Comparison of Ultra-Wideband Range Processing and Filtering for Indoor Localization

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***Abstract*—The ability to locate assets and humans will lead to many services such as location based services especially in the material handling domain. The development of Industrial Internet of Things (IIoT) necessitates precise positioning, especially for moving objects in industrial environment. This way, automation processes with less human errors, and more safe environments are feasible. In order to achieve a wide reaching penetration of new control and tracking schemes in the Material Handling Domain (MHD), localization of assets needs to be realized in a cost efficient way with sufficient quality of positioning. The cost and quality of localization need to be weighted against each other and depend on the use case. We investigate variations of a indoor localization system, this is done through acquiring raw measurements from an Ultra Wide-Band (UWB) ranging system and comparing various processing approaches to achieve accurate positioning. We then compare the computational cost and quality of positioning of these approaches. Three multilateration algorithms are compared: gradient descent, least square, and recursive least square. Additionally, we investigate the impact of anchor node placement and additional filtering through a Kalman filter. We show that the maximum positioning error is mitigated by up to 30 % and the mean error by up to 4 % when using additional Kalman filtering of multilateration position estimates at comparably low additional computation cost. Our results suggest there are significant differences of localization quality and computational cost between the examined multilateration methods with no clear correlation of computational cost and positioning quality. We also show that the positioning quality and filtering improvement strongly depends on the UWB anchor height.**

I. Introduction

Localization in industrial spaces plays an increasingly important role in the context of new assistance and safety functions of autonomous machines. The German initiative *Industrie 4.0*, among other things, aims to enhance traditional industries by interconnecting devices with modern communication protocols to enable Machine-to-Machine (M2M) communication, increase productivity and safety as well as support the development of novel approaches for manufacturing and material handling. Localization of workers and mobile machinery plays a crucial role to enable a machine to provide assistance, autonomous and safety functions. The ability to locate assets and humans leads to various services such as mobile advertising, navigation, safety and security. Assets management in industrial environment profits from localization to observe, automate and analyze material handling processes.

To design an appropriate localization system, several factors need to be balanced [1]. In the material handling use case, a system which is able to increase or decrease coverage area, with low latency to be used as a (near-) realtime localization system is preferred. In addition, it should provide appropriate accuracy ranging from meters to centimeters with an appropriate reception range. Also, the design of the system should be cost efficient with low power consumption for longer life time of mobile power sources such as batteries.

The global positioning system (GPS) requires communication with at least four GPS satellites and offers location accuracy of a few meters. It is mainly used in outdoor applications because its accuracy degrades significantly in indoor applications. The GPS signals from satellites hardly penetrates buildings and infrastructure which leads to large positioning errors. Wireless local area network (WiFi) technology became a good candidate for indoor localization applications because of widespread availability of access points. There is no need to have new infrastructure installed for the system but it has disadvantages such as poor accuracy and comparably high power consumption. Ultra wide-band is suitable for indoor localization applications because of the ability to accurately measure the time of flight and therefore the distance to known base stations. It enables localization with comparatively good accuracy, low power consumption, comparatively low cost and high robustness [2], [3], [4]. Because of these advantages, we focus on UWB as a technology for indoor localization and are exploring various localization schemes using UWB in the following chapters.

This paper is structured as follows: Section II describes related work regarding indoor positioning approaches. The approach to produce a position estimate from UWB distance measurements and additional filtering is presented in Section III. We conducted experiments to verify our methods as described in Section IV. The experimental results are presented in Section V. Final conclusions are drawn in Section VI.

II. Related Work

Early systems used for tracking, used infrared (IR) signals to determine the position of objects inside a network that is made of IR sensors connected to centralized location server. This known as active IR positioning system [5]. There is are also passive IR positioning systems based on thermal IR sensors measuring the radiation emitted by objects such as humans [6]. IR systems perform positioning estimation at low cost and small form factor which makes them easy to carry by a person. On the other hand, there are drawbacks such as limited coverage range and accuracy. Also, IR suffers from disturbances when losing line of sight or interference from other light sources such as sunlight.

An alternative to IR is ultrasound, which is sound waves at frequencies above the audible limit of human hearing at approximately 20 KHz. Systems using these sensors often consist of transmitters (anchors) and receivers (tags) using ToA or TDoA techniques to calculate the distances to the anchors. Multilateration is then used to estimate the tag location [7]. The ultrasound signal has several advantages such as a slow propagation speed and a low cost of the transducers. These characteristics of ultrasound make it suitable for indoor positioning systems. Also the accuracy of these systems is quite high, reaching sub-centimeter accuracy. The drawbacks in these systems is the requirement of synchronization between network nodes, limited range coverage of sensors, a negligible penetration in walls and high power consumption compared to other technologies [8].

RFID has become popular and typical application span from asset tracking, service industries, logistics, and manufacturing, to supply chains. This large number of applications drives the price of RFID system down, creating a reliable device for automatic identification. RFID has some desirable features, such as contactless communications, high data rate and security, non-line-of-sight readability, compactness and low cost. With these capabilities, a RFID system is a good candidate for an indoor localization system. However, there are some difficulties in using RFID for localization. For example, it requires extensive infrastructure to accurately determine the location. In addition, most RFID devices lack RSSI functionality, which would help improving the accuracy. Various choices of tags, such as active, passive and semi-active tags, can affect the localization accuracy as well [9].

Bluetooth is specified for wireless personal area networks (WPAN). Bluetooth supports a range of 100 m communication and replaces the IR ports mounted on mobile devices [5]. Bluetooth Low Energy (BLE) supports a similar range with higher energy efficiency, as compared to older versions. Most of the existing BLE based localization solutions rely on received signal strength (RSS) to estimate the distance or proximity to BLE base stations with subsequent multilateration or fingerprinting. The disadvantage of BLE based on RSS is the low accuracy of the distance estimate. Due to its range, low cost and energy efficiency, BLE is a prime candidate for coarse localization. The positioning accuracy varies between 1m to 5m [5], [10], [11].

At the moment, most portable device such as smart phones, laptops and others use WiFi which makes it an ideal candidate for indoor localization, because there is no need for additional infrastructure and extra cost. Popular methods use similar approaches to BLE based localization, such as fingerprints of the Wifi infrastructure signal strength, to achieve indoor localization [12], [13]. However, Wifi based localization also suffers similar drawbacks as BLE based localization, such as coarse accuracy in the range of several meters due to inaccurate ranging and sensitivity to shadowing. The fingerprinting approach may also be combined with other sensors to ease the fingerprint collection process or increase the positioning accuracy [14].

Ultra wide-band (UWB) systems use a bandwidth larger than 500MHz. Due to this, some important features for UWB are high time resolution of its signal and robustness against multipath interference [4]. This makes UWB a very good candidate to use in positioning systems [2], [3]. A comparison of three commercially available UWB localization systems is presented in [15]. The authors document a mean accuracy of 0.49 m for the most precise system. The authors of [16] present a gradient descent approach to produce a robust location estimate from a set of partially erroneous range measurements.

III. Method

Our approach is using UWB infrastructure to measure the distance of the tracked UWB tag to four UWB anchors which are distributed around the area of localization. The measured distances are processed by a multilateration scheme to compute the tracked objects position. This position is then optionally subjected to additional filtering using a Kalman filter. The Kalman filter state includes two dimensional position and velocity. The time update of the filter state employs the usual equations of motion as shown in eq. (1), with $\vec{p}_k$ and $\vec{v}_k$ as the two dimensional vector of position and velocity respectively, and $t_{2\times 2}$ as a diagonal 2×2 matrix of the filter update period t.

$$\begin{pmatrix} \vec{p}_k \\ \vec{v}_k \end{pmatrix} = \begin{pmatrix} I_{2\times 2} & t_{2\times 2} \\ 0_{2\times 2} & I_{2\times 2} \end{pmatrix} \begin{pmatrix} \vec{p}_{k-1} \\ \vec{v}_{k-1} \end{pmatrix} \tag{1}$$

The measurement update maps the received position measurement $\vec{z}_k = \vec{p}_k^{\,m}$ directly onto the filter position state $\vec{p}_k$ of the state vector x according to

$$\vec{z}_k = \vec{p}_k^{\,m} = Hx_k \tag{2}$$

which expands to

$$\begin{pmatrix} p_k^x \\ p_k^y \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix} \begin{pmatrix} \vec{p}_{k-1} \\ \vec{v}_{k-1} \end{pmatrix}. \tag{3}$$

Fig. 1 shows the filtering architecture. The distance measurements from UWB are fed into the multilateration module, producing a position estimate. This estimate is then fed into the Kalman filter as a measurement. The positioning by UWB is evaluated using three different multilateration algorithms.

We are using gradient descent in a slightly modified variant of [17], recursive least squares [18] and the commonly employed least squares method.

The least squares (LS) method is a simple, commonly known method to produce a position estimate from multiple range measurements. Measurement noise and outliers have a direct effect on the position estimate and may cause it to "jump" when tracking a moving target. However, the quality of localization is expected to improve with an increasing number of range measurements. The LS method is also a good candidate for additional Kalman filtering which is expected to compensate jumps in positions due measurement noise, because of the added kinematic model.

The recursive least squares (RLS) method is introduced as a way to produce a position from sequential range measurements to multiple anchor nodes. This way, a positioning estimate can be produced from a minimum number of range estimates. The estimate is refined using further measurements over time. RLS is expected to behave in a similar way to the LS method, because we will only evaluate the final result of the sequential processing of all ranging measurements from one UWB sampling interval. This method is also used without a reference to previous measurements, therefore we expect RLS to "jump" between positioning estimates similar to LS.

The gradient descent (GD) method is chosen because it is shown in literature to be robust against interference. The method is stateful, i.e. it requires an externally defined initial position estimate and will use the previous position state as a basis for the next positioning update using the new measured ranges. Similarly to the Kalman filtered position estimates, this statefulness is expected to increase the positioning accuracy because it compensates measurement noise and outliers to a certain degree. Unlike [16], we are refraining from the exclusion of range measurements outliers before the actual computation of the new position and base the employed implementation on [17]. This is done to increase the comparability against LS and RLS approaches which include outliers in the position updates.

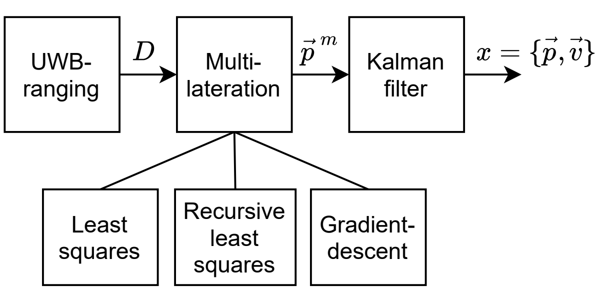

Figure 1: Flow of data from ranging via UWB producing a set of range measurements D to position estimate $\vec{p}^{\,m}$ through multilateration to a filtered position and velocity estimate x.

IV. Experimental setup

We conduct two experiments to compare the proposed positioning algorithms. The Decawave MDEK1001 is used as the UWB system, sampling the range measurements to anchor stations at 10 Hz. The anchor stations are placed at varying heights in the corners of a 3.0 m x 3.9 m area as seen in Fig. 2. In the first experiment 4 anchors are placed at same height of 2.05 m. The second experiment features anchors A_1 to A_4 respectively at heights of 2.49 m, 1.65 m, 2.05 m and 1.19 m. The varying anchor heights are chosen to provoke non-line of sight conditions, potentially diminishing the ranging accuracy and therefore the positioning quality. This allows us to examine how the positioning algorithms behave in adverse conditions.

All measurements are collected using a hand-held UWB tag that initiates the ranging measurements to the anchor nodes. A person is completing one trip around the area for experiment 1 and a almost a full trip in experiment 2 following the ground truth as seen in Fig. 2. The data is recorded first and then evaluated offline using Matlab. We are measuring the positioning accuracy as the distance from the ground truth. The hand held UWB tag is held above the ground truth which is marked on the ground. Minimal positioning errors due to human error are expected.

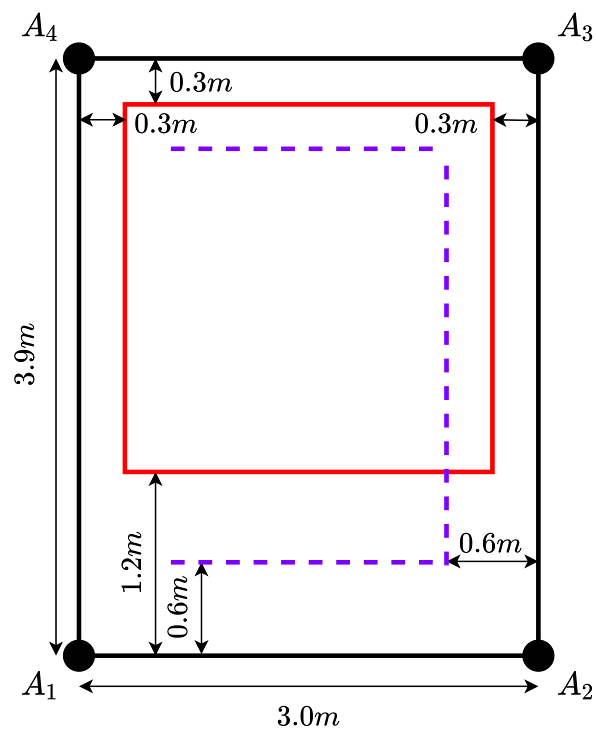

Figure 2: Setup of the positioning experiments. The red line shows ground truth of experiment 1, the dashed purple line marks experiment 2. UWB anchor stations A_1 to A_5 are marked as black dots.

V. Experimental results

The measurement results are shown in Tables I and II, as well as Fig. 3 and 4 for experiments 1 and 2 respectively.

The measurements show a distinct difference in accuracy for the three multilateration methods. In every case RLS

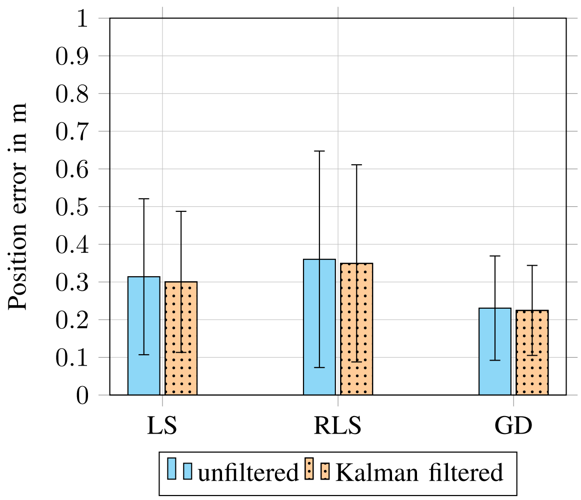

Figure 3: Mean distance from ground truth and the standard deviation as error bars for experiment 1 using UWB anchors at a fixed height of 2.05 m.

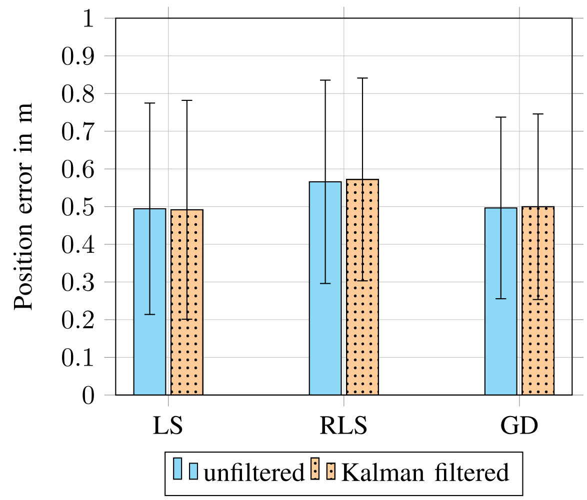

Figure 4: Mean distance from ground truth and the standard deviation as error bars for experiment 2 using UWB anchors at a heights ranging from 1.65 m to 2.49 m.

behaves worse than LS or GD, while GD performs best in both experiments. The positioning accuracy benefits from additional filtering especially due to the reduction in outliers. The improvement of the mean accuracy is relatively minor. Experiment 2 suggests that systematic errors due to a relatively static offset are not mitigated through additional filtering. However, more experiments are needed to reliably define the influence of varying ranging error types on different positioning methods.

In experiment 1, GD shows the best accuracy with a mean error of 0.225 m after filtering and a maximum error of 0.69 m before and 0.59 m after filtering. The biggest improvement of 30.6 % of the maximum error by additional filtering is achieved for RLS, followed by LS with an improvement by 26.9 %. The improvement of mean accuracy through filtering is relatively minor and ranges between 2.6 % and 4.3 % for GD and LS with RLS in between. Fig. 5 shows the plot of the positioning by GD and the filtered trajectory.

The changed anchor heights show a distinct effect on the accuracy in experiment 2. Here, the mean error about doubled for all multilateration methods. However, compared to experiment 1, the maximum error is less for LS and RLS and increased for GD. This suggests a systematic ranging error, possibly due to the on average decreased anchor height and consequently increased signal shadowing from the localized persons body. This increases the distances for the majority of the range measurements and leads to a relatively pronounced offset in certain parts of the track. Additional filtering has no significant impact on the mean accuracy in experiment 2 and lessens the maximum error by about 3.9 % for RLS and GD and by 8.4 % for LS. This leads to a maximum positioning error close to 1 m for every algorithm after filtering.

Besides the positioning accuracy, we also investigated the average computation time needed to process one position update with each multilateration method and additional Kalman

TABLE I: Average and maximum distance to ground truth in experiment 1 with and without additional Kalman filtering in meters. Percentage of change due to filtering.

	w/o filtering		w/ filtering	
	mean	max	mean	max
LS	0.314	1.411	0.300 (-4.33 %)	1.032 (-26.87 %)
RLS	0.360	1.931	0.349 (-2.98 %)	1.340 (-30.59 %)
GD	0.231	0.691	0.225 (-2.62 %)	0.587 (-15.11 %)

filter. The results are presented in Table III. The timings were measured using a laptop with 2.6 GHz Intel i7-6700HQ CPU using the *timeit()* function of Matlab R2018b. The results show a significant difference for the multilateration methods, with LS being 43 times faster than RLS and 116 times faster than GD. Processing one position update with the Kalman filter only needs 6 μs in contrast to the 39 μs of one LS update. This shows that the reduction of maximum errors through additional filtering is rather inexpensive. In order to estimate the trade-off between computation time and accuracy, we calculate a trade-off metric by multiplying the mean positioning error in cm with the computation time in ms. The results are also shown in Table III. LS leads by this metric while RLS achieves about half the score of GD. Although GD performs best in terms of accuracy, it is disproportionately expensive to compute. LS however, delivers an exceptional trade-off between computation time and accuracy. The drawbacks

TABLE II: Average and maximum distance to ground truth in experiment 2 with and without additional Kalman filtering in meters. Percentage of change due to filtering.

	w/o filtering		w/ filtering	
	mean	max	mean	max
LS	0.494	1.136	0.492 (-0.55 %)	1.039 (-8.54 %)
RLS	0.566	1.106	0.572 (1.12 %)	1.061 (-3.99 %)
GD	0.497	1.037	0.500 (0.63 %)	0.997 (-3.87 %)

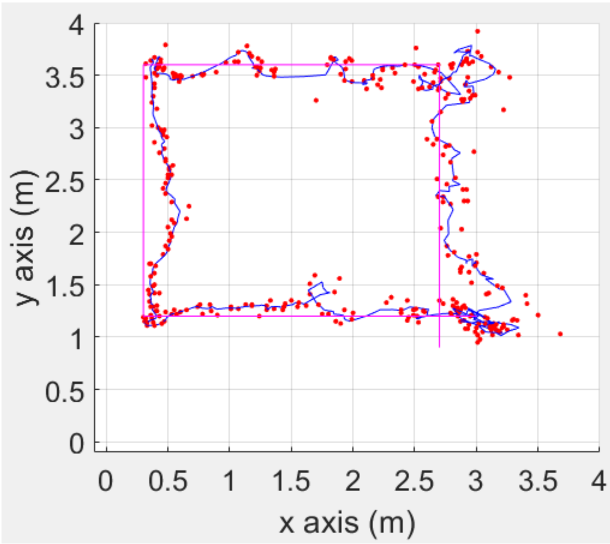

Figure 5: Plot of the positioning by GD as red points and the filtered trajectory as a blue line.

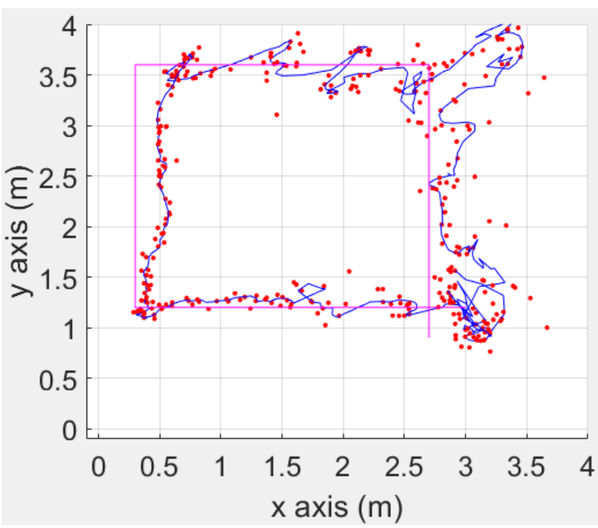

Figure 6: Plot of the positioning by LS as red points and the filtered trajectory as a blue line. Compared to GD, more outliers and a significant deviation from ground truth, also with filtering, are visible.

of "jumping" position solutions and high maximum errors compared to GD can be mitigated partly by additional and inexpensive Kalman filtering. This shows clearly, that the trade off between computation time and positioning accuracy is not linear between the examined methods.

It has to be noted that the authors of [18] state that the RLS algorithm is not specifically adapted to moving targets due to the low update rate of their UWB system which is reflected in our results. The computation time of RLS may also be improved: using the latest position estimate as a initial solution for the next positioning update, instead of computing a new initial estimate with each new set of measurements. However,

TABLE III: Median computation time of one position update of the multilateration methods and the Kalman filter and the positioning error by computation time tradeoff metric $meanError_{cm} * t_{comp}$ of experiments 1 and 2 normalized to 0..1.

	LS	RLS	GD	Kalman filter
computation time (ms)	0.039	1.686	4.54	0.006
trade-off for exp. 1	0.0117	0.5800	1	
trade-off for exp. 2	0.0086	0.4232	1	

the results already show a reduced accuracy compared to the solution by LS. Using an recent estimate may introduce further errors to the RLS solution. This may be mitigated by the use of a Kalman filter state prediction estimate that produces predictions with a greater frequency than measurement updates from RLS. When appropriately parametrized, the Kalman filter prediction may be sufficiently close to the actual state previous to new measurements and therefore provide a sufficiently accurate initial state for a new RLS solution at very low computation cost. We see potential for future work here. Additionally, as the authors state themselves, several costly computations of inverse matrices may be pre-computed and read from memory for every anchor configuration used in a ranging update. However, this is also true for LS.

VI. Conclusion

This paper presents a comparison of indoor localization schemes that may be used in the material handling domain for cranes, hoists, and other moving objects, or individuals. UWB has proven to be a cost-effective and accurate solution for indoor localization applications and was therefore chosen. By placing UWB anchor points at specific positions, moving objects or individuals that are provided with a UWB tag can be localized with centimeter precision in an indoor environment such as a factory hall. The measured distances between anchor points and tag are processed with various multilateration algorithms (gradient descent, recursive and conventional least squares method) in order to calculate the position of the moving object. Finally, the position can be optionally filtered by a Kalman filter, e.g., in order to compensate jumps in positions resulting from noisy measurements. We show that the maximum positioning error is mitigated by up to 30 % and the mean error by up to 4 % when using additional Kalman filtering of multilateration position estimates at comparably low additional computation cost. Our results show there are significant differences of localization quality and computational cost between the examined multilateration methods with no clear correlation of computational cost and positioning quality. We also show that the positioning quality and filtering improvement strongly depends on the UWB anchor placement. However, varying walking paths are tested in experiment 1 and 2, which limits the comparability of both experiments. Prospectively, step counting algorithms and other positioning sensors could be used to increase the reliability of the position estimation in non-line-of-sight parts, between UWB anchors and tag, of the indoor environment.

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