The evolutionary dynamics of group-level terrorist network

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Abstract. In the age of globalization and information, terrorist groups cooperate and interact with each other frequently and have formed a complex and dynamic system. For the purpose to explore the evolutionary dynamics of transnational terrorism, the paper mapped location-based networks to model the terrorism system, followed with preference attachment model to discover laws that how terrorism developed. The work gave an outline about how terrorist groups evolved and explained how terrorism would develop and expand. The findings would supply significant suggestion to counterterrorism organizations.

1 Introduction

The attack against America on September 11th, 2001 brought terrorism to the center of global politics, at the same time greatly expanded the community of terrorism scholars and motivated efforts for new and innovative research approaches from many disciplines. A key aspect of studying terrorism is to investigate the organizational dynamics and the mechanism by which its structure grows and changes over time [1].

Analysis of terrorist activities have often been qualitative in nature, with studies pertaining to the inner-working of individual terrorist organizations and chronologies of terrorist events. [2] In most recent publications, social networks within location is a feasible pattern to reveal some new principles in social systems. David gave a paradigm to infer social ties from geographic coincidences and verified the effectiveness in 2010 [3]. In terrorism related researches, *LBSN* is used mainly in two aspects. On one hand, some researches focus on those who engage in terrorism, and have uncovered additional details on the micro-dynamics and internal working of how organization plan and conduct terrorist attacks that have been previously unknown[8,9]. On the other hand, scholars worked on the group level to reveal the collaborative and competitive relationships among goups[10]. Olivier J. Walther mapped the violent extremist networks in north-west Africa, which contains tens of

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groups, based on adjacent borders[11]. The rich achievement has settled the base of *LBSN* in terrorism research.

Networks evolve over time through the creation and deletion of links among a set of actors [12]. Literatures proposed the dynamic models for mechanisms of network formation and transformation [13, 14]. One of the important aspect in the network dynamic exploring is the growth mode. The proposal of *BA* model transmitted the concept of network growth at the same time introduced the scale-free networks [15, 16]. Following this work, Jeong [17] built a model to test and verify preferential attachment for evolving scale-free networks by testing four most usual-used complex networks. Gergely Palla [18] gave another statistical method to detect the growth mode. Both of the method used a property-distribution idea. The problem is that all the models are built on the premise of complex network, whose nodes sized at 10^5. It could be ineffective when directly applied in small scaled social networks.

Here in this paper, we firstly mapped the inter-groups network and group-location network, with the basis of geo-spatial methods to infer network ties, combining with mining the similarity of groups' behavior. Followed is the preference attachment model to reveal the orientation of the next coming formation of both network and geography distribution. Finally we reached the conclusion and correspondingly gave our policy advice.

2 The evolutionary model of the inter-group terrorist network

2.1 The network model.

(1) The inter-group networks

A network $G(N,M)$ is a finite, nonempty set $V(G)=\{v_1,\ldots,v_N\}$ of vertics (or nodes) together with (a possibly empty) set $E(G)=\{e_1,\ldots,e_M\}$ of edges (or links). Each edge, $e=e(i,j)\in E(G)$, connects vertex *i* to *j*. Two vertices, *i* and *j*, are said to be adjacent if $e(i,j)\in E(G)$. Each node, $v\in G$ could have a set of actions, noted as $Action=\{t,l,p,o,r\}$, whose elements represent *time* (*t*), *location* (*l*), *participants* (*p*), *objects* (*o*), and the *results* (*r*), respectively. Mining the behavior modes of the vertices according to different research purpose helps to confirm the required types of link.

Terrorist groups could be correlated by different types of relationships, group collaborating and the border overlapping are commonly used ones. The others, such as similarity, flows, as well as interactions could be the links, too [24]. And here in this research, we choose the *similarity*. In the past forty years, terrorism evolves along with the groups themselves, including regrouping, merging, separating, and collaborating. *Similarity*, especially in the political destination, is the base of all the behaviors, and could be represented by two patterns, *action coincidence* and *attribute coherence*. For two groups, g_1 and g_2, the definitions of the relationship are given as follows.

Definition 1: action coincidence

An action coincidence, denoted as e_{ac}, is the relationship mined from the view of a space-time view. $e_{ac}(g_1,g_2)\in E$, if and only if:

$$\exists e_1 \in g_1.Action, e_2 \in g_2.Action \ \& \ e_1.t = e_2.t, e_1.l = e_2.l \ .$$

Definition 2: attribute coherence

The attribute coherence, written as e_{at}, is a statical relation $e_{at}(g_1,g_2)\in E$ if and only if:

$$overlap\left(g_1.Action\left(l,o\right),g_2.Action\left(l,o\right)\right) > threshold\ .$$

For example, if group g_1 attack location l_i at a frequence of f_i while group g_2 at a frequence of h_i, the *overlap* function could be calculated as:

$$overlap\left(g_1,g_2\right)=\sum_i \min\left(f_i,h_i\right) \tag{1}$$

The boundary of ties depends on the value of *threshold*. Each pair of groups has a value of *overlap* ranges from 0 to 1. Using 0.1 as the precision, the number of effective ties (*TN*) as the dependent variable, the function can be present as:

$$TN = f(threshold) \tag{2}$$

(2) The geography-group network

In a 2-mode network, noted as G_{gc}, $V(G)$ contains two types of nodes, denoted as $V\left(G\right)=K_1 \bigcup K_2$, $e\left(i,j\right)\in E$, if and only if $i\in K_1, j\in K_2$ For a group *g* in the network G_{gg}, if $\exists A$ that satisfies $C\in g.A.l$,then, $e\left(C,g\right)\in E\left(A.t\right)$

2.2 The preferential attachment model

(1) An introduction and improvement to preferential attachment model

Longitudinal networks evolve over time through the creation or deletion of links or vertices. Modeling the highly interconnected nature of various social, biological and communication systems as networks has attracted much attention in the last few years. Studies have revealed that most evolving network models are based on two ingredients[13]: *growth* and *preferential attachment*. At present, the most widely accepted model is proposed by Cargely Palla[18] and Albert Barabasi [14]. For the specific property ρ , one can construct the cumulative ρ distribution of the objects chosen by the process between *t* and *t*+1, denoted by $w_{t\to t+1}\left(\rho\right)$. The value of $w_{t\to t+1}\left(\rho^*\right)$ equals to the number of objects chosen in the process that has a ρ value larger than $\rho*$ at *t*.

$$W(\rho)=\sum_{t=0}^{t_{\max}-1}\frac{w_{t\to t+1}(\rho)}{P_t(\rho)} \tag{3}$$

The variation trend is used to test the preference of nodes. The $W\left(\rho\right)$ for a mechanism with no preference would appear to be a flat function. However, if it is an increasing function, the objects with larger ρ are favored, which is reversely to the decreasing function.

However, the model always asks for a large set of nodes (a rate of *10*^{6}) to avoid the frequently newly-joint value of property ρ, which would leads to the result the measured values for larger ρ^* is less than theoretical values, Thus an improvement is needed to avoid the impact on the later joint properties. The concept of quantile is introduced and shows a better effect. For a numeric property ρ, the specific value ρ^* could be transformed into the quantile respectively, using the formula:

$$p(\rho^*)=\mathrm{P}(\rho\le\rho^*) \tag{4}$$

We have tested the above improved method on simulated networks with known mechanisms. *i)* uniform attachment (new nodes are attached to a randomly selected old nodes), *ii)* high degree preferential attachment (new nodes are attached to old ones with probability in *BA* model) . For each test, we change the node size from 30 to 500. The figures shows that the method has the ability to deal with small-scale networks.

The improved model gets the ability to reflect the overall trend of the network growth. There are still shortages, taking the *BA* model as example, the lines should show a linear increasing while in the result the heading part is almost horizontal while the tail increase fast. It is understandable since the degree distribution follows the power-law function, leading to the result that nodes with lowest degree takes up a big part in the all nodes. However, the model is still available to reflect the overall growth mode.

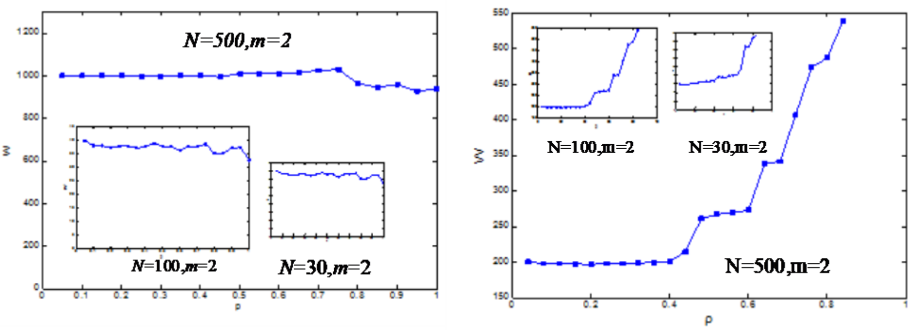

Fig. 2. Results for the improved model.

3 Experiment and results

3.1 Data description and preprocessing

The dataset compiled for this research are mainly from the global terrorism database (*GTD*2014 [19]). The database constructed by START contains terrorism incidents from 1970 to 2013 and gives the information about when and where they happened, who carried out them and the structural data for the processes and consequences.

However, the database unavoidably has problems of incompleteness and incorrectness of infor-mation. Of all the items, over a half are lack of the group or the coordinate information. And some value of attributes are fuzzy, such as 'unknown' and 'individual' . The incorrectness concludes the du-plication, mistake, and rough. Since the items come from multiple patterns, it is really hard work to confirm the accuracy. More important, governments have not reached an agreement on the definition of terrorism. Thus, some of the items in the database could be honored activities in some nations.

Items in the database contain more than 120 thousand activities of over 3000 terrorist groups. However, most of the groups didn't matters much. They disappeared after only a few attacks and caused little threat. The others are active in only a permanent areas solely. Thus, the first noise reduction was made before mapping the network.

The network is composed of 262 nodes with a density of 0.0144. Incidents carried out by the groups in the network takes up more than 90% of that recorded in the *GTD 2014* with clear group declarations. Also, the network covers incidents happends in most continents most threatening groups, such as *Al Qa'ida*, *Hamas*, *ISI*. And the geography-group network

G_{gc} is visualized in figure 6, in which the the quares are groups from G_{gg} and the spots represent for countries which the group attacked.

3.2 The Growth model

The preferential attachment is measured both for G_{gg} and G_{gc}. And for the accumulative network G_{gg}, the result is shown in figure 4.

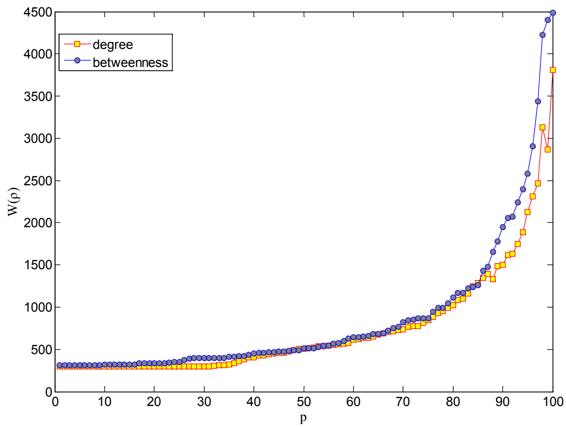

Fig. 4. The preference attachment of G_{gg}.

Both of the two attribute share the same trend. New nodes prefer to attach more centralized neighbors, which has an amazing similarity with the result for the *BA* models in figure 2. The phenomenon indicate a chain reaction, that is, the more important a group is, the more important it will be. In such a growth mode, the network will always have a few central nodes and many satellite nodes. Let alone the external forces, Al Qa'ida should be the center of global counterterrorism for a long time. And the organizational formation and operation process would be followed by other terrorist groups even after it disappears.

As a supplement, the geo-based network G_{gc} was tested by the model, too. And the results are shown in figure 5.

All the four pairs of curves has an orientation to increase with the selected properties. And three pairs shows a similar preference for both the creation and deletion processes, while the other one, the links process measured with degree behaves different. If the gradient change is considers, the nodes process has an accelerate procedure while the links process increase more gently. However, the nodes process is smoother for both properties. Thus, some rules for terrorism spatial preference have been revealed.

(1)Creation and deletion, to some degree, reached a dynamic balance in the terrorism network. Despiting the same increase orientation, the high overlap ratio for W, in a statistical sence, reflects that the numbers of groups as well as link emerge and disappear each year are almost same. And it is corresponded to the facts that the number of active groups every year keeps almost the same in GTD.

(2)Countries with higher property values owns higher preference for terrorist groups and more frequent group supersedure. It is not a good phenomenon, since the supersedure always means the better ones replacing the worse ones, the regional situation of terrorism would go into a vicious spiral.

(3) Degree for countries has certain abilities to reflect the terrorism situation, although not as well as the terrorism result.

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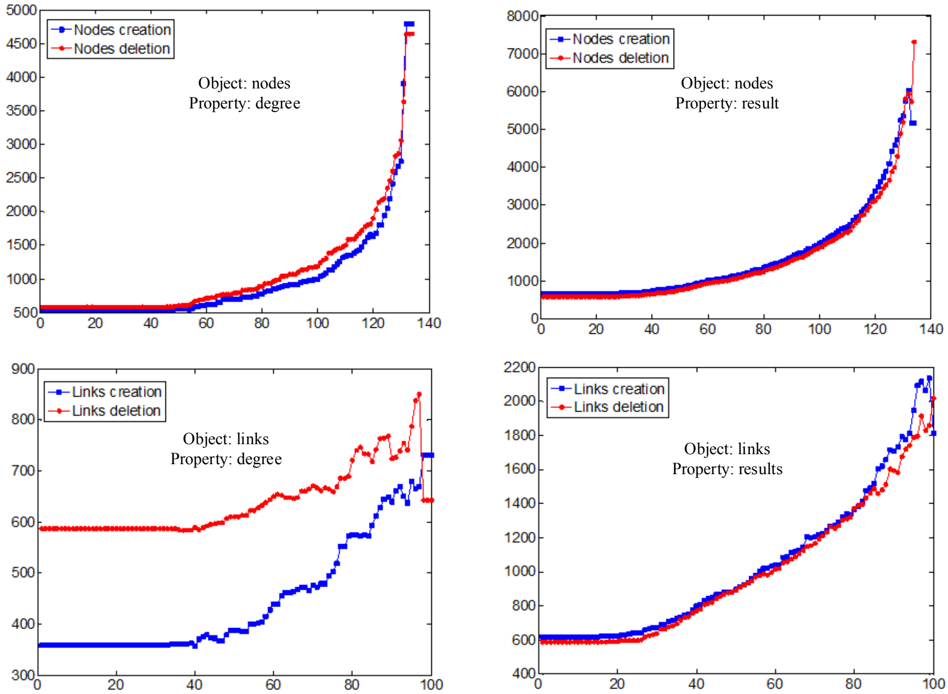

Fig. 5. The geography preference of terrorist groups.

4 Conclusion and discussion

This paper studies the inner dynamics of inter-groups networks of global terrorism by the longitudinal and spatial process. Our main conclusions are summarized as follows.

For the main terrorism network, the new groups have an obvious preference to the high centralized nodes. The preference would result in a scale-free like network, in which few nodes are of high degree. It indicates that with the development of terrorism, there will be an aggregation effect. Al Qa'ida and ISIS, who have become the synonymous of terrorism in the past decades strongly support the phenomenon.

There is spatial transition, too. The transition happened in two aspects. The group-region network indicates that the regional terrorism kept a dynamic balance although the growth is a bit faster than the disappearance. Thus, in a relatively long time, the geography center could be steady, mostly in South East and South Asia.

In conclusion, this work gives a new sight into the inner dynamics of transnational terrorist groups. With the application of longitudinal social network analysis, the dynamics on different views and attributes are explored. Based on the conclusion, we can clearly have a glance at the future terrorism: more international, more hurtful, and more centralized. Also, the work alert the rough decision on disrupt terrorist groups. According to the conclusions, the following suggestions are reached.

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