Tip of the Spear: Developing Predictive Military Planning Tools Using Hidden Markov Models

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Abstract

The evolution of the modern battlefield is increasingly complex as new technologies emerge. However, the nature of the battlefield still can be explained by Baron De Jomini's "Grand Tactics." Military planners' success is in their ability to develop synergy through layering effects of a complex system at a decisive point on the battlefield. Synergistic effects require subject matter experts (SME) working in planning cells to integrate systems and units in time and space. This paper explores the application of Hidden Markov Models (HMMs) to enhance existing Correlation of Forces and Means (COFM) calculators as predictive tools in military planning. Current tools focus on a 3 to 1 force ratio for an offensive operation adjusted with a scalar referred to as a equivalent factor. These tools lack the ability to identify the physics of the battlefield in time and space. The utilization of wargames during planning and training provides a venue for serious games to improve planning tools. This study employs scenarios generated in OneSAF, ranging from simple platoon-level ambushes to combined arms maneuver featuring rotary wing assets requiring a shaping effort to ensure favorable COFMs. The focus is leveraging HMMs to establish a time-series indicator of success probability using potentially observable data, with an emphasis on communication dynamics. In this study, we examine observable communication by data generated through both visual and direct contact. Through observation of contact between forces will provide a predictor of the hidden state of relative advantage, in time and space. With the data generated by the OneSAF simulation, the HMM determines the states of the operation and probability of success while minimizing required presence inside the units.

Introduction

Current events have demonstrated the importance of military planning for success of an operation. When Russia invaded Ukraine, many experts expected the surprise and tempo achieved by Russia was going to allow them to achieve strategic victory within days. Over 600 days later the war has continued with the eventual end more uncertain than ever. One review of the initial stages identified key factors that were missed in the Russian planning strategy that compounded and allowed for Ukraine to conduct a successful defense (Gian, 2022). Shaping efforts, defined as utilizing long range lethal and non-lethal effects, were not used to provide a favorable force ratio for the advancing army. Instead, the Russian military opted for surprise. In addition, modern militaries conduct a continuous three-day planning cycle for target selection, engagement, and assessment. The Russian military's initial planned targeting was effective, but they did not maintain the continuous planned cycle to assess effectiveness and reengage targets. Their target selection was not focused to complement the light agile force conducting the invasion. The lack of organic fires required the Russians' strategic fires to shift from the deep area to close area. This further highlighted issues in the Russian planning of their collection assets not being in position to provide effective observations to detect or assess (Gian, 2022).

The study and planning of war is an endeavor that has been around for recorded history. Modern study of the theory of maneuver warfare is anchored in the principles of Baron De Jomini's Art of War (1862). Jomini wrote that "Grand tactics is the art of making good combinations preliminary to battles, as well as during their progress" (Jomini, 1862, 179). He provides the framework for battlefield geometry, tempo, and determining a temporal state of relative advantage to mass forces and achieving a tactical advantage. His theory focuses on uniformed forces that fought on the battlefield, where they could mass forces and maneuver. He states his universal theory of war does not directly translate to pesky counter insurgencies or irregular warfare like he witnessed in Spain (Jomini, 1862).

Force Ratios

Planning force ratios were derived from Jomini's grand tactics. Current planning guidance states to be successful in an offensive operation against a prepared defense, the at-

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tacking force needs a 3:1 combat ratio (ATP 5-0.2-1, 2020). It would require 3 companies of armor to achieve victory over 1 company of armor in the prepared defense. See Table 1.

Table 1: Force Ratio

Friendly Mission	Position	Friendly to Enemy Ratio
Attack	Prepared	3 to 1
Attack	Hasty	2.5 to 1
Defend	Hasty	1 to 2.5
Defend	Prepared	1 to 3

Correlation of Forces and Means Calculator

Assessing force ratios becomes more complex as friendly and enemy weapons systems diverge in capability. For instance, a Bradley mechanized fighting vehicle looks similar to a tank, but a company of Bradleys would not fair well against a company of Abrams Main Battle Tanks. Planners use a tool called the Correlation of Forces and Means (COFM) calculator (Figure 1) to assist in simplifying these multivariate calculations. The calculator looks at the units composing the force and takes the size of a type of a unit and applies a scalar referred to as force equivalent factor. It repeats this method until all like units' relative power is added together. Then it conducts the same for the opposition force to achieve a force ratio. (CGSC, 1999).

$$\frac{\sum FriendlyUnitSize_n * ForceEquivlant_n}{\sum OppositionUnitSize_n * ForceEquivlant_n} = \text{Force Ratio}$$

Figure 1: COFM Calculator (COFM, 1999)

	A	B	C	D	E	F	G	H	I	J
1	Force Ratios									
2	Friendly Forces					Enemy Forces				
3	Number	Strength	Type	F.E.	Total	Number	Strength	Type	F.E.	Total
4	2	100%	Infantry Bn (M2)	1.00	2.00	4	80%	Infantry Bn (BMP-1 / 2)	0.51	1.63
5	1	100%	Armor Bn (M1A2)	1.30	1.30	2	80%	Tank Bn (MIB 40xT80)	1.00	1.60
6	1	100%	155(SP) Bn (M109A6)(Paladin)	1.50	1.50	3	80%	2S1 Bn	0.90	2.16
7	0	100%	-----			3	80%	2S3 Bn	1.05	2.52
8		100%				2	40%	2S5 Bn	1.13	0.90
9		100%				2	40%	BM 21 Bn	3.15	2.52
10		100%					100%			
11		100%					100%			
12		100%					100%			
13		100%					100%			
14	Friendly Force Equivalent				4.80	Enemy Force Equivalent				11.34
15	Ratio of Friendly to Enemy					Ratio of Enemy to Friendly				
16	0.42:1					2.36:1				
17	Deliberate Defense			<- Mission ->				Hasty Attack		
18	40%			<- Est. Losses ->				25%		

This model works well at communicating an aggregate view of a combined arms unit in comparison to another combined arms unit. This provides an additive view of forces, where the side that is able to mass the most forces should be able to achieve victory. If strategy was this simple the Russian invasion would have resulted in a different outcome.

Temporal Advantage and Target Pairing

Two factors that affect the ability to mass forces are achieving a temporal advantage and the ability to conduct target pairing.

Target pairing refers to the over match of certain weapon systems against one another, resulting in a binary outcome. A simple way to look at target pairing is the game rock, paper, scissors. As applied to battlefield, the attack helicopter will beat a main battle tank, the tank will beat an air-defense unit, and the air-defense unit will beat the attack helicopter. In turn, the force equivalent factors used in the COFM calculator are unable to predict accurately the outcome of those operations. Units continue to fight as a combined arms to provide synergistic effects for the units and reduce the enemy's ability to conduct target pairing.

To achieve target pairing, planners look to achieve a temporal advantage. SME provide input to ensure weapon pairing Effects are sequenced and timed to achieve temporal advantage. Effects that diminish a node on the system reduce its effectiveness temporarily which allows for success. During the planning process SME examine these potential pairings with other variables and determine conditions or states that can achieve the decisive operation. This results in large planning footprints that are of high value for the enemy to target and destroy.

Related Work

Machine Learning in Air Force Simulations

Improving the ability to accurately predict relative combat power allows for the development of simulations to provide support to research and training. The Air Force is conducting data driven approaches for predicting military operations, which is an emerging field of study. One study evaluating the Mosaic theory of air power employment used Machine Learning and a random forest algorithm. (MacAllister et al, 2021). Using the random forest algorithm, they were able to predict successfully at an 80% rate when they were able to see both red and blue. When they were only able to see the blue force, the result dropped to 60% in scenario simulations. The result was significant given the complexity of the scenarios and the goal to make the scenarios as balanced as possible. However, while the technique was able to identify what features were important, it did not provide context on how they are important.

Markov Models in Sport Prediction

Markov models have been proven to predict outcomes to include science, economics, and gambling. Goldner (2011) researched using Markov models to predict success of a football drive using and absorbing Markov Chain. In his research he defined absorption states as plays that resulted in a touch down, field goal, punt, or turnover. His model then would vary the prediction based on where the drive started. Through this calculation he can provide a tool to predict the number of plays prior to an absorption state which could assist in play calling. Similarly, in a combat operation, there are similar absorption states. Absorption states would include achieving the decisive point in a military operation (victory) or culmination prior to the objective (defeat). This would be able to provide military planners an analytic perspective on predicting tempo and developing plan sequels. To enter these states is not confined to combat losses but can be affected by other variables such as logistical requirements, terrain, or civil authorities. (Goldner, 2011)

Strumbelj (2012) used Markov models to predict outcomes of basketball games. His research provided a similar predictive capability as other statistical methods, but the Markov chain provided more information of the game during the progression of play. Of interest was his separation of probabilities between key phases of the play. Through study of the game, he partitioned the game based on critical event. For instance, the last minute of play in the fourth quarter plays much differently than the rest of the game. The transition matrix was separated to include this. This separation by critical events translates to a more holistic planner tool that can change calculations based off phase. This affords planners with context not achieved through the random tree algorithm. This methodology could be applied to weapon pairings at critical events. (Strumbelj, 2012)

Purpose of this Study

The purpose of this research is to provide a way to modernize planning tools. The research has two objectives. First, the research will focus on demonstrating that Hidden Markov Models can be used for predicting outcomes of simple scenarios of even forces. Secondly, the research will also attempt to demonstrate and exemplify how a Hidden Markov Model can be used to provide a predictor of a scenario with uneven forces in a scenario requiring exploiting target pairing to gain success.

Methodology

Scenarios

Two scenarios were developed using OneSAF (PEO-STRI, 2023). OneSAF is a program of record for the US Army modeling and simulation community. It has been accredited to support US Army experimentation. The two scenarios described below were chosen because they highlight the issues with utilizing the force ratios for prediction success.

The first scenario was a platoon ambush where through the utilization of surprise, the attacking force is able to achieve greater results. ATP 3-21.8 defines an ambush as "a variation of attack from concealed positions against a moving or temporarily halted enemy. It can include an assault to close with and destroy the target or as an attack by fire" (7-40, 2024). This scenario consists of an assault force, support, and security force. The behaviors are complex and scripted by the OneSAF simulation minimizing simulation controller requirements. This replicates the task 07-PLT-9010: Platoon ambush. As defined, the scenario is an attack against a hasty defense doctrinally requiring a 2.5 to 1 force ratio. The simulation was conducted with identical infantry platoons resulting in a 1 to 1 force ratio.

The second scenario is a more complex scenario focusing on target pairing and shaping requirements. In this scenario the friendly force consists of an armor battalion and an attack helicopter company versus an opposition force consisting of an armor battalion in the defense. This result in a COFM calculation of 2.43 to 1. Without the friendly attack aviation, the ratio is 1.3 to 1. This operation was conducted in three phases. Phase 1 consisted of shaping. The purpose of this phase was to achieve temporal advantage. During this phase the attack aviation company conducted an attack out of contact to develop a more manageable force ratio to conduct offensive operations. Phase 2 consisted of the friendly unit's movement to the attack positions. Phase 3 consisted of the attack on the enemy in the defense with the purpose to destroy the remaining enemy.

Hidden States

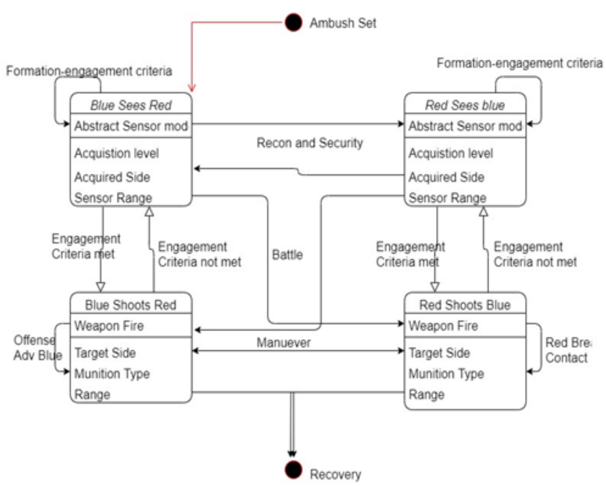
In a Hidden Markov Model there are hidden states that are not directly observable. The states rely on the emission probabilities of the observable states. This research identifies two hidden states that provide planners with a predictive measure for the scenario. The hidden states are Friendly Momentum and Opposition Momentum. Momentum is based off the tactical term for decisive point, defined as "allowing commanders to gain a marked advantage over an enemy and greatly influence the outcome of a battle." (FM 1.02.1, 2021, 1-28) Through this identification of the momentum hidden states, users will be able to use this with current planning tools to provide more certainty in planning analysis.

By controlling the simulation, it is easy to identify which force has more combat power, or which force is in a position of relative advantage to achieve the decisive point. This technique relies on a clear picture of the scenario that does not always translate to real world operations.

Observable States

OneSAF generates data for the entire scenario, individual units, and their interactions. For example, for each engagement, data is recorded to include the location of the shooter, the location of the one who was shot, unit type, range, munition type sensor data and more. This data provides a perfect picture of what occurred in the simulation. With the goal to make a tool for future use the HMM focused a simple data feed on contact. The two forms of contact in the scenario were visual and direct fire. Simply described as did red see blue, did blue see red, did red shoot blue, and did blue shoot red. This data is a minimalistic approach to situational understanding and could be applied to collection techniques in live training events. Each time a unit gains a visual contact with another unit a report would be given to the higher command. Likewise, each time a unit is in direct fire contact a subsequent report would be given. The volume of the reporting is what is being viewed as the indicator, not the specific data inside the report with one exception of range.

Figure 2: Observable State Concept Chart



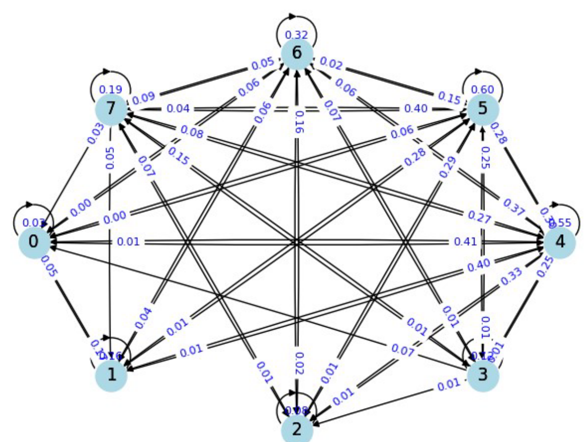
The transitions between four states (Figure 2) are indicative of what is occurring in the scenario. First, looking at blue sees red. When blue sees red the likely transition is for another blue unit to see red. In the ambush scenario this is when the friendly force is set and waiting for engagement criteria to be met. When engagement criteria is met, the state will transition to blue shoots red. The unit will remain in direct fire state until the engagement criteria is no longer met, and it returns to searching to gain contact. The other main transition is that red sees blue. When the transition between those states occurs, it becomes indicative of the reconnaissance and Security fight. From the state of red sees blue, it can transition to red shoots blue. In the ambush scenario this demonstrates the behavior of breaking contact, where the unit will suppress while the other part of the unit will retrograde. When the transition moves between all states more than likely a battle will take place. During this point of the fight the preponderance of the states being in red or blue will be the indicator of the momentum hidden states.

The range of the report is included to provide a subcategory of either a near classifier or a far classifier. The range delimiter is looking at the last third as a far, while the first two thirds are considered the near. In increasing complexity scenarios, this same concept capturing reports would be included in indirect firing.

Data Pre-Processing

For this research, data was generated using OneSAF. Each Scenario was conducted 20 times with 10 to train the model and 10 to validate the model. We extracted three of the available files. The first two were the weapons firing data and the sensor data. As described in the observable states, we captured the event, with executer side and the range. The third file provided force strength data. The strength data is utilized for evaluating the model against the COFM Calculations. The files were ordered and merged based off time stamp. Data was further cleaned to allow for the highest priority recorded per time stamp. The priority was based off contact, where direct fire contact was prioritized over visual contact. Then actioners side where the opposition force was prioritized. Then finally distance. The states were classified into an 8-state model. The time stamps were normalized to compare the HMM to the scenario. The mode of the observable state was taken to show the preponderance of states during the time stamp. Figure 3 shows the transitions between observable states.

Figure 3: Scenario 1 Observable State Transition Chart



This model was created using the embedded algorithms in HMMLearn version 0.3.0 (2023). The program received the state input and created a sequence of a to h based on observed states. Then we conducted sequence padding to the maximum sequence length to ensure uniform length. The HMM was initialized with hidden state transition matrix and emission values. Utilizing the Baum-Welch algorithm, the HMM was fit to half of the iterations. The algorithm iteratively refines model parameters to maximize the likelihood of the observed sequences given the model. This resulted in the fitted emission probability table (Table 2, 3) and hidden state transition matrix (Table 4, 5).

Table 2: Fitted Emission Probabilities Scenario 1

	Friendly Momentum	Opposition Momentum
Blue Shoot Near	.083	.003
Blue Shoots Far	.010	.002
Red Shoots Near	.006	.013
Red Shoots Far	.013	.004
Blue Sees Near	.280	.670
Blue Sees Far	.560	.010
Red Sees Near	.016	.200
Red Sees Far	.031	.093

Table 3: Fitted Emission Probabilities Scenario 2

	Friendly Momentum	Opposition Momentum
Blue Shoot Near	.999	.0099
Blue Shoots Far	.001	.390
Red Shoots Near	.<.001	.0032
Red Shoots Far	<.001	.033
Blue Sees Near	.<.001	.032
Blue Sees Far	.<.001	.200
Red Sees Near	<.001	.070
Red Sees Far	<.001	.260

Table 4: Hidden State Transition Matrix Scenario 1

	Friendly	Opposition
Friendly	.99	.0089
Opposition	.01	.99

Table 5: Hidden State Transition Matrix Scenario 2

	Friendly	Opposition
Friendly	.999	.001
Opposition	.001	.999

Results

The Hidden Markov Model resulted in early indication of unit success or failure. In the ambush scenario, 88% of the iterations were successfully classified in comparison to the resulting change in force ratio. Of the iterations that correctly identified the outcome, 73% of the time the model predicted the outcome prior to change in force ratio. In the second scenario prediction results were lower, but successfully predicted the outcome 66% of the time. The figures below were generated to provide visualization for the military planner to be able to quickly utilize. There are five horizontal lines that represent the doctrinally prescribed force ratio for the offensive and defensive operations. There is a single solid line that shows the actual force ratio. This force ratio represents what the COFM calculator would show if it was continuously updated with perfect data throughout the scenario. The iterations were scored based on if they accurately reflected the result. Further they were scored if the momentum adjusted prior to the change in force ratio or when combat occurred.

Ambush Results

In the ambush scenario there were two predominant outcomes. The first outcome was a successful ambush where the friendly force executed the ambush and effectively destroyed the opposition force. The other outcome was after the initial engagement, the opposition force was able to successfully withdraw while providing effective covering fire or as the friendly force attempted to clear the engagement area, they missed the remaining opposition force and were successfully engaged. Figure 4 and figure 5 show that dynamic.

Figure 4: HMM Misfire

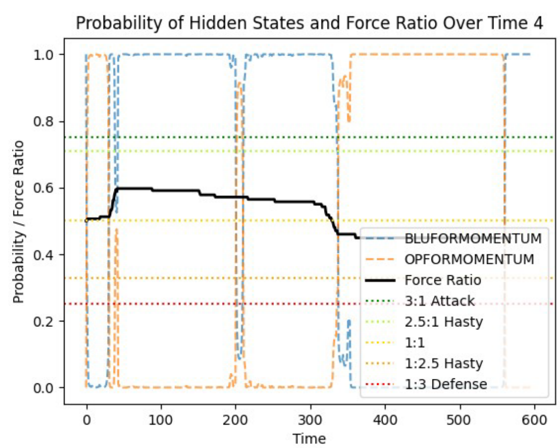
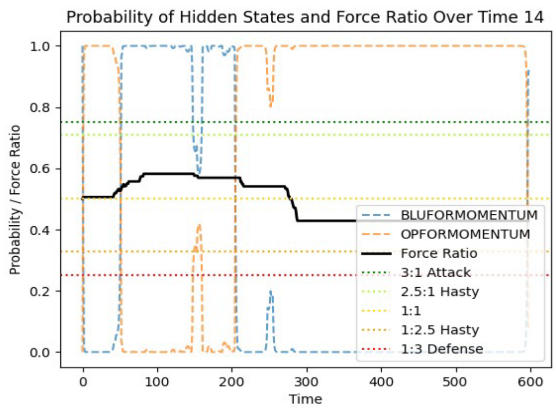


Figure 4 demonstrates when the model failed to both correctly predict and provide a prediction prior to the force ratio. Starting at approximately timestamp 40, the force ratio continues to decrease. During this time the model incorrectly predicts the friendly force still has the momentum. Figure 5 shows that the model successfully predicts the opposition forces' victory correctly and early. This model is interesting in that it successfully predicts the friendly forces' momentum correctly in the beginning of the battle and then successfully transitions to show the opposition force has the momentum and ultimately counters the ambush. This demonstrates the flexibility of the model to receive additional information and adjust its prediction.

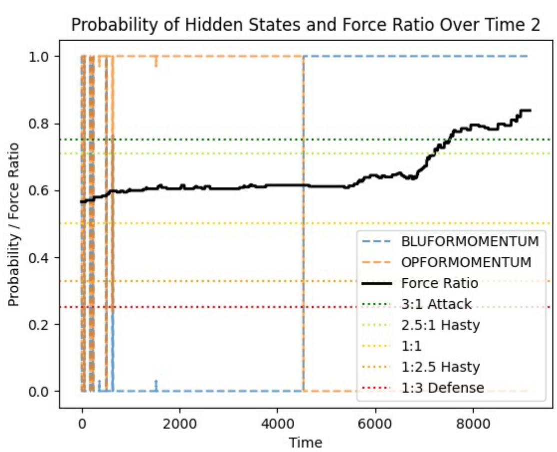
Figure 5: HMM Successful Friendly Momentum



Shaping Scenario Results

The second scenario focused on the Attack Aviation conducting an effective shaping operation to reduce the opposition force 3:1 required for the armor attack. Iterations of this scenario varied on the effectiveness of the shaping operation and the timing of the friendly force engaging the opposition force. Figure 6 demonstrates the model effectively showing success prior to large attrition in the opposition force.

Figure 6: HMM Successful Shaping



Discussion and Future Directions

This experiment demonstrated the value of utilizing HMMs for potential planning tools and to provide support to after action review processes. The HMM was able to indicate the outcome of the operations earlier than having visibility on the actual force ratio derived from the units depicted in the simulation. Further the observed data can be collected without requiring a perfect picture of the operation. This allows for the potential to scale the model to higher echelons.

This experiment was limited in size and scope of the scenario. Each scenario was a single tactical task. In turn there was not an action then counter action which would provide a transition point in understanding the momentum of the fight. The scenario was developed and executed relying on the automated features of OneSAF. Further research is needed to validate these methods with live training scenario. Providing a more complex scenario across multi domain operations would provide observable data to strengthen the HMM's predictive outcome.

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