

Social Sensors for Automatic Data Collection

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ABSTRACT

We propose a social network data collection method that uses wearable social sensors to automatically detect social interactions. This method offers clear advantages over traditional methods since data is automatically collected by electronic sensors rather than humans. We present the design, implementation and deployment of a wearable social sensing platform that can measure and analyze human behavior in a variety of settings and applications. Social sensors are capable of capturing individual and collective patterns of behavior by automatically measuring the amount of face-to-face interaction, conversational dynamics, physical proximity to other people, and physical activity levels. We describe five studies that have been carried out using this platform and discuss other possible application scenarios.

Keywords

Social sensors, social networks, data collection methods.

INTRODUCTION

Standard methods to measure and evaluate human behavior, such as surveys, often suffer from subjectivity and memory effects. Pentland envisioned a device that could accurately and continuously track the behavior of hundreds of humans at the same time, recording even the finest scale behaviors with great accuracy (Pentland, 2006). Such a device would replace expensive and unreliable human observations with automated, computer-mediated ones. The automatic discovery and characterization of face-to-face communication and social interaction would allow us to gather interaction data from large groups of people. This could potentially remove two of the current limitations in the analysis of human behavior: the number of people that can be surveyed, and the frequency with which they can be surveyed.

Social interaction can take on several forms, face-to-face interaction being one of the most frequent and important of them (Kirkman, Rosen, Tesluk and Gibson, 2004). As a result of the digital revolution, people can now communicate with others over long distances using mobile telephones, e-mail, instant messaging clients, video conferencing, and other forms of digital media. However, little has been done to exploit the fact that people already carry with them wearable electronic devices such as cellular phones, PDAs, MP3 players, digital watches, and the like. These devices have the necessary computational power to process and analyze information about their users' behavior. These body-worn sensor networks mean that we can potentially know who talks to whom, and even how they talk to each other.

Even though some devices already incorporate sensors capable of capturing context information, we believe that there is no single platform capable of measuring a wide range of variables such as the amount of face-to-face interaction, non-linguistic social signals, location, physical proximity to other people, and context information to facilitate the study of social networks. There is a clear need for automatic tools to measure individual and group behavior in the social sciences. Researchers often rely on surveys and human observers to study human behavior, however this is often expensive and time consuming. Therefore, we propose the use of wearable social sensors that have proven to be useful and effective in the assessment of human behavior. We predict there will be a large demand for such tools in different research communities and by organizational engineering consulting firms in the near future.

In this paper we present the design, implementation and deployment of a wearable social sensing platform that can measure and analyze human behavior in a variety of settings and applications. We present initial results that demonstrate the usefulness of this data collection method.

The remainder of the paper is structured as follows: The following section describes previous work on wearable social sensors. Next, we present our proposed approach to collecting social network data. We then discuss some advantages of our method over traditional data collection methods. Several studies using our sensing platform are then described. Finally, we discuss different application scenarios and present our conclusions.

PREVIOUS WORK

Wearable ID badges are common devices that employees wear in large organizations to identify themselves to others or to gain access to certain locations or information. The *Active Badge* developed at Xerox PARC in 1992 was one of the first attempts to augment inanimate 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, automatic telephone call forwarding, and computer displays (Weiser, 2002).

More complex badge platforms have been developed after the *Active Badge*. In 1996, the *Thinking Tags* (Borovoy, McDonald, Martin and Resnick, 1996) were the first computationally augmented name tags that were capable of displaying how much two people at a conference or meeting had in common. Two years later they evolved into the *Meme Tags* (Borovoy, Martin, Vemuri, Resnick, Silverman and Hancock, 1998), allowing conference participants to electronically share brief ideas or opinions through a large LCD screen. This later became the *nTAG System*, a commercial solution to improve, measure, and automate meetings and events (nTAG Interactive).

The *Wearable Sensor Badge* developed at Philips Research Labs in 1999 (Farrington, Moore, Tilbury, Church and Biemond, 1999) was capable of detecting simple pre-ambulatory activities using an accelerometer. The *iBadge* (Park, Locher, Savvides, Chen, Muntz and Yuen, 2002) was designed to be worn by children to capture interactions with teachers and common classroom objects.

A wearable sensor package designed to measure face-to-face interactions between people with an infrared (IR) transceiver, a microphone, and two accelerometers (Choudhury, 2003). It was used to learn social interactions from sensory data and model the structure and dynamics of social networks. However, due to its size and weight, users reported feeling somewhat uncomfortable while wearing it. The *UbER Badge* (Laibowitz, Gips, Aylward, Pentland and Paradiso, 2006), developed at the MIT Media Laboratory, is a research platform for facilitating interaction in large groups of people by allowing users to bookmark people and exchange business cards electronically.

The best known commercially available push-to-talk system is the 802.11-based *Vocera Communications System* (Vocera Communications, 2007). Users talk through wearable badges that can be clipped to coat pockets, worn as pendants, or carried in holsters. The system centers on a server that maintains voice dialing phrases, badge session identifiers, e-mail addresses, telephone numbers, and names. Our wearable electronic badge has a similar form factor to the Vocera badge since the latter is already accepted by thousands of users in hospitals, retail stores, and service organizations (Stanford, 2003).

PROPOSED APPROACH

In (Olguin Olguin, Paradiso and Pentland, 2006) we presented the design of a wearable *communicator* badge, a push-to-talk system capable of playing audio messages and reminders through a speaker. Since then, the *communicator* badge has evolved into what we call a *sociometric* badge, a device whose main purpose is to automatically capture individual and collective patterns of behavior. We have manufactured three hundred *sociometric* badges and used them in real organizations to 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, 2007). Figure 1 shows a picture of a *sociometric* badge.



Figure 1. Sociometric badge

As we begin to deploy hundreds and even thousands of wearable sensors on regular workers, hospital patients, and the general population, the question shifts more toward a balance between what information can be gained and their broad, immediate user acceptance. In (Olguin Olguin and Pentland, 2006) we studied human activity recognition using wearable sensors in different parts of the body. We found that the best global activity classification performance was achieved when using three accelerometers placed on the chest, hip and wrist. However, we also found that it is possible to obtain similar results using only two accelerometers placed on the chest and hip. We are convinced that a minimal system formed by the combination of an electronic badge worn around the neck and a mobile phone carried by the user is the best type of platform that would allow us to study human behavior over extended periods of time.

We propose the use of wearable social sensors that have a small form factor and are comfortable to wear over long periods of time. In addition to some of the main features offered by previous badge platforms, our *sociometric* badges are also capable of:

- Recognizing common daily human activities (such as sitting, standing, walking, and running) in real time with at least 80% accuracy on average, using a 3-axis accelerometer combined with a mobile phone containing a second accelerometer and standard pattern recognition algorithms (Olguin Olguin and Pentland, 2006).
- Extracting speech features in real time to capture non-linguistic social signals such as interest and excitement, the amount of influence each person has on another in a social interaction, and unconscious back-and-forth interjections, while ignoring the words themselves in order to assuage privacy concerns (Pentland, 2005).
- Communicating with radio base stations in the 2.4 GHz radio band for sending and receiving information to and from different users, and transferring data. The base stations can either be other badges placed at fixed locations or compatible radio base stations, such as the *Plug* sensor network developed in the Responsive Environments group at the MIT Media Laboratory (Lifton, Feldmeir, Ono, Lewis and Paradiso, 2007).
- Performing indoor user localization by measuring received signal strength and using different triangulation algorithms that can achieve position estimation errors as low as 1.5 meters (Sugano, Kawazoe, Ohta and Murata, 2006).
- Communicating with Bluetooth enabled cell phones, PDAs, and other devices to study user behavior, detect people in close proximity, and even predict people's day-to-day and person-to-person communication with more than 95% accuracy (Eagle and Pentland, 2006).
- Capturing face-to-face interaction time using an IR sensor that can detect when two people wearing badges are facing each other within a 30-degree cone and 1-m distance. (Choudhury, 2003) showed that it was possible to detect face-to-face conversations using an earlier version of the *sociometric* badges with 87% accuracy when looking at segments that lasted at least one minute.

Table 1 summarizes the different features that can be automatically measured in real time by the *sociometric* badges. All features are calculated and time-stamped on a per-minute basis.

Category	Sensor	Features	Notes
Motion	3-axis accelerometer	(1) Mean energy of accelerometer signal (2) Standard deviation of energy (3) Activity level (4) Main activity (sitting, standing, walking, running)	A person is in <i>high</i> activity level when their motion energy is one standard deviation above the mean value of everyone else wearing the badge at the same time. A person is in <i>low</i> activity level if their motion energy is one standard deviation below that mean value, and they are in <i>regular</i> activity level if their motion energy is within one standard deviation of that mean value.
Speech	Microphone	(5) Mean variation in speech signal (volume) (6) Standard deviation of speech variation (7) Percentage of time speaking (8) Percentage of voiced/unvoiced speech (9) Average speaking segment length (10) Speaking speed	The speech signal is passed through a band-pass filter bank that divides the speech frequency spectrum into four bands: f_1 from 85 to 222 Hz, f_2 from 222 to 583 Hz, f_3 from 583 to 1527 Hz, and f_4 from 1527 to 4000 Hz. A voice activity detection algorithm uses these signals to calculate features 7 and 8.
Face-to-face interaction	Infrared transceiver	(11) Total amount of time each badge is detected within the face-to-face interaction range	Face-to-face interaction can be detected when two people wearing badges are facing each other within a 30-degree cone and 1-m distance.
Proximity	Radio frequency transceiver or Bluetooth module	(12) Total amount of time each badge is detected in close proximity (less than 1 meter)	A badge is detected in close proximity using the RSSI (Received Signal Strength Indicator) values from an RF transceiver or Bluetooth module.
Location	Radio frequency transceiver or Bluetooth module	(13) Detected base station number(s) and RSSI values (14) Estimated location	The location is calculated by triangulating the RSSI values from different base stations.

Table 1. List of features measured by the sociometric badge

ADVANTAGES OVER TRADITIONAL SOCIAL NETWORK DATA COLLECTION METHODS

(Hanneman and Riddle, 2005) discuss the advantages and disadvantages of traditional social network data collection methods: *Full network* methods require information about each actor's ties with all other actors to be collected. One example is the flow of e-mail between all pairs of employees in a company. Full network data allows for very powerful descriptions and analyses of social structures. Unfortunately, full network data can also be very expensive and difficult to collect. Obtaining data from every member of a population, and having every member rank or rate every other member can be very challenging tasks in any but the smallest groups. For large groups of people, the task is practically impossible. It is also unclear what the relationship between electronic/survey data and face-to-face interaction is.

Snowball methods begin with a focal actor or set of actors. Each of these actors is asked to name some or all of their ties to other actors. Then, all the actors named (who were not part of the original list) are tracked down and asked for some or all of their ties. The process continues until no new actors are identified, or until we decide to stop. The snowball method can be particularly helpful for tracking down "special" populations (often numerically small sub-sets of people mixed in with large numbers of others). There are two major potential limitations and weaknesses of snowball methods. First, actors who are not connected are not located by this method. The presence and numbers of isolates can be a very important feature of populations for some analytic purposes. The snowball method may tend to overstate the "connectedness" and "solidarity" of populations of actors. Second, there is no guaranteed way of finding all of the connected individuals in the population (Hanneman and Riddle, 2005).

Our proposed approach to capture social networks and measure human behavior has several advantages over existing methods such as direct observation by humans, the use of pervasive cameras to videotape social interactions, and the use of surveys. Direct observation of humans by humans is expensive and limited to a few subjects 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 a single unobtrusive tool. The effort needed to deploy sensors is minimal compared to that of traditional methods. The best example of social sensors that are already carried by millions of users are mobile phones. They know who we talk to, where we go, who we spend time with, and they have the potential to measure the same features that our *sociometric* badges do.

EXPERIMENTS

To demonstrate the effectiveness of our tool, a series of experiments in collaboration with other researchers have been carried out. In this section we describe these experiments and the general procedure that we followed.

Experimental Procedure

Sociometric badges log infrared detections (containing the transmitting badge's ID) every time they are facing other badges, Bluetooth devices' IDs, motion data using a motion sensor, and band-pass filtered audio. Each badge is detectable over Bluetooth and performs a Bluetooth scan every five seconds. The audio is sampled at 8 kHz and averaged over 64 samples so that the raw speech signal cannot be reconstructed in order to maintain privacy. All data is anonymized and each participant has access to their own data upon request.

In addition to the wearable badges, base stations are placed in fixed locations inside a building in order to roughly track the location of interaction events as well as subjects. Base stations are continually discoverable over Bluetooth. A central computer is used for data collection. Badge collected data can be transferred via USB or using a wireless link and uploaded to a server.

At the end of each day participants are asked to respond to a survey that may include some of the following questions:

1. How would you rate your workload today?
2. How hard was it to obtain the information that you needed to do your job?
3. How would you rate the quality of your work group interaction today?
4. How satisfied do you feel with your job performance today?
5. How productive do you think you were today?

Each question can be answered on a 5-point likert scale: (1 = very high) (2 = high) (3 = average) (4 = low) (5 = very low). Post-processing of the data collected using the badges allows us to find relationships among the different features (described in table 1), the participants' subjective ratings to questions like these, and objective performance outcomes (such as productivity ratings, task completion times, delays, among others) depending on the experimental setting.

Identifying 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. This data gave us a very detailed picture of the inner operations of the division (Gloor, et al., 2007).

In this experiment we used e-mail as a representative proxy for electronic communication since it was the most frequently used means of communication among employees of this organization. In future experiments we plan to incorporate other electronic communication channels in our analysis. We found that the number of people in close proximity had a high negative correlation with the number of e-mails exchanged ($r = -0.55$, $p < 0.01$, $N=22$). We can conclude that the greater the

number of people who are in close proximity to an individual, the lower volume of electronic communication the individual will have. This has powerful implications for previous work that has used e-mail communication as a proxy for the social network of an organization. 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 the monthly averages of questions Q4 (job satisfaction) and Q3 (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. A multi-linear regression was fit to model question Q3 (group interaction satisfaction) using total communication and betweenness. We found that this regression had a correlation coefficient of $r=0.62$ with $p=0.01$ (explaining about 30% of the variance in group interaction satisfaction) (Waber, Olguin Olguin, Kim and Pentland).

Measuring Productivity in a Data Services Company

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. Electronic communication was not extensively utilized in this firm for task-related communication, so this data was not collected. 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 energy (feature 2 listed in table 1) across all behavioral groups. A similar relationship was found between variation in the speech signal (feature 5 listed in table 1) 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, Olguin Olguin, Kim and Pentland).

Group Feedback during a Leadership Forum

Students participating in a Leadership Forum held in Tokyo, Japan used *sociometric* badges during the duration of the forum. The Forum brought together 20 students from the US, mostly from universities in Greater Boston area, and 20 students from Japan, mostly from universities in Tokyo area, working in teams of 6 to 8 people. The Forum had three components: a leadership education session, thematic sessions on two contemporary issues, "energy and climate change" and "globalization and manufacturing" (lectures, discussions, and site visits), and an experiential group project that involved creative engineering. Figure 2 shows one team's face-to-face interaction pattern captured by the *sociometric* badges over the course of one week. Half of the students in the team were Japanese (4KF, 4MH, 4YI, 4TS) and the other half were American (4HS, 4GO, 4SI, 4BR). We can observe from the width of the links (turn-taking frequency) that the American students interacted mostly among themselves during the first days and how this pattern changed over the course of the week as the Japanese students became more integrated in the team. We can also see that a new (Japanese) member joined the team on the sixth day (4RK) and that his interaction pattern was very active with team member (4YI), probably because he had to be updated on the status of the project. By the end of the week the interaction pattern of the team became more balanced. The constant interaction pattern between student 4BR and student 4YI may suggest that these students were the "American leader" and the "Japanese leader" in the team, respectively. A more in-depth analysis of the data is necessary in order to verify these observations.

Evaluating Team Performance

Each spring all first-year students in a Master of Public Policy program spend two weeks in an exhaustive study of a particular policy issue. Through readings and briefings by experts on the subject in question, each team of students develops and presents a professional analysis of the policy problem. A group of over 100 students participating in the 2007 exercise wore social sensors for a period of two weeks. In previous years, paper surveys were collected using the traditional *snowball* method. We expect that social sensors will allow us to identify behavioral patterns of high and low performing teams, as well as the team formation process. A similar approach to that of previous experiments will be taken: finding relationships between behavioral features (captured by social sensors) and performance outcomes (completion time, winning team, grades received, among others).

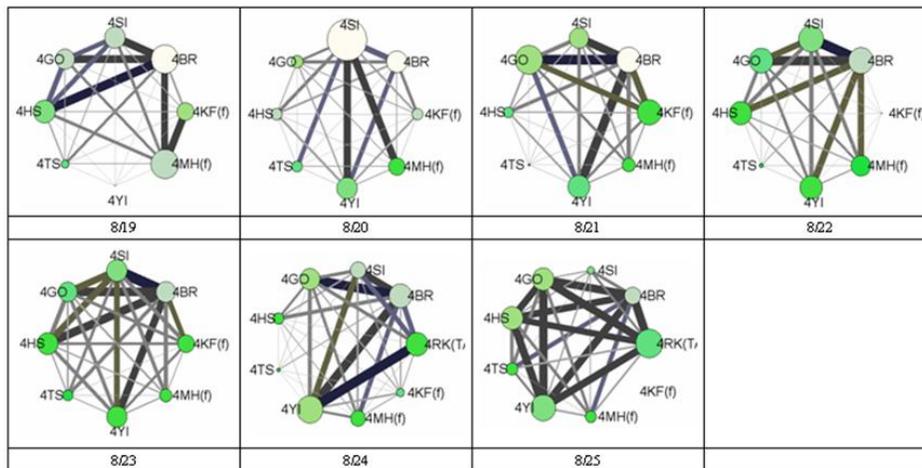


Figure 2. Evolution of a team’s face-to-face interaction pattern over the course of one week. The size of each circle represents the amount of time a person participated in the conversation. The color of the circle represents how interactive each person was based on their turn-taking pattern (the greener, the more interactive), and the width of the edges represents the frequency of turn-taking between two participants. (Image courtesy of Taemie Kim).

Identifying Interaction Patterns in a Hospital’s PACU

An experiment in a Boston hospital’s post anesthesia care unit (PACU) is currently under way. 70 nurses are wearing *sociometric* badges every day (for a period of three weeks). The goal is to identify possible bottlenecks and inefficiencies in patient throughput. We have installed base stations in 30 beds and 10 phones located in this unit. Figure 3 shows a picture of the face-to-face social network captured using sociometric badges in this hospital’s care unit. Previously, a paper-based survey study was conducted in this hospital’s unit (Samarth, 2007). We expect to be able to compare those results with our automatically collected data.

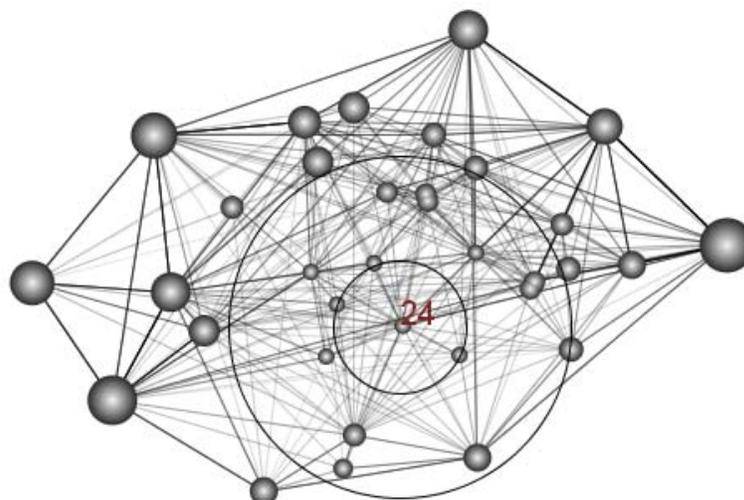


Figure 3. Face-to-face social network captured using sociometric badges (zooming into badge number 24). The smaller circles represent single nurses. Larger circles represent groups of nurses who are tightly interconnected. (Image created using the small-world network visualization tool created by Stephen Frowe).

APPLICATION SCENARIOS

Sensible organizations

Organizations will become truly *sensible* when they start deploying hundreds or thousands of wireless environmental and wearable sensors capable of monitoring human behavior, extracting meaningful information, and providing managers with group performance metrics and employees with self-performance evaluations and recommendations. *Sensible* organizations is a new concept of social sensor network technologies that will help improve organizational practices. Social sensors could potentially measure, analyze, and reveal organizational dynamics by closely looking at interactions and social behavior among employees of an organization. Companies using this type of sensors could have a better understanding of how they work and how they can improve their daily routines in order to increase productivity, innovation, and job satisfaction.

Knowledge management and collaboration tools

Employees working in large organizations often find it difficult to discover colleagues working on similar projects or with similar interests or expertise. A knowledge management system consisting of environmental and wearable sensors, computers, and software that continuously and automatically monitors an organization's social network and its different areas of knowledge and expertise would facilitate information transfer and promote collaboration. Data mining of digital documents, face-to-face interaction, e-mail, instant messaging, and other forms of communication will provide new information on how complex social structures work, how to optimize human interaction, and how to engineer organizations.

The future of healthcare

Carrying an un-obtrusive device that continuously monitors one's health and prevents the most common diseases before they even occur has the potential to revolutionize the healthcare domain. Patients usually go to a doctor once symptoms become apparent. A self-monitoring device that can detect the earliest symptoms of illness and alert its user could prevent some of the most prevalent diseases. (Sung, Marci, and Pentland, 2005) showed that non-invasive behavioral measures such as voice features and body motion are correlated with depression state and can be used to classify emotional state and track the effects of treatment over time. Social sensors could be used as self-monitoring devices that alert their users or their family members of early symptoms of depression. They could also be used to monitor the daily activities of the elderly, detect falls and behavioral changes, and automatically alert a family member or a doctor of a potentially dangerous situation. Another major disease for which a self-monitoring device does not currently exist is obesity. Mobile phones could also be used as social sensors that keep track of energy expenditure, food intake, daily routines, and provide feedback and suggestions to their users.

Personal sales coach

Recent experiments in the have shown that it is possible to measure how persuasive a person is being when talking to others, how interested a person is in a conversation, how much attention a person is paying to someone, and how effective someone is at negotiating by measuring different voice features and body motion (Stoltzman, 2006). Social sensors could be used to track individual and global sales performance in retail stores and give advice on how to interact with clients more effectively. Sales representatives today lack sufficient feedback on their selling capability. Top performing sales representatives usually have good communication skills, exhibit a lot of enthusiasm and energy, and form a personal bond with their clients. Social sensors could also serve as personal sales coach devices that allow sales representatives and managers to reflect about their own performance and improve their sales skills.

Virtual worlds and social networking sites

Millions of users have online profiles in social networking sites (such as Facebook, MySpace, hi5, etc.) or characters in virtual worlds and multiplayer games (such as Second Life, The Sims, World of Warcraft, etc.). Interaction often requires that the user be seated in front of a computer and is currently limited to instant messaging, direct manipulation of virtual characters, and voice or video over IP. Combining the current features of social networking sites and virtual worlds with social sensors would enhance the users' experience by adding mobility and information from the real world.

Children and learning

Classroom behavior and social interactions of children could be studied using social sensors. How much attention are students paying to the teacher? How much does each student participate in a class? How do children socialize? This tool could help behavioral scientists study children development inside and outside of the classroom.

The Future of Privacy

Widespread acceptance of social sensors depends on the ability to guarantee users' privacy as well as to provide added value to the users. The current technology in social sensors allows us to have a very detailed picture of individuals' social networks and their behavior. However, there is a need for proper data management tools that would allow individuals to share only the data that they want to share with whom they want to share it. This platform will enable us to explore how privacy will be adapted in the future, when all of the data that we generate every day (from our cell phones, credit card transactions, e-mails, etc.) will be easily accessible and analyzed using data mining techniques.

CONCLUSION

Wearable social sensors enable social scientists to automatically measure individual and collective patterns of behavior, measure social affinity among individuals, identify human interaction and social network structures. Our experiments demonstrate that social sensors are capable of providing us with information about how people interact, and that a social network captured from a single communication channel does not accurately represent the complete social network structure. Our results and the ease of deployment argue strongly for the use of automatic sensing data collection tools to understand social systems. Our long-term goal is to develop a set of interventions and recommendations that can lead to better individual and organizational performance.

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