Evaluation of Users‘ Effort in a Human-computer Cooperation based Indoor Mobile Location System

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Abstract

Due to the utilization of existing infrastructure and powerful mobile devices, many different indoor localization systems have been booming in recent years. However, most of those systems very focus on technical issues, a few studies investigate usability issues from users' perspective. In this paper, we conduct a case study with 18 participants to study how many effort (e.g., physical and mental workload) users would spend in a human-computer cooperation indoor positioning system. To support the study, we develop a Google Tango tablet based infrastructure-free indoor positioning system, by mapping users' walking trajectory and environmental features. Through the evaluation, we confirm that the workload increases as the increase of required walking distance, specifically for the physical and temporal demands. While positioning in an infrastructure-free environment, the participants were willing to contribute and would walk maximum 50 meters with their mobile devices.

1 Introduction

With increasing requirements on location-based services in an indoor environment, indoor localization attained significance, not only for academic research, but also for commercial purposes. There are a number of infrastructure-tied indoor positioning systems which would provide instant positioning information, such as WiFi-based and RF beacons based systems. However, it is a challenge to complete a large-scale deployment in each building, due to various reasons, like cost, maintenance and complex indoor environments. Once in some emergent situations, such as electric power loss, those systems will not be available.

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To overcome those requirements, in many systems human beings have been involved in the loop of indoor localization - not only as end users, but also as “sensors” (Angemann & Robertson, 2012). They wear devices with inertial sensors and are tracked for localization. Besides, usability is not an aspect of common localization, as cases of lacking confidence or unavailability of signals are counteracted only technically. Once users are a part of the loop, usability issues (e.g., workload, fault tolerance and accessibility) have to be taken into account in the period of deployment and evaluation.

Due to the advantages of emerging 3D time-of-flight (ToF) infrared cameras, in addition to sensing the 3D world and creating 3D maps, the devices would provide new approaches to interact with physical environment, such as motion tracking, area learning and indoor positioning. Benefiting from its powerful features, a Google Tango-like mobile device would boom infrastructure-free indoor localization systems, for instance, Winterhalter et al. (2015) presented an accurate infrastructure-free indoor localization system based on tracking walking trajectory, acquired from a Tango tablet. However, it is not clear how much effort (e.g., walking distance, and workload) a user would like to spend in such a human-computer cooperation based indoor positioning system.

In this paper, we address a user study to investigate how much effort users would spend while using an infrastructure-free indoor localization system by tracking users’ walking trajectories and matching with environmental features. As an intersection is an important cue (e.g., the number of connections and the angle of the connections) to locate on a topological indoor map, we propose to have a 3D scanning of visited hallway intersections for extracting their 3D features (e.g., openings) while tracking with a Tango tablet. When users are at an intersection with unique 3D features, they can be localized instantly. Otherwise, they are asked to walk to a nearby intersection until enough information for topological map matching is acquired. Since the proposed method requires users to scan intersections and walk a considerable distance, we conducted an experimental study to investigate usability of the method. Besides completing a questionnaire to get foundational insight into users’ general disposition to involvement in a localization process, 18 participants in 2 groups (with and without WiFi localization experiences) took part in an evaluation of usability and workload.

2 Related Work

Benefiting from the Global Positioning Systems (GPS), people can instantly localize themselves in outdoor environments. However, due to the blocked GPS signals in indoor environments, manifold indoor positioning approaches have been studied in the last decade as surveyed by (Fallah et al., 2013).

2.1 Infrastructure-free Indoor Positioning Technology

Aiming at avoiding expensive installations, many localization approaches have been proposed to make use of existing infrastructures, for instance, by analyzing GSM signals and magnetic fields (e.g., (Xie et al., 2014)). The image processing based visual localization (Mulloni et al., 2009), including Google’s Area Learning, is a popular and low-cost approach. However, aspects of quality and distinctiveness of the query images (e.g., blurred images, images captured in a low light condition) impact the location estimation. Besides, changes of indoor scenes may lead to incorrect localization. Google’s Area Learning also needs a pre-scan stage to collect environmental data in advance, as well as a large database.

2.2 Human-computer Cooperation based Indoor Localization

The human-computer cooperation based indoor localization is an infrastructure-free method, but it requires users’ contributions. Similarly to common and reliable approaches in robotic that collect odometric data with local measurements of ultrasound, laser or infrared sensors to perform map matching, tracking of human movements using dead-reckoning is possible with wearable inertial sensors, like FootSLAM (Angemann & Robertson, 2012). However, the accumulation of measurement errors reduces accuracy of localization in a long-term tracking. To prevent the accumulated errors, several mixed systems combine human-tracking and Wi-Fi signals, e.g., ARLEL (Jiang et al., 2012) or magnetic fields, e.g., MaLoc (Winterhalter et al., 2015). Just as early systems, those combined methods require human labor for measuring signal strengths in buildings. In addition to various sensor fusion based methods, recently several indoor navigation systems employ human feedback for compensating the shortcomings or measurement errors of digital sensors. In RedPin (Bolliger 2008) users are allowed to input corresponding room names/numbers while collecting WiFi fingerprints. The Navatar system (Fallah et al., 2012) needs visually impaired users to explicitly confirm landmarks to compensate accumulated sensor errors.

Human beings are different to robots who can follow commands completely (e.g., walking, turning, and scanning) while positioning. The human factors (e.g., workload and willing) must to be considered while using an indoor navigation system. However, there were a few studies, like the Navatar system, which investigate work load when users were in the loop of indoor localization, in terms of mental and physical demands.

3 Tango Positioning System

To support the evaluation, we developed a lightweight indoor positioning system with a Tango tablet, namely Tango Positioning System (TPS). The limited range of the built-in ToF camera is ca. 4.5m. A 2D floor plan is required in advance for the TPS.

3.1 The Concept

The basic idea of TPS is to collect topological information of hallway intersections or their connections, which might contain intrinsic unique features for positioning. Figure 1 presents how to locate a user at an intersection on the basis of unique physical environmental features, captured by a 3D ToF camera.

If the TPS cannot locate a user after scanning an intersection, the user has to walk to a next intersection and hold the tablet for detecting the length of the path via motion tracking. Once a new intersection is scanned, the system generates a connected graph consisting of visited intersections and walking trajectory. Graph matching is performed to determine the user's location. To match a connected intersection graph, the topological information consists of individual intersection information, the number of intersections, and the length and angles of connected paths.

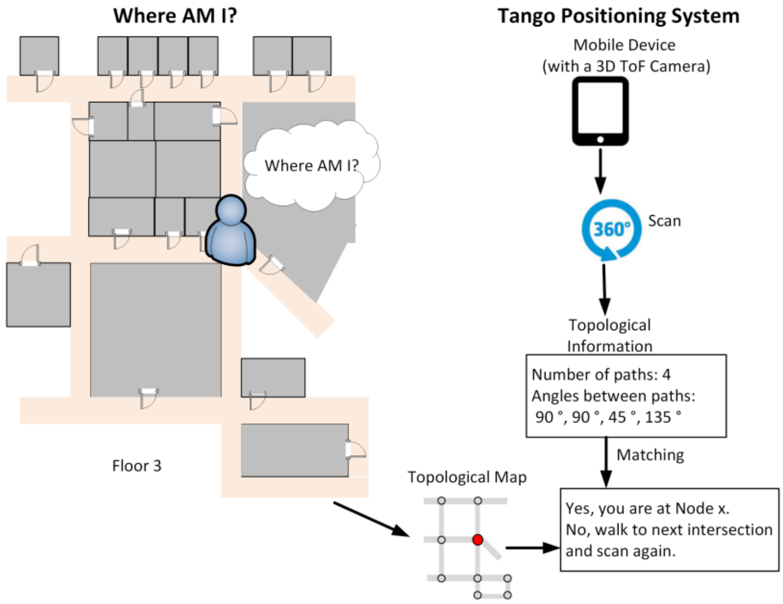

Figure 1. A user positioning himself via TPS at an intersection with unique physical features

3.2 The Software Modules

In order to locate users, TPS consists of 4 key software modules, which are listed below:

The 3D Intersection Feature Extractor Module acquires physical features of intersections by processing the 3D point cloud data captured by the ToF infrared cameraA fast K-NN based 3D point cloud clustering algorithm is used to segment walls (Klasing et al., 2008).

The Motion Tracking Module, creates and updates global 3D coordinates during scanning of intersections and walking trajectory. In the current version of TPS, we made use of Google's APIs to implement the motion tracking module via fusion of inertial measurements and motion tracking data.

The Matching Intersection Module matches unique intersections or a topological graph corresponding to intersections with a given floor map. This module consists of two matching algorithms. One algorithm identifies a unique intersection by analyzing its physical features (number of paths, angles, lengths between paths). Another algorithm identifies a graph representing visited intersections and their connections on a given topological map. To reduce impact of measurement errors (e.g., openings’ angles and distance of two intersections) while matching, a series of tolerance values has been set.

The User Interface Module allows users to interact with TPS and displays the final position (see Fig. 2), including 4 sub-windows which indicate the calculating part, the intersection scanning, the walking trajectory and the final result of the position.

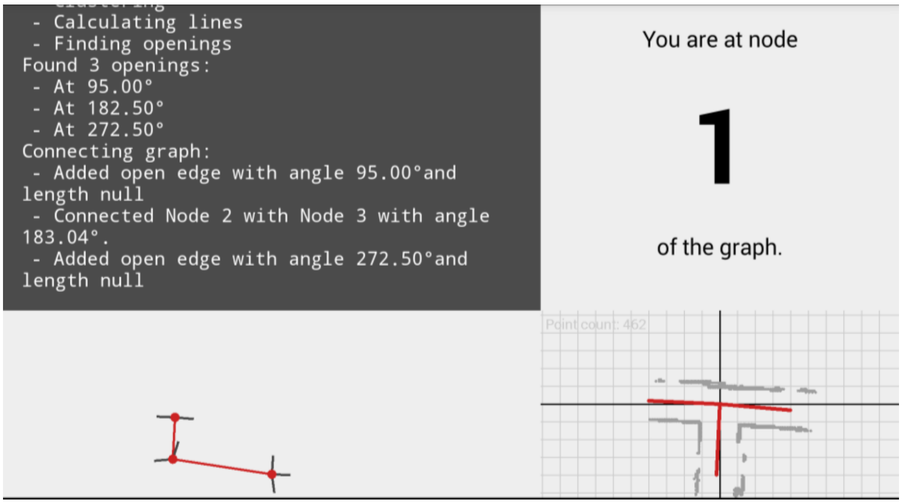

Figure 2. The basic user interface of TPS with 4 sub-sections

4 User Evaluation

4.1 Participants

Eighteen participants (8 females), 21 to 40 years old (M = 29.5, SD = 5.4), were recruited from within the university community. Nine of them had experience in using instant indoor positioning systems, such as Wi-Fi or beacon-based approaches.

4.2 Preparation

4.2.1 Creating a topological map for the tests

For our evaluation, we selected one floor of a modern university building (ca. 2380 m^2), consisting of two similar parts with 7 intersections in total (see Figure 3). We developed an in-house software to create topological maps (with an XML-based data structure) from imported indoor floor plans, and each intersection had a unique number. Intersection 5 (I5) is a unique intersection which consists of two openings.

Figure 3. The topological map of the floor for the evaluation

4.2.2 Experimental settings

To speed up the process of scanning intersections, TPS only keeps those parts of the point cloud whose y-value between -0.25 and 0.25. For clustering walls, it looks for 3 nearest neighbored points (K = 3) that in a radius of 0.2 meters, and minimum number of points in a cluster is 15. Openings are detected with a min. length of 2.5 meters and a min. width of 1.0 meters. To improve accuracy of our graph matching, angle tolerance is set to 30° and the tolerance of the intersections' distance is 10 meters.

4.3 Main Trials

4.3.1 Tasks and procedure

Each participant had to locate themselves in 3 trials, respectively. The 3 test routes consisted of 1 - 3 intersections (i.e., Route 1: I5; Route 2: from I6 to I3; Route 3: from I3 to I2, I1). After a training about how to make use of TPS, each participant was guided to the corresponding intersections for the 3 main trials. In each trial, they were asked to find out the unique number of the intersection where they were. In order to avoid an influencing effect by the 6 possible combinations of routes, orders of test routes were counterbalanced. When each trial was finished, a NASA Task Load Index (TLX) based questionnaire was conducted to assess workload on 7-point scales (1: strongly positive – 7: strongly negative).

4.3.2 Study design

In daily life, some people might have the indoor localization experience by using installed infrastructure, such as Wi-Fi hotspots or beacons, where users would locate themselves instantly and do not need to walk or be tracked. This study investigates whether and how they accept the concept of human-computer cooperative localization, by comparing with the participants who do not have such indoor localization experience. Therefore, we designed the study as following:

Between-subject Variables. There was one between-subject variable: user group. The factor of user group consists of 2 levels, where *Group 1* had instant indoor positioning experience and *Group 2* had none.

Within-subject Variables. The test routes were the independent within-subject variable. The route factor has 3 levels according to the number of intersections.

5 Results

5.1 Objective Measurements

Training Time: The average training time for Group 1 (with instant indoor positioning experience) was 396 seconds (SD: 98.9) and for Group 2 was 412 seconds (SD: 136.9). There was no significant main effect for the user group factor.

Success Rate: 3 participants failed to find out the correct number of the final intersection in Route 2, and 2 failures occurred in Route 3. Thus, the mean success rate was 100%, 83.3% and 88.9% in Route 1, Route 2 and Route 3, respectively.

Completion Time: Table 1 and Table 2 illustrate the completion time by the participants from Group 1 and Group 2, respectively. A mixed ANOVA showed that the route factor had a significant effect on the completion time (Wilks' $\lambda = .077$, $F(2, 11) = 65.56$, $p < .001$). A post hoc Tukey test showed that Route 3 (M: 154.4, SD: 12.2) required significantly more time than Route 1 (M: 28.8, SD: 12.2) and Route 2 (M: 124.9, SD: 13.4).

5.2 Subjective Feedback on Workload Assessments

With increasing number of visited intersections, the related workload increased for both groups regarding all 7 workload assessments (i.e., ease to use, mental demand, physical demand, temporal demand, performance, effort, and frustration), see Table 1 and Table 2. A mixed ANOVA showed no significant main effect of the group factor on the 6 workload assessments, but a significant main effect for the 6 workload assessments by the route factor (Ease of use: $\lambda = .495$, $F(2, 15) = 7.662$, $p = .005$; Mental: $\lambda = .537$, $F(2, 15) = 6.456$, $p = .009$; Physical: $\lambda = .28$, $F(2, 15) = 19.319$, $p < .001$; Temporal: $\lambda = .346$, $F(2, 15) = 14.207$, $p < .001$; Performance: $\lambda = .413$, $F(2, 15) = 10.65$, $p = .001$; Effort: $\lambda = .528$, $F(2, 15) = 6.696$, $p = .008$; Frustration: $\lambda = .401$, $F(2, 15) = 11.197$, $p = .001$). Furthermore, there was no significant main effect for the sum workload by the user group, but the route factor had a significant main effect (λ = .236, F (2, 15) = 24.302, p < .001). No interaction effects were significant.

	Time (s)	Ease of Use	Mental	Physical	Temporal	Perfor-mance	Effort	Frustration
Route1	26	2.22	1.67	1.89	1.89	1.56	1.78	1.22
Route2	139	3.11	2.22	3. 0	3.0	2.56	2.44	2.44
Route3	167	3.78	2.22	3.67	4.22	2.44	3.11	2.56

Table 1: Participants' completion time and workload assessments in Group 1

	Time (s)	Ease of Use	Mental	Physical	Temporal	Perfor-mance	Effort	Frustration
Route1	30	2.22	1.44	2.44	2.33	1.89	2.22	1.33
Route2	110	2.33	2	2.78	2.78	2.22	2.67	2
Route3	141	2.89	2.22	3.33	3	3	3.11	2.22

Table 2: Participants' completion time and workload assessments in Group 2

5.3 Post-questionnaire

Table 3 indicates both groups ranked the proposed method intuitive (Median of Group 1 = 6; Median of Group 2 = 5) and very understandable (Median of Group 1 = 7; Median of Group 2 = 6). They thought the cost of the proposed method was not high, in terms of time, physical and mental demand. In particular, the participants from Group 1 (Median = 4) who had instant indoor positioning experience were less interested in utilizing such a system in the future, than the participants from Group 2 (Median = 6). A Mann-Whitney U test showed that there was a significant main effect for future use by the group factor (U: 16.5, p = .029).

The participants from Group 1 (M: 2.22; SD: 0.83) and Group 2 (M: 2.56; SD: 1.01) had similar opinions on the maximum number of visited intersections. 30%, 30%, 20% and 20% of the participants would maximally visit 20 meters, 30 meters, 50 meters and 100 meters, respectively. 10 participants reported a perfect TPS-like system should only need to visit/scan one intersection, and 6 thought visiting 2 intersections sufficient. One participant would accept to visit 3 intersections. However, one participant would not visit one intersection at all, as he expects instant indoor positioning to work anywhere. Group 1 (M: 1.22; SD: 0.83) expected to visit less intersections in a perfect TPS-like system than Group 2 (M: 1. 56; SD: 0.53), though differences were not significant.

	Intuitive	**Understandable**	**Cost**	**Future Use**
G1	6	7	5	4
G2	5	6	5	6

Table 3. The participants' median ratings on Q8 – Q11 (1: strongly negative – 7: strongly positive)

Regarding to the advantages, most of them liked the system did not require any construction of infrastructure and expensive online calculation. They criticized they had to hold the tablet with both hands while walking.

5.4 Discussion and Limitations

For a human-computer cooperation based indoor localization system, it is necessary to reconsider balancing system capabilities and users' workload. It is labor- and cost-consuming to install and maintain infrastructures for sophisticated localization systems. In contrast to robotic indoor localization which requires high accuracy, users may use their capabilities to locate exact targets in many cases if a not accurate position is provided.

All participants highly agreed that TPS was very easy to understand after a short introduction practice. It was confirmed that TPS did not require high mental demands to utilize. However, with the increase of walking distance and the number of visited intersections, participants' work load increased as well, specifically in terms of the physical and temporal demand. Considering the participants reports, they would accept to maximally visit 2.39 intersections on average and 80% of them preferred to walk less than 50 meters. A TPS-like system, therefore, should localize users in one or two intersections.

Most of the participants suggested TPS would be useful in large office buildings or hospitals with many intersections, specifically in an environment with a bad light condition. All of them preferred to not rely on local infrastructure, and liked the concept that they would interact with the system while localizing. They had strong interest to use such a system in the future, and the participants with instant indoor localization experiences less than the ones who had not. Perhaps, it is promising to combine the two types of localization methods together in one system, and then users would use the human-computer cooperation localization in case the indoor localization infrastructure is not available. Besides, as our proposed method is based on the 2D floor plan (e.g., the connections of an intersection and the distance between them), for multiple floor buildings where the 2D floor plan of each floor would be similar, it is a challenge to use the proposed method to self-localization.

6 Conclusions & Future Work

In this paper, we investigate how much effort users would spend for a human-cooperation indoor localization system. To support this study, we develop an infrastructure-free indoor localization prototype which employs a handhold device with a built-in 3D ToF infrared camera and inertial sensors. Via 3D scanning and extracting physical features of intersections (e.g., the number of openings, their angles and distances), and mapping users' walking trajectory, the prototype would locate users at an intersection on a given 2D floor plan. Experiments with 18 participants indicated their workload increased with the increase of walking distance and the number of visited intersections, specifically for the physical and temporal demands. The participants reported they were willing to contribute for indoor positioning systems, for examples, they would maximally walk 50 meters, and visit two intersections.

The proposed system can be improved at several aspects. Firstly, it is important to detect more physical environmental features of intersections, in order to quickly locate a unique intersection. Besides, unique indoor facilities (e.g., pillar, stairs) would be cues for improving the localization speed. Though the Google Tango tablet is not available on the market, there are some similar RGB-D camera based wearable systems which can use the concept for indoor localization, like for blind indoor navigation (Zeng et al., 2017).

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