Ekahau Positioning Engine 2.0:
802.11-based Wireless LAN positioning system

An Ekahau Technology Document

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1 Overview

1.1 Introduction to Ekahau Positioning Engine

Ekahau Positioning Engine (EPE) offers a practical 802.11b-based Wireless LAN indoor positioning system that requires no proprietary hardware additions to the network. Ekahau's patent-pending technology is based on process called "site calibration" to build accurate positioning model for solving locations. Ekahau's technology features up to 1 meter (3 feet) average accuracy, enabling both people and asset tracking.

Ekahau Positioning Engine is designed to be used as a WLAN positioning server, or integrated with vertical software applications or hardware. It is a powerful Java™ software component that provides user and asset coordinates (x, y, floor) and tracking features to client applications. The EPE incorporates a stand-alone Manager application for drawing Ekahau Tracking Rails™, recording site calibration data, analysing positioning accuracy, displaying network coverage, and tracking wireless devices.

Ekahau's calibration-based approach is radically different from other positioning techniques, which are mostly based on signal propagation and triangulation for solving the location. These engineering-driven technologies are computationally intensive and they require exact information about the network topology (such as receiver locations, directions, power levels, or walls), which is not a requirement in Ekahau's approach.

Positioning Engine has been exhaustively tested with leading WLAN equipment. Ekahau technology offers more comprehensive feature set than any competing technology on the market:

- Works in any 802.11b compatible WLAN network.
- Software only, no proprietary hardware needed.
- Provides up to 1 meter average accuracy in 2.4 GHz frequency.
- Up to 200 location calculations per second with standard Pentium III PC hardware.
- Fast application connectivity to Positioning Engine via Ekahau Java SDK, or full OEM integration into your software or hardware.
- Complements other (outdoor / indoor) positioning technologies.
- Java-based – portable to virtually any platform.

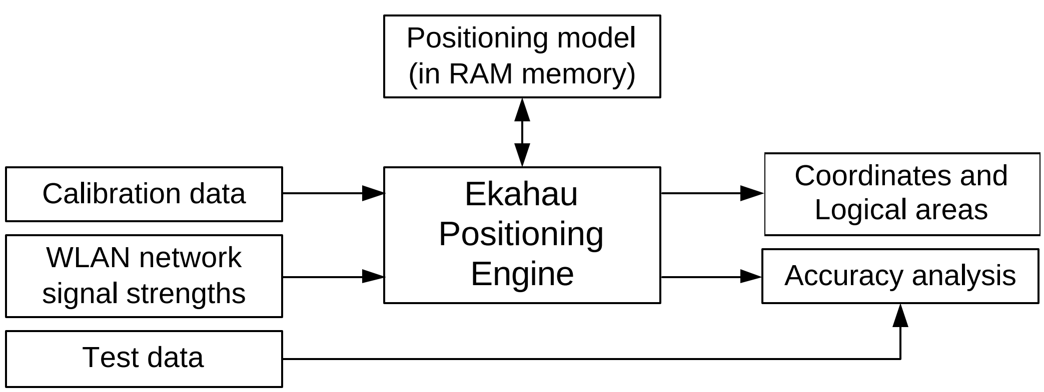

Figure 1: Ekahau Positioning Engine I/O.

1.2 Positioning with Ekahau technology

To increase positioning accuracy and stability, Ekahau Tracking Rails™ are first drawn with Ekahau Manager to define the allowed moving paths. This is done by importing a floor plan of the site (a BMP, PNG, or JPG image) and using the Tracking Rail tool to place the tracking rails.

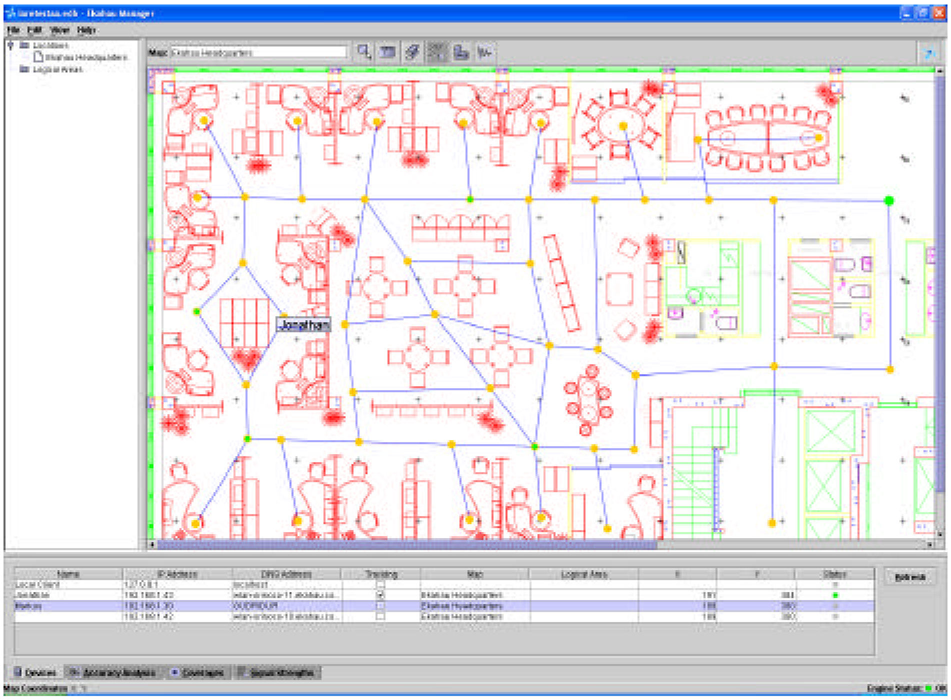

Figure 2: Ekahau Manager displaying an office map and Tracking Rails for defining the allowed moving paths.

After placing the tracking rails on the floor-plan, the positioning site is calibrated by walking along the tracking rails and recording sample points with the calibration tool along the corridors and rooms, one between 3-5 meters. Each sample point contains user-clicked map coordinates and variable amount of received signal strength intensity (RSSI) samples and other network information. Calibrating a 1,000 square meter area takes about an hour.

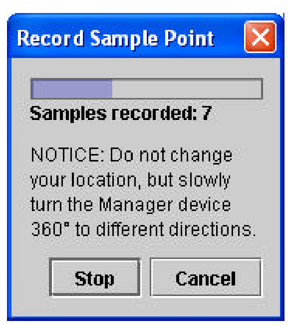

Figure 3: Ekahau Manager with the Record Sample Point dialog.

After calibrating the site, client devices can be easily tracked on the map by selecting their checkboxes. The ready positioning model can be saved to the Positioning Engine to allow applications retrieve the client device location coordinates from the Positioning Engine.

Positioning Engine queries signal strength information from the client devices. Using the calibrated positioning model and mathematical algorithms, it creates an accurate estimate of each location and displays the location in Ekahau Manager's map window, or returns the coordinates and other related information via Ekahau SDK.

The location accuracy can be verified with Ekahau Manager. You can collect another set of test data and analyze its accuracy. You can check average location error, variance of location measurements, and error vectors of location measurements.

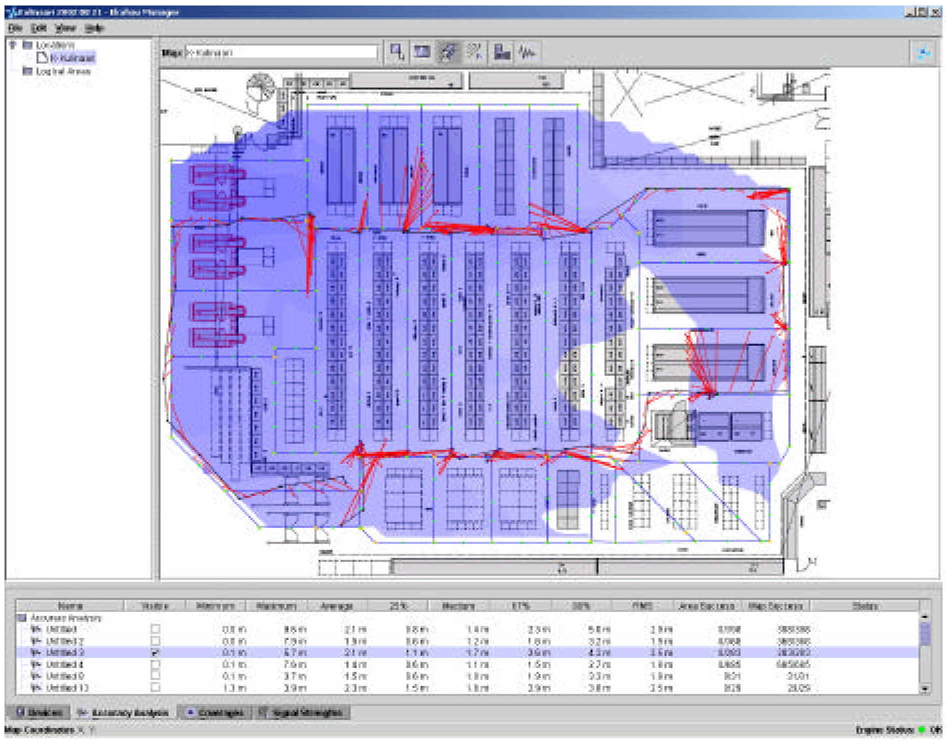

Figure 4: Ekahau Manager displaying the accuracy analysis error vectors.
Each red vector describes the difference between the actual (clicked) and estimated (calculated) location. Shorter lines mean smaller errors.

2 Technology

Positioning is made possible by the fact that certain quantities measurable in wireless networks vary with respect to the physical location where the measurement is done. This variability is caused by factors such as the distance and the angle between the location of the transmitter and the location of the receiver, and the properties of the surrounding physical environment, such as the location, shape and material of reflecting/absorbing surfaces like walls, furniture etc.

Unfortunately, measuring these location-dependent signals accurately is difficult mainly because of the so called multi-path problem (Rayleigh fading): the signal measurements are inherently noisy as the radio signals travel between the transmitter and receiver along several alternative paths, and each path is affected by different environmental factors. What is worse, some of the environmental factors are dynamically changing due to presence of humans, variation in air humidity and so on. The situation is especially problematic when there is no line-of-sight (LOS) between the transmitter and the receiver as in this case the signal travelling distance is not necessarily the same as the direct physical distance.

When building a system for positioning, the two most important technological issues are the following: First, one needs to decide the location-dependent variables to be used for positioning, and how to obtain the required measurements. The most commonly used location-sensitive variables in positioning are time-based variables like time or time difference, angle of arrival, and signal strength related variables like the received signal strength indicator (RSSI). Second, one needs to decide how to use these measurements for location estimation. For solving these two sub-problems, Ekahau has developed methods that are both theoretically and empirically validated. In the following we will describe the Ekahau approach in more detail, and compare it to alternative solutions.

2.1 Step 1: Choosing the location-dependent variables to be measured

2.1.1 Timing-based approaches

As the distance between the transmitter and the receiver is in principle directly proportional to the time it takes for the electromagnetic signal to travel the distance, many positioning technologies use time as the variable to be used as the basis for positioning. However, as the signals travel more or less at the speed of light, this means that the clocks used need to be extremely accurate in order to be able to achieve feasible positioning accuracy. Obviously, the shorter the distance between the transmitters and the receiver, the more accurate the clocks must be. What is more, all the clocks used in the system need to be carefully synchronized. Unfortunately, the hardware components in the standard commercial wireless networks (such as GSM, CDMA or WLAN) do not meet these requirements. For this reason, to be able to use time-based positioning techniques such as TDOA (time difference of arrival) or EOTD (enhanced observed time difference), one has to add special-purpose hardware to the network infrastructure.

Although the timing-based approaches can be implemented by adding dedicated hardware to the network infrastructure, it is unclear whether this type of an approach can be made accurate enough for practical applications, especially indoors where the distances are relatively short. Another problem is that the time measurements are very difficult to be made accurate in commercial high-frequency wireless networks such as WLAN or GSM, since the higher the frequency, the more the surrounding environment affects signal propagation, making the multi-path problem discussed in the beginning of Chapter 2 more and more difficult.

Of course, the more positioning-specific dedicated hardware is added to the system infrastructure, the easier the positioning task in principle becomes. An extreme case is the global positioning system (GPS), where the whole network is designed for positioning, consisting of several transmitting satellites orbiting the world, and special-purpose receiver chipsets in the mobile handsets. As the distances between the satellites and the handsets are relatively long, the requirements for the hardware clocks are not as strict as in ground-based wireless networks. What is more, the radio frequency used is relatively low so that the signals are in principle not as sensitive to multi-path problems as standard wireless networks. Consequently, with this type of a special-purpose global network it is possible in optimal conditions to achieve a very good positioning accuracy.

However, it is evident that the GPS approach has some major drawbacks. First of all, working on low-frequency bands, the GPS network is unsuitable for data transmitting purposes, so it can only be used for positioning, and another wireless network is required for transferring data. Moreover, although the low-frequency signals are in principle less sensitive to multipath problems, the signals are so weak that they usually cannot penetrate through building ceilings or walls. This means that GPS does not usually work indoors, or even outdoors in locations with narrow spaces surrounded by high buildings, where the buildings block one or more of the GPS satellite signals. Unfortunately such locations are exactly those where large densities of mobile users and services can be found, and hence high volume location-based services become possible (c.f. Manhattan).

These shortcomings of the traditional GPS positioning have motivated the assisted GPS (A-GPS) approach, where new stationary GPS servers are placed on the ground level to work as "pseudo satellites". Consequently, an A-GPS positioning system is a compromise between the fully ground-level timing-based approaches and the satellite-based GPS. The cost of setting up such an infrastructure is high, but of course much less than the cost of building a new GPS network.

One interesting approach for solving the above mentioned problems may emerge in the future if new devices based on ultrawide bandwidth (UWB) impulse radio signals become available. The time-modulated UWB signals seem to be in theory quite robust with respect to the multipath problem, and moreover, the UWB devices must be inherently equipped with accurate clocks as this approach is based on very short time-modulated pulses and hence extremely exact timing is a prerequisite for this technology to work in the first place. The full potentiality of this approach can be examined if this approach will be selected as the basis for the wireless networks of the future.

In summary, the common drawback in the timing-based approaches is that they all require expensive special-purpose hardware to be added in the network infrastructure. An additional problem with the GPS approach is that it also requires a dedicated chipset on the receiving handset terminal. This makes the mobile devices not only non-standard and more expensive, but also significantly increases handset weight and power consumption.

2.1.2 The angle of arrival approach

In the angle of arrival (AOA) approach to positioning the location-dependent variable is the signal direction, or more precisely, the angle at which the signal arrives to special multi-element directional antennas placed at the base stations. Naturally, a single directional antenna gives only the bearing, not the distance, of the transmitter, so several directional antennas located well apart are required for positioning. For accurate positioning the angle measurements need to be relative accurate, but as discussed earlier, achieving high accuracy measurements in wireless networks is difficult because of the multipath problem and other factors affecting the signals. Consequently, the main drawback of this approach is the price of the directional antennas to be added in the network, as the required high-precision angle-sensitive measuring equipment is relatively expensive.

Another problem with the AOA approach is that great care needs to be taken in network planning so that the base stations and the directional antennas are placed in such a manner that positioning is possible at any location (problems occur whenever two base stations are approximately in the same direction, but at a different distance). On the other hand, if the network with the directional antennas is too optimized for positioning, the resulting setup may be a poor solution for data transfer, which of course is usually the primary function of wireless networks.

2.1.3 The Ekahau approach

Ekahau Positioning Engine (EPE) uses the received signal strength indicator (RSSI), also known as the received signal level (RXLev), as the basis for positioning. However, it should be emphasized that unlike most of the competing technologies, the probabilistic framework developed by Ekahau (see Section 2.2.) works with any location-dependent variable. This means that the EPE could as well use for example the timing-based variables for positioning, if such data was available, or even use both the RSSI and timing-based signals together. The main reason for using RSSI in the current version is that this type of measurements are available in all standard wireless networks, as the measurements are typically used in network planning for enhancing the quality of service. Consequently, *the Ekahau positioning software can be used without any changes to the existing network infrastructure*. Another benefit is that the signal strength values change relatively smoothly with respect to changes in location, which means that the RSSI approach is not as sensitive to measuring errors as the timing-based or AOA approaches

When using the RSSI signals, two alternatives are possible: one can either measure at the mobile handset the signals transmitted by the base station, or one can measure at the base station the signals sent by the handset. Ekahau has chosen to use the first approach because these signals are stronger and more consistent as the transmitting base stations are hooked up to an electricity outlet. The mobile handsets use portable batteries so the power levels are low, and the devices may go to a battery saving mode if the battery is running out. It should be noted, however, that this does not mean that Ekahau is committed to a handset-based solution where the positioning software needs to be installed in the handset — a server-based solution is equally well possible as long as the handsets send their measurements to the positioning server.

2.2 Step 2: Location estimation

Once the location-dependent variable has been chosen as the basis for positioning, the next question is to ask how to solve the positioning problem — how to determine the location from this type of observations. More precisely, the goal is to build a mathematical predictive model, which takes as inputs the chosen type of signal information identified by the mobile terminal and outputs the estimate of location coordinates of the mobile terminal in question. Location variable can be discrete or nominal (like “room B226” or “lobby”), or continuous (x, y, and z in pixels or distance units).

2.2.1 The cell of origin approach

The simplest solution to this problem is the so-called Cell-ID positioning, also known as the COO (cell of origin) method. In this approach the current location is assumed to be the same as the location of the base station to which the mobile terminal is currently associated (the base station from where the current feed of data is arriving over the wireless radio way). As the associated base station is often the same as the station with the strongest detected signal at the current location, and as the strongest signal comes often from the nearest base station, this location estimate makes intuitively some sense. However, it is obvious that the accuracy can even in optimal conditions only be relative to the distances between the base stations. In WLAN environments this can be dozens of meters, and in GSM networks hundreds or even thousands of meters. What is more, the associated base station is not necessarily the station with the strongest signal, and moreover, the strongest signal may often not come from the nearest base station. Consequently, the COO approach is generally quite inaccurate and unreliable and thus not feasible for practical applications, unless the requirements for the positioning method are extremely low.

The above problems with the COO approach can be overcome by decreasing the transmitting power of the signal sources so that the signal can be detected only at the immediate vicinity of the transmitter. This is the idea behind the radio frequency identification (RFID) tags and similar devices. However, in order to enable accurate positioning everywhere, a huge number of RFID readers should be placed around the environment so that their individual coverage areas together would cover the whole area. On the other hand, if positioning is required only at designated spots (like for example only at the doorways), then this type of an approach may be quite feasible, and has in fact been adopted in many warehousing applications and similar environments (with the cost of purchasing the dedicated RFID hardware and software).

2.2.2 Triangulation-based approaches

Another commonly used approach for solving the positioning problem is based on the idea of triangulation. In this approach, one constructs a function that outputs the distance to each base station, given the measured signals. If the distance to at least three base stations can be determined, then the intersection of the three circles around the base stations at the estimated distances gives the current location of the mobile terminal.

However, when applied in practice, the triangulation-type approaches face severe problems. The main problem is that the signal measurements are inherently noisy due the *multipath* problem and other factors, as discussed in the beginning of the section. If one or more of the distance estimates are of poor quality, then the circles drawn around the base stations may not intersect at all, in which case the method does not produce a location estimate at all. The approach also breaks down completely if signals from less than three base stations are observable — this is the cause for failures with the GPS approach in places with high surrounding obstacles. Furthermore, the locations of the base stations needs to be known, otherwise positioning becomes totally impossible.

2.2.3 The Ekahau approach

In order to overcome the above problems, Ekahau has developed a probabilistic positioning framework, where the world is taken to be stochastic, not deterministic, and one accepts the fact that the measured signals are inherently noisy.

A *probabilistic model* assigns a probability for each possible location (L) given observations (O) consisting for example of the reception level (RXLev) of each channel:

(1) P (L|O) = P (O|L) P (L) / P (O)

- P (O| L) is the conditional probability of obtaining observations O at location L.
- P (L) is the prior probability of location L.
- P (O) is a normalizing constant.

The formula above is an example of an application of a mathematical theorem known as the Bayes rule. Based on probability theory, this theorem gives a formal way to quantify uncertainty, and it defines a rule for refining a hypothesis by factoring in additional evidence and background information, and leads to a number representing the degree of probability that the hypothesis (in our case, location estimate) is true.

In order to make the theoretically elegant probabilistic framework to work in practice, a number of important problems need to be solved. For solving these problems, Ekahau has developed two innovative approaches, *model calibration* and *rail tracking*. These innovations are based on more than 10 years of intensive research at the CoSCo research group at Helsinki Institute for Information Technology, one of the leading research groups in the world in the area of stochastic modeling. The Ekahau positioning technology utilizes the latest advances in decision theory, probabilistic modeling and information theory, exploiting the new theoretical results behind concepts such as Bayesian networks, hidden Markov models, stochastic complexity and on-line competitive learning.

2.2.3.1 Model calibration

As can be seen from formula (1), the key issue in the probabilistic approach to positioning is to estimate the probability distributions of the measured signals O in different locations L; in other words, we need to determine the conditional probabilities P(O|L). Traditionally this problem would be attacked by using the so called signal propagation approach: if one knows the physical locations of the base stations, then by using the laws of physics one could try to estimate the probability distributions of the measured signals O in different locations at different distance and angle from the transmitter. However, unfortunately real-world environments are so complex that in reality the transmitted s ignals do not behave "nicely", but are affected greatly by the multi-path problem discussed earlier and the specific characteristics of the surrounding environment.

One possible approach to solving the above problem would be to increase the complexity of the model of the environment. This means that instead of just marking the locations of the base stations, one could also mark the locations, shapes and materials of all the objects in the environment, and then try to estimate how the signals propagate in this particular specific environment. However, discovering the general laws determining the behaviour of electromagnetic signals in various conditions is extremely demanding. Furthermore, it would be a laborious task to describe in detail the physical environment consisting of walls, windows and furniture of different material and shape.

In contrast to the signal propagation method described above, Ekahau has adopted a radically different approach, where instead of viewing positioning as an engineering problem, the problem is treated as a *machine learning* problem. In this approach the environment is not modelled explicitly, but implicitly by using a representative sample of site-specific calibration measurements as input. By using this type of calibration dat a and elaborate state-of-the art machine learning algorithms, it is possible to construct a site-specific model of the environment very quickly and easily. Note that with this type of an approach, the system does not need to be told anything about the wireless environment explicitly, not even the locations of the base stations.

In the framework adopted by Ekahau, the calibration data is fitted to a probabilistic model. In principle other machine learning approaches could be used as well — an example of suchan approach to positioning is the nearest neighbor algorithm adopted by Bahl et al. In our studies we have found the probabilistic approach, based on the elaborate probability theory framework, to be more robust than the more heuristic alternatives. Furthermore, the probabilistic models are also computationally efficient, while for example the computational complexity of the nearest neighbour algorithm increases rapidly as more and more calibration data is being collected. Finally, non-probabilistic approaches do not extend to the Hidden Markov Model framework behind the innovative rail tracking approach described in the next section.

2.2.3.2 Rail tracking

The probabilistic positioning framework described above can be further improved by making the following observations. First, it is intuitively clear that current location of the mobile terminal is very probably near the place where the terminal was one or two seconds ago. So it is clear that positioning accuracy can be further enhanced by *tracking,* meaning a process where not only the current observations are considered, but the full history of observations is taken into account when locating the user. Second, if one wishes to record the position history of a tracked mobile terminal, it would make sense to distinguish legal paths from illegal paths, illegal paths meaning for instance paths going through walls. Similarly, if one wishes to apply the positioning framework for path optimisation (for example, for suggesting a path from the current location of a customer in a mall to the nearest place with the requested service), the suggested path should be legal. All these problems can be solved in the innovative ***rail tracking*** approach developed at Ekahau.

In rail tracking, the legal paths in the environment are first marked by using Ekahau Manager, a graphical point-and-click tool included in the Ekahau Positioning Engine 2.0 software package. With this additional information, it is now possible to transform the site-specific calibration data into a Hidden Markov Model (HMM), which is a natural extension of the probabilistic framework described above to solve the tracking problem. Well known instances of HMM models are the Kalman filter and the extended Kalman filter (EKF). In the HMM framework the full history of the located object can be taken into account in the positioning process. What is more, this approach also solves the problems associated with the illegal paths, as only the legal paths provided by the user will be considered. It should also be noticed that the extension to the HMM framework is a specific characteristic of the generic probabilistic framework adopted, and developing a similar non-probabilistic solution would be extremely difficult.

3 Positioning in Action

Ekahau has a unique approach to indoor positioning through the adopted machine learning paradigm and advanced probability mathematics. In calibration a positioning model is inferred from a set of calibration data (sample points) in order to let Ekahau Positioning Engine obtain predictions concerning an unforeseen set of positioning data. Future versions of EPE will contain a possibility to alternatively point out the base station locations on the map so that the model can be constructed from this information alone, without calibration. This type of an approach would yield much poorer accuracy, but it could be a sensible strategy in very large outside areas where calibration requires more time. In indoor environments it usually makes sense to use calibration for enhanced accuracy, since empirical field tests have shown that the calibration procedure is very quick and easy to perform.

When calibration is used, the system is first trained by recording network data in various known locations. Based on the network data and associated (user-given) locations, a positioning model is produced. The model represents the network characteristics at any (free) network location.

For accuracy analysis, separate test data from known locations is recorded and compared against the positioning model. The accuracy is presented as a natural loss-function (distance from true location).

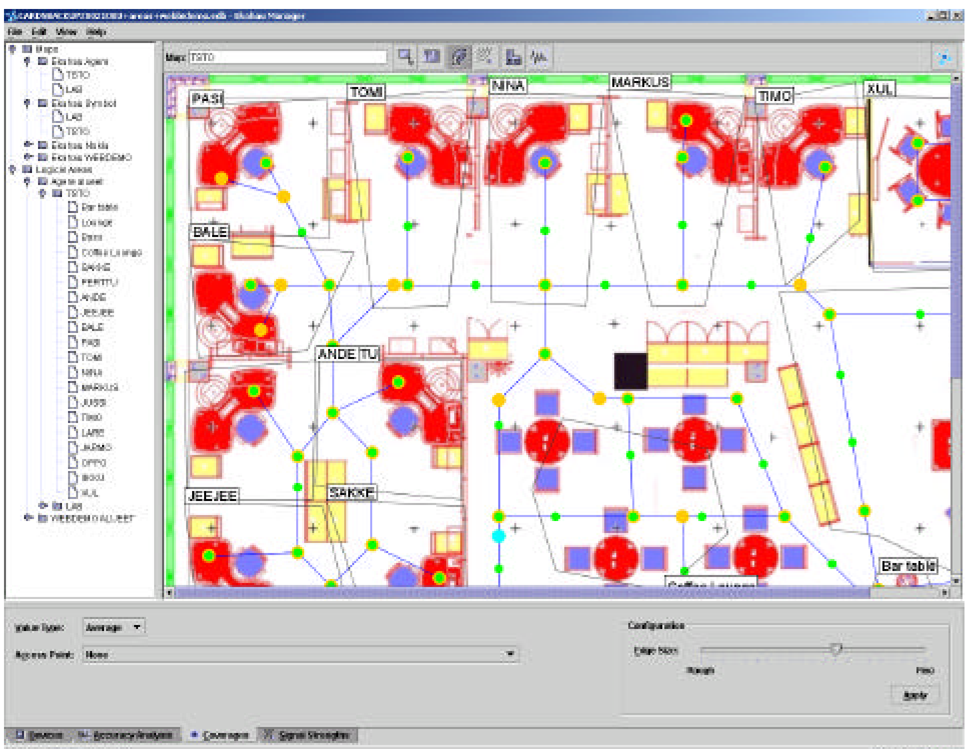

Figure 5: Ekahau Manager with Tracking Rails and Logical Areas.

Ekahau Positioning Engine has been empirically tested in various environments. Each environment has unique characteristics, and therefore also the experienced positioning accuracy varies a little bit. For example, issues as the number and placement of access points, size and topology of the area, and used equipment affect positioning. In the following we describe the result of a typical set of experiments.

3.1 Experiment overview

Positioning accuracy depends on several variables. The main objective of the experiment described in this section was to analyze how the variables shown in Figure 6 affect positioning accuracy. As a test environment, we used a medium-size office site (16x40 meters, 640 square meters) consisting of structures made of concrete, wood, and glass. The base map of the site is shown in Figure 7.

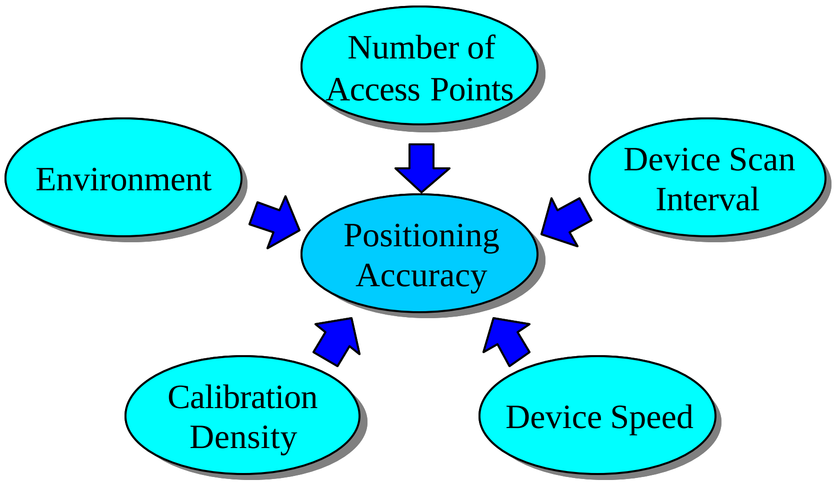

Figure 6: Variables affecting the positioning accuracy.

In order to study how the number and placement of access points affects positioning accuracy, as many as seven WLAN access points were used. The placement and orientation of the access points (AP) is shown as arrows in Figure xx. The number of AP's is much greater than actually necessary to set-up a WLAN network for a site of this size; for normal data transfer 2-3 AP's should be adequate. The benefit of calibrating with so many AP's was that we needed to calibrate only once and then could automatically generate different set-ups having 1-7 access points by removing signal data of access points not used. For example, to analyse the positioning accuracy with 3 access points, we generated all possible 3-combinations (210 different set-ups!) and ran the analysis with each of them.

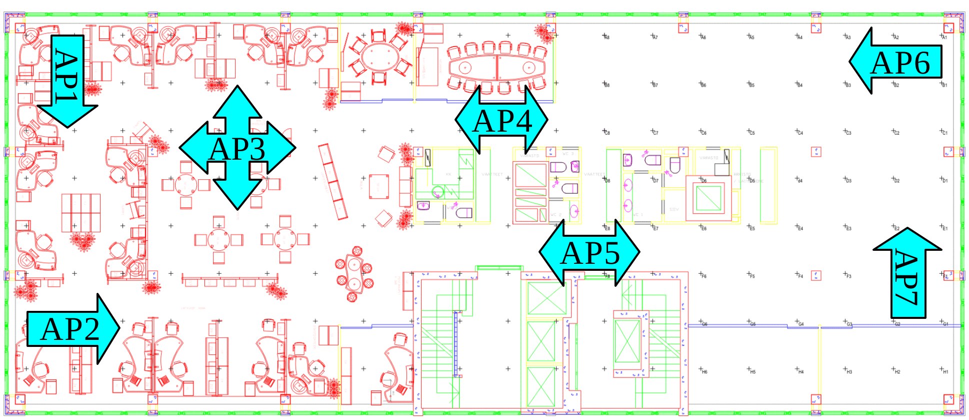

Figure 7: Placement of access points in the experiment.

Another goal was to find out how much calibration effort is necessary to reach a reasonable accuracy. Therefore, we calibrated the site extensively so that the distance between adjacent sample points was 1-2 meters. Using this dense calibration, we could automatically generate calibrations having less sample points simply by removing sample points one by one until the desired sample point density was reached.

To gain realistic results, we used test data that was independent of the calibration data. If both calibration and test data were collected at the same time, accuracy estimates could be too optimistic, even if sophisticated empirical methods like cross-validation were used. In practice, test cases were recorded using the Accuracy Analysis tool of the Ekahau Manager. Figure 8 shows one of the six test cases used in the analysis. The black line is the actual route traveled and red arrows express the difference between real location and estimated location.

Figure 8: Accuracy analysis error vectors (red) and test route (black).

To study the effect of device speed without actually collecting the same test case several times with different speeds, we manipulated the time stamps recorded into test cases. For example, to double the speed of a test case, we manipulated time stamps so that the time between mouse clicks was only half of the original. Similarly, to simulate different scan intervals, we removed some of the signal observations until the desired average scan interval was reached. This way we ensured that the changes in the positioning accuracy are really caused by an adjustment of the parameter under study.

To analyze the positioning accuracy in different type of environments (corridors, open areas, etc.), we divided the floor into areas of four different categories: open area, corridor, room, and open office. The division is shown in Figure 9. For each location estimate, we checked in which area the true location resided and finally calculated average positioning errors for each environment category.

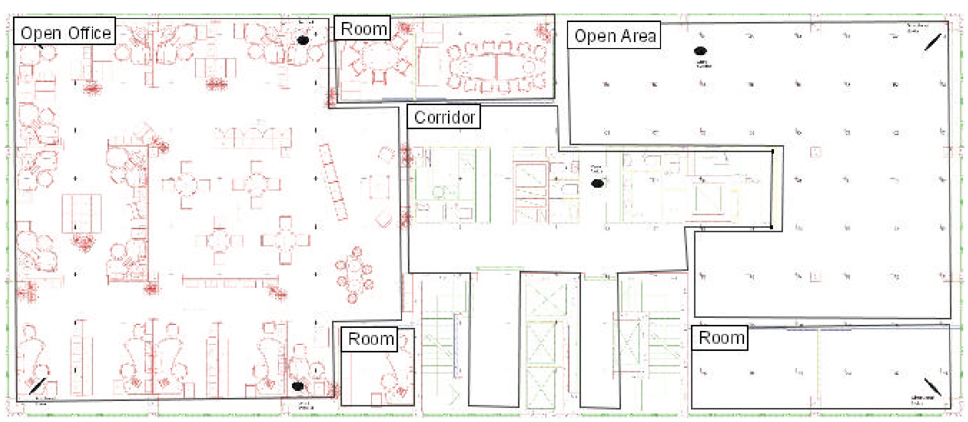

Figure 9: Test area divided into four different categories.

3.2 Results

Table 1 summarizes the results of the experiments. Each graph has two curves presenting the accuracy of the two positioning estimate types provided by the Ekahau Positioning Engine. The curves labelled as “1s delay” show the average positioning error for location estimates delivered with 1 second delay. This is the most real-time location estimate EPE can provide, but not as accurate as when 5 seconds delay is allowed (curves labelled as “5s delay”).

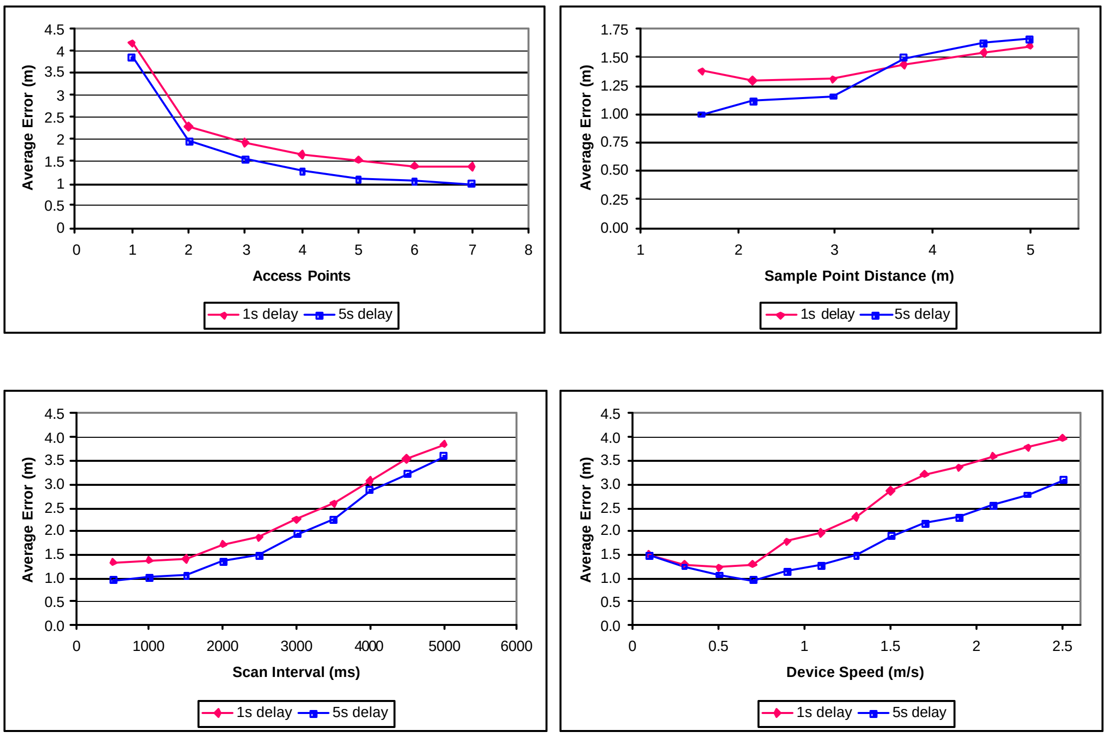

Table 1: The positioning accuracy graphs.

As can be seen from the accuracy graphs, the Ekahau positioning technology can reach one (1) meter average error under optimal conditions. In the test environment used, this required 5-7 access points, dense calibration (sample point distance 2 meters) and fast scan rate (500-1500 ms scan interval). An interesting phenomenon is that the best positioning results are achieved when the speed of the tracked device is about 0.7 meters/second (typical walking speed). This is due the fact that when the device is moving, the RSSI values vary enough to let EPE take full advantage of tracking history. When the device is still, the RSSI values are nearly stable, and EPE may not be able to distinguish between places having nearly equal RSSI fingerprints.

Reasonable positioning accuracy can be achieved with much easier requirements. Three access points, 4 meter distance between sample points and 1.5 second scan interval is enough to reach a 1.5 meter error in average. However, if only few access points are available, they must be carefully placed to make positioning accurate. Table 2 below shows which access points combinations gave the best positioning results for each access point number in our tests. The “rule of thumb” is that one should place AP’s as far from each other as possible and “break the symmetry”, i.e. make sure that exactly the same RSSI values are not observed in locations far from each other. For example, placing two AP’s into opposite corners of a square-shaped area is a bad idea, because the RSSI values on the other corners would be identical.

Access Points	AP1	AP2	AP3	AP4	AP5	AP6	AP7	Average Error
1		X						3.87 m
2	X					X		1.95 m
3	X				X	X		1.54 m
4		X	X		X		X	1.26 m
5	X	X	X		X		X	1.09 m
6	X	X	X		X	X	X	1.03 m
7	X	X	X	X	X	X	X	1.00 m

Table 2: Average positioning error when using different number of APs.

Figure 10 gives a rough estimate on what kind of areas Ekahau's positioning is strongest. However, the test environment was too small to make serious conclusions on this issue. However, it can be clearly seen that the average error is much smaller in corridors than for example in open areas. The worst average error was obtained in the meeting rooms. However, as can be seen from the error vectors in Figure 4, the situation is not as bad as it may seem if we only look at the numbers. EPE can well locate the device in correct rooms, but cannot tell in which corner of the room the device is.

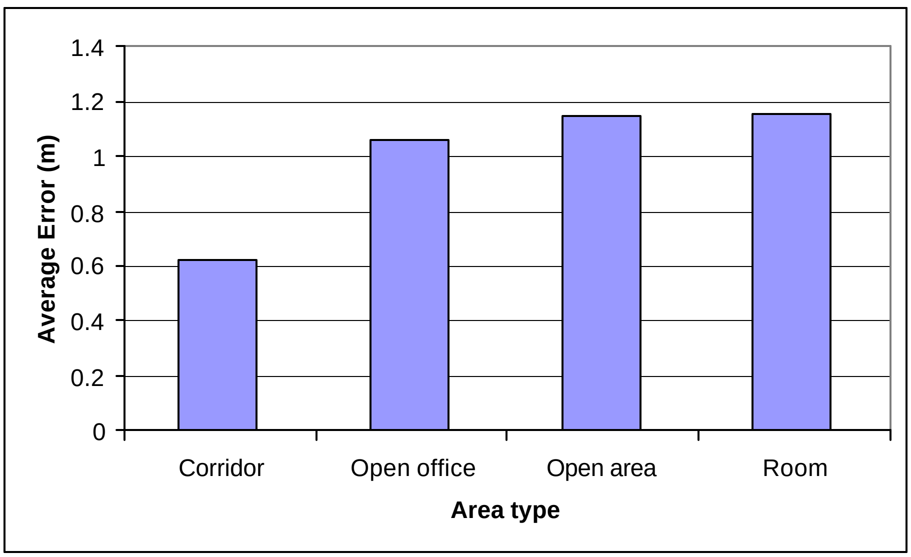

Figure 10: Estimate on Ekahau positioning accuracy in different areas.

4 Positioning Technology Comparison

	Ekahau	RFID	TDOA	AOA	A-GPS	EOTD	COO
Accuracy	2 m	50 cm-2 meters [1]	50-200 m	Up to 50 m	15-50 m	50-400 m	10-50 m [2]
Continuous tracking	Yes	No	Yes	Yes	Yes	Yes	Yes
Proprietary hardware	No	Reader/tag	No	Yes	New mobile phones	New mobile phones	No
Resource requirements	Low	Low	Low	Low	High	High	Low
Availability	WLAN	Readers required	Rural	Rural	Indoor & urban	Rural	Everywhere
Works with WLAN	Yes	No	Yes	Yes	No	Yes	No
Software-based	Yes	No	Yes	Yes	No	No	Yes
Calibration	Yes	No	No	No	No	No	No
Penetration	All WLAN	Low, requires readers	Mobile users	Mobile users	Mobile users	Mobile users	Mobile users
Cost	Low	Low (USD 10-1000)	Very high	Very high	High	High	Low
Roll out time	Fast	Fast	Slow	Slow	Slow	Slow	Fast
Frequencies	2.4 GHz	50 kHz-2.5 GHz	Any	Any	800, 1900 MHz + 1575.42 MHz	Any	800, 1900 MHz
Line of sight	Not required	Not required	Not required	Not required	Not required	Not required	Not required

[1] Requires very short distances between the reader and the tag (passive tags function up to 50 centimeters, active tags up to 2 meters). Range may be reduced if reading at high speed is needed.

[2] The accuracy of the technology is highly dependent on access point density.

5 Conclusions

The modeling approach to positioning chosen by Ekahau Positioning Engine has inherent advantages that ensure a long-term technological edge:

- **The most accurate indoor positioning system**. Average accuracy of up to 1 meter can be cost-effectively obtained in 802.11b WLAN environments.
- **Built using industry-standard Java language**. It is tested with leading WLAN equipment. Java enables portability between operating systems.
- Compatible with major WLAN network adapters.
- **High refresh rate and low latency**. Positioning Engine is optimized for quick and reliable coordinate processing. Up to 200 client devices per second can be located with standard Pentium III PC hardware.
- **Low processing power requirements**. Modeling-based approach is computationally very efficient and highly scalable.
- Software-only solution.
- **Compatible technology**. Can be adapted to current and future technologies such as WLAN, GSM, GPRS, Bluetooth, and UMTS.
- **Utilizes fully network topology information**. A pure signal-based model can be built offline with signal measurements, if no other information is available.
- **Works dynamically in constantly changing environments**. Tolerates changes due to the introduction of new components to the network, or changing traffic patterns that confuse any fixed model.
- **Supports hybrid models** that utilize various sources (e.g., WLAN and A-GPS, RFID) of information.
- Calibration process improves the predictive capability.

6 Contact Information

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7 Legal Notice

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