UNIVERSITY OF OULU

FACULTY OF INFORMATION TECHNOLOGY AND ELECTRICAL ENGINEERING

Arash Sattari

Understanding Collaborative Workspaces: Spatial Affordances & Time Constraints

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ABSTRACT

This thesis presents a generic solution for indoor positioning and movement monitoring, positioning data collection and analysis with the aim of improving the interior design of collaborative workspaces. Since the nature of the work and the work attitude of employees varies in different workspaces, no general workspace layout can be applied to all situations. Tailoring workspaces according to the exact needs and requirements of the employees can improve collaboration and productivity.

Here, an indoor positioning system based on Bluetooth Low Energy technology was designed and implemented in a pilot area (an IT company), and the position of the employees was monitored during a two months period. The pilot area consisted of an open workplace with workstations for nine employees and two sets of coffee tables, four meeting rooms, two coffee rooms and a soundproof phone booth. Thirteen remixes (BLE signal receivers) provided full coverage over the pilot area, while light durable BLE beacons, which were carried by employees acted as BLE signal broadcasters. The RSSIs of the broadcasted signals from the beacons were recorded by each remix within the range of the signal and the gathered data was stored in a database.

The gathered RSSI data was normalized to decrease the effect of workspace obstacles on the signal strength. To predict the position of beacons based on the recorded RSSIs, a few approaches were tested, and the most accurate one was chosen, which provided an above 95% accuracy in predicting the position of each beacon every 3 minutes. This approach was a combination of fingerprinting with a Machine Learning-based Random Forest Classifier.

The obtained position results were then used to extract various information about the usage pattern of different workspace areas to accurately access the current layout and the needs of the employees.

Key words: Bluetooth Low Energy technology, indoor positioning, RSSI, fingerprinting, collaborative workspace, machine learning, data visualization.

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FOREWORD

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LIST OF ABBREVIATIONS AND SYMBOLS

AR	Augmented Reality
BLE	Bluetooth Low Energy
CCD	Charge-Coupled Device
FM	Frequency Modulation
GNSS	Global Navigation Satellite Systems
GPS	Global Positioning System
GSM	Global System for Mobile communications
HTTPS	Hypertext Transfer Protocol Secure
IPS	Indoor Positioning System
IR	Infrared Radiation
ISM	Industrial, Scientific and Medical
ITC	Information Technology Company
JSON	JavaScript Object Notation
LoS	Line of Sight
LPD	Low Power Device
ML	Machine Learning
PBL	Problem-Based Learning
PDA	personal digital assistants
RFID	Radio Frequency IDentification
RSSI	Received Signal Strength Indicators
SDK	Software Development Kit
SIM	Subscriber Identification Module
SVC	Support Vector Classifier
ToA	Time of Arrival
UMTS	Universal Mobile Telecommunications System
UWB	Ultra Wide Band
VR	Virtual Reality
WLAN	Wireless Local Area Networks
WPAN	Wireless Personal Area Networks

1. INTRODUCTION

1.1. Collaboration enhancement through customized workspace layout

Effective collaboration and teamwork is an essential approach to promoting creativity and innovation, since in many cases, extensive complex problems are difficult to solve by a single individual [2][3]. In collaboration, two or more people work together with a task to achieve a shared goal. But other than the creation of shared knowledge with the aim of problem-solving, collaboration also leads to the individual learning of the participants who are engaged in the process. A collaborative process can involve multiple interactions, such as mutual explaining, elaborative questioning justifying one's opinions and reasoning, reflecting upon one's knowledge and arguing [7][5]. During a collaboration, through the processes mentioned above, the team members can learn from each other and as a team. This learning often can be depicted as informal learning (as there usually is not an intentional "teaching" practice) [4][9] and is referred to as Problem-Based Learning (PBL) [6]. Thus, learning from colleagues in collaboration can be a practical way of acquiring new information.

Nearly all science-driven businesses today see the value of fluent collaborative work as high-performance teamwork [4]. This is especially the case in teams which requires a lot of communication while working on a multidisciplinary project or an extensive task during short development time. An Employee in a business with high skill requirements is an expert in a specific domain. So, a very central aspect in successful collaboration is that how different members of a highly skilled team (each with own skill set) can motivate and spar each other to find a solution to a problem [4][8]. Many organizations are now actively pursuing more effective collaborative work through any possible means, one of which is a customized modern workspace.

Of course, successful collaboration can never be fully attributed to the workspace. However, it can often be attributed to encounters and discussions in small teams that inspire scientists to try new approaches. These inspirational events alongside individual scientific work can be significantly supported by space, which finally leads to increased efficiency [14]. For example, it's been shown that people communicate three times more often in a multi-space area than in a cell-space area. While, time spent on individual research increases from 5% to 29% when going from cell-offices to multi-space areas – leaving more time for people to work and think on their own [13].

The rate of communication also depends on the sitting arrangement of employees in the workspace. For example, considering that face-to-face interaction is an efficient collaboration method, the placement of employees in the room affects how often a spontaneous discussion might start between them [4][39]. Face-to-face interaction is proven to be more efficient compared to asynchronous means of communications, such as emails and phone calls since it includes facial expressions and tone of voices that helps in interpreting the communicated information [4]. On the other hand, in a shared multi-space office, frequent communication can also be a disadvantage, since the discussions might cause a distraction for those who are not participating in it [4][37][38]. This trade-off between increased discussion probability versus uncontrollable noise and loss of privacy further emphasizes the value of common areas. Communication and collaboration can also be supported with different tools, such as a whiteboard, TVs, projectors, etc. to make it possible to sketch, view and store information in a shared medium for later use [4].

1.2. Motivation and aims

As mentioned above, the value of a proper workspace layout in promoting collaboration and innovation has been stressed in many studies and general statistics exist, to some extent, on effect of different workspace layout choices on the efficiency of collaboration, which helps in designing a collaborative environment. But although information such as the ones given above holds in many cases, an optimum customized workspace layout should be tailored to the needs of specific cases, e.g. the team members' research attitude, workspace area specifications and the type of business in question. So, it is beneficial to have easily implementable methods of relating workspace arrangement to collaboration efficiency that can be applied to particular cases individually. This will bring the possibility to test different layouts in a specific workspace and monitor and interpret the results of the change through data collection.

To gain insight into the importance and requirements of customizable workspaces in today's vast variety of working areas (each with own specific needs), a quantitative study (survey) was conducted to collect data about the important features of a well-designed workspace. The survey was performed from 6th to 10th of February 2018 at 'Stockholm Furniture & Light Fair', using printed questionnaires. In total 59 interior design experts and enthusiasts, including 27 women and 29 men, participated in the survey. Among the participants, ~37% were architects and designers and the rest were administered, managers, retailers, etc. Participants were randomly chosen from the fair visitors.

The results showed that there is no uniform opinion on issues which can influence workspace design, even among the experts of this field. For example, 18.6% believe that sharing a work environment has a very important role in supporting multiple use of a space. However 35.6% think it has a moderate degree of importance. There was not a unanimous opinion even in issues that might have previously been assumed obvious such as the importance of having a private workspace when working alone. The questionnaire used for the above-mentioned assessments and its detailed results can be found in Appendix I. These results, once again emphasize the importance of tailored workspaces, and the necessity of a method to collect accurate data on the needs of a specific group of users sharing a specific work area.

Previous research about collaboration in workplaces has been using a wide range of methods from qualitative and quantitative methodology, for example [37][38][39] to name a few. However, a method is still needed that can evaluate collaboration through monitoring employees' activities covering the whole workspace area during workdays. This way, the effect of a specific layout on collaboration efficiency can be comprehensively analysed. This thesis is an attempt in introducing such a method that can be easily tailored to any given workspace.

For evaluating our proposed method, a conventional office space in a software development organization was selected. This kind of organization fits perfectly the purpose of this study, since modern software development teams include highly skilled individuals each with specific set of skills which need to tightly collaborate during a short development time to develop a solution to customer's problem.

In order to fulfil the requirement, employees' position within the workspace area is monitored constantly during a two-month long period through a Bluetooth-based indoor positioning system installed in the establishment. The implemented indoor positioning system does not depend on the specification of this certain establishment and can be re-implemented easily and cheaply in any workplace. It causes minimum disturbance to employees' work and addresses privacy issues.

2. BACKGROUND

2.1. Overview of indoor positioning techniques and systems

An Indoor Positioning System (IPS) is a system that locates objects or people inside a building using a variety of sensory and communication methods and devices [16][17]. Here, a summary of the indoor positioning sensor technologies is given. It should be noted that the accuracy and coverage values are based on the average of the majority of sensor specifications. There are many exceptions in each case which might not fall into the mentioned ranges. Also, only the main measuring principles are mentioned.

Satellite positioning systems, which are the main and most efficient method used in outdoor applications, cannot be used indoors since microwaves will be attenuated and scattered by roofs, walls and other objects. However, **High Sensitivity GNSS** (Global Navigation Satellite Systems) receivers are becoming more sensitive and can receive satellite signals inside buildings made of wood or bricks with a 10m accuracy and accepting acquisition times in order of 20s, but many issues remain unsolved [12][17].

Camera Based indoor positioning systems are based on the processing and evaluation of video data. These methods either use Fixed Camera Systems, in which the position of the target is estimated based on its position within the captured image, or Mobile Camera Systems, in which the mobile target's location can be known by detection of several landmarks placed in known positions or by extracting environment features [26]. Vision-based systems achieve accuracy levels between tens of µm and dm with update rates as high as tens of Hz [17][26]. The covered areas of the systems differ between few square meters and large room sizes. With the increase in CCD sensor chips' data transmission rate and computational capabilities (through high-performance image processing algorithms), this technology promises very efficient and low-cost positioning solutions in the near future [17][26].

Ultrasound technology uses ultrasonic waves to measure distance (travel time of the waves) between a fixed-point station and a mobile target. In order to implement such an indoor positioning system, multiple ultrasonic receivers are needed (mounted permanently at the ceiling or walls) and they must be synchronized (usually via faster IR or radio waves). Although this localization technique is relatively cheap and has the capability to reflect most of the indoor objects, an ultrasonic localization system has many intrinsic disadvantages, such as multipath propagation (which limits the accuracy to cm level), complexity of a large-scale implementation, and most important of all, frequency changes due to the Doppler shift and a strong temperature dependency. The strong decay profile of acoustic waves limits system's operating range to ~10m [17][26].

Magnetic Localization is based on the magnetic interferences caused by steel structures of buildings that create local variations in the Earth's magnetic field. Compass chips of smartphones can sense and record these variations to map indoor locations [21]. In applications that walls need to be penetrated, the magnetic localization is advantageous [17]. Magnetic positioning appears to be the most cost-effective indoor positioning technique and very promising, because it does not require any additional hardware, but it's not still widespread.

WLAN (Wireless Local Area Networks) can also be used for indoor positioning purposes. Since WLAN access points are readily available in many buildings and the technology can be used with standard smartphone devices, the systems based on it are easily implementable and cost-effective. WLAN has a long range of 50-100m. Another advantage of using WLAN is that line of sight is not required. Fingerprinting based on RSSI (Received Signal Strength Indicators) values is the common method used in WLAN indoors positioning [22][24][25] since it can be used with commercially available devices. Depending on the density of calibration points, this method can have accuracies in the range of 2-50m. WLAN positioning system is the most widespread approach for indoor localization [17].

Localization based on **Cellular Networks** is based on measuring power levels and antenna patterns. It uses the locations of nearby antennas to infer the mobile device's position. It requires a mobile device with an appropriate communication interface (GSM/UMTS) and a SIM card, but the process does not require an active call. Cellular network-based localization has a coverage of tens of kilometres but with low accuracy, and unlike WLAN, it operates in the licensed bands, where there is no interference from other devices operating at the same frequency [17][20].

Infrared Radiation (IR) is a common localization technology which is based on communication of infrared emitters and receivers. Systems based on high-resolution infrared sensors have sub-mm accuracy, but systems based on active beacons or those using natural radiation are mainly used for rough positional estimation (e.g. presence of movement in a confined area) [17]. Since IR beam does not penetrate through walls, it is possible to obtain confinement of the signals inside the room. Moreover, radio electromagnetic interference can be avoided and the power of transmitted IR signal can be easily adjusted to cover only the area of interest. On the other hand, there are also several drawbacks, such as multipath errors, high system and maintenance costs and requirement of a Line of Sight (LoS) between transmitter and receiver [23].

RFID (Radio Frequency IDentification) uses electromagnetic transmission between RF compatible integrated circuit in RFID readers and tags (which could be passive or active, i.e. operating without or with a battery). Most RFID systems rely on proximity detection of permanently mounted tags to locate mobile readers. Therefore, the accuracy of an RFID system is directly related to the density of tag deployment and reading ranges. Some long-range active RFID systems can also use signal strength information to improve the positioning accuracy. The main application of RFID location systems is navigation guidance for users in indoor environments [17][30].

Ultra Wide Band (UWB) positioning technology is based on sending very short sub-nanosecond pulses, with a low duty cycle of ~1/1000. On the spectral domain, UWB transmits a signal over multiple bands of frequencies simultaneously, from 3.1 to 10.6 GHz [30]. UWB tags consume less power than conventional RF tags with no interference from other RF signals due to the very short signal and difference in radio spectrum used. Very short UWB also solves the problem of multipath environments, due to the possibility of filtering delayed versions of the signal [17][30]. At the same time, the signal passes easily through walls, equipment and clothing [31]. However, metallic and liquid materials cause UWB signal interference. Short-pulse waveforms permit an accurate determination of the precise ToA (Time of Arrival) making positioning at cm-level possible. The reason why UWB has not entered the mass market is that it requires dedicated transmitter-receiver infrastructure [17].

Bluetooth is a technology originally meant for proximity, not offering a pinned location like GPS. However, large-scale indoor positioning system based on Bluetooth Low Energy (BLE) beacons have been implemented in practical applications. Since Bluetooth is a low-cost and low-power technology, it is efficient for designing indoor localization systems. A more detailed explanation of BLE technology is given in the following section since it has been selected for this study.

Many other technologies also exist which are not mentioned here, since although they are categorized as indoor localization systems, the available systems based on them would not serve the purpose of this study for different reasons such as high cost, low accuracy, difficult implementation, being optimized for other applications, etc. A few of such technologies are ZigBee, FM radio, radar and inertial sensors technologies [17][23][26][30].

2.2. Bluetooth Low Energy (BLE) technology

Bluetooth is a wireless standard for Wireless Personal Area Networks (WPANs) and operates in the unlicensed 2.4 GHz Industrial, Scientific and Medical (ISM) band. Operating in the same radio band as WiFi, it was introduced to address some of WiFi's shortcomings, the most important WiFi being a power-hungry protocol. The highest specified power level (class 3) of the Bluetooth standard has a maximum power output of only 1mW (0dBm). Bluetooth Low Energy (BLE) technology (designed by the Bluetooth Special Interest Group) provides even lower power consumption and cost while maintaining a similar communication range compared to classic Bluetooth. The use of BLE technology enables the use of batteries for months, without having to resort to external power supplies [16][17][27].

Bluetooth was designed primarily as a short-range energy-efficient protocol for exchanging information between devices, characterised by very short messages with minimal overhead. The standard has main capabilities of simple proximity sensing, high security, low cost, low power and small size [17][27]. Compared to WLAN, the range is shorter (communication ranges of 5-10m depending on the propagation conditions such as LoS, material coverage and antenna configuration [17]). This short-range dictates a much larger number of devices for providing adequate coverage since the indoor positioning system needs to cover every possible location within the area of interest, not only the proximity to BLE beacons (transmitters) [27]. But, on the positive side, with a short range of Bluetooth devices, the distance from a beacon can be inferred without any complexity. In effect, if a mobile device detects a Bluetooth beacon, then it is very likely that the beacon is only a few meters away, as opposed to other technologies in which a beacon may be detected even if it is two buildings away [28].

The drawback of using Bluetooth technology in positioning is that, in each location finding, it runs the device discovery procedure; due to this, it significantly increases the localization latency (10–30s). Since the Bluetooth sensor does not stay in inquiry mode for 5s during its 10s cycle, the off-the-shelf Bluetooth device might have a latency unsuitable for real-time positioning applications [17]. Another disadvantage of a Bluetooth-based localization system (when used without any modifications) is that it can only provide accuracy about from 2-3m [26], which might make it unsuitable for applications where high precision is needed.

The most common measuring principle used with BLE technology is based on **RSSI**, i.e. measurement of the strength of an incoming radio signal. RSSI is a relative indicator measured in dBm. The RSSI of a Bluetooth device is obtained by starting the inquiry procedure from a second device. The RSSI will then be included in the devices' response to the inquiry, meaning that it is not necessary for two devices to actually be connected or even be paired [40]. Due to external factors influencing radio waves—such as absorption, interference, or diffraction—RSSI tends to fluctuate. The further away the device is from the beacon, the more unstable RSSI becomes.

The problem that is usually encountered in RSSI-based techniques is that there is no direct relationship between the signal strength and the distance. Of course, the further a device is from the beacon, the smaller RSSI value, but, distance readings are prone to fluctuation because they depend on some external factors. Radio waves are susceptible to multipath propagation, diffraction, absorption or interference. Phone's and device's antenna orientation and beacon's settings also have an impact.

The **fingerprinting** technique almost entirely avoids this problem, as it is not at all concerned with the distance, but rather tries to obtain a unique combination of RSSIs that distinguishes a location from all other locations. The fingerprinting technique is based on a radio map, which is a collection of fingerprints. A fingerprint is a set of radio signals measured at a particular location, in which each signal is associated with the beacon from which it was emitted. This technique comprises an offline phase, in which a database of signal strengths from different Wi-Fi access points taken at different points across the area of interest (fingerprint map) is created. An online phase, the user scans the signal strengths in the wireless network and sends the data to the database, which will find the closest match, and return the likeliest location of the user place [40][41].

There have been many technologies using BLE beacons for indoor positioning. Since the introduction of the iBeacon protocol in 2013, many vendors have made iBeacon-compatible hardware beacons. BLE beacons have increasingly become one of the essential building blocks for the future of the Internet of Things, with a wide variety of use cases and possibilities [1], such as customer analytics, operational analytics and revenue improvement, targeted ads and messages, real-time mapping and traffic monitoring and indoor positioning [11]. The iBeacon protocol is based on Bluetooth low energy proximity sensing. The beacon transmits a universally unique identifier, which is then detected by an iBeacon compatible app or operating system. The identifier and several bytes sent with it can be used to determine the device's physical location or trigger a location-based action on the device.

Like WiFi, Bluetooth is embedded in most devices. So, the use of Bluetooth technology in indoor positioning usually does not require any additional hardware, because user's devices are already equipped with Bluetooth technology. Also, Bluetooth tags can be used as small size transceivers. Like any other Bluetooth device, each tag has a unique ID, which can be used to locate the Bluetooth tag. Indoor positioning using BLE beacons has significant advantages in indoor areas that do not have a fixed wireless infrastructure, especially when combined with software solutions [26].

2.3. Applications of indoor positioning in space monitoring and data collection

Indoor positioning has already found a vast variety of applications ranging from location-based services and medical care to construction, scene modelling and mapping [17]. Here, we mention a few examples of applications in which indoor positioning systems were used for space monitoring and data collection. Indoor positioning systems have been used in a variety of establishments (e.g. stores, restaurants, libraries, museums, hospitals and campuses) with the aim of providing data for optimization of services, guidance, navigation, advertisement to users, etc. Most positioning systems were either based on WLAN or Bluetooth, simply due to lower cost, more availability, easier implementation and already-included sensors in hand-held devices. It should be mentioned that many positioning systems have been proposed in the literature, but here the focus is given to only the ones which have been implemented in practical situations.

In [1], BLE beacons were used to detect entrance and exit events in an on-campus dining hall during finals week. The study relied on a long range of beacon detection (5 to 50 meters, depending on the environment it was situated in) to detect the presence of the user in the dining hall. The beacon data was collected through a common institutional app (installed in users' Android or IOS operating systems) with the main purpose of providing users with institutionally relevant information and services. Beacon information from this app includes the major and minor study subject of the user and the time stamp of each time the phone entered and exited the range of a beacon.

This study aimed to analyse visitation patterns such as the number of users in the dining hall during finals week or times per day that users visited the dining hall to provide institution's dining services department with useful information from the operational perspective. Nearly 800 unique users were recorded entering and exiting the dining hall during the week.

The study took advantage of the range of beacon detection, instead of using the more specific RSSI value from the beacon. Since just beacon entrance and exit information was used to detect visits, many estimations were taken in data analysis of finding out entrance and exit times. The results only covered one week out of the entire school year, and only one possible campus eating option (the dining hall). Also, since user phones were used as Bluetooth sensors, if a phone's Bluetooth were off, the user would go unnoticed.

In [10], the quality of three different indoor positioning algorithms based on values of WLAN RSSI was tested using smartphones and personal digital assistants (PDAs). Two measuring test environments, namely, an empty seminar room (scale: approx. 15m x 7m) and a museum showroom (scale: approx. 30m x 11m), four different types of PDAs (Dell, Fujitsu, HP, T-Mobile) and two types of access points (Netgear, Lancom) were used. The locations were equipped with four access points at the outer corners below the room's ceiling.

Interpolated radio maps of access points were plotted, and integrity and calibration measurements were performed in the test environments. Then, a field trial was carried out within a museum using a developed a digital museum guide application, which was based on a client-server architecture with PDAs acting as clients and a total 136 participating visitors. The access points were mounted in the four corners of museum rooms, as was in the test environments and the current user position was calculated every two seconds. The frequency map of calculated user positions was presented to show the popular visiting areas.

Based on the test series of random walks, mean and standard deviation of distance between real position and calculated position were found to be 2-3m and 1-1.5m, respectively (depending on the algorithm used).

In [19], an indoor positioning of users (shoppers) was presented, which used a network of BLE beacons implemented in a wholesale store. The presented experimental work used an area of approximately 800m^2 containing 25 BLE beacons (although the full deployment was said to include 136 beacons over an area of ~ 6000m^2). The store was laid out as a grid, with a series of aisles each with a series of tall metal shelving units. This study benefited from a large beacon deployment in a live commercial environment (i.e. not a controlled or constructed environment). It provides a valuable experimental platform compared to other studies which were done on smaller scales, for example [10][1][18].

The study aimed to accurately determine the closest product section to the user while shopping in the store, using RSSI readings from multiple beacons. The position across the width of the aisle was not important. A node-graph model of user location was used, which was designed to represent the location layout. So, the positioning problem was reduced to that of locating the user on the edge of a node graph.

Users already had access to an app which had been widely adopted by store's customers. The objective was to add location-dependent services and data, including navigation information, which could be configured by the user depending on their requirements. Three proposed positioning methods were evaluated: nearest beacon (baseline), averaged beacon-pair ranging, and a particle filter based tracking method with mean accuracies of 2m, 1.7m and 1.2m respectively. The results were presented from three separate data runs in the same section of the store, over a pathway of length 85m.

In [18][35], indoor occupancy patterns and related user behaviour was studied through 30-day monitoring of a university library using a Wi-Fi-based indoor positioning system. Six Wi-Fi detection nodes (together with a triangulation algorithm) were used to determine the location of Wi-Fi-enabled devices, including smartphones, laptops and tablets. In total, 1666 visits belonging to 1282 distinct MAC addresses were generated from the raw data gathered in this experiment.

Based on the collected data (using cluster analysis), occupancy duration patterns, such as the frequency of users taking breaks between consecutive long-occupancy periods, the popularity of different hours during the opening time and the popularity of space or space utilization by members of the library were analysed.

Most users were found to belong to the short-occupancy one-time visitor type (less than one minute). Different analyses were performed on the data such as cross-correlations between various occupancy parameters which revealed for example the following relations: the pattern of user arrival times at the library was found to be significantly correlated with their study durations; no device showed a pattern of repeat visit after midnight, and the majority of long-occupancy users tended not to have frequent breaks with some taking no break for four hours.

The sensor data included the location of WiFi devices, their MAC addresses, and the test time. Privacy issues were addressed properly with MAC address-truncation in the data processing, where only the second half of each of the 12-digit MAC address was kept in the data processing and analysis.

One drawback of using MAC addresses as individual visitors is that nowadays people have more than one devices connected to WiFi, e.g., smartphone, laptop, smartwatch, etc. It means that three different MAC addresses might belong to the same person, but in this approach, they are considered as three different users.

In [29], a self-regulated learning system was developed in one of China's National Libraries to assist users with an intuitive book search process. The system combines mobile Augmented Reality (AR) and indoor navigation to solve spatial and domain unawareness in physical libraries.

As the indoor positioning system, a commercial technology (BuildNGO developed by SAILS) was used that also provided smartphone navigation apps. The system's management module utilized wireless signals of Bluetooth 4.0, Wi-Fi access point (equipment developed by the same company) on site and the building floor plan to display positioning information or navigation path on handheld devices.

The AR module allowed the user to see the positions of AR virtual objects in the real space through the smartphone camera. To compute the relative positions of AR objects and the user, data transmission between the above-mentioned indoor positioning calculating agent and AR computing agent was required, so that the positions of virtual objects could be displayed on the smartphone. The AR navigation function integrated the information of reading paths (automatically recommended readings on specific topics), learning path (personalized preferences and records of the user), the real-space locations, real-time dynamic information, book introductions and readers' comments to help readers have access to the topic-related books efficiently.

Though implemented, the study lacked results on the performance of the indoor positioning system in practice (e.g. covered area, range, accuracy, etc.) and user satisfaction. Also, as mentioned by the authors, user privacy and data security issues were not considered.

In [36], the feasibility of a WiFi-based indoor positioning system for real construction sites was investigated. Also, a practical worker tracking application was developed. A series of experiments were conducted at a shield tunnel construction site. Specifically, there were three locations at which the tests were carried out: a stairway area, an entrance area, and a boring-machine area.

The WiFi-based positioning system was configured with active tags, access points, and a server computer. The active tags (installed on the worker's helmets) were used to collect the signal strength and access point's ID (mounted in fixed locations), and periodically sent information on signal strength (received from access points in its vicinity) and IDs of access points to the server computer through a wireless network. The system was developed using the fingerprint RSSI method for the received signal from each access point.

The WiFi-based positioning system's accuracy was reported to be less than 5m. Overall, the level of positional accuracy and durability of the system was reported to be sufficient to be used at tunnel construction sites, thus can be extended to systems for tracking the approximate locations of workers at construction sites. It was also suggested to use this system for monitoring the locations of other construction resources such as vehicles and materials at construction sites.

In [42], an indoor localization system, based on RFID technology and a hierarchical structure of classifiers is introduced. This system was designed to work in presence if disturbance is coming from other electronic devices or shielded walls in a hospital.

The system was put to experiment in the emergency unit (48 rooms covering about 4000 m^2) with the aim of locating the room where a specific patient lies.

The deployed infrastructure relies on RFID technology and consists of three different sensors. Each sensor on frequencies LPD 433 MHz, 446 MHz and 860 MHz to keep the frequency range as confined as possible to minimize interference. Patients are equipped with an active RFID Tag in a bracelet which sent a signal on a user-defined time interval basis. The duration of each signal is limited to a few milliseconds, resulting in a need for a change of battery only once in three months. Signals sent from tags are received from several antennas (RFID receivers) which store the tag's ID and the strength of the incoming signal.

The data acquired by different antennas positioned in the building were processed by a multi-classifier system. The main challenge was mentioned to be missing values (only third of the acquired data were valid and usable). In 98% of cases, the system localizes the correct room (83%) or one of its adjacency (15%).

2.4. Visualisation of indoor positioning data

Visualization has a significant effect on discovering and understanding the stories in data sets. As the saying goes, "a picture is worth a thousand words" [32]. A well-visualized data set as a plot or picture can present information which cannot be discovered in a table immediately. In the same way, in a data positioning-based project, the visual representation approach of data has a key role in understanding and analysing the data and evidence. A proper visualization method for positioning data can be different in each project and depends on what the user desires to extract from the data; for instance, the user might be interested in the pattern of movements or just curious about the occupancy information. But, in most cases, a well-designed visualization of time-series position data set should be able to answer these questions:

- Does the subject exist in a specific place at a specific time?
- How many subjects are in a location in a specific period?
- How is the pattern of movements of the subjects?

There are multiple visualization techniques which can be used for presenting the positioning data, e.g. two/ three-dimensional plots or augmented and virtual reality. A short overview of these methods is given in the following subchapters.

2.4.1. 2D visualization

Heat map (Figure 1a) is one of the 2D visualization methods which is being used widely to present positioning data. For example, in [34], heat maps have been used to depict the position of a football player in the court during a game. In [1], a heat map was used to present the number of user in a dining hall during a specific period. Heat maps are useful tools for showing position trend of subjects using a colour gradient. The heat map can provide a lot of information without using numbers. They allow users to easily detect distinct groups of data set and outliers as well. On the other hand, comparing hues in a heat map can be less precise than another type of 2D visualization method such as bar charts.

Scatterplot (Figure 1b) is another approach that is being used besides heat map to present the positioning data. In a scatterplot, each data or cluster of data is represented by a point. The strength of scatterplots is that they can depict large quantities of data and make it easy to see the density of presence of the subject across the different locations. A scatterplot can provide more information by adding shape, size and colour to the points. For instance, the position data of shoppers in a store shown on a scatter plot can easily show which section of the store is being used more frequently by shoppers. Also, giving distinct colours to the male and female shoppers will allow the researcher to see more information about the store visitors shopping tendencies based on their gender. Besides the advantage of using scatterplots, discretization of values can be mentioned as a drawback of them.

Neither heat maps nor scatterplots can show the pattern of the subject's movements. **Connected scatterplots** (Figure 1c) are a tool which can be used to present the movements of the subjects over time. They are being used widely to depict the continuous movement of the ball or a player on the field in a football, basketball, hockey, etc. in a match using lines. These sort of plots are very useful for overviewing change over time (e.g. in a game, the density of the lines can represent the trend of how the game is played).

(a) (b) (c)

Figure 1 Example presentations of positioning data using: a) heat map b) scatterplot c) connected scatterplot.

2.4.2. Augmented and virtual reality

Since Augment Reality (AR) and Virtual Reality (VR) have turned into commercial technologies, they have found their place in different fields such as gaming, manufacturing, medical, path planning, visualization, etc.

Data visualization using augmented and virtual reality offer new methods of interacting with data which traditional two-dimensional methods are not able to. The user can walk through data in a 3D AR or VR environment which can use colour, sound, movement and even touch to represent data. Figure 2 shows an example of a combined heat map and AR visualization.

Augmented reality has been employed in multiple applications using indoor positioning to represent the information obtained based on collected indoor positioning data. Most of such applications use smartphones and tablet devices to implement AR. Today, people take their smartphones with themselves everywhere they go, meaning that the hardware needed to implement an AR application is almost available everywhere. This is a key advantage of using smartphones for AR application is that many already own the required hardware and know how to use it. In [29], an AR navigation function for a library was implemented using smartphones and Bluetooth indoor positioning data. The system used AR virtual objects on top of real space (through the smartphones' camera), to navigate the users toward the books they were looking for. In another example, the UK's second largest airport, Gatwick implemented an indoor positioning system using a network of around 2000 beacons. They introduced an AR wayfinding system which guided the passengers to their destinations at the airport [33].

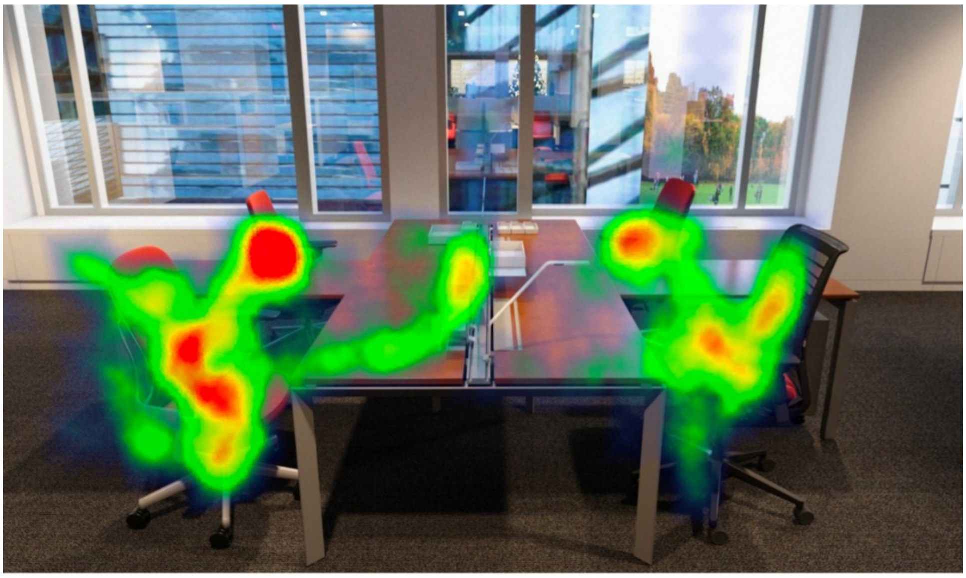

Figure 2 Example presentations of positioning data with augmented reality.

Using virtual reality for positioning data visualization can be beneficial especially when the data has a z-value (depth). Mapping positioning data in a virtual model of the place which data are collected in gives the user a possibility to see the data and the place in the same frame. Users also can look at to data from any viewpoint or move through them. It can help the users to more easily interpret the data to find the information they are looking for.

3. DESIGN AND IMPLEMENTATION

In this study, we have developed a BLE-based indoor positioning system to track the position of employees in a pilot workplace for two months to discover how the employees use different sections of the pilot area. This data can then be used to design a more collaborative and work-efficient environment through optimized customization of the workspace according to the specific needs of employees. The pilot area was in an Information Technology Company (ITC) based in Oulu, which consisted of four meeting rooms, two coffee rooms, a soundproof phone booth and an open workplace, in which nine employees were working.

For the application of creating an optimized collaborative workspace, a 2-3m position accuracy and an update rate of once every few minutes is adequate. The reason is that personal workspaces are around the same size as the chosen position accuracy, and visits or movements with less duration than a few minutes are considered too short to affect design changes. A well-designed BLE indoor positioning system was needed to allow us to determine the position of a BLE beacon (either carried by a person or attached to an object, e.g. office furniture) with the required positon accuracy and update rate.

Six of the employees volunteered to participate in the study by carrying BLE beacons with themselves during the two months' monitoring time. The implemented positioning system was based on BLE technology, which gathered RSSI data from 13 BLE receivers every 30 seconds and stored them in a database. The stored data was then fed to position prediction methods which determined the positon of each employee every 3 minutes with an above 95% accuracy (Chapter 4).

In this chapter, we explain the design requirements, system architecture, overall implementation (setup and monitoring) of the BLE-based position system.

3.1. System requirements

This section lists the requirements that had to be considered before designing the system:

- Transmitter devices to broadcast the BLE signals. They should have been light enough to be carried conveniently by the employees during the two months study time span. Also, the transmitters' battery had to last for during this period to avoid losing valuable data due to uncharged transmitters.
- Receiver devices to collect BLE broadcasts from the transmitters. They must have had the ability to log the data locally and also to transfer them over the internet to a database.
- All the beacons' received RSSIs from all the beacons (transmitters) must be been saved for positioning analysis and further evaluation.
- The designed indoor positioning method and system should not have depended on the current specific workplace, and with minimum changes, it should have been implementable in other workplaces.
- The system should have been robust and reliably should have worked continuously at least for two months.

- The system should be designed in such a way that it could be monitored remotely to insure every device was operating properly, and in case of a problem, it could be fixed as soon as possible not to lose any data.
- It must have caused a minimum disturbance to employees' work, and their privacy should have been preserved as well. For example, no personal data should have been saved, and no part of the system should have been installed in places where the employees were using for work purposes (e.g. desk, drawers, etc.).

3.2. BLE transmitter and receivers

As mentioned before, Bluetooth beacon technology is used to generate and transmit the BLE signals. Beacons are small size (a few cubic centimetres) devices that continuously transmit signals to any Bluetooth capable devices (e.g. smartphones, tablets, PCs, etc.) in their broadcast range. They can communicate with multiple devices simultaneously. In the classic use of Bluetooth, devices must pair to each other to be able to start a communication. This can cause latency in a continuous positioning system. Unlike conventional Bluetooth devices, beacons do not need pairing or connecting to broadcast data. They can transmit their data into space, even when no specific recipient is determined. As a result, any BLE device in their broadcast range can scan and pick up the transmitted data. This feature of Bluetooth called "undirected advertising" [43].

Beacon hardware is affordable and easy to use, which make it a suitable choice for different purposes such as positioning, occupancy determination, effective advertising, etc. Nowadays, there are various commercial Bluetooth beacons available for indoor positioning. Ebeoo [46], Confidex [47], IBKS [48] and Estimote [44] beacons are a few examples of such beacons. Estimote beacons were chosen as BLE transmitters in this study due to the following specifications, which matches well with the design requirements of this study. Figure 3 shows two different types of Estimote beacons.

(a) (b)

Figure 3 Two types of Estimote beacons: (a) Sticker beacons, and (b) Proximity beacons [44].

Each Estimote beacon has a 32-bit ARM processor. Beacons come with an Estimote Software Development Kit (SDK), which makes adjusting the beacon settings such as range, advertising interval, etc. easily possible for the developer. The beacons are designed to run on battery power, which can last for months or even years depending on the beacon's model. Also, they have built-in temperature and accelerometer sensors. Table 1 shows some of the specifications of the Sticker Beacons which were used in this study [44].

Table 1 Esimote Sticker beacon specifications

Battery Life	Range	Thickness	iBeacon or Eddystone packets	Additional Packets	Built-in sensors
1 year	7 m	6 mm	1 at a time	connectivity, nearable with telemetry	accelerometer, temperature

BLE compatible devices automatically recognize beacons, which are in their proximity (i.e. within the beacon's signal range). In this case, such devices are permanently located in specific locations within the pilot area. These devices have an associated app installed that will receive, recognize and store beacons' broadcast signals. Beacons cannot receive or collect any data. They just broadcast Bluetooth signals with in a predetermined fashion that can be defined by the developer.

Almost any BLE compatible device, such as smartphones, tablets, Android PCs, can be used to receive beacons' data packets. In this study, 'Remix Mini' devices were used as BLE receiver devices. The Remix Mini is a compact and small size PC, which uses an Android operating system called Remix OS and support Bluetooth 4.0 [45]. Their Android platform allows us to develop and use required android application. Meanwhile its multiple IOs such as HDMI and USB let us connect interaction interfaces (mouse, keyboard and screen) to perform checks or monitor their operation. Besides, remixes support both Wi-Fi and Ethernet that provides a more robust internet connection compared to smartphones' data or Wi-Fi connections. These features make them ideal for our purpose in this project.

3.3. System architecture

Figure 4 shows the components of the main architecture. AWARE [49] Android framework has been used in the Remix Mini devices to receive the RSSI from the beacons. In the abstract, AWARE is an Android framework dedicated to instruments, which lets developers and researchers log and share android devices hardware and software data. The AWARE plugins can be used to transform data into more understandable information. It also provides online storage on the AWARE server. In our case, AWARE provided us with the requirement to save data locally on remixes and the AWARE server as well, and to take advantage of the pre-existent AWARE APIs.

Figure 4 Architecture of the implemented BLE-based positioning system.

Visible beacons (whose signals are received) are being scanned every 30 seconds for required data, such as beacon ID, respective RSSI value, etc. This data is then saved locally in an SQLite database. Also, an AWARE Data Sync Service is running in the background uploading the collected data to a server every 30 minutes. The server is an AWARE dashboard with a MySQL database, and data are transferred over an HTTPS secure connection under JSON (JavaScript Object Notation) format. Figure 5 shows a high-level architecture of the indoor positioning subsystems, which collect the beacons' data and stores them.

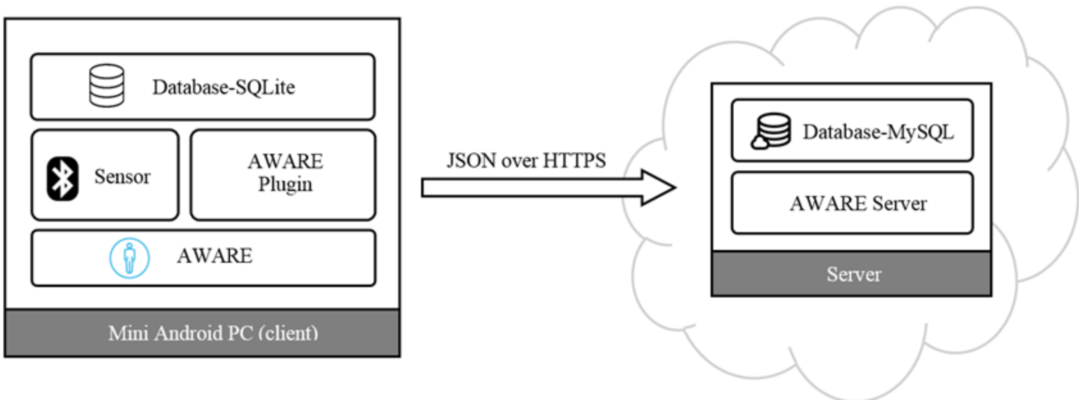

Figure 5 The indoor positioning system's data collection and storage subsystems.

3.4. Data structure

As mentioned, data are stored both in an SQLite database locally and in a MySQL database on the AWARE server. Both of databases consist of a *nearable_data* table and use the same data structure (Table 2). The main data fields used for calculating the beacon position are *timestamp, device_id, estimote_id* and *RSSI*. *Accelerometer* and *temperature* data were not required for indoor positioning in this project. Nevertheless, they were collected for the further analysis, which is beyond the scope of this study (please refer to chapter 5 for further suggestions on applications of such measured data).

Estimote_appearance shows the appearance of the beacon, which make it easier to find out, quickly and at first glance, to which beacon and respective carrier a data set belongs. As can be seen in Figure 3, Estimote Sticker beacons come in different colours, and have different figures printed on them (i.e. Lemon Tart, Blueberry Pie, etc.) for easy identification without the need to check the ID-related data. *Estimote_battery* keeps the beacons' battery level status, which can have three levels, namely, Low, Medium or High.

Table 2 Data structure

Table field	Field type	Description
_id	INTEGER	primary key, auto incremented
timestamp	REAL	unixtime milliseconds since 1970
device_id	TEXT	remix device UUID
estimote_appearance	TEXT	scanned beacon's appearance
estimote_id	TEXT	scanned beacon's ID
estimote_battery	TEXT	scanned beacon's battery status
temperature	TEXT	ambient temperature
x_accelerometer	TEXT	scanned beacon acceleration along x-axis
y_accelerometer	TEXT	scanned beacon acceleration along y-axis
z_accelerometer	TEXT	scanned beacon acceleration along z-axis
orientation	TEXT	the orientation of the scanned beacon
rssi	TEXT	the RSSI dB to the scanned beacon
is_moving	TEXT	the motion status of the scanned beacon

3.5. Indoor positioning system setup

An application of indoor positioning system is to guide people to their destinations in places such as airports, train stations, libraries, large stores, etc. In such usage, usually beacons are installed in fix positions, and an associated app on users' smartphone use device BLE to listen to broadcasted data, and determine the user location. Therefore, in such approach, the user's smartphone works as BLE signals receiver for the system.

Since nowadays almost all the people carry a smartphone with themselves, implementing this method is cost-effective. Also, users do not need to carry any extra device with them.

Using this approach in our indoor positioning system, in which the objective is to track employees' location in the pilot area continuously, means that they have to have their mobile phone with them all the time, even when they go for a short chat with a colleague or visiting the kitchen for a glass of water. Also, the employees must keep their phones' Bluetooth on during work time, which they tend not to because of the battery charging issues. To overcome these issues, we used the beacons as the moving part of the system. Therefore, each of the six employees was asked to attach a beacon to his shirt or key chain (figure 6). Batteries of Estimote beacons, which we used, could last for around one year; there was no need to replace the batteries during the data collection period. Still, as mentioned in section 3.4, the beacons' battery state of charge was collected to make sure no beacon ran out of the battery.

Figure 6 The beacons were attached to the employees' shirt or keychain.

In an RSSI-based BLE indoor positioning method, the strength of beacon BLE signals collected by the receiver varies due to the proximity level of a beacon to the receiver. Hence, using an individual remix in an area can provide only an estimation of how close a beacon to the remix is, but cannot determine the exact location of the beacon (Figure 7a). The dotted circle around each remix in Figure 7 depicts the possible locations of the beacon that can be estimated from the data received by that specific remix. To be able to determine a more accurate estimation of the location of the beacon, the BLE signal of the beacon must be scanned simultaneously by three (or more remixes) located in different positions (Figure 7b). The intersection of possible location circles of these three remixes results in a unique position, which is the location of the transmitting beacon.

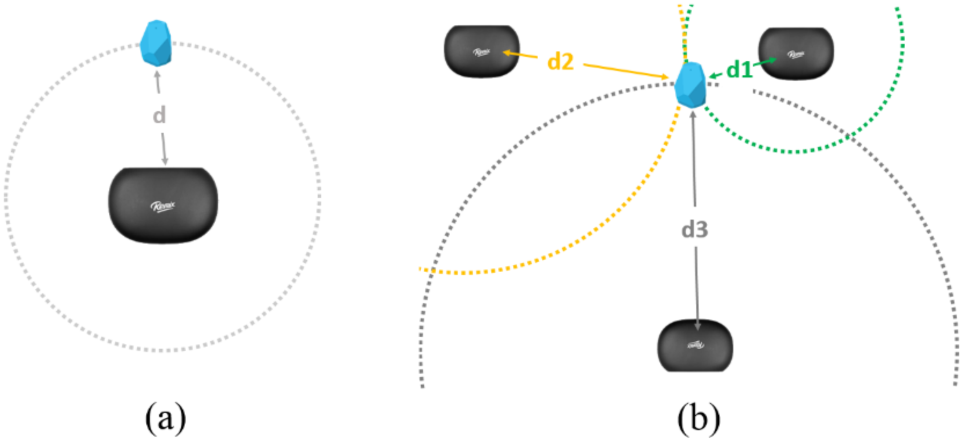

Figure 7 (a) proximity estimation using one remix, and (b) position estimation using three remixes.

The pilot area consisted of an open workplace, four meeting rooms, two coffee rooms and a soundproof phone booth. The designed positioning system should have been able to determine the location of the employees within the open workplace, but for the rest of rooms, such as coffee or meeting rooms, it was only needed to determine whether employees are present or not. Hence, only one remix as a receiver was installed per area in such rooms.

Figure 8 shows the layout of the pilot area and location that remixes had been installed. To cover all the pilot area, 13 remixes were installed in total, six of which were located in an open workplace area. The open working area (91 m^2) consisted of workstations for nine employees and two sets of coffee tables.

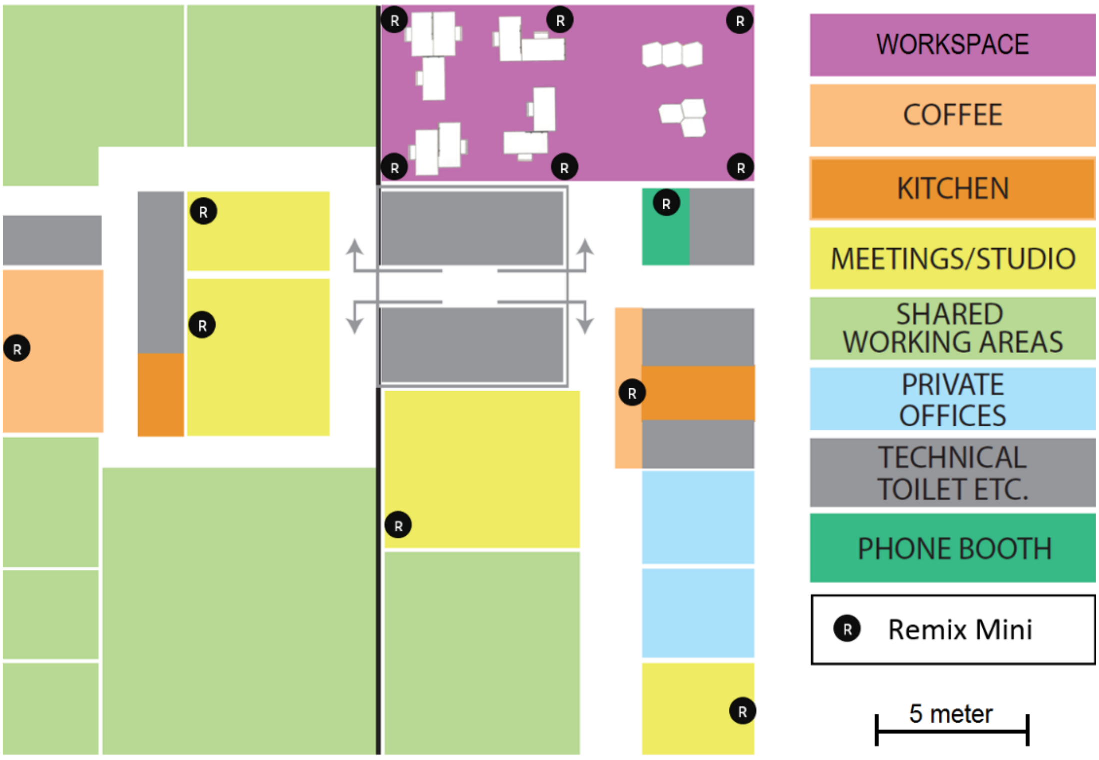

Figure 8 The layout of the pilot area and location of installed remixes.

After a preliminary test, it was revealed that the mini remixes could not provide a reliable internet connection over their Wi-Fi in all the pilot area. To solve the problem, a Wi-Fi extender was used together with each mini remix to improve the Wi-Fi signal strength and extend the coverage of the existing wireless network. Remixes were connected to the Wi-Fi extenders through a LAN connection. Since the BLE receivers only required a power outlet with no required installation (plug and play), this setup can be implemented with no change in the future applications. Figure 9 shows a few examples of the BLE receivers that were installed in the pilot area.

Figure 9 BLE receivers installed in the pilot area

3.6. Monitoring the system

As illustrated in the previous section, to determine the position of a beacon, three or more remixes must receive BLE data that were broadcasted by a beacon. The more remixes receive the beacon data, the more accurate and reliable position prediction we have. Hence, it was important to make sure that all the remixes were working properly. The remixes should have been monitored to detect the possible failures and resolve them as soon as possible. For instance, a remix might have been unplugged by mistake. For this purpose, an R script (Figure 10) was used to monitor how the remixes were receiving and collecting data. Figure 11 visualizes how often each remix records data during working hours of a day. The vertical axis shows the thirteen remixes that were installed in the pilot area. Each circle on the plot represents a single record of data that was transmitted by a beacon. Therefore, each row set of plotted data with a specific colour shows how the related remix collected data during the day. For example, remix 1 to 6 were located in the open workspace, therefore, when one of those remixes received a broadcasted data from a beacon, in most of the cases the five other remixes must have received it as well. So, if there was no data from one of these remixes for a period and meanwhile the rest of the remixes were recording data, it was considered as a sign of failure, and the remixes should have been checked.

```r
require (RMySQL)
library(lubridate)
library(ggplot2)

mydb = dbConnect(MySQL(), user="root", password="Ubicomp7066", port=3306, host="localhost", dbname="innostava_2")
locations <- fetch(dbSendQuery(mydb,"select * from nearable_data where timestamp < 1516802400000 and timestamp >
                            1516773600000 order by timestamp desc"), n=-1)
dbDisconnect(mydb)

officebeacons <- c(
  "31bb9317-6a05-45e2-8248-fabb5890a6c7", "9fc52184-4910-46bd-a4fe-1e22fe989698", "7e48111e-9df8-4578-be36-0ad20ccf175f",
  "ab8166e3-ddfc-463d-beb4-d25b73c85916", "4ac77381-5e7f-4096-964f-90c835a4899e", "7d3de429-09b6-467a-8f9d-6fec421d5f67",
  "6b418a31-86b4-4f57-ab43-430c5c68d213", "5c63a6c2-dcee-414e-8656-b1727faa391c", "62935039-57d1-442c-9103-749fe17327b9",
  "6d888e80-69bd-47c3-8c3a-7c39ed8d6f6f", "482a579d-cd2a-49f2-8511-1fad8ad4d34a", "2c1f0a5e-4274-4d36-9883-8bd27decf637",
  "a1c39b1f-e5f6-4c96-b7e4-23cdcddbc74f"
)

officebeacons_Labels <- c("1", "2", "3", "4", "5", "6",
                          "7", "8", "9",
                          "A", "B", "C", "D")

locations <- subset(locations, device_id %in% officebeacons)

locations$day <- as.Date(as.POSIXct(locations$timestamp/1000, origin="1970-01-01"))
locations$wday <- wday(as.POSIXct(locations$timestamp/1000, origin="1970-01-01"))
locations$hour <- hour(as.POSIXct(locations$timestamp/1000, origin="1970-01-01"))
locations$minute <- minute(as.POSIXct(locations$timestamp/1000, origin="1970-01-01"))

locations$device_id <- factor(locations$device_id, levels=c(officebeacons), labels = c(officebeacons_Labels))

days <- c("Saturday", "Sunday","Monday","Tuesday","Wednesday","Thursday","Friday")

for (d in unique(as.character(locations$day))) {
  d_loc <- subset(locations, day == d)

  g <- ggplot(subset(d_loc, hour > 7 & hour < 16 ), aes(x=(hour*60)+minute, y=device_id, fill=device_id, color=device_id))
  g <- g + theme(axis.text=element_text(size=20),
          axis.title=element_text(size=22,face="bold"))
  g <- g + geom_jitter(alpha=.3, size=3)
  g <- g + ggtitle(paste(days[d_loc$wday[1]], d))
  g <- g + scale_y_discrete(drop=FALSE)
  g <- g + scale_x_continuous(limits=c(8*60, 16*60), breaks=c(8*60,10*60,12*60,14*60,16*60), labels=c("8am","10am","12am",
                                                                                                        "2pm","4pm"))
  g <- g + guides(fill=FALSE, color=FALSE)
  print(g)
  ggsave(paste(d, ".png", sep=""), device="png", height=9, width=12)
}
```

Figure 10 R script to monitor how the remixes were receiving and collecting data

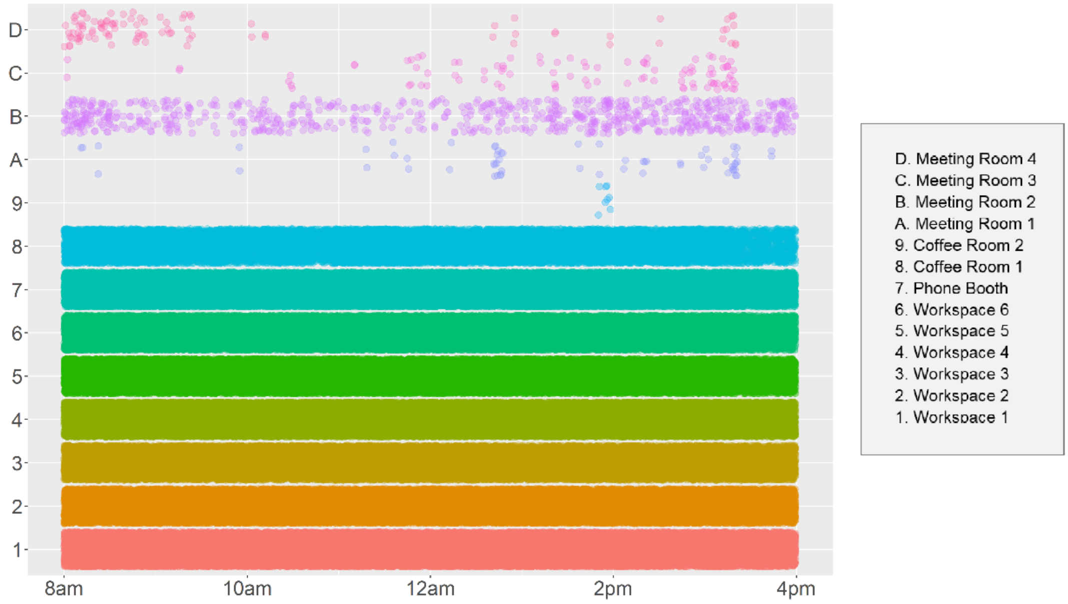

Figure 11 How often each remix records data during working hours of a day.

The implemented system was functional since Dec 23rd, 2017, and collect data until Feb 18th, 2018, for 58 days.

4. DATA ANALYSIS AND RESULTS

In this chapter, we describe how the positions of employees in the pilot area were determined based on the data that had been gathered using the implemented system (BLE beacons and remixes). It illustrates multiple approaches that were tested to predict the positions based on the RSSIs and compare the advantages and disadvantage of them. We also explain how the data, which was gathered in the AWARE database, was manipulated to prepare it for predicting the positions. Finally, it shows the positioning data evaluation results and describes how they can be used for better interior design.

4.1. Extracting the RSSIs

To determine the position of a beacon at a specific time, we need to know the strength of the BLE signals received by each of the remixes at the desired time. As described in section 3.3, each remix scans for all the visible beacons every 30 seconds and logs its data (e.g. own ID) and the broadcasted BLE data of the found beacons (e.g. beacon's ID, received RSSI, etc.). Since there was no communication between the remixes themselves, the scanning process of the remixes was not synchronous. Hence, remixes might have scanned a specific beacon at different times (at the worst case with a time difference of up to 15 seconds). This could potentially cause inaccuracy in determining the positions and frequency of position update.

Here, to address the asynchronous data collection of the remixes, the total time span (nearly two months) was divided to 30-second time windows and all the received RSSIs of a specific beacon by any remix within a specific 30-second time window was assumed simultaneously. Figure 12 is a simplified flowchart that shows how this task was accomplished for a specific beacon and given 30-second time window. This process was then repeated for every 30-second time window and all the beacons.

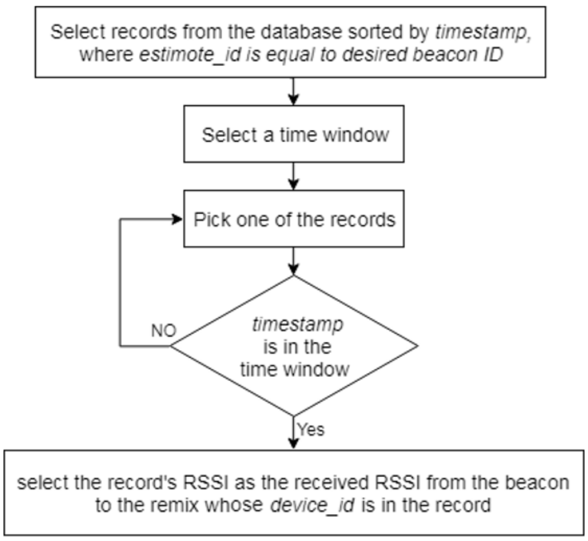

Figure 12 Finding all the RSSIs received by remixes from a specific beacon within a specific time window

A Python script was written to perform the algorithm mentioned above and extract the required data from the *nearable_data* table of the database. The extracted data was stored in a table named *posRSSI*s in a localhost MySQL database. Each record in this table contains fifteen fields, which are *timestamp*, *estimote_id* and *rssi_1* to *rssi_13* (Table 3). In the other word, $record_i$ (the i[th] record in the database) includes the strength of the BLE signals received by each of the remixes all over the pilot area from the beacon with $estimote\_id_i$, at the time of $timestamp_i$. The beginning of the time window, within which the RSSIs were assumed simultaneous, was considered as the timestamp for the given record.

Table 3 '*posRSSIs*' table in the localhost MySQL database

Table Field	estimote_id	timestamp	rssi_1	rssi_2	…	rssi_12	rssi_13
Field type	TEXT	REAL	INTEGER	INTEGER	…	INTEGER	INTEGER

4.2. Positioning based on the collected BLE RSSIs

This section illustrates multiple approaches that were tested to predict the positions based on the RSSIs and compare the advantages and disadvantage of them.

4.2.1. Distance Prediction by a Logarithmic Model

There is a recognizable relationship between the strength of a received BLE signal and the distance between its broadcaster and receiver. There are multiple theoretical and empirical formulas, which can determine the distance according to the RSSI. As the first approach in this thesis, we used a commonly used logarithmic model (1) which proposed by [50]:

$$[P_r(d)]_{dBm} = [P_r(d_0)]_{dB} - 10nlg\left(\frac{d}{d_0}\right) \quad (1)$$

Where $[P_r(d)]_{dBm}$ represents the RSSI, d is the distance from the BLE transmitter source to the receiver in meters, $[P_r(d_0)]_{dBm}$ is a reference RSSI measured at d_0 and n is attenuation factor. The formula can be simplified to (2) by measuring the reference RSSI at one meter away from the BLE transmitter [51]. We used this formula to calculate the distance between the beacons and receivers.

$$P = A - 10nlgd \quad (2)$$

To calculate the attenuation factor, the RSSI of the beacons were measured at different distances. Table 4 shows the average of the measured RSSIs. Then the attenuation factor was calculated using (3) based on the average RSSIs of Table 4.

$$n = \frac{A - P}{10lgd} \tag{3}$$

Table 4 Average of measured RSSIs at multiple distances

Average of RSSIs	Distance
-73 dBm	1m
-80 dBm	3m
-89 dBm	5m

The initial results of applying this method indicated that in sections of the pilot area, in which were in the proximity of a remix and in which there was no major obstacle, distance prediction had an acceptable accuracy, which met the predefined goals of this study. However, as the distance between the beacons and remix increased, the prediction accuracy decreased significantly. Table 5 shows a comparison between some actual and calculated distances of a beacon from a remix that was installed in a deserted corridor.

Table 5 Estimated distances based on the logarithmic model

Actual Distances (m)	**Estimated Distances (m)**
1m	0.76 – 1.96
3m	2.58 – 5.43
5m	6.65 – 11.45

The RSSI that is received by a remix is easily influenced by some external factors such as, multipath propagation, diffraction, absorption or interference. Therefore, in areas with large obstacles (e.g. furniture, monitors, etc.), which forms the major part of our pilot area; the RSSIs values were wildly fluctuating. Because of this, the predicted positioning results using this method for the areas such as the open workplace was noticeably unreliable and was not able to fulfil the goals of the thesis.

4.2.2. Fingerprinting

As the next step, a fingerprinting method along with machine learning algorithms was used to predict the positions of the beacons. To create the fingerprint map, the open workspace area was divided into multiple smaller subsections. Then, a collection of fingerprints was created for each one of the defined subsections. A fingerprint is a set of BLE signal strength that is received to all the existing receivers from a single beacon, which is located in one of the subsection. Therefore, in this case, with 13 remixes as the receivers, each fingerprint contains thirteen RSSI values and a label to specify to which subsection the fingerprint belongs. Figure 13 shows three different fingerprints obtained from the working space. The derived fingerprint map can be used to predict in which subsection a beacon is, by comparing the RSSIs of beacons with the RSSIs of subsections' fingerprints existing in the map.

Figure 13 Creating the fingerprint map of the open workspace

It is clear that more fingerprint subsections for an area lead to a higher position prediction accuracy. To create the fingerprint map of the pilot area, we divided it into 18 subsections. The open workspace was divided into 11 subsections, nine for the employees 'workstations and two for the coffee tables. The seven remaining subsections covered the meeting rooms, coffee rooms and the phone booth. Since in these remaining areas only the presence of the employees had to be detected, each one was considered as one subsection.

We did the fingerprinting after working hours to avoid any disturbance to the employees' work. For each subsection, we collected adequate fingerprints to cover most of the situations in which an employee could be within that subsection. For instance, the fingerprints of a workstation were obtained for different cases of a beacon being in the pocket, attached to the chest, left on different parts of the desk or carried by an employee sitting behind the desk, standing beside the desk and so on. In total, 5539 of single fingerprints formed the fingerprint map.

4.2.3. Predicting the positions using machine learning

With Machine Learning (ML) instead of relying on hard-coded rules, we use algorithms to train classifiers to learn from examples and try to make predictions according to their experience. An example contains a set of data, which are named as features, and a class, to which the features belong. The class is also called target or label. In an ML approach, a classifier is trained using a set of examples (training data). The classifier tries to understand how the features of the examples are related to their classes, to create a model for prediction. Then, if a new input is given to the ML classifier, its features are analyzed using the model obtained from the training data (examples) to predict a class for the input data. Figure 14 shows a simplified diagram of how ML predicts the class.

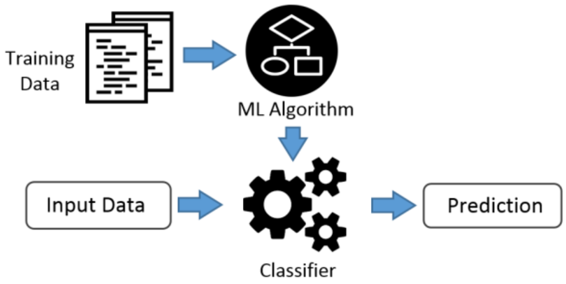

Figure 14 Simplified diagram of prediction using machine learning.

As Figure 14 shows, the first step to predict the location of the beacons using ML is to collect the training data. In this study, we used the fingerprint map of the pilot area, as the training data set. Therefore, each fingerprint is an example of the training data. As described in the previous section, each fingerprint contains thirteen RSSIs received from a beacon to remixes and a class that shows the subsection the beacon was in when the RSSIs were collected.

The ML algorithm approach does not rely on a program tailored to a specific problem. As a result, it can be used to solve different problems without the need to be rewritten. For example, if any aspect of the study, such as the interior design of the pilot area, BLE hardware or even the complete pilot area, changes, we merely need a new fingerprint map to be able to predict the locations using ML.

There are many types of ML classifiers (Linear Regression, Decision Tree, SVM, kNN, Random Forest, etc.). In this thesis, we tested the Random Forest classifier and the Support Vector Classifier (SVC) to predict the locations. The following sections describe how each method was implemented and how the results of each method were evaluated. In the training and evaluation process, 90% of fingerprints were used as the training data and the rest 10% as the test set for evaluation.

4.2.3.1. Random Forest Classifier

The Random Forest algorithm for finding the location of the beacon based on its received RSSI data to 13 remixes was implemented using scikit-learn in Python. Scikit-learn is a free ML library developed for Python.

Random forest algorithm uses a decision tree model, which is similar to a flowchart using branches to depict all the possible outcomes. The idea is to do two-option decisions (binary decisions) based on the values or attributes of the inputs data features to split the inputs corresponding to the defined classes.

In a Random Forest algorithm, the number of trees *(n_estimators)* for supervised learning has to be specified. More trees lead to better decision accuracy, but the result found in [52] shows that simply setting the number of trees to the computationally possible largest value is not the best choice. The other important parameter that has to be set in a Random Forest algorithm is *max_depth*. It points to the maximum depth that each tree in the forest can have. A larger *max_depth* allows the algorithm to have more binary decisions and capture more information about the input data.

To tune *n_estimators* and *max_depth* in our Random Forest algorithm, simulations were performed to find out how the location prediction error varies with changing these two parameters. The simulations were done using three different test sets, each one consisting of around 10% of the fingerprint map data (chosen randomly). Figurer 15 shows the average prediction errors for the three test data sets, while *n_estimators* is changed from one to 200 by steps of one and the result of the simulations for *max_depth* changing from one to 40 by steps of one is shown in Figure 16.

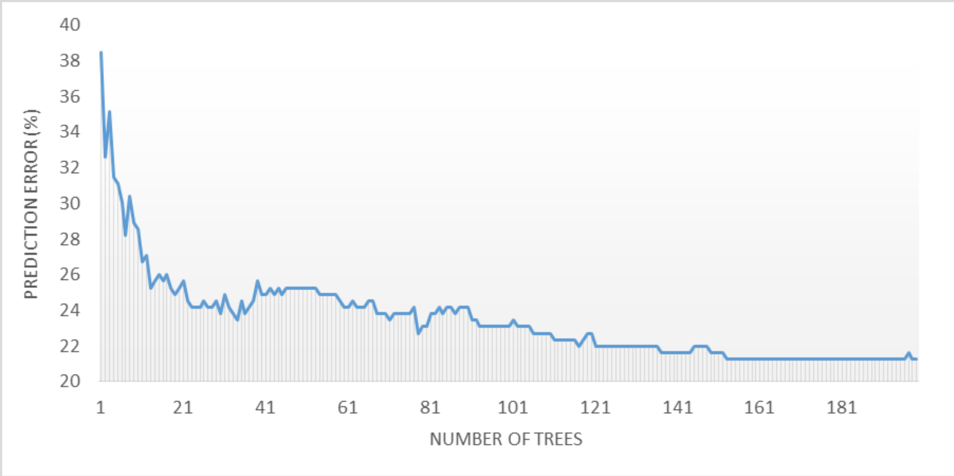

Figure 15 Prediction error for different n_estimators of the Random Forest algorithm (maximum depth is set to 10).

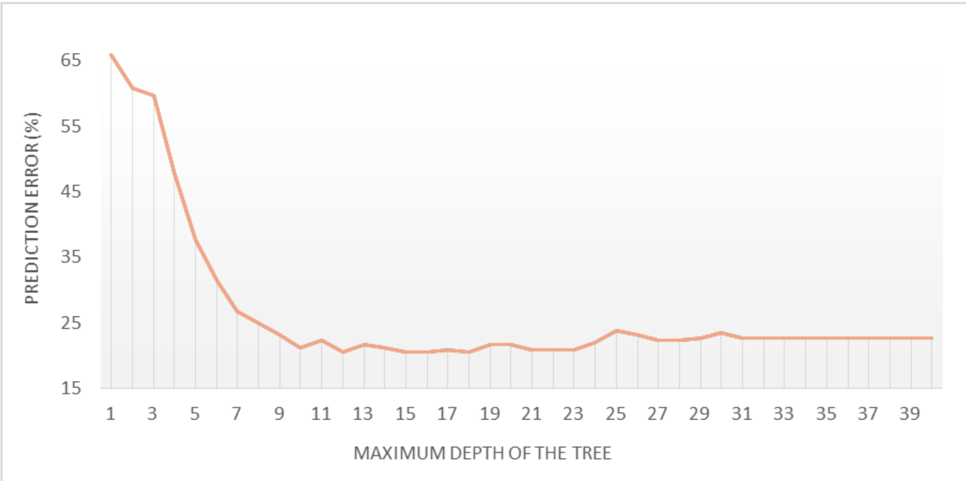

Figure 16 Prediction error for different max_depth of the Random Forest algorithm (number of trees is set to 155).

The result of simulation for a number of trees indicate that the prediction error converges to a constant number when the number of trees is increased beyond 155. Also, the simulations for maximum depth of trees show that algorithm performance converges around 33, and increasing the maximum depth dose not reduce the prediction error. Hence, in our Random Forest algorithm, we set the number of trees to 155 and the maximum depth to 33.

The simulation result based on the same three test data used for the algorithm tuning showed that the Random Forest with the above-mentioned parameters could predict the location of the beacons with a 77.3% accuracy. In the areas such as the coffee rooms, meeting rooms and phone booth that the defined subsections were larger, the prediction accuracy was 85.3%, and for the open workspace area, where the subsections were smaller and closer to each other, the predictions were 70.2% accurate.

4.2.3.2. Support Vector Classifier

The second algorithm that was tested to find the beacon locations was super vector ML algorithm, which again was implemented using scikit-learn in Python. The objective of an SVC algorithm is to find an optimum hyperplane that distinctly classifies the data points so that the distance between hyperplane and data points is maximum. The most important parameters that need to be set in an SVC algorithm are the *kernel, C* and *gamma*. Kernel specifies the type of hyperplane to be used in the algorithm, which can be linear or nonlinear. The C parameter sets a tradeoff between maximizing decision boundary and correct classification. The gamma parameter in a nonlinear kernel defines how precisely it fits the training data.

We evaluate the accuracy of SVC algorithm in predicting the location of the beacon, using two different kernels, one linear and one nonlinear (*RBF*). The gamma and C parameters were optimized using the same process that was used to tune the Random Forest algorithm parameters. Also, the test data used to evaluate the performance of the kernels were the same test data that was used for evaluating the Random Forest algorithm. The prediction accuracy results of the SVC algorithms can be seen in table 6.

Table 6 Prediction accuracy results of the SVC algorithms

Kernel type	**All over the pilot area**	**Workspace area**	**Meeting rooms, coffee rooms and phone booth**
Linear	61.9 %	44.5 %	81.4%
RBF	47.8%	35.2%	57.6%

As Table 6 shows, the SVC algorithm using linear kernel has a higher prediction accuracy than the nonlinear one. However, it still is less accurate compared to the Random Forest algorithm, while being much slower. Figure 17 compares the training time of the Random Forest algorithm with linear SVC, while training based on different sizes of training data sets.

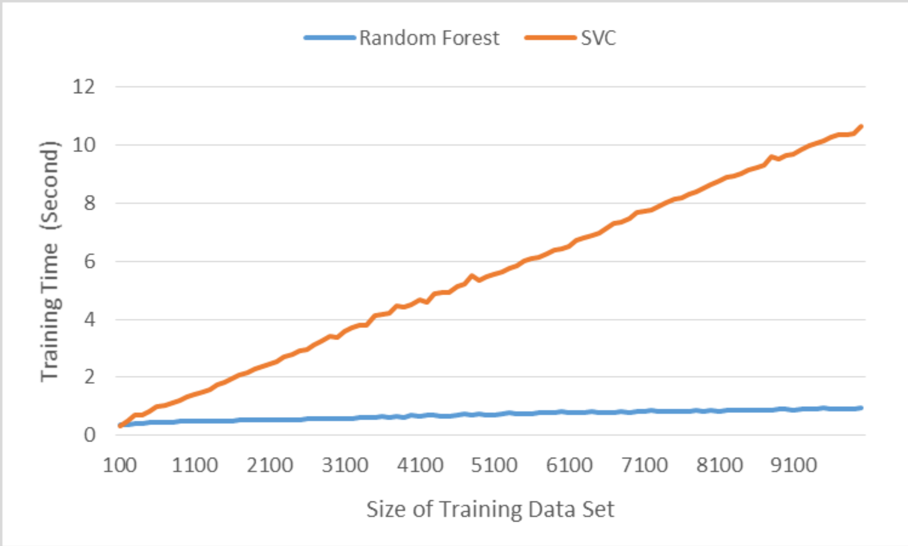

Figure 17 Random Forest algorithm and linear SVC training speed comparison

4.2.4. From RSSIs to Predicted Positions

According to results obtained in 4.2.3.1 and 4.2.3.2 the Random Forest algorithm was chosen to be used for analyzing all the beacons' data, which was collected during 58 days of the study (*posRSSIs*), to predict the location of the employees.

To further increase the prediction accuracy, some pre-processing on the input features were performed. The pre-processing technique was normalizing all the records in the posRSSIs table. Since there were many obstacles (e.g. workstation dividers), especially in the open workplace area, the absorption effect on the RSSIs is a factor that can cause an error in the position predictions. Normalizing the RSSIs reduces the impact of absorption phenomenon on the RSSIs. Equations (4) and (5) show how the RSSIs of each record was normalized between 0 and 100:

$$RSSI'_i = 100 + RSSI_i \tag{4}$$

$$RSSI = \left(\frac{RSSI'_i}{max(RSSI'_1, RSSI'_2, \dots, RSSI'_{13})}\right) \times 100 \tag{5}$$

where $RSSI_i$ is one of the thirteen RSSIs existing in a single record and $RSSI$ represent its normalized value. Combing the Random Forest algorithm simulations result, mentioned in Section 4.2.3.1 revealed that a considerable part of prediction errors occurs while a beacon is in a workstation, which is connected to another workstation. Hence, if the position of a specific employee was predicted in a workstation, situated in close proximity of employee's own workstation, we considered the employee's position to be his own workstation. Figure 18 shows the layout of the open workspace in the pilot area. For example, if the position of the employee who works in workstation 7 is predicted to be workstation 6 or 7, the position will be considered as 7. However, if the predicted position is anything except these two locations, the predicted position will be considered as the location where employee the is in.

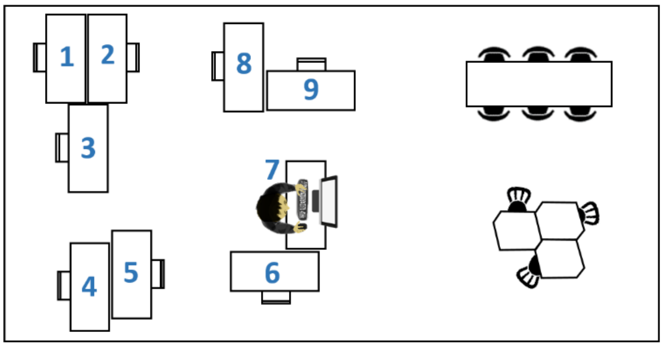

Figure 18 Layout of the open workspace area

After the position of all beacons was predicted every 30 seconds, every six consecutive predictions were grouped (forming 3 minutes time windows). Then, among these six predicted positions, the one, which was repeated most often, was considered as the location where the employee had been, during the 3 minutes time window.

Figure 19 shows the complete flow to produce the location of the employees from the RSSI database for the whole two months period, during which beacons data were collected. This approach was evaluated using the same test data that was used to evaluate the SVC and Random Forest algorithm in Sections 4.2.3.2 and 4.2.3.1. The simulation results showed that it has a 95.4% prediction accuracy in the workspace area and 95.8% in the coffee rooms, meeting rooms and a phone booth.

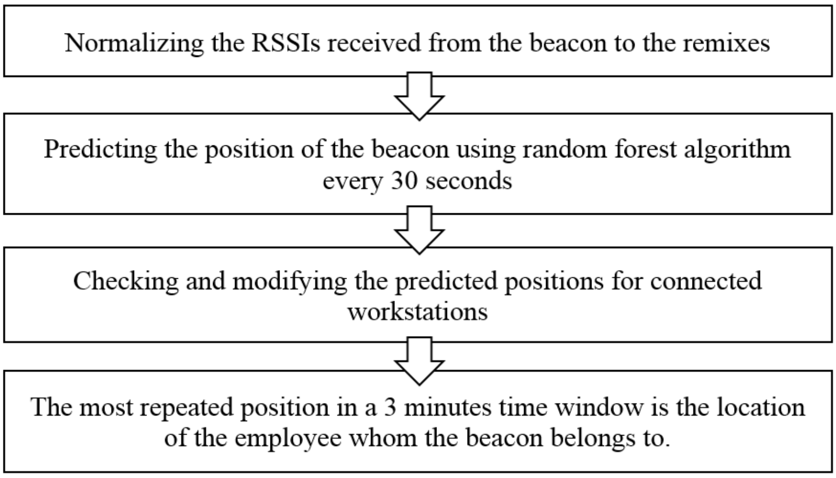

Figure 19 Flowchart of RSSI data analysis

4.3. Analysis of Positions Data

This section discusses some examples of the types of information that can be extracted from the employees' position data. It also provides data visualization using some of the methods discussed in chapter 2.4.1 The visualizations are based on the results gathered and analyzed using the implemented BLE positioning system in chapter 3 and processing and location prediction methods of chapter4, respectively.

Knowing the pattern in which each employee has used different sections of the pilot area, can provide useful information to tailor the area in such a way that covers the need of the employees better. Figure 20 shows a heat map presentation of how an individual employee has moved in the pilot area within 10 days. This sort of heatmaps can tell us, with which colleagues each one of the employees needs to collaborate more. This way, the workstations' locations can be rearranged, so that the employees who have more shared work can be situated near each other for ease of access and discussion. This arrangement can provide a better collaboration between the employees, which will lead to an increase in productivity. Also, it reduces the movement of employees in the working area and improves their concentration. These heat maps can also provide more information on which meeting room or coffee rooms are preferred by the employees to better access their needs.

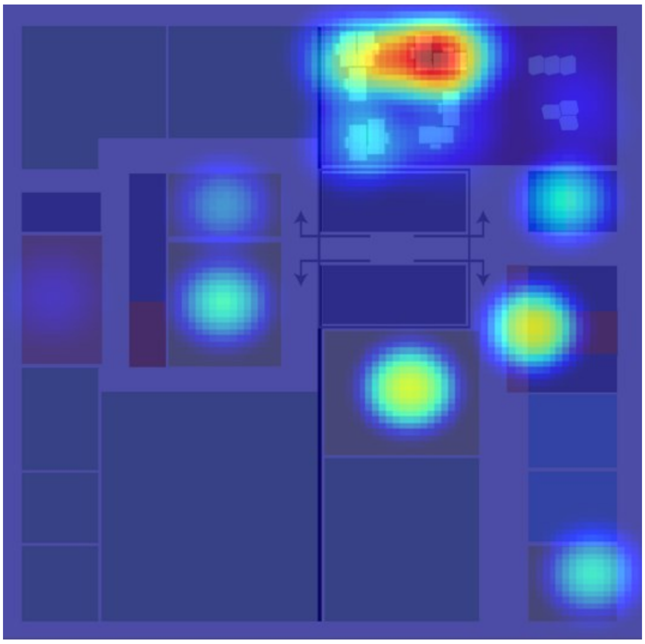

Figure 20 Heat map of an employee's movement in the pilot area within 10 days

Figure 21 depicts how a coffee room was visited during the different working hours within 10 days. As can be seen from the chart bar, as the work day elapses employees tend to visit the coffee room more, and between 3 pm to 3:30 pm is the most popular time during which the coffee room was visited. These type of charts can provide information on the rush hours of the coffee rooms (or any shared space) and the number of visits during those popular periods. As a result, the designers can have a better estimation of the facilities that the coffee room needs to host the employees functionally even during the times with the highest numbers of the visit. The evaluations showed that each visit in this coffee room would take on average 7 minutes with the longest visit having been 28 minutes.

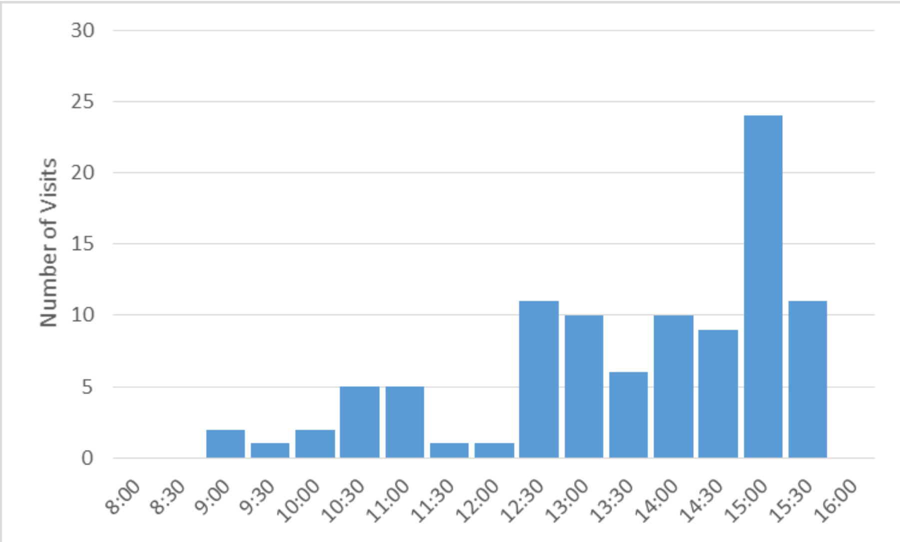

Figure 21 Coffee room visits during working hours within 10 days

As mentioned before, there were four different meeting rooms in the pilot area, each with different sizes, facilities, furniture and lighting. Figure 22 is a pie chart in which each section represents the proportional percentage of each meeting room usage. This sort of data helps the designer know which meeting room is more popular. This way, he or she can try to find the strengths of that meeting room's design and improve the other meeting rooms accordingly.

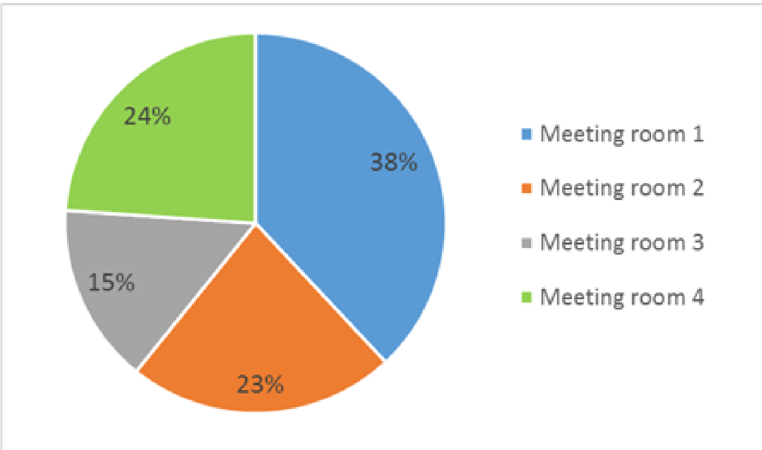

Figure 22 Meeting room usage chart

The line graphs of Figure 23 show, in more details, how often each meeting room was visited during working hours within a ten days period. Evaluation of the employees' positions can also provide more information about the usage meeting rooms such as how long each meeting on average take, the average number of participants and so on. For example, the evaluations showed that on average each meeting in *meeting room 1* took 22 minutes with the longest meeting being 84 minutes. Considering these numbers, the designer can select suitable furniture for better convenience during an average meeting.

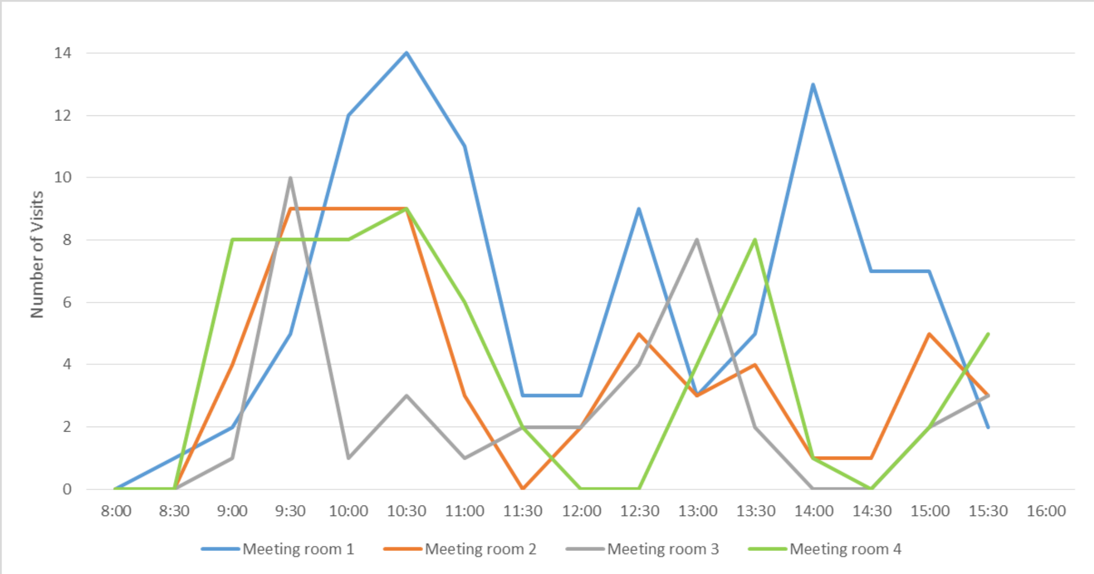

Figure 23 meeting room visits during working hours within a ten days period

Uses of the employees' positions analysis are not only limited to improving the interior design of a working area and increasing employees' productivity. As an example, we can take advantage of such analyzed data to improve the health care of the employees at work by monitoring their working pattern. There are several types of research such as [53][54] that show working with computers for a long period without taking breaks, increases the risk of getting into some health problems. Therefore, using the positioning data, the employees who continuously work for a long period can be detected and sent a notification to remind them to take a break. The evaluation results showed that on average, the employees who participated in this research had been working continuously for 18 minutes, and the longest period that an employee had worked without taking a break was 95 minutes.

5. SUMMARY AND DISCUSSION

The thesis presents an indoor positioning and movement monitoring system in a real company space. Positioning data collection and analysis was done with the aim of discovering how the employees are using different sections of a working area, to improve the interior design of the collaborative workspace. Since the nature of the work and the work attitude of employees varies in different workspaces, no general workspace layout can be applied to all workspaces. Therefore, having an objective view about how the people are moving in a workspace and use different sections can provide the interior designers with valuable information about the employees' needs. To get a better grasp of the importance and practicality of this research, a survey was conducted among 59 experts and enthusiasts of interior design. The result of the survey proved that there is no generic answer to the problem of efficient workspace design, and each area should be tailored to the needs of the employees.

Here, an indoor positioning system based on Bluetooth Low Energy technology was designed and implemented in a pilot area (an IT company), and position of the employees was monitored during a two months period. The pilot area consisted of an open workplace with workstations for nine employees and two sets of coffee tables, four meeting rooms, two coffee rooms and a soundproof phone booth, which was $218m^2$ in total. The main goals of the system implementation were for it to be low-disturbance, easily re-implementable, durable and accurate.

Full coverage over the pilot area was provided using thirteen remixes (BLE signal receivers), while light, durable BLE beacons, which Estimote Sticker beacons were carried by six of the employees, acted as BLE signal broadcasters. The broadcasted data from the beacons (e.g. RSSIs, timestamps, beacon id, acceleration data, etc.) were recorded by each remix within the range of the signal, and the gathered data was stored locally in an SQLite database and a MySQL database on the AWARE server as well.

The gathered RSSI data was normalized to decrease the effect of workspace obstacles on the signal strength. Three different approaches were tested to investigate the accuracy of predicting the position of beacons based on the recorded RSSIs. One relied on a theoretical logarithmic model, and two were machine learning algorithms using Random Forest classifier and the Support Vector Classifier (SVC). Among these tested methods, a combination of fingerprinting with a Machine Learning-based Random Forest Classifier provided the best result with an above 95% accuracy in predicting the position of each beacon every 3 minutes.

The obtained position results were then used to extract various information about the usage pattern of different workspace areas to accurately access the current layout and the needs of the employees. A few examples of such information were provided using different visualization methods.

Although the results obtained satisfied the aims of the thesis, there can be a few improvements suggested for future studies:

- In this study, we used remixes (receivers) that were not synchronized. This translated to a 0-15 second-time difference in a RSSI scan of one beacon by different remixes. This caused some inaccuracy in position prediction especially while beacons are moving. Syncing the remixes can completely remove this error.
- Remixes can be installed on the ceiling, if possible, to decrease the effect of RSSI fluctuation due to obstacles within the monitored area.

- Adding the accelerometers data to RSSI can add more information about the beacon's movement that can be useful in predicting its position with higher accuracy and update rate.
- We had also installed beacons on some of the furniture and office supplies (e.g. whiteboard) in the pilot area. Analysis of these beacons' data was not in the scope of this thesis, but it can be analysed to discover how people are moving and using these office supplies.
- The questionnaires results showed that the light and acoustic comfort are two important factors to the users. So, gathering and analysing the brightness and noise level data of the work area can help the designers in investigating the relation between these two factors and workplace efficiency.

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7. APPENDICES

Appendix 1. Survey questionnaire and results

Appendix 1. Survey questionnaire and results

What is a good office like?

This survey is part of InnoStaVa-research project.

Tell us something about yourself!

Primary profession

- [ ] Architect
- [ ] Designer
- [ ] Retail
- [ ] Marketing
- [ ] Administration
- [ ] Government
- [ ] Education
- [ ] Student
- [ ] Other

Age ________

Gender

- [ ] Female
- [ ] Male
- [ ] Prefer not to say
- [ ] Other

What is a good office like?

Note on the terminology used in this survey:
A work environment contains several individual workspaces with one or more workstations.

In your opinion, which one of the following themes is <u>the most important</u> in an office environment?

- [ ] Acoustic comfort
- [ ] Privacy
- [ ] Daylight
- [ ] Lighting
- [ ] Colors
- [ ] Materials
- [ ] Other

In your opinion, how many persons should share a workspace?

- [ ] 1 person
- [ ] 2-4 persons
- [ ] 5-10 persons
- [ ] 11-20 persons
- [ ] More

In your opinion, how important the following themes are in shared work environments?

	Not important				**Very important**
Shared workspace supports distraction free working	1	2	3	4	5
Shared workspace supports collaboration	1	2	3	4	5
Shared work environment provides different spaces for different activities	1	2	3	4	5
Shared work environment supports multiple uses of the same space	1	2	3	4	5

Optional comments

<u>WORKING ALONE</u>

In your opinion, how important the following themes are when working alone?

	Not important				Very important
Private workspace	1	2	3	4	5
Distraction free workspace	1	2	3	4	5
Your own personal workstation	1	2	3	4	5
Ability to choose and change your workstation	1	2	3	4	5
Tools for visualization of your ideas and information	1	2	3	4	5
Access to digital and virtual communication services	1	2	3	4	5

Would you change your workstation when you need to concentrate?

- ☐ Yes, I like to change my workstation often
- ☐ Yes, I would change my workstation if I would have to
- ☐ No, I would rather not
- ☐ No, absolutely not

TEAMWORK

In your opinion, how important the following themes are when working as a team?

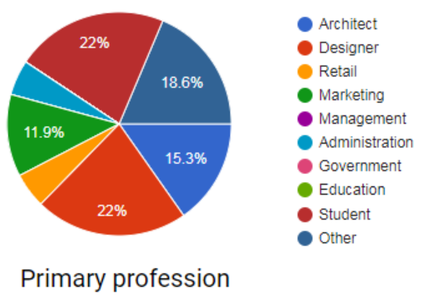
	Not important				Very important
Shared workspace	1	2	3	4	5
Ability to choose a workspace dedicated for teamwork	1	2	3	4	5
Ability to discuss and communicate without disturbing others	1	2	3	4	5
Tools for visualization of your ideas and information	1	2	3	4	5
Access to digital and virtual communication services	1	2	3	4	5

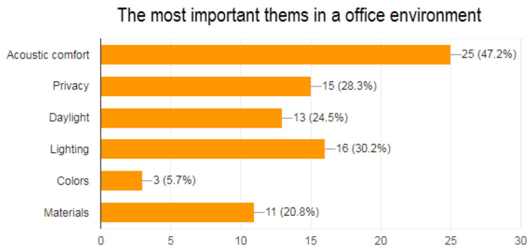
Would you change your workspace when you work as a team?

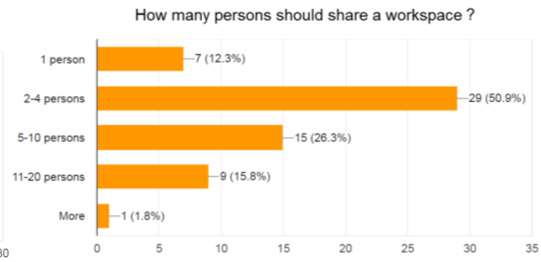
- ☐ Yes, I like to change my workspace often
- ☐ Yes, I would change my workspace if I would have to
- ☐ No, I would rather not
- ☐ No, absolutely not

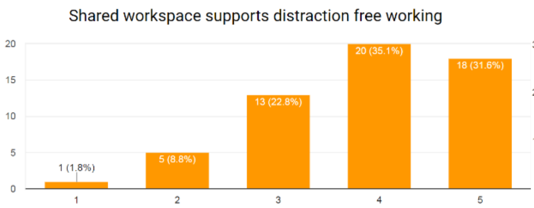
Optional comments

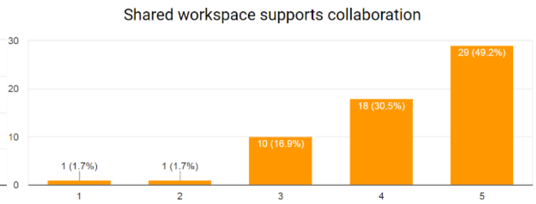
What is a good office like?

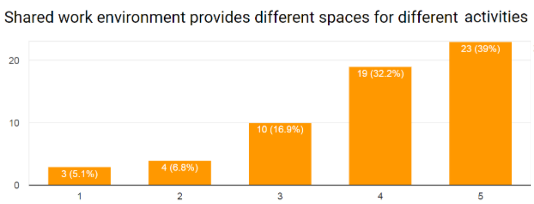

22%
18.6%
11.9%
15.3%
22%
Architect
Designer
Retail
Marketing
Management
Administration
Government
Education
Student
Other
Primary profession

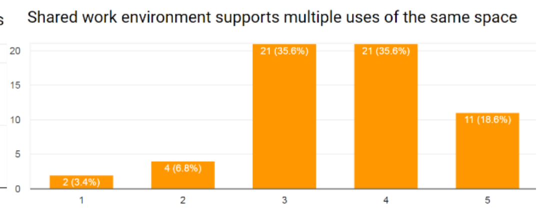

The most important thems in a office environment
Acoustic comfort
25 (47.2%)
Privacy
15 (28.3%)
Daylight
13 (24.5%)
Lighting
16 (30.2%)
Colors
3 (5.7%)
Materials
11 (20.8%)

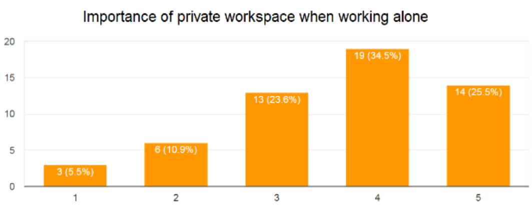

How many persons should share a workspace ?
1 person
7 (12.3%)
2-4 persons
29 (50.9%)
5-10 persons
15 (26.3%)
11-20 persons
9 (15.8%)
More
1 (1.8%)

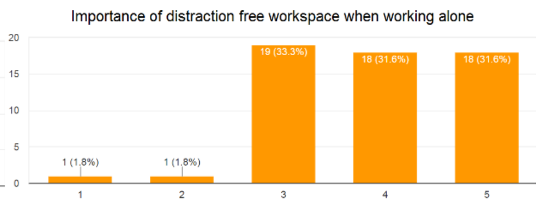

Shared workspace supports distraction free working
1 (1.8%)
5 (8.8%)
13 (22.8%)
20 (35.1%)
18 (31.6%)

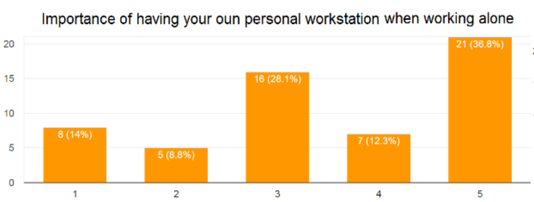

Shared workspace supports collaboration
1 (1.7%)
1 (1.7%)
10 (16.9%)
18 (30.5%)
29 (49.2%)

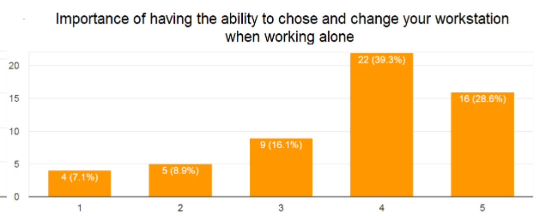

Shared work environment provides different spaces for different activities
3 (5.1%)
4 (6.8%)
10 (16.9%)
19 (32.2%)
23 (39%)

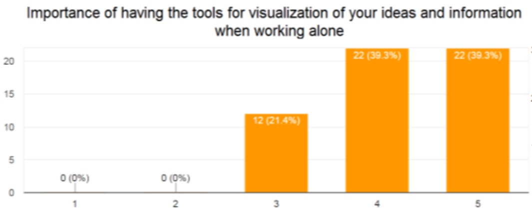

Shared work environment supports multiple uses of the same space
2 (3.4%)
4 (6.8%)
21 (35.6%)
21 (35.6%)
11 (18.6%)

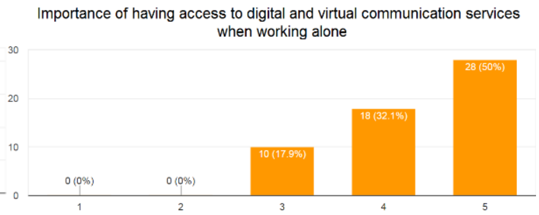

Importance of private workspace when working alone
3 (5.5%)
6 (10.9%)
13 (23.6%)
19 (34.5%)
14 (25.5%)

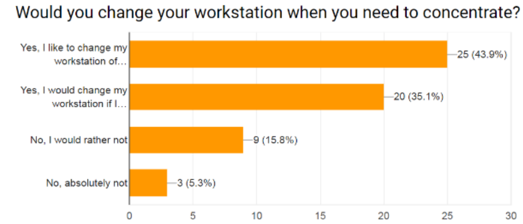

Importance of distraction free workspace when working alone
1 (1.8%)
1 (1.8%)
19 (33.3%)
18 (31.6%)
18 (31.6%)

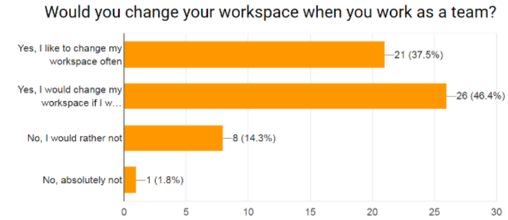

Importance of having your oun personal workstation when working alone
8 (14%)
5 (8.8%)
16 (28.1%)
7 (12.3%)
21 (36.8%)

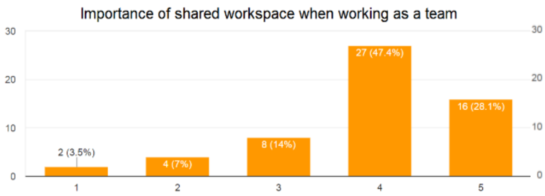

Importance of having the ability to chose and change your workstation when working alone
4 (7.1%)
5 (8.9%)
9 (16.1%)
22 (39.3%)
16 (28.6%)

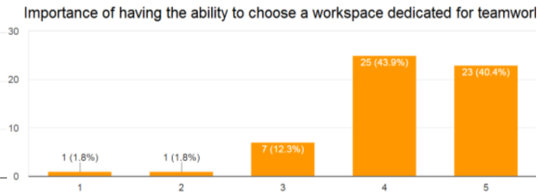

Importance of having the tools for visualization of your ideas and information when working alone
0 (0%)
0 (0%)
12 (21.4%)
22 (39.3%)
22 (39.3%)

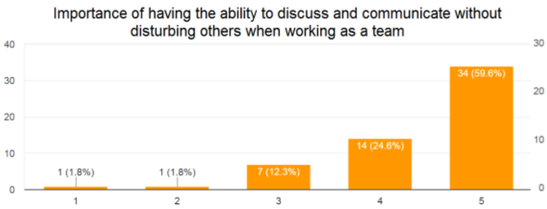

Importance of having access to digital and virtual communication services when working alone
0 (0%)
0 (0%)
10 (17.9%)
18 (32.1%)
28 (50%)

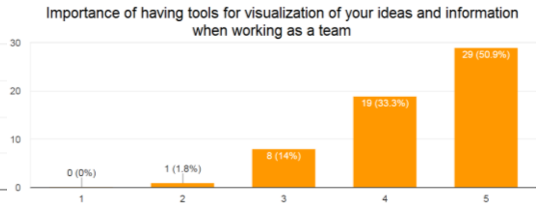

Would you change your workstation when you need to concentrate?
Yes, I like to change my workstation of…
25 (43.9%)
Yes, I would change my workstation if I…
20 (35.1%)
No, I would rather not
9 (15.8%)
No, absolutely not
3 (5.3%)

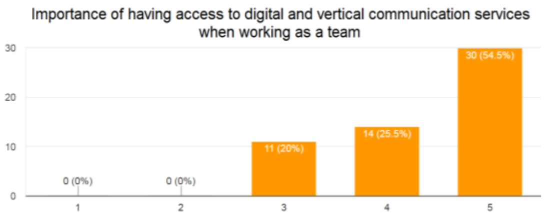

Would you change your workspace when you work as a team?
Yes, I like to change my workspace often
21 (37.5%)
Yes, I would change my workspace if I w…
26 (46.4%)
No, I would rather not
8 (14.3%)
No, absolutely not
1 (1.8%)


Importance of shared workspace when working as a team
2 (3.5%)
4 (7%)
8 (14%)
27 (47.4%)
16 (28.1%)


Importance of having the ability to choose a workspace dedicated for teamworl
1 (1.8%)
1 (1.8%)
7 (12.3%)
25 (43.9%)
23 (40.4%)


Importance of having the ability to discuss and communicate without disturbing others when working as a team
1 (1.8%)
1 (1.8%)
7 (12.3%)
14 (24.6%)
34 (59.6%)


Importance of having tools for visualization of your ideas and information when working as a team
0 (0%)
1 (1.8%)
8 (14%)
19 (33.3%)
29 (50.9%)


Importance of having access to digital and vertical communication services when working as a team
0 (0%)
0 (0%)
11 (20%)
14 (25.5%)
30 (54.5%)