Sensor-based organisational design and engineering

Daniel Olguín-Olguín* and Alex Pentland

Media Laboratory,
Massachusetts Institute of Technology,
20 Ames St. E15-386, Cambridge, MA 02139, USA
E-mail: dolguin@media.mit.edu
E-mail: pentland@media.mit.edu
*Corresponding author

Abstract: We propose a sensor-based organisational design and engineering (ODE) approach that combines behavioural sensor data with other sources of information such as e-mail, surveys and performance data in order to design interventions aimed at improving organisational outcomes. We discuss relevant theory and technology backgrounds and describe the general requirements of a sensor-based organisational design and engineering system. We present an experimental platform that combines sensor measurements, pattern recognition algorithms, statistical analysis, social network analysis and feedback mechanisms to study the relationship between social signalling behaviour and face-to-face (f2f) interaction networks, with job attitudes and performance. We describe three case studies that we have conducted in several organisations using our experimental platform and the methodology that we have followed. The first study looks at e-mail and f2f networks in a marketing division of a bank. The second study analyses the effects of nurses' social behaviour on patients' length of stay in the post-anaesthesia care unit of a hospital. Finally, the third study analyses the effects of retail bank employees' social behaviour on sales performance.

Keywords: organisational design; organisational engineering; organisational behaviour; sociometric badges; social sensors; interventions.

Biographical notes: Daniel Olguín-Olguín is a PhD candidate at the Massachusetts Institute of Technology, Media Laboratory. He is a member of the Human Dynamics Group and his research is at the intersection of human behaviour sensing, pattern recognition, social network analysis and organisational design and engineering. He received his BS in Electronics and Communications Engineering and his MS in Electronic Systems Engineering, both from Tecnológico de Monterrey (Monterrey Campus, Mexico) in 2003 and 2005 respectively and his Master in Media Arts and Sciences from the Massachusetts Institute of Technology in 2007.

Alex (Sandy) Pentland is a pioneer in wearable computers, mobile information systems, technology for developing countries, consumer health, and computational social science. He is one of the most-cited computer scientists in the world, and has won numerous international awards in the arts, sciences and engineering. He is the Co-Founder of the Wearable Computing Research Community, the Autonomous Mental Development Research Community, and the Center for Future Health. He was formerly the Academic Head of the MIT

Media Laboratory and is now the MIT Toshiba Professor of Media Arts and Sciences. He is the Founder and Faculty Director of the Human Dynamics group.

1 Introduction

Who are the experts within an organisation? Who has the most decision-making influence? Recently, managers have started mining data from e-mail, web pages, and other digital media for clues that will help answer such questions (Aral et al., 2007; Bulkley and Van Alstyne, 2006). However, studies of office interactions indicate that as much as 80% of work time is sometimes spent in spoken conversation (Allen, 1997), and that critical pieces of information are transmitted by word of mouth in a serendipitous fashion (Cross et al., 2001; Kraut et al., 2002). Because of the efficiency and the ease of use of electronically mediated communication, there is a temptation to think that it will replace relationships based on f2f interaction. However, Nohria and Eccles (2000) argue that electronically mediated communication cannot and should not replace all f2f interaction because of issues of uncertainty, ambiguity, and risk, and that there is a minimum ratio of f2f to electronically mediated exchange that is vital to maintain in order for network organisations to work effectively. How can we then incorporate information about f2f interaction into formal models of organisational communication? Fortunately, the data infrastructure for mining real-world interactions is already in place. Most working professionals already carry electronic badges and mobile phones that can be enhanced with electronic sensors and computational power in order to automatically capture f2f interactions.

The human dynamics group at the MIT media laboratory has shown that commonplace wearable technology can be used to characterise the f2f interactions of employees and to map out a company's informal organisational chart (Choudhury and Pentland, 2003; Pentland et al., 2005; Pentland, 2006; Eagle and Pentland, 2009; Olguín-Olguín et al., 2009a, 2009b). This capability can be an extraordinary resource for team formation and knowledge management. The new reality-mined data allow us to cluster people on the basis of profiles generated from an aggregate of f2f conversation, e-mail, chat logs, location, web data, and other communication channels. This clustering, in turn, enables us to identify collaboration or lack thereof. For instance, if two groups working on similar tasks never talk f2f, it may be a sign that they are not coordinating their efforts.

Moreover, by leveraging recent advances in machine learning, we can build computational models that simulate the effects of organisational disruptions in existing social networks. We could, for example, predict the organisational effects of merging two departments. Such data-driven models help us transcend the traditional organisational chart, allowing organisations to manage themselves on the basis of actual communication behaviour. We expect that by aggregating this information, interpreting it in terms of work tasks, and modelling the dynamics of the interactions, we will be able to better understand and manage complex organisations. We must also, however, provide for the protection of privacy (for instance, by giving employees control over their information) and create an atmosphere of transparency by including the manager's interactions as part of the initiative.

Our goal is to design organisational interventions aimed at enhancing individual and group performance by applying statistical analysis and simulation techniques to behavioural sensor data combined with other sources of information such as text documents, e-mail, surveys, and performance data. With this goal in mind, we have devised a sensor-based ODE approach to study the relationship between social signalling behaviour, f2f communication patterns and social network characteristics, with organisational performance metrics such as task efficiency, productivity and job satisfaction. We have deployed an experimental research platform under naturalistic settings and we are now validating our approach with larger and more complex organisations. Our approach is based upon the following propositions:

Proposition 1   Social signalling behaviour and f2f interaction networks can be automatically captured using electronic sensors.

Proposition 2   Social signalling behaviour is correlated with a variety of organisationally relevant outcomes such as performance and job satisfaction.

Proposition 3   F2f interaction network characteristics are predictive of individual and group performance.

In this article, we present the results from three case studies where we have instrumented several participants with electronic badges capable of measuring social signals (i.e., non-verbal cues extracted from speech and body movement), f2f interaction, and physical proximity. Each of the three case studies are different in nature due to the difficulty in obtaining access to organisational performance data and digital communication records, as well as the complexity involved in deploying an experimental research platform under naturalistic settings in real organisations. The data that were made available to us by each organisation were also slightly different in nature, therefore each case study addresses one or more hypotheses (specified in the corresponding sections) that support our research propositions.

We begin with a brief review of ODE theory (Section 2). We then present an overview of technologies for sensing and modelling human behaviour (Section 3). Next, we describe the general requirements for a sensor-based ODE system (Section 4) and our research methodology (Section 5). We describe several case studies and discuss potential organisational design interventions that we are currently exploring (Section 6). Finally, we present our conclusions and discuss further implications of the proposed approach (Section 7).

2 Theory background

2.1 Organisational design

The basic goal of organisational research has been to discover what kinds of organisational 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 organisational structures will be most effective in said situations (Tushman and Nadler, 1978).

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

A recent approach that brings together organisation and information systems research and that focuses on building and deploying computer-based tools for organisational design was proposed by Magalhães and Rito Silva (2009). They address the need to bring together the engineering and the design of organisations and define ODE as 'the application of social science and computer science research and practice to the study and implementation of new organisational designs, including the integrated structuring, modelling, development and deployment of artefacts and people'. They draw a parallel with the agile software development process and suggest a combination of short observation stage, where the relevant parts of the organisation's design are observed, followed by a rapid intervention design and deployment stage. This process would go on continuously as a sequence of short observation steps, followed by short intervention steps. In later sections of this article it will become clear why this process fits our proposed sensor-based approach.

2.2 *Organisational engineering*

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

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

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

The work of Carley (2002) at Carnegie Melon University is particularly relevant to the design of organisational engineering systems. She has proposed that the same techniques used to engineer a product to meet some set of specifications can be applied to organisations and that it should be possible to design an organisation, group, or team, so that it is 'optimal' given some set of criteria (Carley and Kamneva, 2004). We believe this approach could be complemented with sensor data from social interactions in order to initialise simulation parameters and solve optimisation problems.

2.3 *Organisational intervention theory*

Cummings and Worley (2009) define organisational development as 'a process that applies a broad range of behavioural science knowledge and practices to help

organisations build their capacity to change and to achieve greater effectiveness, including increased financial performance, customer satisfaction, and organisation member engagement'. Organisational interventions are change processes that imply an intentional entry into an ongoing system of relationships (Rothwell et al., 2010). There are many possible ways to engineer organisational interventions, therefore we will only describe some background theory related to the proposed interventions that we present in Section 6.

2.3.1 Physical environment

Proximity among people in an organisation is known to exert considerable influence on f2f communication, coordination, balance of members' contribution, mutual support, effort, and cohesion (Hoegl and Proserpio, 2004). The seminal work of Allen (1971) uses a dyadic measure of physical distance in terms of feet or meters that refers to pairs of physical locations that do not vary in reciprocal distance over time. Monge et al. (1985) define organisational proximity as 'the extent to which people in an organisation share the same physical locations at the same time providing an opportunity or psychological obligation to engage in f2f communication'. Monge et al. (1985) observed daily variations in organisational proximity as well as day-to-day regularities by asking employees from a software systems firm to indicate, in 15-minute intervals, where they spent their time during all five days of a typical work week. Their research suggests that the expected level of organisational proximity at any point in time and the patterns across time is a function of the nature of the physical facilities, the nature of the work, and the reporting relations. Several organisational interventions that rely on the modification of the physical environment to promote f2f interaction in the workplace (e.g., office layout redesign and office renovation) have been studied (Heubach et al., 1995; Shpuza, 2006; Zagenczyk et al., 2007).

2.3.2 Feedback intervention theory

According to Alder (2007), performance feedback has been a topic of interest to organisational behaviour and organisational psychology researchers for over a century due to the fact that feedback affects numerous organisationally relevant outcomes such as employees' job motivation, satisfaction, absenteeism and turnover. Kluger and DeNisi (1998) proposed the first comprehensive theory of feedback. Their feedback intervention theory (FIT) assumes that behaviour is regulated by comparisons to standards or goals and that feedback interventions affect behaviour by changing individuals' locus of attention. Alder (2007) examined the effect of computer performance monitoring (CPM)-based feedback on individual's task performance and found that allowing participants to control the amount and frequency of feedback they received enhanced their desire to respond to their feedback with improved performance.

Coaching can help individual learning and development. Individual feedback may help to understand the effects of one's own behaviour on others. Individual feedback can take many forms, such as personal feedback, norm-based assessments, surveys, 360° feedback, and tests (Boonstra, 2004). Recent research on real-time feedback interventions has shown that is possible to modify group's behaviour by displaying information about group interaction dynamics in real time (DiMicco et al., 2004; Kim and Pentland, 2009). Laboratory study results show that sociometric feedback helps groups achieve higher

interactivity levels and better communication (Kim et al., 2008). In a recent study, Kim et al. (2010) found that when given feedback on their communication patterns, individuals became more cooperative, increasing the overall performance of the group. These results indicate that real-time sociometric feedback can indeed change group dynamics and enhance group performance.

2.3.3 *Continuous change*

There are two different kinds of organisational change: one of them is 'episodic change', which is discontinuous and intermittent; and the other is 'continuous change', which is ongoing, evolving, and incremental (Weick and Quinn, 2004). The distinctive quality of continuous change is the idea that small continuous adjustments, created simultaneously across units, can cumulate and create substantial change.

One focal point of organisational development is making changes in an organisation's culture (Rothwell et al., 2010). Intervention methods based on culture are mainly in the form of large-scale training and communication programmes. According to Boonstra (2004), the first step in cultural change is to assess the organisational culture by using survey feedback or by bringing groups together to identify values and underlying assumptions. The next step is to identify cultural assumptions that will aid in getting to shared goals, and cultural assumptions that hinder goals being achieved. After a reflective diagnosis, an action plan is developed to determine what steps might be appropriate. Finally, the execution of the action plan is monitored by members of the organisation with the help of a facilitator. Culture change is a continuous change process.

3   Technology background: sensing and modelling human behaviour

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 the emerging field of 'computational social science' that leverages the capacity to collect and analyse data with an unprecedented breadth and scale (Lazer et al., 2009). 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 behaviour and social interactions.

In this section we present an overview of the state of the art in individual behaviour recognition from sensor data and social signalling behaviour. We also present a brief overview of pattern recognition methods in social network analysis for the automatic identification of groups and the study of social network evolution.

3.1 *Individual behaviour and social signalling*

Human sensing refers to the use of sensors to capture human behavioural signals including facial expressions, body gestures, non-linguistic vocalisations, and vocal intonations (Pantic et al., 2007). Context sensing also plays an important role in understanding human behaviour and its goal is to characterise the situation in which

specific behaviours are displayed (who, where, what, how, when and why). The ultimate goal of human and context sensing is to automatically interpret the sensed behavioural signals to understand and describe the observed behaviours (Harter et al., 1999; Gellersen et al., 2002; Jones and Brown, 2002; Mantyjarvi et al., 2004).

We are interested in recognising human behaviour from sensor data at the individual and group levels, as well as combining pattern recognition methods with dynamic social network analysis, with the goal of creating a general framework for modelling group dynamics. At the individual level, researchers have applied pattern recognition methods to sensor data that capture several aspects of human behaviour such as primitive motor activities, e.g., standing, walking, running, etc. (Mantyjarvi et al., 2001; Lee and Mase, 2002; Kern and Schiele, 2003); complex or high-level activities, e.g., working on computer, having a phone conversation, etc. (Bao and Intille, 2004); body posture, facial expressions, hand gestures, and displacement patterns.

Another aspect of individual behaviour is the unconscious signals displayed during social interactions. According to Pentland (2008), these 'honest' signals can be measured by analysing the timing, energy, and variability of speech and body movement patterns. He describes four different types of honest signals in humans: influence (the extent to which one person causes the other person's pattern of speaking to match their own pattern), mimicry (the reflexive copying of one person by another during a conversation), activity (speaking time and energy), and consistency (low variability in the speech signal). The pattern of signalling behaviour and social roles largely determines the pattern of communication within an organisation. Consequently, the dynamics of group interaction can be inferred from the pattern of communication. For instance, dominant, high-influence individuals cause the pattern of communication to flow through them, making them more central in the organisation.

At the group level, we are interested in automatically identifying f2f interactions, conversations, and conversation dynamics. A wide range of studies has shown that hand-coded analyses of communication in teams can predict performance (Foltz and Martin, 2009). 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 (Bowers et al., 1998). 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. According to Foltz and Martin (2009), to develop a human performance model, one needs to find out if, and the degree to which, a relationship between communication and performance exists. Computational models must accurately measure features in communication that relate to measures of team performance. To create such model, recent advances in the fields of computational cognitive models (e.g., latent semantic analysis, or LSA, social network analysis, and pattern recognition techniques (e.g., clustering, classification, generalisation) can be leveraged.

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, organisations, 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 (Wasserman and Faust, 1994).

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

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

Social networks, in which people build relationships with others through some common interest, can be visualised as a large graph with people as nodes and connections as links between the nodes. Social network analysis examines the structure of the graph and extracts meaningful organisational data out of the graph (Krebs, 2008). Complete network data is difficult to collect. Four primary data collection techniques are questionnaire, interview, observational, and archival methods. We propose the use of electronic data collection methods that use wearable sensors to capture f2f interactions (Olguín-Olguín and Pentland, 2008).

Pattern recognition methods have also been applied in social network analysis. Clustering techniques have been used to identify communities and study their evolution over time (Mishra et al., 2007). An important property found in many networks is community structure, in which network nodes are joined together in tightly knit groups, between which there are only looser connections. (Girvan and Newman, 2002) proposed a method for detecting such communities, built around the idea of using centrality indices to find community boundaries. Palla et al. (2007) developed a new algorithm based on clique percolation that allows to investigate the time dependence of overlapping communities on a large scale and to uncover basic relationships characterising community evolution.

Some of the most recent analytical developments are in the form of exponential random graph models (Robins et al., 2007), which allow the modelling of complex patterns of dependencies at different levels of analysis. Other developments in modelling longitudinal social networks allow the use of fine-grained data on social interactions and could also be used in sensor-based organisational systems (Snijders, 2001, 2006; Snijders et al., 2006, 2009).

4   Proposed sensor-based ODE approach

Organisational data mining (ODM) leverages data mining tools and techniques to enhance the decision-making process by transforming data into valuable and actionable knowledge to gain a competitive advantage (Nemati and Barko, 2004). Advances in ODM technology have helped organisations optimise internal resource allocations while better understanding and responding to the needs of their customers. By applying ODM techniques and pattern recognition algorithms to behavioural sensor data, it is possible to recognise social patterns, infer relationships, identify socially significant locations, and model organisational rhythms (Eagle and Pentland, 2006).

To the best of our knowledge, organisational studies have not yet incorporated data from social interactions in the workplace collected using electronic sensors. We propose the use of sensors capable of automatically identifying, quantifying and characterising social interactions in order to incorporate this rich and untapped information (which was not possible to measure with such detail before) into formal organisational models. Our proposed sensor-based approach would augment, rather than replace, traditional methods of gathering social interaction data such as surveys or ethnographic studies by incorporating behavioural sensor data into current ODE practices.

Our research group has developed several tools for analysing 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 non-linguistic social signals are particularly powerful for analysing and predicting human behaviour, sometimes exceeding even expert human capabilities (Pentland et al., 2005). Our goal is to be able to map behavioural patterns to quantifiable outcomes and provide employees and managers with feedback that allows them to adjust their behaviour in order to optimise a desired outcome. Our proposed approach includes the following steps:

1   Capturing the interactions and social behaviour of employees, managers and customers using wearable and/or environmental sensors. Other sources of information that can be incorporated into the system are any form of digital records (e.g., e-mail, chat, phone logs).

2   Performing data mining and pattern recognition to extract meaningful information from these data.

3   Combining the extracted information with performance data (e.g., sales, tasks, timing) and finding relationships between objective measurements and performance outcomes.

4   Generating feedback in the form of graphs, interactive visualisations, reports, or real-time audio-visual feedback for employees, managers and/or customers in order to improve organisational performance and customer satisfaction.

5   Designing and implementing organisational interventions based on behaviour simulation and prediction.

6   Continuous measurement and performance assessment.

4.1   System specifications

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

- Environmental sensors that monitor the current conditions of the workplace (temperature, light, movement, activity, sound, video, etc.) and that can be used as base stations.

- Wearable sensors that employees carry around and that measure human behaviour (social interaction, activities, location, etc.). These can be mobile devices such as cell phones, PDAs, or electronic badges that collect data, communicate with a database (via Ethernet or wirelessly) to retrieve information, and provide feedback to their users.

- Software that automatically identifies relevant keywords in documents, web pages, e-mail, and instant messaging communication.

- A database that stores all the information collected by the environmental, wearable and software sensors (who-knows-what, who-knows-who, and where-is-who).

- Simulation and data mining algorithms.

- Feedback and visualisation mechanisms.

4.2   Environmental sensors

Figure 1   Sensor-based system for ODE (block diagram)
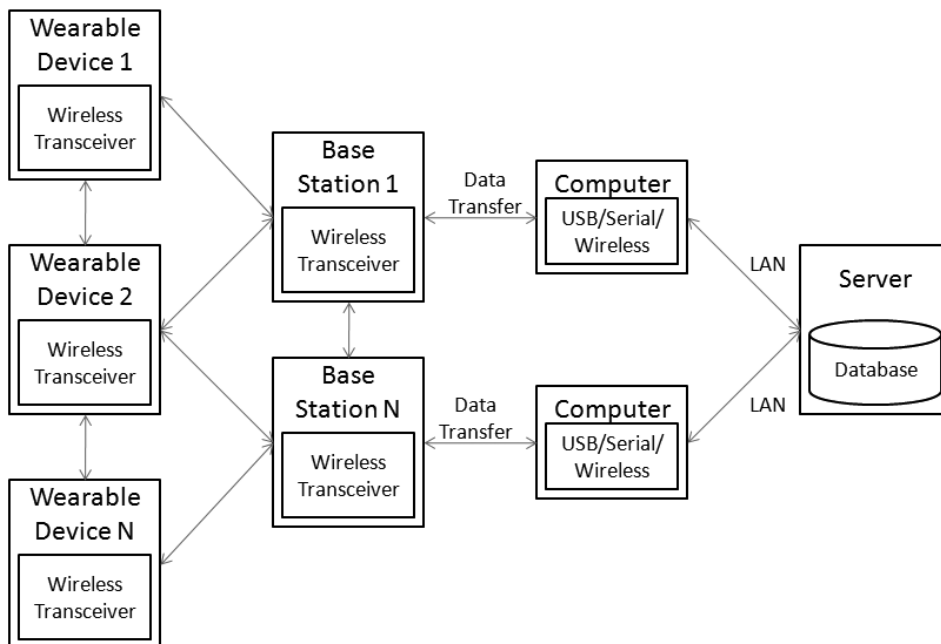
In addition to the wearable sensors, base stations can be placed in fixed locations inside a building in order to track the location of interaction events as well as subjects. A central computer can be used for data collection. Data from the wearable sensors is transferred wirelessly to the base stations 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.

4.3 *Wearable sensors*

Wearable sensing devices may include: electronic badges, mobile phones, wrist-mounted devices, head-mounted devices, and electronic textiles, among others. These wearable devices could function as self-contained monitoring devices or communicate with each other and with fixed radio base stations in a wireless sensor network. The wearable sensing devices should have a small form factor, be comfortable to wear over long periods of time, and have a long battery life. Figure 2 shows the block diagram of an exemplary wearable device. Ideally, they should be able to:

• recognise 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 localisation by measuring received signal strength and implementing triangulation algorithms

• capture f2f interactions.

Figure 2   Exemplary wearable data capturing device (block diagram)
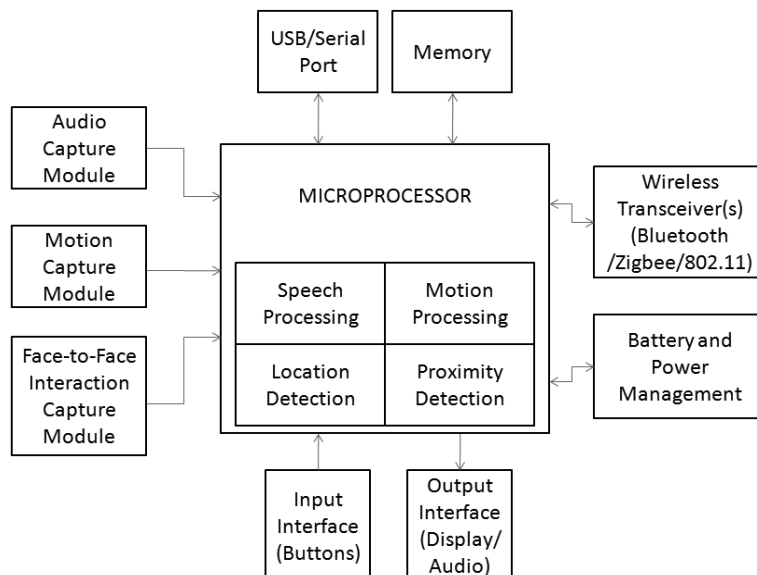
4.4   Database

A database containing individual attributes (values, attitudes, self-concept, abilities, personality, job satisfaction, etc.); sociometric data captured from sensors (speaking state, speaking style, motion state, location, f2f 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 organisation must be maintained in order to manage the vast amounts of information generated by the system. Database software includes: MySQL, Microsoft SQL Server, Oracle, and IBM DB2. Analysis software includes: Matlab, Microsoft Visual Studio, UCINET, among others.

4.5   Feedback and visualisation software

By aggregating information from sensor data, interpreting it, and modelling the dynamics of human interactions, one can create sensor-based feedback systems that help us better understand and manage complex organisations. Performance dashboards are becoming increasingly popular, but how to structure this feedback, particularly when it comes from sensor data, is an unanswered question. Feedback on group dynamics has been proven to help with the performance of small group collaboration (Kim and Pentland, 2009). Kim et al. (2009) have proposed a system to detect group dynamics and provide feedback according to a group's goals. By synchronising multiple wearers' sociometric data, it is possible get information such as turn-taking, influence, body movement mimicry, and similarities in behaviour. This information is then visualised in order to provide real-time feedback on group dynamics.

4.6   Organisational reengineering process

We envision short cycles of measurement-feedback-intervention-measurement until significant improvements have been reached. The first measurement phase may last a few weeks or up to a few months. The feedback phase can happen in real time (while sociometric data is being collected), or after the first measurement phase. Interventions have to be implemented soon after the feedback phase, and the second measurement phase can be carried out a few days or weeks after the intervention has been put into practice. The second measurement phase is confirmatory step and the entire cycle can be repeated again.

5   Methodology

In order to test our proposed approach we developed the sociometric badges, wearable electronic sensors capable of detecting f2f interactions, conversations, body movement, and physical proximity (Olguín-Olguín, 2007). Figure 3 shows a picture of a sociometric badge. This badge is capable of extracting speech features without recording the content of conversations in order to maintain privacy, and of wirelessly transferring data to a central server. We have used them in several organisations to capture f2f communication patterns and study the relationship between collective behaviour and performance

outcomes, such as productivity and job satisfaction (Olguín-Olguín et al., 2009a, 2009b; Wu et al., 2008).

Figure 3 Sociometric badge (see online version for colours)

The design of the sociometric badges was motivated by the fact that a large number of organisations already require employees to wear RFID name tags that identify them and grant them access to several locations and resources. These traditional RFID name tags are usually worn around the neck or clipped to the users clothing. With the rapid miniaturisation of electronics, it is now possible to augment RFID badges with more sensors and computational power that allow us to capture human behaviour without requiring any additional effort on the users side. By capturing individual and collective patterns of human behaviour with sociometric badges and correlating these behaviours with individual and group performance, it is possible to identify successful vs. unsuccessful teams, high performing teams, and predict group outcomes. The added value for the users is the feedback that they can receive about their daily behaviours and interactions with others, and how these behaviours affect their individual and group performance.

5.1 Measurements

The following is a list of some of the automatic measurements that can be obtained with the sociometric badges, and that we have used in our studies:

1 Body movement activity (x_1): Minute-by-minute body energy captured by a motion sensor.

2 Consistency of body movement (x_2): This measurement is negatively proportional to the minute-by-minute variation in body movement activity and is related to being in a state of 'flow' (Csikszentmihalyi, 1991).

3 Speech activity (x_3): Minute-by-minute speech energy captured by a microphone.

4 Consistency of speech (x_4): This measurement is negatively proportional to the minute-by-minute variation in speech energy and is related to mental focus and determination (Pentland, 2008).

5 Speaking time (x_5): Minute-by-minute percentage of speaking time.

6   f2f interaction time (x_6): Minute-by-minute number of f2f infrared (IR) detections divided by the maximum transmission rate.

7   Time in close proximity (x_7): Minute-by-minute number of radio packet detections over a radio signal strength threshold, divided by the maximum transmission rate. A 2.4 GHz radio transceiver is used to send and receive data packets.

8   Degree (x_8): Number of different participants with whom there was f2f interaction, normalised by the maximum number of participants. It is derived from the f2f IR detection network.

9   Centrality (x_9): It reflects the extent to which interactions are concentrated in a small number of individuals rather than distributed equally among all members of a social network (Sparrowe et al., 2001). It is calculated from the f2f IR detection network.

5.2   Social signals derived from body movement

A three-axis accelerometer is sampled at $f_s = 50$ Hz and the acceleration signal vector magnitude $|\overrightarrow{a_i}|$ provides a measure of the degree of body movement activity that includes the effect of signal variations in the three axes of acceleration. $|\overrightarrow{a_i}|$ is calculated on the normalised ith acceleration sample as follows:

$$|\overrightarrow{a_i}| = \sqrt{a_{x_i}^2 + a_{y_i}^2 + a_{z_i}^2} \tag{1}$$

Body movement activity (x_1) is calculated by averaging the acceleration signal magnitude for all samples in each one-minute interval. The consistency of body movement (x_2) is obtained by calculating the standard deviation of the accelerometer signal magnitude for all samples in each one-minute interval and subtracting this value from a constant (i.e., k = 1) that represents zero-variation or 100% consistency.

5.3   Social signals derived from speech

The speech signal is sampled at $f_s = 8,000$ Hz since the voice frequency band ranges from 300 to 3,400 Hz approximately. The voiced speech of a typical adult male has a fundamental frequency between 85 and 155 Hz, and that of a typical adult female between 165 and 255 Hz (Baken, 1987). Several speech enhancement and speech recognition front-end systems based on band-pass filter banks have been shown to be effective in detecting speech. The sociometric badges have an analogue band-pass filter bank that divides the speech frequency spectrum (85, 4,000) Hz into four frequency bands: f_1 from 85 to 222 Hz, f_2 from 222 to 583 Hz, f_3 from 583 to 1,527 Hz, and f_4 from 1,527 to 4,000 Hz.

We compute the speech volume modulation from the output of filter 1, since that is where the majority of the speaking energy resides. The speech activity or volume modulation per minute (x_3) is obtained by averaging all samples in each one-minute interval. The consistency of speech (x_4) is obtained by calculating the standard deviation of the speech volume modulation for all samples in each one-minute interval and subtracting this value from a constant (i.e., k = 1) that represents zero-variation or 100% consistency. The amount of speaking time per minute (x_5) is calculated by counting the

number of voiced samples in one minute that are greater than a given threshold and dividing this count by the number of speech samples for each one-minute interval. We determined an experimental threshold for each of the four band-pass filters in order to detect voiced and unvoiced speech. The speech detection can also be implemented using other digital signal processing algorithms.

5.4 F2f interaction

IR transmissions can be used as a proxy for the detection of f2f interaction between people (Choudhury and Pentland, 2003). In order for one badge to be detected through IR, two sociometric badges must have a direct line of sight and the receiving badge's IR sensor must be within the transmitting badge's IR signal cone of height $h \leq 1$ meter and radius $r \leq h \tan \theta$, where $\theta = \pm 15°$. We define the amount of f2f interaction (x_6) as the total number of IR detections per minute divided by the IR transmission rate (TR_{ir}).

5.5 Social network features derived from the f2f interaction network

The social network features (x_8 and x_9) can be calculated using the f2f IR detection adjacency matrix. We have used conventional social network analysis as described in (Wasserman and Faust, 1994). In particular, we have measured degree, betweenness centrality and cohesion. Degree measures the number of direct interaction partners. Betweenness centrality is a measure of power and influence within a group. Cohesion is a measure of how well an actor's acquaintances are connected to each other. We used the UCINET 6 software package to compute these social network features (Hanneman, 2005).

5.6 Time in close proximity

Radio signal strength indicator (RSSI) is a measure of the signal strength between transmitting and receiving devices. An average threshold was determined experimentally in order to detect when two badges were in close proximity to each other (at a distance of less than three meters) by collecting RSSI measurements over an extended period of time under different environmental conditions. The range of RSSI values for the radio transceiver in the badge is (-128, 127) and the experimental average threshold was found to be $RSSI_{th} = 50$. The time spent in close proximity (x_7) is calculated by dividing the number of radio packets with $RSSI > RSSI_{th}$ by the radio transmission rate (TR_{radio}).

5.7 Data collection and implementation procedure

For each of the case studies that we describe in Section 6, subjects were recruited a few weeks in advance by each of the participating organisations. They received information about the purpose of the study, a detailed description of the sociometric badge measurements, and signed a consent form to participate in non-biomedical research. We followed research protocol No. 0403000377 approved by the Massachusetts Institute of Technology's Committee on the Use of Humans as Experimental Subjects (COUHES).

Each participant was instructed to wear a sociometric badge every day from the moment they arrived at work and until they left the study site. Each participant was

assigned a unique badge number and all related data (e.g., survey data, e-mail data, performance data) that were made available to us by each participating organisation were previously anonymised and assigned each participant's badge number. At the end of each day participants were asked to answer a short survey that included several questions about job attitudes (e.g., job satisfaction, optimism, trust, quality of group interaction, stress, etc.) and perceived performance. Each question could be answered using a 5- or 7-point Likert scale (with values going from low to high). On the first day of the badge platform deployment the researchers explained in person the purpose of the study to the participants and answered any related questions.

The badges can also work as base stations that are placed in fixed known locations in order to detect when the study participants are in close proximity to each location, and track their displacement patterns over time. The sociometric badges and base stations broadcast their ID every five seconds using a 2.4 GHz transceiver ($TR_{radio} = 12$ transmissions per minute) and each time another badge or base station receives a radio packet it logs the sender's ID and the radio signal strength. The sociometric badges also transmit their ID every two seconds using an IR transceiver ($TR_{ir} = 30$ transmissions per minute). The badges can transfer the data in real time to the base stations which in turn transfer the data to a central server. Each person's data can also be stored locally on the badges and transferred over USB at the end of the data collection period.

6   Case studies

6.1   Combining electronic and f2f communication networks

6.1.1   Experimental setting

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). In total we collected 2,200 hours of data (100 hours per employee) and 880 reciprocal e-mails. The division contained four functional teams consisting of either three or four employees. Each of these teams was overseen by a manager, who was in turn supervised by a mid-level manager. These mid-level managers were responsible for two teams, and they reported directly to the division manager. The bank division had an interesting physical layout, as it was split across two floors with six rooms on the second floor and four rooms on the third floor. Some teams were co-located in a single room while others had employees from multiple teams in them. In fact, one of the reasons this division was interested in the study was to determine precisely what effect this physical layout had on the interactions that occurred within the division.

The objective of the study was to use data collected using the sociometric badges to correlate temporal changes in social interaction patterns 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 an ongoing study on the impact of electronic communications on the business performance of teams (Oster, 2007).

6.1.2   Hypotheses

Previous studies have attempted to extract social network structures by looking at e-mail only (Bird et al., 2006), and not at f2f networks due to the difficulty of collecting such

data. Our first hypothesis (H1-A) was that *the more time spent in close proximity to someone (x_7), the lower volume of e-mail exchanged*.

There has been extensive research on the occurrence of communication overload and its effects (Baum et al., 1982; Gardner and Winder, 1998; Hiltz and Turoff, 1985). Individuals who become overloaded with communication responsibilities have difficulty focusing on the tasks at hand and coping with their other responsibilities (Kerr and Hiltz, 1982). Subsequently, their overall level of satisfaction with their situation will decrease (Gardner and Winder, 1998). If we are able to capture both f2f and electronic communication, then we should be able to gauge the degree of communication overload experienced by an individual. This led us to our second hypothesis (H1-B): *the greater the amount of total communication an individual has (f2f interaction time (x_6) and e-mail volume), the lower level of satisfaction the individual will have because of communication overload*. Similarly, Brass (1985) found that people with higher betweenness centrality had lower levels of satisfaction. Hence our third hypothesis (H1-C): *the more central (x_9) an individual is in the organisation, the lower level of satisfaction the individual will have*.

6.1.3 Findings

We found that the time spent in close proximity to others had a high negative correlation with the number of e-mails exchanged ($r = -0.55$, $p < 0.01$, N = 22 employees). This has powerful implications for previous work that has used e-mail communication as a proxy for the social network of an organisation. When we examined the total communication (e-mail and f2f) of each individual, we found that it had a high negative correlation with the monthly averages of the survey questions on job satisfaction and group interaction satisfaction ($r = -0.48$ and $r = -0.53$ respectively, with $p < 0.05$ and N = 22 employees in both cases). This is consistent with hypothesis H1-B, namely that as an individual engages in more and more communication, their satisfaction level decreases. It is important to note that this relationship was not found when examining f2f and e-mail data separately; the data had to be combined. This result stresses the importance of capturing f2f communication, since if only e-mail data is collected significant measures of social context are lost (Waber et al., 2008).

We also found that total communication betweenness centrality was negatively correlated with the monthly average of group interaction satisfaction ($r = -0.49$, $p < 0.05$, N = 22 employees) and therefore is consistent with hypothesis H1-C. This strong negative correlation was found only in the communication network of total communication, not in separate observations of f2f and e-mail. Hence we can understand that the individual's role in the communication network, including both co-present and electronic communication, is a strong indicator of an employee's satisfaction level (Waber et al., 2008).

6.1.4 Proposed organisational intervention

Based on these findings and the theory on organisational interventions discussed in Section 2.3.1, we suggested as a possible intervention to modify the employees' team configuration and seating arrangement in order to minimise the physical distance among members of each team, as well as the distance between teams that interacted the most.

This would ideally promote more f2f interaction and reduce the amount of e-mail, resulting in less communication overload. This could also be reflected in an increase of job and group interaction satisfaction over the long term. Since our findings are purely correlational, one way to establish the direction of causality would be to implement the proposed intervention and measure the communication patterns again in order to verify if indeed closer proximity reduces the amount of e-mail. The same can be said of the relationship between total communication and job satisfaction. In fact, based on the insights gained from this study, an organisational restructuring of the division was carried out. The four-team structure was reconfigured into a three-team structure. The decision of this restructuring was supported both by the expert knowledge of the department manager and by the social network analysis results. Employees were not allocated to specific teams using the badge data because the study was done on a completely anonymous basis. Even though a second sociometric measurement phase has not been performed, the three-team structure exists until today.

The results of this first study were encouraging and supportive of our first two propositions. Namely, that f2f interaction networks can be automatically captured using electronic sensors, and that f2f network characteristics are correlated with organisational outcomes such as job satisfaction. With this in mind we wanted to test if these measurements were also correlated with objective performance metrics and how effective they were at predicting performance. We will now discuss the findings of two more case studies for which we were actually able to obtain performance data.

6.2   Predicting patient outcomes from nurses' behaviour in a hospital setting

6.2.1   Experimental setting

We instrumented a group of 67 nurses working in the post-anaesthesia care unit (PACU) of a Boston area hospital with sociometric badges. Each nurse wore a sociometric badge every day for a period of 27 days. In total we collected 3,906 hours of data. The mean number of hours each participant wore a badge was 7.18 hours per day (± 4.17). During this period a total of 1128 patients were admitted to the PACU, with an average length of stay (LOS) of 235.66 (± 261.76) minutes. We placed base stations next to each bed and phone in the PACU in order to detect when the nurses were in close proximity to a bed or a phone and track their location and displacement patterns. There were 37 beds in the PACU, with only 30 being used during the study and 12 phones distributed around the room.

The hospital has 50 operation rooms (OR). After surgery is completed, patients are taken to the PACU, where they are kept under supervision until they recover from anaesthesia. Thereafter they are admitted to the floor units where they convalesce before being discharged. Patients without assigned beds on the floors are kept in the PACU until vacancies on the floors can be found. The PACU is a critical intermediary step in the surgical patient throughput system and it consistently experiences delays of various kinds. These delays cause hold ups in the OR resulting in schedule disruptions, overtime work and productivity losses. This translates into loss of revenue for the hospital since the health-care system reimburses a fixed sum for a particular surgical procedure irrespective of the patient's LOS in the hospital (Samarth, 2007).

6.2.2 Hypotheses

Reducing the patient's LOS within the PACU can control or even lower costs. The length of time a patient remains in the PACU is medically attributed to the anaesthetic drugs used during the operation and additional side effects that may occur, such as nausea and vomiting (Zollinger and Saywell, 1999). Previous studies demonstrate that as many as 20% of patients experience delayed discharge from the PACU and over half of the delays may be personnel-related or due to personnel shortages and inefficiencies (Meyer, 2006). Our hypothesis (H2-A) was that nurses' social signalling behaviour and f2f interaction patterns would be predictive of patients' LOS.

6.2.3 Findings

We were able to explain 68% of the variation (adjusted $R^2 = 0.68$) in the daily average LOS in minutes (N = 20 work days) using aggregated sociometric badge features across nurses. Daily badge features calculated at the individual level were only slightly correlated with performance (LOS). However, the daily variation across nurses, denoted as $\sigma(x)$, in physical activity intensity $\sigma(x_1)$, f2f interaction time $\sigma(x_6)$, degree $\sigma(x_8)$, and centrality $\sigma(x_9)$ were highly correlated with performance and therefore were used as predictor variables (Olguín-Olguín et al., 2009a). Table 1 shows the regression coefficients used to predict the daily average LOS. Low variation across the nurses' level of activity (i.e., nurses' level of activity alternating between high and low during the day); high variation across the nurses' f2f interaction time (i.e., periods of intense f2f interaction alternating with periods of low f2f interaction); high variation across the nurses' degree (i.e., nurses with a high number of interacting partners and nurses with a low number of interacting partners); and low variation in centrality (i.e., a few central nurses), were predictive of extended LOS. These results support our third research proposition: Social signalling behaviour and f2f network characteristics are predictive of group performance.

Table 1 Prediction of daily average LOS in minutes from the variation in badge features across subjects

Predictors	Coefficient
Intercept	$\beta_0 = 304.46$
Physical activity $\sigma(x_1)$	$\beta_1 = -1{,}198.51$
f2f time $\sigma(x_6)$	$\beta_2 = 2{,}048.53$
Degree $\sigma(x_8)$	$\beta_3 = 5.60$
Centrality $\sigma(x_9)$	$\beta_4 = -135.017$

Notes: $R^2 = 0.75$, adjusted $R^2 = 0.68$, F = 10.51, p < 0.0005, N = 20 days

6.2.4 Proposed organisational intervention

In the context of the PACU these results can be interpreted as either most PACU nurses being busy (high activity levels) or waiting for bed availability (low activity levels). The variation across the nurses' f2f interaction time could be an indicator of poor

communication among nurses. The variation in the nurses' degree (number of interacting partners) indicates that some nurses interact with many more nurses, while some others barely interact. Finally, the variation across nurses' centrality is a clear indication of a few central people dominating the f2f network. Drawing from the research on real-time feedback interventions presented in Section 2.3.2, one possible intervention in this case would be to install a real-time display that shows a map of the PACU and overlays information about the nurses' location, displacement patterns, activity levels, and f2f interaction with patients and nurses. This would give instantaneous feedback to the nurses and PACU managers about the current activity and stress levels in the PACU, and help them manage their capacity in a more effective way. This could also potentially save costs to the hospital by minimising the number of delays, reducing the patients' LOS, and providing better care to the patients.

Incorporating behavioural sensor data from the nurses' activity levels and f2f interaction patterns into existing patient scheduling systems, e.g., the web-based tracking application proposed by Meyer et al. (2006), could potentially save costs to the hospital by minimising the number of delays, reducing the patients' LOS, and providing better care to the patients.

6.3   Comparing sales performance across branches of a retail bank

6.3.1   Experimental setting

A sociometric badge study was carried out in three branches of a bank in the Czech Republic. Fifty two employees and six managers participated in the study and wore the badges every day for 20 working days. In total, we collected 4,800 hours of sensor data. Branch 1 was of small physical size (five participants working in the same floor), branch two was of large physical size (31 participants distributed across two floors), and branch three was of medium size (16 participants in the same floor). Each participant was part of one of six teams: management team, three retail teams, and two small and medium enterprise (SME) teams. Daily surveys were administered and included items such as commitment, job satisfaction, stress, optimism, and team effectiveness among others. Objective data including information such as the total number of meetings with clients, proactive calls, and sales were made available to us. Each of the teams was characterised by individuals with:

1   a variety of positions from the front-line to senior management

2   a variety of clients, e.g., personal retail bankers serving individuals, SME

3   specialising in a variety of products such as investment portfolios and credit facilities.

While participation in the study was encouraged, no employee refused to participate. In return for participation, participants were promised a presentation of team level feedback with respect to social networking patterns, as well as identity-protected individual level feedback regarding their individual position within the social network. To protect identities, sealed envelopes were given to individuals containing their individual level data, coded by a randomly assigned employee number so that names were never attached to personal data.

6.3.2 Hypotheses

We studied the relationship between several behavioural features captured by the sociometric badges, and employee self-perceptions (from surveys) and productivity data. After visiting the three branches we observed different office layouts that we believed would lead to different communication patterns. By talking to the manager and the participants of each branch we also perceived differences in employees' job attitudes. Therefore, our first hypothesis (H3-A) was that *differences in behaviour across branches would be reflected in differences in job attitudes*. Following on the results from the previous case study, our second hypothesis (H3-B) was that *social signalling behaviour and f2f interaction patterns would be predictive of employees' performance (monthly number of product sales)*.

6.3.3 Findings

In order to test hypothesis H3-A, we performed one-way analysis of variance (ANOVA) tests on each of the job attitude survey items and each of the badge measurements. These tests revealed significant differences among the three branches. We can see from the results shown in Table 2, that Branch 2 (large physical size) was significantly different from the other two branches in that it had the highest (monthly average) survey ratings of optimism, trust, acceptance, and limitlessness, on a scale from 1 (low) to 7 (high). Along with this difference in attitude we found a difference in behaviour, with their badge measurements showing a significantly lower normalised degree, and lower centrality. However, there were no significant differences in the individual monthly number of sales across the three branches.

Table 2 Significant differences across the three branches in terms of job attitudes and f2f social network features (ANOVA)

Variable	Branch 1	Branch 2	Branch 3	F-value	p-value
Optimism	$\mu_o = 4.28$	$\mu_o = 5.48$	$\mu_o = 5.10$	$F = 4.42$	$p < 0.05$
Trust	$\mu_t = 3.38$	$\mu_t = 4.67$	$\mu_t = 3.85$	$F = 4.59$	$p < 0.05$
Acceptance	$\mu_a = 4.29$	$\mu_a = 5.27$	$\mu_a = 4.45$	$F = 3.82$	$p < 0.05$
Limitlessness	$\mu_l = 3.94$	$\mu_l = 4.95$	$\mu_l = 4.30$	$F = 3.47$	$p < 0.05$
Degree	$x_8 = 0.63$	$x_8 = 0.16$	$x_8 = 0.38$	$F = 45.09$	$p < 0.00001$
Centrality	$x_9 = 13.9$	$x_9 = 2.24$	$x_9 = 7.56$	$F = 26.45$	$p < 0.00001$

Note: N = 52 employees

In other words, Branches 1 and 3 had similar group dynamics (f2f social network characteristics), while Branch 2 was very different. These different group dynamics were correlated with very different attitudes about their job and outlook on the future. Surprisingly, all three branches had a very similar average performance (monthly number of sales) despite having very different group dynamics.

Even though the average number of sales was not significantly different across the three branches, it is clear that employees in Branches 1 and 3 have different f2f communication patterns and job attitudes from employees in branch 2. Therefore, we grouped employees in Branches 1 (small size) and 3 (medium size) and created a regression model to predict the individual number of monthly sales using the f2f social

network features as predictors and controlling for team (0 for retail, 1 for SME), sex (0 for male, 1 for female), age, and tenure. Table 3 shows the regression model obtained for employees in Branches 1 and 3.

Table 3   Model 1 prediction of monthly sales for Branches 1 and 3 using monthly f2f social network features as predictor variables

Predictors	Coefficient
Intercept	$\beta_0 = 109.00$
Team (0 retail, 1 SME)	$\beta_t = -13.36$
Sex (0 male, 1 female)	$\beta_s = 3.56$
Age	$\beta_a = -0.66$
Tenure	$\beta_n = 0.31$
f2f time x_6	$\beta_6 = -1.30$
*Degree x_8	$\beta_8 = 115.13$
*Centrality x_9	$\beta_9 = -3.33$

Notes: $R^2 = 0.68$, adjusted $R^2 = 0.46$, F = 3.12, *p < 0.05, N = 21 employees

In this model, the most significant predictors are degree and centrality. Having a higher number of f2f interacting co-workers (x_8), and lower centrality (x_9) predicted higher sales. The control variables were not significant, which indicates that team, age, sex, and tenure do not have an effect on the number of sales. This model explains 46% of the variation in sales (adjusted $R^2 = 0.46$). Even though the average sales performance is similar to that of Branch 2, these behaviours occurred in an environment of lower optimism, trust, acceptance, and limitlessness. Table 4 shows the regression model obtained for the individual number of monthly sales for employees in Branch 2 using the same predictor variables.

Table 4   Model 2 prediction of monthly sales for Branch 2 using monthly f2f social network features as predictor variables

Predictors	Coefficient
Intercept	$\beta_0 = 59.32$
Team (0 retail, 1 SME)	$\beta_t = -4.94$
Sex (0 male, 1 female)	$\beta_s = -21.26$
Age	$\beta_a = -0.76$
Tenure	$\beta_n = 0.77$
*f2f time x_6	$\beta_6 = -0.85$
Degree x_8	$\beta_8 = 25.28$
Centrality x_9	$\beta_9 = -0.69$

Notes: $R^2 = 0.72$, adjusted $R^2 = 0.57$, F = 4.61, *p < 0.01, N = 23 employees

This model explains 57% of the variation in sales (adjusted $R^2 = 0.57$) when controlling for team, sex, age, and tenure. The most significant predictor was the amount of f2f interaction time with co-workers. Having a higher amount of time spent in f2f interaction with co-workers (x_6), higher number of f2f interacting co-workers (x_8), and lower centrality (x_9) predicted higher sales. Even though the average sales performance was

similar to that of Branches 1 and 3, employees' self-perceptions were higher in terms of optimism, trust, acceptance, and limitlessness.

It is interesting to note how the f2f interaction time x_6 has a negative sign as predictor in model 1 ($\beta_6 = -1.30$) and a positive sign in model 2 ($\beta_6 = 0.85$). This means that the more time employees in Branches 1 and 3 spent interacting f2f with co-workers, the lower predicted number of sales. This relationship is the opposite for Branch 2: the more time employees spent interacting f2f with other co-workers, the higher predicted number of sales. This difference could be due to the differences in job attitudes. Even though degree and centrality are not statistically significant predictors in model 2, the sign relationship is the same as in model 1. This implies that despite differences in job attitudes, similar social network characteristics are reflected on performance. In general, higher degree (or number of f2f interacting partners) and lower centrality were predictive of higher sales across the three branches. These results, along with those from our second case study support our third research proposition: Social signalling behaviour and f2f network characteristics are predictive of individual and group performance.

6.3.4 Proposed organisational intervention

Overall, higher degree was predictive of higher sales but it was also indicative of lower scores in the job attitude survey. However, f2f interaction time was predictive of higher sales in the branch with higher job attitude scores, but indicative of lower sales in the branch with lower job attitude scores. Thereby, one obvious question that arises from this analysis is: What is the best trade-off between the number of interacting f2f partners (degree) and f2f interaction time that maximises both performance and job attitudes? This is a very difficult question to answer since there are other variables and dependencies involved that we cannot measure. However, we can draw from the literature on f2f interaction and research that argues that f2f interaction helps actors to align commitments, motivates effort, and increases trust (Nohria and Eccles, 1992; Storper and Venables, 2004), as well as on the theory on continuous change presented in Section 2.3.3 to suggest that one possible intervention to increase the overall level of job attitudes would be to promote a culture similar to that of Branch 2 in the other two branches. A longer time-frame study would probably reveal significant differences in performance across the three branches, with Branch 2 being higher performing and more resilient over the long term. By implementing a continuous training programme that tries to reproduce the work environment, communication patterns (decentralised network), and interaction behaviours observed in Branch 2, one could expect to see changes in job attitudes and performance in the other two branches.

7 Conclusions and future work

We have discussed several technologies for sensing and modelling human behaviour, and proposed a sensor-based ODE approach. By bringing together computational models, human sensing, data mining, and social network analysis we believe it is possible to create a closed loop system that uses digital information, sensor data, performance and productivity data as inputs. Data mining algorithms and social network analysis can be applied to these inputs, and computational models created from the results of the data analysis. Finally, simulations and feedback mechanisms would be reported to the users of

the system in order to design interventions aimed at improving organisational outcomes. These changes may include: restructuring the organisational chart, restructuring teams, changing the physical office layout in order to facilitate communication and mobility patterns, or promoting specific behaviours.

Our proposed approach to measure human behaviour has several advantages over existing methods such as direct observation by humans, the use of pervasive cameras to videotape social interactions, or the use of surveys. Direct observation of humans by humans is expensive and limited to a few people per observer, and observers do not always agree. Deploying pervasive cameras is extremely expensive and their range of measurement is constrained to a particular place. The use of surveys only is subjective, inaccurate, and time consuming. In contrast, it is a great advantage to be able to automatically capture the behaviour of hundreds of people at the same time with unobtrusive sensors. The use of pervasive sensors has allowed us to study human behaviour with unprecedented levels of detail. By capturing individual behaviours such as the amount of f2f interaction, speaking patterns, and non-linguistic social signals; and aggregating them at the group level, it is possible to assess group performance and design organisational interventions aimed at improving performance.

Even though we have only discussed a few application scenarios we believe the possibilities for the proposed sensor-based approach are much broader. We presented results from one study in which we compared electronic and f2f communication and found a negative correlation between physical proximity and the amount of e-mail exchanged. The total amount of communication was also negatively correlated with job satisfaction, and centrality was negatively correlated with group interaction satisfaction. We proposed to modify the employees' seating arrangement in order to minimise the physical distance among members of a team, promote f2f interaction, and reduce communication overload. The results from our second study show that it was possible to assess the overall performance of a PACU by analysing aggregated behavioural features across all nurses working in the unit as a group. Finally, in the third case study we were able to observe different group dynamics and job attitudes in three branches of a retail bank and estimate the monthly number of sales from the f2f network features.

Future work includes designing, simulating and implementing organisational interventions, as well as validating them in a second sociometric measurement phase. Further applications of our work include automatic clustering of people to maximise team performance as well as dynamic visualisations of team processes. Some implications that this work has for future studies and future technologies for ODE are:

- studies confirming social science theories based on human observation will be corroborated using automatic sensing tools on larger populations

- further collaboration tools and technologies that make use of behavioural sensor data to promote collective intelligence in organisations will emerge

- human behaviour is already being captured and analysed in organisations

- most of the required infrastructure and sensors are already in place (sensors, location, software, etc.) and eventually will be exploited

- users should have the right to manage their privacy settings, have access to their data, know what kind of data is being collected, and decide how their data will be utilised

- privacy concerns will be overcome by the potential benefits for the users and the organisations.

We would like to conclude this article with the following quote:

> "The most significant advances in our scientific understanding of organisational phenomena will come from those efforts in which organisational process theories are tested with organisational process research methods" (Monge et al., 1985).

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