Urban Positioning on a Smartphone: Real-time Shadow Matching Using GNSS and 3D City Models

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BIOGRAPHY

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Prof Marek Ziebart is Professor of Space Geodesy at UCL, Vice Dean for Research in the Faculty of Engineering Science, and Director of SGNL. In 2007, *GPS World* named him as one of the 50 Leaders to Watch for his contributions to the global navigation and positioning industry. He holds a PhD in Satellite Geodesy and Astrodynamics, and is a member of the International GNSS Service Governing Board. He is a contributor to news items and documentaries on BBC Radio and Television. He has carried out numerous consultancies and research contracts, including for NASA, the US Air Force, the European Space Agency, the UK Hydrographic Office, and Ordnance Survey.

ABSTRACT

The poor performance of global navigation satellite system (GNSS) user equipment in urban canyons is a well-known problem, particularly in the cross-street direction. However, the accuracy in the cross-street direction is of great importance in Intelligent Transportation Systems (ITS) and land navigation systems for lane identification, in location-based advertisement (LBA) for targeting suitable consumers and many other location-based services (LBS).

To tackle this problem, a new approach, shadow matching, has been proposed, assisted by knowledge derived from 3D models of buildings. In this work, a new smartphone-based positioning system using 3D city models is designed. The system is then implemented in an application (app, or software) on the Android operating system. With a number of optimizations developed, for the first time, a demonstration is performed on a smartphone using real-time GPS and GLONASS data stream. The computational efficiency of the system is thus verified, showing its potential for larger scale deployment. Experiments were conducted at four different locations, providing a statistical performance analysis of the new system. Analysis was conducted to evaluate the performance of the system. The experimental results show that the proposed system outperforms the conventional GNSS positioning solution provided by GNSS chips on smartphones, reducing the cross-street positioning error by 69.2 % on average.

It should be noted that the system does not require any additional hardware or real-time rendering of 3D scenes. It is therefore power-efficient and cost-effective. The system is also expandable to work with Beidou (Compass) and Galileo in the future, with potentially improved performance.

KEY WORDS

Smartphone, Personal Navigation Device (PND), Urban Canyons, 3D City Model, Shadow Matching, GNSS, Real Time, 3D map, 3D GIS

1. INTRODUCTION

The poor performance of global navigation satellite systems (GNSS) user equipment in urban canyons in terms of both accuracy and solution availability is a well-known problem (Wang et al., 2012b). This problem arises where there are tall buildings or narrow streets. The direct line-of-sight (LOS) signals from many, sometimes most, of the satellites are blocked. Without direct signals from four or more satellites, an accurate position solution cannot be determined. Sometimes, a degraded position solution may be obtained by making use of signals that can only be received by reflection off a building; these are known as non-line-of-sight (NLOS) signals (Ercek et al., 2005, Viandier et al., 2008).

As well as affecting the number of available GNSS signals, an urban canyon also affects the geometry of positioning solutions, which causes lower accuracy in the cross-street direction. This is because signals with lines of sight going across the street are much more likely to be blocked by buildings than signals with lines of sight going along the street. This is illustrated by Figure 1. As a result, the signal geometry, and hence the positioning accuracy, is much better along the direction of the street than across the street (Groves, 2011).

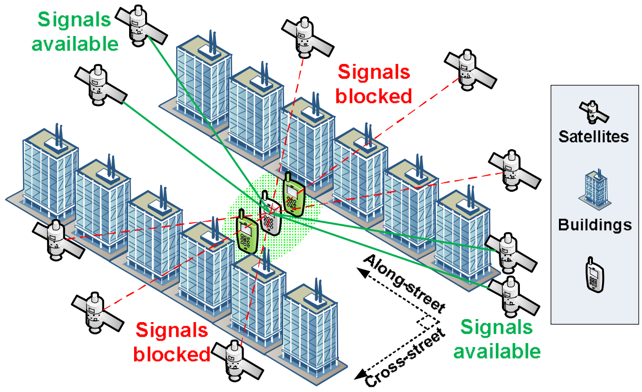

Figure 1: Satellite signals with lines of sight (LOS) going across the street are much more likely to be blocked by buildings than signals with LOS going along the street.

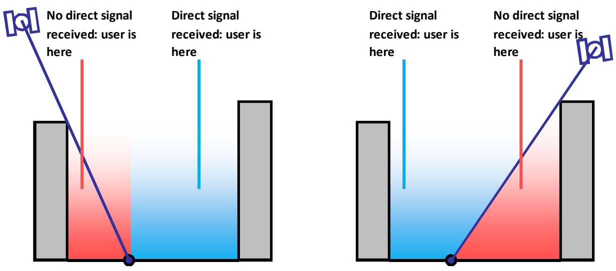

Figure 2: The shadow-matching concept: using direct signal reception to localise position (Groves, (2011)).

However, the accuracy in the cross-street direction can be of great importance to daily life. Vehicle lane detection for lane guidance systems and intelligent transportation systems (ITS), location-based advertising (LBA), augmented-reality applications, and step-by-step guidance for the visually impaired and for tourists all require sufficient positioning accuracy to perform their functions (You et al., 2008, Broll et al., 2008, Rashid et al., 2005).

For improving navigation performance in highly built-up areas, a variety of navigation sensors has been used to enhance or augment GNSS. Road vehicles typically combine GNSS with odometers and map-matching algorithms, while pedestrian navigation users may combine GNSS with cell phone signals, Wi-Fi and/or dead reckoning using inertial sensors, magnetic compass and barometric altimeter (Groves, 2013a, Farrell, 2008). A selection of these sensors can help mobile phone users to recognize motion states, consequently context-adaptive algorithms can be applied to improve the positioning performance (Susi et al., 2013, Pei et al., 2013, Groves, 2013a, Kamisaka et al., 2011). While these approaches improve the availability and robustness of the position solution, they do not particularly improve the cross-street accuracy.

As 3D building models are becoming more accurate and widely available (Bradbury et al., 2007), they are treated as a new data source for urban navigation and are used to improve positioning performance in urban canyons. Some research utilises 3D city models to detect and eliminate non-line-of-sight (NLOS) or multipath errors, in order to improve GNSS positioning accuracy (Peyraud et al., 2013, Groves et al., 2012a, Bourdeau and Sahmoudi, 2012, Obst et al., 2012, Peyret et al., 2011, Bradbury et al., 2007). Another line of research that utilises 3D city models for navigation is the evaluation of GNSS positioning performance with 3D ray tracing or ray intersection techniques (Ji et al., 2010, Kim et al., 2009, Kleijer et al., 2009 , Bradbury, 2007, Suh and Shibasaki, 2007, Wang et al., 2012b, Costa, 2011). This line of research demonstrates the practical potential of shadow matching, the technique focused in this work. Furthermore, 3D city models are also applied to enhance map matching (Piñana-Díaz et al., 2012) and image matching in land vehicle navigation (Cappelle et al., 2011).

Shadow matching has been proposed to improve the cross-street accuracy using GNSS, assisted by knowledge derived from 3D city models (Groves, 2011, Tiberius and Verbree, 2004, Yozevitch, 2012). Due to obstruction by buildings in urban canyons, signal reception from GNSS satellites is highly dependent on position within a street. The expectation for which signals are available can be predicted using a 3D city model. Consequently, by determining whether a direct signal is being received from a given satellite, the user can localize their position to within one of two areas of the street. Figure 2 illustrates this. With a number of satellites contributed to this process, a positioning solution can be provided.

The work of this paper is based on the first author's doctoral research since 2010, when the shadow matching principle was proposed at UCL (Groves, 2011). The performance of GNSS in urban canyons was first evaluated and verified by 3D city models (Wang et al., 2012b). Then, a preliminary shadow-matching algorithm was developed and demonstrated the ability to distinguish the pavement from a vehicle lane, and identify the correct side of the street using real-world GPS and GLONASS measurements (Wang et al., 2011, Groves et al., 2012b). Furthermore, a new scheme has been proposed that takes account of the effects of satellite signal diffraction and reflection by weighting the scores based on diffraction modelling and the signal-to-noise ratio (SNR). This was shown to improve the navigation solution of geodetic GPS and GLONASS receivers (Wang et al., 2012a, Wang et al., 2013a). Recently, GNSS data collected on a smartphone was processed using a shadow-matching algorithm on a PC; however, comprehensive analysis is due to be conducted and the computation efficiency needs to be addressed (Wang et al., 2013b).

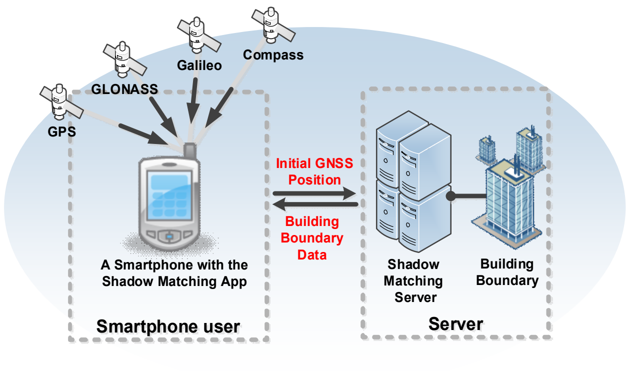

Figure 3: The overall system architecture design

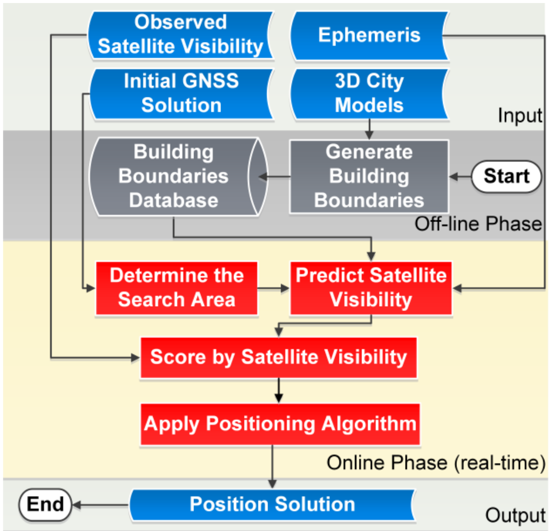

Figure 4: A workflow of the improved shadow-matching algorithm.

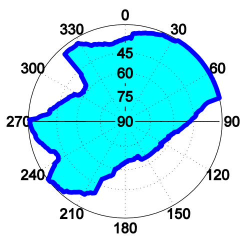

Figure 5: An example of a building boundary as azimuth-elevation pairs in a sky plot. (The centre of the plot correspond to a 90º elevation or normal incidence)

This paper presents a significant development of shadow matching – a smartphone-based shadow-matching system that works in real time. The motivation of the work in this paper comes from two perspectives. First, most potential applications of shadow matching use consumer-grade GNSS user equipment, whereas previous shadow matching algorithms were mainly tested using geodetic GNSS receivers (Wang et al., 2012a). The consumer-grade GNSS receivers normally cost much less, and can be subject to worse signal reception, more severe multipath reception and stronger non-line of sight (NLOS) reception due to the low gain and linear polarization of consumer-grade GNSS antennae. These differences can degrade shadow-matching performance. Thus, research is required to investigate shadow-matching performance using consumer-grade GNSS receivers with smartphone antennae. Furthermore, smartphones and personal navigation devices (PND) normally have much less computational capability in comparison with a desktop computer or laptop, whereas the existing algorithm has only been run on personal computers. Its computational efficiency has not previously been tested. Thus, optimization of the shadow matching system to make it suitable for smartphone-grade devices is worth investigation. The low-grade antenna and low-computational power of smartphones are the two obstacles. They are also the scope of this paper, which proposes and implements a smartphone-based system, aiming at meters-level cross-street accuracy in urban canyons, and assess the real-time positioning performance.

A summary of the design of the real-time shadow-matching system and its optimizations in pre-processing building boundaries are presented in Section 2. Section 3 then describes the details of application development on the Android operating system. An assessment of real-time experiments is presented in Section 4, with different criteria applied to compare the performance between the conventional GNSS navigation solution and the shadow-matching system solution. Section 5 discusses the feasibility of larger scale implementation. Finally, in Section 6, conclusions are drawn.

2. SYSTEM DESIGN AND OPTIMIZATION FOR REAL-TIME APPLICATIONS

This section introduces the design of a new real-time shadow-matching positioning system, with explanations of key design choices. Section 2.1 introduces the overall architecture of the new positioning system. The shadow-matching algorithm is then described. Algorithm improvements, which are essential to real-time efficiency, are given in Section 2.2.

2.1 System Architecture Design for a Real-time Positioning System with Shadow Matching

In a full implementation of a shadow-matching system, there is a server interacting with a smartphone user. The smartphone first sends a positioning request with an initial GNSS position to the server. The server then gathers the building boundary data that assists in shadow-matching positioning (to be explained in more detail in Section 2.2) according to the user's initial position and sends them back to the user. Finally, the smartphone performs the shadow-matching algorithm and acquires a positioning solution. The overall architecture of the shadow-matching system is illustrated in Figure 3.

In terms of algorithm design, shadow matching has two phases – the offline phase (the preparation step) and the online phase (the real-time positioning), which are executed in four steps, as illustrated in Figure 4 in red. An off-line phase is conducted to generate a grid of building boundaries. At the beginning of the online phase, the search area is defined for the shadow-matching position solution, based on the initial GNSS position. For the second step, the satellite visibility at each grid position is predicted using the building boundaries generated from the 3D city model. After that, the difference between prediction and observation is evaluated using a scoring scheme, providing a score for each grid point in search area. Finally, the shadow-matching positioning solution is generated by a modified k-nearest-neighbours algorithm, which averages the grid points with the highest scores. Each of the steps is described in more detail below.

A full implementation would also incorporate context detection to determine whether the user is in an indoor, urban or open environment (GROVES, 2013b). The shadow-matching algorithm would then only be called in urban contexts.

Step 0: Generate a Grid of Building Boundaries (off-line phase)

In the off-line phase, building boundaries on a grid of outdoor locations are generated. The boundaries are from a GNSS user's perspective, with the buildings edge determined for each azimuth (from 0 to 360°) as a series of elevation angles. The results from this step show where the building edges are located within an azimuth-elevation sky plot. Figure 5 shows an example of a building boundary computed from a candidate user location. Once the building boundary has been computed, it may be stored and reused in the online phase to predict satellite visibility by simply comparing the elevation of a satellite with the elevation of the building boundary at the same azimuth. A software toolkit for generating the grid of building boundaries from a 3D city model was developed in C++.

Step 1: Determine the Search Area for Candidate Positions from the Building Boundaries on a Grid

Before the first step of the shadow-matching algorithm, an initial GNSS position is required. In an urban environment, the GNSS accuracy is often poor (Misra and Enge, 2010). Therefore, it is important to minimize the impact of non-line-of-sight reception and multipath interference on the position solution (Jiang and Groves, 2012, Jiang et al., 2011, GROVES et al., 2013, Groves and Jiang, 2013). Other available positioning methods (e.g. Wi-Fi or Cell network solution) may be introduced in this step when the blockage is too great in urban canyons for GNSS to give a solution or when GNSS gives less accurate positioning than other positioning methods (e.g. Wi-Fi).

The first step defines the search area in which the candidate positions are located for the shadow-matching position solution. A search area is defined based on the initial position. A simple implementation can be to draw a fixed-radius circle centred at the initialized position, but more advanced algorithms can be developed to use the knowledge of satellite geometry to optimize the search area.

For instance, if the initial position is generated using a conventional GNSS solution, the signal geometry, and hence the positioning accuracy, will be much better along the direction of the street than across the street. This is because an urban canyon affects the geometry of the available GNSS signals. Signals with lines of sight going across the street are much more likely to be blocked by buildings than signals with lines of sight going along the street. Therefore, the conventional GNSS solution has a lower accuracy across the street and a higher accuracy down the street, which is complementary to the shadow-matching algorithm.

Thus, the down-street component of a conventional GNSS solution can be used as a reference to define the search area and thus generate candidate user positions with a greater range of possibilities in the cross-street direction. This is illustrated by the two green mobile phones besides the initial GNSS solution of the user in Figure 1, with the green area representing the search area centred at the initial position. A more advanced shadow-matching algorithm would vary the size of its search area based on an assessment of the quality of the received satellite signals.

Step 2: Predict Satellite Visibility at Each Candidate Position

In the second step, performed at each candidate position, each satellite's elevation is compared with the building boundary elevation at the same azimuth. The satellite is predicted to be visible if the satellite is above the building boundary. With pre-computed building boundaries, this step can be computationally efficient.

Step 3: Satellite Visibility Scoring

For the third step, the similarity between predictions and observations, of the satellite visibility, is evaluated. The candidate positions with the better matches will then be weighted higher in the shadow-matching positioning solution. There are two stages for calculating a score for a candidate position. Firstly, each satellite above the elevation mask angle is given a score, calculated based on the predicted and observed visibility. Secondly, the position scoring function, evaluates the overall degree of match between predicted and observed satellite visibility for each possible user position. This is illustrated in (1).

$$f_{pos}(j) = \sum_{i=1}^{n} f_{sat}(i, j, SS) \tag{1}$$

where $f_{pos}(j)$ is the position score for grid point j ; $f_{sat}(i, j, SS)$ is the score of satellite i at grid point j using the scoring scheme SS. SS is the scoring scheme which defines a score based on predicted and observed satellite visibility. n is the number of satellites above the elevation mask angle.

By the end of this step, each candidate position should have a score to represent the degree to which it matches the observed satellite visibility, and thus how likely it is that each candidate position is close to the true location.

Different scoring schemes can be applied at this stage. Figure 6 shows the 2 by 2 scoring scheme used in this work. This scheme only considers direct line-of-sight (LOS) signals. Other schemes can take into account diffraction and reflection effects. The difference between various scoring schemes is out of the scope of this paper. More details can be found in previous work (Wang et al., 2012b).

Step 4: Positioning Using Scores at Candidate Positions

The last step of the shadow-matching algorithm is to generate a positioning solution using the scores from each candidate position. Shadow matching uses the pattern-matching positioning method (Groves, 2013a). As the process of Wi-Fi fingerprinting is similar to this process, the algorithms used in Wi-Fi fingerprinting may be investigated for their potential implementation in shadow matching. Potential algorithms include, but are not limited to, k-weighted nearest neighbours, the Bayesian inference received signal strength (RSS) location method, and the particle filter.

In this work, a method similar to k-nearest neighbours is used to estimate the location, averaging the grid positions with the highest scores. With the current scoring system, scores take integer values. Therefore, several grid points typically share the highest score. The points in the grid with highest scores are regarded as nearest neighbours. For L nearest neighbours, the location estimate is obtained using (2):

$$\text{Northing} = \frac{1}{L} \cdot \sum_{i=1}^{L} n_i; \quad \text{Easting} = \frac{1}{L} \cdot \sum_{i=1}^{L} e_i \qquad (2)$$

where n_i and e_i are, respectively, the northing and easting coordinates of the i^{th} high-scoring candidate positions. Note that L varies from epoch to epoch depending on how many candidate positions share the highest score.

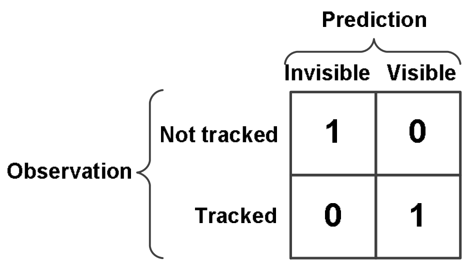

Figure 6: The 2-by-2 scoring scheme giving the score for each satellite in shadow matching

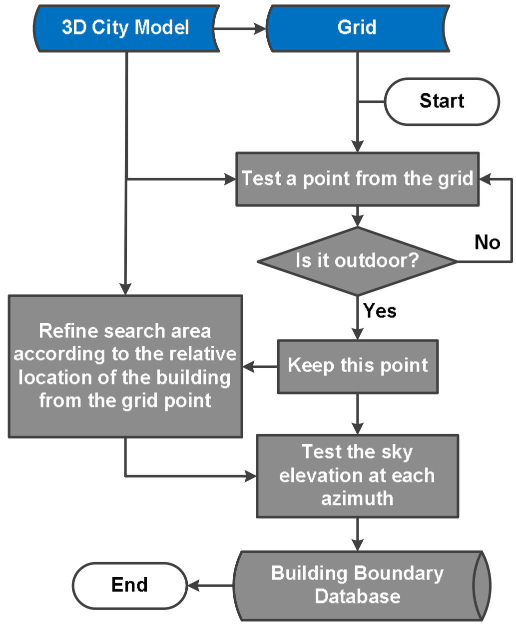

Figure 7: The process that generates the grid of building boundaries

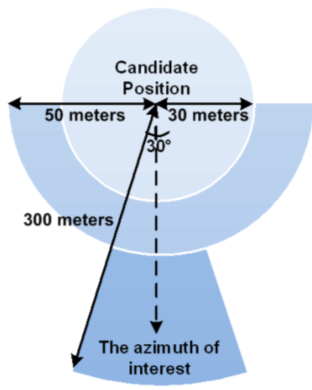

Figure 8: The optimization used in building boundary generation by refining city models according to location of a candidate user position and an azimuth of interest. (Aerial perspective, the figure is not drawn to scale)

3. APPLICATION IMPROVEMENTS FOR REAL-TIME EFFICIENCY

The main strategy for improving real-time efficiency is that the building boundaries are pre-computed and stored in a server. From the perspective of mobile devices, the system trades time and computing power to a one-off processing requirement at the server side. Specifically, this is achieved by representing the 3D model in a specially designed form - building boundaries at each candidate position. The logic behind this strategy is that the vast amount of data in a 3D city model is not of direct interest to the shadow-matching algorithm. The interest is where the edges of the buildings are located from a user's perspective. Thus, utilizing this knowledge, only the building boundaries at each candidate position are abstracted from the 3D model. This method saves real-time computational load because individual mobile devices do not need to compute the building boundaries on the fly. Instead, they can simply request building boundaries at a certain range of locations, or cache a desired region.

Using stored building boundaries, fewer than fifty comparison and addition operations are required to calculate an overall shadow matching score for one candidate position with two GNSS constellations. Therefore, shadow matching may be performed in real time on a mobile device with several hundred candidate positions, where necessary.

The optimized process in the off-line phase can be broken into four steps. In the beginning, a horizontal grid of points with 3-meter spacing, covering the 3D city model area, is generated. The height is set to be 1.5 meters above the terrain height measured in the 3D city model. Second, a pre-processing step is developed to eliminate indoor points from the generated grid in the first step, because the current shadow-matching algorithm is designed to work outdoors. Outdoor points are distinguished from indoor ones by testing whether the elevation angle of the sky at each azimuth is 90 degrees. Further details of the algorithms testing line-of-sight visibility can be found in a previous paper (Wang et al., 2012b). Thirdly, buildings that are unlikely to block satellite signals are eliminated from the search area, based on checks of their relative location from the candidate position of interest. Details are explained further for this optimization below. Finally, the lowest elevation angle for a visible sky at each azimuth is tested to determine the building boundary at each outdoor candidate position. Figure 7 illustrates these four process of building boundary generation.

In order to improve the efficiency of the offline phase, in the third step, only buildings that are close to the candidate position and in the direction of interest are tested. Figure 8 illustrates this search area. It should be noted that the parameters used in this example are manually selected based on knowledge of the 3D city model used in this work. Appropriate changes should be made if using another type of city model. Without optimization, it takes an estimated 6 days to perform the process at a grid of candidate positions with 3-meter spacing across a 500 m by 500 m area, using a computer with a CPU speed of 2.67 GHz. After optimization, the time required to generate building boundaries at the same grid of points was reduced to 10 hours, a 93% reduction in time compared to the original algorithm.

4. APPLICATION DEVELOPMENT ON ANDROID DEVICES

An application (app) that runs on the Android operating system has been developed. This section briefly introduces the smartphone and the operating system involved in this work, with more detailed descriptions of the application development.

4.1 The smartphone and the Android operating system

The smartphone used in this work is a Samsung Galaxy S3 smartphone. It receives both GPS and GLONASS satellites with Assisted-GPS (A-GPS or AGPS) capability. The smartphone runs on the Android operating system, a Linux-based operating system primarily for mobile devices. It is one of the most common smartphone systems. According to the figures released from analyst firm International Data Corporation (IDC), Android smartphone shipments account for 75% of all smartphones shipped worldwide in the third quarter 2012 (ICD).

4.2 App development

The app has been developed in Java using Eclipse, a software development environment (SDE). The app was built on Standard Android platform 4.0.3, using the Android Application programming interface (API) to retrieve information from the GNSS chip. In this implementation, the building boundary data is stored on the SD card.

The Android operation system listens to the real-time GNSS messages from the GNSS chip, interprets GNSS information from them, and provides the information to app developers through the Android API. The public interface GpsStatus.Listener outputs, in real-time, the information provided by the GNSS chip, and contains a number of attributes. The useful attributes for this application include the azimuth, elevation and SNR of GPS and GLONASS satellites in view. The latest location determined by the GNSS chip is output by the public interface LocationListener. This data feeds into the shadow matching positioning engine, together with the building boundary data stored on an SD card. The new positioning engine then computes user's position based on the conventional GNSS solution. Finally, the positioning results are displayed on maps using the Google Maps API. The flowchart of the app is illustrated in Figure 9.

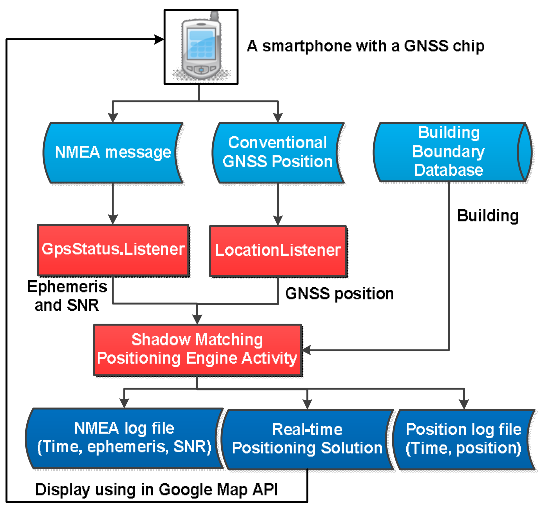

Figure 9: The flowchart of the real-time application running on Android devices.

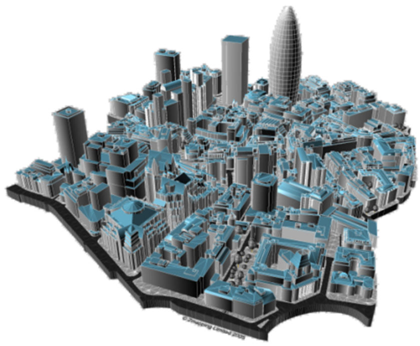

Figure 10: Part of the 3D model of London used in the experiments

Figure 11: Photos taken at the experimental sites, showing the urban environments in experiments G2.

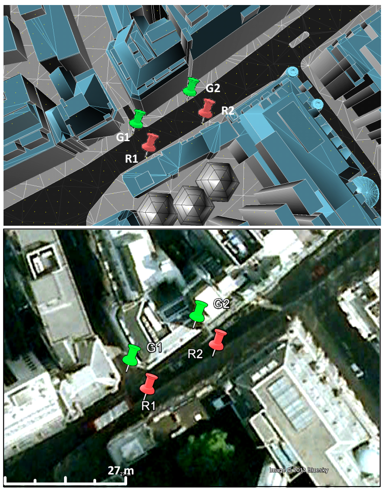

Figure 12: An aerial view of the experimental site on Fenchurch Street: 3D city model (above) and satellite image (below)

Figure 13: A photo of the real-time experiment using the developed shadow-matching application on the smartphone at site G2.

5. REAL-TIME EXPERIMENTS AND PERFORMANCE ASSESSMENT

To evaluate the performance of a real-time shadow matching system on smartphones, experiments were conducted in central London. Section 4.1 outlines the 3D city model and the test sites, and describes the configuration of the shadow-matching system. A typical example of the real-time experiments is described in Section 4.2. Recorded GNSS data is then processed using an identical algorithm to that in the real-time system. Section 4.3 shows the scoring maps, which are important intermediate results of the shadow-matching system. The positioning results compared between the new system and conventional GNSS positioning are given in Section 4.4.

5.1 Experimental Settings

A 3D city model of the Aldgate area of central London, supplied by ZMapping Ltd, was used. The model has a high level of detail and decimetre-level accuracy. Figure 10 shows part of the city model used in this work.

Four experimental locations with different road conditions were selected on Fenchurch Street, a built-up urban area. Figure 11 shows photos taken at the street, showing the urban environments. Two of the sites, named G1 and R1, were located at a ‘T’ junction between Fenchurch Street and Fenchurch Buildings Road. The other two sites, named G2 and R2, were selected between junctions on Fenchurch Street. In addition, G1 and R1 are located on opposite side of the street, enabling the new system to also be tested for its ability to distinguish the correct side of the street. The same layout applies to G2 and R2. All sites were selected on the footpath close to the traffic lanes. Figure 12 shows an aerial view of the city model and a satellite image, illustrating the settings of the four experimental sites. The truth model is set using the 3D city model. The slight offset between the city model and the satellite image is caused by the geometric distortions of the satellite images.

Before the experiment, in the offline phase of this work, a grid with 3-meter spacing was generated. Indoor points were then eliminated and building boundaries were determined at outdoor points, as described earlier in Section 2. The building boundaries were stored in a specially defined format in a database, and pre-loaded on the smartphone used in this experiment.

Real-time shadow-matching positioning was performed on a Samsung Galaxy S3 smartphone with a 5-second interval. The experimenter stood at each location for 6 minutes. Both GPS and GLONASS observations were used. Real-time satellite visibility information and positioning results were recorded at 1-second interval for later analysis.

5.2 Real-time experiment

A real-time shadow-matching positioning experiment was conducted. The typical processing time for the system was found to be 1-2 seconds.

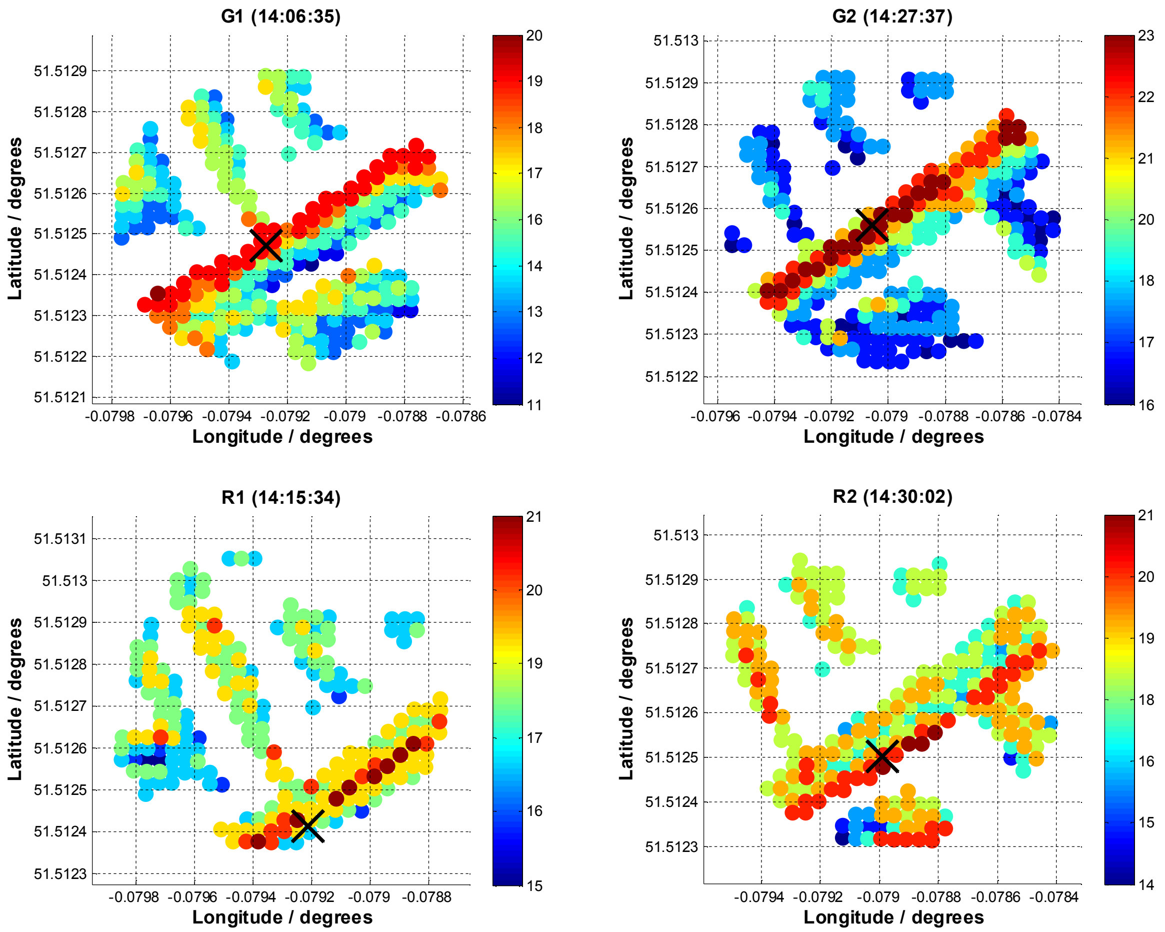

Figure 14: Shadow-matching scoring map at one epoch for four experimental sites.

Figure 13 shows a photo taken in the real-time experiment using the developed shadow-matching application (app) at site G2. As the application is a prototype of the real-time shadow-matching system, both the conventional GNSS solution of the smartphone GNSS chip and the positioning solution of the new system are displayed to the experimenter for a real-time comparison. The blue points are the conventional GNSS solutions, while the red points represent the solutions of the new system. The true location of the experimenter at G2 can be found in Figure 12. It is shown in Figure 13 that the conventional solutions are on the wrong side of the street, and distributed sparsely in the cross-street direction in comparison with the solutions of the new system. The shadow-matching real-time solutions are distributed more consistently in the across-street direction, on the correct side of the street. This is in line with the expected benefits of the new system which gives better across-street accuracy.

5.3 Analysis on algorithm scoring results

In real-time, a 40-meter radius candidate circle, centred at the conventional GNSS positioning solution provided by smartphone GNSS chip, is used to generate candidate positions defining the search region for the shadow-matching technique. The pre-calculated candidate grid of building boundaries (i.e. the off-line phase database) is loaded at this stage. At each observation epoch, a comparison is made between the predicted and observed satellite visibility, and the score scheme is applied accordingly. To illustrate the distribution of scores at the grid points, Figure 14 shows examples of the score maps at each experimental location. The coloured dots represent the candidate positions. The scale represents the score obtained for the candidate position in the shadow-matching algorithm, with higher scores representing a higher confidence level that the user is at this location. The true location of the experimental site is shown by a black cross in each colour map.

In Figure 14, it is clearly demonstrated that the shadow-matching algorithm is sensitive to changes in the cross-street direction, but less sensitive in the down-street direction. This is in line with expectations, and complements conventional GNSS positioning which is generally more precise in the down-street direction in urban areas due to the signal geometry. Combining the cross-street shadow-matching solution with the down-street conventional GNSS is an approach to intelligent urban positioning (IUP) (Groves et al., 2012a).

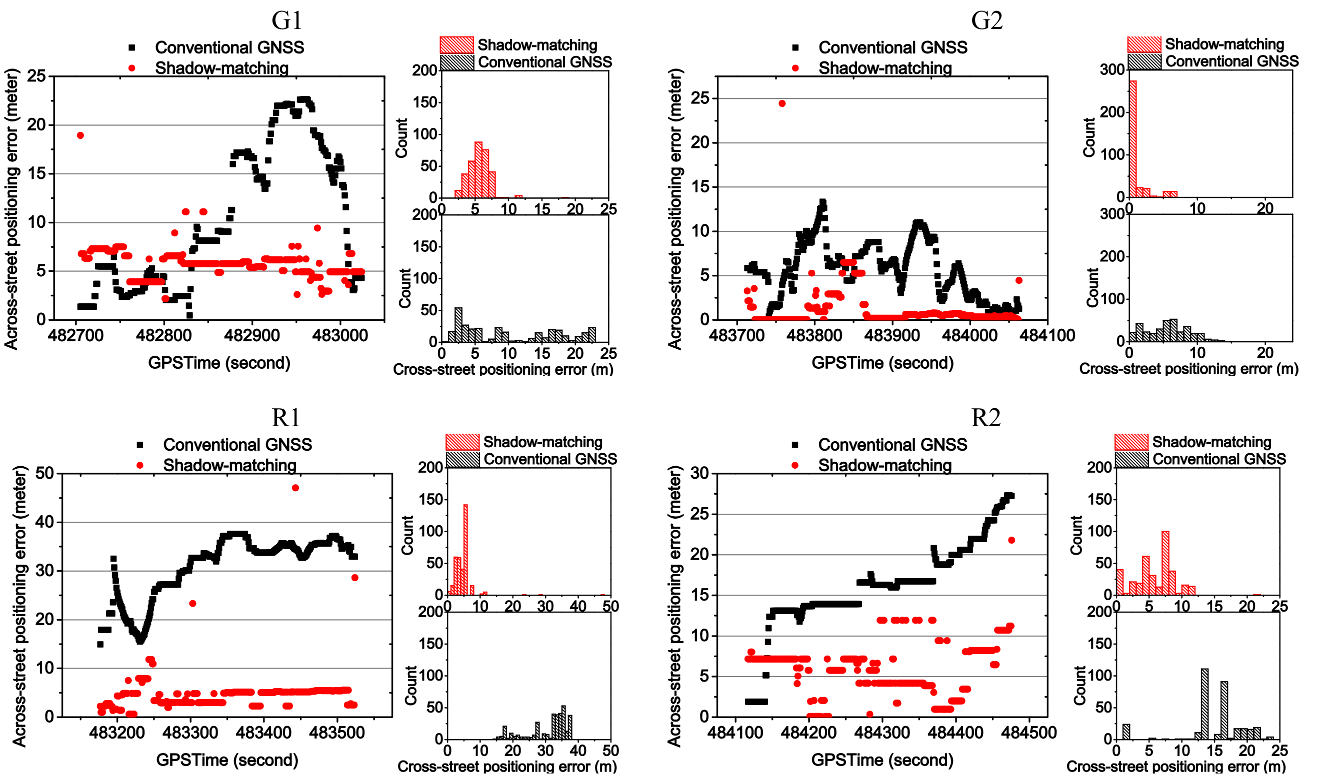

Figure 15: Comparison of cross-street positioning error between conventional GNSS solution provided by the smartphone and the shadow-matching solution, both based on real-time data.

There are some spaces between buildings that fall within the search area, but the highest scoring points are predominantly in the correct street. It can also be inferred from Figure 14 that in most cases, the highest score areas (dark red) appear on the correct side of the street. However, the high scores do not always appear at the expected area, mainly due to non-line-of-sight (NLOS) reception. Applying different scoring matrixes may reduce the effect imposed by NLOS receptions, but it is out of the scope of this paper. In order to further analyse the consistency of positioning performance of the implemented positioning system over the whole period of the experiment, more analysis is presented in the Section 4.4.

5.4 Performance comparison with conventional GNSS positioning

In this section, the overall performance of the real-time shadow-matching positioning system is assessed and compared with the conventional GNSS solution from the GNSS chip in the Samsung Galaxy S3 smartphone, both in real-time. The performance in the cross-street direction is the main concern.

To assess the performance of real-time shadow matching against the conventional GNSS positioning solution, the position errors are transformed from local coordinates (Northing and Easting) to the along-street and across-street directions. Figure 15 shows the positioning results of the conventional GNSS navigation solution from the smartphone GNSS chip, compared with the shadow-matching positioning results, expressed as errors in the across-street direction. It shows that, in most cases, the shadow matching solution outperforms the conventional GNSS positioning solution. The shadow matching solution has improved the conventional positioning error, in the across-street direction, from typically 10 - 40 meters to within 5 meters in the most epochs. In the case of G2 (upper-right in Figure 15), the shadow-matching solution accuracy is better than 2m in most epochs.

On the right side of each sub-figure in Figure 15, the position error distribution is compared between the shadow-matching solution and the conventional solution. It is shown that shadow matching improves the positioning accuracy, reducing the average error to less than 5 meters on average in each case.

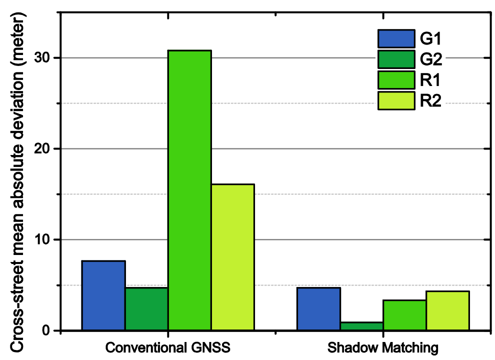

Figure 16: Comparison of the cross-street mean absolute deviation over all epochs between the conventional GNSS positioning solution and the shadow-matching solution.

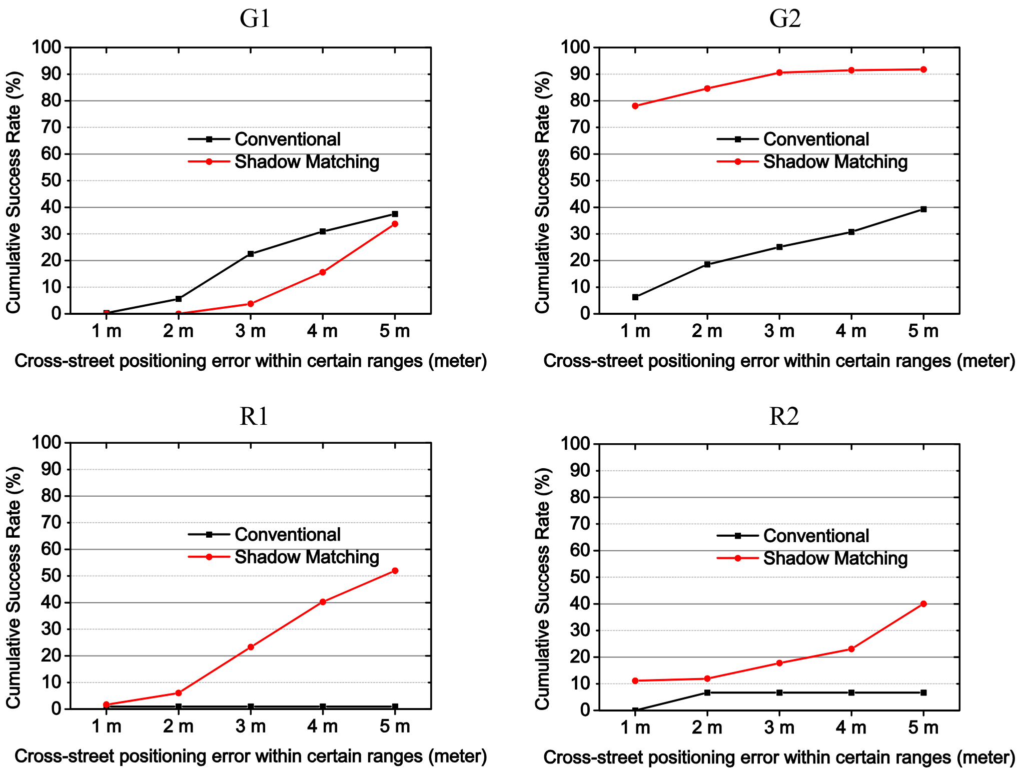

Figure 17: Success rate of cross-street positioning error within certain ranges, compared between the new positioning system and the conventional GNSS solution.

In order to evaluate the performance across all of the epochs, a statistical analysis was performed. An indicator, mean absolute derivation (MAD), was used to evaluate the performance from this perspective. In order to show the improvements of shadow matching over conventional GNSS positioning, the MADs at each site are compared in Figure 16. The bar shows the mean across-street positioning error using the conventional and shadow-matching algorithm, respectively. It should be noted that the statistics cover a 6-minute observation period, during which the constellation geometry changed slowly, so the results are highly correlated, temporally, allowing consistency of the system to be evaluated. It is shown in Figure 16 that the across street positioning performance of shadow matching is significantly better than conventional GNSS positioning solution. The shadow-matching positioning algorithm reduced the average cross-street error by 36.9%, 77.6%, 90.8% and 71.3% for G1, G2, R1, and R2 respectively. The new positioning system reduces the cross-street positioning error from 14.81 m of the conventional solution to 3.33 m of the new system, averaged over all four experimental sites. This is a 77.5% reduction of cross-street positioning errors on average. The RMS difference shows that the consistency of the shadow-matching solution also outperforms the conventional solution.

Further statistical comparisons have been conducted to assess the positioning performance as a success rate over 6 minutes, and the results are shown in Figure 17. As the street is around 10m wide, a positioning accuracy of less than 5m is considered good enough to determine the correct side of the street, while a positioning accuracy better than 2m is considered good enough to distinguish the footpath from a traffic lane. Averaged over the four experimental sites, the success rate using shadow matching for determining the correct side of a street is 54.4%, significantly improved from the success rate of 20.9% for the conventional solution. The success rate of distinguishing the footpath from a traffic lane is 25.6% for shadow matching, also considerably increased from 7.7%, for the conventional GNSS positioning.

Figure 18 shows the positioning results of the new system compared with the conventional GNSS solution in Google Earth. The blue dots represent the locations of the conventional GNSS solution, recorded in real-time. The purple dots denote the positioning solutions provided by the new system. The tags represent the true location of the site in each case. It can be seen that typically, the new system gives solutions more consistent with each other in cross-street direction. The solutions also have better accuracy in the cross-street direction, compared to the conventional solution. However, the conventional solution is more accurate in the along-street direction, in line with expectations.

The shadow matching positioning system is a suitable complementation to conventional GNSS positioning. As shadow matching improves the cross-street positioning significantly, it shows a high potential to be combined with conventional GNSS and other possible techniques for better overall performance (Groves et al., 2012a).

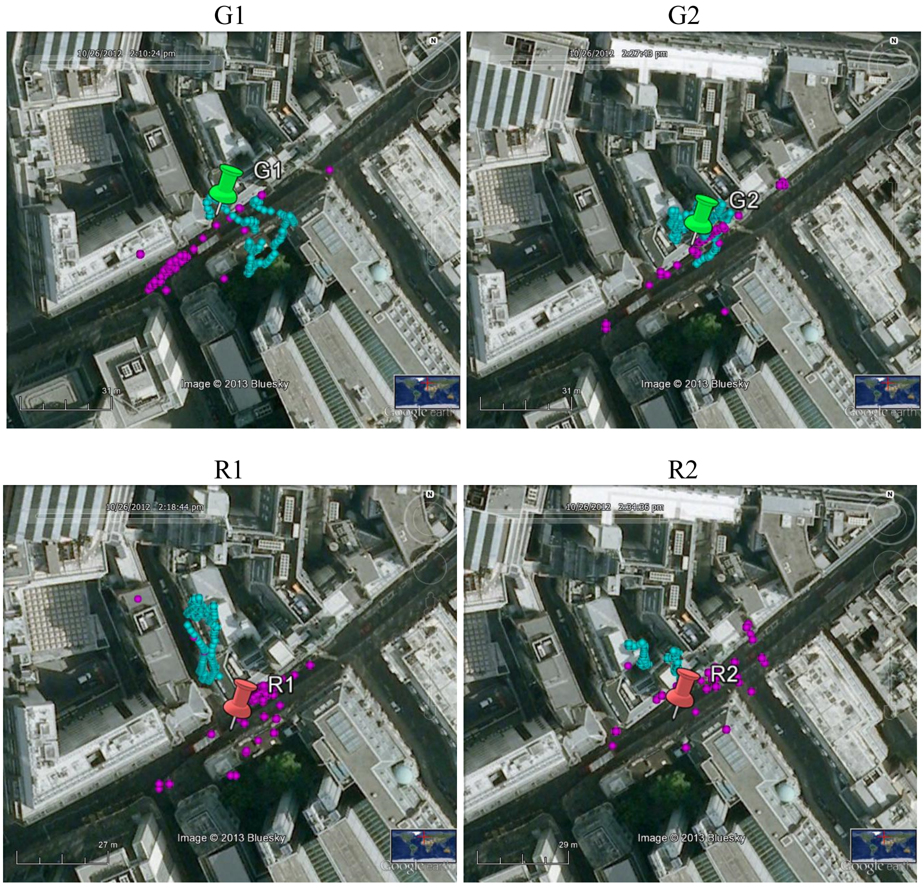

Figure 18: The positioning solution shown in Google Earth satellite image view (The blue dots represent the locations of the conventional GNSS solution. The purple dots denote the positioning solutions provided by the new system. The tags represent the true location of the site in each case. Image © 2013 Bluesky)

It should be noted that selection of a suitable grid spacing of building boundaries influences the performance and speed of the shadow matching system. The current implementation of the real-time shadow-matching system utilizes a grid of building boundaries with 3-meter spacing. It already shows a significant performance improvement in comparison with conventional GNSS positioning. A grid with 2-meter spacing, 1-meter spacing or even denser spacing can potentially be applied. In this work, a 1-meter spacing was also tested, providing an improved performance of 5% in terms of reduction of mean error averaged over the four sites. However, using the grid with 1-meter spacing requires roughly 9 times more computational time in comparison with using a grid with 3-meter spacing. Clearly, there is a trade-off between the accuracy of the shadow-matching system and the running time. The reason a grid with 3-meter spacing is finally used in the real-time system is that it gives the best compromise between performance and speed.

6. FEASIBILITY ASSESSMENT - TOWARDS LARGER SCALE IMPLEMENTATION

This section presents an assessment from the perspective of feasibility of deploying the system into larger scale.

6.1 Availability of 3D City Models and Satellite Information

The shadow-matching system depends on 3D or 2.5D city models to improve positioning. The availability of the models is of importance. Fortunately, there are an increasing number of 3D city models available through the internet. A few commercial examples include Google Maps 3D by Google Inc., iOS 3D Maps by Apple Inc., Bing Maps 3D by Microsoft Corporation, Nokia Maps 3D WebGL and Edushi 3D Maps. In addition to the commercial 3D maps, some free and cheap 3D maps are provided by some organisations, including Open Street Maps 3D (OSM-3D).

The satellite tracking information required by the new system in real-time has also been available to use. The shadow-matching system only requires information on whether the satellites are tracked or not, instead of pseudo-range or carrier phase measurements. It is provided on regular basis in NMEA sentences by most consumer-grade GNSS receivers. With the signal-to-noise ratio (SNR) message also regularly available through NMEA sentences, shadow matching will provide more reliable performance (Wang et al., 2012a). In addition, both the Android and the Windows Phone operating systems provide an API for developers to get this information in real-time.

6.2 Data Storage and Transfer Requirements

Shadow matching requires the knowledge of the building boundaries to work. Thus, the building boundaries database should be transferred to the user device on the fly or pre-downloaded (Groves et al., 2012b). Building boundaries with 1-degree resolution in azimuth at a grid point require about 300 bytes of storage, without compression.

With a 3×3 meter grid, a 1km long 20m wide street would contain 2222 grid points, which would require 651 kB of data storage. If the similarities between adjacent azimuths are exploited for compressing data, substantial data compression should be possible; perhaps up to a factor of ten. A 4 GB flash drive could store 6292 – 62920 km of road network. The Great London metropolitan area contains about 15,000 km of road. However, the built-up areas that require shadow matching for better positioning may be 10% of the total. Thus, it may be practical to preload the building boundaries onto a smartphone.

An alternative method is to transfer the data over the mobile network as required. On a 100-meter long 20-meter wide street, only 222 grid points are needed for shadow matching, which requires 141 kB of data. Transferring this would take less than two seconds using the 3G mobile phone network with a normal data plan.

Thus, in practice, it is feasible to implement shadow-matching system on a smartphone, a PND, or other consumer-grade navigation device.

6.3 Demand from Applications

Meters-level across-street accuracy in urban areas benefits a number of existing LBS and creates new applications. For example, vehicle lane detection is feasible with meters-level across-street accuracy. Although lane guidance systems are now common for in-car navigation systems, a lane detection system may enable a lane guidance system to guide the correct lane. Similarly, intelligent transportation systems (ITS) may use this technique to direct individual vehicles for maximizing traffic flow, and for prioritizing emergency vehicles. In situations where crossing the road takes considerable effort for pedestrians, location-based advertising (LBA) systems could use this technique to target the most suitable customers on the same side of the street. Some augmented-reality games may enhance the experience of the players through more accurate positioning. Perhaps most importantly, step-by-step guidance for the visually impaired and for tourists requires high positioning accuracy in urban areas in order to work. Navigation in mountainous regions could also benefit from this system when a digital elevation model (DEM) is available.

7. CONCLUSIONS

A new smartphone-based shadow-matching system, assisted by knowledge derived from 3D models of the buildings, has been designed. The new system is optimized to improve computational efficiency to account for the low processing power and limited storage on smartphones. The design of the real-time shadow-matching system and the optimizations has then been implemented, with details explained. A shadow-matching application (app) for Android operating system has been developed.

Furthermore, with the previous shadow-matching algorithms tested mainly on personal computers, for the first time, a demonstration is performed on a smartphone with real-time GNSS data stream. The computational efficiency of the system is thus verified, showing its potential for larger scale deployment. The experiment was conducted at four different locations, providing a statistical performance assessment of the new system. Analysis was conducted to evaluate the performance of the system. The experimental results show that the proposed system outperforms the conventional GNSS positioning solution, reducing the cross-street positioning error by 69.2% on average.

Finally, the feasibility of deploying the new system on a larger scale is discussed, with three aspects analysed – availability of the required information, data storage and transfer requirements and market demands.

As discussed in the introduction and Section 5.3, the meters-level across-street accuracy in urban areas benefits a variety of applications from Intelligent Transportation Systems (ITS) and land navigation systems for lane identification, location-based advertisement (LBA) for targeting suitable consumers, step-by-step guidance for the visually impaired and for tourists, to many other location-based services (LBS).

It should be noted that the system does not require real-time rendering of 3D scenes or any additional hardware, making it power-efficient and cost-effective. An increasing number of smartphones have multi-core processors, enabling parallel processing techniques to be exploited for improved efficiency of shadow matching. The system is also expandable to work with Galileo and Beidou (Compass) in the future, with potentially improved performance.

In the future, the shadow-matching system can be implemented on a smartphone, a PND, or other consumer-grade navigation device, as part of an intelligent positioning system, whereby the cross-street position is determined mainly by shadow matching and the along-street position mainly by conventional ranging-based GNSS positioning (Groves et al., 2012a). Multi-epoch kinematic positioning using shadow matching can also be investigated, which utilize knowledge from different epochs for better positioning performance.

Other techniques, such as Wi-Fi positioning, inertial sensors and pressure sensors, could be added to improve the overall positioning performance. In the long term, shadow matching could form part of a new generation of multi-sensor integrated navigation system alongside techniques such as environmental feature matching (Walter et al., 2013), low-cost array-based inertial measurement units (Martin et al., 2013), opportunistic radio navigation and context adaptivity (Groves et al., 2013c).

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