Intent Inference Using a Potential Field Model of Environmental Influences

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Abstract
-Intent inferencing is the ability to predict an opposing force's (OPFOR) high level goals. This is accomplished by the interpretation of the OPFOR's disposition, movements, and actions within the context of known OPFOR doctrine and knowledge of the environment. For example, given likely OPFOR force size, composition, disposition, observations of recent activity, obstacles in the terrain, cultural features such as bridges, roads, and key terrain, intent inferencing will be able to predict the opposing force's high level goal and likely behavior for achieving it. This paper describes an algorithm for intent inferencing on an enemy force with track data, recent movements by OPFOR forces across terrain, terrain from a GIS database, and OPFOR doctrine as input. This algorithm uses artificial potential fields to discover field parameters of paths that best relate sensed track data from the movements of individual enemy aggregates to hypothesized goals. Hypothesized goals for individual aggregates are then combined with enemy doctrine to discover the intent of several aggregates acting in concert.

Keywords: Intent inference, artificial potential field, information fusion.

1 Introduction

In the military domain, adversarial intent inference is traditionally achieved by the manual fusion of heterogeneous sources of information. These sources include textual reports, maps, and low level sensor fusion products like force aggregates. Moreover, it is the people that are fusers providing additional background knowledge in the process. Because of the increasing availability of cheap sensors and the maturation of network technology, analysts have timely access to terabytes of high fidelity information about battlefield state. This has created cognitive overload. As a result, it is becoming increasingly difficult to fuse this low level information and extract useful inferences about enemy intent from it quickly enough to positively influence the decisions of military commanders.

The battlefield is a noisy, uncertain, and despite increasingly available networked sensors, still only partially observable environment. Many of the proposed approaches to adversarial intent inference which rely on recognition of tactical maneuvers e.g. [1] use Bayesian techniques that encode team maneuvers by statistics on low level information like the velocities and trajectories of individual team members while they are executing a particular strategy. When faced with a novel situation these statistics are used to calculate the posterior probability that the team is executing a certain maneuver. Such statistical techniques have proven effective at recognizing team strategies in sports [1]. However, it is unlikely that such techniques would be effective in the uncertain, dynamic, partially observable, and noisy environment of a battlefield. In team sports there are a small number of players and the movements of all of them are visible at all times. There are also a few clearly defined objectives and the terrain is usually featureless. In contrast military operations are conducted in a variety of terrains with a myriad of objectives both concrete and abstract each of which could have many sub goals necessary to achieve them. Furthermore, in the military domain hundreds of individuals and vehicles may participate in cooperative action to achieve high-level goals. In this environment statistical techniques are likely to be victim to the curse of dimensionality. Hidden Markov Models (HMMs) have been successfully employed for multi-agent plan recognition [2]. However, thus far HMMs have only been proven effective for inference in domains with relatively small feature spaces. Systems that rely on symbolic reasoning e.g. [3,4,5] have had success in developing models of adversarial plans. However, [3] uses a rule-base to reason about enemy intent and rule-bases are error prone and time consuming to both construct and maintain. Furthermore 3, 4, and 5 all rely heavily on user input to provide symbols and annotate them.

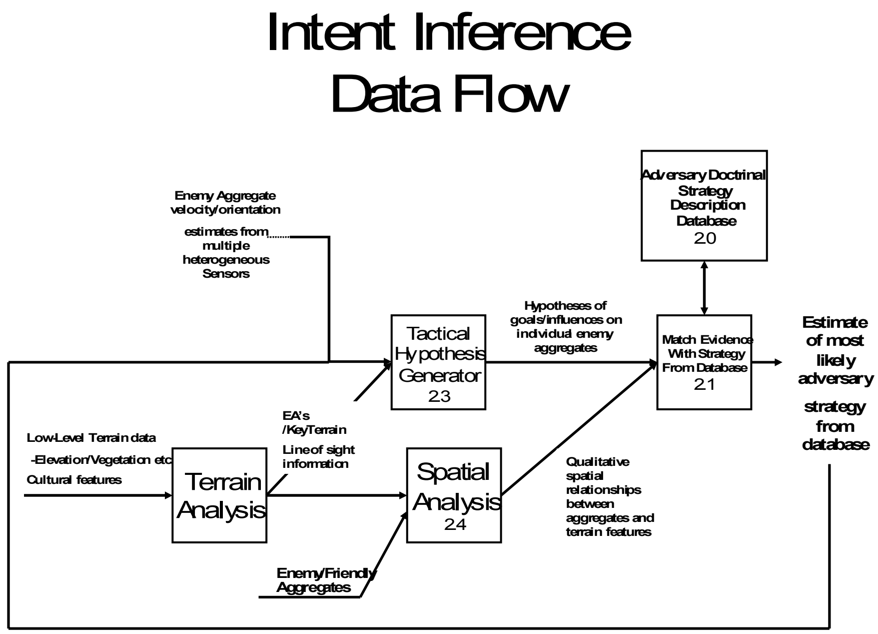

Figure 1 Illustration of Intent Inference Data Flow

Our main contribution is to provide a model of tactical maneuvers based on the analogous physical system of the potential field associated with a grid of electrical resistors. Using this model we can automatically extract and annotate high-level symbols directly by fusing low-level map and heterogeneous sensor data. This model is computationally tractable for systems of thousands of variables and is governed by well studied principles of physics. Furthermore, the model is analytically appealing and generalizable. Concepts of resistance and flow are inherent to any domain that requires adversarial reasoning in the context of moving agents, particularly the military domain. Because of this domain specific concepts can be mapped easily to our model by simply associating domain specific concepts with the physical quantities of resistance and current in our model. The data flow of our intent inference model is illustrated by Figure 1. Military operations are inherently structured. It would be impossible to coordinate large numbers of troops and equipment without training personnel in set strategies for achieving operational goals. These strategies are usually recorded as abstract descriptions and diagrams of specific strategies for various types of operations. An example of an operation is an offensive maneuver to capture key terrain. Documents that contain such information are referred to as doctrine. We propose to exploit this inherent structure by using doctrinal descriptions of tactical operations as templates. We are developing algorithms to fuse situation assessment products with dynamic battlefield sensor data to match against these templates. Furthermore, if we can recognize a particular tactic in an early phase then we can use the doctrinal template to predict future phases of enemy action. Figure 2 shows a typical

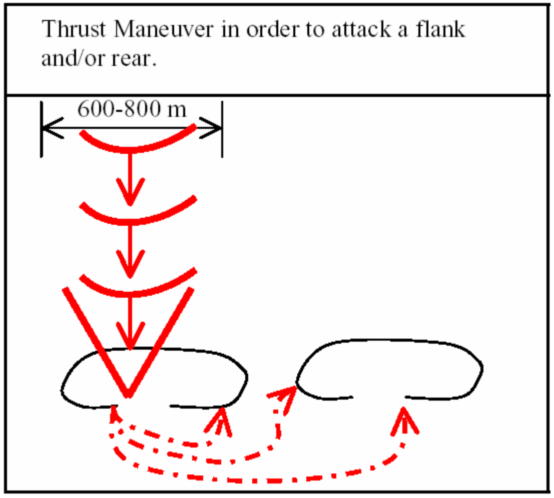

Figure 2 Thrust maneuver

doctrinal template for an offensive maneuver called a thrust. In our system the doctrinal descriptions of preferred enemy strategies are encoded in a database as shown in Figure 1. The description of the representation of these strategies is found in section 2.0. Section 2.1 describes how evidence received from heterogeneous sensors is matched to the most likely enemy doctrinal strategy in the database. Section 2.2 describes the electrical circuit model. Section 2.3 explains how the model can be used to generate hypotheses about the intent of a maneuvering enemy military unit. Section 2.4 describes algorithms for extracting qualitative spatial relationships between battlefield entities.

1.1 Explanation of Key Terrain

Terrain provides an important context for the analysis of intent in a military scenario. Terrain analysts fuse low-level terrain information like elevation and vegetation type, data on weapon systems range and effectiveness, weather, and enemy doctrine to identify high level terrain features like engagement areas (EAs) and Key Terrain. An engagement area is a position in the terrain where a military force will mass weapons fire on an enemy. Typically engagement areas are located in an area of the terrain with little concealment along a likely OPFOR avenue of approach. Key terrain is any area the seizure of which gives a marked advantage to a combatant in a military engagement. These high-level terrain features are critical in the analysis of enemy Courses of Action (COAs). A course of action is a detailed plan for the accomplishment of a military mission, including the arrangement and deployment of forces both spatially and temporally. Courses of action are described with reference to high-level terrain features because these areas are typically where much of the action in a military engagement takes place. Key terrain is also often the goal of tactical maneuvers. Any model of tactical maneuver that uses hypothesized goals as features must include high-level terrain features as possible goals.

1.2 Basic Scenario

The following is the basic scenario that we use in our investigation of modeling tactical maneuvers. There is a battalion-sized echelon of blue forces in a defensive posture on a particular terrain. Blue forces are represented by a set of platoons (B1,B2,…,Bn). The terrain itself is represented as a grid (x,y) with an associated set of Key terrain features (K1,K2,…,Kn). A battalion of red forces is on an offensive maneuver against the blue forces. The red battalion is represented by the set of platoons (R1,R2,...,Rn). A set of templates (T1,T2,...,Tn) reflect doctrinal OPFOR strategies. Each member of the set R can act independently or in a group. The challenge is, given track data for Ri's, to match the current scenario with one of the templates Ti or to identify the scenario as a yet unseen template and to update this assessment as the scenario unfolds

2.0 Strategy Representation

A doctrinal OPFOR strategy can be decomposed into a set of goals and the sub-goals necessary to achieve them including the temporal relationships between those sub-goals. Sub-goals can in turn be described in terms of the actions necessary to achieve them as well as the important objects (key terrain, enemy units) involved. We represent OPFOR doctrinal strategies as directed graphs where nodes represent high-level goals (e.g. Defeat, Occupy, Observe), actions required to achieve goals (e.g. Move to observation point, Assemble), and objects (e.g. Key terrain, OPFOR units) that are involved. Graph edges represent the relationship between a goal and its associated sub-goals, as well as the relationship between actions the actor and the object of the action. By goal we mean a goal in space or a member of the opposing team. Although the notion of a goal is much richer than this, quite often high-level goals in team strategy can be described in terms of spatial goals and opposing team members. For example, the sub-goal assigned to a RED platoon in a military engagement might be to occupy a tactically strong position along an escape route in the rear of a BLUE force platoon.

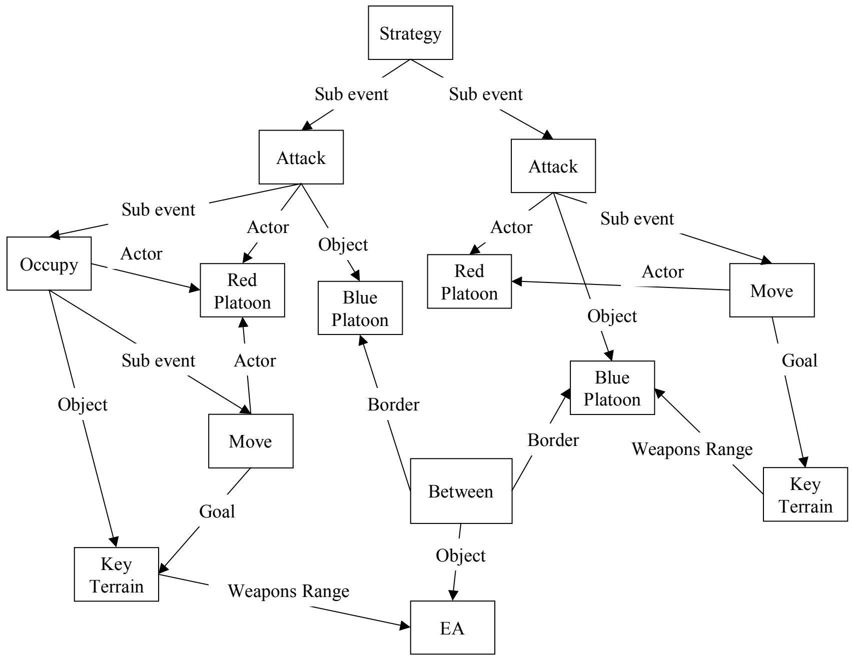

Figure 3 Graph representation of a doctrinal strategy

A high level description for the goal of this platoon might be, *to prevent the retreat of the BLUE force platoon*. However we contend that for the purpose of recognizing this strategy that the spatial goal itself, in this case the tactically strong position, put in the context of is topographical relation to other important entities in the scenario, that is, in the rear of the BLUE force platoon and within weapons range of the RED force platoon is sufficient for encoding this strategy and recognizing it in the future. Finally, edges also represent spatial relationships between objects. The spatial relationship *between* is exceptional and is represented as a node because it relates three objects and as such cannot be represented as a graph edge. Figure 3 shows an example of the graph representing the doctrinal strategy described by Figure 8.

2.1 Strategy Recognition

When presented with a novel battlefield scenario, our system builds a Situation Graph from the evidence of enemy activity and disposition obtained from sensors. The Situation Graph has the same format as the Strategy Graph described in Section 2.0. Sections 2.3 and 2.4 describe how heterogeneous sensor data is fused with terrain data and mapped to Situation Graph nodes. Sub-graph isomorphism using a technique from [6] is used to find the Strategy Graph in the database with the best match to the current Situation Graph. The Strategy Graph with the best match is simply the one with the most nodes and edges in common with the Situation Graph. The Strategy Graph with the best match is identified as the most likely enemy strategy being executed in the current scenario. Matched nodes in the Situation Graph which correspond to Key Terrain are then the best places to task sensors in order to refine the situation assessment.

2.2 Artificial Potential Fields

We use an Artificial Potential Field as our model of a tactical maneuver. Artificial potential fields have been used successfully in robotics [7] for path planning to simultaneously identify a goal for the robot as well as to encode local reactive behaviors. We use the potential field associated with a grid of electrical resistors configured as in Figure 4 to associate low-level data on enemy units with high-level goals and reactive behavior. Each cell as shown in Figure 4(a) is associated with a grid cell in the battlefield as shown in Figure 4(b).

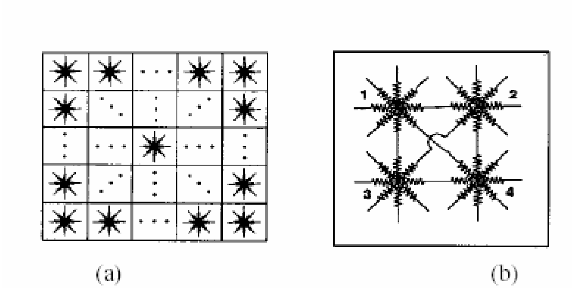

Figure 4 Grid of resistors used to model tactical manuevers

Each grid cell has eight associated resistors centrally tied and attached to the eight neighboring cells. These resistances are analogous to the difficulty, in tactical terms, for a unit moving between a grid cell and its eight neighbors. The following factors contribute to the tactical resistance of a battlefield grid position:

- Canalization
- Presence of adversary units and weapon systems
- Weather
- Terrain trafficability
- Distance to goal
- Concealment and Cover
- Cultural features
- Visibility of adversary units

For a given grid cell, we associate with each of these n factors a resistance R_i. The net resistance of the eight resistors for a grid cell is then given by Equation 1, for details on how the aforementioned features are mapped into resistances see [8]

$$R(x, y) = \sum_{i=1}^{n} w_i \cdot R_i \qquad (1)$$

I

The weights w_i then represent the importance of each of these influences on the resulting resistance for a grid cell. The last item is a factor that reduces the resistance of a grid cell and its coefficient in equation 1 is always negative. This is meant to capture the intuition that a unit on a reconnaissance mission is more likely to pass through grid cells with visibility on adversary units and hence such cells have a lower resistance for such a unit.

We associate a spatial goal $G(x_g,y_g)$ with respect to a maneuvering unit $R(x_t,y_t)$, where (xr_t,yr_t) is the position of unit R at time t, by connecting the terminals of a time dependent voltage souce $V_g(t_a,t_b)$ between grid cells (x_g,y_g) and (xr_t,yr_t). The voltage source is time dependent in that it turns on at time t_a and turns off at time t_b. The voltage of the voltage source remains constant in the range (ta<t<tb).

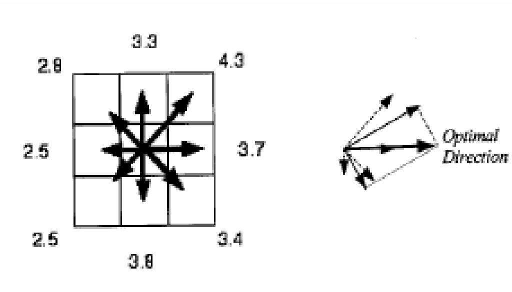

Figure 5 Current flow vectors for a grid cell

For a given grid cell, the resulting current flow in each of its eight resistors is represented by a vector as shown in Figure 5. The direction of the vector is determined by the direction of current flow in the resistor. The magnitude of the vector is determined by the magnitude of the current through the resistor. For each grid cell a resultant vector is calculated by summing these eight vectors and a field as shown in Figure 7 results. Following the field vectors leads to the Goal G(x,y). We have used this model successfully to determine avenues of approach and engagement areas in a piece of terrain [8]. Avenues of approach to a goal are determined by following the steepest field gradient to the goal. Engagement areas are located by finding the points along the aforementioned avenues that have maximum current flow. Figure 2 shows a comparison between a tactical annotation of a map done by an SME and one conducted by our terrain reasoning system. This system also identifies the Key Terrain Features that are input to our intent inference system as shown in Figure 1. Empirical evidence based on experiments tells us that this model captures some of the intuition of military tactical maneuvers [8].

The following summarized from [7] explains the equations that govern current flow through the grid of resistors during the aforementioned time range. Consider a volume *V* that encloses a charge *Q*. For a stationary volume with current density *D* and charge density *p,* Equation 2 holds.

$$I = \oint_S D \cdot ds = -\frac{dQ}{dt} = -\frac{d}{dt}\int_V p \cdot dv \quad (2)$$

Equation 2 relates the current leaving a region with the current density vector through the surface. For steady currents charge density does not vary with time. Considering this, we get Equation 3 which is a statement of Kirchoff's Current Law (KCL).

$$\oint\!\!\oint_S D \cdot ds = 0 \Rightarrow \sum_j Ij = 0 \qquad (3)$$

KCL tells us that the algebraic sum of the current entering and leaving a region is zero. Our grid of resistors model is a discretized version of a surface. As such KCL can be applied to each node of the resistor network. This results in a system of linear equations that can be solved using LU decomposition. We solve this system of equations using GNUCAP [9] an open-source circuit simulation program that we agentified using the RETSINA agent architecture [10].

2.3 Tactical Hypothesis Generation

The APF concept was proposed by Khatib [11] as a way to directly relate high level goals and undesired states to low level control in robots. The concept has also been used successfully in target tracking applications [12,13]. This method associates an attractive potential function with goals in the environment and a repulsive potential function with obstacles. These potential functions then define the potential at each point in the environment with respect to the goals and obstacles. The gradient of the potential function at a point gives a force vector. This force vector can then be used directly as a control input to the robot. In this way, goals as well as policy for the reaction to objects in the environment are encoded. Furthermore, these equations directly link low-level attributes like the position and trajectory of the robot at points in space with its spatial goals. It seems reasonable that if the APF has been used successfully to relate high-level goals to low level position and velocity data for agents that the APF would be a good starting point for a functional form to encode the reverse process. That is to relate low-level sensor estimates of OPFOR velocity and position to possible high-level goals. This is the goal of intent inference (third level fusion).

We use the potential field model described in section 2.2 to relate low level position and velocity estimates of OPFOR units with high level spatial goals. This field is parameterized by (w1,w2,…,wn), the coefficients of the resistances associated with environmental influences from Equation 1, as well as by $V_G(t_a,t_b)$ the voltage source associated with goal G. Consider an OPFOR unit X. A reasonable a-priori estimate for the possible spatial goal of OPFOR unit X is given by the set:

$$\{G_1, G_2, ..., Gm\}$$
$$\forall_i G_i \in K \bigcup B$$

where K is the set of Key Terrain Features and B is the set of all possible blue force aggregates.

We associate with each Gi from this set the voltage $V_{Gi}(t_1,t_n)$. We represent the state of unit X over the interval (ta,tb) by the tuple:

$$\text{State(X)} = \{V_{Gi}(t_a,t_b), w1, w2, \ldots, wn\}$$

This state tuple represents a hypothesis about the environmental influences on the unit R. For example, a high voltage Vy associated with a prospective goal that is a RED platoon Y and a high coefficient of resistance wi associated with areas under the influence of blue units suggests that unit X is maneuvering to reinforce Y while avoiding detection by BLUE units. Conversely, a high voltage associated with a blue unit Z suggests that X is maneuvering to attack Z. Finally, a high negative coefficient associated with areas with a good view of BLUE units might suggest that X is on a reconnaissance mission. The types of vehicles in unit X would also serve to strengthen or weaken these hypotheses. When applied to the circuit grid model described in section 2.2 these state parameters produce a field of vectors as shown in Figure 7. For each of these examples we call the vector field associated with its respective tuple an *influence field* for the unit X.

We expect the maneuver of unit X to be most consistent with the influence field associated with the correct tactical hypothesis about X. That is if the tactical maneuver hypothesis that we propose for State(X) is correct, then we expect the maneuver of X to generally follow the flow of the vectors in the associated influence field. Given a time series of position and orientation estimates for unit X obtained from sensors:

$\{(x_{t1},y_{t1},\Theta_{tr1}),(xt2,yt2,\Theta_{tr2}),\ldots,(xtn,ytn,\Theta_{trn})\}$,

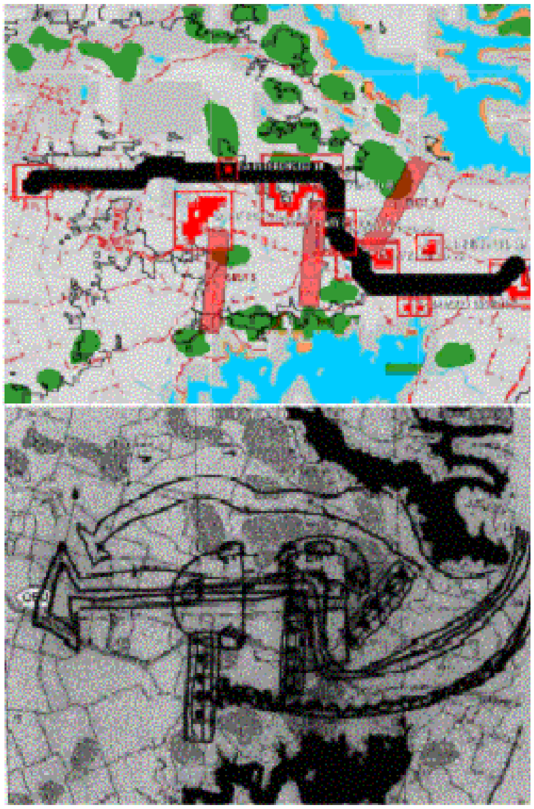

Figure 6 Comparison of automated and SME tactical annotations

where (x,y) is a grid position estimate and Θ an orientation estimate, we can directly compare these estimates to the vectors in exemplar influence fields associated with tactical maneuver hypotheses. We are experimenting with several machine learning algorithms for regressing parameters of exemplar influence fields from examples of various tactical maneuvers provided by military subject matter experts. A vector in exemplar influence field f at grid position x_f y_f can be represented as $(x_f, y_f, \Theta f)$. To generate a tactical maneuver hypothesis we construct the vectors:

$$Ox = (\Theta t1, \Theta t2, \ldots, \Theta tn)$$

And m vectors (one for each possible goal) of the form:

$$Ofi = (\Theta f1, \Theta f2, \ldots, \Theta fn)$$

where the $\Theta ti's$ in Ox are the orientation estimates for R on the interval (a,b) and the $\Theta fi's$ are the orientations of the vectors in the influence field generated for prospective goal Gi and $(x_{fi}, y_{fi}) = (x_{ti}, y_{ti})$. A simple nearest neighbor selection criteria with a euclidean distance metric is used to pick the Ofi that is closest to Ox. The resulting hypothesis is then that the spatial goal of unit X is Gi and the tactical maneuver associated with exemplar f is identified as the most likely tactical maneuver for unit X.

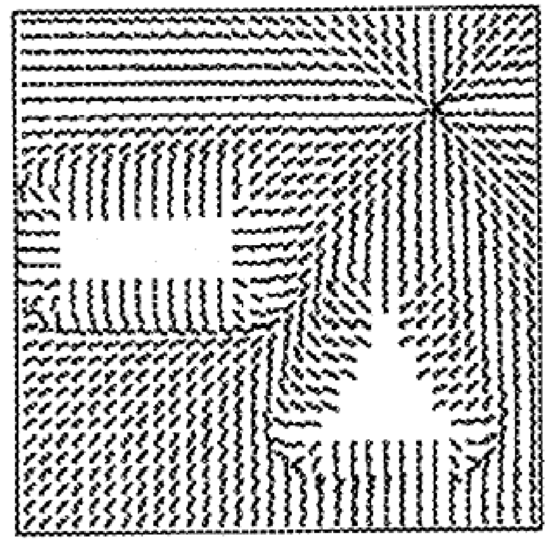

Figure 7 Vector Potential/Influence Field

2.4 Spatial Relationships

In many tactical maneuvers the spatial configuration of the goals of the component maneuvers are an important consideration. For example consider the strategy illustrated by Figure 2. The maneuver is directed at two adjacent military units. The first is defeated and this opens up a hole in the defense allowing a subsequent attack at the rear of the second unit. Consider another example of a strategy where a REDFOR unit A occupies a position near an engagement area that lies between a BLUEFOR unit X and a reserve BLUEFOR unit Y on the main avenue that connects them. This position allows REDFOR unit A to simultaneously cut off a route of support and escape. A second REDFOR unit B engages the main BLUEFOR unit X from the front. If BLUEFOR unit X attempts to retreat and rendezvous with unit Y then it will be attacked at the engagement area. This tactical scenario is illustrated in Figure 8. Red units are represented by the red ovals. A line extending from the oval illustrates the rear of a unit. This line also gives the orientation of a unit. The red box shows the location of an engagement area and the gray areas represent untrafficable terrain. There are several spatial relationships that are important in describing the aforementioned strategies. These include qualitative relationships such as *near*, *adjacent*, and *between*.

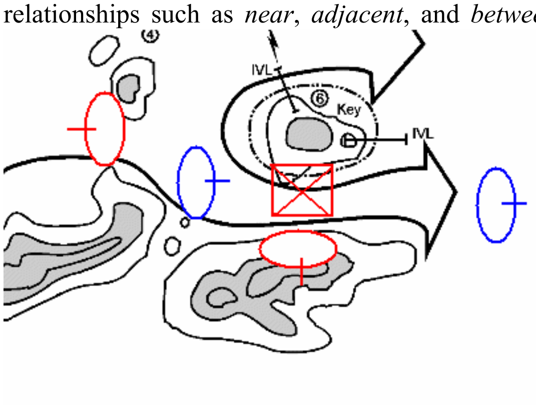

Figure 8 Illustration of a doctrinal Strategy

Like [3] we determine relationships of physical and visual proximity using the Voronoi diagram and it's dual the Delauney triangulation. For a set of input points in the 2D Euclidean plane, the Voronoi diagram associated with those input points is a graph whose edges separate the plane into polygonal cells in such a way that there is a cell corresponding to each input point. Any points that fall within a cell associated with a given input point are closer to that input point than to any other input point. For example if we want to calculate which REDFOR units are *near* a given engagement area, then we form the Voronoi diagram of the centroids of all engagement areas and any REDFOR units falling within the cell associated with a given EA are identified as *near* it. We use our circuit model to approximate the concept *between*. In tactical terms when a military unit or a key terrain feature is described as being between two points, this usually means that it exists on an Avenue of Approach that links the two points. To determine if a point is between two other points. We connect two points in the terrain A and B with the terminals of the circuit, if a significant amount of current with respect to the surroundings, flows through point C then we say that C is *between* A and B.

Conclusion

Reliable predictions of future enemy actions based on the fusion of environmental information (terrain, weather, etc.) with sensor data, doctrine and historical data (third level fusion) is critical to the success of military operations. We are still early in the process of refining our models for intent inference and designing experiments to test their efficacy. However, earlier use of these models in our work in military terrain analysis suggests that they will prove effective.

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