BikeLoc: a Real-time High-Precision Bicycle Localization System Using Synthetic Aperture Radar

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ABSTRACT

In recent years we have witnessed the rapid development of smart bicycles. For example, Mobike [1] is able to interact with smartphones. As we all known, accurate bicycle localization system is one of the most critical technologies for the development of smart bicycles. However, GPS's error is at meter-level and it performs poorly under skyscrapers and in tunnels.

In this paper, we propose BikeLoc, a novel and accurate bicycle localization system that can achieve submeter location granularity without requiring fingerprinting of the environment. BikeLoc is based on a subtle combination of the wheel of a bicycle and Commercial Off-The-Shelf (COTS) Wi-Fi devices. The core design of BikeLoc is to leverage three antennas installed on one wheel to emulate large circular antenna arrays using Synthetic Aperture Radar (SAR). Previous work on circular SAR is based on the far-field assumption, which means the translation of the antenna array is limited and insignificant compared with the rotation. However, in bicycle's application scenario, the translation and rotation are simultaneous and comparable. Our core contribution is the ability to perform SAR without the above assumption. We implement BikeLoc on a real bicycle and empirically demonstrate tens of centimeters localization accuracy for 3-D localization.

[1]Mobike is one bike sharing platform. http://mobike.com

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CCS CONCEPTS

• **Computer systems organization** → **Special purpose systems**; • **Networks** → *Mobile networks*;

KEYWORDS

Wireless; Localization; SAR

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1 INTRODUCTION

In recent years, we have witnessed the rapid development of smart cars, and this trend is now extending toward smart bicycles. The smart bicycles, such as Mobike and ofo, which provide real-time rental service boom all over China, Singapore, and many other countries. These bikes which are equipped with GPS, Bluetooth, and other electronic instruments are widely accepted by the community.

However, as one of the cornerstones for the smart bicycles, localization system is still unsatisfying. The most widely used one is GPS, but its error is at meter-level and it performs poorly under skyscrapers and in tunnels[1]. Unfortunately, the most common application scenario for bicycles is the bustling city center that full of high-rise buildings. A major cause of these problems is that GPS is realized by satellites high in the space, so the localization accuracy is diminished by the long distance and the signal can be easily blocked by the high-rise. In contrast, under the tall buildings, we usually have good Wi-Fi access points coverage, and the locations of many access points (AP) are available in public databases[2]. Therefore, if we are able to calculate a bike's position relative to these APs, we can localize it.

In principle, if a bicycle can be equipped with a large antenna array, it will be able to accurately identify the incident angle of incoming signals. Then, it can calculate its position relative to the neighboring Wi-Fi APs using simple geometry. However, it is infeasible to mount a large antenna array on a bike. To address this challenge, we present BikeLoc, an outdoor bicycle localization system that enables three antennas mounted on a wheel to emulate a large antenna array. Specifically, one antenna is in the middle and two are on the boundary of the rigid part. When a bicycle moves, each pair of antennas will form a virtual circle array relative to each other. Then, we can perform SAR on them to accurately estimate the spatial direction of the nearby APs. If a known roadside access point transmits wireless signals, bicycle A with virtual antenna array can calculate a precise absolute position via incident angle. If vehicle B transmits wireless signals, bicycle A with virtual antenna array can calculate a precise relative position.

Ideally, our goal is to achieve tens of centimeters accuracy for bicycle localization. Since an 802.11n AP works at $5.8GHz$ spectrum and the diameter of the wheel is usually $0.5m$, if the distance between AP and the wheel is around $25m$, the theoretical accuracy could reach centimeter level according to Circular Synthetic Aperture Radar (CSAR)[3].

However, traditional CSAR is based on the far-field assumption that Angle-Of-Arriving (AOA) is identical along antennas' trajectories[8]. In BikeLoc, because the moving distance of the bicycle is long, we cannot keep this assumption. We make an important observation on computing the incident angle in BikeLoc's scenario. That is, if we directly use all the snapshots during the wheel turns a full round to solve the equations in traditional CSAR, we will get the AOA of incoming signal when the wheel is in the middle of this round. Then, using the rotation angle of the wheel measured by the motion sensor between the middle point and current position, we can calculate the relative distance between them. At this point, we achieve real-time localization.

In addition to high accuracy, a good bicycle localization system should also meet two other requirements: 1) Lightweight and Hidden. The system should not impose new burdens to the ride or diminish the aesthetics of the bikes. 2) Low power consumption. Bicycles, no matter carrying small generators or batteries, can provide very limited power. BikeLoc is very promising to meet these two requirements. It has only three main components: antennas, a wireless card, and a little computing power. The antennas can be hidden in the rim, the wireless card and computing power can be integrated with other electronic components. Although our prototype cannot meet these requirements, the real commercial version can certainly meet these two requirements.

We implement BikeLoc on a laptop running Ubuntu Linux equipped with Intel 5300 wireless NIC. Three external antennas are connected to NIC and fixed on the front wheel of a bicycle. BikeLoc is built on the 802.11 CSI tool [4] to obtain the wireless channels. We use JY901 Motion Sensor(i.e. an accelerometer, gyroscope, and compass) to measure the orientation of the antenna array, which can leverage the ground magnitude value to calibrate the attitude angle real-timely to avoid drifting. We use a TP-Link WDR6300 router as the transmitter.

Our experiments reveal that BikeLoc is able to achieve a median of accuracy of $1.5°$ in AOA estimation. In the standard setting, BikeLoc can attain sub-meter accuracy with only two APs in localizing the middle point of one turning. The median of accuracy will be improved to $18.1cm$ when the number of APs is increased to eight. Combined with our localization method using motion sensor, BikeLoc is able to achieve sub-meter level real-time 3-D localization, and the median of accuracy can be improved to $26cm$ when there are eight APs around and the computational power is sufficient.

The main contributions of this paper are as follows:

- We propose a novel method to localize bicycles, which combines the wheel of a bicycle with the Wi-Fi devices. We employ SAR to mimic large circular arrays to accurately estimate the incident angle of the signals transmitted from roadside access points, and then use the angles to position the bike.
- We make the key observation that we can use all the snapshots during the wheel turns one round to estimate the AOA when the wheel is in the middle of the round. This enables us to position long-distance moving objects.
- We implement BikeLoc on a real bicycle. Experiments and simulations reveal that our system can achieve high accuracy in AOA estimation and tens of centimeters localization accuracy.

2 BIKELOC

2.1 Problem Statement

The problem we investigated is an outdoor localization system dedicated to bicycle. Firstly, it should be more accurate than GPS. That is to achieve tens of centimeters of accuracy. Secondly, it should be able to function well under skyscrapers, where GPS functions poorly yet an important application scenario for the bicycle.

2.2 Overview of BikeLoc

BikeLoc enables accurate bicycle localization with minimal extra infrastructure and no fingerprinting. The core design of BikeLoc is the combination of the wheel of the bicycle and COTS Wi-Fi devices to perform SAR. This combination is illustrated in Fig. 1. Three antennas

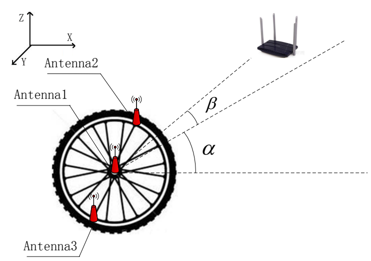


Figure 1: Sketch of BikeLoc

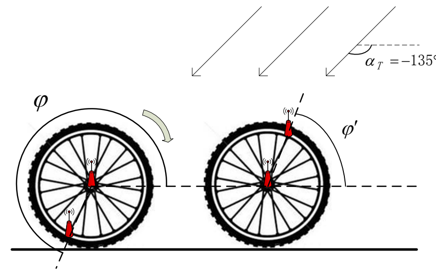


Figure 2: SAR with Two Antennas

are equipped in a wheel of a bicycle. Antenna 1 is fixed in the center of the wheel and Antenna 2 and 3 are symmetrically fixed on the boundary of the rigid part. So the relative position of the three antennas is always the same. When a bicycle moves, Antenna 2 will form a virtual circle array relative to $A1$, so as $A3$ and $A1$, $A3$ and $A2$. If a known roadside access point transmits wireless signals, bicycle A with virtual antenna array can calculate a precise absolute position via incident angle.

Questions might be drawn around why BikeLoc equips the antennas on the wheel but not the other positions? That is because we employ a special formulation of SAR in BikeLoc, which is transient-resilient. The advantage of this formulation of SAR is that it only requires us to input the angle of rotation besides the wireless channel to compute AOA of the signals. The angle of rotation can be accurately measured by the gyroscope in commercial motion sensor [20]. In this formulation, the antennas are required to rotate relative to each other. To fit in this special formulation, the wheel is obviously the best choice. In contrast, if we mount the antennas on the other part of the bike, for example, the frame of the bike, then we need to employ linear shape SAR, which will further require millimeter-level measurement of the antennas' trajectories. This can not be achieved by commercial motion sensors. To help you better understand the accuracy required, in 802.11a/n, even a small error of $2cm$ in trajectory can lead to an error of 60 degrees in identifying the direction of the source[8].

2.3 Synthetic Aperture Radar

The main idea of SAR is to leverage few antennas mounted on a moving platform to mimic a large antenna array. To be specific, when the antennas move along their trajectories, they will continually measure the multipath signal broadcast from the transmitting source. The combination of the recordings from these multiple antenna positions forms a large antenna array. One can simply apply standard antenna array equations on them to compute the multipath profile. The estimation of the incident angle is carried out by calculating the relative power among each direction. The angle having the greatest relative power is the incident angle.

To see how SAR works more formally, let's begin with a special case of SAR[8] that is simple yet particularly relevant to the design of BikeLoc, which is shown in Fig. 2. In this case, we use SAR to enable two antennas to mimic a circular antenna array. Suppose there are two receiving antennas and one transmitter on a two-dimension plane. The distance between the two receiving antennas is fixed, denoted by r. The transmitter and the receiving antennas are far apart so that in the receiver's view, AOA of the incoming signals are identical along their trajectories, denoted by α_T. Let the receiving antenna vector rotate and take n snapshots of the channels. The wireless channels h measured by one antenna can be depicted by a complex number[13]:

$$h = \frac{1}{d_0} e^{\frac{-j2\pi}{\lambda} d_0} \tag{1}$$

Where d_0 is the distance between the transmitter and receiver, and λ the signal wavelength. Then, the relative wireless channels[8] between the two antennas can be depicted by:

$$\hat{h}_i = h_{2,i} h_{1,i}^* = \frac{1}{d^2} e^{\frac{-j2\pi}{\lambda}(d + rcos(\alpha_T - \phi_i))} \tag{2}$$

Where $h_{1,i}$ and $h_{2,i}$ are the wireless channels measured by antenna 1 and 2 at their ith snapshots. $(.)^*$ denotes the complex conjugate. ϕ_i is the antenna vector's orientation at snapshot i. Then, we use SAR to compute the relative signal power along each direction. The relative power $P(\alpha)$ along direction α is depicted by:

$$P(\alpha) = \left| \frac{1}{n} \sum_{i=1}^{n} \hat{h}_i e^{\frac{+j2\pi}{\lambda} rcos(\alpha_T - \phi_i)} \right|^2 \tag{3}$$

$P(\alpha)$ reaches its maximum when $\alpha = \alpha_T$. That is to say, we can identify the spatial direction of AP by examine where $P(\alpha)$ reaches its maximum. Note that the orientation ϕ_i is required to calculate the power profile besides wireless channels. Therefore, a gyroscope is required in BikeLoc to provide orientation of the antenna vector.

2.4 Generalizing to Three Dimensions

Eq. 3 can be easily generalized to three dimensions. Suppose a signal arrives from azimuthal angle α and

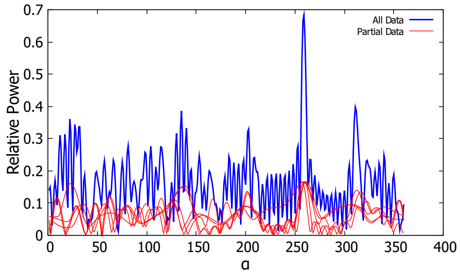


Figure 3: Relative Power

polar angle β, as shown in Fig. 1. From basic geometry, we can derive the multipath profile by slightly modifying Eq. 3 as:

$$P(\alpha) = \left| \frac{1}{n} \sum_{i=1}^{n} \hat{h}_i e^{\frac{\pm j2\pi}{\lambda} r cos(\alpha - \phi_i) sin(\beta - \theta_i)} \right|^2 \quad (4)$$

Where ϕ_i is the antenna vector's azimuthal angle and θ_i is the polar angle at snapshot i.

2.5 Core Design Of BikeLoc

The former formulation of SAR mimicking a circular array is based on the assumption that the AOAs of signals are identical along the antennas' trajectories. This assumption is valid if and only if the moving distance of receiving antennas is far less than the distance between AP and receiving antennas, and the moving distance is smaller than the grain of localization accuracy[8, 17]. However, we can not keep this assumption in BikeLoc. Because the rotation of the antenna vectors and the rotation of the wheel are bound. To achieve an accurate AOA estimation, the antenna vectors need to spin at least one round to take enough snapshots at different positions. However, during this process, the wheel also forwards about $3m$. Since we want to achieve centimeter-level localization accuracy, we obviously can not assume the AOA to be the same in the range of $3m$.

We make an important observation on computing the incident angle in BikeLoc's scenario. That is if we directly input to the Eq. 3 the relative channel measured during the wheel turns one round, it would output the AOA when the wheel is at half round. For example, let a wheel spin around once. When it starts, suppose the AOA is 250°. And when it ends, the AOA is 260°. Then, the antennas will record the wireless channel from 250° to 260°. If we slice these data into small parts and use each part to calculate relative power independently, each part will produce a peak at its actual AOA and many noisy peaks around it. The superposition of these peaks will form a new high peak roughly at $\frac{250+260}{2} = 255°$, which is approximately the AOA at the middle of the spinning as illustrated in Fig 3. Moreover, superposition of the noise peaks at other degrees is not likely to generate other high noise peaks, because these noise peaks generally distribute randomly. That's because the noisy peaks are not correlated to each other.

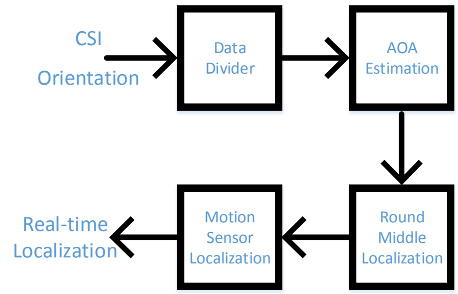


Figure 4: Block Diagram of BikeLoc

Based on the above observation, we present the block diagram of BikeLoc, which is illustrated in Fig. 4.

- First, the data divider is responsible for extract the part of data that is within one turn. This is realized by monitoring the altitude acquired from the gyroscope. When it sees the altitude changed 360°, the divider will record the starting time and the ending time of it and cut out that part of data.
- Second, we perform SAR on those data parts to estimate the AOA when the wheel is in the middle of a turning.
- Third, calculate the 3-D location of the bicycle when the wheel is in the middle of a turning. Because the height of the bicycle is fixed, its z-coordinate is fixed. So we only need to calculate its location on the X-Y plane. Theoretically, knowing the direction of only one AP and the height of the wheel is enough for localization using triangulation. However, the localization accuracy is acceptable only when the AP is set at 10m high, which it is not consistent with the real-world scenario. So, we need to perform SAR to at least two APs simultaneously to estimate their spatial direction. Then, we use triangulation to position the wheel using the polar angle toward the APs. If there are more than two access points, localization accuracy can be improved using least-square fitting.
- Fourth, calculate the 3-D global location of the bicycle real-timely. Based on the real-time orientation information acquired from the gyroscope, we can calculate the current position of the wheel relative to the position when the wheel is at half round. When we combine them, we can localize the bicycle real-timely.

3 IMPLEMENTATION

At the bike side of BikeLoc, we implement the system using a laptop running Ubuntu Linux equipped with Intel 5300 wireless NIC. Three external antennas are connected to NIC and mounted on the front wheel of

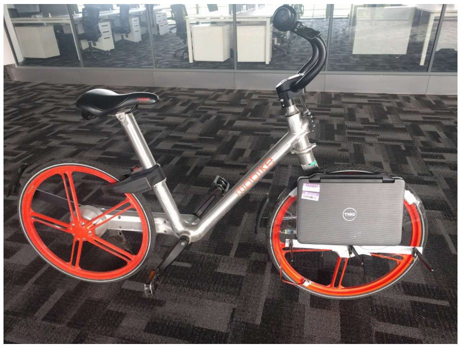


Figure 5: BikeLoc testbed

a bicycle, as shown in Fig. 5. BikeLoc is built on the 802.11 CSI tool to obtain the wireless channels. We use JY901 Motion Sensor (i.e. an accelerometer, gyroscope, and compass) to measure the orientation of the antenna vectors, which is also mounted on the wheel. At the AP side, we use one TP-Link WDR6300 router, which is configured to use IEEE 802.11a/n and operates in the $5GHz$ Wi-Fi frequency band. Between bike and AP, we configure the laptop to deliver 100 beacons per second to elicit responses from AP and then measure the wireless channels between them.

We conducted our experiments in an open space in our university. A single access point was present and the bicycle was placed at several randomly chosen places $10m$ to $20m$ away from the transmitting source with no obstruction in the middle. At each place, we walk forth the bicycle along a line at a speed of $1m/s$. We obtain the locations of the AP and the middle points to centimeter-level accuracy through direct measurements.

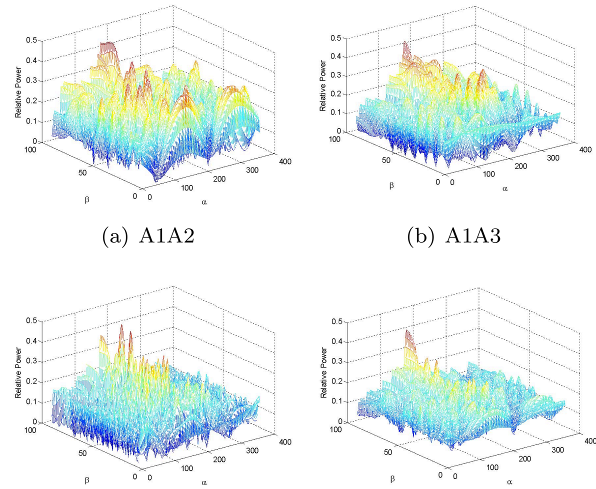
4 EXPERIMENT RESULTS

We present three categories of results to evaluate BikeLoc: 1) Computing Angle of Arrival in 3-D space. 2) Localizing bicycles in the middle of a round in 3-D. 3) Localizing bicycles real-timely using motion sensors in 3-D.

4.1 Multipath Profile Estimation

In this part, we will show the multipath profiles we measured in experiments and how to use them to identify the spatial direction of the AP.

We first make the three antennas into three pairs and perform SAR on them independently. Ideally, in the strong line-of-sight scenario, each pair can estimate the spatial direction of the AP independently through checking the coordinate of the highest peak in its estimated multipath profile. However, the real experimental results are disappointing, which are shown in Fig. 6(a)-6(c). The direct path peak is overwhelmed by the multipath peaks. That is because the antennas are very close to the ground, then, the multipath signals scattered from the



(a) A1A2 (b) A1A3

(c) A2A3 (d) Sum

Figure 6: Multipath Profiles

ground are very strong. There are also signals scattered from the bike and the rider.

We make an observation that after we add up these muitipath profiles, the resulted multipath profile possesses only one prominent peak, which is toward the direction of the AP. The result is shown in Fig. 6(d). The reason is that the direct path is the same for each pair of antennas, while the multipaths are different. After the adding, the height of the direct path peak is tripled while the multipath peaks barely grow. Therefore, the adding is a effective way to find the direction of the AP.

4.2 Angle of Arrival Estimation

In this experiment, we measure BikeLoc's accuracy of angle-of-arrival estimation in polar angle (θ).

Fig. 7 shows that the antenna pair $A1A2$, $A1A3$ and $A2A3$ (the antennas are numbered in Fig. 1) achieve median of accuracy of 7.2°, 7.4° and 11.2° in polar angle respectively. Therefore, each pair is not good enough to independently estimate AOA accurately. We observe that the median of accuracy of the summed result is significantly improved to 1.5°. Furthermore, we surprisingly find that the antenna pair $A2A3$ with the longest distance achieves the lowest accuracy, which is not consistent with the theory. That might be caused by engineering reasons. The two antennas at the edge are relatively easy to vibrate, and the influence of vibration on the accuracy is significant. Vibration with the range about $5mm$ can lead to more than 10° error. The middle antenna's vibration is relatively small because its movement is smooth. Thus the antenna pairs with the middle antenna have higher accuracy. Thus, it is very important to build a solid frame for antennas in BikeLoc.

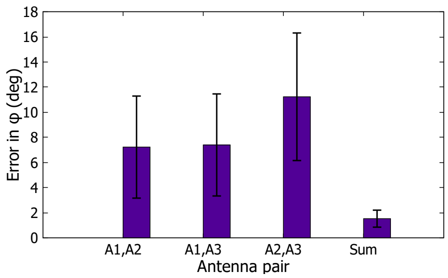


Figure 7: AOA Estimation Accuracy

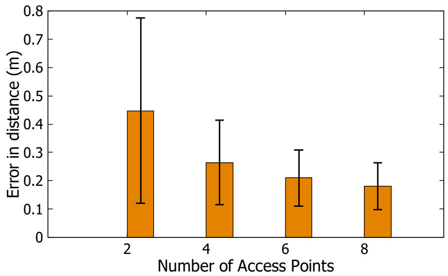


Figure 8: Localization Accuracy v.s. # APs.

5 SIMULATION RESULTS

5.1 Middle Round Localization

We use simulation to evaluate BikeLoc's accuracy in positioning bicycle in the middle of spinning one round. We use simulations because our prototype can only measure the channels of one AP currently, but it can be extended to multi-AP scenario in the future[8].

We first generate n routers in random places $10m$ to $30m$ away from the bicycle. Then, we randomly generate estimated polar angle toward each router according to Fig. 7. Finally, we use the least-square fitting to calculate the estimated location of the bicycle, the result is shown in Fig. 8. The result shows that when there are only two APs, BikeLoc can already achieve sub-meter level localization accuracy. When the number of APs is increased to eight, the median of localization accuracy can be improved to $18.1cm$.

5.2 Motion Sensor Localization

We conducted several simulations to evaluate the localization accuracy of Motion Sensor Localization module, which is presented in Section 2.5. Our simulation is based on our observation on the real data acquired from the gyroscope. We did not conduct real experiment because it is difficult to find a high-accuracy real-time localization system to serve as the benchmark.

The Motion Sensor uses Euler angles to describe the orientation of itself, so as the wheel. It can measure two of the three angles highly accurately with an error less than 1°. For the third angle, after filtered the anomalous points, the accuracy of measurement of the rotation angle is no more than 10° during the wheel spins one round. The performances of the three angles are different because the gyroscope can leverage the geomagnetic field to correct the drift problem for only two angles. The traditional method to correct the third angle is to use gravitational field.[20] However, this method requires the gyroscope to be kept standing, which is not achievable on a spinning wheel.

Table 1: Upper Bound of Error in Distance of Motion Sensor Localization

	Angle of the Wheel's Rotation		
	0.5 Round	1 Round	1.5 Round
Error (cm)	5.5	21.9	49.3

Since it is difficult to simulate the complex data acquired from the gyroscope, we turn to simulate the worst case here. Assume the measurement error of the three angles to be 1°, 1° and 10° during the wheel spinning one round. The radius of the wheel to be $0.5m$. The results of simulations are shown in Tab. 1. The result shows that even in the worst case the Motion Sensor localization is able to achieve tens of centimeter's accuracy.

6 RELATED WORK

Both academia and industry pay great attentions to the localization problem. The most related works are about SAR-based indoor localization, but they can not fit in bicycle localization scenario. For example, some require the system to move along a well-controlled trajectory or be equipped with advanced motion sensor[15, 16], or restrict the transition distance to be less than $0.5m$[8]. Another work needs a specialized large antenna array[17].

Another category of related works fall into the broad indoor localization. Typical works include new device COIN-GPS based [11], fingerprint map based [19], RFID based [18], device-free [10], prediction based [7], smartphone based [14], and multi-modal data analysis based [9] localization methods. Nevertheless, these works are not suitable in outdoor scenarios.

Just a few works study the outdoor localization problems. For example, ALPS [6] is based on landmark, Faster GPS [5] adopts sparse FFT to accelerate the computation, and COBWEB [12] studies the robust map update. However, none of them focus on accurate localization.

7 CONCLUSION

This paper presents BikeLoc, a bicycle localization system to achieve tens of centimeters of accuracy, with minimal infrastructure and no fingerprinting. BikeLoc leverages SAR to enable three antennas mounted on a wheel to mimic large antenna array so that it can accurately estimate the spatial direction of the nearby access point. We implement BikeLoc on a real bicycle and demonstrate its high accuracy in localization.

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