Navigating Indoors Using Decision Points

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Abstract. We present a novel user interface concept for indoor navigation which uses directional arrows and panorama images of decision points, such as turns, along the route. The interface supports the mental model of landmark-based navigation, can be used on- and offline, and is highly tolerant to localization inaccuracy.
We evaluated the system in a real-world user study where decision points proved to be as efficient for navigation as continuous route instructions and panorama updates. We gained valuable insights on the role of feedback and of the frequency of decision points with relation to user confidence and satisfaction. Based on our experiences, we summarize lessons learned that inspire and guide the further design of UIs for pedestrian navigation systems in indoor environments.

Keywords: Indoor Navigation, Visual Localization, Virtual Reality, Panorama, Decision Points, User Interfaces.

1 Introduction and Related Work

While location-based services are meanwhile standard applications outdoors, localization and navigation inside buildings is still a hot topic in research [1]. Usage scenarios include (but are not limited to) museum visits, shopping tours in a mall, or passenger support at the airport. As GPS reception is indoors often difficult or unavailable, and WLAN- or marker-based technologies require a costly infrastructure or augmentation of the building [2, 3], *vision-based localization* [4] is a promising technique that can work in any environment. Images captured with the mobile phone are compared to reference images (using feature matching) to determine the location and orientation of the device.

However, location estimates cannot always be perfectly accurate, since not all locations provide sufficient distinctive visual features for locating the user. In order to still provide reliable indoor navigation, the user interface (UI) of a system giving live route instructions needs to tackle the not always perfect accuracy of the underlying localization technique.

Navigation and location-based applications often use augmented reality (AR) interfaces (cf. e.g. [5], [6]), but AR overlays are sensitive to wrong orientation or localization estimates. Since landmarks can increase users' confidence and reduce their cognitive load [7], we compared AR for indoor navigation with a new panorama-based approach in earlier work [8]. The latter shows a 360° view of the current location, together with navigation instructions embedded in the image, whenever a new location estimate is available (usually every few meters). In a large-scale study, we compared the perceived guidance quality of those approaches depending on localization accuracy [9]. We simulated different types of inaccuracy (localization errors, orientation errors, or both combined) and showed that AR instructions are prone to be misoriented or misaligned with the real-world scene in case of wrong location or orientation estimates. By contrast, matching panorama photos with the real world allowed users to orient themselves also in case of significant localization errors. Overall, users perceived panoramas to be more reliable in practice, compared to AR. Yet, we also learned that updating panoramas every few meters is not optimal: if the shown locations were incorrect (in the low-accuracy case), users were easily irritated, and rapid changes of the interface were reported to have a disturbing effect.

To overcome these shortcomings, in this paper, we present the novel concept of decision-point-based navigation (DPBN), which is a further development of the previously presented panorama visualization [9]. DPBN is more robust to localization errors and allows navigating even in case of failures of the localization system. In the subsequent section, we explain the concept and implementation of DPBN and report on its experimental evaluation. We evaluated the system in a comparative real-world user study, where DPBN proved to be as efficient as the conventional panorama approach. We also investigated usage patterns and gathered subjective feedback using questionnaires. Based on the gained insights, we summarize lessons learned that inspire and guide the further design of UIs for vision-based navigation systems.

2 Decision-Point-Based Navigation

Instead of refreshing screen content as soon as a new location estimate is available, our new concept confines to panoramas of *decision points* [10]. We describe the path to the destination as a sequence of route segments, each of them having a length and an angle indicating the relation to the next segment. We call the nodes connecting route segments *decision points*, as these locations require an decisive action from the user, be it a turn or a waypoint choice. In that sense, they differ from the widely used concept of *landmarks*, as landmarks not necessarily occur only at decision points [11], and sometimes not even lie on the route. Furthermore, decision points are not necessarily prominent (like landmarks usually are), but simply provide a visual impression of the location. For each decision point, the route description contains a 360° panorama image shot at that position, and a superimposed navigation arrow illustrating the turn angle (see Fig. 1, left, for example views along a route). Our concept provides several

advantages compared to the conventional continuous panorama approach [10].
Error Tolerance. During localization, the panorama of the subsequent decision point is automatically loaded (see Fig. 1, right). Let d be the distance between two subsequent decision points (typically ranging between few meters and several dozens of meters in large buildings), the system works correctly when the localization uncertainty is below $d/2$, which makes it highly error-tolerant.
Robustness to Localization Failure. As the route instructions are downloaded to the device, the user can flick through a list of panoramas representing the route summary step by step, both online and offline (i.e., without active localization). This means that even when localization temporarily fails (e.g., because query images are not discriminative enough or no WLAN signal is available), users can navigate with help of the decision point instructions.
Mental Model Familiarity. The interface conforms to the familiar mental model of self-orientation and route instruction memorization (e.g. "turn right in the hall in front of the library, then walk straight ahead until the elevator and turn left just before..."). In particular, landmark-based orientation [12] is supported, as decision points are depicted as images.

2.1 Implementation

We implemented a mobile navigation application prototype in Android 2.3 (see a screenshot in the right of Fig. 1). 360° panorama images are created out of sets of six photos of each location that have previously been recorded with a panorama camera mounted on a mapping trolley. When using vision-based localization, a building has to be mapped for anyway, so obtaining those images is no supplementary effort. Images are projected on meshes that embody a sphere, surrounding the user's point of view. Alpha masks are added to each image to smooth the borders and to create continuous panoramas.

By an experimenter app, location information can be sent to the client app at the desired position of the route. Using this *Wizard of Oz* approach, navigation instructions on a predefined path can be replayed in a controlled way, enabling reproducible conditions in a study. This implementation simulates the final system, in which query images taken with the phone's camera would be sent to a server that performs image matching and returns a location estimate.

2.2 Interaction Concept

Users can look around in the virtual view by dragging panoramas left or right using the well-known drag gesture. On release, the panorama automatically resets to the centered position, indicating the walking direction. In manual mode, a swipe up or down shows the panorama of the next or previous decision point, so that users can browse the sequence of turn instructions to the destination.

We also added the possibility to retrieve the closest panorama to the current location (relocalization). Since vision-based relocalization would normally require taking a reference image, in our implementation this feature is triggered by raising the phone to eye height (detected by the accelerometer) [8].

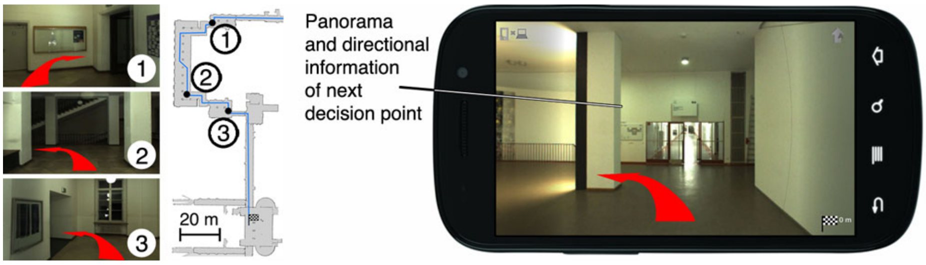


Fig. 1. A route description is represented by a sequence of panoramas (obtained from reference image data) at decision points and turn instructions. Left: Three examples of correspondences of decision point locations in a map and displayed panoramas. Right: Even if vision-based localization is inaccurate, the user interface can display the next decision point's panorama, which allows reliable landmark-based self-orientation.

3 Evaluation

The system was evaluated in a real-world study to investigate the following research questions (RQ).
RQ1. *Does DPBN have an effect on efficiency?*
Are users as fast as with continuous panoramas, or do they need more time to reach their destination when the interface only shows them decision points?
RQ2. *Is DPBN as convenient as continuous panoramas?*
Besides the quantitative comparison, we investigated which mode users prefer and how well they feel guided in either DPBN or the continuous mode.
RQ3. *What usage patterns can be identified?*
Beyond that, we were interested in observing usage patterns and strategies with panorama-based navigation. We therefore let subjects use the system in offline mode to see what we could learn for designing an ideal route description.

3.1 Design and Participants

The study had three conditions: continuous panoramas (in the following referred to as *Continuous*), automatic decision points (*DPBN-auto*) and manual decision points (*DPBN-manual*). *Continuous* denotes the mode in which panoramas of the current location with navigation instructions were updated every few meters. In *DPBN-auto*, only the panorama and navigation instruction of the respective next decision point were shown. In *DPBN-manual*, the panorama images and navigation instructions of *all* decision points were available to subjects in offline mode, and were not updated automatically. Instead, subjects could swipe back and forth between the decision point instructions manually.

Each participant ran through all conditions (within-subjects design). To avoid learning effects, for each of the three conditions, a different path inside our university main building was used. The three paths were 332, 220 and 316 meters long. The order of conditions was counterbalanced using a Latin square design. Consequently, all conditions were performed on each of the three paths the same number of times.

We recruited 12 participants not associated with our university and not familiar with the building the study took place in. Three subjects were female, nine male, the average age was 25. Subjects were rather experienced with smartphone usage (75%); one person had previously used indoor navigation.

3.2 Proceeding and Data Collection

Prior to the experiment, subjects were briefly introduced to the prototype and its modes of interaction. Subsequently, the experimental task was assigned, consisting of three navigation tasks to a destination which was not revealed in advance. Thereby, it was made sure that subjects had to rely solely on the navigation system. The experimenter walked closely behind the subject and sent the panorama images to the subject's device using the *Wizard of Oz* application. Depending on the condition, subjects got to view panoramas of their current location, updated every few meters (*Continuous*), or only of the next decision point (*DPBN-auto*). Location updates were also sent in *DBPN-manual* mode, but panoramas did not change automatically on the screen. This ground truth data was used to compare actual locations with the panoramas that subjects selected manually.

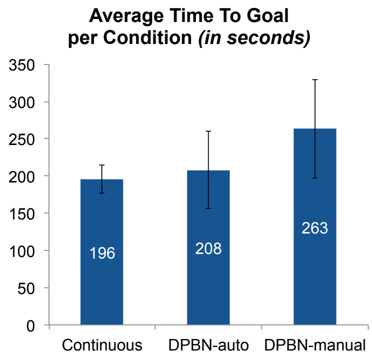
In all conditions, we measured the time until the destination was reached. In *DPBN-manual*, we logged all user interactions on the smartphone and recorded when a location update was received. By this, we were afterwards able to compare the decision point viewed by the user, as well as the 'correct' next decision point. This helped to the identification of 'strategies' when dealing with panoramas in manual mode. At the end of the experiment, we collected subjective data with a questionnaire.

3.3 Results and Discussion

RQ1. Subjects took on average 196 seconds (SD[3] = 19.1) to the destination in *Continuous*, 208 seconds (SD = 51.6) in *DPBN-auto* and 263 seconds (SD = 65.9) in *DPBN-manual*. Results are visualized in the left diagram in Fig. 2. Measurements in all conditions were normally distributed ($p \gg 0.05$ in a Kolmogorov-Smirnov test). A t-test showed no significant difference between *Continuous* and *DPBN-auto* ($p > 0.05$), but between all other conditions with $p < 0.005$. *DPBN-auto* is hence essentially as efficient as the *Continuous* mode. By contrast, subjects needed significantly more time in *DPBN-manual*.

RQ2. In questionnaires after the experiments, subjects gave qualitative feedback to five statements *S1* to *S5* (see the tables on the right of Fig. 2). Results are indicated on Likert scales ranging from 1 (strongly disagree) to 5 (strongly agree). Participants rated the *Continuous* mode more pleasing to use than both DPBN conditions (*S1*, 4.7 vs. 3.0). Likewise, they felt guided better to the destination (*S2*) in continuous mode (4.8) than in the DPBN (3.7 in automatic, 3.4 in manual

[3] We abbreviate standard deviations in the following with SD.



Statement	Condition	A	SD
S1: I found the method pleasing to use.	Continuous	4.7	0.5
	DPBN (auto)	3.0	1.0
	DPBN (manual)	3.0	1.0
S2: I felt guided well to the goal.	Continuous	4.8	0.5
	DPBN (auto)	3.7	1.0
	DPBN (manual)	3.4	0.8

Statement	A	SD
S3: Decision points are sufficient for orientation.	3.8	0.5
S4: The ability to relocalize myself is useful.	4.9	0.3
S5: Moving up the phone to relocalize is convenient.	4.5	0.5

Fig. 2. Left: average time per condition to reach the destination in the study using our navigation system prototype. The error bars indicate standard deviations. Right: Qualitative feedback on the system. The average agreement (A) to statements S1 to S5 is indicated on a 5-step Likert scale (1 = strongly disagree, 5 = strongly agree). SD indicates the standard deviation.

mode). While those results imply that subjects were less satisfied with DPBN, there is above-average agreement of 3.8 (SD = 0.5) that decision points are sufficient for orientation (*S3*). This is a hint that the DPBN principle essentially works (as confirmed by the results for RQ1), but has received less acceptance with subjects. In order to find out how acceptance could be further increased, we will take the observed user behavior in manual mode (RQ3) into account.

RQ3. The subjects' strategies we have identified can be summarized in two elementary behaviors. One group always displayed the decision point lying ahead, walked until the shown location was reached, and swiped then to the next decision point. These subjects almost never made use of the relocalization feature. The other group relocalized very frequently, sometimes only in (difficult) parts of the route, so that the effect was almost similar to the *Continuous* condition. The relocalization feature (*S4*) was in general considered extremely useful (4.9, SD = 0.3), and the mode of interaction to relocalize by moving up the phone (*S5*) was perceived as convenient (4.5, SD = 0.5).

A possible explanation for frequent relocalization is that subjects felt unconfident while walking without any confirmation until they reached the next decision point, so that they used the relocalization feature to request an intermediate 'control' point, checking if still on the right way. This hypothesis can also explain the low acceptance ratings of DPBN in *S1* and *S2*, compared to the *Continuous* mode. While in *DPBN-auto* on average only 10.3 locations were shown per path, 52.3 decision points were used on average in *Continuous*. In the *DPBN-manual* condition, subjects on average swiped 15.3 times to a new decision point and used 9.3 times the relocalization function. The latter numbers lie in between the extrema of the continuous mode and *DPBN-auto*, indicating that a compromise between the two could be a solution to increase acceptance of DPBN mode in general.

3.4 Lessons Learned

Based on our experimental results, we identified the following lessons learned and proposals for improving the current system.

- Subjects reached the destination with *DPBN-auto* as fast as with continuous panoramas (the time difference was not statistically significant). The panorama update frequency can thus be reduced without affecting performance. Yet, the system gains in reliability, since determining the next decision point requires a lower localization accuracy compared to permanent localization precise to the meter.
- Considering the sum of relocalizations and swipes in *DPBN-manual*, subjects averagely viewed less panoramas than in *Continuous*, indicating that such frequent updates are not necessary all the time. However, since they viewed more panoramas in *DPBN-manual* than in *DPBN-auto*, and frequently used the relocalization feature, subjects' confidence was apparently not high enough in *DPBN-auto*. A more frequent confirmation if still on the right path is required, e.g. by adding intermediate panoramas if the distance between decision points exceeds a certain threshold. Confirmations to stay on the route could in particular be helpful if the user has to follow a long hallway on which she has many options to turn off.
- To make it easier to detect whether a decision point is reached, a distance estimation until the currently displayed panorama could be shown. Already passed decision points could be marked so that users can see at a glance which part of the route has already been completed in the list of panoramas.
- When the user is walking fast, signifying she is sure about her way, DPBN could be used. As she slows down, e.g. in case of uncertainty (detected through the phone's accelerometer), the system could switch automatically into the continuous mode to give more hints for orientation.
- To simplify matching between the virtual and the real world, significant objects, such as fire extinguishers, showcases or signage, can be highlighted in the panorama. Those panoramas already exist as static images on the server, hence there are no time constraints for object detection.

4 Conclusion

We have presented a novel interface for vision-based indoor navigation using decision points (DPBN) which is very robust in case of localization inaccuracy. It even can guide the user if localization temporarily fails (manual mode). Decision-point-based guidance could also be interesting for non-vision-based localization techniques, such as beacon- or marker-based approaches where no continuous localization is available.

In a real-world study, we showed that DPBN is as efficient as continuous panorama-based navigation. However, more confirmative information is required to increase users' confidence and satisfaction. In future work, we will use our lessons learned to improve the prototype in the aforementioned directions and to identify appropriate candidates for further decision points. We will also compare our approach against a 2D map, which could provide a better overview of the total route than the list of decision points alone, and serve as alternative information source for guidance.

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