Performance assessment of 3D-mapping-aided GNSS part 2: Environment and mapping

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Abstract
A full performance assessment of 3D-mapping-aided (3DMA) global navigation satellite systems (GNSS) in dense urban areas is presented. This second part of a two-part paper focuses on the effects of the surrounding environment and 3D mapping, based on data collected in London using a u-blox EVK M8T GNSS receiver. Conventional GNSS, shadow matching, 3DMA ranging, and integrated 3DMA GNSS all perform best when the proportion of directly visible sky is high, the building height to street width ratio is low, and the average building height is below 20 m. 3DMA GNSS methods demonstrate maximum benefit at sky visibilities of 15% to 35%. All methods exhibit poorer accuracy in environments dominated by glass and steel buildings. Temporary features, such as large buses and lorries, also degrade 3DMA accuracy. Using full 3D city models gives significantly higher accuracy than simple block models, and missing buildings lead to larger positioning errors. Further enhancements to the 3DMA GNSS algorithms are recommended.

1 | INTRODUCTION

Conventional global navigation satellite system (GNSS) positioning is poor in dense urban areas because buildings block, reflect, and diffract the signals. Many different studies have now shown that 3D mapping of the buildings can be used to substantially improve GNSS positioning accuracy in these environments. This two-part paper presents a comprehensive assessment of the performance that can be achieved by 3D-mapping-aided (3DMA) GNSS and the different factors that affect it, which may be divided into four categories: algorithm design, user equipment design, the environment, and mapping quality. The first part of the paper focused on the effects of the algorithm design and the user equipment, together with a discussion of the practical implementation of 3DMA GNSS. This second part investigates how performance is affected by the surrounding environment, including sky visibility, building height and street width, building materials, and passing vehicles, and by the quality of the mapping data. Recommendations for improving the algorithms are then made based on the results of the study as a whole.

An improvement in the real-time position accuracy of low-cost GNSS user equipment in dense urban areas to 5 m or better would benefit many different potential applications. These include situation awareness of emergency, security, and military personnel and vehicles; emergency caller location; mobile mapping; tracking vulnerable people and valuable assets; intelligent mobility; location-based services; location-based charging; augmented reality; and enforcement of curfews, restraining orders,
and other court orders. A further accuracy improvement to around 2 m would also enable navigation for the visually impaired; lane-level road positioning for intelligent transportation systems; aerial surveillance for law enforcement, emergency management, building management, and newsgathering; and advanced rail signaling.

The first part of this paper began with a review of the different 3DMA GNSS algorithms that have been implemented by researchers around the world. This was followed by a description of the 3DMA GNSS position algorithms used for the present study. These build on several previous studies at University College London (UCL). Using 3D mapping to aid a conventional ranging-based least squares GNSS positioning algorithm improves its accuracy by about a factor of two in challenging environments; this technique is used for initialization. Better performance is obtained using a likelihood-based 3DMA ranging algorithm that scores candidate position hypotheses according to the correspondence between measured and predicted pseudoranges. Shadow matching determines position by comparing the measured signal availability with that predicted over a grid of candidate positions using 3D mapping. In dense urban environments, 3DMA ranging algorithms substantially improve the positioning accuracy in the along-street direction, but shadow matching is typically more accurate in the across-street direction. Therefore, best performance is usually obtained by combining the two techniques together, which can be done in the position domain with a suitable direction-dependent weighting of the two position solutions or in the hypothesis-domain by combining the two sets of candidate position hypothesis scores before extracting a common position solution.

A full assessment of the 3DMA GNSS algorithms was presented, based on experimental data collected in London using Leica Viva GS15 and u-blox EVK-M8T GNSS receivers, and a Nexus 9 Android tablet. Best performance in the along-street direction was obtained using the likelihood-based 3DMA ranging algorithm, while shadow-matching performance was no better than conventional GNSS positioning. In the across-street direction, shadow matching gave slightly better performance than likelihood-based 3DMA ranging, with best results obtained by combining them using hypothesis-domain integration. The hypothesis-domain integrated solution also gave the best overall horizontal position accuracy. Position-domain integration gave slightly poorer results than likelihood-based 3DMA ranging on its own. These trends were consistent across all of the receivers. For all positioning methods, the Leica Viva gave better results than the u-blox receiver, which, in turn, gave better results than the Nexus 9 Android tablet. This is largely because of the difference in antenna design. The root mean square (RMS) horizontal position errors using the Leica, u-blox, and Nexus receivers with a 1-m grid spacing were 3.5, 4.7, and 4.9 m, respectively, compared with 23.6, 26.4, and 31.0 m using conventional GNSS positioning, about a factor of six improvement.

All positioning methods were approximately twice as accurate in the City of London, a traditional European city environment, than in the Canary Wharf district, a modern urban environment. This is because the Canary Wharf buildings are taller, further apart, and reflect GNSS signals more strongly than most City of London buildings. Better performance was obtained in both districts by calibrating the 3DMA GNSS algorithms using data from only that environment. Therefore, further development of the algorithms to account for environmental variation is likely to be beneficial.

The practicalities of real-time implementation were also discussed. The algorithms have now been implemented in real time on both a Raspberry Pi 3 and a Galaxy S8+ Android smartphone, taking about 400 milliseconds to process an epoch of data on both devices with a 1-m candidate position grid spacing. Other grid spacings were also assessed. The maximum viable grid spacing was about 5 m. Compared with a 1-m grid spacing, this reduced the position accuracy by 30% to 40% and reduced the processing load by about a factor of 25.

This second part of the paper begins with an explanation of how the environment affects 3DMA GNSS performance, considering conventional GNSS error sources, the building geometry, building materials, and environmental complexity. This is then followed by a description of the experimental methodology for the environment and mapping quality study. Results are then presented showing how 3DMA GNSS performance is affected by the surrounding environment, including sky visibility, building height and street width, building materials, and passing vehicles. This is followed by a discussion of the impact of the mapping data quality on 3DMA GNSS, including further experimental results. Based on the results of both parts of this study, recommendations are then made for improvements to the design of the 3DMA GNSS algorithms to improve accuracy and resilience. Finally, the conclusions are summarized. Parts of the paper build on the theoretical discussion of shadow-matching error sources and potential algorithm improvements in Groves et al extending them to 3DMA GNSS ranging.

2 | HOW THE ENVIRONMENT IMPACTS 3DMA GNSS

Here, the environment is defined as everything that affects the performance of 3DMA GNSS apart from the
user equipment, algorithm design, and mapping. Thus, the satellites, atmosphere, interference sources, vehicles, and people are considered as well as the effects of the surrounding buildings. The section begins by reviewing conventional GNSS error sources, including ephemeris and satellite clock errors, atmospheric effects, multipath, and non-line-of-sight (NLOS) reception. The impact of the building geometry in urban areas is then discussed, considering the density scale and distribution of the buildings. This is followed by a discussion of the impact of the building surfaces, considering both their material and shape. Finally, environmental complexity is discussed, including partial blockage, diffraction, and the effects of street furniture, vehicles, people, foliage, and interference.

2.1 | Conventional GNSS error sources

The dominant error sources in conventional GNSS positioning are the ephemeris and satellite clock prediction errors, ionospheric and tropospheric refraction, signal tracking errors due to radio frequency and thermal noise, multipath interference, and NLOS reception.\(^8,9\) All of these errors apart from NLOS reception impact most 3DMA GNSS ranging algorithms in exactly the same way as conventional GNSS positioning; the use of 3D mapping just mitigates the NLOS reception errors.

After NLOS reception, multipath interference is often the dominant error in dense urban areas. Its impact depends on the antenna and receiver design as discussed\(^1\) in part 1. 3DMA GNSS ranging can potentially be extended to predict, which signals are likely to be multipath contaminated. Furthermore, if signal processing techniques are used to separate out the different components of a received multipath signal, the reflected components can be treated as additional NLOS signals used to enhance 3DMA GNSS positioning.\(^10,11\)

Shadow matching is not normally affected at all by the ephemeris, satellite clock, ionosphere, and troposphere errors. Signal tracking errors are usually irrelevant unless they are large enough to introduce errors in the carrier-power-to-noise-density ratio, \(C/N_0\), measurement process. However, radio frequency and thermal noise do introduce \(C/N_0\) measurement errors. With a 1-second averaging time, the \(C/N_0\) measurement noise SD is about 1 dB-Hz at 20 dB-Hz, increasing to about 3 dB-Hz at 15 dB-Hz.\(^12\) Shadow matching uses the GNSS \(C/N_0\) measurements to determine which signals are received via direct line of sight (LOS). NLOS reception of weak signals thus has minimal impact. However, a strong NLOS signal can be confused with a direct LOS signal. This is a particular problem for smartphones and tablets as their antennas do not distinguish between right- and left-hand circular polarization as discussed\(^1\) in part 1. Multipath interference can be constructive or destructive, depending on the relative phase of the signal components. Constructive multipath interference increases the measured \(C/N_0\), while destructive multipath interference decreases it. Both direct LOS and NLOS signals can be subject to multipath interference, so it can potentially cause misidentification of both LOS signals as NLOS and NLOS signals as LOS. A further issue is that the transmission power varies, both between satellites and over time as a satellite ages. Treating the probability that each observed signal is direct LOS as a continuous function of the measured \(C/N_0\)\(^1,4,13\) minimizes the impact of these effects at the expense of sensitivity. With this approach, the shadow-matching position solution is dominated by the weakest and strongest signals, which are easiest to classify.

2.2 | Building geometry

In dense urban areas, there are three ways in which the geometry of the surrounding buildings can affect 3DMA GNSS positioning: density, scale, and distribution. The denser the environment, the more direct lines of sight to satellites are blocked by buildings. This can be quantified using sky visibility, the proportion of solid angle above the horizon that is unobstructed by buildings. Another metric is the building-height-to-street-width ratio. For conventional GNSS positioning, the higher the sky visibility, the more direct LOS signals received and thus the better the accuracy. The same relationship holds for 3DMA GNSS ranging. For the likelihood-based 3DMA ranging algorithm used here,\(^1,3\) the pseudorange error standard deviation is substantially larger for NLOS measurements than for the direct LOS measurements, so they contribute less information to the position solution. This has been verified with pole-based tests demonstrating better performance higher up where the sky visibility is higher.\(^14\) For 3DMA GNSS ranging algorithms that incorporate NLOS path delay predictions,\(^15,16\) the NLOS pseudorange error standard deviation is much smaller, but still larger than for the direct LOS measurements.

For shadow matching, the relationship between sky visibility and positioning performance is more complex. Shadow matching relies on there being satellites that are directly visible in some parts of the street and blocked by buildings in others. More of these partially visible satellites should yield more accurate and reliable shadow matching. If the sky visibility is very high, the environment will be open, and most satellites will be directly visible except very close to buildings. Shadow matching will not work well under these conditions; it will only
be able to determine when the user equipment is close to a building. Conversely, if the sky visibility is very low, most satellites will be blocked at all candidate positions, leaving only a few available for shadow matching. Thus, there should be an optimum sky visibility at which best performance is obtained.

The next environmental factor to consider is scale. Buildings farther apart from each other result in larger path delays for reflected signals. This leads to a larger NLOS pseudorange error standard deviation for the likelihood-based 3DMA ranging algorithm used here. Furthermore, longer path delays (up to about half a code chip) lead to larger multipath errors, so the accuracy of the direct LOS pseudoranges is also degraded. For shadow matching, the buildings divide the environment into regions where each signal can be directly received and regions where it cannot. The bigger the buildings and spaces between them, the larger these regions will be and the coarser shadow matching will become. The impacts of diffraction and building boundary resolution (discussed below) will scale similarly. Thus, shadow-matching accuracy should be directly proportional to the scale of the environment.

The final factor to consider is the building distribution relative to the user position. For ranging, each signal provides positioning information along its direction of propagation. When the user is in a midstreet location, buildings will typically block direct LOS signals in the cross-street direction, while direct LOS signals will still be received along the direction of the street. As explained above, the 3DMA ranging algorithms used here will therefore provide more accurate positioning in the along-street direction. When the user is at an intersection or a gap between buildings, more direct LOS signals will be received in the cross-street direction so the 3DMA ranging position accuracy in that direction should be better (in the along-street direction, the number of direct LOS signals and positioning accuracy should be similar to the midstreet case).

For shadow matching, it is the along-street positioning performance that varies. In a midstreet location with buildings of similar height and minimal gaps between them, there will be little variation in GNSS signal shadowing along the street, so shadow matching will only provide positioning information in the across-street direction. At an intersection or where there are gaps between buildings or height variation, signal shadowing will vary in both the along-street and cross-street directions, enabling a two-dimensional position solution to be obtained from shadow matching. Some examples are presented in Groves et al.

A further issue is that buildings can be distributed in such a way that the same combination of GNSS signals is predicted to be direct LOS at several locations within the search area. This can result in the shadow-matching likelihood distribution having maxima in several different places, a phenomenon that can occur in both repeating environments and nonrepeating environments. Hypothesis-domain integration with likelihood-based 3DMA GNSS ranging usually removes this ambiguity.

### 2.3 Building surfaces

Different materials interact differently with GNSS signals. Metal and metallized glass surfaces are strong specular reflectors; stone and brick are much weaker reflectors, while nonmetallized glass is transparent to GNSS signals. The shape of the surface is also important. The signal path between satellite and user is not a simple ray, but is instead determined by Fresnel zones. Consequently, the radius of the effective signal footprint where it interacts with an object in the signal path is \( \sqrt{r/\lambda_{ca}} \), where \( r \) is the distance of the object from the user antenna, and \( \lambda_{ca} \) is the carrier wavelength. Thus, for a building about 10 m away, the diameter of the signal footprint is about 3 m. Variations in the building surface over this area will affect how GNSS signals are reflected. Reflections from protrusions and indentations of a few centimeters can destructively interfere, reducing the overall strength of the reflection. Facets at different orientations will reflect signals in different directions, while irregularities on the scale of a few centimeters lead to scattering instead of specular reflection.

The overall effect is that reflected GNSS signals are stronger in modern city environments, dominated by buildings with large metallized glass and metal surfaces, than in more traditional environments, dominated by brick and stone buildings with conventional nonmetallized glass windows. For 3DMA (and conventional) GNSS ranging, stronger reflected signals increase the size of the pseudorange errors because of multipath interference, degrading positioning accuracy. For shadow matching, stronger NLOS signals are more difficult to distinguish from direct LOS signals using \( C/N_0 \) measurements, while the increased multipath interference increases the \( C/N_0 \) variance for both types of signals; thus, positioning performance is degraded. The experimental results confirm that these effects impact positioning performance.

### 2.4 Environmental complexity

The 3DMA GNSS algorithms assessed here assumed that a GNSS signal is either blocked by a building or directly
received. However, real GNSS signal propagation in urban environments is more complex than this. Because of the size of the Fresnel zones, a GNSS signal can be partially blocked by a building so, as a satellite moves behind a building, the received signal strength drops off gradually. GNSS signals can also diffract around obstacles, producing a spatially varying pattern of constructive and destructive interference. Thus, as a satellite continues to move behind a building, an oscillating received signal strength will be observed within a steadily reducing envelope. Direct signals are potentially receivable when the LOS to the satellite is within about 5° of the building boundary. However, because of the oscillatory diffraction pattern, it is difficult to predict exactly where they will be received. Receiving direct LOS signals where they are not predicted can degrade 3DMA GNSS positioning accuracy through incorrect scoring of candidate positions. For shadow matching, this is only an issue for strong diffracted signals received close to the shadowed area as any weak diffracted signals that are received are assumed to be NLOS. Predicting the “diffraction region” at the edge of buildings was attempted in Wang et al but this had little effect on shadow-matching performance. For likelihood-based 3DMA ranging, diffracted signals can be incorrectly scored using the NLOS pseudorange error distribution. However, a weak diffracted signal will often be received alongside a stronger reflected signal, in which case the NLOS distribution would be correct.

A further assumption of the algorithms is that only buildings impact GNSS reception. However, the signals are also affected by other objects in the surrounding environment that are impractical to model, particularly road vehicles. Thus, a signal that would normally be direct LOS could be temporarily blocked, while a strong reflection could be received at locations where a signal is normally weak. This impacts both shadow matching and 3DMA ranging. High-sided vehicles, such as London’s double-decker buses, are a particular problem, as demonstrated in the experimental results section. Street furniture, such as bus shelters, vending booths, telephone kiosks, and advertising displays can also have an impact. However, if this is significant, they can be incorporated within the 3D city model.

Signal attenuation by trees is also a problem. When the receiver is directly underneath a tree, signals from high-elevation satellites are likely to pass through more foliage, resulting in direct LOS signals being attenuated more than NLOS signals. For shadow matching, a reduction in \( C/N_0 \) for some direct LOS signals would result in them being incorrectly classed as NLOS, leading to incorrect scoring of all candidate positions. 3DMA GNSS ranging performance is degraded simply because fewer direct LOS signals are received.

Signals can also be attenuated when the receiver is in a vehicle, bag, or pocket, while interference reduces \( C/N_0 \). Again, this would disrupt shadow matching through direct LOS signals being incorrectly classed as NLOS. However, as all received signals would be attenuated, it should be possible to detect this and recalibrate the algorithms accordingly. 3DMA ranging would be impacted through reception of fewer GNSS signals, although it would typically be less useful NLOS measurements that would be lost.

### 3 EXPERIMENTAL METHODOLOGY

Our proposed 3DMA GNSS positioning approach combines four algorithms, described in part 1 of the paper. A least squares 3DMA GNSS ranging algorithm that exploits the conventional GNSS position is used to initialize the likelihood-based 3DMA GNSS ranging algorithm and the shadow-matching algorithm. The integration algorithm is performed using a hypothesis-domain integration approach that computes a joint position solution from likelihood-based 3DMA ranging and shadow matching. The empirically determined tuning parameters were the same as those described in part 1 of the paper as the new test sites were only visited once. Both 3DMA ranging algorithms and the shadow-matching algorithm use precomputed building boundaries, derived from 3D mapping as described in Adjrad and Groves.

GNSS measurements, comprising GPS and GLONASS, were collected in June and July 2017 using a u-blox EVK-M8T GNSS receiver logging data at 1 Hz for 2 minutes at each individual location. u-blox data collection was performed by interfacing the GNSS receiver to a Raspberry Pi 2 (via USB). The Raspberry Pi was configured as a Wi-Fi hotspot, enabling system configuration and data logging, controlled via an Android smartphone running a mobile secure shell (SSH) application. Figure 1 illustrates the hardware used.

Measurements were obtained within four areas of London shown in Figures 2, 3, and 4 (disks illustrate data collection locations) and summarized in Table 1. The experiment locations were chosen to provide variations in building materials, street azimuth, sky visibility, building height, and street width. UCL campus experiment sites (Figure 2, right group) were selected for the medium-rise building heights and different building materials, with the occasional high-rise building; Figure 5 (top left) shows an example. Regent’s Place experiment sites (Figure 2, left group) were composed of high-rise glass and steel buildings with narrow street widths as shown in Figure 5 (top right). The City of London experiment sites (Figure 3)
were selected for a variety of sky visibility and a balance between high-rise and medium-rise buildings, typical of an old city center with modern developments; Figure 5 (bottom left) shows an example. Finally, the Canary Wharf experiment sites (Figure 4) were selected to provide a large-scale environment with significant gaps between buildings and mostly steel and glass building materials as shown in Figure 5 (bottom right). At each experiment site, data were logged on either side of the street where possible. This enabled comparison of positioning performance between opposite sides of the street. Thus, many of the sites shown in Figures 2–4 comprise two test positions. Each test location is independent of the others because 3DMA GNSS performance depends on the interaction of the satellite signals with the buildings, which are different for each location.

The GNSS antenna was held about 1.1 m above the ground to represent a similar height to which phones are held. Laser Disto measurements were made from the experiment location to nearby landmarks (corners of buildings and other visible mapped features). These distance measurements were used on the Ordnance Survey MasterMap of the area where the experiment was performed to extract the coordinates of the test positions in British National Grid (BNG) eastings and northings.

In addition to GNSS data collection and coordinate calculations, information about the urban environment was recorded at each site. Each experiment site was classified with a number of environmental parameters as follows:

1. Building materials were observed manually and classified as mainly brick and stone, mainly glass and steel, or a mixture of types.
2. Street position was observed manually and classified as along the middle of a street or at an intersection.
3. Anomalies, such as passing vehicles, were noted.
4. Sky visibility was determined by taking a photo of the sky at each test position using a wide angle “fish-eye” lens on a smartphone, which was approximately level.
FIGURE 3  The City of London experiment sites (OS MasterMap™ Crown copyright/database right 2017) [Color figure can be viewed at wileyonlinelibrary.com and www.ion.org]

FIGURE 4  Canary Wharf experiment sites (OS MasterMap™ Crown copyright/database right 2017) [Color figure can be viewed at wileyonlinelibrary.com and www.ion.org]
in the horizontal plane. Images of the sky at each experiment site were analyzed in Photoshop to calculate the percentage of sky visibility. The sky view photos were also compared with the building boundaries plots to assess how similar the real world was compared with the city model. Figure 6 shows example sky photos taken at low, medium, and high sky visibility sites.

5. The building-height-to-street-width ratio \( (h/w) \) is computed by selecting the azimuth at which the sum of the building boundary at that azimuth and the building boundary in the opposing direction are highest; this is generally perpendicular to the street direction. The height to distance ratio \( (h_i/d_i) \) in direction \( i \) is then \( \tan \theta_i \), where \( \theta_i \) is the building boundary elevation in that direction. Giving equal weighting to

### Table 1: Data collection dates and sites

<table>
<thead>
<tr>
<th>Location</th>
<th>Region of Interest Central Coordinates (British National Grid)</th>
<th>Data Collection Date(s)</th>
<th>Number of Test Positions</th>
</tr>
</thead>
<tbody>
<tr>
<td>UCL Campus</td>
<td>529577 mE, 182253 mN</td>
<td>08/06/2017</td>
<td>24</td>
</tr>
<tr>
<td>Regent's Place</td>
<td>529116 mE, 182345 mN</td>
<td>08/06/2017</td>
<td>17</td>
</tr>
<tr>
<td></td>
<td></td>
<td>12/06/2017</td>
<td></td>
</tr>
<tr>
<td>The City of London</td>
<td>532103 mE, 181243 mN</td>
<td>05/07/2017</td>
<td>58</td>
</tr>
<tr>
<td>Canary Wharf</td>
<td>537575 mE, 180181 mN</td>
<td>28/07/2017</td>
<td>11</td>
</tr>
</tbody>
</table>

Abbreviation: UCL, University College London.

**Figure 5** Photographs of University College London (UCL) campus site F1 (top left), Regent’s Place site F21 (top right), City of London site C16 (bottom left), and Canary Wharf site CW2 (bottom right) [Color figure can be viewed at wileyonlinelibrary.com and www.ion.org]
both directions results in $h/w = (\tan \theta_1 + \tan \theta_2)/4$, noting that $w = d_1 + d_2$.

6. The street width is the sum of the distance to the nearest building in the direction used to calculate $h/w$ above and the distance to the nearest building in the opposite direction.

7. The building height is the product of the street width and $h/w$, calculated as described above.

4 | **3DMA GNSS PERFORMANCE VARIATION ACROSS DIFFERENT ENVIRONMENTS**

Table 2 and Figure 7 show the overall GNSS positioning performance and average environmental characteristics at the main test areas, each of which is selected to represent a different type of urban environment. The glass/steel site proportion is the proportion of the sites containing mainly glass and steel buildings (mixed sites count as half and half). All positioning methods performed better in the City of London than in the other areas. The mean sky visibility is similar for each area. However, Canary Wharf has much higher buildings than the other areas and is dominated by glass and steel, while the Regent's Place and UCL area have the narrowest streets. This suggests that building height, street width, and building materials all impact positioning accuracy. Comparing the City of London and Canary Wharf results with those obtained in part 1 of the paper at different locations within the same general areas, it can be seen that the 3DMA ranging and integrated 3DMA GNSS results obtained here are poorer. There are three potential reasons for this. First, the part 1 datasets were collected at weekends and the part 2 datasets during working days. Therefore, the part 2 data will have been impacted more by passing vehicles and people. Second, some of the part 2 data were collected near irregularly shaped buildings, which are not as well represented by level of detail (LoD) 1 3D mapping used to generate these results. Finally, the data for calibrating the 3DMA GNSS algorithms were collected from the same sites as the part 1 test data so the calibration parameters will be more suited to those sites. The effects of passing vehicles and mapping quality are assessed later in this paper, while calibration was assessed in part 1.

Examining the overall positioning RMS error across all 110 test positions, a factor of 4.2 accuracy improvement was achieved in positioning by using the

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**TABLE 2** Overall positioning performance and environmental characteristics at each test area

<table>
<thead>
<tr>
<th>Area</th>
<th>Overall RMS Positioning Error, m</th>
<th>Environment Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Conventional GNSS</td>
<td>Shadow Matching</td>
</tr>
<tr>
<td>Regent’s Place and UCL</td>
<td>34.8</td>
<td>24.5</td>
</tr>
<tr>
<td>City of London</td>
<td>7.7</td>
<td>8.9</td>
</tr>
<tr>
<td>Canary Wharf</td>
<td>32.1</td>
<td>18.8</td>
</tr>
<tr>
<td>All Sites</td>
<td>24.2</td>
<td>17.4</td>
</tr>
</tbody>
</table>

Abbreviations: 3DMA, 3D-mapping-aided; GNSS, global navigation satellite systems; RMS, root mean square; UCL, University College London.
3DMA integrated approach (which will be referred to in the subsequent plots as integrated 3DMA or hypothesis domain integration [HDI]) compared with conventional GNSS (Conv). The individual positioning algorithms, shadow matching (SM) and 3DMA ranging (likelihood-based ranging [LBR]), resulted in a factor of 1.4 and 2.9 improvement, respectively, compared with conventional GNSS.

Figure 8 shows the RMS horizontal positioning error for each test position as a function of sky visibility for each positioning method. As expected, conventional GNSS and 3DMA GNSS give better performance when the sky visibility is higher, but there is significant variation in accuracy for locations with similar sky visibility. Shadow-matching performance is largely independent of sky visibility, while the integrated 3DMA GNSS accuracy improves slightly as with increasing sky positioning. Figure 9 shows the ratio of the RMS horizontal positioning error using conventional GNSS positioning to that using shadow matching, 3DMA ranging, and integrated 3DMA GNSS positioning. Here, a clear trend can be seen with the relative positioning performance of the different methods highly correlated with the sky visibility. All 3DMA GNSS methods demonstrate maximum benefit at sky visibilities between about 15% and 35%, with significant benefit between 10% and 60%. There is much more variation in performance ratio with sky visibility in the across-street direction than in the along-street direction. These results also confirm the findings in part 1 that shadow matching is more beneficial for across-street positioning and 3DMA GNSS ranging for along-street positioning. In the along-street
direction, the shadow-matching solution is often worse than the conventional GNSS solution.

Moving on to the variation in positioning performance with building-height-to-street-width ratio \( h/w \), all positioning methods exhibit the highest accuracy for \( h/w \) values less than one; above that, there is no clear relationship between absolute accuracy and \( h/w \). Figure 10 shows the ratio of the RMS positioning error using conventional GNSS positioning to that using the 3DMA GNSS methods as a function of \( h/w \). The along-street ratio for all methods is largely independent of the building-height-to-street-width ratio. However, the across-street results show that shadow

![Figure 9](image-url)
matching and integrated 3DMA GNSS produce maximum benefit for h/w ratios between 3 and 6, with 3DMA GNSS ranging performance largely independent of h/w. The overall horizontal RMS position error also shows greatest improvement for h/w ratios between 3 and 6.

The variation in positioning performance with the ratio of NLOS to direct LOS satellites (determined using the building boundary at each true position) was also examined. However, significant relationships were not observed.

Moving on to the scale of the environment, Figure 11 shows the RMS horizontal positioning error of each positioning method for different building heights and street widths, each grouped into three ranges. The accuracy of
all of the positioning methods is better for buildings in the shortest category (less than 20 m), where fewer signals will be subject to NLOS reception and severe multipath interference. However, 3DMA GNSS techniques produce a greater improvement in accuracy for buildings higher than 20 m. Differences in performance between the 20- to 40-m and more than 40-m height categories are small (noting that the sample size is small for width less than 7 m and height less than 40 m). Moving on to street width, the 3DMA GNSS ranging is more accurate for narrower streets, with the integrated 3DMA GNSS solution showing a similar trend (again noting the small sample size for width less than 7 m and height less than 40 m). This is consistent with path delays for reflected signals being shorter in narrower streets.

Figure 12 shows the RMS horizontal positioning error of each positioning method for midstreet and intersection locations. 3DMA ranging performance is not significantly different, while the other positioning methods show better performance for the midstreet locations. These are surprising results as the sky visibility is much higher for the intersections. However, the ratio of NLOS to LOS signals is very similar. Thus, although there are more direct LOS signals at intersections, there are also more strong NLOS signals.

Figure 13 shows the RMS horizontal positioning error of each positioning method for different building materials. For all positioning methods, better results are obtained in brick/stone environments than in glass/steel environments. This is consistent with glass and steel
buildings producing stronger reflected GNSS signals. Conventional GNSS position errors are about 50% bigger in the glass/steel environments, whereas the 3DMA GNSS methods only exhibit slightly larger errors in glass/steel environments. Separate comparisons were made for subsets of data grouped according to sky visibility, h/w ratio, average building height, and street width. However, the trends were consistent across all datasets. Thus, the impact of building material is independent of those of scale and geometry.

At a site in Canary Wharf (CW1), it was noted during field work that a large vehicle (double-decker bus) was stationary at nearby traffic lights. Figure 14 shows the position errors from each method as a function of elapsed time. During the epochs highlighted, the bus was stationary in front of the user collecting the data. Following this, the bus moved away, and no other vehicle was obstructing the antenna sky view. Examining the horizontal error for the four positioning methods, it can be seen that the presence of the bus degraded the positioning error by 5 to 10 m for all methods. A similar trend was observed at site CW5 where a large lorry was stationary at traffic lights in front of the user.

5 EFFECT OF MAPPING QUALITY

City Generic Markup Language (GML) is the Open Geospatial Consortium’s approved standard for storage and exchange of virtual 3D city models. It defines 3D city models as having five different levels of detail (LoD). LoD0 is a digital terrain model. LoD1, sometimes called a 2.5D model, is a block model without any roof structures; ie, all the buildings have flat roofs. LoD2 is a full 3D city model having explicit roof structures and potentially associated texture. LoD3 is an exterior architectural model, while LoD4 is an exterior and interior architectural model. Figure 15 shows two 3D models of the same area of London, derived from LoD1 and LoD2 data, respectively. The complex building in the center is poorly represented by the LoD1 data. Note also that the building in the top left was recently demolished, so the LoD1 data are out-of-date.
Commonly, 3D spatial data are constructed using 2D building outlines and a digital surface model (DSM), which provides building height information. In previous studies, buildings have been represented in varying levels of complexity within a Geographic Information System (GIS). For example, a low-resolution 1-m LIDAR model was used for NLOS and multipath mapping and a high LoD 3D city model was used for representing the environment in Virtual Reality Modeling Language (VRML) format. 3D building models have also been combined with terrestrial photogrammetry to produce highly detailed architectural models for aiding vehicle localization—matching real-world with simulated images to constrain the position solution. City models are commonly stored using a boundary-representation approach, where each face (wall, floor, and roof) of a building is described separately and a collection of faces is grouped to represent the building. Each face is typically represented as a set of triangles. The greater the LoD, the greater the number of triangles used. Although using 3D GIS has been shown to improve GNSS positioning performance, the use of city models is not without limitations. How errors and approximations in the models impact 3DMA GNSS is discussed below, followed by the results of some experiments.

5.1 | How mapping errors impact 3DMA GNSS

Errors due to approximations in the city model directly lead to errors in the shadow-matching solution. If a modeled building is displaced horizontally by 1 m from its true position, the shadows it casts will also be displaced by 1 m, so a shadow-matching position derived only from that building would be in error by 1 m. In practice, multiple buildings are used, so the contribution to the shadow-matching position error will be a weighted average of the individual building displacements. For likelihood-based 3DMA GNSS ranging, the relationship between mapping errors and the ensuing positioning error is less direct; incorrect placement of signal shadows due to mapping errors will result in the corresponding pseudorange measurement being scored using the wrong error distribution at certain candidate positions.

LoD1 city models represent roofs as flat and are created by a process of “extrusion,” which builds these models by taking 2D buildings to a given height. The provided height may vary depending on the data source and could be an average height for the roof, an eaves height, or a ridge height. Furthermore, real roofs may be pitched, while flat roofs may include perimeter walls, lift shaft and stairwell heads, and other furniture, such as fans and satellite dishes. Even many LoD2 models may omit these features. In practice, any roof feature that is visible from the ground can impact (ground level) shadow matching.

The error in the shadow position due to a vertical error, $\delta h$, in the city model is $\delta h / \tan \theta$, where $\theta$ is the satellite elevation angle, as shown in Figure 16. 3DMA GNSS is thus more susceptible to roof modelling errors that impact low-elevation satellites. Measurements from these satellites could potentially be given lower weighting to compensate for this.

The extrusion process used to generate LoD1 models can be problematic for buildings whose shape varies with height, for example, where narrower towers rise from a wider base. An example of this can be seen in Figure 15. This can lead to predicted signal shadows that are essentially wrong, with several of these disrupting shadow matching and degrading 3DMA GNSS ranging. The experimental results presented below compare 3DMA GNSS performance with LoD1 and LoD2 data across a range of sites.

An obvious source of errors in 3DMA GNSS is out-of-date city models. As 3D mapping is relatively underused,
it is not currently updated as frequently as 2D mapping. For example, Ordnance Survey’s 2D MasterMap product is updated every 6 weeks. If a building is present in the real world, but absent from the city model, or vice versa, large errors are likely to arise, particularly for shadow matching. A particular problem is buildings under construction, which can change on a daily basis. The impact of this on 3DMA GNSS performance is assessed by deliberately deleting a building from the 3D city model. Finally, errors can be introduced in the building boundary generation process. Here, buildings within a 300-m radius of each candidate position are considered as potential obstacles. However, if a signal is not obstructed within this area, but is obstructed by a building outside it, an incorrect building boundary will be computed. This will produce similar 3DMA GNSS errors to those that result from a missing building. Problems are most likely to occur where distance buildings are much taller than the immediately surrounding buildings, which is not the case for the test sites used here. A simple solution is to consider buildings within a larger area, but this increases the processing load of the building boundary generation algorithms. Thus, a more flexible approach is needed.

The resolution of the building boundary data also impacts performance. How this translates into positioning resolution depends on how far away the buildings are. A 1° azimuth resolution corresponds to a 0.35-m signal shadow resolution on the ground for a building 20 m away and a 1.75-m shadow resolution for a building 100 m away. An elevation resolution of \( \Delta \theta \) leads to a signal shadow resolution of \( 2d\Delta \theta / \sin 2\theta = h\Delta \theta / \sin^2 \theta \), where \( d \) is the distance to the building and \( h \) its height. Thus, for an elevation resolution of 0.7°, the shadow resolution for a 40-m-high building at a distance of 40 m is 1 m. For shadow matching, the positioning resolution is the same as the shadow resolution on the ground. For likelihood-based 3DMA GNSS ranging, the relationship is less direct; incorrect placement of signal shadows will result in the corresponding pseudorange measurement being scored using the wrong error distribution at certain candidate positions. Changing the building boundary resolution does not impact the processing load of the 3DMA GNSS algorithms, but it does impact processing load of the building boundary computation and the amount of data that must be stored and/or downloaded. Experimental assessment is a subject for future research.

5.2 | Experiments

For data collected at 20 sites, 14 in the City of London and six in the UCL campus area (highlighted by the blue area in Figures 2 and 3), 3DMA GNSS solutions were recomputed using building boundaries computed form the Bluesky LoD2 3D mapping error. The conventional GNSS RMS horizontal positioning error for these 20 sites was 18.7 m. Using the LoD1 Ordnance Survey mapping data used for the rest of the study, the RMS horizontal positioning errors for shadow matching, 3DMA ranging, and the integrated solution were 9.8, 4.3, and 3.9 m, respectively. Using the LoD2 Bluesky data, the RMS positioning errors were 6.1 m for shadow matching, 3.3 m for 3DMA ranging, and 2.5 m for integrated 3DMA GNSS. Figure 17 illustrates this. These results suggest that using a higher LoD model would significantly benefit 3DMA GNSS performance. Note, however, that there is more processing cost for computing the building boundaries using LoD2 data compared with LoD1. For these test sites, it took five times longer to compute building boundaries using the LoD2 data.

Figure 18 illustrates a case study location where we have deliberately deleted a building from the Bluesky LoD2 mapping data used to generate the building boundaries. The conventional GNSS horizontal position error for this example was 6.8 m, while the integrated 3DMA GNSS position error using the unaltered 3D model was 3.8 m. Using the 3D model with the building highlighted in Figure 18 deleted resulted in the 3DMA GNSS position error increasing to 11.4 m, larger than the conventional GNSS positioning error here. Note that the position solution shifted to the north-west, the direction of the deliberately deleted building. This example highlights the importance of using an accurate and up-to-date 3D mapping data for our 3DMA approach to achieve its best results.
Based on the results of this study, several enhancements to the 3DMA GNSS algorithms are recommended. Multi-epoch filtered positioning, outlier detection, improved statistical models, self-calibration, and context adaptation are discussed in turn.

6.1 | Multi-epoch 3DMA GNSS

The present study is limited to single-epoch positioning, which is appropriate for location-based services that only require a one-time position fix and tracking applications that only update every few minutes. For navigation and continuous positioning applications, an update is typically required every second. In conventional GNSS positioning, using filtering to combine measurements from successive epochs gives a much better accuracy than computing an independent position solution at each epoch.9 Several authors have also demonstrated the benefit of using a particle filter to combine measurements from multiple epochs for shadow matching,27-29 3DMA GNSS ranging,15 and integrated 3DMA GNSS positioning.30

There is thus a need to develop a multi-epoch filtered version of the 3DMA GNSS algorithms presented here in order to improve accuracy for continuous...
positioning applications. Because building boundaries are precomputed over a regular grid of candidate positions, which are then scored by the 3DMA GNSS algorithms using the received GNSS measurements, a grid filter is proposed instead of a particle filter. Both filters can represent nonlinear position likelihood distributions using a set of candidate position hypotheses. The key difference is that a particle filter’s hypotheses have equal likelihood (following the resampling step) and an irregular distribution in state space (position in this case) whereas the grid filter’s hypotheses are regularly distributed, forming a grid, but with unequal likelihoods. The grid-based approach better represents the physics of the problem. As shown in part 1 of this study, position hypothesis spacing of less than a meter brings no significant performance benefit as the GNSS signal Fresnel zones are about this size in urban areas. Conversely, a spacing of more than 5 m does not capture the variation of the environment sufficiently and can lead to 3DMA GNSS failing. Preliminary grid filter results for a static pedestrian, walking pedestrian, and road vehicle will be presented in Groves and Adjrud.31

6.2 | Outlier detection

As shown in the results, significant 3DMA GNSS positioning errors can occur when the satellite visibility predictions do not match reality due to erroneous or out-of-date mapping or unpredictable objects, such as buses and lorries. In these cases, the contributions from the affected signals to the candidate position hypothesis scoring grid will be wrong. However, other signals received at the same time will be unaffected. Thus, there is potential to deploy consistency-based outlier detection9 to identify the affected signals and remove them from the positioning process.

Consistency checking of conventional GNSS ranging measurements forms part of the receiver autonomous integrity monitoring (RAIM) process. Techniques for ranging measurements include the solution separation, range comparison, and least squares residual methods.32 Consistency checking by solution separation computes a set of parallel positioning solutions, each excluding signals from one satellite. If one or more measurements is faulty, these solutions will diverge. However, to identify the faulty signal, solutions excluding two satellites must then be computed so that consistency checking may be performed with each satellite in turn completely excluded. In 3DMA GNSS, the underlying causes of outliers will often impact multiple satellites, typically those with similar lines of sight. Consequently, a large number of position solutions, based on different satellite combinations, will be needed for consistency checking. Thus, the processing load could be excessive.

The 3DMA GNSS equivalent of the range comparison and least squares residual consistency checking methods is to compare each single-satellite candidate position hypothesis scoring grid (combining shadow matching with 3DMA GNSS ranging) with a reference scoring grid. The reference grid may be generated from all satellite signals or from all except the satellite under test. However, because outliers can be correlated across multiple satellites with similar lines of sight, it may be better to exclude satellites with similar azimuths to the test satellite from the reference grid. Alternatively, an all-satellite scoring grid may be compared with scoring grids excluding data from the satellite(s) under test. Where the difference between the compared grids (appropriately normalized) exceeds a certain threshold, the satellite signal under test can be assumed to be affected by an outlier and excluded from the final position hypothesis scoring grid. For multi-epoch 3DMA GNSS, innovation filtering can potentially be used, for example, by comparing single-satellite scoring grids with a reference grid generated from previous measurements and predicted forward to the current epoch.

To minimize the impact of mapping errors, affected building boundary data should be marked as not for use and the mapping supplier alerted so that they can correct their maps. However, distinguishing mapping errors from other anomalies requires multiple visits to the affected area. Thus, it is best to use a crowdsourcing approach, whereby outlier data from multiple users are sent to a central server. This can then identify mapping errors and send alerts to users that mark particular regions of the building boundary data and the 3D city model it is based on as “do not use.” This is particularly useful for construction sites that change on a daily basis.

6.3 | Improved statistical models

Scoring of the candidate position hypotheses relies on statistical distributions of the direct LOS and NLOS pseudorange measurement errors in the likelihood-based 3DMA GNSS ranging algorithm and of the direct LOS and NLOS $C/N_0$ measurements in the shadow-matching algorithm. The coefficients of these models are empirically determined from calibration data. However, the results of part 1 of this study have shown that different coefficients give best positioning performance in different environments.1

Using different statistical models for different environments is not practical, so new models that give
good results under a wide range of conditions are needed. These should account for additional parameters, including the following:

- Street width: Pseudorange errors due to NLOS reception and multipath are typically larger when buildings are further apart.
- Building material: NLOS signals are stronger when reflected by metal and metallized glass surfaces, affecting shadow matching and increasing multipath errors.
- Elevation angle: Low-elevation signals are affected more by mapping errors.

Other parameters, such as building height, height-to-width ratio, sky visibility, and satellite-street azimuth difference should also be considered. Different model coefficients will likely be needed for high-bandwidth signals, such as GPS L5, and low-bandwidth signals, such as GPS C/A code, and may also be beneficial for the different constellations.

6.4 | Self-calibration and context adaptation

Different calibration of the statistical models for both shadow matching and 3DMA GNSS ranging is needed for each antenna and receiver design. Although manually calibrating for user equipment, such as a smartphone or geodetic receiver, is not a problem, calibrating for each individual model is impractical. Therefore, some method of automatic recalibration of the statistical models is needed, potentially based on long-term $C/N_0$ and measurement residual statistics.

For best shadow-matching performance, variation in individual satellite transmission powers should also be taken into account. Long-term $C/N_0$ statistics gathered by the device could be used. Alternatively, transmit powers obtained from a monitor station could be distributed to users with the building boundary or other 3D mapping data.

3DMA GNSS algorithms also need to be able to react quickly to the receiver being placed in a car, pocket, or bag and to the presence of interference. A simple approach is to use the $C/N_0$ of the strongest received signals to rescale all of the $C/N_0$ measurements to match an open-environment model. Alternatively, behavioral context detection techniques can be used to detect the placement of mobile device. Environmental context detection is also useful for determining when to use 3DMA GNSS; the technique is not designed to be used indoors and conventional GNSS positioning is adequate in open environments. Finer classification of urban environments using context detection could also be used to select appropriate coefficients for the statistical models used by the 3DMA GNSS algorithms.

7 | CONCLUSIONS

The effects of the surrounding environment and the 3D mapping quality on 3DMA GNSS have been assessed, both theoretically and experimentally. Conventional GNSS, shadow matching, 3DMA ranging, and integrated 3DMA GNSS results have been compared under a wide range of conditions.

As predicted, all positioning methods perform best when the proportion of sky that is directly visible is high, the building-height-to-street-width ratio is low, and the average building height is below 20 m as there are more direct LOS signals under these conditions. For a given sky visibility or height to width ratio, there is considerable variation in absolute positioning accuracy. In terms of relative accuracy, all 3DMA GNSS methods demonstrate maximum benefit at sky visibilities between about 15% and 35%, with significant benefit between 10% and 60%. Shadow matching also demonstrates maximum benefit for building-height-to-street-width ratios between 3 and 6, while 3DMA GNSS ranging performance relative to conventional GNSS is independent of this parameter. However, 3DMA GNSS ranging does perform better in narrower streets.

All positioning methods exhibit poorer accuracy in environments dominated by glass and steel buildings, regardless of other environmental factors, as these buildings produce stronger reflected GNSS signals, increasing multipath errors and making it more difficult to distinguish LOS and NLOS signals using $C/N_0$. Temporary features of the environment, such as large buses and lorries, also degrade 3DMA GNSS accuracy as their blockage of GNSS signals cannot be predicted using 3D mapping.

The LoD of the 3D mapping also affects performance with use of full 3D city models (LoD 2) giving a 35% reduction in position errors compared with simple block models that do not account for variations in building cross section with height (LoD 1). Missing buildings due to mapping errors or construction activity also lead to larger positioning errors.

Based on the results of both parts of the study, further enhancements to the 3DMA GNSS algorithms are recommended, including multi-epoch filtered positioning, outlier detection, improved statistical models, self-calibration, and context adaptation.
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