Demo : Measuring Distance Traveled by an Object using WiFi-CSI and IMU Fusion

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***Abstract*—Accurately measuring the distance traveled by an object or odometry, in indoor environments is important in many applications such as video-game controller tracking or robot route guidance. While the distance traveled by an object can be simply measured using an accelerometer, it is well-known that distances measured with accelerometers suffer from large drift errors. In this paper, we demonstrate WIO, a WiFi-assisted Inertial Odometry technique that uses WiFi signals as an auxiliary source of information to correct such drift errors. The key intuition behind WIO is that, among multiple paths of a transmitted WiFi signal that arrive at a moving object equipped with a WiFi receiver, WIO can isolate the path that is most parallel to the object's direction of motion and use the change in the length of that path as an estimate of the traversed distance. WIO then fuses this distance estimate with the distance measured from an accelerometer on-board the object to correct drift errors. We implement WIO using commodity devices, and evaluate it on a robot car. Our results demonstrate an average error of just 4.37% in estimating the distance traversed by the car.**

I. Introduction

Odometry is the process of measuring the distance traversed by an object over a given period of time. Accurate odometry is important in several indoor applications such as robotics to perform simultaneous localization and mapping. While accurate odometry has been achieved for outdoor scenarios using GPS, accurate odometry for indoor scenarios is still an unsolved problem. The most common odometry approach for indoor scenarios is *inertial* odometry. In inertial odometry, an inertial measurement unit (IMU), often comprised of an accelerometer and a gyroscope, is first attached to an object and then the distance moved by the object over the desired period of time is measured by double integration of the acceleration values reported by the IMU's accelerometer. Because such IMUs are very power efficient and are available on almost all latest hand-held and wearable devices, *inertial* odometry is the most ubiquitous odometry technique for indoor scenarios. However, the distance measured only with inertial odometry faces the well-known problem of large drift errors over time, where the growing accumulation of errors after successive double integrations results in large drifts in the estimated distance. Thus, despite the appeal of being ubiquitous, pure inertial odometry is widely considered to be error-prone in most real-world applications.

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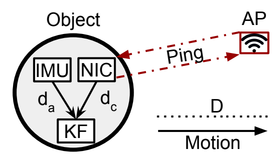

Fig. 1: Design Principle of WIO

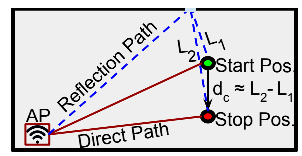

Fig. 2: Finding Distance using WiFi path length

A common solution to overcome such drift errors in pure inertial odometry is to augment it with an auxiliary source of information, *e.g.* a camera, and use that information to correct the drift. Among the existing auxiliary sources of information, WiFi signals are of recent interest, as WiFi communication, just like IMUs, has become very power efficient and ubiquitous on most hand-held and wearable devices. However, the current WiFi-assisted inertial odometry approaches *e.g.* [1], [2] have a number of limitations, as they may : 1) not work indoors, 2) require regular fingerprinting, 3) violate WiFi communication standards by hopping across multiple WiFi channels or 4) require multiple WiFi access points(APs). Therefore, in this paper, we demonstrate WIO, a WiFi-assisted Inertial Odometry scheme that uses WiFi signals from a single AP as the auxiliary source of information to correct the drift errors in pure inertial odometry, without having any of the above limitations.

II. Design

Fig. 1 shows the design principle of WIO. A movable object of interest, such as a robot, for which odometry is desired, is equipped with a WiFi NIC and an IMU. A WiFi AP is also deployed in the indoor environment surrounding the object, but not necessarily in the same room. The object periodically pings the AP as it moves and collects channel state information (CSI) from its WiFi NIC, while simultaneously recording acceleration measurements from its IMU. Since the indoor environment typically has multiple WiFi signal reflectors such as walls, the measured CSI is actually the sum of all amplitude and phase changes of the transmitted WiFi signal propagating along the direct path as well as the reflection paths, collectively known as multipaths. Therefore, WIO takes a continuous stream of multipath CSI and Acceleration measurements during the object's motion, and aims to periodically compute $\hat{D}$, an estimate of the total distance D traversed by the object. To compute $\hat{D}$, WIO performs two steps for every finite measurement period (*e.g.* 1 sec). First, WIO obtains two estimates of the distance traversed by the object during that measurement period: an estimate d_a from the acceleration measurements and an estimate d_c from the CSI measurements. Second, it employs a Kalman filter(KF) to update $\hat{D}$ by adding d_a to the previous value of $\hat{D}$ and then correct any drift in the updated $\hat{D}$ using d_c. Thus, $\hat{D}$ which is initialized to zero, represents the KF estimate of the distance traversed by the object until a given measurement period.

To estimate d_a, WIO performs standard double integration. However, to estimate d_c, WIO aims to first estimate the motion-induced change in the path lengths of all multipaths and then select the path whose path length change best approximates the traversed distance. Fig. 2 provides an example, where the movement of an object of interest results in a change in the path length of both the direct path (maroon colored lines) and a reflection path (blue dashed lines with path length changing from L_1 to L_2). WIO can obtain such changes in the length of all multipaths during the object's motion by applying the CSI based Path-Length Change model proposed in [3]. However, since this model provides only an estimate of the changes in multipath length, WIO further applies two key insights to select the signal propagation path whose path length change best approximates the traversed distance: 1) *The signal propagation path that is exactly parallel to the direction of the object's motion undergoes a change in path length that is exactly equal to the distance traveled by the object in that measurement period*, and 2) *The signal propagation path that is exactly parallel to the direction of the object's motion undergoes the highest Doppler Frequency Shift(DFS) and therefore, the greatest change in path length among all multipaths*. Thus, if WIO selects the path with the greatest change in path length during a given measurement period, it has essentially selected the path that is most parallel to the direction of the object's motion. This idea is also illustrated in Figure 2, where compared to the direct path, the reflection path visibly undergoes the greatest change in path length which is almost equal to the distance moved by the object, as it is more parallel to the direction of the object's motion. Consequently, the estimated path length change of the most parallel path can be used as d_c during the measurement period. Therefore, WIO performs the following three steps to measure d_c. First, WIO applies Fourier Transform on the CSI power measurements after a denoising step to extract unique frequencies in the CSI. Second, WIO selects the highest frequency component F_k in the FFT output (*i.e.* highest DFS) with a magnitude greater than an empirical threshold. Finally, WIO generates a distance estimate $d_c \approx F_k \lambda$ where λ is the wavelength of the WiFi signal (*e.g.* 5cm) and then passes it to the KF.

III. Implementation

We implement WIO on a portable platform as shown in Fig. 3. To collect CSI measurements, we attach an Intel 5300 WiFi NIC and three antennas to a HummingBoard Pro inside a $15 \times 10 \times 5$ cm cardboard box, as shown below along with a Lithium-ion battery. Next, to collect acceleration measurements, we attach an Invensense MPU-6050 IMU mounted on a GY-521 breakout board, to an Arduino Uno. We then screw the Arduino Uno to the front of the cardboard box and connect it to the HummingBoard via USB. Finally, we mount the portable platform on a line-following robot car. The car is controlled by another Arduino Uno, which takes a digital input from the HummingBoard for starting or stopping the car along a line measuring 5m across a room.

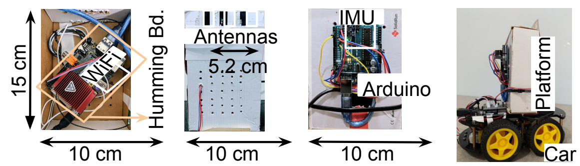

Fig. 3: Prototype and Deployment on a robot car

To demonstrate WIO, we execute a program on the HummingBoard which operates in three steps. First, the program directs the Arduino Uno mounted on the cardboard box to forward the acceleration values from the IMU at 500Hz and at the same time directs a background program to forward the CSI measurements from the Intel CSI Tool. The background program triggers the CSI measurements by pinging a nearby AP (Netgear Nighthawk R6700) at 500hz in the 5GHz band with a wavelength $\lambda = 5.2cm$. Second, the program directs the Arduino Uno of the car to start and then continuously produces a KF-distance estimate at the end of each measurement period set to 1 second using the incoming acceleration and CSI measurements. Third, the program directs the Arduino Uno of the car to stop after a preset duration. The last KF-distance estimate then gives the total distance traveled by the car. We run the car on the line ten times, with five runs in either direction and find that WIO estimates distance traversed by the car with a mean error of just 4.37%. Finally, we refer the reader to [4] for a more elaborate technical description of WIO and its performance on human and drone objects.

Acknowledgment

This work is supported in part by the National Science Foundation, under grant # CNS 1565609.

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