Sensor-Based Organizational Engineering

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ABSTRACT
We propose the use of wearable and environmental sensors to capture and model social interactions in the workplace, combined with data mining techniques and social network analysis for organizational engineering applications. By combining behavioral sensor data with other sources of information such as text-mined documents, surveys, and performance data, it is possible to optimize organizations.

Categories and Subject Descriptors
H.5.3 [**Information Interfaces and Presentation**]: Group Organization Interfaces— *Organizational Design*; K.4.3 [**Computers and Society**]: Organizational Impacts— *Reengineering.*

General Terms
Management, Measurement, Performance, Human Factors.

Keywords
Organizational Engineering, Organizational Behavior, Sensors, Data Mining, Social Network Analysis.

1. INTRODUCTION
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 [27].

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 [22]. 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 [7].

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Research in organizational theory and organizational behavior has contributed to the creation of a new field known as organizational engineering, which seeks 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 [19].

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 organizations i.e. office layout, team assignment, and organizational structures [17]. Our goal is 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. In the following sections we discuss related work and describe a sensor-based organizational engineering system.

2. RELATED WORK
2.1 Human Behavior Sensing
Human sensing refers to the use of sensors to capture human behavioral signals including facial expressions, body gestures, nonlinguistic vocalizations, and vocal intonations [20]. 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 [1], [3], [6], [8], [9], [13], [28]. 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 [21].

2.2 Human Behavior Modeling
It is possible to recognize human behavior from sensor data at the individual and group levels. By applying pattern recognition methods and dynamic social network analysis to the sensor data, we can model and optimize group dynamics.

At the individual level, researchers have applied pattern recognition methods to several aspects of human behavior such as primitive motor activities (i.e. standing, walking, running, etc.), complex or high-level activities (i.e. cooking, washing dishes, etc.), body posture, facial expressions, hand gestures, and displacement patterns (i.e. location tracking). Previous work in human activity recognition using accelerometers has shown that it is possible to classify in real time several postures and activities, however most of the early work on human activity recognition from sensor data has focused on the identification of a specific activity in a particular scenario, such as sitting on a chair or walking. More recently, there has been increasing interest on modeling more complex patterns of behavior over extended periods of time [18].

At the group level, it is possible to automatically identify face-to-face interactions, conversations, and conversation dynamics. A wide range of studies has shown that hand-coded analyses of communication in teams can predict performance [4]. These studies have looked at the frequency, patterns and content of communication. For instance, an analysis of the communication patterns of aircrews in flight simulation experiments revealed significant differences between successful and unsuccessful crews [2]. In some cases, high-performing teams communicate with higher overall frequency than low-performing teams, but in other cases, this finding has not been supported. In [5], the author reviews more than a hundred different works addressing the computational modeling of interaction management, internal states, personality traits, and social relationships in small group conversations. His review focuses on small groups, non-verbal behavior, computational models, and face-to-face conversations.

3. MAKING SENSE OF SENSOR DATA

3.1 Data Mining

Organizational Data Mining (ODM) leverages data processing tools and techniques to enhance the decision-making process by transforming data into valuable and actionable knowledge to gain a competitive advantage [14]. Advances in ODM technology have helped organizations optimize internal resource allocations while better understanding and responding to the needs of their customers.

To date, research on human interactions has relied mainly on one-time, self-reported data on relationships. New technologies, such as video surveillance, e-mail, and mobile phones, offer a moment-by-moment picture of interactions over extended periods of time, providing information about both the structure and content of relationships. This has given rise to an emerging field of "computational social science" that leverages the capacity to collect and analyze data with an unprecedented breadth and scale [12]. Vast amounts of data are created everyday from the use of personal electronic devices such as mobile phones and RFID cards. This calls for the use of pattern recognition and data mining techniques to uncover hidden structures of human behavior and social interactions.

There is an enormous potential in applying data mining techniques to behavioral sensor data for organizational engineering purposes. 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.

3.2 Social Network Analysis

A social network consists of a set of actors (or nodes) and the relations (or ties) between these actors. Actors may be individuals, groups, organizations, or entire communities, and relations may span across or within levels of analysis. These relational variables are defined and measured at the dyadic level and can include a wide variety of social and physical ties, each of which may have a number of different basic properties [29].

Social network analysis is 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 [23].

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 analyzes 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" [11]. Recent developments in modeling longitudinal social networks allow the use of fine-grained data on social interactions that could be applied in organizational engineering systems [24], [25], [26]. Furthermore, the use of wearable sensors to automatically capture face-to-face interactions offers a great advantage over traditional social network data collection methods [16].

4. PROPOSED SENSOR-BASED SYSTEM

We propose a sensor-based organizational engineering system with the following characteristics: (1) It captures the interactions and social behavior of employees, managers, and customers using wearable and/or environmental sensors (i.e. *sociometric badges* [15]). (2) It incorporates other sources of information in the form of digital records (i.e. e-mail, chat, phone logs). (2) It performs data mining and social network analysis to extract meaningful information from the sensor data and other sources of information. (3) It combines the extracted information with performance data (i.e. sales, tasks, timing) and finds relationships between objective measurements and performance outcomes. (4) It generates 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) It includes behavior simulation, prediction and modification. (6) It allows for continuous measurement and performance assessment.

4.1 System Specifications

A sensor-based system for organizational engineering 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:

4.1.1 Wearable Sensors

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. They should be capable of measuring human behavior i.e. social interactions, activities, location, etc.

Wearable sensing devices may include: electronic badges, mobile phones, wrist-mounted devices, head-mounted devices, and electronic textiles, among others. These wearable devices can 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; and capture face-to-face interactions.

4.1.2 Environmental Sensors

Environmental sensors can be used to monitor the current conditions of the workplace (temperature, light, movement, activity, sound, video, etc.). 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.

4.1.3 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.

4.1.4 Software

A data processing module that implements data mining techniques and social network analysis is required in order to extract meaningful information from the sensor data and the personal data contained in the organizational engineering database. Applications such as wikis, social networking sites, user profiles, dashboards, and virtual worlds can be built on top of the data processing module. Simulation and visualization software also play an important role in sensor-based organizational engineering systems.

4.1.5 Feedback Mechanisms

By aggregating information from sensor data, interpreting it, and modeling the dynamics of human interactions, one can create sensor-based feedback systems that help us better understand and manage complex organizations. In [10] we proposed several sensor-based feedback systems at the individual, group, and organizational levels.

5. DISCUSSION

The use of pervasive wearable and environmental sensors has made it possible to collect large amounts of data on physical social interactions. While labeling large amounts of data is unrealistic and time consuming, applying unsupervised learning methods to this type of data is possible. This allows us to accurately identify and characterize group behavior (i.e. face-to-face interactions, meetings, conversations, etc.) in large groups of people. By applying dynamic models (dynamic Bayesian networks and dynamic social network analysis) to the automatically identified social interactions it is possible to model interactions at different time scales, from milli-second-level conversational dynamics, to larger time granularities such as day-to-day face-to-face interactions.

Being able to accurately predict the creation and extinction of ties in a social network recreated from data on physical interactions has a huge potential impact in research areas such as the study of team formation, organizational dynamics, the evolution of friendship networks, and the spread of disease, among many others.

By bringing together human sensing, data mining, and social network analysis we believe it is possible to create a closed loop system that uses digital information, sensor data, performance and productivity data as inputs. Data mining algorithms and social network analysis are applied to these inputs in order to create computational models. Finally, simulations and feedback mechanisms are used to optimize organizational designs. Organizational engineering applications include: automatic team assignment, physical office layout design, communications and mobility patterns analysis, training, and behavior modification, among others.

6. REFERENCES

[1] Bharatula, N. B., Stager, M., Lukowicz, P., & Troster, G. (2005). Empirical Study of Design Choices in Multi-Sensor Context Recognition Systems. *Proceedings of the 2nd International Forum on Applied Wearable Computing*, (pp. 1-15). Zurich, Switzerland.

[2] Bowers, C. A., Jentsch, F., Salas, E., & Braun, C. C. (1998). Analyzing communication sequences for team training needs assessment. *Human Factors* , 672-679.

[3] Cakmakci, O., Coutaz, J., Laerhoven, K. V., & Gellersen, H.-w. (2002). Context awareness in systems with limited resources. *Proceedings of the 3rd Workshop on Artificial Intelligence in Mobile Systems*, (pp. 21-29).

[4] Foltz, P. W., & Martin, M. J. (2009). Automated Communication Analysis of Teams. In E. Salas, G. F. Goodwin, & S. Burke, *Team Effectiveness in Complex Organizations* (pp. 411-431). New York, NY: Taylor & Francis Group.

[5] Gatica-Perez, D. (2009). Automatic nonverbal analysis of social interaction in small groups: A review. *Image and Vision Computing* .

[6] Gellersen, H. W., Schmidt, A., & Beigl, M. (2002). Multi-Sensor Context-Awareness in Mobile Devices and Smart Artefacts. *Mobile Networks and Applications , 7* (5), 341-351.

[7] Gibson, J. L., Ivancevich, J. M., Donnelly, J. H., & Konopaske, R. (2009). *Organizations: Behavior, Structure, Processes.* New York, NY: McGraw-Hill Irwin.

[8] Harter, A., Hopper, A., Steggles, P., Ward, A., & Webster, P. (1999). The anatomy of a context-aware application. *Proceedings of the 5th Annual ACM/IEEE International Conference on Mobile Computing and Networking*, (pp. 59-68). Seattle, WA.

[9] Jones, G. J., & Brown, P. J. (2002). Challenges and Opportunities for Context-Aware Retrieval on Mobile Devices. *Proceedings of the Workshop on Mobile Personal Information Retrieval at the 25th Annual International ACM SIGIR Conference*, (pp. 47-56). Tampere, Finland.

[10] Kim, T., Olguin-Olguin, D., Waber, B. N., & Pentland, A. (2009). Sensor-Based Feedback Systems in Organizational Computing. *Workshop on Social Computing with Mobile Phones and Sensors at the 2009 IEEE International Conference on Social Computing*, (pp. 1-4). Vancouver, BC.

[11] Krebs, V. (2008). *Social Network Analysis*. Retrieved 26 2008, April, from Orgnet: http://www.orgnet.com/sna.html

[12] Lazer, D., Pentland, A., Adamic, L., Aral, S., Barabási, A.-L., Brewer, D., et al. (2009). Computational Social Science. *Science , 323*, 721-723.

[13] Mantyjarvy, J., Himberg, J., Kangas, P., Tuomela, U., & Huuskonen, P. (2004). Sensor signal data set for exploring context recognition of mobile devices. *Proceedings of the 2nd International Conference on Pervasive Computing*, (pp. 1-6).

[14] Nemati, H. R., & Barko, C. D. (2004). *Organizational Data Mining: Leveraging Enterprise Data Resources for Optimal Performance.* London: Idea Group Publishing.

[15] Olguin-Olguin, D. (2007, May). Sociometric badges: Wearable technology for measuring human behavior. *Master's Thesis* . Cambridge, MA, USA: Massachusetts Institute of Technology.

[16] Olguin-Olguin, D., & Pentland, A. (2008). Social Sensors for Automatic Data Collection. *14th Americas Conference on Information Systems* (pp. 1-10). Toronto, ON: AIS.

[17] Olguin-Olguin, D., Waber, B., Kim, T., Mohan, A., Ara, K., & Pentland, A. (2009). Sensible Organizations: Technology and Methodology for Automatically Measuring Organizational Behavior. *IEEE Transactions on Systems, Man, and Cybernetics-Part B: Cybernetics* , 43-55.

[18] Oliver, N., & Horvitz, E. (2005). A Comparison of HMMs and Dynamic Bayesian Networks for Recognizing Office Activities. In *User Modeling* (Vol. 3538/2005, pp. 199-209). Springer Berlin / Heidelberg.

[19] Organizational Engineering Institute. (2007). *Organizational Research and Knowledge*. Retrieved 12 19, 2007, from Organizational Engineering Institute: http://www.oeinstitute.org/index.htm

[20] Pantic, M., Pentland, A., Nijholt, A., & Hunag, T. S. (2007). Human Computing and Machine Understanding of Human Behavior: A Survey. In T. H. al., *Human Computing* (pp. 47-71). Berlin, Germany: Springer-Verlag.

[21] Pentland, A. (2005). Socially aware computation and communication. *IEEE Computer , 38* (3), 33-40.

[22] Robbins, S. P. (2005). *Essentials of Organizational Behavior.* Upper Saddle River, NJ: Pearson Prentice Hall.

[23] Slaughter, A. J., Yu, J., & Koehly, L. M. (2009). Social Network Analysis: Understanding the Role of Context in Small Groups and Organizations. In E. Salas, G. F. Goodwin, & S. Burke, *Team Effectiveness in Complex Organizations* (pp. 433-459). Taylor & Francis Group LLC.

[24] Snijders, T. A. (2009). Introduction to stochastic actor-based models for network dynamics. *Social Networks* .

[25] Snijders, T. A. (2006). New Specifications for Exponential Random Graph Models. *Sociological Methodology* , 99-153.

[26] Snijders, T. A. (2001). The Statistical Evaluation of Social Network Dynamics. *Sociological Methodology* , 361-395.

[27] Tushman, M. L., & Nadler, D. A. (1978). Information Processing as an Integrating Cocept in Organizational Design. *Academy of Management Review* , 613-624.

[28] Van Laerhoven, K., Schmidt, A., & Gellersen, H. W. (2002). Multi-sensor context aware clothing. *Proceedings of the 6th International Symposium on Wearable Computers*, (pp. 49-56).

[29] Wasserman, S., & Faust, K. (1994). *Social Network Analysis: Methods and Applications.* Cambridge University Press: London.