Abstract

The spread of radical ideologies is a key to fanaticism, recruitment and terrorist activities. Hence, preventing such activities requires predictive models capable of identifying areas and agents before occurrence of catastrophic terrorist act. In this paper, we develop a model that captures a radicalization mechanism through several intermediate stages of individuals. We propose a radicalization mechanism using individual-based approach constructed from epidemiological model of contagion. Our model builds on insights from contagion models used in theoretical epidemiology and entails a mechanism for controlling the spread of radical ideologies on social spatial networks by identifying suspicious individuals and monitoring them, and taking action when necessary. We show how our model can combat the development of terrorist networks even with limited information on a target terrorist network.

Key words: radicalization mechanism, contagion, socio-spatial network, counter-terrorism measures, control mechanism

1 Introduction

Current counter-terrorism efforts have focused on either scattering, killing or capturing a terrorist organization’s core leadership, reducing the threat from its central core operatives, foot-soldiers and leaders. However, terrorist organizations continue to spread at an alarming rate in many parts of the world, as a result creating subcultures within communities. Since 9-11, the threat from radicalized Salafist-Jihadists has changed, and has been limited to U.S. interests and that of its allies overseas. Recent events in London, Madrid, Bali, and Amsterdam illustrate new trends in the involvement of local communities in terrorist activities, in which local terrorist organizations and residents utilize terrorist acts as their ideological inspirations. Different forms of terrorist threats have emerged in European, Canadian, and Australian cities where most of the terrorist attempted and successful attacks such as Madrid 2004, Amsterdam Hofstad group, London 2005, Toronto 18 Case and Australia’s Operation Pendennis, have been diasporic in nature. Such a change requires a new framework to combating terrorism and reducing the number of possible terrorist acts.

In this paper, following the paradigm of Castillo-Chavez and Song (2003) and Cherif and Castillo-Chavez (forthcoming), we model the process of the emergence and radicalization of terrorist networks, which is vital for both better understanding the nature of terrorist networks and also developing effective counterterrorist measures even when...
our information of terrorist organizations is not sufficient. This understanding also increases our knowledge of the mechanisms of evolution of cultural norms.

2 Brief Review of Terrorist Networks Literature

Recent literature has provided various mechanisms of counter-terrorism measures. Keohane and Zeckhauser (2003) list four fundamental ways in which a state can defend its citizens against terrorist groups: 1) stock reduction; 2) flow control 3) averting actions and; 4) amelioration. Among these four ways, the first two are the most relevant in designing a strategy to control terrorist networks formation and activities. Stock reduction refers to directly reducing the stock of terror capital. For example, military action directed toward terrorist organizations or the state supporting them belongs to this category although stock reduction does not necessarily involve military action. And the second option entails "[i]dentifying so-called 'charitable organizations’ with ties to terrorist groups and applying diplomatic pressure to state sponsors” to cut off the flow of funds (Keohane and Zeckhauser 2003:205). Other scholars (Castillo-Chavez and Song 2003; Cherif and Castillo-Chavez (forthcoming)) suggest the reduction in recruitment pool as the one of the most effective mechanism in reducing the stock of terror capital.

A control strategy must entail these two components, which are related in the sense that both components require the knowledge of a targeted terrorist network. Current counter-terrorism measure sometime do not produce the intended results. Removing key leaders in a terrorist network without considering the overall organizational structure and tools produces only temporary outcomes. However, we often times lack information on such a network and even when data are available, we face a large number of missing cases for two reasons. Firstly, as compared to criminal networks such as drug trafficking networks, terrorist networks take action much less frequently, which derives from at least the following two factors: (1) the terrorist network’s ability to undertake action fluctuate considerably in a short-term because it is affected by shifts in public opinion (Keohane and Zeckhauser 2003); and (2) attacks undertaken by terrorist networks are usually ideology-oriented rather than reward-oriented. As several researchers (e.g. Pyszczynski et al. 2009; Richardson 2006) posit, this is one fundamental characteristic that differentiate terrorism from criminal acts. Indeed, Richardson (2006) states that terrorists usually act in the service of a set of their righteous ideals. Hence, terrorist acts usually are political and rarely involves psychopathology or material deprivation (Turk 2004). When the objective is ideological, actions tend to take place less frequently because a network may wait for the right moment to act (Morselli et al. 2007).

Secondly, unlike other types of criminal networks that are centralized and hierarchial, terrorist networks tend to be more decentralized (Morselli et al. 2007; Tucker 2001). Therefore, identifying central players in terrorist networks that is suggested by Akbar Hussain (2007) often does not work because of the above noted nature of such networks aggravated by possible camouflage. Besides, identifying important ties or flows is often a difficult task since "structures with a proven level of endurance and an established reputation” including terrorist networks tend to opt for security rather than efficiency (Erickson 1981:144; Morselli et al. 2007).

The problem of missing data is aggravated by the fact that unlike criminal networks such as drug-trafficking networks, terrorist networks, especially transnational terrorist networks such as Al Qaeda, tend to have members from quite diverse backgrounds in terms of their nationality, educational status, socioeconomic status, and ethnicity (Raab and Milward 2003). This is especially the case among today’s modern terrorist networks as compared to "traditional” terrorist organizations such as the Irish Republican Army (IRA) or the Kurdish Workers’ Party (PKK) that tend to recruit members from a specific population (Takeyh and Gvosdev 2002).

Given the above noted characteristics, controlling terrorist networks is a cumbersome task. In this paper, we present a new mechanism of controlling terrorist networks that entails taking advantage of our knowledge about terrorist organizations albeit limited, and also, lessens the dilemma for authorities when dealing with terrorist organizations. That is, minimizing publicity for these organizations while preventing them from destructive acts (Turk 2004). As will be discussed, our abstract mechanism is designed in such a way that it can be improved without transforming its fundamental structure by adding the knowledge obtain while implementing the mechanism through the update of relevant parameters using, for example, Bayesian inference. Finally, since our mechanism examines both how terrorist networks propagate and can be controlled, it will be useful for us to understand how and why individuals become terrorists. We develop a contagion (Bettencourt et al 2006; Bartholomew 1982) stylized system to model the dynamics of radicalization and a method of effective control of such social contagion process.
3 Model Description

This section provides the description of the proposed model and key assumptions we have made. The section is divided into four parts: network generation and characterization, radicalization mechanism, control mechanism and simulation approach. In the network section, we provide the method of generating socio-spatial network and characterization of its property. In the radicalization mechanism section, we follow mathematical and theoretical epidemiological approach of social contagion to modeling the spread or transmission mechanism and the recruitment process of radicalism in an idealized community. To the best of our knowledge, only few papers have employed this methodological approach of understanding the transmission mechanism of radical and fanatic behaviors (Castillo-Chavez and Song (2003); Cherif and Castillo-Chavez (forthcoming); Santonja et al 2008; Stauffer and Sahni 2006). In the last two subsections, we propose a new method of control mechanism and agent-based simulation approaches, which help identify the tipping points that facilitate the radicalization process to take place and spread.

3.1 Network Generation and Characterization

We use a network approach to represent the contact structure of agents in an idealized society or community. In our construction, individuals are represented by vertices with contacts between members denoted by edges. An edge represents the contact between vertices that can allow transmission of ideology. In our agent-based model, the network edges are created in such a way that a parameterized average density is achieved while maintaining the appropriate distribution. We connect two agents or nodes using a half-Gaussian spatial or socio-spatial distribution of width $D$ (Keeling 1999; Keeling 2000):

$$p = \frac{n}{2\pi D^2} e^{-\frac{d^2}{2D^2}}$$

(1)

where $d$ is the distance between two agents which can loosely be defined as affinity, family, friendships, neighbors, similarity, etc... The parameter $n$ is the average number of contacts or degree in the network, and $D$ is the spatial length-scale. The parameter $D$ measures the socio-spatial preferential vicinity. For instance, small $D$ exhibits local dynamics where agents will preferentially connect to other agents within their socio-spatial vicinity, while large $D$ provides global connection where agents can be connected to distant agents. In other words, the chance of a link between two individuals decreases as the distance between them increases such that ideological infection is transmitted preferentially to individuals in the proximity (whether it is locational, ideological, socio-economical or socio-psychological proximity). This construction of the network allows us to use the parameter $D$ as a proxy for

![Fig. 1](image)

Fig. 1. The plots show graphs and distribution of length of edge for two different values of $D$. On the left, the figure shows distribution of length of edge for $D = 1$ with Clustering Coefficient $= .15$. Similarly on the right, the length of edge distribution for network with $D = 10$ and Clustering Coefficient $= .015$ is shown. In all these graphs, we assume an average number of contacts ($n = 8$) (inset) and degree distributions are similar. However, the average length of edges are different. Network with $D = 1$ has smaller average length than that of network with $D = 10$. These calculations and results are due to Cohen et al 2007.
clustering coefficient, which can determine transmissibility of ideology, while maintaining small contact size (Watts and Strogatz 1998; Kelling 1999; Keeling 2000; Read and Keeling 2003; Keeling and Eames 2005) as shown in Fig. 1 (Cohen et al 2007). For instance, lower values of $D$ yield networks with higher clustering coefficients, while higher values of $D$ produce networks with lower coefficients, hence the mean length of an edge increases with $D$ while maintaining the likelihood of shorter length. Spatial networks, such as the one presented in this paper, usually exhibit a reasonably high degree of heterogeneity.

<table>
<thead>
<tr>
<th>States</th>
<th>Definition</th>
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<tbody>
<tr>
<td>$G$</td>
<td>Non-core groups or general population</td>
</tr>
<tr>
<td>$S$</td>
<td>Susceptible individuals</td>
</tr>
<tr>
<td>$I$</td>
<td>Indoctrinized individuals</td>
</tr>
<tr>
<td>$R$</td>
<td>Radicalized individuals</td>
</tr>
<tr>
<td>$R_s$</td>
<td>Foot-soldiers</td>
</tr>
<tr>
<td>$R_L$</td>
<td>Leaders</td>
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Table 1

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Definition</th>
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<tbody>
<tr>
<td>$\gamma$</td>
<td>birth/recruitment rate</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>rate of self-identification</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>rate of indoctrinization</td>
</tr>
<tr>
<td>$\beta_3$</td>
<td>rate of radicalization</td>
</tr>
<tr>
<td>$\mu$</td>
<td>natural death/exit rate/residence rate</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>rate of militancy</td>
</tr>
<tr>
<td>$\varphi$</td>
<td>proportion of militant</td>
</tr>
<tr>
<td>$d$</td>
<td>death rate due to terrorism</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>leadership reduction proportion</td>
</tr>
</tbody>
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Table 2

3.2 Modeling Radicalization Mechanism: Transmission on the Network

We first derive a macro-level formulation of radicalization mechanism using tools from theoretical and mathematical epidemiology, which is later use to describe micro-interactions between agent in section 3.4. We divide the population of interest, $P$ (e.g. $P = G + C$), into two sub-populations mainly core ($C = S + I + R + R_s + R_L$) and non-core groups ($G$). The non-core group (general populace) $G$, consists of individuals who have not enter or have not come in contact with radical ideology. The stage is usually the source of recruitment pool. The core group consists of individuals susceptible (self-identified), semi-radical or moderate $I$ (indoctrination), Radical $R$ (Jihadization). The susceptible group includes members of the population who have not yet been converted into adapting the ideology but have begun to explore Salafi-Islam ideology and gradually gravitate toward radical ideas. Semi-radical includes those who have been converted and as well as those who may not be fully committed. These individuals go through indoctrination stage in which they intensify their beliefs and radical views are reinforced. The radical group consists of individuals who have internalized extreme ideology and have accepted their duties as Jihadists and holy warriors or Mujahedeens. It is from this subgroup that terrorism groups emerge. The radical group is further subdivided into two groups: foot-soldiers $R_s$ and leaders and operatives $R_L$. The ansatz describing the radicalization mechanism is
given as:

\[ G' = \gamma P - \beta_1 GC \frac{P}{C} - \mu G \]  

(2)

\[ S' = \beta_1 GC \frac{P}{C} - \mu S - \beta_2 SI \frac{I + R + R_s + R_L}{C} \]  

(3)

\[ I' = \beta_2 SI \frac{I + R + R_s + R_L}{C} - \mu I - \beta_3 I \frac{R + R_s + R_L}{C} \]  

(4)

\[ R' = \beta_3 I \frac{R + R_s + R_L}{C} - \mu R - \alpha R \]  

(5)

\[ R_s' = \alpha \varphi R - \mu R_s - dR_s \]  

(6)

\[ R_L' = \alpha (1 - \varphi) R - \mu R_L - \kappa dR_L \]  

(7)

where \( 0 < \kappa < 1 \), and the parameter descriptions are given in the table 1 below. The core population recruits individuals from the non-core population at the per capita rate of \( \beta_1 \), which is replenished at an assumed rate \( \gamma \). The per capita rates of \( \beta_1 \) (self-identification rate), \( \beta_2 \) (indoctrinization rate), \( \beta_3 \) (radicalization rate) measure the strength of the recruitment into susceptible, semi-radical and radical, respectively. The parameter \( \mu \) is the rate at which individuals leave the system, for example dying naturally, while \( d \) and \( \kappa d \) are the terrorist activities induced mortality or removal rates (e.g. suicide bombing, died in counter-terrorist attack) for foot-soldiers and leaders, respectively. We assume that proportion of radicals become foot-soldiers (\( \varphi \)) and leaders (\( 1 - \varphi \)) at the transition rate of militancy \( \alpha \). The conversion rates from self-identified to indoctrinized, and from indoctrinized to radicalized individual is given as \( \frac{\beta_2 SI + R_s + R_L}{C} \) and \( \frac{\beta_3 I + R_s + R_L}{C} \), respectively. The mathematical analysis of a model similar to the one presented in this paper has been presented elsewhere (Castillo-Chavez and Song 2003; Cherif and Castillo-Chavez (forthcoming)). However, this model differs greatly from previous models of social contagions (Bettencourt et al 2006; Bartholomew 1982; Santonja et al 2008; Stauffer and Sahini 2006) in that it incorporates mechanism for individuals who fall out of the recruitment process, and additionally includes foot-soldiers and leadership compartmental classes. In this paper, we focus primarily on individual-based modeling (or agent-based model) adapting the above formalism to propose effective control mechanism.

3.3 Heuristic Agent-based Control Mechanism

As an effort to prevent the spread of radicalization and the emergence of terrorist networks, we propose a three-step heuristic agent-based (individual-based) control mechanism based on the above radicalization process model. The three steps are namely identification, monitoring and action. In the identification step, the objective is to identify potential foot-soldiers and the leaders. In order to achieve economically feasible and effective control, the semi-radicals, the susceptible and the general populace are not under control. In contrast, the radicals are randomly investigated, as they are closest to turn into foot-soldiers or the leaders. Recent observation of resurgence of terrorist recruits in Afghanistan shows that, for example, individuals attending Madrasa schools are easy target for Taliban and Al-Qaeda due to the fact most of these individuals have already completed the first three stages of radicalization (Eqs. 3-5); and share similar ideology. As a result, it is natural to target the radicals within this social context. In our
heuristic framework of control, these three-steps are abstract construct of control mechanism. In the identification step, radical individuals are identified as potential terrorists at a certain identification rate, depending on the accuracy of our information about the terrorist networks or organizations. Once they have been identified, monitoring stage begins, where radicals are put under surveillance for a certain period, the length of which is flexible and depends on the efficacy of the counter-terrorist measures and resources. Abstractly, monitoring may entail gathering information or surveillance in its literal sense. It may also mean, in the case of Madrasa schools, providing aids through non-military agencies that can moderate their ideology, which results in reducing terrorist recruitment pool. In the simulation presented in this paper, we assume that the identified radicals will be monitored in at most three years. If they turn into either foot-soldiers and the leaders within this surveillance period, actions will be taken to remove, arrest or kill them. If this change does not occur, no actions will be taken against them and the surveillance will be tentatively over for these specific radicals.

3.4 Individual-Based Model (IBM) Simulations

In the proposed model, we use macro-level dynamics (Eqs. 2-7) to derive and implement appropriate micro-interaction dynamics between agents using networked social spatial contacts (Eq. 1). We use Netlogo programming platform to perform our agent-based (individual-based) simulations. Each individual is given a set of distributed attributes (e.g. age, education, desperation, income level, etc...), and we define individual propensity, \( \theta_i = \sum_{j=1}^{\vert A \vert} p_j \theta_{ij} \), as a convex combination (where \( \vert A \vert \) is the number of attributes and \( \sum_{j=1}^{\vert A \vert} p_j = 1 \)) of its attributes. We use convex combination assumption because of difficulty associated with understanding which social experiences, interactions and conditions that increase the likelihood of becoming radicals. For example, statistics shows that income alone is not a sufficient and necessary condition for suicide bombers involved in September 11 and London events. For transmission of radical ideology, we define ideological transmissibility \( \tau_i \) of each agent as a normalized propensity \( \theta_i \). The transmissibility \( \tau_i \) is given as:

\[
\tau_i = \frac{\theta_i}{\sum_{i=1}^{N} \theta_i}
\]

where \( N \) is total number of agents. We assume that many of the formed opinions, and observed and realized behavioral dynamics are rooted in the social structures or contexts to which they belong. As a result, once an individual enters the susceptible class with individual transmissibility \( \tau_i \) for each month that s/he is in contact with radicalized individuals. For example, a susceptible begins radicalization process with probability \( p_0 = 1 - (1 - \tau_i)^k \), where \( k \) is the number of radicalized contacts in a given month. We assume that individuals who have been influenced by
radical ideology for the first time transition to indoctrinized class. Similar probability is generated for progressions from indoctrinized class to radical group. At any given time, it is assumed that individuals can leave the class at a rate of $\mu$. For simplicity, individuals who leave the system, at $d$, $d$, and $kd$, are reintroduced into the system but with different links for consistency and in order to maintain constant total population. We assume that only active radicals can be militants at a militancy rate $\alpha$, where proportions $\varphi$ and $1 - \varphi$ become foot-soldiers and leaders, respectively.

4 Results and Discussion

Previous military-based counter-terrorist measures have focused primarily on eliminating foot-soldiers and core leaders. However, because of decentralized nature of most terrorist organization, these measures have proven unsuccessful. From the mathematical analysis of the Eqs. 2-7, we know that the radicalization process allows four thresholds. In order to sustain the core group ($C$) and to have recruitment pool for terrorist membership, $R_1 = \frac{\beta_1}{\mu} \geq 1$ must be satisfied. This condition is similar to results found in (Castillo-Chavez and Song 2003; Cherif and Castillo-Chavez (forthcoming)). The threshold $R_1 \geq 1$ is a necessary condition for establishment of core group. Since there are always recruitment pool in the general population or non-core ($G$), the core population can be established whenever the rates of self-identification or residence time $\frac{1}{\mu}$ are large or long enough. However, to maintain radical groups and terrorist, $R_1 = \frac{\beta_1}{\mu} \geq 1$ and $R_2 = \frac{\beta_2}{\mu} \geq 1$, and $R_3 = \frac{\beta_3}{\mu} \geq 1$ must be satisfied, respectively. As shown in Figs. 4-5, as we increase the militancy rate the number of terrorist members increases (see Fig. 4). However, as we increase the identification rate of control, we observe different dynamics. If we fix militancy rate and increase self-identification rate, we observe that percent of removed radicals increases linearly (see Fig. 5). If the self-identification rate is fixed and militancy rate is assumed to vary, the percent of removed radicals exhibit threshold phenomena. The percent of removed radicals increases initially to a critical value before decreasing slightly and remaining constant afterward. This suggests that it is impossible to eradicate terrorism when the rate of militancy or recruitment of radicals into terrorism is high. In fact, the result provides an insight into why some terrorist organizations collapsed or were weakened (Sendero Luminoso or Shining Path) while others are not (Hezbollah in Lebanon), under similar counter-terrorist measures.

Fig. 4. Caption coming soon

Our simulations suggests that, in the case of Shining Path, the recruitment sources were substantially diminished. The recruitment pool of Shining was reduced, for instance, in two ways: the organization imposed taxes on their supporters (farmers), and expansion into urban areas where their supports were minimal. Because of these and its organizational structure where no clear promotional mechanism was put in place, the organization collapsed when their leader, Abimael Guzman, was arrested in 1992. As a result, the strength of the organization has diminished even though some members are actively engaged in sporadic terrorist and drug trafficking activities. Unlike Shining Path, Hezbollah has persisted despite of similar counter-terrorist measures taken by Israel over the years. In contrast
Counter-Terrorist Id. Rate = .2

Counter-Terrorist Id. Rate = .6

Counter-Terrorist Id. Rate = 1

Fig. 5. Caption coming soon
to Shining Path. *Hezbollah* has clear promotional mechanism; has not expanded their reach beyond their regions of interests; and has continuously tried to maintain its recruitment pools through various measures (e.g. charity, social welfare, education).

In term of counter-terrorist measures, the counter-terrorism policy of Israel was not effective and efficient in defeating *Hezbollah*. The measures focus on targeting leadership of *Hezbollah*. Therefore, from our simulations, terrorist organizations can only be defeating *if and only if* there is a decline the recruitment pool and organizational strength, and the organizations have weaker promotional mechanism in place. In other words, it is impossible to defeat such terrorist organizations without reducing the strength of the organization through reduction in the number of foot-soldiers and leaders, and forcing the organization to adopt weaker leadership promotion mechanism. If a terrorist organization has a weaker promotional mechanism, then counter-terrorism measures that target the core leaderships may produce the desire outcomes (e.g. disintegration, collapse of the organization). This was the case in the aforementioned collapse of Shining Path. If targeting leaders fail, it usual produces or creates factions within the organization, hence reducing its strength and effectiveness. However, this approach does not work well on organizations with stronger promotional mechanism and large decentralized recruitment pool like *Hezbollah* and *Al-Qaeda*.

5 Conclusion

In this paper, we have investigated the dynamics of radicalization process on socio-spatial networks. The proposed individual-based model exploits social contagion mechanism based on epidemiological model, in which individuals were assigned a set of attributes. The proposed model is simplified descriptions of the intrinsics of radicalization that produce realized social dynamics of terrorism. Our formalism allows us to include socio-economic, psychopathological and individual attributes in order to produce heterogeneity in the population. A detail descriptions coupled with data could improve our understanding of radicalization process and recruitment mechanism, and could allow for more effective and efficient implementation counter-terrorist control measures.

Acknowledgements

This work was undertaking while the authors were participants in Complex Systems Summer School, organized by Santa Fe Institute (SFI) in June 2009. We also thank Dr. Tom Carter for his help on Netlogo.

References


