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MEASURING THE EFFECTS OF KNOWLEDGE ON COMBAT OPERATIONS

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Although it is clear that information has a far-reaching effect, quantifying or measuring that effect is far from well understood. Such an understanding is important to the Army, particularly at time when it is spending a considerable amount of its scarce investment capital on establishing information age links across its forces (the so-called *digitization* of the Army). As it transforms itself, the Army needs information-age analytic tools to help it make the best choices possible. Chief among the analytic tools required are: (1) an acceptable quantifiable measure of *valuable information*, that is, information that adds to the commander's *knowledge* of the combat situation he faces, and (2) measures of effectiveness (MOEs) that reflect the effects of knowledge on military outcomes. In this paper, we suggest a probability model of knowledge using information entropy to measure the amount of uncertainty in the commander's current knowledge of the battlespace, his current *situation awareness*. The knowledge metric developed is also used to explain relative *information superiority* and a way of thinking quantitatively about *information dominance*. Finally, we illustrate the use of the metric with a new measure of non-linear dominant maneuver that incorporates knowledge and speed to assess the degree to which a friendly unit controls a battlespace.

INTRODUCTION

Information has always been an integral part of military operations, from the earliest days of organized combat to today's modern armies. Commanders have always devoted considerable resources to improving intelligence reconnaissance and surveillance techniques while at the same time attempting to protect information about their own forces from the enemy through concealment and deception. The assumption is that the more a commander knows about the situation on the battlefield – especially what he knows about the enemy forces, the better he is able to employ his forces and therefore prevail over the enemy.[1] Indeed, there are several historical examples that bear this out. In discussing Cyberwar for example, Arquilla and Ronfeldt (1993) describe how twelfth century Mongols used information to prevail against superior armies.

> "...Mongol doctrine relied for success almost entirely on learning exactly where their enemies were, while keeping their own whereabouts a secret until they attacked. This enabled them, despite chronic inferiority in numbers, to overthrow the finest, largest armies of Imperial China, Islam, and Christendom."

Unfortunately, little has been done to establish a clear relationship between information and the outcome of military operations.[2] Part of the problem is that, unlike combat power, it is difficult to understand the many ways information affects military operations. For example, suppose the friendly ground commander knows the location of only 30% of the enemy forces. There are several situation dependent actions he might take:

- If he possesses a large array of weapons with a commensurably large stockpile of ammunition, he might target the known 30% with precision weapons and attack other "hunch" locations with area weapons. In this case, the limited knowledge would result in 30% or more of the enemy's force destroyed – a "good" outcome.

- If he feels that his combat power is inferior to the enemy's, or that he has insufficient weapons to guarantee the destruction of the known 30% of the enemy force, he may choose to avoid combat until he can obtain more weapons and more information or until he achieves some other tactical advantage. This outcome is favorable to the enemy in that the enemy commander might take advantage of the delay to launch his own attack.

- If he has just enough combat power to destroy the entire enemy force, he may wish to delay until more information is available concerning the disposition of the other 70% of the enemy force in the hope that he can "make every shot count". As in the previous case, delay could favor the enemy.

If we add what the enemy commander knows, several other possibilities arise. The point is that there appears to be no tidy relationship between information available to the commander and the best way to proceed. Several other factors need to be assessed. However, this does not mean that we can do nothing. There are several "first principles" that can be extracted by examining some special cases. In this paper we make an attempt by proceeding from a simple example to develop a knowledge metric and then by applying this metric to a measure of combat outcome.

KNOWLEDGE AND VALUE

Information possesses two important attributes, *value* and *quality*. Information has value if it informs the commander and thereby adds to his knowledge of the combat situation. Consequently, when we refer to "knowledge" we really mean relevant and therefore "valuable information." Information quality depends upon its accuracy, timeliness and completeness. It is not always the case therefore, that valuable information or knowledge is of high quality. Conversely, quality information may have little or no value, i.e., it may be extraneous information of little or no value and thus may even detract from knowledge.

In gathering information from sensors and sources, the commander seeks information that has value, usually expressed in terms of Critical Elements of Information (CEI). The problem is that he is rarely able to accurately assess the quality of the information he receives. Consequently, he must generally assume that part of what he "knows" may be inaccurate. Continuing with the simple example above, the valuable information to the friendly commander is the location of the enemy forces. We asserted in the example that he "knows" the location of 30% of those forces. We said nothing of the quality of that information. Suppose that the enemy was capable of using sophisticated deception techniques so that only half of the known forces are actually where the friendly commander thinks they are. This raises several issues with respect to the decisions the commander might make. If he suspects he is being deceived, he may choose to wait in all cases until more reliable (i.e., quality) information is available. If he does not suspect, then he may act as before, producing different, and perhaps less desirable, outcomes.

This suggests a useful information taxonomy. Suppose we let K be the measure of valuable information or knowledge available to the commander. In some cases, K may be a simple count as for example, in the preceding simple example. If the enemy force consists of N entities (units say) capable of being targeted, then $K = .3N$. That is, the commander knows the location of $.3N$ of the enemy units. For both sides, then K has two components: knowledge that is of high quality and knowledge that is of little or no quality, and $K = K_c + K_i$. In the example, $K_c = K_i = .15N$. Typically, K is multidimensional, consisting of several information elements such as enemy posture, unit(s) identifications, etc. It is important to note with all of this that the commander likely does not know that he is being deceived and therefore although this construct may be useful for analysis, it must be used cautiously.

MEASURING KNOWLEDGE

In a combat area of operations, gaining knowledge is as much a contest as is maneuver and the effective application of firepower. Once a unit arrives in the area of operations, we can expect it to be configured for offensive or defensive operations. The enemy is now a full player, actively attempting to achieve its objectives and at the same time, preventing the friendly forces from achieving theirs. For this reason, we consider relative measures beginning with *relative knowledge*. We start with three definitions:

Definition 1: A unit *controls* an area when it is able to operate within the area at will. It does not imply that the enemy is excluded from the area, only that the friendly unit is able to exert its influence at will at all points in the area and at all times.

Definition 2: The *unit control radius* is the minimum of the following: the maximum effective range of the unit's organic and supporting indirect fire weapon systems, the maximum effective range of its organic and supporting sensor systems, and the radius of its assigned area of operations.

Definition 3: *Knowledge* is the degree to which a unit commander has cognizance of enemy and friendly force dispositions within its control radius, i.e., has *situational awareness.* We denote unit knowledge for Blue unit *i* and Red unit *j* as $K_{B,i}$ and $K_{R,j}$ respectively.

Situational awareness in Definition 3 can be equated to knowledge about the CEI and would include such problematic elements as assessments of enemy posture and intent. The CEI or relevant information elements are the ingredients needed to formulate the *common picture* of the battlespace and the degree to which this picture is clear to the unit commander constitutes his situational awareness, or knowledge. We may learn of enemy intent directly from sources and sensors, or it may be inferred from the knowledge the commander possesses about enemy force dispositions.

A Probability Model

Although knowledge is multidimensional, for purposes of this discussion, we will continue to assume a single element of information constitutes the CEI. Expanding the discussion to include multidimensional cases just complicates the mathematics while obscuring the message.[3]

Continuing with the earlier example, we assume that the CEI consists only of the location of the enemy targets (or a critical subset of them such as the location of all artillery batteries). Suppose, for example, the friendly commander has intelligence information that indicates that the enemy order of battle consists of n enemy units (targets). For simplicity, we assume that all of the units are the same and the friendly commander wishes to locate those within his control radius in order to bring them under fire. We let U represent the number of units located within the control radius, ($U \in \{0,1,2,\cdots,n\}$). We assume U is a random variable and $P(U = u)$ is the probability that u of the n targets within his control radius have been located.

The initial distribution on U depends upon the information available to the commander from his sensors and sources. On initial deployment, the information available is generally provided by the Initial Preparation of the Battlefield (IPB) process. In the worst case, no information concerning the location of enemy units is available and therefore $P(U = u) = 1/(n+1)$. That is, it is equally likely that any number of enemy units, up to n, are located within his control radius. As additional sensor reports arrive, the probability distribution is refined. Ideally the final distribution assigns probability 1 for $U = \mu$ and 0 for $U \neq \mu$. However, in reality, it may be the case that the location of several of the units (targets) will not be known with certainty in time for the commander to make a decision.

Before proceeding further, it is useful to examine some of the important factors that affect the probability distribution on U:

1. **The number of confirming reports:** Multiple confirming reports on the location of enemy targets tends to concentrate all of the probability on some fixed number of units in the control radius, u_f, so that $P(U = u_f) \to 1$ and $P(U \neq u_f) \to 0$.

2. **The number of dis-confirming reports:** Dis-confirming reports increase uncertainty especially if the reports are from equally reliable sources. The effect on $P(U = u)$ is that it tends to "flatten", the worst case being $P(U = u) = 1/(n+1)$. Both this phenomenon and the first factor are included in the formulation of the knowledge metric below.

3. **The reliability of the sensors and sources:** In some cases, the assessment of reliability is subjective, especially when assessing the reliability of human intelligence sources (HUMINT). Sensor platforms generally have an engineered reliability that varies with environmental conditions. Unreliable reports tend to be discounted and possibly ignored if the reliability is sufficiently degraded. To the extent they are not ignored however, the effect on $P(U = u)$ is the same as in the second factor.

4. **Terrain occlusions:** Sensors and sources requiring clear fields of "vision" are severely degraded by terrain occlusions. The effect is to reduce the number of reports therefore slowing the convergence of $P(U = u)$.

5. **Multiple phenomenology:** Confirming reports on units from different sensor types increases the reliability of the reported detections and therefore speeds the convergence of $P(U = u)$.

6. **The age of the information received:** The lack of recent reports reverses the convergence effects of any previous reports on the location of the enemy targets—especially if we assume that we are confronting a maneuvering enemy.

Evaluating Sensor Reports

This suggests that we must next examine how the sensor reports refine the probability distribution on U. We begin by letting $V \in \{0,1,2,\ldots,n\}$ represent the number of enemy units in the friendly commander's control radius whose location has been reported by the sensor suite.

V is also taken to be a random variable and $P(V=v)$ is the probability that the number of units within the control radius located by the sensor suite is v. However, this number is conditioned on the (unknown) number of enemy units in the control radius, μ. Consequently, we focus on $P(V=v \mid U=\mu)$ for $\mu \leq n$.[4] If we assume that the sensor reporting is capable of locating each single enemy target with probability q, then the conditional probability is binomial with distribution:

$$P(V=v \mid U=\mu)=b(v:\mu,q)=\binom{\mu}{v}q^{v}(1-q)^{\mu-v} \text{ for } v=0,1,\ldots,\mu.$$

This construct can easily be adapted to accommodate varying levels of resolution. At the lowest level, q is a composite probability representing combined probability that all sensors and sources can locate a target. At a higher level, we let q_j be the probability that sensor j locates a single target. Both levels are amenable to the updating and knowledge calculations that follow.

We next assume that the commander must make a decision within some period of time thus limiting the number of sensor reports that can be used to refine the initial probability distribution. If we further assume that sensor reports are processed as they arrive, then $P_i(U=\mu \mid V=v)$ for all $\mu=0,1,\ldots,n$ at the ith sensor report is given by Bayes' formula:

$$P_i(U=\mu \mid V=v)=\frac{P_{i-1}(U=\mu)b(v:\mu,q)}{\sum_{u=0}^{n}P_{i-1}(U=u)b(v:u,q)},$$

where the prior probability for the ith sensor report is $P_{i-1}(U=\mu)=P_{i-1}(U=\mu \mid V=v)$. In this formulation, a sensor report consists of an estimate on the location of v targets within the control radius.

Information Entropy Model

As each sensor report is processed, the commander's knowledge changes as reflected in the changing probability distribution, $P_i(U \mid V=v)$. A useful way to measure the current amount of knowledge is through the use of information entropy or "Shannon information" (See Blahut

(1988) and Shannon (1948)). Information entropy is a measure of the average amount of information in a probability distribution and is defined as:

$$H[P_i(U \mid V = v)] = H_i(U \mid V = v) = -\sum_{u=0}^{n} P_i(U = u \mid V = v)\ln[P_i(U = u \mid V = v)]$$

The entropy function is maximized when the information in the probability distribution is at its lowest (greatest level of uncertainty). Operationally, this occurs when the friendly commander has no sensor assets to deploy and he has no prior knowledge of the location of any of the n enemy targets. In this case, we have $P_0(U = u) = 1/(n+1)$. It is easy to verify that the entropy in this distribution is $H_0(U) = \ln(n+1)$. Conversely, if the ith sensor report confirms with certainty, the location of μ units within the control radius, then $P_i(U = \mu \mid V = \mu) = 1.0$ and $P_i(U \neq \mu \mid V = \mu) = 0$. It is also easy to verify that the entropy in this distribution is 0. At any sensor report, the degree of *certainty* in the updated probability distribution is $\ln(n+1) - H_i(U \mid V = v)$. Knowledge then can be measured using the normalized form of certainty or:

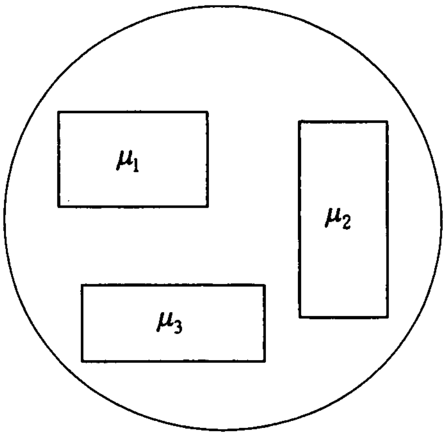


Fig 1: Control radius TAIs

$$K_i(U \mid V = v) = \frac{\ln(n+1) - H_i(U \mid V = v)}{\ln(n+1)}.$$

A normalized form is used for easier comparison of relative knowledge later. This is similar to expressing losses as a fraction of the original force size. The author has referred to this formulation for knowledge as "residual knowledge" thus reflecting the fact that it is based on the remaining uncertainty in the probability distribution (Perry and Moffat (1997)). In subsequent discussions, we drop the subscript on K.

More important than knowing the location of the targets within the control radius, is knowing the location of the enemy targets in the jth Target Area of Interest (TAI). Figure 1 depicts a control area with 3 TAIs. If, in ground truth, the number of enemy targets in each is μ_j, then we have that $\sum_j \mu_j \leq n$. For simplicity, we assume that the TAIs do not overlap so that knowledge is the sum of the knowledge the friendly unit commander has about the location of the enemy targets within the TAIs. In this case, $K = \sum_{j=1}^{3} \omega_j K_j$ where K_j is the knowledge gained concerning the location of targets in TAI_j, and ω_j is the relative importance placed on TAI_j by the friendly commander ($\sum_{j=1}^{3} \omega_j = 1$). A non-weighted average is also possible so that $K = \frac{1}{3}\sum_{j=1}^{3} K_j$. The knowledge metric in this case is a weighted average over the TAIs and represents the commander's level of situational awareness.

Relative Knowledge

Returning now to our original definitions, we have that the "side" knowledge is the average of the side's unit knowledge or $K_B = \frac{1}{m}\sum_{i=1}^{m} K_{B,i}$, and $K_R = \frac{1}{s}\sum_{i=1}^{s} K_{R,i}$. Relative knowledge or relative situational awareness is then defined to be the ratio of the two or:

$$\Gamma = \frac{K_B}{K_R}, K_R \neq 0.$$

Note that the ratio, Γ, is unbounded from above and bounded by 0 from below.

Information Superiority

There is an expectation (fairly widespread) that the information-age Army of the future will enjoy *information superiority*—and the more specific question is how much information superiority the Army might need to enjoy in order to be effective in that future. A "vision" of information superiority pervades Army Vision 2010 (AV 2010), in which such superiority is defined as the "capability to collect, process, and disseminate an uninterrupted flow of information while exploiting or denying an adversary's ability to do the same."[5].

By Defining relative knowledge, Γ, as above, we have a way to assess relative information superiority between Red and Blue:

- If $K_B > K_R$ then $\Gamma > 1$ and Blue has information superiority.

- If $K_B < K_R$ then $\Gamma < 1$ and Red has information superiority.
- If $K_B = K_R$ then $\Gamma = 1$ and there is no information advantage.

Information Dominance

Unlike information superiority, the meaning of *information dominance* is less clear. Other than to state that Information Operations (IO) are conducted to gain information dominance, *AV 2010* is vague about just what it means except to state that:

> "[IO] consists of both offensive and defensive efforts to create a disparity *between what we know about our battlespace and operations within it and what the enemy knows about his battlespace.*" (Emphasis added.)

It would appear that information dominance is achieved when the "disparity" between Blue and Red knowledge is sufficiently large. An information gap definition of dominance implies that for Blue to enjoy information dominance, the difference between Blue and Red knowledge exceeds some threshold value. The relative knowledge metric can also be used to define information dominance by defining values for Γ that correspond to the requisite difference between the two side's knowledge metrics. Suppose we let $0 < \beta < 1$ be the requisite gap to ensure information dominance. For Blue to enjoy information dominance then we must first have that $K_B > K_R$ (information superiority is a prerequisite for information dominance) and that $1 \geq K_B - K_R \geq \beta$. Dividing both sides by K_R gives us the inequality:

$$\frac{1}{K_R} \geq \Gamma - 1 \geq \frac{\beta}{K_R}.$$

This generates the following bounds on Γ:

$$1 + \frac{\beta}{K_R} \leq \Gamma \leq 1 + \frac{1}{K_R}.$$

A similar calculation can be made to assess the bounds on Γ for Red information dominance. Therefore, given a requisite knowledge gap for information dominance, we can specify conditions on relative knowledge that must be met to ensure that dominance is maintained. Thus we infer a relationship between information superiority and information dominance.

It seems logical to discuss information dominance occurring at some point where one or both sides have a knowledge that exceeds some threshold. That is, there is a qualitative difference between relative knowledge of $\Gamma = 2$ when $K_B = .01$ and $K_R = .005$ and when $K_B = .8$ and $K_R = .4$. Furthermore, we cannot assume that this threshold is the same for both Red and Blue. It may be that the two sides may have different information requirements. If we set the threshold levels to be $0 < \delta_R, \delta_B < 1$, for Red and Blue respectively, then information dominance depends upon the relationship between K_B and K_R and between δ_B and δ_R. Figure 2 summarizes the various information dominance possibilities.

Note that in the "neither dominate" case, it is still possible for one or the other side to possesses

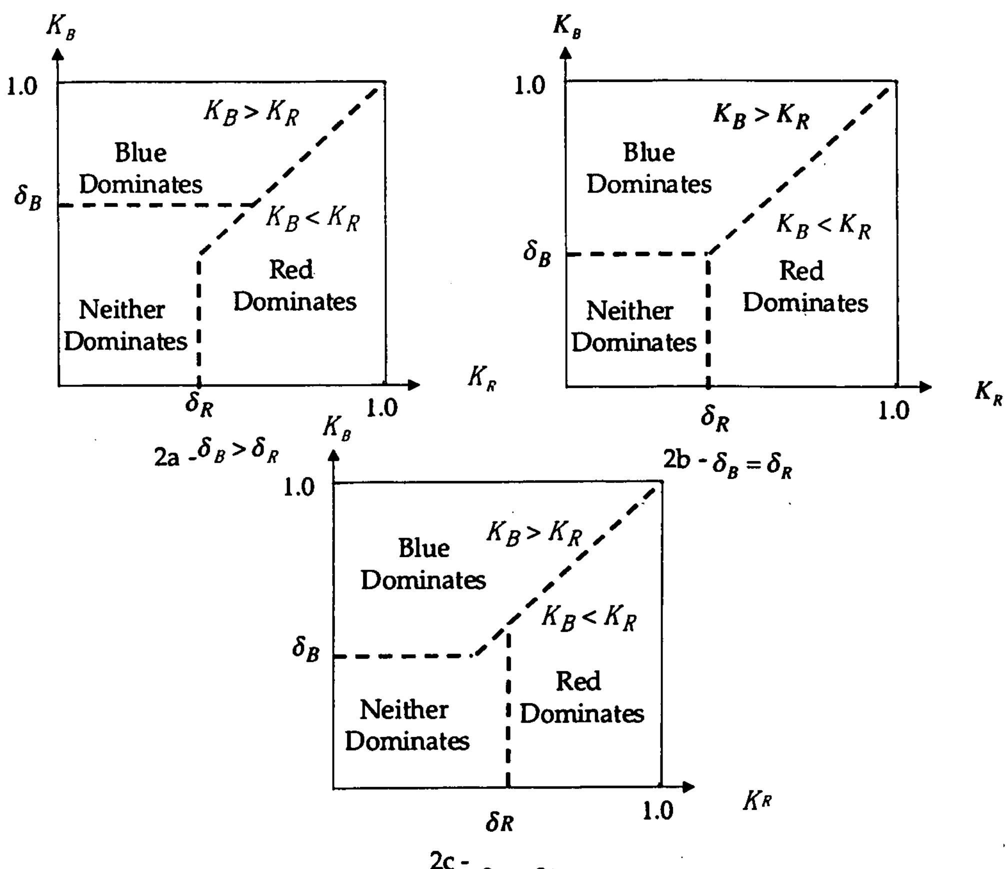


Fig 2 - Information Dominance

information superiority when neither has information dominance. In the other two regions, either Blue or Red enjoys information superiority as well as information dominance.

The diagram helps to understand the relationship between information superiority and information dominance. If, as stated in AV 2010, information operations are used to gain information dominance by increasing the gap between Blue and Red knowledge, then we can see that Blue would use offensive operations to destroy, disrupt and deceive Red C4ISR to move to the upper left of the diagram. Similarly, Red would do the same to move to the lower right. It is not clear just how useful this construct is in analysis. Assigning meaning to the fractional threshold values may be problematic. However, it is useful to illustrate the effects of information dominance in situations where one side or the other enjoys information superiority.

In subsequent calculations, knowledge and relative knowledge are used to assess the effect of information superiority and dominance (or the lack of them) on an information-age measure of combat effectiveness.

THE EFFECTS OF KNOWLEDGE

Next, we examine how traditional measures of combat might be replaced or modified by information-age measures that account for the expanding role of information in combat operations. Traditional measures of combat outcome are generally attrition-based and consist of such metrics as the force loss exchange ratio (FLER), surviving friendly forces and the movement of the forward line of troops (FLOT). Although these metrics will continue to apply in some cases, success on the non-linear battlefield of the future will not focus entirely on inflicting or avoiding casualties, but rather increased emphasis will be placed on *dominating maneuver* to achieve operational objectives. One measure of dominant maneuver is battlespace control. That is, to what extent does the friendly commander control a three-dimensional area of operations.

Battlespace Control

The control of an area of operations depends upon the ability to exercise actual or virtual presence in the area. Implicit in the term "presence" is the ability to prevail in any encounter with the enemy. Battlespace control should take on increasing relevance as ground units gain the technologies -- e.g., networks of joint sensors, enhanced command and control systems, -- that promise to give them enhanced situational awareness. In addition, technologies such as more efficient propulsion systems, lighter and more maneuverable weapons systems will allow maneuvering units to quickly move to threatened areas of the battlefield. This, then, should enable future Army units to dominate large areas without maintaining physical contact with each other to the extent that armies have since the First World War.

Dominating the Battlespace

The degree to which a unit controls the overall battlespace can be measured in terms of its engagement geometry and the geometry of the target Named Areas of Interest (NAIs). The assumption implicit in such a measure is that in the future, combat units will be deployed to widely dispersed locations in the AO to control areas deemed critical to the overall success of the campaign. The coordination of widely dispersed forces places a premium on advanced command and control systems that increase the commander's knowledge of the combat situation. We also expect that future forces will be capable of moving faster than today's forces thus increasing the battlespace they are able to control as a function of time as well as distance. Speed then is another component of battlespace control. In developing a metric that adequately reflects the essential aspects of battlespace control in the future, the geometry of the friendly force employment, its ability to collect, process and disseminate information and the speed at which it is able to deploy and re-deploy must be considered.

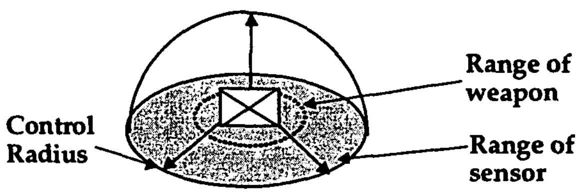


Fig. 3--Battlespace Geometry

Relative Geometry

The unit employment geometry is a hemisphere (Figure 3) with radius r_i, the unit *control radius*. Therefore we can calculate the battlespace controlled by unit *i* to be:

$$B_i = \frac{2\pi}{3} r_i^3$$

and the total battlespace controlled by the friendly forces to be, *B*, the sum of the space controlled by its units or

$$B \leq \frac{2\pi}{3} \sum_i r_i^3 .$$

The inequality refers to the possibility that several of the units may overlap coverage.

The NAIs in the AO are generally described as rectangular areas (although they need not be). If we consider the space above the NAI as part of the battlespace, then the quantity comparable to B is $N = \sum_j N_j$ where N_j is the volume of the jth NAI. Battlespace control then can be measured in terms of the relative size of B and N.

If we let D represent the control metric, we observe two basic conditions. First, if the friendly force is too far removed from the NAI, it is not able to exercise control over it. We can describe this in terms of overlapping space, i.e., if $B \cap N = \varnothing$, then the measure of battlespace control is 0 or $D = 0$. Secondly, if $B \cap N \neq \varnothing$, then there is some overlap between B and N, and dominance can be defined to be the ratio of the overlap to the size of N. If B is contained in N ($B \subset N$), then $D = \frac{B}{N}$. If N is contained in B ($N \subset B$), then $D = 1$. For all other cases, $D = \frac{S(B \cap N)}{N}$, where $S(B \cap N)$ is the volume of the overlap. We now examine the contribution of speed and knowledge to D.

Speed

Beginning with speed, we develop a factor of D that reflects the degree to which the Blue units are able to move from one NAI to another and thereby increase the battlespace they control. Consider the following example. Suppose the AO consists of 5 NAIs as depicted in Figure 4. The black dots in the NAIs represent the ideal location from which the NAI can be controlled. The distance between NAI_i and NAI_j is denoted as $d_{i,j}$. If we assume that all of the units in the force are positioned to cover at least one NAI, then what

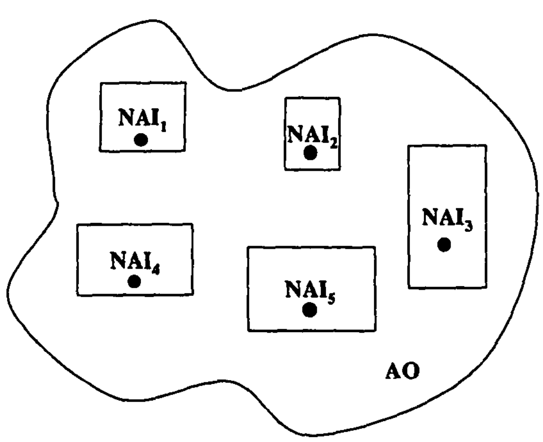
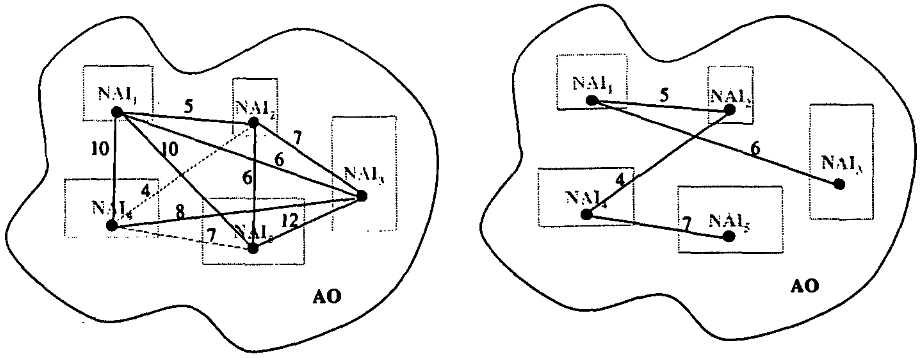


Fig. 4: AO with 5 NAIs

we would like is some measure of the time required for any or all of the units in the AO to move to another NAI. One way to do this is to find the shortest total distance that connects all of the NAIs and assess the time it would take to traverse this distance at the nominal unit speed. We do not mean to imply that any single unit would travel this distance, rather we seek a one-dimensional measure of a two-dimensional space that serves as an upper bound on the actual distances traveled. Another approach would be to find the longest distance between NAIs and use this as the measure. The argument in this latter case being that at nominal unit speed, all other moves can be accomplished in the time it takes to move the maximum distance.

In this work, we choose to use the former more conservative, *minimal spanning tree* approach (Ford and Fulkerson (1962)). Figure 5a records the distances between the NAIs and Figure 5b depicts the minimal spanning tree. The total minimum distance in this special case is $d = 22$.

For simplicity, we now assume that all units travel at the same nominal speed everywhere in the AO. We can easily relax this assumption without too much difficulty if the units involved in



a. NAI Network **b. Minimal Spanning Tree**

Fig. 5: Minimum Distance to all NAIs

the force are dissimilar and therefore travel at varying speeds along the connecting routes or if the move is opposed, or in some other way the path is impaired. The time required by any of the units to travel the 22 unit distance is $\tau = d/s$ where s is the nominal speed of the friendly units in the force.

The objective of this analysis is to illustrate how speed effects the ability of the force to control the battlespace. We would expect that as τ gets small, i.e., as either the distances get smaller or the units can travel faster, the ability of the force to cover the battlespace and therefore improve its ability to control it, increases. Mathematically, we seek a function of τ, $g(\tau)$, that increases in value as τ decreases. One such function is $g(\tau) = e^{-a\tau}$ for $\tau \geq 0$. In this formulation, the exponential coefficient, $a > 0$, is a *shape* parameter. Its function is to model the rate at which the curve depicted in Figure 6 approaches 0 as τ gets large. For large *a*, $g(\tau)$ decreases rapidly whereas for small *a*, the reverse is true. In one sense, we can refer to $g(\tau)$ as an *agility* factor, i.e., a measure of the degree to which the force is capable of maneuvering between NAIs.

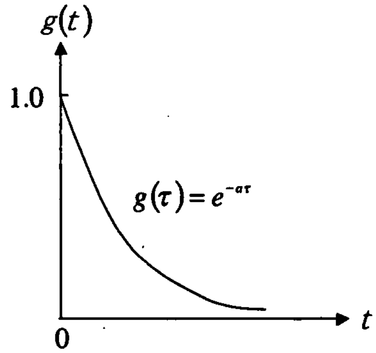


Fig. 6: Force Agility Factor

A rapid force will experience a large agility factor in that the time required for it to travel to all of the NAIs will be relatively small. Conversely, as the force slows down, the agility factor decreases because of the increased time required traveling to the NAIs. Finally, we note that the factor is between 0 and 1 and therefore can be applied directly to the battlespace control metric, *D*, so that we get $D' = g(\tau)D$. Agility then is a force divisor! That is, if control of the battlespace is predicated in any way on relocating units, then the time required to do this – however quickly – detracts from battlespace control. Using the agility factor in this way highlights the fact that in the absence of $g(\tau)$, the metric *D* is overstated.

Knowledge

We now examine the effects of knowledge on battlespace control. Recall that the knowledge metric was defined as the ratio of Blue to Red knowledge densities or $\Gamma = K_B / K_R$ and that therefore $\Gamma \in [0, \infty)$. If $\Gamma < 1$, then Red has information superiority over blue; if $\Gamma > 1$, Blue has information superiority; and if $\Gamma = 1$, both are equally competent and information is not a factor.[6] If we apply this directly to the agility modified battlespace control metric, we get:

$$D'' = RD' = \Gamma g(\tau)D.$$

For $\Gamma < 1$, the battlespace metric is reduced indicating that Red information superiority has an adverse effect on Blue's ability to control the battlespace. For $\Gamma > 1$, the metric is increased reflecting the value of Blue's information superiority on battlespace control. For $\Gamma = 1$, Blue and Red are equally capable and information has no effect on battlespace control. In this case, it is clear that when Blue enjoys information superiority ($\Gamma > 1$), knowledge is indeed a force multiplier.

SUMMARY

The critical variable for determining the contours of the information-age Army is information. The degree of information superiority that one side might be able to achieve over the other is a necessary component of effectiveness.

Gaining knowledge is as much a contest as is maneuver and the effective application of firepower in military operations. Thus, we have focused here on the development of a measure of relative knowledge using a traditional probability model. Knowledge or valuable information is then measured as the uncertainty resident in the probability distribution over the battlespace situation. The probability distribution is modified through the use of Bayesian methods to account for periodic sensor reports.

The relative knowledge metric may be useful in quantifying information superiority and in developing a model of information dominance. The high degree of superiority that one side can conceivably obtain over another in the information-age is what makes this construct so critical and potentially revolutionary, on the one hand. On the other hand, if neither side can achieve information dominance over the other -- or even significant degrees of information superiority -- in an information-age contest, that era's technologies and its much heralded benefits may not prove to be as one-sided or decisive, for either side, as enthusiasts tend to assume.

First and foremost among MOEs for the Army of the future should be those that measure the effect of knowledge on combat operations. Ground forces may no longer measure success or failure by their ability to maintain a continuous FLOT but, rather, by the amount of both immediate and surrounding battlespace a given unit can control at a particular time. Even if FLOT movement continues to endure as an important yardstick, its measurement will be affected by the role that information plays in such calculations (a subject explored in Darilek et al (1999)). The ability to maneuver ground units more effectively than at present (to maximize their operational reach) is what information-age technologies promise to provide. The metrics introduced in this paper offer a beginning at understanding the relation between knowledge and its effect on combat outcomes in a quantifiable way.

ENDNOTES

[1] This generally implies that the commander is willing and able to act on the information made available to him, that is, it is possible for a commander to go down to defeat knowing a great deal about the enemy and friendly situation. In this work, we assume that information of value will be acted upon.

[2] There have been some attempts. For example, Strukel et al (1993) developed a detailed model of reconnaissance and showed how information from sensors and sources reduced the amount of entropy present in the probability distribution on target location. Conolly and Pierce (1988) suggest simple target search models that use the increase in Shannon information about targets to develop optimal search strategies. Although not stated explicitly, these models assume that optimal search algorithms lead to improved combat outcomes. Similarly, Strukle and associates assume that increased efficiency in locating targets improves combat outcomes. However, in neither case is there a mention of how combat outcomes are affected. Another attempt is reported in W. Perry and J. Moffat (1997). However, combat outcome is measured only in terms of enemy and friendly attrition. The use of information to avoid combat or to achieve other objectives was not explored.

[3] For example, location of a unit can be modeled as a bivariate normal distribution. Unit type can be estimated by comparing equipment counts against templates. The equipment counts are binomial but because several pieces of equipment comprise a unit type, the resulting distribution is multinomial. These concepts are more fully developed in Perry and Sullivan (1999).

[4] It is possible, of course, to have $\mu > n$ provided that we allow for false reports. The Poisson distribution would be appropriate in this case. For simplicity, we omit this complication here. See Perry and Moffat (1997) for a complete treatment of false targets in the same context.

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[5] For a discussion of "information superiority" and "information dominance", see *Army Vision 2010*, p17, also *Concept for Future Joint Operations: Expanding Joint Vision 2010* Chapter 5.

[6] This may not be true in all cases. If the number of alternative hypotheses for Blue, n, is large compared to the number for Red, m, or vice versa, then either $\ln(m+1) >> \ln(n+1)$ or vice versa and normalization may mask this anomaly.

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