumer based on these factors. The approach aims to increase the number of high priority messages that can be sent to an information consumer given constraints on the networked system. See Figure 2 for a notional illustration. Producers of data (P) push data to the prioritization algorithm. A queuing methodology orders the messages through an optimization algorithm based on multiple factors (size, specific prioritization, bandwidth), and then facilitates distribution to the Consumer of the information (C). A dynamic approach is needed to organize data flow in potentially high data volume or delayed, intermittent, low-bandwidth conditions.

The approach can be translated into a mixed integer programming problem and solved by most optimization packages while guaranteeing that the solutions obtained are optimal. The goal is to maximize the expected priority weighted throughput:

$$max_x \sum_i P_i x_i \, p_i (1 - k_i)$$

Where:

- x_i, the decision variable, is $\in$ 0,1 and represents the decision to choose the ith event,
- p is the priority of that event,
- P is the probability that the event, if chosen, will reach its destination based on packet size and bandwidth, and
- k is 1 if the recipient has already received the event or is aware of the event and zero otherwise.

While the current formulation of the objective includes the probability of messages being received and the knowledge of the recipient, it is currently focused on maximizing the priority-weighted throughput for the current moment and not considering future steps and possible arrivals. These additional considerations greatly increase the problem complexity but can be included in the framework for future work. The above can be maximized under multiple constraints:

$$\sum_i x_i \, b_i C_{i,c} \leq B_c \; \forall \, c$$
$$\sum_i x_i \, R_{i,r} \leq A_r \; \forall \, r$$

Where:

- b_i is the bandwidth of the ith event message,
- B_c is the total bandwidth of the c^{th} communication channel,
- $C_{i,c}$ is the channel-event matrix with elements equal to 1 if an event is to go through that channel and zero otherwise,
- A_r is the cognitive bandwidth of the r^{th} recipient, and

- $R_{i,r}$ is the recipient-event matrix with elements equal to 1 if the event is to go to that recipient and zero otherwise.

LIMITATIONS AND CONSIDERATIONS FOR THE APPROACH

Zero-shot classification methods can be highly resource intensive. A message must be run through the model once for each topic, potentially many for military operational contexts, and while each run may take only a fraction of a second, a large number of topics can cause this computation time to add up. This is a trivial difference in situations where the messages are already expected to be delayed, such as in denied, intermittent or low-bandwidth (DIL) conditions, but it may add a problematic processing delay for urgent messages in normal network conditions. Further usage of rules-based systems for topics where this is tenable, as well as building more complex topics through Boolean logic on singular topics (e.g., combat and within town) allow for more fine-tuned topic distillation with negligible additional processing power.

These models are also large, typically requiring 1-2 GB to store the trained model. The importance of this factor must be considered when determining how to deploy the AI-based prioritization algorithms being explored in the MISTec program. If the elements are running on a centralized server, this is a trivial amount of storage. If prioritizations have to be run on end-user devices in the field as part of mobile command, then it is likely to be a concern. Usage of model pruning and optimization algorithms to decrease size, as well as intrinsically more compact pretrained models, should be further explored to determine the tradeoffs between topic classification accuracy and storage capacity.

In theory, event relevance could be used directly as the priority. The results of the task analysis, however, emphasize that each user may expect a different ranking system to be used to create event priorities based on their unique information requirements and the roles they play in the mission. Preferences and situational conditions may also impact ranking outcomes per information user. As an example, some domain experts preferred priority to start at 0 and go to 5, while others preferred a system of ranking on a scale from 1 to 10. The raw relevance determined by the prioritization algorithm is an integer ranging from zero to infinity, not within a finite range, and thus a dynamic scaling approach must be employed to transform these raw values into a final, user-presented prioritization score. Additional factors, such as the subjective opinion of a user, role, etc. may also influence operational priority of an event. The equation for relevance can be expanded to include important individual factors and effects explicitly.

Using only a small set of CCIRs as training data has a risk of overfitting to a small portion of the training set. Fortunately, the prioritization algorithm treats CCIRs and messages as the same mathematical objects. As such, additional sample messages can also be used as training data in the system, given user-provided prioritizations to train the system on. Perhaps even more importantly, this process allows for a human-in-the-loop retraining of the prioritization algorithm in real-time. If a message arrives with a prioritization value that the user disagrees with, user-provided feedback that the priority should be higher or lower allows that message to be immediately added to the training set. Because the heavy computation in this system is front-loaded into the topic classification step, retraining the linear prioritization algorithm is extremely rapid, taking only a fraction of a second to derive new matrices used to compute priorities for incoming events. This process allows such a system to continue learning in the field and become further individualized for a user's needs and preferences.

SUMMARY

High information load, time sensitivity, and delayed, intermittent and low-bandwidth (DIL) environments will benefit from advanced data analysis techniques like these explored in the MISTec project. The program is working toward a set of rule-based and AI-supported algorithms, enabling the right data to be routed to the right commander at the right time. Given mission CCIRs and other operational parameters, the prioritization and queuing methods derive insights on a commander's dynamic prioritized information needs. The incoming data from multimodal sources are analyzed through natural language processing-powered AI to identify individualized priorities for each incoming datapoint. A dynamic messaging priority queue ensures data is optimally routed to individuals, accounting for potentially changing channel bandwidth. Commander feedback to the system can facilitate recomputing priorities and ongoing model refinement and personalization. The resulting product has the capacity to provide benefit to military information superiority through direct integration with command displays and common operating environments. Future work should evaluate methods that further the quality and effectiveness of the algorithms' priority predictions and information queueing, as well as explore how such a technology can be integrated into existing or emerging military information systems and platforms.

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