Understanding face to face interactions in a collaborative setting

Methods and applications

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Abstract. Extensive studies have shown that face-to-face interactions are a critical component in a work environment. It is an effective communication method that builds trust between team members and creates social ties between colleagues to ease future collaboration. In this paper we present our interaction analysis system that utilized an indoor tracking system to provide insights on the spatial usage and interaction dynamics in collaborative spaces. This gives space layout designers and managers quick feedback on the performance of the space and its occupancies and allows interventions and evaluations to be conducted to fine-tune the space layout or organization structure to achieve optimal performance. We demonstrate our system with data collected from a recent international design workshop.

Keywords: Face-to-face collaboration, indoor tracking, social interaction analysis, team management, workspace design.

1 Introduction

In recent years we have seen a growing interest in monitoring human movement to understand social behaviors for a range of applications from context aware advertising to security and surveillance. This is pushing cutting edge research and development in the field of wireless sensor networks, data mining and visual analytics to develop more effective and efficient ways to track, model and visualize the dynamics of social interactions. For our research we are tapping into this rich multi-disciplinary knowledge to study the dynamics of social interactions that occur in a collaborative teamwork environment.

The pioneer in this field is Alex Pentland who leads the MIT’s Human Dynamics Lab. They have deployed their multimodal wearable sensor system “Sociometric Badges” to study interaction patterns in many large organizations [1]. The Sociometric Badge system extends the traditional laborious data collection techniques in studying collaborative interactions in design processes [2-3] and professional workplaces [4]. Apart from collecting longitude data for studying organizational-wide behaviors, a version of the Sociometric badge system is designed to provide real-time
feedback on the dynamics of a face-to-face interaction, such as a team meeting, to promote better team integration.

Recent findings coming out of the Human Dynamics Lab show that the pattern of social interactions, especially face-to-face interactions, is a very good indicator of the productivity and creativity of a team [1]. Extensive field studies have linked employee productivities with office layout [4]. We see this as a great opportunity for the architecture profession to join and contribute to the discussion of what the future workplace should be.

The center of the Sociometric Badge system is a multimodal data device that records the wearer’s physical movement, voice levels and proximity to others [5]. In many situations this may not be appropriate. Our work focuses on a different approach. Our system is more adaptable in terms of input source and output format. We utilized a commercially available proximity-based indoor tracking system to provide ongoing input data for analysis. The tracking data is processed to produce real-time reports on the face-to-face interaction. The analysis process and resulting visualization is supported by supplementary contextual data from the client. We believe an efficient system is one that is customizable to our client’s needs, which are expected to evolve over time.

We have compiled our research into a deployable system. We have targeted our system for two applications. The real time analysis results allow managers and project teams to monitor the development of projects as they evolve and enable them to respond to changing needs more effectively and efficiently. Our system can also be used to provide reports and feedback on the optimal office layout and the organization structures that operate within it.

In the remainder of this paper we will first introduce the methodology of our system. Next, each stage of our system will be described in detail and be supported by related work. The capability of our system for real world application is demonstrated with a case study. The paper will conclude with a discussion of its two suggested applications and recommendations for implementation in other contexts.
2 Methodology

2.1 Data collection

Adaptation of face-to-face interactions research into industry practice is lagging behind the acceptance of Big Data and virtual communication mining due to the hurdle of deploying a data collection system. Established methods to collect face-to-face interaction data such as questionnaires, surveys or direct observations are resource intensive, subjective and thus hard to integrate into the everyday management decision-making process or design process.

We are interested in tracking human interactions during the subjects’ normal work environment. Tracking data can be in the form of position tracking that records the trajectory of people as they move around, proximity tracking that records the distance between people and/or a person and surroundings [6], or association logging that detects interaction events based on multiple input criteria [5,7]. Lui [8] and Gu [9] surveyed tracking methods and applications. Current wireless sensor networks (WSN) development have achieved indoor positioning accuracy of less than a meter [10].

A suitable data collection system should be automated and non-intrusive. Automation reduces repetitive manual labor and enables a continuous data stream to be available for live analysis and decision-making. We advocate for ethical care to our study participants that ensures participation is voluntary and consensual. A non-intrusive set up, such as a wearable tracking tag that can be removed, allows our participants to have control of their privacy.
When possible, supplementary data should also be collected. These include floor plans, organizational diagram, project description and schedule, as well as automated contextual data such as ambient sound level and other environmental conditions. This information helps us to contextualize and evaluate our analysis.

### 2.2 Behavior modeling

For us to get meaningful results, we need to build a behavior model that describes the scenarios that we wish to observe. A behavior model needs to be defined and constructed from the collected tracking data, supplemented by the context data. This is one of the opportunities for us to guide the analysis system to be specific on what it is that we are interested in.

Regarding proximity in face-to-face interactions, the classic proxemics theory of Edward T. Hall [11] categorized the four types of interactions (intimate, personal, social-consultive and public) by person-to-person proximity. Waber [12] used spatial constraints such as desk, corridor, floor and building separations to categorize interaction distances. Research in office layout found that both the frequency and the duration of interactions are correlated with employee performance [13]. Frequency and duration can be combined to produce a complex proximity measure [14].

We propose to divide behavior modeling into two components. Firstly filter the input data stream to remove irrelevant data. For example if we wish to study evolution of collaboration dynamics within project teams, we would need to process the data to identify events of collaboration and participants that were involved in those events. Let us suppose that the organization that we are studying supplied us with a list of participants that belonged to a particular project. Through proximity tracking we can identify when the project members met and for how long. If we know the locations of the meetings through position tracking or environmental proximity tracking, or we have access to the project schedules, we can isolate the meetings that were project related.

Once we have a list of individuals and a list of events that link subsets of the individuals together, we can construct an interaction network that represents the behavior model that is specific to our query. We can also introduce dynamics into the network by adding the time variable. With the interaction network at hand we are now set to apply a large array of complex network based analysis and visualization to extract meaning from our behavior model.

### 2.3 Analysis

Complex Network Analysis (CNA) is a multidisciplinary field of research that investigates relations (network links) between a set of individual identities (network nodes) that are representations of real world phenomena, ranging from human biology to the World Wide Web. Supported by rapid growth in computing power, data collection and storage capacity, CNA is a relatively active area with contributions, both from and to, computer science, mathematics, sociology, biology to name a few.
By constructing our behavior model as a complex network we can apply CNA methods to examine the behavior at multiple levels. We can compare behaviors of individuals by observing their position and importance within the network; group certain individuals together based on contextual attributes and observe interaction within and between the groups; and observe interactions between individuals at the organizational level to get an overview of the underlying structure of the behavior.

Social network centrality measures such as degree, closeness and betweenness [15] are network analysis methods that calculate the importance of a network node within the network. They are calculated based on the number of links a node has (degree), how easily a node can reach the rest of the nodes in the network (closeness) and how critical a node is to the structure of the network (betweenness). Translated to our context an individual with a high degree measure indicates he/she was quite active, since that individual had lots of interactions with a range of people. Looking at the closeness measure allows us to pick out the more integrated individuals; they may not have met with the most people but they tend to have the best idea of how everyone is going, since news (or gossip) travels through fewer paths to reach them. If you want to know the employee you shouldn’t lose, then the betweenness measure would be a good indicator: a person with a high betweenness measure indicates that he or she is the critical node between two sections of the network, if you take him or her out part of the organization may fall apart unless new links are made elsewhere.

In the context of face-to-face interactions in a collaborative work environment we are working with what is called “Small-world networks”, where the people an individual interacts with are mostly likely to also be interacting themselves, or “friends of friends are also friends” [14], [16]. This node level or network level property is called clustering or transitivity [17]. Within a project group an even transitivity means that there was a healthy communication flow between the group members. Another network property of interest is cohesion [18]. Similar to the betweenness centrality measure, cohesion represents how many nodes need to be removed to disconnect the network, it observes how close knit a group is. Studies have shown that at different stages of the creative process different interaction network structure (represented by its cohesiveness) should be encouraged: A star-like diverse network is suitable at the conceptual discovery stage where the project is collecting ideas; a cohesive network is good for the development stage where everyone works together towards the final goal [12]. Both transitivity and cohesion are applicable at a group level as well as the overall organizational level.

Another aspect of group behavior worth investigating, especially in the architectural and design context, is the spatial preference of behaviors. This builds on the proximity analysis component of the behavior modeling stage where we utilized distance dependent proximity readings to generate interaction links. This is best represented graphically, overlaid on a floor plan, to demonstrate the relationship between individual/group/overall activity intensity and space usage.

As behavior is highly dependent on the context, we recommend a more qualitative approach to representing analysis results. Through network visualizations we can compare the change in the behavior pattern across time samples and groups. Supplementary data such as project roles and team assignment can also be included in
the graphical composition of the visualizations to introduce contextual information to assist with result comprehension.

In the remainder of the paper we will demonstrate a combination of the introduced method with a set of real world data collected by the author.

3 Case study

We have collected data from a recent international design workshop attended by students and professionals from the design industry, based on a collaborative teamwork framework where the attendees formed several project teams. The collaborative workshop event aimed to encourage positive interaction within the teams to work towards a common project outcome, stimulate interactions between teams to exchange ideas and skills as well as foster new social, professional and academic connections. Over the course of four days, we have tracked the movement of more than fifty participants using an indoor tracking system.

A set of supplementary data were also collected:

- The development of the project teams was documented through a set of time-lapse cameras.
- Field notes recorded through participant observation by two of the Authors.
- From the workshop organizer we obtained a floor plan with the project activity allocations’ noted (Fig. 2).
- From the individuals that agreed to participate in the tracking exercise we collected their name and project assignment.
- Publically available information collected were:
  - Workshop schedule, project descriptions, proposed project schedules and names of the project leaders and participants.
Fig. 2. Case study: the floor plan of the workshop. Main activity spaces are marked. Twenty-two tracking beacons (blue dots) were installed near to the activity spaces, where possible, placed in a relatively regular fashion. There were a total of eleven project groups participating in this workshop, out of which tracking data from eight of the project groups were analyzed for this paper.

3.1 Data collection and preparation

The data collection occurred over four days of the workshop event that included: three days of workshop days, one final day of daytime offsite presentation and evening exhibition onsite. During the workshop days the participants had access to the space from approximately 8 am to midnight.

The tracking data collection was conducted using an off-the-shelf ZigBee-based indoor tracking system, which periodically outputs proximities of wearable tags to several static tracking beacons. This allows us to estimate the position of people in a preset space when the tags were carried: the tag position estimates were calculated as the mean X, Y coordinates of the detected beacons’ coordinates, weighted with the corresponding beacon RSSI readings. A log of the position was recorded in a database for further analysis.

Fig. 3. Tracking data showing spatial usage of the eight represented project groups.

3.2 Behavior modeling

We constructed our behavior model based on the tracking tag positions. Data was grouped into 10-minute data samples. Statistical analysis was applied to calculate an activity center and an active area for each of the tags that were present during the data sample. A tag area threshold, determined from experimentation, was applied to
remove idle tags. These tags were most likely to be left on the table or in the person’s bag thus did not represent the behavior of the person it was assigned to.

Proximity analysis was applied to all of the remaining active tags:

1. Distance was calculated between all of the active tags detected in the same data sample. This generated a list of proximities between active tag pairs.
2. Referring to the tagged person’s project assignment, we categorized the proximity list into in-group proximity and out-group proximity.
3. The out-group proximity threshold of 3-meters was applied to extract a list of out-group interaction tag pairs. The 3-meters threshold was determined from onsite observation and in consideration of Edward Hall’s 10 feet personal-social proxemics threshold [11].
4. As the activity of each of the projects differ, ranging from computer-based work to large physical prototype construction, an adaptive in-group proximity threshold was required. Through experimentation, we found that the mean distance values achieved a good balance between removing tag pairs that were too distant to be effectively communicating face-to-face and preserving sufficient activity tag links to model in-group behavior.

The interaction network was constructed from a subset of the proximity list, characterized by a time range and/or the participants in the interactions:

- The interaction network node represents the list of active tags present during the proximity list. The node attributes were: tagged individual’s project allocation and role, the list and count of the activity center coordinates that the tag was calculated to have visited and the activity centers’ corresponding active area size.
- The interaction network links represent the pairs of activity tag nodes from the proximity list. The link attributes were: in-group/out-group categorization, the coordinates of the link (taken as the mid-point between the connected two tag coordinates).
Fig. 4. Demonstrating the adaptive in-group proximity thresholds (marked). The line plots represent the density distribution of the in-group proximity pair for each of the eight project groups. The color-shaded backgrounds represent all of the out-group proximity pairs that the project group participated in. The gray background represents the distribution of all of the calculated proximity pairs. Looking at the in-group proximity lines, we can see that the RN and DS groups have shape narrow peaks close to the origin, this tells us these groups were physically static. This agrees with the onsite observation: RN and DS were computer-based design projects. Also observe the SG in-group proximity line has two peaks, this indicates the SG group had two modes of operation: our field notes confirms that during this data sample period a select members of the group were tasked to man the project table and others left to visit other projects. Compare the color-shaded out-group proximity with the workshop result in gray, focusing on the region near the group mean threshold, tells us the amount of distraction the group experience and produce. For example for FBR its out-group proximity distribution closely matched with its in-group distribution, translates to that for FBR members within their work radius it is nearly as likely to encounter someone from a different project than one from their own.
This is the interaction network that models the behavior of the workshop compiled over the whole data collection period. The network layout was optimized using the force-directed Large Graph Layout algorithm [19-20]. The nodes were colored by their project allocation, and the shape indicates the individuals’ roles: square represented the project leaders and circles represented the participants. As expected the interaction network visualization showed a clustering behavior that coincided with the individuals’ project allocation. The variance between the project groups suggests difference in work patterns, for example the light green (RS), yellow (RN) and orange (SE) project group members appeared to have mingled more with each other.

### 3.3 Analysis and visualizations

The force-directed network layout (demonstrated in Fig. 5) gives us a good visual overview of the strategic importance each individual contributed to the overall workshop interactions. We can highlight different behaviors by applying the three aforementioned social network centrality measures to the interaction network. Fig. 6 demonstrates the behaviors of individuals in the workshop during an afternoon...
session (day 2), using the automated network layout node placement with the node size representing the centrality measure scores.

A cohesive group interaction network represents a healthy collaborative teamwork. This is best represented graphically by constructing an in-group interaction network for each of the project group by extracting the network links that connects the nodes belonging to the same group. A circular node layout was used, as it is best for presenting the interaction patterns. The node shape identifies project roles; node size represents the number of interactions that individual had participated in. A fully cohesive network is one where a balanced network links exist between all of its team members, this is more common in a facilitated meeting; for project work a biased interaction network was expected, as the ones shown in Fig. 7. Our field notes and supplementary data confirmed that during the represented time sample, there were distributions of the tasks to form sub-groups within projects.

In a collaborative co-located work environment, such as the one from the case study workshop, the amount and diversity of out-group activity can be both a blessing and a curse: too much interaction between different groups distracts the team from working on their own projects, but not enough out-group interaction most likely shows that the project has not explored the skillsets and expertise from people outside the project. As seen in Fig. 8, with reference to the floor plan in Fig. 2, project PM was more isolated and had limited interactions with other projects. Interestingly both of the ST (teal) and SG (purple) teams were relatively centrally located but its members did not interact much with other project teams either.

It is worth investigating when a project team was shown to be involved in a large amount of out-group interactions, identify with whom (Fig. 9) and where those interactions occurred (Fig. 10), and if more contextual information is available, check whether the interactions level was a distraction to the teams involved. In the case of the neighboring projects SE and RN the interaction was disruptive and a few screens were requested to construct a barrier between the two project spaces.

Interaction dynamics are difficult to quantify and measure. Presenting the organization-wide analysis result alongside results from individual groups (such as Fig. 8 and Fig. 10) helps the viewer to understand the variation and cause of the interactions. Organization wide dynamics can also be perceived through comparing visualization across time sample. To this end, we divided the data into timed sample blocks: each day’s data was separated into morning (8 am to 1 pm), afternoon (1 pm to 6 pm) and evening (6pm to 8am of the next day), resulting in twelve sample blocks. We then constructed an interaction network for each of the sample blocks and generated the organization interaction diagram based on the degree centrality measure (Fig. 11) and the interaction spatial map (Fig. 12).
Fig. 6. Organization interaction diagrams as recorded during the afternoon session of day 2 of the workshop, using the degree (left), closeness (middle) and betweenness (right) measures represented as node sizes. These respectively corresponded to emphasis on the individuals’ activeness, integration and criticalness, with the node size represents the measure value, and the color indicate the individual’s project allocation.
Fig. 7. In-group behaviors of the eight project groups as recorded during the afternoon session of the day 2 of the workshop. The node shape indicates the individuals’ role: square represented the project leaders and circles represented the participants. From the variations in the weight of the interactions between project group members we can observe sub groups have formed in the projects.

Fig. 8. Ratio between in-group interactions and out-group interactions compared across the eight project groups. Due to its spatial isolation (as seen in Fig. 3), project PM (red) had limited interactions with other projects. Interestingly the SG and ST teams were relatively centrally located but its members did not interact much with other project teams.
Fig. 9. Out-group behaviors of each of the project groups, the interaction participants are highlighted in the organization interaction diagram. Interesting observation comparing SG and FBR projects: although SG team had conducted more in-group interactions during this workshop session, it has met up with a large proportion of the workshop participants; whereas FBR group member’s out-group interactions were more frequent but more selective.

Fig. 10. Interaction spatial maps, top: Locations of where the project groups engaged in in-group interactions (colored) and out-group interactions (gray); bottom: The group data is combined to produce the spatial interaction map for the organization.
Fig. 11. The organizational-wide interaction diagrams, individual level interaction intensity are emphasized by the size of the individual nodes (degree centrality). Day 1 to 3 were workshop days, day 4 was the final day consisting of a daytime offsite presentation and evening onsite exhibition. Node color represents project associations. As we can see from the twelve sequential diagrams, as expected, the interactions that occurred showed high project clustering preference, but of more interest to us is that through these diagrams we can also observe variations between the sample time periods: The interactions became more project orientated as time progressed towards the conclusions of the workshop (on day 3), this is vastly different from the interactions that occurred during the exhibition (evening of day 4) when people mingled while visiting each other’s project exhibit.
Fig. 12. The organization-wide spatial interaction maps showing the locations of in-group interactions (colored pink) and out-group interactions (black), as recorded by the four days of tracking data. Presented spatially and sequentially we can clearly observe the change in the spatial usage of the workshop as the workshop progressed. The increase in in-group interaction intensity observed from the interaction diagram shown in Fig. 11 can also be seen here: The color intensity in the day 3 diagrams is more evenly distributed compared with day 1 and 2.

3.4 Interpretation

As mentioned above, goals of the outcome of the workshop are to provide an environment for attendees to participant in one of the allocated projects, as well as to stimulate idea exchange and foster new personal connections between the attendees. For many people this was a constant balancing act, “I really wanted to see the other projects, but I needed to get this done first.” Project PM (colored red) had requested an isolated space to provide a stable test environment for its experiments. From Fig. 11 we could see the impact of this spatial segmentation had on the workshop-wide interaction network: the PM members had formed a close-knit cluster with little interactions with others. Some relief from this isolation can be seen on the afternoons of day 1 and day 2, when the workshop had organized presentations attended by everyone, although it is clear that this temporal integration had little long-term impact. From this we can conclude that spatial segmentation should be avoided in future workshops, in cases where a controlled environment is required, temporal partition is preferable to permanent separation of project spaces.
Too much spatial overlap can also introduce issues. Project SE (orange) was assigned two spaces, one in the building atrium, one in the bottom left end of the long open studio space. This meant there was regular traffic between these two spaces, directly impacting the operation of the RN (yellow) group. Before long, two movable screens were put in place to provide partition between RN’s space and SE’s space. In this case, the Fig. 10 spatial heat maps clearly demonstrate the disadvantaged situation of the RN project: they have the smallest in-group heat map because their in-group interaction was over flooded by the distractions from their neighbors. This could also be seen from the Fig. 4 proximity distribution. The RN group had the narrower in-group proximity plot; this indicates that the RN had positioned themselves physically close to each other, most likely to stay away from the foot traffic. In comparison, project FBR (purple) was also centrally located with possible distractions coming from three sides, but as seen in Fig. 10, they managed more undistracted in-group interactions. This was because the FBR was allocated a wide space, which acted as buffer to protect the project from unintentional distractions. Based on these observations and interpretations, we recommend that future workshop space allocation consider traffic distractions around projects and allocate additional buffer spaces to projects that may be affected.

Looking across the time samples (Fig. 11 and Fig. 12), we could detect the increase in the preference of in-group interactions throughout the workshop as the projects progressed closer to completion (end of day 3). The organization-wide interaction diagram (Fig. 11) became more clustered according to project colors, and the spatial map (Fig. 12) became more saturated with in-group interactions. This is an accurate indication of the status of the healthy project progress.

4 Applications

We have presented a proximity-based interaction analysis system to give us insights into many aspects of the collaborative environment. In this section, we will demonstrate how our methods can be used for other real world applications.

4.1 Office Spaces

Office spaces have shifted from individual cell based configuration towards a flexible open-plan with mixed-use zoning configuration. Driven by commercial incentives [4], and supported by research suggesting that an increase in informal interactions between employees have positive contribution to productivity [1], [12-13], this trend is sure to continue.

Although the literature still debates the quantity and quality of interaction that achieves best workplace performance, extensive research supports the proposition that the geometrical layout influences human behavior and communication patterns between individuals [13].

Existing organization-planning studies are still heavily dependent on a questionnaire approach to collect interaction data. Questionnaires are known to be
subjective and have a low response rate. In comparison, our wearable sensors data collector is non-intrusive and is capable of providing automatic and objective interactive data. Our analysis system can then generate live reports on the current interaction patterns in the workplace. For optimal organization performance, interaction patterns should match the organization structure and task dependencies. Our reports (Fig. 7-11) allow organizers to identify and encourage positive interactions as well as implement early intervention to remove distractions.

Ongoing spatial usage evaluation is required to ensure the compatibility between the spatial layout and the intended interactions. Current space auditing processes are still manual observation based, require timed visits by observers to each of the designated spaces to conduct head counts. Our interaction analysis system can automatically produce historic reports of the space usage (Fig. 10 and Fig. 12). This information is valuable for the active management of workplaces [4]. For example, the outcomes from the interaction analysis can be used to flag spaces that require activation and recommend reconfiguration of employee desk allocation.

4.2 Project Management

A project team can use the in-group interaction diagram (Fig. 7) to manage the communications in the team. The team members can become more aware of the dynamic of the in-group interactions through monitoring the real-time report of the in-group interactions. This should encourage a more balanced contribution of the team members, build trust and integration within the team and contribute to better overall performance. The out-group interaction diagram (Fig. 9) is useful to identify expertise from the organization to be included in the project.

On a higher level, company management can also gain insights from interaction analysis. From the individual level analysis such as degree and betweenness centrality measures (Fig. 6) we can discover persons and relationships that may require additional support or to be encouraged through reward. A combination of face-to-face in-group engagement and out-group exploration is indicative of the creativity and productive level of a project team [1]. Although the context of each project can be unique, the availability of live and historic interaction data allows the managers to have close engagement with the teams to find the winning formula for best performance.

4.3 Remark

It is important to refer to other contextual information before making any judgment on the performance of the individual or a group. Each scenario is unique, and how people interact also changes with time. When possible, multiple data sources should be tracked and fed into the behavior model. The face-to-face interaction analysis methods presented in this paper can be easily adapted to be applied to other interaction data sources, such as email communications, social media engagement and other virtual interactions. Those data sources can be combined with tracking data
through additional proximity analysis methods, such as multi-criteria threshold, or be processed independently and combined with tracking data results at the visualization stage through the use of graphical annotations or overlays.

5 Conclusion

In this paper we present our development of a face-to-face interaction analysis system that is targeted for use in collaborative work environments to generate insights on how people interact with each other.

We have demonstrated the capability of our system using the data recorded at a recent international design workshop. By focusing on visual presentations our analysis methods were able to uncover insightful engagement patterns that informed us of a range of dynamic behaviors including participant engagements, project group collaboration and overall workshop dynamic. In specific to this case study, our analysis was able to identify scenarios of interest and provide recommendations for the planning of future events.

The system and methods presented here have applications in increasing the program compatibility of office layout designs, supporting an active workspace management for efficient facility usage, as well as improving team performance at both an individual and a management level.

Our research contributes to the advancement in the field of architecture and computation by connecting our profession with the cutting-edge development in social mining and people analytics, thus preparing us to actively engage with the changing social context that is surely to come with “the next city”.

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