Channel impulse response based vehicle analysis in tunnels

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***Abstract*—Indoor localization and positioning is of vital importance in numerous applications. In particular, in the case of emergency events, locating and tracking of the victims, objects and rescue personnel in harsh indoor environments is still challenging. In this paper, two different approaches for the obstruction detection inside the road tunnel are analysed. Both methods are based on the analysing channel impulse responses (CIRs). The first parametric approach tests the use of root mean squared signal delay spread to recognize the object in an empty tunnel. Because the recognition of additional objects in already occupied tunnel is unreliable, more complex machine learning approach is also tested. The convolutional neural network (CNN) classification model for the LoS/NLoS channel detection is able to detect the object in an empty tunnel with the accuracy of more than 90%, whereas the presented multiple objects scenarios can be successfully resolved in more than 80%.**

Keywords— convolutional neural network, ray tracing, root mean squared delay spread, positioning in tunnels, ultra-wide band (UWB)

I. Introduction

Information on people and device positions is essential for provisioning several future services and also required in many future and current applications. The precise, accurate and reliable self positioning and neighbouring object location estimation is vital for emerging autonomous driving. Currently positions of devices and people in emergency and unexpected events attract significant interest of the research community. Two classes of positioning approaches exist [1], namely active and passive approach. The active approach assumes an object with unknown position, i.e. agent, actively participating in positioning procedure, meaning either *(i)* it senses its environment and calculates its position based on past and current observation or *(ii)* it wears an active tag that transmits a signal which is received by spatially distributed anchors, i.e. devices with known location. Tag's location is then estimated by observing the signal properties. Two well-known systems which use the active position approach are GPS systems and positing of mobiles within the cellular radio network. On the other hand, in passive positioning approach no cooperation of agents in the positioning procedure is expected. Typical representatives of passive positioning make use of radar technology, camera systems and laser scanners [2]. The above approaches have several critical limitations, in particular limited performance in environments with low visibility, high cost, line of sight requirements between anchors and agents, and environment pollution with radar signal.

In multipath radio environments the ultra-wide band (UWB) radio technology is often applied in short range communications due to its robustness to the multipath. Additionally, UWB technology has an ability to measure round trip delay for active indoor agent positioning. Several studies already improve the agent positioning by classifying radio links in line of sight (LoS) and non-LoS (NLoS) by processing channel impulse responses (CIR) [3]. The impact of mining machinery on CIR in multiple-input-multiple-output (MIMO) UWB system was studied in [4]. In this paper we reverse the problem discussed in [4] and try to answer the question whether CIR can be applied to detect vehicles in tunnels. We assume tunnels equipped by wireless sensor networks employing UWB radio technology. The system can also be used to measure the environmental parameters such as temperature, humidity and air quality in order to control the tunnel ventilation system and traffic. In the case of an accident, with the smoke severely limiting the visibility of surveillance cameras, it is of high importance to detect the vehicle positions by some other form of passive localization.

In this respect we run a measurement campaign in the tunnel used for firefighter trainings. The set of nodes based on Decawave DW1000 chipset was placed near the tunnel walls in zig-zag pattern, while the vehicles were placed in different positions along the tunnel. Two approaches were tested to detect vehicle position, one based on analysing the CIR observing RMS delay spread and the other one based on the machine learning algorithm. Two dataset are used to test algorithms, one obtained by measurement and the second one by computer simulations.

The paper is organized as follows. After the introduction, two obstruction detection approaches analysed in the paper are described. In Section III measurement campaign is presented including the tunnel environment and measurement procedure. Simulation environment and scenarios are described in Section IV while the results of the proposed approaches are presented in Section V. Finally, concluding remarks including future work are given in Section VI.

II. Obstruction detection approaches

Vehicles located between transmitter and receiver affect the wireless channel due to possible blocking LoS, introducing additional scattering and reflection. In this paper a link represents a fixed radio transmitter and a fixed receiver, which estimates CIR, received signal strength, RMS delay spread, distance, and can detect LoS/NLoS channel condition. In order to determine in tunnel vehicle presence and possibly its location we tested two approaches.

The first approach is based on analysing received signal RMS delay spread between the different Tx/Rx pairs mounted on the opposite sides of the tunnel. Widely accepted model of power delay profile is Saleh Valenzuela model [5]

$$h_{discr}(t) = \sum_{l=0}^{L} \sum_{k=0}^{K} a_{k,l} \exp\left(j\phi_{k,l}\right) \delta(t - T_l - \tau_{k,l}) \quad (1)$$

where $a_{k,l}$ is the tap weight of the k-th component in the l-th cluster, T_l is the delay of the l-th cluster, and $\tau_{k,l}$ is the delay of the k-th multipath component relative to the l-th cluster arrival time T_l. The phases $\phi_{k,l}$ are uniformly distributed in the range $[0,2\pi]$. The model assumes rays arriving to the receiver in clusters and each cluster consisting of several multiple components. In [6] the parameters for different indoor radio environment for UWB radio technology were published, but not for communications in tunnels. Analysing the decay of the average energy in cluster, and decay of energy per cluster the LoS and NLoS condition can be detected. The start and the end of each cluster have to be found, which is challenging in highly scattering environments [7]. In this study we applied more common approach which is based on observation of RMS delay spread σ

$$\sigma = \sqrt{\frac{\sum_k \tau_k^2 \beta_k^2}{\sum_k \beta_k^2} - \left(\frac{\sum_k \tau_k^2 \beta_k^2}{\sum_k \beta_k^2}\right)^2} \quad (2)$$

to estimate vehicle presence. We hypothesized that a vehicle in the tunnel will increase the delay spread due to multiple reflection and signal blocking.

In the second approach the convolutional neural network (CNN) based classification model for LoS/NLoS channel detection was used [8]. Since the pulse based physical layer allows efficient measurement of the CIR, significantly larger information-rich content can be collected in comparison to what can be obtained by measuring only several channel parameters. The CNN is used due to ability to learn complex models and superior input shift invariance which omits the need for input data pre-processing and deriving low-dimensional input vectors from CIR. The CNN structure is implemented using Keras with TensorFlow [9] backend, an open source neural network library and open source library for numerical computation using data flow graphs, respectively. CNNs are fed by 1-dimensionnal input traces in the form of measured and simulated CIR data.

In the first step the CNN are trained by measured/simulated data using predefined subset of data. CIR measured by DW1000 UWB has 992 bins for the 16 MHz pulse repetition frequency (PRF) and 1016 samples for the 64 MHz PRF with a resolution of approximately 1 ns (1/2 of the 499.2 MHz period). Since 152 bins in each CIR hold most of the information regarding the environment propagation characteristics, they were used during the learning and classification process.

In the second step the model performance in the sense of the vehicle presence detection based on NLoS/LoS classification was evaluated. Thus, some standard metrics based on confusion matrix were calculated [10]. Four categories of the resulting assignment exists, namely; true positive (TP), true negative (TN), false positive (FP) and false negative (FN). Performance metrics applied for the results evaluation are *(i) accuracy* which provides the percentage of correctly classified instances (*(TP+TN)/(TP+TN+FP+FN)*), *(ii) precision* (per-class) which for example represents the percentage of correctly classified NLoS instances within all the instances that were classified as NLoS instances (*TP/(TP+FP)*) or opposite for LoS and *(iii) recall* as a true positive rate (per-class) or a fraction of correctly classified instances within the NLoS or LoS class (*TP/(TP+FN)*).

III. Measurement campaign

The UWB channel characteristics were investigated by CIR measurements in a tunnel built for training of firefighters. For the wide-band channel measurements the IEEE 802.15.4 compliant UWB chipset from DecaWave was used.

A. Environment

A slightly curved training tunnel is located in the training centre for civil protection and disaster relief in Ig, Slovenia. The tunnel construction, shape and the dimensions are depicted in Fig 1. The slightly bended tunnel is 30 m long, has an arch cross section and is 9.6 m wide and 6.6 m high. The floor is asphalted while the walls consists of reinforced concrete up to the 1.6 m height and the rest of the arch is of iron sheet metal. The last section of the tunnel was occupied by the wreckage of a bus, a truck and a van which enables studying of UWB channel characteristic in real emergency situations.

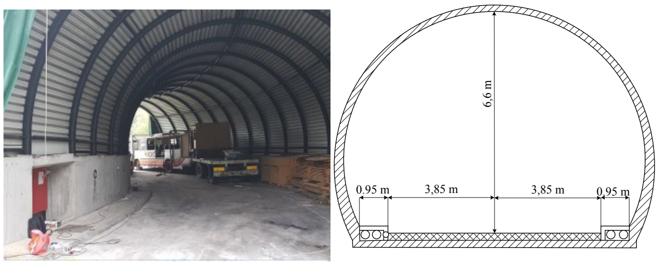
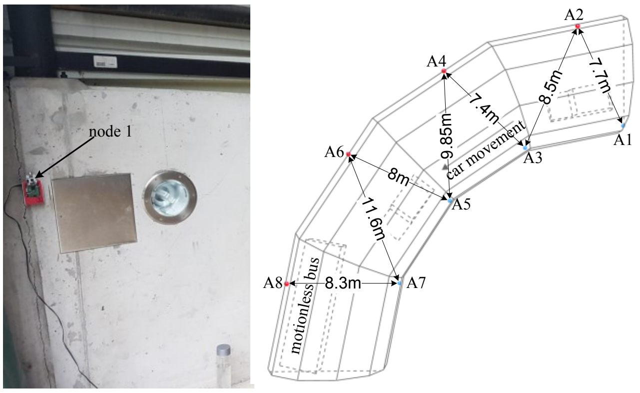


Fig. 1. Tunnel construction and cross-section dimensions

B. Measurement procedure

The measurement system is comprised of eight DecaWave DW1000 UWB pulse radios [11] with a firmware supporting fast measurement acquisition and enabling flexibility in experimental environment. UWB radios were mounted on the concrete walls, four on each side of the tunnel. The photo of the measurement setup together with the Tx/Rx positions and distance between them are depicted in Fig 2. In order to detect the vehicles of different size the nodes were mounted 1.3 m above the ground. The distance between nodes on the same side was set to 7 m while the distances between adjacent nodes across the tunnel vary due to the tunnel bend.

The CIR measurements were performed among all eight nodes on all 6 available channels [11] with preamble length of 1024 symbols and pulse repetition frequency of 64 MHz. In order to enable communication also among the farthest nodes the Tx amplifier gain was set to 33.5 dB.



a) b)

Fig. 2. Measurement setup; a) photo at the location and b) Tx/Rx positions with moving car and motionless bus

In the first step the measurements were performed only with the wrecks located in the last part of the tunnel. In order to analyse the presence of the vehicles in the tunnel we add 18 scenarios with a car (4.2 m long, 1.8 m wide and 1.5 m high) moving along the tunnel by 1 m steps. We run 12 measurements between two nodes for each channel settings at each car position. In the configuration with 8 nodes 56 omnidirectional links exist and thus more than 80.000 measurements were captured for 20 tested scenarios.

IV. Simulation environment and scenarios

Accurate channel modelling with the ability of predicting CIR requires the use of physical models. When accompanied with detailed knowledge of the environment geometry, advanced RF ray-tracing techniques can take into account the majority of paths the real wave-front would traverse and model actual physical phenomena responsible for propagation of electromagnetic waves. Advanced channel characteristics, including CIR can be calculated from multipath traces, which are not readily available in pure statistical propagation predictions.

A. Ray tracing simulator

Our in-house radio frequency ray tracing tool based on the brute force shooting and bouncing rays was used to simulate CIR. The simulator has already been proven in several projects with telecommunication industry in indoor and outdoor scenarios [3]. However, tunnel environment is specific due to curved surfaces and some compromises such as the use of segmented walls had to be done in scenario description.

Full 3D simulator effectively traces a large number of rays from the transmitting source in all directions into the scene. The initial set of launched rays needs to be separated uniformly by icosahedral grids. Using geometrical optics concepts in describing radio frequency propagation implies that initial rays are an abstraction of a single wave-front spreading into space. Subsequent electromagnetic interactions with matter initiate new wave-fronts, described by another sets of reflected, refracted, diffracted or scattered rays. The signal evaluation at given observation point combines these wave-fronts freely, in the same way as if they are being transmitted by multiple independent sources.

Reflection and refraction phenomena on the boundaries between propagation media are modelled using Fresnel equations for electric and magnetic field amplitudes while edge diffraction modelling is done using the geometrical theory of diffraction [12]. The simulator detects a ray close to a reception point and thus a wave-front by introducing a sphere object with variable non-zero radius and by inspecting the intersecting rays. Bloom filtering [13] is used to select unique wave-fronts. Further, the antenna patterns, the attenuation caused by the propagation through material as well as the signal spreading loss needed to be accounted for. Multipath components of a narrowband impulse response are thus readily available as delayed signal phasors.

Simulated CIR is modelled as a sum of time-varying number of multipath components in a tap-delayed linear filter and may be formulated as

$$h(\tau) = \sum_{i=1}^{L} \alpha_i \delta(\tau - \tau_i), \qquad (3)$$

where each of L taps represents a multipath component of polarity sign-extended ($\pm$) real amplitude α, multiplied by time delayed Dirac-Delta function. The depth of simulation, i.e., the number of interactions each ray is allowed to encounter, was set to 30. Only reflections were simulated because most of surfaces are made of metal or steel-reinforced concrete. Allowing up to 150 dB signal loss per multipath component and initially launching 671 million rays, a single simulation typically took 10 minutes to complete.

B. Simulation specifics

Computing $h(\tau)$ by ray tracing is not as straightforward because ray paths, amplitudes and propagation delays are functions of frequency. Ray-tracing evaluates signal at a single frequency, thus computing only narrowband CIR valid for a bandwidth limited transmission. Sub-band divided ray tracing has been proposed in [14] to fully evaluate (3). The method involves multiple simulation runs for a number of centre frequencies of complementary sub-bands. These narrowband CIRs are then combined together in frequency space. Inverse Fourier transform gives the final CIR over wider bandwidth. However, simulations were not expected to reproduce measured CIRs with high accuracy due to the discrepancies between the model and reality (tunnel curvature, presence of metal columns, use of corrugated sheet metal, insufficient car details modelling). Therefore, we only simulate narrowband CIRs at 3993.6 MHz centre frequency of the impulse radio.

C. Simulated scenarios

Narrowband CIRs were computed for 16 combinations of Rx/Tx pairs and 18 car locations. The tunnel geometry, the transmission and reception points as well as car route are presented in Fig 2b). Motionless bus was placed at the end of a tunnel. The tunnel curvature was approximated by flat patches. Most of the patches are made of metal with the lowest arc segments and ground plane assumed to have electric properties of steel-reinforced concrete (ε_r=9, μ_r=1, σ=0.09 S/m) and asphalt mixture (ε_r=5.7, μ_r=1, σ=0.0005 S/m), respectively. Both, the transmission and the reception were simulated assuming ideal vertically oriented dipole antennas.

V. VEHICLE POSITION ESTIMATION BY SIMULATED AND MEASURED CIR

Proposed approaches are based on CIR which holds RMS delay information and enables machine learning NLoS link classification. Fig. 3 clearly shows the difference between the LoS CIR for link A1-A2 (car at 0 m) and NLoS channel state for the same link with a car 4 m intothe tunnel.

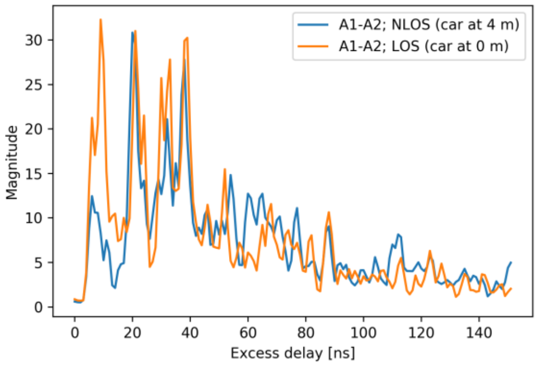


Fig. 3. CIR Los/NLoS comparission

A. Root mean squared (RMS) delay spread approach

The median RMS delay spread as a function of vehicle position is plotted in Fig 4. Median RMS delay spread was estimated from 72 RMS delay spreads calculated from 12 CIR measurements at 6 different UWB channels per each radio link. The RMS delay spread increases, if the vehicle fully blocks line of sight condition between nodes and there is no other vehicle nearby, for example curves A1-A2 and A1-A4. However, if other objects are located close to the vehicle, its presence in the tunnel is not easy to identify, i.e. curves A1-A6 and A1-A8. We also found that the tunnel curvature brings additional increase in the RMS delay spread, which significantly limits the applicability of RMS delay spread for vehicle presence identification.

B. NLOS link classification

LoS/NLoS link classification is the first machine learning approach for vehicle detection. If there an obstruction in the first Fresnel zone, the link is marked as NLoS link, while if there is not the link is marked as LoS link.

Classification algorithm was implemented using machine learning libraries Keras, TensorFlow and scikit-learn. A convolutional neural network (CNN) with the following structure was constructed: 3 convolutional layers, pooling layer, 2 convolutional layers, pooling layer, fully-connected layer with dropout regularization and readout layer with softmax activation. ReLu activation function was selected as a general activation function for all neurons since their good influence on the training performance and convergence. Batch regularization was also used to prevent the excessive local build-ups of weights and Adam optimization algorithm with the initial learning rate η=0.0001 because of the good overall performance on various types of problems.

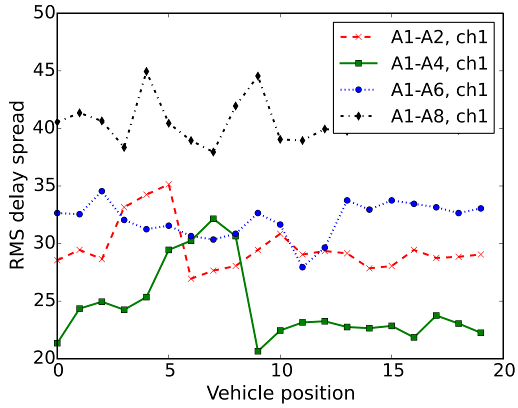


Fig. 4. Mean RMS delay dependence on vehicle position

To properly evaluate the model performance, 9-fold cross-validation approach was selected. There are 9 training and validation sets, where in each set 2 neighbouring car positions were selected as a validation set. Validation car positions are presented in Table II and IV. Input to the CNN classifier is a raw CIR data extracted from the full CIR accumulator on a DW1000 UWB radio. Input sample was created cutting the CIR from the start marker (identified with algorithm inside radio) to the maximum excess delay of 152.244 ns.

TABLE I. CLASSIFICATION PERFORMANCE OF REAL MEASUREMENTS AND SIMULATED SAMPLES

		Accuracy [%]	Precision [%]	Recall [%]	Sample
Measured	LOS	92.1	85.4	93.0	1250
	NLOS		96.1	91.7	2386
Simulated	LOS	95.8	95.3	96.6	75
	NLOS		96.4	95.0	69

TABLE II. CLASSIFICATION PERFORMANCE FOR INDIVIDUAL VEHICLE POSITIONS

Accuracy [%]	0-1m	2-3m	4-5m	6-7m	8-9m	10-11m	12-13m	14-15m	16-17m
Measured	96	87.6	93.9	93.9	91.2	94.8	93.9	92.1	85.5
Simulated	100	93.8	93.8	93.8	96.9	96.9	94.8	96.9	96.9

Table I and Table II present the NLoS classification results. In Table I the general classification performance is presented with general classification accuracy for simulated and measured data, respectively. For each class (LoS or NLoS) there are precision and recall performances with the supporting number of samples for the corresponding test. In Table II the evaluation of individual validation folds is presented in a form of per-validation folds accuracies. Classification results show that machine learning approach for NLoS classification with CNN works as a very reliable NLoS detector in both simulated and measurement-based cases.

C. Vehicle presence detection

As we want to detect the vehicles regardless if there are other signal obstructions in the tunnel, we changed the LoS/NLoS information into the vehicle presence information (NPRES/PRES) for the second machine learning approach. In this case we assume the scattering from the vehicle can be distinguished from scattering caused by other object. Links with a moving vehicle on a direct path between the transmitter and the receiver were marked as PRES and all other links as NPRES.

TABLE III. VEHICLE PRESENCE CLASSIFICATION PERFORMANCE

		Accuracy [%]	Precision [%]	Recall [%]	Sample
Measured	NPRES	79.3	81.8	91.3	2552
	PRES		69.8	49.7	1084
Simulated	NPRES	77.0	69.1	99.3	107
	PRES		98.7	53.9	37

TABLE IV. VEHICLE PRESENCE CLASSIFICATION PERFORMANCE FOR INDIVIDUAL VEHICLE POSITIONS

Accuracy [%]	0-1m	2-3m	4-5m	6-7m	8-9m	10-11m	12-13m	14-15m	16-17m
Measured	92.3	86.8	81.4	77.9	67.8	75.4	79.8	80.5	71.9
Simulated	71.0	75.0	75.0	75.0	75.0	75.0	75.0	81.3	90.6

We repeated the general classification performance and per-position performance tests. General classification performance is presented in Table III. The classification performance based on the measurements is compared to the classification performance of simulated samples. The simulations are not affected by the measurement noise and give slightly better results. Despite that the simulated approach being better than measurement-based approach the approach with vehicle detection on links in already occupied tunnel works very unreliable according to the results in Table IV. To improve the performance of vehicle detection in a tunnel, approach detecting the vehicle presence in a sector of a tunnel based on a CIR data from many radio links should be used instead of a sole presence on a link.

VI. Conclusion

In this paper we try to identify vehicle position in a tunnel analysing the CIR measured by UWB communication technology. We placed the wireless sensors on a zig-zag pattern along the curved tunnel built for firefighters training. We tested two approaches, namely the first one observing RMS delay spread, and the second one based on machine learning approach. The results revealed that the method based on analysing RMS delay spread can detect the vehicle in the tunnel if there are no additional scatterers located along the path between transmitter and receiver, or nearby the transmitter or receiver. The method can be improved by analysing the decay of inter and intra cluster components. While using machine learning approach the results for classification the link as LoS and NLoS gives excellent results in terms of accuracy, precision and recall, meaning LoS and NLoS approach can be applied for detection of a single vehicle in a tunnel. However, when we try to detect vehicle at the presence of the wrecks, which also blocks the LoS channel the results are not so convincing. The similar results are obtained by processing simulated and measured CIR. In order to detect the car presence nearby the wrecks the training samples have to be chosen to reflect three cases, namely empty tunnel, vehicle in the tunnel and vehicle in the tunnel close to the wrecks.

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