Evaluation of a Location Reporting System for mmWave Communication

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Abstract. This paper presents a sampling alignment data processing (SADP) methodology for un-synchronized data to evaluate the precision and accuracy of a positioning system (the Google Tango system); this location system is used to control beams of directional antennas for a 5th generation communication system using millimeter Wave (mmWave) links. The test mathematical model is described in details to derive the sampling alignment data processing. The SADP is used to evaluate the indoor and outdoor scenarios for the Google Tango position system, and we conclude that the Tango system precision is impacted by the tester's behaviors, environment characteristics, and weather conditions. The evaluation results show the suitability of the Tango system as a location reporting system for our mmWave communication system.

Keywords: Position system · mmWave communication · Google Tango
Data fusion · Sampling alignment data processing · Error analysis

1 Introduction

Millimeter Wave (mmWave) communication has become a hot topic in recent years, especially for 5th Generation and Ad-hoc communication systems. But with mmWave, the signal attenuation is very high at the high frequencies used for communication. In order to compensate for this attenuation, directional antennas must be used to improve the range of the communication link. Directional antennas provide the additional benefits of reducing the interference to other nodes and improving the security of the communication link (by reducing the risk of jamming and eavesdropping [1, 2] by other parties). In order to preserve a wide coverage for the communication system, multiple directional antennas must be used and a system must be provided with the capability to select the best antenna to communicate with a given mobile station based on its position.

In the communication scenarios considered in this paper, the stationary basestation has several directional antennas to be able to concentrate the radio signal in different directions, but only one directional antenna can transmit at any given time. In order to select the best antenna to communicate with a mobile user station, accurate and precise position information about the moving station is required. This location information is used by the algorithm running on the basestation, to select the best antenna.

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In this project, we use the Google Tango smartphone/tablet to provide the location information. Since the data captured is not aligned in time and location, we propose a sampling alignment data processing method to evaluate the performance.

In Sect. 2 we review indoor and outdoor position techniques and systems. Section 3 provides an overview of the architecture of the system presented in this paper. Section 4 provides an evaluation of the performance of the Google Tango systems for several test cases. It also describes the method designed to process the data so that we can derive a quantitative analysis of the results for different scenarios considered here.

2 Literature Review

Various systems are available to provide location estimation; these systems are based on satellites systems, RF detection, inertial sensors [3], image recognition, or a combination of several of these techniques.

Global Navigation Satellite System (GNSS) is the generic term for navigation systems using satellites to provide autonomous geo-spatial positioning with global coverage [4]. It is often referred to as: GPS, GLONASS, Galileo, or Beidou based on the regional satellite constellation used for positioning. By accessing the signal information from multiple satellites, the location system can provide accurate and precise location information.

GPS is a mature technology. GPS-enabled smartphones are typically accurate to be within a 4.9 m [5] if a clear view of the sky is available to the smartphone. A GPS system will not be able to work indoor since the device does not have a clear view of the sky. This can also happen in tunnels and in “urban canyons” where the signals from the satellites are blocked by high rise building.

The GNSS accuracy has significantly improved with the use of more satellite constellations and the development of wide-area augmentation systems (WAAS) [6]. To improve the accuracy of GPS systems, differential GPS systems have been developed [7]. In a differential system, a network of stationary ground-based reference stations broadcast the difference between their position indicated by their GPS and their known fixed location to provide a correction to nearby mobile GPS devices. Differential GPS can achieve accuracy up to cm level; they are used in certain industrial applications and in agricultural applications but they are very expensive.

For positioning systems based on Radio Frequency (RF) signals, we focus on indoor system since many of these systems are focused on indoor applications. These systems can be classified into several types depending on various aspects such as: where the RF positioning signal originates, the frequency of this signal, and whether the system is self-contained or it requires several units to be deployed [3]. The RF signals can be from wireless local area networks (WLAN) systems, from cellular communication towers, or generated by a moving equipment itself or by a dedicated infrastructure deployed specifically for localization (such as Near Field Communication, and Radio Frequency Identification systems). These systems use received signal strength, time of arrival or time difference of arrival (from different sources) to estimate the location of a device. During the estimation process, the system collects the fingerprint of the signal and it then uses a triangulation algorithm to calculate the position information. Since there is no good model for indoor radio multipath, some new methods are proposed, such as scene analysis, and radio mapping.

Simultaneous Localization and Mapping (SLAM) is a popular research topic, which the system constructs and/or updates a map of an unknown environment while simultaneously it keeps track of its location within it [8, 9] by using variety sensors. The sensors can be categorized into laser-based, sonar-based, and vision-based systems. The mathematical process methods include Kalman filters and Bayes' rules. Some open SLAM methods have been published in [10].

3 System Architecture

3.1 Test System

An application running on Tango device, captures the position updates from the device's operating system and hardware in the form of an (x, y, z) tuple for the coordinates and 3 angles (yaw, pitch, and roll) indicating the orientation of the device at that location. This 6-tuple is referred as Pose [11] in the Tango terminology. In our application, we use this information to infer the position of the mobile user device with respect to the basestation, and push the (x, y, z) coordinates updates to the basestation using a protocol called MQTT (Message Queue Telemetry Transport) [12].

The mobile user station provides its location to the fixed basestation over a separate control channel. The MQTT server on the basestation would receive these locations and make them available to all MQTT clients that have registered interest, in our case this being the location data analysis software. The antenna selection algorithm can then use this location information to select the best antenna to communicate with a given mobile station as shown in Fig. 1.

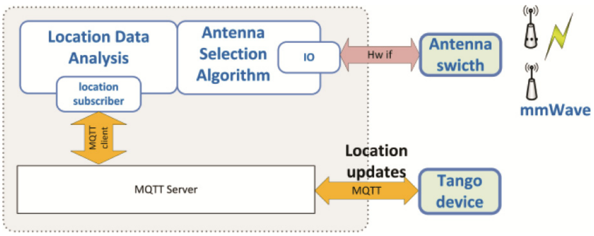

Fig. 1. System architecture

3.2 Google Tango [13]

Google has developed an Android device (tablet or smartphone) for accurate indoor positioning. The system has a wide-angle camera, a depth sensing camera, and accurate inertial sensor timestamping, as well as software application programming interface to access these capabilities. This system fuses the information from these sensors to provide location information; if area learning has previously been done in the location of interest, it will also report location with respect to the point of reference for this learned area. The Tango Area Learning gives the device the ability to see and remember the key visual features of a physical space, such as the edges, corners, other unique features and it uses this information to locate the Tango device within this frame of reference; the Tango can also recognize the area and improve the accuracy of its position reporting. The Tango system also uses the SLAM to track and save the data.

3.3 Test Scenarios

Our mmWave system works indoor and for certain cases outdoor. We tested the Tango positioning system for the following 4 scenarios to check its performance.

Indoor Office Layout: This test is a standard indoor open office layout. The layout includes cubicles with 5-feet tall partitions and common sitting area for meetings. The goal for using this layout is to check behavior of the positioning system for typical office layouts.

Indoor Multilevel Layout: This test layout includes two tunnels (connecting buildings), stairs, and a cafeteria (a large common area). The goal of this layout is to check the 3-D accuracy of the positioning system.

Outdoor, Snow Covered Parking Lot: This outdoor test layout includes a snow covered parking lot. The intention is to check whether Tango can work in this kind of outdoor set-up (where the snow cover might reduce the number of distinguishing features captured by the Tango system).

Outdoor, Sunny Courtyard: This outdoor test layout is at a city hall courtyard (City of Ottawa), and there are trees, light poles, and status as shown in Fig. 4. The intention is to check whether the Tango can work well in sunny situations where the strong sunlight might affect the Tango camera system.

4 Location Data Analysis

4.1 Method to Capture the Data

The location data is captured by a person walking the same route at the same speed multiple times. The position data is recorded every 0.5 s. Each test scenario is captured 10 times. Since each test run is carried by a same person, this introduces variations in the parameters for each test run, which include:

- Not exactly the exact same routes for each test run
- Not exactly the same speed between different test runs
- Not exactly the same speed within one test run.

The raw data captured for the four scenarios is shown in Fig. 2.

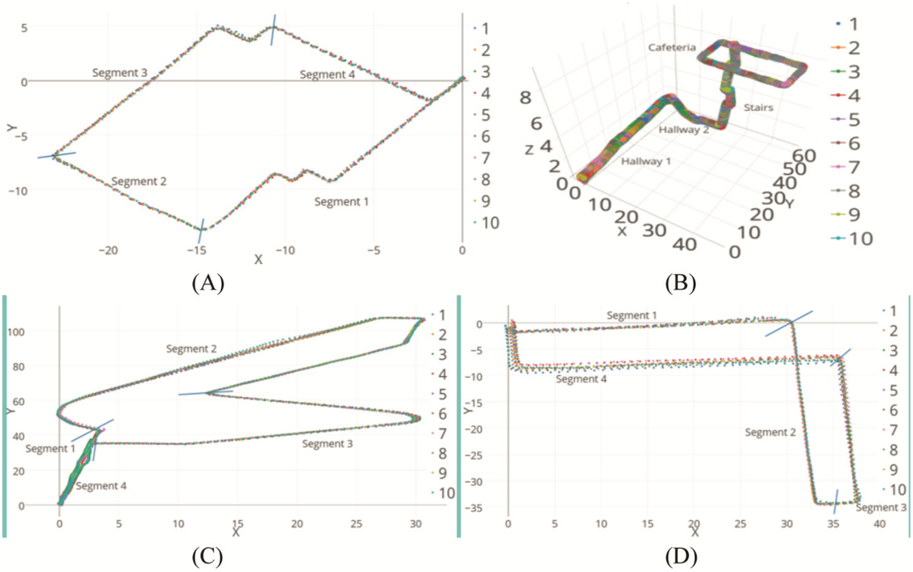

Fig. 2. Test result for the four scenarios, (A) Indoor office, (B) Indoor multilevel layout, (C) Snow covered parking lot, and (D) Sunny courtyard. For each scenario, we show the segments.

4.2 Mathematical Model

Let $s(t)$ be the location at time t and let $v(t)$ be the speed at the time t. The location of the time t will be:

$$s(t) = \int_0^t v(\tau)d\tau + \partial_t \tag{1}$$

Here, $s(t)$is the 3-D vector (x, y, z) as Tango can report 3-D data relative to the starting point of the learned area. And, ∂_t is the error offset of the location with the planned true route at the time t. The offset can be due to variations in the person's standing postures or due to other factors, like avoiding other people during a test run. This offset is a random parameter. In this project, we assume that ∂_t is a variable distributed according to the Gaussian distribution with the mean value equal to zero.

$$\partial(t) = \frac{1}{\propto \sqrt{2\pi}} e^{-t^2/2a^2} \tag{2}$$

For the Gaussian distribution, we can use average value to approach the "true value". So we need to do multiple test runs to obtain the mean. In this project, we ran the tests 10 times for each test scenario.

Since our data sample interval is very short (0.5 s in our test), we can assume that the speed is uniform during this time period; calling it v_t for each test run, we can then change Eq. (1) to:

$$s^i_{t_j} = \sum\nolimits_{j=0}^{t_j} v^i_j \Delta + \partial^i_{t_j} \tag{3}$$

Here, the superscript i means the i-th test run, j means the j-th time stamp and Δ is the sample interval. For all test runs, we can calculate the average $s^i_{t_j}$ as follows:

$$\overline{s_{t_j}} = \frac{1}{M}\sum\nolimits_{i=1}^{M}\left(\sum\nolimits_{j=0}^{t_j} v^i_j \Delta + \partial^i_{t_j}\right) = \frac{1}{M}\sum\nolimits_{i=1}^{M}\sum\nolimits_{j=0}^{t_j} v^i_j \Delta + \frac{1}{M}\sum\nolimits_{i=1}^{M} \partial^i_{t_j} \tag{4}$$

Where M is the number of test runs. The second part is zero due to the Gaussian distribution. Also, we can change the summation order as follows:

$$\overline{s_{t_j}} = \frac{1}{M}\sum\nolimits_{j=0}^{t_j}\sum\nolimits_{i=1}^{M} v^i_j \Delta = \sum\nolimits_{j=0}^{t_j}\frac{1}{M}\sum\nolimits_{i=1}^{M} v^i_j \Delta \tag{5}$$

Now, we can use each interval average of $\overline{s_{t_j}}$ as the "**true location**" of the route.

However, we cannot assume that different test runs have the same speed. Therefore, we cannot calculate the average directly as we can see from Fig. 3. The speeds are different for the different test runs, the locations at time t_j are also different.

To adjust the data to the same relative location, we use a resampling [14] method to align all the test runs sample data in a given location segment. The sampling alignment lines are shown in Fig. 3. After alignment, the data samples can be combined to calculate the mean and standard deviation of locations.

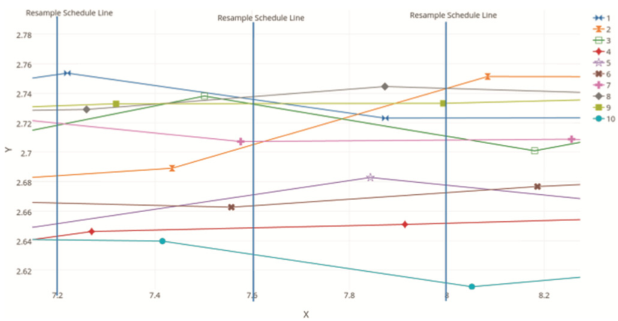

Fig. 3. Resampling data to align them together (x and y in meters)

4.3 Part1: Comparison on Different Test Scenarios Procedures

Initial Process

Since the tester may be stationary for a short moment at the beginning and the end of a test run, this stationary data should be removed. Stationary data means distance between the $s^i_{t_j}$ and $s^i_{t_{j+1}}$ are close to zero (no movement).

Segmentation

We partition the test runs in different segments to show that the location precision is affected by different factors of the environments. Therefore we need to define some segmentation points to segment the entire route. For each test scenario,

- We manually choose a suitable segmentation points in the route.
- For each walking test run, we use the Euclidean distance to find the closest to the segmentation points.
- We calculate the number of samples in each segment.
- We find the median number of the whole test runs M for the same segment.

Resampling

For each segment, we use a resampling function to ensure that a given segment has the same number of samples (the median number obtained from each segment) across the different test runs. We resample by interpolating the points using a cubic spline.

Calculating Metrics

We calculate the mean for the location accuracy and standard deviation (SD) for the location precision. Then, we calculate the Cumulative Distribution Function (CDF) for each test scenario to evaluate the precision for each segment in different test scenarios. The CDF provides a better visual representation of the results.

4.4 Part 2: System Error Estimation

The goal of this test is to estimate the SD of ∂_{t} in Eq. (1), which is the system error due to the person's position and the Tango accumulated error. To do this test, we run n times test runs. For each test, the person starts and ends a route at the exact same location. At the time t_j, we calculate the SD of the location s_{t_j}.

We know the SD equation is:

$$\sigma = \sqrt{\frac{1}{M}\sum\nolimits_{i=1}^{M}\left(s_{t_j}^{i} - \overline{s_{t_j}}\right)^2} \tag{6}$$

Considering Eqs. (1) and (2), we have

$$\sigma = \sqrt{\frac{1}{M}\sum\nolimits_{i=1}^{M}\left(s_{t_j}^{i} + \partial_{t_j} - \overline{s_{t_j}}\right)^2} \tag{7}$$

Since $\overline{s_{t_j}}$ is approximate to S_{t_j}

$$\sigma\sqrt{\frac{1}{M}\sum\nolimits_{i=1}^{M}\left(S_{t_j} + \partial_{t_j} - S_{t_j}\right)^2} = \sqrt{\frac{1}{M}\sum\nolimits_{i=1}^{M}\left(\partial_{t_j}\right)^2} \tag{8}$$

4.5 Test Results

Segments in an indoor office environment

As shown in Table 1, we can see that in an indoor setting, all the segments yield good precision reporting. In the indoor environments there are many objects in the field of view of the Tango system, and the system uses this information to get better results. In segment 4 we see that the SD is double compared to the other segments because there is a long hallway with few distinguishing features in segment 4. With fewer distinguishing features the accuracy of Tango drops.

Table 1. SD of the all four scenarios

Scenarios	Seg. 1	Seg. 2	Seg. 3	Seg. 4
Indoor office	0.162474	0.151679	0.148068	0.287468
Indoor multilevel	0.48877	0.44967	0.18591	0.42809
Sunny outdoor	0.547403	0.271107	0.386391	0.837084
Snow covered	0.545117	0.941061	0.405412	0.567393

Segments in a multilevel environment

As shown in Table 1, we can see that the Tango can work well in the indoor multilevel environment. The hallway segments (Seg. 1 and Seg. 2) have a similar accuracy. The stairs (Seg. 3) have the best accuracy because there are many features for the Tango to recognize such as steps and hand rails. Each step on the stairs has a height of 0.18 m which is similar to the SD of the test. The cafeteria (Seg. 4) has poor accuracy in this scenario. This is due to the cafeteria being very open. The accuracy of the hallways is poor because the hallways have few distinguishing features for the device to recognize. We notice that the change in elevation does not affect the accuracy of the Tango.

Segments in a sunny outdoor courtyard environment

As shown in Table 1, there are four segments in the outdoor courtyard scenario. In Fig. 4, segment 1 is in red, segment 2 is in green, segment 3 is in blue, and segment 4 is in yellow. Segment 1 and 4 are wide areas. The camera in segment 1 is in the shades and the camera in segment 4 is pointing toward the sunlight. Segment 2 and 3 have many trees which help the Tango system recognize the environment, segment 2 is closer to a building and segment 3 is in the middle of the area. We can see that results for segment 2 and 3 are better than that for segment 1 and 4; segment 2 obtains the best results and segment 4 has worse results than segment 1 because of the sunlight affects the camera.

Segments in a snow covered parking lot

As shown in Table 1, there are four segments in the snow covered parking lot as shown in Fig. 2**C**. For this scenario, segment 1 and 4 are very similar since they correspond to the same path in opposite directions. In segment 2 we see a drop in accuracy because in this segment the Tango system is in an open area parking lot where there are few objects to help the Tango recognize the environment. In segment 3 we see that the accuracy is better since the Tango system is on a sidewalk with many objects for the Tango to use as reference but the accuracy on the sidewalks is reduced because of the sunlight reflection on the snow.

CDF

In the CDF shown in Fig. 6, the y-axis is the cumulative probability within the distance error specified by x-axis. So, the curve with higher position has better performance. From the CDF figure, we can see that

- Tango works best for indoor scenarios.
- Tango, outdoor, works better in constrained areas with many distinctive features.

System Error Estimation

In this test, we estimate the system error offset listed in Eq. (1). The tester walks to a specific point and stay there for several seconds. The resulting position data is plotted in Fig. 5. The different colors show the final locations for different test runs. We can see when the tester tries to reach the same final locations; he ends up standing at slightly different places. The points of the same color represent the captured data while the tester is standing still at this location for several seconds. The position variations in the x and y directions are shown in centimeters. Those errors could be introduced by the tester's posture change while holding the Tango device. As we discussed before, we assume these errors follow a normal distribution. We calculate the SD of all the data and the value is less than 0.08 m, which includes the position error, the final location decision error, and also the Tango device error for this area leaning.

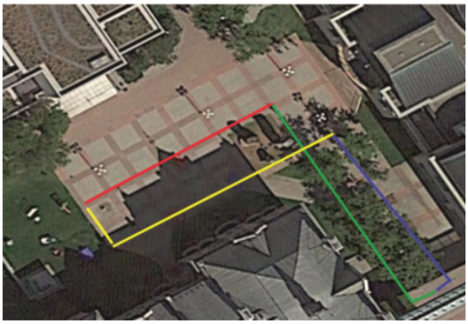

Fig. 4. Segments for the outdoor courtyard (Color figure online)

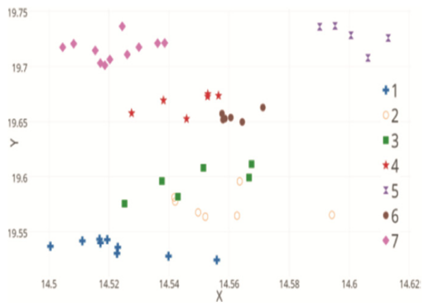

Fig. 5. Cluster of destination points (Color figure online)

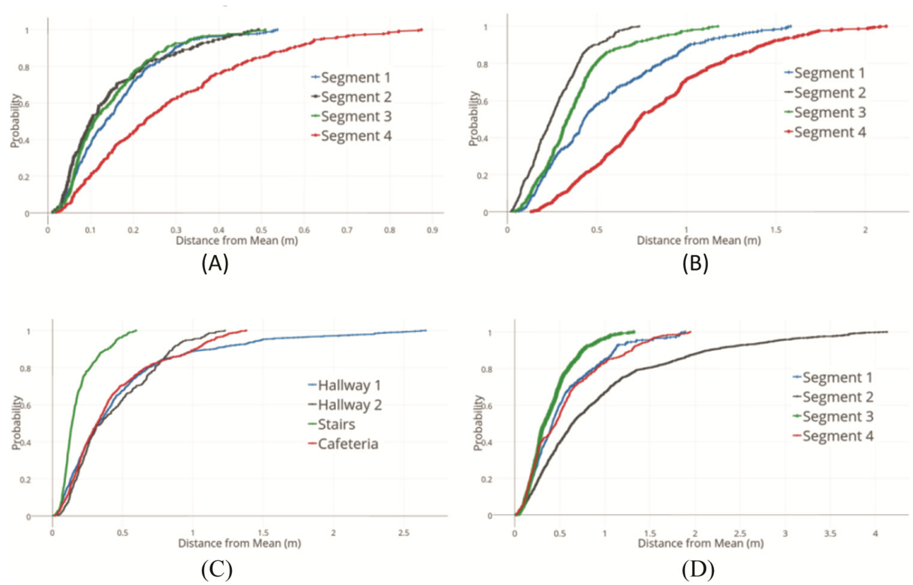

Fig. 6. CDFs for: (A) Indoor office, (B) Indoor multilevel layout, (C) Snow covered parking lot, and (D) Sunny courtyard.

5 Conclusions

In this paper, we have developed a sampling alignment data processing method to evaluate the Tango location system used to control the directional antenna beams in an mmWave communication system. It has been found that the Tango system gives good location accuracy for both indoor and outdoor scenarios (if enough distinctive features are available in the scenery). This system provides better accuracy and precision for the scenarios with more distinctive features, such as an indoor multilevel scenario with staircases and handrails. The location precision is impacted by the tester's behavior, environment characteristics, and weather conditions. The calibration procedure proposed in the paper can be used to further minimize the location error and improve the final accuracy. The evaluation results show the suitability of the Tango system as a location reporting system for mmWave communication system.

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