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POSITIONING PAPER:

Visual Analysis of Social Networks in a Counter-Insurgency Context

Topic 4: Information and Knowledge Exploitation

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1 Abstract

Over the last several years, the Canadian Forces (CF) have been called to conduct operations taking place in very complex counter-insurgency (COIN) environments. The Canadian COIN doctrine emphasizes the political and social issues that are an intrinsic part of the current CF operations. In parallel, literature as well as our allies' military practice and research reiterate the value of analysing social networks in order to increase situational awareness in such contexts. With this regard, Defence R&D Canada has initiated a research project to explore an intelligence capability for social networks analysis (SNA) in a COIN context. The paper first describes the SNA capability approach encompassed within this research project. Second, it mentions some of the perceived visualisation requirements for such a SNA capability for the CF. This would include supporting the realization of five essential functionalities related to the capability: (1) Characterizing COIN strategy and objectives being pursued; (2) Specifying data sources used to represent and analyse the social network (SN); (3) Representing the SN of interest; (4) Analysing SNs and enabling sense-making; and (5) Ensuring SNA products usability. Finally, the paper highlights some of the foreseen challenges for such a SNA capability and the corresponding usage of visualisation.

2 Introduction

The context of military operations has changed significantly since the end of the Cold War and into the Global War on Terror. For instance, military forces are now faced with an elusive and changing adversary who is technologically innovative. Multiple theatres of operations have to be considered and operations must be conducted in a Joint, Interagency, Multinational and Public (JIMP) environment. Table 1 depicts a number of the elements of the new context.

Table 1: Context of new military operations [DLCD, 2009]

Cold War Context	New Military Context
Well defined strategic context (Cold War)	Poorly defined strategic context (Global War on Terror)
Static theatre of operations	Multiple theatres of operations
Single spectrum operation	Full spectrum engagement
Well defined adversary	Elusive and changing adversary
Technologically predictable enemy	Technologically innovative enemy
Structured enemy forces	Networked enemy forces
Corps construct	Battle group construct
Rigid and concentrated forces	Adaptable and dispersed forces
Long term evolution cycle	Very short term evolution cycle
Limited third party considerations	Crowded JIMP environment
Controlled info sphere	Uncontrollable info sphere

Since then, the Canadian Forces and their allies have been increasingly involved in missions taking place in this new context of operation. Along with this changing situation, a corresponding vocabulary started to be created or reactivated as for instance the terms of “irregular warfare”, “asymmetric threat”, (counter) “improvise explosive device” ((C)-IED) or (counter) “insurgency”.

In 2006, the US Department of Defense (DoD) clearly started to use the following definition of "Irregular Warfare" [DoD 2007]:

> *"A violent struggle among state and non-state actors for legitimacy and influence over the relevant populations. IW favors indirect and asymmetric approaches, though it may employ the full range of military and other capacities, in order to erode an adversary's power, influence, and will. It is inherently a protracted struggle that will test the resolve of our Nation and our strategic partners."*

With respect to the term "insurgency", the CF COIN doctrine [DND/CF 2008] defines it as being "a part of a wider set of irregular activities and threats to a secure and stable environment". "Irregular activity" may be defined as: "behaviour that attempts to effect or prevent change through the illegal use, or threat, of violence, conducted by ideologically or criminally motivated non-regular forces, groups or individuals, as a challenge to authority". Within this context, it is understood that the insurgents will search to acquire the support from the population and in parallel will potentially conduct violent activities directed against the government in place or any instances supporting it. One well known of those violent and criminal activities our Forces and allies are facing is the usage of IEDs by the insurgents.

These definitions stress some essential element; first they refer to asymmetric approaches by opposition to the conventional threats that were known up to the cold war period. Second they clearly position the importance of gaining local population support as the fundamental objective of such warfare. Finally they integrate the notion of having to counter a certain level of threat directed toward our country as well as our partners.

COIN and its related aspect of C-IED are two major issues of DND/CF's vision and mission. These developing situations involving asymmetric warfare require from the CF and their allies, to develop the corresponding strategies and doctrines to deal with the situation adequately. As a result, in 2006 the US ARMY developed and published a COIN Manual [DoD 2006] along with the proposed COIN tactics [DoD 2009] in 2009. In the mean time, the CF established its COIN doctrine in 2008 [DND/CF 2008].

All of these documents as well as the above definitions pertaining to the domain of COIN, highlight the significance of a civil-military collaboration required to conduct activities in a context of insurgency. Consequently, COIN strategy requires embracing an appropriate balance of military and non-military coordinated interventions along with the involvement of the local population representatives. The appropriate equilibrium of those components will vary with the context in which the specific COIN objectives will take place.

3 Social network analysis and counterinsurgency

In order to bring a clearer understanding of the context in which COIN is taking place, there is the necessity to comprehend the social as well as cultural dimensions surrounding COIN activities. These socio-cultural aspects is of critical importance to the commander for its mission success and consequently to the overall effort in progressing through the COIN strategy and its underlying objectives. In a situation of insurgency, notwithstanding the fact that there are not two identical insurgencies, there remains a common cornerstone in all of them, which is to gain support from the local population. This specific objective is the one of the insurgents as well as of all instances aiming at countering the insurgency. This statement has significant implications; first the military individuals need to understand the impact of their own and their allies' actions on the population support or allegiance but also the impact of the insurgents' action on the same population. Everyone would agree that performing such an understanding requires analysing the local population. This would then include a certain level of white[1] situation awareness (SA). Second, even in the case where an analysis of the insurgents is the main focus, it would also require from our Forces to understand the local population. Indeed, according to the type of insurgency, the insurgents' community has various levels of overlapping or connections with the local communities. Insurgents are an integral part of the population or else a sub-set of it.

SNA is rooted in the "premise that social life is created primarily and most importantly by relations and the patterns formed by these relations" [Marin and Wellman 2010]. Indeed, social networks are formally defined as "a set of nodes (or network members) that are tied by one or more types of relations" [Wasserman and Faust 1994]. SNA started at the beginning of the twentieth century and was concretized by Jacob L. Moreno publication in sociometry in 1934 "Who Shall Survive?" Since then, SNA has beneficiated from advancements in mathematical sciences more specifically, the domain of graph theory, as well as from the emergence and development of computers. It is only during the last decade that researches on SNA have converged towards understanding or uncovering insurgent or else terrorist networks. As previously mentioned, modern conflicts are fluid, have many facets and are affected by the interplay of multiple influences, people and activities. In such a context SNA is well positioned to enable the militaries to better understand the different social networks involved in the situation being faced. Those social networks can either be the ones of the insurgents, the local population or even the ones of our allied organisations. SNA techniques and methods can help in revealing the adversarial networks, their composition, structures, characteristics, as well as connections with other social networks. Also, SNA can contribute to an awareness of different religious, ideological and ethnic concerns taking place in the different areas of interest. Visualising and monitoring social networks and their evolution enable the prediction of behaviours or events, which can be essential components of threat analysis for the defence domain. Recognizing the limitations in trying to fully control elements and behaviour of complex systems, there is opportunity through SNA techniques and methods, to be able to understand and eventually to influence some of the identified social networks and their interdependencies. This understanding of social networks begins with the identification of the parties involved, including state and an increasing number of non-state actors, neutrals and the non-engaged who influence.

It is with this perspective in mind that DRDC has started to research on SNA for the benefit of the DND/CF. In 2010 a new applied research project called "Social Network Analysis in Counterinsurgency" (SNAC) has started. It relies on the premise that improving intelligence products through advanced SNA and visualisation/interaction will contribute to better decision making regarding the most appropriate response for a given situation. In a COIN context, using SNA in order to enable efficient targeting is one way to defeat or weaken insurgent networks. However, to face highly complex situations and deal with asymmetric threats, the intelligence function has to derive and disseminate a clear understanding of the social and cultural aspects of these situations and threats. From a social sciences perspective, SNA can support the intelligence function through a better understanding of the social networks their structures and how to best influence or else weaken them in the case of insurgent networks.

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[1] White situational awareness includes things such as infrastructure analysis (e.g. buildings, lines of communications) and population analysis (political, economic, cultural (ethnic/racial/tribal/religious), education, health, welfare, language, history and key personalities).

3.1 An intelligence SNA capability

The main objective of the SNAC project is to improve intelligence analysis capability taking place in a COIN context through the exploitation of social network analysis techniques and methods. In this research, these techniques, methods as well as corresponding technologies are being investigated by means of the development of a SNA proof-of-concept prototype. While existing tools and technologies will be investigated, the current project aims at identifying and enabling the different components of a full SNA capability. SNA cannot be summarized to the sole use of technologies supporting the exploitation of some SNA measures like the usual betweeness, centrality, and a few others. An intelligence SNA capability requires enlarging the scope of the activities to be performed prior and after the analysis itself.

3.2 Social network analysis capability framework

As depicted in Figure 1, the starting point of the intelligence SNA capability will be defined by the military needs based on the COIN strategy and its underlying objectives (1). These latest combined to the desired effects pursued by the militaries, will permit to identify more precisely the social networks of interest and the analysis to be performed on them (2). By doing this, the analyst seeks to identify the variables involved in the question being asked.

In turn, once the variables identified, it is based on them that meaningful datasets can be identified and extracted (3) in order to represent the social networks of interest and perform analysis. Many types of data sources will be considered as inputs to SNA. Among them will be internal data sources as well as sources already providing social network information in a digitized format as for instance the social networking technologies. The data collected should first permit to represent the social networks of interest and their significant features (4) and second initiate the related analysis (5). The result of such analysis will either specify the need for further refinement of the SNA to be performed or else provide intelligence SNA product (6) related to the initial issue based on the COIN objective. Such an intelligence SNA product will greatly help to understand better the situation but it should also be combined with additional relevant intelligence analysis enabling to cover a large scope of the initial issue expressed. Overall, this will enhance the sense-making process of the analysts.

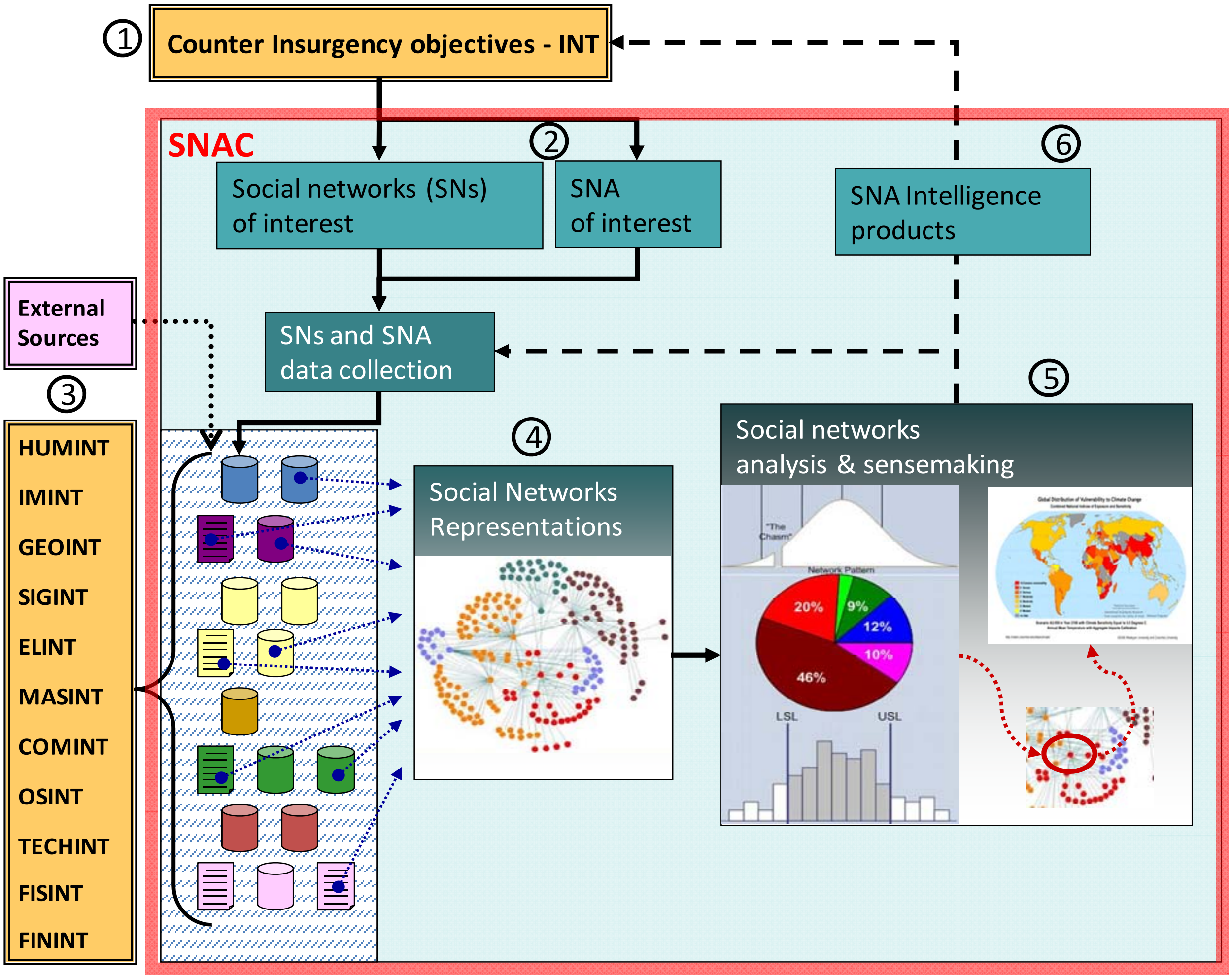


Figure 1. SNA capability framework

While the scope of the project is COIN and the intelligence, it is envisioned as a more generic capability of SNA which could be used in different contexts. SNA should be performed as a constant activity complementary to other intelligence analysis activities. Similarly, while being built for the purpose of the intelligence function, the capability in itself and its different components should also be transitioned to the command and control function and consequently achieving a more meaningfully bridge between the two functions.

4 Visualisation and SNA

4.1 Objectives of visualisation

Social networks analysis can be very complex. The multiple dimensions of the information and the quantity of linkages to understand may lead to a cognitive overload. It is essential to fully exploit the power of information visualisation. Information visualisation is defined as: "the use of computer-supported, interactive, visual representations of abstract data to amplify cognition" [Card et al 1999]. This definition refers to two essential parts contributing to information visualisation: the first is the cognitive ability of the human to perceive and make a mental representation of information or a situation; the second is the supporting technology that allows the presentation of this information or situation.

Information visualisation has constituted a significant research area, which studied various human cognitive characteristics such as pre-attention and inattentional blindness and explored and developed various techniques to represent information in a salient way and provide efficient interaction. “Information visualisation promises to help us speed our understanding and action in a world of increasing information volumes” [Card 2008].

More recently, Visual Analytics has emerged as a multidisciplinary field of research that leverages information visualisation and a number of other disciplines. “Visual analytics is the science of analytical reasoning facilitated by interactive visual interfaces” [Thomas and Cook 2005]. Visual Analytics focuses on the following areas:

- Analytical reasoning techniques that enable users to obtain deep insights that directly support assessment, planning, and decision making;
- Visual representations and interaction techniques that take advantage of the human eye’s broad bandwidth pathway into the mind to allow users to see, explore, and understand large amounts of information at once;
- Data representations and transformations that convert all types of conflicting and dynamic data in ways that support visualisation and analysis;
- Techniques to support production, presentation, and dissemination of the results of an analysis to communicate information in the appropriate context to a variety of audiences’ [Thomas and Cook 2005].

4.2 Visualisation for an intelligence SNA capability

Much advancement has been accomplished since SNA inception but it is only during the last decade [Perer and Shneiderman 2008] that the number of researches on visualisation to support SNA has significantly increased. As mentioned by Alt et al [2010], “creating meaningful visualisations of multi-dimensional human, social, cultural, and behavioural data will provide greater insights to operational decision makers across a large variety of problem domains”. SNA is one of those insights builders related to the “social” dimension and critical to nowadays types of operations of the CF and their allies.

In order to understand the importance and interrelationship between SNA and visualisation, we could refer to Bonsignore et al [2009], who position SNA tools and techniques at the intersection of Social Computing and Visual Analytics. In this perspective, SNA is considered as an exploration of complex sets of relationships within social systems to discover and make visible codifiable patterns of interactions.

There exist many different ways to leverage the value of visualisation for a SNA capability. Nevertheless, the current developments in visualisation for the purpose of SNA still very much focus on the visual presentation and explorations using graphs. In order to better analyse and extract meanings from SNA, additional visualisation methods need to be considered. For instance, Perer and Shneiderman [2006, 2008, and 2009] very much emphasize the need to combine on a same display information about the network as a graph along with the statistics about the graphs.

In the same way that we envision a full intelligence SNA capability, we recognize the importance of visualisation for each of the components of such a capability. This section will explain how visualisation is taken into consideration for each of these components.

4.2.1 Visualising initial COIN strategy and objective

The starting point of the proposed intelligence SNA capability is the specification of the COIN objectives. In the domain of SNA, it is of critical importance to understand the exact context and specific objectives in relation to the analysis to be performed. In most instances, the analyst must describe such context in order to characterise the social network of interest as well as to determine the analysis to be performed on them. This is the second stage of the proposed Intelligence SNA capability. For instance, if someone is interested in understanding, for a specific region of interest, what reconstruction projects are being undertaken; they might be interested in identifying the social networks of the allied organisations supporting the projects as well as the level of allegiance of the different villages in that region. In most cases, once having identified those social networks, the analyst is also asked to describe in details the features of the community (social networks). This is a particularly important task to perform in order to ensure a meaningful analysis. On the other hand, for some specific social networks, the culture and social ties (features) of the community are sometime hard to understand and consequently to specify. Indeed, our militaries are not always completely knowledgeable about the particular socio-cultural aspect of the communities that interest them. To overcome this issue, some authors, like Chen J. et al [2009], specifically developed a method where visualisation assists the user in finding appropriate parameters to describe the communities of interest. This helps the end-user to refine his/her analysis and come up with more meaningful results. His method could be understood as a network mining visualisation method enabling sense-making and in our case a more adapted connection to the initial objective pursued.

4.2.2 Data sources, data sets, and data visualisation

Visualisation should also be exploited in order to support the analyst in his/her understanding of the data used to characterise the social network as well as to perform analysis on it. Understanding the data can mean several things in this context. First, from a SNA perspective, it is of crucial importance for the analyst to grasp the signification of the selected data (variables) in relation to the features to be observed. Another important element for the analyst is to understand the limitations of the data from which the analysis is drawn from. The elements impacting this are the data source reliability, the data integrity, the data set completeness as well as its representativeness. Indeed, the analyst is supposed to understand the level of resilience of the SNA measures to be used in connection to the data set limitations. The issue of representativeness of the data set should be encountered at two different levels. The first one corresponds to the representativeness of the sampling taken from a larger network. The second level considers the extent to which the social network representation is actually descriptive of the social network as it exists in the real world. Appropriate visualisation techniques should be leveraged in order to support the analyst with understanding all those issues involving the data and data sets.

Finally, information related to the context of the data before its extraction should be appropriately revealed to the analyst and transferred along with the data itself in order to better capture the meaning of the data and the analysis results.

4.2.3 Tailored representation of social networks

There are several important aspects in social network representation. The first one has to do with the selected computational language to represent a social network; the selected representation language needs to be computer readable. The second aspect involves the adequacy of the visual presentation of the social network to the end-user. Indeed, even before applying any type of analysis or measure to the network, the simple fact of suitably representing the different components of the network can bring to the analyst a certain level of understanding of the social network. Now there exist several languages to represent the different components of a network, there also exist different perspectives that can be taken in order to visually present the social network to the analyst. Both, the selected representation techniques and the visual presentations require relying on the end-user needs and objectives. This representation issue is not trivial, as an example, DeJordy et al [2007] mentioned that there remain a number of issues to be solved in order to adequately visualise proximity between nodes that are taking place in a qualitative environment, as for instance with two nodes of a certain semantic proximity. Finally, as mentioned by Brandes et al [2008], an interesting point in enabling a visual presentation of social networks is to permit the comparison between social networks based on the average composition of each, their structures or topology. Figure 2 provides an example of how such visual presentation can support the analysis of social networks. In this example, visual means are used to enable the end-user interpretation of the differences between the topology of several (sub)networks.

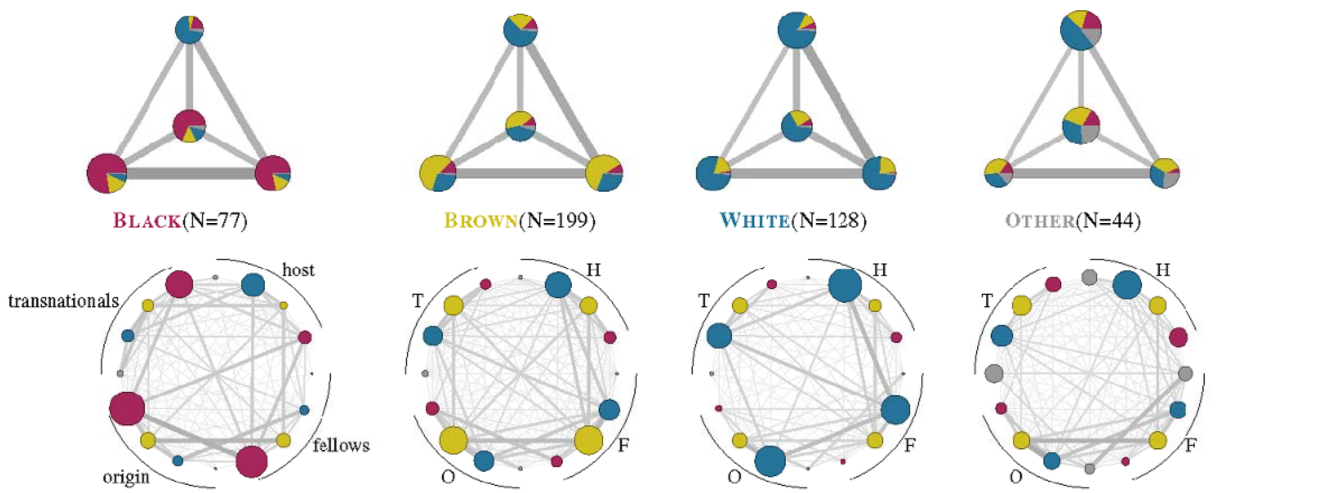
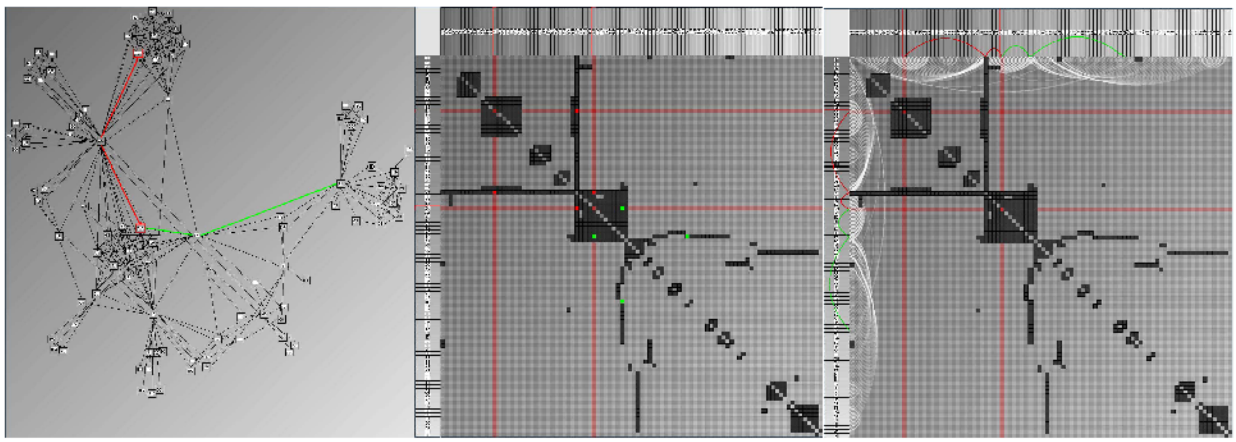


Figure 2. Comparison of subclasses network topology using circular layout [Brandes et al 2008]

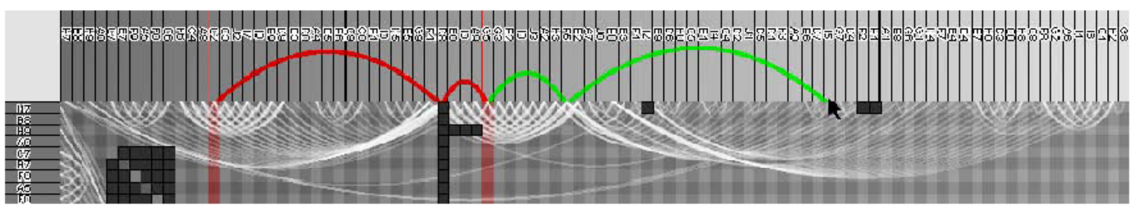
4.2.4 Analysis of social networks and sense-making

The analysis of social network and sense-making are without doubt the activities where visualisation value is the most exploited and researched on currently. The initial efforts were mostly focusing on different ways to visualise graphs and some of the measures applied to the social network as for instance the betweeness centrality. With the advancement of visualisation techniques and methods, the focus shifted from basic visualisation to analysis enabled through visualisation techniques. With respect to the current envisioned capability, there are many visualisation analysis techniques that will be considered. These techniques should enable the analysis of nodes but also the analysis of links, which are historically less considered than the nodes. Henry and Fekete [2007] underline the importance of visually presenting the links in order to permit analysts to uncover and understand paths in social networks.

Also, during the last few years, along with the emergence of technology solutions, the data collected about social network have grown exponentially leading to the creation of very large and cluttered social networks. In order to discover and understand critical paths, for instance, in such social networks, visual solutions of all sorts need to be considered as it is proposed with MatLink [Henry and Fekete 2007] in Figure 3.



(a) Node-Link(NL) (b) Matrix(MAT) (c) MatLink



(d) Zoom on MatLink

Figure 3. MatLink [Henry and Fekete 2007] – Example of an integration of different visual solution

Another very important analysis capacity reinforced through visualisation techniques is to expand the analysis of the network from several nodes and their relationships to the consideration of multiple types of nodes and relationships extracted as patterns [Leung and Carmichael 2010]. Being able to extract patterns is a very important aspect of social network visualisation and analysis. Indeed, once a pattern is identified and extracted, similar patterns can be then searched for either in the same social network or else in other social networks of similar nature.

Visualisation should also play an essential role in facilitating the comparison or highlighting the relations between different analyses. Comparisons can be considered several ways. First it can aim at comparing the same metric but applied differently on a same social network as it could be done for instance when comparing the results from a “centrality” measure or else a “centrality sensitivity” measure [Correa et al 2010]. Second it can aim at comparing the same type of analysis of the same network of interest but at different timings. Some would actually consider those networks as different but within our capability framework it would be more valuable to consider those as the same but enriched network. Third, it could be to compare the results from a number of analyses but between different networks. Figure 4 provides an example of this last type of comparison, ManyNets [Freire et al 2010] is not specifically generated for social networks but it could be applied to those.

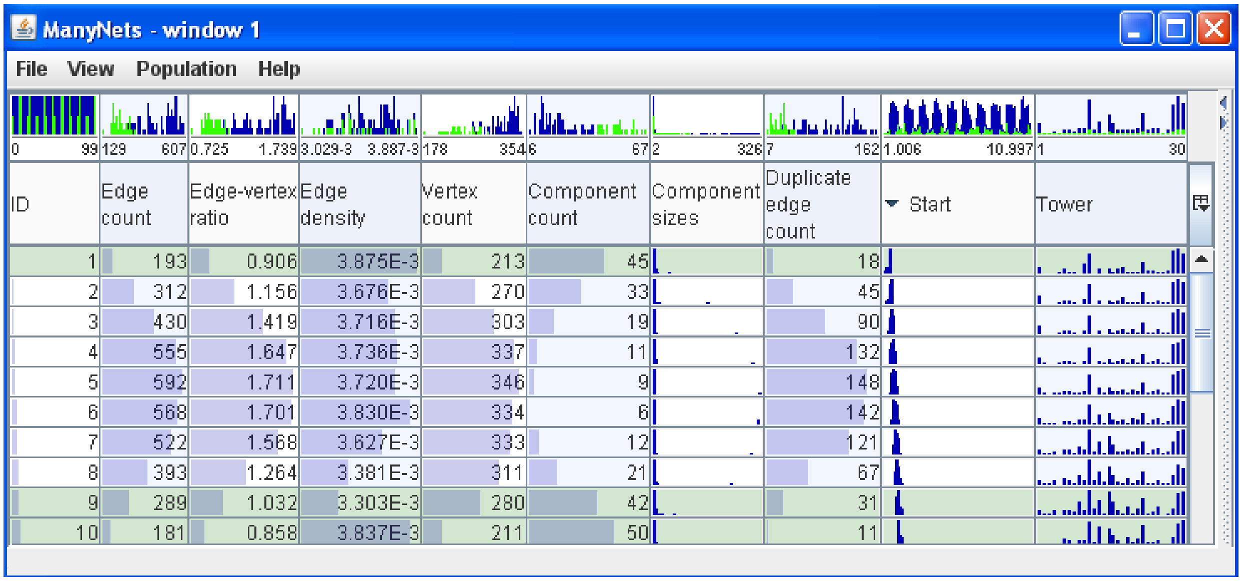


Figure 4. ManyNets – Networks characteristics comparison [Freire et al 2010]

Social networks are, as mentioned before, composed of nodes and edges, or so called links, but they are also composed of many attributes characterizing these nodes as well as the links within the social network. Moreover, for some authors [Perer and Shneiderman 2006] once specific SNA metrics are applied, their results can be attached to certain nodes or links and turned into one of their attribute. An example of this would be to assign a high centrality result to a specific node in the network and then keeping records of the measure as an attribute of the node itself. Currently, most of SNA applications permit the visualisation of the nodes and the edges or else portions of the networks but only a few of them like GraphDice [Bezerianos et al 2010], GeoSom [Wu et al 2006], or GraphScape [Xu et al 2007] make an attempt at visually presenting these attributes [Jusifu et al 2010]. The following figure demonstrates how GraphDice combines different visual presentations including the main visualization (the top portion of the figure from "a" to "e" components) and the actors, the links as well as their respective attributes (the bottom portion of the figure; "f" and "g" components).

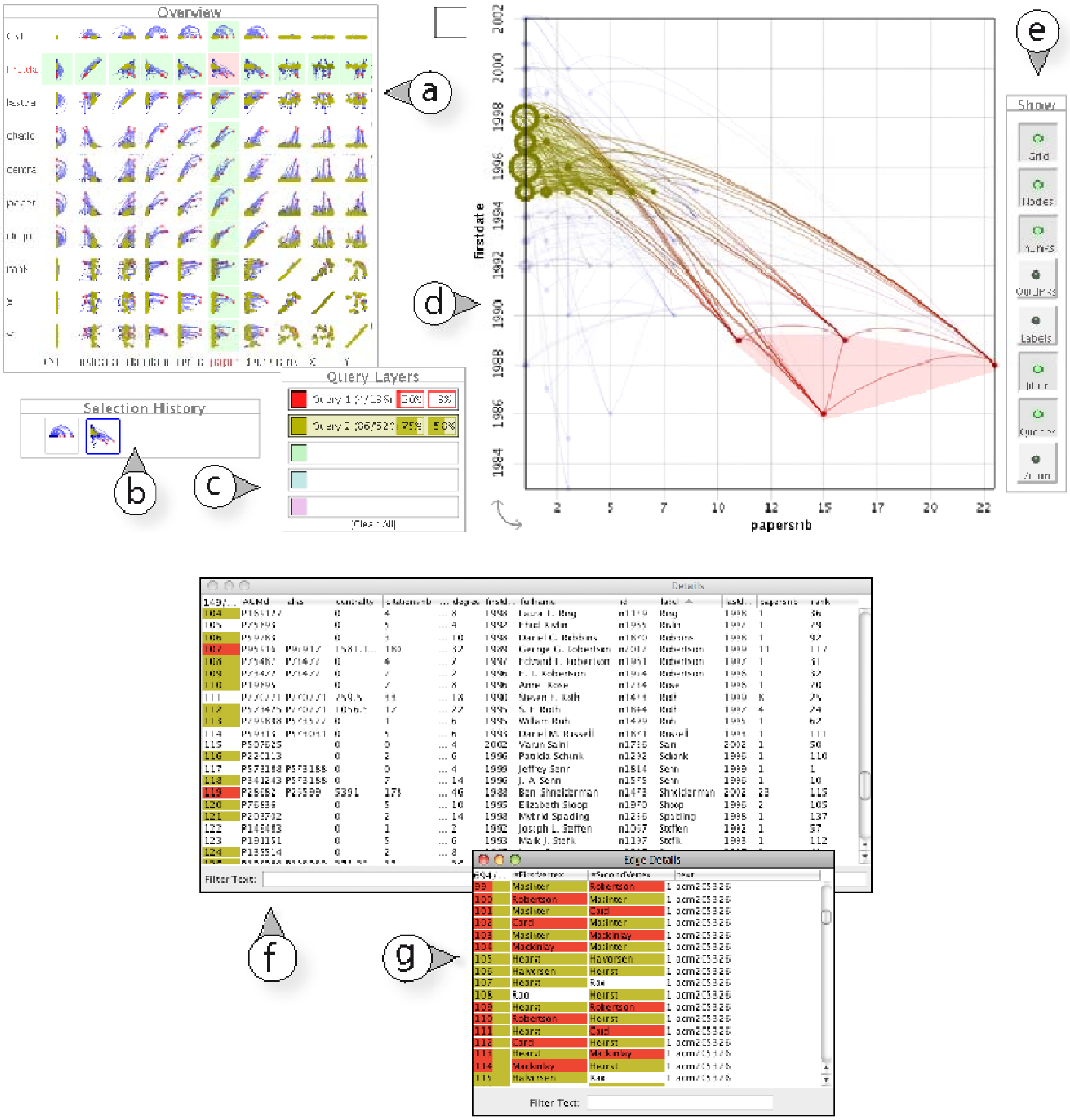


Figure 5. GraphDice – Information from social networks [Bezerianos et al 2010]

SNA can provide a certain level of information about nodes or individuals within a social network. Within the current COIN context of interest, an interesting portion of analysing social networks is to identify and characterise communities (clusters). Initially some methods were elaborated to identify clusters (hierarchical clustering [Wasserman and Faust 1994]) in social network analysis. Unfortunately, these methods had some drawbacks as for instance the fact that nodes needed to be in separated clusters and once groupings were performed at an earlier stage of analysis, these grouped nodes could not be disjoined later on. It is well known that societies are complex systems and that individuals are usually part of multiple communities [Henry et al 2008]. This reality should be visually presented to the analysts in order for them to understand the overlapping portion of different communities. Some authors like Chen J. et al [2009] developed methods to overcome such an issue and encompass communities' overlaps in the real world. Figure 6 is a screenshot of Meerkat, a tool enabling visualisation and community mining of social networks. The tool includes functionalities to permit visualisation of communities overlap [Chen J. et al 2010].

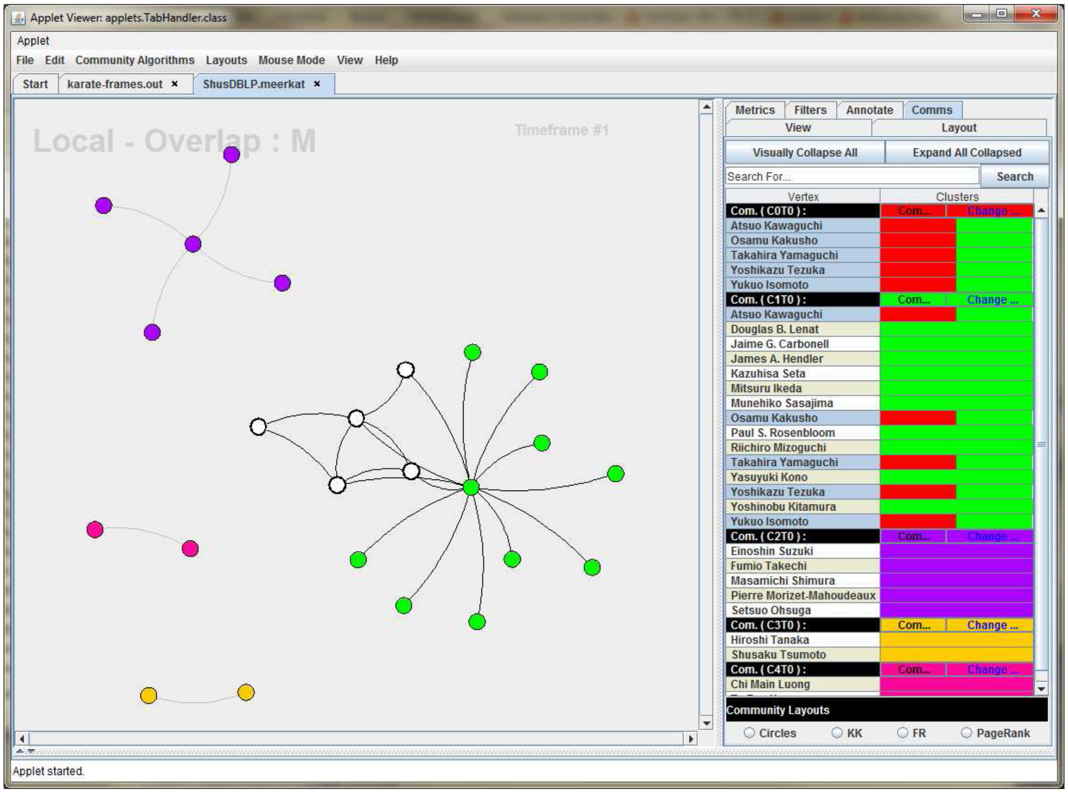


Figure 6. MeerKat – Screenshot with the community overlap option enabled [Chen J. et al 2010]

Understanding specific network measures about the nodes and links is very important but another essential element is to understand the topology or the network structure itself. Some social networks visualisation techniques can reveal important structural features of the social network [Brandes et al 2008]. These particular structural features, through adapted visualisation, can then unable the comparison of two or more networks where some topological differences or similarities can be highlighted as for instance, differences between ways to communicate or transmit orders in a network. In order to ease the interpretation, visualisation techniques should encounter different ways of visualising the network information as for instance combining graphs, matrices, tables, graphics or even text. Figure 7 provides an example of such a combination [Collins and Carpendale 2007]. Perer and Shneiderman [2008] focused on such a "Connect interaction" concept, in his case, it resulted in presenting side by side statistics/data and a graph visualisation of the social network in order to diminish the distraction in the exploratory processes when analysts have to switch back and forth between the two. His work is based on the results from researches demonstrating that combining statistics and network graphs actually combines the visual as well as the language capacities of the end-users and therefore contribute to the reduction of cognitive overload [Ware 2008].

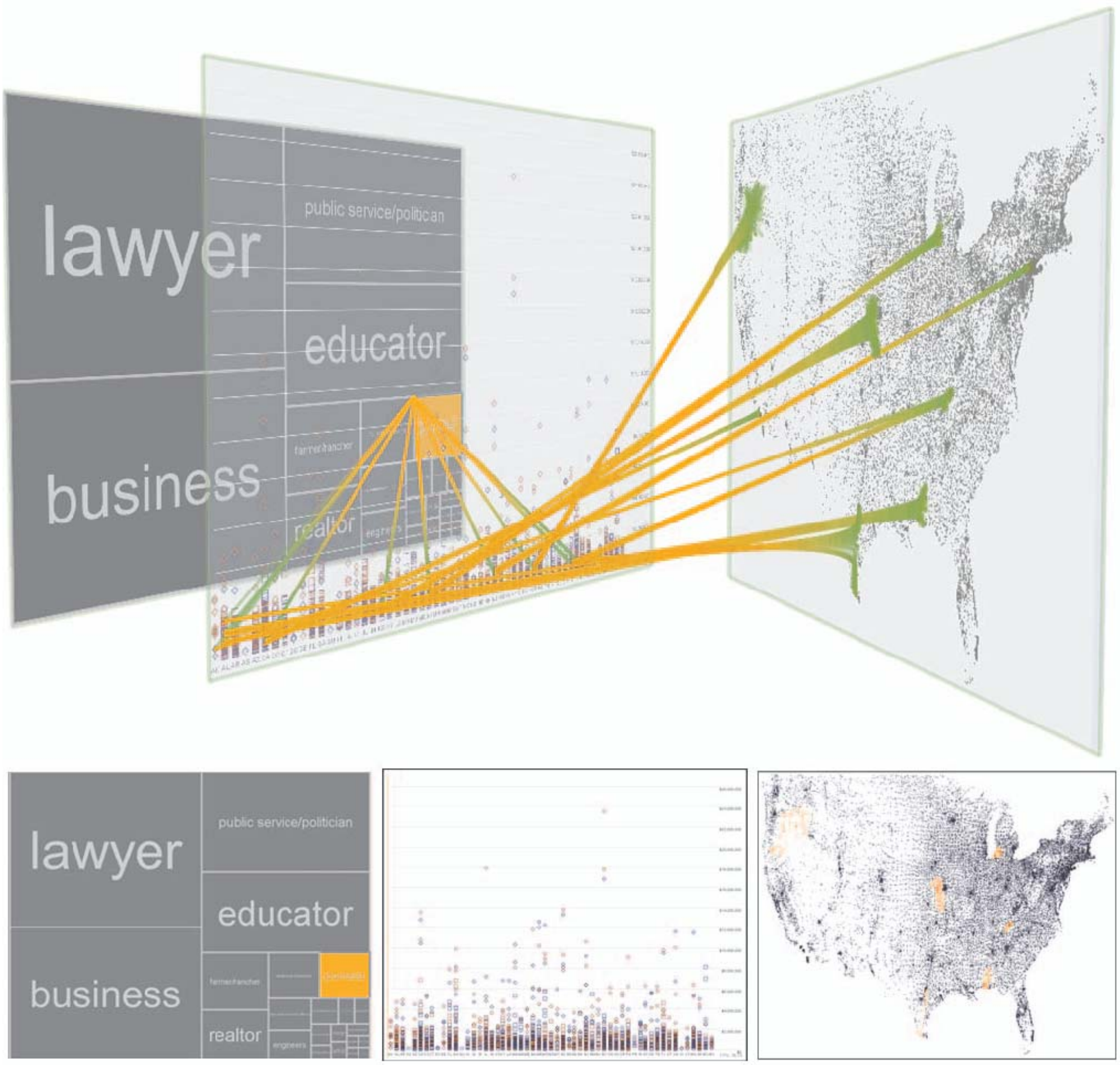


Figure 7. VisLink – relationships between different representations of a social network [Collins and Carpendale 2007]

Krempel [2009] also summarizes different basic visualisation variables that should be taken into consideration when having to impart on representing networks such as the usage of color, size, shape, lines. He proposes an example of the usage of shape and color to communicate some type of network information overload [Ware 2008]. In Figure 8, Collins et al [2009] manipulate isocontours to denote relations existing between different nodes.

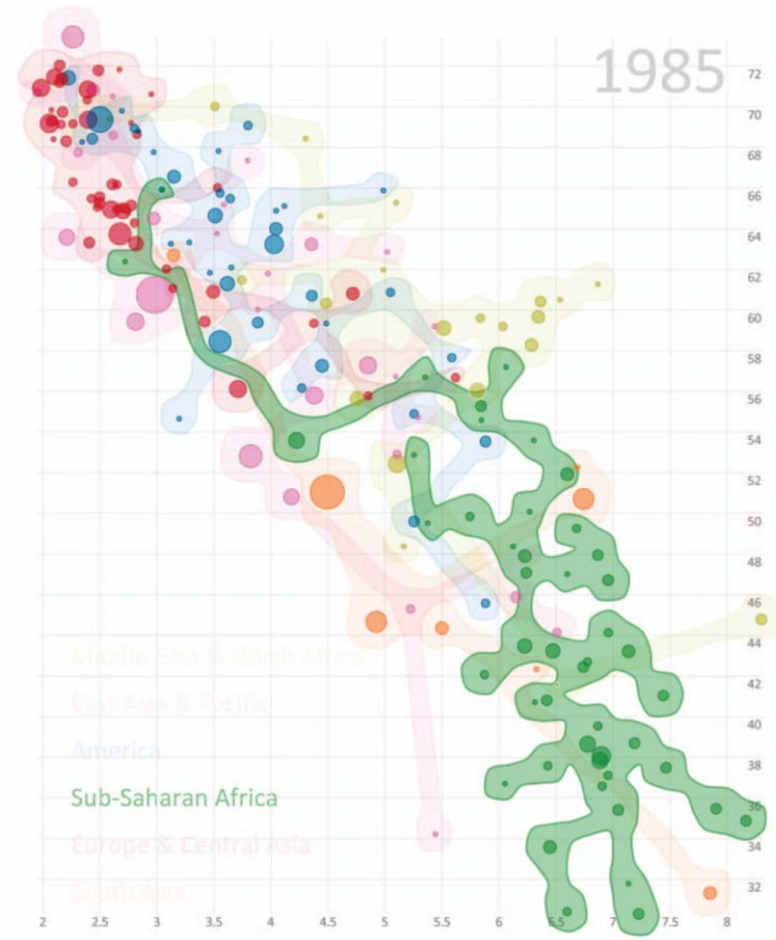


Figure 8. Bubble Sets – Set relations with isocontours [Collins et al 2009]

4.2.5 SNA products usability

The usability of the SNA product refers to first the content of the intelligence SNA product and to what extent it corresponds to the initial objective pursued. Second, from a visualisation perspective it refers to the extent to which the format of the product is tailored to the requester's needs. Some authors [Alt et al 2010] stress the importance of a customizable capability of the visual display. Such customizable capability would address the aspects of the analysis of particular interest in the encountered situation. Usually this implies taking into consideration the role and the tasks of the requester as they do not all focus on the same aspects. It is therefore important for the analyst to take a minimum of time, to collaboratively clarify, with the requester the components that should be the focus of the analysis.

One element to be particularly careful with is the interpretation (sense-making) of the SNA product. This should be done while being aware of the limitations of the data used to perform the analysis as well as the sampling method employed. Again, visualisation techniques should be considered in order to bring those interdependencies to bear to the military end-user and to the analyst.

4.3 SNA Capability and visualisation challenges

While visualisation is perceived as a force multiplier in the context of SNA, many authors also put the accent on how much visualisation tools can present a variety of challenges to the analytic community even more when presenting information on the non-traditional dimensions of the battlefield encompassed by the social domain.

Along with any analysis of social networks, come different types of challenges depending of the context or else the pursued objectives through the usage of SNA techniques. We are not making any exception with the proposed Intelligence SNA capability. Some of the challenges come from the specific military domains we have to operate in, as for instance: the time constraints to respect the battle space tempo; the issue of man power to perform SNA; the multiple analysis levels for SNA (e.g. individual, group, organisations); the different data sources and their corresponding required levels of security, the various levels of expertise from the analysts in performing SNA; the necessity to consider the spatiotemporal aspects of SNA, etc. This section introduces some of those challenges but with a special highlight on how visualisation could possibly help.

4.3.1 Challenge 1: SNA and complex situations

In the COIN context, in order to understand clearly the impact of the military actions, there is a need to consider the metrics used by the decision makers in order to evaluate their progress with respect to the COIN objectives. As previously mentioned, the achievements of COIN objectives do not reside solely in military activities neither do they require taking into account uniquely the red (adversary) activities, structures or social networks. Indeed, the complexity of the COIN environment compels one to take into consideration social data at large, which in nature are also complex data [Alt et al 2010]. Krempel [2009] suggested that advanced visualisation techniques should be able to help solving complex knowledge in an efficient way. In our situation, COIN complex environments combined with social data complexity necessitate providing the end-user with multiple types of visual displays. These displays should be connected to one another but also be flexible enough to permit a shift of focus towards specific elements of interest pertaining to the situation being faced. The “Linked Views” concept explains such connectivity between the different displays where all views reflect any change. Lohrenz et al [2009] also propose a model with color density and saliency improvements in order to enhance the readability of complex geospatial networks (Figure 9).

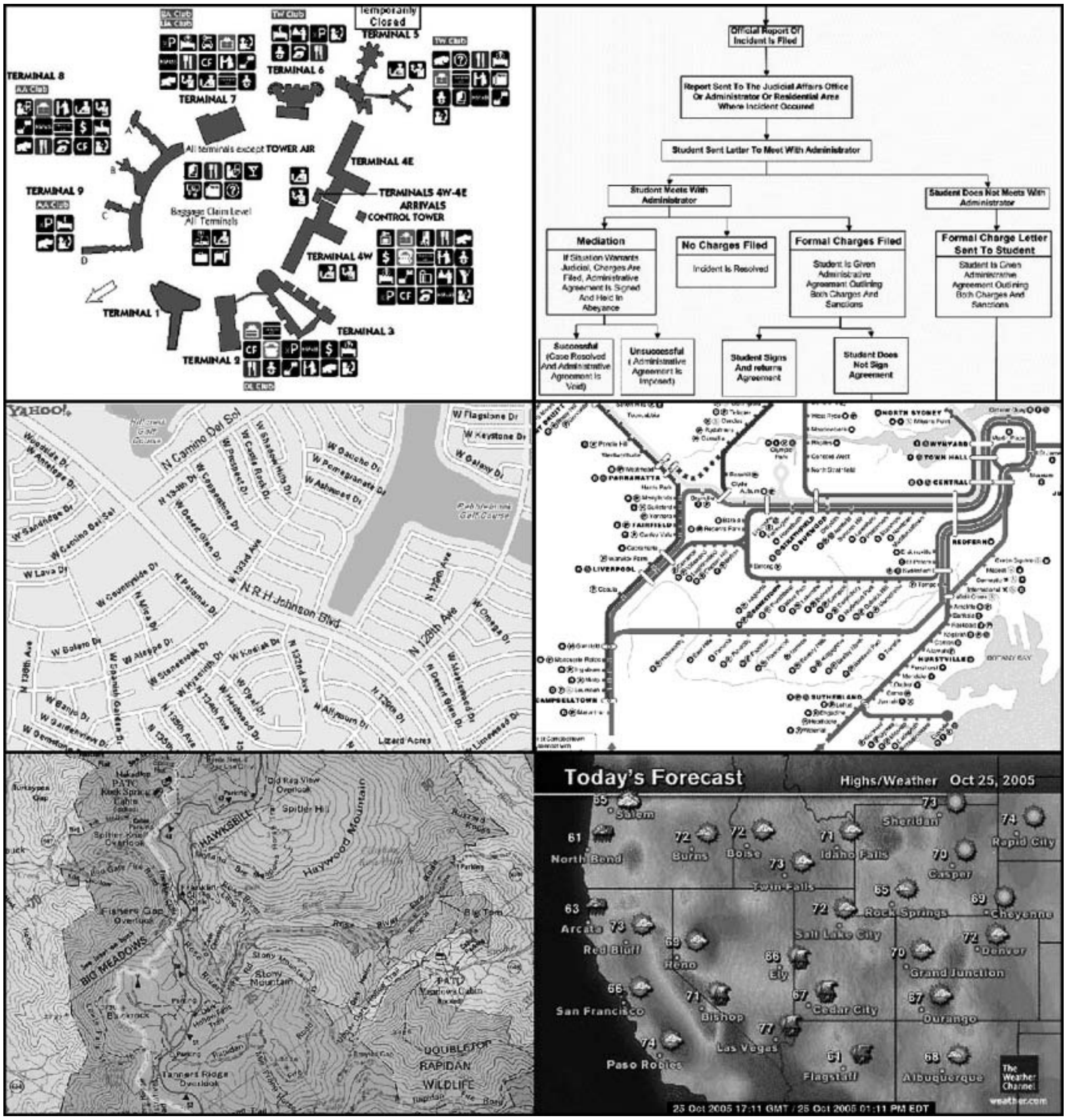


Figure 9. Examples of graphic displays during one of Lohrenz et al [2009] experiment

While social data and information are recognized to be essential to the understanding of a situation particularly taking place in an irregular warfare environment, it is also recognized to be quite difficult to enable visualisation of social data and even more, the understanding of social analysis by non technical people [Alt et al 2010]. Visualising social information or analysis is best performed if the context is taken into consideration; first the context of the information being looked at but also the context of the end-user along with the elements of interest to him/her. In a defence environment this usually falls down to the intelligence analyst position rather than specifically to the individual preferences. For instance, a number of individuals, while still performing the same intelligence analysis task, might be focusing on different specific geographic spaces or else specific topics of interest. When having to take over from one another, the shift hand over should be performed seamlessly, providing the analyst with a clear picture of the endurable elements of the situation as well as its latest changes.

4.3.2 *Challenge 2: Large amount of data*

Along with the advancement of technologies, including web technologies, the amount of data available to include in SNA has tremendously increased. This is also true in SNA taking place in a COIN context. At the present time, there is still much research and work being performed in order to enable a certain level of automated extraction of these data, particularly from unstructured data sets. Nevertheless, as mentioned by Henry and Fekete [2007], "the need to visualise large social networks is growing as hardware capabilities make analysing large networks feasible and many new data sets become available. Unfortunately, the visualisations in existing systems do not satisfactorily resolve the basic dilemma of being readable both for the global structure of the network and also for detailed analysis of local communities." Figure 10 is an hybrid representation for social networks proposed by Henry et al [2007]. They suggest combining two well known representations, the node-link to depict the global structure and matrices representation to portray the specific analysis of communities.

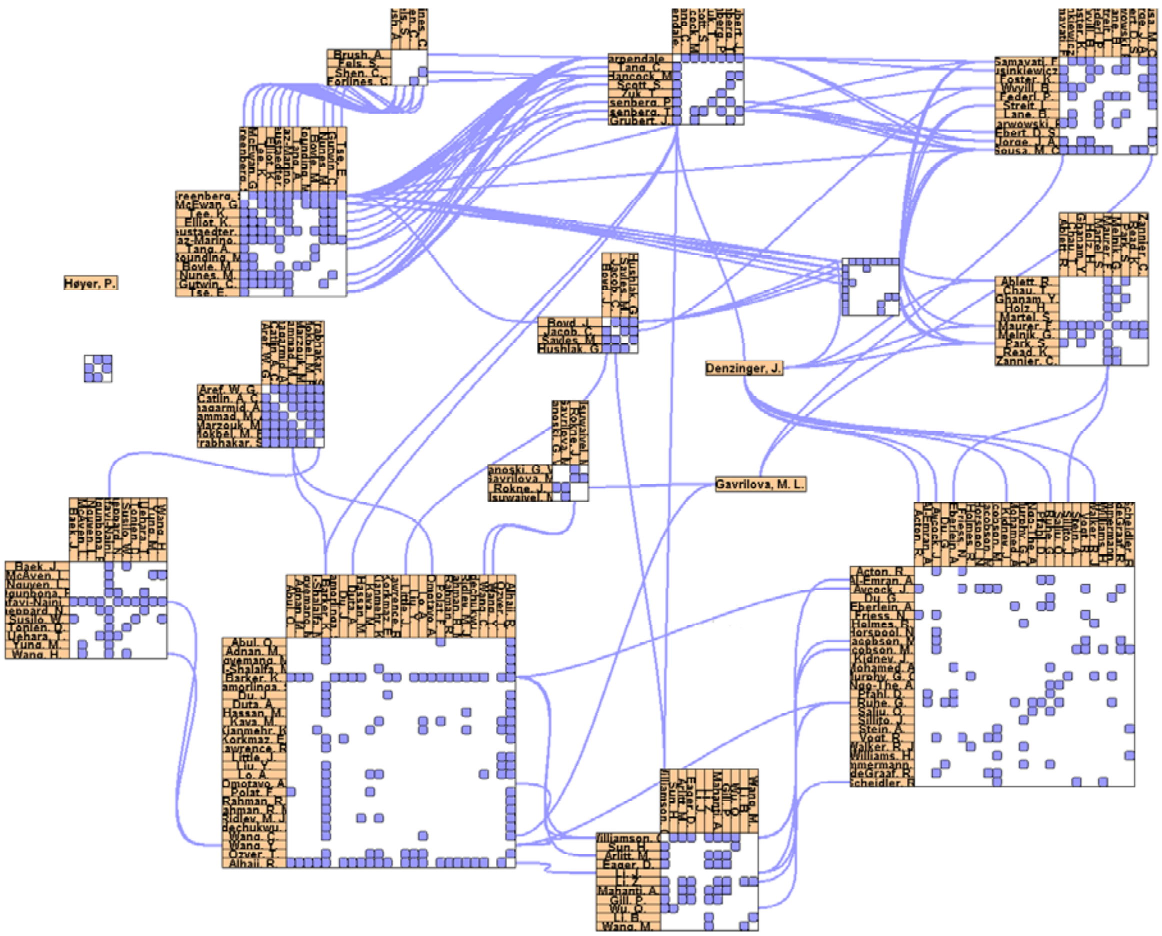


Figure 10. NodeTrix – Visualisation for large social networks [Henry et al 2007]

Our proposed SNA capability leans toward such a model as it is positioned at the converging roads of SNA and data mining techniques. As mentioned by Memon and Larsen [2006], although SNA is not conventionally considered as a data mining technique, it is especially suitable for mining a large volume of association data to discover hidden structural patterns in social networks. Some authors, like Chen J. et al [2009] have considered some visualisation techniques based on data mining. More specifically, their method aims at identifying and extracting overlapping community structures from networks. Other authors [Brandes et al 2008] propose techniques to extract and compare clusters from a large social network in order to subsequently extend the analysis to other similar networks of interest.

The envisioned SNA capability is looking at dealing with very large amounts of data. The capability should be able to encounter a large number of nodes and links as well as their respective attributes. Some tools, like Pajek [Batagelj and Mrvar 2003] specifically focus on the analysis and visualisation of extremely large networks. Moreover, on top of these data about the nodes, links and attributes; the temporal data must be added. The temporal data might address the time at which a specific link between two or more nodes has been observed but also other metadata such as time of the report describing the observation or else the time of the data entry in the data base. The same effort could be performed with respect to the spatial component. All of these metadata may be used as building the context of the data itself; element of critical importance in complex environments like ours.

In the case of Krempel [2005], he suggests certain algorithms in order to adequately arrange the visualisation of the nodes. For instance, he uses centrality measures to enable the identification of nodes of importance requiring the best position. While Krempel uses such measures; for the current research purposes, it would be relevant to identify, for specific analyses, what measures should be used to enhance the visual display. Indeed, depending on the analysis of interest different measures should be matched to specific displays. Other authors do take complementary stand points, using for instance "time" as the variable to identify the best structural positioning of the node [Harrer et al 2009].

Finally, one of the most difficult factors is that insurgent networks are, to some extent, part or sub-clusters of a larger local population. Visualisation techniques should enable to uncover those clusters and the degree in which they overlap. But, consequently this means the manipulation of even larger social networks.

4.3.3 Challenge 3: Making sense of the analysis

For the analysis phase, once analyses have been performed on social networks, there are still a number of remaining activities to realise in order to achieve sense-making about the situation being faced. These additional activities can also be greatly supported by visualisation techniques and more specifically Visual Analytics techniques.

As previously mentioned, in SNA, visualisation techniques concentrate a lot on graphs visualisation. We believe that additional types of visualisation techniques should be considered in order to unable sense-making from the analyses performed on the social networks. Stein et al [2010] propose a new approach to visualise social networks. Their approach adapts pixel-oriented visualisation techniques to social networks as an addition to traditional graph visualisations (Figure 11).

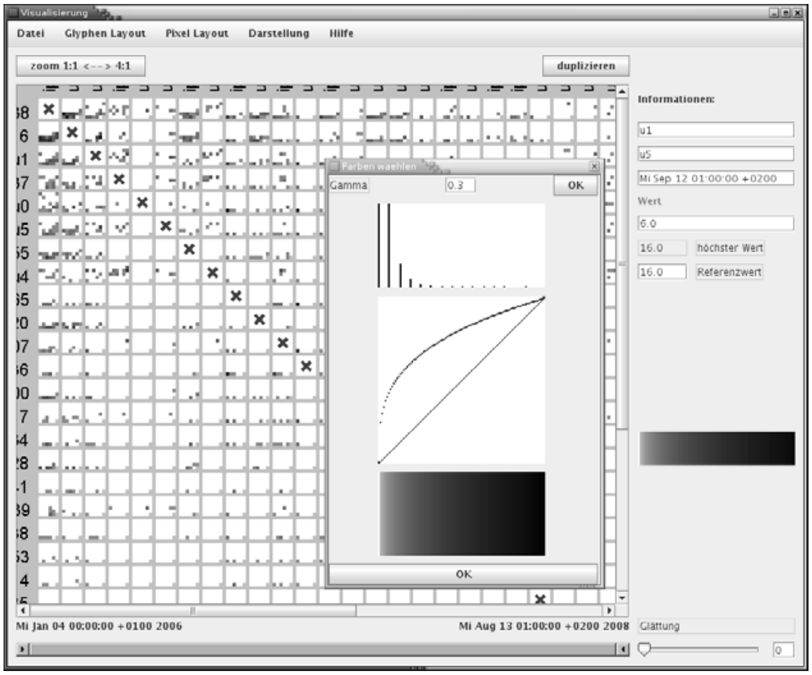


***Figure 11. Graphical user interface of PONVA - Pixel-oriented visualisation of the network matrix*[Stein et al 2010]**

With respect to graph visualisation per se, some authors are considering the need to provide a better structure to the graphs and data in order to understand them more adequately and build sense-making. Peng and SiKun [2009] propose to use a domain ontology model for the field of social network analysis and to facilitate visualisation of the social network.

In addition, one essential component in building sense-making around social networks is to consider visualisation techniques that enable grasping the social networks evolution and changes over time. Indeed, social networks are made of human beings and by nature are determined to change over time. To enable such an understanding, the analyst must extract an endurable state of the social network along with indicators of changes of the social network for subsequent analysis. Visualisation becomes clearly critical when the attempt is made to provide a comprehensive view of the social network evolution along the elements of interest to the end-user. In a COIN context, it can play an important role in SNA in order to evaluate the impact of our actions. This is another reason why SNA visualisation should also enable to depict the changes in the social networks following, for instance a specific event in time. Moreover, with respect to the defence domain, there is an attempt to clarify if these social networks changes are really imputable to the action performed and to what extent. Due to the complex situation settings, most of the time the changes can only be observed and the causal relations between specific changes against a perceived related action suggested. Nevertheless, research is being conducted and some meaningful insights are proposed with respect to this topic of social structure changes over time [Bourqui et al 2009, Kang et al 2007, Gloor et al 2004]. The researches undertaken by Bourqui et al [2009] are particularly interesting in the context of the foreseen SNA capability as they are looking at identifying the changing relationship in a social network through visualisation. They particularly focus on discovering important events by observing changes in the social structure and based on this, infer roles hierarchy. Luo et al [2009] make one step further in sense-making by attempting to enable a prediction based on the network – and its cliques – dynamic analysis; they propose a dynamic core detection algorithm.

Another essential element in SNA is the space variable and more specifically in relation to the geospatial domain. Khalili et al [2009] mention that, whilst a node's position has considerable potential for carrying information regarding network patterns and structures, no spatial information is usually encoded. This is despite the fact that already Wellman [1996] underlined the importance of social entities spatial properties. Once integrated with social network data, the spatial properties have a great potential of revealing insights into hidden patterns behind communities or with respect to specific individuals within communities. Moreover, the SNA envisioned capability in this defence domain, needs to take into consideration the fact that geography has always been a privileged framework of reference for the militaries.

Once those principles of geospatial and temporal are combined, there emerge a new interest in understanding and capturing the spatiotemporal aspect as for instance with respect to the moving of people to and from different areas. This is of critical interest even if most researches have been performed in urban areas [Chen W. et al 2010] and for different contexts than the COIN.

4.3.4 Challenge 4: Collective social network analysis

In the COIN context, performing SNA is a very difficult task for many reasons. Just to name a few, we could firstly reiterate how much this specific COIN context is complex and requires encountering multiple types of social networks. These social networks are, to some extent, related to one another and identifying those connections and overlaps is also part of the SNA. Secondly, the analysts have to work with some covert networks, which are quite difficult to understand or difficult to collect data on [Roberts 2010]. Moreover, in some cases they are at war with those covert networks. Thirdly, in many instances, they are performing SNA on societies and cultures that they are less used to deal with and this aspect could be a research area in itself.

All of these above mentioned components are incentives to undertake a collective approach to social network analysis. Indeed, with respect to the COIN operations in which our Forces are involved, the Canadian Forces are not the only instance on site; many other military and non-military organisations are present. These organisations can be either local or coming from external settings. In many cases, these organisations are also performing their own type of social network analysis with various levels of resources and in all cases, these organisations hold critical pieces of information that could contribute to our own SNA activities.

Finally, it is worth to note that the Canadian Forces analysts are usually not required to exclusively perform SNA. Even if such social information is considered as essential, they also have to perform several other types of analysis. Therefore SNA brings one aspect of the full picture built collectively where SNA reaches its full potential once combined with other types of analysis pertaining to the situation. Even with respect to this final point, visualisation is considered as important to ease the development of a SNA capability. For instance, visualisation could provide information on what portion of the full analysis SNA is responding to. In the case of SNA performed by other organisations, a comparison of the results could be visually provided to the end-user. This could also include highlighting what type of SNA related information other organisations can provide and should then be considered to actively collaborate with.

5 Conclusion

This paper describes a new applied research project undertaken at DRDC Valcartier. The project focuses on enabling the development of a social network analysis capability for the intelligence domain. Developing such a capability, requires enlarging the research scope to the activities to be performed prior and after the analysis of the social network itself. In this paper we discussed some of these activities and how visualisation is perceived as potentially facilitating them. Among those activities, we discussed first how visualisation could help clarifying the issues the analyst is attempting to respond to in the context of COIN. Subsequently, we highlighted the importance and impact of the data and datasets for the capability efficiency. The capability would require visualising the data, their sources and the data sets from the standpoint of their integrity, reliability or limitations. Following this issue, we discussed how visualisation is also fundamental in attempting to represent the social networks of interest in order to bring some initial insights to the analysts. Then, the paper presented the analysis and its related activities facilitating sense-making based on them.

The following section dived into a number of challenges related to either the setting up of a SNA capability or else the selection of some types of visualisation. Four major challenges are expected to be encountered. The first challenge relates to complexity; the complexity of the COIN context but also the complexity of visualising social data. The second challenge discusses some aspects related to the incremental amount of data to deal with. Technological progresses, including web technologies, increased the quantity of available data to perform SNA. Consequently, this will require a better computational capability in order to run the measures but also to consider some technological advancement in visualisation of very large networks. The third identified challenge relates to enabling sense-making from the analysis. At this stage, the temporal and spatial components have already been identified by numerous researchers as unavoidable functionalities in visualisation of social network analysis. The last challenge identified in this paper stresses the importance of working collectively in attempting to perform SNA. This is true at the analysis level within the organisation as well as with different external organisations that are either performing some types of SNA or else host data or data sets of importance to the CF to perform SNA.

6 Future research

This paper is only positioning the perceived importance of visualisation techniques and technology in support of a SNA capability. Many researchers are working on various aspects of social networks visualisation and whilst it would be great to consider all of them, our efforts need to first focus on the essential ones in the context that our CF are facing. In that effect, the CF will soon have identified their main SNA requirements for such a capability. In light of those requirements, different visualisation techniques will require to be more thoroughly considered and evaluated.

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