Survey on Resource Positioning

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Abstract: In the last decade, positioning has become a steadily growing research topic. The increase in use and availability of wireless networks has allowed for an ever growing exchange of information and increased communication capabilities. Mobile applications offer resource positioning, which can help in different areas of society. These applications can be used to track people with special needs or elderly people, to help people navigate through the city, or to allow parents to know the whereabouts of their children. The objective of this survey is to describe the numerous positioning techniques and methods used to address the positioning problem, and determine their overall performance in outdoor and indoor settings based on a set of metrics. To facilitate the understanding of our work, a set of comparison tables is elaborated based on the method's performance, along with a brief discussion for each table. Finally, we review the work of other authors in positioning.

Keywords: Positioning, positioning techniques, triangulation, fingerprinting, positioning, vision analysis.

1. Introduction

In recent years, there has been a notorious increase in the use of wireless systems. Currently, wireless technologies are widely used in medical, industrial, logistical, transportation, as well as many other application areas [Pah02]. The wide availability of wireless information access has brought along a high demand for accurate positioning in wireless networks, for both indoor and outdoor environments [Hig01]. By means of a positioning technique, a mobile device can either gather the information about its position or can be localized from elsewhere.

This strongly emerging interest in positioning is driven by several factors. At first, the great success of wireless systems is essentially explained by the mobility they enable, which is coupled with uncertainty. However, this uncertainty is often not desired in applications like industrial manufacturing, network organization and many other applications, and the only means to efficiently overcome it is to know the position of our assets. Security and integrity also benefit strongly from local positioning, using information on the data origin, the propagation path, and the destination. Last but not least, the data capacity of wireless networks is inherently limited, so an intelligent context-dependent information transfer is needed [Vos03]. One essential context variable is the positioning of mobile devices.

Positioning can be roughly divided in two categories, based on the environment in which they work best. These two categories are *outdoor positioning*, and *indoor positioning*. In outdoor environments, the GPS, a satellite-based positioning system, is currently the most widely used. It offers maximum coverage for positioning in these environments with relatively little effort [Hof93]. GPS cannot be deployed for indoor use, because line-of-sight (LOS) transmission between receivers and satellites is not possible in an indoor environment. Compared with outdoor, indoor environments are more complex. There are various obstacles [Lad04], for example, walls, equipment, human beings, all influencing the propagation of electromagnetic waves, which lead to multi-path effects. Some interference and noise sources from other wired and wireless networks also degrade the accuracy of positioning. The building geometry, the mobility of people and the atmospheric conditions result in multi-path and environmental effects [Gu09].

Some authors believe that the positioning problem for outdoor environments has a concrete solution in the form of the Global Positioning System [Gu09]. Nevertheless, the appearance of new technologies and the proliferation of wireless and mobile networks has allowed for positioning to remain an open area, filled with research opportunities [Pra02, Liu07, Gu09]. This is especially true for indoor environments, where research attention has increased, thanks to the aforementioned availability of wireless networks and mobile devices. Important research issues include: the degree of accuracy of the positioning information, the delay in estimating a position, the amount of position estimation requests that can be processed simultaneously, and the coverage of the positioning service. Another important issue is the reliability of the positioning process. Some access points may be disabled because of local power failures, management, upgrades, or even accidents. In such cases, the user should still be able to use positioning services, though with reduced capabilities.

Different applications may require different types of positioning information. According to Hightower et al. [Hig01], the main types are physical positioning, symbolic positioning, absolute positioning, and relative positioning. Physical positioning is expressed in the form of coordinates, which identify a point on a 2-D or 3-D map. The widely used coordinate systems are degree/minutes/seconds (DMS), degree decimal minutes, and universal transverse mercator (UTM). Symbolic positioning expresses a location in a natural-language way, such as in the office, in the third-floor bedroom, etc. Absolute positioning uses a shared reference grid for all located objects. Relative positioning depends on its own frame of reference, and its information is usually based on the proximity to known reference points or base stations [Liu07]. Depending on the technique used by a positioning system, one or more of these types of positioning information will be required for the positioning process.

In this work, we will address the different techniques used to estimate the position of users and devices (resources), and offer a comparison of the performance of these techniques in both indoor and outdoor environments. Section 2 addresses the notion of positioning, as well as current positioning techniques and their most commonly used methods. In Section 3, we describe the set of metrics that will be used to measure the performance of the techniques. Section 4 contains the comparison tables and discussion of the performance of each method. Section 5 reviews the work of other authors in positioning, and Section 6 shows the conclusions to which we arrived during the elaboration of this survey and possible extensions of this work.

2. Resource Positioning

In the last few years, there has been a growing interest in Context-aware Systems, specifically those that provide Location-aware or Location-based information services. These services are accessible through mobile devices by means of a communication network, and allow resources to determine their current position [Mar99]. Originally, positioning was used only to assist Emergency-911 calls, but is now considered one of the potential market drivers in the telecommunications industry. Promising applications of positioning include vehicle navigation, fraud detection, resource management and automated billing [May07], among others.

Positioning technologies have become commonplace in different aspects of everyday life [Zei02]. In order to meet the needs of users and offer adaptive and convenient personal services, the positioning information of a resource can be provided by a positioning system at different places, such as home, office, etc. There have been different approaches to solve the positioning problem, each attempting to address positioning depending on the context in which these systems are deployed [Hig01], such as GPS for outdoors, and fingerprinting or proximity for indoor environments.

Accurate positioning can be applied to areas such as commercial applications, public safety services and military systems [Pra02]. There is an increasing need for indoor positioning systems to track people with special needs, e.g. the elderly, children who are away from visual supervision, and visually impaired people. These systems would allow location of on-demand resources (e.g. portable equipment or people) in physical environments, like hospitals or warehouses. They could also be used to track inmates and guards inside a prison. All of these scenarios apply for outdoor positioning systems as well, especially in public safety and military applications.

A positioning system is usually composed of several physical components: (1) one or more mobile devices usually carried around or attached to a resource; (2) a communication network that supports user-to-service interaction; (3) a service and application provider to processes the positioning requests; and (4) a positioning component to provide the current location [Rui10]. There are usually two kinds of positioning components: base stations and mobile devices. Base stations are fixed in a known location, in contrast to mobile devices. Base stations continuously transmit a signal that is measured at the resources location (for autonomous positioning devices), or wait to receive a signal sent by a mobile device (for remote positioning devices).

This section presents a review of the most widely used techniques to address the positioning problem. In general, most positioning methods attempt to perform measurements on one or more signals, processing these measurements in order to estimate the position of a resource. A positioning system uses different kinds of signals and varied techniques to determine a resource's position, depending on the technologies used [Hig01]. These technologies can be categorized in four groups: Infrared, radio frequency, ultrasound, and inertial, with radio frequency signals being the most popular [Rui10]. We will not address these technologies any further in this survey.

Based on the information measured and how the position estimation is performed, we can classify positioning techniques in four groups: (1) Triangulation techniques, (2) proximity-based techniques, (3) fingerprinting techniques, and (4) Scene Analysis techniques. Triangulation uses the properties of triangles to determine a target resource position. Proximity assigns the closest base station's position to a target resource. Fingerprinting averages the signals received from a resource to resolve its position in a grid. Vision analysis uses image or video captures and computational vision to position resources in a given environment. The triangulation, fingerprinting and vision analysis techniques can provide absolute, relative and proximity position information, while the proximity technique only provides proximity information.

2.1. Triangulation

Triangulation uses the geometric properties of triangles (i.e. distance and angles) and a set of reference points with known locations to estimate the position of a resource. The accuracy of this technique improves when more reference points are used for the estimation process. An advantage of this method is that it involves a small setup effort in order to start calculating the resources location. Triangulation has two derivations: Lateration and angulation [Hig01].

Lateration, also known as range measurement, estimates the position of a resource measuring its distance to at least three reference points with known geographical coordinates. Then, using the direction or length of the vector drawn between the location to be estimated and the reference points, it is possible to calculate the absolute position of the desired resource [Ver11]. Five methods are commonly used to estimate positions using lateration: Time of Arrival, Time Difference of Arrival, Round-trip Time of Flight, Received Signal Strength, and Signal Attenuation. GPS, a special case of lateration method, and is also addressed in this section.

Time of Arrival (TOA): The TOA method assumes that the distance between two resources is directly proportional to the propagation time of a message between them. TOA-based positioning systems measure the one-way propagation time, and then proceed to calculate the distance between the transmitter and the receiver of the message. In order to enable 2-D positioning, TOA measurements must be made with respect to signals from at least three reference points [Fan90]. For 3-D positioning, an additional reference point is needed. In general, direct TOA has two problems: (1) The clock of all participants has to be precisely synchronized; and (2) a time-stamp must be labeled in the message in order for the measuring unit to discern the distance the signal has traveled.

Time Difference of Arrival (TDOA): The general idea of the TDOA method is to determine the relative position of a resource by examining the difference in time at which its signal arrives at multiple measuring units. Thus, a target's position can be estimated from the intersections of two or more TDOA measurements. For each of these measurements, the target must lie on a hyperboloid with a constant range difference between the two measuring units. Two hyperbolas are formed from TDOA measurements at three fixed measuring units to provide an intersection point, which locates the target resource [Fan90]. Note that the receivers do not need to know the absolute time at which the pulse was transmitted; only the time difference is relevant. Fig. 1 helps illustrate how TDOA works.

Round-tripTime of Flight (RTOF): This method is used to measure the time-of-flight of a signal traveling from the target resource to the measuring unit and back [Gün05]. In RTOF, a less strict relative clock synchronization than that of TOA is required, though both methods use the same range measurement mechanism. The measuring unit is considered a common radar, with the target responding to an interrogating radar signal, and the complete roundtrip propagation time being calculated by the measuring units. However, it is still difficult for a measuring unit to know the exact delay/processing time it takes the target to return the signal. In long or medium-range systems, this delay could be ignored if it is small in comparison to the transmission time. However, for short-range systems, such as those used for indoor location, this delay cannot be ignored.

Received Signal Phase (RSP): Also known as Carrier Signal Phase of Arrival, this method uses the carrier phase (or phase difference) of a frequency range to estimate the position of a target [Pov10]. To understand how RSP works, assume that all participating devices emit sinusoidal signals of the same frequency with a zero phase offset. The RSP method calculates the phase difference of all signals received at the target, estimating its position based on those calculations. For an indoor positioning system, it is possible to use the signal phase method together with TOA/TDOA or RSS method to fine-tune the location positioning. However, this method requires a direct LOS signal path; otherwise it will cause more errors, especially in indoor environments.

Received Signal Strength (RSS): Also known as Signal Attenuation, RSS estimates the position of a resource by measuring its distance from a set of measuring units based on the attenuation of emitted signal strengths [Ji04]. RSS calculates the signal path-loss due to propagation, using theoretical and empirical models to translate the difference between emitted and the received signal strength into a range estimate. RSS requires an important setup effort, and can be affected by multipath fading and shadowing present in indoor environments. Using multiple measurements from several base stations could help overcome this problem, increasing the accuracy. Also, the spacing between grid points influences the position estimation. Decreasing the spacing increases the database size without gaining accuracy (values measured 15cm apart will be more or less the same) [Pra02]. On the other hand, increasing it reduces the search space but drastically decreases the accuracy.

Global Positioning System (GPS): GPS is a satellite-based positioning system, currently the most widely used in outdoor environments because it provides maximum coverage. GPS capability can be added to various devices simply by adding GPS cards and accessories to these devices. This enables position-based services such as navigation, tourism, etc. [Hof93]. However, GPS cannot be deployed for indoor use, because LOS transmission between receivers and satellites is not possible in an indoor environment.

A GPS receiver calculates its position by precisely timing the signals sent by GPS satellites high above the Earth. Each satellite continually transmits messages that include the time the message was transmitted, and the satellite position at time of message transmission. The receiver uses the messages it receives to calculate the transit time of each message and to determine its distance to each satellite. These distances and the satellites positions are used to compute the position of the receiver [Van01].

At least three satellites are required to calculate a target’s position, since space has three dimensions and it is assumed that the target is near the Earth's surface. However, even a tiny clock error, multiplied by the speed at which satellite signals propagate (the speed of light), results in a large positional error. Therefore, receivers usually employ four or more satellites to resolve their position, although fewer satellites can be used in special cases. If a positioning variable is already known (i.e. altitude), a receiver can compute its position accurately using only three satellites. When fewer than four satellites are accessible, some GPS receivers may use additional clues or assumptions (such as reusing the last known altitude, dead reckoning, or inertial navigation) to give a less accurate or degraded position estimation [Bul00]. GPS has some disadvantages: Its accuracy depends on the number of visible satellites; its setup time can be quite long, many minutes in the worst case; and power consumption can be high. Moreover, GPS does not work indoor or when satellites are in shadow [Tre04].

Angulation or direction of arrival (DOA) calculates the position of a resource by computing the angles relative to two or more reference points with known geographical coordinates. Then, it uses the angle of the vector drawn between the location to be estimated and the reference points to calculate the absolute position of the desired resource [Ver11]. The most well-known method used for angulation is Angle of Arrival (AOA).

In AOA, the location of a target resource can be estimated using the intersection of several pairs of angle direction lines, each formed by the circular radius from a base station or a beacon station to the mobile target. AOA methods use at least two known reference points and two measured angles to derive the 2-D location of the target resource. This estimation, commonly referred to as *direction finding*, can be accomplished either with directional antennae or with an array of antennae [Che06]. The advantages of AOA are that a position estimate may be determined with fewer measuring units than lateration, three for 3-D and two for 2-D positioning. Also, no time-synchronization between measuring units is required. The disadvantages include relatively large and complex hardware requirements, as well as location estimate degradation as the mobile target moves farther from the measuring units.

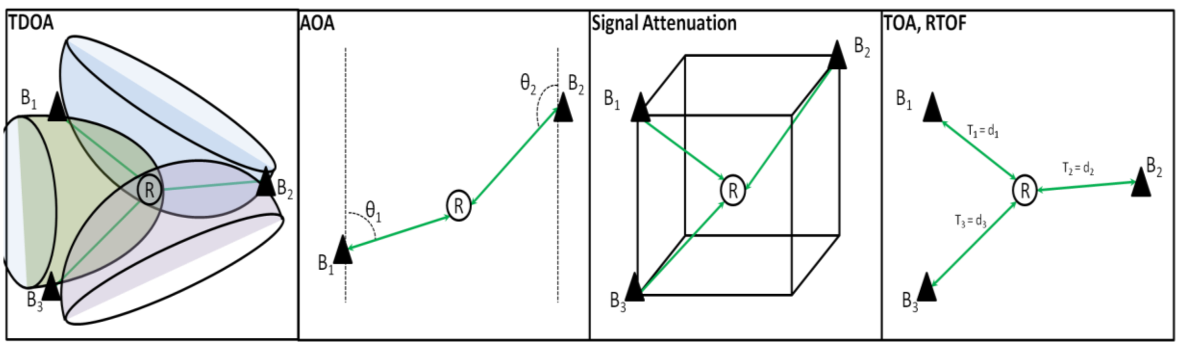

Fig 1: Positioning methods used in Triangulation.

2.2. Proximity

Proximity algorithms provide symbolic relative location information. Proximity usually relies upon a dense grid of detectors, each having a well-known position. When a mobile target is detected by a single antenna, it is considered to be collocated with it. When more than one station detects the mobile target, it is considered to be collocated with the one that receives the strongest signal [Bra06], or at the interception area of both stations. The accuracy of this positioning strategy could be high, depending on the detection technology used and the number of detectors deployed in the physical environment. The greater the density of detectors, the higher the precision. This method is relatively simple to implement over different types of physical media, although an important setup effort is required on early deployment stages. In particular, positioning systems using infrared radiation (IR) and radio frequency identification (RFID) are often based on this method.

Cell ID (CID): This method, also known as Cell of Origin, relies on the fact that mobile cellular networks can identify the approximate position of a mobile handset by knowing which cell site the device is using at a given time [Tre04]. A base station covers a set of cells, each with a known position and identified by a unique Cell-ID. Cells are grouped into clusters, each of them identified by a Location Area Identifier (LAI). A mobile target continuously selects a cell and exchanges data with its corresponding base station. In turn, each station broadcasts both the LAI and the Cell-ID to its cells. Since the mobile targets are always receiving these broadcast messages, they always know their corresponding Cell-ID. This allows the mobile targets to approximate their position using the geographical coordinates of their corresponding base station, independent of the target's absolute position within the cell. The main benefit of Cell-ID is that it is already in use today and can be supported by all mobile handsets.

Radio Frequency Identification (RFID): The radio frequency identification (RFID) is a means of storing and retrieving data through electromagnetic transmission to a radio-frequency compatible integrated circuit. RFID as a wireless technology enables flexible and cheap identification of individual person or device [Cho04], and is commonly used in complex indoor environments such as office, hospital, etc. There are two kinds of RFID technologies, passive RFID and active RFID [Gu09]. With passive RFID, a tracked tag is only a receiver, making them small and inexpensive at the cost of a reduced coverage range. Active RFID tags are transceivers, which actively transmit their identification and other information; this makes the cost of tags higher but provides a greater coverage area of active tags.

Closest-Neighbor (CN) Algorithm: Consider a group of base stations arranged in a regular grid. Each of these stations is located L meters away from its closest adjacent station. In order to determine the position of a particular resource, each station performs a distance measurement to that resource. Let d_i be the distance measurement performed by base station i, which is located at $R_i = [x_i, y_i]$. The CN algorithm estimates the position of the resource as that of the station that is located closest to that resource. In other words, the position of a resource is the value of R_i for which the corresponding distance measurement, d_i is the minimum in the set [Kan04].

Least Square (LS) Algorithm: This method focuses on minimizing the value of the objective function $f(x) = \sum_{i=1}^{N}\left(\sqrt{(x - x_i)^2 + (y - y_i)^2 - d_i}\right)^2$, where N is the number of reference base stations. The square-root term is the distance between a point (x, y) in the Cartesian coordinate system and a reference base station located at the point (x_i, y_i), and d_i is known as the residual of the estimate. Given that this is a minimizing function, the closer we approach the target resource's position, the lower the function's value would be. At $f(x) = 0$, we would be at the target's position. In practice, however, the set of distance measurements, d_i $(1 \leq i \leq N)$ always contains errors, so the function will never be zero even at the target's position. These errors are related to synchronization mismatches between the transmitter and receiver devices, (known as systematic error), or due to obstructed LOS (OLOS) channel conditions (known as channel-related errors) [Kan04]. OLOS channel conditions generally result in the strongest signal being received with longer delay, with the resulting distance measurement being longer than it should be.

2.3. Fingerprinting

Also known as Scene Analysis, this technique calculates the position of resources in a bounded physical space by comparing the current measurements of a given set of signals with pre-measured data related to particular locations. Typically, the strategy involves two phases: an offline training phase and an online estimation phase. During the offline phase, samples of location related data (e.g. Wi-Fi received signals strength) are collected for the whole physical space considered for the estimation process. During the online stage, the currently observed signal strengths of a resource are used in conjunction with the previously collected data to figure out an estimated position for the target resource. The fingerprinting technique is simple to deploy compared to AOA or TDOA techniques [Kae04], but is costly to implement over a large area. Instead of depending on accurate estimates of angle or distance to determine the location, location fingerprinting associates location-dependent characteristics (such as signal attenuation) with a location and uses these characteristics to infer location position. This technique is quite accurate, but involves an important effort to collect samples during the offline phase [Ver11]. One of the main challenges to this technique is that the signal emitted by the resources could be affected by diffraction, reflection, and scattering in indoor environments. Fingerprinting can be performed by using pattern recognition based methods and probabilistic methods.

Pattern Recognition-based fingerprinting methods apply pattern recognition algorithms over a set of signals (usually the signal strength) to determine the current position of a resource. Some of the most used methods for fingerprinting are k-Nearest Neighbor, Support Vector Machine, Smallest M-vertex polygon, and Neural Networks.

k-Nearest Neighbor Averaging Method (kNN): The kNN averaging uses the online signal strength to search for k closest matches of known locations in signal space from a previously built signal database, by means of the root mean square errors principle [Was05]. In this approach, k is a parameter that can be adapted in order to improve performance. By averaging these k location candidates with or without adopting the distances in signal space as weights, an estimated location is obtained via weighted kNN or unweighted kNN.

Support Vector Machine (SVM): A widely used technique for data classification and regression, SVM is a tool for statistical analysis and machine learning. SVMs have been used extensively for a wide range of applications in science, medicine, and engineering with excellent empirical performance [Cri00]. Support vector classification of multiple classes and support vector regression have been successfully used in location fingerprinting by treating the positioning problem as a classification problem [Liu07].

Smallest M-vertex Polygon (SMP): SMP uses the online signal strength values to search for candidate locations in signal space with respect to each signal transmitter separately. M-vertex polygons are formed by choosing at least one candidate from each transmitter (assuming a total of M transmitters). Averaging the coordinates of vertices of the smallest polygon (the one with the shortest perimeter) gives the position estimate of a target resource [Liu07].

Neural Networks: Usually, a multi-layer perceptron (MLP) network with one hidden layer is used for neural-networks-based positioning system [Was05]. During the offline stage, the signal strength and the corresponding location coordinates are adopted as the inputs and the targets for the training purpose. After the training stage, appropriate weights are obtained. The input vector of signal strengths is multiplied by the trained input weight matrix, and then added with input layer bias, if a bias is chosen. The result is put into the transfer function of the hidden layer neuron, and the output of the function is multiplied by the trained hidden layer weight matrix, and then added to the hidden layer bias if it is chosen. The output of the system is a two-element vector for 2-D or a three-element vector for 3-D estimated location.

Probabilistic fingerprinting methods make an estimation of the probability of a resource being at a certain place given the observed measurements at each location [Kon04]. Moreover, connections and divisions between different places could be considered, since someone cannot walk through a wall. This approach is more complex and requires more computational power, but usually presents better results. The most commonly used method for probabilistic fingerprinting are the Bayes' Theorem and Markov Chains.

Bayes' Theorem Probabilistic Method (BT): This method addresses positioning as a classification problem [Kon04]. Assuming that there are n candidate locations $\{L_1, L_2, L_3, \ldots, L_n\}$, and s is the observed signal strength vector during the online stage, the following decision rule can be obtained: Choose L_i if $P(L_i|s) > P(L_j|s)$, for $i, j = 1,2,3, \ldots, n; j \neq i$. Here, $P(L_i|s)$ denotes the probability that the mobile node is in location L_i, given that the received signal vector is s [Liu07]. Also assume that $P(L_i)$ is the probability that the mobile node is in location L_i. The given decision rule is based on posteriori probability. Using Bayes' formula, and assuming that $P(L_i) > P(L_j)$ for $i, j = 1,2,3, \ldots, n$, we choose L_i if $P(s|L_i) > P(s|L_j)$, for $i, j = 1,2,3, \ldots, n; j \neq i$, based on the likelihood that $P(s|L_i)$ is the probability that the signal vector s is received given that the mobile node is located in location L_i.

Markov Chains Positioning (MC): The key idea of Markov Chains positioning is to compute and update a probability distribution over all possible locations in the environment [Bur98]. Let $l = \langle x, y, \Theta \rangle$ denote a location in the state space of a target resource. The distribution, denoted by $P(L_t = l)$ expresses the target's subjective belief for being at position l at time t. Initially, $P(L_{t0})$ reflects the initial state of knowledge: if the target knows its initial position, $P(L_{t0})$ is centered on the correct location; if a resource does not know its initial location, $P(L_{t0})$ is uniformly distributed to reflect the global uncertainty of the resource. $P(L)$ is updated whenever new sensor readings are received, allowing for positioning. This method is usually combined with vision analysis techniques for robot navigation [Bur98].

2.4. Vision Analysis

This technique analyzes images received from one or more capturing points (e.g. cameras located in the surveillance area), in order to try to identify a target resource [Bru00]. Real-time analysis of images could be appropriate if the number of objects to be tracked is small, otherwise, it is more efficient to combine this technique with some of the previous ones to reduce the number of images required for the analysis. Using vision analysis involves an important effort during the setup phase, because they rely heavily on monitoring equipment.

In vision-based positioning systems, a low price camera can cover a large area, and the targets require no additional devices for the position estimation. While vision analysis has unique advantages over other positioning systems, it also presents unique challenges. Privacy is an issue due to the nature of vision analysis, where multiple images of the targets are acquired. Since the position estimations are based on the saved vision information in a database, it needs to be updated if there is any change in the environment, like moving a desk from one side of the room to the other [Gu09].

Vision-based positioning systems can also be greatly influenced by interference sources, such as weather, light, etc. For example, the turning on and off a light in a room reduces the detection accuracy of a target's position. A person's appearance in an image varies significantly due to posture, facing direction, distance from the camera, and occlusions [Bru00]. Moreover, trying to position multiple resources moving around at the same time is still a challenge, due to the high computational requirements of this technique. Although a variety of algorithms can overcome most of these difficulties, a solution must work fast enough to make the system responsive to the room's occupants. The Simultaneous Localization and Mapping technique tries to address these problems.

Simultaneous Localization and Mapping (SLAM) addresses the problem of a resource (usually a robot) navigating an unknown environment. While navigating the environment, the robot seeks to acquire a map of its environment, and at the same time it wishes to localize itself using its map [Mon02]. The use of SLAM can be motivated by two different needs: Detailed environment models, or an accurate sense of a mobile robot's location. SLAM serves both purposes, but we will focus only in the positioning part. SLAM can be achieved through extended Kalman filters, graph-based optimization techniques, and particle filtering, among other navigation techniques.

Extended Kalman Filters (EKF): Historically, EKF [May90] is the earliest and perhaps the most influential SLAM algorithm. First, a map with all known landmarks must be stored in a database accessible to the robot. If the identity of an observed landmark is unknown, EKF cannot be applied. The robot compares which of the landmarks stored in the database most likely corresponds to a landmark just observed, using this information to estimate its current position. The proximity estimation to a landmark considers measurement noise and actual uncertainty using Mahalanobis distance [DeM00], which is a weighted quadratic distance, to gauge similarity between observed and stored data. To minimize the chances of false data associations, many implementations use visible features to distinguish individual landmarks and associate groups of landmarks observed simultaneously [Thr08]. A key limitation of the EKF solution to the SLAM problem lies in the quadratic nature of the covariance matrix. A number of researchers have proposed extensions to the EKF SLAM algorithms that gain remarkable scalability through decomposing the map into sub-maps, for which co-variances are maintained separately. EKF SLAM has been applied successfully to a large range of navigation problems, involving airborne, underwater, indoor, and various other vehicles [Thr08].

Graph-Based Optimization (GO): This method addresses the SLAM problem through nonlinear sparse optimization. Landmarks and robot locations can be thought of as nodes in a graph. Every consecutive pair of positions $\{x_t - 1, x_t\}$ is tied together by an arc that represents the information conveyed by the odometry reading u_t. Other arcs exist between locations x_t and landmarks m_i, assuming that at time t the robot sensed landmark i. Arcs in this graph are soft constraints. Relaxing these constraints yields the robot's best estimate for the map and the full path [Lu97]. GO SLAM can scale to much higher dimensional maps than EKF SLAM. Unlike EKF, GOT does not use a covariance matrix, which translates into less used space and lower update times, depending on the size of the map [Thr08]. Although the update time of the graph is constant and the amount of memory required is linear, optimizations can be expensive. Finding the optimal data association is suspected to be an NP-hard problem, although in practice the number of plausible assignments is usually small.

Particle Methods (PM): This SLAM method is based on particle filters. In this paradigm, a particle represents a concrete guess of the value of the current state (position) of a robot based on observed landmarks. By collecting a set of particles, the particle filters capture a representative sample of the path distribution of the robot [Mon02], allowing for an estimation of its position. Under controlled conditions, the particle filter has been shown to approach the true path as the particle set size goes to infinity. The key problem with this method is that the space of maps and robot paths is immense, exponentially scaling with the dimension of the underlying state space [Mon03].

3. Metrics for Positioning Performance

The performance of a positioning technique cannot be measured only by its accuracy. There is an evident difference between acceptable performance values for indoor and outdoor environments, even when the same technique is being used in both scenarios. For this reason, a number of metrics are required to perform an accurate benchmark. The following set of metrics has been considered for our classification: Accuracy, precision, scalability, complexity, deployment cost, and robustness. Usually, a positioning system offers a tradeoff between some of the metrics, such as sacrificing some accuracy to lower complexity and so on. These tradeoffs depend entirely on the application needs of the system.

Since authors have used different ranges to measure their own results, we have established a simple interval-based qualitative measuring scale for our evaluation: *Low*, *medium*, and *high* scores. Our scale is based on the maximum and minimum values observed for each metric in other authors' work. If the exact values are not available, an estimation is made based on a similar method's performance. For example, a low score in accuracy would mean that the target's position can be pointed to a wide area, whereas a high score would indicate that its exact position can be pinpointed with little distance error. A low score in deployment cost would mean that there is little to no installation and training effort in order to put it online, and a medium score would mean that the effort is within normal boundaries. A medium score in robustness would indicate that the method is able to cope with some data loss, while a high score would mean that it can, to some extent, keep positioning the target with heavy data loss (at least for a time).

3.1. Accuracy

Also known as location error, accuracy is the most important requirement of positioning systems. Usually, mean distance error is adopted as the performance metric, which is the average Euclidean distance between the estimated location and the true location. Accuracy can be considered to be a potential bias, or systematic effect/offset of a positioning system. The higher the accuracy, the better the system; however, there is often a tradeoff between accuracy and other characteristics.

The intervals we have considered for accuracy take into account how well a positioning method estimates the position of a resource with respect to its real position. The scale must be different for indoor and outdoor environments, because of the inherent difference between them. Outdoors, a *high* score in accuracy would mean that the method can position a target within less than 15m of its real position [Mou01]; a *medium* score means that the method has an up to 30m estimation error; and a *low* score means that the method has an error greater than 30m. Indoors, a *high* score requires that the positioning method estimates the target's position at less than 1m from its real position [Was05]; a *medium* score allows for up to 3m estimation error, and a *low* score anything beyond that.

3.2. Precision

Location precision considers how consistently a positioning technique works, i.e., it is a measure of the robustness of the positioning technique as it reveals the variation in its performance over many trials. Accuracy only considers the value of mean distance errors, while cumulative probability functions of the distance error are used to measure precision. For example, one system has a location precision of 90% within 2.3 m, and 95% within 3.5 m; another one has a precision of 50% within 2.3m and 95% within 3.3m. We could choose the former system because of its higher precision. It is important to use the average precision and not the highest precision, due to a common problem with most positioning methods: when closing in to the target, the accuracy consistency error tends to increase. This means that different position estimations made from the same readings could determine different positions when close to the target.

We have considered that an average precision of at least 90% for both indoor and outdoor environments would earn a *high* score [Rui10, Vos03]. A *medium* score requires that the method reaches at least 80% precision, and a *low* score indicates that the average precision is below that value.

3.3. Scalability

The scalability of a positioning system in determined based on its performance when the positioning scope changes. A positioning system may need to scale on two axes: geography and density. Geographic scaling implies covering different volumes of areas without important performance issues. Usually, performance degrades when the distance between transmitter and receiver increases. Density scaling requires that the performance is not affected by a great number of simultaneous estimation requests. When the coverage area increases, or when positioning multiple targets in a crowded area, wireless signal channels may become congested, requiring additional calculations or more communication infrastructure to perform positioning. Another measure of scalability is the dimensional space of the positioning system, i.e. whether it can locate objects in 2-D or 3-D space, or both.

The score in scalability for a positioning method is based on its capacity to support positioning over large areas, and the amount of targets that can be located simultaneously. It should be noted that there is a huge difference in ranges between outdoor and an indoor environments: a coverage area two kilometers wide is relatively small for outdoor positioning, while it would be unmanageable for indoor positioning systems. Tradeoffs between these requirements are also taken into account when assigning a score to a method.

A *high* score implies that an outdoor method supports coverage areas in the range of Kilometers, with hundreds of simultaneous targets. For indoor methods, a *high* score requires them to cover a large area (i.e. a building, or a large warehouse) and provide service to dozens of targets. A *medium* score for outdoor methods means that the coverage area is hundreds of meters wide, and can support at least a hundred targets; indoors, the coverage area has to be medium-sized (i.e., a floor of a building) and able to support over ten targets. Methods with a coverage area below 100m for outdoor and 10m for indoor methods, or able to service less than a hundred targets for outdoor or ten targets for indoor attain a *low* score.

3.4. Complexity

Complexity of a positioning system can be attributed to hardware, software, and operation factors. If the computations of a positioning algorithm are performed on a centralized server side, the positioning could be calculated quickly due to powerful processing capability and sufficient power supply. If this computation is carried out on the mobile unit side, the effects of complexity become evident. Most mobile units lack powerful processing units and long battery life; thus, we would prefer positioning algorithms with low complexity. It is difficult to derive the analytic complexity formulae of different positioning techniques, so we only consider the computing time, location rate, and location lag, which is the delay between a mobile target moving to a new location and the reporting of the new position.

It is difficult to determine an exact threshold for the complexity scores. Different methods have diverse results depending on the conditions of the environment [Liu07, Gu09, Van01, Rui10]. These scores apply for both indoor and outdoor environments. It is important to note that the higher the complexity, the lower the score on this metric. To achieve a *high* score in complexity, the computing requirements, location rate and location lag of a method must be low. This means that little computing power is needed to locate a target, and the updates on its current position occur often and with little or no delay. A *medium* score represents the need for an above-average processing unit, less position updates, and longer time between these updates. A *low* score would imply that the method requires great amounts of CP or HW, or a combination of both.

3.5. Overall Cost

The overall cost of a positioning system may depend on many factors such as money, time, space, weight, and energy: Energy is an important cost factor of a system, for it determines how long it can remain active. The time factor is related to installation and maintenance (see deployment cost). Mobile units may have tight space and weight constraints, as is the case with mobile devices. In some instances, we can consider *sunk costs*, which reduce the overall cost of a positioning system by taking advantage of existing infrastructure. For example, some mobile units like electronic article surveillance tags and passive RFID tags are completely energy passive, only responding to external fields. This means they could have an unlimited lifetime, unlike most mobile units (devices with rechargeable battery) that have a lifetime of several hours per charge.

A specific threshold for the overall cost score of a method cannot be established, due to the amount of features that need to be taken into account [Che04, Tre04]. We have considered that the cost in money and physical space are the most important for mobile positioning, so a *high* score would imply that a method does not require special, costly or burdensome equipment. A *medium* score would mean that at least one of the aforementioned factors is required for the method to work, and a *low* score that a method requires at least two of these factors. Note that a lower score in this metric is better, because it implies less cost.

3.6. Deployment Cost

The cost of deploying the physical component of a positioning system is highly dependent of the positioning technique and technologies that will be used during the positioning process. This of course includes the equipment installation, man or machine power required for this, and the training necessary for the method to work. The effort required to put the system online should also be considered as a deployment cost. For example, a positioning system layered over a wireless network may be considered to have a low deployment cost if all the necessary units of that network have already been purchased and set-up for other purposes [Pra02].

The deployment cost accrues for equipment installation, the effort to put the system online, and the cost of training the system. The lower the score, the better the performance of the method in the deployment cost metric. A method would attain a *low score* if is there is little or no need for additional or cumbersome equipment installation, such as cameras or cable networks, or that the configuration and training phases are fairly cheap. A *medium* score would indicate that a mild effort is required on more than one cost factor, or a great effort in only one cost factor. A *high* score would mean that a considerable effort is required during installation, configuration or training phases.

3.7. Robustness

A positioning system is expected to operate normally even when some signals are not available, or bear values off the accepted range. Sometimes, the signal from a transmitter unit is totally blocked, so the signal cannot be obtained from some measuring units. The only information to estimate the location is the signal from other measuring units. Other times, measuring units in a harsh environment could be out of function or damaged, sending faulty signals or no signals at all. A positioning system has to make use of this incomplete or faulty information as best as it can to successfully position a resource, even if the results are not as accurate as they would be on normal circumstances.

Our scale for evaluating robustness depends on how well a positioning method estimates the position of a resource, even with interference from different signals or structures, loss of signals due to damaged transmitters, or attenuation from environmental conditions. A *high* score means that the method can accurately position a target in the given environment (indoor or outdoor), even while under heavy interference or signal loss. A *medium* score indicates that the method can overcome a mild degree of interference, signal loss, or both, with only a small negative effect on the results. A *low* score is obtained when the method is unable to function properly, or is prone to give poor results when working under such conditions.

3.8. Other Metrics

Some authors mention additional metrics in their own works. These metrics have not been included in our classification, mainly due to the fact that they escape the scope of the survey. However, some of them present interesting ideas, and would allow to fine tune our classification in future iterations. This section addresses some of these metrics.

The *integrity risk* is defined by Gilliéron et al. [Gil04] as the probability that a user will experience a position error larger than a specified limit without an alarm. They also consider the *continuity of service* as the requirement for a navigation service to be available for the user over a minimum time interval; and the *availability* of the navigation service, which is established by simultaneously fulfilling accuracy and integrity.

Hightower et al. [Hig01] define *recognition* as the capacity of a positioning technique to identify objects in order to take a specific actions based on their location. They also define *limitation* as the capacity of a positioning technique to work in different environments.

Gu et al. [Gu09] propose *security and privacy* as the degree of user control of the usability of their personal location information and history. *Fault tolerance*, akin to robustness, is the ability of the positioning system to keep operating, even during malfunctions. *User preference* takes into account the level of comfort of the users (devices should be wireless, small, lightweight, have low power consumption, etc.). *Commercial availability* determines how readily available the design details are. Finally, *limitations* refer to positioning technology issues and other technical problems in the systems.

4. Discussion of Positioning Methods Performance

The metrics discussed in the previous section can be used to elaborate a comparison of the performance of the positioning methods reviewed in this survey. There are two sets of tables for each positioning technique, the first contains the metric scores for outdoor, and the second for indoor. The rows of each of these tables list the methods used by the techniques, and the columns the metrics. Each cell contains the score of the row's method and column's metric for the given technique. A brief discussion is presented for each table.

4.1. Triangulation

The methods considered are time of arrival (TOA), time differential of arrival (TDOA), roundtrip time of flight (RTOF), Received Signal Strength, (RSS), Received Signal Phase (RSP), GPS, and angle of arrival (AOA). Since TOA, TDOA and RTOF work under the same basic principle, they all share common traits, and therefore display a similar performance. The same holds for the RSS and RSP methods, which work under similar assumptions. GPS' results are included only in the table outdoor environments, since multipath effects prevent it from working in indoor environments (without taking into account hybrid-GPS methods).

Table 1: Performance of triangulation positioning methods in indoor environments

Indoor	Accuracy	Precision	Scalability	Complexity	Overall Cost	Deployment Cost	Robustness
TOA	High	High	High	Medium	Medium	Low	Medium
TDOA	High	High	Medium	High	High	Low	High
RTOF	High	High	Medium	High	High	Low	High
RSP	Medium	High	Medium	Medium	Low	Low	Medium
RSS	Medium	Medium	Medium	Medium	Low	Low	Medium
AOA	High	Medium	Medium	High	High	Medium	Medium

Performance of TOA, TDOA and RTOF on Indoor Environments

These methods are quite accurate, being able to position targets in the range of tens of centimeters with a high precision rate [Gu09]. However, synchronization errors might have adverse effects on the signal measurements [Vos03]. TOA's complexity is medium-high, since it is difficult to implement [Gu09]. TDOA and RTOF are even more complex due their complicated hardware needs [Fuk03] and the computational power essential to diminish positioning errors

[Vos03]. The overall cost of TOA depends on how the tradeoff between accuracy and error mitigation is addressed [Vos03]. This cost is relatively high for TDOA and RTOF, due to the special hardware requirements [Fuk03]. The deployment cost for all of them requires only a small setup effort [Ver11], mainly because it uses existing infrastructure. As for robustness, a greater distance from the reference points induces a higher positioning error, due to time delay [Gu09]. This is especially true for TOA, since TDOA and RTOF have countermeasures to deal with these errors [Rui10].

Performance of RSP and RSS on Indoor Environments

The RSS and RSP methods have an average accuracy, usually off by a few meters in the worst case [Fuk03]. This is mainly due to multipath effect and loss of signal strength present in indoor scenarios [Fel03]. Inside a building, the variation of the signal strength with distance is significant due to obstruction from walls and furniture [Pra02]. For RSS, multipath fading makes it poorly scalable [Ji04], while RSP has problems coping with an increased number of mobile clients [Pra02]. This also affects the complexity, accuracy and precision of these methods; increasing the granularity of the coverage area would require more calculations and would allow for more positioning errors in close quarters. The deployment cost is quite low thanks to the fact that RSS and RSP use available infrastructure (usually access points) to deploy the positioning system with minimum additional devices [Pra02].

Performance of AOA on Indoor Environments

The accuracy of AOA depends on the accuracy of the angle measurements [Liu07]. Its precision is consistent as long as the angle measurements are not affected by external factors. The calculations for AOA positioning are high due to the amount of operations needed to estimate distance and angles from the reference points to the target, heightening its complexity [Rui10]. Expensive equipment is also required, as well as a setup and calibration phase [Che04]. Also, the degradation of signals due to distance from base stations affects accuracy, leading to false positives on the current position [Rui10], and a small error in the measurement of an angle could cause a huge position error when the target is far from the reference points [Con02].

Table 2: Performance of triangulation positioning methods in outdoor environments

Outdoor	Accuracy	Precision	Scalability	Complexity	Overall Cost	Deployment Cost	Robustness
TOA	High	High	High	Medium	Medium	Low	Medium
TDOA	High	High	Medium	High	High	Low	High
RTOF	High	High	Medium	High	High	Low	Medium
RSP	Low	Low	Low	High	High	Low	Medium
RSS	Medium	Low	Low	High	High	Low	Medium
AOA	High	Medium	Low	High	High	Medium	Medium
GPS	High	High	High	Low	Low	Low	Medium

Performance of TOA, TDOA and RTOF on Outdoor Environments

These methods have medium-high accuracy in outdoor environments, with a 30m estimation error under favorable conditions [Mou01], and reliable precision. TDOA and RTOF have better accuracy and precision than TOA, at the cost of increased complexity and the need for special equipment. This is due to the use of multiple signal measurements to estimate positions, though synchronization errors might still affect these measurements [Vos03]. Moreover, a greater distance from the reference points induces additional error due to signal time delay [Gu09], and an accurate synchronization between all participants is of utmost importance in order to obtain results [Che04]. Only a small effort is needed to setup a system using these positioning methods [Ver11].

Performance of RSP and RSS on Outdoor Environments
The RSP and RSS methods have diminished accuracy outdoors, mainly because of environmental effects that affect the signal measurements; precision is also affected by these effects. For RSS, scalability becomes a major issue due to the size of the coverage area; a greater area requires more calculations, a bigger position database, and possibly additional equipment. The deployment cost remains low due to possibility of reusing available infrastructure to deploy the positioning system with minimum additional devices. As for robustness, there are more open spaces and fewer obstacles outdoors, so the effects of multipath and loss of signal found on indoor environments are not such a big problem. However, these issues are replaced by environmental effects, such as sunlight and fog, which increase the estimation error.

Performance of AOA on Outdoor Environments
AOA's performance remains almost the same as that of observed indoors. The most evident variation is in scalability; the increased coverage area of an outdoor environment requires additional computational power. This requirement also affects the complexity and overall cost of this method. AOA has some problems coping with objects around the trajectory of the signals, affecting the estimation and therefore decreasing its score on the robustness metric [Che04].

Performance of GPS on Outdoor Environments
The accuracy of GPS has an estimation error of up to 15m on the ground, with a precision of 95% any time of the day [Mou01]. GPS has low computational requirements, especially for mobile devices [Van01]. A cheap GPS transceiver is all a device requires to enable GPS positioning. Scalability is not an issue, since countless people have been using this method worldwide at every hour of the day since its public release. Its use is so popular that the cost of GPS capable devices is available for everyone, though some more accurate and precise modern devices are out of common people's monetary reach [Baj02]. Since GPS uses an array of satellites and a simple mobile transceiver unit, its deployment cost is also inexpensive. Even so, this method's accuracy can be affected by environmental effects and atmospheric conditions [Gu09].

4.2. Proximity

For proximity, the methods considered are Cell-ID (CID), Radio-frequency ID (RFID), closest neighbor (CN), and least square (LS).

Table 3: Comparison of proximity positioning methods in indoor environments

Indoor	Accuracy	Precision	Scalability	Complexity	Overall Cost	Deployment Cost	Robustness
CID	Low	Low	High	Low	Low	Low	High
RFID	High	High	Low	Low	Low	High	Low
CN	Low	High	Low	Medium	Low	High	Low
LS	Medium	Medium	Medium	High	Low	High	Medium

Performance of CID on Indoor Environments

Given the nature of CID, its accuracy and precision are especially low in indoor environments [Zei02]. Although CID positioning systems are able to support a large quantity of users at the same time with relatively little computational effort, the huge drawback of accuracy and precision is too much of a problem to be a competitive method. It remains an inexpensive technology, because infrastructure exists for use in mobile cellphone communication [Tre04]. The deployment cost of a CID positioning system is also low for the same reason.

Performance of RFID on Indoor Environments

RFID is one of the most widely used positioning methods in indoor environments. It has a high degree of accuracy and precision, both in active and passive positioning. The nature of the tags used for RFID positioning does not allow for a great coverage area [Gu09], though these tags are remarkably cheap. However, in order to install the tags in the coverage area, a huge deployment effort is needed [Gu09]; this effort increases as the coverage area grows. The RFID method requires little computational power to perform estimations [Cho04], though it is relatively weak against interference from foreign elements between the transmitters and the receiver devices, such as clothes [Gu09].

Performance of CN on Indoor Environments

CN determines the position of the target as the position of its closest base station, making it a weak solution for indoor scenarios. Moreover, since this method tends to choose the same base station for a given signal measurement interval, its precision could be deceitfully high, even when the accuracy is low. CN is an iterative process, requiring a moderate amount of computational power. However, no special equipment is required to perform the estimations, aside from the transmitters and receivers. Still, the setup and training phases of this method require an important deployment effort.

Performance of LS on Indoor Environments

The LS method has modest accuracy, though it has precision issues due to synchronization and obstructed LOS [Kan04]. It can support a relatively large number of positioning targets, but this number depends on the size of the coverage area. Since LS uses an iterative minimization function, it requires moderate computational power to perform the estimations [Con02]. As with other proximity methods, an important deployment effort is required during the setup stage.

Table 4: Comparison of proximity positioning methods in outdoor environments

Outdoor	Accuracy	Precision	Scalability	Complexity	Overall Cost	Deployment Cost	Robustness
CID	Low	Low	High	Low	Low	Low	High
RFID	Low	High	Low	Low	Medium	High	Low
CN	Low	Medium	Low	High	Low	High	Low
LS	Low	Medium	Low	High	Low	High	Medium

Performance of CID on Outdoor Environments

CID's performance in outdoor environments is similar to that observed for indoor, with a low accuracy due to the way it estimates a target's position. Both the accuracy and precision of CID are highly dependent on the size of the coverage area, which can range 200m to over 30Km [Mou01]. However, it still supports a larger quantity of simultaneous requests than other methods with relatively little computational effort. CID is inexpensive due to reusing of infrastructure and requires little deployment effort for the same reason.

Performance of RFID on Outdoor Environments

RFID is a poor choice for outdoors, due to its small effective coverage area and large deployment cost. For these reasons, RFID is not used in outdoor environments, except for parking lots, warehouses and the like. RFID accuracy outdoors score is low because of the tag's limited range, though its precision is still reliable, to an extent. To overcome this problem, more RF tags area needed, increasing the overall cost and deployment cost without much gain in accuracy. Moreover, environmental conditions such as sunlight and fog affect the signal measurements, although the OLOS problem is reduced due to the open areas and less obstacles.

Performance of CN on Outdoor Environments

The CN method's accuracy is akin to that observed for CID. It can only estimate the position of a resource at the exact position of its closest base station [Kan04]. Although it has a good precision due to the iterative refining of the estimations, the size of the coverage area of outdoor scenarios renders this method's computing requirements almost unbearable for most computational equipments. Thus, special, more powerful processing units are required. Its overall cost remains low despite that. An important effort must be made during the setup and training of this method.

Performance of LS on Outdoor Environments

The LS method's accuracy score in outdoor scenarios is low due to the increased size of the coverage area. Since LS is an iterative process, a small error at an early iteration could adversely affect the final position estimation. Its precision remains the same, though it cannot support too many positioning targets due to the intense computational effort required to apply the minimizing function [Con02]. This method also requires an important effort during setup stages.

4.3. Fingerprinting

The methods considered are k-closest neighbor (kNN), support vector machines (SVM), smallest vertex polygon (SMP), neural networks (NN), Bayes theorem (BT), and Markov Chains (MC). Given the nature of fingerprinting, it is seldom used for outdoor positioning due to scalability and complexity issues. For this reason, we only considered indoor environments for our comparison. A common trait most fingerprinting methods share is that a small change in the layout of the environment or the position of emitter devices would require retraining the system. The NN and MC methods have a similar behavior, and are discussed together.

Table 5: Comparison of fingerprinting positioning methods in indoor environments

Indoor	Accuracy	Precision	Scalability	Complexity	Overall Cost	Deployment Cost	Robustness
kNN	High	High	Medium	High	High	High	Medium
SVM	High	Medium	High	Medium	Medium	High	Medium
SMP	High	Medium	Medium	High	High	High	Medium
NN	High	High	High	Medium	Medium	Medium	High
BT	High	High	Medium	High	High	High	Medium
MC	High	High	Medium	High	High	High	Medium

Performance of kNN on Indoor Environments
The kNN positioning method has a great accuracy at close range (2.4m at 50m, 1.26 at 25m), but it quickly deteriorates when closing in to the target [Was05]. This is due to an innate problem of the kNN algorithm: similar readings (i.e. close points) increase the probability of an estimation error. Even though the kNN algorithm doesn't always compute position in the same way, it has a remarkable precision [Rui10]. A problem with kNN is that greater granularity (more fingerprints) increases the computational needs and requires a greater training effort [Was05].

Performance of SVM on Indoor Environments
The SVM method has a high accuracy rate, though its precision can be affected by similar readings of signals coming from different points. An advantage of this method is its scalability; it is able to support a large amount of simultaneous targets and can be easily adapted to position resources in 3-D environments, thanks to its multi-dimensional approach. However, the complexity of the operations required for the positioning estimations demands a powerful computing infrastructure. As with other fingerprinting methods, changes in the transmitter's layout imply retraining [Rui10], a stage that implies a significant deployment effort for SVM.

Performance of SMP on Indoor Environments
SMP calculates target positions via averaging, which leads to a relatively high accuracy in most cases, but a high precision error rate [Liu07]. It cannot cope with an increased number of positioning targets, because of the computational power required to make the averaging calculations. This impacts SMP's score in both scalability and complexity. As with other fingerprinting methods, changes in the transmitter's layout imply retraining [Rui10].

Performance of NN on Indoor Environments
NN has great accuracy at close range (2.94m at 50m, 1.39m at 25m) [Was05], with a slightly lower precision than other fingerprinting methods. A strong point of NN is that they have better performance than other methods when the training database is very large, though it still requires a moderate amount of training and computing power to carry out acceptable estimations.

Performance of BT and MC on Indoor Environments
The BT and MC fingerprinting have greater accuracy at greater distances from the reference points, which decreases at closer distance [Cas01, Bur98]. Since both methods work under probability assumptions, their complexity is relative to the size of the coverage area and amount of targets [Rui10]. A "re-sampling" can be done at any time for the BT method, allowing the users to adjust marginal distributions of access points when a change invalidates the current signal calibration. This includes changes in access points configuration [Cas01]. A drawback of the MC method is the enormous size of its state space, which grows with each new state update [Bur98].

4.4. Vision Analysis

The methods considered are the extended Kalman filters (EKF), graph-based optimization techniques (GO), and the particle filters method (PF). Most SLAM methods have varying accuracy and precision due to the fact that the position of the target is estimated based on the map elaborated by the correspondent method. Though vision analysis can be applied to outdoor scenarios, its maximum effective coverage area is not large enough to compete with other methods. For this reason, we only included the scores for indoor performance for this technique.

Moreover, exact values to set an interval for the scores of some of the metrics could not be found in the reviewed literature.

Table 6: Performance of vision-based positioning methods in indoor environments

Indoor	Accuracy	Precision	Scalability	Complexity	Overall Cost	Deployment Cost	Robustness
EKF	Medium	--	Medium	High	--	--	Low
GO	Medium	--	High	Medium	--	--	Medium
PF	High	--	Low	High	--	--	Low

Performance of SLAM EKF on Indoor Environments

The complexity of EKF is high due to the quadratic matrix used for calculating co-variance [Thr08]. Some variants of the EKF algorithm allow it to scale to environments of greater size by decomposing them into sub-maps with different co-variances. A robot navigating with EKF might not recognize observed landmarks even when they are in the training database, leading to inability to determine a position. This uncertainty of estimation results in a low score in robustness for EKF.

Performance of SLAM GO on Indoor Environments

This method allows for different levels of complexity, diminishing the computational power requirement [Lu97], allowing GO to scale to bigger environments than other vision analysis methods. The lack of a co-variance matrix makes it space-wise and also faster at updates, depending on the size of the training map [Thr08]. Additionally, even though the memory usage and update time of GO is constant, optimizations can be expensive and require retraining.

Performance of SLAM PF on Indoor Environments

Particle filters converge to the true position of a target under some minor assumptions and conditions [Mon02], however if these assumptions are wrong, the accuracy diminishes. The space of maps and paths grows with each update on the target's position, requiring additional storage and faster processors. This is important due to the filters' exponential growth rate with each state update [Mon03].

5. Related Work

Gu et al. [Gu09] presented a set of indoor positioning systems, categorizing them based on the way they determine the location of resources. For each system, the advantages, disadvantages and limitations are addressed. Then, an evaluation of these methods is presented, based on the following set of metrics: security and privacy, cost, performance, robustness, complexity, user preference, availability and limitations. They state that combining positioning techniques and technologies can improve the quality of positioning services. Finally, they describe some of the current location sensing technologies and positioning projects in development at the time.

In their work, Ruiz-López et al. [Rui10] provide a survey of various techniques and technologies for positioning services, with their relative advantages and disadvantages based on metrics, which they call *functional requirements*. They believe it is necessary to take the environment into consideration before deciding which positioning technology and technique should be used for a specific scenario. They also mention that different methods can be combined to improve accuracy on certain settings, and that the integration of indoor and outdoor technologies may help to develop more efficient and robust systems. Finally, they hint the need for positioning services based on interoperable components, allowing the combining of positioning techniques and the technologies that support them in order to build hybrid systems. This would allow those components to be replaced and switched between them easily.

Liu et al. [Liu07] elaborated an extensive survey on indoor positioning techniques and systems. They discuss three positioning techniques (to which they refer as algorithms) and some of the positioning methods used to implement them, describing several tradeoffs of the methods based in a performance measurement criteria. Then, a review of at the time current positioning systems and solutions is offered, based on the technology used by their authors (such as GPS-based, RFID-based or cellular-based). This taxonomy is condensed into a set of tables showing for each solution the technology used, the algorithms, and their performance on the metrics defined in their work.

Zeimpekis et al. [Zei02] present an overview of positioning techniques, grouping them based on where the positioning process is carried out (self positioning or remote positioning). They follow with a discussion of potential mobile applications and services that would benefit from the use of positioning techniques. They elaborate a taxonomy of indoor and outdoor positioning services, grouping them in two categories: Business-to-Consumer, and Business-to-Business. Finally, they discuss limitations and research challenges on mobile positioning techniques for indoor and outdoor environments.

The work of Kanaan et al. [Kan04] presents a comparison of various geo-location algorithms for indoor scenarios. After describing these algorithms, they define *Channel Models* as the contextual conditions that introduce different amounts errors to the measurements; these channel conditions are Line-of-Sight (LOS), Obstructed LOS (OLOS), and mixed of them. A set of comparison tables for the reviewed algorithms for each channel condition is presented, with an evaluation of the performance of these algorithms in relation to the size of the indoor area over which a user is to be located.

Hightower et al. [Hig01] developed a taxonomy to allow an easier evaluation of positioning systems. First, they established the differences between physical position and symbolic location, and between absolute and relative positioning. Then, they established metrics to evaluate their taxonomy, including localized location computation capability, accuracy, precision, scale, recognition, cost and limitations. The taxonomy is then used to survey some of them at the time current research and commercial positioning technologies. Finally, they established that future work should generally focus on lowering cost, reducing deployment cost, improving scalability, and creating flexible systems than on improving accuracy or precision.

The paper presented by Madigan et al. [Mad05] present a positioning approach that allows the estimation of multiple wireless clients based on a Bayesian hierarchical model. Although it works only for indoor scenarios with available wireless networks, its results are similar to those of other methods. The innovation of the method presented by Madigan is the introduction of a fully adaptive zero profiling approach to location estimation that can track multiple targets simultaneously. The approach allows incorporating specific types of prior knowledge to improve the positioning process and results.

6. Conclusions and Future Work

This paper offers a survey of current positioning indoor and outdoor techniques and methods, and is intended to serve as a guide for researchers and investigators on common positioning techniques. A detailed description of the most well known methods of positioning is offered, classified based on the technique they use to estimate positions. Using evaluation criteria based on metrics, the performance of these methods and the tradeoffs among them are presented. The comparison offered in Section 5 shows that every method has limitations, so tradeoffs must be established. We believe that this comparison could allow developers to determine the best positioning technique for a given scenario, or choosing which techniques to combine into a single positioning system.

Positioning is an open field, full of research opportunities. The appearance of new technologies and scientific breakthroughs combined with the availability of wireless networks and mobile devices allows for different practical applications for positioning services. This is especially true for mobile devices, in particular smartphones. Social networks and advertising companies have begun using the position of users to offer services, and to publish content on the web. The growth in demand of positioning services requires that new approaches are taken, and new paths are discovered as new technologies and new demands for positioning services appear.

Possible future work includes an extension of this work, adding additional metrics and less known positioning methods. Research on new or hybrid positioning methods would allow overcoming present limitations of positioning and allow for better services. These hybrid methods could help decrease the impact of tradeoffs, and increase accuracy and precision. Another area of research would be the integration of indoor and outdoor scenarios, allowing for a single positioning system to track a target both indoors and outdoors using different positioning methods. The improvement of current positioning devices (i.e. transmitters and receivers) could help overcome these challenges, and could also allow the deployment of sensors in areas that are not covered by a positioning system. This would be especially useful in emergency situations, such as earthquakes or floods.

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8. Annex

Multipath Effect: In wireless telecommunications, multipath is the propagation phenomenon that results in radio signals reaching the receiving antenna by two or more paths. Causes of multipath include atmospheric ducting, ionospheric reflection and refraction, and reflection from water bodies and terrestrial objects such as mountains and buildings [Ji04].

Line-of-sight (LOS) propagation refers to electromagnetic radiation or acoustic wave propagation. Electromagnetic transmission includes light emissions traveling in a straight line. The rays or waves may be diffracted, refracted, reflected, or absorbed by atmosphere and obstructions with material and generally cannot travel over the horizon or behind obstacles [Kan04].

Obstructed Line-of-Sight (OLOS) or Non-Line-of-Sight (NLOS) is a term often used in radio communications to describe a radio channel or link where there is no visual line of sight (LOS) between the transmitting antenna and the receiving antenna. In this context LOS is taken either as a straight line free of any form of visual obstruction, even if it is actually too distant to see with the unaided human eye, or as a virtual LOS (i.e. as a straight line through visually obstructing material), thus leaving sufficient transmission for radio waves to be detected [Kan04].