CRIMEFIGHTER ASSISTANT
A Knowledge Management Tool for Terrorist Network Analysis

Uffe Kock Wiil, Jolanata Gniadek and Nasrullah Memon
Counterterrorism Research Lab, The Maersk Mc-Kinney Moller Institute, University of Southern Denmark
Campusvej 55, 5230 Odense M, Denmark

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Abstract: A terrorist network is a special kind of social network with emphasis on both secrecy and efficiency. Such networks (consisting of nodes and links) need to be analyzed and visualized in order to gain a deeper knowledge and understanding that enables network destabilization. Previous research on terrorist network analysis has to a large degree focused on analysis of nodes. This paper presents the CrimeFighter Assistant, a novel knowledge management tool for terrorist network analysis. CrimeFighter Assistant treats links as first class objects and provides a better balance between network, node, and link analysis.

1 INTRODUCTION

A terrorist network is a special kind of social network with emphasis on both secrecy and efficiency. Such networks are intentionally structured to ensure efficient communication between members without being detected (Baccara and Bar-Isaac 2009; Lindelauf, Borm, and Hamers 2009; Enders and Su 2007; Baker and Faulkner 1993; Latora and Marchiori 2004).

Knowledge about the structure and organization of terrorist networks is important for both terrorism investigation and the development of effective strategies to prevent terrorist attacks. Theory from the knowledge management field plays an important role in dealing with terrorist information. Knowledge management processes, tools, and techniques can help intelligence analysts in various ways when trying to make sense of the vast amount of data being collected in relation to terrorism (Wiil, Memon, and Gniadek 2009). The collected data needs to be analyzed and visualized in order to gain a deeper knowledge and understanding of the terrorist network.

A terrorist network can be modeled as a generalized network (graph) consisting of nodes and links. Nodes are entities (people, places, events, etc.) and links are relationships between the entities. Techniques from social network analysis (SNA) and graph theory (Wassermann and Faust 1994) can be used to identify key nodes in the network, which is helpful for network destabilization purposes. Taking out key nodes will decrease the ability of the terrorist network to function normally (Carley, Lee, and Krackhardt 2001).

Previous research on terrorist network analysis (TNA) has to a large degree focused on analysis of nodes. Links are seldom first class objects in the terrorism domain models with the same properties as nodes. This is in contrast to the fact that the links between the nodes provide at least as much relevant information about the network as the nodes themselves (Gloor and Zhao 2006).

A terrorism domain model with both nodes and links as first class objects will allow for a better balance between analysis of nodes and analysis of links, which will result in more precise knowledge about the terrorist network. This paper presents the CrimeFighter Assistant, a novel knowledge management tool for TNA that supports a balanced analysis of network, node, and link measures to address the above issue.

Section 2 briefly describes our overall knowledge management approach to counterterrorism called CrimeFighter. In Section 3, we present the CrimeFighter Assistant tool for TNA. In Section 4, we demonstrate the use and evaluate our tool through a case study of the 2002 Bali bombing. Section 5 compares our approach with related work. Section 6 concludes the paper and discusses future work.

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2 KNOWLEDGE MANAGEMENT FOR COUNTERTERRORISM

The CrimeFighter toolbox for counterterrorism is a novel approach to TNA. The goal is to provide a number of desktop tools that are grouped into three overall software packages each containing knowledge management tools and services relevant to counterterrorism (Wiil, Memon, and Gniadek 2009). These tools and services are designed and implemented to enable them to interoperate and exchange information. The CrimeFighter toolbox is depicted in Figure 1.

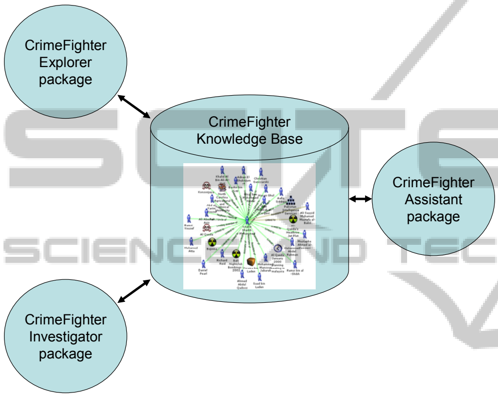


Figure 1: The CrimeFighter toolbox for counterterrorism.

The Explorer and Investigator packages each support different knowledge management processes that result in generation of terrorist networks consisting of nodes and links. These terrorist networks are stored in the knowledge base. The Assistant package provides various features to analyze and visualize networks – as generated by the Explorer and Investigator packages.

The research on CrimeFighter can be divided into four overall areas:

1. **CrimeFighter Explorer** is a software package with various services aimed at acquiring data from open sources and extracting valuable information from the data by processing it in various ways (filtering, mining, etc.).
2. **CrimeFighter Investigator** is a software package that provides various services that enables an intelligence analyst to work with emergent and evolving structure of terrorist networks to uncover new relationships between people, places, events, etc.
3. **CrimeFighter Assistant** is a software package with various services that supports analysis and visualization of terrorist networks. TNA is aimed at finding new patterns and gaining a deeper knowledge and understanding about terrorist networks. Terrorist network visualization deals with the complex task of visualizing the structure of terrorist networks.
4. **CrimeFighter toolbox architecture**. In order for the developed tools and services to be able to interoperate and exchange information, the overall software architecture of the toolbox must enable a service in one package to use a service in another package. For instance, the structure generated by the services of the Investigator package must be able to use the analysis and visualization services available in the Assistant package.

The remainder of this paper focuses on describing the various TNA and visualization techniques available in the CrimeFighter Assistant. As mentioned, the starting point for TNA is the existence of a network structure. Hence, much knowledge management work needs to take place prior to network analysis. These prerequisite knowledge management processes (see Wiil, Memon, and Gniadek 2009 for details) are not the focus of this paper.

3 CRIMEFIGHTER ASSISTANT

The goal from an intelligence analysis perspective is to support the analysts in making informed decisions regarding possible actions to destabilize the network by determining the most important nodes and links in the network.

Looking at the diversity of terrorist groups (e.g., al-Qaeda, ETA, or Liberation Tigers of Tamil Eelam), the way they work, their goals, and their means are different. Therefore, using just one strategy to counter them is impossible.

To gain the best possible knowledge and understanding about a terrorist network, one should analyze the network as a whole together with the properties of its nodes and the properties of its links. Various questions might be asked in this process, such as:

Network Measures:

- How covert is the network?
- How efficient is the network?
- What is the density of the network?

- What is the trade-off between secrecy and efficiency in the network?

Node Measures:

- Who are the central (important) persons in the network?
- What makes the person important?
- What role does a particular person have?
- How is the network affected after removal of a particular node?

Link Measures:

- What links are important for communication in the network?
- How important is a particular link in relation to network efficiency and secrecy?
- What is the information backbone of the network?

Answering the above questions without any tools to support the task would be very time consuming. CrimeFighter Assistant provides various TNA features that can support intelligence analysts in answering the above questions.

In the following sections, the system architecture and analysis and visualization features are presented.

3.1 System Architecture

The overall system architecture of CrimeFighter Assistant is shown in Figure 2.

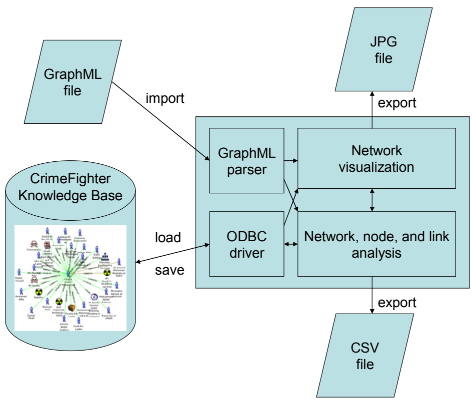


Figure 2: CrimeFighter Assistant system architecture.

CrimeFighter Assistant provides two primary features: network, node, and link analysis and network visualization. Networks can be loaded from the knowledge base or from GraphML files. GraphML is extensively used in SNA applications. Therefore, CrimeFighter Assistant supports this file format as an interchange format to provide interoperability with other SNA and TNA tools. Network data stored in GraphML files can be loaded into the workspace and the same analysis and visualizations can be performed as for network data stored in the CrimeFighter knowledge base.

Analysis results can be exported to CSV (comma-separated values) format to be used in other applications such as Microsoft Excel. Visualized networks can be exported to a printable format (JPEG format). Visualization is based on the JUNG (Java Universal Network/Graph) library (O'Madadhain et. al 2005). The entire package is coded in Java.

3.2 Analysis and Visualization

A screenshot of CrimeFighter Assistant is shown in Figure 3. The panel to the left is used for visualizing the network, while the panel to the right is used for displaying network, node, and link analysis results. If the user clicks on a node or a link in the analysis results part, the corresponding node or link in the network visualization part will be highlighted in red.

A number of analysis measures are supported. Some standard domain independent SNA measures are relevant also for analysis of terrorist networks. However, there is also a need for specialized TNA measures that take into account the specifics of terrorist networks. The measures listed below in black font color are standard SNA measures (Wassermann and Faust 1994), while the measures listed in red font color are specific TNA measures (secrecy, efficiency, performance, position role index, and link importance).

A few definitions are needed regarding graphs to explain the analysis measures.

A graph G consists of two sets of information: a set of nodes, $N = \{n_1, n_2, \ldots, n_n\}$, and a set of links $L = \{l_1, l_2, \ldots, l_l\}$ between pairs of nodes. There are n nodes and l links. In a graph, each link is an unordered pair of distinct nodes, $l_k = \{n_i, n_j\}$.

Additional relevant definitions are:

- **Size** is defined as the number of nodes (n) in the network.
- **Nodal degree** is defined as the number of links that are incident with the node.
- A **cluster** is a part of the graph with high density of nodes and links between them.
- The **average shortest path** is the average length of the geodesic between two nodes.

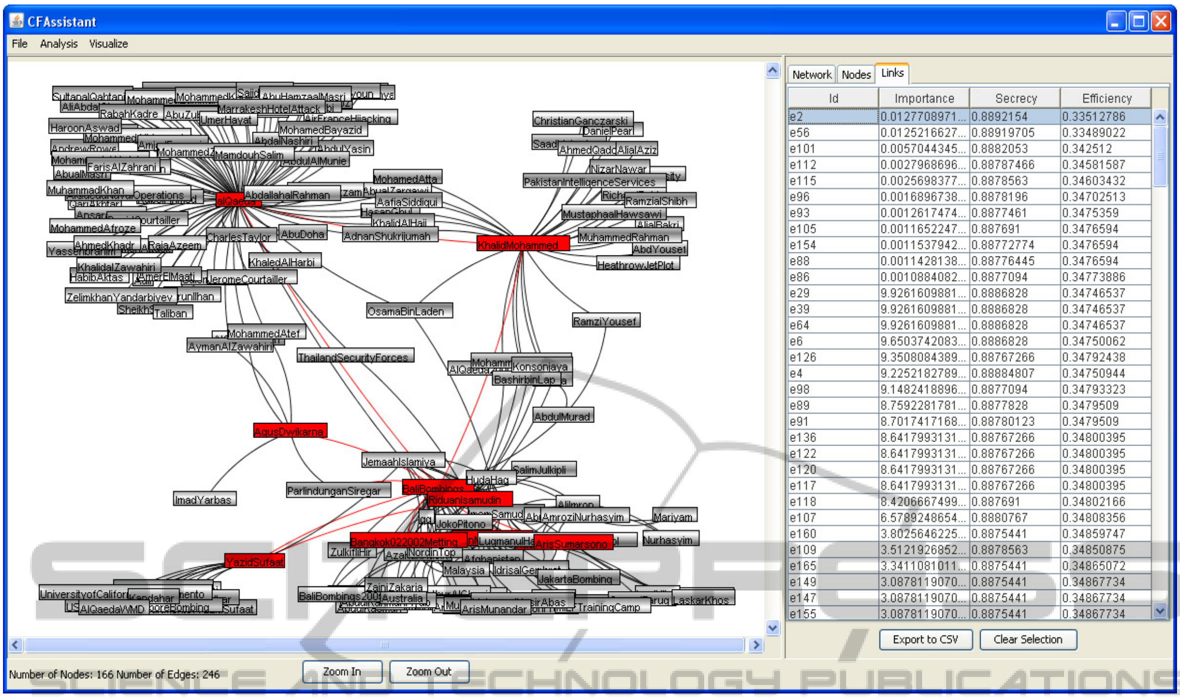


Figure 3: A screenshot of CrimeFighter Assistant.

3.2.1 Network Analysis

The following network measures are supported:

- **Density** is the number of links (l) in proportion to the number of links that are possible in G (if all nodes where connected to each other).
- **Diameter** is the maximum distance between any pair of nodes in the network (calculated using the shortest path).
- According to Lindelauf, Borm, and Hamers (2009), **secrecy** is a measure which is defined by two parameters: the exposure probability and the link detection probability. The exposure probability applies to individual nodes and depends on the location in the structure. It is defined as the probability of a member of the network to be detected as a terrorist. Link detection probability represents the chance of exposure of a part of the network if a member is detected. The secrecy depends on the number of links, the number of nodes, and their degree. The higher the degree of nodes, the lower the secrecy is in the network.
- According to Latora and Marchiori (2004), **efficiency** is a measure to quantify how efficiently the nodes of a network can exchange information. To calculate the efficiency of a network, all the shortest path lengths between any pair of nodes in the graph must be calculated. The assumption is made that every link can be used to transfer information in the network. The efficiency is calculated in two parts: (1) the inverse of the sum of the shortest paths between any pair of nodes are calculated; (2) the result from (1) is divided by the possible number of pairs of nodes to find the average efficiency of the network.
- According to Lindelauf, Borm, and Hamers (2009), **performance** is a measure of the overall performance of a network calculated as the product between secrecy and efficiency. This measure is used to assess the performance of the network in the light of the goals of terrorist network to reach a balance between secrecy and efficiency.

Lindelauf, Borm, and Hamers (2009) use the term information performance instead of efficiency. Information performance is calculated in a manner similar to efficiency as proposed by Latora and Marchiori (2004).

3.2.2 Node Analysis

The following node measures are supported:

- **Degree Centrality**. A node is central when it has many ties (links) to other nodes in the network. This kind of centrality is measured by the degree of the node. The higher the degree, the more central the node is.
- **Closeness Centrality** indicates that a node is central when it has easy access to other nodes in the network. This means that the average distance (calculated as the shortest path) to other nodes in the network is small.
- **Betweenness Centrality**. Usually, not all nodes are connected to each other in a network. Therefore, a path from one node to another may go through one or more intermediate nodes. Betweenness centrality is measured as the frequency of occurrence of a node on the geodesic connecting other pairs of nodes. A high frequency indicates a central node.
- **Eigenvector Centrality** is like a recursive version of degree centrality. A node is central to the extent that the node is connected to other nodes that are central. A node that is high on eigenvector centrality is connected to many nodes that are themselves connected to many nodes.
- According to Memon (2007), **position role index** (PRI) is a measure aimed at making a distinction between the gatekeeper and follower roles. PRI evolved from testing efficiency of a network based on the assumption that a network without followers has a higher efficiency as followers are less connected within the structure. PRI is measured as the change of network efficiency after removal of a node. A high PRI value indicates a large loss of efficiency, if a particular node is removed.

3.2.3 Link Analysis

The following link measures are supported:

- **Link Betweenness** measures the frequency of link occurrence on the geodesic connecting pairs of nodes (Girvan and Newman 2002). Link betweenness indicates how much information flows via a particular link. The assumption is that communication flows along the shortest path. A high frequency indicates a central link.
- According to Wiil, Gniadek, and Memon (2010), **link importance** measures how important a particular link is in a terrorist network by measuring how the removal of the link will affect the secrecy and efficiency (performance) of the network. A high loss of efficiency (when removing the link) indicates an important link.

3.2.4 Visualization

CrimeFighter Assistant can visualize networks using various visualization layouts (Di Battista et al. 1994):

- Fruchterman-Reingold layout
- Kamada-Kawai layout
- Spring layout
- Radial layout
- Self-organizing map layout
- Tree layout

The user decides which layout is the most appropriate for a given network by selecting a menu item in the “Visualize” menu. It is possible to switch between different layouts at any time by simply selecting a different menu item.

In network visualizations with many nodes, vertices might overlap. This might make the graph somewhat unclear. To cope with this issue, a zooming feature has been added.

4 CASE STUDY: 2002 BALI BOMBING

At 23:05 on October 12, 2002 an electronically-triggered bomb blew apart Paddy's Bar, a popular night spot in Kuta on the Indonesian island of Bali. Seconds later, as the terrified and injured customers fled, another more powerful bomb hidden in a white Mitsubishi minivan detonated in front of the Sari Club across the street. 202 victims died in the explosions and more than 200 were injured. (Wise 2005).

Members of the South East Asian militant network Jemaah Islamiah were responsible for the attack. It is believed that Riduan Isamuddin (a.k.a. Hambali) ordered a new strategy of hitting soft targets such as nightclubs and bars. Hambali, who is currently in US custody in Guantanamo Bay, is believed to have been the South East Asian contact for Osama Bin Laden's al-Qaeda network. But he is not thought to have played an active part in the Bali plotting. Instead, 43-year-old Islamic teacher Mukhlas (a.k.a. Huda bin Abdul Haq) was convicted as the overall coordinator of the attacks. He also recruited two of his younger brothers, Amrozi and Ali Imron, to play key roles in the attack.

Important roles were also played by Imam Samudra (a.k.a. Abdul Aziz), Azahari Husin (a Malaysian who was alleged to be Jemaah Islamiah’s top bomb-making expert and to have helped assemble the Bali bombs; he was killed by police in eastern Indonesian in November 2005) and alleged bomb-maker Noordin Mohammad Top (killed during a police raid in Solo, Central Java in September 2009). (BBC News 2010).

Additionally, Khalid Sheikh Mohammed (leading member of 9/11 attacks) confessed during his hearing at Guantanamo Bay on March 10, 2007 to have been the leader of the Bali bombing plot.

The perpetrators mentioned above were not the only ones involved in planning and carrying out the attack. Therefore based on known facts, a terrorist network for the Bali bombing can be built. The dataset used in this case study is based on the work by Memon (2007).

CrimeFighter Assistant will be used to analyze the network, nodes, and links in order to be able to answer the various questions raised in the previous section.

After loading the Bali bombing data set, the status bar shows basic information about the network (number of nodes and links/edges) and the various options for network analysis and visualization become active. Figure 4 shows the status bar after loading the Bali bombing network.

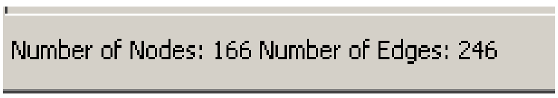
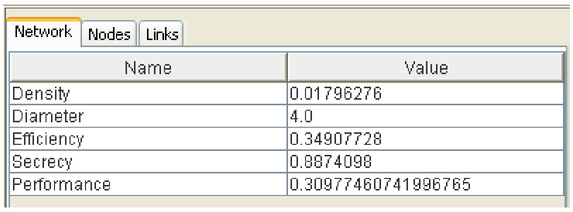


Figure 4: Status bar after loading the Bali bombing network.

4.1 Network Analysis

The result of the network analysis is shown in the right side panel of CrimeFighter Assistant (see Figure 5).

The Bali bombing network is sparsely connected: for 166 nodes only 246 links (edges) exists. Hence, the density of the network is low (0.0179): only 1.8 % of all possible links between nodes exist.



Network | Nodes | Links

Name	Value
Density	0.01796276
Diameter	4.0
Efficiency	0.34907728
Secrecy	0.8874098
Performance	0.30977460741996765

Figure 5: Network analysis results.

The structure of the network consists of stars (clusters of people) that are loosely connected with each other. Three overall clusters can be identified: centered on al-Qaeda, Khalid Sheikh Mohammed (the leader of the plot), and the people directly responsible for the attack, respectively. The only dense segment is formed by the people directly responsible for the attack (see Figure 6).

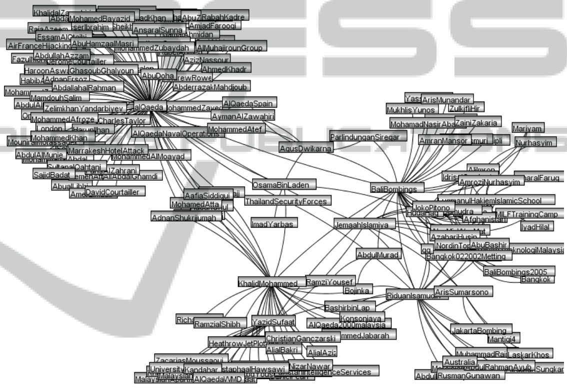


Figure 6: Bali bombing network structure.

The diameter of the network is 4 meaning that the largest distance between any pair of nodes is 4. Taking the diameter and the star structure (clusters) into account, information does not need to travel very far in the network.

The structure has a direct impact on the secrecy, efficiency, and performance of the network. The terrorist had to work with a high level of secrecy, which is reflected in the structure of the network. A star structure (excluding the center node) is resistant for uncovering since the other nodes only know one other member. The secrecy value for the network is 0.89, which means that the structure of the network provided a high level of covertness. The high level of secrecy had an impact on the communication possibilities. The efficiency of the network is 0.35. This is however still a high value taking under consideration the conditions in which the terrorist group operated. The overall performance of the network is 0.31 – measured as the trade-off between secrecy and efficiency.

Table 1: Node analysis results from the Bali bombing network.

Name	Degree	Eigenvector	Closeness	Betweenness	PRI
Khalid Sheikh Mohammed	30	0,060020	2,000000	3118,940177	0,064867
Riduan Isamuddin	23	0,046400	2,457831	1610,549559	0,027781
Huda bin Abdul Haq	12	0,024307	2,566265	169,652490	0,000803
Yazid Sufaat	12	0,024291	2,578313	1441,260256	0,030670
Wan Min Wan Mat	11	0,022286	2,596386	366,862572	0,004090
Imam Samudra	9	0,018222	2,686747	118,365560	0,000254
Azahari Husin	9	0,018231	2,710843	176,577028	0,000249
Amrozi Nurhasyim	8	0,016209	2,698795	201,889424	0,000229
Noordin Mohammad Top	8	0,016194	2,704819	163,530717	0,000218
Ali Imron	7	0,014199	2,698795	160,470996	0,000193
Agus Dwikarna	6	0,011954	2,740964	235,378571	0,003376
Aris Sumarsono	5	0,010080	2,746988	372,804052	0,006535
Osama Bin Laden	3	0,006208	2,349398	55,888300	0,000852
Aafia Siddiqui	2	0,004173	2,530120	0,000000	0,000575
Adnan Shukrijumah	2	0,004173	2,530120	0,000000	0,000575
Mohamed Atta	2	0,004173	2,530120	0,000000	0,000575
Abual Zarqawi	2	0,004173	2,530120	0,000000	0,000575
Hasan Ghul	2	0,004173	2,530120	0,000000	0,000575
Khalid AlHajj	2	0,004173	2,530120	0,000000	0,000575

The similar values for the 9/11 network is a density of 0.08, a diameter of 5, a secrecy of 0.86, an efficiency of 0.34, and an overall performance of the network of 0.29. Hence, the Bali bombing network managed to have a good trade-off between secrecy and efficiency due to the star-like structure combined with a more densely connected cluster of people taking directly part in the attack.

4.2 Node Analysis

The results of analyzing the nodes in the Bali bombing network are shown in Table 1. The five different node centralities (degree, eigenvector, closeness, betweenness, and PRI) explained in the previous section have been calculated. The table shows the results of the most important nodes ordered according to the degree centrality (highest at the top).

Khalid Shaikh Mohammed has the highest score in all the centrality measures. Thus, the analysis strongly indicates that he is the most important person in the network. According to his confession mentioned earlier, he was in fact the leader of the plot.

Also, Riduan Isamuddin (believed to be responsible for strategy) and Huda bin Abdul Haq (coordinator of the attack) are both ranked very high according to the centrality measures. The PRI values suggest that Khalid Shaikh Mohammed, Riduan Isamuddin, and Yazid Sufaat were sources of information and gatekeepers. Yazid Sufaat is believed to be the supplier of explosives. Removal of those nodes would lead to the highest decrease in network efficiency.

4.3 Link Analysis

The results of analyzing the links in the Bali bombing network are shown in Table 2. The link analysis measures described in the previous section have been calculated. The table shows link betweenness and link importance for the most important links. The influence of each link in relation to secrecy and efficiency has also been calculated. The secrecy and efficiency columns show how these values will be affected in case the link is removed. The links are ordered according to their link importance values (highest at the top).

The three most important links (e2, e56, and e101) connect the three overall clusters in the network centered on al-Qaeda, Khalid Sheikh Mohammed, and the Bali bombing actors. Other important links connect the individual members that were directly responsible for the attack.

Figure 7 shows the Bali bombing network with the 10 most important links highlighted in red. The most important links points out the information backbone of the network. Important communication takes place between the three clusters and inside the cluster directly responsible for the attack.

Table 2: Link analysis results from the Bali bombing network.

Link id	Betweenness	Importance	Secrecy	Efficiency
e2	3063,266036	0,012770897	0,8892154	0,33512786
e56	1662	0,012521663	0,88919705	0,33489022
e101	1037,131532	0,005704435	0,8882053	0,342512
e112	889,328022	0,00279687	0,88787466	0,34581587
e115	366	0,002569838	0,8878563	0,34603432
e96	249,8333333	0,001689674	0,8878196	0,34702513
e93	335,6526446	0,001261747	0,8877461	0,3475359
e105	160	0,001165225	0,887691	0,3476594
e154	206,6336996	0,001153794	0,88772774	0,3476594
e88	270,5785714	0,001142814	0,88776445	0,3476594
e86	175,0131868	0,001088408	0,8877094	0,34773886
e29	177,4738095	9,93E-04	0,8886828	0,34746537
e39	177,4738095	9,93E-04	0,8886828	0,34746537
e64	177,4738095	9,93E-04	0,8886828	0,34746537
e6	335,9455458	9,65E-04	0,8886828	0,34750062

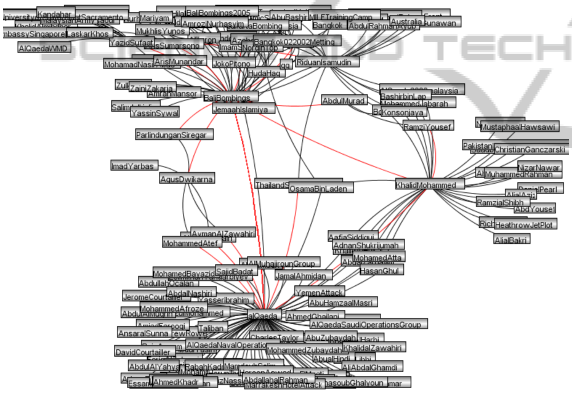


Figure 7: The 10 most important links in the Bali bombing network.

The results of the link analysis point in the same direction as the results of the node and network analysis. Important links are to a high degree connected to what was found to be important nodes (further indicating the importance of those nodes). Also, important links connect the three overall clusters of the network (further emphasizing the use of clusters to structure the network to achieve a good trade-off between secrecy and efficiency).

4.4 Summary

A case study of the 2002 Bali bombing was used to show that the network, node, and link analysis features of CrimeFighter Assistant can provide significant help in answering the important questions related to destabilization of terrorist networks (see Section 3).

5 COMPARISON TO RELATED WORK

We have studied various existing software packages for SNA and TNA to see what features they include:

1. Network Workbench (NWB Team 2006)
2. Social Networks Visualizer (SocNetV 2010)
3. UCINET (2010)
4. Visione (Brandes and Wagner 2003)
5. VisuaLyzer (2010)
6. Pajek (Batagelj and Mrvar 2010)
7. NetMiner (2010)
8. Analyst's Notebook 8.5 (i2 2010)
9. *iMiner* (Memon 2007)
10. CrimeFighter Assistant

We have compared the software packages against some of the network, node, and link analysis features available in CrimeFighter. Table 3 summarizes our results. A minus (–) indicates that the feature is not supported. A plus (+) indicates that the feature is supported. All the examined software packages support visualization of network structures – some more advanced than others. The software packages for SNA (1 to 7) as well as Analyst's Notebook (8), a commercial tool for analysis and visualization that is widely used by law enforcement and intelligence agencies, support to a varying degree the ordinary SNA features, but do not support

Table 3: Comparison of analysis features in SNA and TNA software packages.

	1	2	3	4	5	6	7	8	9	10
Secrecy	–	–	–	–	–	–	–	–	–	+
Efficiency	–	–	–	–	–	–	–	–	+	+
Performance	–	–	–	–	–	–	–	–	–	+
Degree centrality	–	+	+	+	+	+	+	+	+	+
Closeness centrality	+	+	+	+	+	+	+	+	+	+
Betweenness centrality	+	+	+	+	+	+	+	+	+	+
PRI	–	–	–	–	–	–	–	–	+	+
Link betweenness	–	–	+	+	–	+	+	+	–	+
Link importance	–	–	–	–	–	–	–	–	–	+

the domain specific TNA features (secrecy, efficiency, performance, PRI, and link importance). *iMiner* (Memon 2007) which is also a TNA tool supports both SNA and TNA features, but lack some of the latest TNA features that were reported in the research literature after the tool was developed (secrecy, performance, and link importance). On the other hand, some of the software packages (1 to 8) provide many features not currently supported in CrimeFighter Assistant such as detecting communities, k-plex, k-core, clustering coefficients, etc.

Additional TNA features have been proposed in the literature by Memon (2007):

- **Detecting Hidden Hierarchy.** This method aims to identify hidden hierarchical structures in horizontal networks. The method uses SNA measures and graph theory to indicate parent-child relationships of nodes in the network.

- **Subgroup Detection.** A terrorist network can often be partitioned into cells (subgroups) consisting of individuals who interact closely with each other. This method uses SNA measures and graph theory to indicate clusters (subgroups) in relation to a particular node and the diameter from that node.

Rhodes (2009) proposed the use of Bayesian inference techniques to **predict missing links** in a covert network, demonstrated through a case study of the Greek terrorist group November 17. The assumption is that during the analysis of terrorist networks it is unlikely that the intelligence analysts have an overview of the full terrorist network. Prediction of missing links can be a useful method to gain deeper understanding and conduct detailed analysis of the terrorist network.

CrimeFigther Assistant provides many of the typical SNA features as well as features dedicated for TNA. Some of the latest TNA features are so far only implemented in CrimeFigther Assistant, thus making the tool unique in certain aspects. However, there are still a number of SNA and TNA features (detecting hidden hierarchy, subgroup detection, link prediction, k-plex, etc.) that can be implemented in future versions to make CrimeFigther Assistant a more complete tool for TNA.

6 CONCLUSIONS AND FUTURE WORK

This paper has described the CrimeFigther Assistant knowledge management tool for TNA. The network, node, and link analysis features of the tool were demonstrated based on a case study of the 2002 Bali bombing. CrimeFigther Assistant provides the following contributions:

- CrimeFigther Assistant supports a balanced approach to TNA focusing on network, node, and link analysis as an attempt to support intelligence analysts in making informed decisions regarding possible actions to take to destabilize a terrorist network.

- CrimeFighter Assistant provides the first implementation of the link importance measure proposed by Wiil, Gniadek, and Memon (2010).

- CrimeFighter Assistant also provides the first implementation of the secrecy, efficiency, and performance measures proposed by Lindelauf, Borm, and Hamers (2009).

Future work will focus on improving and further developing the tool in various ways:

- We plan to include new algorithms for TNA including detecting hidden hierarchy, subgroup detection, and link prediction.
- We are currently looking into how link weights can be incorporated, since not all links are equally important. We believe that incorporation of link weights will result in more precise link analysis measures.
- We wish to optimize the existing TNA algorithms to perform more efficient to be able to analyze large networks of thousands of nodes and links.
- We are currently including additional data sets to test and evaluate the usefulness of the tool more thoroughly.

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