SENSIBLE ORGANIZATIONS: A SENSOR-BASED SYSTEM FOR ORGANIZATIONAL DESIGN AND ENGINEERING

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ABSTRACT

We propose a sensor-based organizational design system capable of measuring social interactions in the workplace. By combining behavioral sensor data with other sources of information such as text-mined documents, surveys, and performance data we can re-engineer organizations and make better informed decisions. The proposed system combines sensor measurements, pattern recognition algorithms, simulation and optimization techniques, social network analysis, and feedback mechanisms that aim at continuously monitoring and improving individual and group performance. We describe the system's general specifications and discuss preliminary studies that we have conducted in several organizations using an experimental sensing platform.

1. INTRODUCTION

Who are the experts within an organization? Who has the most decision-making influence? Recently, managers have started mining data from e-mail, web pages, and other digital media for clues that will help answer such questions. Studies of office interactions indicate that as much as 80 percent of work time is sometimes spent in spoken conversation (Allen, 1997), and that critical pieces of information are transmitted by word of mouth in a serendipitous fashion. Fortunately, the data infrastructure for mining real-world interactions is already in place. Most working professionals already carry electronic badges and mobile phones that can be enhanced with a few sensors and computational power.

The Human Dynamics research group at the MIT Media Laboratory is demonstrating that commonplace wearable technology can be used to characterize the face-to-face interactions of employees and to map out a company's de facto organizational chart (Choudhury & Pentland, 2003; Pentland et al., 2005; Pentland, 2006; Eagle & Pentland, 2006; Olguin-Olguin et al., 2009a, 2009b). This capability can be an extraordinary resource for team formation and knowledge management. The new reality-mined data allow us to cluster people on the basis of profiles generated from an aggregate of conversation, e-mail, location, and web data. This clustering, in turn, enables us to identify collaboration or lack thereof. For instance, if two groups working on mobile commerce never talk face-to-face, that is a clear sign that they are not coordinating their efforts.

By leveraging recent advances in machine learning, we can build computational models that simulate the effects of organizational disruptions in existing social networks. We could, for example, predict the organizational effects of merging two departments. Such data-driven models help us transcend the traditional organizational chart, allowing organizations to form groups on the basis of communication behavior rather than hierarchy. It's our belief that active analysis of interactions within the workplace can radically improve the functioning of an organization. We expect that by aggregating this information, interpreting it in terms of work tasks, and modeling the dynamics of the interactions, we will be better able to understand and manage complex organizations. We must also, however, provide for the protection of privacy (for instance, by giving employees control over their information) and create an atmosphere of transparency by including the manager's interactions as part of the initiative. If employees can scrutinize their bosses' behavior, they're less likely to object to making their own interactions visible.

To test out this technology, we have deployed a sensing platform in several organizations to study communication patterns, task efficiency, productivity outcomes, and predict optimal configurations of groups. We are now validating this approach with larger and more complex organizations and we expect to see commercial applications in the near future. We begin this article with a brief review of organizational research and a summary of technologies for organizational design. Next, we describe the general requirements for a sensor-based organizational design system and present the experimental sensing platform that we have implemented and tested in several real organizations. We describe preliminary studies and discuss other potential applications and ideas that we are currently exploring. Finally, we present our conclusions and discuss further implications of the proposed technology.

2. ORGANIZATIONAL RESEARCH AND TECHNOLOGIES FOR ORGANIZATIONAL DESIGN

The basic goal of organizational research has been to discover what kinds of organizational designs or structures will be most effective in different situations, as well as to identify variables that will enable researchers to make consistent and valid predictions of what kinds of organizational structures will be most effective in different situations (Tushman & Nadler, 1978).

Organizational behavior is the systematic study of the actions and attributes that people exhibit within organizations. It seeks to replace intuitive explanations with systematic study: that is, the use of scientific evidence gathered under controlled conditions and measured and interpreted in a rigorous manner to attribute cause and effect (Robbins, 2005). This still-emerging field attempts to help managers understand people better so that productivity improvements, customer satisfaction, and a better competitive position can be achieved through better management practices (Gibson et al., 2009).

To understand how individual behavior (problem solving, communication, movement, etc.) affects performance, it is necessary to take into consideration several variables that directly influence individual behavior, such as abilities and skills, personality, perception, attitudes, values, and experience among others. Behavior is also affected by a number of environmental variables such as the organizational structure, policies and rules, resources, and job design. While the individual variables are most likely fixed and do not change much over time, the environmental variables can be continuously manipulated in order to modify individual behavior and promote a desired outcome.

Research in organizational theory and organizational behavior has contributed to the creation of a new field known as organizational engineering:

> Its focus is to increase the efficiency, productivity, communication, and coordination of groups of people. These may include teams, departments, divisions, committees and many other forms of goal directed organizations. Focusing on how relationships and information are structured allows groups to be "engineered" to produce superior results on a consistent basis (Organizational Engineering Institute, 2007).

Tourish & Hargie (2009) argue that modern research on organizational communication must turn its efforts to exploring the in-situ, moment-to-moment, everyday communication practices of organization members. This means extending communication research beyond self-report techniques that rarely capture the full complexities of really occurring organizational behavior.

To the best of our knowledge, organizational studies have not yet incorporated data from social interactions in the workplace collected using electronic sensors. We propose the use of sensors capable of automatically identifying, quantifying and characterizing social interactions in order to incorporate this rich and untapped information, which was not possible to measure with such detail before, into formal organizational models. Our proposed approach could augment traditional methods of gathering social interaction data such as surveys or ethnographic studies.

In addition to the classical organizational engineering perspectives, we have identified several technologies that we consider to be relevant to the field of organizational engineering and that we propose to incorporate in a sensor-based organizational design system.

2.1 COMPUTATIONAL ORGANIZATIONAL ENGINEERING

Within the field of organizational engineering there exist several relatively disconnected perspectives (Castro Melo Godinho de Matos, 2007): (i) Business Engineering is concerned with automation, elimination of bureaucracy, simplification of work flows, refinement of information infrastructure, and elimination of unnecessary work (Martin, 1995); (ii) Enterprise Architecture is concerned with the role that information technology plays in organizations and with the adaptation that most enterprises have to face in order to remain competitive in the process of change (Winter & Fisher, 2007); (iii) the Language Action Perspective sees communication as a form of action and considers that people act through language (Winograd, 1986; Reijswound & Lind, 1998; Dietz, 2002); (iv) and Computational Organization Theory studies organizations as computational entities (Carley, 1995).

The work of Carley (2002) at Carnegie Melon University is particularly relevant to the design of organizational engineering systems. She has proposed that ‘the same techniques used to engineer a product to meet some set of specifications can be applied to organizations and that it should be possible to design an organization, group, or team, so that it is “optimal” given some set of criteria’ (Carley & Kamneva, 2004). Her group has focused on several computational simulation tools for organizational design: (i) agent-based models that simulate the behaviors of the actors who make up a social system, and where the behavior of the social system is not modeled directly, rather the system’s behavior emerges from the interaction of its agents; (ii) systems dynamics models that focus on modeling the behavior of the system as a whole; and (iii) cellular automata models for studying local interactions (Harrison et al., 2007). We believe this approach could be complemented with data from real social interactions in order to initialize simulation parameters and solve optimization problems.

2.2 HUMAN BEHAVIOR SENSING AND MODELING

Human sensing refers to the use of sensors to capture human behavioral signals including facial expressions, body gestures, nonlinguistic vocalizations, and vocal intonations (Pantic et al., 2007). Context sensing also plays an important role in understanding human behavior and its goal is to characterize the situation in which specific behaviors are displayed (who, where, what, how, when and why). There is a large body of research in context sensing using wearable and environmental sensors (Harter et al., 1999; Jones & Brown, 2002; Van Laerhoven et al., 2002; Gellersen et al., 2002; Jones & Brown, 2002; Mantyjarvy et al., 2004). The ultimate goal of human and context sensing is to automatically interpret the sensed behavioral signals to understand and describe the observed behaviors.

Our research group has developed several tools for analyzing voice patterns and quantifying social context in human interaction, as well as several socially aware platforms that objectively measure different aspects of social context, including non-linguistic social signals measured by a person’s tone of voice, movements or gestures. We have found that nonlinguistic social signals are particularly powerful for analyzing and predicting human behavior, sometimes exceeding even expert human capabilities (Pentland, 2005).

2.3 DATA MINING IN ORGANIZATIONS

Organizational Data Mining (ODM) is defined as 'leveraging data mining tools and techniques to enhance the decision-making process by transforming data into valuable and actionable knowledge to gain a competitive advantage' (Nemati & Barko, 2004). Advances in ODM technology have helped organizations optimize internal resource allocations while better understanding and responding to the needs of their customers.

There is an enormous potential in applying data mining techniques to the domain of organizational design. People working in large companies usually find it difficult to identify other people working on similar projects or with specific skills or knowledge. Text mining of digital documents (websites, profiles, working papers, reading papers, e-mail) would make it possible to update or automatically create a user's profile based on mined expertise from the text contained in these documents. Information obtained in this way can be combined with information from sensor data and allow people to connect with others who have the required know-how to help them solve a specific problem. Individuals should be able to set their own privacy rules and specify which documents can be used for text mining by storing them in a specific directory for example.

2.4 SOCIAL NETWORK ANALYSIS

Social network analysis represents a collection of techniques for identifying, describing, and explaining various kinds of structures among individuals, groups, and organizations:

> It is a set of tools used to help account for the relationships or interactions of individuals who interact within a given social context. Specially, network methods can be used to describe the often complex web of ties between people in a group. These relations can be examined at many different levels, revealing information about the network as a whole as well as about individual actors within the network (Slaughter, Yu & Koehly, 2009).

Social networks, in which people build relationships with others through some common interest, can be visualized as a large graph with people as nodes and connections as links between the nodes. Social network analysis examines the structure of the graph and extracts meaningful organizational data out of the graph. Formally defined, social network analysis is 'the mapping and measuring of relationships and flows between people, groups, organizations, computers, web sites, and other information/knowledge processing entities' (Krebs, 2008).

Complete network data is difficult to collect. Four primary data collection techniques are questionnaire, interview, observational, and archival methods. We propose the use of electronic data collection methods that use wearable sensors to capture face-to-face interactions (Olguin-Olguin & Pentland, 2008). Recent developments in modeling longitudinal social networks allow the use of fine-grained data on social interactions that could be applied in organizational design systems (Snijders, 2001, 2006, 2009).

3. SENSOR-BASED SYSTEM FOR ORGANIZATIONAL DESIGN AND ENGINEERING

We have developed a set of tools and methods to automatically capture, measure, and analyze human behavior in organizational settings in order to improve performance and optimize organizational structures and decisions i.e. office layout, team formation, and organizational structure (Olguin-Olguin et al., 2009b). Our goal is to be able to map behavioral patterns to quantifiable outcomes and provide employees and managers with feedback that allows them to adjust their behavior in order to optimize a desired outcome. Our proposed approach includes the following steps:

1. Capturing the interactions and social behavior of employees, managers and customers using wearable and/or environmental sensors (while assuring privacy). Other sources of information that can be incorporated into the system are any form of digital records (i.e. e-mail, chat, phone logs).
2. Performing data mining and pattern recognition to extract meaningful information from these data.
3. Combining the extracted information with performance data (i.e. sales, tasks, timing) and finding relationships between objective measurements and performance outcomes.
4. Generating feedback in the form of graphs, interactive visualizations, reports, or real-time audio-visual feedback for employees, managers and/or customers in order to improve organizational performance and customer satisfaction.
5. Behavior simulation, prediction and modification.
6. Continuous measurement and performance assessment.

3.1 SYSTEM SPECIFICATIONS

A sensor-based system for organizational design consists of environmental and wearable sensors, computers, and software that continuously and automatically measure individual and collective patterns of behavior, identifies organizational structures, quantifies group dynamics, and provides feedback to its users. The purpose of such system is to improve productivity, efficiency, and/or communication patterns within an organization. The proposed system is composed of one or more wearable sensing devices functioning in a wireless sensor network, one or more radio base stations, a computer system, and several data processing algorithms. The system may include some or all of the following:

- Environmental sensors that monitor the current conditions of the workplace (temperature, light, movement, activity, sound, video, etc.).
- Wearable sensors that employees carry around and that measure human behavior (social interaction, activities, location, etc.). These can be mobile devices such as cell phones, PDAs, or electronic badges that collect data, communicate with a database (via Ethernet or wirelessly) to retrieve information, and provide feedback to their users.
- Software that automatically identifies relevant keywords in documents, web pages, e-mail, and instant messaging communication.
- A database that stores all the information collected by the environmental, wearable and software sensors (who-knows-what, who-knows-who, and where-is-who).

- Simulation and data mining algorithms.
- Feedback and visualization mechanisms.

3.2 ENVIRONMENTAL SENSORS

In addition to the wearable sensors, base stations can be placed in fixed locations inside a building in order to track the location of interaction events as well as subjects. A central computer can be used for data collection. Data from the wearable sensors is transferred wirelessly to the base stations and then uploaded to a server. The base stations may contain environmental sensors (temperature, light, sound, movement, activity, etc.) that capture the current conditions in an office environment, such as the number of people walking by, ambient noise, temperature and lighting conditions.

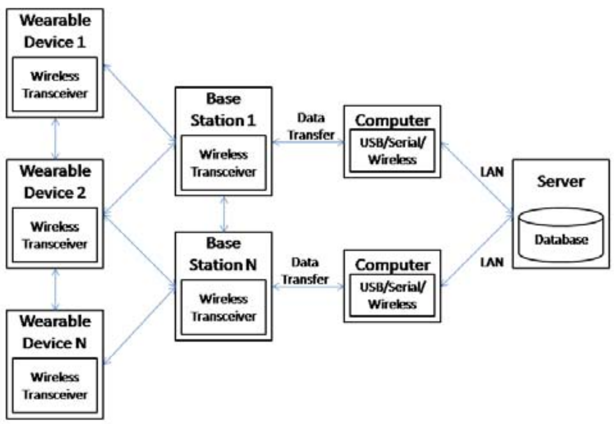

Figure 1. Sensor-based organizational engineering system (block diagram)

3.3 WEARABLE SENSORS

Wearable sensing devices may include: electronic badges, mobile phones, wrist-mounted devices, head-mounted devices, and electronic textiles, among others. These wearable devices could function as self-contained monitoring devices or communicate with each other and with fixed radio base stations in a wireless sensor network. The wearable sensing devices should have a small form factor, be comfortable to wear over long periods of time, and have a long battery life. Ideally, they should be able to:

- Recognize common daily human activities (such as sitting, standing, walking, and running) in real time.
- Extract speech features in real time to capture non-linguistic social signals such as interest and excitement, and unconscious back-and-forth interjections, while ignoring the words in order to assuage privacy concerns.
- Communicate with base stations over radio and measure the radio signal strength (to estimate proximity and location).

- Perform indoor user localization by measuring received signal strength and implementing triangulation algorithms.
- Capture face-to-face interactions.

The system that we have implemented uses *sociometric badges*, wearable sensors that can automatically measure individual and collective patterns of behavior, predict human behavior from unconscious social signals, identify social affinity among individuals working in the same team, and enhance social interactions by providing feedback to the users of our system (Olguin-Olguin D., 2007). Figure 2 shows the block diagram of a sociometric badge.

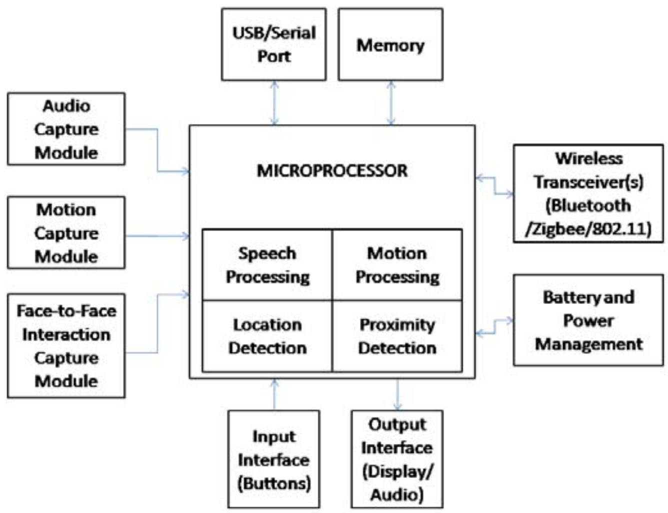

Figure 2 Sociometric badge (block diagram).

The wearable sensing device may include one or more of the following modules:

Module	Sensors	Measurements
Audio	Electret or MEMS-type microphone	Speech detection and segmentation, speaking time, speech features (energy, pitch, speaking rate, etc.), non-linguistic signals (activity, emphasis, mirroring, engagement)
Motion	Accelerometers, inclinometers, gyroscopes, piezoelectric vibration sensors	Body movement detection, body energy level, body postures (sitting, standing, lying down, etc.) and physical activities (walking, running, etc.)
Face-to-face interaction	Infrared transceivers, CMOS cameras	Time spent in face-to-face interactions

Proximity	Ultrasonic sensors, sonar, radio transceivers (i.e. Zigbee, WiFi, Bluetooth)	Proximity to other people and base stations (from radio signal strength)
Location	Radio transceivers (i.e. Zigbee, WiFi, Bluetooth)	Triangulation (from radio signal strength)
Input interface	Buttons, keyboard, touch screen, haptic interface	
Output interface	Speaker, LCD, light emitting diodes	
Memory	Flash, RAM, SD card	
Processor	Microprocessor/DSP	
Power	Battery and power management circuitry	

3.4 DATABASE

A database containing individual attributes (values, attitudes, self-concept, abilities, personality, job satisfaction, etc.); sociometric data captured from sensors (speaking state, speaking style, motion state, location, face-to-face interaction, proximity, etc.); group attributes (team assignment, communication frequency, social network features derived from the sociometric data); and performance data (projects or tasks, completion time, success/failure, resources, follow-ups, etc.) from each person in an organization must be maintained in order to manage the vast amounts of information generated by the system. Database software includes: MySQL, Microsoft SQL Server, Oracle, and IBM DB2. Figure 3 shows a sample database structure.

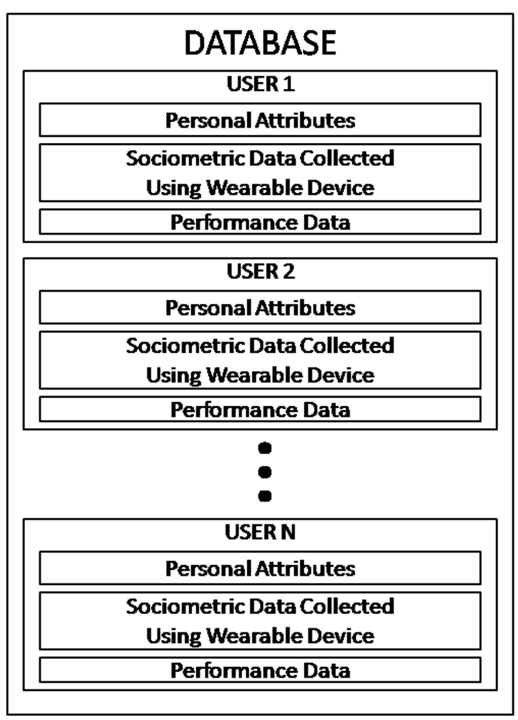

Figure 3. Organizational Design System Database

The data is processed following these steps:

1. Personal attributes and job performance data are entered into the database.
2. Sociometric data from each user wearing a sensing device is collected in real time.
3. Sociometric data is transferred in real time to the nearest base station.
4. Sociometric data is then transferred from the base station to a computer terminal.
5. Sociometric data is then transferred from the computer terminal to a central server and inserted into the database.
6. Sociometric data is accessed from the database and analyzed. Analysis software includes: Matlab, Microsoft Visual Studio, UCINET, among others.
7. Behavioral feedback is provided to each user wearing a sensing device.

Figure 4 shows the organizational engineering process flow diagram.

1. Access personal attributes, sociometric data, and performance data.
2. Apply data mining and data processing algorithms.
3. Find relationship between desired/undesired performance outcomes and sociometric data.
4. Find relationship between personal attributes and sociometric data.
5. Set individual and group performance goals.
6. Provide users with feedback in order to induce behavioral changes and achieve the desired goals.
7. If the goals are reached, reward users and set new goals.
8. If the goals have not been reached, predict future performance outcomes based on the sociometric data, and re-structure the organization based on personal attributes, desired outcomes and predicted performance.

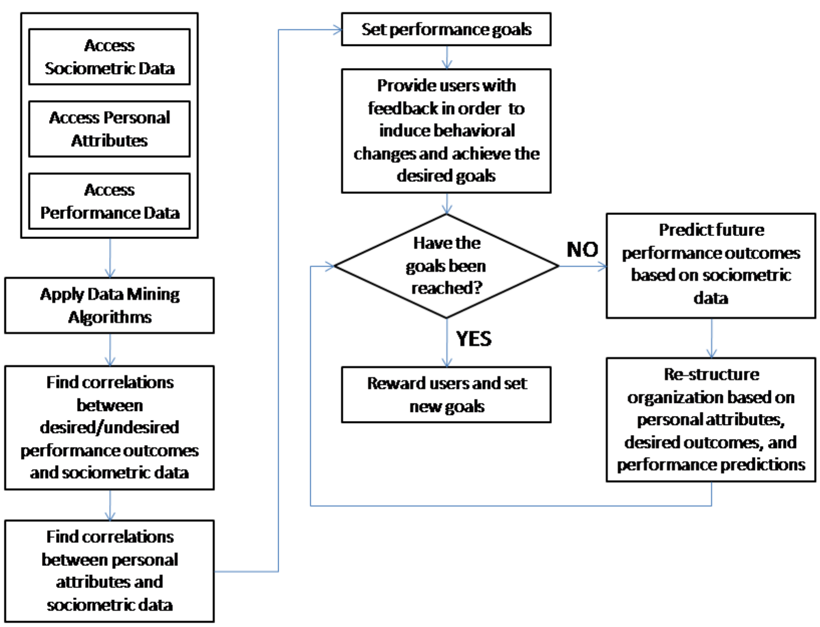

Figure 4. Organizational engineering process (flow diagram)

4. CASE STUDIES

4.1 CAPTURING COMMUNICATION PATTERNS IN A BANK

We instrumented a group of 22 employees (distributed into four teams) working in the marketing division of a bank in Germany for a period of one month (20 working days). Each employee was instructed to wear a *sociometric* badge every day from the moment they arrived at work until they left their office. In total we collected 2,200 hours of data (100 hours per employee) and 880 reciprocal e-mails.

The objective of the experiment was to use data collected using our wearable social sensors 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 satisfaction data as part of a case study on the impact of electronic communications on the business performance of teams.

We found that the number of people in close proximity had a high negative correlation with the number of e-mails exchanged ($r=-0.55$, $p<0.01$, $N=22$). When we examined the total communication (e-mail and face-to-face) of each individual, we found that it had a very high negative correlation with job satisfaction and group interaction satisfaction ($r=-0.48$ and $r=-0.53$ respectively, with $p<0.05$ and $N=22$ in both cases). This tells us that as an individual engages in more and more communication, their satisfaction level decreases (Olguin-Olguin et al., 2009b).

4.2 MEASURING TASK-LEVEL PRODUCTIVITY

Sociometric badges were deployed for a period of one month (20 working days) at a Chicago-area data server configuration firm that consisted of 28 employees, with 23 participating in the study. In total, 1,900 hours of data were collected, with a median of 80 hours per employee.

The analysis examined employee behavior at the task level rather than at the individual level. Employees in the department were assigned a computer system configuration task in a first come first served fashion. These configurations were automatically assigned a difficulty (basic, complex, or advanced, in ascending order of difficulty) based on the configuration characteristics. The employee submitted the completed configuration as well as the price back to the salesman, and the employee was placed at the back of the queue for task assignment. The exact start and end time of the task was logged, and the number of follow-ups that were required after the configuration is completed was also recorded in the database. The task completion times and number of follow-ups were compared across four behavioral clusters determined by the variation in physical activity and speech activity captured by the sociometric badges.

Results indicate that these behavioral clusters exhibit completion times and number of follow-ups that vary according to physical activity levels and speaking time. Completion time had a significant correlation ($r=0.50$, $p<0.001$) with the standard deviation of physical energy across all behavioral groups. A similar relationship was found between variation in the speech signal and completion time ($r=0.59$, $p<0.001$) for cases in which the subject spoke to others during the task.

The number of follow-ups was correlated with completion time ($r=0.57$, $p<0.001$), this effect being much stronger when the subjects were not speaking during the task ($r=0.67$, $p<0.001$) (Waber et al., 2008).

Using the same dataset, Wu et al. (2008) found that complex tasks and tasks that required more follow-ups increased the completion time significantly. While the total number of face-to-face interactions had no effect on completion time, the network size was associated with a 5% decrease in the speed with which employees complete tasks on average. In contrast, network reach and network betweenness increased the speed of task completion by 3% and 11% respectively. Another interesting finding was that cohesion (degree to which an actor's contacts are connected to each other) in the face-to-face communication network doubled the speed of task completion (Wu et al., 2008).

4.3 STUDYING NURSE BEHAVIOR AND PATIENT OUTCOMES IN A HOSPITAL SETTING

We instrumented a group of 67 nurses working in the Post Anesthesia Care Unit (PACU) of a Boston area hospital with sociometric badges. Each nurse wore a sociometric badge every day for a period of 27 days. In total we collected 3,906 hours of data. The mean number of hours each participant wore a badge was 7.18 hours per day (±4.17). During this period a total of 1128 patients were admitted to the PACU, with an average length of stay (LOS) of 235.66 (±261.76) minutes (Olguin-Olguin et al., 2009a).

We were able to explain the variation in the daily average LOS in minutes ($R^2=0.79$) and the daily average number of outgoing delays ($R^2=0.56$) from the aggregated sociometric badge features across subjects. In the case of LOS, the variation in physical activity intensity, face-to-face interaction time, and time in close proximity to a phone across subjects played an important role. When estimating the daily number of delays the variation across subjects in physical activity and proximity to a phone were the most predictive features.

Low variation across the nurses' level of activity (either all nurses having high levels of activity or low levels of activity) and high variation across the nurses' face-to-face interaction time was an indication of extended LOS. On the other hand, high variation across the nurses' daily activity levels (having alternate periods of high activity and low activity during the day), coupled with a high variation in the time they spend in close proximity to a phone, was an indication of increased number of delays in the PACU.

5. FUTURE APPLICATIONS

5.1 CALL CENTERS

We have recently deployed our system at a bank's call center, where a group of 80 employees (working in four different teams) and managers used sociometric badges for a month. Daily productivity metrics have been made available to us: number of phone calls handled, average call handle time, speaking time, and system use time, among others. Preliminary results seem to indicate that cohesion in the face-to-face social network (captured with our system's wearable sensors) is negatively correlated with the average handle time. This is in agreement with the results obtained by (Wu et al., 2008) and has several implications for the call center's operations.

We are currently working on feedback mechanisms to present real-time information to managers and are also preparing general recommendations to improve the performance in the call center. For instance, one possible intervention would be to change the way employee's breaks are currently scheduled. Instead of minimizing the number of people taking a break at the same time (how it is currently done), changing the breaks' schedule so that more people working in the same team can take a break at the same time. This would allow members of the teams to form more cohesive ties over time, and allow knowledge sharing, which in turn would lead to a reduction in the average call handle time. We plan to instrument the same teams after implementing these changes in order to test our system.

5.2 SOFTWARE DEVELOPMENT TEAMS

Another potential application of our system is to improve the performance of software development teams. Communication among programmers working in co-located and distributed teams is crucial for the success of software development projects. Being able to visualize communication patterns in real time would be of great advantage to project managers. Having access to a feedback system that bridges the communication gap in distributed teams by incorporating some of the lost social signals would also be advantageous (Kim & Pentland, 2009). We are currently collaborating with other institutions to instrument several software development teams and collect data on communication patterns and their relationship with productivity and quality outcomes.

5.3 RETAIL STORES

Sensor-based organizational design systems can also be used is in retail stores. Sales representatives suffer from the lack of personal productivity tools that would help them improve their strategy. Top performing sales representatives usually have good communication skills, exhibit a lot of enthusiasm and energy and form a personal bond with their clients.

Allowing sales representatives and managers to reflect on their own performance can drastically improve sales skills and increase sales. By creating an instant feedback loop that provides a thorough analysis of performance, sales representatives can learn from their mistakes and accelerate their performance from sale to sale.

Recent experiments have shown that it is also possible to measure how persuasive a person is being when talking to someone, how interested a person is in a conversation, how much attention a person is paying to someone, and how effective is someone at negotiating, all by measuring voice features (Stoltzman, 2006), (Curhan & Pentland, 2007). The sensor-based system that we propose in this paper could analyze the body movement and voice data received from the wearable sensors and display feedback when prompted by the user. It could keep track of individual sales performance as well as global performance and give advice on how to make interaction with the customers more effective.

6. CONCLUSIONS

We have discussed several technologies for organizational design and engineering, and proposed to incorporate them into a single sensor-based system for organizational design. By bringing together computational models, human sensing, data mining, and social network analysis we believe it is possible to create a closed loop system that would use digital information, sensor data, performance and productivity data as inputs. Data mining algorithms and social network analysis can then be applied to these inputs, and computational models created from the results of the data analysis. Finally, simulations and feedback mechanisms would be reported to the users of the system in order to make changes to an existing organization. These changes may include: restructuring the organizational chart, restructuring teams, changing the physical office layout in order to facilitate communication and mobility patterns, or changing individual behaviors.

Our proposed approach to measure human behavior has several advantages over existing methods such as direct observation by humans, the use of pervasive cameras to videotape social interactions, or 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. Deploying pervasive cameras is extremely expensive and their range of measurement is constrained to a particular place. The use of surveys is subjective, inaccurate, and time consuming. In contrast, it is a great advantage to be able to automatically capture the behavior of hundreds of people at the same time with unobtrusive sensors.

Large organizations are not truly sensible to what happens within their internal structures and to how information is transferred from employee to employee. There are often delays and inefficiencies in the information transfer process. Organizations could potentially become more "sensible" to this problem by deploying ubiquitous computing sensor platforms that will help them manage their know-how in better ways. Not only organizations but individuals would benefit from such platforms since they would be able to perform their jobs more efficiently and achieve greater personal satisfaction. Even though we have only discussed a few application scenarios we believe the possibilities for the proposed sensor-based system are much broader.

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