Pedestrian Navigation with Degraded GPS Signal: Investigating the Effects of Visualizing Position Uncertainty

Stefano Burigat
stefano.burigat@uniud.it

Luca Chittaro
luca.chittaro@uniud.it

HCI Lab
Department of Mathematics and Computer Science
University of Udine
Via delle Scienze 206, 33100, Udine, Italy

ABSTRACT
GPS-based pedestrian navigation can be difficult when GPS position readings are inaccurate or unavailable. In this paper, we report on a user study we carried out to investigate whether different visualizations of the uncertainty associated to user position can help users navigate outdoors when the GPS signal is degraded. In the study, we compared a basic visualization that displays only the last accurate position of the user during GPS signal degradation, and two visualizations that dynamically estimate the area where the user might be, displaying it respectively as a circle and as colored street segments. While we did not find any difference among the three visualizations in terms of the accuracy with which users assessed their position, we found that the "streets coloring" visualization required a significantly lower workload compared to the basic visualization and was perceived to be more beneficial by users.

Author Keywords
Mobile devices, visualization, navigation, uncertainty, field study, GPS

ACM Classification Keywords
H.5.2 Information Interfaces and Presentation: Evaluation, screen design, Graphical User Interfaces (GUI)

General Terms
Human Factors, Experimentation

INTRODUCTION
Nowadays, GPS-based navigation systems are commonly used to support people in their outdoor activities, helping them to determine their position in the environment and reach destinations of interest. Although GPS-based systems were initially meant for car navigation, the widespread integration of GPS receivers and applications such as Google Maps Mobile or Ovi Maps in a variety of mobile devices can benefit pedestrians.

However, properly supporting pedestrian navigation is more challenging than supporting car navigation. On-board car navigation systems typically use more sensitive GPS receivers and can exploit information provided by car sensors, such as instantaneous speed and steering angle, to predict position more accurately. Moreover, pedestrians often move in urban or dense foliage areas where the GPS signal is highly degraded or unavailable. In such cases, the accuracy of position estimation becomes a crucial issue. As a consequence of GPS signal degradation, users could become disoriented, need more cognitive resources to reconcile their actual position with the information provided by the navigation application or, worse, they can take inaccurate position indications literally, getting lost without realizing it. Crabtree et al. [7], for example, point out the major impact that limited coverage and accuracy had on the "Can You See Me Now?" game, where participants were chased through a 3D virtual model of a city by performers who had to use PDAs and GPS units to catch them. To partially mitigate navigation problems, some pedestrian navigation systems warn the user when the GPS signal reaches a significant level of degradation, typically through some message or other visual indication of the GPS status. Except for a marker of the last accurate position estimate, the user gets no navigation support for the entire duration of the degradation but is at least aware of the problem.

A more complex but effective approach to assist users in navigating an area when the GPS signal is degraded consists of exploiting additional or alternative sources of data to improve position accuracy. For example, over the years, researchers have investigated how to properly use sensors such as accelerometers, magnetometers and gyroscopes in combination with the GPS to get more accurate estimates of user position. The growing availability of these types of sensors in current mobile devices is making such a solution feasible to support pedestrian navigation, albeit current

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implementations have been shown to be sufficiently accurate only over short distances [9, 14]. WiFi and cell-based telecommunication technologies (e.g., GSM, UMTS) have also found application in navigation systems as a way to provide coarse estimates of user position in case of unavailability of accurate GPS data [22, 6].

In this paper, we explore the effectiveness and user acceptance of a different approach to support user navigation with degraded GPS signal. Rather than exploiting additional sources of positioning data, which require the availability of appropriate sensors or other technological infrastructure, we investigate whether it is possible to reduce user uncertainty about their position by visualizing an estimate of the area where the user might be located, thus making the position uncertainty explicit. The idea of displaying the position of an object tracked through GPS as an area that takes into consideration uncertainty has been scarcely studied. Applications such as Google Maps Mobile display the user position as a dot with a halo whose size is approximately proportional to the uncertainty associated to the position (which depends on the intrinsic measurement error of the positioning technology). However, when the next position reading is unavailable or position uncertainty varies significantly over a short period of time, due to highly degraded GPS data, the usefulness of the solution becomes questionable. To cope with this problem, we extended the idea of displaying uncertainty, designing two solutions that dynamically estimate where the user might be, even when there is no position reading. One solution displays the estimated area as a continuously expanding circle centered on the last accurately known GPS position. The other solution dynamically colors the streets where the user might be, starting from the last known GPS position to explore the street network. We integrated the two solutions in a prototype navigation system we developed to study pedestrian navigation and designed a field study to investigate their effectiveness compared to a basic visualization that shows only the last accurate GPS position. Our goal in the study was to understand if the proposed solutions could help users be more accurate in estimating their position and assess the cognitive demand they impose on the user.

The paper is organized as follows. Section 2 presents related work on pedestrian navigation, focusing on the issue of improving GPS data accuracy and displaying position uncertainty. Section 3 introduces the visualizations of position uncertainty and the pedestrian navigation system we developed to test them. In Sections 4, 5 and 6, we respectively describe the experimental evaluation we carried out, report about the results we obtained and discuss them. Finally, Section 6 contains concluding remarks.

RELATED WORK

In this section, we discuss solutions that have been proposed in the literature to improve the accuracy of position estimates by exploiting additional sensor data. We also present related work on the visualization of uncertainty for navigation assistance in pedestrian scenarios.

Improving accuracy through additional sensor data

In typical pedestrian scenarios, the negative effects of the various factors that affect the accuracy of GPS data are severe and lead to extremely low accuracy [19]. Most methods for improving accuracy rely on external information being integrated into the position calculation process. Some of these methods, such as Wide Area Augmentation System (WAAS), Differential GPS (DGPS), and Assisted GPS (AGPS), are based on transmitting additional information about sources of error (e.g., clock drift, ephemeris, or ionospheric delay), relying on the availability of additional infrastructure (e.g., ground stations, wireless cellular networks) and compatible receivers. The transmission of error correction information is an increasingly used solution to improve GPS accuracy but does not take into consideration the factors that most affect accuracy in pedestrian scenarios, such as multipath, satellite visibility and satellite geometry. Additional methods are thus needed to help pedestrians navigate in case of degraded GPS signal.

Another method to improve position accuracy is based on the use of Inertial Navigation Systems (INS), i.e. self-contained systems equipped with sensors such as accelerometers and gyroscopes to measure position, velocity and attitude information of moving objects. Despite their accurate short-term position estimates, INS cannot replace GPS as a navigation system because sensor errors lead to deteriorating accuracy over time [17]. Thus, GPS and INS are often paired together to overcome the problems associated with each system, using techniques such as Kalman filtering [18] or neural networks [20] to integrate the measurements. GPS long-term accuracy allows one to update both INS position and velocity estimates, preventing the long-term accumulation of errors, while the accurate short-term information provided by INS allows one to compensate for GPS limitations. It must be stressed that solutions to combine GPS and INS need both accelerometers and gyroscopes, which are not commonly available in a mobile phone. Moreover, GPS/INS integration requires computationally intensive algorithms that are unsuitable for devices with limited computational resources.

WiFi and cell-based telecommunications technologies can also be used to improve positioning when GPS data is unreliable. WiFi location was first experimented indoor in the RADAR project [1]. The Place Lab project [15] showed how outdoor WiFi location, based on listening for the cell IDs of radio beacons and referencing the beacons positions in a cached database, can reach median accuracies ranging between 15 and 60 meters. However, outdoor WiFi coverage is nowhere nearly as widespread as GPS coverage and often depends on the availability of multiple independent networks that are not guaranteed to be continuously operating. Varshavsky and colleagues [22] show that a localization solution based on GSM technology is a sufficient and attractive option for a wide range of location-aware applications, achieving median localization accuracies of 5 and 75 meters for indoor and outdoor environments, respectively. However, GSM-based solutions need calibration data about the geographic area where they will be used and depend on the availability of cell and channel information (e.g., signal strength) that network operators are not always willing to make public.

Pedestrian navigation and uncertainty visualization

Over the past few years, much research has been carried out to investigate how to best support pedestrian navigation by appropriate visualizations of navigation information to the user. A significant amount of this research has focused on issues related to the display of navigation information (e.g., maps) on the small screen of devices [4], on the development of mobile guides to provide users in the field with context-aware information and services [2] and on the presentation of route planning information and directions for wayfinding [13]. However, most of this work does not take into consideration the uncertainty associated to positioning information, unrealistically assuming such information to be always accurate. A very limited effort has been devoted to study solutions to provide users with visual information about the uncertainty intrinsically associated to position readings. This is consistent with the general lack of attention for the visualization of uncertainty in other domains [21]. Lodha et al. [16] proposed to draw positions of moving entities as filled circles that gradually fade away as the probability that the tracked object is away from the observed position decreases. Over time, a brush-stroke-like tube is thus generated to display the region of uncertainty. Baus et al. [3] studied how to perform map adaptation for pedestrian navigation according to user's walking speed and accuracy of positional information. They encoded the precision of positional information in the size of the dot which represents user's current position on the map. A less accurate positional information results in a bigger dot. To the best of our knowledge, only one study by Dearman et al. [8] explored whether making uncertainty visually explicit could be actually helpful in allowing users to assess their position more accurately. The study involved a client-side, beacon-based GSM location system and found that visualizing uncertainty as a ring centered on the predicted position of points of interest had a beneficial effect on users during a search task in a geographic area, especially when the ring size displayed a dynamic estimate of the distance between the actual position and the predicted position of the user and the target.

A PEDESTRIAN NAVIGATION SYSTEM WITH POSITION UNCERTAINTY VISUALIZATION

To more easily investigate navigation support in pedestrian scenarios, we designed and developed a GPS-based navigation system for mobile devices that uses a modular architecture. The architecture makes it easy to update, add and switch-off modules according to our needs. In its current form, the system consists of 3 main modules. The *GPS data filter* operates on the raw data supplied by the GPS receiver and outputs an estimated user position together with an uncertainty value associated to such position (the higher the uncertainty, the lower the position accuracy). Through this module, we were also able to manually manipulate the uncertainty values to make them arbitrarily high when we wanted to simulate degraded GPS signal during the study. The *dynamics simulator* is responsible for computing the area where the user might be when the uncertainty value provided by the GPS data filter is high (i.e., the GPS signal is degraded or unavailable). The *interface manager* manages the user interface and displays navigation information.

Dynamics simulator

The dynamics simulator contains the logic to make position uncertainty explicit in case of degraded GPS signal, thus making it possible to generate the visualizations we considered in the study. The module activates when the GPS signal is degraded, receiving the last known accurate position of the user from the GPS data filter. It can operate in three different ways. In *basic mode*, it simply outputs the position it received from the GPS data filter for the whole duration of the degradation.

In *street mode*, the dynamics simulator exploits street network information about the area in which the user is moving. Figures 1a-c show an example of how this mode works. If a user starts at position P at time 0 (Fig. 1a), she can move towards node A or node B with equal probability. Knowing her average speed (which we derive from the sequence of position estimates provided by the GPS data filter), the simulator can predict that at time t_1 the user should be in the area highlighted in Fig. 1b. At time t_2, the area will be larger, as shown in Fig. 1c. Note that we assume an equal probability for the user to take any of the segments at node B. In practice, the dynamics simulator employs a timed Breadth First Search (BFS) algorithm to explore a street network, using segment length and user's average speed to determine which streets (or portion of streets) the

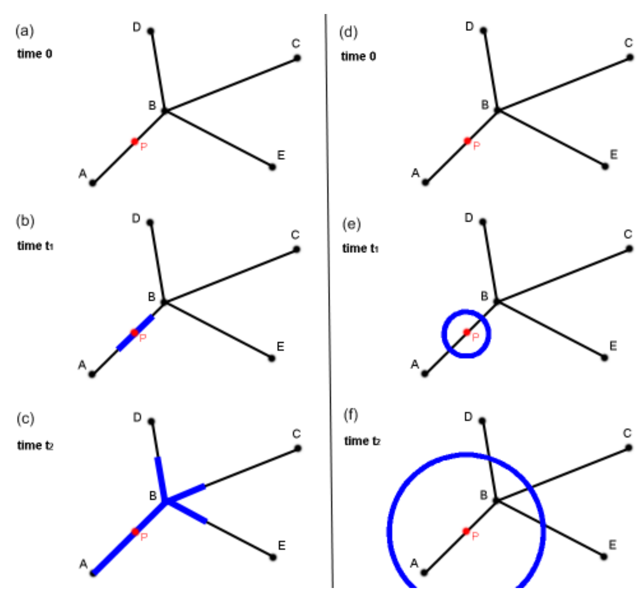

Figure 1. (a-c) Example of area prediction in street mode: starting from position P at time 0, the simulator predicts the street segments along which the user might be. (d-f) Example of area prediction in circle mode: starting from position P at time 0, the simulator predicts the circular area where the user might be.

user might be walking on.

In *circle mode*, the dynamics simulator computes the circular area where the user might be around the position P received from the GPS data filter. In particular, we assume that a user, whose last position was P, could have subsequently moved in any direction over $360°$. To determine the radius of the circular area, we multiply the average speed of the user by the time elapsed since the degradation started. Figure 1d-f shows an example of this mode.

Interface manager

The interface manager displays the user interface and manages interaction with the user. Figure 2 shows the interface when the GPS signal is not degraded. At the bottom, a row of buttons allows access to various system features and a text message informs users about the status of the GPS. The upper portion of the screen is devoted to the map of the area the user is currently navigating. On the map, a blue dot surrounded by an animated ring shows users their actual position in the area. While navigating, the map automatically scrolls to keep user position at the center. Predefined paths can be displayed in light red on the map, as shown in the figure.

Figure 2. A screenshot of the interface of the pedestrian navigation system used in the evaluation during normal operation. The blue dot highlights the current user position.

In case of degraded GPS signal, the interface manager uses the information provided by the dynamics simulator to display three possible visualizations of user position, one for each of the operating modes of the dynamics simulator. When the simulator is in basic mode, the animated blue dot is replaced by a static grey dot whose position does not change for the whole duration of the degradation (*basic visualization*). With this visualization, users always see the same information during GPS signal degradation (Fig. 3a-b). When the dynamics simulator is in street mode, the interface manager highlights with transparent color the streets (or portion of streets) the user might be walking on (*street coloring visualization*), starting from the last accurate user position. As Fig. 3c and 3d illustrate, the highlighted area includes more and more streets as time passes and users see a progressive coloring of the streets over time. When the

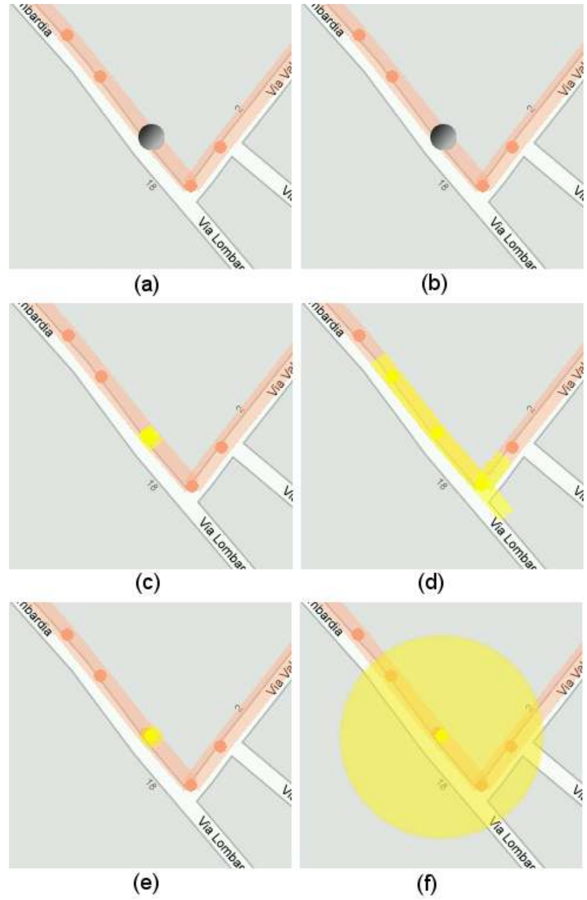

Figure 3. (to be seen in color) (a-b) Basic visualization; (c-d) street coloring visualization; (e-f) circle visualization.

dynamics simulator is in circle mode, the interface manager displays a transparent circle centered on the last accurate user position and the circle size grows over time (*circle visualization*). Figures 3e and 3f show this visualization using the same data used in Fig. 3c and 3d. Note that circle visualization is similar in appearance but actually differs from the ring visualization proposed in [8]. Our implementation does not make use of the measurement error of each position estimate to compute the size of each circle, exploiting instead knowledge of the motion of each user (in particular the average speed) to predict the area where the user might be. It is thus possible to employ our solution even when no position readings are available, in which case the error of a position estimate would be undefined.

EXPERIMENTAL EVALUATION

To evaluate the visualizations of position uncertainty, we carried out an experiment in which users navigated outdoors with the support of the system, following predefined paths displayed on the screen. In predefined sections of the path, we simulated a high degradation of the GPS signal, activating one of the considered visualizations. In these areas, users were required to continue following the path. We used accelerometer data to make the work of the dynamics simulator smarter in the areas where the

GPS signal was degraded, by automatically stopping the dynamics simulator when the user stopped moving and resuming it when the user started walking again. This makes the computation of user position more accurate. After a set distance from the point where the degradation started, users were required by the system to indicate where they thought to be on the map using the stylus. Figure 3 shows an example of what users could see at the beginning of the degradation and at the instant they were asked about their position with the three visualizations. After pinpointing their position, users could resume their walk.

Figure 4. The three paths we used in the study.

The evaluation has been carried out in a residential district which had low traffic conditions and sidewalks on all its streets to walk safely. The district was large enough to let us identify the three non-intersecting paths we needed. The paths, shown in Fig. 4, were approximately 350 meters long and had the same complexity in terms of number of turns and number and complexity of junctions. We monitored the paths over a one week period before the start of the study to guarantee that there were no GPS problems along them. Along each path, we identified 3 circular areas in which to simulate GPS signal degradation with the system. Each area was 70 meters in diameter. We took care to identify areas of similar complexity across the three paths: one area along a straight stretch, one area in proximity of a T-shaped junction and one area in proximity of a 4-way junction. Each path contained the three areas in a different order to avoid learning effects during the tests. Figure 5 shows examples of the three types of areas.

Participants

Eighteen users, 13 male and 5 female, were recruited to take part in the study. We discarded the data we collected for two of the male users because we detected serious GPS reception problems that could have affected user performance during the evaluation. The age of the remaining 16 users ranged from 20 to 40, averaging at 26. Ten users were Computer Science students while the other 6 were members of the Mathematics and Computer Science department unfamiliar with this research. Table 1 shows users' average degree of familiarity with mobile devices, maps and navigation systems. Higher values correspond to higher familiarity. The data reveals that participants to our study were typically highly familiar with mobile devices and desktop digital mapping applications (e.g., Google Maps) while being relatively less familiar with the use of pedestrian navigation systems and digital mapping applications on mobile devices.

Mobile devices	M = 5.31, SD = 1.96
Mobile devices with touchscreen	M = 4.69, SD = 2.06
Paper maps	M = 4.25, SD = 1.61
Desktop digital maps	M = 5.56, SD = 1.46
Mobile digital maps	M = 4.13, SD = 2.13
Car navigation systems	M = 4.81, SD = 2.29
Pedestrian navigation systems	M = 4.00, SD = 2.22

Table 1. Participants average degree of familiarity with mobile devices, maps and navigation systems. Values could range from 1 (low familiarity) to 7 (high familiarity).

Materials

The study was carried out on an Asus P535 Windows Mobile phone with integrated GPS, and augmented with an accelerometer. The touchscreen was 2.8-inch in size and had a resolution of 240x320 pixels. The portion of the screen devoted to display the map was 240x226 pixels and showed an area of approximately 100x100 meters. Users had to interact with the screen using the phone stylus rather than their fingers to guarantee that they could accurately point out their position on the map when required during the test. Power saving features were disabled to provide maximum performance and keep the screen lit during the whole test.

We prepared several questionnaires that were administered to users in different phases of the study:

- A *demographic* questionnaire was used to collect data about users (age, sex, occupation) and their familiarity with mobile devices, maps and navigation systems. Familiarity was measured on a 7-levels Likert scale were 1 corresponded to low familiarity and 7 to high familiarity.
- The *Santa Barbara Sense of Direction Scale* [12] was used to measure the spatial ability of users. The questionnaire consists of 15 self-referential statements about some aspect of environmental spatial cognition. Users could indicate their level of agreement with each statement on a 7-levels scale ranging from 1 ("strongly agree") to 7 ("strongly disagree"). Approximately half of the items were stated positively (e.g., "I'm very good at reading maps") and half negatively (e.g., "I have trouble understanding directions"). In scoring, positively stated items were reversed so that a higher score indicates better spatial abilities. Sums of the 15 items were used for the analysis.
- A *perceived accuracy* questionnaire was administered to users by the system at the end of each phase in which they were required to indicate their position on the map. The questionnaire consisted of a single item that measured on a 7-levels scale how much users thought to have been accurate in estimating their position. The scale ranged from 1 ("not much accurate") to 7 ("very accurate").

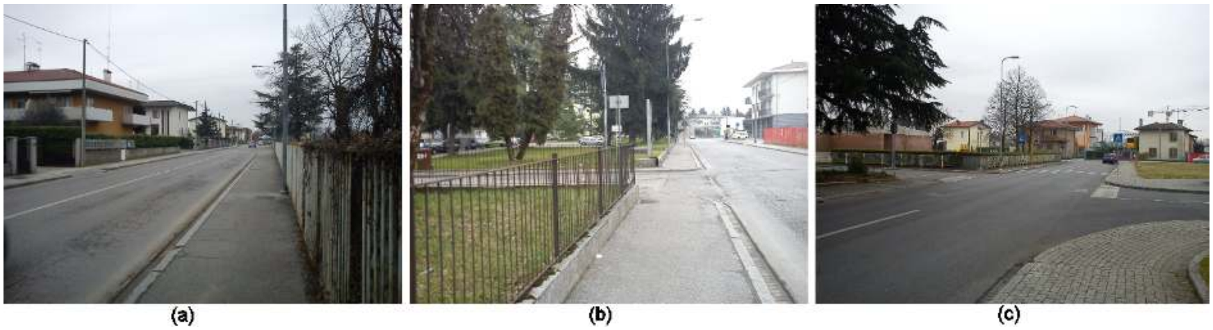

Figure 5. Example of the three types of areas where users got degraded GPS signal: (a) straight stretch, (b) T-shape junction, (c) 4-way junction.

- A *perceived usefulness* questionnaire was administered at the end of each path and was used to measure how much the considered visualization of uncertainty, the background map, and the highlighted path were useful in helping users to assess their position. The three items were phrased as statements (e.g., “The background map has been useful in assessing my position”) and users could indicate their level of agreement with each statement on a 7-levels scale ranging from 1 (“strongly agree”) to 7 (“strongly disagree”).

- The *NASA Task Load Index (TLX)* [11] was used to measure subjective mental workload experienced by users to assess their position and point it out on the map. NASA-TLX is a subjective workload assessment technique that derives an overall score based on a weighted average of ratings on six subscales: mental demand, physical demand, temporal demand, performance, effort, and frustration level. We administered to users a computerized version of the NASA-TLX (installed on the device) at the end of each path [5]. Scores could range in the 1-100 interval.

- After users completed all three test paths, they were asked to order the three visualizations they had used according to their preference in a *preference* questionnaire. Draws were allowed.

Design and procedure

According to a within-groups design, each subject was asked to follow three paths, one for each of the visualization conditions. We used a Latin square design to guarantee that the order of execution of the three paths and the order of the three conditions changed independently for each subject in such a way that:

- Every condition was presented an approximately equal number of times as a first, second, and third condition.

- Every path was covered an approximately equal number of times as a first, second, and third path.

- There was no fixed association between a specific path and a specific condition. This was meant to counterbalance the effects of a possibly higher navigational difficulty of a path over the others.

Subjects initially filled the demographic questionnaire and the Santa Barbara Sense of Direction Scale in a room inside a building. They were then informed about the task they had to carry out. The experimenter described the three visualizations, first on paper and then by means of a demo on the device using simulated GPS data. Users were then led outdoors in the area of the test and went through a training session lasting about 15-20 minutes in which they walked along three short paths, one for each of the three considered visualizations. All three paths contained two areas where we simulated unavailability of the GPS signal. During training, users could ask questions to the experimenter to clarify possible doubts.

Users then followed the three test paths, carrying out the required task. At the beginning of each test path, the experimenter waited until GPS position readings were sufficiently accurate and then gave the device to the user, who had to tap on a ”Start” button to begin. Along each path, the navigation system monitored the user’s position and activated one of the three visualizations in the predefined areas, simulating degradation of the GPS signal. After users walked for about 35 meters (measured through the GPS) in one of the areas with degraded GPS signal, the system warned the user by means of vibration and a sound, froze the visualization and required her to assess her position and indicate it on the displayed map. Users could use the information displayed on the screen as well as look around to orient themselves. After having pinpointed their position, users were presented by the system with the perceived accuracy question. After the questionnaire, the navigation system reverted to normal operation, showing user position based on actual GPS data and users could resume walking along the path. The experimenter discreetly followed and observed subjects, walking a few meters behind them to avoid influencing their navigation and marking on a detailed paper map of the area their exact position when they stopped to assess their position. At the end of the path, the experimenter administered the perceived usefulness questionnaire and the NASA-TLX. Users were then led to the subsequent path. The preference questionnaire was finally administered after subjects had completed the three paths. On average, the time needed to complete the evaluation for each subject was around an hour and 20 minutes.

We collected the following additional data during the test through automatic logging code:

- Complete GPS data for all paths, in NMEA format. This data was used to replay all paths offline to check for possible problems that could have not been clearly noticeable during the tests. For example, this allowed us to find out that GPS position estimates had been significantly inaccurate during part of a path in two of the tests. Since GPS data was used internally by the system to compute critical information (such as walked distance in the areas with degraded GPS signal), we discarded all the data of the two affected subjects, as previously mentioned.
- The map coordinates of the points tapped by users when they were required to assess their position in the areas with degraded GPS signal. These points were compared with the exact positions that were recorded by the experimenter on paper when following users along paths. The difference between the two points defines the user's accuracy error in position assessment.
- The time users took to pinpoint their position on the on-screen map when asked by the navigation system.

RESULTS

In this section, we report the results of the analysis of the following dependent variables: user's accuracy error in position assessment, time needed by users to pinpoint their position, user's perceived accuracy of their position assessments, perceived usefulness of the displayed data during position assessment, mental workload, subjective preference. We also analyzed possible correlations between accuracy error, user's spatial ability and speed difference.

Accuracy error

Figure 6 shows the mean accuracy error for the three visualizations we considered. The data was subjected to the Shapiro-Wilk test of normality prior to further analysis. The test did not reveal deviations from the normal distribution. A one-way repeated measures analysis of variance (ANOVA) was thus employed on the data. The within-subjects factor was the type of visualization with three levels: basic visualization (BAS in tables), circle visualization (CIR in tables), and street coloring visualization (STR in tables). The ANOVA did not reveal any significant effect ($F(2, 45) = 2.004, p = 0.15$).

Position assessment time

Figure 7 shows the mean time users took to assess and pinpoint their position. The Shapiro-Wilk test of normality did not reveal deviations from the normal distribution and the subsequent ANOVA did not reveal any significant effect (($F(2, 45) = 0.04, p = 0.96$)).

Perceived accuracy

We employed Friedman's test to analyze user's perceived accuracy of their position assessments. Means are shown in Fig. 8. The analysis did not reveal a significant effect ($T = 3.97, p = 0.14$).

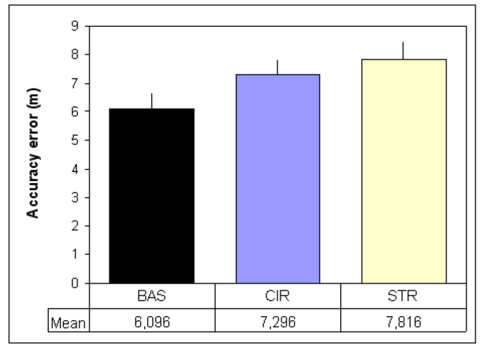

Figure 6. Mean accuracy error (with standard error bars) for the three visualizations.

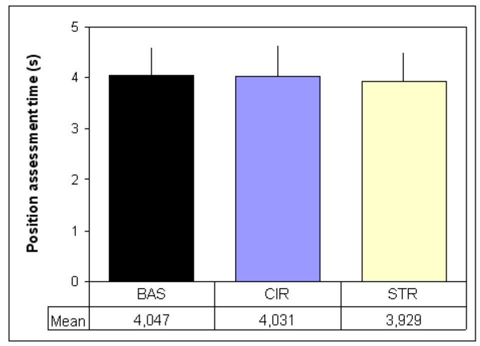

Figure 7. Mean position assessment time (with standard error bars) for the three visualizations.

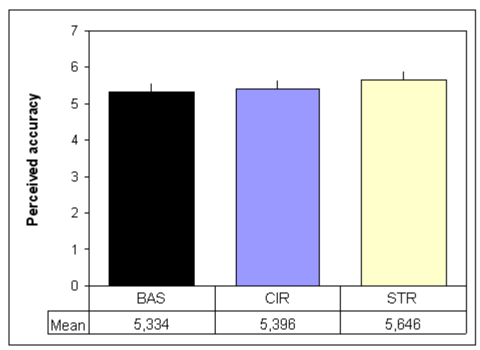

Figure 8. Mean perceived accuracy (with standard error bars) for the three visualizations.

Perceived usefulness of displayed data

Friedman's test was used to analyze the data on perceived usefulness of the considered visualization, the background map, and the highlighted path (Fig. 9). The analysis pointed out a statistically significant difference in perceived usefulness among the three visualizations ($T = 16.1, p < 0.001$). Dunn's Multiple Comparison post-hoc test was then used to compare pairs of means and revealed that the street coloring visualization was perceived to be more useful than the basic visualization ($p < 0.05$).

We also found a significant effect when comparing perceived usefulness of the basic visualization with that of the

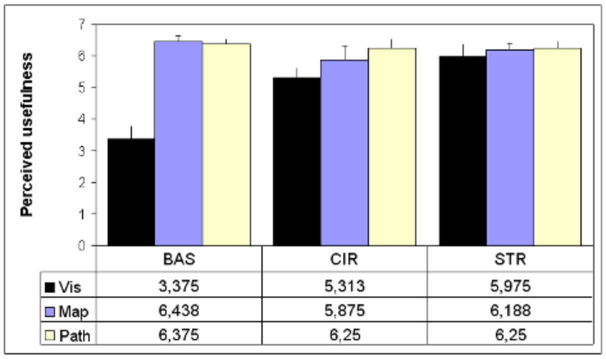

Figure 9. Mean perceived usefulness of the visualizations, background map, and highlighted path (with standard error bars), grouped by visualization.

background map and of the highlighted path ($T = 19.9, p < 0.001$). Dunn's post-hoc test revealed that users found the basic visualization to be less useful than the background map ($p < 0.05$) and the highlighted path ($p < 0.05$).

Subjective mental workload

Figure 10 shows means of the subjective mental workload we measured with the NASA-TLX. We report means of both the overall score and of the six individual subscale ratings: mental demand (MD), physical demand (PD), temporal demand (TD), performance (PE), effort (EF), and frustration level (FL). A one-way ANOVA on the overall scores pointed out a significant effect ($F(2, 45) = 4.28, p < 0.05$). Tukey's post-hoc test revealed a statistically significant difference in overall workload between basic visualization and street coloring visualization ($q = 4.1, p < 0.05$), with the first requiring a higher workload. ANOVA on subscale ratings pointed out a significant effect for mental demand ($F(2, 45) = 6.37, p < 0.005$) and effort ($F(2, 45) = 8.37, p < 0.005$). Tukey's test revealed that the street coloring visualization required a lower mental demand compared to the basic visualization ($q = 5.02, p < 0.05$) and that both circle ($q = 4.74, p < 0.05$) and street coloring ($q = 5.24, p < 0.05$) visualizations required a lower effort compared to the basic visualization.

Subjective preference

The analysis of subjective preference data (means are shown in Fig. 11) was carried out with Friedman's test and pointed out a statistically significant effect ($T = 10.07, p < 0.01$). Dunn's post-hoc test revealed a statistically significant difference in preference between the street coloring visualization and the basic visualization ($p < 0.05$) with users preferring the former to the latter.

Correlations

Using Pearson's test, we found a strong negative correlation between accuracy error and user's spatial ability for the basic visualization ($r = -0.54, p < 0.05$). The spatial ability score ranged from 40 to 87 on a possible 15-105 scale ($M = 62.56, s.d. = 13.83$). We did not find significant correlations between accuracy error and position assessment time.

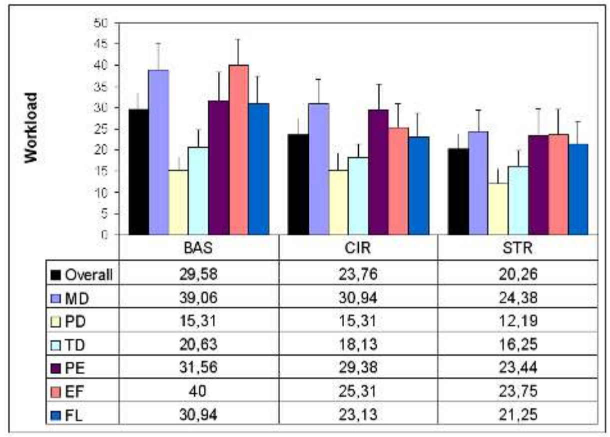

Figure 10. Mean overall and subscale workload ratings (with standard error bars) for the three visualizations.

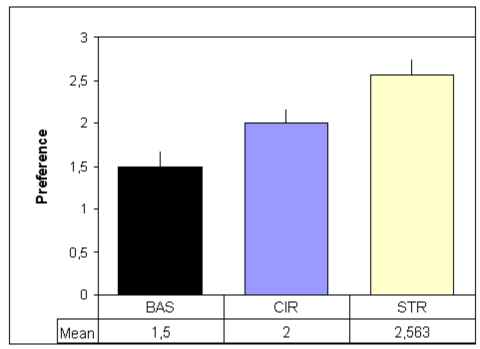

Figure 11. Mean preference (with standard error bars) for the three visualizations.

DISCUSSION

Overall, we found significant results for the different users' subjective measures while the analysis of performance data did not highlight significant differences. Users found the visualizations of uncertainty, in particular the street coloring visualization, much more useful and much less complex than the basic visualization, even if their performance did not seem to be positively affected.

Results concerning perceived usefulness reveal that users perceived the streets coloring visualization to be significantly more helpful than the basic visualization. Users trusted the visualization and thought it was as essential as background map and path highlighting to help them assess their position. When using the basic visualization, users relied instead almost exclusively on the map and the path, probably using the dot which points out out their last accurate GPS position as a reference to quickly determine which was the part of the map they needed to match with the physical environment. The difference in perceived usefulness between circle visualization and basic visualization was large but unfortunately did not reach significance. The slightly lower score for circle visualization compared to street coloring visualization was probably due to the fact that the former seems to cover a bigger area on the screen and requires more mental effort to identify the network of streets within it.

NASA-TLX data provided interesting insights. The basic visualization scored worst in most ratings and differences reached significance compared to the street coloring visualization for overall score, mental demand and effort. Large differences were also found between basic and circle visualization, even if they reached significance only for the effort subscale. These results show that users found the task of assessing their position particularly demanding and complex with the basic visualization. In that condition, users were basically forced to rely on their spatial ability to try to match what they saw on the map with the physical environment. Indeed, users with high spatial ability were able to be more accurate than users with low spatial ability, as highlighted by the negative correlation we found between user's spatial ability and accuracy error. The higher amount of cognitive resources users need to spend to accomplish their level of performance with the basic visualization has important implications: if users need more resources to use the visualization, they can devote less resources to other activities such as monitoring the environment around them. Awareness of surrounding events and environment could thus be lower, which might have negative consequences for the user. The other two visualizations required instead less cognitive resources, probably because they clearly highlighted the area on which users could focus their attention to determine their position.

Given the results we found for perceived usefulness and NASA-TLX, user preference for the street coloring visualization over the basic visualization is not surprising and provides further evidence that this solution was better received than the others.

Unlike subjective data, performance data did not provide evidence of differences among the three visualizations. The average accuracy error was about 18% of the walked distance under degraded GPS signal for the basic visualization, 21% for the circle visualization and 24% for the streets coloring visualization but the differences were not statistically significant. Interestingly, user's spatial ability had a significant influence on accuracy error in the basic visualization condition, as highlighted by the negative correlation between the two measures (users with high spatial ability were more accurate than users with low spatial ability), but no significant correlation was found for the other two visualizations, which might mean that uncertainty visualization makes spatial ability less important in position assessment. Analysis of position assessment times did not provide useful insights: no significant differences were found among the three conditions. From a purely performance-oriented point of view, we have thus no evidence that the circle and street coloring visualizations help users to be more accurate in the assessment of their position compared to having no uncertainty visualization. There might be several possible reasons for such a result: (i) users might not have trusted the two visualizations and assessed their position without using them; (ii) users might have trusted the visualizations but were not able to appropriately employ them; (iii) users might have spent more effort in assessing their position when using the basic visualization, thus counterbalancing the possible positive effect of the other two visualizations. Subjective data on perceived usefulness weakens hypothesis (i) above, at least for the street coloring visualization. NASA-TLX data seems to substantiate hypothesis (iii). It should be also noted that the time needed to carry out a task does not automatically increase in a significant way when users spend more effort in doing it. Thus, the lack of an increase in the mean position assessment time in the basic visualization condition cannot be used to disprove hypothesis (iii). With respect to hypothesis (ii), we have instead not enough data to comment on its strength.

CONCLUSIONS

The study we presented in this paper investigated the effects of visualizing the uncertainty associated to user position to support pedestrian navigation when the GPS signal is degraded. Overall, we found that making users visually aware of the uncertainty, displaying the area where users might be, either as a dynamic circle or by coloring streets, does not seem to provide advantages in terms of performance metrics (the accuracy with which users can assess their position and the time they need to assess it). However, users perceived that the visualization of uncertainty provided benefits. In particular, the streets coloring visualization required a significantly lower workload compared to a basic visualization that only shows the last accurate position of the user for the entire duration of GPS signal degradation. Moreover, it was perceived to be more useful and was clearly preferred by users. The integration of the streets coloring visualization in pedestrian navigation systems might thus be useful. The circle visualization could be instead useful in special conditions such as rural environments without roads and provides similar benefits in terms of mental workload.

Several open questions demand further investigation. For example, we measured performance only in terms of error in position estimation after relatively short distances with degraded GPS signal. Apart from the occasional turn, users did not have complex strategic decisions to take. More complex paths and bigger areas with degraded GPS signal would be needed to investigate performance at the strategic level. Another open question concerns the effect of the background map. In our study, we used the classic abstract maps provided by Google Maps. However, satellite maps are also commonly available and can provide a higher level of detail on a given area. Such detail could be helpful in better supporting user position assessment. On the other hand, it should be noted that past studies found abstract maps to be more effective than aerial photographs in route-following tasks in a geographic area [10]. Satellite maps are also updated less frequently compared to abstract maps, and using an outdated map can cause confusion and errors in navigating an area. For example, the satellite map (available on Google Earth) of the area where we carried out the study missed some roads and buildings that were built in recent years. In the future, we plan to investigate these open issues to continue our exploration of uncertainty visualization.

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