Positioning in Indoor Mobile Systems

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1. Introduction

At present times people travel far greater distances on daily bases than our not so distanced ancestors had travelled in their lifetimes. Technological revolution had brought human race in an excited state and steered it towards globalization. Nevertheless, the process of globalization is not all about new and faster means of transportation or about people covering superior distances. Immense amount of information, ubiquitous and easily accessible, formulate the essence of this process. Consequently, ways through which the information flows are getting too saturated for free usage so, for example, frequency spectrum had become a vital natural resource with a price tagged on its lease. However, the price of not having the information is usually much higher. By employing various wireless technologies we are trying to make the most efficient use of frequency spectrum. These new technologies have brought along the inherent habit of users to be able to exchange information regardless of their whereabouts. Higher uncertainty of the user's position has produced increase in the amount of information contained in its position. As a result, services built on the location awareness capabilities of the mobile devices and/or networks, usually referred to as Location Based Services (LBS, also referred to as LoCation Services – LCS), have been created. Example of services using the mobile location can be: location of emergency calls, mobile yellow pages, tracking and monitoring, location sensitive billing, commercials, etc. With the development of these services, more efforts are being pushed into producing the maximum of location-dependent information from a wireless technology. Simply, greater the amount of information available – more accurate the location[ϕ] estimate is.

Whereas in outdoor environment the satellite-based positioning techniques, such as the Global Positioning System (GPS), have considerable advantages in terms of accuracy, the problem of position determination in an indoor environment is much farther from having a unique solution. Cellular-based, Computer vision, IrDA (Infrared Data Association), ultrasound, satellite-based (Indoor GPS) and RF (Radio Frequency) systems can be used to

[ϕ] Sometimes, in literature, the words position and location have different meaning. Most often, position translates to the set of numerical values (such as geographical coordinates) which describe the user's placement, whereas the location usually refers to the descriptive information depicting the user's whereabouts (such as Picadilly Circus, London, UK). Nevertheless, this work treats both words interchangeably.

obtain the user’s position indoors. Positioning technologies, specific for indoor environment, such as computer vision, IrDA and ultrasound require deployment of additional infrastructural elements. On the other hand, the performances of the satellite- and cellular-based positioning technologies are often unsatisfactory for typical LBSs in an indoor environment. Due to the proliferation of IEEE 802.11 clients and infrastructure networks, and the fact that a broad scope of LBSs can be brought into an existing WLAN network without the need for additional infrastructure, WLAN positioning techniques are relevant and established subjects to intensive research.

2. Performance Parameters and Approaches to Positioning

The determination of user's location can be seen as a simple mechanism consisting in calculating the whereabouts of the user. Those whereabouts could be descriptively expressed or in terms of geographic or some other coordinates. Nonetheless, it is practically impossible to obtain the exact location of a user, in 100% of the cases, regardless of the user and its environment (Collomb, 2002). Therefore, it is only an estimate of the user’s location that can be obtained and, it is very important to know how proximate the actual location and location estimate are. To achieve that, it is necessary to characterise this location estimate. On the other hand, it is also significant to describe the positioning technique itself in terms of its practicality and viability. All this is generally done through a set of performance parameters: Accuracy (Distance Error, Uncertainty, Confidence, and Distance error’s Cumulative Distribution Function), Coverage and Availability, Latency, Direction and Velocity, Scalability, Complexity and Cost effectiveness.

The first group of performance parameters is used to characterise the quality of a location estimate.

Accuracy – This is undoubtedly the most important performance parameter as it illustrates the essential characteristic of a positioning technique. This parameter enables to determine whether the calculated position is close to the exact position. This parameter is composite and consists of three different values that must be taken into account:

- Distance Error,
- Uncertainty, and
- Confidence.

The Distance Error corresponds to the difference between the exact location of the user (i.e. of his/her terminal) and the calculated position, obtained through a position determination method. It is also referred to as Location Error or Quadratic Error in terms of two-dimensional positioning. Distance Error is generally expressed in units of length, such as meters.

Determining the Distance Error can be very useful in depicting the particular position determination cases. However, in order to express the positioning capabilities of a technique it is usually much more suitable to exploit the Distance Error statistics via Uncertainty and Confidence parameters.

Bearing in mind that the calculated user's location is not the exact location but is biased by the Distance Error, it can be seen that the calculated position does not enable resolving the single point at which the user is located, rather an area. Depending on the positioning techniques used, this area may have different shapes (e.g. a circle, an ellipse, an annuli, etc). For that reason, the Uncertainty value represents the distance from the "centre" of this area

to the edge of the furthest boundary of this area. In other words, the Uncertainty value can be seen as the maximum potential Distance Error. The value of uncertainty is expressed with the same unit as for the Distance Error.
However, the Uncertainty value is not sufficient to describe the Accuracy of a positioning technique. The determination of the Uncertainty value goes through a statistical process and does not enable to guarantee that 100% of the calculated positions have a Distance Error lower than the Uncertainty value. That is the reason why the Uncertainty value is usually associated with a Confidence value, which expresses the degree of confidence that one can have into the position estimate. This degree of confidence is generally expressed in percentage or as a value of probability.
As a consequence, it is the combination of Uncertainty and Confidence that validly describe the accuracy of a positioning technique.
The other way of expressing the Accuracy, i.e. the performance or requirements associated to location determination, is through the Distance error's Cumulative Distribution Function (CDF). This approach is more comprehensive and inclusive due to the fact that a particular Uncertainty, Confidence pair can always be read of the graph for each and every Confidence or Uncertainty value. When assessing the technique's suitability for LBSs, expressing the Accuracy of a positioning technique through an Uncertainty, Confidence pair might be descriptive enough for a certain LBS. On the other hand, stating a positioning technique's CDF is more general and depicts the technique's accuracy for all potential LBSs.
Coverage and Availability – Accuracy is not the only parameter to be considered in order to characterise a location estimate. Coverage and Availability must be considered too. These two parameters are linked together:

- The Coverage area for a positioning method corresponds to the area in which the location service is potentially available, and
- The Availability expresses the percentage of time during which the location service is available in the coverage area and provides the required level of performance.

Latency – Location information makes sense only if it is obtained within a timeframe which remains acceptable for the provision of the LBSs. Latency represents the period of time between the position request and the provision of the location estimate and it is generally expressed in seconds.
Direction and Velocity – Although the herein presented work is restrained to the initial position determination algorithms, there are additional tracking algorithms that rely on multiple sequential position determinations in order to estimate the speed vector of the user. In such cases, two additional parameters have to be calculated: the Direction followed by the user and his/hers Velocity. These parameters are generally expressed in degrees and meters per second, respectively.
Scalability – The scalability is a desired and welcomed characteristic of a positioning system. It represents the positioning system's ability to readily respond to any augmentation. The augmentation can be in terms of Coverage area, Availability, frequency and total number of positioning requests, etc.
Complexity – There are many definitions for complexity depending on the domain of application. Nevertheless, in terms of positioning systems, complexity is most often referred to as the property that describes the difficulty of setting up the positioning system.
Cost effectiveness – This abstract characteristic of a positioning system is not entirely independent of its other performance parameters (e.g. Complexity and Scalability).

For example, the greater the Complexity of the system, the lower the Cost effectiveness. One of the ways of describing it is as a ratio between the benefits it provides (how broad range of LBSs it enables) and the costs it induces for the user.

As can be seen from the aforementioned, the latter three parameters don't have standardized units and are usually of descriptive nature.

The approaches and metrics used in order to obtain the user's position are also worth discussing. There are a few fundamental methods of acquiring the user's location:

1) Based on the identification of "base station" to which the user is associated (Cell-ID or Cell of Origin – COO) – This simple approach assumes that the estimated location of a user is equal to the location of a "base station" to which the user is associated. In other words, the user is estimated to be in a location of the "nearest" node of the network. This method is used both in indoor and outdoor environments (GSM, UMTS). Its popularity, despite inferior performances, is due to the simplicity of implementation. Obviously, the accuracy is proportional to the density of the network nods.

2) Based on the time of signal arrival (Time of Arrival – TOA) – Being that the waves (electromagnetic, light and sound) are propagating through the free space at constant speed, it is possible to asses the distance between the transmitter and a receiver based on the time that the wave propagates in-between those two points. This approach assumes that the receiver is informed of the exact time of signal's departure. Being that this is not always easily accomplished, the alternative approach takes into account the time needed for signal to propagate in both directions (Round Trip Time – RTT). This way, one station is transmitting the predefined sequence. The other station, upon receiving the sequence, after a strictly defined time interval (used for allowing the stations of different processing power to process the received information), resends the sequence. The station that initially sent the sequence can now, by subtracting the known interval of time that the signal was delayed at second station from the measured time interval, asses the time that signal propagated to the other station and back and, consequently, the distance between the stations. This approach is less dificoult to implement than TOA, since it does not require the stations to be synchronised.

3) The distance between the stations can be measured based on the differences in times of signal arrival (Time Difference of Arrival – TDOA) – With this approach, the problem of precisely synchronised time in transmitter and receiver is resolved by using several receivers that are synchronised whereas the transceiver, whose location is being determined, does not have to be synchronised with the receivers. Upon receipt of the transmitted signal, a network node computes the differences in times of the signal's arrival at different receivers. Based on that calculation, the user's location is determined as a cross section of two or more hyperboles. Owing to that, these techniques are often referred to as hyperbolic techniques.

4) Based on the signal's angle of arrival (Angle of Arrival – AOA or Direction of Arrival – DOA) – The idea, with this approach, is to have directional antennas which can detect the angle of arrival of the signal with the maximal strength or coherent phase. This procedure grants the spatial angle to a point where the signal originated (and whose location is determined). Vice versa, the mobile terminal can determine the angle of arrival of the signal from the known reference transmitters. Being that this approach is often implemented through the use of antenna arrays, the latter approach can have significant impact on the mobile terminal and is, therefore, less commonly exercised.

5) Based on the received signal strength (Received Signal Strength Indication – RSSI) – The free space signal propagation is characterised with predictable attenuation dependent on the distance from the source. Moreover, in real conditions, the attenuation also largely depends on the obstacles and the configuration of the propagation path. That is why there are various mathematical models which describe the wave propagation for diverse surroundings and, ultimately, estimate the signal attenuation for the observed environment. This approach grants the distance of the entity whose position is being determined, to one or more transmitters.
6) Based on the fingerprint of the location (Database Correlation or Location Fingerprinting) – With this approach, the certain, location dependant, information is acquired in as many Reference Points (RPs) across the coverage area of the technique. This data is stored into so called Location Fingerprints Database. Afterwards, when the actual position determination process takes place, the information gathered at the unknown location is compared with the pre-stored data and the entity's position is estimated at a location of a pre-stored fingerprint from the database whose data are "closest" to the measured data.
Most often, the estimated position with TOA and RSSI approaches is determined by lateration. The process of lateration consists of determining the position of the entity when the distance between the entity and one or more points with identified positions (i.e. refernce points) is known. To uniquely laterate the position in N-dimensional space, the distances to N+1 reference points ought to be known. With TDOA approach, the estimated position is obtained as a cross-section of two or more hyperbolas in two-dimensional space, or three or more hyperbolic surfaces in case of three-dimensional space. The process of angulation is employed with AOA and DOA approaches. This process estimates the location of a user as a cross-section of at least two rays (half-lines) originating at known locations. The lateration and angulation processes are depicted in Fig. 1. As for the Location Fingerprinting approach, the estimated location is obtained by utilizing the correlation algorithm of some sort. This algorithm determines, following a certain metric, the "closeness" of the gathered data to the pre-stored samples from the location fingerprinting database.
Apart from these, basic, approaches, there are a number of other choices and hybrid techniques that combine the aforementioned approaches when determining the estimated position of the user.

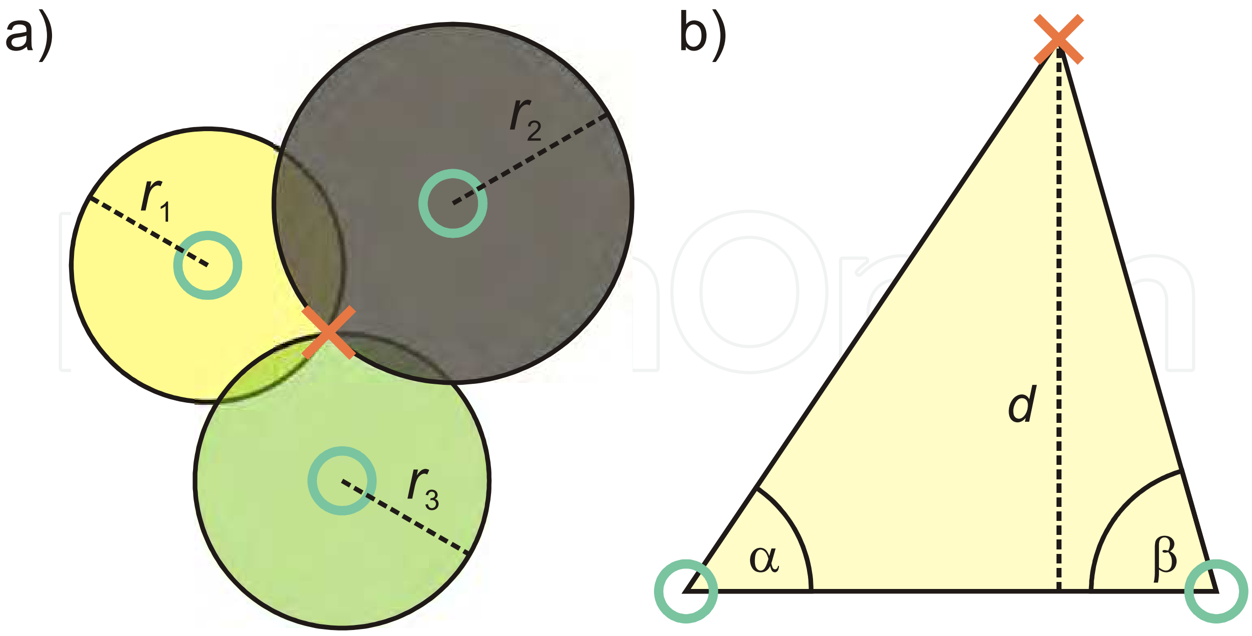


Fig. 1. The processes of estimating a user location: a) Lateration and b) Angulation (Green circles represent the known positions and the red cross stands for the estimated location)

3. Classifications of Positioning Systems

There are more than a few classifications of positioning systems. While some of them are very strict, others can be very arbitrary and overlapping. Without the need to judge or justify any of them, the most common ones are given herein.

Regarding the type of provided information, positioning techniques can be split into two main categories: Absolute and Relative positioning.

Absolute positioning methods consist in determining user location from scratch, generally by using a receiver and a terrestrial or satellite infrastructure. A well-known example of systems based on "absolute positioning" is the American GPS.

Relative positioning methods consist in determining user location by calculating the movements made from an initial position which is known. These methods do not rely on an external infrastructure, but require additional sensors (e.g. accelerometers, gyroscopes, odometers, etc). Inertial Navigation Systems used in commercial and military aircrafts are a good example of systems based on relative positioning.

LBSs currently offered by wireless telecommunication operators or by service providers are all based on absolute positioning methods and not on relative positioning methods, since these services are offered to users whose initial position is generally not known.

Within the "absolute positioning" family, the measurements and processing required for determining user's location can be performed in many different ways and rely on different means. Thus, many different absolute positioning methods can be used for determining user's location. These methods can be clustered into different groups, depending on the infrastructure used. Hence, the positioning techniques can be divided into:

- Satellite-based,
- PLMN-based (Public Land Mobile Network based), and
- Other (such as: WLAN, Bluetooth, RFID, UWB, etc).

The first group, which is known by the largest audience, is the "Satellite positioning" group. This group relates to the positioning methods which are based on the use of orbiting satellites, such as the GPS, Glonass or Galileo. Many applications and services based on satellite positioning have been developed during the past years (e.g. in-vehicle navigation, fleet management, tracking and tracing applications, etc). They generally require the use of dedicated receivers. Today, more and more devices such as PDAs or mobile phones include a satellite positioning capability, and this trend should persist in the future.
The second group, the "PLMN positioning" group, corresponds to the location techniques which have been developed for public land mobile networks. Initially deployed in the US under the pressure of the FCC mandate which forces US carriers to locate users placing calls to the 911 emergency number, location technologies are now being implemented in most of European wireless telecommunication networks for commercial purposes. Most of cellular positioning methods are incorporated in mobile telecommunication standards (2G/2.5G/3G/3.5G), but some solutions remain based on proprietary techniques.
The third and last group, the "Other positioning" group, corresponds to those technologies which have not been developed specifically for positioning purposes, but that can be used, in addition to their primary function, for determining user's location. These technologies encompass WLAN and Bluetooth for instance.
Another distinction can be made, depending on the "place" where the position calculation is made. In some cases, the main processing is performed at the terminal level. In other cases, the main processing is performed in the network. Therefore, the positioning techniques can be classified into:

- Network-based (also referred to as mobile-assisted), and
- Terminal- or Mobile-based (also referred to as network-assisted).

Satellite technologies, as a rule, fit in the Terminal-based positioning techniques. As for the positioning techniques from the PLMN and other groups, they can not be *apriori* associated to either of the Terminal- or Network-based groups.
Finally, the positioning techniques can be classified according to the environment of their coverage. Hence, the positioning techniques can be divided into:

- Outdoor, and
- Indoor.

Although there are intense research efforts to adopt the Satellite-based positioning techniques for Indoor environment, thay are still considered to fit into Outdoor groop. PLMN-based positioning can be implemented in both Indoor and Outdoor envornments, whereas techniques from "Other" group usually fit Indoor environments.
Positioning techniques designed for a particular Indoor environment in most cases fit into Relative positioning group.
Bearing in mind the ongoing convergence process of telecommunication systems and numerous, newly developed, hybrid positioning techniques, the indoor/outdoor categorization as well as other aforementioned classifications ought to be regarded more as guidelines than as strict lines that divide techniques into disjoint sets.

4. Non-Radio Indoor Positioning Systems

This section contains a brief overview of the non-radio positioning systems most commonly used in indoor environment.

4.1 IrDA Positioning Systems

IrDA technologies are based on devices with infrared light transceivers. This light occupies the part of spectrum between the visible light and the radio-waves. Upon encountering an obstacle, such as wall, the major part of the IR light's energy is being absorbed. Therefore, in order to communicate properly, two IR devices must have unobstructed Line of Sight (LoS) path between them. This poses a limitation for employing this technology in positioning purposes.

The most popular application of this technology for positioning use is the "Active Badge" technique (Want et al., 1992). The person or entity, whose position is being determined, possesses a device, badge alike, which periodically emits its ID code via IR transmitter. The IR sensors must be deployed in the coverage area (building). The position of the user is then determined based on the Cell-ID principle. With respect to the attributes of the IR light, the sensors must be deployed in every room in which the positioning feature is needed. Consequently, the accuracy of this technique is on a room level.

Other techniques based on this technology offer various accuracy and applications. The systems with greater number of IR receivers and transmitters on each device are proposed (Krohn et al., 2005). These systems are able to accurately estimate the position of a mobile communication device (e.g. PDA, laptop, digital camera, etc.) in order to allow them to automatically synchronise or perform other location dependent tasks. These activities are supposed to be performed on a flat, table alike surface. The obtained distance error is less than 20cm in more than 90% of the cases. On the other hand, there are systems that augment the "Active Badge" technique by using more IR sensors, micro VGA display and, optionally, video cameras. These systems provide so called Argumented Reality (Maeda et al., 2003). The typical application of an Argumented Reality system would be for the museum environment, where the visitor would be, via micro display (in eyeglasses, for example), fed with the information related to the exhibit he is currently experiencing.

4.2 Ultrasound Positioning Systems

The term ultrasound is related to the high frequency sound waves, above the part of spectrum perceivable to the human ear (20kHz). Although the ultrasound is most frequently used in medicine, there are other areas of application such as: biomedicine, industry (e.g. flow-meters), chemistry, military applications (sonic weapon), etc. As for the positioning purposes, the greatest benefit of using the ultrasound positioning is the product of a fact that ultrasound propagates through the air at limited speed, which is by far smaller than the speed of light. Therefore, the implementation of techniques based on time of flight (i.e. TOA, TDOA) of signal is very much facilitated. Moreover, the mechanic nature of sound waves grants ultrasound positioning techniques immunity to electromagnetic interference which could also be considered as an advantage. It ought to be pointed out that ultrasound waves do not penetrate, but rather reflect of walls. Therefore, the ultrasound receiver, in order to detect the signal, must be in the same room as transmitter but LoS is not necessary.

Ultrasound positioning systems can be classified according to the number of ultrasound "base stations" (transmitters and/or receivers) in each room (Dijk, 2004). The basic ultrasound positioning technique comprises one receiver in each room, and a ultrasound emitting tag which is worn by the entity that needs to be positioned. In this case, the

accuracy is on the level of the room. These systems are commercially available for some time now.
More sophisticated ultrasound positioning systems invoke the use of a greater number of transmitters in each room as well as the use of RF (seldom IR) signals for precise determining the time delay (Fraser, 2006). In this case, the controlling unit, which is connected to all the ultrasound emitters in one room as well as with RF transmitter, determines the exact time when each of the transmitters is about to send its chirps. Commonly, the RF signal is emitted first and then the chirps from all ultrasound transmitters are emitted separated by known time intervals. The receiver, knowing the separating time intervals and the propagation speed of RF and ultrasound waves, can now calculate, based on the time it received each of the chirps, the distance to each of the ultrasound emitters. The position is then determined by lateration. Consequently, for three-dimensional positioning at least four transmitters per room are required. The accuracy is in range of 10cm in 90% of the cases.
Furthermore, the system that eliminates the need for RF transmitter has been developed (McCarthy & Muller, 2003). With this system, the processing power of the receiver can be reduced, and the whole system is less complex. The transmitters are cyclically emitting chirps in constant time intervals whereas the receiver is employing an extended Kalman filter for resolving the chirp transmission and receipt times.

5. Indoor Radio Positioning Systems

The RF positioning techniques employ different parts of the frequency spectrum. Some are implemented on existent short-range radio interfaces and serve as added services, while others are especially developed for positioning. The most common RF technologies which, through the use of these techniques, enable positioning are: RFID, UWB, Bluetooth and WLAN.

5.1 RFID (Radio-Frequency IDentification) Positioning Systems

The beginnings of this technology go far back to the time of the Second World War Over the recent years, due to the cheaper RFID components, the expansion of this technology is occurring.
RFID system consists of tags, reader with antenna and accompanying software. The tags are usually placed on entities whose position needs to be determined. The Line of Sight between the tag and a reader is usually not necessary. The tags can contain additional information apart from its ID code which broadens the usage this technology.
There are three types of RFID tags:

- Passive tags do not have their own power supply. In order to operate, they use the energy, induced on their antenna, from the incoming radio wave from the reader. Using that energy, the passive tag replays by emitting its ID code and, optionally, additional information. Passive tags have very limited range (from a few cm up to a couple of meters). Their advantage is within the scope of cheap construction, compact size and cheap production.
- Active tags are encompassed with power supply witch enables them unrestrictive signal emission. This kind of tags is more reliable and immune to highly polluted RF environments. Their range can go up to a few hundreds of meters.

- Semi-active tags are equipped with battery power supply. Recent constructions enable a battery life span of more than 10 years.

RFID devices can operate in different frequency bands: 100 – 500 kHz, 10 - 15 MHz, 850 – 900 MHz, and 2.4 – 5.8 GHz (Don Chon et al., 2004).
RFID positioning techniques are based on knowing the position of the reader. When the tagged object enters the range of the reader, its position is assumed to be equal to the position of the reader (similar to Cell-ID). Correspondingly, it is possible to deploy tags across the coverage area. In that case the reader is mounted on the entity whose position is being determined. The accuracy depends on the density of deployed objects (tags/readers) across the coverage area. With active tags, the positioning accuracy can be upgraded with the RSSI information.
Most common application areas of RFID technology are in replacing the barcode readers, product tracking and management, personal documents identification, identification implants for humans and animals, etc. It is interesting to mention that the latter aforementioned application raises numerous ethical issues and there are organized groups worldwide opposing the implementation of this technology.

5.2 Bluetooth Positioning Systems

Bluetooth is a short-range, low-consumption radio interface for data and voice communication (Muller, 2001). Initially conceived in the mid 90s by the Ericsson Mobile Communication as a technology that ought to replace the cable in personal communications, Bluetooth shortly gained significant popularity. Ericsson was joined by IBM, Microsoft, Nokia and Toshiba. They formed Bluetooth Special Interest Group (SIG) with an aim to standardize Bluetooth specifications. Independent group, called Local Positioning Working Group, had a goal of developing the Bluetooth profile which would define the position calculation algorithm as well as the type and format of the messages that would enable Bluetooth devices to exchange position information.
The basic Bluetooth specification does not support positioning services per se (Bluetooth Special Interest Group Specification Volume 1 and 2, 2001). In absence of such support, various research efforts have produced diverse solutions. Bahl and Padmanabhan used the RSSI information for in-building locating and tracking (Bahl & Padmanabhan, 2000). Patil introduced the concept of reference tags and readers (Patil, 2002). He also investigated separately cases when Bluetooth supports and does not give support to RSSI parameter. On the other hand, the research by Hallberg, Nilsson and Synnes goes to saying that RSSI parameter is unreliable for positioning purposes and that its employment ought to be avoided with Bluetooth positioning systems (Thapa & Case, 2003).
In addition, there are ideas of exploiting other parameters than RSSI for positioning purposes. Link Quality and Bit Error Rate (BER) are most commonly referred in this context. However, it should be stated that these solutions are still under development, and that Link Quality is not uniquely defined and is therefore dependent on the equipment manufacturer. Also, BER parameter is not defined in the basic Bluetooth specifications and must be extrapolated from the message received as a response to echo command supported at L2CAP layer. All in all, these parameters undoubtedly contain location dependent information, but the extraction of that information is still subject to research.
The accuracy of Bluetooth positioning systems is decreasing with the increase in the maximal range of the system (Hallberget al., 2003). That is, with the range increase, the

positioning system uncertainty is increased as well, therefore the accuracy is worsened. The improvement of accuracy can be achieved through communicating with more than one Bluetooth nodes and possibly utilizing some of the aforementioned parameters (RSSI, Link Quality, BER). Finally, the major application of Bluetooth technology is expected in ad-hoc networks and the positioning techniques and LBS should be conceived and designed accordingly.

5.3 UWB (Ultra-WideBand) Positioning Systems

Ultra-wideband is a short-range high data throughput technology. The ultra-wideband signal is defined (Harmer, 2004) as a radio-signal that occupies at least either 500MHz of frequency spectrum or 20% of the central frequency of the band. There are many ways in which the UWB signal can be generated. Two, most important from the positioning point of view, are:

1) Impulse UWB – By generating very short impulses, with sub nanosecond duration, that are mutually separated several tenths of nanoseconds. Clearly, this signal inherently possesses very wide band.

2) Frequency Hopped UWB – By generating the typical DSSS (Direct-Sequence Spread Spectrum) with the signal spectrum ranging from 10 to 20MHz which is then hopped around 1GHz frequency, applying between 10 and 100 thousands of hops per second.

Unlike conventional radio-signals, the impulse UWB signals are practically immune to multipath propagation problems. With conventional signals, the reflected component of the signal is, in its large part, overlapped with the component that is travelling the direct path. Hence, the direct and reflected component interfere at the receiver causing fading. Contrary to that, with impulse UWB technology, due to the very short pulse duration, the reflected component is most often arriving at the receiver after the direct component has been completely received. With respect to this feature, the UWB positioning techniques utilising high resolution TOA approach come as the logical choice. Typically, the position accuracy of 1m in more than 95% of the cases is achievable.

Employing the mobile nods of the UWB network for accuracy improvement is also under research. Computer simulation (Eltaher & Kaiser, 2005) shows that the positioning error could be further reduced by employing a larger number of antennas with the beamforming capabilities.

Bearing in mind the amount of research in this area, the wider scale commercialisation of indoor UWB positioning systems can be expected in proximate future.

5.4 WLAN Positioning Systems

Positioning techniques in WLAN networks are growing in popularity. The reason for this can be looked in-between the widespread of 802.11 networks and the fact that a broad scope of LBSs can be brought into an existing network without the need for any additional infrastructure. There are a number of approaches to the positioning problem in WLAN networks. Unquestionably, the most popular ones are based on the Received Signal Strength Information (RSSI). Nevertheless, there are other approaches that depend on timing measurements or require additional hardware but offer superior accuracy and/or faster implementation in return (Llombart et al., 2008; King et al., 2006; Sayrafian-Pour & Kaspar, 2005).

Positioning with the use of RSSI parameter can be, in its essence, regarded as the path loss estimation problem. The nature of the path loss prediction in an indoor environment is extremely complex and dependent on a wide variety of assumptions (e.g. type of the building, construction, materials, doors, windows, etc.)(Nešković et al, 2000). Even if these basic parameters are known, precise estimation of the path loss remains a fairly complex task.

Depending on the side on which the position calculation process takes place, positioning in WLAN networks with the use of RSSI parameter can be either network-based or client-based. Whereas the client-based solutions gather the RSSI vector from the radio-visible APs, the network-based solutions have a central positioning engine which collects the client's signal strength vector from the APs and produces the position estimate. The network-based solutions do not require clients to have a specific software installed which is of great essence for security purposes. Moreover, the client does not need to be associated with the network – the positioning can be done solely based on the probe requests the client sends (in case of active scanning). Network-based solutions could also have an important advantage over the client-based ones when used in WLAN networks employing the Automatic Radio Management (ARM). This centralized mechanism is used to obtain the optimal radio coverage by changing the channel assignment and adjusting the output power and/or radiation pattern of the APs. Contrary to the client-based solutions, the network-based positioning engine could take into account the changes made by ARM mechanism while the ARM mechanism would present a setback for the client-based solutions. On the other hand, client's Network Interface Cards do not have to be consistent regarding the radiated power which may, depending on the positioning algorithm used, present an analogue problem for network-based solutions. In this work, for explanatory purposes, usually the client-based solution will be presented. However, the reader should keep an open mind towards the analogue network-based option.

Regarding the approach used to determine the user's position, WLAN positioning techniques can be categorised as: propagation model based, fingerprinting based or hybrid.

Propagation model based techniques rely on statistically derived mathematical expressions that relate the distance of an AP with the client's received signal strength. The estimated position of the user is then obtained by lateration. Therefore, if there are less than three radio-visible APs (for two-dimensional positioning) the estimated user's position is ambiguous. Also, the model derived for one specific indoor environment is usually not applicable to other indoor environments.

Fingerprinting techniques are most commonly used for WLAN positioning. They are conducted in two phases: the off-line or training phase, and the on-line or positioning phase. The off-line phase comprises collecting the RSSI vectors from various APs and storing them, along with the position of the measurement, into a fingerprinting database. In the on-line phase, the estimate of the user's position is determined by "comparing the likeliness" of the RSSI vector measured during the on-line phase with the previously stored vectors in the database. The fingerprinting process is shown in Fig. 2. These techniques have yielded better performance than other positioning techniques, but are believed to have a longer set-up time.

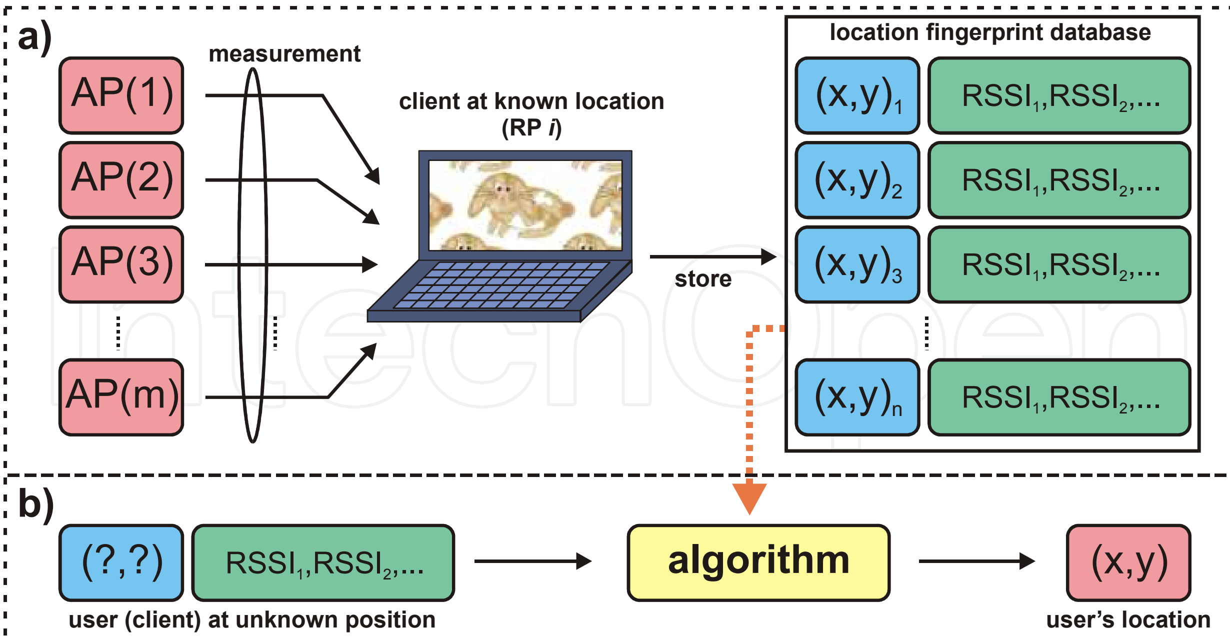


Fig. 2. Two phases of positioning: a) training phase – mobile client is recording RSSI vectors across RPs and stores them in fingerprint database, and b) positioning phase – based on the measured RSSI vector and database access, the algorithm estimates the user's location

Hybrid techniques combine features from both propagation modelling and fingerprinting approaches, opting for better performances than propagation model techniques and shorter set-up time than fingerprinting techniques (Wang & Jia, 2007).

The prospects of using RSSI parameter for indoor positioning were first systematically analysed in "RADAR" (Bahl & Padmanabhan, 2000). According to this research, it is better to use RSSI than SNR (Signal to Noise Ratio) for positioning purposes since the RSSI parameter is much more dependent on the client's position than SNR. Two algorithms to establish the user's location were proposed. The first one is the Nearest Neighbour (NN) algorithm which compares the RSSI vector of a mobile client against the RSSI vectors previously stored in the fingerprinting base. An extension to the proposed algorithm was also considered: the estimated location is not identified as only one RP whose RSSI vector is closest to the observed RSSI vector, but calculated as a "middle" point of k closest RPs (kNN algorithm). This analysis has shown that algorithm performance improved for $k = 2$ and $k = 3$. For larger k, the performance had started to decrease. The second algorithm is based on a simple propagation model with Rician distribution assumed. It ought to be emphasized that both approaches require a minimum of three radio visible access points (APs). The measuring campaign comprised 70 RPs. At each RP measurements were made for four orientations of the receiver, and each measurement was averaged from 20 samples.

To produce the maximum amount of information from the received RSSI vectors, the Bayesian approach was proposed (Li et al., 2006). This concept yields better results than the NN algorithm. The Bayes rule can be written as:

$$p\left(l_t \mid o_t\right) = p\left(o_t \mid l_t\right) p\left(l_t\right) N \tag{1}$$

where l_t is location at time t, o_t is the observed RSSI vector at time t, while N is a normalizing factor that enables the sum of all probabilities to be equal to 1. In other words, at a given time t, the probability that a client is at location l_t, if the received RSSI vector is o_t, is equal to the product of the probability to observe RSSI vector o_t at location l_t and the probability that the client can be found at location l_t. The process of estimating client's location is based on calculating the conditional probability $p(l_t|o_t)$ for each RP. The estimated client's location is equal to the RP with the greatest conditional probability. To accomplish this task, two terms on the right hand side of Eq. (1) ought to be calculated. The first term, also referred to as the likelihood function, can be calculated based on the RSSI map (for all RP) using any approach that will yield probability density function of observation o_t for all RPs. As for the a priori probability $p(l_t)$, it ought to be calculated according to the client's habits. However, for most cases the assumption of uniform distribution across all RPs is valid. The measurements were made at 70 RPs. As with the previously discussed techniques, the measurements were made for four orientations of a receiver, and each measurement was averaged from 20 samples.

Another project, named Horus (Youssef & Agrawala, 2005; Eckert, 2005), had the goal of providing high positioning accuracy with low computational demands. This is also a probabilistic approach in which time series of the received signal strength are modelled using Gaussian distributions. Due to the time dependence of the signal strength from an observed AP, the authors of this project have shown that the time autocorrelation between the time adjacent samples of signal strength can be as high as 0.9. To describe and benefit from such behaviour, they have suggested the following autoregressive model:

$$s_t = \alpha s_{t-1} + (1-\alpha)\upsilon_t, \quad 0 \le \alpha \le 1 \tag{2}$$

where υ_t is the noise process and s_t is a stationary array of samples from the observed AP.

Throughout the off-line phase, the value of parameter α is assessed at each RP and stored into the database along with Gaussian distribution parameters μ and σ. In the on-line phase, Gaussian distribution is modified according to the corresponding values of α retrieved from the fingerprinting database. Alike to the kNN algorithm, the Horus system estimates the client's location as a weight centre of k RPs with the highest probabilities. The principal difference to the kNN algorithm is that, in case of Horus system, the k most likely RP are multiplied with their corresponding probabilities. For verification purposes, the authors made measurements at 612 RPs, and each measurement was averaged from 110 samples.

More relevant information about the statistical modelling approach towards location estimation can be found in (Roos et al., 2002) and in the references found therein.

Battiti et al. (2002) were the first to consider using Artificial Neural Networks (ANNs) for positioning in WLAN networks. This approach does not insist upon a detailed knowledge of the indoor structure, propagation characteristics, or the position of APs. A multilayer feedforward network with two layers and one-step secant training function was used. The number of units in the hidden layer was varied. No degradation in performance was observed when the number of units grew above the optimal number. For verification purposes, measurements were made at 56 RPs, and each measurement was averaged from 100 samples.

In most studies, WLAN positioning techniques are compared on the subject of their accuracy while other attributes of a positioning technique such as latency, scalability, and

complexity are neglected. Another aspect that is seldom analyzed is size of the environment in which the technique is implemented.
It also ought to be pointed out that averaging the RSSI vectors in the on-line phase has an immense impact on the technique's latency, so the scope of location based services that could be utilized with such techniques is significantly narrowed. Moreover, bearing in mind that all presented approaches require at least three radio-visible APs in each RP (which is seldom the case in most WLAN installations), feasibility of sound frequency planning is uncertain. Consequently, the degradation of packet data services is inevitable with respect to positioning in larger indoor areas (i.e. large number of APs is required). Enabling the radio-visibility of three APs across the indoor environment is usually constructively irrational and economically unjustified. Hence, the presented techniques cannot be applied to the majority of existing WLAN networks optimized for packet data services.
Finally, there are other studies that accompany the research for sophisticated positioning in WLAN networks. Other relevant research efforts comprise the impact of Network Interface Card on the RSSI parameter, compensation of small-scale variations of RSSI, clustering of locations to reduce the computational cost of positioning, use of spatial and frequency diversity, methods for generating a larger location fingerprinting database by interpolation, and unequal fusing of RSSI from different APs (Kaemarungsi, 2006; Youssef & Agrawala, 2003; Ramachandran & Jagannathan, 2007; Li et al., 2005; Zhang et al.,2008).

6. Cascade-Connected ANN Structures for WLAN Positioning

The ANNs are an optimisation technique known to yield good results with noise polluted processes (Hasoun, 1995). They are generally classified as a fingerprinting technique. In the off-line phase, the set of collected RSSI fingerprints is used to train the network and set its inner coefficients to perform the positioning function. In the on-line phase, the trained network replaces trilateration and position determination processes.
Two basic concepts, a single ANN and a set of cascade-connected ANNs structures with space partitioning, have been presented herein. These models were implemented in Matlab and verified on a 147m x 67m test bed with eight APs. For training purposes, the *traingda* – gradient descent training function with adaptive learning rate was selected. All neural units had the hyperbolic tangent sigmoid transfer function. Being that the input probability distribution function of RSSI values is near Gaussian, the Mean Square Error (MSE) was selected as a criterion function (Hanson, 1988).
Regarding the purpose that ANN is intended for and, moreover, the nature of the problem, it has been concluded that multilayer feedforward neural networks with error backpropagation have substantial advantages in comparison to other structures (Nešković, 2000). The outer interfaces of the ANN must match the number of the APs on the input side (i.e. eight inputs), and the number of coordinates as outputs (i.e. two outputs).
Multilayer feedforward networks can have one or more hidden layers with perceptron units. The hidden layers with corresponding perceptron units form the inner structure of the ANN. There is no exact analytical method for determining the optimal inner structure of the network. However, there are algorithms that, starting with an intentionally oversized network, reduce the number of units and converge to the optimal network structure. Also, there are other algorithms such as the cascade correlation learning architecture (Fahlman & Lebiere, 1990) that build the network towards the optimal structure during the training

process. However, being aware of the fact that these procedures can be complex and that determining the most optimal structure was not the central scope of this research, we intentionally slightly oversized our network's inner structure knowing that an oversized network will not yield degradation in performance. We also adopted that the first hidden layer ought to have more perceptrons than the input layer so that the input information is quantified and fragmented into smaller pieces (Shang & Wah, 1996). The number of perceptrons in the following hidden layers ought to decrease, converging to the number of perceptrons in the output layer. Bearing that in mind, the chosen structure for single ANN (type 1) approach consisted of the input layer, three hidden layers and the output layer. The number of perceptrons per layer was (from input to output) 8-15-9-5-2.
When utilizing space partitioning, the positioning process is split into two stages where each stage could be implemented with the most suitable model. In this case, the two-step space partitioning is implemented utilizing cascade-connected ANNs. The block scheme of this system is shown in Fig. 2.

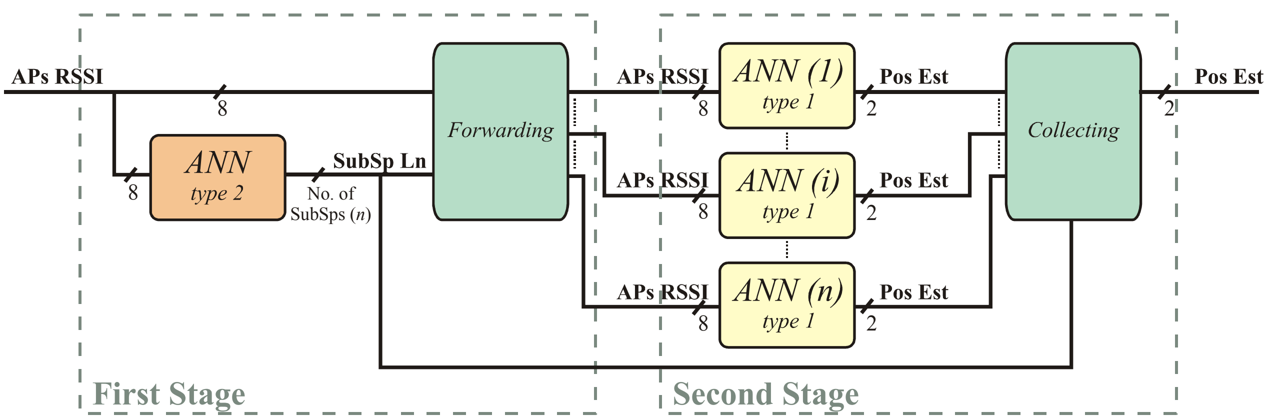


Fig. 2. Cascade-connected ANNs system structure (the input is the observed RSSI signal vector, **APs RSSI**, and the position estimate vector, **Pos Est**, is the output)

In the first stage, an ANN (type 2) is used to determine the likeliness of a measured RSSI vector belonging to one of the subspaces. This ANN (type 2) has 8 inputs and the number of outputs is equal to the number of subspaces the environment is partitioned to. Each output corresponds to the likeliness that a received RSSI vector originates from a particular subspace. The outputs of the type 2 ANN, **SubSp Ln**, are connected to the Forwarding block which, depending on the inputs, employs only one of the second stage networks by forwarding the **APs RSSI** vector.
The inner structure of ANN (type 2) is designed using the same guidelines as with the single ANN model. Therefore, it also has three hidden layers and the number of perceptron units in those layers is varied to fit the different number of subspaces. The second stage ANNs are type 1 networks with structure identical to the previously described ANN used with the single ANN approach.
In the off-line phase, type 2 ANN is trained with the fingerprinting database that originates from the whole environment. The targeted output vector has only one non-zero element (equal to 1). The index of that element corresponds to the number of the subspace from which the RSSI vector originates. Type 1 networks are trained following the training methodology from the single ANN approach with the only difference being that each type 1 ANN is trained with only the part of the fingerprinting database which originates from a particular subspace.

In the on-line phase, the first stage ANN estimates the likeliness that the received RSSI vector originates from a particular subspace. The Forwarding block then determines the most likely subspace by searching for the maximum value in the output vector from the ANN (type 2) and forwards the **APs RSSI** vector only to the second stage ANN that correspond to that subspace. The appropriate second stage ANN then determines the estimated position of the user and, finally, the collecting block forwards that estimate to the structure output.
Several space separation patterns were chosen yielding a different number of subspaces ranging from 4 to 44. The space partitioning patterns that have been employed are shown in Fig. 3.

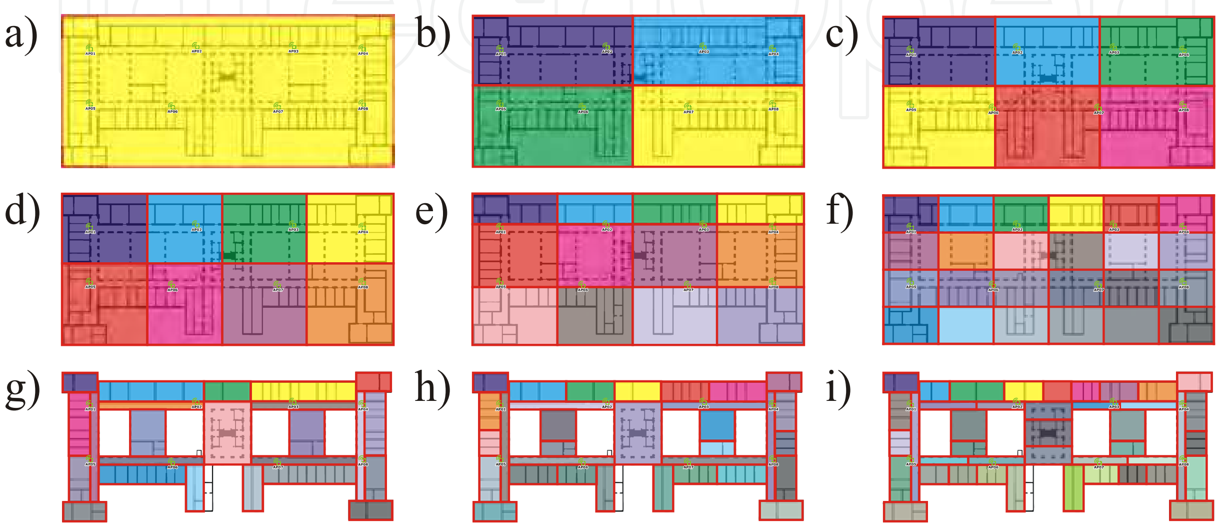


Fig. 3. Space partitioning patterns: a) no space partitioning (1x1), b) 2x2, c) 2x3, d) 2x4, e) 3x4, f) 4x6, g) x24, h) x32, and i) x44

The partitions with a smaller number of subspaces were made on geometrical bases. However, with the increase in the number of subspaces, the subspace size decreased until it came to a room size level. It was then worth to consider partitioning space in an other manner. Starting with 24 subspaces (which was also portioned on geometrical bases), the partitions were made on "logical" bases (i.e. x24, x32 and x44). This logical separation opted for subspaces to be as homogeneous in the propagation manner as possible (e.g. partitioning was made trough walls wherever possible). Note, the single ANN model is herein referred to as 1x1 partitioning.
For the purpose of determining the optimal training parameters, as well as the optimal training duration, the complete set of measurements was split into two subsets. The larger subset was used to train the ANNs, while the smaller, containing measurements from a 100 randomly chosen RPs, was used to validate the obtained models.
The results obtained for different space partition patterns, for optimally trained ANNs, are presented in Table 1.
From Table 1, it can be seen that, with geometrical partitioning, the overall median and average distance errors decrease with the increase in number of subspaces. This behaviour is even more emphasized with the distance errors in the correctly chosen subspace which confirms the influence of environment size on positioning accuracy. When concerning the logical partitioning, slightly better results are obtained for 24 subspaces (4x6 vs. x24) but, with the further increase in the number of subspaces, the average distance error is starting to rise again. Also, with the increase in the number of subspaces the probability of correct

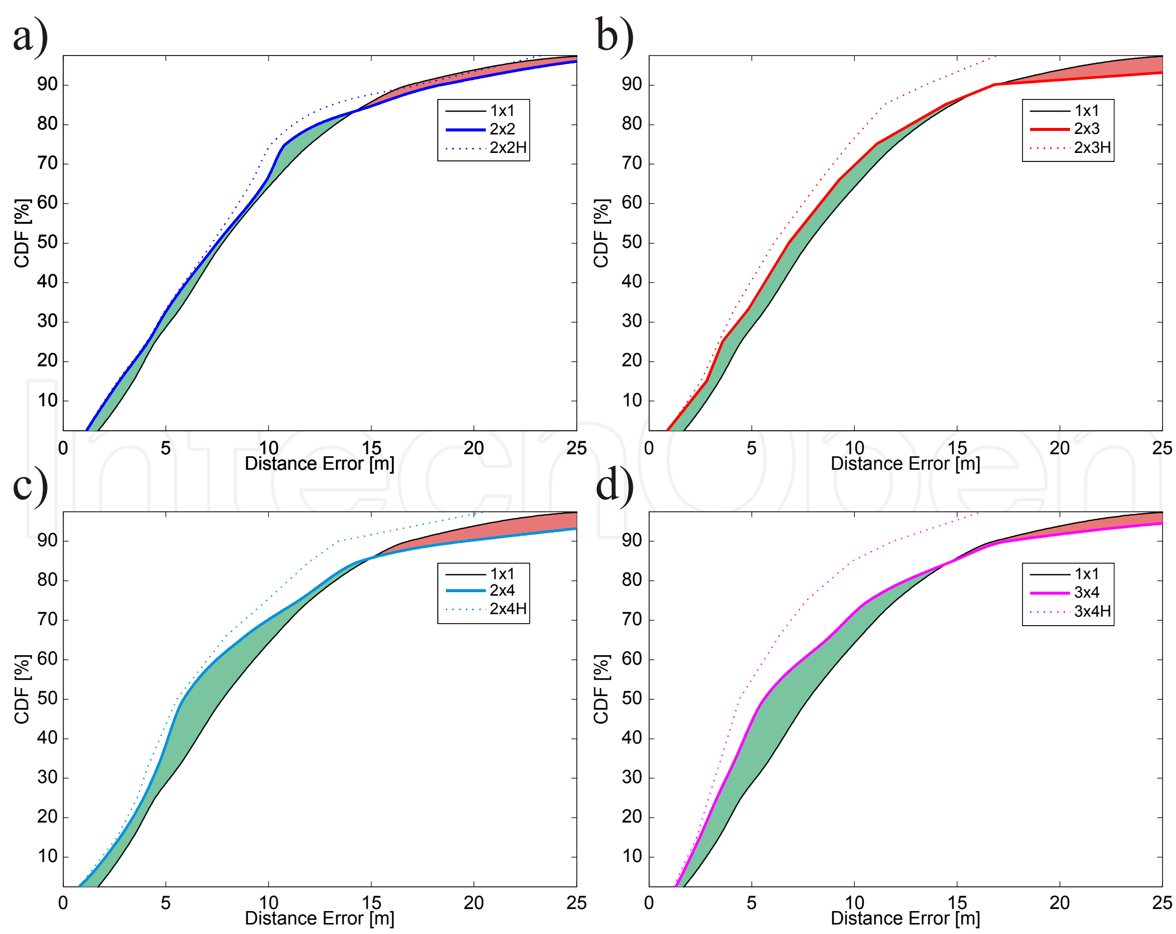
subspace being chosen declines as expected while the probability of correct room estimation rises from 26% for a 1x1 positioning to as much as 66% for a x24 configuration, after which it starts declining a little.

Pattern	1x1	2x2	2x3	2x4	3x4	4x6	x24	x32	x44
Overall Average DE[a] [m]	9.26	9.00	8.97	8.91	8.54	8.28	8.14	8.58	9.11
Overall Median DE[a] [m]	7.75	7.49	6.87	5.86	5.59	5.10	4.57	4.70	4.44
Average DE[a] in IS[b] [m]	-	21.3	22.7	21.2	19.0	18.0	18.4	19.5	19.2
Median DE[a] in IS[b] [m]	-	15.4	17.4	15.3	16.3	14.7	17.5	15.8	16.1
Average DE[a] in CS[c] [m]	9.26	8.35	6.99	6.96	5.76	4.20	4.07	3.78	3.72
Median DE[a] in CS[c] [m]	7.75	7.33	6.13	5.52	4.40	3.87	3.56	3.39	3.32
Probability of CSE[d]	1.00	0.95	0.87	0.86	0.79	0.71	0.72	0.69	0.65
Probability of CRE[e]	0.26	0.42	0.48	0.52	0.58	0.62	0.66	0.62	0.61

[a] Distance Error, [b] Incorrect Subspace, [c] Correct Subspace , [d] Correct Subspace Estimation, [e] Correct Room Estimation

Table 1. Performance overview for different partitioning patterns

To better understand and discuss the performances of cascade-connected ANNs with space partitioning, we observed and compared the distance error's Cumulative Distribution Function (CDF) of a single ANN approach with the cascade-connected ANNs. Fig. 4. shows the obtained CDFs for representative space partitioning patterns.



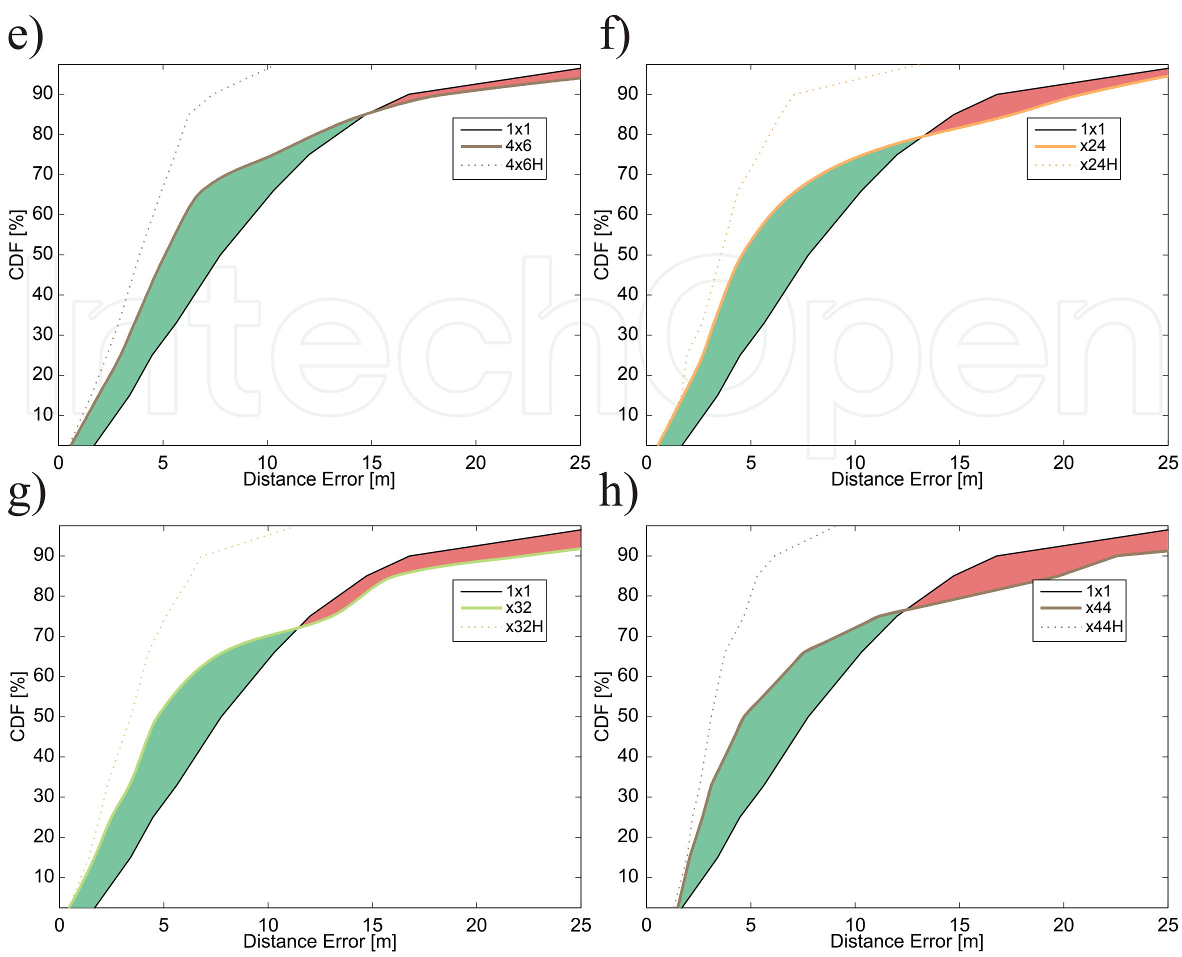


Fig. 4. Cumulative Distribution Function of distance error: a) 1x1and 2x2 partitioning and correct subspace estimation – 2x2 H; b) 1x1and 2x3 partitioning and correct subspace estimation – 2x3 H; c) 1x1and 2x4 partitioning and correct subspace estimation – 2x4 H; d) 1x1and 3x4 partitioning and correct subspace estimation – 3x4 H; e) 1x1and 4x6 partitioning and correct subspace estimation – 4x6 H; f) 1x1and x24 partitioning and correct subspace estimation – x24 H; g) 1x1and x32 partitioning and correct subspace estimation – x32 H; h) 1x1and x44 partitioning and correct subspace estimation – x44 H

The green filled areas on Fig. 4. could be considered as a partitioning gain in comparison to 1x1 positioning, while the red filled areas could be considered as partitioning loss. It can be seen that, with geometrical partitioning, Fig. 4. a) – e), the gain areas are increasing with the increase in the number of subspaces. When concerning logical space partitioning Fig. 4 f) – h), it can be noticed that the best performances are obtained with x24 pattern – average distance error 8.14m, median error 4.57m. With the further increase in the number of subspaces, the benefit of decreasing the median error has faded, even though the median error in correct subspace continues to decrease, whereas the average distance error is starting to rise again due to the augmentation in probability of incorrectly chosen subspace. In other words, with the further increase in the number of subspaces, the partitioning gain surfaces are still expanding however, the partitioning loss surfaces are rising as well. Furthermore, it should be noticed that with the increase in the number of subspaces, the CDF is starting to create a knee roughly around 60th percentile. This has two effects: the green surfaces are getting larger as discussed and the crossing angle between the space partitioning model and 1x1 positioning is increasing while the crossing point between the two is being pushed towards lower percentiles. The latter of the two effects has a negative impact on positioning performances.

Finally, if the Average DE in correct subspace, from Table 1, is compared with the average subspace area (the total area size divided by the number of subspaces), it can be seen that with the increase in size of the subspaces the increase in average error is getting saturated. So, given the constant RPs and APs density, the further increase in size of the test bed should induce only the minor rise of the DE. This also goes to say that the chosen verification environment was large enough to comprehensively explore the influence of the test bed size on positioning accuracy.

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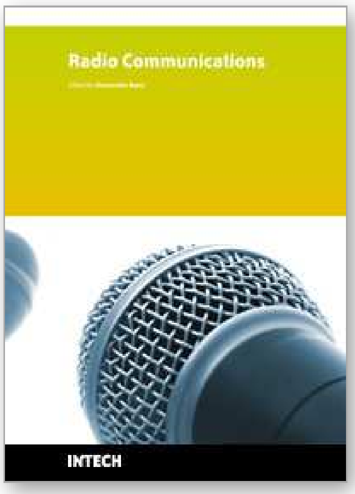

Radio Communications

Edited by Alessandro Bazzi

ISBN 978-953-307-091-9

Hard cover, 712 pages

Publisher InTech

Published online 01, April, 2010

Published in print edition April, 2010

In the last decades the restless evolution of information and communication technologies (ICT) brought to a deep transformation of our habits. The growth of the Internet and the advances in hardware and software implementations modified our way to communicate and to share information. In this book, an overview of the major issues faced today by researchers in the field of radio communications is given through 35 high quality chapters written by specialists working in universities and research centers all over the world. Various aspects will be deeply discussed: channel modeling, beamforming, multiple antennas, cooperative networks, opportunistic scheduling, advanced admission control, handover management, systems performance assessment, routing issues in mobility conditions, localization, web security. Advanced techniques for the radio resource management will be discussed both in single and multiple radio technologies; either in infrastructure, mesh or ad hoc networks.

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