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LUVI: Lightweight UWB-VIO based relative positioning for AR-IoT applications

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ABSTRACT

In this paper, we propose LUVI, Lightweight UWB-VIO relative positioning method for indoor localization. Recent designs of handheld and embedded devices feature various technologies which have the means to enhance localization performance in indoor environments. These include visual odometry based on cameras and augmented reality, and communication hardware such as UWB. Integration of such technologies to exploit their advantages allows us to compensate for each other's errors in measurement. This improves the overall function of future services, such as visual representation of sensing information from sensors in areas that are not physically visible. However, existing work cannot fully exploit these technologies to high extent, often inducing high errors or wasted resources. LUVI is a novel localization method which estimates the location of a target object using relative coordinates of estimator devices without the aid of definitive coordinates. LUVI focuses on utilization of lightweight management of virtual anchors for localization, with functions that reduce the computing and communication complexity while maintaining the accuracy and improving energy efficiency of the localization. Our work has been fully implemented and tested in several indoor environments, showing robustness to NLOS while significantly reducing computational complexity, and up to 30% lower average error.

1. Introduction

Evolutions in portable devices introduce to us new technologies to enhance user experience and customer satisfaction, through communication, graphics, sensing, and processing improvements. One notable aspect, such as recent smartphone designs, is introducing modules which can be used to enable and enhance indoor localization capabilities. In particular, ultrawideband (UWB) technology is resurfacing among leading industries and manufacturers, and being exploited for location awareness and security. Several flagship mobile products, from iPhone 11 Pro and Galaxy Note 20 Ultra, supports UWB communication capabilities, which can be utilized in the future for indoor location-based services such as smarter car keys [1], indoor navigation [2], and various augmented reality (AR) applications [3]. Every smartphone will be equipped with UWB as an essential feature in the near future, complementing other communication technologies such as Bluetooth and Wi-Fi.

One of the greatest potentials of UWB is that it can be used to provide *relative positioning* for indoor localization. Relative positioning is a method to estimate target device coordinates without requiring an

infrastructure or pre-defined coordinates in the indoor environment, which can be used as a reference. Instead, two devices are required to provide relative positioning: (1) A device which obtains its own coordinate system (by measuring displacement through embedded sensors such as camera or IMU) performs ranging using UWB wireless communication to measure relative distance, and (2) another device which usually has fixed position and provides data labeled with relative position. This is important for many future indoor service and application aspects which cannot use infrastructure-based positioning, such as spontaneous creation of or dramatic changes in the indoor environment (e.g. disaster, tactical, or hazardous sites). Especially, IoT sensor data labeled with the centimeter level will be incredibly attractive for AR applications, but it presents challenges: We want our applications to operate with high efficiency without requiring any additional complex and expensive device such as pre-installed positioning infrastructure. Ultimately, we want to perform a device-to-device relative positioning that places the target device in the coordinate system of the mobile device.

Since UWB technology only measures distance and cannot provide an actual reference point on the indoor environment, it is often used in

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combination with visual inertial odometry (VIO) in augmented reality (AR) applications [3] and robotics [4,5]. Measurements must be made at multiple points while recording device displacement to estimate relative position as a point on the actual environment. VIO performs well for measuring device displacement and hence combining UWB's ranging and VIO displacement capabilities allows the virtual anchor (VA) concept to be applied in such systems. VAs are virtual static points for a mobile device recorded on a coordinate whenever a ranging attempt is done.

Fig. 1 shows that adding multiple device positions to the ranging record allows VA based relative positioning. A mobile device traverses around a tag (stationary smartphone, start tag, or IoT sensor) and accumulates VAs. The mobile device estimates tag's location using a multi-lateralization algorithm, such as time difference of arrival (TDoA), which is used for traditional indoor positioning. This VA based system is not only simple to configure and implement, but also robust against obstacles due to VA angle variety and density around the tag.

Fig. 2 compares traditional UWB and VA based indoor positioning systems. The major difference is that the former estimates the mobile device position using a fixed number of references, whereas the latter makes the mobile move while acting as an anchor, creating a number of references (VA) to localize the tags. Although VA relative positioning provides great advantages, it also poses several challenging issues. First, computational complexity and energy efficiency should be carefully considered. It is more beneficial to increase VA sampling rate and generate more VAs to mitigate ranging error for high-accuracy estimation, but this comes at the cost of additional complexity and energy consumption. This affects both the mobile device and stationary tag since the mobile device's position estimation based on a large number of

accumulated VAs slows the position estimation process and requires a number of communication, whereas tags are generally very energy constrained. Therefore, it is important to reduce VA generation while maintaining positioning accuracy. Second, Non-Line of Sight (NLOS) factors affect accuracy in indoor environments. VA records created in an NLOS environment are generally more erroneous, but cannot be easily distinguished.

This paper proposes LUVI, a lightweight UWB-VIO based relative positioning method that maximizes UWB positioning usability by combining it with VIO to perform device-to-device positioning without requiring preinstalled infrastructure or pre-learning.

LUVI incorporates various modules for intelligent VA generation control and calculation, maintaining overall system performance while reducing complexity. The main module is based on lightweight VA selection. Our preliminary study analyzed various factors such as VA number and placement with respect position estimation accuracy [6]. We showed that eliminating certain VAs in the TDoA that contain redundant information does not affect accuracy but reduces calculation complexity. Note that, we named it as a VA selection algorithm based on position clustering. Although effective, the eventual system could benefit further from other factors, e.g. the VA selection algorithm was only beneficial for mobile devices, whereas energy consumption remained constant since tags continue to consume communication energy for VA creation. Therefore, in our LUVI, we introduce a new module for an adaptive ranging module which intelligently decides whether a ranging attempt should be made or not. The decision is made locally by the mobile device to temporarily halt ranging, e.g. if the current estimation is already accurate and no further estimation is required, or an

NLOS environment is detected and further estimation is a waste of

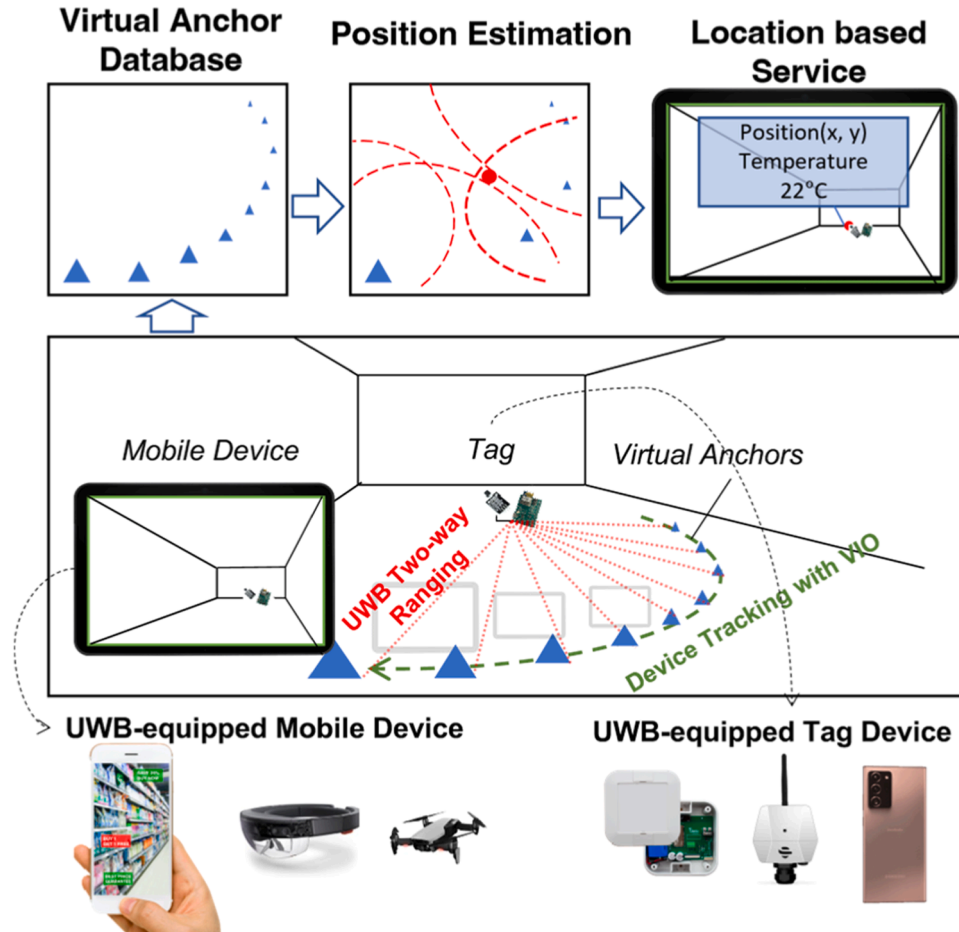


Fig. 1. Virtual anchor based relative positioning system.

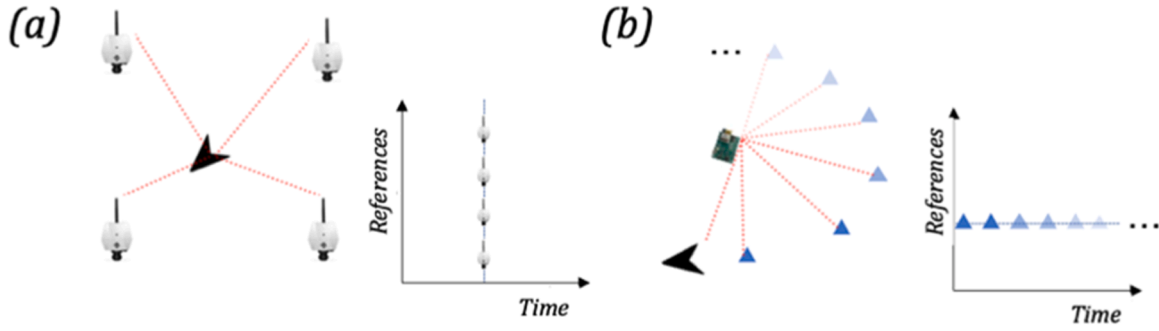


Fig. 2. Ranging based position estimation for (a) traditional and (b) virtual anchor based positioning systems.

resource. LUVI was fully implemented and tested using an actual testbed and evaluated under several practical scenarios. Performance evaluation confirmed that LUVI was robust to NLOS and reduces average error by up to 30% while dramatically reducing computational complexity.

The remainder of this paper is organized as follows. Section 2 describes three key technologies for the LUVI, and Section 3 describes LUVI and key components in detail. Section 4 discusses the virtual anchor selection scheme details to reduce its computing overhead. Section 5 describes the adaptive ranging algorithm for reducing communication overhead and improving robustness in harsh indoor environments. Section 6 discusses experimental results with actual devices. Finally, Section 7 discusses some limitations and observations and concludes the paper.

2. Background and related work

2.1. Ultra-wideband technology

UWB is attracting considerable attention for high-precision positioning. The Federal Communications Commission (FCC) [7] defines UWB as utilizing radios with signal bandwidths above 500 MHz. Previously, UWB communication technology has been focused on high-speed transmission, low power, and other research aspects. However, impulse radio ultra-wideband (IR-UWB) communication technology has become another attractive option due to high-precision positioning advantages rather than data transmission. Since IR-UWB (which we reference generally as UWB in our context) uses a very short pulse signal, which has excellent distance resolution and signal to noise ratio (SNR) compared with other communication technologies [8]. Furthermore, significant progress has been made in recent years with the release of the 802.15.4z standard [9], which includes improvements in data speed, security, and power consumption [10].

Although UWB has excellent performance in ideal environments, it still has relatively unstable performance when there is an obstacle between the sender and receiver due to multipath problems, reflection, diffraction, and energy loss through the medium.

Methods that can be used for location measurement in UWB are usually divided into Time-of-Arrival(ToF) and Angle-of-Arrival(AoA) methods. ToF estimates the time a signal travels between two devices. on the other hand, AoA estimates tag position by measuring the angle between the antenna and the device using two or more antennas, hence multiple samples from multiple tags are not required. However, since AoA only considers the angle between sender and receiver, ToF must be used at the same time to estimate the distance. Although AoA does not require time synchronization or complicated calculations, small directional antenna errors can greatly affect accuracy [11]. Current commercial solutions, such as Samsung's Smart Tag [12] and Apple's Air Tag [13] adopt this method for device-to-device relative positioning to find the tag.

Two way (TWR) or one way ranging (OWR) are commonly used for ranging between two devices using UWB's ToF measurement. TWR is

achieved by calculating the distance to each anchor by estimating ToF from the time that the target tag sends packets to the anchor and receives an acknowledgement message. Multiple ToFs acquired from multiple tags allow the device to calculate ultimate positioning using time-of-arrival (ToA) estimation. This does not require advanced device-to-device synchronization and easily implemented, but network overhead is relatively large due to repetitive communication. In contrast, OWR uses the time difference between when the packet arrives at each anchor when the tag signals the anchor. Since it is a one-way transmission without acknowledgement message, the total round-trip time is unknown. Collecting time differences also allows the device to perform hyperbolic estimation to calculate Time Difference of Arrival(TDoA) and ultimately measure relative position. Various approaches have been proposed to solve these equations, such as LS method, Chan's Algorithm, and Taylor Algorithm [14,15]. They are advantageous when multiple tags occur in the network due to less network overhead because only one signal is sent [16].

In all these methods, the factor that causes most errors in UWB localization is NLOS. The first path signal that goes straight to the receiver is clearly observed in line-of-sight communication, i.e., no obstacles, but NLOS waveforms are unclear, which makes it difficult to determine the first path [17]. Identifying and correcting this error has great interest and various studies are currently in progress.

An NLOS identification to statistically analyze ranging estimation was proposed decades ago [18,19], with more advanced methods being subsequently proposed based on channel impulse response (CIR) with more information becoming available. Yu et al. [20] extracted various statistical features from CIR and identify NLOS by learning trends for each feature in a particular environment. It is also possible to extract features and classify NLOS using deep learning [21–23].

The approaches discussed above achieve acceptable performance, but have limitations to operate on commercial mobile devices or resource constrained devices, as follows.

- 1 Neural network based measurements consume considerable resource for each ranging moment;
- 2 Feature extraction or pre-learning-based methods cannot be used in ad-hoc scenarios since they require preliminary learning on the space; and
- 3 Although it should be driven in the application layer for versatility, it is difficult to obtain low-level features such as CIR on commercial terminals.

This paper shows that NLOS identification using LUVI, a re-visiting statistic for relevant ranging estimations, can perform well in these systems while avoiding problems discussed above.

2.2. Augmented reality and visual inertial odometry

Augmented reality (AR) is defined as augmenting virtual information from the digital to physical realm. One key AR element in our context is

to display radio signal information in the correct location. Current AR applications depend on the device GPS tracking [24] to identify where to visually render data using markers such as QR codes [25] or neural network based object recognition [26]. However, GPS approaches are difficult to apply in indoor environments or when precise rendering is required. Although vision based approaches using markers or neural networks seems reasonable for AR, they cannot find objects behind obstacles or outside the camera field of view, and radio signals are not visible. Therefore, radio signal based positioning is suitable to complement current object tracking methods in AR.

On the other hand, understanding of physical space in AR is built on the VO (Visual Odometry) [27]. It is a method of measuring camera position and pose relative to the starting position of the device. VO iteratively matches a set of key points in two consecutive images. This process estimates the movement of the camera between the two images. To improve the performance of VO, visual simultaneous localization and mapping (VSLAM) technology is applicable [28]. SLAM reconstructs the target space into two or three-dimensional information using a mono or stereo camera, Lidar, RGB-D camera, etc., and utilizes accumulated knowledge to tune previously measured position and pose. Additionally, the integration of IMU into VSLAM is called VIO or VISLAM [29]. The IMU compensates for the disadvantages of VSLAM. Even when the camera is not visible, the pose of the device can be estimated through the IMU and the movement measurement in the physical world's metric scale can be obtained, which is not possible with only VSLAM.

2.3. UWB and VIO fusion

Only the distance between the two objects can be measured using UWB standalone systems, whereas odometry using VSLAM or IMU can estimate device displacement. However, these methods suffer from error accumulation and cannot take advantage of communicating with other devices. Research on the convergence of VIO and UWB is being conducted in various ways. For example, Zheng et al. [30] proposed the convergence of VIO and UWB to estimate the relative position of multiple robots. Martel et al. [31] proposes another example, dealing with the positioning of UWB devices in an AR environment. In this study, a method similar to a virtual anchor was used to display sensor information on a head-up display. To the best of our knowledge, LUVI is the first to address mainly how to computationally efficiently compute historical data (Virtual Anchors) for measurements in the VIO-UWB fusion problem. On the other hand, prior studies have corrected device position estimation through mutual complementation from two technologies [32] or using it for relative positioning (particularly for robotics and aerial drones) [2,4,5]. In particular, UWB can reduce SLAM drift and

improve performance [33,34]. However, LUVI differs from current studies in that the positioning system not only corresponds to a harsh NLOS environment, but is also a lightweight system capable to operate on resourceconstrained mobile devices.

3. Details of LUVI

Fig. 3 shows the relative positioning system with LUVI designed to operate within a mobile device that performs position estimation using UWB tags already deployed in the target area, but without depending on any infrastructure or pre-learning. Thus, LUVI receives input from UWB ranging and VIO, and provides relative coordinates to the stationary tags. Calculated relative coordinates from LUVI are then used by location services, e.g. rendering location labelled data on AR application. LUVI comprises five main modules: relative position estimator; VA generator, database manager, and selector; and adaptive ranging that includes NLOS identification.

3.1. Virtual anchor generator

The VA generator module creates a VA by recording the mobile device displacement from the VIO when obtaining the UWB ranging value. VAs in a 2D coordinate system M originating from where the VIO session started can be structured as

$$V = \{(t, x, y, r_i) | (x, y) \in M, i \in Tags\}, \quad (1)$$

where x and y are the device displacement in M at timestamp t .

Measured distance r_i at timestamp t is obtained by ranging with tag i . The system generates a VA at predetermined time periods and stores it in the database vector V . This sampling period can be adjusted for different network situations, which we discuss in more detail in the adaptive ranging algorithm. Errors that occur in VIO, such as drift, will affect the final estimation by causing drift in the position of the affected VAs. However, in this study, it is out of scope, but if error correction such as loop closing is applied in the VIO module itself, the position values of VAs can be corrected in LUVI as well.

3.2. Virtual anchor database manager

Generated VAs are stored in the VA database. The relative position estimator module can estimate the tag's position (x, y) with 3 or more VAs in the database. If the position of tag j needs to be estimated, then V_j can be extracted from V as

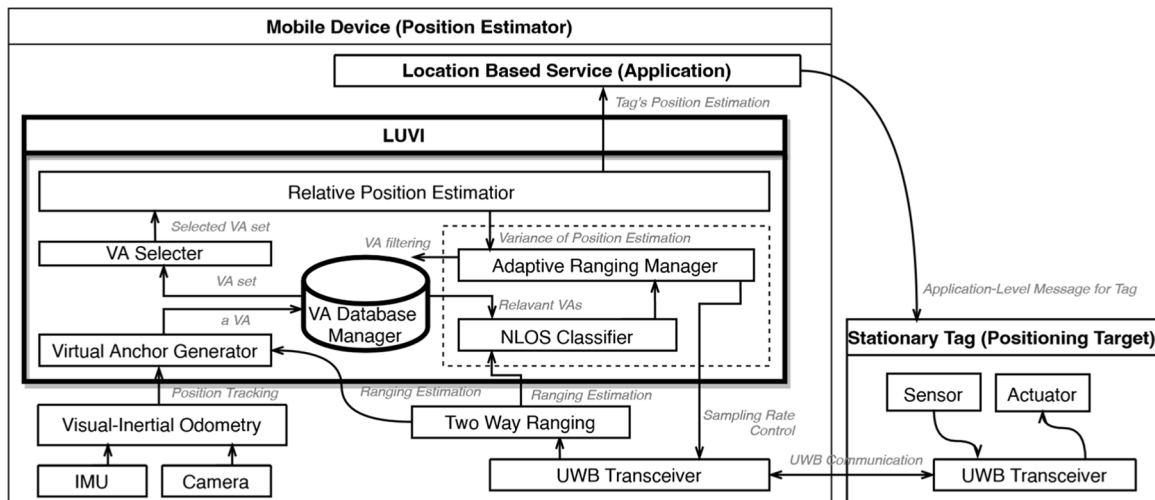


Fig. 3. A Diagram of LUVI.

$$V_j = \{V' \in V | i=j\}, \quad (2)$$

which can be considered as a query result for tag j in the database.

The proposed LUVI requires storing sufficiently large number of VAs to cope with errors that may occur in ranging. However, high VA sampling rate can occupy too much memory, and increase computational complexity.

VAs created a long time ago may also deteriorate positioning accuracy due to error accumulation in VIO [35]. Therefore, implementing the VA database as an appropriately sized circular buffer can not only limit the database size, but can also address the error accumulation problem.

3.3. Virtual anchor selector

The number of VAs stored in the database steadily increases as the system continues to operate. Using many VAs to estimate the position improves position estimation accuracy, but also increases computational complexity for relative position estimation because computational complexity for position estimator is $O(n^3)$, where n is the number of VAs in the database. This not only increases device's energy consumption, but also affects real-time relative position calculation. The detailed empirical analysis for this issue from our preliminary work [6] showed that 100 VAs can cause 70–100 ms delay per calculation. Another insight from that earlier study was that accuracy increased with increasing VA count for the position estimator, benefits more if the VAs are situated at various angles around the tag to overcome geometric dilution of precision (GDOP) [36]. Therefore, LUVI selects a limited number (k) VAs using a VA selector rather than passing the entire set to the position estimator, hence reducing computation while maintaining or increasing system accuracy. Thus, LUVI computational complexity for position estimation reduces to $O(n)$, while improving positioning accuracy. Section 4 discusses the VA selection algorithm in detail.

3.4. Relative position estimator

We use a TDOA-based approach for relative position estimation. The mathematical model used in TDOA can be a hyperbolic equation, depending on the number of anchors and their position. In this context, the unknown parameters in the equation represent the tag's position and can be estimated using optimization methods such as maximum likelihood estimation (MLE). Chan's Algorithm(CA) [15] is a widely used method for Time Difference of Arrival (TDOA) estimation. It uses MLE to perform TDOA estimation in an error prone environment.

The position estimator module inputs k VAs and calculates the final relative tag position. Let (x,y) be the position for tag i at time t . The noise free value for $\{*\}$ is $\{*\}^0$ and $z_a = [z_p^T, r]^T$ is an unknown vector, where $z_p = [x,y]^T$. From CA, the error vector can be derived as

$$\psi = h - G_a z_a^0, \quad (3)$$

where

$$h = \frac{1}{2} \begin{bmatrix} (r_{2,i} - r_{1,i})^2 - (x_2^2 - x_1^2)^2 + (y_1^2 - y_2^2)^2 \\ (r_{3,i} - r_{1,i})^2 - (x_3^2 - x_1^2)^2 + (y_2^2 - y_3^2)^2 \\ \dots \\ (r_{k,i} - r_{1,i})^2 - (x_k^2 - x_1^2)^2 + (y_k^2 - y_1^2)^2 \end{bmatrix} \quad (4)$$

And

$$G_a = - \begin{bmatrix} x_2 - x_1 & y_2 - y_1 & r_{2,i} - r_{1,i} \\ x_3 - x_1 & y_3 - y_1 & r_{3,i} - r_{1,i} \\ \dots & \dots & \dots \\ x_k - x_1 & y_k - y_1 & r_{k,i} - r_{1,i} \end{bmatrix} \quad (5)$$

where ψ is a Gaussian random vector in a covariance matrix,

$$\psi = E[\psi\psi^T], \quad (6)$$

and (3) is a set of nonlinear equations for x and y .

If there is no relationship between x , y , and $r_{(1,i)}$, then this problem can be solved using least squares, assuming the elements are independent,

$$r_{(k,i)}^2 \approx (x_k - x)^2 + (y_k - y)^2 \quad (7)$$

The final location for tag i in M can be obtained by considering element z_a independent,

$$z_a = \operatorname{argmin}\{(h - G_a z_a)^T \cdot \Psi^{-1}(h - G_a z_a)\}. \quad (8)$$

3.5. Adaptive ranging manager

The adaptive ranging manager (ARM) minimizes unnecessary ranging by adjusting the ranging period according to the surrounding environment and situation, i.e., it adaptively controls the system sampling rate. The proposed LUVI can maintain estimated relative position in the system despite the lower sampling rate using VIO. The ARM is activated after the LUVI position estimator achieves a certain accuracy level. The adaptive ranging algorithm determines whether the position estimate converges from the NLOS identification and position estimation, evaluates ranging quality through periodic NLOS identification after activation, and selectively stores the results in the VA database. Therefore, NLOS identification is a very important LUVI component. Advantages from implementing ARM includes reduced communication resource by reducing ranging, consequently reducing UWB battery consumption and improving operation time; and minimizing accuracy impacts from large error-causing obstacles such as concrete walls.

Section 5 discusses the adaptive ranging algorithm in detail.

4. Virtual anchor selection

The objective of the main VA selection algorithm is to limit the number of VAs processed in the relative position estimator, and guarantee the selected VAs' angular diversity for a tag to overcome GDOP. Therefore, Algorithm 1 shows that VA selection algorithm in the VA selector module attributes coordinates to UWB tags in the network. We

Algorithm 1

Virtual anchor selection.

```

1      Function selectVirtualAnchorsForTagT ( $V, k$ )
2      input: Constant  $k$ , set of virtual anchors  $V$  for tag  $T$ 
3      output: Set of selected  $k$  virtual anchors  $V'$  for tag  $T$ 
4      if  $|V_i| < k$  then,
5           $|V_i| \leftarrow V$ 
6      else
7           $x_{min} \leftarrow \{x' | x' \leq \forall x, v(x, y, r) \in V\}$ 
8           $x_{max} \leftarrow \{x' | x' \geq \forall x, v(x, y, r) \in V\}$ 
9           $y_{min} \leftarrow \{y' | y' \leq \forall y, v(x, y, r) \in V\}$ 
10          $y_{max} \leftarrow \{y' | y' \geq \forall y, v(x, y, r) \in V\}$ 
11         for  $i \leftarrow 0$  to  $\lfloor \sqrt{k} \rfloor$  do
12             for  $j \leftarrow 0$  to  $\lfloor \sqrt{k} \rfloor$  do
13                  $V_{i,j} \leftarrow \{v(x, y, r) |$ 
14                      $x_{min} + i \frac{(x_{max} - x_{min})}{\sqrt{k}} \leq x \leq x_{min} + (i+1) \frac{(x_{max} - x_{min})}{\sqrt{k}},$ 
15                      $y_{min} + j \frac{(y_{max} - y_{min})}{\sqrt{k}} \leq y \leq y_{min} + (j+1) \frac{(y_{max} - y_{min})}{\sqrt{k}},$ 
16                      $v(x, y, r) \in V\}$ 
17                  $V' \leftarrow V' + \{v'(x', y', r') | r' \leq r, v(x, y, r) \in V_{i,j}\}$ 
18             end
19         end
20     if  $|V'| < k$  then
21          $V' \leftarrow V'$ 
22         + selectVirtualAnchorsForTagT ( $V - V', k - |V'|$ )
23     end
24 end

```

first assume a constant k , i.e., the number of VAs to be selected from VA database V . Constant k also represents the target number of clusters to be created in the map. Map size is defined as the VA minimum and maximum coordinates furthest from the tag, but within transmission distance. Therefore, we create a virtual rectangular map with the tag in its center, and then divide the map into k clusters. However, each cluster may not have the same number of VAs due to location estimator movement and VA placement.

Several rules are required for the proposed clustering process,

- 1 Clusters should be equal size, and
- 2 Clusters should be uniformly distributed in the map;

to ensure the selected VAs have uniform distribution among themselves, eliminating proximity or LOS redundancy. Once the clusters are correctly defined, each cluster is iterated to select the best VA. Various methods can be employed to select the best VA within a cluster, we simply select the VA with least closest physical distance to the tag. Although simple, this method can be efficient because UWB ranging, based on transmitted signal ToA within the tag and the estimator, generally has positive bias errors. Thus, errors are more likely to be overestimated, and hence selecting the closest VA guarantees the highest chance to mitigate overestimation. The selected VA from each cluster is stored as a subset (V').

However, one or more clusters may not have a single VA situated inside its area, causing $|V'| < k$ from just one iteration of the algorithm. In this case, the algorithm makes another iteration to select one more VA from another cluster. If $|V'| = k$, the algorithm returns $|V'|$, which is used for hyperbolic estimation to calculate the coordinates.

5. Adaptive ranging

Adaptive ranging is based on results from the positioning estimator and NLOS identification. This section describes NLOS determination in LUVI, and then the adaptive ranging algorithm. LUVI determines NLOS based on measured ranging variance within a particular window size. The method is relatively lightweight compared to current NLOS identification methods, such as channel response analysis techniques using machine learning [20], and can be easily implemented in commercial devices where it is difficult to access low-level channel data. In particular, this approach can guarantee realtime performance compared with current approaches because it consumes less computing resources.

LUVI evaluates measurement spread based on root mean square error (RMSE) for the most recently measured VA window W with size w of VA ranging records. Linear regression f can be fitted with w ranging values generated with same time interval as the x-axis. We used linear regression rather than averaging to consider mobile device movement relative to the VA window size w . Therefore,

$$RMSE = \sqrt{\frac{\sum_{i=1}^w (r_i - \hat{r}_i)^2}{N}} \quad (9)$$

where i is the index in W and \hat{r}_i is the estimated ranging value for index i with f .

We normalize RMSE (NRMSE) as a metric for NLOS identification using the difference between maximum and minimum ranging values in the window,

$$NRMSE = \frac{RMSE}{r_{max} - r_{min}}. \quad (10)$$

Thus, NLOS is determined by whether this result is greater than a predefined threshold. The threshold can be defined relative to the error rate guaranteed by UWB transceiver hardware ranging performance in the line-of-sight environment.

Fig. 4 shows the adaptive ranging structure. When the LUVI session is initialized, it samples the VA by performing ranging. The system

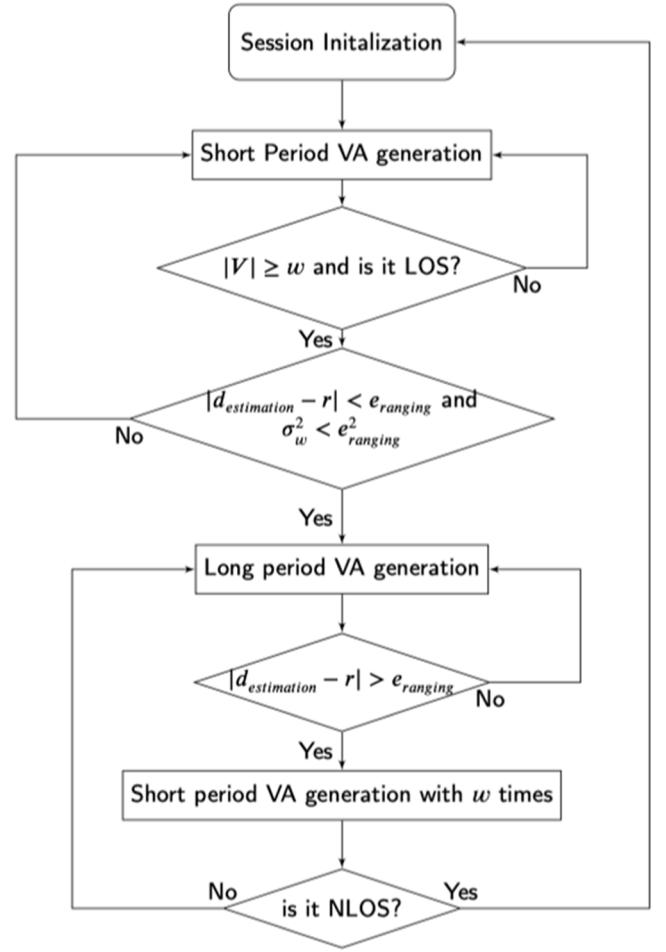


Fig. 4. Proposed adaptive ranging algorithm.

proceeds with NLOS identification every VA sampling period once the number of VAs in the system exceeds the window size. If it is not determined as an NLOS situation, the system evaluates whether the positioning result has high confidence using two conditions: first, the distance between the most recently measured ranging value and the relative position estimated on the existing relative coordinates must be less than the threshold; and second, we consider whether the estimation results are converging, i.e., when the current w VA variance (σ_w^2) is less than the threshold. The ARM orders the VA generator to sample VAs with longer period when the above conditions are met, creating less VAs.

Although LUVI is running on a longer VA sampling rate, it continuously compares the latest ranging results r and distance $d_{estimation}$ by tracking relative coordinates. The system evaluates whether this result is due to the NLOS environment if these results exhibit significant differences. If the difference is deemed to be caused by NLOS, then the current sampling rate is maintained to reduce erroneous VAs from being created; whereas if the difference between measurement and tracing is not caused by NLOS, then this could be due to error accumulation in the VIO, or the tag was physically transferred. In this case, LUVI re-initializes the adaptive ranging algorithm and reverts to the original short ranging period. Short and long period ranging values can be empirically selected depending on the network environment or by the network manager to control energy efficiency.

6. Implementation and performance evaluation

The performance of LUVI is evaluated via testbed implementation through actual UWB devices, to acquire more accurate measuring from

realistic environments. We believe that this is very important, especially compared to simulations and simple mathematical modeling, which may not take into account various external effects that may easily affect the performance of location estimation. The experimental scenario assumes that a user walks indoors and LUVI displays an IoT tag location on an AR application. The purpose is to display the tag at the correct location in the AR application coordinate system, hence we define the VIO origin as the tag's ground truth, and the estimated distance from the origin as error.

We developed LUVI's experiment application using the Samsung Galaxy Note 20 Ultra. The tag pair does the ranging, and the mobile device does the LUVI by synthesizing the VIO tracking values and ranging values from the ARCore and tag respectively. Our application is developed powered by ARCore [37], which is a popular AR platform by Google. It embeds VIO to track the motion of a device in the real world and estimate its pose. So, we utilized the VIO embedded in ARCore to implement LUVI.

At the time of our research, there were no open APIs available to enable low-level UWB communication control on current commercial smartphones. Therefore, we built the testbed shown in Fig. 5 using Decawave's DWM1001 module [38]. When the tags on each side are ranging, the mobile-device side tag send its ranging value to the mobile device over BLE in real time. Also, the mobile device can also turn ranging on and off or control the frequency of the ranging by BLE.

Experiments were conducted in two different environments. The first environment (open space) was an indoor place free from obstacles, such as an auditorium, whereas the second environment (office) included obstacles that UWB can penetrate, such as partitions and furniture, and concrete walls that UWB cannot penetrate causes errors due to NLOS and reflections. Table 1 shows the parameters used in this experiment.

Subsequent experiments defined positioning error on the VIO coordinate system managed by the device itself. Therefore, error was the distance between tag position estimated by the system using the position estimator and the position pre-configured in device's coordinate system.

6.1. Position estimator comparison

We used Chan's algorithm (CA) [13] for the LUVI position estimator. This section explains why CA is suitable for calculating positions in a VA based environment. Another commonly used algorithm for solving multi-lateral problem is the Taylor series (TS) algorithm [39], which achieves good performance for small number of references is small but has heavy computational burden since it requires significant iterations for each reference to the approximate solution. Fig. 6 shows that TS error

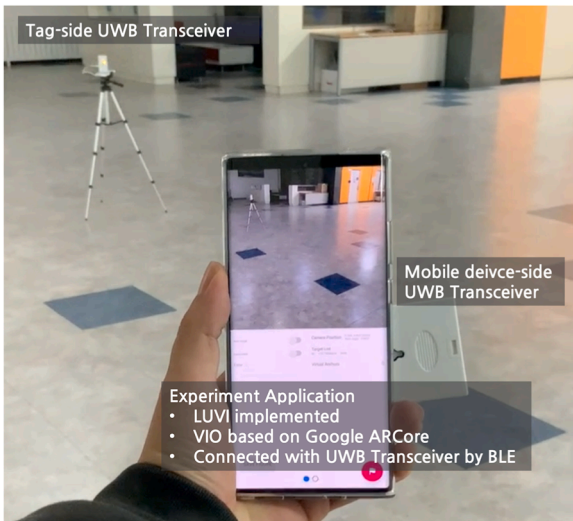


Fig. 5. LUVI testbed.

Table 1
Experiment parameters.

Parameters	Values
Experiment time	120s
Experiment size	100 m ²
Short period	100 ms
Long period	5000 ms
k (default)	10
Window size w	10

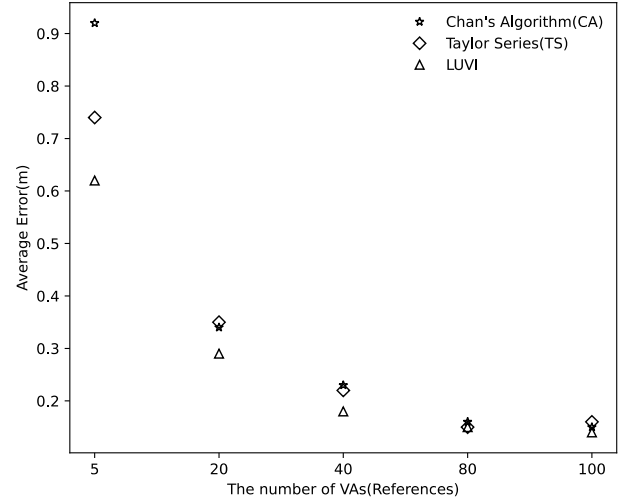


Fig. 6. Position estimation technique performances.

is smaller when the number of references is very small, but the difference between the two methods reduces as VA increases. Elapsed time was measured on the mobile device.

Fig. 7 compares the average elapsed time from 10 experiments in office environment. TS consumes considerable computing resources compared with CA, hence CA is more suitable for LUVI, which requires a large number of VAs to estimate positions.

6.2. Virtual anchor selection algorithm

The VA selection algorithm was evaluated by analyzing the VA data collected in the experiments. We conducted 10 experiments with random mobility in both environments (open space and office). Then extracted k virtual anchors for accuracy and time complexity analysis,

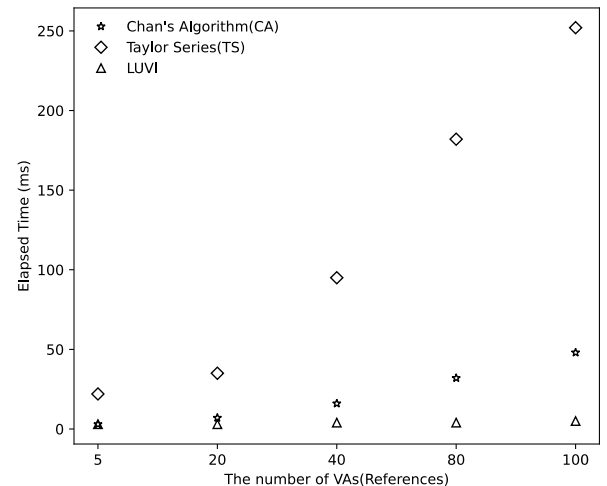


Fig. 7. Position estimation technique burdens.

from LUVI database for each experiment, according to the VA selection and number. We also evaluated the random method, selecting k VAs in a completely random manner.

Figs. 8 and 9 show the total number of VAs generated in one experiment, the VAs finally selected by the selection algorithm, and the estimated positions during an experiment. The VAs shown in the figure is generated on the trajectory of the mobile device, and LUVI's VA selection algorithm selects VAs in various locations. Since the number of VAs is small near the start of the experiment, the tag is estimated at a position slightly farther than the ground truth, but the error decreases as enough VAs accumulate over time.

Figs. 10 and 11 show experimental results for the open space and office environments, respectively. All methods guarantee positioning error about 10 cm when $k = 10$ in the open space environment, which is close to the ranging error guaranteed by the hardware. Thus, open space accuracy did not change significantly as k increases. LUVI achieves lower error for all k compared with the other approaches in the office environment, verifying that LUVI can select VAs with better ranging quality in noisy environments. In particular, when $k = 10$, the average error decreases by 30%, from 23 cm with random selection to 16 cm with the VA selection algorithm. Error increases slightly with increasing k in the noisy office environment, due to forced additional inclusion of VAs, which may degrade the overall performance due to NLOS ranging.

Fig. 12 shows computational complexity with respect to k . Calculation delay increases exponentially if the position estimator obtains a VA set without selection. However, random and LUVI selection algorithms exhibit no delay differences as k increases. LUVI guarantees similar or even better results compared with random, particularly in harsh environments.

Finally, in order to analyze how the GDOP affects the localization results, we also analyzed the distribution angle of VA relative to the target tag as shown in Fig. 13. LUVI shows that as the angle gets smaller, the positioning error significantly increases due to the GDOP problem, but the error can be relatively reduced compared to random selection.

6.3. Adaptive ranging algorithm

We first analyze the effects of ranging period on accuracy to evaluate the performance of adaptive ranging algorithm. The scenario of the experiment is that the tag is placed in the center of the office and mobile devices moves randomly inside the office until about 70 s, then it goes out into a hallway separated by a concrete wall that the UWB cannot penetrate from 70 to 105 s, and then it returns to the office. Fig. 14 shows error with respect to time moving along the same path in the

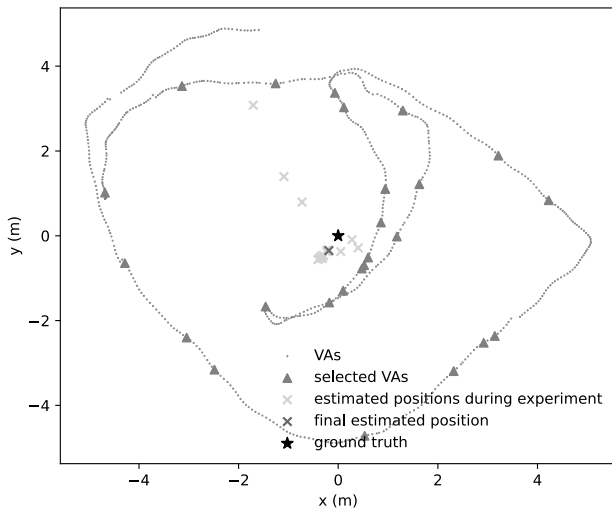


Fig. 8. Trajectories of VAs and estimated position in the open space environment.

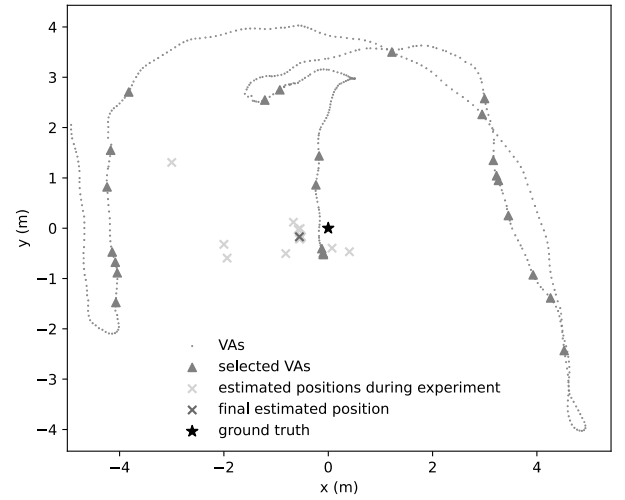


Fig. 9. Trajectories of VAs and estimated position in the office environment.

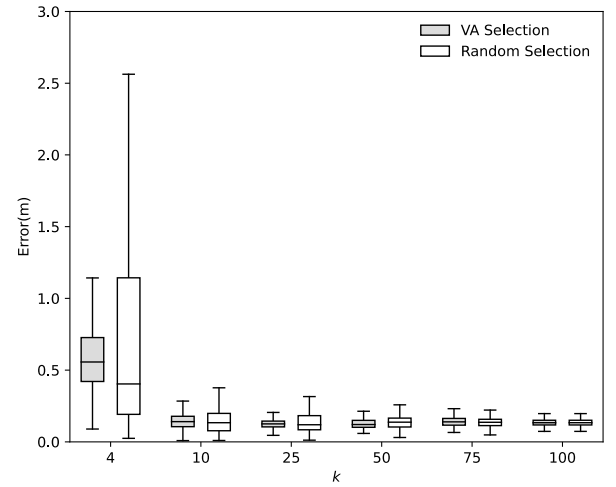


Fig. 10. Positioning error in the open space environment.

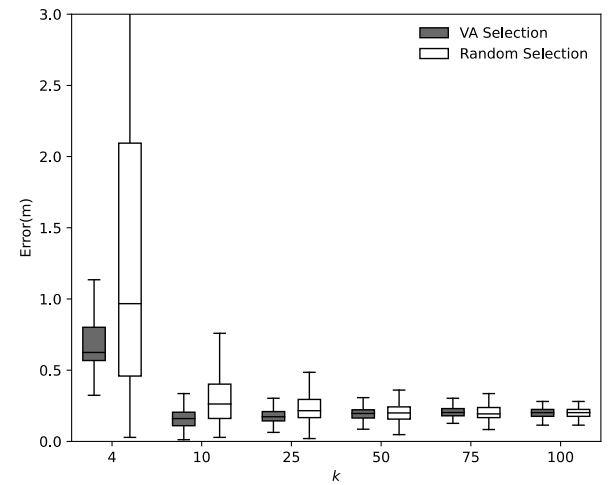


Fig. 11. Positioning error in the office environment.

office environment at 100, 500, and 1000 ms performance, respectively. Shorter ranging cycles approach the correct answer more quickly. Performance for all ranging cycles exhibit no significant differences beyond 80 s.

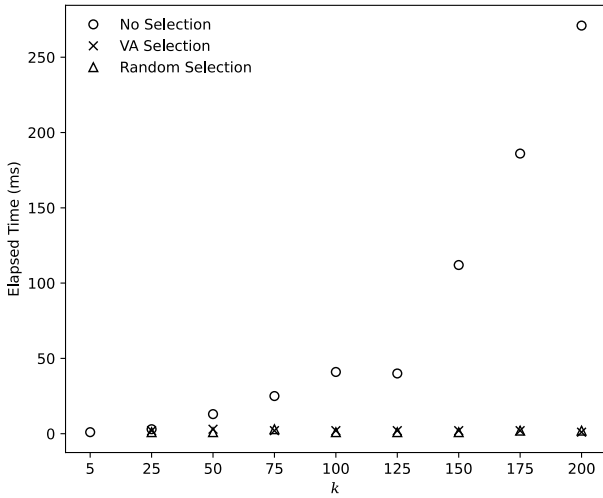


Fig. 12. Elapsed time to calculate tag positions.

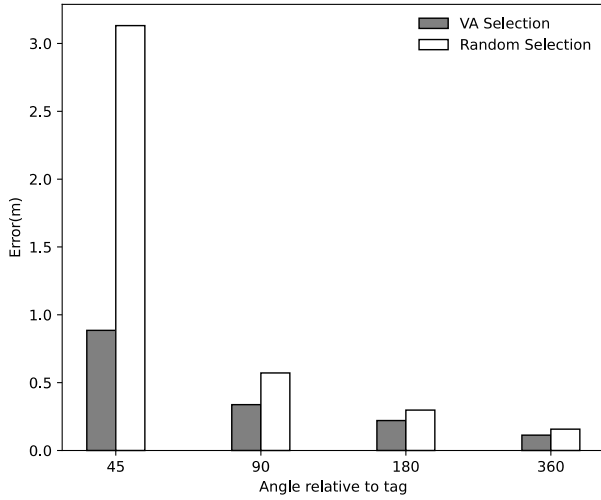


Fig. 13. Positioning error according to the angle relative to the target.

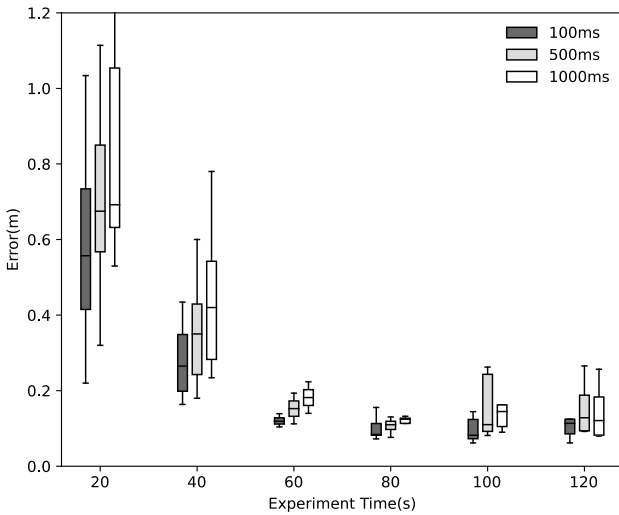


Fig. 14. Position estimation error by period.

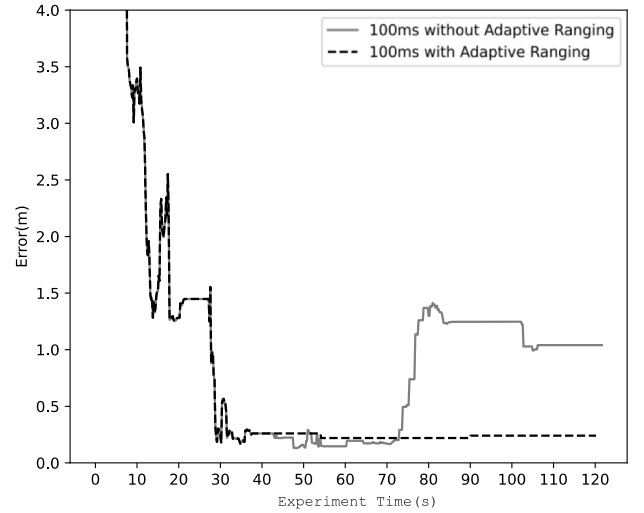


Fig. 15. Adaptive ranging effects on error.

Fig. 15 shows position estimation accuracy over time using adaptive ranging. Initially there is no difference because adaptive ranging also functions with the short period (100 ms). Adaptive ranging changes into long period mode (1000 ms) after 37 s, which nevertheless guarantees the same level of accuracy. However, the mobile device exited the room into the hallway at 70 s, and the concrete wall blocks ranging from the tag. From this time until 85 s, when the signal is completely blocked, the ranging value with error passed to Multipath will increase the ranging error. On the other hand, adaptive ranging performs intelligently, being aware of the situation, and ignores VAs created in the erroneous environment. The traditional ranging method, without adaptive ranging, induces errors which result from incorrect ranging measurements.

Fig. 16 shows the number of virtual anchors created by LUVI. Similar to the case of position accuracy, creation of virtual anchor significantly reduces from about 37 s, while new anchors created from 70 s are also in lower numbers, due to reduced sampling for NLOS identification. Therefore, LUVI's adaptive ranging can not only robustly adjust to harsh NLOS environments, but also reduce communication complexity and power resources.

7. Conclusions

This paper proposes LUVI, a lightweight relative positioning method for indoor positioning using integrated UWB and VIO environments. LUVI's objective is to reduce resource consumption during ranging,

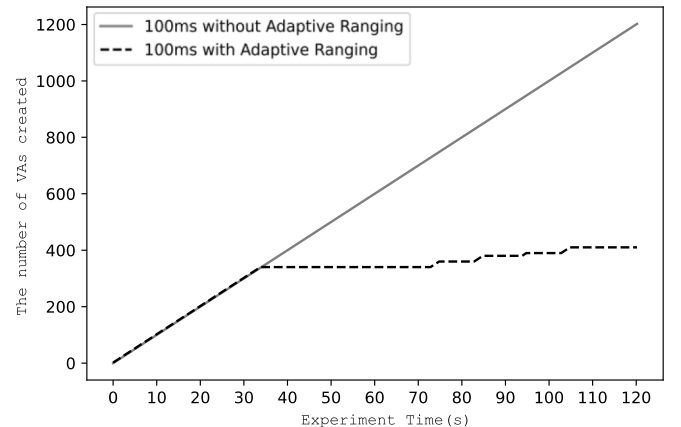


Fig. 16. Adaptive ranging effects on VA creation.

while providing robust performance in obstacle-induced noisy environments. In particular, LUVI offers a practical implementation for future practical applications, thanks to recent flagship mobile devices equipped with UWB chips.

Various current applications, such as Apple's Find My with Air tag [11], estimate approximate target positions using AoA, which allows users to estimate measuring device angle simultaneously with ranging. In contrast, LUVI collects VA and uses the TDoA algorithm to estimate target angle and actual position. However, position estimation via AoA can be significantly degraded in NLOS environments, due to multipath propagation. Thus, LUVI and AoA based positioning can inter-operate, or AoA-based positioning can be augmented into the LUVI to further strengthen positioning accuracy and improve user experience, rather than being comparative counterparts.

LUVI incorporates VA selection and adaptive ranging, which not only reduces computing complexity to linear order, but also dramatically reduces power consumption during wireless communication for ranging. This also helps to obtain better positioning accuracy and robustness against NLOS environments. Thus, the proposed technology can be applied with low cost and high efficiency in various fields, including disaster response, facility management, and indoor commerce. For future research, we will consider more complex mobile environments where multiple mobile devices may exist. In such cases, as each device maintains and calculates the location of tags in a local manner, each VA map is incompatible to each other. To solve this problem, intelligent real-time map merging algorithms are required through cloud or ad hoc networks.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Young-Bae Ko has patent Object location measurement method and augmented reality service providing device using the same licensed to Industry Academic Cooperation Foundation of Ajou University.

Data availability

Data will be made available on request.

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