18th ICCRTS

"C2 in Underdeveloped, Degraded and Denied Operational Environments"

****

Enabling Efficient Intelligence Analysis in Degraded Environments

Topic 3: Data, Information and Knowledge

Régine Lecocq*
Valérie Lavigne
Defence Scientists

Defence R&D Canada – Valcartier
2459 Pie-XI North, Quebec City, QC, G3J 1X5, Canada
Phone: 1 (418) 844 4000 Fax: 1 (418) 844 4538
Email: Firstname.Surname@drdc-rddc.gc.ca

(*): Point of contact author
E-mail: Regine.lecocq@drdc-rddc.gc.ca

1 Abstract

When facing decisions in underdeveloped, degraded and denied environments, the commanders are likely to rely even more heavily on efficient intelligence analysis. Unfortunately, most of the time, the data gathered in these environments will be uncertain, ambiguous and incomplete. Tools enabling fast and thorough analysis are thus required. Use of automated processing alone is vulnerable to data deficiencies and human judgment is essential to ensure intelligence products validity. Interactive visual interfaces offer a strong approach for enabling human analysis by leveraging the high bandwidth visual pathway into the human mind and unique human visual pattern finding abilities. We proposed visual analytics tools to support sensemaking and improve social network analysis in a counter-insurgency context. Our prototype is composed of a series of independent but coordinated generic widgets that can be applied to a broad range of application domains. Among the proposed analysis tools are: a Multi-timelines widget for temporal events and situation evolution analysis; a Magnets Grid widget for multi-dimensional information exploration; and a record browser of Visual Summary Cards widget for fast visual identification of key information elements and comparison between entities. We also expose the concepts underlying an additional widget currently in definition. The Graph Analytics widget combines a visual presentation of graph diagrams composed of nodes and links to other visual presentations of the analyses outputs like ranking, statistical results or else the semantic meaning of links based on a social network ontology.

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 some elements of the new context, which create such a degraded and denied environment for our military forces.

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

The Canadian Forces (CF) and the allies have been increasingly involved in missions taking place in this new context of operation. The commanders having to proceed to decision making in such context rely more heavily on efficient intelligence analyses.

The intelligence function itself, along with its complex tasks, is also impacted by the complexity of the environment. For instance, the context of counter-insurgency (COIN), under which this research project is taking place, is bringing its own additional components of complexity. 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". An "irregular activity" may be defined as: "behaviour that attempts to affect 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". While insurgent groups can be tightly connected to criminal or terrorist networks [Lonsdale 2008], their motivation is different as it is initially a political one expressed through oppositions to the government in place or any instance supporting it. These definitions stress some essential elements. First they refer to asymmetric approaches by opposition to the conventional threats that were known up to the cold war period[1]. Second, they clearly position the importance of gaining local population support as the fundamental objective of such warfare from both the insurgents as well as the military forces standpoints. This implies that the line between the local population and the adversaries is blurred. In essence, an insurgency emerges from inside a country, and the insurgents networks are usually embedded in local communities. Therefore, making sense of the situation requires not only understanding the insurgent networks, but also their connections to other networks like the criminal or terrorist networks as well as the local population networks. This would then include a certain level of white[2] situation awareness (SA) partly accessible through social network analysis techniques and methods. Such difficulties in understanding these systems and how each part impact on one another are exacerbated by the cultural differences between the local communities and the military personnel.

3 An intelligence SNA capability

3.1 Sensemaking and SNA

The concept of sensemaking is central to the military domain and tightly connected to situation awareness. Sensemaking can be understood as "a process to successively build and refine representations and fit data with representations to meet the requirements of a task" [Russell et al. 1993]. The process described by Russell et al. [1993] envisions sensemaking as the quest for successive representation that best support the task to be performed. This perspective on sensemaking was more deeply explored in the context of intelligence analysis activities by Pirolli and Card [2005] with their "Notional model of sensemaking loop for intelligence analysis" depicted in Figure 1.

---

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

2 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).

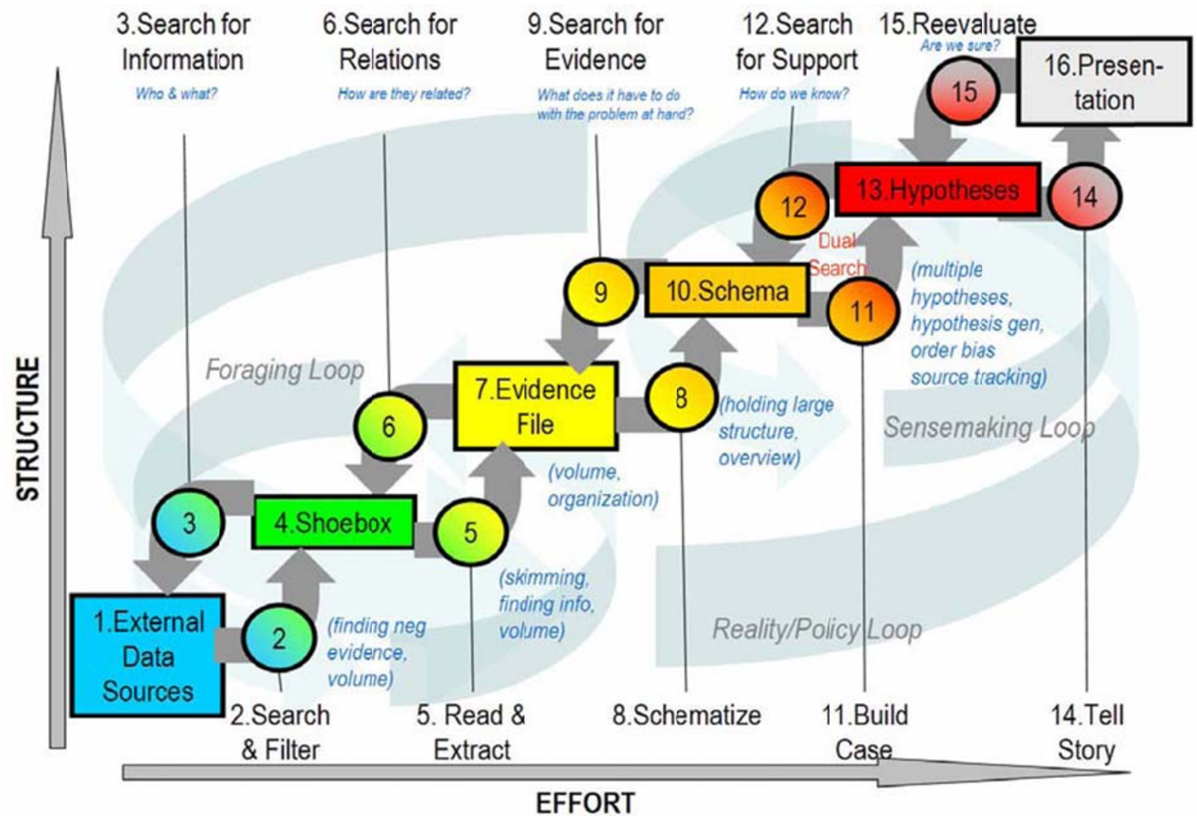

Figure 1. Notional model of sensemaking loop for intelligence analysis [Pirolli and Card 2005]

As exposed in Pirolli and Card's model, in order to achieve sensemaking, many different tasks are required to be performed, each one supported by some types of representations. Furthermore, these tasks are considered as complex ones and in essence they differ from well-structured tasks in several ways. During the Computer Human Information (CHI) 2008 Workshop on Sensemaking, Scholtz [2008] summarized these differences discussed in Redish [2007] and Redish and Scholtz [2007]:

- "Information overload is endemic. People have to locate the relevant information/sources and focus only on those.
- Data analysis and recursive decision-making are cognitively very burdensome; people have little cognitive workload available for dealing with unusable interfaces.
- Information is often incomplete or even unreliable.
- In some domains, there may be no way to know if the result one gets is right or wrong.
- In many domains time may be critical. Good decisions made too late are bad decisions.
- Domain experts may not be computer experts. The demands of their work may make it difficult for them to put much time or effort into the learning curve of new programs.

- Software systems for complex problem solving often consist of several components and visualizations. We must evaluate the individual components and/or visualizations as well as the entire system.
- Information for many of these tasks is not static but changes over time. This dynamic nature increases the complexity of the task.
- Complex problems often require multiple domain experts to collaborate. This presents a challenge in combining multiple perspectives."

In the counter-insurgency context or other ones strongly related to socio-cultural aspects, when an intelligence analyst attempts to make sense of the situation by conducting these tasks, some of the required pieces of information can be extracted by analyzing social networks[3]. Tools enabling fast and thorough social network analysis are thus required. However, use of automated processing alone is vulnerable to data deficiencies and human judgment is essential to ensure intelligence products validity. Interactive visual interfaces offer a strong approach for enabling human analysis by leveraging the high bandwidth visual pathway into the human mind and unique human visual pattern finding abilities. Therefore, we proposed visual analytics tools to support sensemaking and improving social network analysis in a counter-insurgency context.

3.2 Social network analysis research project

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[4]. It relies on the premise that improving intelligence products through advanced SNA and visualisation/interaction will contribute to increase sensemaking and situation awareness leading to better decision making [Lecocq et al 2011]. 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.

While existing tools and technologies will be investigated, the current research project aims at identifying and enabling the different components of a full SNA capability. SNA cannot be summarized as the sole use of technologies supporting the exploitation of some SNA measures like the usual betweenness centrality, and a few others. An intelligence SNA capability requires enlarging the scope to include the activities to be performed prior and after the analysis itself.

3.2.1 Social network analysis capability framework

As depicted in Figure 2, 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 analyses to be performed

---

[3] Unfortunately, as underlined by Gou et al. [2012], existing social network analysis tools often overlook users' needs for sensemaking activities that help to gather, synthesize, and organize information about the social data.

[4] For more details on the SNAC project please refer to Lecocq, Lavigne and Gouin [2011].

on them (2). By doing this, the analyst seeks to identify the variables involved in the questions being asked.

In turn, once the variables have been 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 the 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 on SNA product (6) related to the initial issue based on the COIN objective. Such an intelligence SNA product will greatly help to better understand the situation, but it should also be combined with additional relevant intelligence analysis enabling to cover a larger scope of the initial issue expressed. Overall, this will enhance the sensemaking process of the analysts.

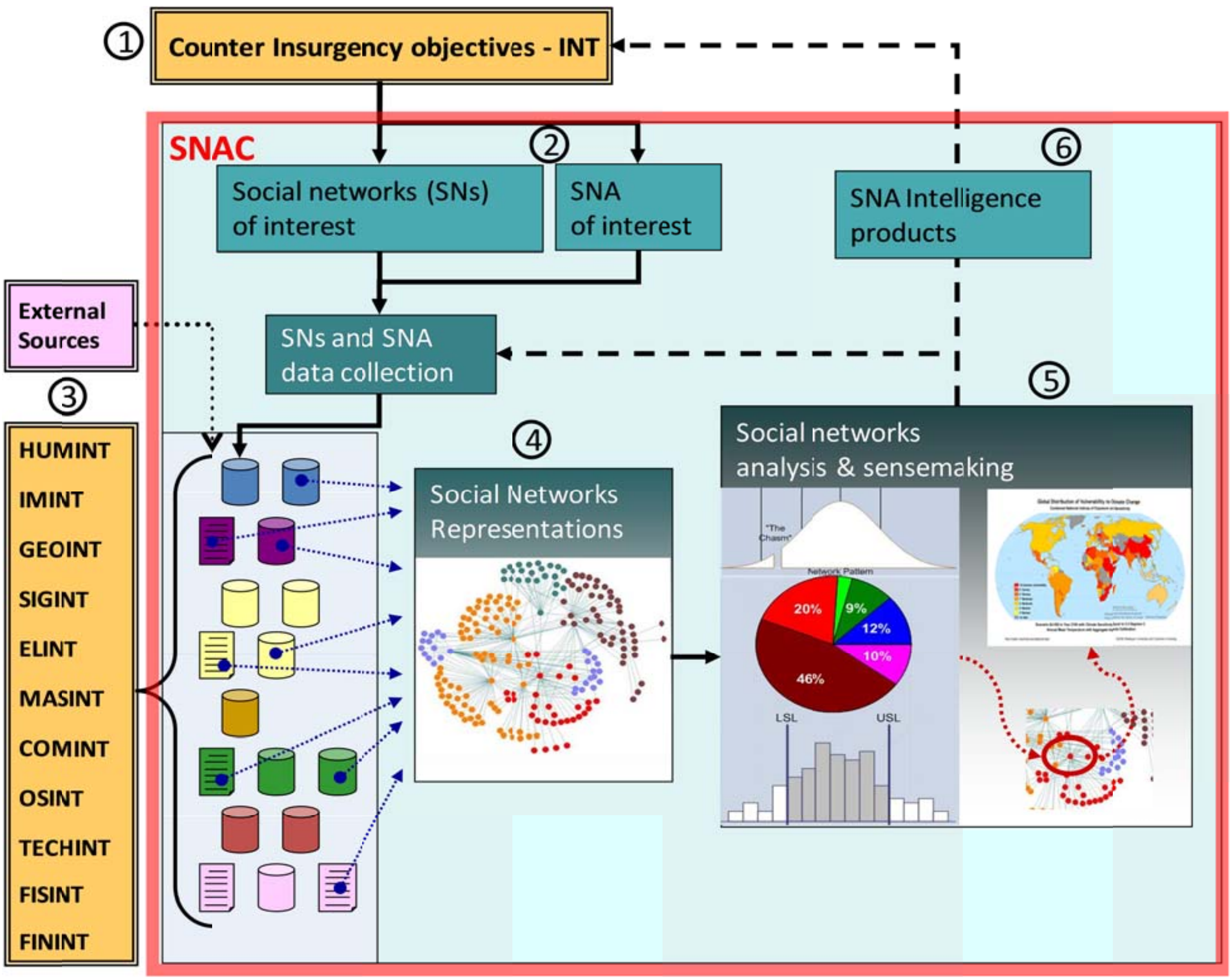

Figure 2. SNA capability framework

While the scope of the project is COIN and 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 achieve a more meaningful bridge between the two functions.

3.2.2 Visualisation and visual analytics

In the context of this research project, analyses of social networks are performed for the benefits of the intelligence function and consequently in support to decision making. SNA requires complex tasks holding the same characteristics than the ones described by Sholtz [2008] in the previous section. Indeed, 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 constitutes a significant research area, which studies various human cognitive characteristics such as pre-attention and inattentional blindness. It also explores and develops 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 Visualisation and SNA

In the context of this project, we consider that interactive visual interfaces offer a strong approach for enabling human analysis by leveraging the high bandwidth visual pathway into the human mind and unique human visual pattern finding abilities. We proposed visual analytics tools to support sensemaking and improve social network analysis in a counter-insurgency context. The research team levered different representation formats best supported by visualization and visual analytics techniques for the development of a social network analysis capability as exposed in the framework. Here again, visual analytics techniques come in support of each component of the framework and not only the analysis portion. In terms of complexity, these analyses have to encounter many covert networks, which in essence are surreptitious; making data about them more difficult to collect [Roberts 2010]. The analyses of social networks performed in this context have to take into considerations missing data and the reliability of the source the data is extracted from. Actually, SNA is prone to numerous errors, specifically due to misunderstandings about the meaning and the quality of the data supporting the analysis. In 2011, a report was published following a workshop on the “challenges in computational social modeling and simulation for national security decision-making”. The importance of SNA was largely discussed during the workshop and Jeffrey C. Johnson[5] [2011] stressed the importance of developing a science of errors. In the prototype, visualisation techniques are pursued in order to help the analyst understand the limits of the analysis in relation to the data supporting it. In many cases, analysts need to know from which data sources the data are extracted and their reliability. Also, the analyst needs to be able to grasp the extent to which data are missing and its impact on the performed analysis of the social network or else to what level the computed measure is prone to misleading based on missing data.

In a previous paper, Lecocq et al [2011] looked at each component of visualisation for the full spectrum of the SNA prototype development in the context of this research project. They mentioned a number of challenges they were facing while attempting to develop such a SNA capability, as well as some important elements when leveraging visual analytics techniques and methods. To name a few:

- Social networks analyses results should be explored through combined visual means and not solely by presenting a graph diagram depicting some components of the social network structure;
- The analyst should benefit from sensemaking tools in order to understand the data used to characterise the social network as well as to perform analysis on it. This implies the integration of the semantics about the selected data into the visual analytics tools. Other information could also be integrated, as for instance, the limitation of the data set and the corresponding resilience of the SNA measures to missing data;
- The capacity to manage large amount of data and visualise large graphs in a meaningful way is required in the context of this research project;

[5] Paper presented at the DTRA/Sandia Workshop on Challenges in Computational Social Science. Santa Fe, New Mexico. October 25-28, 2010

- Visual analytics techniques should be carefully utilized when attempting to perform analyses of social networks in a complex context like a counter-insurgency environment.

Since then a number of elaborations have been performed and the following section describes four different visualisation widgets foreseen to be part of the SNA proof-of-concept prototype. Each of these widgets was implemented using Service Oriented Architecture (SOA) principles, providing them enough flexibility to be used in different contexts of operation. Indeed, three of these widgets were initially developed for maritime domain awareness purposes and are being transposed to the COIN context. The fourth widget, the “Graph Analytics” widget, is currently under definition and will soon be developed for the purpose of the SNAC research project. Likewise the first three widgets, this one could also be transposed to other contexts like the maritime domain in order to leverage graph analytics techniques.

The fact that the visual analytics techniques are exploited through the use of widgets, is supported by several rationales. Indeed, the intelligence analysts, in the Canadian Forces, are not solely dedicating their time to perform social network analysis alone. Intelligence analysts have to perform many different types of analyses, all pertaining to a same situation being faced. SNA is critical for some aspects but will never hold the entire solution in itself. Therefore, in order to reach a certain level of sensemaking, it is important to combine visual techniques involving networks with other ones like the semantic of the relationship, the geographical information, the anomaly detection, or else the time window of interest. Krempel [2009] suggested that advanced visualisation techniques should be able to help solving complex situations 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. The development under the format of composable widgets enables to select the ones that are the most relevant to a specific situation and that will enable the human ability to rapidly detect patterns and reach sensemaking. These widgets remain connected to one another, creating enough flexibility to permit a shift of focus towards specific elements of interest pertaining to the situation being faced.

4.1 Visual Summary Cards widget

The visual summary cards widget shows all the key characteristics of a node, or so called social entity (individual, group or organization), at a single glance. A card can include:

- a unique photo representing the node;
- a word cloud summary of the related intelligence documents from which social network data were extracted from;
- snapshots of the social networks for various dimensions; this would be based on the results from the Graph Analytics widget; and
- icons showing different characteristics, such as: the social entity allegiance; tribal affiliation; criminal or insurgency activities involvements; nationality; religious, political or C2 known roles.

A record browser allows flipping rapidly through a virtual deck of summary cards so that the analyst can find nodes of interest quickly using visual cues. We use visual graphical representations of the relevant information instead of textual descriptions in order to take advantage of human visual pattern finding abilities. This browser also allows the analyst to select a particular card and keep it on the left side of the display thus enabling a rapid visual comparison with the others cards of the deck.

Figure 3 shows a mock-up of what an insurgent card will look like. This visualisation is currently adapted to the intelligence use-cases in COIN. For instance, it is envisioned that the Summary Card will support the intelligence analyst in identifying a social entity from a particular social network. Such a social entity will hold characteristics of interest and will be considered as a profile of reference. The profile of reference is then processed using social network analysis services in order to identify similar ones either from the same network (the network of reference) or from other networks. The similarity analyses results are ranked providing a list of promising social entities. The widget is then used to rapidly scan the extracted social entities using the analyst ability and expertise to validate or discard some of the social entities presented on summary cards. In turn, when performing this task, the analyst can discover additional patterns of characteristics that are associated with a specific role/position such as an attack facilitator, or characteristics that correspond to the profile of an influential insurgent leader. The analyst can then decide to run a new similarity analysis based on this refined profile of reference.

The Visual Summary Cards are also of interest to increase white situation awareness by representing higher level nodes such as political groups, tribes or non-governmental organizations.

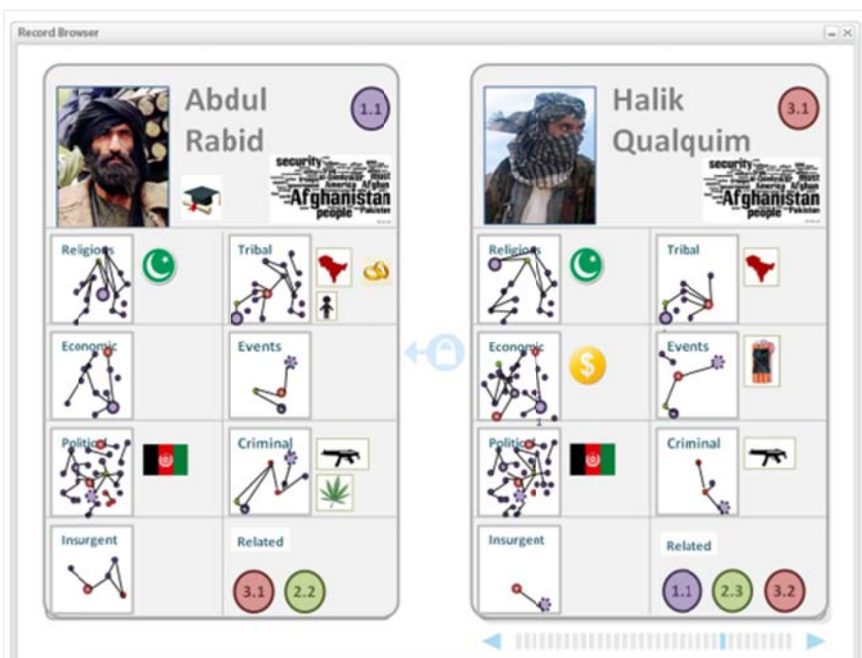

Figure 3 – Visual Summary Cards in the Record Browser

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 or links. This widget leverages the notion, also proposed by other researchers [Perer and Shneiderman 2006], that once specific SNA metrics are applied on a social entity, the result can be attached to certain nodes and turned into one of their attribute or characteristic. An example of this would be to calculate a closeness centrality result to the profile of reference and search for other social entities with similar values and 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]. Nevertheless, as exposed by Gou et al. [2012], existing social network analysis tools are usually weak in supporting complex analytical tasks involving such relationship between the structural (SNA measure like the closeness centrality) and the social data like some of the characteristics of the social entity.

This widget is very important in helping the analyst to expand the analysis of the social network from one node and its relationships to the consideration of other similar profiles and patterns in social networks.

4.2 Magnets grid widget

Moving away from the graph can help focus on other characteristics of the social network. For that purpose, we propose an extended version of the Dust & Magnets concept from [Soo Yi et al. 2005] for social networks analysis. The Magnets Grid widget is a multi-dimensional interactive visualization app for exploring simultaneously multiple characteristics of a social entity. The observation of multiple properties of the social nodes can lead to insights about how they are correlated, uncorrelated, or negatively correlated. Here again, this exploration can lead the analyst to detect trends, patterns and outliers. Based on these discovered trends, the analyst can subsequently run different analyses on selected social networks.

In Figure 4, the canvas located on the left side contains the dots representing any type of nodes/social entity (individuals, groups or organizations). Adding labelled magnets to the display area will cause the dots to be attracted to them according to metrics that were computed from the social network or the intelligence data gathered about each node. In our extended version, optional constraints can be added to the axes to keep the dots inside columns, rows or grid boundaries.

Figure 4 – Magnets Grid for social network analysis.

A possible use of the Magnets Grid would be to identify potential threatening tribes or individuals that have been associated with violent events in the past. In Figure 4, for example, the dots correspond to nodes about individuals and the x axis is constrained by tribal groups, allowing dots to move only within the vertical band where they belong. The magnets Government Support and Insurgent Support were added to the canvas. When the analyst interacts with a magnet, the dots move according to the metrics that were computed for those magnets. In addition to colour coding which was associated to the main role/responsibility of the nodes, the size of the dot was associated with the number of reports about violent incidents that are mentioning the individual. The full power of this visual analytic widget lies in its interactivity as the analyst gets a feeling of the attraction of the various magnets by moving them, which is not easily graspable with a static view. However, we added optional attraction arrows that can be turned on to show the force exerted by each magnets on selected nodes, thus resolving the ambiguity surrounding a dot laying between two magnets by showing if it is equally attracted to both or not attracted at all.

Another value of the Magnets Grid will be to enable the analyst to investigate properties of interest in order to gain insights about existing trends or patterns. Once the insight is gained, the analyst can more rigorously make sense of the situation by investigating, for instance, a measure of assortativity on the network. Assortativity is the identification of selective linkings that take place between the nodes of a graph. This notion can be quantified by an assortative coefficient [Newman, 2003 and 2003b]. Moreover, some types of assortativity can also be characterized based on node graph measurements or else properties; Newman [2003] refers to such assortativity as “degree correlation”. An identified selective linking based on a specific property for instance would then permit monitoring the emergence of favorable conditions of these linking in the network or other ones.

The value of the Magnet Grid widget is similar to the Summary Cards ones, but this widget, beyond the identification of trends, opens the research area for predictions as well as uncovering hidden or missing data. As mentioned in Lecocq [Lecocq et al. 2011], one essential component in building sensemaking around social networks is to consider visualisation techniques that enable grasping the social networks evolution or predicting some of its changes over time. Change detection and prediction are definitely not trivial areas of research and they require a lot of caution due to the uncertainty attached to any prediction, or else the data set quality that the prediction analyses are run on.

4.3 Multi-timelines widget

The Multi-timelines widget shows multiple coordinated timelines along with key variables to make sense of temporal information. Looking at timelines for different areas, one can explore the effects for taken actions and possibly predict what the outcome of proposed actions could be by comparing timelines from other areas when similar actions were taken. In Figure 5, the effects of an operation on the coalition allegiance from different tribal groups are explored. The changes in population allegiance are reflected by the occurrence of various positive or negative events, like a warm/cold welcome from local leaders or the presence/absence of children greeting the soldiers, which are recorded in observations or reports.

Figure 5 – Multi-timelines widget showing the effect of an operation on coalition support from different tribal groups

Like in the Lifelines 2 application [Wang et al. 2010], the timelines can be aligned on a selected event type to analyse repeatability of temporal patterns. In Figure 6, the effects of coalition operations over time are compared for a selected tribe over different time periods. This could lead to findings related to which types of intervention are the most effective, or how long the forces should remain in an area in order to gain a durable population support or allegiance to coalition.

Figure 6 – Multi-timelines widget allowing the comparison of the effect of operations on coalition support of a specific tribe at different periods in time

Another way to make use of this widget is to compare several individuals' pattern of life in order to discover trends for a same profile, or else links between individuals. The comparison can be made based on the analysis of an affiliation network between individuals and certain time stamped events or meetings that can be aligned temporarily.

The identification and understanding of any patterns, like the ones identified through the Multi-Timelines widget, also acts as indicators of potential missing data. For instance, these missing data can correspond to events that should have taken place while they were not observed, or else the participation of a social entity to a known event.

Finally, this widget constitutes an important building block to a SNA capability since it takes into consideration the time component. Indeed, any attempt to make predictions or else to identify changes in a social network requires the management of the time variable.

4.4 Graph analytics widget

This fourth widget is only being defined currently and its development is expected to take place during the coming year. This widget is aligned to the graph analytics domain and this is where it takes its name from. Graph analytics is a sub-area of visual analytics, and is described by Wong et al. [2011] as a "transdisciplinary R&D area, involving information retrieval, data management, human-computer interaction, computer graphics, and visualization".

There exist many different ways to leverage the value of visualisation and visual analytics for a SNA capability. However, most of the current technologies focus solely on visualising networks and their structure under the presentation of a graph diagram composed of nodes and links. Through the different widgets exposed in this paper we demonstrate the importance of several other means than a graph in order to make sense of a social network in a degraded and denied environment. Nevertheless, the visual presentation of a graph as a diagram composed of nodes and links still bring other types of understanding about the social network being studied. In order to better analyse and extract meanings from SNA, additional visualisation methods need to complement such visual presentation. 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 diagram along with the statistics about the graphs. This is how the "graph analytics” widget is viewed since it will combine the visual presentation of the social network as a graph diagram with the analyses results that were performed on the network, some being statistical results. This perspective is based on the results from researches demonstrating that combining statistics and network graphs, involves the visual as well as the language capacities of the end-users and therefore contribute to the reduction of cognitive overload [Ware 2008].

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 sensemaking. 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. Similarly, this widget aims at supporting sensemaking as it goes beyond the initial visual information provided about the network structure. The widget is defined to connect the different graph components, like a node, a link or a property about one or the other, to a semantic meaning from an ontology. These properties are important and meaningful to the analysts, leading them more easily to sensemaking.

5 Discussion and future research

This paper describes some of the embraced visual analytics concepts in an 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 to and after the analysis of the social network itself. In this paper we discussed some of these activities and how visualisation is perceived as facilitating them.

Intelligence analysis is composed of many complex tasks and is tightly related to increasing sensemaking. While automation and systems can greatly support the analyst. It is critical to maintain the human in the loop. Analysts have a wealth of experience that can be tapped using advanced visual analytics techniques. Our prototype is composed of a series of independent but coordinated generic visual widgets that can be applied to a broad range of application domains for the benefit of the analyst. Among the proposed analysis tools are: a multi-timelines widget for temporal events and situation evolution analysis; a magnets grid widget for multi-dimensional information exploration; and a record browser of summary cards for fast visual identification of key information elements and comparison between entities. We also expose the concepts underlying an additional widget currently in definition. The Graph Analytics widget combines a visual presentation of graph diagrams composed of nodes and links to other visual presentations of processing outputs like ranking, statistical results or else the semantic meaning of links based on a social network ontology.

Since the instigation of the first three widgets, they were always foreseen as being transitioned to the SNAC research project; this is the effort being currently conducted. Also, the fourth widget that is discussed, the Graph Analytics widget, is currently under definition and its development is foreseen to take place during this year as well. Finally, other additional widgets are also considered like the Map and Timeline widget, which allows the user to interactively view positional data. Currently this widget, also developed for the maritime domain, enables the user to view vessels positions as well as to select a time window for which tracks will be visible on the map. Transposition of this widget is also considered for the SNAC project since it could be used for many different purposes like, for instance, communication tracking against insurgent events taking place.

Many technology-driven tools that are built pretend to impact sensemaking activities but the quantitative or qualitative measure of such impact is still underdeveloped. Scholtz [2008] reported progress and challenges in evaluating tools for sensemaking with a list of metrics resulting from a workshop discussion for visual analysis environments. It is our plan to make use of some of these metrics in the evaluation of the widgets for the SNAC project. Meanwhile, the first three widgets that were initially developed for the maritime domain were created in a generic way and respecting SOA principles. They were well received by the maritime domain community and a more systematic evaluation will take place by the end of 2013.

These four widgets each consider some of the visualization and visual analytics issues and challenges as exposed by Lecocq et al. [2011]. Nevertheless, some of the aspects are not yet covered and will be part of future research on the topic.

6 References

Bezerianos, A., Chevalier, F., Dragicevic, P., Elmqvist, N., & Fekete, J.-D, (2010), *GraphDice: A System for Exploring Multivariate Social Networks*, In proceedings of the Computer Graphics Forum, vol. 29 , no. 3, pp. 863-872.

Card, S., (2008), *Information visualization*, In Sears, A. & Jacko, J.A., *The Human-Computer Interaction Handbook: Fundamentals, Evolving Technologies, and Emerging Applications*, Lawrence Erlbaum Assoc Inc.

Card, S., Mackinlay, J., & Shneiderman, B., (1999), *Readings in Information Visualization: Using Vision to Think*, Morgan Kaufmann Publishers.

Department of National Defence and Canadian Forces (DND/CF), (2008), *Counter-Insurgency Operations*, B-GL-323-004/FP-003.

Directorate of Land Concepts and Designs (DLCD), DND/CF, (2009), *Toward Land Operations 2021: Studies in Support of the Army of Tomorrow Force Employment Concepts*. B-GL-310-001/AF-001, Kingston, Canada.

Gou, L., Zhang, X. (L.), Luo, A., and Anderson, P.F., (2012), *SocialNetSense: Supporting sensemaking of social and structural features in networks with interactive visualization*, IEEE, Visual Analytics Science and Technology (VAST), pp. 133-142.

Johnson, J.C., (2011), *Grave Error: Towards a Science of Error in Social Network Analysis and Modeling in the National Security Context*, In McNamara, L.A., Trucano, T.G., and Gieseler, C., *Challenges*, In Computational Social Modeling and Simulation for National Security Decision-Making, Report, Defense Threat Reduction Agency Advanced Systems and Concepts Office Report Number ASCO, p. 263.

Jusufi, I., Dingjie, Y., & Kerren, A., (2010), *The Network Lens: Interactive Exploration of Multivariate Networks Using Visual Filtering*, Proceedings of the 14th International Conference on Information Visualisation (IV '10), pp. 35-42.

Krempel, L., (2009), *Network Visualisation*, In Scott, J. & Carrington J.P, *Handbook of Social Network Analysis*, Sage Eds., London/New Delhi.

Lecocq, R., Lavigne, V., and Gouin, D., (2011), *Visual Analysis of Social Networks in a Counter-Insurgency Context*, Proceedings of the 16th International Command and Control Research and Technology Symposium ICCRTS, Québec, Canada.

Lonsdale, M.V., (2008), *Criminal Activity in an Insurgent environment & Counterinsurgency: une étude de cas – Afghanistan 2001-2008*, Université Pantheon-Assas, Paris II. DOI : http://www.drmcc.org/spip.php?article328 , last accessed: February 1st, 2013.

Newman, M.E.J. (2003), *The structure and function of complex networks*, Society for Industrial and Applied Mathematics - SIAM Review, vol. 45 #2, pp. 167-256.

Newman, M. E. J. (2003b), *Mixing patterns in networks*, Physical Review E, vol. 67, pp. 1-13.

Peng, W. & SiKun, L., (2009), *Social Network Visualization via Domain Ontology*, International conference on Information Engineering and Computer Science, IEEE, pp. 1-4.

Perer, A. & Shneiderman, B., (2009), *Integrating Statistics and Visualisation for Exploratory Power: From Long-Term Case Studies to Design Guidelines*, IEEE Transactions on Computer Graphics and Applications, vol. 29 , no. 3, pp. 39-51.

Perer, A. & Shneiderman, B., (2008), *Integrating statistics and visualization - case studies of gaining clarity during exploratory data analysis*, In proceedings of the SIGCHI conference on Human factors in computing systems, pp. 265-274.

Perer, A. & Shneiderman, B., (2006), *Balancing Systematic and Flexible Exploration of Social Networks*, IEEE Transactions on Visualization and Computer Graphics , vol.12, no. 5, pp. 693-700.

Pirolli, P. and Card, S.K., (2005), *The sensemaking process and leverage points for analyst technology*, In the Proceedings of the 2005 International Conference on Intelligence Analysis McLean, VA: Office of the Assistant Director of Central Intelligence for Analysis and Production.

Redish, J., (2007), *Expanding Usability Testing to Evaluate Complex Systems*, Journal of Usability Studies, vol. 2, #3, pp.102-111.

Redish, J. C. and Scholtz, J., (2007), *Evaluating complex information systems for domain experts*, paper presented at a symposium on HCI and Information Design to Communicate Complex Information, Memphis, US.

Roberts, N.C., (2010), *Tracking and disrupting dark networks: Challenges of data collection and analysis*, Information Systems Frontiers, vol. 13, no. 1, pp. 5-19.

Russell, D.M, Stefik, M., Pirolli, P., and Card, S.K., (1993), *The cost structure of sensemaking*, In proceedings of the International Conference on Human-Computer Interaction (INTERCHI), pp. 24-29, Amsterdam, The Netherlands.

Scholtz, J., (2008), *Progress and Challenges in Evaluating Tools for Sensemaking*, ACM Computer Human Information (CHI) conference Workshop on Sensemaking, Florence, Italy.

Soo Yi, J., Melton, R., Stasko, J. and Jacko, J. (2005), *Dust & Magnet: Multivariate Information Visualization using a Magnet Metaphor*, Information Visualization, vol. 4, #4, pp. 239-256.

Thomas, J.J. & Cook, K.A., (2005), *Illuminating the Path: The Research and Development Agenda for Visual Analytics*, IEEE Computer Society Press, DOI: http://nvac.pnl.gov/agenda.stm#book.

Wang, T., Wongsuphasawat, K., Plaisant, C. and Shneiderman, B. (2010), *Visual Information Seeking in Multiple Electronic Health Records: Design Recommendations and A Process Model*, Proceedings of the 1st ACM International Informatics Symposium (IHI '10), 2010, p. 46-55.

Ware, C., (2008), *Visual thinking for design*, In Kaufmann, M., *Interactive Technologies*, Morgan Kaufmann.

Wong, P.C., Chen, C., Görg, C., Shneiderman, B., Stasko, J.T., and Thomas, J., (2011), *Graph Analytics-Lessons Learned and Challenges Ahead*, IEEE Computer Graphics and Applications, pp. 18-29.

Wu, Y., Takatsuka, M., & Webber, R., (2006), Visualizing Multivariate Network Using GeoSOM and Spherical Disk Layout, In proceedings of the IEEE Symposium on Information Visualization, Maryland, USA.

Xu, K., Cunningham, A., Hong, S.-H., & Thomas B.H., (2007), *Graphscape: integrated multivariate network visualization*, In Proceedings of the 6th International Asia-Pacific Symposium on Visualization, Sydney, Australia, pp. 33-40.