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ORIGINAL ARTICLE

Bearing-based selection in mobile spatial interaction

Steven Strachan · Roderick Murray-Smith

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Abstract We introduce a mobile spatial interactive application that uses a combination of a GPS, inertial sensing, gestural interaction, probabilistic models and Monte Carlo sampling, with vibration and audio feedback. This system allows the probing or querying of targets in a local area, based on a model of the local environment and specific context variables of interest, to enable a rich, embodied and location–aware spatial interaction. An experiment was conducted to investigate how spatial target selection at different distances, target separations and target widths is affected by a system with added 'typical' noise characteristics. Results showed that the successful selection of targets in the virtual environment is maximised with a combination of high angular separation and angular width.

Keywords GPS Navigation · Uncertainty · Monte Carlo · Feedback · Audio · Tracking · Probabilistic display · Context · Selection

1 Introduction

Mobile spatial interaction is an emerging field prompted by the growth of increasingly powerful and multi-functional mobile devices. The provision of context or location-aware information while 'on the move' has become increasingly relevant in recent years. This information has traditionally been delivered in a static, visual way via tools such as *Yahoo! Local* or *Google Maps*. The ability to interact with this data in a rich and natural manner is now possible and with the incorporation of inertial sensing into mass market devices a wealth of opportunity has emerged for the development of applications with a dynamic, intuitive, natural, flowing and embodied style of interaction. Methods of interaction with the mobile internet are currently limited to traditional screen and button-based techniques. These techniques are visually demanding, time consuming, not contextually sensitive and can become hazardous in situations where the user is required to focus their attention on more safety critical tasks. Instead, techniques that take more advantage of the users other senses (such as the audio or touch senses) are considered more appropriate for systems to be used whilst 'on the move' [1–4]. And with the introduction of gesture-based systems to the commercial market, such as the Nintendo Wii or the Samsung SCH-S310 mobile phone, making gesture-based techniques more socially acceptable, these techniques are becoming increasingly relevant in this domain [5, 6].

Cheverst et al. [7] introduced the notion of information *push* versus information *pull* for location-aware systems. A 'pull' system is one where the emphasis is on the user to decide when context-aware information is presented to them. They can then pull this information to their device. A 'push' system, on the other hand, is based on information being presented automatically to the user, which is triggered by contextual events. The system we describe here takes the form of a highly interactive 'push-pull' system with elements of both but with slightly more emphasis on the 'pull' aspect. Our system both empowers and provides a sense of control to the user as they probe the geo-coded information in their immediate environment and actively

S. Strachan (✉)
Hamilton Institute, NUI Maynooth, Maynooth, Ireland
e-mail: steven.strachan@nuim.ie

R. Murray-Smith
Department of Computing Science, University of Glasgow, Glasgow, UK
e-mail: rod@dcs.gla.ac.uk

pull information from their surroundings, rather than relying on the system to push the information to them. This system differs from other context-aware applications in that we can directly interact in an 'eyes-free' manner with the hybrid physical/virtual environment and any information that may be placed there, eliminating the user's dependence on visual feedback from the device screen.

We first quantify the main sources of error and uncertainty that can be detrimental to this kind of system, focussing primarily on the effects of bearing and positional error. We introduce a framework which deals with this uncertainty and provide the first steps in quantifying the effects of bearing based uncertainty on a pointing task given varying target sizes and separations.

2 Related work

The representation and sensing of context is an important but challenging area of research for location-aware mobile applications. Some of the earliest work on mobile context-aware computing includes that of Abowd et al. [8] who describe the construction of a context-aware tour guide. Similarly Feiner et al. [9] describe a self-contained backpack-based system that includes magnetometers and accelerometers for head orientation tracking and a differential GPS for location information. Cheverst et al. [10] also describe an intelligent electronic tourist guide, *GUIDE*, which was built to overcome many of the limitations of the traditional information and navigation tools available to city visitors. Their system combines mobile computing technology with a positioning system to present city visitors with information tailored to both their personal and environmental contexts. Although these "backpack" based outdoor systems have been successful proof-of-concept prototypes, they lack the convenience of a fully hand-held system.

Although GPS is the most often used positioning system for location-aware applications, there exist a number of systems which use other forms of positioning technology such as Wi-Fi or GPRS cell based positioning. Drozd et al. [11] describe a game for mobile phones, *Hitchers*, that makes use of cellular positioning. Players create digital hitch hikers, giving them names, destinations and questions to ask other players, and then drop them into their current phone cell. Players then search their current cell for hitchers, pick them up, answer their questions, carry them to new locations and drop them again. One example of a system that combines the use of GPS, Wi-Fi and GSM cell positioning to provide a position estimate is Navizon [12], detailed in [13]. This system uses GPS to build a database of WiFi and GSM sources through war driving and a position is provided to a user who queries this database with information about which Wi-Fi points and cell towers with which they are currently in contact. Such hybrid approaches lead to variable accuracy as, for example, we move from one form of positioning to another and such systems can benefit from interfaces designed with this in mind. Kontkanen et al. [14] describe probabilistic approaches to locationing in wireless radio networks and demonstrate the utility of a probabilistic modelling framework in solving location estimation problems. An example use of this kind of approach is given in [15], which shows that it is possible to derive complex behavioral patterns and device location from collected Bluetooth data.

The development of smaller and more powerful devices has led to the emergence of an increasing number of applications on hand-held devices for truly mobile context and location aware computing. Some completely handheld applications make use of the screen and cameras available on these devices. Baillie et al. [16] describe a context-aware application in a fully contained handheld system which combines GPS and attitude information in order to visualise a virtual image of a building in the present or past on screen by simply pointing their device at that building. There are also a number of systems using mobile devices, that aim to attach digital information to locations in the real-world. E-grafitti [17] is a context-aware application, which senses a user's location and displays notes dependent on that location. They conduct a field study with 57 participants, finding the idea of location-specific notes was something that appealed to users. Espinoza et al. [18] describe a similar system, GeoNotes, arguing that location-based systems must allow users to participate as content providers in order to achieve a social and dynamic information space. Their system attempts to blur the boundary between physical and digital space while at the same time striving to socially enhance digital space by letting users leave virtual messages, which are linked to specific geographical positions.

The exposure of locally relevant information has become an active area of research. Rantanen et al. [19] describe their novel radar style interface for accessing messages placed in the real world to create an interface that "strives to create an isomorphic representation of the virtual content relative to the directly observable physical world". As a consequence they remove the need for a map of the locality and provide the user with an intuitive graphical representation of information in that area, unlike the systems described before which use a list-based interface and present a much lower positional resolution. An initial field trial encouragingly indicates that location-based aspects have a role to play in facilitating mobile communication. Simon and Fröhlich [20] describe a system that displays locally relevant wikipedia articles using a GPS equipped PDA and Jones et al. [21, 22] have introduced a handheld system designed to expose to users what other people have searched for in a particular location with the aim of providing useful insights into the 'character' of that location or context. Interaction with this information is a new area of research. Fröhlich and Simon describe their *GeoPointing* [23] system that allows a user to point at an object and discover information about that object. They describe a study conducted with 'real world' conditions highlighting the problems associated with GPS uncertainty in differing contexts. Faisal [24] describes early work on algorithms for pointing error correction. He develops an efficient error compensation model to reduce the discrepancy between the line-of-sight of the eye and the pointer direction.

There are significant social and safety advantages to a non-visual, eyes-free display in a mobile context where visual attention is likely to be directed towards tasks not involving the device display. As such, the utility of the navigation system is greatly enhanced by the accurate presentation of the feedback in the audio and haptic modalities. This is also important in a social sense since it allows people to concentrate more on social interactions rather than focussing their attention on a small screen. There are context-aware augmented reality systems which focus completely on the audio sense, leaving a user's visual attention free. Bederson [25] describes a prototype automated tour guide which superimposes audio on the world based on a user's location. Users in a museum may hear information about exhibits in their local vicinity using a hand held device and sensors located in the ceiling of the museum. Another example is the *GuideShoes* [26] application, a shoe-based GPS navigation system, which consists of a pair of shoes, equipped with a GPS and CPU. They describe the use of *emons*, short musical "emotional cues", to guide a user to their desired location. Similarly Stahl [27] describes a system designed to guide customers round a zoo using spatial audio. The audio is sourced in the direction of the enclosure of a particular kind of animal where the sound of that animal can be heard. He finds that a 'lightweight' navigational aid can be sufficient for way-finding tasks in certain environments. Increasingly music is being used as a mechanism for guiding users with context-aware applications. Work on music-based guidance includes the *gpsTunes* [28, 29] system where initial testing of a prototypical system had shown that it was possible for users to navigate in the real world using a combined audio/GPS player to aid navigation along specified trajectories. Similar systems include *Melodious Walkabout* [30] and *OnTrack* [31]. Other work which utilises music as a tool for influencing a user in this mobile domain was conducted by Oliver et al. [32] who constructed a system that takes advantage of the influence of music in exercise performance, enabling users to more easily achieve their exercise goals. It works by selecting music depending on a user's jogging speed and on their current heart rate. Likewise, Elliott et al. [33] describes a context aware music player, which makes real time choices of music based on user pace.

3 Uncertainty

The issue of uncertainty is an important one for mobile, instrumented, continuously sensing systems. The kind of system we present here is susceptible to a range of uncertainties from a number of sources. These sources can be broken into two main categories. 'Human sources' and 'sensor sources'. Sensor sources can include the fact that we are required to sense things indirectly, such as the heading of the device from magnetometers or the tilt of the device from accelerometers. Any disturbances to the data from these sensors can in turn affect the estimates inferred from them. Magnetic anomalies can cause deviations in heading estimates and significant movements (e.g., gait, muscle tremor, vehicle motion), sensed by the accelerometers, can affect the estimation of the tilt of the device. There is also considerable and varying uncertainty from the kind of positioning system we choose to use. For example, there are significant and well documented problems with the spatially varying uncertainty arising from shadowing and reflection artifacts in GPS fixation [34]. Seager et al. [35] conducted a study, designed to assess the usefulness of the GPS position information displayed by a commercial GPS navigation system, which found that during a navigation task users perceived the position information to be "at best, redundant and, at worst, confusing". This was thought to be directly related to the inaccuracy of the software position estimate, caused by lags with the GPS data and inaccuracy with the map matching algorithm. Likewise wireless positioning systems can display complicated behaviour and so an important design decision is how much of this inaccuracy to present to the user so that they can appropriately modify their behaviour to improve their location accuracy. In the GPS case, Seager advocates the explicit display of uncertainty to the user in the form of an icon with variable size.

Human sources of error are physiological in nature. Any purposeful movement generated from the human body is inherently variable and this affects the range of readings measured on the sensors and the accuracy with which we can define one particular movement. Our system is also susceptible to tremor from our muscles, which injects a further level of uncertainty. Morrison and Keogh [36], whilst investigating the effects of tremor in goal-directed pointing tasks found that the influence of tremor increased significantly for tasks that required more accuracy. These kind of systematic physiological effects are something that must be considered when designing systems of this nature.

3.1 Heading uncertainty

Our system makes use of bearing data calculated from a combination of integrated magnetometers and accelerometers. The earth has a magnetic field that resembles that of a simple bar magnet with field lines originating at the south pole and and terminating at the north pole. The field lines have slightly varying strength and direction at different points around the earth but at a local level we can think of these fields as being constant and use them as a reference for the direction our sensor is pointing, given a suitable calibration. Determination of the compass heading is achieved by first rotating the magnetometer data into the horizontal plane, that is, the plane perpendicular to the Earth's gravitational vector, using accelerometer data then using this magnetometer data to calculate a heading value for the device [37]. Most systems would assume complete accuracy from this heading estimate but in reality any measured uncertainty in the magnetometer and accelerometer data is propagated through to the final heading calculation meaning that we do not have a pinpoint accurate heading measurement with which to work.

Figure 1 illustrates how any uncertainty in the calculated compass heading is propagated as we project into the distance. In an ideal world there would be no noise from the sensor and θ in Fig. 1 would be 0. It is then simple to define some distance d and be completely certain about the point in space at which at we are aiming. In the real world we are faced with uncertainties in the calculated compass heading. So, using basic trigonometry, it can be shown that if we point at an object with an uncertainty of θ in the compass heading estimate, this corresponds to a possible discrepancy at distance d_1 of $r_1 = d_1\tan(\theta)$) and at distance d_2 of $r_2 = d_2\tan(\theta)$.

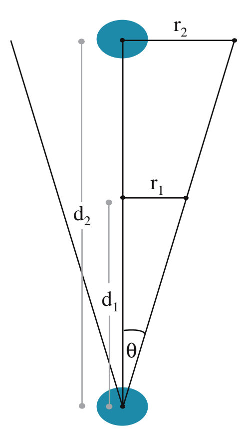

Fig. 1 Accuracy in the point of interest is decreased for increasing θ, the measured uncertainty on our heading estimate and d, the distance to the point of interest

3.1.1 Illustration

As an example of how this uncertainty in the heading estimate varies between users, a simple pointing task was devised whereby five different participants were asked to point at two targets 5 times for 25 s each time. Both targets were identical small lamp posts situated on campus. Target 1 was positioned approximately 15 m away and target 2 was positioned approximately 80 m away. Figure 2a shows a histogram for the measured bearing for a sensor sitting on a stable platform (i.e., not in a human hand), Fig. 2b and c shows histograms for two of the five participants both for the close and far targets. As we can see from Fig. 2a, in a situation where the sensor is stationary and undisturbed we still observe a standard deviation of 0.67° on the heading estimate. The standard deviation over all the participants for the close target task was 2.32° and for the far target task was 2.04°. At a distance of 15 m this measured standard deviation corresponds to a maximum measurement error of $15\tan(2\pi\theta/360)$ = 0.60m and at a distance of 80 m this corresponds to a maximum error of $80\tan(2\pi\theta/360)$ = 3.24 m. So obviously if this uncertainty is not treated appropriately it can have detrimental effects on the use of this kind of system.

Data was also recorded for a walking task. The device was pointed at the far target as a user walked towards it for a slow walk and a fast walk. For the walking task the measured standard deviation was 9.54° for the slow case and 27.48° for the fast case, which corresponds to a spread of 13.44 m for the slow case (Fig. 3a) and 41.6 m for the fast case (Fig. 3b) at a distance of 80 m. This level of uncertainty can render this kind of system unusable. It is clear though that accuracy can be increased significantly if the user simply stops walking and if this uncertainty is fed back this will be clear to the user. It is possible that, with appropriate filtering of foot steps from the accelerometer signal, that uncertainty whilst walking can be reduced significantly. Figure 4 shows that it is possible to average the received bearing signal over a users gait cycle in order to reduce the uncertainty in the bearing signal whilst walking.

3.2 Position uncertainty

For any location-aware system, uncertainty and inaccuracy in the estimated position can be critical to the effective use and acceptance of the system. GPS determined locations can be very uncertain in situations where a user is in a built up area or at a high latitude, for example. For a discussion of the potential error sources in GPS see [38]. This inaccuracy is also apparent if we move to a different kind of positioning system such as GSM cell triangulation or Wi-Fi-based positioning. These systems display considerable variability in the level of uncertainty in their position

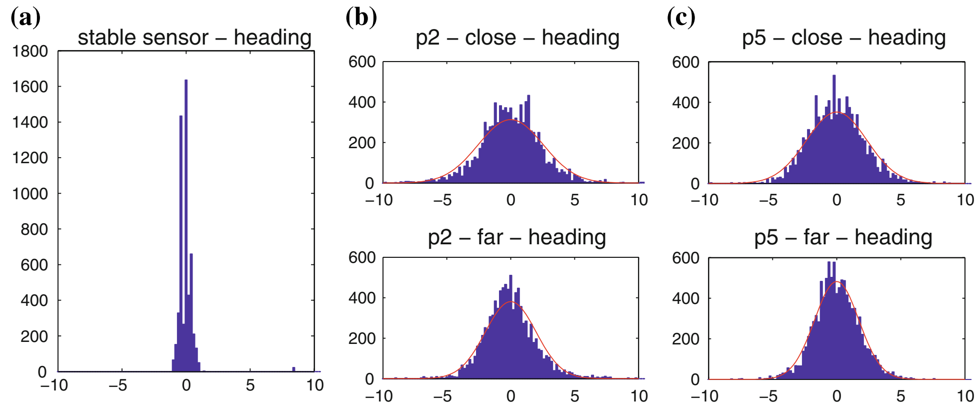

Fig. 2 **a** Histogram for data recorded from our sensor situated on a stable surface. **b** and **c** show histograms for heading data recorded from two different participants for a close target and a far target

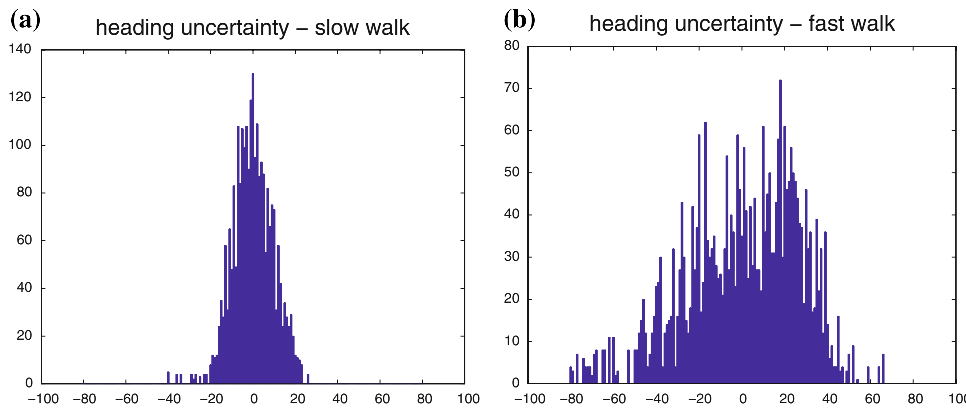

Fig. 3 Histograms for heading data recorded for the walking task. Uncertainty in the heading estimate is increased significantly when a user is walking (**a**). Much higher uncertainty is observed for a faster walking pace (**b**)

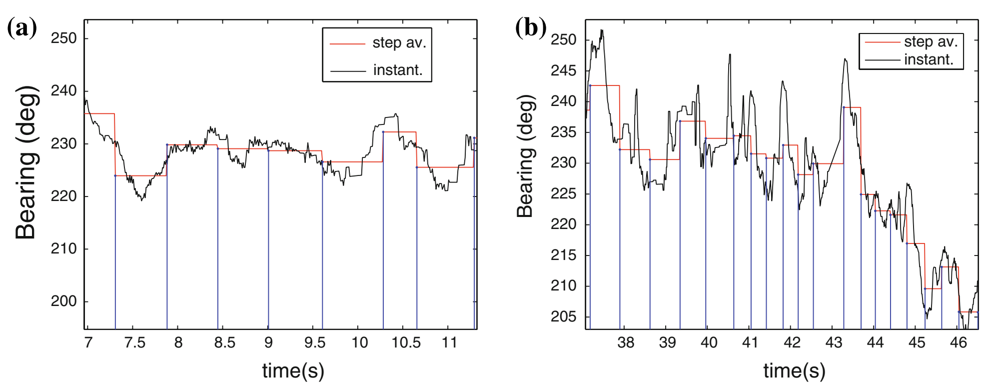

Fig. 4 Foot steps (*blue circles*) are recorded from accelerometer data and used to average the raw bearing signal (*black line*) for a slow walking case (*left*) and a jogging case (*right*)

estimates and any movement between two different kinds of positioning system, for example, moving from an outdoor positioning system with fairly high resolution estimates to an indoor positioning system with fairly low resolution estimates, can cause sudden and large changes in the measured uncertainty. Figure 5 shows the estimated position for device over a 15 min period in very good conditions on the top of a building with a mean hdop value of 0.82. As we can see from Fig. 5, even with good conditions in a relatively unobstructed environment the standard deviation of the estimated position from the GPS is 1.46 m in the latitude estimate and 0.96 m in the longitude estimate. Although more than sufficient for motor vehicle and aircraft applications, this likely to disrupt any pedestrian based location-aware system that requires the kind of detailed interaction we desire and places constraints on target placement and separation. It is unlikely though that in typical use, a user is going to have such good conditions. Figure 6 shows GPS data logged in the case where the GPS antenna is attached to the side of the same building, effectively shadowed from a number of potential satellites.

In this case the standard deviation of the estimated position from the GPS is 3.95 m in the latitude coordinate and 13.55 m in the longitude coordinate in what are likely to be much more typical conditions for this kind of system.

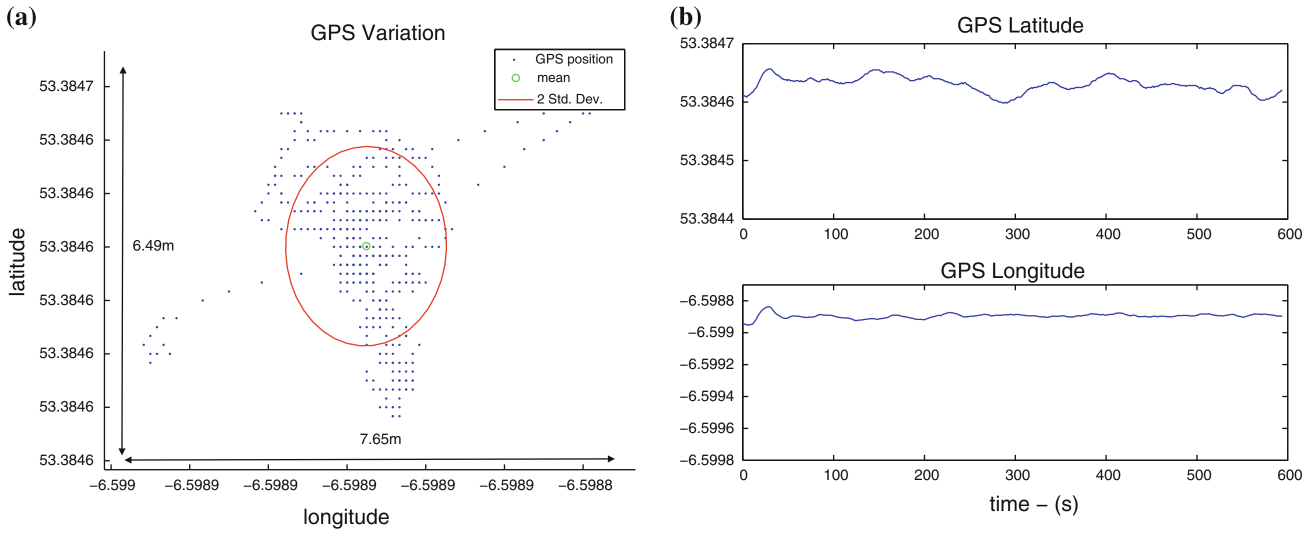

Fig. 5 *Left* GPS data recorded in a static position in very good conditions with a mean hdop value of 0.82. *Right* Corresponding time series for data over the 10 minute period. GPS device used was a Nokia LD-3W

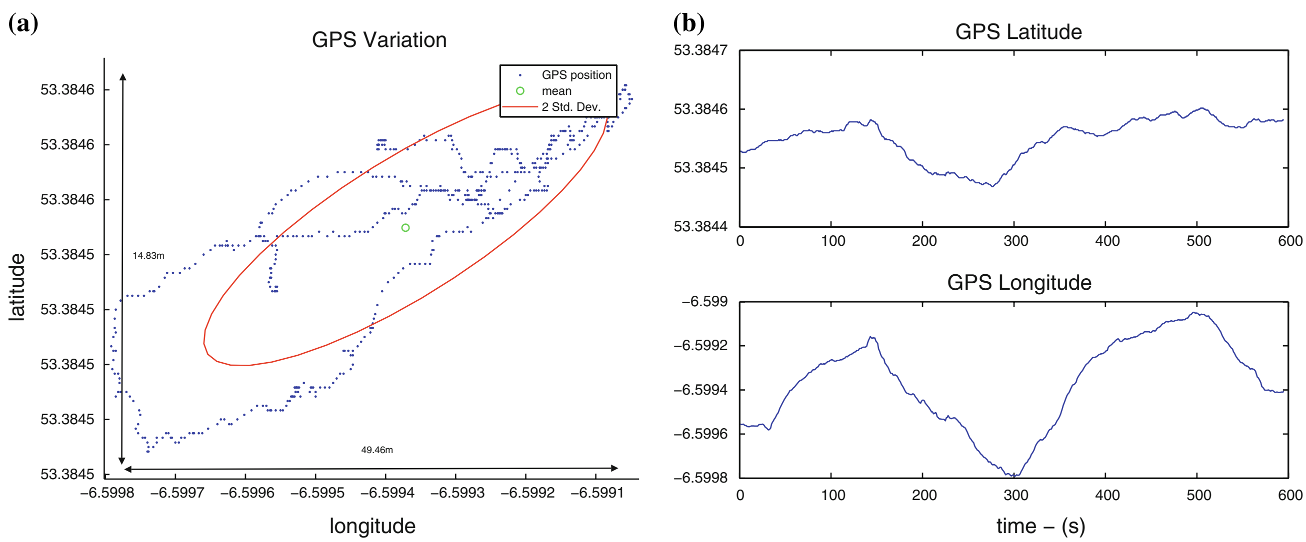

Fig. 6 *Left* GPS data recorded in a static position in normal conditions with a mean hdop value of 3.25. *Right* Corresponding time series for data over the 10 min period. GPS device used was a Nokia LD-3W

It is clear then that the appropriate treatment of this uncertainty is essential.

4 A probabilistic approach

In our system we explicitly use the display of uncertainty to assist the user in their navigation of and interaction with the local environment. Our display fully represents all estimated uncertainty in the prediction of which areas in the local environment the user may be interested in, and where and how they are likely to move to them. This is achieved in a probabilistic way via the combination of a model of the local environment, knowledge of our sensor noise and Monte Carlo sampling.

Using knowledge of the main sources of uncertainty and constraints in the local environment, it is possible to infer potential future user positions via Monte Carlo simulations. The inference mechanism is coupled with feedback to give the user a display of the distribution of potential future states or positions providing appropriate information to make a reasonable choice of actions. Simply approximating our position in the local area with a single best estimate, as is commonly done in current navigation software, gives a user unreasonable confidence in the accuracy of a system and prevents the interactor from choosing an optimal strategy for dealing with the true state of the world. Unrealistically precise feedback can make smooth, stable control difficult; this "jumpy" interaction is familiar to users of conventional GPS devices where the postulated location may sporadically shift in an unpredictable manner. Displaying the position density, which incorporates the best estimate of the uncertainty of the system, means that the user can appropriately simplify their behaviour when limited information is available [39], achieving a graceful, interpretable degradation in interaction performance. For example, if a user points at a target and there is a sudden jump in the estimated position a loss of feedback might lead to a loss of trust in the system.

The major novel feature of this system is the browsing interface which facilitates active probing of the locality. This is achieved by projecting possible paths into the future from some location along a given heading. As the information from our sensors is uncertain, any prediction by the system of where in the locality we are interested will inherit this uncertainty. Ideally, an estimate of a user's area of interest or potential future locations would be represented as a probability density function over the whole navigable space, taking into account available information such as areas in the locality where the user would usually move to or has moved to in the past, or sensor noise models, for example. This function, however, is generally extremely complex for non-trivial landscapes, and no solution of simple form is available. Instead, we approximate using a set of samples drawn from the density, known as Monte Carlo sampling [40]. It is much more computationally efficient to draw such approximating samples than it is to directly evaluate the full probability density function.

For our browsing task, a simple algorithm for sampling future possible trajectories is as follows:

- Draw samples $x^0 \ldots x^S$ from a distribution ε around the current state. This distribution represents the sensor uncertainty at the initial position (e.g., from the shadow maps described later).
- For each step t until some horizon T:
  - $x^s_t = x^s_{t-1} + h + l(x^s_t) + \sigma(x^s_t)$ where $\sigma(x^s_t)$ represents the model noise at the new point x^s_t (Gaussian, in our examples), and $l(x^s_t)$ represents the derivative of the likelihood map at that point. h is the heading from our magnetometers. $\sigma(x^s_t)$ can be a constant value or a more complex function; for example, from a map indicating the resolution or quality of the likelihood map.
- Display the samples x^s_T

This is similar to the *Hamiltonian* (or *hybrid*) Monte Carlo sampling process; Chap. 30 of MacKay [40] has further details.

4.1 User defined context landscapes

The process described above can be imagined as a beam of particles flowing out from around an initial state, probing into likely destinations or areas of interest. A straightforward propagation of particles through the locality in time would lead to a fairly simple distribution of points at the time horizon, which would be unlikely to model possible user destinations effectively. It is extremely unlikely, for example, that the user would be inside a solid wall at any point in the future or at the top of a mountain in the next 5 min. This straightforward propagation of the particles also takes no account of the varying uncertainty in sensor measurements.

To represent these varying positional likelihoods we use a likelihood map, giving a probability p of being in a particular position (as measured by the sensors) in the mapped area. An example of such a map is shown in Fig. 7; in this example the buildings have very low likelihood and there is increased likelihood around pathways on the map. It is also possible for particles to flow along walls and round the corners of buildings, channeling themselves into areas of increased likelihood. In this example, the landscape is generated by hand from an existing map, but such landscapes can also, for example, be derived automatically from digital photogrammetry maps or generated from a users general behaviour or location history.

Representation of uncertainty in the measured position can take the form of occlusion maps generated from knowledge of the geometry of potential occlusions(for example, see [41]). As an example we have constructed a simple static occlusion map with a raytracing technique based on currently locked satellite positions. An example combined sensor uncertainty map resulting from estimated shadow positions is shown in Fig. 8.

It is possible to include these sensor uncertainty maps in the sampling algorithm by modulating the diffusion parameter ε at each time step by the calculated sensor uncertainty at the point. The total sensor uncertainty will be a combination of the map input and accuracy reading produced by the GPS device itself. The accuracy of a GPS fix is also computed in the sensor hardware in real-time. This includes the number of satellites which have locks and more specific data giving the fix quality. For example, the "horizontal dilution of precision" provides us with a scaling factor for the current uncertainty from 1 to 50. These values are combined with the a priori sensor maps to obtain a certainty estimate for the current location.

In the simplest way the propagation algorithm can be modified to take account of these maps simply by removing particles at a rate inversely proportional to their likelihood given their current position and the sensor uncertainty at that point. For increased computational throughput; however, our implementation instead modifies the dynamics of the

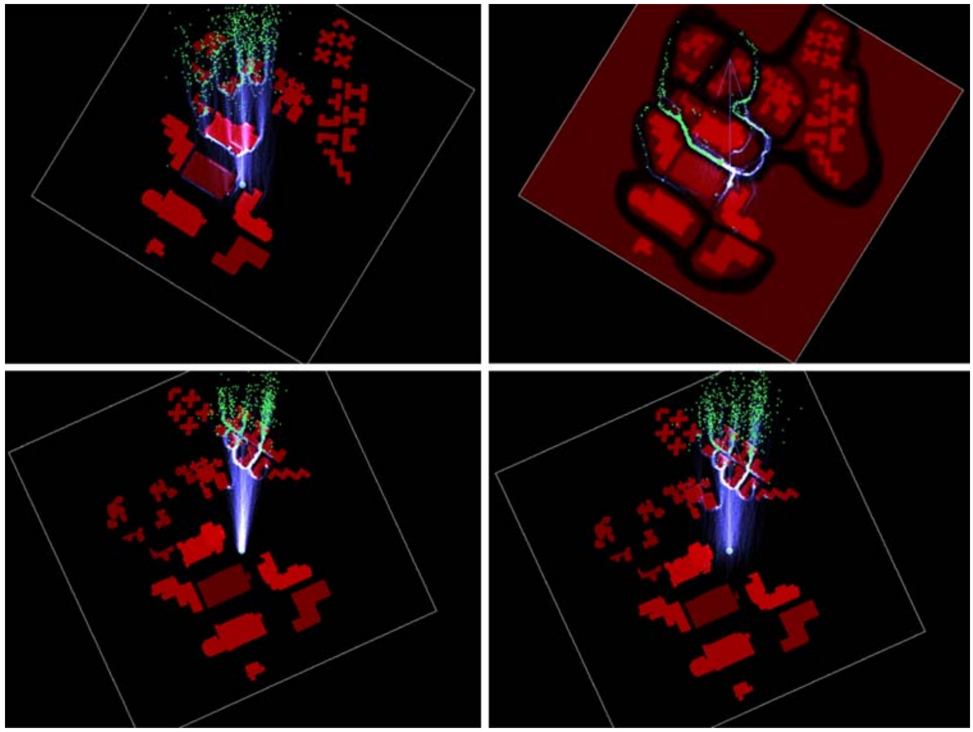

Fig. 7 Particles flowing around the campus likelihood map. *Higher red values* indicate lower probability. The particle paths are illustrated in *blue*; the samples at the time horizon are highlighted as *bright green dots*. From *top left to bottom right*: *top-left* shows particles on likelihood map which is a model for walking behaviour and *top-right* shows the effect of a more constrained map which, in this case, models a user on a bike, where particles tend to flow along available paths. *Bottom-left and bottom-right* show the effect of the GPS shadow map on the propagation; *bottom-left* is a point outside of shadow, while *bottom-right* is a nearby point with heavy shadowing. The increased dispersion in the more shadowed case is clear

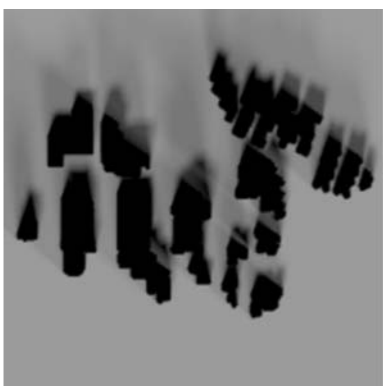

Fig. 8 Estimated GPS shadows for the test campus region. *Shadows* are computed via a raytracing algorithm, based on satellite azimuth/elevation and an estimated height map for buildings in the area. *Darker regions* have less satellite coverage

particles such that they are deflected away from regions which are less likely or more diffuse, causing the samples to "flow" across the surface (i.e., by following the gradients of the map much like a ball bearing on an uneven surface). This produces a browsing system that channels Monte Carlo samples towards regions of increased likelihood, following traversable paths and avoiding obstacles in a natural manner.

5 The gpsTunes system

The current system runs on a Samsung Q1 Ultra Mobile PC with a bluetooth connection to a sensing hardware accessory for kinaesthetic expression (SHAKE) inertial sensing pack as shown in Fig. 9a. This device contains the magnetometers, accelerometers and vibration device that we required for this study as well as gyroscopes, capacitive sensing and an analog input for external sensors. Users interact with the system by scanning the local environment with the SHAKE device. The direction in which the user is pointing is taken from the compass heading. Accelerometers are used to monitor the orientation (pitch and roll) of the device with respect to gravity, which we can use to control the level of 'look-ahead'. If the user wishes to look-ahead into the space in front (effectively projecting the Monte Carlo predictions further ahead in time) they tilt the device forward. If they wish to bring the predictions back to their current position they tilt the device back again, effectively pulling the device to their chest as illustrated in Fig. 9b. By scanning via a variable time horizon the interactor can effectively project their current location into the distance (as with user 2 in Fig. 10) to examine any objects of interest or bring the particle cloud in close (as with user 1 in Fig. 10) to examine nearby objects. A user can obtain information about the space around them by listening and feeling for impacts that we can intuitively think of as being generated by the particles impacting with targets in our virtual environment (analogous to ball bearings hitting a surface. Different kinds of surface produce different impact sounds). We can also listen for slight changes in the audio or haptic texture which may be generated differently for different contextual areas. This way

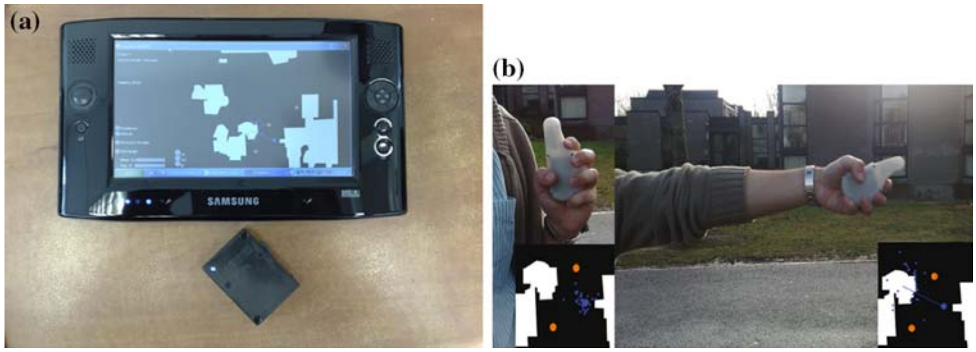

Fig. 9 **a** The equipment used to run the system. Samsung Q1 UMPC and the SHAKE inertial sensing device. **b** Tilting the device forward looks into the distance (effectively projecting the Monte Carlo predictions further ahead in time as illustrated in the inset). Tilting the device back again, or pulling it towards the chest, bring the predictions back to the current position

Fig. 10 User 1 takes a passive approach to interacting with the density with particles spread around the body. User 2 takes a more active and embodied approach to interacting with the density and any objects, which that 'contextual' density may contain. Interacting with different kinds of density can produce different kinds of response from the system.

of interacting enables a user to obtain information from the area around them without the explicit need to move to that particular area as is the case with most location-aware systems. A user of our system can effectively say "what would I feel if I was over there?". This way of thinking allows users to take a much more active, embodied and empowering approach to the querying and retrieval of information from their current context that would be extremely difficult to implement in a responsive manner without uncertain feedback.

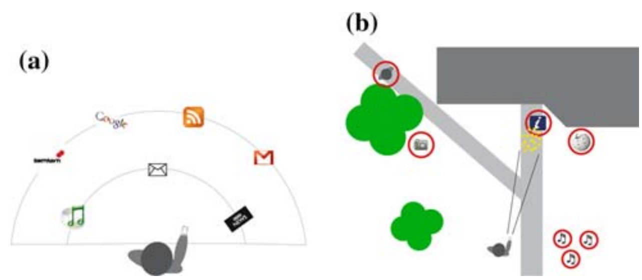

Fig. 11 **a** A user has a number of objects arranged around himself which he can point at to activate. The objects are arranged in a layered fashion creating more space. **b** The local area has a number of objects left there by other users with which it is possible to interact

6 Scenarios

There are a number of applications for this kind of system. The predictive and probabilistic nature opens up a wealth of opportunity for a more advanced form of route planning or map matching, for example. We choose to focus though, on the use of this system for mobile spatial interaction, as a tool for interacting, probing and querying information in the local environment. The notion of egocentric and exocentric interfaces becomes important here. Marentakis and Brewster [42] in their work with a spatial audio interfaces, define an egocentric display to be one where the sound position is fixed to the user and remains unchanged no matter what the direction of the user, whereas in an exocentric interface, sound position is fixed to the world and is updated in real time based on the direction of the user relative to the sounds. In an egocentric setting we have the ability to build highly personal spatial interfaces. Exocentric spatial interfaces on the other hand are much more open and expansive. An exocentric interface, in this context, becomes a place to store information in specific locations or discover information left by other people, creating new opportunities for the exploration and analysis of the social mechanisms for this kind of interaction or sharing of experiences.

The egocentric version of this system effectively becomes a highly personal eyes-free desktop for the user with his personal items stored on and around his body, a similar concept to [6], as in shown Fig. 11a. We may imagine a situation where a user is out and receives a text message. He points his device at where he usually keeps his text messages and the message appears. He then decides that he would like to listen to some music so he points the device in the direction he usually keeps his mp3 player. This is a basic example but we also have here the opportunity to create a layered-ego system where by the user can create increasingly large rings of items around his body, all of which are selectable with skillful use of the system.

In an exocentric interface the user places items in specific locations in the world around him. As illustrated in Fig. 11b, the user may interact with, for example, the geocoded wikipedia article about the building ahead of him. He may interact with the object containing information about that building or look at some photographs left outside the building by other users. He may even get the attention of his friend who is close by or browse some music files that have been left in that specific location. This is effectively a form of geo-coded Internet for users to interact with whilst mobile and paves the way for a new kind of highly interactive mobile internet. Another application of this kind of system is for the provision of information in public spaces, at a train station, for example. A user could access timetable or train information just by pointing their device at the train station, or a specific part of the train station as soon as they were in range. They could then negotiate their way through a hierarchical system to find out information about their specific train. Just as train stations use specific colouring and fonts for signage, the kind of feedback provided in this context would be specific to that train station context.

7 Experiment

7.1 Background

We have shown previously that the explicit display of uncertainty to a user can significantly improve their interaction with the local environment when compared to a system that assumes complete accuracy [43]. So what limits do 'typical' noise characteristics place on the overall system design both in a high uncertainty walking situation and a lower uncertainty still situation? How far apart can we place targets and what size can we make these targets in the virtual environment without it becoming impossible to accurately resolve more than one target? And what effect, if any, does the distance of a target have on user performance?

7.2 Set-up

To answer these questions an experiment was conducted with eight participants. Each participant was given a brief introduction to the system with a visual example and were allowed to practice for a number of minutes before the trial began. The trial took place outdoors and involved users remaining in a static position (with simulated noise added to this position in order to mimic the effects of an uncertain position estimate), scanning the area ahead for three different targets with each target having it's own distinct impact sound, described to the users as 'pop', 'plastic' and 'metal'. This set-up is illustrated in Fig. 12. The typical noise characteristics measured in Sect. 3 for both the walking and standing still conditions were added to the system, a standard deviation of 20.41° for the high uncertainty trial and a standard deviation of 2.3° for the lower uncertainty trial were added to the heading estimate and a standard deviation of 3 m was added to the GPS position estimate.

The experiment was conducted in two main parts (eight participants for each). In part 1a, participants were asked to complete two acquisitions of each target with the measured low uncertainty for four different distances, d (7.5, 12.5, 17.5 and 22.5 m corresponding to tilt angles of 20°, 13.3°, 6.6° and 0°) and 4 different target angular separations, θ_s (20°, 30°, 40° and 50°) with the aim of investigating both the effect of varying distance on target acquisition and the effect of varying angular separation on target acquisition at this lower uncertainty level. Throughout this part of the experiment the angular size of the targets, θ_t was kept constant at 9° for each value of d and θ_s. This meant that effectively the targets were increasing in size as they were moved further into the distance.

Part 1b of the experiment involved the participants again completing two acquisitions of each target for 4 different distances but this time for a constant angular separation and varying angular width of the target for angular widths of 10°, 16°, 24° and 32°.

Part 2 of the experiment consisted of the same set-up as part 1 but with a higher uncertainty added to the system in order to observe the effects of the high uncertainty levels

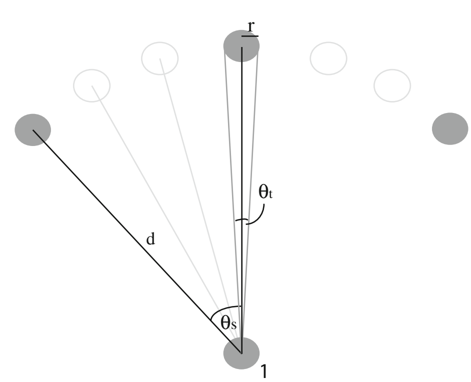

Fig. 12 Users stand at position 1 and scan the area ahead. The angular size of the target is represented by θ_t and the angular separation of the targets is represented by θ_s. The distance d to the target is also varied throughout the experiment

observed in the walking task. Part 2 of the experiment took place in the same static location used for part 1. Although this is slightly unrealistic, as actual walking data is likely to introduce different kinds of disturbance, it was necessary in order to compare the high and low uncertainty cases in a valid way. The presentation of each combination of values for each part was given in a counterbalanced order.

Selection of a target was achieved by activating a capacitive switch on the device when the participant believed that they had the best possible fix on the target and had isolated the particular impact sound for that target. They are then requested to select the next target and this continues until the end of the run. The impact energy level signals the number of impacts on each target and was measured and recorded for each acquisition. This allows us to examine any clear acquisitions or any cross-talk between acquisitions.

7.3 Results

7.3.1 Low uncertainty experiment: Part 1

In part 1a of the experiment, out of a possible 96 selections the average correct selection rate over all participants was 69.7%. The average *clear* correct selection rate, where 'clear' indicates that the target with the highest energy level is at least 10% higher than the next highest, was 61.3% over all the conditions. Figure 13a shows how the number of successful selections varies for different distances. There is a slight improvement overall at higher distance (corresponding to a lower device tilt angle) indicating not necessarily that the participants were more comfortable with higher distances but that the participants are more comfortable when the device was flatter in their hand. Figure 13b shows the number of successful selections for varying angular separation, θ_s. There is a general increase in the number of clear selections for higher angular separation indicating, as we might expect, that in general the participants found the task easier if the targets were further apart.

In part 1b of the experiment (to examine the effects of varying angular width) participants were more successful with an average of 81% correct selections in the 'non-clear' case but slightly less successful in the 'clear' case with 54.2% correct selections. Figure 14a shows how the number of successful selections varies for increasing distance. Participants perform consistently better for the targets at lower distance (corresponding to a higher tilt angle). As distance increases participants are slightly more successful. Figure 14b shows the number of successful selections for varying angular width, θ_t. This shows that participants were less successful in making clear selections for increasing angular width (i.e., decreasing space between targets) of the target. But if we observe Fig. 14c for the case of correct 'non clear' selections only we see that the number of correct selections actually increases slightly for large angular width. And if we observe Fig. 15 we see that there is a slight decrease in selection times for increasing angular width, indicating that participants were finding it easier to locate these targets. It is likely then that participants were becoming much less precise for the perceived easier task and so the number of clear selections was decreasing with the decreasing concentration or attention of the user.

7.3.2 High uncertainty experiment: Part 2

In part 2a of the experiment the average correct selection rate over all participants was 70%. The average *clear* correct selection rate was 50% over all the conditions. Figure 16a shows how the number of successful selections varies for different distances. There is a slight improvement overall at higher distance (lower device tilt angle) indicating again that participants were more comfortable when the device is flatter in their hand. This is backed up if we examine Fig. 17, which shows the selection times for clear selections over increasing distance. We observe a decrease

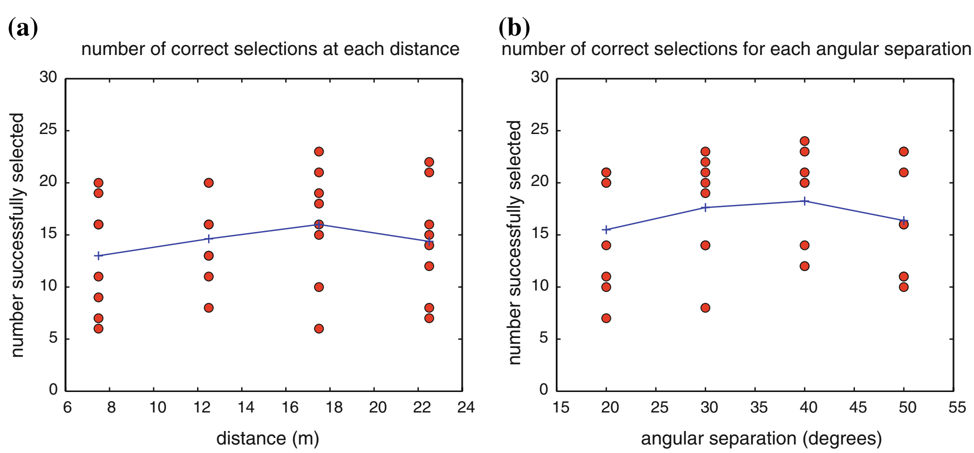

Fig. 13 **a** Each column shows the results for each distance with *red circles* indicating the number of clear correct selections for each user in part 1a of the experiment. *Blue crosses* indicate the mean value for that distance. **b** Each column shows the results for each angular separation with *red circles* showing the number of clear correct selections for each user in part 1a of the experiment

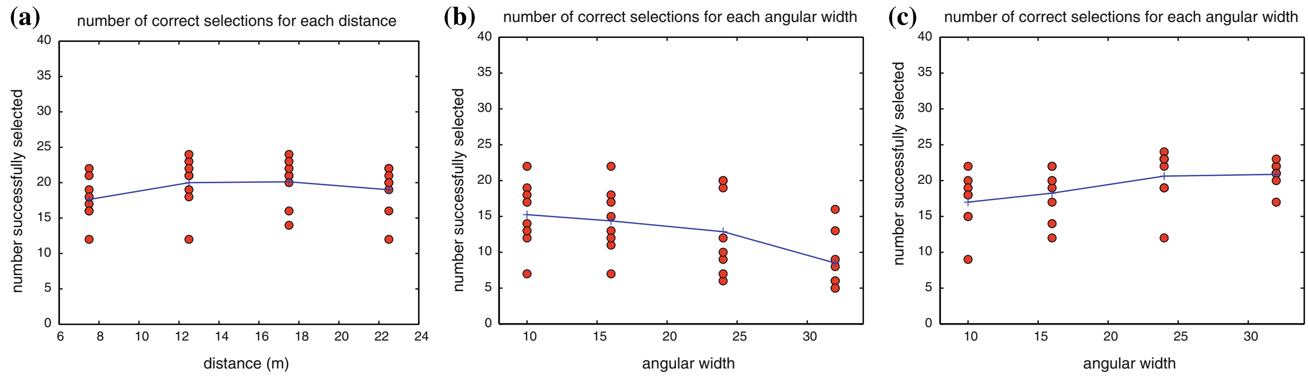

Fig. 14 **a** *Red circles* show the number of clear correct selections for each user in part 1b of the experiment, with blue crosses indicating the mean value for that distance. **b** The number of clear correct selections in part 1b of the experiment drops for increasing angular width where as the number of correct 'non-clear' selections actually increases for increasing angular width indicating that participants become less accurate as the perceived difficulty of the task decreases as illustrated in **c**

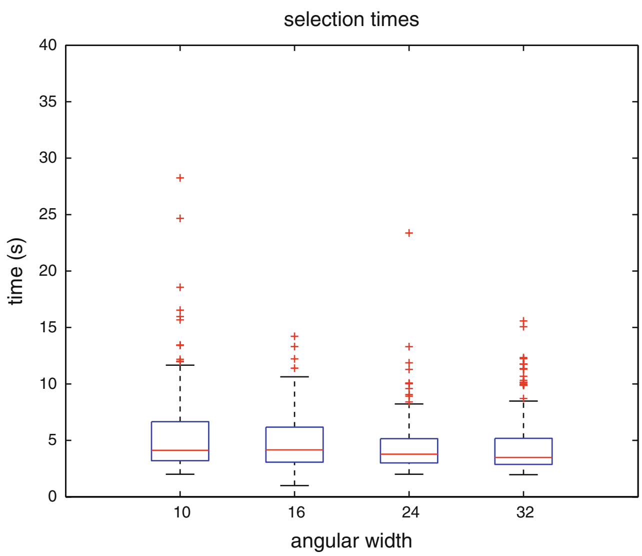

Fig. 15 Mean selection times for each target for varying target angular width in part 1b of the experiment. Selection time decreases slightly with increasing angular width

in the selection time for higher distances, indicating that users found this configuration slightly easier. It is likely then that the increased uncertainty at shorter distances, corresponding to higher tilt angles, severely affected performance at this distance. Figure 16b shows the number of successful selections for varying angular separation, θ_s. There is a general increase in the number of clear selections for higher angular separation as was the case in part 1a. There is also a decrease in the selection times for increasing angular separation (Fig. 18) indicating that in general the participants found the task easier if the targets were further apart, which is what we had expect from a system with such high uncertainty.

In part 2b of the experiment participants were slightly more successful with an average of 82.3% correct selections and 60.3% clear correct selections. Figure 20a shows how the number of successful selections varies for increasing distance. There is little variation as distance increases. If we observe the corresponding selection times for each distance as shown in Fig. 19 we see that there is a general decrease in selection time as the distance is increased or as the required tilt level of the device is decreased, confirming somewhat that which was observed in part 2a of the experiment. It is interesting that this was not observed in part 1 of the experiment for lower uncertainty, indicating again that high uncertainty is a significant limiting factor. Figure 20b shows the number of successful selections for varying angular width, θ_t. We observe that participants were less successful in making clear selections for increasing angular width of the target, as was also observed in part 1b of the experiment. But if we observe Fig. 20c for the case of correct 'non clear' selections only there is again little variation for increasing angular width. This indicates that while participants found it easy to select targets with large width, there is a point where *clear* selections become very difficult as angular size is increased, particularly where there is high uncertainty. Looking at Fig. 21 we see that there is a slight decrease in the selection time as angular width increases for both the left and right targets but not for the center target. This indicates that in the case with maximum angular width users were finding it difficult to localise one individual set of impact sounds. In the left and right target case it is possible to move to the outer edge of target to isolate one kind of impact sound but in the center target case this is not possible. Again, this shows that high uncertainty in a system places limits on the system design.

8 Discussion

This experiment has shown that users can isolate their desired targets effectively with a basic system that

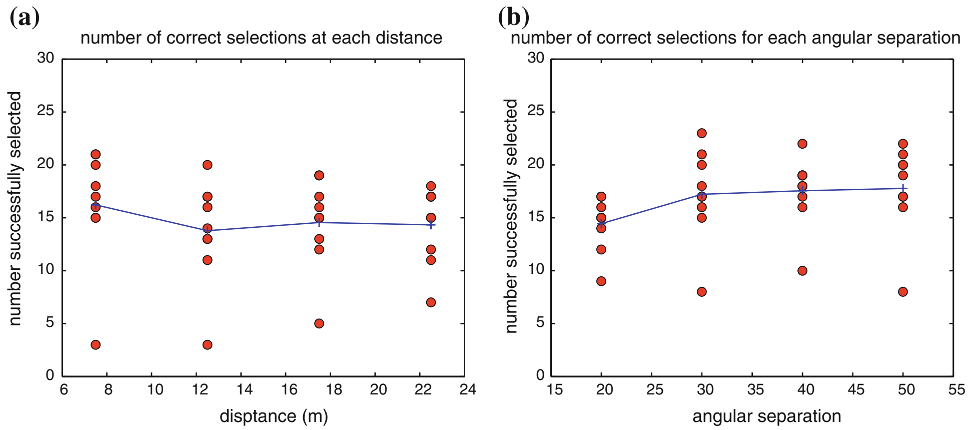

Fig. 16 **a** Each column shows the number of correct selections for varying distance in part 2a of the experiment. *Red circles* show the number of clear correct selections for each user, with blue crosses indicating the mean value for that distance. **b** Each column shows the number of correct selections for varying angular separation. The *red circles* show the number of clear correct selections for each user

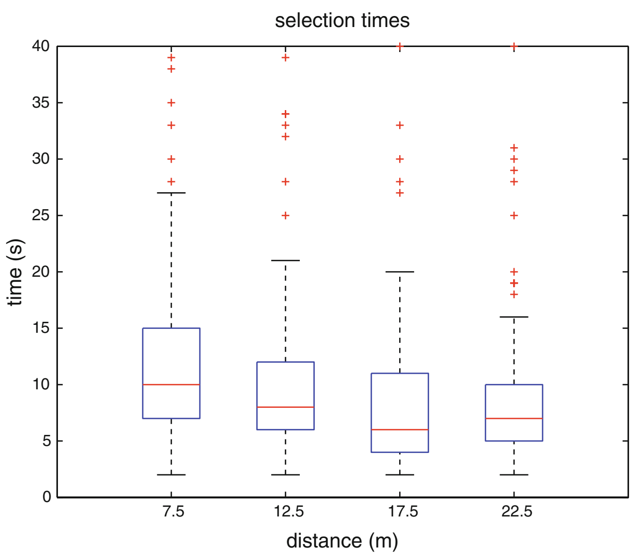

Fig. 17 Selection times for each target for varying distance in part 2a of the experiment. Selection time decreases with increasing distance to the target

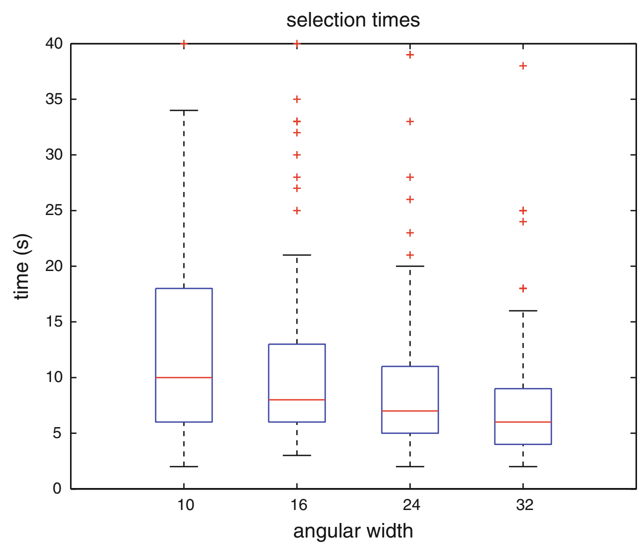

Fig. 18 Selection times for each target for varying angular separation in part 2a of the experiment. Selection time decreases with increasing angular separation

incorporates 'typical' noise conditions. It has shown that although the range of distances used in this experiment was perhaps smaller than it could have been (using a 30° range mapped to a 15 m distance), in the high uncertainty case users tended to be slightly quicker and slightly more effective at higher distance, corresponding to a lower tilt angle of the device. This is almost certainly down to the increased uncertainty making selection at lower distance (higher tilt) much more difficult. In the low uncertainty case it was found that increasing width (decreasing tilt) had little effect on the results. It must be mentioned that this experiment was more a test of effects of varying the tilt angle of a device since no real world objects were being used for the pointing task.

The varying angular separation experiment has, quite intuitively, illustrated to us that users are more effective with increasing distance between targets. At lower separations users tend to take longer to select the target due to

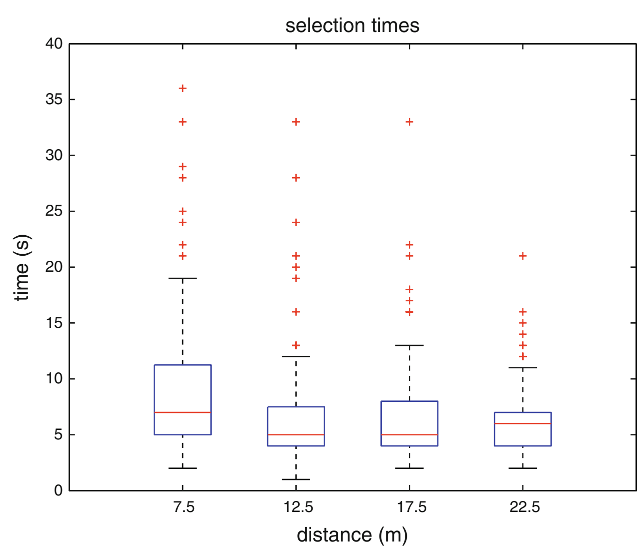

Fig. 19 Selection times for each target for varying distance in part 2b of the experiment. Selection time decreases with increasing distance to the target

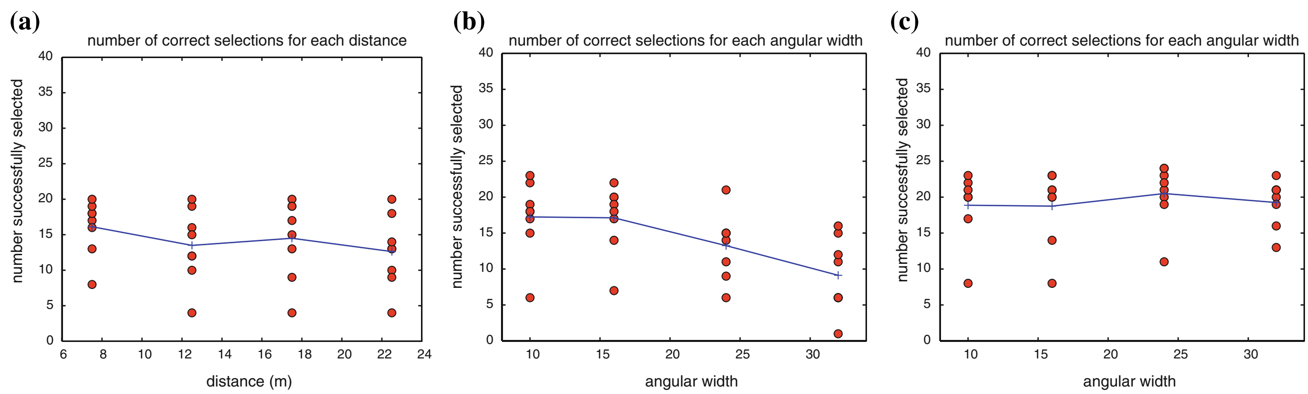

Fig. 20 **a** *Red circles* show the number of clear correct selections for each user in part 2b of the experiment, with *blue crosses* indicating the mean value for that distance. **b** *Red circles* show the number of clear correct selections for each user in part 2b of the experiment for increasing angular width. **c** *Red circles* show the number of non-clear correct selections for each user in part 2b of the experiment for increasing angular width. This shows that although users were failing to select the correct target clearly, they were still selecting the correct target indicating that perhaps less effort is expended on the perceived easier task

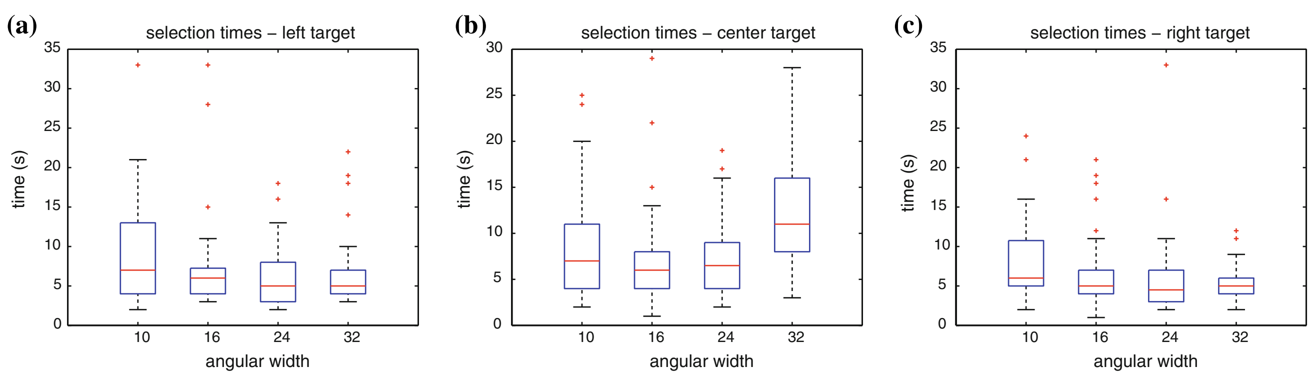

Fig. 21 Selection times for each target for varying target angular width in part 2b of the experiment. Selection time decreases slightly with increasing angular width for the left and right targets but not for the center target. This is due to the space between targets decreasing as the size of the target is increased making it increasingly difficult to clearly select the center target without any interference from the other targets. For both the left and the right targets a clear selection was possible if the user focussed their selections on the outer edge of the target

significant cross-talk between the targets, especially in the case with high uncertainty, although the minimum separation between targets obviously depends on this level of uncertainty in a particular environment or context.

The varying angular width experiment for both the high and low uncertainty cases provided an intriguing insight to the design of this kind of system. In the low uncertainty case it was found that as the width of the target is increased users in general become more successful. But the accuracy of their target selections decreases significantly. This is thought to be due to the participants taking a less accurate approach when the task was perceived to be significantly easier.

In the high uncertainty case the number of successful and clear selections was found to fall off with increasing width. This was found to be due to the decreasing distance between the targets as the width increases leading to increasing cross-talk between neighbouring targets. The more successful participants were found to combat this by moving to the outer-edge of the target in order to isolate the correct impact sound but this was not possible with the center target, leading to much higher selection times for this target with higher angular width. Designers of this kind of system then should be aware that although increasing the width of a target will, in general, increase the ease of selection for that target, care has to be taken not to decrease too much the distance to any neighbouring targets. Highest success was achieved in this experiment for angular widths between 10° and 24°, implying a minimum distance between targets of 26°.

The system described here is a basic one and highlights some of the problems that may be encountered but there exist a number of possible ways in which this basic system that incorporates typical noise conditions can be improved. One possible improvement to this kind of system could be the use of a more complicated kind of dynamic adaptation of the system. For example, attractors could be placed around targets that channel our particle probe to that particular target, reducing, if not eradicating, any cross-talk between targets and allowing users to focus on a particular target with greater ease. The explicit use of natural constraints in our environment can be used to channel our probe into particular locations. For example, a natural building corridor may exist in the real world that could be incorporated into the virtual environment and used to channel our probe and constrain it to any natural openings in the real world where targets may be placed.

9 Conclusions

This paper has introduced a new framework for providing a highly interactive and embodied context-based querying mechanism to location-aware mobile spatial interactive applications. We have quantified the main sources of error present in this kind of system, focussing primarily on the effect of bearing and positional errors and have introduced and described a probabilistic framework which deals with these sources of uncertainty.

An experiment was conducted to analyse the effect on bearing-based selections in a virtual environment of varying target distance, target width and angular size. Although it is difficult to give precise values after these initial experiments, it was found that effective selection is maintained down to 26° separation with a 9° target width in the high uncertainty case. In the low uncertainty case it was found that effective selection was maintained even at the lowest limit examined in this experiment, that is, up to 20° separation with a 10° target width.

9.1 Outlook

There is great scope for extension of the ideas presented in this paper. The implementation of this kind of system on a commercial mobile phone is the next step and requires only the incorporation of magnetometers and accelerometers into a device for accurate heading and tilt determination. The audio and vibrotactile feedback used at the moment is relatively simple and there exist many degrees-of-freedom in the display, which could be used creatively, balancing the artistic presentation of the system augmenting the physical environment with the information content available. As the richness of the models and feedback mechanisms develop, we might find exciting new ways of engaging with this augmented environment. For example, it may become possible to perceive the shapes and sizes of objects as we are interacting with them in the virtual environment, and sculpt them interactively using a mobile device.

In this work we have shown that with the use of uncertain feedback it is possible for users to rapidly select objects in a virtual environment. Without uncertain feedback target selection would be slower and less precise unless targets were made very large and spaced far apart. Future work in this area must include a study of how to deal with uncertainty from walking user data compared to static user data and in particular how to graciously move between these two levels of uncertainty. It is likely that in this high uncertainty walking or jogging environments that new methods of target access will need to be designed.

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