Understanding Aspects of Pilgrimage using Social Networks derived from Smartphones

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Abstract

The Hajj pilgrimage to Makkah and Madinah is one of the biggest annual events in the world, where millions of people congregate for religious rituals over several days. The main challenge for organizers and participants is to ensure a smooth flow through the activities and a safe, healthy and spiritual journey during the pilgrimage. A deep knowledge of how the pilgrims behave during this event is a precondition for improving these issues. One approach to understand the behaviors of pilgrims is a social network analysis based on spatial proximity information. In this work we use a proximity system to identify pilgrims social networks and apply social network analysis to (i) estimate the experience level of the pilgrims and differentiate leaders from followers, (ii) observe how groups of pilgrims are created around prayers and (iii) identify density peaks and recognize changes in group formation over time. The suggested proximity system is created by merging ANT\textsuperscript{+} and Bluetooth, two inhomogeneous peer-to-peer systems. Merging is facilitated by using (i) social rules of pilgrims, (ii) existing wearable devices and (iii) GPS location information. Proposed methods are applied on data collected from 41 participants during their 8 day pilgrimage.

Keywords: Social Network Analysis, Smartphones, Pilgrimage, Proximity, Bluetooth, ANT\textsuperscript{+}

1. Introduction and Motivation

1.1. Hajj Pilgrimage and its main Challenges

Pilgrimage is a journey in search of spiritual relief and is important to people of many different religions. Recent statistics show that the total number of people participating in pilgrimages from various religious faiths is growing [2]. The annual pilgrimage for Muslims is called Hajj. During Hajj, 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. Umrah, also known as the ”lesser pilgrimage”, is the visit to the sacred sites outside the period of Hajj (for details see, e.g., [11]).

Even though Hajj is one of the biggest and oldest events in the world, little research has been carried out to objectively monitor the pilgrims and understand their behavior during the different stages of pilgrimage. The challenges regarding Hajj are of two broader levels. First, of the organizational - global - level; and, second, of the individual level. At the global level, the challenges are of the crowd monitoring and management type. Here, the main concerns revolve around enabling a smooth flow through the activities for the pilgrims, and transporting them from a site to another. The second level, the individual one, is concerned with enabling a safe, healthy and truly spiritual journey through the pilgrimage. To ensure these, a deeper understanding of the whole event, and thus, further, broader-scale studies are needed.

1.2. Understanding Aspects of Hajj using Social Networks

Of the roughly 3 million yearly pilgrims, the majority come from abroad. These are organized in contingents according to the countries they are arriving from. These contingents are further divided into better
manageable groups of up to about 200, which are led by pre-assigned guides with thorough knowledge of
the local surroundings and the itinerary of the pilgrimage. Despite this, there can be several factors that
cause inefficiency in the monitoring and management process, and thus difficulties of various types, for those
responsible and for the pilgrims as well. Among these factors, besides lack of information and experience,
age, crowdedness, panic, etc., could be insufficient guiding. The number of guides is usually only a few, if not
a single one, and this can be challenging, considering that for most pilgrims it is the very first time they find
themselves in those places. One way to alleviate this burden is by delegating the responsibility of guiding
and supervising onto possible leaders within the groups. And, to find these possible leaders, one needs to
understand the process of leader formation, by studying the social networking within the groups. Also, it
can be safely assumed that, due to the nature of the gathering, these groups have a lot in common, as far as
their expected behavior. Thus, the hierarchical delegation of the responsibility of guiding and supervising
could lead toward easing the tasks of maintaining the security and smooth flow of the pilgrimage. Moreover,
such achievements would help in the overall well-being of the pilgrims, by providing them the safety of being
closely supervised and carefully guided, in an environment in which they are most probably found for the
first time in their lives.

So, as a means of learning about these aspects, including the leader/follower differentiation aspect, we
utilize the monitoring of social networks of pilgrims within the group. We do this, by deciding to study the
pilgrim group behavior around and during the daily prayers. The five daily prayers are the most frequent
activities during Hajj. There are several rituals performed, other than the daily prayers, such as, the Tawaf
and Sa’i rituals, the supplication on the mount of Arafat, etc, but we believe that the construction of
social networks around prayer times is a very appropriate starting point. For this, we see the following
reasons: each pilgrim performs five prayers per 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; the routines around the prayers are very structured, which simplifies the annotations;
the fixed and synchronized schedule concerning prayer activities enables comparison of data. Besides the
aforementioned leader differentiation, another point of interest would be if – and how – group behavior
changes with time. Hence, we included the analysis of the clustering property of social networks over time.
Also, the time segmentation approach was meant as an attempt to find possible stages of the ritual, i.e. the
prayer, that show distinct characteristics in the group behavior.

As was mentioned, the approach in carrying out the study was to utilize social networks. Social scientists
have introduced social network analysis (SNA) methods to better understand and interpret relationships
between individuals and between groups within communities. Having constructed these networks, we use
state-of-the-art SNA features to understand the following aspects of pilgrimage:

• estimate the experience level of the pilgrims, i.e. differentiate leaders and followers,
• observe how groups of pilgrims are created around prayers, i.e. validate the separation intervals around
  prayer times, and
• identify density peaks and recognize different communities and sub-groups within larger groups, i.e.
  analyze the clustering property of social networks over time.

1.3. Social Networks based on Proximity Data

A key question from a technical point of view is how data can be obtained to reconstruct social networks.
To identify these networks one can measure the proximity between individuals within a group. Individuals
who are often spatially close to each other are potentially also linked in a social sense. One possibility to
estimate spatial proximity is to measure the absolute positions of individuals and then derive 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.

In this work we use two peer-to-peer proximity sensing systems to construct the social networks, and on
top of that, we use, among others, the GPS positioning to improve these networks.
1.4. Proximity Information derived from different Sensing Systems

We build social networks from spatial proximity data collected using two different communication protocols, ANT+ and Bluetooth (BT).

ANT+ is a proprietary wireless technology designed for sensor networks. Its low complexity, together with the low power consumption has made it to penetrate the sports and fitness equipments market, where it is mainly used for constructing personal sensor networks for performance and health monitoring.\(^1\) BT is also a wireless technology for building personal area networks and exchanging data over short distances. It is implemented in billions of mobile devices and other equipments, making it the most widely implemented short range wireless network.\(^2\) Both, ANT+ and BT operate on the 2.4 GHz ISM frequency band.

To simulate a real-life scenario where people use different devices, featuring different sensor modalities and to draw the most complete picture of the spatial proximities between individuals, it is advantageous to merge data from inhomogeneous systems into one common representation.

An illustration of the comparison of aspects of the two technologies is given in Table 1. The figures are partly taken from literature, while others are empirically estimated from our study.

<table>
<thead>
<tr>
<th>Criterion</th>
<th>ANT+</th>
<th>BT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effective range</td>
<td>&lt; 20 m [13]</td>
<td>10 m (Class 2)</td>
</tr>
<tr>
<td>Energy Consumption</td>
<td>Low</td>
<td>Medium</td>
</tr>
<tr>
<td>Privacy</td>
<td>High (Pseudo ID)</td>
<td>Medium (MAC)</td>
</tr>
<tr>
<td>Availability</td>
<td>Only in Sony Xperia</td>
<td>No restriction</td>
</tr>
<tr>
<td>Implications</td>
<td>WiFi issues</td>
<td>BT headset</td>
</tr>
<tr>
<td>Sampling Period</td>
<td>&lt; 10 s</td>
<td>&lt; 20 s</td>
</tr>
</tbody>
</table>

Table 1: Comparison between ANT+ and BT.

In real-life there is not just one uniform system used by everyone, instead multiple systems coexist, based on the criteria that specific applications demand. The goal is not to quantitatively compare different systems, but we show how a given environment can be exploited to get best results - even when involving data from inhomogeneous sensor sources. Anyway, a comparison of ANT+ and BT networks in our context is not possible since there is no ground-truth reference system available.

We used GPS based proximity solely for supportive or reinforcing purposes, and not for comparison to the other peer-to-peer proximity sensing systems either. Another reason is that GPS cannot guarantee reliable accuracy and availability in cases when the people carrying the devices are inside buildings (Mosques).

1.5. Related Work

Olguin et al. [23], show how to measure and analyze organizational human behavior by using proximity information, for example: time spent in close proximity to other people, which is computed by special wearable electronic badges. Nowadays, the emerging technologies of smartphones have replaced the wearable sensors as sensing devices. The work in [10] uses BT links to identify friendship networks by detecting people sharing the same space. Do et al. [9] 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 [12, 13], 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 simplified lab environments and settings. There are few technical challenges and the noise levels, i.e., the external influences, are highly predictable.

\(^1\)http://www.thisisant.com
\(^2\)http://www.bluetooth.com
The concept of node "centrality" in networks has been heavily studied so far [4, 5, 7]. Freeman [14] formalized three different measures of centrality: degree, closeness and betweenness. The influence of Eigenvector centrality as a node centrality is discussed in [24]. In this work, we identify which of these centrality features can be used to differentiate "leaders", the more experienced pilgrims, and the inexperienced "followers". A similar work was done by Yano et al [26] where they studied the relationship between "pitchers", people who are more talkative, and less communicative "catchers" by monitoring people's movements and measuring the energy level of their voices. There also exist other features such as the Bonacich’s power feature [4] which quantifies the power of a node as a function of the number of connections and the connections of the neighborhood, i.e. one node is powerful if it is connected to many less powerful nodes, or the number of shortest paths that a node is being part of. In a more recent study [6], the author introduces two approaches defined as finding key players for a purpose of spreading something through the network by using key players as seeds, or for disrupting the network by removing key nodes.

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 [16, 17] the authors describe two frameworks that provide pilgrim tracking using smartphones, with the goal of improving transportation infrastructure and crowd management services. In [15] simulation tools are built to support pilgrims in navigating through religious sites.

1.6. Contributions

The contribution of this work is extending the state-of-the-art in the following three aspects:

• We implement two types of peer-to-peer proximity sensor nodes, using smartphones with BT and ANT+ technology and suggest a method for merging these inhomogeneous sensor sources into one common proximity matrix. Interconnection between both systems is achieved by using additional infrastructure, incorporating GPS positioning and applying knowledge of cultural and social rules.

• Based on the created social networks and using state-of-the-art SNA features we answer three research questions: can we (i) predict the experience level of a pilgrim, (ii) show the validity of intervals around prayers and (iii) see changes in clustering property of social networks over time.

• We apply our methods to a data collection with n=41 participants during 8 days in a real-life scenario and describe practical challenges.

1.7. Paper Organization

The rest of the paper is structured as follows: The next section describes the data collection approach and the sensors used. Section 3 explains the merging of the two inhomogeneous peer-to-peer proximity systems, namely ANT+ and BT, by using auxiliary data from other sources. This section is based on our previous work [20]. However, here we provide a more detailed explanation of the proximity merging approach, particularly, we explain the technique with a concrete example involving 3 ANT+ and 4 BT users. Then in Section 4, we show the results of SNA applied to answer the three research questions mentioned above. In the last two sections, we discuss the limitations, conclude the work and show possible improvements.

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 [19].

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 Figure 1.

![Crosswise distribution of ANT+ and BT smartphones between couples, i.e. a man and a wife of a different couple get the same technology.](image)

2.3. Wearable Devices

Amongst the 41 smartphone participants were also 10 pilgrims wearing the chest strap Zephyr Bioharness. These devices, designed to gather bio-physiological data of the body, were used for another independent study [21]. 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:

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

In Section 4.2 we graphically and quantitatively evaluate the data processing schedule to see whether the interval separation is reasonable.

Within each section (except TP) the time is divided into TW = 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.

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3http://www.zephyranywhere.com
Figure 2: Data is separated into four time varying intervals based on two distinct prayer calls. Each interval is divided into smaller chunks of 3 minutes, lower bounded by the minimum sampling frequency of sensing devices. The proximity state in each 3 minute window is represented by an adjacency matrix.

For each window, we create an adjacency matrix $A$, an $N \times N$ 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., saw user $j$, and 0 otherwise, with $N$ being the number of users.

3. Merging Inhomogeneous Proximity Sensor Systems

In this section we provide a formal definition of the inhomogeneous proximity merging approach and complement it with a concrete example. Then, we explain each step of the processing chain and show how to construct proximity from different modalities such as communication protocols (ANT+ and BT), wearable devices, social rules and location data. Finally, we evaluate the merging process by means of graphical representations and quantitative analysis.

3.1. System Overview

Figure 3 shows a general overview of the steps involved in processing the proximity data.

Figure 3: Initial input comes from the two inhomogeneous systems ANT+ and BT in the form of binary symmetric adjacency matrices $A$ and $B$, which are then merged into one matrix $M$. Merging is further complemented by adding proximity information derived from three more modalities: Zephyr, social rules and GPS.
Two inhomogeneous systems, ANT+ and BT, provide the initial inputs. ANT+ proximity data is represented as a binary symmetric adjacency matrix $A^{19 \times 19}$ of size equal to the number of participants (19). Similarly, BT proximity data is an adjacency matrix $B^{22 \times 22}$ of size 22. These two matrices are merged into one matrix $M^{41 \times 41}$ of size equal to the total number of smartphones (41), using the operator "⋄" as follows:

$$M = \begin{pmatrix}
0 & \cdots & 0 \\
\vdots & \ddots & \vdots \\
0 & \cdots & 0
\end{pmatrix}, \quad M_{1:19,1:19} = A, \quad M_{20:41,20:41} = B. \quad (1)$$

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 ($41 \times 41$). "+" is the matrix logical OR operator. $Z$ is the adjacency matrix filled out with information gathered from the Zephyr wearable sensors. $M_Z = M + Z$ 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 $R$. $M_{ZR} = M_Z + R$ 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 $P = M_{ZR} + G$ contains all previous proximity information. The initial merged matrix $M$ is improved by filling the zero matrix scores in each step of the chain.

Figures 4 and 5 show an example scenario involving 7 users, labeled with numbers from 1 to 7. Users 1–3 were equipped with ANT+ devices and 4–7 had BT smartphones. The proximity state of the two systems is shown using matrices $A$ and $B$. From matrix $A$, we observe that users 1 and 3 were in proximity range, while matrix $B$ shows users 4 and 7 being close to each other. Proximity from the Zephyr wearable sensors, denoted in matrix $Z$, discovers two more connections, between users 1 and 5, and 3 and 6. Taking advantage of the social relationship of the couple (users 3 and 5) and their child (user 7), we derive additional proximity information which is denoted in matrix $R$. The results of proximity derived from GPS are shown in matrix $G$. The first merging step groups the two matrices $A$ and $B$ together in a third matrix $M$ (see Figure 5). Information from each of the supplementary proximity matrices is added to matrix $M$ using matrix logical OR operator to obtain the final result in matrix $P$.

3.2. ANT+ and BT Proximities

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 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 s 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 individuals, e.g., \( a_{i,j} = 1 \) indicates that in the ANT+ group, the users \( i \) and \( j \) are in proximity range. Moreover, the matrices are symmetric, i.e., if user \( i \) sees user \( j \), then user \( j \) sees user \( i \) as well. Figure 6 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.

Figure 5: Example of 4 continued. The first merging step involves grouping together matrices A and B into one matrix M. The two colored parts of M correspond to matrix A and B. Each subsequent matrix, is the result of adding proximity information coming from the exemplary matrices Z, R and G, with new connections being highlighted.

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.

3.4. Social Rules for Proximity

From discussions with experts, and after clarification with participating pilgrims, we learned 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, (Figure 7 left).
2. One child is always together with one of the parents, (Figure 7 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 H2 and W1, 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.

![Diagram](image)

Figure 7: Visual illustration of the two social rules for proximity: the companionship of a woman (left) and the presence of parents with a child (right).

### 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 $-1\sigma$ 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 8 shows the GPS locations of some users in the mosques of Madinah and Makkah for one time interval.

![GPS Locations](image)

Figure 8: Visualized GPS user locations in Madinah (left) and Makkah (right) with ANT+ users (1-19) in red and BT users (20-41) in blue.

The simplest way to construct the adjacency matrices $G$ is for each user to calculate the physical distance to all other users and to fill in the corresponding element of $G$ in case the distance is below a threshold, e.g., 10m. This procedure is due to the run time complexity of $O(n^2)$ not feasible for the case when the number of users would scale up to a high number. To mitigate this problem, we propose the following
approach: Firstly, the full cloud of points is divided roughly into clusters using the density based scan algorithm (DBScan). Then, walking through these clusters, parts of $G$ 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 algorithms is efficient. On the other side, a higher number of clusters can lead to errors in proximity detection, when, e.g., two real neighbors are not assigned to the same cluster. Figure 9 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.

![Figure 9: Radius parameter sweeping of the DBScan algorithm. The plot shows the proximity detection error for different values of radius using three distinct sliding windows.](image)

3.6. Evaluation of the Merging

Using features from social network analysis, we assess the quality of proximity merging with graphical representation and quantitative evaluation.

We aggregate the proximity data, i.e, average adjacency matrices, over a time interval $T$ and extract the following state-of-the-art SNA features [8]:

- **Average node Eigenvector centrality (ANEC)**
  NEC is a measure of the impact of a node in a network. A high Eigenvector score for a node means that it is connected to other nodes with high scores. It is useful to determine who is connected to the most connected nodes.

- **Network density (ND)**
  ND is the ratio of links over the total number of possible links between all pairs of nodes. It is a measure of how well connected a network is. The higher the value of ND the more connected a network is and the lower the ND the sparser a network is. It is commonly used for comparing networks or different parts within a single network.
Network clustering coefficient (NCC)

CC provides a figure of how much nodes in a network have a tendency to cluster together. In some studies, CC is called *transitivity* [22]. A definition of CC given by Watts and Strogatz [25] first defines a variable:

\[
C_i = \frac{\text{number of triangles connected to node } i}{\text{number of triples centered on node } i}.
\]

The clustering coefficient for the whole network is the average of node clustering coefficients:

\[
C = \frac{1}{n} \sum_{i} C_i.
\]

The variable \(C_i\) is referred as the density of the neighborhood of a node \(i\). Higher values of \(C\) are as a result of higher neighborhood densities which results in less clusters in the network.

### 3.6.1. Graphical Representation

Figure 10 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.

### 3.6.2. Quantitative Evaluation

Table 2 lists the SNA features of all matrices described in Figure 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 \(G\) 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 \(M\), \(M_Z\), and \(M_{ZR}\), we can see a small decrease of NCC at each step. The value at \(M_{ZR}\) is 16% smaller than the baseline of \(G\). 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 cumulative plot and the pie chart are shown in Figure 11. 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.

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

<table>
<thead>
<tr>
<th></th>
<th>M</th>
<th>Z</th>
<th>M_Z</th>
<th>R</th>
<th>M_ZR</th>
<th>G</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANEC</td>
<td>0.0994</td>
<td>0.0955</td>
<td>0.1123</td>
<td>0.0528</td>
<td>0.1263</td>
<td>0.1024</td>
<td>0.1301</td>
</tr>
<tr>
<td>ND</td>
<td>0.0182</td>
<td>0.0078</td>
<td>0.0236</td>
<td>0.0202</td>
<td>0.0394</td>
<td>0.0048</td>
<td>0.0429</td>
</tr>
<tr>
<td>NCC</td>
<td>0.5265</td>
<td>0.3008</td>
<td>0.4870</td>
<td>0.0661</td>
<td>0.4196</td>
<td>0.5784</td>
<td>0.5497</td>
</tr>
</tbody>
</table>

Table 2: Overview of ANEC, ND and NCC features computed on the matrices used in merging the two inhomogeneous systems from Figure 3.
(a) Step 1 (M); ND = 0.0182. No links between ANT+ and BT.

(b) Step 2 (Mz); ND = 0.0236. Merging of systems.

(c) Step 3 (MzR); ND = 0.0394. Significant increase of ND.

(d) Step 4 (P); ND = 0.0429. Final state of the network.

Figure 10: Proximity data visualizations of the interval T_S for a prayer. ANT+ and BT nodes are shown in red squares and blue circles, respectively. The size of a node indicates the total number of connections (both incoming and outgoing), while the width of the edge between two nodes shows the frequency of being in proximity during the period of observation.
4. Group Behavior Analysis

Using the results about how to construct proximity systems, we are now able to answer questions related to social networks and to understand the grouping behavior of pilgrims around the rituals of prayer. In the next three sections the following research questions are discussed:

- Can we differentiate leaders from followers within pilgrims?
- Is the separation of the data schedule intervals reasonable?
- Is there a change in group formation of the pilgrims from the beginning of pilgrimage until the end?

4.1. Differentiating Leaders from Followers

We aim to find which variables from SNA centrality features and from questionnaire data can be used to differentiate leaders from followers. A leader is an individual with a high experience in pilgrimage. We were provided with experience assessment scores [1-10] for each subject in our study from two experts in the area of pilgrimage. They based their assessments on observations of users while performing pilgrimage. In addition to the Eigenvector centrality feature which was used in Section 3.6 to assess the centrality property of the merged proximity network, here, we use two additional centrality features:

- **Node degree centrality (NDC)**
  NDC is the first and simplest degree centrality features. In undirected graphs, NDC is the number of incoming and outgoing links of a node. It is a measure of a node’s connectedness, influence or popularity. High values suggest that a node is central and/or powerful.

- **Node betweenness centrality (NBC)**
  NBC is the number of shortest paths that pass through a node divided by the total number of shortest paths in a network. Similarly to NDC, high values of NBC are used to identify the most central nodes in a network. It is commonly used to determine points where network would break apart.

Subjects filled a questionnaire by providing the following information: age, gender, number of previous pilgrimages, language skills (Arabic and English) and whether accompanied by any family member in the pilgrimage.
We use multi-linear regression models to separately identify which variables from centrality features on one side and from the questionnaire data on the other side can be used to predict the subject’s level of expertise, i.e., differentiate leaders from followers.

For each user, we aggregate proximity matrices over all prayer intervals and compute the three centrality features resulting in the matrix

\[
X = \begin{bmatrix}
x_{11} & x_{12} & x_{13} \\
v & w & z \\
x_{n1} & x_{n2} & x_{n3}
\end{bmatrix},
\]

where \( n = 41 \) is the total number of users, and \( \{x_{i1}, x_{i2}, x_{i3}\} = \{\text{NDC, NBC, NEC}\} \). The model is of the form

\[
y_i = \beta_0 + x_{i1} \cdot \beta_1 + x_{i2} \cdot \beta_2 + x_{i3} \cdot \beta_3 + \epsilon_i = x_i^T \beta + \epsilon_i,
\]

where \( y_i \) is the experience score of user \( i \). The linear regression analysis yields \( \beta = [-0.479, 0.073, -1.953], R^2 = 0.262 \) and \( p = 0.045 \). The significantly low \( p \) value shows that \( \beta_1 \) and \( \beta_3 \) can be included in the model, whereas \( \beta_2 \) can be omitted since it does not contribute for prediction. We also computed a pairwise linear correlation between the assessment score vector \( y \) and centrality feature columns of matrix \( X \). The low negative correlation value of \(-0.01\) between the second predictor variable, i.e., the betweenness centrality, and the experience scores also suggests that this variable can be omitted from the regression model.

In a same fashion, a multi linear regression model was also applied to the questionnaire data: age, gender, previous visits, language skills, and family companion. The analysis provide the estimated coefficients for the questionnaire data \( \beta = [1.800, -0.277, 2.022, 3.859, -0.163], R^2 = 0.732 \) and \( p = 0.001 \). The low \( p \) value shows that the combination of these predictors does significantly predict experience of pilgrims. Nevertheless, a pairwise correlation test shows that gender and family companion can be skipped from the regression model.

4.2. Schedule Interval Assessment

In Section 2.4 we have defined time intervals around the prayers (\( T_S, T_G, T_P \) and \( T_T \)). For each interval, the network density (ND) of all users and prayers is calculated, and applying ANOVA to these four ND values, we assess the validity of the interval segmentations.

![ANOVA box plot of ND in the four time intervals of the data processing schedule.](image)

Figure 12: ANOVA box plot of ND in the four time intervals of the data processing schedule. The variance of ND during the \( T_P \) Static Prayer interval is very low as there are no position changes. ND values pass the significance test (\( p = 0.007 \)), confirming that the data processing segmentation is reasonable.
Figure 12 shows the box plot of the ANOVA output. The variance of ND in $T_P$ is, as expected, very small because, this interval is the shortest and there are no position changes of pilgrims while performing prayers. ND values pass the significance test with $p = 0.007$, which confirms that our initial time segmentation is reasonable.

Figure 13 visualizes the proximity of subjects during the four defined intervals around a prayer using narrative charts. Subjects are represented by colored lines and those who are in a proximity range are shown by closely connected lines. Lines that are apart represent groups that are not in proximity range. In Section 3.2 we explained that subjects are in proximity range if the underlying proximity technology (ANT+ or BT) can discover each other. Thus, the distance between lines in the narrative chart is not proportional to the physical distance of groups. Moreover, cluster starts and ends are denoted by vertical gray lines while merging and splitting are represented by line curvatures. We can see that the behavior of groups is different during the defined time intervals around the prayers.

We observe that during $T_G$, group clusters are not consistent and there are a lot of merges and splits. During $T_G$ and $T_T$ there are far more clusters of pilgrims which are headed toward the mosque and perform the prayer. After prayer is finished, pilgrims are spread again which is visible in $T_T$.
4.3. Time Analysis

In addition to the Clustering Coefficient (CC) feature, that was used in Section 3.6 where we evaluated the merging of the two inhomogeneous systems ANT+ and BT, we also use the Number of Connected Components (NCC) to examine the structures of social networks over time.

- **Number of Connected Components (NCC)**

  NCC is a measure of how well connected a network is. It has been used in testing the resilience and robustness of networks. A graph that is not fully connected is decomposed into several connected subgraphs. In a graph $G$, the number of connected sub-graphs is equal to the number of 0 eigenvalues of its Laplacian matrix $[18]$. This matrix is defined as $L = D - A$, where $A$ is the heavily used adjacency matrix from previous sections and $D$ is the diagonal matrix which contains information about the degree of each node.

Initially, social graphs represented by adjacency matrices were created from aggregated prayer intervals. CC and NCC features were extracted from each adjacency matrix. Then, we averaged all the $CC_i$ and $NCC_i$ feature pairs that were computed from prayers of the same day. Figure 14 plots these averaged values during the 8 days of the data collection in Madinah and Makkah. We observe that the longer subjects stay in pilgrimage the more confident they get and separate into smaller subgroups. We can also see how the number of connected groups decreases due to pilgrims moving to Makkah. Initially they are less confident in the new city, but the same increasing trend of number of connected components continues afterwards.

![Figure 14: There is a decreasing trend on the Clustering Coefficient, and contrary an increasing trend on the Number of Connected Components over time. This suggests that subjects have started to group based on their social preferences.](image)

In the second part of pilgrimage, there is a decrease in the CC values suggesting that subjects have started to group based on their social preferences. This is also visible from the increasing trend of NCC values. Figure 15 shows pilgrim social graphs of two exemplary prayers from Day 1 and 6. We observe that the network in Day 1 is a fully connected graph and the network of Day 6 is represented by 7 connected components or sub-graphs.
In summary, the big group divides into small group as the time passes. We suppose that this is due to the pilgrims getting acquainted with the sites/places and activities, something which in turn would make them more comfortable and confident in themselves, thus not feeling like they need to follow as much as in the beginning stages.

5. Discussions and Limitations

In each of the steps of merging ANT+ and BT proximity systems there are limitations and challenges. The GPS sampling frequency and the distance threshold of 10m for GPS locations to be declared as nearby, 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 rules that we assume to be true might practically not always be followed. There are also other rules that we have not considered so far. Then, beside rules with probability equal to 1, there are also rules with a lower probability. In such cases we can not use the simple if-then-else method, but rather, we would have to apply probabilistic models, e.g., HMM.

While it is true that these social rules are specific to the Hajj pilgrimage and are barely extensible to other types of crowd events, the idea behind this approach is well applicable further beyond. And that is, that relevant prior information related to the event, derived from aspects of the very nature of the event, can be looked into for help to increase the efficiency and quality of approaches of studies. In a different type of gathering, such as the traditional Zurich folk festival, as prior knowledge we know that people almost never come alone, rather they tend to enjoy themselves in groups. Blanke et al. [3] use participatory data derived from GPS to build crowd density maps. Battery consumption of GPS-sensing is one of the major problems, and one method to alleviate this problem might be the use of the prior knowledge that participants are most probably in groups. After groups are identified in a first step, sensing can be alternated within the group members.

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http://www.zuerifaescht.ch
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. The time intervals were manually annotated. It would be also interesting to find the borders of the segmentation dynamically and to do the analysis on the intervals afterwards.

We considered three SNA centrality features to predict the level of experience of pilgrims. These features are based on the number of connections that a node has. It could be also useful to try additional features such as the Bonacich's power feature [4] or features used to find key players in a network [6]. Moreover, the number of survey questions was rather limited and the introduction of more sophisticated questions from social science research that can help in predicting the pilgrims experience, is needed.

By analyzing the clustering property and the change of the number of connected social network components over time, we observed that pilgrims have a tendency to divide into smaller communities, but we did not analyze what are the lines of interest of such divisions. It would also be interesting to analyze more such principal divisions and additional characteristics such as degree, betweenness and centrality distribution, degree correlations size of largest and second largest components, etc. This can help to better understand the network structure effects.

We understand that in order to get a more complete picture of group behavior within the bigger crowd of all the pilgrims, we would need to increase the total number of participants and to also study the interactions between groups from different contingents and countries.

6. Conclusions 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 analysis is collected from 41 participants during an Umrah pilgrimage in Spring 2013.

Using the results about how to construct proximity systems, we were able to answer questions related to social network analysis and to understand the grouping behavior of pilgrims around the rituals of prayer. We identified key variables from SNA centrality features and pilgrim questionnaire data, and built linear regression models to predict the experience level of pilgrims.

We then validated our assumption of the time intervals \((T_S, T_G, T_P, T_T)\) around a prayer. We used ANOVA to test for statistical difference of the network density feature in the four intervals. The intervals of a randomly chosen prayer were visualized using a narrative chart to furthermore observe the differences of pilgrim clusters between these four intervals.

The clustering property and the number of connected components of pilgrim social networks were analyzed over time. As subjects were getting familiar with the environment and each other, we observed that they had a tendency to cluster into smaller communities.

We have not considered the collected voice and environmental sound of the pilgrims devices yet. Incorporating the amount of speech can enhance the existing approach of differentiating pilgrim leaders from followers. And, the crowd density estimation from the sound could be used as an additional source for proximity detection.

In this work, we have focused on the rituals of prayer only. However, the Hajj pilgrimage consists of other important rituals as well. Therefore, we plan to apply our analysis to other pilgrimage rituals and stages, and to answer more key questions related to social networks of pilgrims.

The upcoming annual Hajj pilgrimages offer the next opportunity to improve and evaluate our work.
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