A Probabilistic Computational Model for Identifying Organizational Structures from Uncertain Message Data

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Abstract—The knowledge of the principles and goals under which an adversary organization operates is required to predict its future activities. To implement successful counter-actions, additional knowledge of the specifics of the organizational structures, such as command, communication, control, and information access networks, as well as responsibility distribution among members of the organization, is required. In this paper, we employ a Hidden Markov Random Field (HMRF) model and a graph matching algorithm to discover the attributes of and relationships among organizational members, assets, environment areas, and mission tasks. We focus on identifying the mapping between hypothesized nodes of enemy command organization and tracked individuals and resources. This also allows us to compute the posterior energy function quantifying the belief that the observed data has been generated by a particular organization. The experiment results show that our probabilistic model and the Simulated Annealing search algorithm can accurately identify the different organizational structures and achieve correct node mappings among organizational members.

I. INTRODUCTION

Analysis of the structures of organizations, ranging from the more structured command systems of a conventional military to the decentralized and elusive insurgent and terrorist groups, suggests that strong relationships exist between the structure, resources, and objectives of those organizations and the resulting actions [7]. The organizational members act in their assigned missions by accomplishing tasks and these activities may leave detectable clues or events in the information space. The dynamic evolution of these events creates patterns of organizational activities, which may be related, linked, and tracked over time [1], [8]. More significantly, the patterns can be used to discover the underlying organizational structure. The observed data, however, is very sparse, which creates a challenge to connect relatively few enabling events embedded within massive amounts of data flowing into the government’s intelligence and counter-terrorism agencies [2].

In recent years, two categories of modeling efforts for detecting organizational structures are attracting increasing attention. The first is based on deterministic linear least squares and graph eigenspace projection, which is also termed the spectral graph theory [4], [3], [5]. This is a family of techniques that aim to characterize the global structural properties of graphs using the eigenvalues and eigenvectors of the adjacency matrix [3]. The eigenvalues of a graph are intimately connected to important structural features, and the associated eigenvectors can be used to discover the clusters and other local features, such as node and link attributes. Scott [4] showed how to recover correspondences via singular value decomposition (SVD) on the point association matrix between different images. Shapiro [5] extended this method to a point proximity matrix, which is constructed by computing the Gaussian weighted distance between points. However, these methods have their limitations: they require the two graphs to be of equal size; when the two graphs are large, the eigenvalue methods are computationally inefficient.

The second class of methods employ a probabilistic approach, such as probabilistic relaxation labeling, and Markov random fields. The probabilistic methods assume that the structure is defined probabilistically for graph elements and their relations. The identification of structure involves optimizing
a likelihood function that quantifies the match between a hypothesized graph and the observations. Typically, a finite mixture (FM) model is assumed, where univariate or multivariate observations are considered as being drawn from a mixture density. The FM model is the most frequently employed statistical model, but it is clear that the FM model only describes the data statistically. No spatial information about the data is utilized [6]. The graph structures are spatially distributed, which renders the FM model incomplete.

To overcome this drawback, we introduce a Hidden Markov Random Field (HMRF) theory as a model to formulate the graph matching problem. In section II, after a brief review of Hidden Markov Random Fields (HMRF), we formulate our organizational structure identification problem as a mixed-integer optimization problem that minimizes the a posteriori energy that characterizes the match between a hypothesized graph (model graph) and a data graph. A Simulated Annealing (SA) algorithm used to minimize the a posteriori energy search is presented in section III, where the computational challenges for the organizational structure identification problem are discussed. In section IV, we describe our team-in-the-loop experiment and the data fogging process. Finally, the paper concludes with a summary and open topics that need to be explored in the future.

II. Modeling and Problem Formulation

The problem of structural discovery is very complex: the observed data does not relate to the structure directly; instead, it relates to its manifestation in the form of activities and processes that are enabled by the organizational structure(s) and performed by the organization’s members. Therefore, the algorithms to reconstruct the organization from observations alone would need to search through a very large space of possible structures. Given historic data and the availability of subject-matter experts, we can instead pose the problem as one of hypotheses testing, where the set of predefined hypotheses about the enemy organization and its subelements, albeit very large, is given. The problem then becomes one of rank-ordering these predefined hypotheses on the basis of how best they match (or explain) the observed data.

We employ a Hidden Markov Random Field (HMRF) model and a graph matching approach to find the degree of match between hypothesized organizational structures and the observed data. A hypothesized organization and the observed data are modeled as a model graph and a data graph, respectively. The graphs are the Markov Random Fields, where each node is correlated (related) with its neighboring nodes via links. Graph matching is performed to find a score between each pair of model and data graphs. For $H$ hypotheses, one needs to solve $H$ graph matching problems. The hypothesis with the highest score (rank) would be the most likely organization that could have generated the observed data.

A. Hidden Markov Random Field (HMRF)

Different from the hidden Markov models (HMM), which are defined as one-dimensional Markov chains, a hidden Markov random field (HMRF) model is a hidden two-dimensional stochastic process that is termed a Markov random field (MRF). Similar to HMM, the state sequence of each node in HMRF cannot be observed directly, but only through a sequence of observations. Each observation is assumed to be a stochastic function of the state sequence. Mathematically, a HMRF model is characterized as follows:

- Let $S = \{1, \cdots, M\}$ denote a finite set of sites (nodes), the random field $X = \{X_i, i \in S\}$
is an underlying MRF assuming values in a finite state space \( L = \{1, \ldots, l\} \). Let \( x \) denote a configuration of \( X \) and \( \chi \) be the set of all possible configurations so that
\[
\chi = \{x = (x_1, \ldots, x_M) | x_i \in L, i \in S\} \quad (1)
\]
The conditional probability in an HMRF satisfies the following neighborhood properties:
\[
P(X_i = x_i | x_{S-\{i\}}) = P(X_i = x_i | x_j, j \in N(i)) \quad (2)
\]
where \( N(i) \) is the set of neighbors of site \( i \).
- The state of \( X \) is unobservable and its prior probability distribution is given by
  \[
P(x) = Z^{-1} \exp(-U(x)) \quad (3)
\]
  where \( Z = \sum \exp(-U(x)) \) is a normalizing constant called the partition function, and \( U(x) \) is an energy function of the form
  \[
  U(x) = \sum_{e \in C} V_e(x) \quad (4)
  \]
  where \( C \) is the set of all possible cliques in the HMRF and \( V_e(x) \) is the clique potential.
- Similarly, let \( Y = \{Y_i, i \in S\} \) denote an observable random field with a finite state space \( D = \{1, \ldots, d\} \). Given any particular configuration, \( x_i \in \chi \), every \( Y_i \) follows a known conditional probability distribution \( p(y_i | x_i) \) with the functional form \( f(y_i; \theta_l) \), where \( \theta_l \) are the parameters characterizing the distribution. For any \( x_i \in \chi \), the random variables \( Y_i \) are assumed to be conditionally independent
  \[
P(y|x) = \prod_{i \in S} P(y_i | x_i) \quad (5)
\]
Based on the above assumptions, the joint probability of \( (X, Y) \), given \( X_i \)'s neighborhood configuration, \( x_{N(i)} \), is
\[
P(y_i, x_i | x_{N(i)}) = P(y_i | x_i) P(x_i | x_{N(i)}) \quad (6)
\]
Thus, the marginal probability distribution of \( Y_i \) depends on the parameter set \( \theta = \{\theta_l, l \in L\} \), and \( x_{N(i)} \). It is given by
\[
P(y_i | x_{N(i)}, \theta_l) = \sum_{l \in L} P(y_i, l | x_{N(i)}, \theta_l)
= \sum_{l \in L} f(y_i; \theta_l) P(l | x_{N(i)}) \quad (7)
\]
We call this the hidden Markov random field (HMRF) model.

B. The HMRF graph matching model

Consider two attributed graphs, \( G_M = (V_M, E_M) \) and \( G_D = (V_D, E_D) \), representing a hypothesis graph (or model graph) and a data (observation) graph, respectively. The sets \( V_M, E_M, V_D, \) and \( E_D \), represent the set of vertices (nodes) and edges (links) of the model graph and data graph, respectively. The data graph consists of noisy nodes so that both graphs do not, in general, have the same number of vertices. Therefore, we augment the set of model graph nodes \( V_M \) with a null node such that it corresponds to an invalid mapping. A single vertex in the graph \( G_M \) is denoted by \( X_i \) and that in the graph \( G_D \) by \( Y_a \). Each vertex in \( G_M \) is specified by an attribute vector:
\[
A_M^{(i)} = \{a_1, \ldots, a_{K_1}\} (0 \leq i \leq |V_M|) \quad (8)
\]
Thus, there are \( K_1 \) attribute types associated with our graph matching problem. Similarly, the binary relations derived from pairs of vertices is
\[
A_M^{(i,j)} = \{a_1, \ldots, a_{K_2}\} (0 \leq i, j \leq |V_M|) \quad (9)
\]
As a consequence, there are \( K_2 \) different types of relations between each pair of vertices \( X_i \) and \( X_j \), in the graph matching problem.

A corresponding data graph can also be constructed from \( G_D \), where observation vertex \( \alpha \) has \( K_1 \) attributes
\[
A_D^{(\alpha)} = \{a_1, \ldots, a_{K_1}\} (1 \leq \alpha \leq |V_D|) \quad (10)
\]
and there are $K_2$ relations between vertices $\alpha$ and $\beta$

$$A^{(\alpha, \beta)}_D = \{a_{\alpha, \beta}^{(1)}, \ldots, a_{\alpha, \beta}^{(K_2)}\} (1 \leq \alpha, \beta \leq |V_D|) \quad (11)$$

We denote the attributes of model and data as

$$A_M = \{\{A_M^{(i)}\}, \{A_M^{(j)}\}: 0 \leq i, j \leq |V_M|\}$$

$$A_D = \{\{A_D^{(\alpha)}\}, \{A_D^{(\alpha, \beta)}\}: 1 \leq \alpha, \beta \leq |V_D|\} \quad (12)$$

We define a mapping function $f$, which maps each node in $V_D$ to nodes in $V_M$ and thus maps edges (relations) in $E_D$ to $E_M$.

$$f : V_D \rightarrow V_M$$

$$f : E_D \rightarrow E_M$$

$f$ is a set of mapping functions of single node, which is given by

$$f = \{f_\alpha \in V_M | \alpha \in V_D\}. \quad (14)$$

$f_\alpha = 0$ means a mapping of two nodes containing a null node.

Now, we express the objective of graph matching problem as one of maximizing the a posteriori (MAP) probability of match with respect to the mapping function $f$. The function $f$ can be quantified by labels, configurations, correspondence matrix, etc. For simplicity of notation, we use $f$ to represent all these quantities. Then, by using HMRF theory, the MAP problem can be transformed into one of minimizing the posterior energy (negative logarithm of posterior probability of match) given observations (i.e., measurements of attributes). Formally:

$$f^* = \arg \max_f P(f|G_D, G_M) \quad (15)$$

where $f^*$ is the optimal mapping. Replacing $G_M$ and $G_D$ by their attributes and observations of attributes, so that equation (15) becomes

$$f^* = \arg \max_f P(f|A_D, A_M) \quad (16)$$

Since $A_M$ is known, we omit it from equation (16). Thus,

$$f^* = \arg \max_f P(f|A_D) \quad (17)$$

Recalling that

$$P(f|A_D) \propto P(A_D|f) \cdot P(f) \quad (18)$$

we have

$$f^* = \arg \max_f P(A_D|f) \cdot P(f)$$

$$= \arg \min_f -(\log P(A_D|f) + \log P(f)) \quad (19)$$

We derive expressions for $P(A_D|f)$ and $P(f)$ next.

The mapping set $f$ is a set of hidden Markov variables, whose joint probability distribution is

$$P(f) = \frac{1}{Z} \exp(-U(f)) \quad (20)$$

where $Z$ is a normalization constant, and $U(f)$ is the energy function given by

$$U(f) = \sum_{\alpha \in V_D} \Phi_1(f_\alpha) + \sum_{\alpha \in V_D} \sum_{\beta \in N(\alpha)} \Phi_2(f_{\alpha, \beta}) \quad (21)$$

where $\Phi_1(f_\alpha)$ is a single-site potential function, which is defined as

$$\Phi_1(f_\alpha) = \begin{cases} \phi_{01} & \text{if } f_\alpha = 0 \\ 0 & \text{otherwise} \end{cases} \quad (22)$$

Here $\phi_{01}$ is a positive constant. If $f_\alpha$ is a NULL mapping, it incurs a penalty of $\phi_{01}$; otherwise, no penalty is imposed. The pair-site potential is defined as

$$\Phi_2(f_{\alpha, \beta}) = \begin{cases} \phi_{02} & \text{if } f_\alpha = 0 \text{ or } f_\beta = 0 \\ 0 & \text{otherwise} \end{cases} \quad (23)$$

where $\phi_{02}$ is a positive constant. If either $f_\alpha$ or $f_\beta$ is a NULL mapping, it incurs a penalty of $\phi_{02}$; otherwise, no penalty is imposed.

Based on conditional independence assumption in Eq. (5) of the HMRF model, the likelihood function $P(A_D|f)$ can be factorized as

$$P(A_D|f) = \prod_{\alpha \in V_D} P(A_D^{(\alpha)}|f_\alpha) \quad (24)$$

Then, the energy function is given by

$$U(A_D|f) = \sum_{\alpha \in V_D, f_\alpha \neq 0} \Phi_1(A_D^{(\alpha)}|f_\alpha) + \sum_{\alpha \in V_D, f_\alpha \neq 0} \sum_{\beta \in N(\alpha)} \Phi_2(A_D^{(\alpha, \beta)}|f_{\alpha, \beta}) \quad (25)$$
C. Noisy Observation Model

Now, we construct an observation model. We assume that: (i) the observations of both vertex attributes and relational attributes are multi-variate Gaussian; (ii) For different vertices and relations, they are independent. Thus,

\[ A_D^{(a)} = f_a + e_1 ; A_D^{(a,b)} = f_{a,b} + e_2 \]  \hspace{1cm} (26)

where \( e_1 \sim N(0, \Sigma_1) \) and \( e_2 \sim N(0, \Sigma_2) \) are Gaussian noise variables with zero mean and co-variance matrices \( \Sigma_1 \) and \( \Sigma_2 \), respectively. The likelihood potentials are

\[ \Phi_1(A_D^{(a)}|f_a) = (A_D^{(a)} - f_a)'(2\Sigma_1)^{-1}(A_D^{(a)} - f_a) \]  \hspace{1cm} (27)

and

\[ \Phi_2(A_D^{(a,b)}|f_{a,b}) = (A_D^{(a,b)} - f_{a,b})'(2\Sigma_2)^{-1}(A_D^{(a,b)} - f_{a,b}) \]  \hspace{1cm} (28)

Thus, the posterior energy is given by

\[
U(f|A_D) = U(f) + U(A_D|f) \\
= \sum_{a \in V_D} \Phi_1(f_a) + \sum_{a \in V_D} \sum_{\beta \in N(a)} \Phi_2(f_{a,b}) + \\
\sum_{a \in V_D} \Phi_1(A_D^{(a)}|f_a) + \sum_{a \in V_D} \sum_{\beta \in N(a)} \Phi_2(A_D^{(a,b)}|f_{a,b})
\]  \hspace{1cm} (29)

The MAP estimation is equivalent to minimizing the posterior energy function (recall negative sign in the exponential term of (20))

\[ f^* = \arg \min_{f} (U(f) + U(A_D|f)) \]  \hspace{1cm} (30)

III. Solution Approaches

Given the Hidden Markov Random Field (HMRF) model described above for graph matching, the optimal solution is obtained by computing a mapping vector \( F^* = \{ f_1^*, \cdots, f_a^* \} \) for the nodes in \( G_D \), such that the posterior energy in (29) is minimized. Since the number of nodes in both \( G_M \) and \( G_D \) can be large (e.g., several hundred), exhaustive search over the solution space is impractical for real-world problems.

In our work, the data and model graphs have multiple attributes associated with each node and edge. In addition, the energy function, although quadratic, has dependent variables with multinomial structure. Consequently, we used classical stochastic search methods for finding solutions that minimize the energy function. In these methods, randomness plays a crucial role in search and learning. The general approach is to bias the search toward regions where we expect the solution to be, and allow randomness to help find good solutions and escape from local minima. There are two general classes of such methods: Simulated Annealing (SA) and Evolutionary Algorithms (EA). The former is based on concepts and techniques from physics, and the latter is inspired by the evolutionary concepts from biology. Because the SA has many successes in pattern recognition, we employ it as the solution method for our problem.

We start with a randomized mapping and select a high initial “temperature” \( T(0) \) to initiate the search process. Next, we calculate the posterior energy based on the current mapping, \( U_a \). Then, randomly exchange the mappings of two nodes in the graph, and calculate the posterior energy, \( U_b \). If this candidate state has a lower energy, accept this change. If, however, the energy is higher, accept this change with a probability equal to

\[ e^{-(U_b-U_a)/T} \]  \hspace{1cm} (31)

The occasional acceptance of a mapping that is less favorable is crucial to the success of SA. The key benefit is that it allows the system to escape from local energy minima. The algorithm continues to select and test for a certain number of iterations before the temperature is lowered. When the temperature is low, the probability that a less favorable mapping will be acceptable is small, and the search is akin to a greedy descent algorithm. The SA terminates
Simulated Annealing Algorithm for Graph Matching

Initialization: \( T(0), F^{(0)}, k_{max}, P_{max} \), calculate \( U(0) \).

Do

Do select two nodes \( i, j \) \((i, j \in G_D)\) randomly; suppose their mappings are \( f_i \) and \( f_j \), respectively

Calculate \( U_a(k) \) according to (29)

Exchange the mappings of nodes \( i \) and \( j \), calculate \( U_b(k) \)

If \( U_a(k) < U_b(k) \), accept the exchange

Else if \( e^{-(U_b(k) - U_a(k))/T(k)} > \text{Rand}(0,1) \), accept the exchange

Until max polling number \( P_{max} \) has reached

End

Fig. 1. Simulated Annealing Algorithm for Graph Matching

<table>
<thead>
<tr>
<th>Name</th>
<th>#</th>
<th>Description</th>
<th>Blue</th>
<th>Red</th>
<th>Brown</th>
<th>Green</th>
</tr>
</thead>
<tbody>
<tr>
<td>BMT</td>
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<td>Bomb Maker Team</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>SNP</td>
<td>2</td>
<td>Sniper</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>MTR</td>
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<td>Mortar</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>IT</td>
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<td>Intel Team</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>TRK</td>
<td>5</td>
<td>Truck</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

(1) Resources of C2 Organizations

(2) C2 Nodes & Command Structure

(3) Control Structure

(4) Communication Structure

when the temperature is very low. The procedure for the stochastic SA is shown in Fig. 1.

IV. EXPERIMENTAL RESULTS

A. Scenario & Hypothesis Space

A terrorist organization (Fig. 2-a) is comprised of bomb makers, snipers, mortars, intelligence teams and truck drivers. The top commander (black, Fig. 2-b) sets the initial conditions and provides the overall intent for an operation. Four sub-commanders, blue, green, brown and red, distribute the responsibilities among lower-level units, and coordinate these seemingly independent activities to achieve the mission objectives (Fig. 2-c). The fundamental need for communications (Fig. 2-d) significantly constrains the options for both command and control, making communications infrastructure a critical feature of a \( C^2 \) system. Discovering the organization’s intent and identifying its \( C^2 \) structure are crucial to prevent devastating effects of a terrorist attack.

In our experiment, we compare the human and algorithmic performance in discovering the command and control (\( C^2 \)) structures of enemy organizations. We describe the command and control organization as a collection of command and control nodes and resources connected via command, control, communication, and mission structures.

The data in excel format for three types of organizations, i.e. divisional organization (D), functional organization (F), and hybrid organization (I) are given. The D organization and F organization (illustrated in Fig. 3) are two extreme cases of organizational structures considered here. In a D organization, a commander controls multiple types of resources and has general knowledge of these resources; the activities conducted by the members in this organization are restricted to a certain geographic area of responsibility. On the other had, a commander in a F organization controls a single resource type and has specialized knowledge on the resource the commander controls. Thus, the operations of a F organization cross multiple geographic regions. An I organization has an organizational structure that is a hybrid of D and F organizations. The seven instances of hypothesized organizations are built within these three types of organizational structures. In Fig. 3, we assume that the organization consists of two decision-makers (DMs), with two platforms (\( P_1 \) and \( P_2 \)) assigned to each. We consider two resource types (type 1 and type 2). In the D organization, each DM owns two types of resources, and in the F organization, each DM owns
First, we take a base-line D organization (hypothesis 4) and generate observed data from it according to the noise categories shown in Table II. We perform graph matching between this observed data and all the hypothesized organizations. The final posterior energies from the graph matching algorithm are shown in Table III. From the table, we note that when noise levels are low and medium, the algorithm can achieve the lowest posteriori energy when mapped to hypothesis 4, which means that it can correctly identify the organization. However, when the noise level is high, the consequent posterior energy shows that hypothesized organizations 2 and 7 are identified. Hypotheses 2 and 7 are both D organizations, which indicates that the algorithm can identify the right organizational structure even under a very uncertain environment.

Next, we conducted sensitivity analysis of the algorithm. In this study, we sought to find a “break point” for the algorithm, wherein the high levels of uncertainty would not allow the algorithm to recognize the correct organization and perform actor-role mapping with a high enough accuracy. We define the accuracy of the algorithm as the percentage of right node mapping between a data graph \( G_D \) and a hypothesis graph \( G_M \), which is given by

\[
A = \frac{|f^{(\text{correct})}|}{|f^*|} \quad (32)
\]

where the \(|f^*|\) is the total number of node mappings and \(|f^{(\text{correct})}|\) is the number of correct node mappings.

We have taken as a baseline the D organizational
TABLE III
THE POSTERIOR ENERGY FOR THE MATCHING BETWEEN DATA 1 AND ALL HYPOTHESES (AVERAGE OVER 100 RUNS)

<table>
<thead>
<tr>
<th></th>
<th>Low-1</th>
<th>Med-1</th>
<th>Med-2</th>
<th>High-1</th>
<th>High-2</th>
<th>High-3</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1</td>
<td>12755.45</td>
<td>9892.957</td>
<td>9367.813</td>
<td>9345.836</td>
<td>10473.46</td>
<td>11303.34</td>
</tr>
<tr>
<td>H2</td>
<td>8493.332</td>
<td>7312.286</td>
<td>7562.282</td>
<td>7845.814</td>
<td>8956.673</td>
<td>9355.44</td>
</tr>
<tr>
<td>H3</td>
<td>13000.934</td>
<td>10773.38</td>
<td>9822.085</td>
<td>10342.396</td>
<td>11323.73</td>
<td>11934.56</td>
</tr>
<tr>
<td>H4</td>
<td>378.356</td>
<td>2333.348</td>
<td>5778.076</td>
<td>8003.642</td>
<td>10804.83</td>
<td>11608.34</td>
</tr>
<tr>
<td>H5</td>
<td>8659.563</td>
<td>8244.214</td>
<td>8822.71</td>
<td>9717.784</td>
<td>10999.561</td>
<td>11966.83</td>
</tr>
<tr>
<td>H6</td>
<td>8045.265</td>
<td>7633.452</td>
<td>8496.039</td>
<td>9031.028</td>
<td>9989.328</td>
<td>12779.36</td>
</tr>
<tr>
<td>H7</td>
<td>23234.46</td>
<td>16524.44</td>
<td>10675.156</td>
<td>8734.258</td>
<td>7991.395</td>
<td>9899.73</td>
</tr>
</tbody>
</table>

Organizational structure identification accuracy

Fig. 4. Organizational structure identification accuracy

structure. The resulting accuracy of the algorithm is shown in Fig. 4. We can see that the algorithm’s accuracy degrades between “Med-1” and “Med-2” data points (around 40% missing data and 25% deceptions). When the uncertainty reaches very high, the algorithm breaks down and can hardly identify the correct actor node.

V. CONCLUSION

In this paper, we integrated a probabilistic graph model, specifically a Hidden-Markov Random Field (HMRF) model, and a graph matching approach to identify hidden organizational structures from message data. The model and the methodology enable the computation of an energy function of the hypothesized organizational structure and processes, given the observed behavior of members in the organization. The focus of the paper was on identifying the mappings between hypothesized nodes of enemy command organization and tracked individuals and resources. The hypothesized organizations are predefined in the knowledge library according to available intelligence regarding similar enemy organizations, well-known structural forms from organizational theories, as well as specific existing structures that analysts propose. Our modeling framework has great potential to enhance the capabilities of discovering competitive organizations and terrorist networks.

REFERENCES