Modeling Social Interactions in Real Work Environments

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ABSTRACT

We present a study for modeling the behavioral patterns of employees and keeping track of the social interactions among people in a real work environment. The main advantage of our approach to capture social interactions in a work environment is the use of off-the-shelf tools and devices - like smartphones available on the market - and the utilization of the discovered patterns for the optimum distribution of employees in a office building. We carried out an experiment in our building at Fernfachhochschule Schweiz and captured data about physical proximity, virtual interactions (i.e., email exchange) and individual performance satisfaction of 20 employees for 8 working days, during their working hours. The objective of the experiment was to investigate the interaction patterns of employees in relation to four aspects: quantity, space, performance and organization. Besides confirming the existence of different social interaction types, we also provide insights in how distance between office spaces affects type and amount of social interaction. Further, we describe the influence of contacts among workers on their performance. Finally, our analysis emphasizes the importance of an employee's role in terms of number of physical and virtual interactions.

Categories and Subject Descriptors

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General Terms

Measurement, Experimentation, Human Factors

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Keywords

Behavioral patterns; organizational behavior; social interaction; social computing

1. INTRODUCTION

Understanding how people interact through the aid of computational tools and tracking technologies has become of remarkable interest in the last few years. These computational approaches potentially impact multiple walks of human life including health, wellness, productivity, mobility, transportation, education, shopping and sustenance [15]. Further, recent works have also highlighted the importance of analyzing human behavior and social interactions in organizational settings [11]. The insights gained from studies can be beneficial both for organizations and employees. For example, it is well known that social interactions are crucial for any kind of innovation process [12] and about 80% of really innovative ideas appear in personal interactions [1],[13]. Most of the studies in literature on the detection of social interactions are used to enforce organizational effectiveness [11] or to foster individual well-being in the workplace [4]. However, these studies do not consider the placement of employees based on their social interactions that could lead to overall high well-being, productivity and satisfaction. In this paper, we describe our feasibility analysis to fill this gap by interpreting and understanding social interactions among people and present how social interactions could be useful to distribute people in a work environment and could promote satisfaction, productivity and well-being of employees. We collected data about employee's contacts, their frequency and duration, at our Fernfachhochschule Schweiz (FFHS) building. We leveraged off-the-shelf software tools to design and develop a pilot system to keep track of physical and virtual interactions between employees. To detect physical proximity, we used an Android App based on Bluetooth technology, which is able to detect other Bluetooth devices in close proximity. Two types of virtual interactions were captured: email exchange and Instant Messaging (IM). We conducted an experiment that involved 20 employees of FFHS. They wore a smartphone on their arm for 8 working days, from the moment they arrived at work until they left their office. We collected data about their encounters and tracked their email and IM communications. We also obtained self-reported in-

dividual performance satisfaction data through an on-line survey, which was configured to get the levels of productivity, concentration and well-being of employees, on a daily basis. All collected information was properly anonymized. We first formulated some hypotheses on the interaction patterns of employees in relation to four aspects: quantity, space, performance and organization. We subsequently analyzed collected data. Because most of the individuals communicated electronically through one or more channels we could not measure, data collected from IM was not sufficient to allow a meaningful analysis. Despite this, we were able to verify our hypotheses and found that (a) there exist different social interaction types; (b) the less the physical distance between office spaces the more the number and the duration of contacts; (c) virtual interaction is reduced when people can physically interact with each other; (d) the idea that if people are always out of office they may have more email contacts is questionable; (e) the performance of employees is not affected by their contacts with direct supervisors; (f) concentration and productivity of workers are positively correlated; (g) the centrality of an individual impacts number of contacts. These results validate our feasibility analysis aimed at showing that, by taking into account social interactions and combining this information with data about physical/virtual contacts, it is possible to place employees in work environments in a way that optimizes their levels of productivity, concentration and well-being.
The remainder of this paper is organized as follows. Section 2 describes the background and previous work on social interactions in the context of work environments. Section 3 describes the proposed platform and technology to automatically measure organizational behavior. Section 4 presents experimental results. Finally, Section 5 presents the conclusion and future work.

2. RELATED WORKS

Understanding social interactions among people in workplaces and organizations with the use of technology has attracted the research community in recent years. The work done in the Reality Mining project demonstrates the potential of analyzing human behavior through a wearable computing platform that could measure face-to-face interaction in a workplace environment [11]. Social interactions among people can also be detected by analyzing walking patterns transitions [9]. To infer social interactions among people in a real environment, the main challenge is the tracking of people, which is complex because it should be the less obtrusive as possible. A common approach is to extract information from videos captured in unconstrained environments, using the tracking-by-detection paradigm [2], [3], [16]. Further, several studies leveraged tracking technologies to understand interactions among employees in real environments. Examples of these studies are Chen et al. [8] [7] [6], where a system that extracts locations and head poses of people from videos captured in a research lab was used to detect interactions in groups for social behavior analysis. Also some studies have worked towards the detection of social networks and the identification of groups leaders [17] in a work environment. The works done so far do not consider the importance of spatial placement of people based on their social interactions and behavior. The authors in [5] present the impact of building change on social behavior of people. In our work, we capture and analyze physical and virtual social interactions among people by utilizing off-the-shelf smart phones. Similarly to [7], we also investigate the dynamics of social interactions and their impact on the performance of workers. Further, we study the social interactions among people from the spatial point of view and present a feasibility analysis to show how social interactions could be utilized in optimum placement of employees.

Figure 1: A smartphone for measuring physical proximity.

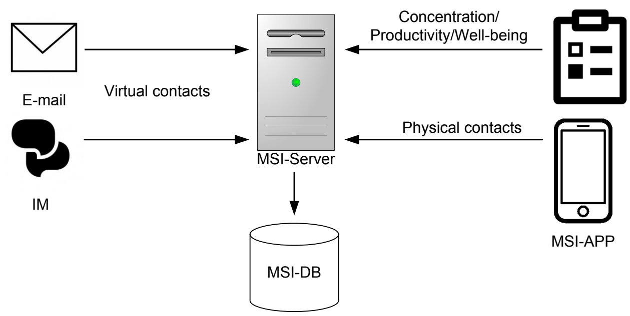

Figure 2: Software architecture of the platform.

3. SYSTEM DESIGN

In this section, we present the software architecture of the platform we implemented to register physical and virtual interactions, and describe the methodology for automatically measuring human behavior in organizational settings. The main hardware components of the platform are the smartphones - which are worn by employees as shown in Figure 1 - and the server.

The platform (Figure 2) comprises two software modules (MSI-App and MSI-Server), which respectively run at the smartphone (client) and server premises. It also includes a central database (MSI-DB) for storing details about physical contacts, virtual contacts and self-reported levels of productivity, concentration, and well-being. The MSI-App is an Android App that runs on Bluetooth enabled mobile phones. It performs Bluetooth scans to discover nearby devices and register physical contacts between employees (their time and duration), stores this information on a local database and periodically transmits data about contacts to the MSI-Server. The MSI-Server carries out the following tasks:

- It periodically reads data about virtual contacts and stores it on the MSI-DB. Details about virtual contacts

are sent to the MSI-Server via customized tools that are described in the next section.
- It receives data about physical contacts from the MSI-App and stores it on the MSI-DB.

3.1 Tracking of Virtual Interactions

The server used at FFHS for handling emails is Microsoft Exchange Server 2008. To track email exchanges, we used the *Get-MessageTrackingLog* power shell command, which exports Mailbox server log files to a comma separated value (CSV) file. The command was included in a script launched every day at a fixed time. In addition to the filtering of only selected e-mail exchanges, the script uploaded the filtered log to a folder of the MSI-Server, where it was processed to store information about email exchanges into the MSI-DB.

3.2 Physical Proximity Detection

The MSI-App uses Bluetooth technology to detect other Bluetooth devices in close proximity in an omnidirectional fashion (within a 8m radius). It periodically performs a scan to search for nearby devices, checks the received signal strength level emitted by nearby devices, and registers only devices that are below a fixed threshold. Although a Bluetooth device found in the neighborhood does not necessarily means that employees are interacting with each other, we can assume that they are in close proximity, so they are having a physical interaction.

The MSI-App is designed to minimize the impact on energy consumption during its operation, while keeping the data collection as complete as possible. It is driven by *i)* Bluetooth scan results and status update, *ii)* a watchdog timer that detects Bluetooth failure and freezes and *iii)* a scheduler that minimizes the number of times the application is active. This design makes it possible to run the data collection phase for approximatively 16 hours, using a Bluetooth 3.0 smartphone. The same approach allows a Bluetooth Low Energy enabled smartphone to have a more marginal impact on battery life.

4. EXPERIMENTS

4.1 Experimental Setup

For our study, we recruited 20 employees of FFHS, on a voluntary basis. During introductory meetings, they were provided with detailed information about the purpose of the study, the treatment of data, the devices they would be using and the information monitored. All participants signed a consent form, which explained that all data would be anonymized and included a clause stating that they could withdraw from the study at any point. Each participant generated for himself a personal alphanumeric code, based on provided instructions. Although the limited number of participants and the small amount of data captured would easily allow to identify participants and their attitudes, we were interested only in the actual data and their correlations. In addition, we clearly had no interest in breaking the trust that has been given to us.

The organizational chart is shown in Figure 3. Employees are distributed into 5 different departments and split across 4 floors of the FFHS building. The average age was 38 years. Each employee has only a direct supervisor. Four supervisors were involved in the experiment. Each employee also had one of the following roles: *researcher*, *head* (of any department), *leader* (a team-leader within a department), *manager* (without responsibility for employees) and *assistant*.

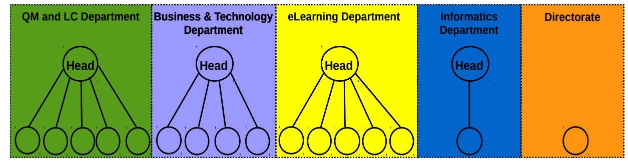

Figure 3: Organizational chart of the Departments.

We assigned a smartphone for a period of 8 working days to all participants of the study. We used the Huawei Ascend P1 model, which has Android OS v4.0, Bluetooth v3.0 and 4 GB internal memory. To avoid they could forget to carry their smartphones along, employees were instructed to wear a phone on an arm support every day, from the moment they arrived at work until they left their office.

We also got self-reported individual performance satisfaction data through an on-line survey, which was configured to get daily the levels of productivity, concentration, well-being of employees, on a five point scale. All data (including demographic information) were received in an anonymized form, using the alphanumeric code described above. The survey included the following questions:

- How do you evaluate your current productivity?
- How do you assess your current concentration in carrying out the work tasks?
- How did you feel today?

We formulated our questions on the base of those more frequently used in literature [11].

The objective of the experiment was to gather data about social interactions with our pilot system. These data gave us a detailed picture of the inner operations of the division. For this reason, information collected may be subsequently used i) to quantitatively analyse social interactions, ii) to correlate temporal changes in social interaction patterns (including amount of face-to-face interaction, conversational time and physical proximity to other people) with performance of individual actors, and iii)to identify and tailor an optimal work environment for each social interaction type.

4.2 Data Analysis

We collected data about the social interactions between employees and investigated the behavioral patterns of employees. Our analysis took into consideration four aspects:

- *Quantity:* quantitative data about physical and virtual interactions between employees.
- *Space:* correlation between employees' behavior and spatial information.
- *Performance:* correlation between performance (productivity, concentration, and well-being) and physical/virtual contacts. In addition, correlation between performance and role of the person contacted.
- *Organization:* correlation between role of employees and their relationships with other employees.

We formulated a list of hypotheses and checked their compliance.

The first hypothesis derived from an outcome of the "OFFICE 21" project [10], which identified different communication types of workers (i.e., silent, caller, meet & talk, communicator) on the basis of the time, the place and the type of communication. This diversity is due to personality traits (e.g., introverts would prefer to interact virtually, extroverts would prefer to communicate face-to-face), mobility of workers, age, sex. Therefore, we supposed that: *(H1), there are different social interaction types of workers.* There would be thinkable virtual, face-to-face and mixed-types of interaction.

Co-present communication occurs when there is direct face-to-face communication. There are different factors that affect face-to-face communication. For instance, Zahn [18] studied the effects of hierarchical relationships and physical arrangements on face-to-face communication in an office environment. He found that physical distance between offices is associated with reduced communication. However, as the technology at that time was not as developed as now, it remained unclear whether the same results could be applied to virtual communication. Olguín [11] found that physical proximity and email exchange have a negative correlation. Thus, we hypothesized that: *(H2), the type of interaction (virtual vs physical) depends on the distance between employees' work locations. The more the distance, the more the employees will interact with each other virtually and the less the distance between work locations the more the physical interaction.*

By studying the correlation between performance (i.e., productivity, concentration and well-being) and contacts, effective behavioural patterns can be discovered and quantified. This comparison would allow managers and team members to identify which behavioural patterns lead to desirable results and consequently replicate those behaviours. In particular, certain individuals are better at interacting with people and this usually lead to favourable outcomes. We would like to analyze how physical interaction impacts productivity, concentration and well-being. In particular, we would like to check the following hypothesis: *(H3), if an individual engages in more and more communication (physical or virtual), her/his productivity, concentration, and well-being level increase.*

Finally, we studied if there is a correlation between the number of contacts and the role of employees. In particular, we would expect that: *(H4), the higher the role of an employee, the higher the number of physical/virtual contacts.*

4.3 Results

After collecting data about Bluetooth detections, we had to perform filtering on it in order to obtain reliable information about contact time and duration. Our filtering process was based on the power of the received Bluetooth signal strength from nearby smartphones. First, we had to choose a threshold for signal strength to discriminate among valid and not valid contacts. After an empirical analysis of contact samples collected in various indoor scenarios, we set the threshold to -82 dBm. Further, to identify the duration of contacts, we calculated the integral of the signal energy and extracted the temporal interval where the integral was positive. In this way, we were able to identify about 4'300 physical contacts, along with their timestamp and duration. In the following sections, we present the results we obtained for the four different features described above.

4.3.1 Quantity

With regard to the type and number of physical and virtual contacts, we got the following result:

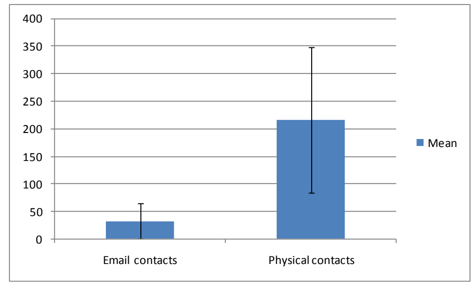

Figure 4: Mean and standard deviation of the number of email and physical contacts.

Table 1: Average number of physical and email contacts per role

Role	no. of phys. ctcs	no. of email ctcs
Assistant	213	12
Head	195	36
Leader	116	44
Manager	146	35
Researcher	263	35

Finding: There exist different social interaction types of workers (those who communicate physically, virtually, both physically and virtually, and hardly at all).
First, there are different social interaction types of workers. Figure 4 shows the mean of the number of email and physical contacts. The graph contains vertical error bars representing the corresponding standard deviation. It can be seen that employees prefer face-to-face communication rather than virtual communication. Furthermore, the standard deviation of the number of email contacts is close to the mean, which indicates that there are employees who hardly communicate via email. From data reported in Table 1, we observe that researches had on an average the highest number of physical contacts. This result might be motivated by researchers' attitude to teamwork. As it can be expected, heads, managers and researchers used email in equal part, mainly because it's a useful communication tool for their work. In contrast, leaders preferred email communication to face-to-face conversation. We further investigated the behavior of researchers and examined in detail the mechanisms of the physical communication intra/inter group and the interaction with their supervisors. We first found that there is a relationship between the size of teams and the logic of physical interactions. More precisely, if the size of the team is small (1 to 3 persons), researchers interact - on average - with their supervisor more frequently than with other members of their group. If the size increases, researchers tend to communicate with other members of their group. Furthermore, as it can be expected, researchers more frequently communicate face-to-face with members of the same group: the average number of physical contacts between members of the same group is indeed higher than the average number of physical contacts for members of the groups with researchers of a different group. Figure 5 and Figure 6 respectively show the organizational structure and the dynamics of the physical communication for researchers.
Finally, we examined whether sex and age could impact the type of interaction. We found out that men interacted face-

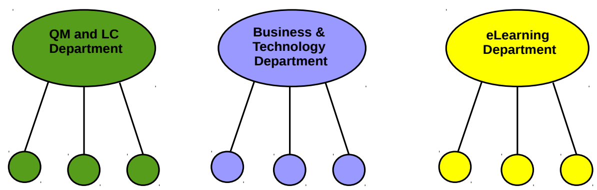

Figure 5: Organizational chart for researchers.

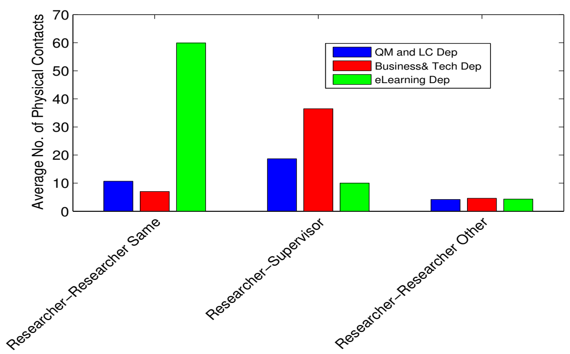

Figure 6: Dynamics of the physical communication for researchers.

to-face more frequently than women. Women interacted more frequently via emails than men. However, since the size of the "males" sample was very small (only 5 persons), this result must be statistical validated and, as such, it will be further investigated in a future work. At last, we did not find any significant difference in the way of interacting (physically or virtually) in relation to the age of participants.

4.3.2 Space

With regard to the spatial aspect, we came to the following conclusions:

Finding: The less the physical distance between employees in a building, the more the contact duration.

Finding: The less the physical distance between employees in a building, the more the number of physical contacts.

To get a measure of the distance between work locations, we computed the distance in terms of number of adjacent offices. For example, if two people stay in the same office, their distance is zero. If two people are in the same floor, their distance is the number of offices between them. If they stay in different floors, we added a factor of ten for each floor between them: this choice was made because the maximum number of offices between people in a floor was nine and for taking into account that moving to a different floor is uncomfortable.

We also analyzed the correlation between asynchronous communication channel (i.e., email contacts) and workplace. We hypothesized (H2) that if people are always out of office, they exchange more emails, while if they are often in the office they have less email contacts. In our analysis we used data about sent emails and working hours, and compared number of days when individuals sent (or NOT) emails while they were (or NOT) in the office. Based on our calculations, we obtained following results:

Finding: In general, when people are in the office they have less email contacts with each other.

This is demonstrated by the fact that the fraction of days when people sent emails while they were in the office is lower compared to the fraction of days when people sent emails while they were NOT in the office.

Finding: There is not clear evidence that if people are always out of office, they use more asynchronous communication channels (i.e., email contacts).

In fact, there are only two cases (out of fourteen) where people exclusively sent emails when they were NOT in the office. In four cases, people sent emails in one day over two, when they were NOT in the office. In five cases, people did NOT send emails at all, when they were NOT in the office.

4.3.3 Performance

We analyzed if there is a correlation between satisfaction, concentration, well-being level and contacts with direct superiors. The performance of a group usually depends on the abilities of its leader. For example, if the leader has good communication skills, the team functions better. In this regard, we compared information about number of physical/virtual contacts with the direct supervisor, per employee, per day, along with information about levels of satisfaction, concentration, well-being. The result was the following:

Finding: There is no correlation between employees' performance and contacts with their direct supervisor.

This finding is probably related to the fact that in the academic world, people tend to work autonomously.

The last finding on performance was the following:

Finding: There is a positive correlation between concentration and productivity of workers.

The Spearman-Rho analysis returned a correlation coefficient $r = 0.596$ with $p < 0.01$. This result has an interesting implication for designing work environments in an office building: if office spaces allow employees to work concentrated, they will be more productive. Furthermore, when the objective is also the optimal distribution of employees, in addition to this rule, employees must be grouped according to the contacts encountered in days where the level of productivity was high.

4.3.4 Organization

To study how the role of employees impacts contacts, we calculated betweenness centrality of the different employees. We used betweenness because it estimates the degree to which an individual is playing an "intermediary" role in a social network, with the potential for control over others [14].

Observing the betweenness calculated from the number of physical contacts, we found that the employees with the highest betweenness were the two heads of departments involved in the experiment. This result endorses the following finding:

Finding: the higher the role (or the centrality) of an employee, the higher the number of physical contacts.

Finally, we calculated the betweenness from the pattern of virtual contacts and discovered that the person with highest betweenness was the manager of human resources. This result extends the last finding in terms of virtual contacts.

5. CONCLUSION AND FUTURE WORK

We presented an analysis of human behavior in an organizational setting based on the implementation and deployment of a software platform. We measured physical and virtual contacts (i.e., email exchanges) between employees, using off-the-shelf technologies and devices. We also evaluated the employees' self-assessment of performance (productivity, concentration and well-being). The analysis performed on the collected data in the course of an experiment that lasted 8 working days allowed us to get a detailed picture of the employees' social interactions and their day-to-day actions. We found that if employees are in close proximity to each other, they prefer physical encounters with considerable contact duration as compared to virtual contacts. Further, our study highlighted how contacts impact performance and the influence of the role on the number of contacts.

Although our study was limited by the number of participants involved, these results gave us a fine-grained picture of the social dynamics within a real work environment. The main contribution of our work is the application of information on social interaction among people for the optimal distribution of people in a workplace, to increase overall well-being and productivity of employees.

In the future, we plan to study other organizational contexts and integrate a localization system for detecting the place where employees meet. This will allow refining social analysis and consequently arranging work environments and employee's distribution in accordance with their needs and current work activities (e.g., additional meeting rooms, collaboration rooms, concentration rooms).

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