Using Future Internet Infrastructure and Smartphones for Mobility Trace Acquisition and Social Interactions Monitoring

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Abstract. Recent activity in the field of Internet-of-Things experimentation has focused on the federation of discrete testbeds, thus placing less effort in the integration of other related technologies, such as smartphones; also, while it is gradually moving to more application-oriented paths, such as urban settings, it has not dealt in large with applications having social networking features. We argue here that current IoT infrastructure, testbeds and related software technologies should be used in such a context, capturing real-world human mobility and social networking interactions, for use in evaluating and fine-tuning realistic mobility models and designing human-centric applications. We discuss a system for producing traces for a new generation of human-centric applications, utilizing technologies such as Bluetooth and focusing on human interactions. We describe the architecture for this system and the respective implementation details presenting two distinct deployments; one in an office environment and another in an exhibition/conference event[1] with 103 active participants combined, thus covering two popular scenarios for human centric applications. Our system provides online, almost real-time, feedback and statistics and its implementation allows for rapid and robust deployment, utilizing mainstream technologies and components.

1 Introduction

Experimentation in the field of Internet-of-Things has currently grown to encompass enormous infrastructure sizes, heterogeneous pools of resources, as well as a large breadth of application scenarios. Research projects such as WISEBED [1] and SmartSantander [2] serve as examples of the aforementioned advancements, depicting the use of federated testbeds of large scale, diverse application scenarios and enormous scale deployment and operation in urban settings. However, certain aspects of current technology and application trends have not been effectively dealt with; namely, the use of smartphones in combination with IoT infrastructure and, on the application side, human mobility and social networking related themes. Instead, the currently utilised application scenarios revolve

[1] FET'11, The European Future Technologies Conference and Exhibition.

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less around human activity and more around monitoring environmental parameters; opening up to additional possibilities with regard to IoT experimentation should provide further insight to the Future Internet.

On the one hand, smartphones are increasingly getting closer to the Internet-of-Things, encompassing at the same time an impressive range of integrated sensors: accelerometers, cameras, gyroscopes, microphones, thermistors, proximity sensors, etc., while also adopting novel technologies like Near Field Communication (NFC). Also, the latest smartphone operating systems also offer enough flexibility for adding external sensing units directly or communicating wirelessly with them. Furthermore, additional functionality and more potent hardware is bridging the gap in capabilities with traditional computing systems.

On the other hand, inferring social and contextual interactions has direct and important applications in our daily lives, uncovering fundamental patterns in social dynamics and coordinated human activity. Deriving accurate models for human activity [4] is of great importance to both social sciences and computer scientists dealing with studies/simulations of mobile users; real-world data can aid tremendously in this direction, since they can provide a realistic means to (re)produce, fine-tune and empirically validate models that attempt to capture the characteristics of human mobility in a variety of environments and situations/occasions. Similarly, recording the daily activity of elders at home using sensors can produce patterns that may help in providing a better quality of life for them. RFID deployments inside a university or enterprise building can reveal communication patterns among students and faculty over time, helping in understanding (in)efficiencies in that respect. Smartphones' proliferation can also aid in delivering similar results [3]. Finally, an interesting issue is to capture, in a qualitative and quantitative manner, the characteristics of meetings, conferences and gatherings where a large amount of people from different backgrounds, disciplines and interests congregate and cooperate.

Therefore, we believe that there is currently a need to add the following perspectives to the Future Internet research agenda and develop:

- architectures and systems for combined experimentation using smartphones and Internet-of-Things devices,
- techniques for sensor-based behaviour profiling and models of behaviour,
- tools that exploit cross-correlations of behavioural profiles of an individual user and across user groups in order to gain new insights and utilise them in selected services and applications of high socio-economic value.

We envisage a domain of Future Internet applications that become possible utilizing semantically rich information derived from real-world mobility and presence traces. Such applications can have as their main focus to perform statistical analysis and provide reports on collected trace data inferring possible interactions among the monitored population. Other ones can analyse the trace data and publish results while the data are still being gathered. Additional applications could use the trace data to predict the future behavior of the observed population, or even extend the results to larger populations. We also consider applications that combine a subset or all of the above functionalities, providing reports on collected data, generating real-time content in parallel with the trace gathering process and predicting the behavior of the monitored population.

Moreover, people in cities work in enterprises, offices, etc., spending considerable time inside such environments. Capturing the collaborative, social and physical behaviour in an organizational context is a critical foundation for managing information, people, and ICT. E.g., customers can be segmented on the basis of common or similar patterns along multiple behavioural feature dimensions such as frequency of face-to-face contacts, commonality of location and similarities in movement patterns, as well as commonness in network and service use. According to the information richness theory, face-to-face interactions are the richest and the most effective medium during daily interactions. These can provide clues of higher quality of social relationships than co-presence indications, leading to better predictive models about user behaviour. These models can be utilised for improving current mobility models of mobile subscribers or consumer models in mobile commerce environments. Furthermore, personalised content streaming, satisfying customer needs and further pushing business activity could be possible by utilising such social networking knowledge, location awareness and recorded data. Additional examples of such applications are a smart mall application that can adaptively push product advertisements and personalised bargain offers to potential customers that move within its premises and a smart conference scenario, whereby interaction statistics and a presence heatmap are generated periodically and reported.

Related to such concepts, we discuss here a system for monitoring large groups of users using a combination of static and mobile IoT infrastructure, targeting multiple application domains, which become possible or are considerably enhanced by analyzing the inferred interactions in space-time-social characteristics dimensions and furthermore exploiting the prediction of future behavior and contacts for individuals or groups of people with common social attributes. Moreover, one should consider our approach in light of the Future Internet vision and current trends such as crowdsourcing and social computing; we expect such enablers to unlock the potential of the Internet-of-Things, since computing is rapidly becoming an integral part of our society. Future systems will orchestrate myriads of nodes, web services, business processes, people and institutions; inferring social interactions is needed to support such a Future Internet vision.

We applied our system in 2 scenarios, an office building and a large conference setting (FET'11) and the results show definite potential in our approach. We present our architecture and current implementation, along with technical issues related to our design choices. Along with the monitoring and archiving functionality of the system, we additionally offer on-line statistics for various features. The proposed solution, considers detection of human interaction and preferences by exploiting Internet of Things infrastructures and novel middle layer mechanisms. We believe that building applications, by adopting the proposed methodology, can leverage innovation capabilities to a wide range of application domains like Smart Cities and Smart Organizations.

1.1 Related Work

An early approach in monitoring the mobility of people or classes of people, the congregation and the interactions among them, was discussed in [5] while in [6] wearable Bluetooth-enabled devices were used. In [7] trials were conducted during CoNEXT'06 and FIRE'07. Subsequent works like [9] focus on the utilization of mobile phones and trials in urban settings. In [10] the authors study data transfer opportunities between wireless devices carried by humans and they observe that the distribution of the inter-contact time (the time gap separating two contacts between the same pair of devices) may be well approximated by a power law over the range.

The recent availability of large-scale datasets, such as mobile-phone records and GPS data, has offered researchers detailed patterns of human behavior. [12] studied human movements using a large quantity of bills, while [13] used mobile phone data from 100K individuals. It was shown that each person is characterized by a time-independent travel distance and a large probability to revisit previously-traversed locations. In [14] the authors introduce two principles that govern human trajectories, exploration and preferential return, which are both unique to human mobility. In [15] individuals' daily routines are proved highly predictable, using principal component analysis. Human contact prediction has also attracted much interest; data mining in social network data (human contact graph) is quite challenging due to the great imbalance in the number of positive and negative cases in training datasets. Most research efforts propose various proximity measures on network topology, to be used as predictors for new contact links [16]. Furthermore, [17] explores the impact of human mobility, as an intrinsic property of human behavior, on contact link prediction. Datasets consisting of parallel geographical, network and contact information are scarce, even today. In [17,18] it is observed that the probability of forming a social tie decays with distance as a power law. Based on that, in [19] the authors propose a method that predicts the location of an individual.

In [20] it is stated that there is need for a precise specification of interaction behaviour in organizations, as information systems require a precise specification for handling all possible situations. They claim that such interaction behaviour is described in business process choreographies, a collection of business steps taking place in a prescribed manner and leading to business objectives. They conclude that using ICT is crucial for designing and developing tools that will allow managers to analyze, synthesize and evaluate ways of managing people, information and technology in public and private sector organizations. Utilizing IoT and pervasive systems in such context further expands the possibilities for real-world and real-time applications that can increase the knowledge about an organization's process intelligence and thus the efficacy of decision making. In [21] the analysis of behavioural signals obtained by wearable badges at the workplace such as face-to-face interactions and modeling the relationship between organizational dynamics and organizational performance based on that, is shown to be an effective management tool that can radically improve the overall operation of the organization.

2 A System for Trace Acquisition - Architecture and Implementation

Our architecture for collecting traces of presence in a Smart City environment is partitioned in 3 tiers. The lower tier contains the fixed location base station trackers and the mobile personal devices (i.e., mobile phones) carried by the monitored population. The mobile personal devices are further divided in simple devices which can be detected by the base station trackers, and mobile trackers which are capable of detecting other mobile devices and nearby base stations.

The base station trackers are placed at fixed locations throughout the monitored area providing the coverage required. These trackers are interconnected using a reliable and sufficiently high-throughput technology (e.g., 100Mbps Ethernet, 802.11g). We currently use the Bluetooth in our enabling devices - it is a ubiquitous technology with which end-users feel comfortable, while IoT nodes and smartphones also usually support it. The scan range of a tracker is typically 10-20 meters, but the system does not impose a specific constraint and can support trackers with varying scan ranges. In most cases, the trackers are placed in proximity of each other so that their scan ranges overlap. In this way, we are able to infer presence of a device at intermediate locations using the received signal strength within a short-time window. Each base station tracker maintains a local log of detected traces in addition to forwarding them towards the local (on site) database. The mobile trackers are utilised to complement the static infrastructure and collect additional traces of mobile phones, even when those are located outside the range of the static base stations. They periodically attempt to transmit their buffered trace data via a WiFi connection to the Application Server, which in turn relays this data to the remote DB Server.

In the second tier, the collected traces from each static tracker are stored in a local database - essentially records of device traces with a corresponding inquiring tracker ID, a timestamp and a RSSI value. These data are also forwarded to the remote database and analysis server, where they are used to produce meaningful results. The Remote Database and Analysis Server is typically accessible over the Internet via a secure connection channel. In the preprocessing stage the trace data are filtered to remove duplicate and invalid entries as well as entries from devices not participating in the monitoring system. Furthermore, for each trace, a specific location is assigned to the mobile device and hence to the person carrying it, by considering the RSSI of the device as measured from involved base stations in a short-time interval around the trace timestamp. The remote DB adopts a more advanced schema that allows taking into consideration a time-schedule of events in different monitored locations, the participants' interests and personal attributes (e.g. age range, scientific background). During the analysis phase, possible interactions among the population are inferred and correlated with their self-reported attributes and scheduled events.

The third tier, is essentially the application layer of the architecture. A web site provides information about the related deployed monitoring application, a description of the system technology, instructions for participation and links to interesting results from the traces analysis. The system will only process traces that correspond to the presence of people who agreed to participate and carry mobile detectable devices, submitting a registration form. In addition to the participation consent, the registration form may request optional information regarding personal attributes of a participant, that will be used to infer behavioral patterns for groups of people that share common attributes. The application layer also includes an automated mechanism that posts links to interesting results with a short description on a Twitter account, which end-users can follow in order to receive updates about the dynamics of the participants' interactions.

Our system architecture was designed with an emphasis on scalability, ease of deployment and simplicity in participation requirements, as well as the ability for people to register online, even after the monitoring deployment has launched. Such flexibility is usually absent in other related systems, both in terms of adding users online, as well as modifying the supporting infrastructure and maintaining overall system stability. The distributed nature of our system results also to an easier and faster installation phase.

Another basic consideration was respecting the privacy and self-reported data of the participants, and the deletion of "external" traces belonging to devices not registered for the particular deployments. Privacy concerns of the participants were answered by the anonymisation of collected data. Since privacy issues should not be perceived by the participants themselves as an afterthought, all were informed prior and during the experiments regarding the data collection aspects of their participation, the future availability of the produced anonymised data sets and our conformance to the related legislation (EU directive 95/46/EC). At the same time, users had control over the software components running on their smartphones and could opt for turning them off anytime.

By utilizing Bluetooth networking, which is supported by the vast majority of the mobile phones that are in use today, certain advantages were evident: participants are only required to carry with them a personal device, the collected trace data can be delivered in real-time, while also the infrastructure cost is cheap to purchase and maintain. Moreover, Bluetooth allows for greater localisation accuracy compared to WiFi, due to its more limited range. It is also easier and safer to setup and operate, due to the inherent features in Bluetooth's design.

2.1 Implementation Details

Mobile Trackers: The mobile trackers are used to complement the static infrastructure and collect additional traces of mobile phones, even when those are located outside the range of the static base stations. The mobile trackers in our implementation are Nokia smartphones with Bluetooth and WiFi support and Android based phones. The mobile application has a simple GUI and offers the option of running hidden as a background application. A mobile tracker performs a periodic inquiry scan for discoverable Bluetooth devices, i.e., users' mobile phones and static base stations. The list of detected devices is stored on a local limited-length buffer of the "active sessions". Each entry contains two timestamps, for the first and last time the device was encountered. If a previously detected device is not seen in a new scan, then its entry is moved in another local buffer ("completed sessions"). Occasionally, the mobile tracker attempts to forward stored sessions to the application server that handles these traces (through WiFi). During such an opportunity, the completed session traces are transmitted first, followed by the active sessions traces. By running the mobile tracker application, a mobile phone is able to detect the base station trackers and can therefore be associated with them without having to operate in discoverable mode. The application server inserts the data from the mobile trackers into a separate table in the remote database.

Basestation Trackers: The base station trackers are hosted on mini PCs or laptops that have Bluetooth dongles attached and are placed at specific fixed locations, providing full coverage for a monitored area. In most cases, the trackers are intentionally placed in proximity of each other so that their scan ranges overlap. This way we are able to infer presence of a device at intermediate locations by evaluating the received signal strength from the same device at each tracker within a short-time window. All trackers are time-synchronized with the local DB server, their Bluetooth interfaces are set in discoverable mode and periodically perform a Bluetooth scan inquiry of a predefined duration. For each detected device a trace entry is created, including a timestamp and a corresponding RSSI value. The traces gathered after an inquiry scan are transmitted towards the local database after the end of the inquiry phase.

Local Database, Remote Database and Analysis Service: We used a MySQL instance on a laptop, while mobile and base station trackers record the users' presence directly in this database instance. Every 5 minutes this local instance pushes the updates, utilizing a CRON daemon and SSH connection to a mirrored MySQL instance hosted at the remote database machine. This remote database server was hosted at the headquarters of CTI and this two step schema was used due to unstable Internet connection and limited processing resources on the devices utilized on site. Our Remote Database consisted of a MS SQL Server 2008. Services deployed and used were MSSQL Server RDBMS, MSSQL Integration Services and MySQL. All functionality and instrumentation at the centralized server was implemented by a set of tasks in the MSSQL Integration Services. Whenever an update took place in the local MySQL instance, all trace records were retrieved and forwarded for processing. Initially, the MAC addresses in the trace records were removed and replaced by a user ID that was correlated with the social attributes of the users. Thus, the subsequent Aggregation and Analysis phases were not aware of the user MAC.

A location ID is then assigned to each trace record in order to verify copresence of users and attendance to events. Using a 1-minute buffer, we lookup the reachable base station trackers for each user and respective RSSI values and form an "observed vector" for the user during that interval. From a set of possible vectors, mapping base stations to sublocations and indicating the trackers' capability of detecting presence for devices, we pick the one more similar to the observed vector. This set of vectors is recorded in a training phase. At the end of this step all trace records were quantized at a 1-minute time interval grain, characterized by location. This set of trace records was used as a fact table in order to be analyzed in a MOLAP Cube in MSSQL Integration Services. Fact records were analyzed by date dimension in a Day, Hour, Minute hierarchy, by "Persons" dimension with social characteristics attributes (age range, profession, etc.), by "Place" and "Event" dimensions. The Event dimension is a function dimension on the "Place" and "Date" dimensions.

3 Deployment and Results Discussion

We deployed our system twice: a) inside our institute building, with 23 Bluetooth-capable base stations, distributed over 3 building levels, monitoring for 27 hours (9am-6pm, 3 days), b) at a large-scale conference event, with 36 base stations (12 mobile), for 27 hours. A total of 103 participants in both events carried with them their mobile phones, with Bluetooth switched on, set to be discoverable. We describe here the main characteristics of the discussed deployments.

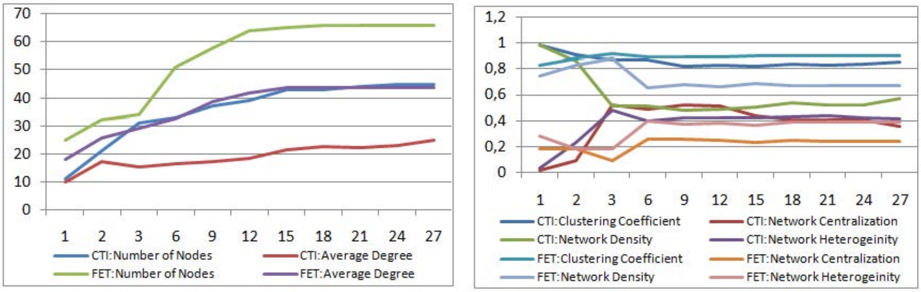
CTI Deployment: In essence, a building-scale IoT infrastructure was used to monitor interactions between co-workers and/or different enterprise departments, in order to infer both online and over time intraconnections and interconnections within such entities. This kind of knowledge could give further insight for optimizing business processes, re-organizing hierarchical structures or re-establishing connections through e.g., reimplementing certain standard procedures or changing the actual physical locations of specific people or departments. CTI's staff consists of a number of research teams and administrative / support staff, with each one housed in discrete parts of the CTI building. Moreover, CTI is situated in a 5-floor building, with the thick walls and steel doors of each floor sector providing isolation in terms of wireless communication between adjacent parts. This provided an advantage in determining the position of participants inside the building more accurately. The setup of the system inside 23 different building rooms overall required 4 hours of work from 3 members of our team. Bluetooth-enabled gateways were used in all rooms, being powered on for the whole duration of the experiment, monitoring all Bluetooth networking activity and reporting to the system, as defined in Section 2. The duration of the experiment prohibited the use of battery-powered gateways, since we wanted the infrastructure to operate largely unattended. The layout of the building also contributed in confining the activity of people interested only in communicating within their own group, allowing the activity of persons behaving as "hubs" between different groups to be more visible. It is interesting to note that we monitored physical presence, and thus interaction in the physical space. As discussed in the next section, it reflects the structure of the institute quite accurately.

FET'11 Deployment: In the second set (conference) of experiments, a number of weeks after our initial deployment, we tested our system in a less controlled environment. The performance fine-tuning after the first set of experiments allowed us to scale the system even further. Since this was a larger scale deployment and was done in harsher conditions, we used a larger team of people to setup and operate the infrastructure, i.e., 5. The setup was completed within 4 hours on the day before the opening of the conference (FET'11) to the public. In contrast with the CTI deployment, the networking isolation offered by walls and doors was not available in this case, making it more difficult to determine the location of participants. Furthermore, we implemented additional components for providing results and statistics, e.g., posting latest information about booth popularity on Twitter and other social networks. Conference participants showed interest towards the statistics, even though they were produced with some minutes of delay. The set of statistics produced included information such as the top 10 popular booths, booths where visitors spend the most time, among others. Apart from visitors, exhibitors also showed interest in statistics about their booth and indicators regarding how their exhibits faired against others.

3.1 Results Discussion

One of our basic findings during deployment and operation of our system is that it is possible to acquire and process human mobility data, extract human interactions and analyse them in almost real time manner, combining widespread technologies and relatively simple and low-cost subsystems. The flow of human trace data from lower infrastructure components is channeled to the web, enriched with the inferred human interaction possibilities and self-reported personal information (e.g., age, profession, interests). By exposing this rich flow of data, new opportunities arise to build interesting applications on top of it (like real world recommendations, searching and discovering people of different knowledge backgrounds and social profiles etc.) or design interconnecting testbeds exchanging complex analyzed information in addition to plain data messages. In such cases, the system design should perceive the information analysis of human interactions as part of a communication protocol running concurrently on top of heterogeneous resources. In both deployments, the assumption that users carry their smartphones constantly with them was largely confirmed, while communication with an IoT infrastructure in a pervasive manner helped to ensure the correct operation of the system with minimal user time consumed.

During the first set of experiments in the CTI building, a series of communication patterns among participants emerged. Fig. 1 (a) reveals a dense network, depicting the gradual cooperation of users. The diameter of the network, was found to be 3, meaning that any two members of the personnel can either communicate directly (one hop), or through at most two intermediate people. These reflect a hierarchical administration structure and strong interaction. Fig. 1 (b) depicting the contact network parameters shows that the network centralization and network heterogeneity is average while the clustering coefficient is quite large, indicating that the contact graph tends to form a clique. Fig. 2(b) depicts interactions of the participants within their own and among other groups (research units) as well. We can observe clearly that some groups have strong intraconnections and strong interconnections with some of the other groups. Such information can be used e.g., in an enterprise to detect inefficiencies in its management structure, or evaluate potential solutions immediately and express



(a) (b)

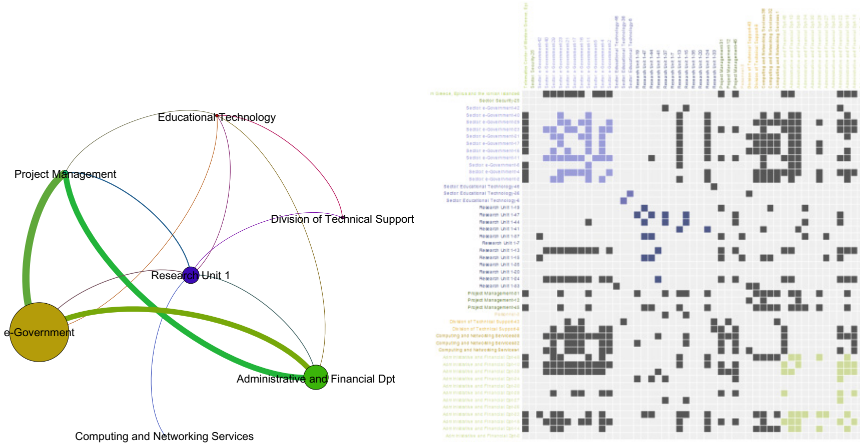
Fig. 1. (a) Rising number of nodes and average degree reflects the users' gradual involvement. (b) The general features characterizing the graph can be captured in relatively little time in both scenaria.

explicitly mobility habits among sections of the institute. Finally, in Fig.2 (a) we also show the intensity of interaction among research units.

In the second set of experiments (FET conference setting), we observed slightly different behaviors. While Fig. 1 (a) reveals for this case a similarly dense network and the diameter of the network is again found to be 3, Fig. 1 (b) depicts a greater tendency to form a clique as the clustering coefficient and network density is large (larger than the CTI deployment). Network centralization is quite low (lower than CTI) while Network Heterogeneity is average again. Fig. 3(b) depicts interactions of the participants among groups of different scientific background. In Fig. 3(a) the distinct number of users who attended each of the 10 most popular booths for each day of FET'11 is presented, while Fig. 4 depicts the average time spent by each Scientific Background group in each booth. Such information was delivered almost online, i.e., with a latency of about 5 minutes, and can be utilised in accessing overall tendencies in such an event and delivering useful statistics to both participants and organisers. Overall, the statistics delivered could reveal "hidden" trends and synergies between different scientific fields, which could otherwise be difficult to recognise.

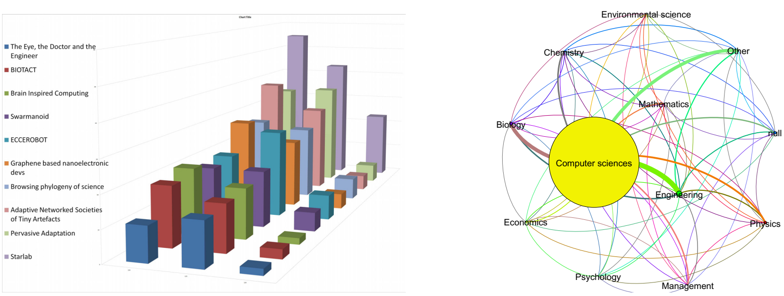
4 Conclusions - Future Work

We believe that recent progress in human mobility modeling and the rise of applications with social networking characteristics should be encompassed in current IoT experimentation activities. In that respect, the fuse of smartphones and IoT infrastructure can enable systems such as the one presented here. We experimented in two discrete scenarios, an office building and a scientific conference hall and deployed our system to capture human mobility and interactions. Our future work will focus on extending the current range of supported mobile platforms and providing a better end-user experience, and also provide traces on an even larger scale, such as in a smart IoT city setting.



(a) (b)

Fig. 2. Interactions among (a) the various groups in CTI - the results reflect largely the hierarchical structure and actual cooperation patterns among groups, (b) interaction matrices reveal strong cooperation among participants' own groups at all times, with varying degree during different times of the day



(a) (b)

Fig. 3. (a) Number of distinct users per booth per day, (b) various groups of participants in FET'11 with different scientific background

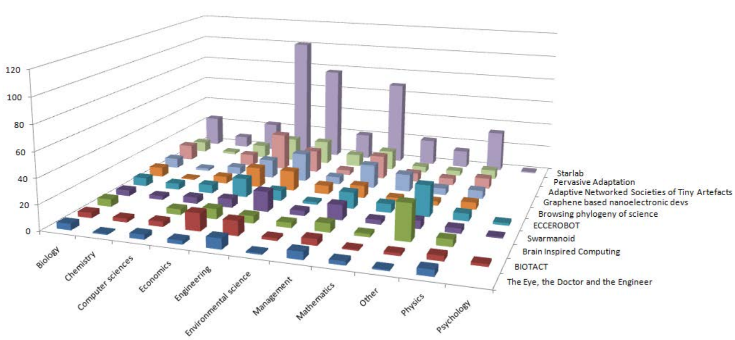


Fig. 4. Average Time (min) each Scientific Background group spent in each booth

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References

1. Coulson, G., et al.: Flexible experimentation in wireless sensor networks. Communications of the ACM (CACM) 55(1), 82–90 (2012)
2. SmartSantader project, `http://smartsantander.eu`
3. Miluzzo, E., et al.: Darwin Phones: the Evolution of Sensing and Inference on Mobile Phones. In: MobiSys 2010, pp. 5–20 (2010)
4. Eagle, N., Pentland, A.: Reality Mining: Sensing Complex Social Systems. In: Personal and Ubiquitous Computing, pp. 255–268 (May 2006)
5. Borovoy, R., et al.: Meme tags and community mirrors: moving from conferences to collaboration. In: CSCW 1998, pp. 159–168 (1998)
6. Hui, P., et al.: Pocket switched networks and human mobility in conference environments. In: WDTN 2005, pp. 244–251 (2005)
7. Nordstrom, E., Diot, C., Gass, R., Gunningberg, P.: Experiences from measuring human mobility using Bluetooth inquiring devices. In: MobiEval 2007, pp. 15–20 (2007)
8. Nicolai, T., Yoneki, E., Behrens, N., Kenn, H.: Exploring Social Context with the Wireless Rope. In: Meersman, R., Tari, Z., Herrero, P. (eds.) OTM 2006 Workshops, part I. LNCS, vol. 4277, pp. 874–883. Springer, Heidelberg (2006)
9. Natarajan, A., Motani, M., Srinivasan, V.: Understanding Urban Interactions from Bluetooth Phone Contact Traces. In: Uhlig, S., Papagiannaki, K., Bonaventure, O. (eds.) PAM 2007. LNCS, vol. 4427, pp. 115–124. Springer, Heidelberg (2007)
10. Chaintreau, A., Hui, P., Crowcroft, J., Diot, C., Gass, R., Scott, J.: Impact of Human Mobility on Opportunistic Forwarding Algorithms. IEEE Transactions on Mobile Computing 6(6), 606–620 (2007)
11. SocioPatterns, `http://www.sociopatterns.org`
12. Brockmann, D., Hufnagel, L., Geisel, T.: The scaling laws of human travel. Nature 439(7075), 462–465 (2006)
13. Gonzalez, M., Hidalgo, C., Barabasi, A.-L.: Understanding individual human mobility patterns. Nature 453(7196), 779–782 (2008)
14. Song, C., Koren, T., Wang, P., Barabasi, A.-L.: Modelling the scaling properties of human mobility. Nature Physics (2010)
15. Eagle, N., Pentland, A.: Eigenbehaviors: Identifying structure in routine. Behavioral Ecology and Sociobiology 63(7), 1057–1066 (2009)
16. Liben-Nowell, D., Kleinberg, J.M.: The link prediction problem for social networks. In: CIKM 2003, pp. 556–559 (2003)
17. Wang, D., Pedreschi, D., Song, C., Giannotti, F., Barabasi, A.-L.: Human Mobility. In: Social Ties, and Link Prediction KDD 2011 (2011)

18. Lambiotte, R., et al.: Geographical dispersal of mobile communication networks. Physica A: Statistical Mechanics and its Applications 387(21), 17 (2008)
19. Backstrom, L., Sun, E., Marlow, C.: Find Me If You Can: Improving Geographical Prediction with Social and Spatial Proximity. North, pp. 61–70. ACM (2010)
20. Decker, G., Weske, M.: Interaction-centric modeling of process choreographies. Inf. Syst. 36, 292–312 (2011)
21. Olguin, D.O., et al.: Sensible Organizations: Technology and Methodology for Automatically Measuring Organizational Behavior. IEEE Transactions on Systems, Man, and Cybernetics 39 (February 2009)