Journal of Information Processing Vol. 16 1–12 (Apr. 2008)

Regular Paper

Sensible Organizations: Changing Our Businesses and Work Styles through Sensor Data

Koji Ara,[†1] Naoto Kanehira,[†2]
Daniel Olguín Olguín,[†3] Benjamin N. Waber,[†3]
Taemie Kim,[†3] Akshay Mohan,[†3] Peter Gloor,[†2]
Robert Laubacher,[†2] Daniel Oster,[†2]
Alex (Sandy) Pentland[†3] and Kazuo Yano[†1]

We introduce the concept of sensor-based applications for the daily business settings of organizations and their individual workers. Wearable sensor devices were developed and deployed in a real organization, a bank, for a month in order to study the effectiveness and potential of using sensors at the organizational level. It was found that patterns of physical interaction changed dynamically while e-mail is more stable from day to day. Different patterns of behavior between people in different rooms and teams ($p < 0.01$), as well as correlations between communication and a worker's subjective productivity, were also identified. By analyzing a fluctuation of network parameters, i.e., "betweenness centrality," it was also found that communication patterns of people are different: some people tend to communicate with the same people in regular frequency (which is hypothesized as a typical pattern of throughput-oriented jobs) while some others drastically changed their communication day by day (which is hypothesized as a pattern of creative jobs). Based on these hypotheses, a reorganization, such that people having similar characteristics work together, was proposed and implemented.

1. Introduction

The study of human behavior has always intrigued social scientists. Pentland showed that non-linguistic social signals are powerful for analyzing human behavior and found correlations between behavior and performance in several tasks [1]: it was possible to predict who would exchange business cards at a meeting, who would come out ahead in a negotiation, even which couples exchange phone numbers. However in the past data complexity had to be sacrificed in favor of smaller sensors, since otherwise heavy, burdensome equipment would be necessary. In addition, battery life limitations allowed experiments to only run for very short periods of time.

Recent technology improvements enable sensors to be worn, not only with location detection, but also with quite rich sensing capabilities, throughout the day. People have started to use such sensors in domains such as health care. Yano hypothesized [2] that technological and societal changes [⋆1] will accelerate the use of sensors in the workplace. We believe analysis and visualization techniques for such wearable sensor data are fundamentally different than the methodologies developed in the past.

We describe a sensor-enabled innovative work style, the "*Sensible Organization* [3]," including potential ways to use sensors in the work place to improve productivity and individuals' business skills.

2. Background and Previous Work

2.1 Socially Aware Systems

Psychologists have firmly established that social signals are a powerful determinant of human behavior and have speculated that these signals may have evolved as a way of establishing hierarchy and group cohesion. The non-linguistic signals that serve as the basis of this collective social discussion are just as important as conscious content for determining human behavior in many situations [4].

Researchers have developed several socially aware platforms for measuring different aspects of social context.

Face-to-face interaction: Choudhury designed a wearable sensor package [5] intended for measuring interactions between people by means of an infra-red (IR) transceiver, a microphone, and two accelerometers.

Location and proximity: Madan [6] has developed software that learned various aspects of people's social lives by mining their face-to-face and phone interactions.

†1 Hitachi Ltd.
†2 Massachusetts Institute of Technology, Sloan School of Management
†3 Massachusetts Institute of Technology, Media Laboratory

⋆1 1) Improvements in technology for miniaturization, long battery life, efficient wireless communications, 2) data-stream changes from download to upload, and 3) the need for white-collar worker in the 21st century to be knowledge-centric.

Motion: Gips[7] used motion sensors and proximity sensors to identify groups of friends taking part at a career fair, the team membership of students participating in a treasure-hunt game, and the company affiliation of visitors attending a conference.

2.2 Wearable Sensor Platform

Wearable badges are common devices that employees wear in organizations to identify themselves to others. The "Active Badge" developed at Xerox PARC was the first attempt to augment name tags with electronics. Containing only a small microprocessor and an infrared transmitter, this badge could broadcast the identity of its wearer and trigger automatic doors, telephone call forwarding, and computer displays[8]. The "nTAG System" is a wearable sensing product to improve, measure, and automate meetings and events[9]. A widely accepted badge system is the "Vocera Communications System"[10] which provides a voice-command interface and enables instant, hands-free conversations.

2.3 Organizational Behaviors and Social Networks

Researchers studying organizational behavior have long investigated communication patterns within and across organizations as well as what implications these patterns have for a variety of efficiency and effectiveness measures, such as employees' satisfaction, operational productivity, knowledge creation, adaptability to changing environments, and, ultimately, financial performance. Attempts have been made to apply the findings of these studies to management practices and intervene in team processes to improve performance. Some of the common attributes associated with efficient and innovative teams are distributed leadership[11], communities of practice[12], or "BA" (shared space for emerging relationships)[13], and psychological safety (a sense of mutual trust in taking interpersonal risks)[14].

The most commonly used tools to measure these features, such as surveys and qualitative or ethnographic observations, however, are subjective and often inaccurate. Recent Internet and e-mail technologies have finally made it possible to capture information on interpersonal communication. This has enabled researchers to analyze social networks in fine detail, and recently this field has attracted a great deal of interest. There is still, however, a gap between managerial concepts and comprehensive reviews and feedback mechanisms in the real physical world. Once sensor technologies become available on a daily basis, they will bridge this gap. We might be able to quantify massive amounts of information in the real world which now are characterized as implicit knowledge and know-how.

3. Approach

3.1 Organization (or Corporate) Level

As Pentland has shown in his previous research[1], we can quantify effective patterns of behavior by studying the correlation between behavioral patterns (e.g., attitudes, communication, and business processes) and performance indicators. For example, comparisons between and within teams would allow managers and team members to identify what behavioral patterns will lead to sought-after results so that they can subsequently replicate those behaviors.

The target number of people at this level is around 20 or more (which is larger than the experimental sizes described in Section 3.2 and Section 3.3) since in this case it is likely that not every subject knows each other. The key to this level of analysis is detecting common behavioral patterns in the organization and aggregating information generated from these patterns using collective intelligence[15] methods, rather than figuring out which particular people are efficient. The analyst, who may be a manager, therefore does not necessarily identify the worker. Alternatively, all data may be anonymized.

Choosing a useful performance indicator is particularly important for this approach. Financial profit is a clear indicator for any business. We should note, however, that many indicators, such as amount of communication, employee satisfaction, and customer satisfaction, lead to increased profits in the long run, so we believe that these indicators are also useful for measuring performance.

Three steps enable the correlation between behaviors and performance to be found statistically.

(1) Collect relevant behavioral data (such as the examples listed in Table 2) and performance data.

(2) Statistically analyze these data to see if a correlation exists. The simplest example is seeing a correlation between the number of interactions and performance. One approach is to check for particular parameters that are assumed to

be important factors in an organization, while another is to check all possible combinations to discover unforeseen relationships.

(3) Check all relations and their significance. The first approach is to focus on factors with significant correlations. If these results are desired and expected, no further action is necessary. If not, the organization should carefully analyze the results and attempt to characterize the causal factors that lead to the unexpected results. For example, let us assume there is a correlation between tone of voice and the success in negotiations. The data do not tell us whether skilled sales people speak with a certain tone because they are sufficiently knowledgeable and confident or whether customers merely feel better when sales people speak in a particular way. In the latter case, training employees to use effective speaking patterns may make sense.

Once effective behavior patterns are found, we can attempt to improve productivity and individual skill by modifying the following factors:

Physical environment: Studies have consistently shown that productivity flourishes in office environments where employees have easy access to one another [16]. Organizations and architects could measure the effects of minute changes in the environment using sensor data.

Information-technology environment: Researchers have recently begun tackling the problem of precisely measuring the effects of changes to the IT environment [17]. Sensors would also allow managers to conduct experiments on their own to determine if providing new tools to parts of the organization would be worth the investment.

Communication methods: Certain teams may be found to work better because of their communication flow, frequency, or participation levels. We can try to make the methods of these teams common knowledge within an organization and even standardize their methods.

Create a new communication environment: Once efficient teams have been identified, we can attempt to disseminate these practices throughout the entire organization through interpersonal knowledge exchange. One option is to restructure teams, while another option is to employ social-networking platforms to accomplish this.

3.2 Team Level

The target at this level is a relatively small number of people who work together with shared goals. They should therefore know one another well, foster mutual learning, and focus on self-improvement to be more innovative and overcome unproductive behaviors. Previous research has mentioned a few important factors within a team, such as roles [11], appropriate participation rates (occasionally equal and sometimes dominant), and appropriate amounts of stress and conflict [18].

Let us examine some approaches to detect these team behaviors using sensors. First, each factor is broken down into typical measurable behaviors. There are three phases: 1) a sign that something is about to happen, 2) a sign that something is happening, and 3) a sign that something has happened. Let us take "stress" as an example. In this case each phase can be operationalized as 1) what kinds of behaviors cause "stress", 2) what are "stress" coping behaviors, and 3) what happens once "stress" has been overcome. Ancona [19] noted that stress with a high probability of loss and a high level of pressure resulted in individual behavioral change, decreased amounts of discussion, increased variations in communication channel usage, decreased amounts of information used, decreased influence of group members, and increased decision centrality. Once this conceptualization of "stress" can be recognized from activities identified from sensor data, even if it is not completely accurate, we can create several new feedback mechanisms that allow teams to maintain appropriate stress levels, as well as discover how those teams behave when stress occurs. If it is possible to compare these behaviors with those in other teams, we will be able to know how efficient teams behave and what are the problems of a troubled team.

Team meetings and meeting reflection play critical roles in the construction of effective teams. Some are purely personal exercises, some are effectively institutionalized, yet others are still limited to educational settings. In previous research, two types of reflection have been identified: process and task reflection. In brief, task reflection targets "what we did," while process reflection targets "how we did it." Various types of information can be obtained using sensors, which may enable more effective process reflection. Past research has attempted to display speaking style [20] for real-time feedback and reflection. These feedback

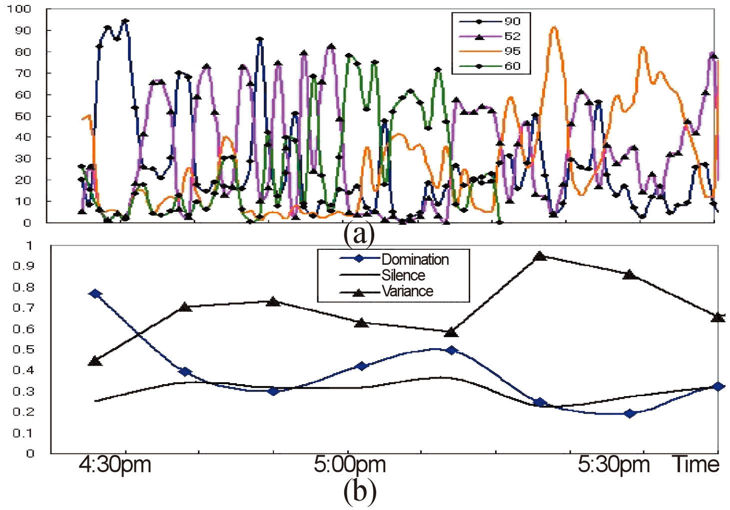

Fig. 1 Visualization of a one-hour conversation among four people: (a) participation rate of each person and, (b) team behavior indicators.

mechanisms were limited in these settings for meetings because it required specialized hardware around a table. However, now that wearable sensing devices have become available, this requirement has vanished.

We now discuss an example that illustrates the dynamics in a one-hour discussion between four people (including two of the authors). The graph at the top of **Fig. 1** shows how long each of the four spoke during one-minute time intervals, and this fine granularity tells us who led the conversation over that interval. For example, person #90 dominated the conversation for the first few minutes, and #52 subsequently responded. After several interchanges, #95 and #60 commented. #60 later took the floor and then grew quiet (he actually left the meeting). Next, #95 actively joined in the conversation. Although it might be difficult for people other than the participants to discover exactly what happened in the meeting and whether this meeting was successful, we found that the participants themselves greatly benefitted from this reflection tool because they understood the context of the data. This information quantitatively reminded them what had transpired, even if their memory of the conversation was not complete.

Table 1 Set of team behavior indicators.

Items	Detail
Degree of domination	If all members talk equally (i.e., if there are four members, each gets 25% of the time), this value decreases.
% of silence	Proportion of time no one was speaking
Total variance in audio signals	Amount of total voice energy calculated from the variance of voice signals

We can also define aggregated indicators, such as those listed in **Table 1**, which enable us to identify how people work together as a team. In Fig. 1, the bottom graph shows transitions in these indicators that correspond to data displayed in the top diagram. From this, we gain the sense that there were approximately three phases of the meeting: first, people spoke for equal lengths and were excited; next they grew quiet in the middle of the conversation when it was dominated by a particular person; and at the end they grew excited again.

We obtained qualitative comments from the participants:

- One participant felt that he had to change his behavior when his participation was much more or less than the others to attain the right balance. Someone also tried to involve other persons with low participation rate.
- Most groups try to change their behaviors as a team rather than identifying an individual problem.

3.3 Individual Level

The true power of sensors can be realized when they are paired with human knowledge [2]. Semantic interpretation of sensor data is possible, but it is not necessary if people reflect on their own behaviors and they remember the context of these behaviors. We rather anticipate sensor data may be retained without semantic information so that individuals are not forced into specific interpretations. This flexibility could accelerate user innovation [21].

We will now discuss some primitive and intuitive feedback tools. For example, there has been extensive work on expressing quantitative and qualitative data using color. Liu proposed visualizing textual context by using color patterns [22]. The Ambient Orb [23] is one example of a commercially available product that

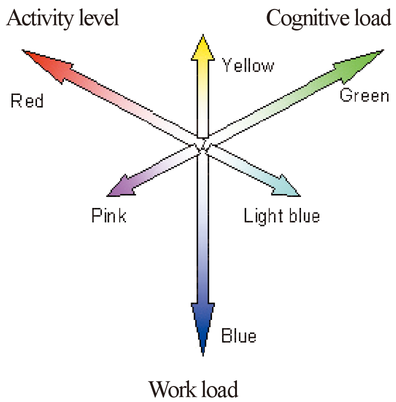

Fig. 2 *Sensible Orb's* color map.

uses this visualization paradigm. It retrieves data such as weather and traffic conditions from the Web and displays the result by mapping them to a color spectrum.

The "*Sensible Orb*" employs a similar visualization methodology. The objective is to intuitively provide users with processed sensing information along multiple dimensions. The Orb indicates the user's activity level, cognitive load, and work load by varying the color of the orb. The color mapping used in the Orb is shown in **Fig. 2**. Activity level, cognitive load, and work load are assigned to the colors red, green, and blue, respectively. Each measurement is a function of the following parameters:

- Activity level: movement energy, number of keys typed.
- Cognitive load: frequency of changing tasks, number of interruptions, number of e-mails to read.
- Work load: Hours of work, number of e-mails sent.

The transition in the user's state can also be represented by the color patterns of the orb. In our case, recent feature values are mapped to the middle of the orb and aggregated features to the edge. The whole orb can then be drawn by interpolating between these two colors. **Figure 3** shows some situations where the user's state is changing.

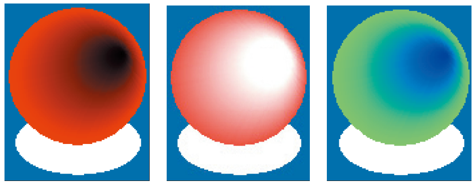

Fig. 3 User's state (a) moving towards lower activity, (b) moving towards a balanced state, and (c) increasing load.

4. Hardware Platform

We have previously designed the hardware and software infrastructure to collect and analyze behavioral data from many individuals over extended periods of time [24]. The badge hardware is compact, as shown in **Fig. 4**, comfortable to wear over long periods of time, and has a long battery life. This badge is capable of:

- Recognizing common daily human activities in real time using a single three-axis accelerometer,
- Extracting speech features in real time to measure nonlinguistic social signals and identify the social context while ignoring the words themselves,
- Interacting with the user through voice commands to quickly locate resources and information,
- Communicating with base stations in the 2.4-GHz band to transfer information to and from different users,
- Localizing indoor users by measuring received signal strength and using triangulation algorithms,
- Communicating with Bluetooth-enabled cell phones, PDAs, and other devices to detect people in close proximity,
- Capturing face-to-face interaction using an IR sensor.

We defined some parameters below:

- IR signals were transmitted (containing the transmitting badge's ID) every two seconds.
- Bluetooth-device IDs were captured every ten seconds. As we configured the

Fig. 4 Wearable badge.

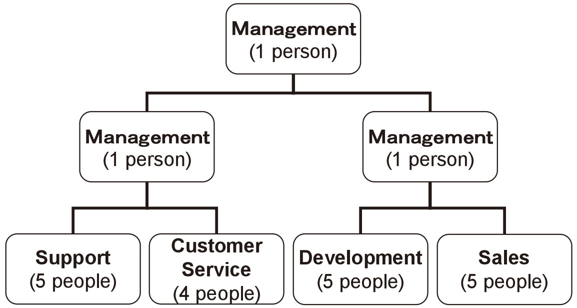

Fig. 5 Organizational chart of the company under examination.

devices to record a limited number of Bluetooth IDs every five seconds, not every device that was within range was logged.

5. Experimental Setting and Results

5.1 Target Organization

We deployed our hardware platform for a period of 20 working days in the marketing division of a bank in Germany that consisted of 22 employees distributed into four teams: development, sales, customer service, and support. The division's organization is shown in **Fig. 5**. Each of these teams was overseen by a manager, who in turn was supervised by a mid-level manager. These mid-level managers were responsible for two teams, and they reported directly to the division manager. We treated the mid- and division-level managers as a single team in the analysis. The division was split across two floors, and some teams were co-located in a single room while others had employees from multiple teams in them.

5.2 Experimental Procedure

One of the reasons we used this bank as an experimental site was their desire to enhance their productivity through a better understanding of their behavior. We also collected e-mail traffic data in this organization before and during the badge platform deployment, and they were already familiar with some of the preliminary results that came from this data. Due to their familiarity with their e-mail communication data, their major interests were (1) common behavioral patterns, (2) the differences between e-mail and face-to-face interaction, and (3) the relationship between behavioral patterns and performance

We deployed another type of badge throughout the bank to roughly track the location of subjects. Fourteen of these badges were distributed across two floors of the bank's building and were continually discoverable over Bluetooth.

We also obtained additional data that supplemented the behavioral information collected using the badge.

- E-mail logs, which only had from, to, and timestamp fields
- Daily surveys, which we used as a subjective measure of performance. Employees were asked to respond to the following questions on a scale from 1 (very high) to 5 (very low) at the end of each day.
  - 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's interactions?
- The bank's objective performance data, such as the number of sales campaigns, sales volume, and customer satisfaction score. These data have not been included in this paper, but we generally hypothesize that more face-to-face interaction is correlated with better performance on harder tasks, while less face-to-face is correlated with better performance on simpler tasks.

In order to recognize behavioral patterns and their effectiveness, we processed the raw data we received into the features listed in **Table 2**. We also used one social network parameter, "betweenness centrality," to understand how central

Table 2 Variables for regression analysis.

Category	Item
Profile	team, room, floor, status (manager/employee)
Motion	average energy per month, % of time in high, medium, and low activity levels
Audio	% of speaking time
IR	betweenness, total number of detections, number of detected people in the same team, same room, same floor, same status, and number of detected people in different teams, rooms, floors, and statuses
Bluetooth	same as IR but calculated with number of Bluetooth detections
E-mail	same as IR but calculated with number of e-mail exchanges
Survey	survey questions Q1 to Q4

people were in the functioning of the organization from a communication standpoint.

5.3 Correlation among Behaviors and Performances

We first calculated the average number of each parameter per day person by person. We then conducted exhaustive linear regression and one way ANOVA analyses between behavioral and performance parameters as described in Section 3.1.

Some findings from the analysis are as follows.

- 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 (and, of course, for the bank as well) that used e-mail communication as a proxy for the social network of an organization, since these two are in fact negatively related.
- The analysis of IR data yielded interesting results on differences across teams ($p < 0.01$). It appeared that there were three types of teams: those with high levels of intra-team communication, those with a moderate amounts, and many with low levels of communication.
- The number of different people that an individual interacted with over the course of the day had a moderate correlation with question Q1 ($r = 0.19$, $p = 0.01$), while the total amount of time spent in face-to-face communication was correlated with the responses to questions Q1, Q2, and Q3 ($r = 0.27$, 0.22, and 0.31; $p = 0.0008$, 0.006, and 0.0001).
- Bluetooth data analysis indicated that the number of people easily accessible was significantly different between people on different floors. People on the one floor had on average 4.08 people who were easily reachable per day, while people on another floor had 15.3 ($p < 0.01$). We posited that people on the latter floor were more stationary, making them more available to others on their team and in their rooms.
- We found that the percentage of time a person was at a low activity level during the day was negatively correlated ($r = -0.202$, $p = 0.01$) with that person's individual perception of productivity (Q1). A low activity level could mean the person was sitting in their office and not moving too much or walking around. This implies that if the percentage of time a person is sitting working in their office increases, so does their individual perception of productivity.
- No significant differences were found in the speaking patterns of employees grouped by team. This may be a curious if people in a particular group, such as customer service, are supposed to talk much more than others.

5.4 Comparison of Different Interaction Channels

We were able to visualize communication within and between teams and individuals by using e-mail and face-to-face interaction data. The number of e-mails exchanged across teams is represented by the thickness of the arcs below each box in **Fig. 6** (a) to (c), and the amount of face-to-face interaction is represented by the thickness of the arcs above each box. It is striking that while e-mails had little variation across days, face-to-face communication changed dramatically day by day.

Figure 7 illustrates a communication network between individual workers (a) through e-mail, (b) through face-to-face, and (c) a combination of both [25]. As these figures show, there are substantial differences between the e-mail and face-to-face networks. That is, there are people who are highly central to the

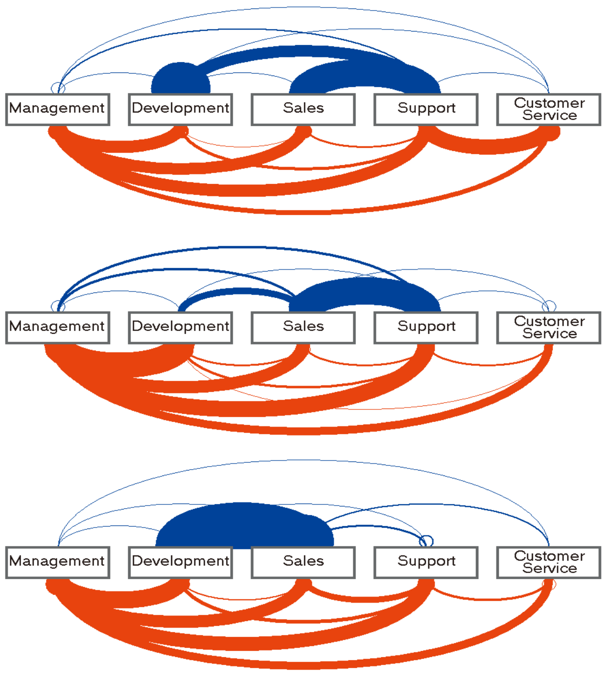

Fig. 6 Face-to-face communication (arcs above each block) vs e-mail traffic (below block) on days 1, 2, and 3.

e-mail network, but peripheral in the face-to-face network, and vice versa.

Combining the e-mail and face-to-face networks leads to a more complete depiction. As Fig. 7 (c) shows, there is a core cluster of well-connected people (the large circle). We hypothesized that face-to-face would provide information on the dynamic characteristics of the organization since the amount of e-mail was relatively stable.

5.5 Characteristics of Each Job Type

Gloor previously hypothesized that a person in a creative job (who needs to create something new) exhibits dynamic and flexible communication patterns, while people in high-performance jobs (who need throughput and accuracy rather than creativity) have stable communication patterns. In Ref. 26), Kidane and Gloor

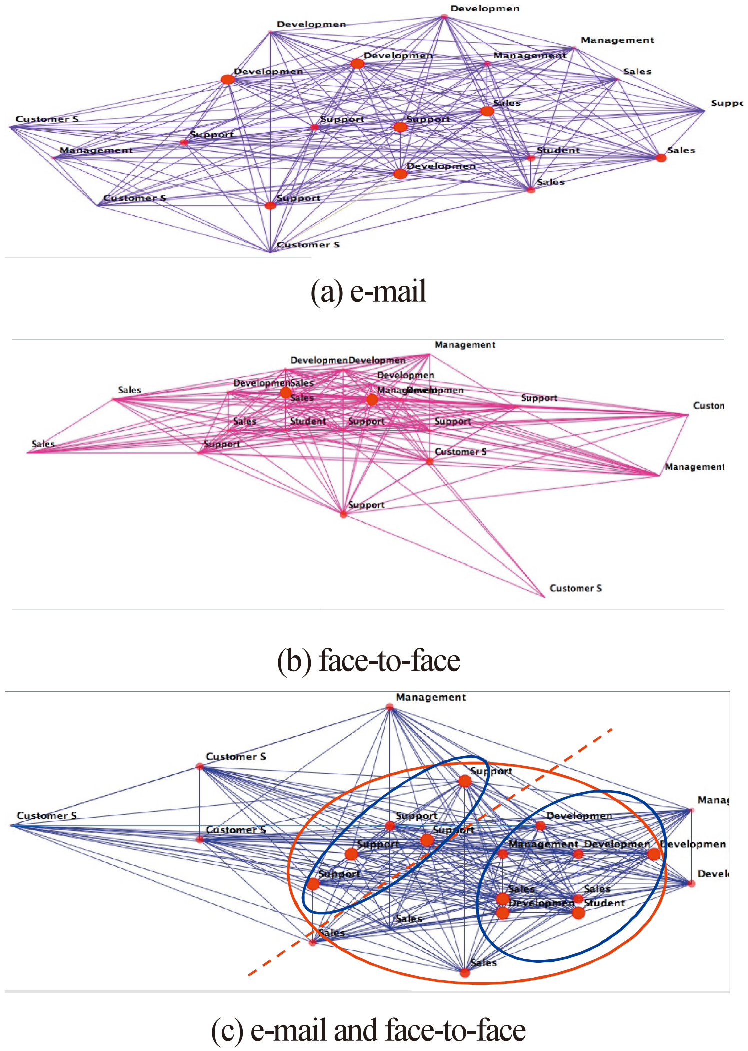

Fig. 7 Communication networks in different channel.

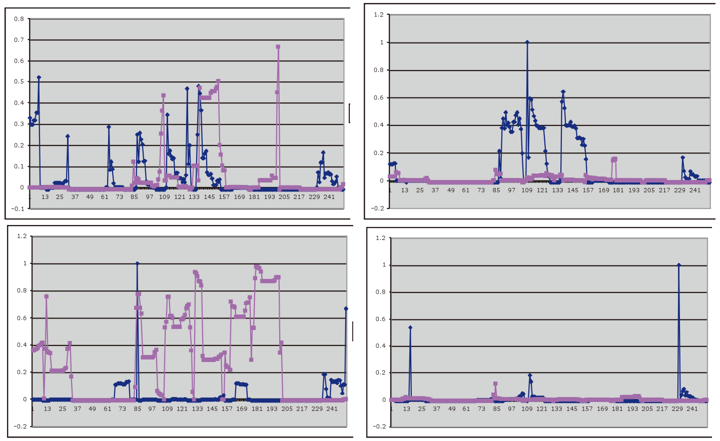

Fig. 8 Fluctuations in the betweenness centrality of individuals.

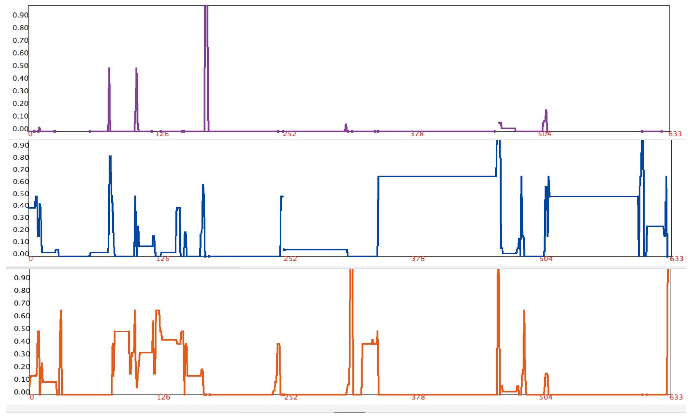

Fig. 9 Fluctuations in betweenness centrality. From top to bottom: customer service, development, and sales.

found a clear separation between high-performing workers and highly creative ones in their communication patterns. Highly creative workers occupy varying network positions: they are occasionally in the center and sometimes peripheral. This means that they exhibit fluctuating betweenness centrality over time in terms of social-network analysis. High performance, on the other hand, has steady betweenness centrality.

Figure 8 illustrates that individual bank employees exhibit a large variance in their communication patterns [25]. The actor in the top-left window who has large fluctuations both in e-mail and face-to-face interactions indicates that they are involved in creative activities, while the steady pattern of the actor in the lower-right window is indicative of a person who communicates very little and continuously, most likely in a high throughput role.

It is possible to conduct the same analysis on the group level. **Figure 9** illustrates the split of the department into creative and high throughput teams. The customer-service team, having the repetitive task of processing new contracts, clearly requires the most throughput, with a steady communication pattern. In contrast, sales and development teams tend to exhibit highly fluctuating communication patterns, which is reasonable because they require creativity in order to plan marketing campaigns and develop the corporate website. As these results show, once we define and quantify the proper indicators, such as a "creative job," we are able to ensure that each team has the capabilities it is supposed to or, if not, find who does have those capabilities.

5.6 Restructuring the Organization

Based on this analysis (the communication patterns and function of each team), we proposed structural changes for this organization:

- Separation of performance-oriented (sales and customer service) and creativity-oriented (development and sales) teams, as indicated by the dotted line in Fig. 7 (c), in order to strengthen these tendencies.
- Trading peoples between development and sales according to their frequency of communication. Sales persons who spoke frequently with the development team may be good candidates for reassignment.

Our proposal was based on a strategy to integrate similar people, although communication between groups could decrease. Of course it is possible to create another proposal based on the concept that people with different skill sets should work together.

After deliberating on these findings, the bank restructured their organizations along the lines of our recommendations. In fact, managers in the bank had planned to modify their organizational structure. While they certainly incorporated a large amount of diverse information into their decision, our proposal supported the manager's qualitative inclinations. We believe that quantitatively aiding qualitative intuition is an extremely beneficial use of sensors. In addition to this reorganization, the bank strongly recommended our analytical approach to an executive committee as a way to increase organizational effectiveness.

6. Conclusion

We presented concepts relating to a sensor-based work style, organizational behavior management, and individual learning processes. In the 17th century, the microscope had a huge impact on the medical and scientific domains. Now an even bigger impact may be realized by continuously recording the real activities of enterprises and individuals supplemented with sophisticated analysis and visualization methodologies. In other words, a "business microscope".

We anticipate that we will be able to acquire deep insights into human beings and their mental models and integrate them into an effective education mechanism to change individual and organizational behavior.

Acknowledgments The authors would like to thank Joseph A. Paradiso, Joshua Lifton, the *Responsive Environments Group* at the MIT Media Laboratory, Thomas Malone at the MIT Sloan School of Management, Ken Endo, Francesca Grippa, Joe Hsueh, Jason Jingan Liu, Elisabeth Megally, Masashi Nakatani, Yasuhiro Ono, Yulia Poltorak, Harry Reddy, Gagan Singh, Reginald Smith, and Daisuke Suzuki for their invaluable help.

References

1) Pentland, A.: Socially aware computation and communication, *IEEE Computer*, Vol.38, No.3 (2005).
2) Yano, K.: What is sensor? Its impact beyond internet, *IPSJ Trans.*, Vol.48, No.2 (2007). (in Japanese)
3) Ara, K., Kanehira, N., Megally, E., Poltorak, Y., Singh, G., Smith, R., Suzuki, D., Mortensen, M., Van Alstyne, M. and Pentland, A.: Sensible organizations inspired by social sensor technologies, MIT Media Laboratory (online), available from ⟨http://vismod.media.mit.edu/tech-reports/TR-602.pdf⟩ (accessed 2007-06-28).
4) Gladwell, M.: *Blink*, Little Brown and Company (2005).
5) Choudhury, T.: Sensing and modeling human networks, Ph.D. dissertation, MIT Media Laboratory (2004).
6) Madan, A. and Pentland, A.: Vibefones: Socially aware mobile phones, *Proc. ISWC*, pp.109–112 (2006).
7) Gips, J.P.: Social motion: Mobile networking through sensing human behavior, Master's thesis, MIT Media Laboratory (2006).
8) Weiser, M.: The computer for the 21st century, *IEEE Pervasive Computing*, pp.19–25 (Jan.-Mar. 2002).
9) nTAG interactive (online), available from ⟨http://www.ntag.com/⟩ (accessed 2007-06-10).
10) Vocera communications (online), available from ⟨http://www.vocera.com⟩ (accessed 2007-06-29).
11) Ancona, D.: Leadership in an Age of Uncertainty (online), available from ⟨http://sloanleadership.mit.edu/pdf/LeadershipinanAgeofUncertainty-researchbrief.pdf⟩ (accessed 2007-06-10).
12) Wenger, E.: *Communities of Practice: Learning, Meaning, and Identity*, Cambridge University Press (1998).
13) Nonaka, I.: *The knowledge-creating company: How Japanese companies create the dynamics of innovation*, Oxford University Press (1995).
14) Senge, P.: *The Fifth Discipline: The Art and Practice of the Learning Organization*: New York: Doubleday (1990).
15) MIT Center for Collective Intelligence (online), available from ⟨http://cci.mit.edu/research/index.html⟩ (accessed 2007-06-29).
16) Baker, W.: *Achieving Success Through Social Capital*, New York, NY: John Wiley & Sons (2000).
17) Sinan, A., Brynjolfsson, E. and Wu, D.: Which came first, IT or productivity? The virtuous cycle of investment & use in enterprise systems, *Proc. International Conference on Information Systems* (2006).
18) Wittenbaum, G.M.: The functional perspective as a lens for understanding groups, *Small Group Research*, Vol.35, pp.17–43 (2004).
19) Gladstein, D.: Group decision making under the tycoon game, *Academy of Management*, Vol.28, No.3 (1985)
20) DiMicco, J.M.: Using visualizations to review a group's interaction dynamics, *CHI* (2006).
21) Hippel, E.V.: *Democratizing Innovation*, The MIT Press (2005).
22) Liu, H. and Maes, P.: The aesthetiscope: Visualizing aesthetic readings of text in color space, *Proc. 18th International FLAIRS Conference* (2005).
23) Ambient devices (online) available from ⟨http://www.ambientdevices.com⟩ (accessed 2007-06-28).
24) Olguín Olguín, D.: Sociometric Badges: Wearable Technology for Measuring Hu-

man Behavior, *MAS Thesis. Massachusetts Institute of Technology* (2007).
25) Gloor, P., Oster, D., Putzke, J., Fischbach, K., Schoder, D., Ara, K., Kim, T., Laubacher, R., Mohan, A., Olguin Olguin, D., Pentland, A. and Waber, B.: Studying Microscopic Peer-to-Peer Communication Patterns, *Proc. Americas Conference on Information Systems* (2007).
26) Kidane, Y. and Gloor, P.: Correlating temporal communication patterns of the Eclipse open source community with performance and creativity, *Computational & Mathematical Organization Theory*, Vol.13 (2007).

(Received June 30, 2007)
(Accepted January 8, 2008)
(Released April 9, 2008)

Koji Ara received the B.Sc. and M.Sc. degrees from Waseda University, Tokyo, Japan, in 1996 and 1998, respectively, both in electrical engineering. In 1998, he joined the Hitachi Central Research Laboratory, Tokyo, Japan, and is now a Researcher at the Hitachi Advanced Research Laboratory. He was a visiting scientist at the MIT Media Laboratory from 2005 to 2007. His research interests include design methodologies and applications for sensor network systems.

Naoto Kanehira is a masters student at MIT Sloan School of Management (Fulbright Scholar) and Harvard Kennedy School of Government (Joint Japan/World Bank Scholar) with prior experiences at McKinsey & Co., UNDP and World Bank/IFC. He graduated from Keio University where he researched at Prof. Tokuda & Prof. Murai's group.

Daniel Olguín Olguín received a B.S. degree in Electronics and Communications Engineering and an M.S. degree in Electronic Systems Engineering, both from Tecnológico de Monterrey Campus Monterrey (Mexico) in 2003 and 2005 respectively. He is currently a doctoral student at the MIT Media Laboratory. His research interests include wearable computing for healthcare applications, machine learning, pattern recognition, context aware computing, body sensor networks and digital signal processing.

Benjamin N. Waber received his B.A. and M.A. in Computer Science from Boston University in 2006. He is currently a doctoral student at the MIT Media Laboratory in the Human Dynamics group. His research interests include social networks, opinion aggregation, computational psychology, and body sensor networks.

Taemie Kim received a B.S. degree in Electrical Engineering and Computer Science from KAIST (Korea) and an M.S. degree in Electrical Engineering from Stanford University in 2003 and 2006 respectively. She is currently a doctoral student at the MIT Media Laboratory. Her research interests include human-computer interaction, computer supported collaborative work and mobile feedback systems.

Akshay Mohan received a Bachelor of Technology from the Indian Institute of Technology–Kanpur (India) and an M.S. degree in Media Arts and Sciences from the MIT Media Laboratory. Since 2004, he has been working as a consultant and researcher in technology design, organizational frameworks and inter-organizational collaborations. His research interests include human behavior modeling and change.

Peter Gloor is a Research Scientist at the MIT Center for Collective Intelligence where he leads a project exploring Collaborative Innovation Networks. He is also teaching at the University of Cologne and at Helsinki University of Technology. His research on visualizing knowledge and analyzing social networks is commercialized by software startup galaxyadvisors. Earlier, Peter was a Partner with Deloitte Consulting, leading its e-business practice for Europe, a Partner with PricewaterhouseCoopers and the Section Leader for Software Engineering at UBS.

Robert Laubacher is a research scientist at MIT's Sloan School of Management, where his work focuses on how information technology is transforming business practices.

Daneil Oster studied Information Systems and Information Management at the University of Cologne, Germany and holds a Master's Degree focusing on Information Management and Organizational Development. He is currently working on his Ph.D. Thesis regarding Social Networks in Enterprises and their impact on business performance. After his traineeship in banking and finance at Kreissparkasse Keln (Cologne) he gained professional experience in fields such as Business Development, IT, Online-Banking and Project Management. He also works for the Center of Applied Social Network Analysis at University of Cologne.

Alex (Sandy) Pentland is a pioneer in mobile information systems, technology for developing countries, consumer health, and smart environments. One of the most-cited computer scientists in the world, with international awards in the Arts, Sciences and Engineering, he was chosen by Newsweek as one of the 100 Americans likely to shape this century. His focus is the development of human-centered technology, and the creation of ventures that take this technology into the real world. His work provides people with a clearer picture of their social environment, and helps companies and communities to reinvent themselves to be both more human and productive. He is Founder and Faculty Director of both MIT's new Legatum Center for Development and Entrepreneurship, and of MIT's Human Dynamics Laboratory.

Kazuo Yano received the B.S., M.S., and Ph.D. degrees from Waseda University, Japan, in 1982, 1984, 1993, respectively. From 1991 to 1992 he was a Visiting Scientist at the Arizona State University. Since he joined Hitachi Ltd. in 1984, he has explored the fusion of technology layers. He has conceived the complementary pass-transistor logic (CPL), which is known to be one of the best energy-efficient logic families, and has also done pioneering work on world-first room-temperature single-electron memories. He supervised research teams of SuperH mobile application processors, which are used for camera phones worldwide. He has expanded activities to life and business microscope, sensor-net, and advanced human interaction. Since 2006, he is a Senior Chief Researcher and the Director of the Human Information Laboratory. He is a Fellow of the IEEE, a member of the Japan Society of Applied Physics, and the IEICE of Japan. He served on Technical Program Committee Members of IEDM, DAC, ASSCC and ASP-DAC, and is serving on TPC of SPOTS and EmNet. He is the Program Co-Chairman/Chairman of 2006/2007 Symposium on VLSI Circuits. He received 1994 IEEE Paul Rappaport Award, the 1996 IEEE Lewis Winner Award and the 1998 IEEE Jack Raper Award, and the Most Promising Scientists Award of 2007 Ettore Majorana International School on Mind, Brain, and Education.