

High resolution dynamical mapping of social interactions with active RFID

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Abstract

In this paper we present an experimental framework to gather data on face-to-face social interactions between individuals, with a high spatial and temporal resolution. We use active Radio Frequency Identification (RFID) devices that assess contacts with one another by exchanging low-power radio packets. When individuals wear the beacons as a badge, a persistent radio contact between the RFID devices can be used as a proxy for a social interaction between individuals. We present the results of a pilot study and a subsequent preliminary data analysis, that provides an assessment of our method and highlights its versatility and applicability in many areas concerned with human dynamics.

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I. INTRODUCTION

Social interaction patterns such as contacts and mixing patterns among individuals have a direct impact on diverse phenomena studied in various research areas. Clear-cut examples are the transmission of infectious diseases by the respiratory or close-contact route, and collective opinion formation. The availability of representative data on such patterns has long been a concern since it used to be notoriously difficult to collect it. The available methods usually rely on surveys and paper-diary methodologies [1] which are often slow, inaccurate, and intrusive. Novel technologies, however, afford new and promising means of collecting this essential data.

Contact patterns data is indeed much needed. Recent studies of e-mail [3] and cellular phone call exchanges [5, 6], collaboration networks [4], sexual contact networks [2], and mobility by air travel [7], have revealed the presence of complex properties and heterogeneities. In particular, the number of interaction partners from one individual to the other is subject to large fluctuations that have non-trivial consequences on the dynamical processes taking place on these networks [8, 9, 10]. A detailed characterization of these structures is therefore of utmost importance for the understanding of many phenomena, and crucially depends on the availability of representative empirical data.

While important progress has been achieved in the last decade or so, more is bound to come, for most of these recent characterizations of complex networks focused on static configurations in which the temporal dimension was not considered, mostly because of lack of data. Examples of properties that arise in this temporal dimension are duration, frequency, concurrency, and causality. For instance, if an individual A meets first B then C, an information or a virus can spread from B to A and then to C, but not from C to B. In the image of a static network in contrast, the links allow propagation in both cases. The fact that these static networks are in fact “summaries” of many different interactions that do not occur simultaneously, might conceal important insights. The few cases in which temporal aspects have been considered in more detail, indeed revealed important consequences [11, 12, 13, 14, 15, 16, 17, 18, 19].

Several more recent studies have demonstrated the potential of using novel technologies such as Bluetooth and Wifi for collecting data on both the structural and temporal aspects of social interaction patterns [16, 18, 19, 20]. However, their spatial resolution in these is

at best of the order of 10 meters, and the temporal resolution of the order of 2-5 minutes. Moreover, these technologies detect local proximity between devices, which does not imply a priori a social interaction between the individuals carrying these devices. Finally, these studies concern small groups and are not easily reproducible.

In this paper, we present a novel experimental framework based on active RFID devices that overcomes these limitations. We discuss a recently performed pilot study, and a data analysis that highlights the main advantages of this new data collection technique. Non-technical accounts and supplementary material can be found on the website of the SocioPatterns project [21].

II. METHODOLOGY, EXPERIMENTS, DATA

A. Active RFID-based experimental framework

The proposed experimental framework aims at measuring the contact patterns of a group of interacting individuals in a spatially bounded setting, such as a set of offices or a conference. The participants are asked to carry small RFID tags [22], henceforth called *beacons*. These beacons continuously broadcast small data packets which are received by a number of stations and relayed through a local network to a server. The stations are installed at fixed locations in the environment. The beacons and stations we used were created by and obtained from the OpenBeacon project [23].

RFID tags acting as beacons can be used to deploy indoors locative systems [24] that track the location of the tags. Problems related to multiple path, phase fluctuations, etc. tend however to limit the precision of the spatial localization of the tags. Because of this, locative technologies are typically not viable, at low cost, to infer face-to-face contact between individuals wearing RFID tags.

Moving from *contact inference* to direct *contact detection* enabled us to bypass these limitations. To this end, we leveraged the OpenBeacon active RFID platform [23] and operate the RFID tags a bi-directional fashion. That is, tags no longer act as simple beacons that passively emit signals to be received and processed by a centralized post-processing set-up. They rather exchange messages in a peer-to-peer fashion to sense their neighborhood and assess directly contacts with nearby tags.

A high spatial resolution of less than $1 - 2$ meters is attained by using very low radio power levels for the contact sensing. Furthermore, assuming that the subjects wear the tags on their chest, the body effectively acts as a shield for the sensing signals. This way, contacts are detected only when participants actually face one another. If a sensed contact persists for a few seconds, then given the short range and the face-to-face requirement, it is reasonable to assume that the experiment is able to detect an ongoing social contact (as e.g. a conversation).

After the beacons detect a contact, they broadcast a report message at a higher power level. These reports are received by the stations and relayed to the monitoring infrastructure. The reports are stored with a time stamp, the ID of the relaying station and the ID of the tags which participate in the contact event (up to 4 simultaneous contacts are recorded, using the current hardware).

After a suitable tuning of the system parameters, we can easily record individual contacts in a crowded room with just a small number of receiving stations. The raw data series is made with an effective sampling frequency under one second. In many instances of data processing, we applied a coarse graining filter using time windows of 20 seconds (see next section). This value is chosen in order to minimize statistical errors, and corresponds moreover to a typical timescale for social interactions. We finally note that messages between tags and/or stations are encrypted and that the entire data management is completely anonymous.

B. Visualization

The pilot studies we conducted so far were accompanied with publicly displayed, dynamic visualizations of the contacts between individuals. This is achieved by defining a contact network in which the beacons/persons are nodes and the contacts are edges. Two different types of visualizations can be displayed, providing snapshots respectively of the *instantaneous* state of the network, and of the *cumulative* state since a given time (e.g. the start of the experiment, or the start of the day in a multi-day experiment). The 'instantaneous' visualization additionally displays marks for the stations, which are positioned in a fixed layout. The location of the beacon marks in the visualization is driven by a force-directed layout algorithm. Springs are associated with both the explicitly shown contact edges and the edges between beacons and stations, which are not shown. The rest length of these

springs is inversely proportional to the strength of the respective contact or beacon-station proximity estimations.

The model is regularly updated based on the live data feed, and the view is updated after each iteration of the algorithm, up to 25 times per second. The result is a continuously morphing network representation in which the marks of beacons that are in contact try to occupy adjacent positions, and to move towards the marks of the closest stations. The other visual encodings are as follows: Edge thickness and transparency encode contact strength; Beacon mark size encodes the number of contacts reported by the beacon; Station mark size encodes the number and proximity of the closest beacons. The main network view is furthermore flanked by a side-bar with various data points and charts, which are dynamically updated as well. Figure 1 shows a snapshot of the visualization. Sample movies can be viewed on the website of the Sociopatterns project [21].

These visualizations were primarily developed to visually follow and inspect the ongoing experiment and as an aid in explaining it, but we also introduced certain affordances. One such feature consists of enabling the participants to tap their beacon by pressing a button. The visualization immediately reacts by highlighting the corresponding beacon mark and temporarily showing a small table with some detailed contextual data in the side-bar. Other affordances that were effectively exploited by the participants are the localization of people and the identification of an observed but unknown contact partner of a known person.

C. A pilot study

We have deployed our measuring infrastructure in a pilot experiment of limited size. The experiment took place during the workshop “Facing the challenge of Infectious Diseases” at the ISI Foundation on October 13 – 17, 2008. Participants to the workshop were offered to volunteer to participate to the experiment, and a large part agreed. This allowed us to gather data in a very dynamical context with periods of high social interaction (coffee and lunch breaks) and other periods in which the participants sit together but (almost) do not interact in a pairwise fashion. The experiment involved about 50 attendees over four days. We placed reporting stations in the main areas in which people were expected to be during the sessions and breaks – namely the conference room, the bar (where coffee breaks were taking place) and the cafeteria area (where lunch was served). We also put a station in the

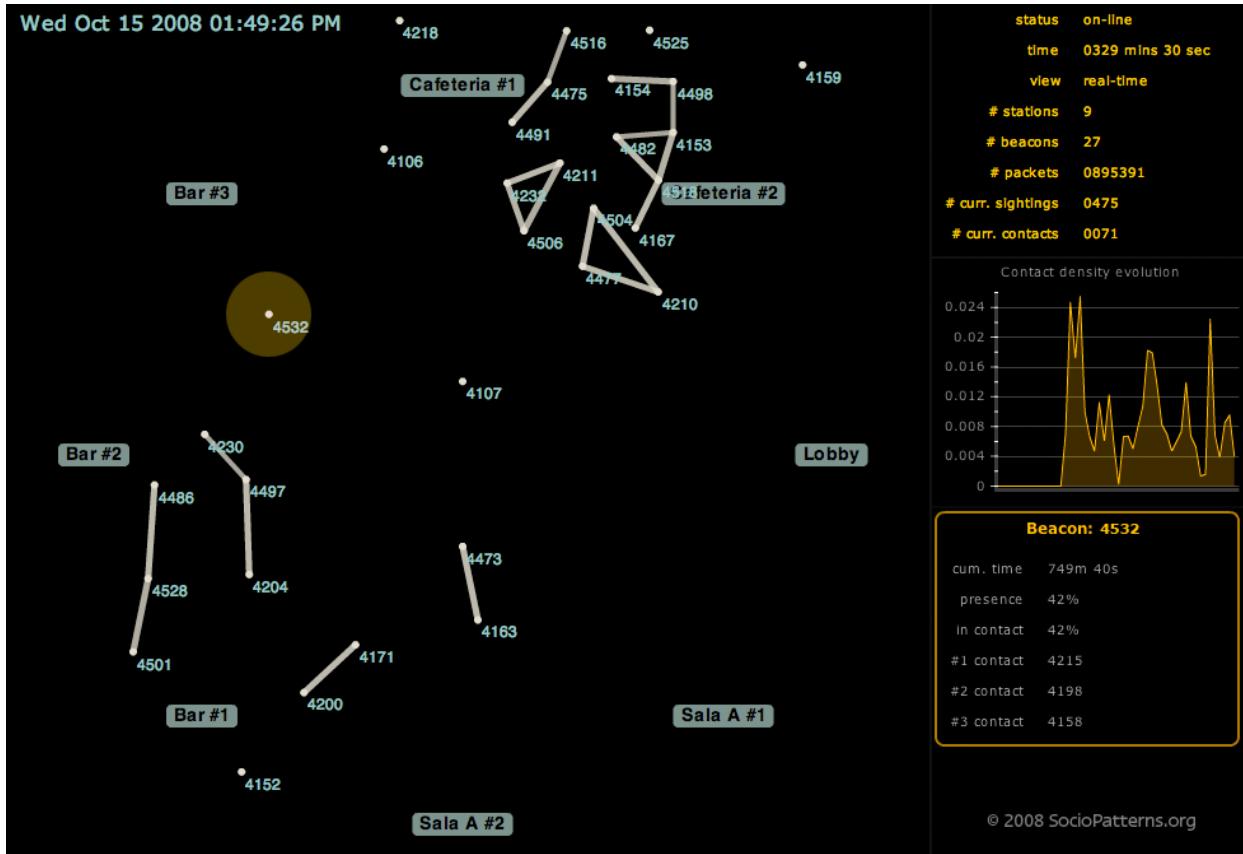


FIG. 1: A snapshot of the visualization. The main view shows the instantaneous state of the contact network at a given time during lunch hour. The beacons are labeled with their IDs, and can also be labeled with available metadata (such as e.g. the actual names of the persons). White edges represent contacts. The beacons are positioned near the stations where their signals are received. The yellow circle behind beacon 4532 highlights a tap while some related data is shown in the side-bar.

lobby which is also suited for discussions (see Figure 2). Figure 1 presents a snapshot of the visualization obtained during the lunch break of the third day of the conference, showing a number of beacons in the cafeteria area where people have lunch, while others are having coffee at the bar.

The new firmware proved to be as much reliable in a real-world setting as it appeared to be in our preliminary experiments. The measuring infrastructure received approximately $2 \cdot 10^6$ data packets per day from the various beacons, among which $5 \cdot 10^5$ packets reporting a contact. Around 150 Mb of raw compressed data were processed. Some caveats have to be reported: because of technical issues (some beacons had to be changed during the

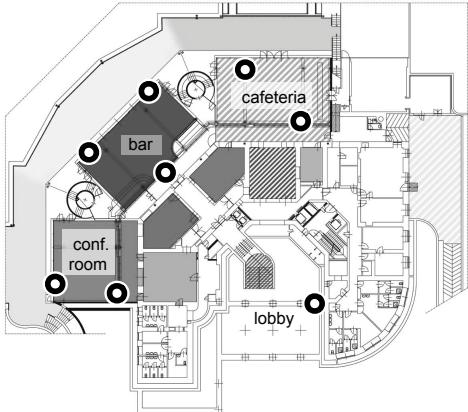
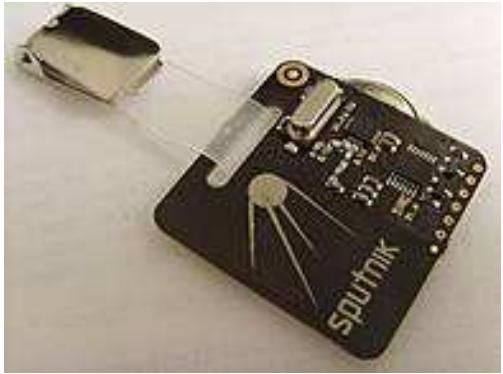


FIG. 2: Left: photo of a beacon (Courtesy of M. Meriac [23]). Right: map of the experiment premises. The circles denote the positions of the reporting stations.

experiment, some batteries failed and had to be replaced), some beacons disappeared from the data for few hours. Moreover, beacons were obviously tracked only when within range of the stations. We will see in the next section that, despite these issues corresponding to sampling problems, the data analysis reveals interesting patterns and shows the large potential of our experimental setup.

III. RESULTS OF THE PILOT STUDY

A. Contacts characterization

Let us first focus on the analysis of the contacts between individuals. We define as a “contact event” between two beacons A and B the exchange of at least one data packet between the two beacons in a $20s$ time-window. We then define as the duration of the contact A-B the time during which packets are exchanged between them at least every $20s$. The contact is considered as broken whenever more than $20s$ occur without a packet exchange. The choice of a $20s$ window is based on the frequency with which packets are sent by beacons, and corresponds to a reasonable time-scale for social interaction (e.g. encounter, brief conversation, etc.). Given this definition, we can measure both the duration of each contact and the intervals between two contacts. Figure 3(left) shows the distribution of the contact durations obtained using the whole dataset collected during the four conference days. A very broad distribution is observed, close to a power-law with exponent $\simeq -2$.

Qualitatively, this behavior is not unexpected: there are comparatively few long-lasting contacts and a multitude of brief contacts. A similar result has been reported for the duration of contacts between Bluetooth devices [19], with different exponents depending on the experimental set-up. Our measurements, however, achieve higher spatial and temporal accuracy than previous studies, and reliably select face-to-face interactions at close range, allowing to detect social interactions of a conversational type. These measurements clearly show that no characteristic time of interaction can be determined but that these interactions can occur on many different timescales.

We checked the robustness of the reported behavior along several lines. First, we verified that the distribution is the same over different periods of time: few hours, a whole day, or the whole conference. We also checked that it is invariant across randomly selected groups of individuals (see Figure 3(left)), showing that each individual has a broad distribution of contact durations. The obtained global heterogeneity therefore stems from an heterogeneity of the contact patterns of each individual, and not from an heterogeneity due to the difference of behavior among individuals. The distribution of contact durations remains unchanged, even by assuming a stricter definition of contact. The left panel of Figure 3 shows the result obtained by defining stronger contacts as the ones in which at least 5 data packets are exchanged in a 20s window (instead of 1 data packet only for the standard definition of a contact event).

Let us now turn to the inter-contact time intervals, for which previous studies [18, 19] have also reported broad distributions. Time intervals between contacts can in fact be defined in three different ways. One can measure the time between any two reported contact events, regardless of the involved beacons, thus yielding a characterization of the global dynamic/social activity of the group under study. We observe a broad distribution close to a power-law with exponent -2.5 (not shown, see the Sociopatterns project website [21]). Different measures, which are more important in relation with spreading processes, focus on (i) the time intervals between two contacts involving a given particular beacon, and (ii) the time intervals between two contacts involving the same pair of beacons. Figure 3(right) displays these distributions, showing that also in this case a broad behavior is obtained. This behavior is robust with respect to possible (heavy) data loss, as shown by the distribution obtained by removing the data coming from 20 randomly selected beacons that represent more than 30% of the whole dataset. The stronger contact definition also yield similar

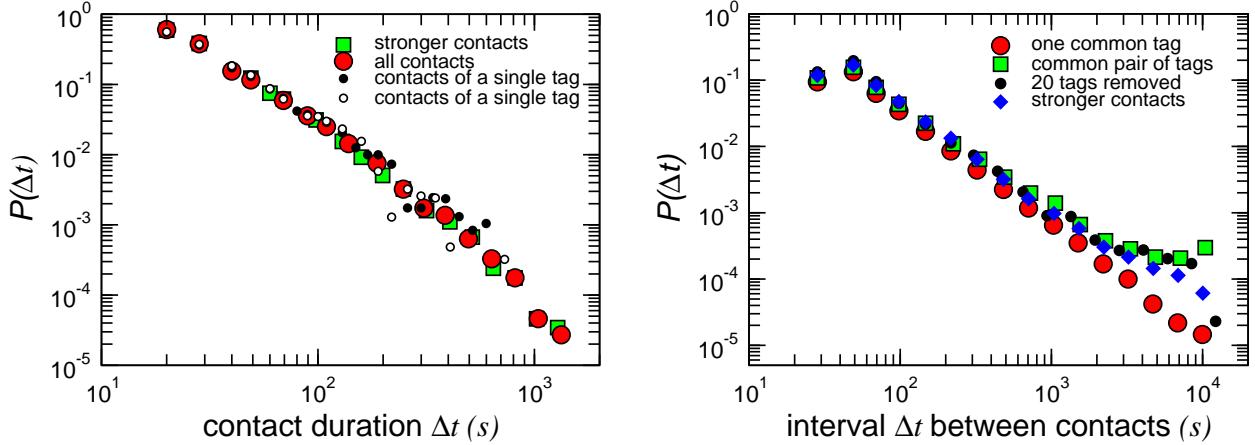


FIG. 3: Left: Distribution of contact durations obtained by considering: all contact events; the stronger contacts only (i.e. exchange of at least 5 data packets between 2 beacons in a 20s time window); the contacts of two individuals selected at random. Right: Distribution of time intervals between contacts: involving at least one common beacon; involving the same pair of beacons; removing 20 randomly selected beacons; considering stronger contacts only.

results.

The results presented here are not unexpected, since bursty behaviors and broad distributions of events durations or inter-event intervals have been reported in other studies on human behavior. It is nonetheless striking to observe that our experimental setup based on a new technology aimed at contact detection yields high quality data within a relatively small experiment, in agreement with the expected behavior. We foresee that larger experiments will allow to obtain larger statistics and to investigate more in detail the social and dynamical aspects of contact and mixing patterns, through a detailed characterization of the links (intermittency, persistence, etc.) and of the nodes (role inference, inclusion of background information, etc.).

B. Social networks

The data on social contacts can be used to build aggregated networks of interactions between individuals on any timescale larger than the time resolution. Individuals are the nodes of the network, and a link of weight w exists between two individuals if w contact events have taken place between them in the chosen time interval. Let us first focus on

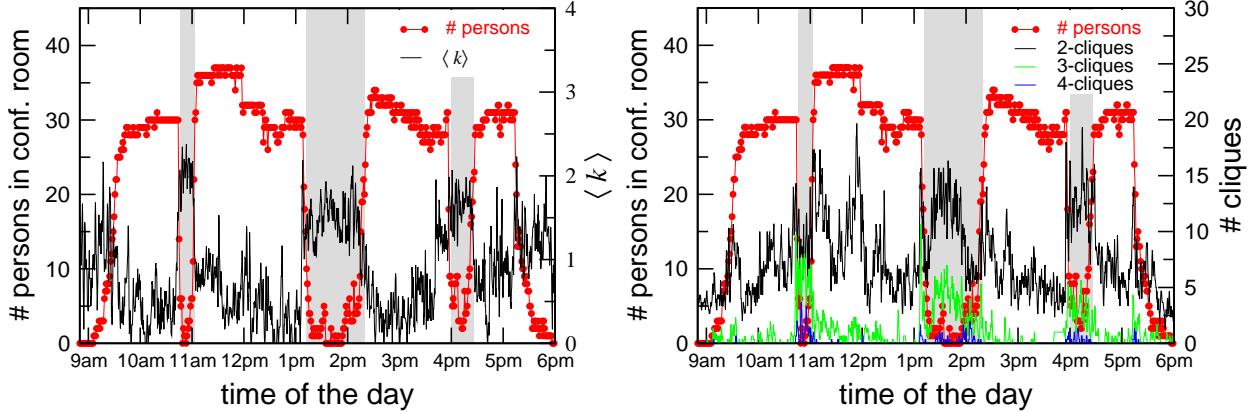


FIG. 4: Number of beacons in the conference room as a function of time, during the third day of the conference. Left: Average degree $\langle k \rangle$ in the instantaneous contact network computed over time windows of $20s$. Right: Number of pairs (2-cliques), triangles (3-cliques), and 4-cliques in the contact network. Note that we consider the maximal cliques, i.e. that the three edges of a triangle are not counted in the number of pairs.

“instantaneous” networks, constructed on short timescales. Figure 4 shows the number of beacons in the conference room as a function of time[26], during the third day of the conference, which was divided into four sessions, separated by two coffee breaks and a lunch break (indicated by the gray areas in the Figure). The data, averaged over time windows of $20s$, clearly shows the attendance of each session, in which most beacons are in the conference room, whereas the breaks are identified by the small number of beacons remaining in the conference room. The left panel also displays the evolution of the average number of contacts per individual during $20s$ periods. Strikingly, the number of contacts per participant is low when the attendance in the conference room is high, whereas a clear increase is observed during each break, clearly signalling that most social interactions occur during the coffee and lunch breaks, though some contacts may occur during the sessions when people typically talk and discuss with their immediate neighbors. This is further highlighted in the right panel of Figure 4, where we display, together with the attendance curve in the conference room, the number of 2-, 3- and 4- cliques in the contact networks aggregated over $20s$ time windows. Note that we consider here maximal cliques, so that the edges of a triangle are not counted as 2-cliques, or that the 4 triangles forming a 4-clique are not counted in the number of 3-cliques. A fluctuating number of pairs is observed during the session, corresponding most

probably to participants turning towards their neighbours, and peaks are observed at the beginning and end of each session and in fact of each talk, when participants have indeed more activity. 3– and 4– cliques are observed almost exclusively during the breaks, as expected since many discussions take place in small groups. It is worth to mention that the small number of 3–cliques observed during the sessions correspond to small groups of participants remaining in the coffee break area for discussions even after the beginning of the session.

The results illustrated in Figure 4 are clearly expected, since social interactions obviously take place during the breaks. However, they point to the ability of our experimental setup of resolving the mixing patterns by directly detecting the contact events. A less elaborate setup, based on the inference of contact events by spatial proximity, would show a large number of cliques (or worse, a unique large clique) during the meeting session where participants are physically close. In addition, Figure 4(right) clearly shows how this technology is able to detect interactions between 3 or 4 people, and not only pairwise interactions.

The data can also be used to construct aggregated networks on longer timescales, for example for a single day or for the whole duration of the experiment. The aggregated network becomes then denser as the aggregation time increases, with an average degree ranging from a value close to 20 for the network aggregated over one day, to approximately 40 for the whole experiment duration, showing that most participants have interacted with each other, which is in fact one of the aims of a small-scale conference. The aggregated networks are interesting in that they show broad distributions of the weights (given by the number of packets exchanged between two beacons) which are a proxy for the effective duration of a social interaction. Without going into a detailed network analysis, we provide in Figure 5 a visualization of the networks of social interactions obtained by aggregating the data for each day of the conference (smaller panels) and for its entire duration (larger graph), with the heterogeneity of links weights and nodes strengths clearly visible.

C. Contagion processes

The dynamic network of contacts provides a realistic setting to perform simulations of contagion processes in the population of individuals, such as rumour or information spreading, opinion formation, or epidemic processes. Particularly relevant is the application to

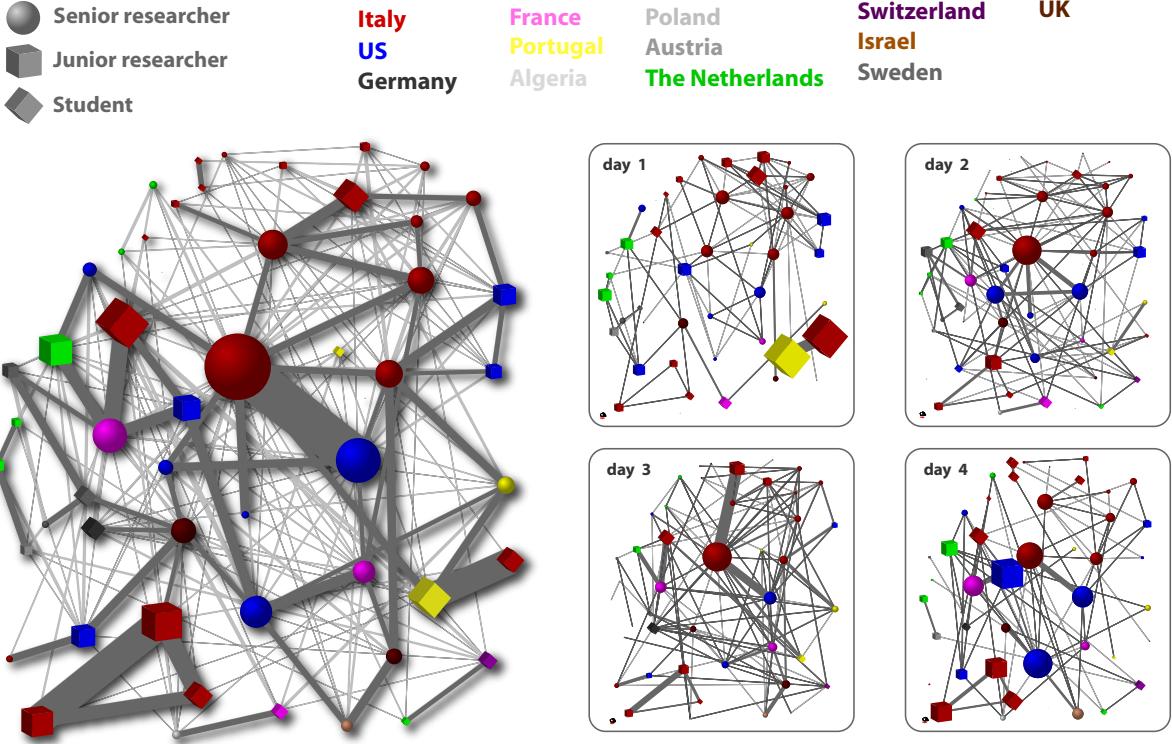


FIG. 5: Social network of contacts between individuals (represented by nodes), aggregated over the whole duration of the conference (larger graph), and for each of the days (smaller panels). The size of each node is proportional to its strength (given by the sum of the weights of its links [7]), and the width of each link is proportional to its weight. The color of each node corresponds to the individual's country of affiliation, and the shape to his/her academic position. For clarity, only links with weight larger than 100 are reported (50 for the smaller panels). As visible from the smaller panels, different interaction patterns are obtained for different days.

the spread of infectious diseases transmitted by the respiratory or close-contact route (as for example influenza, SARS, etc.). Models of epidemic spread on contact networks usually rely on static configurations of networks where the aspects of concurrency and causality are not taken into account. The data collected with our experimental setup can be used for an emulation of a contagion process among individuals where all topological and temporal heterogeneities are considered.

Here we present a very simple example of a contagion process aimed at showing the

feasibility of such studies. We consider the basic Susceptible-Infected (SI) model in which individuals are classified in two mutually exclusive compartments, Susceptible (i.e. able to contract a disease) and Infectious (i.e. infected and able to transmit the infection) [25]. The emulation is performed on the contact data of the third conference day. At the beginning of the day, a randomly selected individual is considered as infectious. During each time window of $20s$, each contact between a susceptible and an infectious individual can result in the contagion of the susceptible that contracts the infection with probability $0.01w$ (where w is the number of packets exchanged between the beacons of the individuals, i.e. a measure of the intensity and duration of the social interaction). Some individuals are set as immune since the start of the emulation, allowing for individuals who are not susceptible to the disease and can never become infectious. Figure 6 displays the number of infectious individuals as a function of time for a single realization of the stochastic model, and for different percentages of initially immune individuals. An interesting pattern is observed, in agreement with the previous analysis: most contagion events occur during the coffee and lunch breaks, where social interactions are more likely to occur. The right panel displays a schematic visualization of the propagation dynamics, shown as a tree in which each newly

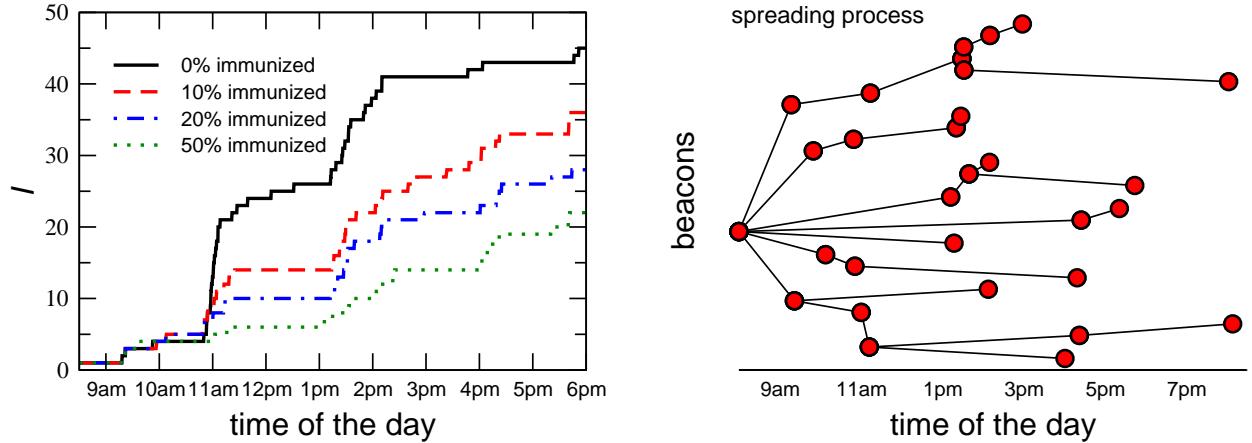


FIG. 6: Left: Evolution of the number of 'Infected' individuals when a single Infectious is introduced at the beginning of the day. For each contact, the transmission probability is $0.01w$ for each $20s$ time window, where w is the number of packets exchanged between the two beacons in contact during this time window. Right: illustration of the contagion events in the population of beacons as a function of time, for 20% initially immune individuals. Black lines indicate the infection from one beacon to another, as they occur in time.

infected beacon is represented as a red disk at the time of its contamination, with lines going from the infecting beacon to the infected one for each contagion event. While this model is overly simplistic and does not aim to reproduce a given realistic epidemic scenario, it offers the possibility of studying simple contagion processes on a realistic dataset, and provides a proof of concept showing how the data gathered through our experimental set-up in proper settings (as e.g. larger social events) can have a crucial value to understand and predict the impact of infectious diseases.

IV. CONCLUSIONS AND PERSPECTIVES

In this paper, we presented a novel experimental set-up which can be used to gather information on social interactions of individuals. The measures are based on active RFID devices, called beacons, that individuals can wear as badges. When two beacons are close enough (typically one meter apart), they can exchange messages and relay them to the measuring infrastructure. The very low power used for the exchanged messages and the absorption of the used frequencies by the human body ensure that contacts are detected only when individuals face each other as in a real social contact. This allows us to obtain data at very high spatial and temporal resolution, as shown in a pilot experiment performed during a recent conference. Here we presented some results of the corresponding data analysis, showing the resolving power of experimental setup, able to discriminate between social interaction and simple physical proximity. We measured the distributions of the duration of social contacts between individuals and of the intervals between contacts, and found broad behaviors. Moreover, we showed how our experimental setup can be used to construct social networks by aggregating the contacts over the required timescale.

Our experimental set-up paves the way for a number of developments and applications. Clearly, more experimental work is needed to obtain larger statistics on contacts durations or frequencies, and to characterize dynamically evolving social networks. The hardware and software could also be upgraded to contain additional information on the individuals and their interactions.

The presented set-up will also allow to study various dynamical phenomena taking place on dynamically evolving contact networks, as briefly illustrated above. Contagion processes, such as rumour spreading, opinion formation, propagation of respiratory or close-contact

infections, take place on the dynamical network of social contacts among individuals. Gathering data on social contacts will allow a better modeling and understanding of the spread of viruses and information.

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