Discussing the State of the Art for “in the wild” Mobile Device Localization

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Abstract
Technologies for spatial and proxemic interaction with mobile devices depend inherently on the ability to obtain information on the device’s position (i.e., to *localize* the device). Numerous technologies have been proposed for this, each with their own strengths and weaknesses, but deciding which one to use in a particular context is challenging. In this paper, we examine current technologies for the localization of mobile devices and categorize them into a taxonomy based on their technological similarity. By considering numerous properties (e.g., precision, battery usage, scalability, required infrastructure, deployment) and discussing how these impact usability in different scenarios, we aim to allow other researchers informed decisions on the localization techniques to use for a particular application case.

Author Keywords
Localization Techniques; in the wild; Mobile Devices

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H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous.

Introduction
Research on spatial interaction with mobile devices has mostly used instrumented devices and rooms such as marker-based tracking [2, 11, 32] (or, in the early days, teth-

Signal Spectrum	radio-, light-, or sound-based
Technical Base	hardware or software base used
Computation Method	position determination method
Localization Approach	positioning or tracking
Precision	metric precision based on literature, ranging from mm to >m
Range	estimated metric range, ranging from km to m
Battery Usage	estimated usage, ranging from none to high
Scalability	scalibility of number of devices, limited or ∞ (unlimited)
Required Infrastructure	infrastructure used, rated by installation effort
Device Instrumentation	required device instrumentation
Deployment Effort	estimated effort of deployment process; none to high
Deployment Costs	estimated costs of deployment; none to high
Examples	related literature
Challenges	existing/important challenges

Table 1: Properties and their possible values for Table 2

ered devices [30]) to determine devices' positions. While this approach enables research on interaction, deploying the developed techniques in the wild has additional requirements: Among others, instrumentation of the mobile device will not be possible in most cases, mobile power consumption and scalability become an issue, and deployment efforts as well as costs need to be considered. Further, requirements often differ depending on the application case. As an example, while many single-device outdoor applications (e.g., wayfinding) work well with coarse positioning, indoor applications (e.g., pointing for data transfer methods [11, 32]) rely on much more precise positioning, while the range of the technique can be as low as a few meters.

In this position paper, we first examine important properties for "in the wild" localization techniques (see Table 1). Based on these properties, we then categorize existing localization techniques into a taxonomy and present these in a tabular form (Table 2). We color-coded the properties in the table to allow to quickly recognize advantages and challenges of the different techniques. Finally, we discuss the requirements of different application cases, with the goal to enable informed decisions on the techniques to use.

Properties of Localization Techniques

First of all, most localization techniques are based on the usage of signal waves and differ in the **signal spectrum** used (e.g., radio, light, sound). This spectrum heavily influences other properties and defines also the main source of disturbance—other waves in the same spectrum (e.g., sun light). All techniques build upon a certain **technical base** and use a specific **computation method**. Depending on the latter one, the **localization approach** can be either a positioning or a tracking approach, i.e., the position can be calculated by the device itself or by the infrastructure. We consider three main performance properties resulting from the signal, technical base and computation method used: The **precision** ranging from millimeters to multiple meters, the signal **range** from a few meters to many kilometers, and the extra device **battery usage** from none to high.

Especially important for "in the wild" application scenarios are properties influencing the deployment of spatial tracking. Regarding the hardware, this involves the **scalability** (i.e., if more devices can be easily incorporated), the **required infrastructure** (i.e., none, existing, or additional), as well as the the need for **additional instrumentation** for consumer devices used. Regarding the scalability, we only differentiate between a (practical) unlimited and a limited scalability (e.g., limited by increasing synchronization problems). Based on the required deployment steps and hardware, we roughly rated all techniques regarding their relative **deployment effort** and **deployment costs** compared to other techniques from none to high. These deployment properties can only serve as rough indicator. Finally, we also list **examples** from related work and name existing main **challenges** of the localization techniques.

Localization Techniques

For our taxonomy, we use the signal spectrum as main category and distinguish between three groups: radio, light, and (ultra-)sound (top level of taxonomy). In each group, we further differentiate between which technical base (2nd level) and computation method (3rd level) is used. We characterize the resulting localization techniques based on the properties described before (see also property overview in Table 1). Furthermore, we color-coded—and thus rated—all property values in three steps (green, yellow, red) roughly indicating their usability. We do not consider techniques based on inertial sensors only (e.g., gyroscope), as they lack the ability of localization relative to other devices. The complete taxonomy is shown in Table 2 at page 3.

Signal Spectrum	Technical Base	Computation Method	Localization Approach	Precision	Range	Battery Usage	Scalability	Required Infrastructure	Device Instrumentation	Deployment Effort	Deployment Costs	Examples	Challenges
radio	GPS	TDOA	positioning	> m	km	low	∞	existing	none	none	none	car navigation	outdoor only
	GSM	RSSI	positioning	> m	km	low	∞	existing	none	none	none	-	mainly in urban regions
		fingerprinting	positioning	m	km	low	∞	existing	none	high	none	[3, 20]	mainly in urban regions, reference model
	WiFi	RSSI	positioning	m	> m	low	∞	existing	none	none	low	[1, 6]	-
		fingerprinting	positioning	< m	> m	low	∞	existing	none	high	low	[1, 3, 16, 35]	reference model
		TOA/TDOA	positioning	m	> m	mid	∞	existing	none	none	low	[34]	multipath effects
		AOA	positioning	< m	m	mid	∞	existing	none	none	low	[12, 33]	multipath effects
	Bluetooth	RSSI	positioning	cm	m	low	limited	none	none	mid	none	[9]	adaptive signale strength
		fingerprinting	positioning	cm	m	low	limited	none	none	high	low	[3, 10]	adpative signale strength, reference model
light	Device RGB Cam	triangulation	positioning	cm	m	high	∞	markers	none	low	low	[15]	limited field of view, marker placement
		RSSI	positioning	m	> m	mid	∞	landmarks	none	high	low	[24]	number and type of required landmarks
		feat. detection	positioning	cm	> m	high	∞	none	none	none	none	[4], Proj. Tango	calibration / training
	External RGB Cam	triangulation	tracking	mm	> m	none	limited	camera	markers	mid	mid	-	limited field of view
		rect. detection	tracking	cm	> m	none	limited	camera	none	low	low	[26]	disturbance from overhead lights
	External IR Cam	triangulation	tracking	mm	> m	none	limited	cameras	markers	mid	high	OptiTrack, Vicon	calibration
		depth (TOF)	tracking	cm	> m	none	limited	camera	none	low	mid	[26, 27]	limited field of view
(ultra-)sound	Audio Devices	fingerprinting	positioning	m	> m	mid	∞	none	none	high	none	[25, 28, 29]	reference model
		TOA	tracking	cm	> m	low	limited	micros	none	mid	mid	[18, 22]	synchronization, multipath effects
		TOA	positioning	cm	> m	mid	∞	speaker	none	mid	low	[13, 19]	synchronization, multipath effects
		RT-TOA	positioning	cm	> m	mid	limited	none	none	none	none	[9, 16, 21, 23]	range internal hardware, multipath effects
		TDOA	tracking	cm	> m	low	limited	micros	none	mid	mid	[7]	multipath effects
		TDOA	positioning	cm	> m	mid	∞	speaker	none	mid	low	[13, 14, 17]	multipath effects

Table 2: Localization techniques and their color-coded properties grouped by signal spectrum and their technical base.

Radio-based
Many existing systems use radio frequency signals for localization, as current commodity hardware support them by default. Most prominently, GPS provides reliable localization at a precision of multiple meters in outdoor scenarios. For indoor scenarios, GSM base stations, WiFi access points and Bluetooth devices can serve as a technical base for localization providing up to meter, sub-meter or centimeter precision respectively. Received signal strength indicators (RSSI) can both be used to directly infer distance [1, 6, 9] or be compared as fingerprint to a prerecorded model of the signal in an area [1, 3, 10, 16, 20, 35]. Techniques leveraging the angle of arrival (AOA) [12, 33], time of arrival (TOA) or time difference of arrival (TDOA) [34] for multiple sources have also been explored.

Light-based
Optical techniques for localization typically incorporate either standard video cameras or infrared (IR) cameras and can be marker-based or not. Further, they can be distinguished into techniques either using an internal camera (i.e., device camera) or external cameras, thus between positioning and tracking systems respectively. For the latter one, professional setups like OptiTrack[1] or Vicon[2] usually track IR-reflecting markers, thus requiring instrumentation of the devices as well as the environment (i.e., placing cameras). Recently, low-cost—but less precise—depth-camera-based systems were presented [26, 27]. These are markerless and thus can be more easily deployed.

Positioning systems using an internal device camera come with the cost of higher battery drain, but often also incorporate a reduced deployment effort. The device camera detects prior installed reference points, e.g., light landmarks [24], markers [15], or image patterns [4], and the device can calculate its position based on these points. With Google's Project Tango[3] there also exists a solution that does not require any installed reference points but detect features of the environment by its own. However, to allow an absolute localization, an initial calibration step is required.

(Ultra-)sound-based
Sound-based techniques are an interesting alternative to the well-established radio- and light-based localization providing centimeter precision at low deployment efforts. Localization can be calculated by determining the distance to reference points from TOA [13, 18, 19, 22] or TDOA [7, 13, 14, 16, 17]. Due to the relatively slow propagation of sound, even standard speakers and microphones achieve sufficient measurement accuracy. Therefore, based on the same techniques both positioning [13, 14] and tracking [7, 18, 22] systems are possible. Using round-trip time of arrival (RT-TOA) [9, 21, 23] localization can also be performed among devices without any external infrastructure, however, providing only relative positioning in this case (RT-TOA can also be used with fixed infrastructure). Similar to RSSI-based fingerprinting, sound profiles of ambient noise [25] and purposely installed sound sources [28] can be utilized for positioning at room level. By recording the reflections of sound signals emitted by the device itself, even centimeter precision is possible [29]. However, changes in temperature and humidity affect sound propagation requiring to take environmental changes into account.

Improving Localization with Sensor Fusion
Combining different localization techniques with complementary attributes can help to improve overall performance. A common scenario is to pair a reliable but less accurate

[1] https://www.optitrack.com/
[2] https://www.vicon.com
[3] https://www.google.com/atap/project-tango/

technique with a less reliable, accurate one (e.g., [3, 9, 13, 16, 26]). Choosing techniques from different signal categories not only evades mutual interference, but also allows to compensate interference in one of them. Further, also internal device sensors (e.g., gyroscope) can be used to enhance localization with fine-grained movement and rotation detection (e.g., Project Tango or [9]).

Discussion & Conclusion

The required properties of localization techniques depend heavily on the application case (e.g., home, office, indoor public spaces, outdoor). For instance, in the context of private or home applications (e.g., [2]) the localization must come at low costs, but can involve instrumentation of rooms or devices and must not support a large number of devices. In offices, the number of devices is still manageable, but device instrumentation is probably not appropriate. One specific application scenario are smart meeting rooms, which might support pointing interactions [4, 5, 8], thus resulting in the highest demand on precision. Both personal and business application cases deploy localization techniques in controlled environments with minor sources of disturbance and small number of devices.

In contrast, indoor public spaces (e.g., shopping mall, museum) are crowded places in which localization techniques must be able to handle many devices at the same time in a larger area. These places often incorporate many barriers (e.g., walls, people) and manifold sources of disturbance, especially for light-based localization techniques (e.g., light installations, reflecting surfaces). A common application case is enabling cross-device interactions between a larger display and personal devices, e.g., to view, explore, or transfer information [4, 31]. In shopping malls, the instrumentation of devices is not feasible and additional infrastructure may have to fulfill some aesthetic requirements, whereas in museums specialized devices can be handed out and visible cameras are more accepted. As example environments for “in the wild” localization, both indoor and outdoor public spaces usually also have to support a wider variety on devices, thus rely more on commodity solutions than personal or business scenarios.

Taking this further, an ideal localization technique would be characterized by requiring only existing consumer hardware, a minimal deployment effort, an unlimited scalability, few sources of disturbance, a low battery usage, and, of course, a high precision. This mainly rules out light-based techniques, as they often require a comprehensive instrumentation or drain the battery. In contrast, radio-based techniques can often be easily deployed as they rely on existing hardware. However, the precision is poorer as for light-based techniques. Sound-based techniques could evolve as an alternative between these two established ones as they offer up to centimeter precision with reasonable deployment effort. Deploying “in the wild” localization systems in a larger scale also raises questions if and how this could affect our society, e.g., regarding privacy concerns (tracking vs. positioning; who has access to tracking data) or environmental aspects (such as noise pollution).

Still, choosing the *right* localization technique depends on the specific application and the resulting interaction style. We are confident that our discussion and presented taxonomy in Table 2 can help to identify the most suitable candidates and thus supports the process of deciding which localization technique to use for a specific application case.

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