



Identifying the global terror hubs and vulnerable motifs using complex network dynamics



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ABSTRACT

Terrorism instills fear in the minds of people and takes away the freedom of individuals to act as they will. Terrorism has turned out to be an international menace today. Here, we study the terrorist attack incidents which occurred in the last half-century across the globe from the open source, Global Terrorism Database, and develop a view on their spatio-temporal dynamics. We construct a complex network of global terrorism and study its growth dynamics, along with the statistical properties of the anti-social network, which are quite intriguing. Normally, each nation pursues its own vision of international security based upon its mandate and particular notions of politics and its policies to counter the threat of terrorism that could naturally include the use of tactical measures and strategic negotiations, or even physical power. We study the network resilience against targeted attacks and random failures, which could guide the counter-terrorist outfits in designing strategies to fight terrorism. We then use a disparity filter method to isolate backbone of the network, and identify the terror hubs and vulnerable motifs of global terrorism. We also examine evolution of the hubs and motifs in a few exemplary cases like Afghanistan, Colombia, India, Israel, Pakistan and the United Kingdom. The dynamics of the terror hubs and the vulnerable motifs that we discover in the network backbone turn out to be very significant, and may provide deep insight on their formations and spreading, and thereby help in contending terrorism or framing public policies that can check their spread.

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1. Introduction

Humans are social animals and since the early days of evolution, they have preferred to form and stay together in groups. These groups have evolved from simple settlements to huge nations; defined by multiple causes like language, common heritage, geographical boundaries, and even ideology. The human cooperation has been a motivating force behind the rapid progress of man [1]. Often evolutionary efforts induced the increase in human cooperation. Various factors, like delayed self-sustenance of young ones, or fear of elimination by neighboring communes competing for similar resources which obstructed the humans to sustain their progeny became reasons for cooperation. This cooperation extended from blood relatives to totally unrelated individuals. Surprisingly, evolution has also been responsible for drawing distinctions among themselves in their bids for the survival of the fittest. This segregation [2,3] can be seen in various forms of race, caste, class, religion, political ideology, etc. Thus, the human social behavior has been extremely convoluted with multiple parameters playing crucial roles. It is extremely difficult to assess the complexity of human social behavior, which has a wide range – co-operations, bonding, conflicts, aggression, coups, wars, etc.

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Similar to conflicts, aggression and wars, which have plagued mankind from antiquity, acts of terrorism – where a small group of individuals which are similarly motivated in fighting another social institution or organization or exercising indiscriminate violence in achieving financial, political, religious or ideological aim is hardly new. Though there is no single definition, terrorism may be broadly defined as a conscious and deliberate attempt to incite fear among masses through violence or the threat of violence to pursue a political or ideological gain [4,5]. The aim of terrorism is not limited to eliminating the target group or destruction of opponent's resources, rather it is specifically carried out to send out a psychological message to the adversary. It is meant to propagate fear among the wider general public which may encompass rival religious or ethnic group, a state government, or an entire country. Even though terrorism has been prevalent ever since modern political landscape has existed, past few decades have seen an exponential increase in terrorist incidents. The scope and nature of terrorist attacks have also evolved rapidly, a fact that became evident to the world on September 11, 2001, when a series of four coordinated attacks were conducted in the United States by the terrorist group al-Qaeda. Academic and social media reports show the increase in number of terrorist acts, as well as terrorist organizations. Furthermore, the stretch of the targeted locations has extended on a global scale. These realities have made it incessantly difficult for counter-terrorist organizations or governments in terminating these terrorist acts.

Apart from solutions by social scientists, physicists have recently tried to provide mathematical models, statistical and network analyses and potential solutions to the menaces of terrorism [6–8], conflicts [9,10] and other social phenomena [11–13]. Like business conglomerates, terrorist organizations have also formed transnational ties. They are inter-connected (in a state) and have links with other terrorist organizations outside of the geographical boundaries of the target state.

In this paper, we develop and present a network-based study [14,15] of identification of terrorist hubs and their vulnerable targets. We analyze the terrorist events obtained from the Global Terrorism Database (GTD) [16,17], which collected reports from the printed and digital media, from 1970 to 2016. It is assumed that the media reports are unbiased and provide fair accounts of the actual events. We construct a complex network of global terrorism and investigate the network characteristics of this *anti-social* network. We study the resilience of the network against targeted attacks and random failures [15,18], which could guide the counter-terrorist outfits in designing strategies to fight terrorism. We also use a disparity filter method [19] to isolate the backbone of this network and identify the terror hubs and vulnerable motifs of global terrorism. We then examine the evolution of the hubs and motifs in a few special cases like Afghanistan, Colombia, India, Israel, Pakistan and the United Kingdom. The backbone evolution reflects the change of relative importance of the terror hubs and the vulnerable motifs, which is in conformity with international affairs, peace accords, etc.

2. Data, methodology and results

2.1. Data description and filtration

The source for this analysis is open-access Global Terrorism Database (GTD), [16,17] generously provided by the National Consortium for the Study of Terrorism and Responses to Terrorism (START), University of Maryland. GTD contains the database of news articles from all over the world. The data provides a detailed account of terrorist events from 1970 to 2016, except for year 1993 for which no data exists. The dataset has 170350 instances divided into 135 attributes. For each instance/event-data, we filtered information such as source, target, date of event, organizations or groups, the location information of the event, as well as latitude, longitude data of actors and the event. The dataset required considerable cleaning before any study could be done. The doubtful events, suggested by dataset itself, were removed. Further, attacks carried out by “Unknown” terrorist organization on “Unknown” targets were also filtered out. The events which had no spatial information in the dataset were removed, too. To maintain the network modularity at the country level, any attack which targeted international community instead of a particular nationality was also not included in the dataset. We finally had 64855 events in 46 years (no records available for year 1993).

2.2. Network construction

We analyze the terrorist attacks over a 46 year period (1970–2016), excluding 1993 (non-availability of data for the given period), such that the temporal granularity of our data analyses is one day. Over a period of time τ , we construct the network of ‘connected’ actors in the following way: Whenever a terrorist source, actor a_1 , attacks a target, actor a_2 , it is recorded as an event E_1 at time $t \in [t_0 : t_0 + \tau]$, an edge or directed link ‘connects’ the source to the target by an arrow of unit weight (could be generalized by weighing the edge by impact of attack, etc.), where t_0 is the initial time in the entire span τ . If another event E_2 within the same time window involves source a_3 and target a_2 , then a_3 is connected to a_2 with a directed link of unit weight. Thus, sources a_1 and a_3 are both connected to the common target a_2 . Aggregating all such events over the time window τ , connected components are formed. Every time the same pair of actors are engaged, the edge mention (weight) increases by unity. Thus, the weight of an edge is the frequency of occurrence of attacks between the pair of source and target.

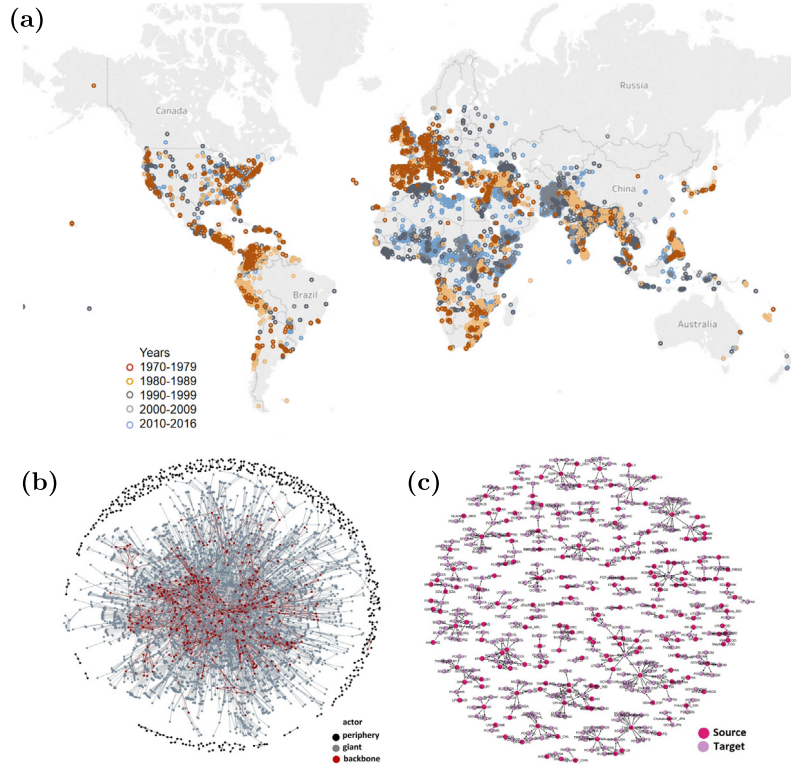


Fig. 1. (a) Spatio-temporal evolution of attacks from 1970–2016. The different colored dots indicate the locations of the attacks, along with the years mentioned in the legend. The map and international boundaries are generated using the proprietary software *Tableau Desktop version 10.5.0*. (b) The aggregated network of terrorism for the period 1970–2016 – Network of terrorist attacks constructed from the history of the events. Two types of actors are involved in the network: Source and target (source nodes refer to the terrorist organizations and target nodes are the victims). Each actor is a node and whenever two actors are involved in an event, a directed link is drawn from source to target. The network has a giant component (gray) in the center, surrounded by 168 peripheral isolated clusters (black), while the nodes colored in red are showing the backbone; the average degree of a node in the network is 3.718. (c) The zoomed-in view of the backbone of the network, which has been identified using the disparity filter with $\alpha_c = 0.01$ (described above). The backbone contains 8% of the total nodes and 4% of total edges (details summarized in [Table 1](#)).

Table 1

Characteristics of the growing backbone structures (with $\alpha_c = 0.01$) in [Fig. 2](#), for the different decades.

Year	Nodes (%)	Edges (%)	Edge mentions (%)	Number of clusters	Average number of neighbors
1970–1980	82 (16)	63 (3)	2490 (38)	20	1.537
1970–1990	179 (17)	156 (4)	12440 (56)	35	1.743
1970–2000	265 (7)	230 (4)	17730 (57)	51	1.736
1970–2010	341 (7)	308 (4)	23707 (57)	60	1.806
1970–2016	470 (8)	427 (4)	40467 (62)	79	1.817

2.3. Disparity filter

To find the backbone structure of a weighted network, we have used an algorithm proposed by Serrano et al. [19]. The disparity filter algorithm extracts the network backbone by considering the relevant edges at all the scales present in the system and exploiting the local heterogeneity and local correlations among the weights. The disparity filter has a cut-off parameter α_c , which determines the number of edges that are reduced in the original network. The filter, however, preserves the cut-off of the degree distribution, the form of the weight distribution, and the clustering coefficient. We discuss the choice of the cut-off parameter α_c below.

2.4. Results

2.4.1. Network structure and backbone using disparity filter

[Fig. 1\(a\)](#) shows the spatio-temporal distribution of the events across the globe; the dots representing the locations, colored according to different decades during which the events occurred. Evidently, past few decades have seen an

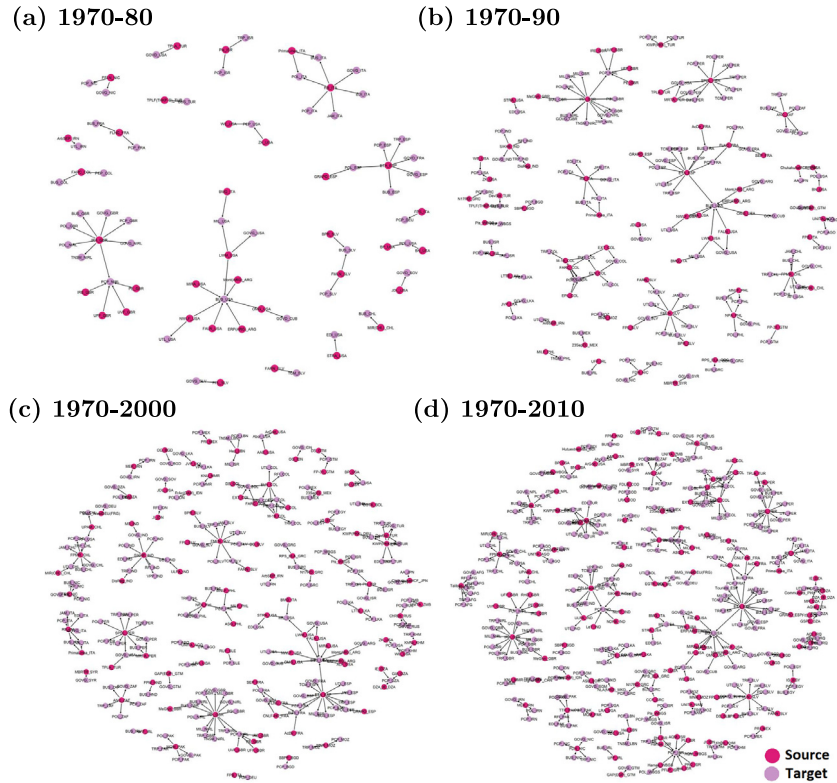


Fig. 2. Decade-wise evolution of the network backbone from 1970–2010 (a–d) (for 1970–2016 shown in Fig. 1). The zoomed-in views of the backbones of the growing network, which have been identified using the disparity filter with $\alpha_c = 0.01$. The characteristics of the growing backbone structure for the different decades are summarized in Table 1.

exponential increase in terrorist incidents (see Supplementary Information Fig. S2, where year-wise evolution along with the associated frequencies of events are depicted). Note that during the period 1970–1990, the maximum value stayed at 2186, while during the period of 1995–2015 this value shot from 364 to 5703, with some fluctuations in between. Fig. 1(b) shows a network aggregated over the period 1970–2016. Two types of actors are involved in the network: source and target (source nodes refer to the terrorist organizations and target nodes are the victims). Each actor is a node and whenever two actors are involved in an event, a directed link is drawn from source to target. The network has a giant component (colored in gray) in the center, surrounded by 168 peripheral isolated clusters (colored in black), while the nodes colored in red are showing the backbone. The zoomed-in view of the backbone structure is shown in Fig. 1(c). The terrorist network for the entire period consists of 5568 nodes, 64855 edge mentions, and 10379 unique edges, with the giant component consists of 5148 nodes. Thus, the giant component encompasses more than 92% of the network nodes, implying that terrorism is closely linked across the globe and the backbone structure encompasses 8% of the total nodes of the network with disparity filter [19] cut-off $\alpha_c = 0.01$ during the period 1970–2016.

The decade-wise evolution of the aggregate network, its giant component (in gray) as well as the backbone (in red) are shown in Fig. S4 of Supplementary Information. Here, we focus more on the evolution of the backbone. Fig. 2 (a–d) show the decade-wise evolution of the network backbone from 1970 to 2010, identified using the disparity filter with $\alpha_c = 0.01$. The comparison of backbone characteristics (as percentage of the total weights $\%W_T$ of the network, total nodes $\%N_T$ in the network and total unique edges $\%E_T$ in the network) with the change in disparity filter cut-off α_c , for the different evolving backbones for the period 1970–1980, 1970–1990, 1970–2000, 1970–2010, and 1970–2016, is summarized in Table 2. We have studied other choices of α_c (see Fig. S5 in Supplementary Information) as well, to check the granularity and details of motifs. In this paper, for filtering the backbone of the network, we choose α_c at 0.01, which captures the motifs at the country level efficiently and provides fairly accurate insights in terms of the participation of the actors (sources and targets).

2.4.2. Network statistical properties

As mentioned earlier, we construct the aggregate network over a given period of time, for the entire 46 years period (1970–2016) as well as for decade-wise period 1970–1980, 1970–1990, 1990–2000, and 1970–2010. Each event is visualized as a link between the source and target involved, which are the nodes, thus creating a network of actors

Table 2

Comparison of backbone characteristics (as percentage figures of the total weights $\%W_T$ of the network, total nodes $\%N_T$ in the network and total unique edges $\%E_T$ in the network) with the change in disparity filter cut-off α_c , for the different evolving backbones.

Year	α_c	$\%W_T$	$\%N_T$	$\%E_T$
1970–1980	0.05	48	9	6
	0.04	45	9	5
	0.03	43	8	4
	0.02	40	7	4
	0.01	38	6	3
Year	α_c	$\%W_T$	$\%N_T$	$\%E_T$
1970–1990	0.05	65	11	7
	0.04	64	10	6
	0.03	62	10	5
	0.02	60	8	5
	0.01	56	7	4
Year	α_c	$\%W_T$	$\%N_T$	$\%E_T$
1970–2000	0.05	65	11	6
	0.04	64	10	6
	0.03	63	9	5
	0.02	61	8	5
	0.01	57	7	4
Year	α_c	$\%W_T$	$\%N_T$	$\%E_T$
1970–2010	0.05	65	12	7
	0.04	64	11	6
	0.03	63	10	5
	0.02	60	9	5
	0.01	57	7	4
Year	α_c	$\%W_T$	$\%N_T$	$\%E_T$
1970–2016	0.05	70	13	7
	0.04	68	12	6
	0.03	67	11	6
	0.02	65	10	5
	0.01	62	8	4

connected by events. The details of the construction is given in the Methods Section 2.2. A typical network is shown in Fig. 1(a) for data aggregated over the year 1970–2016.

We extracted the number of edge mentions w of a unique pair of actors (source–target), as well as the number of unique actors k , one actor is involved with. In terms of the network theory, w is the link weight and k the degree of a node (out-degree for sources and in-degree for targets). While k measures the importance, activity or visibility of a single actor, w measures the frequency of involvement of an actor pair (source–target) in the terrorist events. Since this is a directed network, the nodes have distinct out-degree and in-degree distributions. These quantities are measured decade-wise for the 46 year period (1970–2016) as well as through the whole period (aggregate over 46 years).

We computed the complementary cumulative probability distribution (CCDF) for different quantities for the aggregated network in 1970–1980, 1970–1990, 1970–2000, 1970–2010 and 1970–2016 (refer to Fig. 3 a–f). The complementary cumulative probability density functions for degree $Q(k)$ (out- and in-degrees) and the edge-mentions $Q(w)$, which appear to be broad distributions (stretched-exponentials) (see Fig. 3). The CCDF's $Q(s)$ of the cluster size s for the growing networks are shown in Fig. 3(f); evidently, the outliers correspond to the sizes of the growing giant cluster (as percentage of the total number of nodes in the network): 1210 (83%) (1970–80), 2346 (88%) (1970–90), 3313 (86%) (1970–2000), 4220 (90%) (1970–2010) and 5148 (92%) (1970–2016).

The above results quantitatively characterize the heterogeneity in the activities of the different actors (sources and targets) – while most actors (or actor-pairs) are relatively less active, a few are very active (see Table 3 for the list of top-50 actor pairs). The broad degree distributions show little change with time. Notably, the average clustering coefficient (for directed network [20,21]) of the nodes in the backbone is zero, contrary to most social networks of friendships, collaborations, etc., where typically the average clustering coefficient is high [14,15]. This implies the absence of loops or cyclicity in the network.

2.4.3. Tolerance to attack and failure

We studied the network resilience – how the network breaks down under attack, in order to stop terrorism activities to happen [18]. The largest connected component of the network (i.e., the giant component) is subjected to targeted attack by removal of the most connected nodes (in terms of the source out-degree, which corresponds to a terrorist organization, etc.). As the network is directed, so we start removing the source node with the highest out-degree, followed by the next highest out-degree and so on. This results in rapid fragmentation or destruction of the network by removing all the source

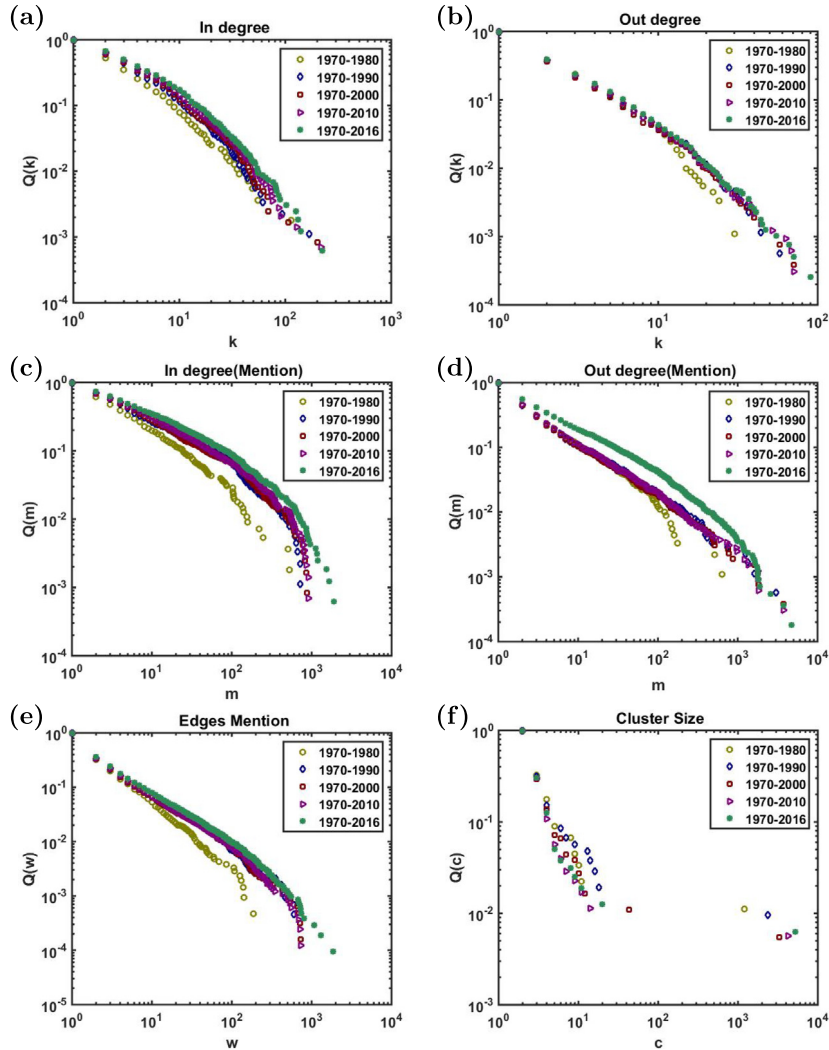


Fig. 3. Structural properties of the network decade-wise: 1970–1980 (light green circle), 1970–1990 (blue diamond), 1970–2000 (red square), 1970–2010 (magenta triangle) and 1970–2016 (green star). (a and b) Plot of the cumulative probability (CCDF) $Q(k)$ that an actor is connected to k others or more (in-degree and out-degree). (c and d) Plot of the cumulative probability (CCDF) $Q(m)$ that an actor is mentioned at least m times (in-degree and out-degree). (e) Plot of the cumulative probability $Q(w)$ that an actor pair is mentioned at least w times. (f) Plot of the cumulative probability (CCDF) for $Q(c)$ that there is a cluster of size larger than c . The size of the largest clusters (seen as outliers) are very large compared to the rest.

nodes in comparison with random node removal. We compute the fraction of nodes present in the largest connected component (GC), which is observed to decrease very quickly, and the average number of nodes in the isolated clusters other than the giant component ($\langle ac \rangle$), with increasing fraction of removed nodes. The network and the giant component are destroyed faster by targeted nodes removal (attack), compared to the random node removal (failure), GC becomes zero after about 33% of the sources are removed through the former method, and about 87% of the sources are removed through the latter, as shown in Fig. 4. The results are very similar to those of the studies by Sharma et al. [9], but we reiterate that in this case we have a directed network and we remove only the source nodes (terrorists).

2.4.4. Motifs and hubs

Using the disparity filter method, we isolated the backbone of network for different time periods and identified the terror hubs and vulnerable motifs of global terrorism. As obvious, only the terror hubs and vulnerable motifs that are very frequently engaged do appear in the backbone. We show in Fig. 5, the evolution of hubs and motifs in a few exemplary cases like Afghanistan (AFG), Colombia (COL), India (IND), Israel (ISR), Pakistan (PAK) and the United Kingdom (GBR). The very fact that the backbone structure evolves indicates that often some terrorist organizations gain more prominence than others. Examining these hubs and motifs, we observe that the *star-structure* occurs quite frequently in the backbone: One source attacking many targets, or one target being attacked by many sources. The backbone structure of ISR grows

Table 3
List of top-50 actor pairs that appear in the backbone structure (1970–2016).

S. No.	Source	Target	Weight	S. No.	Source	Target	Weight
1	Taliban_AFG	POL_AFG	1854	26	IRA_GBR	PCP_NIRL	296
2	ISIL_IRQ	PCP_IRQ	1303	27	NPA_PHL	POL_PHL	293
3	Taliban_AFG	PCP_AFG	1086	28	Houthi_YEM	PCP_YEM	292
4	Taliban_AFG	GOVG_AFG	810	29	NPA_PHL	BUS_PHL	291
5	BH_NGA	PCP_NGA	740	30	CPI-Maoist_IND	GOVG_IND	278
6	SPSL_PER	PCP_PER	733	31	LTTE_LKA	PCP_LKA	275
7	FMLN_SLV	UTL_SLV	713	32	IRA_GBR	BUS_NIRL	270
8	SPSL_PER	GOVG_PER	693	33	TTP_PAK	PCP_PAK	267
9	SPSL_PER	BUS_PER	670	34	FARC_COL	BUS_COL	251
10	SPSL_PER	POL_PER	552	35	KWP(PKK)_TUR	PCP_TUR	245
11	ETA_ESP	POL_ESP	530	36	FMLN_SLV	BUS_SLV	243
12	SPSL_PER	UTL_PER	506	37	ELN_COL	UTL_COL	230
13	ETA_ESP	BUS_ESP	495	38	IRA_GBR	BUS_GBR	222
14	ISIL_IRQ	POL_IRQ	451	39	AQJ_IRQ	PCP_IRQ	221
15	CPI-Maoist_IND	PCP_IND	448	40	Maoists_IND	PCP_IND	219
16	IRA_GBR	POL_NIRL	433	41	NPA_PHL	GOVG_PHL	218
17	FARC_COL	PCP_COL	391	42	BH_NGA	POL_NGA	218
18	ASB_SOM	PCP_SOM	387	43	FARC_COL	UTL_COL	215
19	KWP(PKK)_TUR	POL_TUR	366	44	FARC_COL	GOVG_COL	211
20	FE_NGA	PCP_NGA	361	45	LTTE_LKA	POL_LKA	207
21	CPI-Maoist_IND	POL_IND	341	46	FLNC_FRA	BUS_FRA	204
22	FARC_COL	POL_COL	333	47	NPA_PHL	PCP_PHL	200
23	FMLN_SLV	PCP_SLV	330	48	PE_GBR	PCP_NIRL	196
24	ASB_SOM	GOVG_SOM	324	49	TTP_PAK	POL_PAK	192
25	Maoists_IND	POL_IND	315	50	ETA_ESP	GOVG_ESP	190

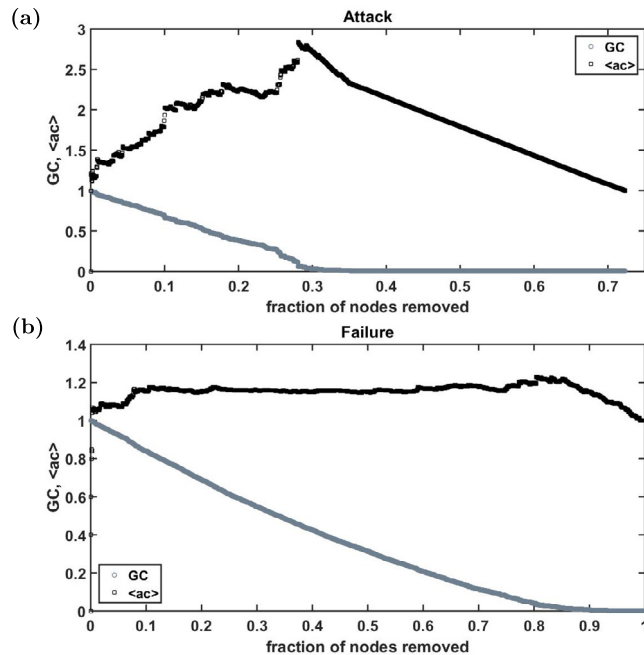


Fig. 4. (a) The structure of the network (directed) under targeted attack: Terrorist source nodes are removed in the sequence of their out-degree starting from the highest out-degree. The plots shows the behavior of the giant component GC (fraction of nodes in the largest connected component) and the average number of nodes in the isolated clusters other than the giant component ($\langle ac \rangle$), with increasing fraction of removed nodes. (b) The structure of the network (directed) under random failure: Nodes having out-degree are removed randomly. The network and the giant component are destroyed faster by targeted nodes removal (attack), compared to the random node removal (failure): GC becomes zero after about 33% of the sources are removed through the former method, and about 87% of the sources are removed through the latter. The results are shown for the network aggregated over 1970–2016.

from a simple structure of 1 source and 2 targets (average degree 1.33) in 1970–1980, to an intricate structure of 14 sources and 6 targets (average degree 1.90) in 1970–2016. Further analysis reveals that before 2000 the Israel-Palestinian conflict was limited to the aggression between the two states. Later, Palestinian organizations like Hamas, Popular Front

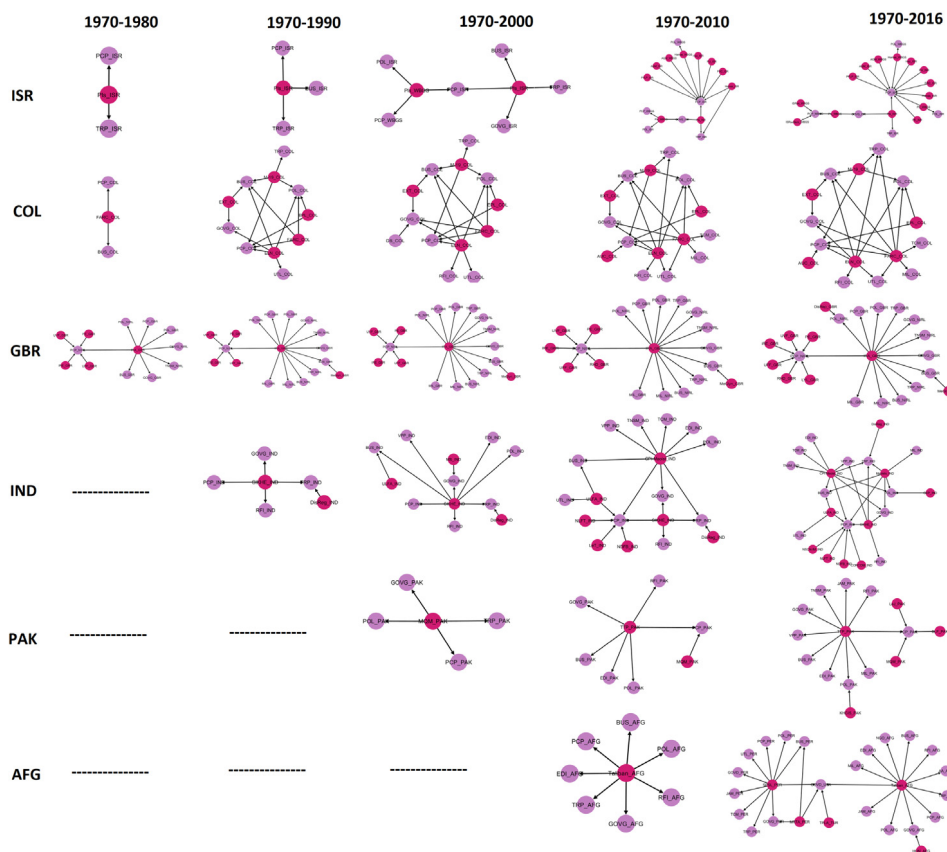


Fig. 5. Cumulative growth of the terror hubs and vulnerable targets in backbones of the countries: Israel (ISR), Columbia (COL), the United Kingdom (GBR), India (IND), Pakistan (PAK) and Afghanistan (AFG) from Fig. 1.

for the Liberation of Palestine, al-Aqsa Martyr's Brigade, etc., assumed prominence in the conflicts against the state of Israel. The backbone structure of GBR remains fairly the same; the average degree grows from 1.85 (1970–1980) to 1.91 (1970–2016); the Irish Republican Army is the main terrorist hub, while the private citizens and property is the most vulnerable target for the entire duration. In COL, the backbone structure grows from a simple 3 node (1 source and 2 targets) in 1970–1980 to a clustered 11 nodes (5 sources and 6 targets) in 1970–1990; the average degree jumps from 1.33 to 2.91. Then it grows steadily to a closely knit structure of 15 nodes (6 sources and 9 targets) at the end of 2016. We observe that till 2000 there is no node for the military, but it appears later as a target. This relates to the fact that military got involved by the state for the eradication of terrorists after the presidential change in 2002.

Fig. 6 shows that in Indian sub-continent, AFG, IND, and PAK are among the nations which have suffered highest terrorist attacks in the recent decades (see Supplementary Information Fig. S2). Interestingly, AFG does not appear in the backbone till 2000, and government (Diplomatic) GOVD_USA is a common target which links two countries AFG and PER. This is typically the case in many other empirical networks, where there exists a node connecting two modules or communities [22]. In AFG and PER, we again see the appearance of star structures, as in GBR. In IND, the rise (and fall) of the attacks by Sikh extremists in the state of Punjab (1980–2000), Separatists India in the state of Jammu and Kashmir (1990–2016), and Maoists in the states of Andhra Pradesh, Bihar, Chattisgarh, Jharkhand, Odisha and West Bengal (2000–2016), are noteworthy. The backbone structure of PAK significantly exposes the change in the prominence of terrorist organizations in various decades. With Muttahida Qami Movement having prominence in the early decades, it is replaced by Tehrik-i-Taliban Pakistan, formed in 2007 in the 2010 decade. Also, Khurasan Chapter of the Islamic State, Lashkar-e-Jhangvi, Baloch Liberation Front have increased their attacks in the current decade, rightly captured in the backbone.

In addition, we have observed in Fig. 2 that El Salvador (SLV) appeared in 1970–1980 and 1970–1990 backbones, but did not appear thereafter; this conforms to the fact that Chapultepec peace accords were signed in 1992 and the terrorist attacks reduced.

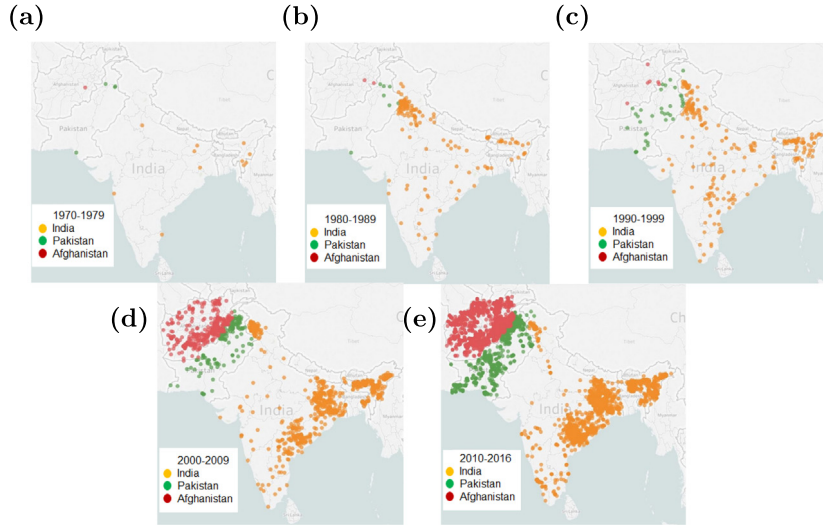


Fig. 6. Spatio-temporal evolution of Indian sub-continent. Event locations decade-wise (a–e), for the countries: Afghanistan (AFG), India (IND) and Pakistan (PAK). The maps and international boundaries are generated using the proprietary software *Tableau Desktop version 10.5.0*. The results are in conformity with the backbone structures of the actor pairs of countries shown in [Table 3](#) and [Fig. 2](#) respectively.

3. Discussion

We have examined the spatio-temporal dynamics of the terrorist events across the globe, using the Global Terrorism Database (GTD) [16,17] from 1970 to 2016. We developed the view of a complex network of global terrorism and studied its growth dynamics. The network always had a giant component, which was in the range of 83% to 92% of the total number of network nodes. The statistical properties of the network were found to be quite robust. The CCDF's for the (in- and out-) degrees (k) and edge mentions (w) seem to be broad (stretched-exponentials). The network resilience results yielded that the giant component disappeared after about 33% of the hubs (in descending order of magnitude) were removed; in the case of random removal of sources, the giant component disappears much slower – only after 87% of the sources were removed.

We isolated the backbone of the terrorist network using the disparity filter method, and identified the terror hubs and vulnerable motifs of global terrorism. We have chosen $\alpha_c = 0.01$ such that it enables us to follow the country-wise evolution of the terror hubs and vulnerable motifs that appear in the backbone structures, and we extracted the backbones of the networks for the different periods of evolution. [Fig. 1\(c\)](#) shows the backbone for the network with the aggregated data from 1970 to 2016, consisting of 470 nodes (8% of the total network), 427 edges (4% of the total network) and 40467 edge mentions (62% of the total network). The backbone nodes primarily lie in the giant component, with few in the periphery. The complete lists of 190 unique sources and 280 unique targets (total 470 nodes) are given in [Tables S2–S3](#) in the Supplementary Information. [Fig. 2](#) shows the growing backbones of the networks for the different decades of evolution. As time evolves, the backbone structure grows (number of nodes and edges increase) and becomes more intricate. The number of nodes, unique edges, edge mentions, number of clusters, and the average number of neighbors a node possesses in the growing backbone structures as shown in [Fig. 2](#), are summarized in [Table 1](#). Interestingly, the number of source–target pairs in the backbone structures – indicated by the number of edges, is around 4% for most years. However, their frequencies of engagement – indicated by the number of edge mentions, grows steadily from 38% (1970–1980) to 62% (1970–2016). The average number of neighbors a node possesses, also increases from 1.537 (1970–1980) to 1.817 (1970–2016).

The backbones for the various decades contain between 8% to 16% of the total number of the nodes; the number of unique edges remains fairly constant around 4% of the total number of edges in the network. Most importantly, the edge mentions (weights) grow from 38% to 62% of the total network, signifying very high frequency of engagement between a small number of source–target pairs. The terror hubs and vulnerable motifs were seen to have star structures more frequently than by chance. The average degree of a node in the backbone increased steadily as time evolved. The average clustering coefficient was always observed to be zero (indicating the absence of triangles or cyclicity) in the growing directed network [20,21], as well as the evolving backbone.

We analyzed the evolutionary structures of the hubs and motifs in Afghanistan, Colombia, India, Israel, Pakistan and the United Kingdom and found very interesting changes in the structures, especially in the Indian sub-continent. The backbone structures of the different countries significantly reflected the changes in the prominence of terrorist organizations in various decades. We also observed that the US citizens, businessmen, and other organizations were often the common

target nodes linking different closed knit communities of terrorist organizations from other countries. The observation that El Salvador appeared only in the backbones of 1970–1980 and 1970–1990 and not thereafter, conforming to the fact that Chapultepec peace accords were signed in 1992, is one of the many significant outcomes of the network backbone analysis. Our results for the range of provided parameters describe the evolution of terrorism in the above countries that emerge from the network analysis. The results are in no way a comment on the previous policies of the Governments of the countries considered.

The political and socioeconomic conditions along with the local circumstances of a region plays key role in framing anti-terrorism policies and elimination of terrorist ties. The inter-disciplinary approaches of network analysis that we have used in this paper, may provide supplementary knowledge and insight on the formation and spreading of terrorism, and thereby help the international security agencies in contending terrorism, as well as produce acumen for the policy makers and experts of international relations.

List of top 50 actor pairs

The list of top-50 actor pairs (source–target abbreviations) along with their weights (frequencies of interactions) that appear in the backbone of the global terrorist network with 470 nodes and 427 unique edges is given in Table 3.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.physa.2019.123113>.

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