Merging Inhomogeneous Proximity Sensor Systems for Social Network Analysis

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Abstract. Proximity information is a valuable source for social network analysis. Smartphone based sensors, like GPS, Bluetooth and ANT+, can be used to obtain proximity information between individuals within a group. However, in real-life scenarios, different people use different devices, featuring different sensor modalities. To draw the most complete picture of the spatial proximities between individuals, it is advantageous to merge data from an inhomogeneous system into one common representation. In this work we describe strategies how to merge data from Bluetooth sensors with data from ANT+ sensors. Interconnection between both systems is achieved using pre-knowledge about social rules and additional infrastructure. Proposed methods are applied to a data collection from 41 participants during an 8 day pilgrimage. Data from peer-to-peer sensors as well as GPS sensors is collected. The merging steps are evaluated by calculating state-of-the art features from social network analysis. Results indicate that the merging steps improve the completeness of the obtained network information while not altering the morphology of the network.

Keywords: Proximity · Smartphones · Bluetooth · ANT+ · Pilgrims

1 Introduction and Motivation

1.1 Social Networks Based on Proximity Data

Social networks are omnipresent and an essential part of many peoples' lives. Social scientists have introduced social network analysis (SNA) methods to better understand and interpret relationships between individuals. They are an important tool to understand individual and group behavior within communities or crowds. This kind of information is not only beneficial for intelligence services but can also be used to improve the security or well-being of individuals at crowd events as well as to improve individualized advertisement campaigns.

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A key question from a technical point of view is how data can be obtained to reconstruct these social networks. Traditional research methods are based on surveys and manual observations. More recently, however, data is collected digitally from communication hubs or online media. Online social network platforms are emerging but can only represent a fraction of the social network, which exists in our offline world. Identifying an offline social network with technical means to convert it into a digital representation is a challenging task.

One approach to identify offline social networks is to measure the proximity between individuals within a group. Individuals who are spatially close to each other are potentially also linked in a social sense. There are several technical tools to measure spatial proximity between individuals. One possibility is to measure the absolute positions of individuals and then calculate their mutual spatial distance. Another method is to use peer-to-peer transceivers, which are worn by the individuals. If one transceiver picks up the signal of another one, the two individuals are considered to be close to each other.

Smartphone based sensors, like GPS, Bluetooth and ANT+, can be used to obtain proximity information between individuals within a group. However, in real-life scenarios, different people use different devices, featuring different sensor modalities. To draw the most complete picture of the spatial proximities between individuals, it is advantageous to merge data from an inhomogeneous system into one common representation.

1.2 Data Collection During Pilgrimage

One of the biggest, global annual events is the Hajj pilgrimage of Muslims. Consequently, we identified it as a particularly useful event to collect data about social networks. During this pilgrimage millions of people from all over the world congregate for religious rituals at holy sites in the cities of Makkah and Madinah and their surrounds. The holy mosque in Makkah covers an area of approximately 350,000 square meters and the holy site in Madinah is approximately 80,000 square meters in size. Umrah, also known as the "lesser pilgrimage", is the visit to the sacred sites outside the period of Hajj (for details see, e.g., [5]).

The pilgrimage of Hajj/Umrah is useful to our study for the following reasons:

- It is a big event and features real-life conditions.
- Daily routines are very structured which simplifies the annotations.
- The fixed and synchronized schedule concerning prayer activities enables comparisons of data.
- Each individual performs five prayers each day, prayers have dynamic, semi-dynamic and static parts and involve re-groupings of the individuals. This ensures a high but still predictable variety of recorded proximity data.
- There are fixed religious rules the pilgrims have to comply with and which can be exploited to de-noise the data.

1.3 Related Work

In [13], organizational human behavior is measured and analyzed by using proximity information, for example: time spent in close proximity to other people, this is determined by special wearable electronic badges. Nowadays, the emerging technologies of smartphones have replaced the wearable sensors as sensing devices. The work in [4] uses Bluetooth (BT) links to identify friendship networks by detecting people sharing the same space. Do et al. [3] demonstrate the usage of smartphone BT as a real, i.e., face-to-face, proximity sensor to identify social networks. In the aforementioned examples the target subjects were employees working in offices or students living on university campuses.

As well as BT, the ANT+ protocol has recently been used as a proximity sensor. In [6] and [7], ANT+ is used for monitoring and assessing the performance of firefighting teams in training scenarios.

The combination of BT and ANT+ has not been an area of significant interest in the literature to date. Most of the studies are performed in controlled lab environments and settings. There are few technical challenges and the noise levels, i.e., the external influences, are highly predictable.

Apart from our work, there are only a few studies about the Hajj pilgrimage and these focus mainly on tracking pilgrims for security issues rather than understanding social networks. For example, in [9] and [10] the authors describe two frameworks that provide pilgrim tracking using smartphones, with the goal of improving transportation infrastructure and crowd management services. In [8] simulation tools are built to support pilgrims in navigating through religious sites.

1.4 Contributions

We present two ways of obtaining proximity data of peers within a crowd, firstly based on peer-to-peer sensor nodes and secondly on positional (GPS) information. Both approaches are discussed qualitatively from a technical point of view. Additionally data collection is performed which enables a quantitative comparison from a practical point of view.

The main contributions and outcomes of our work are as follows:

1. We present the implementation of two types of peer-to-peer proximity sensor nodes, which are based on mobile phones using BT and ANT+ technology respectively. We suggest a method for merging these inhomogeneous sensor sources into one common proximity matrix. Interconnection between both systems is achieved by using additional infrastructure and accessing pre-knowledge about religious and social rules in a specific community, in our example a Muslim community.
2. We present an approach to extract proximity information from position sensor (GPS) data.
3. We apply our methods to a data collection with n=41 participants during 8 days in a real-life scenario and describe practical challenges.
4. Based on this data collection we compare proximity information obtained from peer-to-peer sensors with proximity information based on position data both qualitatively and quantitatively and discuss the results.

2 Data Collection and Data Processing Schedule

In this section, we briefly describe the data collection. More information can be found in our previous work in [11].

2.1 Participants

41 pilgrims, equipped with Android smartphones participated in our study during the Umrah pilgrimage over 8 days. The youngest was a 7 year old boy and the oldest a 53 years old man ($\mu = 30, \sigma = 13$). There were 31 males and 10 females, among which there were 10 couples, 10 children and 11 single participants.

2.2 Smartphone as Sensing Device

As sensing application we extended the Android open sensing framework Funf [1]. The app collects proximity information, absolute GPS location, 3D-acceleration of the device and audio features. The smartphones were configured either as BT devices or as ANT+ devices and were only able to capture nearby devices from the same configuration type. We distributed 22 BT devices (Samsung Galaxy SII, SIII and SIII Mini) and 19 ANT+ devices (Sony Xperia Active and Neo). Participants were encouraged to wear the smartphones in their pockets, preferably for the whole day, but at least around the times of the 5 daily prayers.

We distributed the smartphones based on information gained from personal questionnaires and interviews at the beginning of the study that identified socially connected groups. Two BT devices and two ANT+ devices were given to two couples, crosswise distributed to the four participants as shown in Fig. 1.

2.3 Wearable Devices

Amongst the 41 smartphone participants, there were also 10 pilgrims wearing the chest strap Zephyr Bioharness 3[1]. These devices, designed to gather

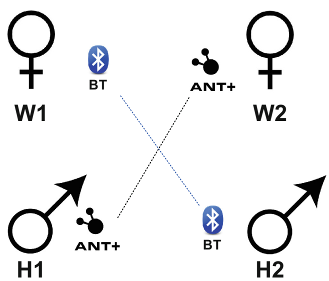


Fig. 1. Crosswise distribution of BT and ANT+ smartphones to two couples, wives (W) and husbands (H)

[1] http://www.zephyranywhere.com

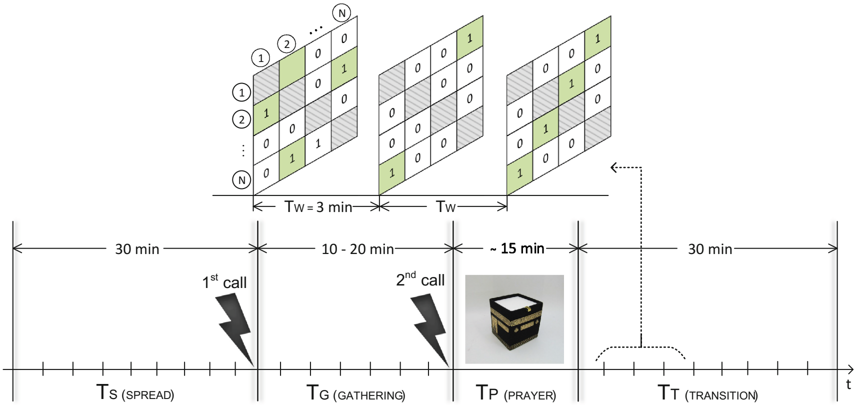


Fig. 2. Data processing schedule with 4 time intervals

bio-physiological data of the body, were used for another independent study [12]. In our work we used these auxiliary devices since they were already available.

2.4 Data Processing Schedule

Within the pilgrimage, we only concentrated on group behavior during and around the prayers, since they are the most frequent events of the day. Figure 2 schematically depicts the data processing schedule around the prayers. Two events, 1st call and 2nd call, define the following four time intervals:

- T_S **Spread Groups:** Pilgrims could be spread in and around the mosque performing rituals, shopping or resting in their hotels. The data collecting starts 30 min before the first call.
- T_G **Gathering:** The first call for prayer informs the people that in the next 10 to 20 min the prayer is going to begin. The pilgrims start to gather from wherever they are.
- T_P **Static Prayer:** The prayer starts immediately after the second call. In this period there is no change in group formations.
- T_T **Transition to** T_S: When the leader of the prayer finalizes the prayer, the people spread again until they reach the initial formations of T_S. Data collection continues for the next 30 min.

Within each section (except T_P) the time is divided into $T_W = 3$ minute windows. This window length is lower bounded by the minimum sampling frequency of all sensing devices, and upper bounded by the time within which we assume the group formation stays constant.

For each window, we create an adjacency matrix $\mathbf{A}$, an $\mathrm{N} \times \mathrm{N}$ matrix with elements a_{ij} being 1 if user i was in proximity of user j during that period of time (T_W), i.e., i saw j, and 0 otherwise, with N being the number of users.

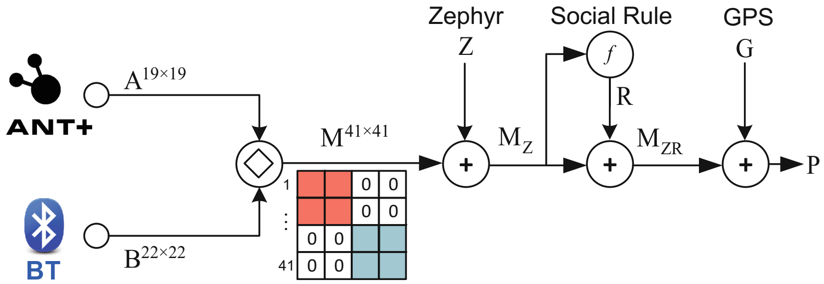


Fig. 3. System overview: from ANT+ and BT to the final adjacency matrix **P**

3 Merging Inhomogeneous Proximity Sensor Systems

3.1 System Overview

Figure 3 shows a general overview of the steps involved in processing the proximity data. Two inhomogeneous systems, ANT+ and BT, provide the initial inputs. ANT+ proximity data is represented as a binary symmetric adjacency matrix $\mathbf{A}^{19\times19}$ of size equal to the number of participants (19). Similarly, BT proximity data is an adjacency matrix $\mathbf{B}^{22\times22}$ of size 22. These two matrices are merged into one matrix $\mathbf{M}^{41\times41}$ of size equal to the total number of smartphones (41), using the operator "$\diamond$", as follows:

$$\mathbf{M} = \begin{pmatrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \end{pmatrix} \;,\; \mathbf{M}_{1:19,1:19} = \mathbf{A} \;, \mathbf{M}_{20:41,20:41} = \mathbf{B} \;. \tag{1}$$

The structure of the merged matrix **M** contains the two systems (colored blocks) and two zero blocks. All following matrices in the processing chain are of equal size (41×41). "+" is the matrix logical OR operator. **Z** is the adjacency matrix filled out with information gathered from the Zephyr wearable sensors. $\mathbf{M}_\mathrm{Z} = \mathbf{M}+\mathbf{Z}$ is the merged matrix with added Zephyr knowledge. Special social rules (f) are applied to the existing proximity matrix. The additional connections extracted from these rules are stored in the adjacency matrix **R**. $\mathbf{M}_\mathrm{ZR} = \mathbf{M}_\mathrm{Z}+\mathbf{R}$ is the previous matrix, with knowledge added from the social rules.

The multi-modal aspect of proximity sensing is enriched by using the GPS sensor as well. The adjacency matrix **G** is built from GPS locations, and the final matrix $\mathbf{P} = \mathbf{M}_\mathrm{ZR}+\mathbf{G}$ contains all previous proximity information.

The initial merged matrix **M** is improved by updating the zero values in each step of the chain.

3.2 ANT+ and BT Proximities

ANT+ is a proprietary wireless sensor network that operates in the 2.4 GHz frequency range. It is mainly available in sport equipment devices such as bike

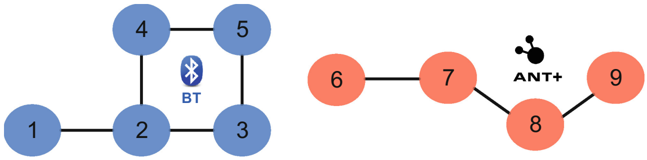


Fig. 4. Social network graphs of ANT+ and BT proximity systems

computers or heart rate monitors. ANT+ radio devices support up to eight logical channels using time division multiplexing on one physical channel.

ANT+ *Search Strategy.* Each device periodically transmits its ID on one of the eight logical channels. Given a list of devices to search for, the remaining seven channels are used to search in parallel for all the devices provided in the list. There is a time out approach for cases when the device being searched is not present in the proximity range.

BT scans were used as means of identifying other BT capable devices that are in the proximity range. In order for a smartphone to be "seen" by other devices, its BT adapter needs to be in discoverable mode. The smartphone devices used in this study are equipped with a Class 2 BT adapter.

BT *Search Strategy.* The BT search algorithm uses methods from the Android API to asynchronously initiate BT scans and retrieve scan results. The scan method performs a 12 second scan and for each newly discovered device a page scan is done to retrieve its BT name.

The scores of the adjacency matrices **A** and **B** provide information about the proximity relationship between each pair of devices, e.g., $a_{i,j} = 1$ indicates that the ANT+ devices i and j are in proximity range. Moreover, the matrices are symmetric, i.e., if i sees j, then j sees i as well. Figure 4 illustrates a social network graph constructed from ANT+ and BT adjacency matrices. The graphs are undirected and because of the inhomogeneity of the systems, there is no link between the two groups.

3.3 Wearable Sensor Proximity

Zephyr wearable sensors were provided to 10 pilgrims. The devices were equipped with a BT adapter for transmitting the logged data to a smartphone and during the study were configured to always be in discoverable mode. From the 10 devices, 6 were assigned to users that were using ANT+ smartphones for proximity sensing, and the other 4 were distributed to BT smartphones users. In this way, the 6 ANT+ smartphones participants contribute to connecting the two inhomogeneous systems, as it appears to the other participants that the 6 users carry both types of smartphones. On the other hand, the 4 BT smartphones users do not contribute directly, however, as they carry 2 discoverable BT devices, it is more likely to be seen by others when they enter the proximity region.

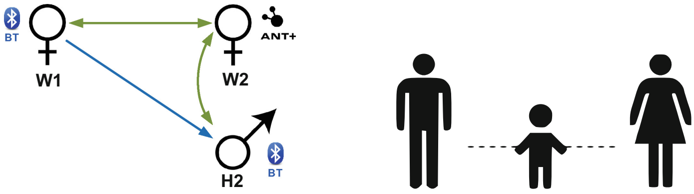


Fig. 5. First and second social rules

3.4 Social Rules for Proximity

From discussions with experts, and after clarification with participating pilgrims, we learnt and applied the following social rules of pilgrims while the Umrah pilgrimage:

1. If a woman (W1) sees a man (H2), then the corresponding wife (W2) of that man is also present (see Fig. 5 left).
2. One child is always together with one of the parents (see Fig. 5 right).

The first rule is particularly helpful, i.e., contributes into merging ANT+ and BT proximity systems, if the distribution of the smartphone types to socially connected pairs is done in the described crosswise manner. We assume that W2 is between W1 and H2, and therefore we apply one further collaborative step: People seen by W2 using ANT+ protocol are added to the proximity range of both W1 and H2, and the intersection of people seen by W1 and H2 are added to the proximity range of W2.

In addition to these rules, most of participants knew each other as well.

3.5 Location Based Proximity

Each GPS location record stores the longitude/latitude coordinates and the accuracy distance (in m) of the estimation position. Location errors are according to Android normally distributed with one standard deviation equal to the estimated accuracy distance. This means that, there is a 68 % chance (cumulative percentage from -1σ to $+1\sigma$) that the correct position is inside the circle with the radius equal to the location accuracy distance.

For each sliding window interval around the prayer, the weighted centroid, i.e., locations with lower accuracy distance are more important, of all GPS points of the same user is calculated. Figure 6 shows the GPS locations of some users in the mosques of Madinah and Makkah for one time interval.

The simplest way to construct the adjacency matrices $\mathbf{G}$ is for each user to calculate the physical distance to all other users and to fill in the corresponding element of $\mathbf{G}$ in case the distance is below a threshold, e.g., 10 m. This procedure is due to the run time complexity of $O(n^2)$ not feasible for a high number of users. To mitigate this problem, we propose the following approach: Firstly, the full cloud of points is divided roughly into clusters using the density based

Fig. 6. Visualized GPS user locations in Madinah and Makkah

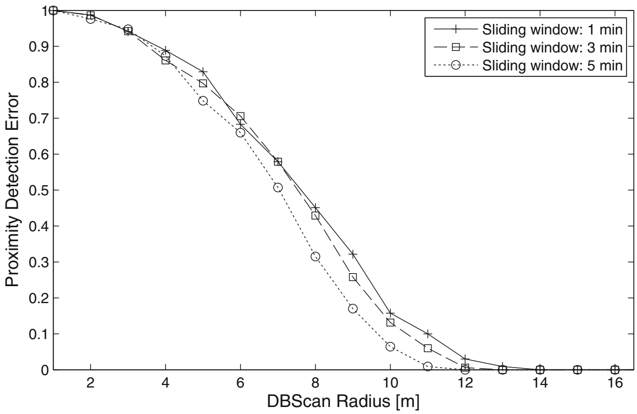


Fig. 7. DBScan parameter sweeping

scan algorithm (DBScan). Then, walking through these clusters, parts of $\mathbf{G}$ are constructed, meaning that the one big problem is divided into many smaller problems. This approach is payed off when the number of clusters is large and the fast DBScan algorithm, with runtime complexity $O(n \cdot \log n)$, is used.

The main parameter of DBScan is the radius of the circle with which the algorithm tries to find clusters in the cloud of points. The higher this parameter is, the less clusters we get and the less the algorithm is efficient. On the other side, a higher number of clusters can lead to errors in proximity detection, when, e.g., two real neighbours are not assigned to the same cluster. Figure 7 shows the normalized proximity detection error in function of the DBScan radius for three different sliding window lengths T_W. The shapes of all T_W look similar and the optimal radius is located at around 13 m.

4 Evaluation

We aggregate the proximity data, i.e., average adjacency matrices, over a time interval T and extract the following SNA state-of-the-art features [2]:

– **Average node eigenvector centrality (ANEC)**
  NEC shows how well a node is connected to the most important nodes. Centrality features are used to identify pitchers (leaders) and catchers (followers).
– **Network density (ND)**
  ND is the ratio of links over the total number of possible links in a network. It measures the network connectivity and is used for comparing networks.
– **Network clustering coefficient (NCC)**
  NCC is the density of network neighbourhoods and can be used for detecting subgroups in a network.

4.1 Graphical Representation

Figure 8 shows an example of proximity data over one interval T_S. Initial ANT+ and BT nodes and connections are plotted in (a). The systems are inhomogeneous and there is no link between them. (b) shows is the state after incorporating proximity data from Zephyr, where the number of links is doubled. The new links between the two systems occur because BT smartphones have indirectly detected the presence of ANT+ devices through the Zephyr BT radios. There is also an improvement within the BT nodes, due to the extra BT signal available from Zephyr. The contribution of applying the pilgrimage social rules is displayed in (c) where the network density increases significantly. And, (d) shows the final state of the network when GPS data are integrated.

4.2 Quantitative Evaluation

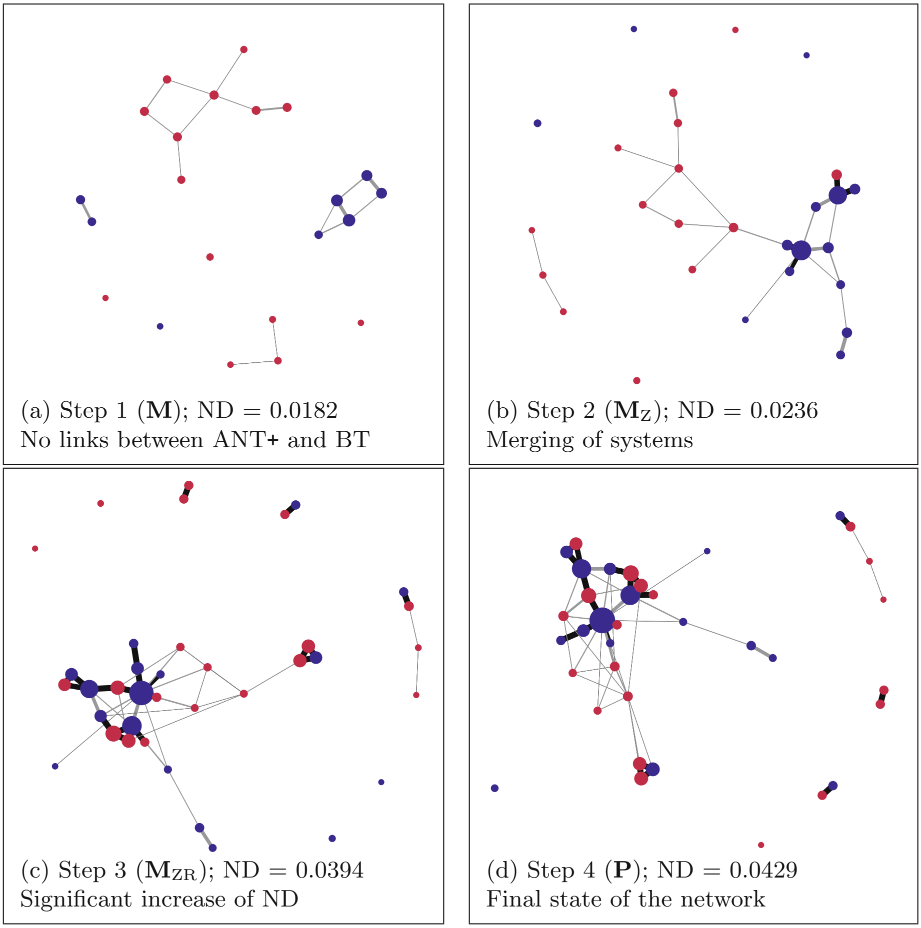
Table 1 lists the SNA features of all matrices described in Fig. 3, averaged over all prayers.

We observe that ANEC is almost constant with a value around 10 %. We can therefore say, that the centrality property of the network, i.e., the information about the importance of people (nodes) is not changed across all merging steps.

For NCC, we take the value of $\mathbf{G}$ as a baseline, because GPS proximity is a fair representation of a homogeneous equivalent network of the two inhomogeneous systems ANT+ and BT. Going through $\mathbf{M}$, $\mathbf{M}_{\mathrm{Z}}$, and $\mathbf{M}_{\mathrm{ZR}}$, we can see a small decrease of NCC at each step. The value at $\mathbf{M}_{\mathrm{ZR}}$ is 16 % smaller than the baseline of $\mathbf{G}$. Thus, we conclude, that the clustering property of the network is moderately worsened compared to the GPS social network.

An increase in ND is observed at all steps. GPS contributes with only 9 % to the overall density, while the social rule with 40 % is the most effective modality for merging. The cummulative plot and the pie chart are shown in Fig. 9.

The colored bars show the ND of the individual auxiliary proximities, while the black bars represent the cumulative ND values of all the previous merging steps. The pie chart illustrates the percentage of ND increase from each proximity system.



(a) Step 1 ($\mathbf{M}$); ND = 0.0182
No links between ANT+ and BT

(b) Step 2 ($\mathbf{M}_Z$); ND = 0.0236
Merging of systems

(c) Step 3 ($\mathbf{M}_{ZR}$); ND = 0.0394
Significant increase of ND

(d) Step 4 ($\mathbf{P}$); ND = 0.0429
Final state of the network

Fig. 8. Proximity data visualizations of the interval T_S for a prayer where ANT+ devices are in red and BT in blue. The size of a node is a figure of the number of total links. The line thickness represents the number of times the two connected nodes have been in proximity range.

Table 1. SNA feature comparison of system steps from Fig. 3

	M	Z	M_Z	R	M_{ZR}	G	P
ANEC	0.0994	0.0955	0.1123	0.0528	0.1263	0.1024	0.1301
ND	0.0182	0.0078	0.0236	0.0202	0.0394	0.0048	0.0429
NCC	0.5265	0.3008	0.4870	0.0661	0.4196	0.5784	0.5497

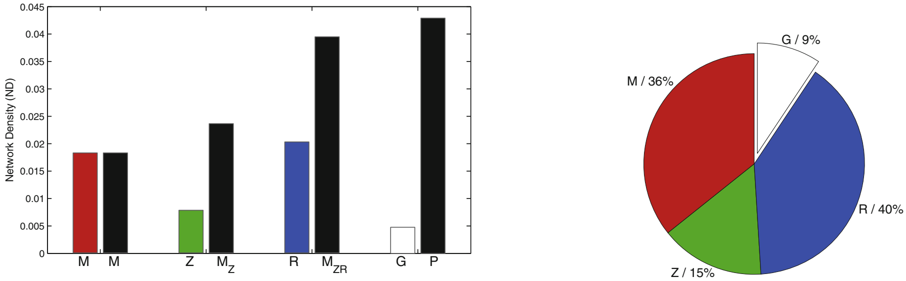


Fig. 9. Evaluation of ND for all system matrices of Fig. 3

These results indicate that the merging steps improve the completeness of the obtained network information while not altering much the morphology of the network.

4.3 Limitations

In each of the steps, there are limitations and challenges. The GPS sampling frequency and the distance threshold of 10 m for GPS locations to be declared as nearby, and the fact that BT can have a larger radius in open air, influence the evaluation and the comparison to other systems. It would be helpful to see how the results change depending on these parameters. The social rule that is valid for the pilgrimage might practically not always be followed. There are also other rules that we have not considered so far. The extracted SNA features are averaged over the whole duration of prayer and around prayer. These features could also be calculated and evaluated separately for the defined time intervals: spread, gathering, prayer, and transition. Moreover, using the extracted SNA features for evaluating the merging process can be premature if generalized to other scenarios. We evaluate the merging of different proximity systems in terms of changes in social network topologies. Since there is no numerical evaluation with absolute numbers, we cannot compare the results of the merged system with the cases where all participants would use ANT+, BT or GPS for spatial proximity.

5 Conclusion and Future Work

In this work, we have shown that it is possible to merge two inhomogeneous peer-to-peer proximity systems, namely ANT+ and BT. We have used auxiliary data derived from wearable sensors and information extracted from special social rules that are valid in the pilgrimage domain. On top of that, we have introduced an approach for computationally efficient proximity estimation from GPS locations to improve the adjacency matrix. Using a graphical representation we have shown how the merging steps influence the network graph. State-of-the-art SNA features are used to evaluate the validity of the merging. The centrality remains constant during all steps, the clustering property is moderately reduced and the overall network density is much higher compared to GPS only, which makes us believe, that GPS can be neglected for proximity estimation where fine grained information is needed. The data for this work is collected from 41 participants during an Umrah pilgrimage in Spring 2013.

As future work, we are planing to incorporate the speech and the environmental sound as an additional source for proximity detection. Moreover, using the results of our work, we are now able to answer questions related to social network analysis and to understand the grouping behaviour of pilgrims around the rituals. The upcoming Hajj pilgrimage offers the next opportunity to improve and evaluate our work.

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