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Understanding Social Behaviors in the Indoor Environment: A complex network approach

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Summary (not exceeding 2 sentences)

A novel complex network interpretation of a set of indoor human-spatial interaction data recorded from an intensive design workshop to reveal the dynamics of social behaviors exhibited by designers in a shared studio environment.

Abstract

Being able to monitor and analyze human interactions in the indoor environment over time has many architectural applications from spatial planning to post occupancy evaluation. In this paper we present our interdisciplinary approach that interprets human-spatial interactions as a complex network. We combine methods and techniques from sensor networks, signal processing, data mining, network theory, and information visualization to form a novel framework that facilitates versatile investigations. We will demonstrate the framework with a real-world case study: we have collected and analyzed human-spatial interaction data from a workshop scenario where multiply design projects were conducted within a shared studio space.

Body text

1 Introduction

A network, in its simplest form, is a collection of discrete *nodes* joined by *links*. Originating in mathematical graph theory, the study and application of network theory has quickly grown into an interdisciplinary field with inputs from physics, biology, computer science, social

science and other areas (Newman, 2010). Through a network approach researchers are able to reduce complex natural phenomena into an abstract form for further analysis of component dependencies and the formation of structural identities.

There has been a growing interest in understanding social interactions in the spatial context. Development of technology enables us to collect large quantities and variations of data, much of which is personally identifiable and geographically tagged. Individuals can be identified by their personal mobile devices and their spatial movement tracked through WiFi, Bluetooth and mobile network or GPS locations. This data can then be analyzed for behavior patterns within the wider social community (Dong et al., 2011, Holleczek et al., 2013).

Our research is conducted along similar lines of inquiry but at the architectural scale. At this scale we are dealing mainly with indoor environments. Compared with the openness of outdoor urban environments, indoor environments are cluttered with people, furniture and walls of various arrangement and composition that make accurate tracking a complex technical problem. The above mentioned tracking technologies that utilize existing infrastructure to provide urban scale tracking data are not easily adaptable to the indoors. At this scale active research focuses on developing applications of individual-spatial tracking technologies. Recent examples include a combined WiFi and GPS based mobile application to support university campus navigation (Biczók et al., 2014); a WiFi-based people behavior knowledge extraction system, to inform organizational facility planning in a hospital (Ruiz-Ruiz et al., 2014) and a Bluetooth-based visitor behavior monitoring system for spatial program management in a museum (Yoshimura et al., 2012). This paper contributes to this field of research by proposing a novel complex network-based approach to conduct effective socio-spatial analysis. We are utilizing the network's focus on relative association rather than precise position to bypass the need for accurate positioning data. We will demonstrate the features and flexibility of our proposal with a case study.
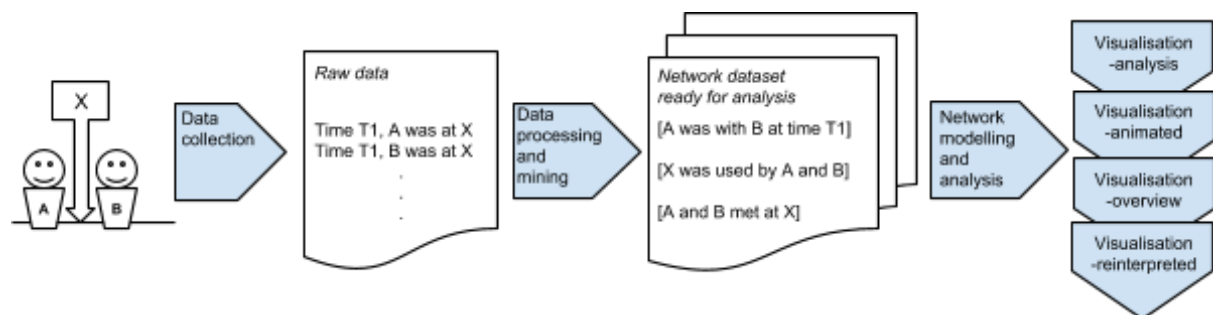
2 Context and methodology

Figure 1: Analysis Workflow

In our study we examine the interaction between groups of people in a spatial context represented by a set of known locations. The data collection system is able to produce a list of records linking individuals to locations at certain times. At any given time this set of "who is at where" forms a (static) 2-mode network. Through network projection (Borgatti and

Everett, 1997) we can transform this network into two 1-mode networks, each representing the implied interactions between the people or the interaction between the locations. (Figure 1) When the data is collected over time, through the process of sampling we are able to construct a dynamic network representation of the changes in interactions.

We are interested in how people behave in a shared space. A university-based intensive workshop was selected as our case study. A group of students were divided into 3 projects that operated in the workshop. Over the course of 6 days they shared one studio space. This setup was intended to fertilize informal cross-project discussions. We recruited 14 participants for our study. They form a good representation of the overall organizational structure of the workshop. (Figure 2)

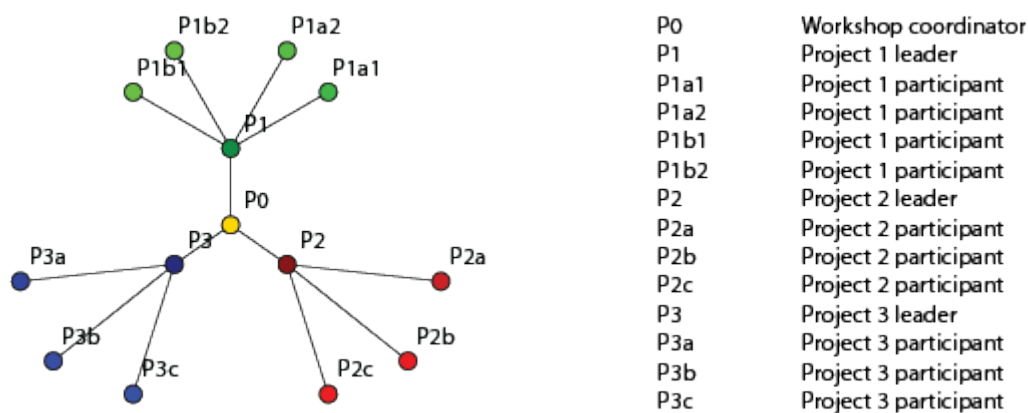|	
P0	Workshop coordinator
P1	Project 1 leader
P1a1	Project 1 participant
P1a2	Project 1 participant
P1b1	Project 1 participant
P1b2	Project 1 participant
P2	Project 2 leader
P2a	Project 2 participant
P2b	Project 2 participant
P2c	Project 2 participant
P3	Project 3 leader
P3a	Project 3 participant
P3b	Project 3 participant
P3c	Project 3 participant

Figure 2: The organizational structure of the 14 tagged individuals (left) and their roles in the workshop (right)

The data collection process consists of three components: a ZigBee-based indoor tracking system, a wireless time-lapse photography capture system and field notes from participant observation. The tracking and time-lapse data capture systems were automated (Figure 3); field notes taken were more ad hoc. This paper focuses on analyzing the data collected from the indoor tracking system (Figure 4) with reference to the photos and field notes when necessary.
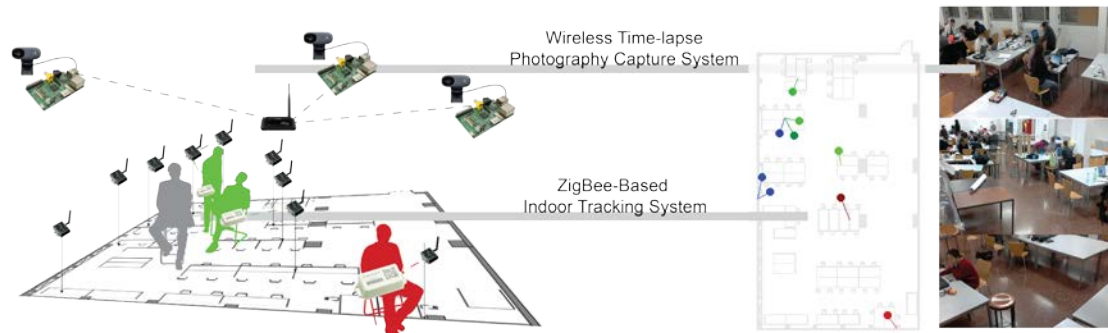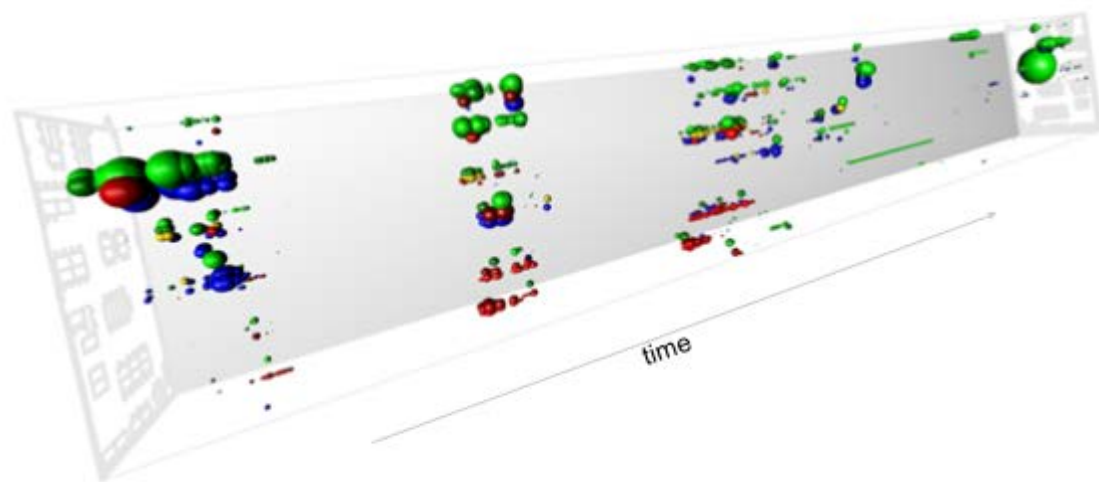
Figure 3: Automated data collection set up

Figure 4: 3D representation Individual's workshop activity as recorded by the ZigBee system

The indoor tracking system is adapted from an off-the-shelf inventory tracking solution that utilizes the active scan and automatic mesh configuration functionalities of the ZigBee protocol to collect the spatial proximity data[1]. Within the workshop space 9 sensors were installed at locations of interest, with the locations being selected based on the expected spatial requirements of the projects. (Figure 5)
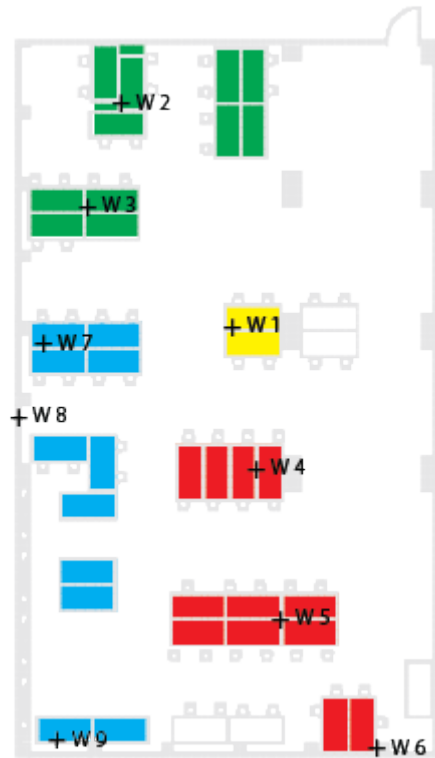
Figure 5: Workshop space with project assigned spaces highlighted with different colors

The tracking system was set up such that one tag could only be registered at one location sensor at a time, based on signal strength which is roughly correlated with proximity. Over a given time period this gave us a list of locations that each tagged individual has visited. We refer to this data as spatial interaction data. The tags were scanned at approximately 6 second intervals, resulting in 125063 tag-location data pairs over the 6 days of recording.
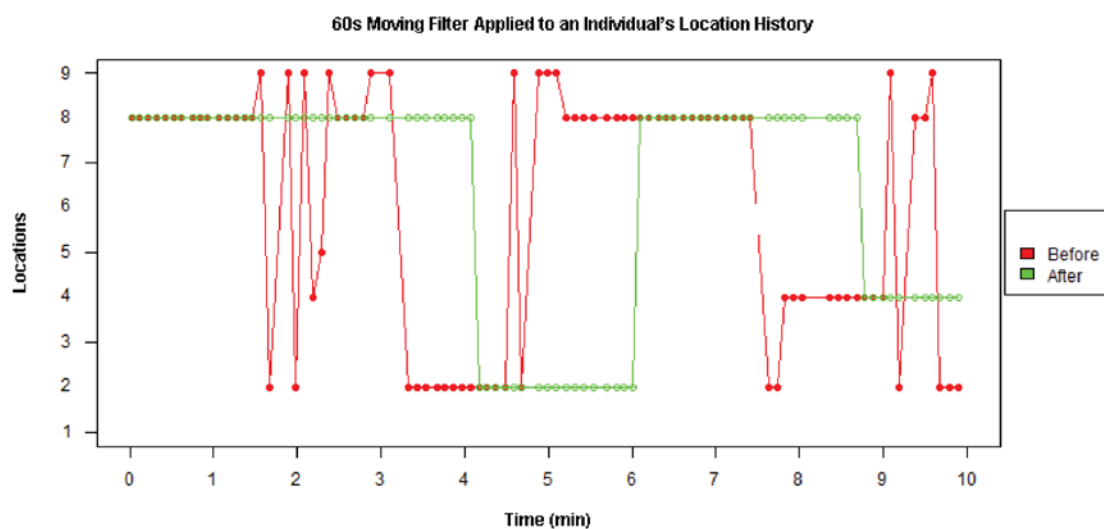

Figure 6: Moving filter

By processing the spatial interaction data with a certain set of criteria we are able to fine tune the behavior that we wish to observe. We first applied a 60 seconds moving low-pass filter on the raw data. (Figure 6) This was to remove the false negative records from incorrect location registration[2] as well as the false positive records from people who briefly walked past a sensor location en-route to their final destination. We divided the stream of spatial interaction data into 10 minute samples to convert the collected data into synchronous datasets for analysis. 10 minute intervals were selected as a reasonable approximation for the duration of an informal conversation. We further simplified the datasets by discarding duplicate entries within each of the time samples, producing a total of 2351 tag-location data pairs from 802 time samples, in which 431 time samples are non-empty.

We form our socio-spatial network by defining the 14 tagged individuals as the set of *social nodes*, with the 9 locations forming the *spatial nodes* of our network. The spatial interaction data are the *links* that connect the social nodes to the spatial nodes. For each time sample a static 2-mode social-spatial network was constructed from the spatial interaction dataset. The network becomes dynamic by letting the network structure evolve across time samples.

3 Analysis options

There are multiple strategies that can be used to interpret the socio-spatial network through a combination of qualitative and quantitative methods.

3.1 Quantitative method - Animated network visualization

We developed a network node placement algorithm to approximate the movement of the tagged individuals for visualization. The algorithm is a variation of the Fruchterman and Reingold layout (Fruchterman and Reingold, 1991), an iterative force-direct network visualization layout algorithm. The Fruchterman and Reingold layout algorithm was developed to use attraction and repulsion calculations to place network nodes for better visual perception of the network. To adapt the Fruchterman and Reingold layout we made the following adjustments regarding the treatment of the nodes:

- To better represent the effect of the spatial nodes on the social nodes, the spatial nodes were drawn to reflect the known spatial locations and kept stationary throughout the visualization. Position updates were only calculated for the social nodes.
- We assume that the movement of the people from one location to another is motivated by interest in something at the destination. In network theory terms the spatial nodes are responsible for the link creation, thus attraction calculations only originate from the spatial nodes. Repulsion force is calculated based on all nodes.
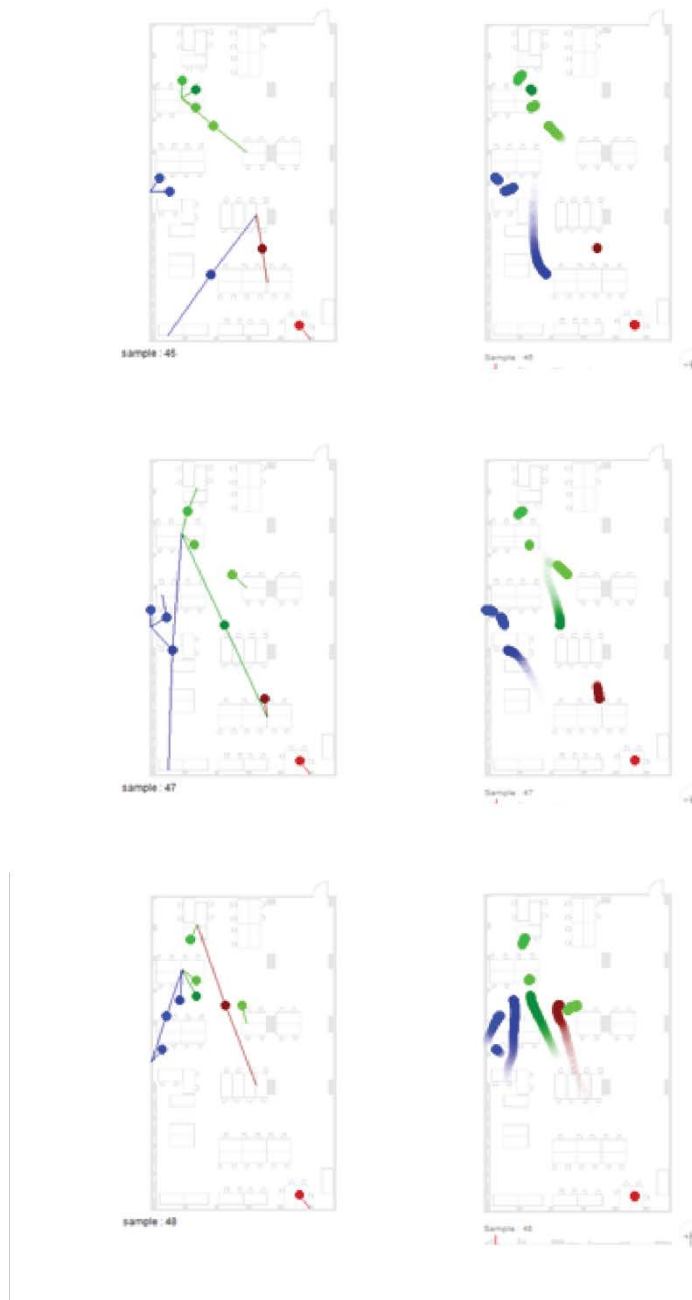
Figure 7: Network data visualizations of the 3 consecutive time samples (sample 46-48). Left: final placement of the social node showing links to the spatial nodes. Right: the transition effect from visualizing the intermediate iteration outcomes

For each time sample the placement was calculated over 50 iterations, with the attraction and repulsion forces exerting a small impact on the positioning of the (social) nodes. The parameters for step size, attraction and repulsion force impact factors are fine-tuned such that when the social nodes are visualized using the outcomes from the iterations it produces a transition effect that is effective in modeling the movement behavior of the people during the time sample. (Figure 7) Considering the number of time samples in this network,

the dynamic nature of the overall network is best viewed as an animated movie using the transition view of the time samples.[3]

As we gave the nodes color assignments that reflected the project assignment of the representing participants, overlaying the time sample's final placement gave us a good indication of the preferred work areas of the coordinator and the three projects. We can observe from Figure 8 that project 1 (green) favored the top left section of the room, project 2 (blue) worked mainly at the center tables and project 3 (red) stayed in the bottom right section. The coordinator (yellow) did not venture much into the working spaces of the three projects.
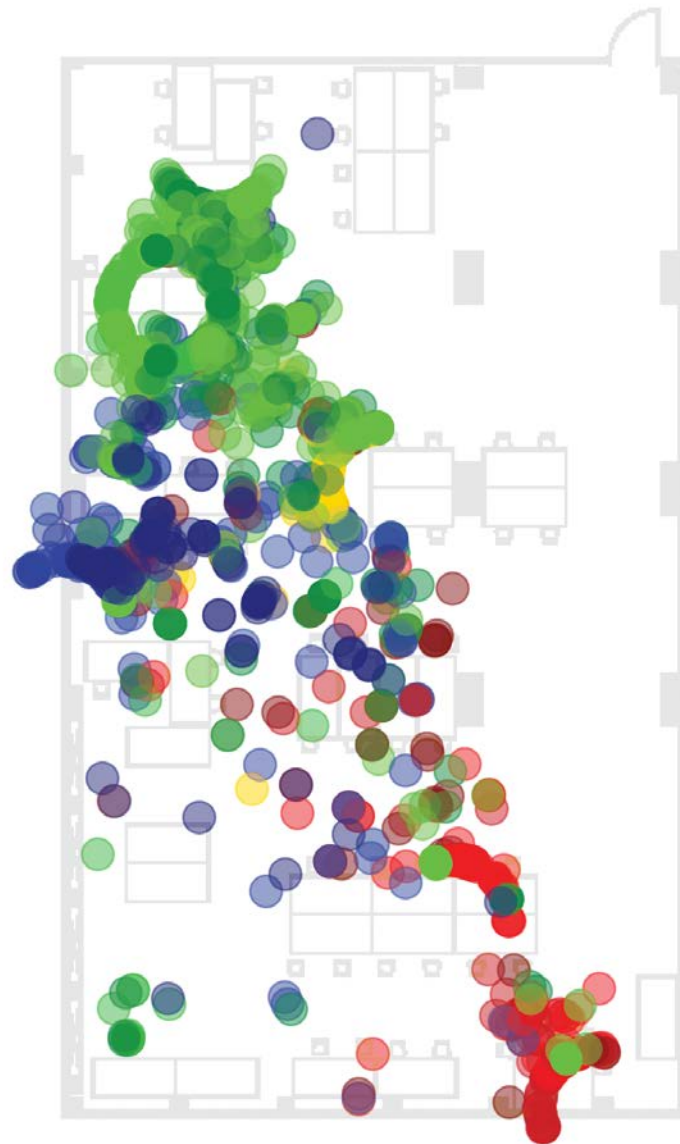

Figure 8: Overlaying node placement from all time samples

3.2 Qualitative method 1 - Social Network Analysis

Social Network Analysis (SNA) is the study of networks that represent social interactions through qualitative measures. To apply SNA to our data we projected the 2-mode socio-spatial network to a 1-mode social network projection: the subset of social nodes that are linked to one spatial node are now connected to each other and the spatial nodes are removed from the network. We selected 3 centrality measures (degree, closeness and betweenness; Freeman, 1979). This allowed us to analyze the social structure between the tagged individuals as presented by the social network (Figure 9 and Figure 10):

- *Degree* is the number of links connecting a node to the network. As it is calculated on the immediate network, it is a measure of the direct interactions a person had. For example a person with a low degree measure indicates this person worked more independently, whereas a person with a high degree measure interacted more with others.

- *Closeness* is the inverse of far-ness, which is in turn calculated as the total number of links a node required to reach all other nodes in the network. This makes closeness a representation of the central-ness of a person. A person with high closeness measure indicates that this person is more connected with the network thus more likely to have a better knowledge of the status of the workshop.

- *Betweenness* is a measure of one node's criticalness on the overall reachability of the network. In our workshop context a person with a high betweenness measure would indicate that this person performed more of the role of a messenger and acted as a bridge between two otherwise separate groups.

Figure 9: Comparing the changes in SNA centrality measures between the tagged individuals across the duration of the workshop using the temporal view
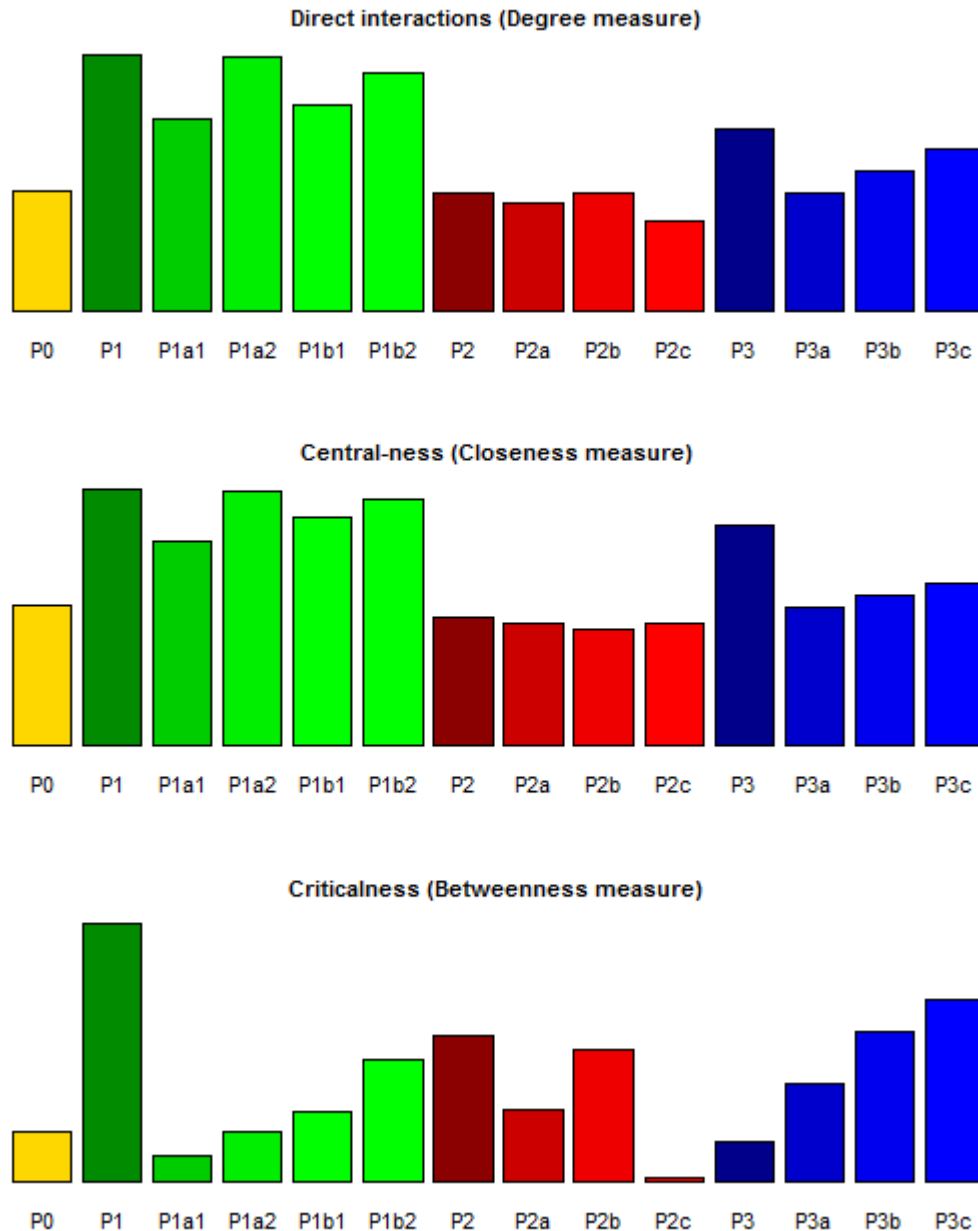
Figure 10: Overview of the SNA centrality measures between the tagged individuals

Apart from presenting analysis outcome across time (temporal view, Figure 9) or summarize in an overview (Figure 10), the SNA centrality measures can be brought into spatial context by plotting using the placement derived from the animated network visualization algorithm. This gives us a spatial view of the social behavior that occurred in the workshop space. (Figure 11) The project-specific color coding allows us to perceive each project as an identity and focus on the distinct project behavior in the spatial context.
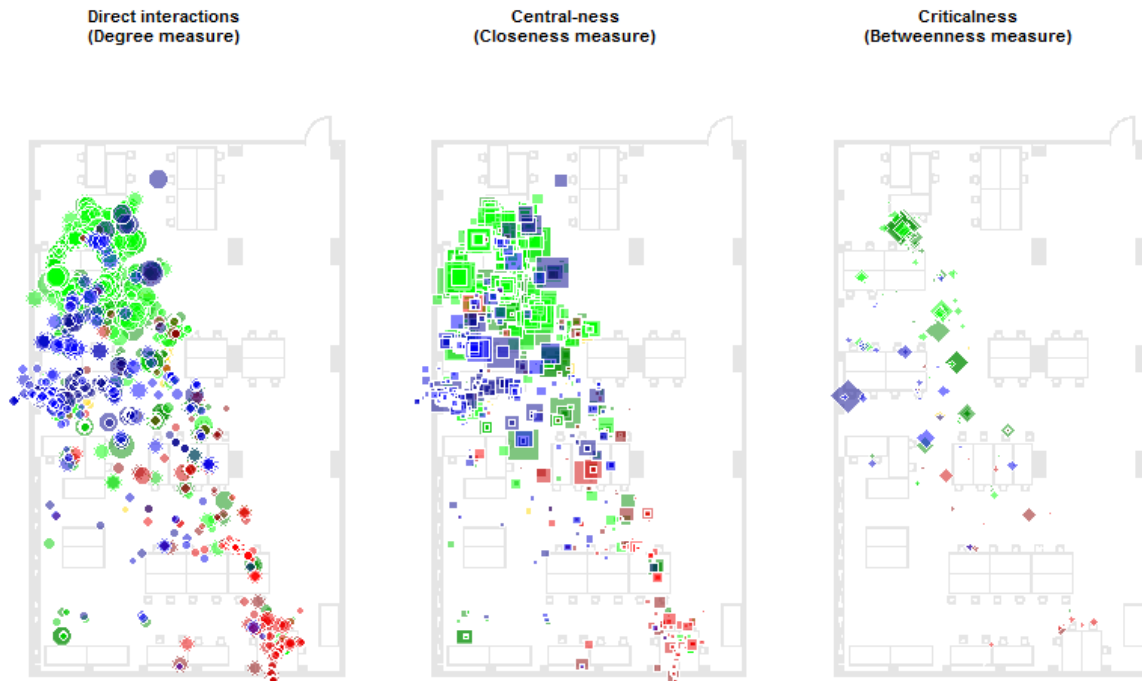
Figure 11: The three SNA centrality measures presented in the spatial view

From Figure 11, we can see that the overall degree distribution is similar to the closeness distribution. This is due to the "thinness" of the network constructed from each time sample - the links between nodes are sparse and short. This means that in any 10 minute time sample the participants had a tendency to stay within the same group of people (the groups are not necessarily formed by people within the same project). In this case the spatial view of the betweenness measure is of most interest: when participants do interact between groups, where does it occur? Compared with projects 2 and 3, project 1 has a scattered distribution of the intergroup interactions, occurring not only in its home base but also into the preferred work area of the other projects.
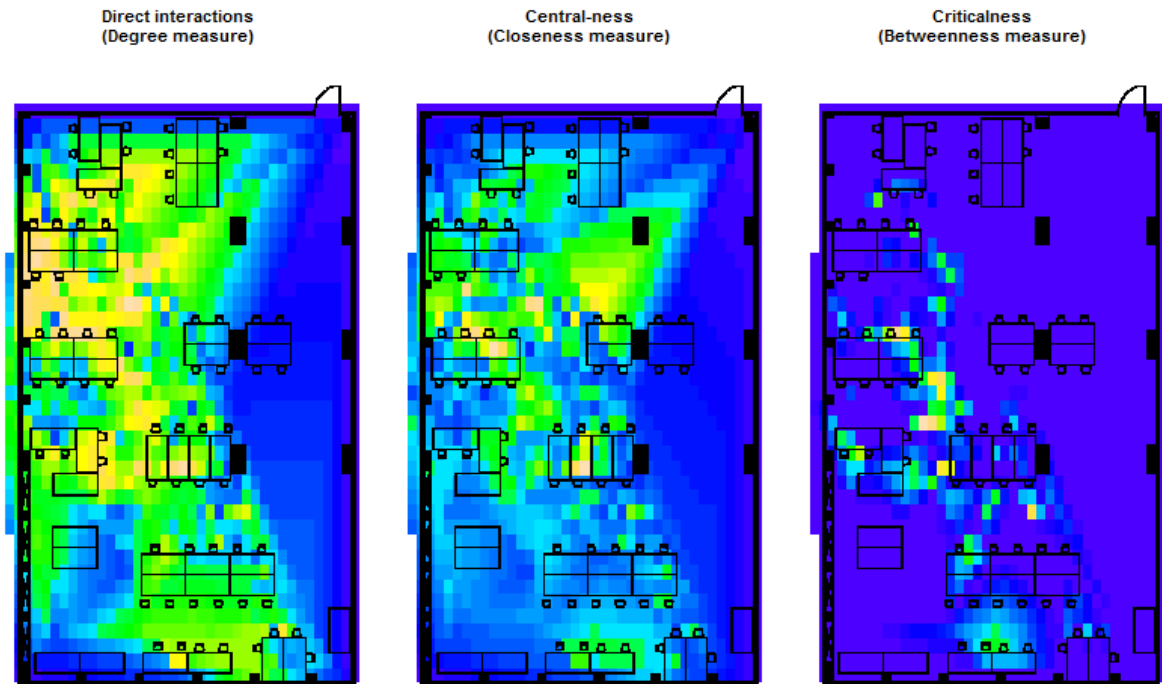
Figure 12: The SNA centrality measures interpolate into heat maps

Each set of centrality measures can also be interpolated over the complete area of the workshop space to produce a heat map representation of the degree, closeness and betweenness distributions. (Figure 12) Interpolating the measures over the workshop space produces a more direct spatial perception of the distribution and intensity of the analysis results.

Figure 13: Two examples of the combined centrality visualization. Mimicking a person for easier interpretation, for each node the "head" represents the degree, the "body" represents closeness and the "diamond" represents the betweenness centrality measures. The combined centrality view improves the perception of the behavior differences between individual nodes.

For better visual perception of the social dynamic as it evolved with time, we recommend the combined centrality visualization where all of the three centrality measures are displayed together for each time samples. (Figure 13) This produces a set of visualization that can be presented as a storyboard or as an animation[4].

3.3 Qualitative method 2 - Complex network analysis

The SNA centrality measures offer a qualitative tool that gives an unbiased and simplistic analysis of the 2-mode socio-spatial interaction network based solely on the information presented in the network dataset. As we have demonstrated above, referring to the network node placement calculation we are able to incorporated spatial context into the analysis outcome.

In this section we present our work on new complex network analysis measures that are based on known "association" attributes of the network nodes. In this application we wish to analyze the effect of the project assignment on the individuals as well as the workshop spatial allocation on the interactions. To do this we have introduced the "group" (in our case the assigned project) attribute to spatial and social nodes. In the previous diagrams we have already incorporated the group attribute in our discussion through the qualitative method of

color labeling. Through our proposed complex network analysis measures we quantitatively analyze the preferences of the individuals regarding their movement between locations.

We propose the following *mobility analysis* measures (Figure 14 and Figure 15):

- Individual measures:
  - "A" or the "at home base": This calculates how often one individual was at the locations assigned to his/her group.
  - "a" or the "away": This is opposite to *at home*; we are interested in how often one individual was presented at the locations not assigned to his/her group.
- In-group activity measures:
  - "AA" or the "home meeting": This is the measure of the in-group activity that occurred at locations assigned to the group. We assume when two individuals from the same group met, they were conducting *in-group* activities.
  - "aa" or the "away meeting": This is the opposite to home meeting, and is concerned with group activities that occurred at locations not assigned to the group.
- Out-group activity measures:
  - "Ab" or the "receiving meeting": While the individual was *at home* how often he/she was visited by a member from another project.
  - "aB" or "visiting meeting": This measures how often one individual visited the work areas of other projects and met with the members of the other projects.
  - "ab" or "neutral meeting": This is how often one individual met with people from another project at a location that was assigned to neither person (neutral grounds).
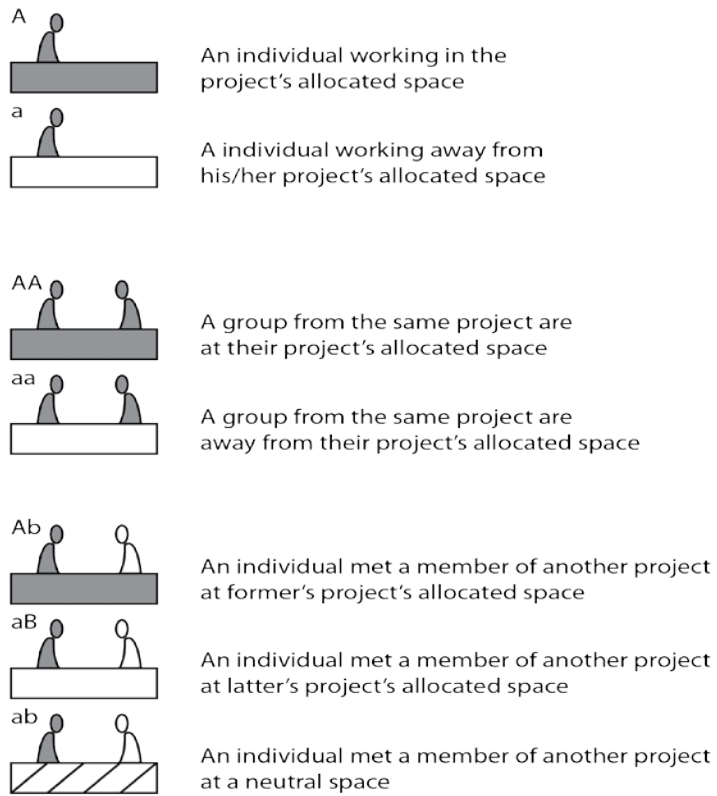
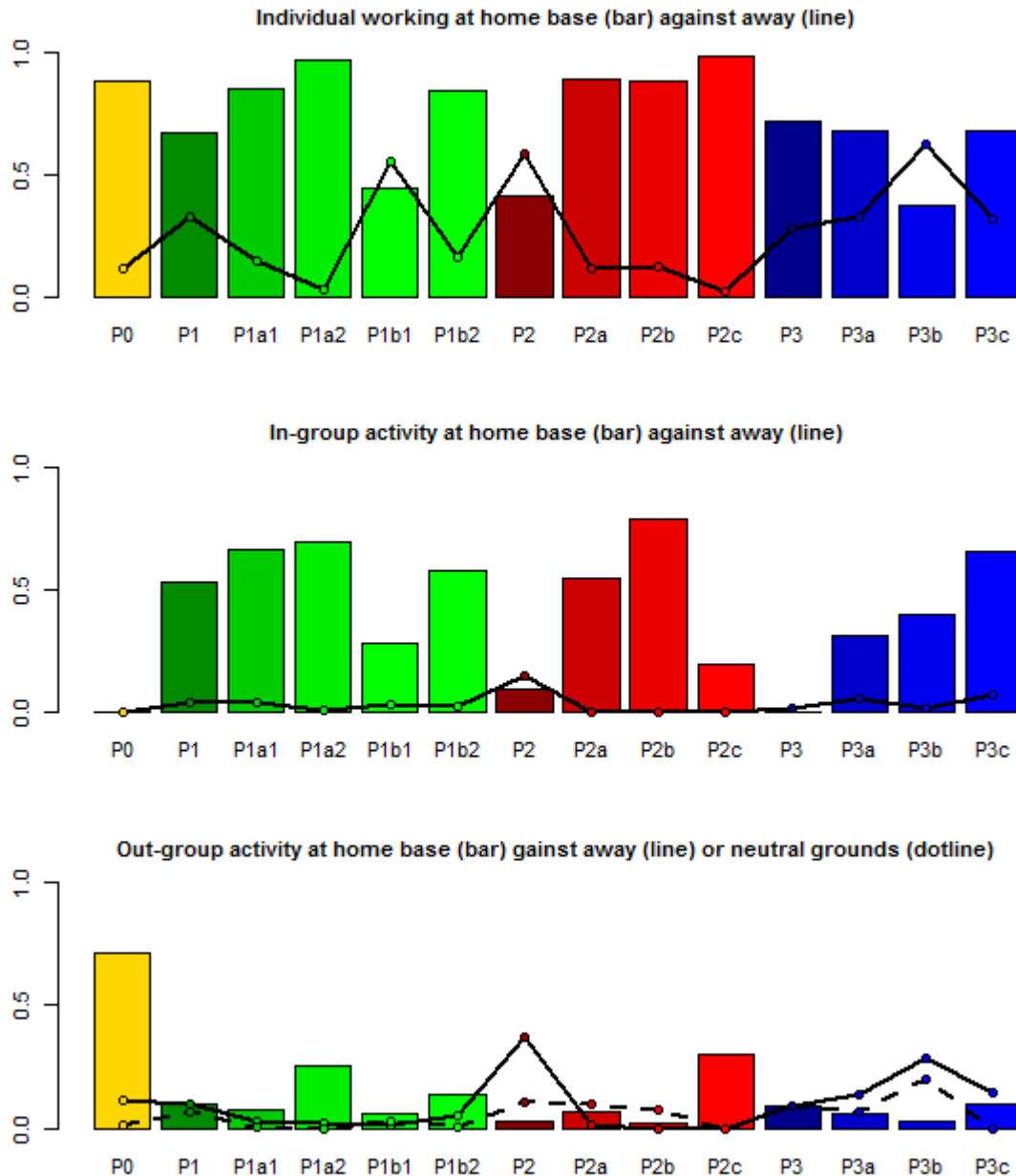Figure 14: Diagram explaining the seven mobility analysis measures

Figure 15: The seven mobility analysis measures applied to evaluate the overall project related behaviors

This set of measures is useful in comparing the working style between individuals and projects. For example, reading Figure 15 we can see that compared with other projects, the members of Project 2 (red), apart from the project leader (dark red), tend to work within their own assigned space (high *at home* measures). Two of these individuals (P2a and P2b) worked closely together (high *home meeting* measures), whereas P2c worked with people from other projects but still within project 2's assigned space (low *in-group activity* measures but high *receiving meeting* measure). Their project leader (P2) appears to have worked differently: he/she worked away from the project (low *in-group activity* measures and *receiving meeting* measure) but closely with member(s) of other project(s) (high *visiting meeting* measures).

Also note that the *in-group activity* measures are not applicable to P0 (the workshop coordinator) as he/she did not have any group members.

Specific information about the workshop interactions can be revealed through query-driven visualization and analysis. Here are a few examples.

3.3.1 Coordinator's queries

The workshop coordinator may wish to get a feeling of how the workshop has progressed as a whole:

- "Did the participants socialize much and mingle with people from other projects?" - Visualize the combined out-group measures (Ab+aB+ab).
- "Were neutral spaces required often for these occasions?" - Visualize the out-group neutral meeting measure (ab).
- "How were the collaborations within the projects?" - Visualize the in-group meeting measures (AA+aa).

Through the temporal view (Figure 16, top) we can see that the workshop participants socialized regularly, and the spatial view (Figure 16, below) shows that interactions between groups were well distributed in the workshop space. This meant that the intention of the workshop leaders "to fertilize informal cross-project discussions" was successful.

Meetings between projects on "neutral grounds" occurred sparsely, and looking at the spatial view it occurred mostly at the center of the workshop space around the coordinator's desk. We suspect these meetings were facilitated by the group members that the spaces were assigned to (such as the coordinator at the coordinator's desk).

Collaboration within the project occurred intensively in the first three days of the workshop. From the fourth day project 2 and 3 seems have changed working structure. To understand this better we put together another diagram of mobility measures of the three projects (Figure 17). From this diagram we could see the drop in recorded collaboration within project 2 and project 3 was actually because the majority members from these two projects were not recorded present in the workshop space.

3.3.2 Project leader's query

A project leader may wish to see the work pattern of the project members. Here we show the seven mobility measures for three members of project 1. We can see that these three participants had similar *in-group* work pattern, and from comparing the *out-group meeting measures* it shows that project leader P1 conducted most of the inter-project activities.
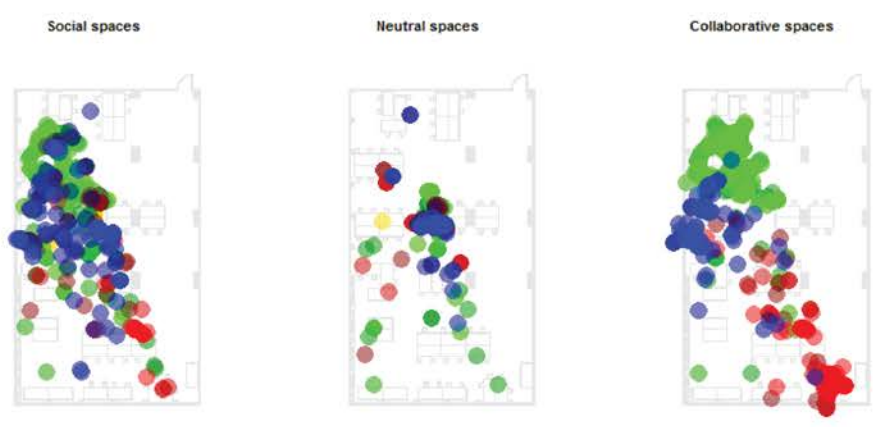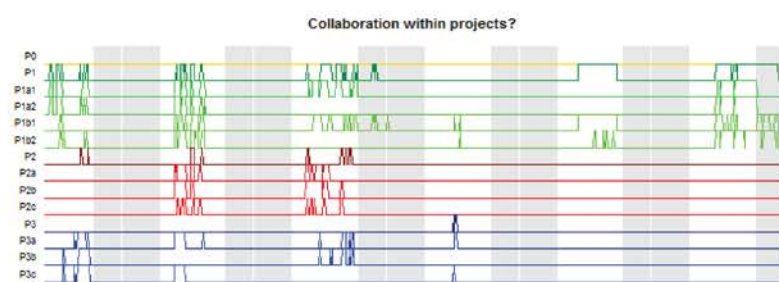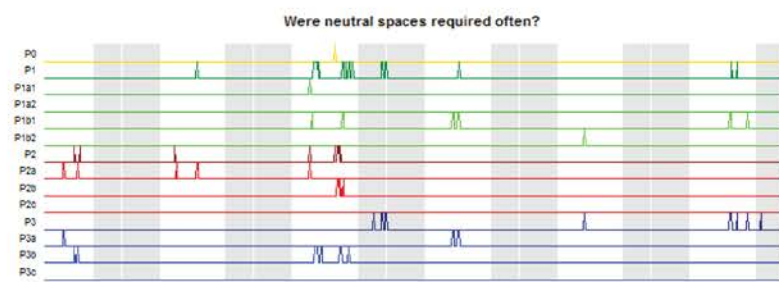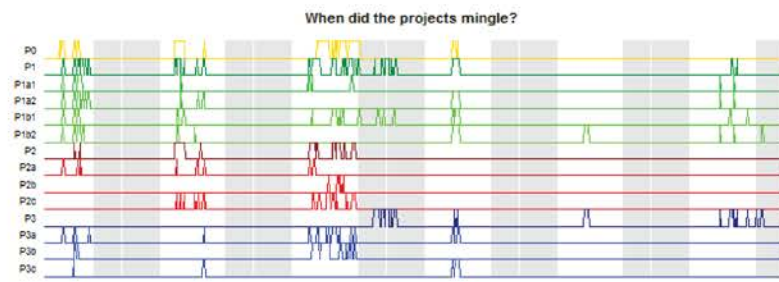
Figure 16: Coordinator's queries

Figure 17: The mobility of the projects: Home (A - fill) versus Away (a - no fill)

Figure 18: Work pattern of the individuals from project 1

4   Discussion

A network is a flexible and versatile data representation structure that allows multi-focused analysis at different scales, from the large scale overview of the workshop activities to the small scale study of the immediate contact of a person. With additional attributes we can further study the impact the known contextual information, such as organization arrangement, spatial setup and workshop scheduling, had on the behavioral network.

Validity of the network analysis is sensitive to the change in sample size and the appearance of sample holes (Costenbader and Valente, 2003). The analysis results should not be used as the sole evidence to evaluate the workshop dynamics. It is important to interpret the data analysis outcome with reference to case-specific contextual information (such as participant observation data, interviews, schedule of activities and past experience). In our study factors such as the planned workshop excursions on day 4, and many participants deciding to work from home on day 5 to 6 because it happened to be a weekend all influenced the appearance of the low activity level presented by the data analysis. Further work to develop a comprehensive visualization and reporting system that incorporates schedule, field notes and photos will improve the validity and comprehension of the results. The event-based model proposed by Simeone and Kalay (2012) is also an interesting alternative to incorporate additional context from field notes and high level activity recognition from the time-lapse photos.

Participant consent, privacy and participation rate are interlinked issues in tracking[5] and in network studies (Borgatti and Molina, 2003). Pervasive technologies such as WiFi and Bluetooth based systems improve user participation and retention by linking tracking activity with an object or service that people require, but the ethical issues of participant consent and equality of these systems are often overlooked (Luger and Rodden, 2013). With standalone systems such as RFID and ZigBee based tracking systems the consent process is much clearer; people can easily remove themselves from the set up by detaching the tags from their person. We believe this feature actually helped us to persuade participants to sign up[6]. In contrast to other large scale ethnographic studies, network studies are based on the direct links between its individual participants. The familiarity of the participants to each other meant that even with the results anonymized, individual identities can still be easily deduced by people familiar with the context study. A comprehensive discussion on the topic of open data is beyond the scope of this paper. The contribution of our paper is that we have demonstrated that our proposed framework is can be used by and for all stakeholders of the study. With this incentive we hope to persuade potential participants to join and be part of similar studies in the future.

5   Conclusion and future work

This paper presented a complex network-based approach to analyzing and visualizing socio-spatial interactions in the indoor space. The versatility of the approach has been demonstrated with a range of qualitative and quantitative methods applied to a real-world case study. In addition to adapting existing network analysis measures we developed an animated network

visualization algorithm and a set of complex network measures to analyze the network interactions based on known group attributes.

We propose that our approach is the basis of a comprehensive tool for project management or post-occupancy evaluation applications. We have already demonstrated with our workshop case study that stakeholders of the project benefit from the proposed analysis of the project dynamics. These insights are useful in collaboration projects where the organization/communication structure is less defined and fluid.

Further work is planned to incorporate the algorithms and analyses presented in this paper into a versatile visual analytic system, based on needs and access level, targeted visualization view will be set up for different roles. Through interacting with the system project managers and other stakeholders would able to have an live update of the progress of the project. Post-occupancy evaluation applications can also benefit from such a the system. For instance space designers and building managers can use the system to monitor and iteratively improve the spatial usage of the building, evaluate it against planned occupancy, and observe its impact on occupants' work performance or social behavior.

Image Captions
Figure 1: Analysis Workflow
Figure 2: The organizational structure of the 14 tagged individuals (left) and their roles in the workshop (right)
Figure 3: Automated data collection set up
Figure 4: 3D representation Individual's workshop activity as recorded by the ZigBee system
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Endnotes:
[1] Indoor Tracking system v2.0, manufactured by DTK Electronics, Shenzhen, China. Product listing URL: http://www.dtkcn.com/
[2] During laboratory testing the ZigBee system was found to provide an average tracking performance of 79% True Positives when recording transition between 2 sensors placed 10 meters apart. For more information on the data collection set up and testing procedure please sees Salim, Flora et al. (2014).
[3] A video of the animation transition view can be found from https://vimeo.com/99713412
[4] The animated video of compare three network visualizations can be viewed at https://vimeo.com/98091919
[5] See the review of data capture techniques in Yoshimura, et al., (2012).
[6] A recurring question asked by potential participants was "will it track me when I go to the bathroom".

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