Velocity estimation for UAVs using ultra wide-band modules

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***Abstract*—In this paper, a 3D velocity estimation solution based on ultra wide-band (UWB) signals is developed for navigation of unmanned aerial vehicles (UAVs) in indoor spaces. The solution incorporates two consecutive gradient descent algorithms for position and velocity estimation, as well as two linear Kalman filters for removing noise on the range measurements and the vertical position estimate. The solution is verified by three experimental scenarios with manual and autonomous flights of a quadrotor. In our implementation, 8 anchors are employed to construct the UWB system, while the Vicon MoCap system is utilized as the ground-truth for assessing the performance of the solution. All proposed algorithms are implemented on a computer on-board the quadrotor, with the low-level control for the quadrotor provided by the PX4 platform.**

I. Introduction

Ultra Wide Band (UWB) signal is a radio frequency signal, with a special feature of having a crisp pulse, compared to the narrow band signals available in WiFi, Bluetooth and ZigBee technologies. This feature makes it better for determining the exact time of transmission and reception of the signal. It is an important feature for a ranging process—the process of distance estimation between a transmitter and a receiver based on the time of flight of a signal. Thus, majority of the indoor position estimation techniques available for the UWB modules are based on the estimation of time of flight for signals sent from multiple anchors (i.e., modules with known position). Among the available techniques, time of arrival (ToA) methods [1], [2], such as one-way ranging (OWR) [3] and two-way ranging (TWR) [4], do not require any time-synchronization among the anchor modules, while the time difference of arrival (TDoA) technique needs the synchronization among the clocks of the anchors [5], [6]. Among these options, the double-sided TWR technique presents a reasonable compromise, considering its accuracy and complexity [7]–[9], and is the method adopted in the current research.

Although many researchers in the last two decades focused on the design of the indoor 2D and 3D position estimation methods and improving their performance, only a few investigations have been conducted on 2D and 3D velocity estimation of a UAV in indoor environments. Alongside the position and attitude, velocity is one of the key states required to be estimated for any mobile robot in order to achieve autonomous navigation [10]. Frequently, motion capture (MoCAP) systems comprised of multiple cameras are used for absolute position and attitude estimation in an indoor environment. Since the MoCAP system provides highly accurate measurements at high rate ($>$ 100Hz), one can use the first time-derivative of the estimated position signal to generate the absolute velocity of the UAV. However, MoCAP systems are expensive and more importantly, not available outside of research labs.

It has been shown that fusing the position estimation data and the acceleration measurement using Kalman or particle filters can lead to an estimation of velocity [11]–[13]. The accuracy of estimated velocity with these methods depends on the noise characteristics of the acceleration measurement. High variances and the presence of biases in the acceleration measurements, as typically observed on quadrotors with multiple rotating propellers, significantly degrade the accuracy of the velocity estimation. In [14], lateral drag forces are incorporated to propose a special extended Kalman filter for estimating the lateral attitudes, (i.e. pitch and roll angles) as well as the horizontal velocity components of a quadrotor. The algorithm needs the measurements of angular velocity of the quadrotor as well as the acceleration vector in the horizontal plane. Moreover, the robot mass and the constant coefficients of the lateral drag forces are required in the algorithm. In [15], a second-order sliding-mode differentiator is utilized for estimating the vertical velocity of a quadrotor, by fusing the acceleration measurements and the vertical position estimated with the OptiTrack MoCAP system.

There are some solutions in literature proposed for velocity estimation of mobile robots, which are not based on the acceleration measurements. In quadrotors, having flexible blades and different blade tip speeds on a rotor provide a slight difference in the generated lift forces on the blades. This leads to a relative flapping up on the advancing blade and a relative pushing down on the retreating blade. This behavior on the blade-driven flying robots is referred to as *blade flapping*. It is shown that by incorporating the induced drag force by blade flapping in the dynamic equations of the quadrotor, an observer can be developed for estimating the horizontal velocity of the quadrotor in its body frame [10]. In [16], a solution based only on the blade flapping concept is suggested for estimating the body-frame velocity of a quadrotor. The algorithm requires information on mass of the robot as well as the parameters for characterizing the propeller thrust, and also measurements of the rotational speed of each motor. Thus, it is not a generic solution that can be implemented on any quadrotor, conveniently. Furthermore, additional experiments need to be conducted to provide the required information on the propellers. An optical flow sensor provides a proper alternative for estimating the velocity of an aerial mobile robot [17], [18]. In this sensor, the rate of change of the features captured by a camera (usually mounted downwards on the quadrotor) are computed in the horizontal plane and then multiplied by the measured range to the features (computed by a sonar range finder) to estimate the 2D velocity of the quadrotor in its body frame. The attitude of the drone is utilized to convert the measured velocity to the inertial frame. However, the accuracy of the velocity estimation by the optical flow sensor strongly depends on the density and texture of features on the ground. Recently, a solution was proposed in [19] that combines the lateral dynamics model of the quadrotor, the angular velocity and acceleration, the magnetometer and the estimated velocity from an optical flow sensor, to provide a clean estimation of the velocity in the body frame. This solution, however, is quite complicated and requires information on the lateral dynamics of the vehicle as well as its mass. In [20], a UWB-based position and velocity estimation solution is proposed and tested for a drone flying in horizontal plane, while the estimation performance along z-axis is poor.

In light of the above limitations, in this paper, a solution for velocity estimation of a quadrotor in inertial frame is provided based on the UWB signals. Although it requires the installation of anchors of the UWB system in the environment where the robot is flying, this solution is relatively simple and cheap. Moreover, the proposed solution does not require any information on the internal dynamics of the robot, nor does it depend on the noisy acceleration measurements. Specifically, the contributions of the paper are as follows:

- we provide a velocity estimation solution based on UWB signals, without requiring acceleration measurements nor dynamics model;
- the full linear state estimation (position and velocity) is implemented on-board the robot and is therefore independent of the ground station.

II. UWB-BASED VELOCITY ESTIMATION SOLUTION

Definition-1. Here, the UWB system is defined as a system including n UWB anchors (where $n \geq 4$) and at-least one UWB tag module. In the system, each tag initiates the double-sided TWR process with each of the UWB anchors in a predefined order, and the anchors reply to the received request. We introduce a local frame of the UWB system, which has a local origin in the working environment. The positions of all UWB anchors are determined in this local frame and the estimated position of the UWB tag module is provided within the same local frame. For a UWB tag, its estimated position is transformed to the local NED frame by just considering the yaw angle of the local UWB frame in the NED frame. The origin of the local NED frame is set to be at the origin of the local UWB frame.

Definition-2. The localization problem in a 3D environment with multiple number of anchors can be formulated as an optimization problem and we employ the gradient descent (GD) method to solve it. In this regard, a representation is considered for the problem, by defining the closest anchor to the tag module as the reference point and subtracting the corresponding range measurement from the range measurements of others anchors [20]. Thus, the localization problem is stated as

$$\underset{\hat{\mathbf{p}}}{\text{minimize}} \ \left(\frac{1}{2}\mathbf{e_p}^T\mathbf{W_p}\mathbf{e_p}\right) , \tag{1}$$

where $\hat{\mathbf{p}} = [\hat{x}, \hat{y}, \hat{z}]^T \in \mathbb{R}^3$ is the estimated 3D position of the tag module and $\mathbf{W_p} \in \mathbb{R}^{m\times m}$ (for $m = n-1$) is a weight matrix for the measurements (defined in *Remark-2*). In addition, we define

$$\mathbf{e_p} = (\mathbf{B_p} - \hat{\mathbf{B}}_\mathbf{p}) \ \in \mathbb{R}^{m\times 1}, \tag{2}$$

where

$$\hat{\mathbf{B}}_\mathbf{p} = \mathbf{A_p}\hat{\mathbf{p}} , \tag{3}$$

in which

$$\mathbf{A_p} = \begin{bmatrix} 2(x_1-x_r) & 2(y_1-y_r) & 2(z_1-z_r) \\ 2(x_2-x_r) & 2(y_2-y_r) & 2(z_2-z_r) \\ 2(x_3-x_r) & 2(y_3-y_r) & 2(z_3-z_r) \\ \vdots & \vdots & \vdots \\ 2(x_m-x_r) & 2(y_m-y_r) & 2(z_m-z_r) \end{bmatrix} \in \mathbb{R}^{m\times 3} ; \tag{4}$$

and

$$\mathbf{B_p} = \begin{bmatrix} (d_r^2-x_r^2-y_r^2-z_r^2)-(d_1^2-x_1^2-y_1^2-z_1^2) \\ (d_r^2-x_r^2-y_r^2-z_r^2)-(d_2^2-x_2^2-y_2^2-z_2^2) \\ (d_r^2-x_r^2-y_r^2-z_r^2)-(d_3^2-x_3^2-y_3^2-z_3^2) \\ \vdots \\ (d_r^2-x_r^2-y_r^2-z_r^2)-(d_m^2-x_m^2-y_m^2-z_m^2) \end{bmatrix} . \tag{5}$$

Note that here $\mathbf{p_i} = [x_i, y_i, z_i]^T$ is the position vector of the ith anchor in the local UWB frame and $d_i \in \mathbb{R}^+$ is the measured distance of the tag module to the ith anchor. Moreover, $r \in \{1, 2, 3, ..., n\}$ is the index of the reference anchor.

Lemma-1. By utilizing GD method on the optimization problem defined in *Definition-2*, the position of the tag module in $3D$ space is updated iteratively at each time-step, using

$$\dot{\hat{\mathbf{p}}} = \boldsymbol{\alpha_p}\mathbf{A_p}^T\mathbf{W_p}\mathbf{e_p} , \tag{6}$$

with an initial solution of $\hat{\mathbf{p}}_\mathbf{0} = [0, 0, 0]^T$. Here, $\boldsymbol{\alpha_p}$ is a diagonal positive definite matrix defined in $\mathbb{R}^{3\times 3}$ and includes the learning rates of GD algorithm along the three axes. Note that in each iteration of the optimization process, the values of the distances in the elements of $\hat{\mathbf{B}}_\mathbf{p}$ are determined by utilizing the previous estimated position of the tag module.

Remark-1. The choice of the reference anchor affects the accuracy and the consistency of the localization results. Here, the nearest anchor to the tag is considered as the reference anchor, it changes as the tag module moves in the environment.

Remark-2. Here, the weight matrix for measurements, $\mathbf{W_p}$, is a diagonal positive-definite matrix where for $i \in [1,n] - \{r\}$, we define

$$\mathbf{W_p}(i,i) = \frac{d_s - d_i}{d_s} \ , \tag{7}$$

where $d_s = \max\{d_i\} + \delta_0$. The parameter $\delta_0 \in \mathbb{R}^+$ is used to avoid a zero value for the diagonal element of $\mathbf{W_p}$ corresponding to the highest measured distance.

Definition-3. Recalling the estimated 3D position of the UWB tag using *Lemma-1*, the Euclidean distance of the tag to the ith anchor can be written as follows (for $i \in [1,n]$)

$$(\hat{x}(t)-x_i)^2+(\hat{y}(t)-y_i)^2+(\hat{z}(t)-z_i)^2 = d_i(t)^2+\delta_i(t) \ , \tag{8}$$

where $\delta_i(t) \in \mathbb{R}$ is the error associated with the estimation process at time t. Differentiating (8) w.r.t. time, we obtain

$$\begin{aligned}\dot{\hat{x}}(t)(\hat{x}(t) - x_i) + \dot{\hat{y}}(t)(\hat{y}(t) - y_i) + \dot{\hat{z}}(t)(\hat{z}(t) - z_i) = \\ \dot{d}_i(t)d_i(t) + \frac{1}{2}\dot{\delta}_i(t) \ .\end{aligned} \tag{9}$$

Furthermore, we consider $\dot{\hat{\mathbf{p}}}(t) = [\dot{\hat{x}}, \dot{\hat{y}}, \dot{\hat{z}}] = [\hat{\dot{x}}, \hat{\dot{y}}, \hat{\dot{z}}] = \hat{\mathbf{v}}(t)$, where $\hat{\mathbf{v}}(t) \in \mathbb{R}^3$ is the estimated absolute 3D velocity of the UWB tag in the local frame of UWB system at time t. Assembling equations (9) for all of the anchors, one obtains

$$\mathbf{A_v} = \begin{bmatrix} (\hat{x}-x_1) & (\hat{y}-y_1) & (\hat{z}-z_1) \\ (\hat{x}-x_2) & (\hat{y}-y_2) & (\hat{z}-z_2) \\ (\hat{x}-x_3) & (\hat{y}-y_3) & (\hat{z}-z_3) \\ \vdots & \vdots & \vdots \\ (\hat{x}-x_n) & (\hat{y}-y_n) & (\hat{z}-z_n) \end{bmatrix} \in \mathbb{R}^{n\times 3}. \tag{10}$$

Furthermore, the optimization problem for velocity estimation is defined as follows

$$\underset{\hat{\mathbf{v}}}{\text{minimize}} \ \ (\frac{1}{2}\mathbf{e_v}^T\mathbf{W_v}\mathbf{e_v}) \ , \tag{11}$$

where $\mathbf{W_v} \in \mathbb{R}^{n\times n}$ is a weight matrix for the measurements and its elements on the main diameter are defined same as in (7). In addition, we define

$$\mathbf{e_v} = (\mathbf{B_v} - \hat{\mathbf{B}}_\mathbf{v}) \in \mathbb{R}^{n\times n} \ , \tag{12}$$

in which

$$\hat{\mathbf{B}}_\mathbf{v} = \mathbf{A_v}\hat{\mathbf{v}} \ , \tag{13}$$

and

$$\mathbf{B_v} = \begin{bmatrix} \dot{d}_1 d_1 + \frac{1}{2}\dot{\delta}_1 \\ \dot{d}_2 d_2 + \frac{1}{2}\dot{\delta}_2 \\ \dot{d}_3 d_3 + \frac{1}{2}\dot{\delta}_3 \\ \vdots \\ \dot{d}_n d_n + \frac{1}{2}\dot{\delta}_n \end{bmatrix} \in \mathbb{R}^{n\times 1} \ . \tag{14}$$

Lemma-2. The same GD method is used to solve the velocity estimation problem in *Definition-3*, as for the position estimation problem. Hence, the velocity of the tag module in $3D$ space is updated iteratively at each time-step, using

$$\dot{\hat{\mathbf{v}}} = \boldsymbol{\alpha_v}\mathbf{A_v}^T\mathbf{W_v}\mathbf{e_v} \ , \tag{15}$$

with the initial solution of $\hat{\mathbf{v}}_\mathbf{0} = [0,0,0]^T$. Here, $\boldsymbol{\alpha_v} \in \mathbb{R}^{3\times 3}$ includes the learning rates of the GD algorithm for velocity estimation along the three axes.

Remark-3. As can be seen from the right-hand side of (9), the time-derivatives of the estimated distances from the tag to all of the anchors as well as the associated estimation errors (i.e., δ_i) are required for the proposed velocity estimation algorithm. To deal with this issue, a sliding-mode differentiator is utilized following the work in [22]–[24]. For a generic scalar variable $h \in \mathbb{R}$, its time-derivative can be computed as

$$\dot{h} = \nu \ , \tag{16}$$

where

$$\begin{aligned} \dot{q} &= \nu \\ \nu &= -k_1|q-h|^{1/2} \ sgn(q-h) + \nu_1 \\ \dot{\nu}_1 &= -k_2 \ sgn(q-h) \end{aligned} \tag{17}$$

with $k_1 > 0$ and $k_2 > 0$ two constant parameters and $sgn(.)$ as the signum function [21].

Lemma-3. On the initial experiments with the proposed position/velocity estimation solutions, it was observed that there is noise on range measurements to the anchors and also in the z-axis position estimate. Consequently, two KFs are proposed for removing the noise on the range measurements (KF-1), as well as noise on the vertical position estimate (KF-2). The linear KF formulation is chosen, since the measurement models for the two mentioned parameters are linear. Each of the range measurements is computed by multiplying the measured time of flight of the corresponding RF signal by the speed of light. Also, the z-axis position estimation is formulated within a set of linear equations in (3). Hence, the motion and measurement models for the filters are formulated as follows:

$$\begin{aligned} \dot{\mathbf{x}} &= \mathbf{A_k}\mathbf{x} \ , \\ w &= \mathbf{C_k}\mathbf{x} \ , \end{aligned} \tag{18}$$

where

$$\mathbf{A_k} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}, \ \ \mathbf{C_k} = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}, \tag{19}$$

and $\mathbf{x} = [d_i; \dot{d}_i; \ddot{d}_i]$ ($i \in [1,n]$) for KF-1, while $\mathbf{x} = [z_t; \dot{z}_t; \ddot{z}_t]$ for KF-2. Here, w is the corresponding measured distance or z-axis estimated position. It is assumed the measurements/estimations have constant second-derivatives. The complete workflow of the solution including the two Kalman filters is depicted in Fig. 1.

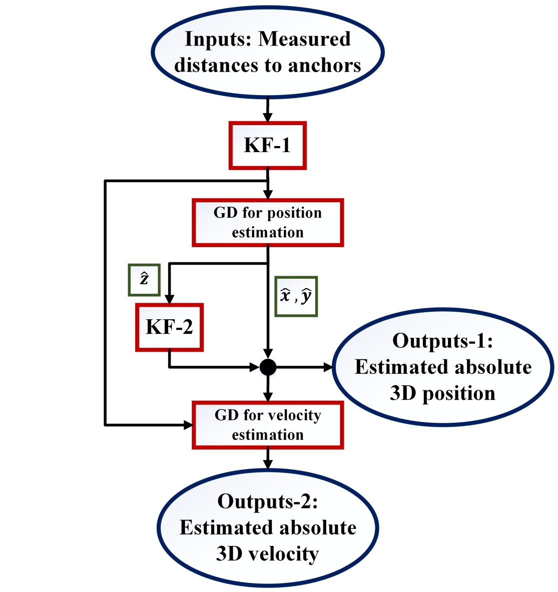

Fig. 1: 3D position and velocity estimation solution workflow based on UWB technologies.

III. Experimental set-up

A. The quadrotor

The experimental test results presented in this manuscript were carried out with a custom built small quadrotor ($\approx 300g$) with the following attached modules (Fig. 2):

- *Nanopi* board, for performing the proposed position/velocity estimation solution on-board, as well as the high-level position/velocity control of the quadrotor, running at 30Hz; here, the tuning parameters of the solution are set as $\boldsymbol{\alpha_p} = 1e$-9 diag$([2, 2, 1])$, $\boldsymbol{\alpha_v} = 1e$-8 diag$([1, 1, 1])$, $k_1 = 10.0$, $k_2 = 1.0$, $\delta_0 = 1000mm$.
- *pixracer* board, for handling the low-level attitude control of the quadrotor using the PX4 autopilot at 100Hz;
- *DWM1001-dev* module as the UWB tag for performing range measurements; it gathers data at 20-30Hz, depending on the number of available UWB anchors.
- To obtain ground-truth measurements with Vicon MoCap system, a rigid body with four markers is added on top of the quadrotor.

The communication between the Nanopi board and the pixracer board is implemented using the UART serial protocol. Similarly, the communication between the Nanopi board and the DWM1001-dev module is provided using UART. The off-set along z-axis of the vehicle between the location of the UWB tag and the centroid of the Vicon markers on the quadrotor is compensated in the results.

B. The UWB system

Here, a UWB system comprised of 8 anchors (see Fig. 2) is utilized for conducting the three test scenarios. Scenario-1 and scenario-3 are conducted at Space-1[1] with the approximate dimensions of $6m \times 6m \times 2.5m$, while Scenario-2 is organized in Space-2[2] with the approximate dimensions of $6m \times 6m \times 4m$, where Vicon MoCap system is available. The UWB system can be installed/uninstalled in either of the spaces conveniently ($\sim$ 30 minutes), attesting to transportability of the system. The Vicon MoCap system has a dedicated ground station for processing the captured data from six cameras which are mounted on the ceiling, and generating the position/orientation of the quadrotor. In both spaces used for our experiments, the anchors are located at the vertices of a cube (see Fig. 3) and the quadrotor is flown within this cube during the experiments. Locations of the anchors in the two spaces are presented in Table I and Table II. Their positions were measured using a measuring tape, to within 1cm accuracy.

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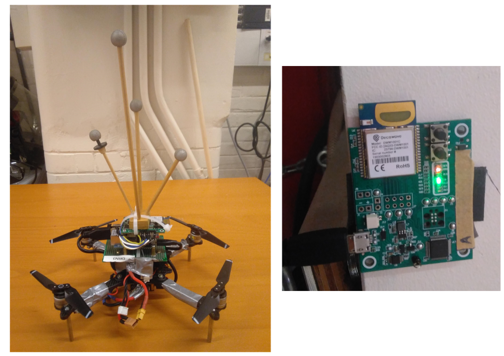

Fig. 2: Left: the quadrotor used for experiments. Markers are added for comparison with Vicon MoCap system. Right: a UWB anchor.

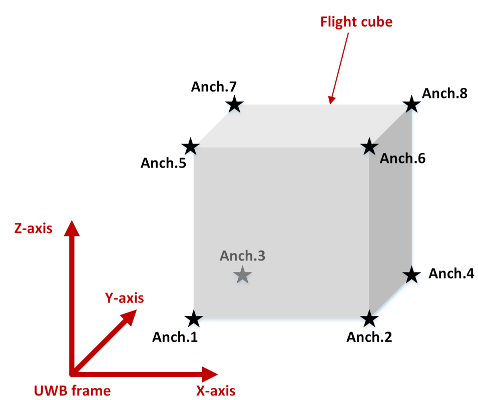

Fig. 3: The UWB system, the UWB frame and the flight cube.

IV. Experimental results

A. Scenario-1: Evaluation of Kalman filters

In this subsection, the use of two linear KFs proposed in *Lemma-3* is evaluated. In this regard, a set of manual

TABLE I: Positions of anchors in UWB frame for experiments of scenario-1 and scenario-3 in Space-1

No.	Position (mm)	No.	Position (mm)
1	$[-500, 0, 250]$	2	$[4880, 0, 250]$
3	$[0, 5920, 280]$	4	$[5590, 5790, 400]$
5	$[0, 0, 2290]$	6	$[4880, 0, 2240]$
7	$[0, 5920, 2390]$	8	$[5260, 5790, 2290]$

TABLE II: Positions of anchors in UWB frame for experiment of scenario-2 in Space-2

No.	Position (mm)	No.	Position (mm)
1	$[1050, 1000, 1000]$	2	$[-1300, 3100, 1000]$
3	$[-5700, -2850, 1000]$	4	$[-5700, 2800, 1000]$
5	$[1050, 1000, 2500]$	6	$[-1300, 3100, 2500]$
7	$[-5700, -2850, 2500]$	8	$[-5700, 2800, 2500]$

flights of the drone is performed to collect the data for the $3D$ position estimation. The evaluation is conducted through a comparative study by including three different cases as follows:

- *Case-1*: The GD algorithms are used without filtering.
- *Case-2*: The GD algorithms are used with KF-2 only.
- *Case-3*: The GD algorithms are used with both filters KF-1 and KF-2.

Results for z-axis position (height) estimation, comparing the above three cases are provided in Fig. 4. As mentioned earlier, the results are logged during a manual flight of the drone in the 3D environment. In that flight, the altitude of the drone was maintained approximately constant at ≃20cm above floor level, while the drone was flying in x-y plane. Case-3 result shows an initial convergence phase introduced by filtering the range measurements to the 8 anchors. As can be seen in Fig. 4, the usage of both KF-1 and KF-2 at the same time, contributes to achieving a smoother position estimation along z-axis.

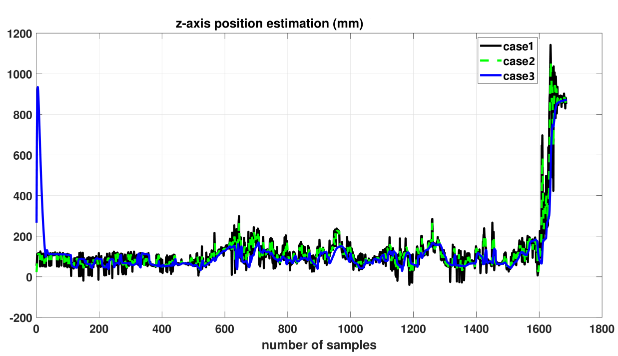

Fig. 4: Estimated z-axis position in three cases. Effect of using two KFs is visible in smoothing the estimate.

B. Scenario-2: Comparison with Vicon MoCap system

In order to evaluate the performance of our UWB-based position/velocity estimation solution, we employ a Vicon MoCap system as the ground-truth. The frequency of position estimation on the Vicon MoCap system is about 70Hz, while the proposed UWB position/velocity estimation tool is providing data at ≃30Hz. The velocity estimate for Vicon MoCap system is computed by using the sliding-mode differentiator in (17) on the estimated position data. The comparison results between the proposed UWB-based solution and Vicon Mocap system are provided in Figs. 5 and 6. Also, the corresponding mean values for the estimation errors are summarized in Table III. It is observed that the position and velocity components in the horizontal plane as estimated from the two measurement systems, are following each other closely. The mean value of position estimation error in the horizontal plane is 180mm and for the velocity estimation, it is 78mm/s. The corresponding mean error values for the z-axis are slightly higher, especially for the velocity estimation. The ranging measurement noise, as well as the estimation errors in horizontal plane contribute to higher errors in z-axis position and velocity estimates. The similar performance for the vertical position estimation has been reported in [20] and [25].

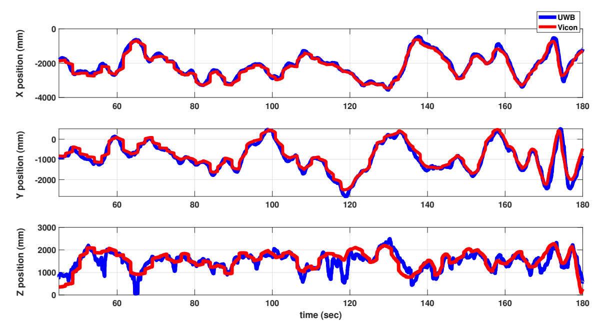

Fig. 5: Comparison of UWB 3D position estimation with Vicon MoCap system.

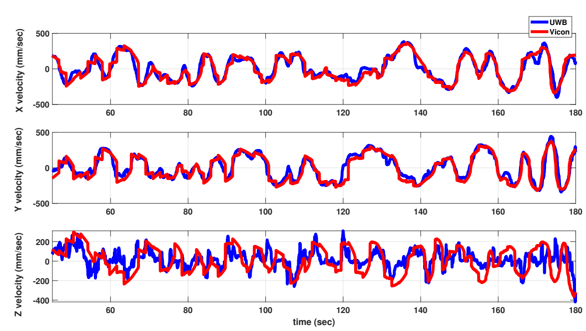

Fig. 6: Comparison of UWB 3D velocity estimation with Vicon MoCap system.

TABLE III: Comparison of UWB system with Vicon MoCap system: mean absolute errors for position/velocity estimates

Estimation error	Mean value	Estimation error	Mean value
x-axis position	116 mm	x-axis velocity	55 mm/s
y-axis position	138 mm	y-axis velocity	56 mm/s
z-axis position	235 mm	z-axis velocity	90 mm/s

C. Scenario-3: Quadrotor autonomous flight

Here, the results for test with autonomous flight of the quadrotor using the proposed UWB position/velocity estimation solution are provided. It is emphasized that the goal of this scenario is not to demonstrate any particular controller, but to show the feasibility of closing the loop with the proposed UWB-based position/velocity estimation solution and achieving reasonable performance for the entire closed-loop system. In this regard, two sets of consecutive PID controllers have been implemented for position and velocity regulation of the drone in 3D space. The frequency of these controllers is set to 30Hz, aligned with the frequency of position/velocity estimation. The desired attitude set-points generated by PID position/velocity controllers are sent to the pixracer on the drone via a MAVLink message. Thus, the attitude controller within the PX4 platform is utilized for determining the desired set-points for the rotational speed of each propeller on the drone. In this test, a desired reference point at $(+3, -2, -0.5)$m in the local NED frame is requested after switching the drone to autonomous flight mode at $t = 20$s. The objective is to allow the drone to reach and hover at the desired set-point. The gains for the PID controllers are tuned by trial-and-error during lots of test flights. The results of this experiment are presented in Fig. 7 to Fig. 10. They confirm that the estimated position and velocity from the proposed UWB-based solution can be combined with a simple closed-loop controller for autonomous flight of the quadrotor in an indoor area. The fluctuations in the tracking errors for the position and velocity of the quadrotor are commensurate with the expected performance in light of the results in Section IV-B, taking into account disturbances on the vehicle and limitations of the controller.

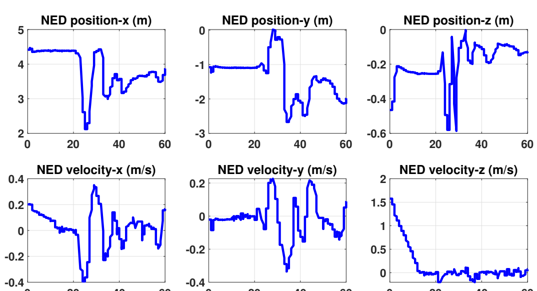

Fig. 7: 3D estimated position/velocity of drone in NED frame. Conversion from UWB frame to NED frame is accomplished by a rotation around z-axis through 35°.

V. Conclusion

In this paper, a solution for the velocity estimation of unmanned aerial vehicles in indoor areas is presented. The solution is based on UWB ranging measurements. It includes two gradient descent optimizations for 3D position and velocity estimations based on the ranging measurements received from multiple fixed anchors. Moreover, two linear Kalman filters are incorporated for removing the noise on the ranging measurements as well as on the z-axis position estimate. The solution is verified in three experimental scenarios. First, it is shown that the use of Kalman filters produces a significant smoothing of the estimates. Then, the accuracy of the proposed velocity estimation solution is evaluated in a 3D environment by comparing with the results from a Vicon MoCap system. It is observed that the velocity estimated data have a mean error of 78mm/s in the horizontal plane, while the mean accuracy of 90mm/s is achieved in the vertical direction. Finally, an autonomous flight of a quadrotor in indoor area is achieved by using the proposed position/velocity estimation solution.

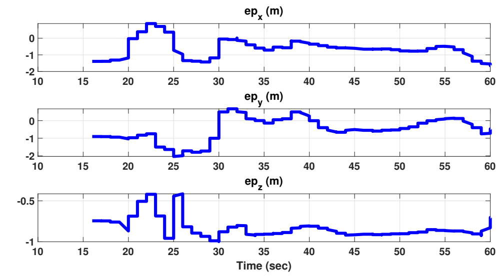

Fig. 8: Position tracking error in NED frame.

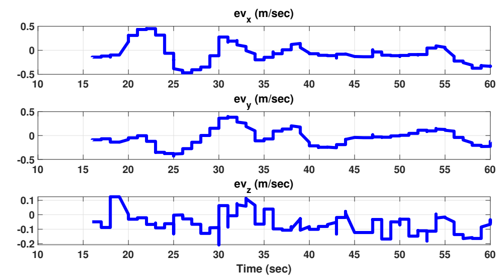

Fig. 9: Velocity tracking error in NED frame.

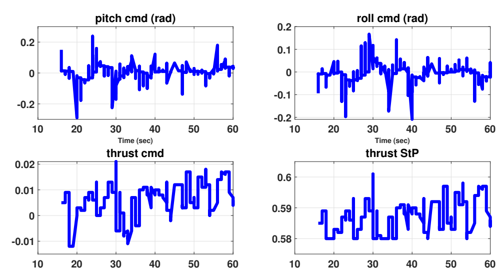

Fig. 10: Attitude set-points for the drone in NED frame. These values are sent to PX4 autopilot. The thrust set-point has a constant term for gravity compensation.

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