Classification of User Positioning Techniques and Systems for Intelligent Environments

Benjamin Wagner, Dirk Timmermann

Institute of Applied Microelectronics and Computer Engineering
University of Rostock
Richard-Wagner-Straße 31
18119 Rostock-Warnemünde
firstname.lastname@uni-rostock.de

Abstract: One of the most important observation parameters for smart environments and ambient intelligence is the position of users. Over the last years huge research efforts have been spent on new algorithms, technologies, and systems for the localization of users and objects. The spread of these technologies results in a wide range of application scenarios and manifold combinations of measurements and algorithms. One fundamental task in designing smart environments is the choice of a localization system which fits into the ambient infrastructure, is applicable to the underlying application scenario, and provides localization results in desired form and accuracy. At this stage, it is very difficult to compare the published systems in order to opt for a specific solution. In this work existing systems and techniques are evaluated and documented under different characteristics facing two goals. The first one is to give an overview about the state of the art of user localization techniques and secondly to make these techniques comparable in order to fit the right technique to a given application. Therefore, intrinsic system characteristics are documented.

1 Introduction

User localization is a challenging issue for creating intelligent environments. For applications like object and asset tracking, workflow optimization and maintenance, information services, healthcare, ambient assisted living and security purposes the reliable knowledge about the user´s position is very important. Since 20 years different researchers and institutions are working on that topic to develop accurate, robust and safe localization systems for different purposes, e.g. Robot self-localization, Localization in wireless sensor networks, User-localization, etc. But the great number of approaches and technologies leads to a great variety of designations, notations and specifications. Different notations often describe the same principles or algorithms. For example the terms “active” and “passive” are used to describe, whether the user has to wear tags to be localized or not. Another interpretation is, whether the localization algorithm is distributed and partly executed on the user-beacons or not. In this paper we propose a set of classification parameters, which can be used to describe every locational system or technique.
The paper is structured as follows. In Section II related works are described. Section III describes the classification parameters. Section IV gives an overview about a selection

of developed systems and approaches classified by the described parameters. At the end we draw conclusions on the applicability of our classification set.

2 Related Work

There are a number of publications with the aim of summarizing localization technologies. Koyuncu et al. [1] investigate advantages and disadvantages of several positioning techniques. They describe some of them in particular and give an overview of comparisons between various examples. Liu et al. [2] focus techniques based on radio frequency and infrared light for surveying wireless indoor positioning systems. The authors describe important measurement techniques divided into triangulation, scene analysis and proximity in detail and create performance metrics, shown in Table 1 to classify the wireless positioning techniques. By these metrics they evaluate a number of systems and describe some of them in detail. Hightower et al. [3] propose another parameter set for evaluation. The authors add information about the position information and computation distribution. Table 1 summarizes the evaluation criteria of the mentioned publications and opposes same significations. Comparing the different available summaries it can be stated, that every work provides a problem specific classification but no cross-technology and new approach compatible structure.

Koyuncu et.Al.[1]	Liu et.Al.[2]	Hightower et.Al.[3]
accuracy	accuracy	accuracy
	precision	precision
range		
signal	wireless technology	
data rate		
principle	positioning algorithm	
cost	cost	cost
	complexity	
	scalability	scale
	space dimension	
	robustness	limitations
		physical / symbolic position
		absolute / relative position
		localized location computation
		recognition

Table 1: Comparison of Survey Parameters

3 Classification Parameters

We provide a division of classification parameters divided into two parameter groups. The System-oriented classification parameters describe the technical properties of the localization technique. The Application-oriented parameters characterize the usage attributes of the specific system. Fig. 1 depicts the described parameter structure.

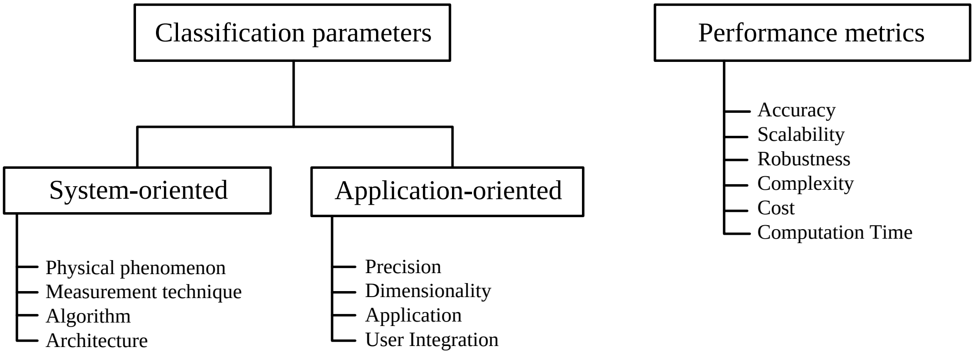

Fig. 1: Classification Parameters

The third group of parameters are the performance metrics. Because of their ability to rate localization approaches and not to describe their structure, they need to be looked at separately from the classification parameters. Secondly performance parameters seem to be the consequence from the systems architecture and can be the basis for comparing the different systems and techniques in contrast to the classification parameters.
In the following we want to describe the particular subdivision of classification parameter groups and common characteristics of current positioning approaches.

3.1 System-oriented Parameters

As mentioned above, System-oriented parameters describe technical specifics of the localization technique. The first parameter is the observed physical phenomenon. Secondly the measurement technique describes the way, the physical phenomenon is measured. Based on these two parameters every positioning system implements a certain algorithm for estimating the user´s position. The last classification parameter describes the systems architecture.

A. Physical phenomenon
A main difference between localization techniques is the used physical phenomenon. The different possibilities shown below could been observed by similar measurement techniques, but provide different advantages and disadvantages concerning accuracy, robustness and scalability.

- Radio Frequency

The most common technology for user localization is the RF-based Global Positioning System (GPS). Using it, makes it possible to achieve sufficient accuracy for outdoor navigation, but it is difficult to operate indoor, because walls attenuate the signals very strong. Much work has been done on indoor positioning using the different radio frequency technologies. In IEEE 802.11 Networks (WLAN) wireless clients can be localized by observing their communication with the gateways. Because WLAN clients

mostly have enough computing power it is possible to implement distributed location algorithms executed either on the client or on the gateway.
The Radio Frequency Identification (RFID) technology can also be used to create indoor localization systems. Either the user could be tagged with RFID-Tags which could be localized by the reader-hardware or a mobile reader could track itself by reading tags fixed in the environment. A very new approach is provided by Lieckfeldt [4] which utilizes passive RFID backscatter for localization purposes.
Furthermore short-range RF-technologies were utilized to create user localization systems like IEEE 802.15.1 (Bluetooth) or IEEE 802.15.4 (Zigbee). The advantage of these technologies is the availability and the wide distribution of commercial user hardware. In contrast to that there are some developed user positioning technologies using other frequency bands. The most promising radio technology is ultra-wideband (UWB) today already used for precise user tracking in commercial products. With UWB high precision with high robustness is possible.
Using already available hardware another often mentioned approach is user mobile phone localization over the Global System for Mobile Communications (GSM). Most approaches using this technology are facing outdoor positioning aims, because the GSM-transmitters are acting as reference points for localization.
Another very interesting approach is suggested by Krumm et al. [5] utilizing FM radio transmissions for user localization.

- Light

Today light based localization techniques use either visible or invisible light. Systems utilizing invisible light most often work with Laser or infrared light. Techniques utilizing visible light are also called videometric. Videocameras are used to create pictures of a certain scene and tracking algorithms are used to derive user positions and movements.

- Sound

Using sound waves two major techniques were investigated. Systems based on ultrasonic use transmissions either from the user-carried tag to reference beacons or from these to the tag. The ultrasonic approaches are highly influenced by sources with similar frequencies, e.g. from bunches of keys or shoes.
Because of that problem some authors provide approaches using the sound of the user itself in the environment, the so called bodysound. Typically a number of microphones is placed on walls or ceiling receiving the sound signals provided by the user.

- Magnetism

Using magnetism for object localization or tracking is another in research and industry mentioned possibility. Magnetic localization systems typically consist of a magnetic field generator or static magnet on one side and magnetic sensors (e.g. Hall-sensors) on the other side. There are approaches using a static magnetic sensor field observing the user wearing a static magnet [6]. Magnetic tracking is also used in applications needing very high accuracies, e.g. Motion Capturing. Therefore the user is equipped with a high number of magnetic sensors. A fixed infrastructure is generating a static magnetic field. The user hardware is then able to calculate a position out of the sensor data. These systems can reach very precise results, but they are typically very sensitive to metallic obstacles and other magnetic fields in the environment.

- Other (pressure, acceleration, etc.)

Systems like the SmartFloor from Georgia Institute of Technology localize users by footstep pressure profiles on the ground. Therefore the authors developed a system consisting of load-cells located under floor panels [7]. These load-cells generate a pressure dependent output-voltage as basis for localization and tracking algorithms. Using direct physical contact, which is nearly insusceptible to disturbances, is a key advantage of this approach [3].

Physical values like user acceleration and direction, measured by multi-axis accelerometers and gyroscopes are used by approaches using dead-reckoning algorithms for detecting the user's motion [8]. These approaches need a reliable user position as starting point. Due to low inaccuracies of the measurements or the calculation results the overall localization accuracy decreases over the observation time.

B. Measurement technique

There are several measurement techniques proposed for the diverse localization algorithms. The most basic measurement technique is simply to take the raw physical value (PV) of the sensor output (e.g. output voltage) as sensor data provided for further analysis. The following techniques are based on a physical signal travelling from a transmitter Tx to a receiver Rx. Figure 2 shows the methods described below.

- Time of Arrival (ToA)

If the signal moves with a constant speed from Tx to Rx the distance between them can be calculated by using the travel duration of the signal between them. So the ToA is the time the signal first arrives at the receiver which is the sum of the transmitting time and the propagation delay [9]. The most important condition for that technique is a time synchronization of sender and receiver.

- Time Difference of Arrival (TDoA)

In difference to TOA this approach suggests using the difference between several signal arriving times. The signal is received by multiple receivers, synchronized in time by e.g. a wired connection.

- Angle of Arrival (AoA)

In addition to distances between sensors the direction of a signal can also be used for calculate precise object locations. Therefore the angle of the arriving signal is detected by using sensor arrays (e.g. antenna arrays, microphone arrays, etc.). At each sensor element a signal arrives with a path difference. These differences can be used to calculate the angle of arrival using the receiver arrays angle to the reference coordinate system and the distance of the unique sensor elements.

- Received Signal Strength (RSS)

Using the received signal strength of an RF-signal provides other possibilities of calculating object positions, e.g. fingerprinting or tomography. The Received Signal Strength Indicator (RSSI) is a voltage value representing the RSS on the receiver unit [9]. Nearly every RF-system provides the possibility to get this value with the received signal. RF-signals are subject to multipath attenuations caused by human or non-human presence. The difference between transmitted and received signal, the signal path loss, is basis for different localization algorithms [2].

- Received Message Data (RMD)

Localization methods based on origin approximation (e.g. Cell of Origin) rely on the information transported by the physical signal. Meta-information like signal strength, time or angle are not relevant. The only condition is a faultless transmission of the inherent message data.

- Real Time of Flight (RToF)

The travelling time of a signal moving from a transmitter to a responding target and back is proposed as the Real Time of Flight. Liu et. al. point out, that this technique do not need an exact time base like TOA, but a more moderate relative clock synchronization. For short-range systems the computation delay of the responding transceiver unit has to be considered very accurate [2]. RTOF is applied onto different technologies, e.g. passive RFID [10] or WLAN [11]. This technique is similar to a conventional radar approach.

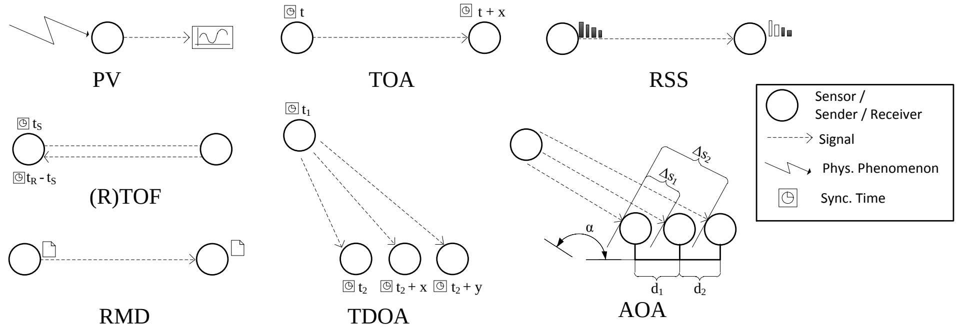

Fig. 2: Measurement techniques

C. Algorithms

There are three main algorithm groups provided in the literature: triangulation, scene analysis and proximity [2], [3], [9]. Concerning the evaluation of this work, two groups have to be added to that classification: estimation and others. In the following the different algorithm classes are clarified.

Triangulation algorithms are based on TOA, TDOA and AOA measurements of distances or angles and uses lateration or angulation for determining the user location.

Utilizing algorithms based on Scene Analysis means to compare present measurements with stored fingerprints on every possible user location. Therefore this is also called Fingerprinting. The data could be ascertained by offline-measurements before an online-localization phase or by geometrical calculations [12].

In contrast to the exact triangulation algorithm proximity approaches work with restrictions about possible objects locations. These constraints are based on connectivity information, antenna radiation patterns and spatial restrictions. Often the centroid of the resulting area is used as object location estimation [9]. Using this result as basis for other algorithms can improve the object location calculation significantly. As a case in point, dead reckoning has to be mentioned. This approach uses physical sensor data like user acceleration and orientation to calculate the new user location, while the user is moving (cp. 1.e.).

Another often used proximity method is Cell of Origin (CoO) or Cell-Identification (Cell-ID). Mobile Networks or coarse grained RFID networks have the possibility to get information about the spatial cell, the user is located in, from a database containing positions of every single transmitter. The precision of this approach is depending on the size of each spatial cluster.

Less common are estimation algorithms: pure probabilistic or stochastic algorithms, computing the most likely location of an object based on the observed data. Some approaches calculate likelihoods for possible user locations and combine it with scene analysis [12]. Probability distributions of user locations could be estimated by classification algorithms (e.g. k-nearest-neighbour (kNN)) [2]. Videometric localization, vision-based technologies except approaches utilizing depth-cameras, use algorithms calculating the shapes of users and object from the delivered pictures itself. This is a case in the field of biotracking[13]. Every videoframe is analysed by classification algorithms followed by tracking algorithms, e.g. particle filters or hidden marcov models.

There are a number of new approaches considered in the last few years, using neural networks and machine learning for object localization. Learning algorithms are applied on an amount of offline calibration data with known user locations similar to scene analysis.

D. Architecture

As great as the variety of user localization systems available today are the provided application scenarios. The systems can be divided into systems using a certain Infrastructure installed in the room providing the localization functionality. Most todays systems are based on a calibrated infrastructure providing the most accurate localization results.

On the other side there are Inertial Systems. In these systems the whole localization hardware is carried by the user and no additional hardware must be installed in the environment. These systems have the most important use case in examining new environments, e.g. mines or tunnels.

3.2 Application-oriented Parameters

As mentioned in Fig. 1 the second group of classification parameters are the application-oriented parameters. They describe how the system is able to meet the requirements of the user. The most important parameter is the Precision of the localization system, which mostly determines its applicability. Secondly the Dimensionality is another important parameter indicating whether the third spatial dimension could be detected or not, important for example for identification purposes. After dealing with possible Applications the way of user integration is an important parameter describing localizing systems.

A. Precision
There are a lot of terms describing the result quality of a localization or positioning system. The most often used term accuracy is no classification parameter. It is a performance characterizing term, because every system is designed to calculate a user's position with a certain precision or granularity. That system property does not allow conclusions on the rightness of the results. In the literature different metrics for precision are proposed. Some authors divide localization systems by granularity into coarse- and fine-grained systems. Systems providing larger areas as localization results are called coarse-grained, because the number of possible user locations is relatively low. These localization areas can also have different size and shape, concerning user needs, e.g. floor, kitchen etc. This method is called Symbolic Localization. In contrast to fine-grained techniques providing a relatively high number of possible user locations. The granularity is an important design parameter depending on the application. For some home automation scenarios it is sufficient to have information about the room, the user is located in. For asset tracking it is important to know where exactly the location of the object is. Given the fact, that this classification does not state the real accuracy, coarse grained systems could have a higher accuracy than fine-grained systems, although the precision is lower.

B. Dimensionality
Most localization systems works with 2-dimensional coordinates. That is sufficient for most applications, because only the positions within a certain area are important and the height of a user is not changing. Some proprietary systems provide pseudo-3D localization by adding the static user height to the 2D results. Only a few systems really determine 3-dimensional user positions. That is most important for applications like motion capturing or user identification.

C. Application
Commonly locational systems can be divided by their field of application into Outdoor and Indoor applicable technologies. Typical Outdoor application scenarios are: Pedestrian and Car Navigation and Tracking, Military Navigation and Positioning or Tourism Services. Typical Indoor application scenarios are: Product Tracking, Logistics, Industrial Automation, Smart Home and Smart Office, Home and Facility Automation, Ambient Assisted Living and Motion Capturing
There are existential differences in requirements for these two groups. For outdoor application an accuracy of a few meters is mostly sufficient. However it is not sufficient for indoor purposes, because even differences of ~1 meter could lead to different recognized user intentions. Furthermore indoor localization systems suffer from obstructions and reflections by obstacles like walls, furniture, large devices or multiple users. This makes it difficult to obtain high accuracies in indoor environments.

D. User-Integration
In this field there are lots of different terms describing the way, the user is integrated in the localization process. Overall systems can be either Device-free or Device-based, whether the localized user or object has to wear additional hardware or not. In Device-based systems this hardware can either be active or passive. Active devices compute the whole localization algorithm by using received sensor data or acts as a part of a

distributed localization algorithm. Passive devices just send or reflect a physical signal and act as part of the sensing architecture of the localization system.
If the localized object is not equipped with additional hardware the technology is termed Device-free localization (DFL). Other terms describing the same issue are “tag-free”, “tagless” or “passive” localization.

4 Techniques and Systems

The following two tables are showing an evaluation of existing localization approaches and proprietary localization systems. This list is not intended to be exhaustive, because over the last years many new approaches arose and some older technologies became less important. The main focus of the evaluation is the localization of users and objects in intelligent environments. Applications like self-localization of robots and hardware was less important. Table 1 is showing the various techniques and systems and their characteristics of the before mentioned classification parameters.

		System-oriented				Application-oriented			
Technology / Approach	**Provider / Institution**	**Physical ph.**	**Meas. techn.**	**Algorithms**	**Architecture**	**Granularity**	**Application**	**User-Integration**	**Dimensionality**
Ubisense	Ubisense Ltd.	RF (UWB)	TDOA + AOA	Deterministic (Trilateration)	Infrastructure	Fine	Indoor	Tag based (active)	2D
RTI	University of Utah	RF (IEEE 802.15.4)	RSS	Tomography	Infrastructure	Fine	Indoor + Outdoor	Tag free	2D
Lieckfeldt et. al.	University of Rostock	RF (UHF-RFID)	RSS	Proximity + Scene Analysis	Infrastructure	Fine	Indoor	Tag free	2D
Landmarc	Michigan State University	RF (308 Mhz RFID)	RSS	Deterministic	Infrastructure	Fine	Indoor	Tag based (active)	3D
SpotON	University of Washington / Xerox	RF	RSS	Deterministic (Triangulation)	Infrastructure	Fine	Indoor	Tag based (active)	3D
RADAR	Microsoft Corp,	RF (WaveLAN)	RSS	Deterministic (Triangulation) Scene Analysis	Infrastructure	Fine	Indoor	Tag based (active)	2D

Table 1: Techniques and Systems (Part 1)

Table 1: Techniques and Systems (Part 2)

Technology / Approach	Provider / Institution	System-oriented				Application-oriented			
		Physical ph.	**Meas. techn.**	**Algorithms**	**Architecture**	**Granularity**	**Application**	**User-Integration**	**Dim.**
Ferret	University of Massachusetts	RF (RFID)	Connectivity	Proximity (Likelihood)	Inertial (tagged Obj.)	Fine	Indoor	Tag based (active)	2D
Schneegans et. al.	University of Tübingen / Bochum	RF (RFID)	Connectivity	Proximity	Inertial (tagged Obj.)	Fine	Indoor	Tag based (active)	2D
Zhang et al.	Hong Kong University	RF	RSS	Proximity	Infrastructure	Fine	Indoor	Tag free	2D
GNSS	Navstar GPS[3]	RF	TOF	Deterministic (Triangulation)	Infrastructure	Fine	Outdoor	Tag based (active)	3D
	Galileo	RF	TOF	Deterministic (Triangulation)	Infrastructure	Fine	Outdoor	Tag based (active)	3D
	GLONASS	RF	TOF	Deterministic (Triangulation)	Infrastructure	Fine	Outdoor	Tag based (active)	3D
Active Badges	Xerox / Univ. of Cambridge	Light (IR)	Connectivity	Proximity	Infractructure	Coarse	Indoor	Tag based (active)	2D
Active Bats	AT&T	Ultrasound	TOA / TOF	Deterministic (Trilateration)	Infrastructure	Fine	Indoor	Tag based (active)	3D
MotionStar	Ascension Techn. Corp.	Magnetic	RSS	Scene Analysis	Infrastructure	Fine	Indoor / Outdoor	Tag based (active)	3D
Cricket	MIT	RF + Ultrasound	TOF	Deterministic (Lateration)	Infrastructure	Coarse	Indoor	Tag based (active/passiv)	3D
PinPoint 3D-iD	RF Technologies	RF	TOF / TDOA	Deterministric (Lateration)	Infrastructure	Fine	Indoor	Tag based (active)	2D
Easy Living	Microsoft Research	Light (3D Videometric)	Vision	Deterministric (Triangulation)	Infrastructure	Fine	Indoor	Tag free	3D
Smart Floor[4]	Georgia Tech	Contact-Pressure (Voltage)	Footprint Profile	Proximity (Nearest Neighboor)	Infrastructure	Coarse	Indoor	Tag free	2D
Mobile Phone Localizing	Spec. Provider	RF (GSM)	RSS	Triangulation	Inertial (Outdoor) Infrastructure (generally)	Coarse	Outdoor / Indoor	Tag based (active)	2D
		RF (GSM)	RMD	Cell of Origin	Inertial (Outdoot) Infrastucture (generally)	Coarse	Outdoor / Indoor	Tag based (active)	2D
	Otsason et. al.	RF (GSM)	RSS	Proximity (Fingerprints, K-Nearest Neighbor)	Inertial (Indoor) Infrastructure (generally)	Coarse	Indoor	Tag based (passive)	3D
SkyLoc	Intel / Univ. of Toronto	RF (GSM)	RSS	Fingerprinting	Inertial	Coarse	Indoor	Tag based (active)	3D
Hähnel et. al.	Intel / Univ. of Freiburg / Univ. of	RF (RFID)	Connectivity	Proximity	Infrastructure	Fine	Indoor	Tag based (active)	2D

Table 1: Techniques and Systems (Part 3)

Technology / Approach	Provider / Institution	System-oriented				Application-oriented			
		Physical ph.	**Meas. techn.**	**Algorithms**	**Architecture**	**Granularity**	**Application**	**User-Integration**	**Dim.**
	Washington								
HIBall Tracker	3rdtech, Inc.	Light (IR)	Connectivity	Deterministic (SCAAT)	Infrastructure	Fine	Indoor	Tag based (active)	3D
BlueTrack	University of Rostock	RF (Bluetooth)	RMD	Scene Analysis	Infrastructure	Coarse	Indoor	Tag based (active)	2D
HORUS	University of Maryland	RF (WLAN)	RSS	Proximity (Fingerprinting)	Infrastructure	Fine	Indoor	Tag based (active)	2D
Randell & Muller	University of Bristol, UK	Ultrasonic	TOA	Deterministic (Triangulation)	Infrastructure	Fine	Indoor	Tag based (active)	2D
MoteTrack	Harvard University, Cambridge	RF (802.15.4)	RSSI + LQI	Proximity (Centroid)	Infrastructure	Fine	Indoor and Outoor	Tag based (active)	2D
INS / PDF Approach	Tampere University of Finland	Acceleration + Laser + RF (GPS)	PV / TOF	Dead Reckoning	Inertial	Fine	Indoor and Outdoor	Tag based (active)	2D
DOLPHIN	University of Tokyo	Ultrasound	TDOA	Deterministic (Triangulation)	Infrastructure	Fine	Indoor	Tag based (active)	3D
Haeberlen et. al.	Rice University	RF (IEEE 802.11)	RSS	Probabilistic	Infrastructure	Coarse	Indoor	Tag based (active)	2D
Ekahau RTL System	Ekahau, Inc.	RF (IEEE 802.11)	RSS	n.a.	Infrastructure	Fine	Indoor	Tag based (active)	2D
RightSPOT	Microsoft Corp,	RF (FM Radio)	RSS	Scene Analysis (Fingerprinting)	Infrastructure	Coarse	Outdoor	Tag based (active)	2D
Ladd et al.	Rice University	RF (802.11b)	RSS	Proximity	Infrastructure	Fine	Indoor	Tag based (active)	2D
Place Lab	Intel Research	RF (802.11 + GSM + Bluetooth)	RSS + Connectivity	Probabilistic	Infrastructure	Fine	Outdoor + Indoor	Tag based (active)	2D
AeroScout	AeroScout	RF (WLAN)	RSS + TDoA	n.a.	Infrastructure	Fine	Outdoor + Indoor	Tag based (active)	2D
MagicMap	HU Berlin	RF (WLAN)	RSS	Scene Analysis	Infrastructure	Fine	Indoor	Tag based (active)	2D
Topaz	Tadlys	RF (Bluetooth)	RMD	Cell of Origin	Infrastructure	Fine	Indoor	Tag based (active)	2D
Kinect	Microsoft Corp.	Light (Depth Videometry)	TOF + Vision	Trilateration + Scene Analysis	Infrastructure	Fine	Indoor	Tag free	3D
Wii	Nintendo	Light (IR) + Acceleration	Vision + PV	Trilateration + Dead Reckoning	Infrastructure	Fine	Indoor	Tag based (active)	3D

5 Conclusion

In this paper we provide a parameter structure for classification of current and future localization technologies for objects and users in intelligent environments.
There is a number of authors evaluating the localization stand of the art in the past using different parameter metrics. There is a lack of comparability between evaluations because there are lots of terms describing the same issue, respectively. We tried to summarize all possible terms for technologies, algorithms and properties in an overall classification. With the proposed parameter classification every localization technology can be described with its immanent properties.
Furthermore existing systems and techniques are evaluated and fitted into the proposed parameter structure, with no intention to be exhaustive. The intrinsic system characteristics are documented.

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