Integrating Geometry-Driven and Data-Driven Positioning via Combinatorial Data Augmentation

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Abstract—Precise positioning has become one core topic in wireless communications by facilitating candidate techniques of B5G. Nevertheless, most existing positioning algorithms, categorized into geometric-driven and data-driven approaches, fail to simultaneously fulfill diversified requirements for practical use, e.g., accuracy, real-time operation, scalability, maintenance, etc. This article aims at introducing a new principle, called combinatorial data augmentation (CDA), a catalyst for the two approaches’ tight integration. We first explain the concept of CDA and its critical advantages over the two standalone approaches. Then, we confirm the CDA’s effectiveness from field experiments based on WiFi round-trip time and inertial measurement units. Lastly, we present its potential beyond positioning, expected to play a critical role in B5G.

I. INTRODUCTION

One indispensable technology to materialize B5G is to precisely estimate users’ locations, called positioning [1]. For example, precise location information facilitates fine-tuning a narrow beam to the corresponding user without searching all possible ranges in a three-dimensional (3D) space. Besides, several intermediate measurements required to estimate the user’s location, such as Angle-of-Departure (AoD), Angle-of-Arrival (AoA), Time-of-Arrival (ToA), and Time-Difference-of-Arrival (TDoA), can be used to construct a map of the concerned surrounding, helping multi-user interference management from a network perspective.

Due to the potential above and various wireless technologies, there are numerous positioning algorithms classified into two approaches. The former is geometry-driven positioning (GP), estimating a user’s location from the intersection between different measurements’ geometric representations, e.g., circles for ToA and hyperbola for TDoA. The latter is data-driven positioning (DP), exploiting numerous datasets to infer a user’s location by matching a few similar data samples therein. However, neither GP nor DP satisfies diversified requirements simultaneously, as summarized below.

• **Accuracy**: GP can provide an acceptable positioning accuracy when Line-of-Sight (LoS) paths exist between anchors and the user, while its accuracy is significantly degraded if some of them become Non-LoS (NLoS). DP has received great attention to addressing the issue by following the recent advancement of machine learning (ML). For example, a well-trained ML model identifies the existence of an LoS path [2] or directly infers the user’s location, called a fingerprint method [3]. Compared to GP, DP provides solid positioning accuracy if its ML model is well-trained enough to reflect the concerned surrounding. Nevertheless, its application to commercial systems remains unsolved due to the following reasons.
  • **Real-Time Operation**: GP has been widely used in practice due to its simple implementation suitable for real-time operation (e.g., Global Positioning System (GPS) and cellular positioning). On the other hand, an ML-based DP requires an offline phase, taking several hours to collect a sufficient number of labeled data and train its ML model until convergence.
  • **Scalability**: Besides, the trained ML model only works well in a specific place in which the training data is collected, whereas it cannot be in other places. As a result, a different ML model should be trained and used in each area, making it challenging to apply DP in various places.
  • **Maintenance**: Though an ML model reflects well on the features at a specific instant, it is sensitive to the wireless environment’s slight changes due to weather, user density, mobility, etc. In other words, a database for DP should be periodically updated to maintain the ML model to the lastest, bringing about high maintenance cost.

One interesting point is that the two approaches’ pros and cons complement each other, calling for their integration to fulfill the above requirements. To this end, this article introduces a novel concept of combinatorial data augmentation (CDA), which plays a bridge between GP and DP to enable their integration. We first elaborate on a key principle of CDA, explaining how the integration addresses the mentioned challenges. Then we experimentally verify CDA’s effectiveness using WiFi Round-Trip Time (RTT) measurements and a smartphone’s inertial measurement units (IMUs). Finally, we point to CDA’s potentials beyond positioning and summarize relevant research issues and opportunities in B5G.

II. COMBINATORIAL DATA AUGMENTATION

This section explains a key principle of CDA and highlights its advantages by integrating the above two standalone approaches.

A. Key Principle

Fig. 1 graphically illustrates an example of CDA with the positioning scenario comprising a single user and $N$ anchors. All anchors are stationary, and their locations are assumed to be known without loss of generality. We consider waveform-based positioning, where the user’s wireless device (e.g.,
smartphone) captures various measurements, such as ToA, TDoA, AoD, and AoA, by hearing the anchors’ waveform transmissions [4]. Given the anchors’ locations and measurements, we target the user’s precise location, the central theme throughout the article.

First, consider an ideal case with LoS paths to all anchors and without measurement error. The user’s location is precisely estimated using GP algorithms, e.g., linear least square through reference selection (LLS-RS) method [5], if the number of anchors $N$ is no less than its minimum for unique positioning, i.e., 3 for ToA/TDoA and 2 for AoD/AoA. Second, in a practical case with NLoS conditions and measurement errors, various obstacles in the concerned surrounding render signal propagations detour from an LoS path and attenuate severely, resulting in degrading positioning accuracy. Besides, the lack of statistical data relevant to the obstacles limits DP usage, making the positioning more challenging.

Instead of relying on the given dataset, the proposed CDA allows us to use DP by generating numerous data from multiple combinations of anchor selections. Specifically, we use $M(< N)$ anchors’ measurements to estimate the user’s location using a conventional GP algorithm. We call the estimate a preliminary estimated location (PEL). It is possible to select $\binom{N}{M}$ combinations of anchors, each of which makes a different PEL in the floor plan, as shown in the middle figure in Fig. 1. By leveraging many PELs, we can apply a wide range of data-analytic algorithms, leading to finding the user’s location precisely without prior knowledge of the concerned surrounding.

B. Advantage of Combinatorial Data Augmentation

The proposed CDA-based positioning approach has the following advantages for overcoming GP and DP’s drawbacks mentioned above, as summarized in Table I.

1) Harnessing the Power of Big Data: Noting that the number of anchor combinations $\binom{N}{M}$ scales as the order of $N^M$, it is reasonable to consider the augmented data as big data when the number of anchors $N$ is sufficiently large. Consequently, it is possible to extract various latent information embedded in the augmented data using several data-analytic techniques, such as clustering, data embedding, and data mining. Some discovered information can guide us to find a user’s location more accurately.

2) Practical Design: CDA does not require training an ML model or updating a database, which are the main drawbacks limiting a conventional DP algorithm’s practicality. Instead, low-complexity GP algorithms are utilized for augmenting a sufficient number of data samples, based on one feasible prerequisite that anchors’ positions are given in advance. It is verified that CDA is effectively implementable on a hand-held device, e.g., a smartphone, whose computation capability is limited (see the video clip in http://asq.kr/XafVr).

3) Compatibility with Existing Algorithms: CDA can work well with various positioning algorithms according to available measurements, extending its usage into various applications. For example, when the multi-path profile of a wireless propagation is given in terms of AoA, AoD, and delay as in [6], it is possible to find multiple PELs by selecting a few paths among the entire ones. Besides, CDA helps pedestrian dead reckoning (PDR) [7], a positioning algorithm using IMU’s sequential measurements. Specifically, PDR’s positioning accuracy is consistently degraded due to accumulated errors. It can be addressed by incorporating other positioning results if each result’s reliability is measurable. In that sense, the spatial distribution of PELs represents the noise level of the current measurement, becoming a statistical belief how much the measurement is reliable than the others. This idea is verified in the sequel.

It is worth noting that a few existing works use similar approaches to CDA. For example, a least median square algorithm (LMeS) is developed in [8] that a PEL with the minimum median square error is considered the user’s location. In [9],

Figure 1: Graphical representation of an integrated positioning approach using CDA.

| Approach | GP Standalone | DP Standalone | CDA-based Integration |
|----------|---------------|---------------|-----------------------|
| Accuracy (LoS) | High | High | High |
| Accuracy (NLoS) | Low | High | High |
| Real-Time Operation | ◦ | × | ◦ |
| Scalability | ◦ | × | ◦ |
| Maintenance Cost | Low | High | Low |
a residual weighting algorithm (RWGH) is proposed by more weighting a PEL with a smaller residual error. On the other hand, the above algorithms utilize only limited information embedded in PEL. If other information is used together, there is room for performance improvement. In the following section, we suggest new approaches by unleashing the full potential of CDA and verify their superiority by comparing with the above existing works.

III. CDA HELPS WiFi RTT POSITIONING: FIELD EXPERIMENT VERIFICATION

This section aims at showing the effectiveness of the CDA approach from field experiments of WiFi positioning. We use an RTT measured by fine timing measurement (FTM), firstly introduced in 802.11mc. FTM can provide a decent RTT measurement at picosecond granularity under an LoS condition. On the other hand, it shares the common limitation of NLoS positioning, confirmed by existing experiment results such as [10]. We mainly focus on explaining how CDA addresses the drawback using a large number of PELs. For readers interested in the experiment in detail, please check our supplementary slides in http://asq.kr/zwmo.

A. Experiment Setting

We conducted field experiments at the underground parking lot in Korea Railroad Research Institute, Uiwang, Korea. We use 10 WiFi APs designed based on Qualcomm IPQ 4018 (N = 10) and one Google Pixel2 XL smartphone, both of which support FTM. We deploy these APs at 2 meters height at different locations. On the other hand, a user holds the smartphone at the height of 1.1 (m). The user walks around the experiment site at a speed of around 4 (km/h), and his smartphone records RTTs and built-in IMUs’ measurements, i.e., accelerometer, gyroscope, and magnetometer, at 34 different measurement positions (MPs). The measured RTTs are translated into the distance between the corresponding AP and the user by multiplying $\frac{c}{2}$ with the light speed $c \approx 3 \cdot 10^8$ (m/sec). The IMUs’ measurements are used for PDR. Given the above observations, we attempt to estimate the MPs’ coordinates.

For CDA, the number of APs needed for deriving one PEL, denoted by $M$, is set to 3. It is the minimum number for unique positioning, but it provides the best positioning accuracy among all possible numbers, explained in the sequel. Given each anchor selection, we use the LLS-RS method in [5] to derive the corresponding PEL. Thus, the number of PELs becomes 120 for each MP.

B. WiFi RTT Localization without PDR

1) Problem Description: First, consider a case without IMUs’ measurements. Then, estimating the user’s location at a specific instant is determined by the corresponding PELs, independent of previous ones. One straightforward way is that their representative value, e.g., median, is deemed the user’s location estimate. In general, a median-based estimator is known to provide solid performance in many localization applications since a few outliers highly different from the others are easily ignored [8]. On the other hand, the median of the entire PELs can be significantly far from the ground truth (see the first figure in Fig. 2). The reason is that the majority of PELs can be severely biased to a particular direction if many NLoS propagations are formed depending on specific environments, i.e., walls, pillars, and parked vehicles.

2) Reliability-Based PEL Filtering: We can overcome the above limitation by picking a few reliable PELs less affected by NLoS environments. To this end, we use the following two metrics quantifying the NLoS effect.

- Residual Error: Due to measurement errors and NLoS propagations, every circle induced by each RTT is unlikely to meet a single point. In other words, the distances from each PEL to APs cannot be the same as those derived from the corresponding RTTs. The sum of these errors is defined as a residual error (RE). A significant RE can appear when the RTTs used for deriving the PEL are severely corrupted. As a result, comparing REs helps speculate which PEL is more reliable to represent the ground truth. On the other hand, it is occasionally observed that a few PELs with small REs can be placed far away from the ground truth. It is thus required to use another metric together.

- RTT sum: A smaller RTT implies that the user is more likely to be located in an LoS sight from the corresponding AP. It inspires us to establish one hypothesis that a PEL with a smaller RTT sum (RS) represents a more...
accurate estimate of the user’s location. The hypothesis is well-verified in our supplementary slides.

Using the above two metrics, we aim at filtering out unreliable PELs by designing a tandem filter as shown in Fig. 2. First, all PELs are sorted in RE’s ascending order. Then, the first filter passes only the top 32% of PELs, while the others are discarded. Next, the remaining PELs are sorted again in RS’s ascending order, and the second filters pass only the top 32% of the PELs. As a result, the number of remaining PELs is thus 12 (10%). Last, the corresponding MP’s coordinates are estimated from the remaining PELs’ median.

3) Performance Evaluation: Fig. 3 illustrates the location estimates’ traces on the floor plan of the experiment site. The solid black line represents the actual user trajectory, and the number inside the circle indicates the corresponding MP’s index. Three benchmarks are considered. The first is LLS-RS without CDA [5]. The second and third ones are the existing algorithms with CDA mentioned above, namely LMeS [8] and RWGH [9], which are representatives of median-based and mean-based estimators, respectively.

Several key observations are made. First, it is verified that CDA effectively mitigates the NLoS effect from the comparison between LLS-RS and the remaining CDA-based techniques. Second, our tandem filtering method outperforms LMeS and RWGH at most MPs, confirming that the remaining PELs after filtering are less corrupted than the others. Note that our filtering operation is based on a relative comparison between given PELs. It always returns the same number of PELs (12 PELs according to the current configuration). In other words, the remaining PELs can also be noisy due to harsh environments. The resulting positioning error can be significant, as shown in MP 18. It is essential to incorporate the previous location estimate and IMU measurements dealt with in the following subsection.

C. WiFi RTT Positioning with PDR

1) Problem Description: Second, consider a case with IMUs’ measurements. Assuming that the user’s mobility pattern remains unchanged between adjacent MPs, his location change becomes a single linear piecewise [11]. It is represented by a movement vector whose first and second elements are moving distances to the directions of $x$ and $y$ axes, respectively. Through this, it is possible to correct the current location estimate by interlocking with the previous one. One typical technique enabling it is a Kalman filter (KF), which is an algorithm denoising corrupted state variables using a series of observations over time. When the user moves between adjacent MPs, two types of estimates are considered as follows.

- **Prediction-Based Estimate**: Define a state variable as the previous location estimate. Then, the current location can be predicted by adding the movement vector into the state variable, called a prediction-based estimate (PE). This process can be written as a matrix multiplication form after a few manipulations, allowing us to use KF. Its accuracy depends on the noisy level of the movement vector, called a process covariance matrix.

- **Measurement-Based Estimate**: Recall that we have multiple RTT measurements. Using the above method without PDR, we can derive another estimate, called a measurement-based estimate (ME), considered as a new observation state. Its noisy level is expressed by a measurement covariance matrix.

Finally, the user’s location estimate can be derived by a weighted linear combination of PE and ME whose weight depends on the corresponding noise covariance matrices. KF is proved to be the optimal estimator when the prediction and measurement errors are Gaussian processes and the two covariance matrices are known. To the final estimate be accurate, it is indeed vital to obtain their good estimates. It is possible to estimate the former accurately using a sequence of
IMU measurements between adjacent MPs. On the other hand, the estimate of the latter relies on the historical data given in advance, making its usage and performance limited [12].

2) Real-Time Update of Measurement Noise Covariance: CDA helps update the measurement covariance matrix by distilling the current measurements’ noisy level from PELs’ spatial distribution. For example, as PELs are more dispersed, the current RTTs tend to be more corrupted, resulting in higher noise variance. Besides, the tandem filter in Fig. 2 plays a role in excluding PELs severely biased. Thus, the remaining PELs tend to follow a Gaussian distribution without bias to a certain direction. As a result, we can compute the measurement covariance matrix as a diagonal matrix whose first and second elements are the variances of the remaining PELs’ x and y coordinates, respectively.

3) Performance Evaluation: Fig. 4 represents the comparison of mean absolute error (MAE) between KFs with a deterministic covariance matrix (conventional) and real-time covariance update (proposed). It is shown that the proposed approach’s positioning result is relatively accurate and stable for most MPs. Recall MP 18 in which the positioning errors remains significant after reliability-based filtering is used. As shown in the circle in Fig. 4, KF attempts to find the user’s location between prediction-based and measurement-based estimates. By reflecting the current measurement’s noisy level into the covariance matrix, the two preliminary estimates’ weights are properly adjusted, leading to estimating the user’s location closer to the ground truth.

D. Design Guidelines & Future Opportunities

In this subsection, we provide several discussions to make the CDA more effective and attractive.

1) Effect of Hyper-Parameters: One remaining issue unspecified yet is to determine the number of anchors required to derive a PEL, denoted by N. To explain, we define a clean RTT as an RTT with an error smaller than 1 (m). We experimentally investigate that the probability of a clean RTT, denoted by δ, is around 0.4 – 0.5 in various indoor environments (e.g., 0.465 in the concerned experiment site). Given δ, the likelihood that all clean RTTs are used to derive a PEL becomes M = (δ)^N, and its expectation is E[N] = (1/δ^N). Thus, it is reasonable to determine N as a deterministic measurement covariance matrix. Its MAE’s mean and standard deviation are 1.478 (m) and 0.958 (m), respectively. On the other hand, the second one, whose color is red, is the proposed approach updating the covariance matrix according to the variance of the remaining PELs. The resultant MAE’s mean and standard deviation are 1.258 (m) and 0.690 (m), respectively. The circle therein illustrates how KF corrects the WiFi RTT’s positioning error at MP 18 by properly weighting prediction-based and measurement-based estimates.

2) Real-Time Update of Measurement Noise Covariance: The first one, whose color is purple, is a benchmark using an identity matrix as a deterministic measurement covariance matrix. Its MAE’s mean and standard deviation are 1.478 (m) and 0.958 (m), respectively. On the other hand, the second one, whose color is red, is the proposed approach updating the covariance matrix according to the variance of the remaining PELs. The resultant MAE’s mean and standard deviation are 1.258 (m) and 0.690 (m), respectively. The circle therein illustrates how KF corrects the WiFi RTT’s positioning error at MP 18 by properly weighting prediction-based and measurement-based estimates.

3) Multi-Point Positioning: So far, we have regarded a user’s position as a single point and aim to estimate it, called single-point positioning. On the other hand, the appearance of various hand-held devices enables us to identify a user’s location using multiple points. The positioning problem can be extended into multi-point positioning [14]. Specifically, these devices share relative location information using various communication protocols, e.g., WiFi, ultra-wideband, Bluetooth, leading to constructing their formation. The multiple devices’ locations can be estimated together while keeping the formation, helping infer the user’s location more precisely when CDA is used. For example, consider different devices’ PELs whose anchor selections are identical. Then, the distance between these PELs should be the same as those between the devices, possibly becoming another reliability indicator of the corresponding anchor selection.

IV. WHEN CDA MEETS 5G AND BEYOND

Departing from raw data points, CDA stands upon augmented representations (i.e., PELs) while reporting their reliability indicators (i.e., RE and RS). Thus far, we have focused on these unique properties of CDA for improving positioning accuracy, which can also be leveraged for enabling emerging high-stake applications in 5G and beyond, as elaborated next.

1) Risk-Aware Decision-Making: Reporting positioning accuracy (e.g., MAE) is not sufficient for carrying out decision-making in mission-critical applications. Instead, it is crucial to understand how reliable the accuracy is. Autonomous driving is one example where emergency braking decisions cannot
Figure 5: A schematic illustration of CDA for accurate positioning (i.e., Vanilla CDA) and its extension to B5G applications. The PELs of CDA, which are augmented representations, are associated with risk indicators (i.e., RE and RS), thereby enabling risk-aware, real-time, and privacy-aware B5G applications.

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