Performance of Support Vector Regression in Correcting UWB Ranging Measurements under LOS/NLOS Conditions

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ABSTRACT

Ultra-wideband technology has recently gained interest due to its inherently fine temporal resolution, which enables precise measurements of the time-of-flight between devices. The accuracy of these measurements depends, among others, on the presence of a free line-of-sight (LOS): in case the latter is partly or fully blocked, the direct path component cannot be accurately identified, leading to large errors in the estimated distance. To cope with this problem, many approaches based on machine learning have been proposed to detect non-line-of-sight (NLOS) conditions and mitigate erroneous ranging measurements. However, the performance of these approaches as a function of various features and different LOS/NLOS conditions has rarely been evaluated on off-the-shelf devices in an exhaustive way.

In this work we systematically benchmark the accuracy of error correction models based on support vector regression. To this end, we perform a large experimental campaign on off-the-shelf ultra-wideband devices, in which we collect 35050 ranging measurements in various environments and different LOS conditions. Our analysis of the collected data shows that a *detection and mitigation* strategy, where measurements are first classified and only corrected if a NLOS condition is detected, can help reducing the root mean square error in NLOS conditions by up to 39%, while preserving the accuracy and precision of measurements in LOS conditions.

CCS CONCEPTS

• Networks → Location based services; **• Computing methodologies → Feature selection**.

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1 INTRODUCTION

Ultra-wideband (UWB) has become one of the most promising technologies for indoor positioning thanks to its robustness and high time-domain resolution. Indeed, UWB devices are nowadays ubiquitous: big players such as Apple and Samsung have started to include UWB radios into their smartphones, whilst car manufacturers such as BMW, Volkswagen, and Tesla will soon rely on this radio technology to enable secure access to their vehicles. The range of UWB-based applications is not limited to mobile and automotive systems, but extends to asset tracking, building control, factory automation, and other location-aware IoT use cases [1].

Most of the indoor positioning systems relying on UWB technology are infrastructure-based, i.e., *anchor* nodes are placed such that there is a direct line-of-sight (LOS) with any of the devices (called *tags*) to be localized in a given area. Clearly, the existence of a free LOS between anchors and tags cannot be fulfilled in any situation, especially, in complex and dynamic environments such as manufacturing halls and multi-room buildings. In cases where the LOS is subject to partial or full occlusion (e.g., due to the presence of humans, furnitures, walls, or other obstacles), the estimated distance between tags and anchors derived from the ranging process is subject to errors that may even be in the order of several meters.

Detection and mitigation of NLOS conditions. Several works have proposed the use of cooperative localization, where tags with high confidence in their estimated position act as anchors to support other nearby tags [2, 3]. For these techniques to succeed, it is fundamental that erroneous ranging measurements caused by non-line-of-sight (NLOS) conditions are detected and corrected based on the information obtained from nearby tags. However, in situations where there are no surrounding devices (i.e., when no alternative measurement is available), a tag needs to autonomously detect the NLOS condition and correct the erroneous ranging measurements with locally-available information only.

To this end, several researchers have explored how UWB nodes can autonomously detect NLOS conditions and/or mitigate their impact on the accuracy of ranging measurements. Approaches vary from simple classifiers based on the received signal strength and first path information [4] to more advanced machine learning (ML) techniques including deep neural networks and support vector machines [5–12]. These ML techniques exploit, for example, the variance of subsequent ranging measurements [6], or information extracted from the channel impulse response (CIR) of received UWB messages such as amplitude and delay spread [8] to correct the measured values and reduce the errors in the estimated distance.

Among the different ML techniques, those based on support vector machines (SVM) have attracted the largest body of work. One of the early studies in this field was conducted by Maranò et al. [7], who obtained a set of indoor measurements using UWB devices, and used it to train an SVM classifier that can distinguish between LOS and NLOS conditions. The authors have further studied the performance of support vector machine regression (SVR) in reducing the

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ranging errors caused by NLOS conditions, showing improvements by up to 60%. In recent years, the performance of SVM schemes to detect NLOS conditions and/or mitigate their impact on the accuracy of UWB ranging measurements has also been compared with different types of convolution neural networks [10], deep neural networks [11], as well as with schemes based on random forests and multilayer perceptron networks [12], showing satisfactory results in different real-world environments.

Limitations of existing work on SVM. Despite this large body of work, many questions remain unanswered about the performance and suitability of SVM schemes to detect NLOS conditions and/or mitigate their impact on the accuracy of UWB ranging measurements. For example, the experiments by Maranò et al. [7] were carried out before the commercialization of the first low-cost UWB transceiver compliant to the IEEE 802.15.4-2011 standard, i.e., the Decawave DW1000. Reproducing their experiments using modern off-the-shelf UWB devices would be important to shed light on the generality of these results. Furthermore, the results in [7] nicely show how effectively different features extracted from the CIR can correct UWB ranging measurements in NLOS conditions, but do not unveil how such corrections affect LOS ranging measurements.

Barral et al. [6] have evaluated the performance of SVM schemes on devices based on the DW1000 radio and reported individual results for LOS and NLOS conditions. However, they only consider the variance of the measured distance and of the received signal strength: this requires the exchange of several messages (which is undesirable due to energy constraints) and does not shed light on the usefulness of the features that can be extracted from a CIR. Conversely, the experiments by Sang et al. [12] focus on features extracted from the CIR provided by the DW1000 radio, but only address NLOS detection, and not how to correct ranging measurements in NLOS conditions. Finally, none of the aforementioned studies discusses the *stability* of the corrected ranging measurements, i.e., whether feeding the SVM scheme with other data collected in the same settings yields similar distance error estimates.

Our contributions. In this paper we fill this gap and perform a large experimental campaign on off-the-shelf UWB devices to shed light on the performance of SVM schemes in detecting LOS/NLOS conditions and in correcting erroneous ranging measurements. We start by collecting more than 35050 distance measurements between two `DWM1001-DEV` devices at 701 different locations. Our dataset, which we make publicly available, includes scenarios where a direct LOS between the devices is available, as well as settings with partial or full signal occlusion. Specifically, we perform measurements in what we call weak LOS conditions (WLOS), where small objects such as monitors, chairs, or people affect the distance estimates, as well as NLOS conditions, where obstacles such as thick walls severely influence the signal propagation. We then extract several features from the received CIR as in [7] and thoroughly benchmark the accuracy of SVM classifiers in detecting NLOS conditions as well as the performance of SVR schemes in correcting erroneous ranging measurements. We do so by systematically analysing the effectiveness of different feature sets, and by breaking down the results for different LOS and NLOS scenarios, in order to study the usability of the approaches. Our analysis on the collected data shows that a *detection and mitigation* strategy, where measurements are first classified and only corrected if a NLOS condition is detected, can help reducing the root mean square error in NLOS conditions by up to 39%, while preserving the accuracy and precision of measurements in LOS conditions. We finally discuss the stability of the distance error predictions, showing that the latter may fluctuate by up to 50 cm in some NLOS measurement settings. Our paper proceeds as follows. After providing some background information on CIR estimates and SVM schemes in Sect. 2 and 3, we describe the experimental setup used in our measurement campaign in Sect. 4 and analyse the obtained results in Sect. 5. We finally conclude the paper in Sect. 6, along with an outlook on future work.

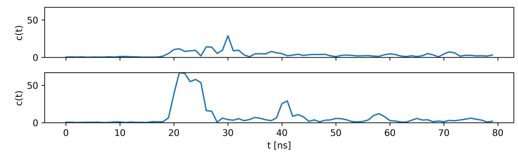

Figure 1: Example of a CIR received by a DW1000 radio in a NLOS condition (top) and a LOS condition (bottom).

2 BACKGROUND ON UWB TECHNOLOGY

UWB-based systems use short pulses for communication: this enables to precisely determine the Time-of-Arrival (ToA) of a message, i.e., the instant in which the radio initiates a packet reception. ToA determination is linked to the detection of the *direct path component*, i.e., the pulse travelling on a straight line between two radios.

To measure the distance between two devices, UWB-based systems exchange several messages and record the time at which packets are transmitted as well as their ToA. These timestamps are used to calculate the Time-of-Flight (ToF) between the devices, which directly relates to the distance across them. However, there are several reasons leading to an incorrect ToF estimation, such as:

- The DW1000 transceiver has a received signal strength (RSS) dependent bias, which is typically corrected via a lookup table, or an equivalent fitted polynomial [13]. Unfortunately, the estimated RSS is not accurate enough to allow a direct calculation of the compensation value. Instead, one calculates the RSS based on the estimated distance and the free-space path loss model. Objects that dampen the signal are not considered in this calculation, which leads to wrong bias compensation values.
- When the direct path between two devices is fully blocked, the receiver may falsely identify one of the multipath components (MPCs), i.e., reflections from walls and scattering from other objects, as the direct path component. This results in large distance estimation errors that may even be in the order of meters.

In contrast to common radios, UWB transceivers additionally provide developers with a channel impulse response (CIR) estimate. This CIR estimate, which is extracted from the preamble of a UWB packet, essentially contains information about the propagation paths of the signal (including the direct path and MPCs) between a transmitter and a receiver. Fig. 1 shows the absolute value $c(t)$ of two normalized CIRs measured under LOS (bottom) and NLOS (top) conditions. In the CIR measured under LOS condition, the first path can easily be detected by the chip, given that the first peak has a higher amplitude and that most of the signal energy is contained within a certain area. In NLOS conditions, however, the signal energy is spread across a longer time interval and the receiver may falsely associate the peak at 30 ns with the direct path.

A simple method to detect NLOS consists in comparing the RSS of the first path component with the overall one. According to [4], one can classify a measurement as LOS condition if the absolute difference between the overall RSS and first path power level (FPPL) is less than 6 dB, and NLOS if it is greater than 10 dB, namely:

$$l = \begin{cases} 1 \;(LOS), & \text{if } |RSS - FPPL| < 6\,dB \\ 0 \;(NLOS), & \text{if } |RSS - FPPL| > 10\,dB \\ 1 - \frac{(RSSI-FPPL)-6}{4}, & \text{otherwise} \end{cases} \quad (1)$$

More advanced NLOS detection schemes exploit ML techniques such as SVMs [7, 8] and deep neural networks [11] to yield better results. Such techniques have also been used to correct UWB ranging measurements in NLOS conditions. In this paper, we focus on SVM solutions, and introduce how they work in the next section.

3 SUPPORT VECTOR MACHINE SOLUTIONS FOR NLOS DETECTION AND MITIGATION

SVMs are a set of machine learning models that are used for data classification as well as regression. Given a set of samples $x_i \in R^n, i = 1...m$, where x_i is an n-dimensional feature vector and $y_i = \{-1, 1\}$ a class label, a Support Vector Classifier (SVC) model is fit such that it can best separate the samples into the two classes $\{-1, 1\}$. During the training of a SVC, a set of training data points (support vectors) are selected and later used in the classification process. In case the data points are non-linear separable, they can be transformed to a higher dimensional space by a mapping function $\phi(x)$. If $\phi(x)$ is chosen properly, the inner product $k(x_i, x_j) = \phi(x_i)\phi(x_j)$ can be computed more efficiently in the higher dimensional space. A common choice is the Radial Basis Function (RBF) Kernel $k(x_i, x_j) = exp(-\gamma \cdot ||x_i - x_j||^2)$, where γ specifies the influence of a single training example [14]. During training, another hyperparameter (C) steers the trade-off between model complexity and misclassification. A trained SVC model contains a set of support vectors $x_i \; i = 1...l$, some coefficients $\mathcal{A}_i \; i = 1...l$, and a constant value b. For later classification, the following formula is used, where $\hat{y}$ is the predicted class of the unseen data point x:

$$\hat{y}(x) = sign[\sum_{i=0}^{l} \mathcal{A}_i \cdot k(x_i, x) + b] \quad (2)$$

Support vector regression (SVR) uses the same principle as the SVC, but instead predicts a continuous output value. An SVR has another important hyperparameter ϵ that specifies during the training phase how much error an SVR model is allowed to make in its prediction, where a low ϵ leads to a more complex model. The SVR inputs are the samples $x_i \in R^n$, with $i = 1...m$, and a continuous value y_i. Consequently, the SVR can be used to predict $\hat{y}$, i.e., the error of the unseen samples x, as follows:

$$\hat{y}(x) = \sum_{i=0}^{l} \mathcal{A}_i \cdot k(x_i, x) + b \quad (3)$$

SVM solutions in the context of UWB systems. As discussed in Sect. 1, solutions based on SVM have been the first used to detect NLOS conditions and to correct ranging measurements with UWB radios. Maranò et al. [7] have shown that SVCs are able to classify measurements into LOS and NLOS based on features extracted from CIR estimates. They have further shown that SVR is able to predict distance errors of measurements under NLOS conditions.

Figure 2: Example of WLOS condition (left) and NLOS condition (right) in our measurement campaign.

Based on their findings, the authors have developed three different strategies to improve UWB-based localization systems. Among them is the *identification and mitigation* strategy, in which measurements are first classified into LOS and NLOS based on the output of a SVC; thereafter, for measurements classified as NLOS, an SVR prediction is used to compensate for the error. In [8], the same authors have extended the work in [7] to also include Gaussian Process Points (GP) and further introduce a *mitigation-only* strategy, in which the measurements are *always* modified (i.e., also those in LOS conditions) based on the prediction of the SVR or GP method.

In this work, we adopt the solutions from [7, 8] and systematically evaluate the performance of the *mitigation and detection* and *mitigation-only* strategies under different real-world conditions.

4 EXPERIMENTAL SETUP

In this section, we describe in detail the setup used in our experimental campaign (Sect. 4.1) and the features we extract from the collected data and use as input for the SVM methods (Sect. 4.2).

4.1 Data Collection

We carry out an extensive measurement campaign using two off-the-shelf Decawave (now Qorvo) `DWM1001-DEV` devices embedding a DW1000 radio. All our measurements are taken using channel 5, which has a center frequency of 6489.6 MHz and a bandwidth of 500 MHz. Furthermore, we employ a transmission power of -14.4 dBm, choose preamble code 9, and set the antenna delay to `0x4050`. We record distance measurements inside a University building in 500 different settings across offices, laboratories, and hallways. For each setting, we carry out 50 individual ranging measurements and record the CIR, the estimated range, as well as other debug parameters outputted by the DW1000 chip. For each measurement, we also measure the true distance using a Leica Total Station TS11, and use this information as a ground truth.

Each measurement setting was manually labeled as LOS, WLOS, and NLOS. We mark as LOS conditions those in which there are no obstacles between the two UWB devices. NLOS scenarios are characterized by obstacles that severely influence the signal propagation (e.g., thick walls) such that multi-path components are severely delayed. WLOS conditions are less distinct, as they are caused by comparably small obstacles (e.g., monitors, chairs, or people) that result in the multi-path components being delayed less severely – also due to diffraction [15]. Fig. 2 shows an example of WLOS condition in a laboratory room where monitors and objects are placed in between the two UWB devices, as well as an example of NLOS condition where the devices are placed around a corner.

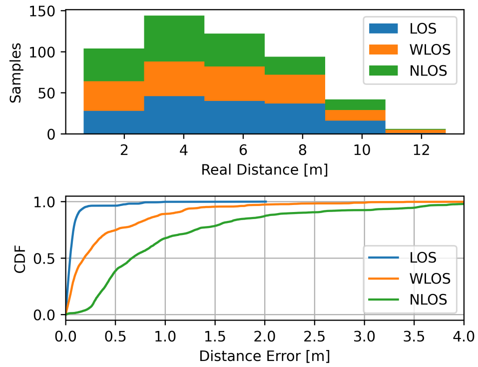

Figure 3: Distribution of samples for LOS, WLOS, and NLOS conditions in our dataset (top) and cumulative distribution function of the measured ranging errors (bottom).

Our dataset, which is publicly available[1], contains measurements taken at distances of up to 12 meters. In most of the traces, the UWB devices are located between 1 and 8 meters away from each other, which is a rather common distance between anchors and tags deployed in office rooms. For the performance evaluation in Sect. 5, we consider only a portion of our dataset (composed of about 511 individual measurement settings), such that for each real distance there is approximately the same number of measurements for LOS, WLOS, and NLOS conditions[2]. Fig. 3 (top) shows the distribution of samples in the dataset used in the final evaluation for LOS, WLOS, and NLOS conditions, whereas Fig. 3 (bottom) depicts the cumulative distribution function (CDF) of the absolute distance errors for each of the different conditions. Ranging measurements in LOS conditions are precise and accurate with a residual error below 0.15 m for 90% of the cases. The residual error at 90% increases to about 1.2 m and 2 m for WLOS and NLOS conditions, respectively.

4.2 Extracted Features

For each ranging measurement we extract nine features, most of which from the recorded CIR $c(t)$ $t = [0, T]$. Features `F1` to `F7` are the same as in [7], whereas `F8` and `F9` have been newly introduced. A brief description of each feature is provided below.

- `F1`: Energy of the CIR

$$\epsilon_c = \int_T^0 |c(t)|^2 dt \tag{4}$$

- `F2`: Maximum amplitude of the CIR

$$c_{max} = \max_t |c(t)| \tag{5}$$

- `F3`: Rise time between two thresholds (i.e., time difference between a lower threshold t_L and a higher threshold t_H)

$$t_{rise} = t_H - t_L \tag{6}$$

$$t_L = min\{t : |c(t)| > \alpha \cdot \sigma_N\} \ ; \ t_H = min\{t : |c(t)| > \beta \cdot c_{max}\}$$

where $\alpha = 6$ and $\beta = 0.6$ based on the empirical results from Maranò et al. [7]. σ_N represents the noise in the CIR and is a value that is directly returned by the DW1000 chip.

- `F4`: Mean excess delay (i.e., the mean delay of MPCs)

$$\tau_{MED} = \int_0^T t \cdot |c(t)|^2 / \epsilon_c dt \tag{7}$$

- `F5`: Mean Square (MS) delay spread (i.e., the time interval over which the strongest MPCs are spread – this delay is referred to as RMS in [7, 8])

$$\tau_{MS} = \int_0^T (t - \tau_{MED})^2 \cdot |c(t)|^2 / \epsilon_c dt \tag{8}$$

- `F6`: Kurtosis (i.e., another way to measure the shape of the probability distribution in the CIR as described in [16])

$$\kappa = \frac{1}{\sigma_{|c|}^4 T} \int_T (|c(t)| - \mu_{|c|})^4 dt \tag{9}$$

$$\mu_{|c|} = \frac{1}{T} \int_T |c(t)| dt \tag{10}$$

$$\sigma_{|c|}^2 = \frac{1}{T} \int_T (|c(t)| - \mu_{|r|}^2) dt \tag{11}$$

- `F7`: The estimated distance $\hat{d}$ returned by the DW1000 chip.
- `F8`: Noise level computed until the threshold t_L used in Eq. 6.

$$\sigma_{|c|}^2 = \frac{1}{t_L} \int_0^{t_L} (|c(t)| - \mu_{|r|}^2) dt \tag{12}$$

- `F9`: Absolute difference between RSS and FPPL as used in Eq. 1

$$\epsilon_d = |RSS - FPPL| \tag{13}$$

$$RSS = 10 \cdot log_{10}(\epsilon_c \cdot 2^{17}) - A[dBm] \tag{14}$$

$$FPPL = 10 \cdot log_{10}(\frac{F_1^2 + F_2^2 + F_3^2}{N^2}) - A[dBm] \tag{15}$$

where A is a constant dependent on the employed pulse repetition frequency, F_1, F_2, F_3 are three points of the amplitude of the detected first path peak, and N is the preamble accumulation count. The latter is reported by the DW1000 chip and indicates how many preamble symbols were used to estimate the CIR.

5 EXPERIMENTAL RESULTS

Our evaluation is based on the SVC and SVR implementation of the `scikit-learn` [14] framework. For training and testing, we use 10 *k-fold* cross-validation as also proposed in [7]. The latter is performed in 10 rounds: first, the dataset is split up into 10 disjoint subsets based on a measurement setting identifier to ensure that all measurements from one setting are within the same subset. Then, in each round, 9 of the subsets are used for training, whilst one is used for testing. This process is repeated until each subset has been used for testing at least once. In each round we take five samples per measurement setting, and use the entire dataset for testing. Feature scaling through standardization is an important step before applying SVM techniques [17]: for this reason, we scale the features such that they have a mean value of 0 and a variance of 1; the test data is scaled according to the training set. To select the correct parameters C and γ for the SVC, as well as ϵ for the SVR, we use a parameter grid search method from `scikit-learn` called *GridSearchCV* [14]. The selected values are close to the standard parameters suggested by the `scikit-learn` SVM framework itself [14], i.e., $C = 1$ and $\gamma = 1/(var(X) * n)$, with n being the number of features and X the features of the training set.

[1] http://iti.tugraz.at/uwb-nlos
[2] We do this to avoid creating an artificial bias, but we have observed that the same trends detailed in Sect. 5 also apply when considering the entire dataset.

		Accuracy		Mean Error				RMS Error			
FS / Classifier	Features	SVC	RSS	All	LOS	WLOS	NLOS	All	LOS	WLOS	NLOS
-	No Mitigation	-	-	0.543	0.037	0.403	1.072	1.000	0.161	0.660	1.506
FS 1	F9	0.68	0.72	-0.224	0.180	-0.063	-0.688	0.850	0.243	0.562	1.266
FS 2	F7	0.07	0.72	-0.216	0.302	-0.093	-0.742	0.839	0.373	0.525	1.234
FS 3	F6,F7	0.50	0.72	-0.199	0.263	-0.063	-0.690	0.831	0.337	0.558	1.217
FS 4	F3,F6,F7	0.65	0.72	-0.144	0.228	0.012	-0.577	0.783	0.336	0.579	1.120
FS 5	F3,F4,F6,F7	0.70	0.72	-0.125	0.228	-0.022	-0.499	0.788	0.399	0.582	1.111
FS 6	F1,F3,F4,F6,F7	0.82	0.72	-0.104	0.159	-0.076	-0.340	0.824	0.331	0.545	1.210
FS 7	F1,F3,F4,F5,F6,F7	0.84	0.72	-0.098	0.177	-0.056	-0.358	0.836	0.338	0.560	1.224
FS 8	F1,F2,F3,F4,F5,F6,F7	0.84	0.72	-0.106	0.164	-0.077	-0.350	0.847	0.319	0.560	1.249
FS 9	F1,F2,F3,F4,F5,F6,F7,F8	0.90	0.72	-0.049	0.093	0.033	-0.235	0.621	0.238	0.418	0.911
FS 10	F1,F2,F3,F4,F5,F6,F7,F8,F9	0.92	0.72	-0.037	0.077	0.055	-0.207	0.639	0.226	0.430	0.942
RSS	F1,F2,F3,F4,F5,F6,F7,F8,F9	0.92	0.72	0.256	0.036	0.273	0.420	0.842	0.168	0.611	1.243
SVC	F1,F2,F3,F4,F5,F6,F7,F8,F9	0.92	0.72	0.033	0.051	0.173	-0.098	0.651	0.177	0.466	0.958

Table 1: Performance of the SVR mitigation strategy on different feature sets (FS) for different conditions. The SVR is trained on LOS, WLOS, and NLOS cases, while the SVC is only trained and evaluated on LOS and NLOS cases.

5.1 NLOS Classification

For the training and evaluation of the accuracy of the classification methods, we consider training samples from the LOS and NLOS data subset only. The reason for this is twofold: on the one hand, samples from the WLOS class cannot be easily separated into distinct NLOS and LOS classes. On the other hand, we are using binary decision in the *detection and mitigation* strategy. The idea is to train the classifier on the well-known class labels of LOS and NLOS, and then let it correct ranging errors also in WLOS conditions in the *detect and mitigation* strategy. For the SVR error prediction, as discussed in Sect. 5.2, no such classification is needed and both training and testing are performed on all conditions. The performance of the RSS- and SVC-based classifiers are evaluated in terms of the F1 score, which measures the accuracy of the classifiers. The F1 score for both methods is shown in Table 1 and is discussed next.

RSS-based NLOS classification. The RSS-based NLOS classifier is the one suggested in [4] and presented in Eq. 1. The output of this simple classifier is a continuous value in the range $1 \geq l \geq 0$. To create a binary classifier, we set a threshold at 0.5: any value above this threshold is considered LOS; NLOS otherwise. This classifier's F1 score is 72% and is reported in Table 1 under the *RSS* column.

SVC-based NLOS classification. We train and evaluate the performance of a SVC for different feature sets (FS) as shown in Table 1. The F1 score of the SVC is shown under the *SVC* column. It is evident that larger FS correlate with an increase of classification accuracy. FS 1 contains the same feature used for the RSS-based NLOS classification and also yields comparable results. FS 2 to 10 are increasingly complex feature sets that result in an increasing classification accuracy, with FS 10 exhibiting the best result with about 92% accuracy. Note that FS 2 to 8 are the same ones used by Maranò et al. [7] and follow the same trends.

5.2 NLOS Mitigation

Our goal is to mitigate ranging errors by training an SVR model that can predict errors of unseen measurements, which are then used for error correction. Therefore, no binary class-labels are needed and it is trained on all LOS/WLOS/NLOS conditions. For training, we first calculate the error of the estimated distance $y_i = \hat{d}_i - d_i$ of a sample i from the training set, where $\hat{d}_i$ is the measured distance and d_i is the true distance. We then train the SVR model based on the calculated errors and the corresponding features from the data samples. The SVR model is then used to predict the distance error $\hat{y}_i$ of the unseen samples of the test set. The performance is evaluated in terms of the mean residual error $ME = \frac{1}{N}\sum_{i=0}^{N}(y_i - \hat{y}_i)$ and residual root mean square error $RRMS = \sqrt{(\frac{1}{N}\sum_{i=0}^{N}(y_i - \hat{y}_i)^2)}$, where N is the number of test samples.

SVR-based NLOS mitigation. Table 1 contains a list of the ME and RRMS for different features under LOS, WLOS, and NLOS conditions. A negative number means that the distance is shorter than the true distance: this happens if the SVR predicts errors that are greater than the actual error is. The "*No Mitigation*" row contains the errors corresponding to the devices' raw measurements. The ME and RRMS error of the raw measurements under LOS conditions is low, which indicates – as expected – that LOS measurements are accurate and precise. FS 1 already reduces the ME and RRMS of the WLOS and NLOS measurements significantly: this aligns with the observation that FS 1 performs reasonably well in the NLOS classification task. However, the ME and RRMS of the LOS conditions are considerably (almost 10 times) worse than those obtained with the raw measurements. FS 2 contains only the measured distance as a feature and can also reduce both ME and RRMS for WLOS/NLOS conditions; however, also in this case, it severely influences the ME and RRMS of measurements taken in LOS conditions. FS 2 to 8 contain the same features used in [7] and exhibit a similar effectiveness in correcting WLOS/NLOS errors. We further introduce FS 9 and FS 10, which enrich the previous features sets with F8 and F9: this yields even better results. Specifically, FS 10 exhibits the lowest ME for the overall, LOS, and WLOS cases; still, applying the SVR-based correction on LOS measurements, increases the error by a few centimeters. Fig. 4 shows the CDF of the absolute errors prior (blue) and after (orange) mitigation for the LOS conditions using FS 10. Clearly, the accuracy under LOS conditions is reduced, whilst it is improved significantly under NLOS. For the WLOS case, greater errors are reduced, but smaller errors are worsened.

SVR-based NLOS detection and mitigation. For the *detection and mitigation* strategy, a measurement is only corrected by the SVR if it was previously classified as NLOS by either the RSS or the SVC classifier. The last two rows in Table 1 show the performance of this strategy based on classification using either the RSS or SVC methods

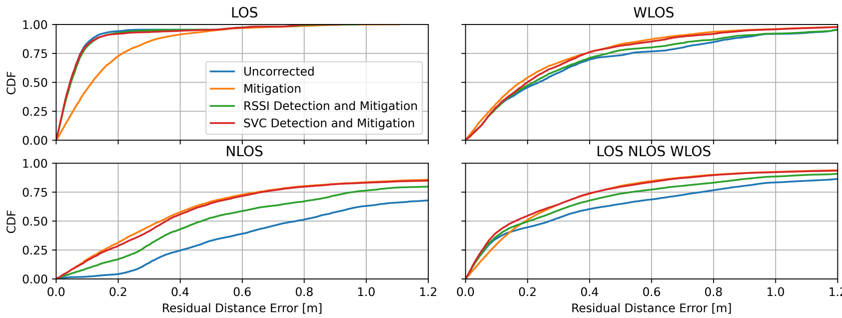

Figure 4: CDF of the residual distance error for different conditions and mitigation strategies.

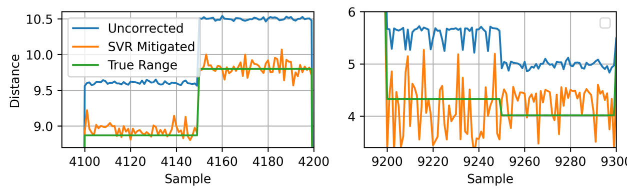

Figure 5: Stability of distance estimations.

(for the SVC, we employ `FS 10`). Compared with the *mitigation-only* strategy, the ME of the LOS measurements is reduced from ≈ 8 cm to 5 cm and to 3.6 cm with the SVC-based and RSS-based classifier, respectively. Still, the error of the measurements taken under LOS conditions is still higher than that of the raw measurements for the SVC classifier. The numbers for the RRMS follow the trend of the ME, where the LOS error is reduced by about 5 and 6 cm. However, the RRMS in WLOS and NLOS conditions slightly increases, since some NLOS measurements may be wrongly classified. Fig. 4 shows the performance of the *detection and mitigation* strategy using both the RSS-based classifier (green) and the SVC-based classifier (red).

5.3 Prediction Variation

During our analysis, we observed that the predicted error value can be subject to great variations even under the same experimental conditions. Each of the plots depicted in Fig. 5 shows the 50 individual distances recorded by the UWB devices in two NLOS settings. The blue line corresponds to the unmodified distance value, the orange line represents the corrected distance value based on the SVR prediction, whereas the green line indicates the true distance.

Fig. 5 (left) shows a relatively stable prediction over the 50 measurements taken in the same settings, with fluctuations in the order of 10–20 cm. Fig. 5 (right) shows fluctuations that are sometimes above 60 cm. Especially in the latter case, if only one distance measurement is taken, one could end up with the same absolute error. We could not find a clear correlation between the experimental conditions and the decrease in prediction stability, although stability is lowest under NLOS conditions. Specifically, the mean standard deviation of the predictions in the same setting is 0.14 for all cases, 0.07 under LOS, 0.15 under WLOS, and 0.2 under NLOS conditions.

6 CONCLUSIONS AND OUTLOOK

In this work we evaluate the performance of SVR-based error correction for UWB-based ranging systems. Our results align with and extend earlier studies showing that LOS measurements are subject to a decreased accuracy and precision under a *mitigation strategy*. We also perform a quick evaluation in terms of R^2 score, which measures how well a model is able to predict the target value: this analysis shows that for NLOS condition the R^2 score is 0.21, for WLOS 0.32 and for all conditions 0.42. Another problem that we identify with our model are large fluctuations even under the same measurement settings: this implies that several measurements should be taken to achieve a good error compensation. Our SVR and SVC model uses 700 and 300 support vectors, respectively, which we consider a reasonable size that can be implemented on an embedded device. In future work we aim to investigate more in detail the WLOS conditions and how to reduce the strong variations in the predicted correction. Moreover, we aim to implement the detection and mitigation strategies directly on an embedded device.

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