A Method of Node Importance Measurement Base on Community Structure in Heterogeneous Combat Networks

Zhaofeng Yang(✉), Yonggang Li, and Jinyu Liu

School of Communication and Electronic, Chongqing University of Posts and Telecommunications, Chongqing, People's Republic of China
yangfengzmc2012@gmail.com

Abstract. The measurement of the importance for the nodes is of great significance to the test and simulation for Heterogeneous Combat Networks (HCN), combat situation assessment and other topics. Due to the complexity of equipment types and styles in such system, traditional algorithms (degrees, betweenness, closeness, eigenvectors) are difficult to achieve both speed and accuracy in identifying the important nodes of Heterogeneous Combat Networks. This paper fully considers the heterogeneity of combat system nodes, and proposes an evaluation model based on community structure, IEBC (importance evaluation based on community), which can measure the importance of each node. We form functional modules (FM) by distinguishing the function of nodes. Then divide the network into communities according to the concentration of FM. Finally, we compare IEBC with traditional ranking models (e.g., degree centrality). After simulation calculation, compared with other algorithms, IEBC takes into account the balance of efficiency and accuracy at the same time.

Keywords: Identification of key nodes · SDI military operation chain · Community detection

1 Introduction

Heterogeneous Combat Networks (HCN) [1] addresses all key aspects of joint operations and military action, which integrates the combat platforms, weapon systems, intelligence reconnaissance, command control, and logistics support systems into an integrative combat system. Because the diversity of missions in network combat and the complexity of combat environment have placed increasing demands on the reliability of HCN. The demand for the reliability of HCN is getting higher and higher, because the diversity of missions in network combat and the complexity of combat environment. Since the nodes and links of such network are vulnerable to targeted attacks by the enemy, it is particularly important to analyze the importance of nodes in HCN [2].

This work is supported by the Defence Advance Research Foundation of China under Grant 61400020109.

H. Gao et al. (Eds.): ChinaCom 2020, LNICST 352, pp. 766–775, 2021.
https://doi.org/10.1007/978-3-030-67720-6_53

At present, the research on the importance of complex network nodes in the military field is still in the preliminary stage. Opsahl *et al*. analyzed the key node identification method based on node centrality, which is measured according to the topological position of the node [3]. But the method is strongly dependent on the network topology. Martin *et al*. proposed that the node betweenness can reflect the dynamic characteristic of the network [4], but it is restricted by the complexity of the algorithm complexity. Freeman [5] improved the important node identification method based on betweenness, and the computational efficiency was reduced, but the versatility was poor. A method that take the approximate flow betweenness of nodes as an indicator for centrality measure is proposed by Liu *et al*. [6].

Most of above-mentioned improvements are designed for calculating betweenness centrality, but HCN is a typical open complex giant system which is composed of many community structures with different sizes. This system will continue to evolve as the battlefield environment changes. The current key node identification method can't be fully applicable to the combat network [7]. Therefore, we investigate the function of different nodes and the community of the nodes. Moreover, the role of nodes in different combat tasks may be different, so the importance of nodes will be constantly changing.

We divide the nodes of HCN into Sensor entities (S), Decider entities (D), Influential entities (I) according to the requirements of combat missions. The completion of specific combat mission benefits from the combination of S, D, and I nodes. Because these nodes form a complete chain of reconnaissance, decision-making and attack. Such S, D, and I nodes will form an observe, orient, decide, and act operational cycle (OODA loop) [8, 9], which forms a functional module (FM) that completes the corresponding tasks. FM are considered building blocks for combat networks. We use a framework that identifies clusters of FM and develop a method, Importance evaluation based on the community (IEBC), that can evaluate node's importance base on community structure in HCN.

The paper is organized as follows: in second part, we introduce the composition of HCN, community structure and functional module. A community identification algorithm and the IEBC framework based on the result of community dividing is proposed in third part, while we performed simulation and result analysis in fourth section. In "Conclusion" section, we summarize our final remarks.

2 Network Structure and Motif

The traditional combat system network is an abstraction of the command and control relationship. It constructs a tree diagram based on such relations in military operations, where leaf nodes are combat entities with different capabilities, and other nodes are centers of command and control at different layers [10] (see Fig. 1).

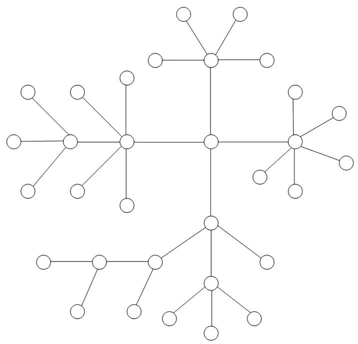

Fig. 1. The traditional combat system network.

With the advent of the information age, the form of combat has changed from traditional platform-centric warfare to network-centric warfare. Information systems have greatly improved combat capabilities. All combat equipment makes full use of information systems to achieve the integration of interconnection and interoperability. All entities share battlefield intelligence, jointly perceive the battlefield situation, and adjust the operation plan in time according to changes in the battlefield situation. Thus, we suggest that HCN is a distributed network.

According to the heterogeneity of nodes in combat network, we divide the nodes into three part [10]. 1) Sensor entities (S). 2) Decider entities (D). 3) Influential entities (I).

Once sensor node (S) finds target, it will transmit the target information to the decider node (such as operational center). The operational center (D) comprehensively analyzes the received information and then issues instructions to the influencer (I) to execute military operations on the target. Finally, the offensive and defensive engagement nodes (I) attack the target. Such a loop is shown in Fig. 2. Therefore, A functional chain of military operations: $S \rightarrow D \rightarrow I$ is formed on the target node, where T is the node in the enemy network. In addition, we consider that the decision maker D will adjust the sensor S according to the changing combat environment. Moreover, the sensor S will also re-detect the combat situation, after the node I conducts military operations on the target T. Thus, four edges should be considered in the function module (Fig. 2 right): $S \rightarrow D, D \rightarrow S, D \rightarrow I, I \rightarrow S$.

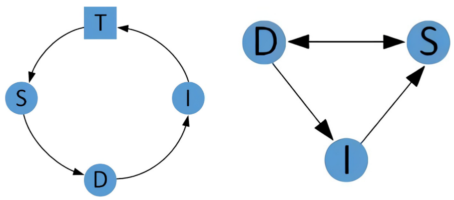

Fig. 2. (left) An operation loop of SDI. (right) The Function Module used in this paper.

The combat area can be continuously expanded based on the FM. The combat space is divided into different communities, then various communities coordinated operations (see in Fig. 3). More precisely, node 24, 22 and 23 compose a FM, and the yellow community consists of four FM.

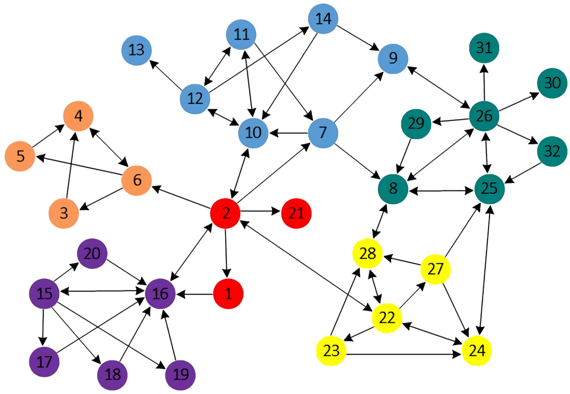

Fig. 3. Combat network detected by Function Modules. (Color figure online)

3 Importance Measurement

3.1 Community Detection

To evaluate the importance of nodes based on the community structure, we must first accurately identify the community structure of the network. The current community detection algorithms [11–13] were mostly for homogeneous networks, and didn't take into account the heterogeneous characteristics of the nodes in Heterogeneous Combat Networks. HCN is depended on FM to complete a military operation. Thus, the community detection of the combat network should take FM as a combined unit. After the detection, the number of functional modules in each community is roughly the same, and the functional modules are destroyed as little as possible. Here we benefit from the high-order clustering of complex networks to define a module conduction rate (MCR). Our algorithm has two goals for finding communities in the network.

- There should be as many nodes as possible in the FM of each community.
- The number of broken FM should be as few as possible.

The above two requirements can be reflected through MCR. When the conduction rate is the smallest, the result of community division is the best [14]. MCR define as follow:

$$RatioCut_M(S_1, S_2, \ldots, S_k) = \frac{1}{2}\sum_{i=1}^{k}\frac{W_M(S_i, \overline{S_i})}{vol_M(S_i)} \tag{1}$$

where $\overline{S_i}$ is the remaining part after removing S_i (see Fig. 4), $W_M\left(S_i, \overline{S_i}\right)$ is the number of broken FM, which at least one node in a FM is in S_i and another node is in $\overline{S_i}$. Also, $vol_M(S_i)$ is number of nodes belonging to function module M in S_i.

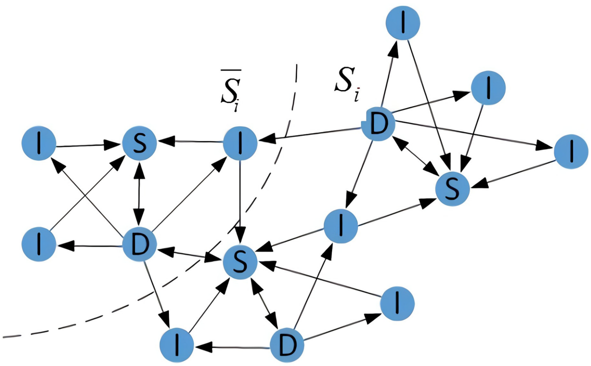

Fig. 4. Community detection process based on functional modules.

As the number of nodes increases, the types of community divisions will increase exponentially. It is an NP problem to accurately calculate the minimum module conduction rate. Therefore, we propose an approximate optimization algorithm to obtain an approximate optimal solution. A spectral graph clustering algorithm based on eigenvector is put forward. This method has high calculation efficiency, is easy to implement, and has approximately optimal mathematics guarantees for the obtained clustering. The approach consists of modular high-order clustering algorithm (algorithm Ψ) and improved K-means clustering sub-algorithm (algorithm Φ). The approach detect community as follow:

- Step 1: Given a network and functional module M, form the module adjacency matrix W_M. Element in matrix: $(W_M)_{ij}$ is the number of modules that contain both node i and j.
- Step 2: Calculate the diagonal matrix of the module adjacency matrix:

$$(D_M)_{ii} = \sum_j (W_M)_{ij} \tag{2}$$

- Step 3: Calculate the Laplacian transformation matrix of the module adjacency matrix:

$$\zeta_M = D_M^{1/2}(D_M - W_M)D_M^{1/2} \tag{3}$$

- Step 4: Calculate the k eigenvectors corresponding to the smallest non-zero eigenvalue of the ζ_M: $Z_1, Z_2, \ldots, Z_k$. Then, arrange k eigenvectors to form an $N \times K$ matrix Z. Take

$$Y_{ij} = \frac{Z_{ij}}{\sqrt{\sum_{j=1}^{k} Z_{ij}^2}} \tag{4}$$

as N k-dimensional row vectors.

- Step 5: The i^{th} row vector of matrix Y represents the node i. Then use the sub-algorithm Φ to group each node.

The sub-algorithm Φ is an improvement of the k-mean algorithm, including the following steps:

- Step 1: Select the initial community center node according to the two indicators of high centrality and discrete distribution. Centrality of node is defined as:

$$\rho_i = (D_M)_{ii} \tag{5}$$

where $(D_M)_{ii}$ is degree of FM, showing in eq. (3). In order to measure the dispersion of nodes in the network, we calculate the minimum value of the distance between a node and other nodes with higher centrality by using the minimum distance $\delta_i (i = 1, 2, \ldots, n)$:

$$\delta_i = \min_{j:\rho_j > \rho_i} (d_{ij}) \tag{6}$$

where d_{ij} is the Euclidean distance between the representative vector (V_k) of node i and node j in matrix Y. If the node has the largest centrality, it is more likely to be selected as the initial central node than other adjacent nodes. Therefore, this article specifies the minimum distance of the node as:

$$\delta_k = \max(\delta_i), i \neq k \tag{7}$$

Considering the two characteristics comprehensively, we select the top k nodes with the largest $\rho_i \delta_i$ as the initial central nodes.

- Step 2: Divide the node into the community to which the nearest central node belongs, by calculating the Euclidean distance between each node and each center node. Then calculate the MCR at this time.
- Step 3: Calculate the average distance between each node and other nodes in each community, and update the node with the smallest average distance as the center node of the community.
- Step 4: Repeat steps 2 and 3, if the center node no longer changes or the number of iterations reaches the upper limit, stop the algorithm. The division result with the smallest MCR is the approximate optimal solution.

3.2 Importance Evaluation Based on Community

The IEBC sorting algorithm implementation process is shown below, the algorithm calculates the IEBC value of each node through a matrix.

- Step 1: Given the network model adjacency matrix and the detect communities by approach proposed in chapter 3.1.
- Step 2: Compute the number of communities connected to nodes i (V_{ic}).
- Step 3: Generate list of IEBCs, and IEBC of each node is count by

$$IEBC_i = \sum_{w=1}^{c} \frac{S_w}{N} V_{ic} \tag{8}$$

where c is the aggregate number of communities in HCN, S_w is the number of nodes in community w.

- Step 4: Sort the IEBC value of each node.

4 Simulation Results and Analysis

There are six kind of links in HCN, as shown in Fig. 5. Combined with the actual military operation, different connection probabilities are given to different links. The connection probability is defined as the ratio of the actual number of links to the number of possible links between two nodes. For example, the connection probability of $D \rightarrow S$ is:

$$P_{D \rightarrow S} = \frac{N_{D \rightarrow S}}{N_D N_S} \tag{9}$$

where $N_{D \rightarrow S}$ is the actual number of links for $D \rightarrow S$, N_D, N_S is the number of nodes S and D.

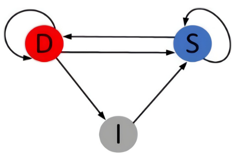

Fig. 5. A simple FM of heterogeneous combat networks.

In this paper, associate with corresponding military applications, 300 S nodes, 150 D nodes, and 550 I nodes are randomly generated. And the given connection probability is: $P_{S \rightarrow S} = 0.025$, $P_{S \rightarrow D} = 0.04$, $P_{D \rightarrow S} = 0.03$, $P_{D \rightarrow D} = 0.185$, $P_{D \rightarrow I} = 0.1$, $P_{I \rightarrow S} = 0.02$.

The ER topology model of HCN constructed according to the above connection probability is shown in Fig. 6.

Communities are divided according to the FM shown in Fig. 2. Then apply several importance ranking methods (Degree centrality, Betweenness centrality, Closeness centrality, Eigenvector centrality [15]) and IEBC to rank the node importance. According to the importance of ranking results, attack the nodes of HCN. As a node is damaged, some nodes connect with it cannot communicate each other, causing the entire HCN to split into many independent connected giant components. We use the number of nodes in maximum connected component (H) and the number of surviving functional modules (N_M) to evaluate the functional robustness of the damaged HCN [10]. The simulation results are as follow figures.

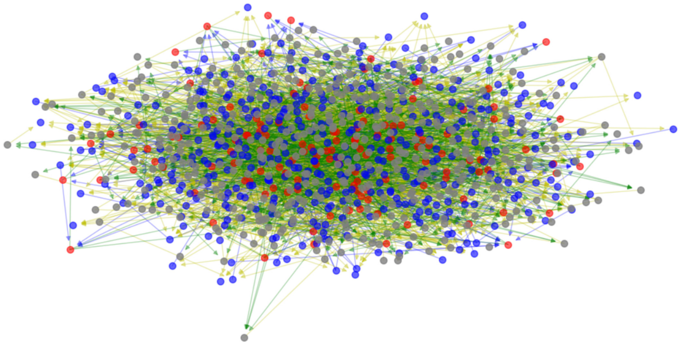

Fig. 6. The ER topology model of HCN. Red represents node D, blue represents node S, and gray represents node I. (Color figure online)

As we can seen in Fig. 7, the trend of H is sharply reduced, and then gradually flattened, which fully illustrates the effectiveness of the algorithm for nodes sorting. In the process of increasing f and attacking nodes with the IEBC measurement result, the decreasing speed of H is faster than other traditional algorithms in the figure. After the important nodes identified by IEBC are damaged, H is already less than 100, when the fraction of f increases to 0.3.

Therefore, it means that the important nodes detected by IEBC are the intermediary nodes with the most links. These intermediate nodes connect communities to each other and are distributed discretely. The existence of these nodes maximizes the spread of information in the community. When such nodes are attacked, the communities will separate, and the size of maximum connected component changes the fastest.

Figure 8 reports that as f increases, attacks on important nodes identified by IEBC N_M decrease the fastest. When the attack intensity is greater than 0.77, it decreases to 0. Therefore, it shows that the nodes detected by IEBC are more important than the nodes identified by degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality. The nodes detected by IEBC are more likely a D node, because N_M decline the fastest as the D node under attack. When all D nodes are damaged, the number of FM reduces to 0.

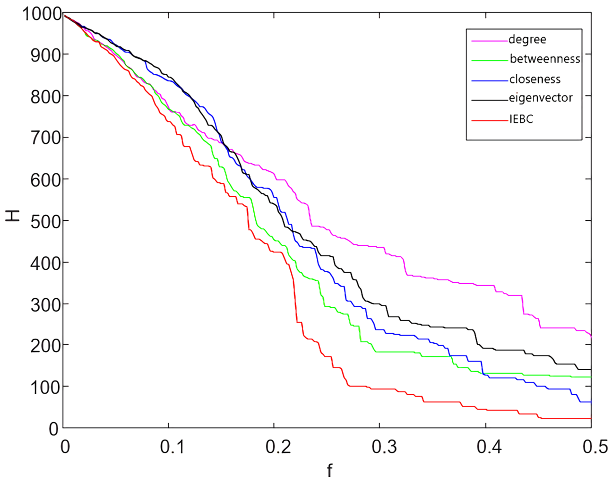

Fig. 7. The number of nodes in surviving maximum connected component (H) varies with the attack intensity (f).

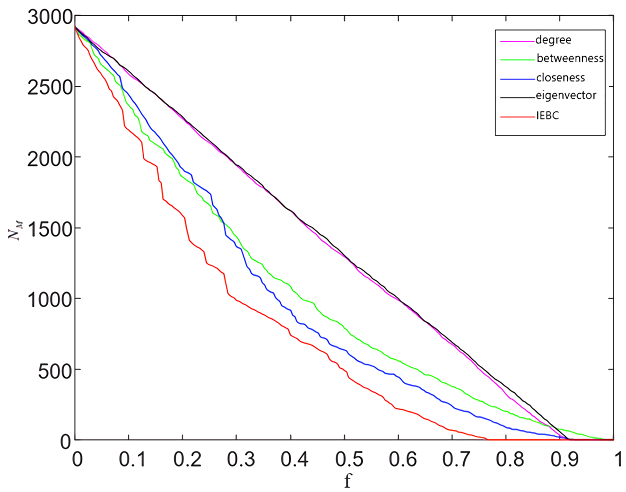

Fig. 8. The number of surviving FM (N_M) varies with attack intensity (f).

5 Conclusion

According to the size of the largest connected component and the number of remaining effective functional modules with the attack intensity, the simulation analysis results show that the effectiveness of IEBC is better than the other methods when measuring the importance of nodes in HCN. IEBC can accurately and quickly determine the key nodes in HCN. In military operations against the enemy, precision strikes can be carried out on key nodes, so that the enemy's system operational effectiveness will rapidly reduced, and the enemy's military communications network will paralyze. Further more, it can also focus on protecting important nodes in our HCN to ensure that the system can continue to maintain its original functions when attacked by the enemy.

References

1. Li, J., Jiang, J., Yang, K., et al.: Research on functional robustness of heterogeneous combat networks. IEEE Syst. J. **13**(2), 1487–1495 (2018)
2. Lu, X.Q., Yang, X.D.: A invulnerability assessment based on importance-degree of node for weighted network under attack with partial information. In: 11th International Conference on Wireless Communications, Networking and Mobile Computing, pp. 1–5. IET, Shanghai (2015)
3. Opsahl, T., Agneessens, F., Skvoretz, J.: Node centrality in weighted networks: Generalizing degree and shortest paths. Soc. Netw. **32**(3), 245–251 (2010)
4. Martin, T., Zhang, X., Newman, M.E.: Localization and centrality in networks. Phys. Rev. E **90**(5–1), 052808 (2014)
5. Freeman, L.C.: Centrality in social networks conceptual clarification. Soc. Netw. **1**(3), 215–239 (1978)
6. Liu, R.J., Guo, S.Z., et al: An approximate flow betweenness based centrality measure for complex network. IEICE Trans. Inf. Syst. **E96-D**, 727–730 (2013)
7. He, H, Li, Z.F., Wang, W.P., et al.: Research on critical node analysis method of new combat SoS. In: IEEE International Systems Engineering Symposium 2018, pp. 1–7. IEEE, Rome (2018)
8. Daniel, F.: A Vision So Noble: John Boyd, the OODA Loop, and America's War on Terror. CreateSpace Independent Publishing Platform (2010)
9. Li, E.Y., Gong, J.X., et al.: Node importance analysis of complex networks for combat systems based on function chain. J. Command Control **4**(01), 42–49 (2018)
10. Yu, J., Wang, W., Zhang, G., Guo, N.: Research on joint operations command system based on complex network. Fire Control Command Control **36**(2), 5–10 (2011)
11. Boccaletti, S., Latora, V., Moreno, Y., et al.: Complex networks: Structure and dynamics. Phys. Rep. **424**(4–5), 175–308 (2006)
12. Fortunato, S.: Community detection in graphs. Phys. Rep. **486**(3–5), 75–174 (2010)
13. Duch, J., Arenas, A.: Community detection in complex networks using extremal optimization. Phys. Rev. E **72**(2), 027104 (2005)
14. Benson, A.R., Gleich, D.F., Leskovec, J.: Higher-order organization of complex networks. Science **353**(6295), 163–166 (2016)
15. Lü, L.Y., Chen, D.B., Ren, X.L., et al.: Vital nodes identification in complex networks. Phys. Rep. **650**, 1–63 (2016)