Organizational Engineering using Sociometric Badges

Benjamin N. Waber, Daniel Olguín Olguín, Taemie Kim, Akshay Mohan, Koji Ara, and Alex (Sandy) Pentland
MIT Media Laboratory, Human Dynamics Group
20 Ames St. Room E15-383
Cambridge, MA 02139
{bwaber, dolguin, taemie, amohan, k_ara, sandy}@media.mit.edu

Abstract

We show how a wearable computing research platform for measuring and analyzing human behavior can be used to understand social systems. Using a wearable sociometric badge capable of automatically measuring the amount of face-to-face interaction, physical proximity to other people, and relative location, we are able to construct a dynamic view of an organization's social network by viewing interactions as links between actors. Combining this with e-mail data, where e-mail exchanges indicate a social tie, we are able to form a robust view of the social network, using proximity information to remove spurious e-mail exchanges. We attempt to use on-body sensors in large groups of people for extended periods of time in naturalistic settings for the purpose of identifying, measuring, and quantifying social interactions, information flow, and organizational dynamics. We discuss how this system can lead to an automatic intervention system that could optimize the social network in real time by facilitating the addition and removal of links based on objective metrics in a socially natural way. We deployed this research platform in a group of 22 employees working in a real organization over a period of one month, and we found that betweenness in the combined social network had a high negative correlation of $r = -0.49$ *(*$p < 0.05$*) with perceived group interaction quality.*

1 Introduction

The problem of how to quantify the strength and characteristics of social ties has been studied for years in the social science community [4, 8, 21]. In the past, researchers have used surveys and the like to discover this information, but these methods often suffer from subjectivity and memory effects. Pentland envisioned a device that could record the behavior of hunderds of individuals with high accuracy and over long periods of time to alleviate these problems [20]. This device would replace the expensive and time-consuming human observations currently used in social science research with reliable and objective computer-mediated ones. This could potentially remove two of the current limitations in the analysis of human behavior: the number of people that can be surveyed, and the frequency with which they can be surveyed.

Data mining of e-mail has also provided important insights into how organizations function and what management practices lead to greater productivity [21], but important communications are usually face-to-face [15]. Some previous research also anticipates the incompleteness of data based on e-mail communication and surveys [13]. Organizations will become truly *sensible* when they start deploying hundreds or thousands of wireless environmental and wearable sensors capable of monitoring human behavior, extracting meaningful information, and providing managers with group performance metrics and employees with self-performance evaluations and recommendations [3].

In this paper we introduce such a platform and show

how it can be used to recognize the properties of social systems. We then look at how this data could be used to make organizations more effective, choosing to use objective computational metrics rather than handcrafted human recommendations.

2 Background and Previous Work

Recently scientists in the field of organizational behavior have also examined ways that entire organizational social networks can be modified to increase productivity and effectiveness [4, 8]. This work has traditionally mapped social networks using surveys and then given recommendations based on expert analysis. Previous work such as [13] and [21] has demonstrated the utility of automatically collecting this data using e-mail logs, but human recommendations are still employed to act on this data.

Eagle and Pentland introduced a system for sensing complex social systems with data collected from mobile phones [11]. Similar to our approach, they demonstrated that by using Bluetooth proximity information, they were able to recognize social patterns in daily user activity, infer relationships, identify socially significant locations, and model organizational rhythms. In an earlier work, they also showed how to combine proximity information with user profile data to facilitate social tie formation between similar individuals [9].

Our research group (the *Human Dynamics Group*) at the MIT Media Laboratory has developed several socially aware platforms to measure different aspects of social context so that we could automate collection of face-to-face interaction data. One of these platforms was the SocioMeter [7], which learned social interactions from sensory data and model the structure and dynamics of social networks using an infrared (IR) transceiver, a microphone, and two accelerometers. In Social Motion [12], Gips used IR tranceivers and radio frequency (RF) scanners capable of detecting other devices within a fixed proximity to infer the underlying social structure of groups of people.

One of the first systems that employed a "wearable badge" paradigm was the *Active Badge*, which used an IR transmitter to, among other things, trigger automatic doors and forward telephone calls automatically. A number of platforms also employed visual feedback using LEDs and LCD displays to facilitate interaction [6, 5, 1]. The *iBadge* [19] was designed to be worn by children to capture interactions with teachers and common classroom objects.

Hardware Platform

We have designed, implemented, and deployed the hardware and software infrastructure to collect and analyze behavioral data from many individuals over extended periods of time. In [16] we presented the design of the wearable *Communicator* badge, which has evolved into the *Sociometric* badge [17]. The *Sociometric* badge can recognize human activities and extract speech features in real time. In addition, it can communicate with Bluetooth enabled cell phones, PDAs, and other devices to study user behavior and detect people in close proximity [9, 14]. The badge can also capture face-to-face interaction time using an IR sensor [7].

We believe our proposed approach to quantifying social relations has several advantages over existing methods such as direct observation by humans and the use of surveys. Direct observation of humans by humans is expensive and limited to a few people per observer, and observers do not always agree. The use of surveys is subjective, inaccurate and time consuming. In contrast, the ability to automatically capture not only visible characteristics of human behavior such as face-to-face interactions, relative location, and motion but also the underlying psychological processes that occur during social interactions in hundreds of people, at the same time and with a single unobtrusive tool, represents a great advantage.

3 Experimental Results

We deployed the research platform described in section 2 for a period of one month (20 working days) in the marketing division of a bank in Germany that consisted of 22 employees distributed into four teams. Each employee was instructed to wear the badge every day from the moment they arrived to work until they left their office. The employee pool has exactly the same number of men as women, but all of the managers are men. The division contains four functional teams consisting of either three or four employees.

Figure 1. Wearable *Sociometric* **badge**

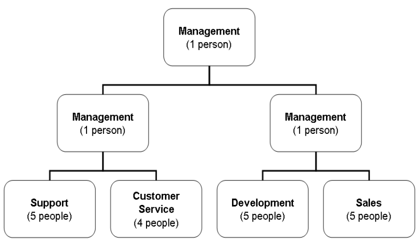

Figure 2. Organizational chart

Each of these teams is overseen by a manager, who is in turn supervised by a mid-level manager. These mid-level managers are responsible for two teams, and they report directly to the division manager. The division's organizational chart is shown in figure 2. We treated the mid- and division-level managers as a single team in the analysis.

The bank division itself also has a very interesting physical layout. The division is split across two floors, and some teams are co-located in a single room while others have employees from multiple teams in them. In fact, one of the reasons this division took such an interest in the experiment was to determine precisely what effect this physical organization had on the interactions that occur within the division.

The objective of the experiment was to use data collected using our wearable electronic badges to correlate temporal changes in social interaction patterns (including amount of face-to-face interaction, conversational time, physical proximity to other people, and physical activity levels) with performance of individual actors and groups. We obtained e-mail logs as well as self-reported individual and group performance data as part of a case study on the impact of electronic communications on the business performance of teams [18]. This data gave us a very detailed picture of the inner operations of the division.

3.1 Experimental Procedure

Two kinds of badges were deployed in this experiment. The first were the badges worn by individuals. These badges logged IR receptions (containing the transmitting badge's ID) every time they were facing other badges, Bluetooth devices' IDs, raw and bandpass filtered audio, and motion data using the accelerometer. Each badge transmitted its own ID via IR every two seconds and was detectable over Bluetooth every ten seconds. The badges are only able to record a limited number of Bluetooth IDs every five seconds, so not every device that is within range is logged. We also had the blue LED blink once a minute as a cue to denote that the badge was operational. The second type of badge we had were base stations deployed throughout the bank to roughly track the location of interaction events as well as subjects. Fourteen of these base stations were distributed across two floors of the bank's building and were continually discoverable over Bluetooth.

At the end of each day employees were asked to respond to an online survey that included the following questions:

- Q1. What was your level of productivity today?
- Q2. What was your level of job satisfaction today?
- Q3. How much work did you do today?
- Q4. What was the quality of your group interaction today?

Each question could be answered according to the following scale: (1 = very high) (2 = high) (3 = average) (4 = low) (5 = very low). In the analysis below we flipped the answer scale for ease of interpretation.

3.2 Face-to-Face Interaction

Methodology

IR can be used as a proxy for the detection of interactions between people. In order for another badge to be detected through IR, the badges must have a direct line of sight to each other with a distance of less than one meter, so it is reasonable to assume that the badge wearers are engaged in some sort of interaction.

Results

Analysis of IR data yielded interesting results on interaction within teams. Different rooms exhibited different communication patterns in this regard ($p < 0.05$) but the difference across teams was striking ($p < 0.01$). It appeared that there were approximately three types of teams: those with high intra-team communication (one team), those with a moderate amount (one team), and many with low communication (three teams).

Interestingly, teams that had more members tended to have more intra-team interaction, noting that these results were normalized by the number of team members. The hypothesis suggested by this finding is that individuals have to achieve a certain level of connectedness that is a function of team size, so that those on lager teams have more intra-team communication. There was a clear dichotomy between teams with higher communication and those with lower communication. The former were teams that were project and product intensive, which naturally require intra-team collaboration, while the latter was involved in individual tasks, support roles, and control roles. These tasks intrinsically require a looser social structure since workers have little need for intra-team communication to accomplish their goals.

We were also able to identify features of face-to-face interaction that are significantly correlated with the survey data. In particular, the number of unique people that an individual interacted with over the course of the day was moderately correlated with question Q1 responses ($r = -0.19$, $p = 0.01$), while the total amount of time spent in face-to-face communication was correlated with the responses for questions Q1, Q2, and Q3 ($r = -0.27, -0.22, -0.31$, $p = 0.0008, 0.006, 0.0001$, respectively).

These findings reinforce the intuition that an overwhelming amount of face-to-face interaction leads to a decrease in productivity and overall happiness. We can also explain this correlation by noting that when individuals engage with a larger number of people they tend to feel overloaded, while if they interact with few people they may feel that they can focus on their work. Looking at causality in the other direction, it may be that interacting with a few individuals simply makes one feel more at ease with their work environment.

3.3 Proximity and Location

Methodology

The badge can detect other Bluetooth devices in close proximity (within ten meters) in an omni-directional fashion. In the past, this functionality has been used to identify location, behavioral patterns, and social ties [10].

Initially we hypothesized that Bluetooth detections could be used to recognize office level locations and conversational groups. However, the large range of the Bluetooth receivers made this task extremely difficult, limiting the resolution of our data.

These constraints caused us to take a different approach to the analysis. Since closer devices are detected more often, we used a probabilistic method to determine what other badges were in the area. We say that a badge was detected for a 5-minute time-frame only if the badge was detected for more than 30% of the time-frame, which accounts for the limited Bluetooth detection rate. We defined a person as easily reachable when a person was detected for over 30 minutes a day.

Results

The number of easily accessible people was significantly different between the people on different floors. People on the second floor had on average 4.08 people easily reachable per day while people on the third floor had 15.3 ($p < 0.01$). This same trend held for inter- and intra-team communication (both $p < 0.01$) and for inter- and intra-room communication ($p < 0.001$ and $p < 0.01$ respectively). We can posit that people on the third floor were more stationary, making them more available to others on their team and in their room. This might be a result of the type of work people are engaged in since most people on the third floor had a job description that required them to be present in their office, resulting in high Bluetooth detection rates.

Our notion of accessibility, however, fails to capture the fact that mobile individuals would likely come into contact with more people than stationary individuals. Thus, it may be more appropriate to say that the people on the third floor are more reachable for planned interactions, while those on the second floor are more reachable for serendipitous interactions.

3.4 E-Mail

Methodology

E-mail has been frequently used to measure social ties between individuals [21]. Not only is it easy to measure, but in the modern workplace employees are increasingly interacting with each other through e-mail. This data is also easily quantifiable, since we know exactly who sent an e-mail to whom and when. Since it only captures digital interactions, it was unclear whether this accurately represented "real world" interactions.

In general, large scale unidirectional e-mails have little value when analyzing one-on-one interaction. Therefore we only considered reciprocated e- mails when examining relationships between individuals.

Results

In the case of e-mail communication, we found that the amount of e-mail exchanged between individuals varied by floor ($p < 0.0005$), with people on the third floor sending considerably less e-mail than individuals on the second floor. This same trend held for inter and intra-team communication ($p < 0.001$). This is a very interesting result since in contrast to proximity, these results did not hold at the room level. That is, when individuals were grouped into rooms there was no significant difference in the amount of e-mail communication. However, when looking at e-mail communication within a room, there was a large difference between rooms ($p < 0.0001$). One room had over double the average e-mail communication of all other teams.

We can view these results as implying that individuals on the second floor have tasks that require high e-mail communication, while those on the third floor require a lower level of e-mail to work effectively. Although individuals tended not to interact too often with in-room others, there was a significant exception. We could infer that this room had a more asynchronous work flow, where individuals needed to work on critical tasks in real time and exchanged trivial information only when free time was available.

3.5 Combined Social Network

Methodology

Another question that arises is how to combine social network data from multiple sources. It is still unclear how many e-mails are equivalent to face-to-face interactions detected over IR, since in general there was no correlation between ties recognized through IR and those found through examining e-mail communication. However, if we normalize the values such that the greatest number of IR hits/e-mails is 1, then we can hope that this will offer a better solution than simply adding the two adjacency matrices together. Ideally, we would use some weighting factor that would discount the e-mail ties by some multiplicative factor because of the intuition that e-mail indicates weaker social ties than face-to-face interaction, but currently we cannot justify choosing a particular factor.

But what does this network represent? We have already shown that proximity is negatively correlated with e-mail exchange, so is it even appropriate to combine this information? If we are interested in how individuals are linked through the myriad communication tools already available to them, then the answer is yes. Two people who work with each other on different continents may not see each other for months at a time, yet they may exchange e-mail frequently. When they meet, they will already have a shared social context to draw upon, and then a stronger relationship can develop. It would be misguided to simply throw out electronic communication information, since in today's world this has become an extremely important interaction channel, albeit still less so than face-to-face interaction.

We must also account for links between actors through e-mail that are entirely absent in the face-to-face network. If two people are seen as accessible to each other over Bluetooth and have no face-to-face interaction but do have e-mail exchanges, there are two possible explanations. The first is that these individuals simply don't know that they are proximate to each other. This is unlikely, since the range of Bluetooth is ten meters and individuals that communicate with each other frequently over e-mail would likely interact if they saw each other in person. Although IR does not detect all face-to-face interactions, over the course of a month it would likely catch one if the individuals occasionally interacted. The second explanation is that a social tie does not exist between these two actors, that they are in fact exchanging e-mail as a matter of their official duties, such as cc-ing all members of the division. Therefore, when combining information we remove e-mail ties that fall into this category.

Results

We found social network features that were not present in the face-to-face or e-mail social networks. Floors differed on many dimensions, most strikingly in total communication ($p < 0.005$), where people on the second floor had nearly twice the communication of those on the third floor. This leads us to believe that the second and third floors have fundamental differences in their behavior patterns, and interestingly this does not manifest itself at the team level. While it will take further analysis to determine the exact cause of this disparity, it may be that proximity to the divisional manager (who is on the second floor) increases communication, or even that climbing an extra flight of stairs makes people talk less.

We were also able to find high correlations between the combined social network features and survey results. Total communication was highly negatively correlated with monthly averages of questions Q2 and Q4 ($r = -0.48, -0.53,$ and $p < 0.05$ in both cases), and this relationship was shared by betweenness for Q4 ($r = -0.49, p < 0.05$), although betweenness and total communication were not significantly correlated. Inter status communication was also highly negatively correlated with Q4 ($r = -0.64, p < 0.005$), and although other features also showed the same trends, they were highly correlated with the above measures. These findings tell us that job satisfaction and perception of group interaction quality are closely tied to the amount of communication. When one is, in general, involved in a large number of interactions, their job satisfaction tends to be low. Causality in the other direction seems quite unlikely.

Additionally, individuals who are socially important over long periods of time, who are involved in a lot of communication, or who have a large number of interactions with individuals with another role tend to much lower evaluations of group interaction. This is a fascinating result, since it implies that not only is interaction with your subordinates and manager draining, but so is being a socially powerful individual. This points to the necessity of aiding central actors in managing their interaction-related stress, since it is evident that those who are overburdened with their communication responsibilities feel that their interaction quality similarly degrades. It may be that a threshold for communication amount and communication type exists, where anything above this level causes a drop in satisfaction. Again, we believe that causality in the other direction is not likely. These results all imply that we have found a useful representation that can give us information about how people interact that a network formed from a single communication channel cannot.

3.6 General Findings

We fit a multilinear regression to questions Q1, Q2, and Q3 on a daily basis using the variables that were significantly correlated with each of them [17]. In each case we were able to capture ten percent of the variance of responses ($p < 0.005$ for all questions). These results imply that we must go to a finer level of analysis to discover the important factors underlying this data.

Over the whole month, proximity from being in the same room, floor, or team had a high negative correlation with the number of e-mails exchanged between people ($r = -0.55$, $p < 0.01$). This has powerful implications for previous work that has used e-mail communication as a proxy for the social network of an organization, since these two are in fact negatively related.

We can attribute this to several factors. First, if you are in close proximity to another individual, it makes more sense to interact with them in the real world rather than send them an e-mail. Second, proximity information also picks up on informal relations, while in this particular organization e-mail is used mainly for business purposes. This is because if you spend a lot of time with someone you are more likely to be their friend and therefore less likely to send an e-mail to them. This result points towards the necessity of having face-to-face interaction information in order to have a full view of the social network.

If we group people by floor, we see that people on the second floor had lower Bluetooth counts and higher e-mail counts than people on the second floor (mean = 4.08, 15.08), $p < 0.01$ and (mean = 96.4, 37.7), $p < 0.001$, respectively. Hence we can posit that people on the third floor are more stationary, staying in their office most of the time, allowing for predictable face-to-face communication and mitigating the need for e-mail. On the other hand, people on the second floor are more mobile, often out of their office, requiring them to use more asynchronous communication channels such as e-mail. This result suggests that while serendipity is important, it causes an individual to be less available for face-to-face communication, thus increasing e-mail exchanges. It would be interesting, however, to examine which way the causality actually goes.

Supporting the high negative correlations between proximity and e-mail activity, we discovered that betweenness in the daily IR social network had a moderately negative correlation with daily e-mail activity ($r = -0.19$, $p < 0.05$). This is an intuitive finding since we would expect these socially powerful individuals to be able to call up information through face-to-face interaction rather than through asynchronous e-mail. Their central position in the network also ensures that they will be privy to a large amount of information, further decreasing the need for e-mail communication.

We examined the correlation between individual social ties detected through Bluetooth and e-mail. The only significant correlation we found was over inter room communication, where $r = -0.1084, p < 0.05$. Interestingly, when we only examined ties where both Bluetooth detections and e-mail communication were present, we obtained a very high correlation on intra status ties ($r = 0.65, p < 0.0001$) and inter floor ties ($r = -0.4, p = 0.01$). The intra status correlation implies that e-mail communication between individuals with the same role increases as their proximate time increases. Causality in the other direction is also possible, with high e-mail communication breeding an increase in proximity through meetings and the like. Corroborating the findings mentioned earlier, if actors spend time with people on other floors, then they are less likely to send them e-mail. We would not expect causality from e-mail communication to lead to decreased proximity, however. The inter room correlation has a similar pattern, although it is much weaker.

4 Social Network Optimization

One potential breakthrough application of real time social network data is the ability to effect changes in the social network in real time as well. Once we have a picture of the ties that exist in an organization, we can shape new ties so that they will create an optimized communication structure in that context. While this may seem distasteful to some, we all manage our relationships. We let certain relationships fade away and actively work to strengthen others. Using data to accomplish the same tasks merely allows you to do this in a more scientific fashion [4].

Even if we ignore the qualms that individuals may have about shaping their interactions, the question is: how do we do it? First we must build a model of the "true" social network. That is, ignoring extraneous interactions and ensuring that all ties are at least occasionally used for communication.

Next, managers could, of course, identify individuals that should be paired up through selection by a human or by recognizing that connecting specific actors would result in a large reduction in the characteristic path length in the social network [22]. They could even set a target characteristic path length and then the system could begin molding the network towards that goal in a greedy fashion. Alternatively, we could proactively change the list of participants that will attend certain meetings so as to facilitate tie creation through propinquity. But simply mechanically attempting to connect individuals by, say, sending both actors e-mails, would neglect using our knowledge of the existing social landscape and the inherent power of social systems. It is also important to remember that individuals can have only a finite number of connections in order for them to maintain and not be overwhelmed by their social ties.

We also must realize that if we wish to use the existing social ties between individuals to create new ties then the system cannot connect all pairs of actors. It would have to create a patchwork of ties that would slowly close the gap between these two actors, in a process we call *tightening*. Tightening consists of creating a link between two target actors by introducing them to actors that they do not have prior ties with and

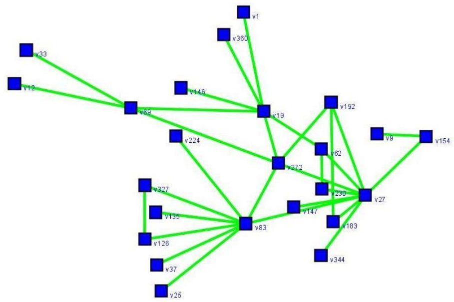

Figure 3. An example social network

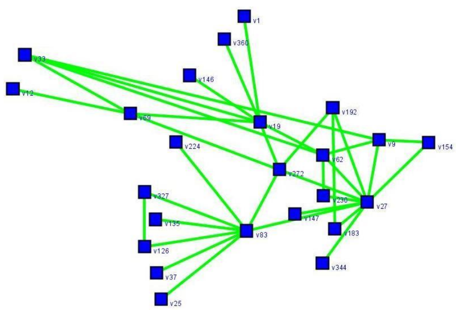

Figure 4. Social network after tightening

are on the shortest path between the targets. The new ties formed in this process must bring the the targets strictly closer to each other, as long as there is not resistance from an actor on the shortest path. If an actor does not want to form a tie with one of the targets, then we can attempt to circumvent them by taking the next shortest path through the network. Both targets connect to each other when they have a common acquaintance who introduces them.

For example, consider the example social network of a fictional organizational department pictured in figure 3, taken from [2]. We can see that the network would derive a large benefit in terms of characteristic path length reduction if we connected v9 and v33, since we assume that because v9 and v33 are in the same department they will have useful information to share with each other.

To tighten this network, the system would operate along the shortest path from v9 to v33, which is v9-v154-v27-v272-v69-v33. First, the system would send an e-mail to v154 asking them to take v27 and v9 for coffee, since it knows that v154 is around the coffee machine with v9 and v27 at different times. Similarly, the system could ask v69 to arrange a meeting between v272 and v33. After these connections occur and the system observes that communication flows continue over an appropriate period of time between v27 and v9, it would ask v27 to take v272 and v9 to lunch. Suppose, however, that this attempted connection failed. The system could attempt to forge this link again, but it would be more advantageous to instead go through the v27-v62-v19-v69-v33 path, since it may be that v272 and v9 are simply not compatible for a relationship. We would continue tightening until we have finally linked v9 and v33, and in the process we have created a much more well-connected social network, the one shown in figure 4. This procedure only created four links before connecting v9 and v33, so applying this process many times to a network will not increase the number of links by a large amount but it will substantially reduce the characteristic path length.

It also makes sense to identify individuals in the network who are *too* central. In this case, the removal of this node from the network would either greatly increase the characteristic path length of the network or split it into fragments. The system could remedy this situation by using tightening, here simply connecting two actors that are in network clusters that are on the opposite sides of the central actor.

Cross and Parker identified communication bottlenecks in the network as a source of significant problems [8]. Our system could attempt to ease the pressure on these bottlenecks by reducing an individual's ties and delegating some of their responsibilities to others. This case is not only more delicate but more difficult than the case in which we want to increase ties. For example, in figure 3 we see that v27 has eleven connections. This may be appropriate, but it may also be important to transfer some of v27's communication to others so that the disatisfaction with interaction that we observed above does not occur. In addition, the organization will respond more quickly in a variety of situations. The system could allow individuals to specify thresholds for communication or interaction before it intervenes. Here it makes more sense not to explicitly direct users, since it is an extremely complex issue to split an individuals task load. Rather, we would attempt to notify the individual themselves as well as their manager so that an appropriate response can be devised. The system could offer suggestions, listing individuals with similar job functions that have a low number of ties who could assume additional communication responsibility.

5 Conclusions and Future Work

We demonstrated the use of a wearable *Sociometric* badge capable of measuring social relations from relative location, proximity, and face-to-face interaction to quantify social relations. We deployed the sociometric badge system in a group of 22 employees in a real organization over a period of one month.

We predicted employees' self-assessment of productivity, job satisfaction, and their own perception of group interaction quality using these automatic measurements. Our analysis of face-to-face interaction time and physical proximity to other people indicated that people in different rooms and teams exhibit different patterns of communication behavior ($p < 0.01$). We found many interesting results involving different communication channels and behavior patterns. An important finding was that physical proximity to other people was strongly negatively correlated with e-mail communication ($r = -0.55$, $p < 0.01$). We combined face-to-face and proximity information with e-mail data to form a robust view of the social network, using proximity information to remove spurious e-mail exchanges. We found that betweenness in the combined social network had a high negative correlation of $r = -0.49$ ($p < 0.05$) with perceived group interaction quality.

We discussed how this system could lead to an automatic intervention system that could optimize the social network in real time through the process of tightening, which connects actors in a socially natural way. In the future we will refine our analytic methodology by looking at the temporal relationships between different features. We will also perform other experiments to gain a more general understanding of how to analyze group behavior.

Our results show that by combining different data modalities for social network analysis it is possible to gain insight into an organization, and pushes for further use of automatic sensing data for computational social science.

Acknowledgments

The authors would like to thank Joseph A. Paradiso, Joshua Lifton, the *Responsive Environments Group* at the MIT Media Laboratory, Nathan Davis, Peter Gloor, Naoto Kanehira, Agustya Mehta, Christopher Moh, Daniel Oster, Daisuke Suzuki, and Alice Yeh for their invaluable help in this project.

References

[1] Ntag interactive. http://www.ntag.com/.

[2] E. Adar. Guess: a language and interface for graph exploration. In *CHI '06: Proceedings of the SIGCHI conference on Human Factors in computing systems*, pages 791–800, New York, NY, USA, 2006. ACM Press.

[3] K. Ara, N. Kanehira, E. Megally, Y. Poltorak, G. Singh, R. Smith, D. Suzuki, M. Mortensen, M. Van Alstyne, and A. Pentland. Sensible organizations inspired by social sensor technologies. Technical report, MIT Media Lab and Sloan School of Management, May 2006. http://vismod.media.mit.edu//tech-reports/TR-602.pdf.

[4] W. Baker. *Achieving Success Through Social Capital*. John Wiley & Sons, New York, NY, 2000.

[5] R. Borovoy, F. Martin, S. Vemuri, M. Resnick, S. B., and C. Hancock. Meme tags and community mirrors: Moving from conferences to collaboration. In *Proceedings of the 1998 ACM Conference on Computer Supported Cooperative Work*, pages 1–10, 1998.

[6] R. Borovoy, M. McDonald, F. Martin, and M. Resnick. Things that blink: Computationally augmented name tags. *IBM Systems Journal*, 35(3):488–495, 1996.

[7] T. Choudhury. *Sensing and Modeling Human Networks*. PhD thesis, MIT Media Laboratory, Feb 2004.

[8] R. L. Cross, A. Parker, and R. Cross. *The Hidden Power of Social Networks: Understanding How Work Really Gets Done in Organizations*. Harvard Business School Press, June 2004.

[9] N. Eagle and A. Pentland. Social serendipity: Mobilizing social software. *Pervasive Computing, IEEE*, 4(2):28–34, 2005.

[10] N. Eagle and A. Pentland. Eigenbehaviors: Identifying structure in routine. In *Ubicomp 2006: The 8th International Conference on Ubiquitous Computing*, 2006.

[11] N. Eagle and A. S. Pentland. Reality mining: Sensing complex social systems. *Personal Ubiquitous Comput.*, 10(4):255–268, 2006.

[12] J. P. Gips. Social motion: Mobile networking through sensing human behavior. Master's thesis, MIT Media Laboratory, Sept 2006.

[13] F. Grippa, A. Zilli, R. Laubacher, and P. Gloor. E-mail may not reflect the social network. In *Proceedings of the North American Association for Computational Social and Organizational Science Conference*, June 2006.

[14] T. Kim, A. Chang, and A. Pentland. Enhancing organizational communication using sociometric badges. In *Proceedings of the 11th International Symposium on Wearable Computers (Submitted)*, 2007.

[15] B. L. Kirkman, B. Rosen, P. Tesluk, and C. B. Gibson. The impact of team empowerment on virtual team performance: the moderating role of face-to-face interaction. *Academy of Management*, 47(2):175–192, 2004.

[16] D. Olguín Olguín, J. A. Paradiso, and A. Pentland. Wearable communicator badge: Designing a new platform for revealing organizational dynamics. In *Proceedings of the 10th International Symposium on Wearable Computers (Student Colloquium)*, pages 4–6, Oct 2006.

[17] D. Olguín Olguín, B. Waber, T. Kim, A. Mohan, K. Ara, and A. Pentland. Sociometric badges: Wearable technology for measuring human behavior. In *Proceedings of the 11th International Symposium on Wearable Computers (Submitted)*, 2007.

[18] D. Oster. Angewandte analyse sozialer netzwerke in unternehmen: Auswirkungen elektronischer kommunikation auf die performanz von teams. Diploma Thesis, University of Cologne Department of Information Systems and Information Management, Germany , 2007.

[19] S. Park, I. Locher, A. Savvides, A. Chen, R. Muntz, and S. Yuen. Design of a wearable sensor badge for smart kindergarten. *Proceedings of the 6th International Symposium on Wearable Computers*, pages 231–238, Oct 2002.

[20] A. Pentland. Automatic mapping and modeling of human networks. *Physica A*, 2006.

[21] A. Sinan, E. Brynjolfsson, and V. A. M. W. Information, technology and information worker productivity: Task level evidence. In *Proceedings of the International Conference on Information Systems*, Dec 2006.

[22] D. J. Watts. *Small Worlds : The Dynamics of Networks between Order and Randomness (Princeton Studies in Complexity)*. Princeton University Press, November 2003.