Multipath Assisted Positioning with Band-Limited Signals in an Urban Environment

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BIOGRAPHIES

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Christian Gentner studied electrical engineering at the University of Applied Science in Ravensburg, with the main topic communication technology and received his Dipl.-Ing. (BA) degree in 2006. During this study he received practical experiences at Rohde & Schwarz in Munich. He continued his study at the University of Ulm until 2009, where he received his M.Sc. degree. He is currently working towards the Ph.D. degree at the Institute of Communications and Navigation of the German Aerospace Center (DLR). His current research focuses on multipath assisted positioning.

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Andreas Roessler is the Rohde & Schwarz Technology Manager focused on LTE-Advanced. With responsibility for the strategic marketing and product portfolio development for LTE-Advanced, Andreas follows the standardization process in 3GPP very closely, particularly on core specifications as well as protocol conformance, RRM and RF conformance specifications for device and base stations testing. He graduated from Otto-von-Guericke University in Magdeburg, Germany, and holds a masters degree in communication engineering and has more than 10 years experience in wireless communication.

Abstract— **While location-awareness in cellular radio networks has arisen more and more interest in recent years, positioning using cellular radio signals might show very weak performance due to shadowing and multipath propagation, especially in urban and indoor scenarios. Beyond, the number of base stations within communication range is often too low for positioning. The standard methods for positioning try to mitigate the effect of multipath propagation on the line-of-sight path. Though, various recently published results show that multipath components arising from reflections and scattering can actually be exploited, and hence the number of base stations required for positioning can be decreased. However, these results are based on the assumption of a high bandwidth, e.g. 100 MHz or more. This is much higher than the bandwidth of cellular signals currently deployed. By performing measurements where we emulate a multipath scenario, we show that the tracking of a receiver is possible using a 3GPP-LTE system of a bandwidth of only 20 MHz in a simple urban scenario. We apply an advanced signal processing algorithm to track multipath components impinging at a moving receiver, and feed those results into a particle filter for position estimation. Our results indicate that tracking the receiver is possible with only two base stations, even if one of them is not in line-of-sight. The positioning error is always below 7 meters.**

I. INTRODUCTION

Many of today's and future applications demand accurate positioning in indoor or urban scenarios. In these situations, positioning with Global Navigation Satellite Systems (GNSSs) achieves only weak performance due to low received signal power as well as shadowing and multipath propagation [1].

In contrast, cellular radio networks, such as the third generation partnership project (3GPP) long-term evolution (LTE), provide excellent coverage in urban and most indoor environments due to a higher signal power compared to GNSSs, which makes them interesting for positioning. Beyond, they are widely available in populated areas. The 3GPP-LTE standard [2] introduces positioning techniques like Assisted GNSS (A-GNSS), cell ID based positioning, observed time difference of arrival (OTDOA), uplink TDOA, and RF pattern matching. While A-GNSS is the most accurate positioning method in open sky environments, it shows weak performance in urban and indoor scenarios as it is still based on GNSSs. Beside A-GNSS, OTDOA is the most accurate method for position estimation, and it is based on measurements of signal propagation delay differences in the downlink. The 3GPP-LTE standard provides optional signal resources for positioning in a 3GPP-LTE network, the so-called Positioning Reference Signals (PRSs), making 3GPP-LTE systems very interesting for positioning. The PRSs are separated in time or frequency for neighbouring base stations. The 3GPP-LTE standard specifies downlink bandwidths from 1.4 MHz up to 20 MHz for the PRSs.

However, in urban scenarios, not only interferences of different base stations and user clock drift, but also shadowing and multipath propagation pose a major challenge for positioning and reduce the position accuracy in these scenarios. In particular, the range estimate of standard algorithms like the delay locked loop is biased in multipath propagation environments. Hence, in an urban or indoor scenario, the positioning accuracy with OTDOA can be in the order of hundreds of meters. In addition, there might be only one or two base stations within communication range of the receiver. If the receiver is not synchronized to the base stations, the receiver needs to be in a communication range of at least three base stations in order to track his position using OTDOAs, provided that his initial position is roughly known. This is necessary in order to avoid the ambiguity of a position estimate based on the intersection of two OTDOA hyperbolas.

Strategies to mitigate multipath effects on the range estimate are usually based on the estimation of the channel impulse response (CIR). These algorithms have in common, that they determine the CIR and remove the influence of the multipath components (MPCs) due to reflections and scattering on the line-of-sight (LOS) path. Contrary to mitigating the multipath propagation, exploiting multipath propagation arouses more and more interest. Current research results show that MPCs can be used for positioning in various ways. One way is to make use of a-priori knowledge of the environment in form of e.g. a floorplan [3], [4], or a multipath fingerprinting database. Other approaches do not assume such a-priori knowledge and interpret each MPC as transmitted from a virtual transmitter. With Channel-SLAM [5] we introduced a novel algorithm that takes one of the latter approaches. Channel-SLAM is an algorithm for which it is essential that the receiver is in motion while the environment in terms of reflecting walls and scatterers is static. It treats each MPC as a LOS signal from a static virtual transmitter whose position is unknown to the receiver. The algorithm estimates the position of the virtual transmitters as well as the receiver position without using a floorplan or fingerprinting techniques.

All the schemes exploiting MPCs highly depend on the ability to resolve and distinguish between received MPCs, which is directly connected to the bandwidth of the used signals. For this reason, most of the current research approaches on multipath assisted positioning assume signals of a high bandwidth, such as ultra-wideband (UWB) signals. For such systems, though, an additional infrastructure has to be built up, and interferences with existing systems need to be considered.

This paper investigates the possibility of using 3GPP-LTE signals band-limited to 20 MHz for pedestrian positioning in an urban scenario. The aim is to resolve single MPCs arriving at a moving receiver by means of an advanced signal processing algorithm, and to thereby track the receiver's position over time. Resolving and tracking MPCs is especially difficult in situations with MPCs arriving at the receiver with small relative delays, such as when the receiver is close to a reflecting wall. Within this paper, we emulate a multipath scenario by hardware, and perform channel measurements in order to track the receiver's position. We demand that the start position of the receiver is known. Also, we assume that we have knowledge of the basic geometry of the scenario and therefore can estimate the positions of the virtual base stations perfectly. We consider this as a first step towards using 3GPP-LTE signals for Channel-SLAM, where the estimation of the positions of the virtual transmitters has to be performed in addition.

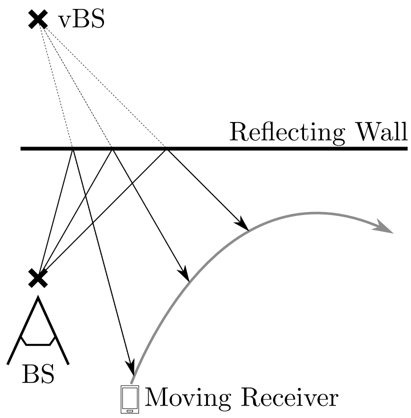

Fig. 1. Signals from base station BS are reflected at the straight wall and can be interpreted as originating from a virtual base station vBS, which is static during the receiver motion.

The paper is structured as follows: Section II describes our tracking algorithm. In Section III, we describe the simulation hardware and the scenario, and show the measurement results. Section IV concludes the paper.

II. Methods and Algorithms

Throughout this paper, we assume a static environment. Therefore, the virtual transmitters emerging from reflections at walls are static as well. This is illustrated in Figure 1. The physical base station (BS) radiates a signal, which is received at the receiver via a non-light-of-sight (NLOS) path due to the reflection at the wall. Hence, this signal can be regarded as being sent from the virtual base station (vBS), whose position is the position of the physical base station mirrored in the wall. When the receiver moves on, the position of the virtual base station does not change. Furthermore, the physical base station BS and the virtual base station vBS are synchronized, as they transmit at the exact same time. Therefore we can assume one virtual base station for every reflection at a static, straight wall. This concept can be extended to a double reflection, and to local scatterers [5]. In the case of a scatterer, the virtual base station will have an additional delay offset to the physical base station, though.

Since the receiver is in motion, the parameters of the single MPCs will change over time. In particular, new paths might arise and existing ones might vanish. In our algorithm,

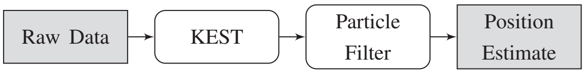

Fig. 2. Overview of the algorithms used: The raw data in form of baseband samples are used by KEST to estimate single paths and track them over time. A particle filter estimates the receiver's position based on these paths.

we implemented a Kalman filter [6] for tracking individual MPCs over time. This Kalman Enhanced Super Resolution Tracking (KEST) algorithm as described in [7] is the core of our signal processing algorithm and allows for a dynamic description of the evolution of the MPCs in terms of delay and amplitude at the receiver. In particular, their overall lifetime, i.e., the distance of receiver movement over which the path is observable, is monitored. This is important, since MPCs of a long lifetime can contribute much better to the tracking of the receiver than MPCs of a short lifetime. The KEST algorithm basically works in two stages: An outer stage keeps track of the number L of MPCs and their corresponding parameters, whereas in the inner stage those parameters of the MPCs are estimated. For this estimation in the inner stage, we use the space-alternating generalized expectation-maximization (SAGE) algorithm [8]. The SAGE algorithm is an extension of the Expectation-Maximization (EM) algorithm that jointly estimates the parameters of impinging waves in mobile radio environments.

We track a pedestrian through an urban environment with a low-cost radio receiver as used in today's smartphones. Since we have only one antenna available and move at a low velocity, no information on the angle of arrival of the received MPCs is assumed. Hence, in the following, the only MPC parameters exploited by the KEST algorithm are delay and amplitude.

In order to estimate the actual position of the receiver, the results of the KEST algorithm are processed in a Recursive Bayesian filter. The state vector consists of the x- and $y-$coordinate of the receiver, as well as of it's current velocity in x- and y-direction. As for any Recursive Bayesian filter, the filtering process consists of two stages, namely the state transition and the measurement stage. For the state transition, a-priori information on how the states changes, the so-called system model, is required. For our simulations, we assume a random walk model. Since we assume the single physical (and hence virtual) base stations to be synchronized among themselves, but not to the receiver, we measure OTDOAs between physical and virtual base stations to feed the particle filter. Although the Kalman Filter is the most prominent representative of Recursive Bayesian filters, it cannot be applied here due to the non-linearity of the measurement model. Instead, we use a Sampling Importance Resampling (SIR) particle filter [9], where the resampling of the single particles is performed at every time step. Figure 2 gives an brief overview of the estimation process.

The mapping from the MPCs estimated by KEST to the physical and virtual base stations is done by a heuristic algorithm, which includes the paths' life times, the regions where they live, the paths' amplitudes and their relative delays.

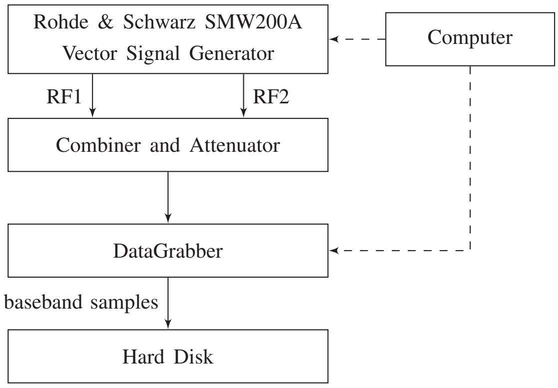

Fig. 3. Overview of the measurement setup: The computer sets the RF paths for the current snapshot at the signal generator and triggers the data grabber, which samples the signal and writes the baseband samples to a hard disk.

TABLE I

PARAMETERS OF THE 3GPP-LTE SIGNALS

Parameter	Value
RF carrier frequency	2.46 GHz
3GGP-LTE bandwidth	20 MHz
3GGP-LTE PRS bandwidth	20 MHz
Number of consecutive PRS subframes	6
Downlink duplexing mode	frequency division duplexing
E_b/N_0	15.84dB

As the KEST algorithm also estimates the number L of paths currently impinging at the receiver, it might happen that not all arriving MPCs are detected by KEST, or that KEST detects additional paths. For the initial estimation of L, we follow the Bayesian information criterion rule as described in [10].

III. MEASUREMENTS

A. Measurement Scenario

Figure 3 gives an overview of the measurement hardware. We use a Rohde & Schwarz *SMW200A Vector Signal Generator*. This powerful signal generator supports the 3GPP-LTE standard, in particular it broadcasts the 3GPP-LTE PRSs, which we use for positioning. The signal generator simultaneously outputs two radio frequency (RF) signals, which correspond in our case to two physical base stations. For every time step, we set the MPCs for each RF front end according to the current time step of the simulation scenario. The two RF signals are then combined and attenuated, and the resulting signal is sampled in a data grabber, which is triggered by the computer. The resulting baseband samples are then stored on a hard disk.

The parameters of the 3GPP-LTE signal used are summarized in Table I.

The measurement scenario is modeled as a simple urban scenario as depicted in Figure 4. Solid black lines represent reflecting walls, whereas black, dashed lines are non-reflecting but blocking walls. We have two physical base stations,

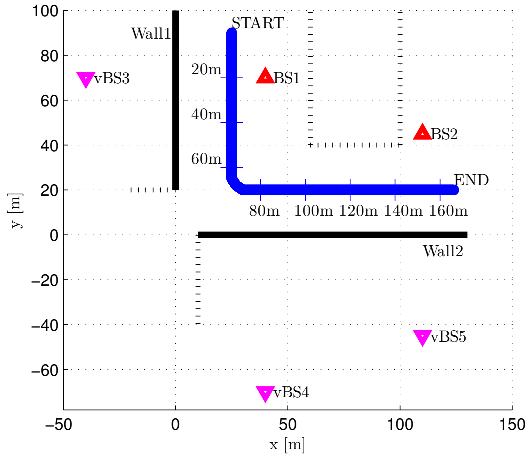

Fig. 4. The simple urban scenario used for the hardware simulations, with physical base stations BS1 and BS2, reflecting walls Wall1 and Wall2, and corresponding virtual base stations vBS3, vBS4, and vBS5. The receiver track is depicted in blue with the start and end positions marked as START respectively END. The traveled distance is marked for every 20 meters. Black, dashed lines are non-reflecting, but blocking walls.

BS1 and BS2, that are represented by red upward triangles. Knowing this floorplan, we can model two virtual base stations for the physical base station BS1. These are vBS3, arising due to reflections of signals originating from BS1 at the wall to the left (marked as Wall1), and vBS4, arising due to reflections of signals from BS1 at the lower wall (marked as Wall2). Similarly, we have one virtual base station vBS5 for the physical base station BS2 due to reflections of signals from BS2 at Wall2. The virtual base stations are depicted by magenta colored downward triangles.

For modeling the communication channel, we apply a simple free-space path loss model in LOS conditions for all base stations. For the virtual transmitters, we additionally attenuate the signals by 3 dB due to reflections at the walls.

The receiver stands still in the beginning for 0.8 seconds and then moves on a track represented by the blue line with a constant velocity of 1.8 meters per second. Every 70 milliseconds, the receiver records a 3GPP-LTE snapshot for post-processing. The start and end positions are indicated by the labels *START* respectively *END*. It is obvious that not all base stations are visible at any receiver position due to blocking by the walls. The exact coordinates of the base stations and the start and end position of the receiver are listed in Table II.

B. Measurement Results

Figures 5 and 6 show the results of the KEST algorithm for the base stations 1 respectively 2.

It can be seen from Figure 5 that the KEST algorithm estimates three paths in the beginning for the physical base station BS1. From their amplitudes and their relative delays combined with the knowledge of the geometry of the scenario and the start position of the receiver, we conclude that the

TABLE II

OBJECTS AND THEIR COORDINATES IN THE MEASUREMENT SCENARIO.

Object	Position
BS1	$(40, 70)$
BS2	$(110, 45)$
vBS3	$(-40, 70)$
vBS4	$(40, -70)$
vBS5	$(110, -45)$
receiver START	$(25, 90)$
receiver END	$(125, 20)$
receiver END	$(125, 20)$

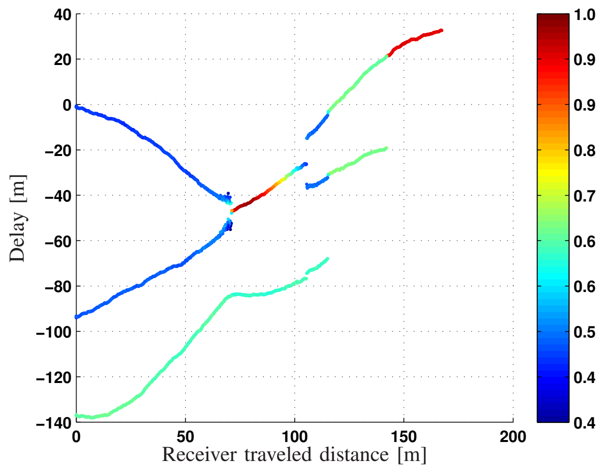

Fig. 5. Results of the KEST algorithm for physical base station BS1. The estimated delay times speed of light is plotted over the receiver traveled distance. The color indicates the normalized, estimated amplitudes in linear domain.

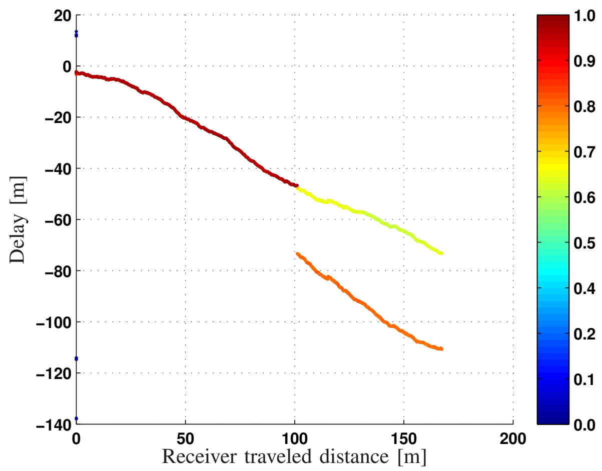

Fig. 6. Results of the KEST algorithm for physical base station BS2. The estimated delay times speed of light is plotted over the receiver traveled distance. The color indicates the normalized, estimated amplitudes in linear domain.

lowest path with an initial delay of approx. -137 meters is the LOS path, whereas the paths above are MPCs reflected at Wall1 respectively Wall2. Note that with a delay in meters, we mean the delay in seconds multiplied by the speed of light. Hence, we interpret those paths as sent from virtual base station vBS3 for the path with an initial delay of approx. -94 meters, respectively from vBS4 for the path with an initial delay of approx. -1 meter. Since we do not assume a synchronization between the physical base stations and the receiver, the actual delays are not of interest, but the relative delays between the paths, as they represent the OTDOAs of different (physical and/or virtual) base stations.

As the receiver moves forward, we see that the paths representing the virtual base stations come very close to each other after approx. 71 meters, as the receiver is in an area where the MPCs arriving from vBS3 and vBS4 are very close to each other in time. In fact, the two MPCs cross each other. We observe that the KEST algorithm is then not able to separate the two MPCs any more. Instead, the two MPCs are interpreted as one wave impinging at the receiver with a higher amplitude. Possible ways to overcome this problem would be to exploit the angle of arrival of the received MPCs by means of an antenna array or, if the velocity of the receiver is high enough, the Doppler shift. We make none of these assumptions within this paper, though.

Only after approx. 106 meters, KEST can resolve those paths again when the difference of their delay grows larger. Having traveled for approx. 115 meters, the LOS path to the physical base station BS1 disappears, whereupon the KEST algorithm loses track of the corresponding path. Similarly, after approx. 142 meters, the track of the MPC arriving from the virtual base station vBS4 is lost.

In Figure 6, the KEST results for the physical base station BS2 indicate that at the start position, the initial model order estimation estimates four paths at delays of -138 meters, -114 meters, -3 meters, and 12 meters. The KEST algorithm however discards all paths but one due to the low amplitudes they have after the very first time step. Again, we conclude that the only surviving path is a NLOS path, since the LOS path is blocked in the scenario for the start position. After approx. 101 meters of traveled distance, the LOS path (below the NLOS path) is detected by the KEST algorithm.

Note again that only the relative delays between the single MPCs are of interest, and we calculate the OTDOAs based on these relative delays. However, since we assume the base stations to be synchronized among each other, it is possible to exploit relative delays between MPCs from different physical base stations.

A big problem we encounter and described above is that KEST treats MPCs from the same physical base station arriving at the receiver with a small relative delay $\Delta\tau$ as only one impinging wave. One explanation therefor is the low bandwidth used: For a higher bandwidth, two waves can be resolved for a much smaller $\Delta\tau$. Hence, as $\Delta\tau$ becomes smaller over time, a system with a higher bandwidth will be able to resolve the two paths for much longer. In the same way, if KEST detects two MPCs of small $\Delta\tau$ as one path and $\Delta\tau$ increases, a higher bandwidth implies that resolving the two paths will happen earlier.

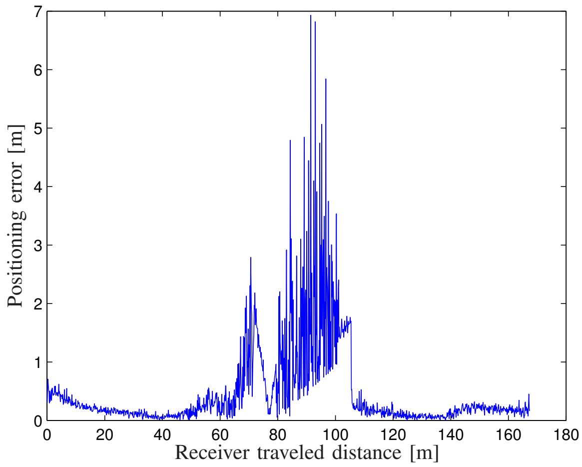

Fig. 7. Positioning error after the particle filter for the receiver traveled distance.

Figure 7 illustrates the positioning error, i.e., the Euclidean distance between true position of the receiver and the best estimate of the particle filter, for every time step. Within the first 65 meters, the positioning works very accurate, the positioning error is considerably below one meter. This is achieved, since the relative delays of the MPCs arriving at the receiver from base stations BS1, vBS3, and vBS4 that are high enough for the KEST algorithm to resolve them (see Figure 5), and all these base stations can be used for positioning. When the relative delays between two of those MPCs become too small and KEST estimates the MPCs from vBS3 and vBS4 as one path arriving from vBS3, this path is biased relative to the MPC arriving from BS1. In addition, the base station vBS4 cannot be used. Hence the error increases until the two MPCs can be resolved again after a traveled distance of approx. 105 meters. This is also where a LOS condition to the second physical base station (BS2) arises and this base station can be exploited. Hence, the positioning error drops significantly after 105 meters.

Figure 8 shows cumulative distribution function (CDF) of the positioning error. It shows the probability for the positioning error to be below a certain value. For example, the positioning error is below 1.44 meters in 90% of the cases as indicated by the dashed line.

Note that with using standard methods for positioning without exploiting the MPCs of the two physical base stations, determining the position of the receiver is not possible, since only two base stations are available. Even more, both physical base stations are simultaneously in LOS of the receiver for only a short range between a traveled distance from approx. 101 to 105 meters.

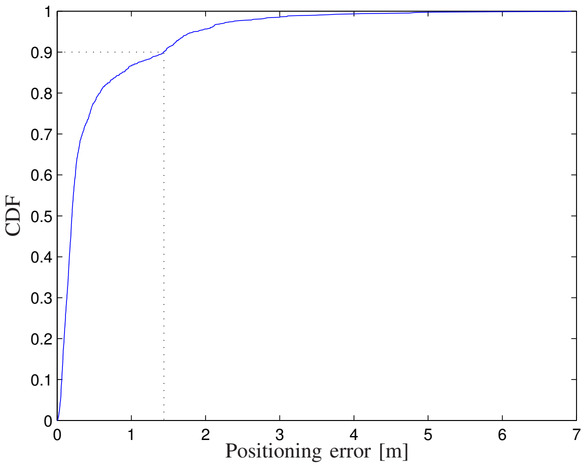

Fig. 8. The cumulative distribution function (CDF) of the positioning error.

IV. Conclusion

This paper shows that tracking a receiver in an urban scenario is possible even under the constraints of the availability of only two base stations and a 3GPP-LTE signaling system of only 20 MHz. This is done by measuring an emulated multipath scenario and by applying an advanced signal processing algorithm for resolving impinging MPCs at the receiver. Since we assume no synchronization between the base stations and the receiver, we exploit the OTDOAs between impinging MPCs as input for a particle filter which tracks the receiver over time. For our scenario, the positioning error is always below one meter if at least three (possibly virtual) base stations are visible and the relative delays of MPCs from the same physical base station are large enough to be resolved by the KEST algorithm. In 90% of the time steps, the positioning error was below 1.44 meters. If two MPCs could not be separated any more, the positioning error was still below seven meters.

Within the scope of this paper, we assumed the basic geometry to be known, and hence the positions of the virtual transmitters to be estimated perfectly. We will work on dropping this assumption in the future, and on applying the Channel-SLAM algorithm on band-limited 3GPP-LTE signals.

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