Evaluation of different wind estimation methods in flight tests with a fixed-wing UAV

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February 5, 2018

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1 Glossary

UAV Unmanned Aerial Vehicle
WCA Wind Correction Angle
UM Unfiltered Method
MAF Moving Average Filter
SWKF Simple Wind Kalman Filter
EKF Extended Kalman Filter
CEKF Calibrating Extended Kalman Filter
IMU Inertial Measurement Unit
GPS Global Positioning System

2 Introduction

In path-following applications on Unmanned Aerial Vehicles (UAVs) one need to know a lot of information. In order to be able to control the aircraft safely, knowledge about the surrounding air masses is helpful. There are several approaches for estimating the current wind vector using a standard sensor suite of Global Positioning System (GPS), Inertial Measurement Unit (IMU) and pitot tube. In the following I will present four different methods for wind estimation and show how they perform in flight with a fixed-wing UAV. In the end I will evaluate and compare the approaches to each other.

3 Tested algorithms

3.1 Unfiltered Method (UM)

The easiest approach for estimating the prevailing wind condition is to directly apply the formula from the wind-triangle (Fig. 1). ψ is the direction where the aircraft's nose is pointing. The Wind Correction Angle (WCA) is the angle the aircraft has to maintain between the desired ground track and its nose to compensate for prevailing wind vector.

$$\vec{V}_w^g = \vec{V}_g^g - \vec{V}_a^g \tag{1}$$

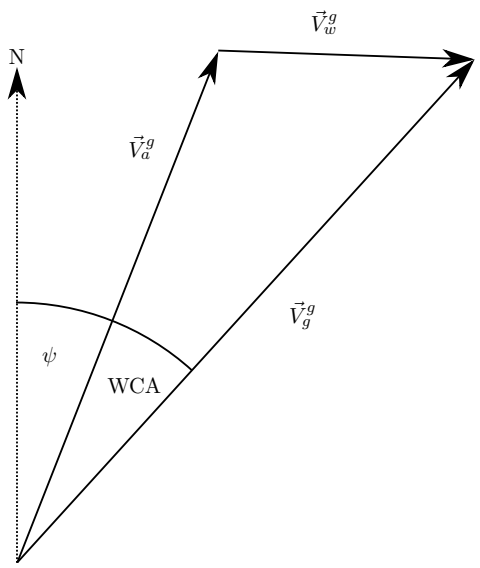

Figure 1: Wind triangle

$\vec{V}_g^g$ is provided by the GPS sensor and the on-board state estimation. $\vec{V}_a^g$ can be obtained by taking the airspeed from the pitot tube, which is ideally the longitudinal component if mounted correctly. So $\vec{V}_a^f = \langle V_{pitot}, 0, 0\rangle^T$ and $\vec{V}_a^g = R_f^g \vec{V}_a^f$ where R_f^g denotes the rotation matrix from body-fixed frame to earth frame and is obtained using the on-board IMU and magnetometer.

3.2 Moving Average Filter (MAF)

3.2.1 Algorithm

The Moving Average Filter computes the the wind-vector $\vec{V}_w^g$ from the UM recursively. The following algorithm is used:

$$\overline{x}_k = \overline{x}_{k-1} + \frac{x_k - x_{k-n}}{n}$$

$\overline{x}_k$ denotes the moving average from iteration step k. x_k is the measurement from the kth iteration and n denotes the number of frames over which the average will be obtained.

3.2.2 Implementation details

In the implementation the average of the iterations of the past 3min is taken. Since we operate the filters with a frequency of 10Hz: $n = 10\text{Hz} * 60\frac{s}{min} * 3min = 1800$. It is also possible to use longer periods of time, e.g. the standard for wind average is 10min. A shorter periods is used, because our flights do not take long enough for a 10min average.

3.2.3 Initialization

On initialization the buffer will be filled with the first measured wind vector $\vec{V}_w^g$.

3.3 Simple Wind Kalman Filter (SWKF)

3.3.1 Algorithm

It is very common to use Kalman Filters for estimating states in robots. The state used in the Simple Wind Kalman Filter (SWKF) is $\hat{x}_k = \langle \vec{V}_g^g, \vec{V}_w^g \rangle^T \in \Re^6$. The measurement vector is $z_k = \langle \vec{V}_g^g, \vec{V}_a^g \rangle^T \in \Re^6$.

Predict	
$\hat{x}_k^- = A\hat{x}_{k-1}$	Predict $\hat{x}_k$
$\hat{P}_k^- = A\hat{P}_{k-1}A^T + Q_k$	Predict covariance matrix $\hat{P}_k$
Update	
$S_k = H_k\hat{P}_k^- H_k^T + R_k$	Calculate innovation
$K_k = \hat{P}_k^- H_k^T S_k^{-1}$	Update Kalman Gain K_k
$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-)$	Estimate $\hat{x}_k$
$\hat{P}_k = (I - K_k H_k)\hat{P}_k^-$	Estimate covariance matrix of $\hat{x}_k$

Table 1: Kalman Filter algorithm

3.3.2 Implementation details

In the model the state is assumed to be constant. So the process matrix $A = I_{6x6}$. The filter will not only work for constant wind fields but also for slowly time-varying wind if the process covariance matrix Q is chosen adequately. In the implementation

$$Q = diag\left[\langle 1, 1, 1, 10^{-4}, 10^{-4}, 10^{-4} \rangle^T\right] * \Delta t^2$$

is used.
The measurement noise matrix R will be denoted by:

$$R = diag\left[\langle 1, 1, 1, 4, 4, 4 \rangle^T\right]$$

3.3.3 Initialization

For running the filter it has to be initialized properly. The calculation will be started right after take-off. The state estimation and the covariance will have to be set to an initial value. In the implementation these values are used:

$$\hat{x}_0 = \langle V_{g0}^g, 0, 0, 0 \rangle^T$$

$$\hat{P}_0 = I_{6x6}$$

3.4 Calibrating Extended Kalman Filter (CEKF)

Airspeed measurements from an uncalibrated pitot tube usually have bias. That has multiple sources. It is important that the pitot tube is mounted on an adequate spot, where the airflow is not disturbed by turbulence caused by the aircraft. Also the tube only measures the pressure difference ΔP between the static air pressure P_{stat} and the total pressure measured in the aircraft's longitudinal direction P_{tot}.

$$\Delta P = P_{\text{tot}} - P_{\text{stat}} \tag{2}$$

$$\Delta P = \frac{1}{2}\rho \left(V_{ax}^f\right)^2 \tag{3}$$

where ρ denotes the air density. The pitot tube assumes a steady temperature, zero air viscosity and no disturbance by the aerodynamic flow of the UAV itself. In larger aircrafts these errors can be eliminated by wind tunnel tests and computer simulations. In smaller low-budget UAVs that effort is not feasible. Cho et al [1] and Johansen et al [2] both proposed similar methods for estimating wind, airspeed and a correction factor for an uncalibrated pitot tube. I will present their approach in this section. The correlation between the airspeed and the differential pressure is given by equation 4.

$$\Delta P = \eta \left(V_{ax}^f\right)^2 \tag{4}$$

where η denotes the calibration factor and V_{ax}^f is the airspeed in the aircraft's longitudinal direction. The estimated state from this filter is $\hat{x}_k = \langle \vec{V}_w^g, \eta, \vec{V}_a^f \rangle^T \in \Re^7$. The measurement vector is $z_k = \langle \vec{V}_g^g, \Delta P \rangle^T$.
The model makes the following assumptions:

$$\dot{\vec{V}}_w^g = 0 \tag{5}$$

$$\dot{\eta} = 0 \tag{6}$$

$$\dot{\vec{V}}_a^f = 0 \tag{7}$$

$$\text{from 1 and 4: } z_k = h(\hat{x}_k) = \left[\vec{V}_w^g + R_f^g \vec{V}_a^f; \eta \left(V_{ax}^f\right)^2\right] \tag{8}$$

The integration of an IMU is also possible. Equation 7 would have to be replaced with equation 9:

$$\dot{\vec{V}}_a^f = a_{CG}^f - \omega \times \vec{V}_a^f \tag{9}$$

where a_{CG}^f denotes the linear acceleration in aircraft body frame and ω describes the angular turn-rates. The IMU is not used in this implementation for simplification reasons.

Due to the simplification from equation 7 the process function $\hat{x}_k^- = f(\hat{x}_{k-1})$ is reduced to $\hat{x}_k^- = A\hat{x}_{k-1}$ with $A = I_{7x7} = F_{k-1}$.
The matrix H_k is the Jacobian matrix from function $h(\hat{x}_k)$ (Eqn. 8).

$$H_k = \begin{pmatrix} 1 & 0 & 0 & 0 & & R_f^g & \\ 0 & 1 & 0 & 0 & & & \\ 0 & 0 & 1 & 0 & & & \\ 0 & 0 & 0 & (V_{ax}^f)^2 & 2\eta V_{ax}^f & 0 & 0 \end{pmatrix} \in \mathbb{R}^{4x7} \tag{10}$$

The process noise and the measurement noise matrix are set to these values:

$$Q = diag\left[\langle 10^{-4}, 10^{-4}, 10^{-4}, 10^{-8}, 0.01, 0.1, 0.1 \rangle^T\right] * \Delta t^2 \tag{11}$$

$$R = diag\left[\langle 1, 1, 1, 10 \rangle^T\right] \tag{12}$$

Predict	
$\hat{x}_k^- = f(\hat{x}_{k-1})$	Predict $\hat{x}_k$
$\hat{P}_k^- = F_{k-1}\hat{P}_{k-1}F_{k-1}^T + Q_k$	Predict covariance matrix $\hat{P}_k$
Update	
$S_k = H_k\hat{P}_k^- H_k^T + R_k$	Calculate innovation
$K_k = \hat{P}_k^- H_k^T S_k^{-1}$	Update Kalman Gain K_k
$\hat{x}_k = \hat{x}_k^- + K_k(z_k - h(\hat{x}_k^-))$	Estimate $\hat{x}_k$
$L_k = (I - K_k H_k)$	
$\hat{P}_k = L_k\hat{P}_k^- L_k^T + K_k R_k K_k^T$	Estimate covariance matrix of $\hat{x}_k$

Table 2: EKF algorithm

3.4.1 Initialization

It is important for this filter to not run it prior takeoff, because η tends to drift away while on ground. After takeoff, the filter will be initialized with

$$\hat{x}_k = \langle 0, 0, 0, 0.5 * \rho_{\text{std}}, R_g^f \vec{V}_g^g \rangle^T \tag{13}$$

$$\hat{P}_k = diag\left[\langle 25, 25, 8, 10^{-3}, 12, 12, 12\rangle^T\right] \tag{14}$$

where $\rho_{\text{std}} = 1.225 kg/m^3$ denotes the air density on sea-level at 15° C and R_g^f is the rotation matrix from earth fixed frame to body fixed frame.

4 Flight test

In the following the just explained estimation approaches will be evaluated: Unfiltered Method (UM), Moving Average Filter (MAF), Simple Wind Kalman Filter (SWKF) and Calibrating Extended Kalman Filter (CEKF).

The tests are flown with a Bormatec Explorer fixed-wing aircraft with a 2.2m wingspan and a weight of approx. 2.5kg (Fig. 2). The filters run with telemetry data input on a ground station with a frequency of 10 Hz. The telemetry link uses the Mavlink protocol. The filter runs using ROS and MAVROS as an interface to Mavlink.

Figure 2: Bormatec Explorer UAV

Figure 3: Flight path

4.1 Location

Our test site was 20km north-east of Pittsburgh at a small airstrip for RC planes on top of a small hill. We had windsocks and a small weather station to have a reference for the wind.
The weather station on the test site showed a ca. 5 - 12 knots (2.6 - 6.2 m/s) wind speed from a direction of ca. 330° on ground level during the day. Unfortunately we were not able to record the on-ground wind data. The historic weather from the Allegheny County Airport (KAGC) 30km south from our testsite shows 4 - 6 knots (2.1 - 3.1 m/s) wind speed.

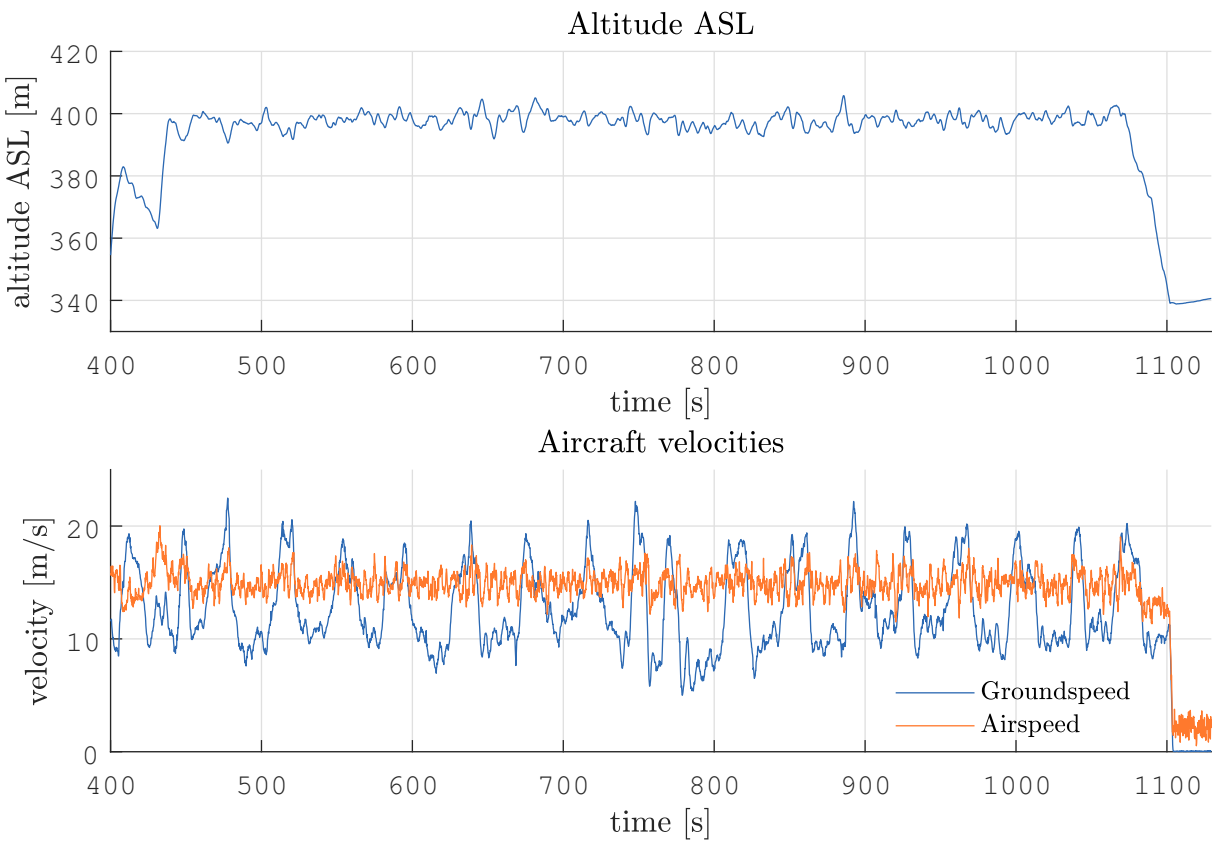

Figure 4: Altitude and velocity profile from test flight

4.2 Flown paths

The test flight used for evaluation took place at an altitude of 50m above ground and an airspeed of ca. 15 m/s. We flew racetrack patterns in multiple direction and different turns (Fig. 3), so we could observe the effect of the wind on the aircraft from various perspectives. The tracks where flown by an autonomous path-following controller which had Dubins as well as trochoid paths as input.
The filters were started right after takeoff to avoid building up a bias from being on ground.

4.3 Wind estimations

4.3.1 Unfiltered Method (UM) and Moving Average Filter (MAF)

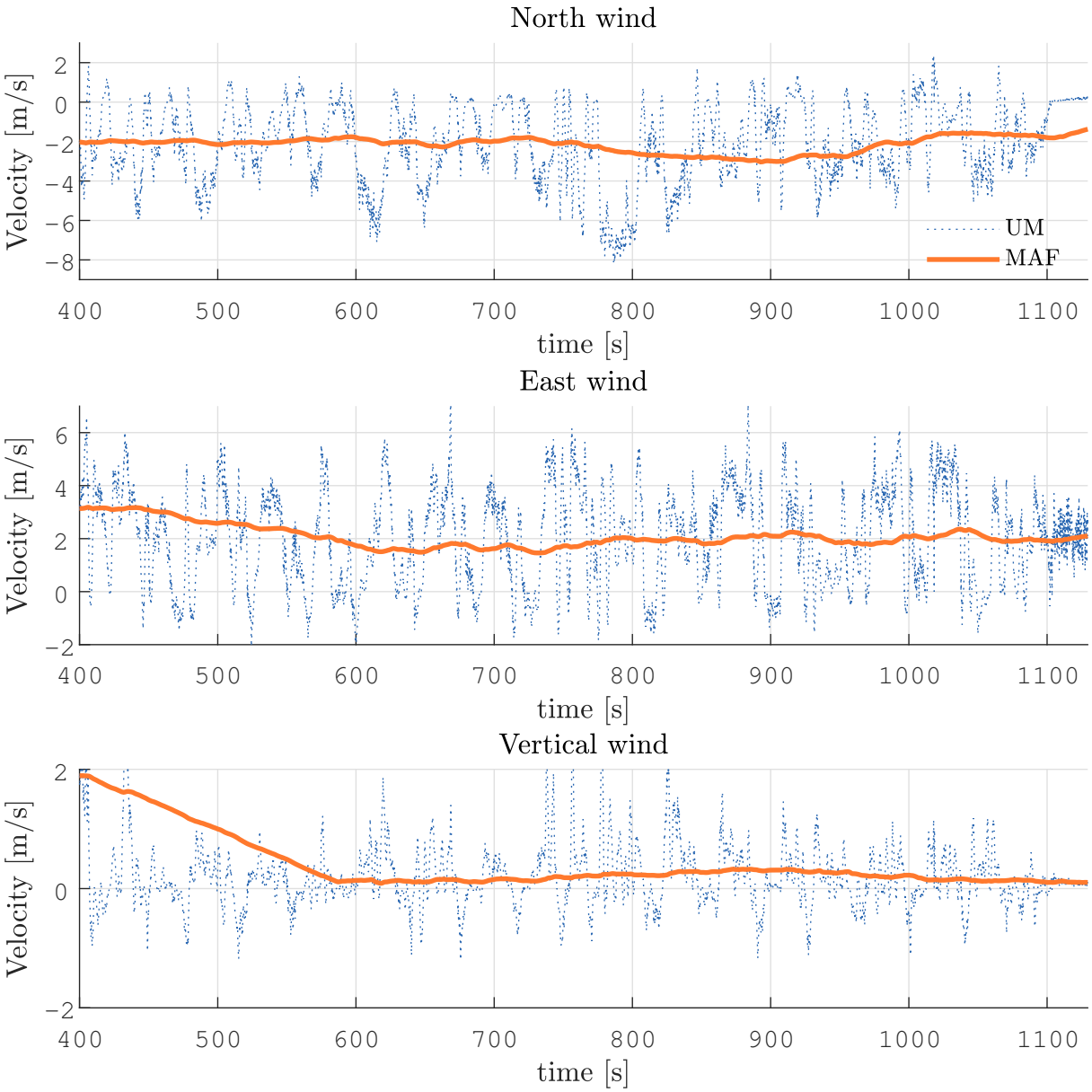

Figure 5: Wind vector estimated by UM and MAF

Figure 5 shows the wind vector components of UM and MAF. The UM has very high noise. The reasons for that is the high measurement noise from the pitot tube. Also the wind triangle does not apply well to turns of the UAV.
The 3min MAF is able to compensate the noise very well. In the plot of the vertical wind one can see the importance of a proper initialization for this kind of filter. If initialized wrongly, the MAF needs 180s to converge to a reasonable value.

4.3.2 Simple Wind Kalman Filter (SWKF)

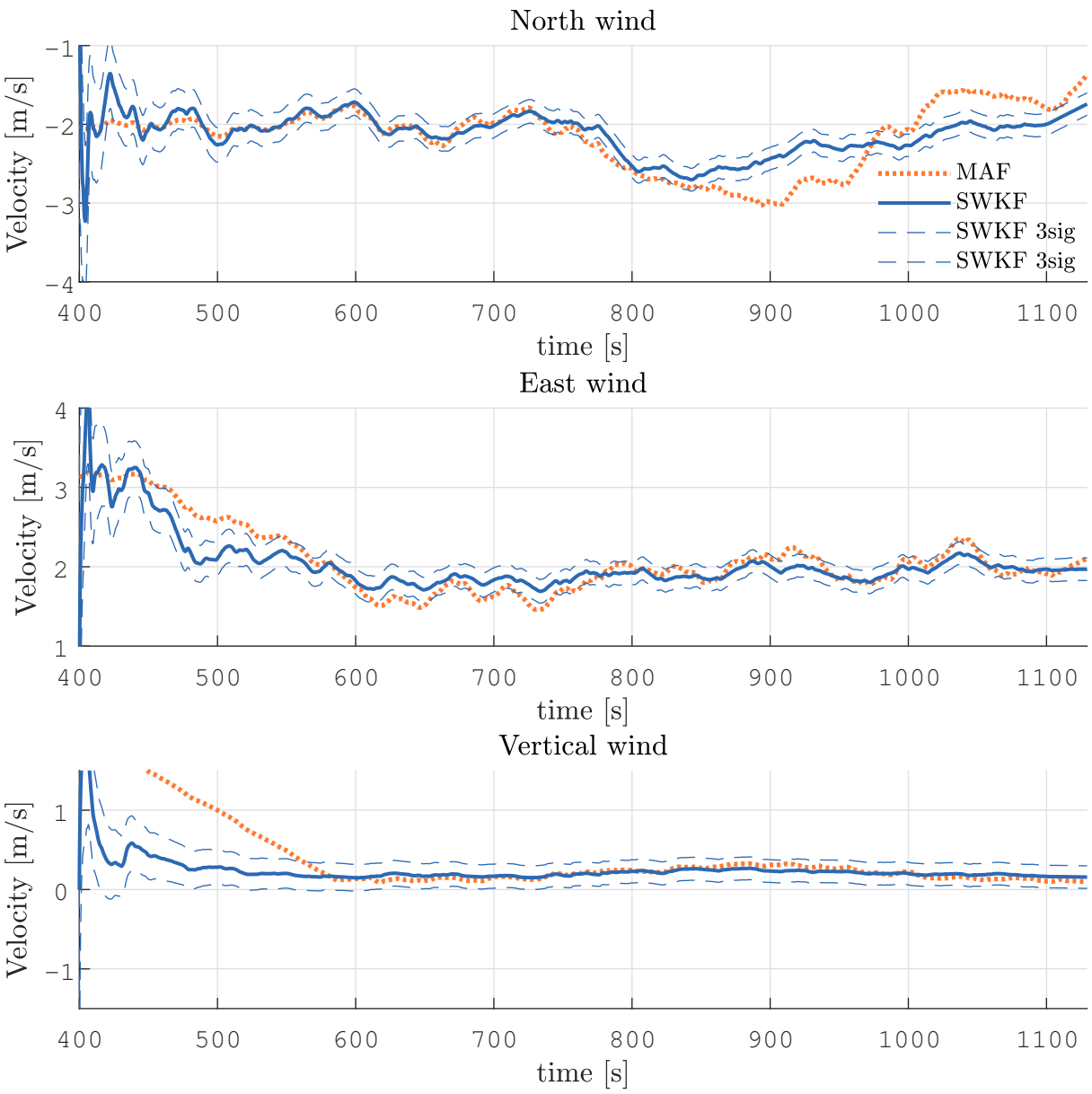

Figure 6: Wind vector estimated by SWKF

The SWKF output is shown in figure 6. The upper and lower 3σ border has been computed from the state covariance matrix $\hat{P}_k$. The filter has converged to reasonable values after ca. 50-60s, which is much faster than the MAF. Other than that, it seems to comply with the MAF. The moving average is within the 3σ borders of the Kalman filter for most of the time. In time interval 800s - 1000s of the North wind it is visible, that the SWKF adapts faster to changes in wind, while the MAF again needs 180s to come to the same conclusions. It could be improved by using a weighted average filter.

4.3.3 Calibrating Extended Kalman Filter (CEKF)

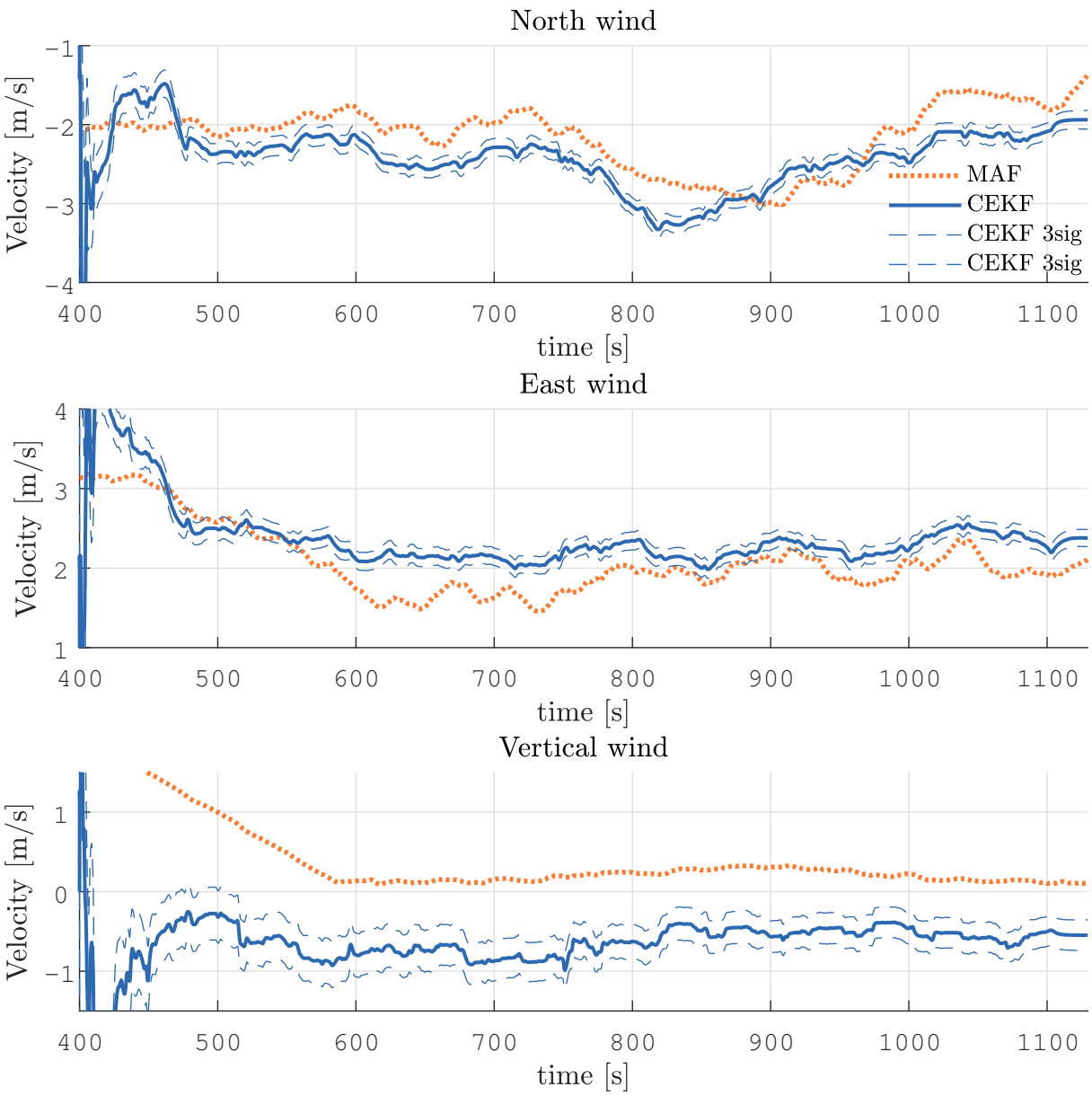

Figure 7: Wind vector estimated by CEKF

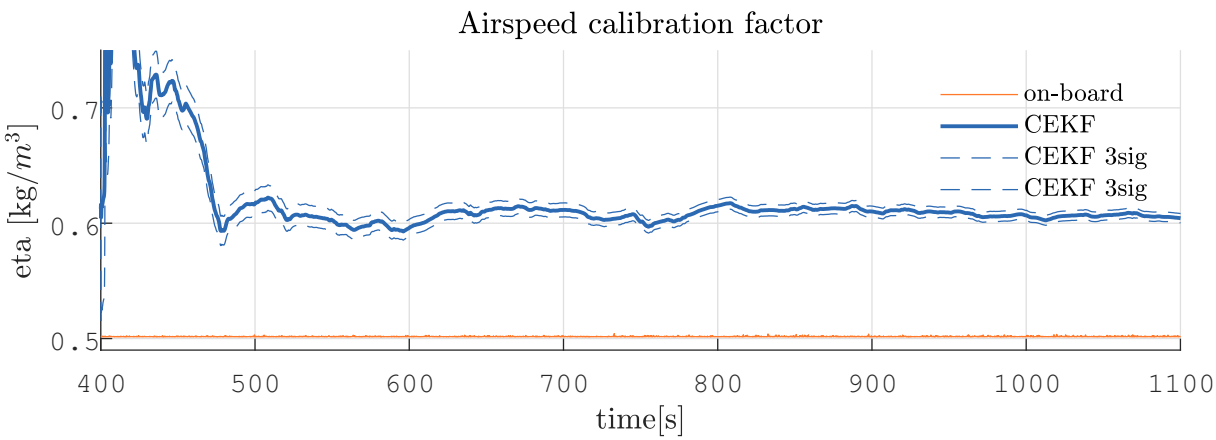

Figure 8: Airspeed calibration factor η from CEKF

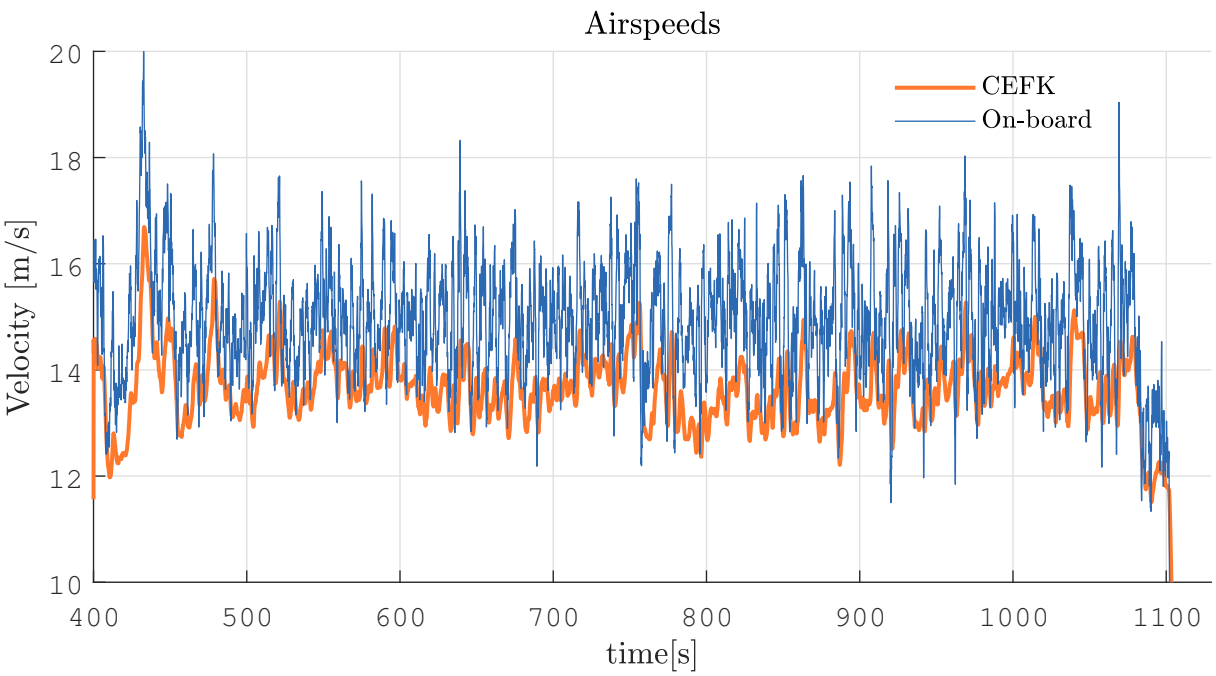

Figure 9: Airspeed estimation from CEKF

The CEKF converges after ca. 60s, which is also the moment of time when it has completed on full turn. Since that filter needs to estimate 3 different physical values ($\vec{V}_w^g$, $\vec{V}_a^f$, η) from only 2 measurement inputs ($\vec{V}_g^g$,ΔP), it has to rely on the changes in attitude of the aircraft. One can think of it as "sensing" the wind in different directions to get which parts of the groundspeed vector are airspeed and what is wind speed.
The CEKF estimated a higher airspeed calibration factor η than the on-board airspeed calculation (Fig. 8). The calibration factor varies between $0.59 - 0.62 kg/m^3$ which are well acceptable values. Due to the higher η, a smaller airspeed (Fig. 9) and a larger wind speed magnitude (Fig. 10) are computed. The direction is similar to the other estimation approaches.

4.3.4 Comparison

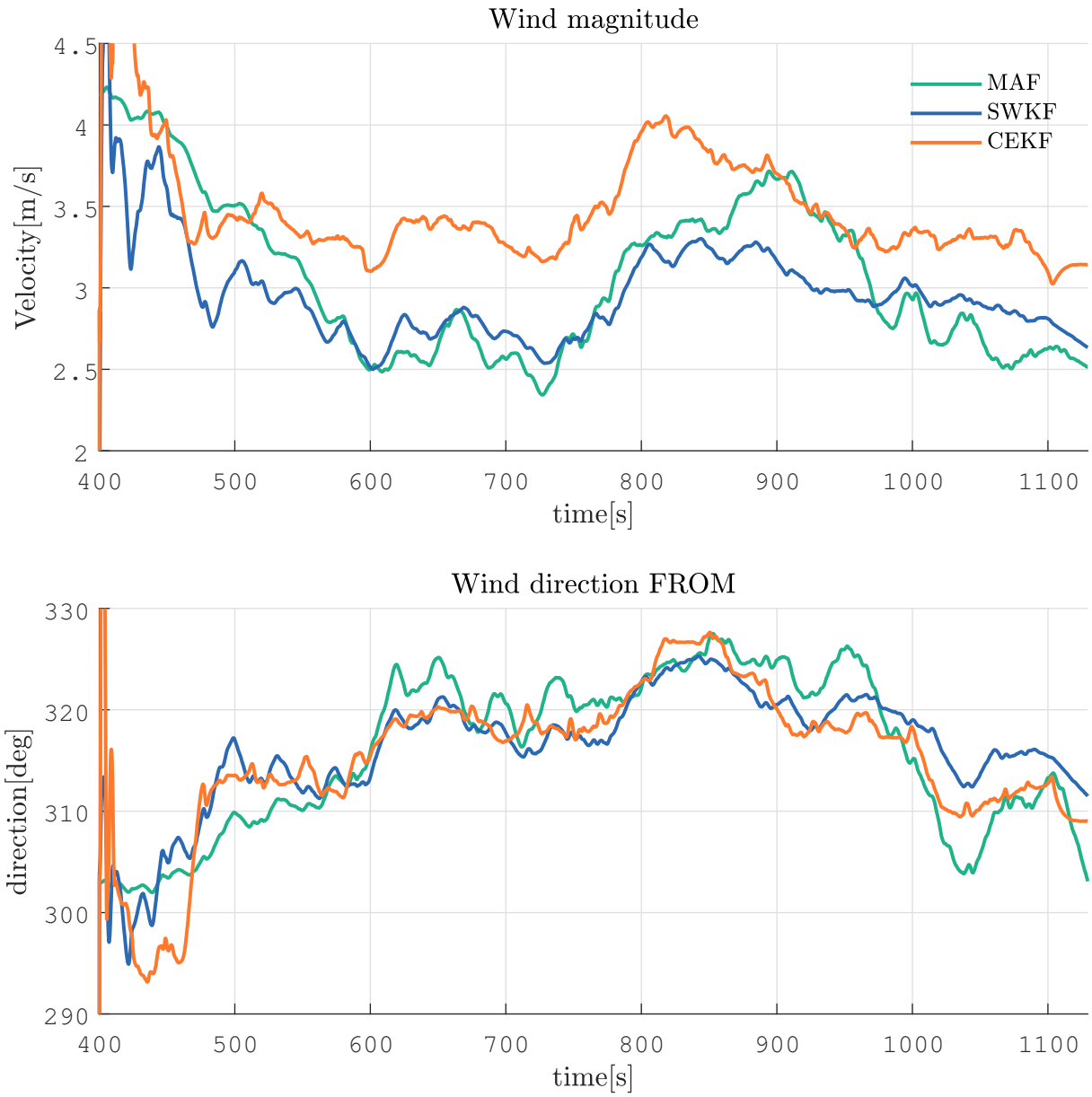

Figure 10: Wind estimation methods compared

All the filters show similar wind directions (Fig. 10). The SWKF and the CEKF show almost complementary directions after they have converged at $t = 460s$. The MAF seems to be lagging behind due to the long averaging time of 3 min.
In terms of magnitude the SWKF and the MAF show similar values due to the same input of airspeed from the on-board estimation. The CEKF has a constant difference of ca. 0.6 m/s (Fig. 10: Wind magnitude, t=600s). This is due to the different estimation of the airspeed as previously explained in section 4.3.3.

5 Evaluation

In order to choose the right wind estimation approach which is suitable for a specific aircraft, some aspects have to be considered. How well is the on-board airspeed estimation? Does the aircraft have a calibrated pitot tube? How precise should the estimation be? How should the wind estimation handle turbulence?
If the aircraft already has a calibrated pitot tube, SWKF or MAF should be sufficient for a good wind speed estimation. The SWKF is more reactive to turbulence, while the MAF has a good low-pass behavior, if initialized well and the averaging period of time is chosen in a reasonable size. 3min seemed to work well. Also the SWKF converges much faster than the MAF.
If the on-board airspeed estimation is not calibrated, the CEKF is the right choice. It can adapt to different air densities under the condition that the aircraft changes its attitude, especially the heading, over time. This means, that this filter is the wrong choice for planes which travel from A to B on a straight line. For those the SWKF and a calibrated pitot tube are the better solution.

6 Suggested future work

The performance of the CEKF might be improved a lot by including linear accelerations and angular velocities as input in the model as described in 3.4. This will also require to change the calculation of F_{k-1} as the Jacobian matrix of $f(\hat{x}_{k-1})$.
Interesting could also be to combine different wind estimation approaches with different time constants to get an idea of which parts of the wind speed are turbulent air. This would require one slow filter and one fast filter.
Also it would be interesting to look at the data from a second independend measuring device on ground to have a reference to compare the results with.

References

[1] A. Cho, J. Kim, S. Lee, and C. Kee. Wind estimation and airspeed calibration using a uav with a single-antenna gps receiver and pitot tube. *IEEE Transactions on Aerospace and Electronic Systems*, 47(1):109–117, January 2011.

[2] T. A. Johansen, A. Cristofaro, K. Sørensen, J. M. Hansen, and T. I. Fossen. On estimation of wind velocity, angle-of-attack and sideslip angle of small uavs using standard sensors. In *2015 International Conference on Unmanned Aircraft Systems (ICUAS)*, pages 510–519, June 2015.