

# Improving the Robustness of Control-Grade Ultra-Wideband Localization

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**Abstract:** Ultra-wideband based localization technologies gained more and more attention over the recent years. Most of the predominant research focusses on two-way ranging based system topologies that feature limited multi-user scalability. This work aims to improve the accuracy and robustness of a highly scalable control-grade time-difference of arrival based localization system. The specific goal addressed in this work is to improve the robustness under non-line-of-sight conditions using ultra-wideband specific signal quality assessment and inertial sensor fusion. The accuracy of the proposed method is experimentally analyzed in two experiments. One experiment evaluates the performance under best-case conditions. A second experiment introduces strong interference through moving assets. Here, an accuracy improvement of over 60 % could be achieved compared to previous results. In order to relate those results, an experimental comparison to a widely used angle of arrival capable state of the art ultra-wideband localization system is made. It could be shown that the proposed method is more accurate than the state of the art in the strong interference scenario.

Keywords: Positioning systems, Ultra-wideband, Time-difference of arrival, Position estimation, Sensor fusion, Inertial measurement unit

## 1. INTRODUCTION AND RELATED WORK

The accuracy of ultra-wideband (UWB) localization systems is limited by the quality of their time of arrival (TOA) estimation. As pointed out by Vossiek et al. (2003), the wider field of wireless positioning faces a technology barrier: limited accuracy keeps it from being applicable to areas like automation and control. Such applications also impose significantly higher requirements on the reliability and robustness of positioning systems. This work aims to further improve the previously developed time-difference of arrival (TDOA)-based UWB localization system ATLAS through the integration of inertial measurement unit (IMU) data at the tags and signal quality assessment (SQA) at the anchors.

Most prior research uses two-way ranging (TWR) based approaches to measure the round-trip time (RTT) and calculate the distance between the nodes that are to be localized. Since this procedure requires a sequential message exchange between the nodes, the channel capacity and therefore the location update rate and number of total nodes is severely limited, see Jiang and Leung (2007). The idea of integrating IMU data with UWB is not new: Hol et al. (2009) proposed tightly coupled UWB/IMU pose estimation using a high-quality IMU and a commercial UWB system. Nyqvist et al. (2015) proposed integrating monocular vision data and fusing it with IMU and UWB readings. Both systems, however, require a side-channel for the transmission of the necessary IMU/vision information to the localization system. Hartmann et al. (2016) evaluate the concept of using additional signal quality data.

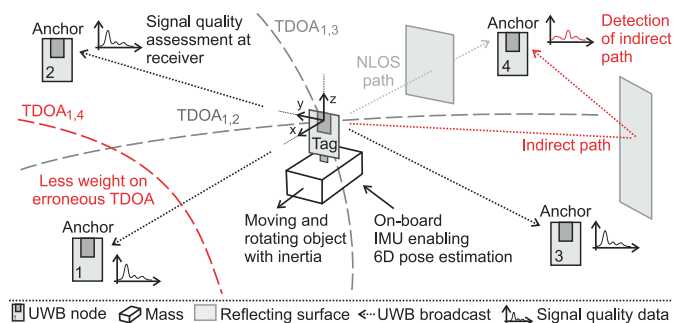


Fig. 1. Illustration of the proposed concept. The localization filter is augmented with inertial measurement and signal quality data to improve the robustness.

Although the signal quality data helped to improve their results, only the ranging error of TWR-based systems was analyzed.

The approach proposed in this work uses inertial sensing to augment position estimation with acceleration data and to supply orientation measurements in order to achieve full 6D pose tracking. The IMU-based orientation is estimated locally using an embedded filter developed by Madgwick et al. (2011). We integrate the resulting orientation and acceleration information as payload into the UWB protocol. We further assess the arrival time measurement at the anchors by considering the signal quality. In order to make use of the additional signal quality data that is available at many UWB receivers, a novel approach is introduced to further increase the robustness of the localization. The ba-

sic concept of the proposed approach is depicted in Fig. 1. Integration of SQA into a TDOA-based topology with its special requirements has, to the best of our knowledge, not yet been conducted. To show the potential of the proposed approach, this work further compares the results to a state of the art commercial system.

Inspired by the availability of low-cost transceiver systems and the opportunity of developing UWB localization towards control-style applications, a wide set of different topologies emerged, ranging from efficient TWR-based approaches, see Kwak and Chong (2010) to time-difference of arrival (TDOA) solutions, which are most prominent in well established commercial systems, see McElroy et al. (2014). Previously, Tiemann et al. (2016) could already show the potential of the localization topology proposed in this work in a robot-specific competition conducted by Potorti et al. (2017). The capability for control-grade applications in ideal environments for UAV-based applications could be shown by Tiemann and Wietfeld (2017). In addition to the traditional evaluation through published experiments, competitions provide a comparable basis in challenging environments, see Lymberopoulos and Liu (2017).

## 2. PROPOSED APPROACH

The general system structure is described by Tiemann et al. (2016). Therefore, only the extensions to the extended Kalman filter (EKF) based positioning filter are described in this work.

### 2.1 IMU Data Fusion

To make use of the raw accelerations provided by the IMU in the positioning filter, some scenario-specific preprocessing is needed. This need is due to interfering signals such as motor vibrations of tracked robots. Furthermore, measurement noise should be filtered out as much as possible. A well established filter for these approaches is the Butterworth low pass filter. The group delay of the Butterworth filter is frequency selective and strongly proportional to the filter order. The passband gain stability as well as the slope of the falling edge are order-proportional as well. As a consequence, filter parameterization is always a trade-off between these aspects, which is depending on the tracking scenario.

Information about a tracked objects acceleration is only useful if it is provided with respect to a static frame of reference. Because of that, a last preparative step is necessary, in which pre-filtered accelerations are projected from sensor coordinates to global coordinates. To do so, the orientation of the sensor w.r.t. global coordinates is required. A Madgwick filter running locally on the mobile node is used for orientation estimation, see Madgwick et al. (2011). The onboard IMU is sampled at a high rate which is used to update the Madgwick filter. The UWB localization typically has a lower update rate. In the proposed system, we transmit the orientation data in the form of quaternions within the UWB frames. The acceleration information is low-pass filtered and then averaged over the interval between transmissions. Further processing in the EKF is therefore done using the latest orientation data and filtered acceleration.

The position vector  $\mathbf{s}_i = (x, y, z)^T$  is tracked based on a constant velocity model in the previous filter design. This design is expanded to a second-order equation of motion by integrating the pre-processed accelerations  $\hat{\mathbf{a}}_i$  at positioning timestep  $i$ . To do so, the control vector  $\mathbf{u}_i$  and its related control-input model  $\mathbf{B}_i$  are formed. Equations (1) and (2) denote the resulting movement model using IMU data over the interval  $T_i$ .

$$\dot{\mathbf{s}}_i = \dot{\mathbf{s}}_{i-1} + \hat{\mathbf{a}}_i T_i \quad (1)$$

Compared to the previous constant velocity model, the filter is now able to react much faster to any movement changes by considering the measured accelerations in form of a second-order motion model.

$$\mathbf{s}_i = \mathbf{s}_{i-1} + \dot{\mathbf{s}}_{i-1} T_i + \hat{\mathbf{a}}_i \frac{T_i^2}{2} \quad (2)$$

The process noise matrix  $\mathbf{Q}_i$  describes uncertainties of the measured and preprocessed accelerations along the different axes, along with additional, application-dependent uncertainties due to unmodeled, higher order, effects of the actual movement.

### 2.2 Signal Quality Assessment

As previously noted, UWB localization is based on the TOA  $\hat{t}_{n,i}$  of the individual frames at each anchor  $n$ . The proposed approach uses a TDOA-based topology with wireless clock synchronization among the anchor nodes. The EKF observation vector  $\mathbf{z}_i$  contains range differences, i.e. the difference between a tags distance  $\hat{\rho}_n$  from an individual anchor and its distance to a reference anchor  $\hat{\rho}_1$ . Ranges are based on measured TOAs and the signal propagation speed  $c$ .

$$\mathbf{z}_i = \begin{bmatrix} \hat{\rho}_{2,i} - \hat{\rho}_{1,i} \\ \hat{\rho}_{3,i} - \hat{\rho}_{1,i} \\ \vdots \\ \hat{\rho}_{N,i} - \hat{\rho}_{1,i} \end{bmatrix} = c \begin{bmatrix} \hat{t}_{2,i} \\ \hat{t}_{3,i} \\ \vdots \\ \hat{t}_{N,i} \end{bmatrix} - c \begin{bmatrix} \hat{t}_{1,i} \\ \hat{t}_{1,i} \\ \vdots \\ \hat{t}_{1,i} \end{bmatrix} \quad (3)$$

The TOA range measurements  $\hat{\rho}$  are commonly modeled as having an error  $\varepsilon_{n,i}$  to the true range  $\rho_{n,i}$  with an independent normal random distribution, assuming that errors at each anchor are uncorrelated, see Patwari et al. (2005). We further assume that TOA measurement errors have zero mean, i.e. the mean range is the actual range, since all clocks in the system are periodically synchronized.

$$\hat{\rho}_{n,i} = \rho_{n,i} - \varepsilon_{n,i} \quad \varepsilon_{n,i} \sim \mathcal{N}(0, \sigma_{n,i}^2) \quad (4)$$

Resulting range difference measurements form a multivariate normal distribution, in which the variance of each element is given by the sum of the contributing range variances (individual anchor and reference anchor),

$$\text{Var}[\hat{\rho}_{n,i} - \hat{\rho}_{1,i}] = \sigma_{n,i}^2 + \sigma_{1,i}^2 \quad (5)$$

while the variance of the reference anchor remains as covariance between each pair of range differences.

$$\text{Cov}[\hat{\rho}_{m,i} - \hat{\rho}_{1,i}, \hat{\rho}_{n,i} - \hat{\rho}_{1,i}] = \sigma_{1,i}^2 \quad (6)$$

The structure of the resulting observation noise matrix  $\mathbf{R}_{r,i}$  is shown in (7) for a set of  $N$  anchors.

$$\mathbf{R}_{r,i} = \begin{bmatrix} \sigma_{2,i}^2 & & & & \\ & \sigma_{3,i}^2 & & & \\ & & \ddots & & \\ & & & \sigma_{N,i}^2 & \\ & & & & \sigma_{1,i}^2 \end{bmatrix} + \begin{bmatrix} 1 & 1 & \dots & 1 \\ 1 & 1 & \dots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \dots & 1 \end{bmatrix} \sigma_{1,i}^2 \quad (7)$$

In order to assess the quality of the individual TOA measurements, additional signal quality information from the receiver is used. Here, a novel method is proposed, combining two major indicators. Neiryneck et al. (2015) propose the ratio of the cumulated power of the received signal correlated with the corresponding reference pulse versus the first path power. This metric is used as an indication for non-line-of-sight (NLOS) conditions that may imply erroneous TOA measurements. In the following, the NLOS indication value, which is a ratio of powers in the logarithmic scale, will be denoted as  $q$ . The higher  $q$ , the more likely is a NLOS condition and conclusively a higher TOA error. The second metric is proposed by Hartmann et al. (2016) to assess the quality of the measured TOA. Here, the ratio of the measurement noise floor of the leading edge detection against the first path power is evaluated in  $h$ . The higher  $h$ , the better is the signal to noise ratio of the received TOA.

This work proposes incorporating those two indicators into the positioning algorithm to significantly improve robustness. We integrate the signal quality assessment into the measurement noise covariance matrix by forming a weighting quotient. The quotient is calculated for each anchor/TOA and every timestep  $i$ , as exemplary shown by (8).

$$\sigma_{1,i}^2 \sim \frac{q_{1,i}}{h_{1,i}} \quad (8)$$

This quotient serves only as a rough indicator of the actual TOA variance. In this context, its main purpose is to create weightings among the TDOAs. On the other hand, some consistency among observation noise matrices needs to be retained. Therefore, a regularization step is introduced as denoted in (9).

$$\mathbf{R}_i = \alpha \frac{\mathbf{R}_{r,i}}{\|\mathbf{R}_{r,i}\|_F} + \begin{bmatrix} 2 & 1 & \dots & 1 \\ 1 & 2 & \dots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \dots & 2 \end{bmatrix} \beta \quad (9)$$

Here, the TDOA measurement noise matrix is scaled by the inverse of its Frobenius norm and by a parameter  $\alpha$ ,

Table 1. ATLAS UWB Anchor Locations

anchor	1	2	3	4	5	6	7	8
x [m]	-1.11	-1.17	1.20	3.54	3.54	3.42	1.20	-1.17
y [m]	0.00	-3.49	-3.49	-3.45	0.02	3.52	3.49	3.49
z [m]	2.05	0.29	2.43	2.55	2.08	0.28	2.16	2.17

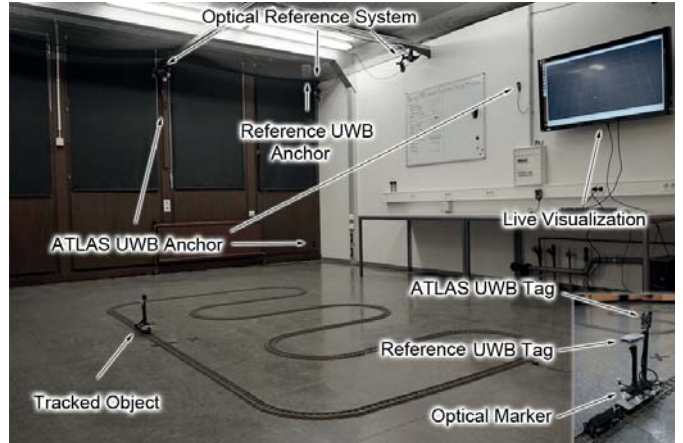


Fig. 2. Experimental setup. Note that the tracked object is equipped with a reference UWB tag, a self-developed ATLAS UWB tag and optical ground-truth markers.

before being added to a matrix parameterized by baseline variance  $\beta$ . Here,  $\alpha$  determines the overall impact of low signal qualities on measurement confidence. Parameter  $\beta$  represents the range-variance of each tag under perfect signal conditions, capturing further effects such as clock drift between synchronizations. As shown in the following experiments, the aspects introduced in this section lead to much more accurate and robust positioning. The filter reacts to varying channel conditions by prioritizing good quality TDOAs over bad quality TDOAs.

### 3. EXPERIMENTAL EVALUATION

The performance of the proposed approach is evaluated in an experimental setup where an object moving along a fixed track is localized by our system and two existing reference systems. High accuracy measurements are obtained using an *Optitrack* optical reference system equipped with eight motion capture cameras and passive markers on the tracked object at a rate of 120 Hz. The second system used for reference is a *Ubisense D4* real-time localization system (RTLS). In addition to TDOA, this system estimates local angles of arrival (AoA) through the use of multiple receivers in one anchor. Azimuth and elevation angle of the arriving signal are processed with a mean update rate of 40 Hz. The positions of the AoA-based UWB anchors are denoted in Tab. 2. The positioning improvements detailed in this work are implemented on the ATLAS TDOA-based UWB localization system. It consists of eight anchor nodes placed as listed in Tab. 1. The firmware of the individual nodes was modified to process, filter, transmit and receive the IMU data and additional UWB diagnostic information. Decawave UWB transceivers and an *InvenSense MPU-9250* IMU are used in the ATLAS nodes. The overall experimental setup is depicted in Fig. 2. Results are col-

Table 2. Reference System Anchor Locations

anchor	1	2	3	4	cal.
x [m]	-0.94	3.25	-0.81	3.23	0.00
y [m]	3.41	3.38	-3.4	-3.41	0.00
z [m]	2.75	2.78	2.75	2.75	0.28
yaw [°]	-63.2	-122.5	62.8	113.4	0.0
pitch [°]	-32.7	-23.2	-31.8	-23.1	0.0

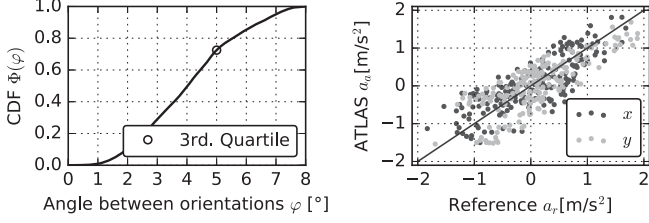


Fig. 3. Cumulative distribution function of the orientation estimation error. Correlation between IMU estimated and reference system estimated accelerations.

lected in multiple runs around the track during which all three systems are tracking the object simultaneously. The proposed positioning filter requires acceleration data with respect to the global coordinate frame. Therefore, the orientation estimation running locally on the node is evaluated first. Here, the filter is initialized during start-up and uses a Madgwick parameter of 0.04. The IMU is sampled at 512 Hz, while the orientation is transmitted with an update rate of 128 Hz. To filter the acceleration, the Butterworth filter is parameterized for the given scenario using a 2<sup>nd</sup> order and a cut-off frequency of 3 Hz. As depicted in Fig. 3, the orientation filter achieves good agreement with the optical reference system.

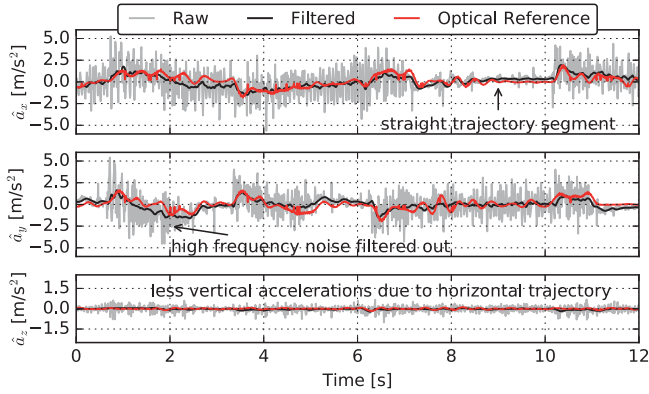


Fig. 4. Time-series of the global frame acceleration estimation on the IMU versus the estimation of the optical reference system.

As a reference for global frame acceleration, the motion capture positions are numerically differentiated. Although only a low-cost IMU is used, the low-pass filtered acceleration, which is used for further motion estimation, matches the reference data over the test track as depicted in Fig. 4. Since the third quartile is consistently below 6°, it is assumed that the orientation error’s contribution to the uncertainty in the estimated global frame acceleration is small. To qualify those results, Fig. 3 shows the correlation between the estimated and the reference-based acceleration. To compare overall system performance, we perform an experiment of ten laps around the test-track. Different localization algorithms, both for the AoA-based reference system and ATLAS, are compared by feeding the collected raw data into both systems’ post processing pipelines with different parametrizations.

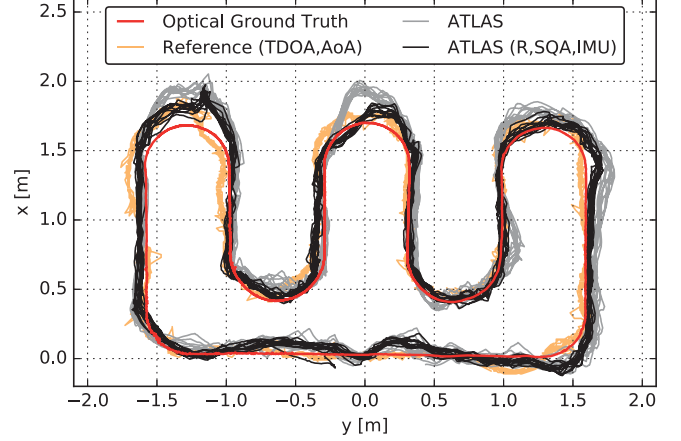


Fig. 5. Top-down trajectory of the experimental results without strong interference. Note that all systems suffer from minor reproducible systematic errors.

### 3.1 Best Case Evaluation without Interference

In order to evaluate the system performance of the ATLAS localization system without strong interference, an experiment in best-case conditions is performed. Each position on the full track has a line-of-sight condition to each individual anchor node. The vehicle on the test track is performing ten repetitions of the track at an average speed of 0.5 m/s.

The resulting trajectories in the horizontal plane are depicted in Fig. 5. The reference trajectory, obtained through the optical reference system is depicted next to the trajectory of the AoA-based reference system, using its best performing filter by fusing TDOA and AoA information. Next to that, the baseline ATLAS trajectory using none of the improvements proposed in this paper and using all proposed improvements is depicted. It is clearly visible that the proposed filter improves the performance of the ATLAS system significantly. The sensor fusion enables the system to compensate large outliers and stay close to the reference trajectory.

To further analyze this effect, a statistical evaluation in the form of violin plots is depicted in Fig. 6. The

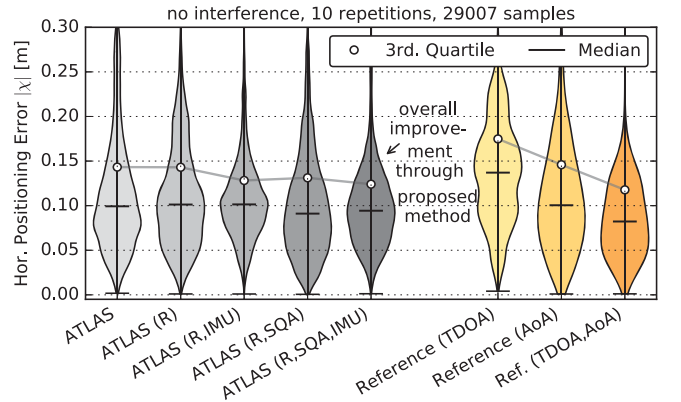


Fig. 6. Accuracy analysis of the proposed stages of improvement for the ATLAS UWB system versus the AoA-based UWB system without strong interference.



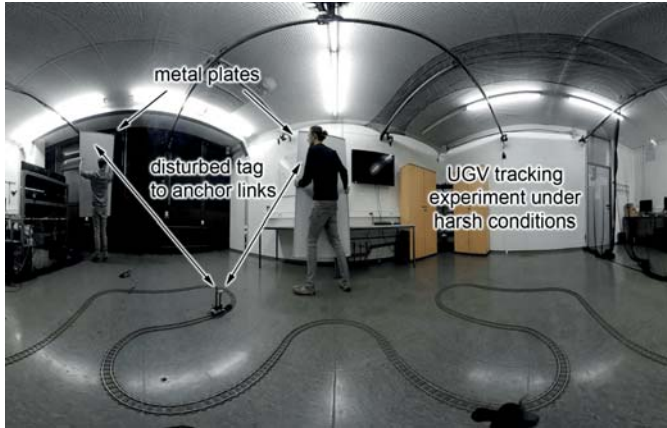


Fig. 7. Introduction of strong interference through mobile metal plates carried through the experimental setup.

different proposed improvements are depicted next to each other. The accuracy improves from the original ATLAS localization at 14 cm for the 3<sup>rd</sup> quartile to 12 cm when using all proposed methods. In order to create a baseline, we also evaluated the accuracy achieved with a state of the art system. Here, the basic system without the special AoA extension delivers a 3<sup>rd</sup> quartile accuracy of 17 cm. When using only AoA it is almost as good as the pure ATLAS localization at 15 cm. However, when combining TDOA and AoA, the AoA-based system is slightly more accurate than the improved ATLAS system at 12 cm. This is simply due to the additional AoA information that comes at the cost of using a multitude of the receivers at each anchor and placing them at a distance that significantly increases the anchor size. Furthermore, the error for the AoA information increases with the physical distance to the anchor nodes. A relatively small experimental setup is considered in this case, the positive effect of the fusion with AoA will decrease in larger setups though.

### 3.2 Evaluation with Strong Interference

For most real-life applications, interference in form of non-line-of-sight or strong reflection is a practical issue. The concept proposed in this work aims to improve the localization performance in such scenarios. Therefore, the experiment described in section 3.1 is repeated including strong interference. Two persons are carrying steel plates through the experimental setup covering individual anchor nodes or the mobile node from multiple sides. This procedure aims to mimic real-life usage of the system in industrial environments where workers are carrying equipment

Table 3. Horiz. Positioning Error Quantiles

	Q(50%) [m]	Q(75%) [m]	Q(90%) [m]	Q(95%) [m]	Q(99%) [m]
ATLAS	0.142	0.233	0.423	0.602	1.021
ATLAS (R)	0.145	0.214	0.329	0.411	0.569
ATLAS (R,IMU)	0.128	0.201	0.329	0.402	0.566
ATLAS (R,SQA)	0.105	0.154	0.226	0.274	0.439
ATLAS (R,SQA,IMU)	0.103	0.144	0.205	0.252	0.418
Ref. (TDOA)	0.168	0.236	0.358	0.463	0.709
Ref. (AoA)	0.145	0.212	0.307	0.371	0.563
Ref. (TDOA,AoA)	0.110	0.153	0.198	0.242	0.466

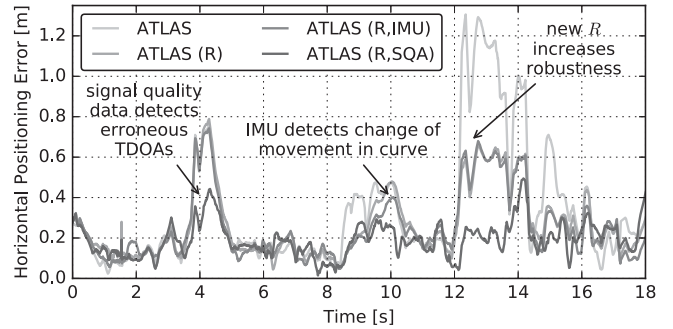


Fig. 8. Time-series of the horizontal positioning error to illustrate the effects of the proposed improvements.

or moving vehicles such as forklifts that are interfering strongly with in-place localization systems.

To illustrate the effect of strong interference, a time-series with horizontal positioning errors for each improvement step is depicted in Fig. 8. The ATLAS localization without interference mitigation suffers from the largest horizontal positioning error. The new noise covariance matrix is eliminating these largest errors by removing the dependency on a single reference anchor and distributing it upon all anchors. The IMU-based information is improving the results slightly by integrating the knowledge about acceleration in curved movements. The signal quality assessment is capable of eliminating most of the erroneous TDOA readings and therefore improves the results significantly.

In order to quantify the effects of the individual improvement steps, Fig. 9 depicts the distribution of horizontal positioning error. It is clearly visible that the proposed improvement steps have a significant effect on the localization accuracy. As expected, the new noise covariance matrix and the signal quality assessment have the largest effect. The original localization has a 3<sup>rd</sup> quartile accuracy of 23 cm. When using all improvement steps, the accuracy can be improved to 14 cm, which is an improvement of more than 60%. Although the AoA-based reference system is using a wired clock synchronization in comparison to the wireless synchronization used by the ATLAS system, its performance in TDOA-only mode is effected significantly under strong interference, with a 3<sup>rd</sup> quartile error at

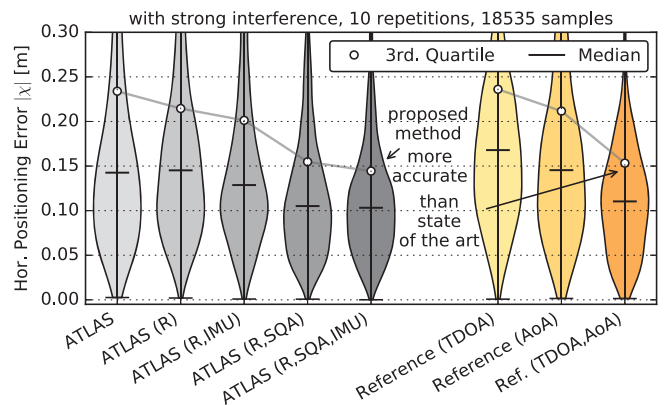


Fig. 9. Accuracy analysis of the proposed stages of improvement for the ATLAS UWB system versus the AoA-based reference system with strong interference.

23 cm. Even when fusing TDOA and AoA information for localization its 3<sup>rd</sup> quartile error is above 15 cm.

The proposed improvements are capable of compensating strong interferences through NLOS conditions induced by large metal objects and persons moving in the localization area. Although the state of the art AoA-based system delivers a slightly higher accuracy in optimal conditions, the proposed method is able to be more accurate in realistic scenarios with strong interference. Furthermore, in comparison to the AoA-based system, the proposed approach is capable of a fully UWB-integrated 6D pose estimation.

#### 4. CONCLUSION AND FUTURE WORK

This paper evaluates the potential of improving TDOA-based UWB localization through sensor fusion using IMU data and signal quality assessment. The previous system capable of only providing positioning data was enhanced to a full 6D pose estimation by adding an inertial sensor based filter running directly on the tag. The newly gained orientation information is highly accurate with a 3<sup>rd</sup> quartile error lower than 6°. The localization accuracy of the proposed method was analyzed in two experiments, with and without strong interference. It was found that the proposed method was able to improve the localization accuracy up to 60 % under strong interference. Furthermore, the proposed approach was experimentally compared to state of the art AoA-based systems achieving a comparable performance in optimal conditions and outperforming the AoA-based system in NLOS conditions. Future work will focus on a more detailed channel response analysis of the received TOAs to further improve the TDOA positioning performance through machine learning. Additionally, an advanced distributed wireless clock synchronization will be designed, implemented and analyzed to increase the system robustness in distributed setups.

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