Speed control and sensor fusion implementation for an autonomous surface vessel using adptative control and extended Kalman filter

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***Abstract*—This paper is about the implementation of an adpatative speed control and a Kalman filter sensor fusion for an autonomous surface vessel (ASV). After an brief explanation of the ship and propeller modeling, the controller design is presented and its stability and convergence analyzed using Lyapunov theory. Then, the Extended Kalman Filter (EKF) formulation is presented. After that, a simulation is done in Python to test the controller and the EKF performance. The result is that the controller can make the ASV speed follow the desired model and the EKF can give an accurate speed measurement despite the noise in the speed sensors.**

***Index Terms*—autonomous surface vessel (ASV), adaptative control, extended kalman filter (EKF), sensor fusion**

I. INTRODUCTION

Autonomous surface vessels (ASV) are ships that are capable of operating without human intervention by observing and sensing their surroundings [1]. Since they can be operated remotely, without the presence of a human crew, they are suitable for work in dangerous areas, like nuclear contaminated sites or underwater mine fields [2].

The control of an ASV is a challenge, because they are highly nonlinear systems, demanding linearizations or nonlinear control techniques [3]. The high quality motion control for USV systems is still a problem in the field of both control theory and robotics, attracting more and more attention from scholars all over the world [4].

Some examples of the linear controllers for ASV found in the literature are the Proportional Integral Derivative (PID) [5], the Model Predictive Control (MPC) [6] and the Linear–Quadratic–Gaussian (LQG) [7]. Nonlinear control techniques can also be found in the literature, like the Adaptive Control (AC) [8], the Fuzzy Logic Control (FLC) [9] and the Nonlinear Model Predictive Control (NMPC) [10].

The objective of this paper is to present the design of an Adaptive Controller [11] for an ASV speed and an Extended Kalman Filter (EKF) [12] to make the sensor fusion of three speed sensors: Global Position System (GPS), Doppler Velocity Logger (DVL) and Inertial Measurement Unit (IMU). The design requirements for the controller are: settling time less than 40 seconds, no overshoot and maximum error in steady state of 1%. For the EKF, the only requirement is to have a maximum error of 1%.

II. MODEL

A three-degree-of-freedom (3-DoF) kinematic model for an underactuated USV is given by [13]:

$$\dot{\eta} = R(\psi)\nu, \tag{1}$$

where $\eta = [x, y, \psi]^T$ are the position (x, y) and the orientation (ψ) of the USV in respect to the inertial frame, $\nu = [u, v, r]^T$ denotes the USV linear and angular velocities defined in the body-fixed frame, with u being the surge velocity, v the sway velocity and r the yaw rate. The rotation matrix is:

$$R(\psi) = \begin{bmatrix} cos(\psi) & -sin(\psi) & 0 \\ sin(\psi) & cos(\psi) & 0 \\ 0 & 0 & 1 \end{bmatrix}. \tag{2}$$

The dynamic equations of an underactuated USV in the horizontal plane can be expressed as [13] [14]:

$$M\dot{\nu} + C(\nu)\nu + D\nu + B\nu|\nu| = \tau, \tag{3}$$

where

$$M = \begin{bmatrix} m_{11} & 0 & 0 \\ 0 & m_{22} & 0 \\ 0 & 0 & m_{33} \end{bmatrix} \tag{4}$$

denotes the ship's mass and additional mass,

$$C = \begin{bmatrix} 0 & 0 & -m_{22}v \\ 0 & 0 & m_{11}u \\ m_{22}v & -m_{11}u & 0 \end{bmatrix} \tag{5}$$

is the Coriolis and centrifugal matrix,

$$D = \begin{bmatrix} d_{11} & 0 & 0 \\ 0 & d_{22} & 0 \\ 0 & 0 & d_{33} \end{bmatrix} \tag{6}$$

denotes the ship's linear and potential damp,

$$B = \begin{bmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{bmatrix} \quad (7)$$

denotes the ship's non-potential hydrodynamic and wind forces and

$$\tau = \begin{Bmatrix} \tau_u \\ \tau_v \\ \tau_r \end{Bmatrix} \quad (8)$$

denotes the forces and momentums in each DoF.

The coefficients used in this paper to represent an hypothetical USV with 15 m of length, 4 m of beam and two propellers are shown in the table below.

TABLE I: Coefficients for an hypothetical USV

M	**value**	**D**	**value**	**B**	**value**
m_{11}	19.8011	d_{11}	0.8208	b_{11}	0.1012
m_{22}	29.2773	d_{22}	0.0017	b_{22}	3.0376
m_{33}	331.1463	d_{33}	0.0004	b_{33}	639.4835

A. Propellers model

As shown in [1], the thrust generated by one propeller is

$$T = K_p \rho n^2 D^4 \quad (9)$$

, where ρ is the water density, n the rotation in the propeller shaft, D the diameter of the propeller and K_t the thrust coefficient, which is function of the advance ratio

$$J = \frac{V_a}{nD}, \quad (10)$$

where V_a is the advance speed, wich is the speed of the water passing through propellers found using the following equation:

$$V_a = (1 - w)u \quad (11)$$

, where w is the wake fraction, depending on the shape of the hull.

The relation between J and K_t for our hypothetical ship is in the table below:

TABLE II: Relation between J and K_t

J	K_t
-1.0000	0.2000
-0.5000	0.3400
0	0.3200
0.7000	0.1200
1.0000	0

B. Simplifications

In order to simplify the ship's modeling, some considerations are going to be made:

- The ship has no forces actuating in sway and yaw directions ($\tau_v = \tau_r = 0$).
- The ship is moving only in surge direction ($v = r = 0$).
- Sea current and wind velocities are negligible, so ship's velocity relative to the water and the wind is equal to the ship surge speed.
- Wake fraction is negligible($V_a = u$).

After those considerations, the dynamic model for the USV can be reduced to

$$m_{11}\dot{u} + d_{11}u + b_{11}u|u| = 2\eta K_t p D^4 n^2, \quad (12)$$

where η is the efficiency of the propellers.

III. Control

The dynamic model can be rewriten as

$$\dot{u} = -du - bu|u| + gn^2, \quad (13)$$

where $d = \frac{d_{11}}{m_{11}}$, $b = \frac{b_{11}}{m_{11}}$ and $g = \frac{2\eta K_t p D^4}{m_{11}}$. Note that g is $g(u, n)$.

Let's

$$\dot{u}_m = -d_m u_m + g_m s \quad (14)$$

be the reference model dynamic that we want our ship to follow, where s is the surge speed setpoint.

A control law such as

$$n = \sqrt{\hat{a}_r s + \hat{a}_u u + \hat{a}_{u|u|} u|u|} \quad (15)$$

can be proposed, where $\hat{a}_r$, $\hat{a}_u$ and $\hat{a}_{u|u|}$ are parameters of the controller. They ideal values are $a_s^* = \frac{g_m}{g}$, $a_u^* = \frac{d - d_m}{g}$ and $a_{u|u|}^* = \frac{b}{g}$, because if they have those values, we have $\dot{u} = \dot{u}_m$, therefore, the system follows the reference model.

The tracking error can be calculated as

$$z = u - u_m \quad (16)$$

and, after some algebraic manipulation, the tracking error's time derivative can be expressed as

$$\dot{z} = \dot{u} - \dot{u}_m = -d_m z + g(u\tilde{a}_u + u|u|\tilde{a}_{u|u|} + s\tilde{a}_s), \quad (17)$$

where $\tilde{a}_s = \hat{a}_s - a_s^*$, $\tilde{a}_u = \hat{a}_u - a_u^*$ and $\tilde{a}_{u|u|} = \hat{a}_{u|u|} - a_{u|u|}^*$ are the parametric errors.

To find $\hat{a}_s$, $\hat{a}_u$ and $\hat{a}_{u|u|}$ values, an adaptation law can be proposed as:

$$\begin{cases} \dot{\hat{a}}_s = -sgn(g)\gamma z s \\ \dot{\hat{a}}_u = -sgn(g)\gamma z u \\ \dot{\hat{a}}_{u|u|} = -sgn(g)\gamma z u|u| \end{cases}, \quad (18)$$

where γ is called adaptation gain and is a control parameter to be tuned.

The stability and convergence of this adaptive control system can be analyzed using Lyapunov theory [11].

Let's consider the following Lyapunov function candidate

$$V = \frac{1}{2}z^2 + \frac{1}{2\gamma}|g|(\tilde{a}_s^2 + \tilde{a}_u^2 + \tilde{a}_{u|u|}^2), \tag{19}$$

that is positive-definite for any z, $\tilde{a}_s$, $\tilde{a}_u$ and $\tilde{a}_{u|u|}$.

Assuming g, a_s^*, a_u^* and $a_{u|u|}^*$ constants, the time derivative of V can be expressed as

$$\dot{V} = z\dot{z} + \frac{|g|}{\gamma}(\tilde{a}_s\dot{\hat{a}}_s + \tilde{a}_u\dot{\hat{a}}_u + \tilde{a}_{u|u|}\dot{\hat{a}}_{u|u|}). \tag{20}$$

After some algebraic manipulation, we have

$$\dot{V} = -d_m z^2, \tag{21}$$

that is a negative semi-definite function, which means that the tracking error $z \to 0$ and parametric errors ($\tilde{a}_s$, $\tilde{a}_u$ and $\tilde{a}_{u|u|}$) are limited.

IV. Extended Kalman Filter

The simplified model in 13 can be rewritten in the difference equation form as:

$$u_{k+1} = F(u_k, n_k) + w_k \tag{22}$$

where w_k is the input white noise contribution to the state and the function $F(u_k, n_k)$ is

$$F(u_k, n_k) = u_k + (-d_0 0 u_k - b_0 u_k|u_k| + g_0 n_k^2)\Delta t. \tag{23}$$

The measurement of each sensor can be writen as:

$$z_k = G(u_k) + v_k, \tag{24}$$

where v_k is the input white noise contribution in each sensor and

$$G(u_k) = \begin{Bmatrix} 1 \\ 1 \\ 1 \end{Bmatrix} u_k. \tag{25}$$

The algorithm for the EKF can be divided in 2 steps: prediction and update.

A. Prediction

In the prediction step, the prior estimate of u_k ($\bar{\hat{u}}_k$) and the prior estimate of the error covariance P ($\bar{P}$) are calculated by:

$$\begin{cases} \bar{\hat{u}}_{k+1} = F(\hat{u}_k, n_k) \\ \bar{P}_{k+1} = A_k P_k A_k^T + Q, \end{cases} \tag{26}$$

where Q is the covariance matrix of w_k and

$$A_k = \frac{\partial F(u_k, n_k)}{\partial u_k} = 1 + (-d_0 - 2b_0 u_k)\Delta t \tag{27}$$

B. Update

In the update step, the prior estimates $\bar{\hat{u}}_k$ and $\bar{P}$ are updated by:

$$\begin{cases} \hat{u}_{k+1} = \bar{\hat{u}}_{k+1} + K_k(z_k + G(\bar{\hat{u}}_k)) \\ P_{k+1} = (I - K_k C_k)\bar{P}_{k+1}, \end{cases} \tag{28}$$

where

$$C_k = \frac{\partial G(u_k)}{\partial u_k} = \begin{Bmatrix} 1 \\ 1 \\ 1 \end{Bmatrix} \tag{29}$$

and K_k is the Kalman gain, calculated by

$$K_k = \bar{P}_{k+1} C_k^T (C_k \bar{P}_{k+1} C_k^T + R)^{-1}, \tag{30}$$

being R a diagonal matrix with the covariances of each element of v_k.

V. Simulations

Using Pydyna, the Python library for simulate ships dynamics used in the Maritime and Waterways Simulator (SHM) from the Numerical Offshore Tank Laboratory of the University of São Paulo (TPN-USP), the control system was simulated for 3 different surge setpoints s.

For a 2% settling time of 40 seconds, the reference model parameters were set as $d_m = g_m = 0.1$. The adaptation gain was set as $gammma = 0.5$ and the initial guess for the parameters d, b and g were $d_0 = 0.0015$, $b_0 = 0.01$ and $g_0 = 0.0049$. The same values were used in the EKF model.

The standard deviation and the sampling rate for each sensor was taken from real sensors' datasheets and they are shown in the table bellow:

TABLE III: Standard deviation and sampling rate for each sensor

Sensor	$\boldsymbol{\sigma}$	$\boldsymbol{f_s}$
GPS [15]	0.03 [m/s]	10 [Hz]
DVL [16]	0.002 [m/s]	10 [Hz]
IMU [17]	5 [μg]	200 [Hz]

A. Surge response

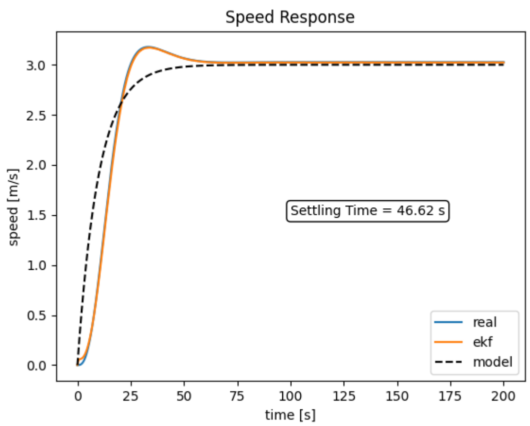

Fig. 1: Simulation for a speed setpoint of 3 m/s

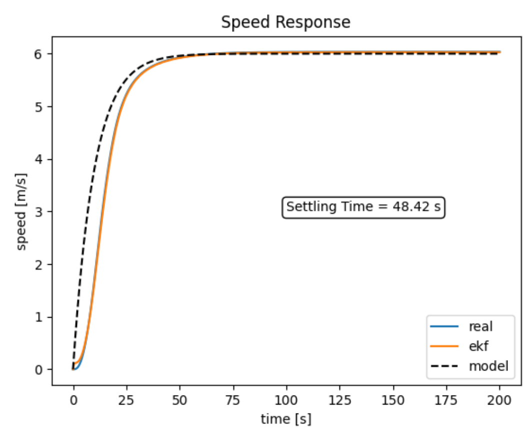

Fig. 2: Simulation for a speed setpoint of 6 m/s

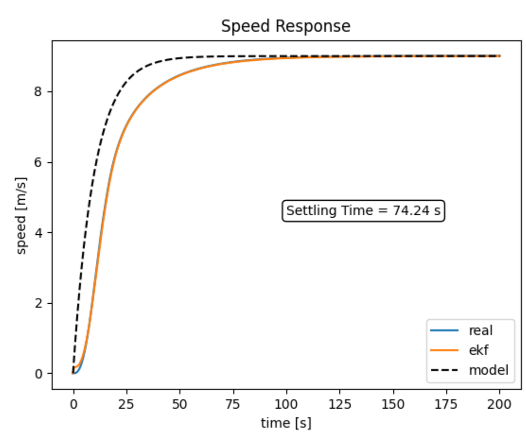

Fig. 3: Simulation for a speed setpoint of 9 m/s

B. Control effort

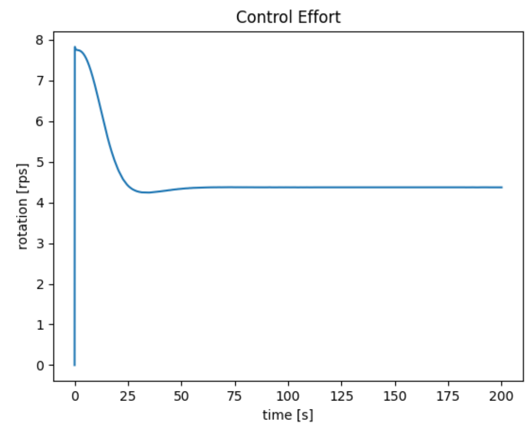

Fig. 4: Simulation for a speed setpoint of 3 m/s

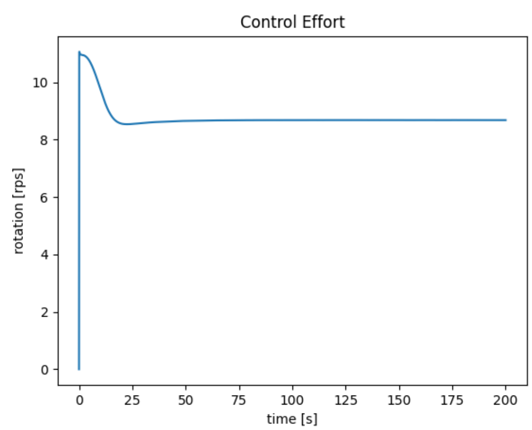

Fig. 5: Simulation for a speed setpoint of 6 m/s

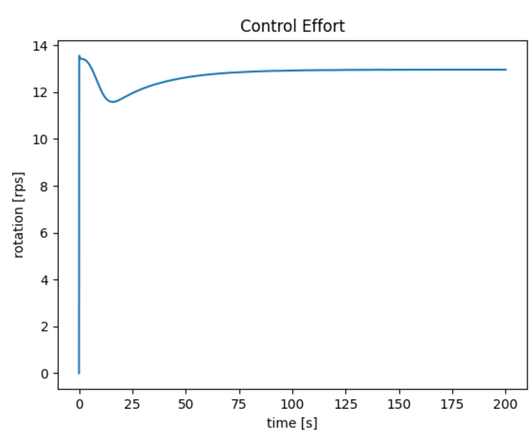

Fig. 6: Simulation for a speed setpoint of 9 m/s

C. Tracking error

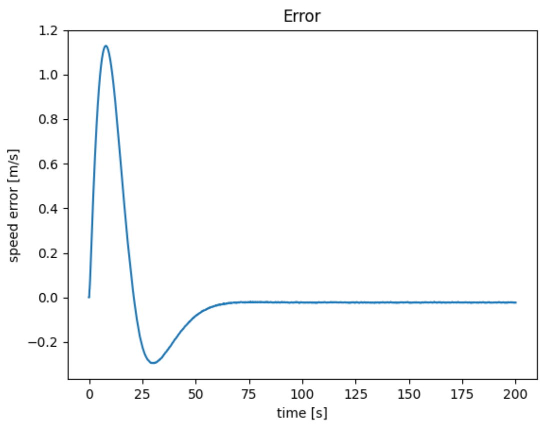

Fig. 7: Simulation for a speed setpoint of 3 m/s

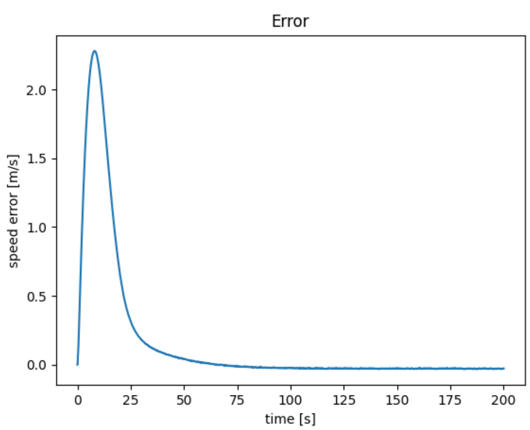

Fig. 8: Simulation for a speed setpoint of 6 m/s

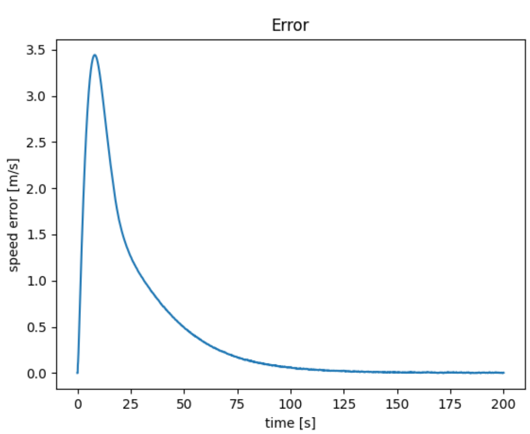

Fig. 9: Simulation for a speed setpoint of 9 m/s

D. Parameters estimation

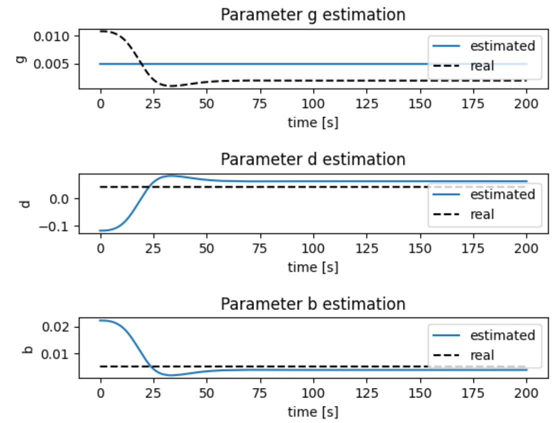

Fig. 10: Simulation for a speed setpoint of 3 m/s

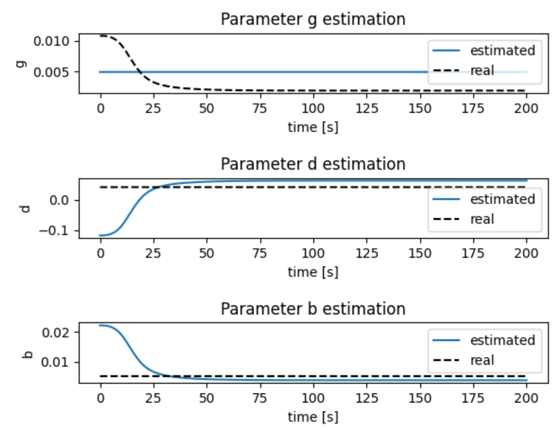

Fig. 11: Simulation for a speed setpoint of 6 m/s

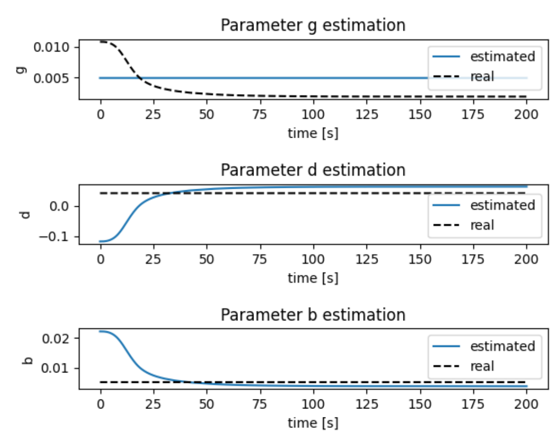

Fig. 12: Simulation for a speed setpoint of 9 m/s

E. Extended Kalman Filter results

For a better visualization, the plot with the output of each sensor and the EFK are going to be displayed for $10 \leq t \leq 100$ s.

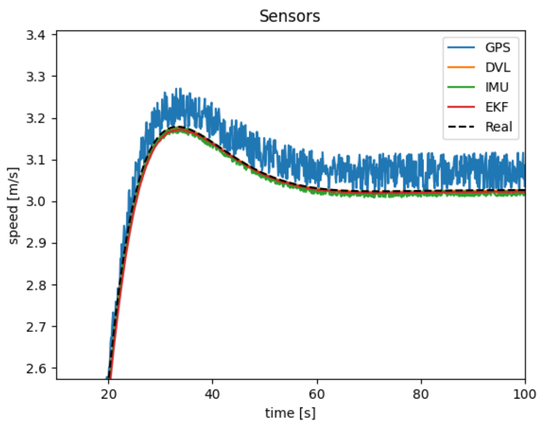

Fig. 13: Simulation for a speed setpoint of 3 m/s

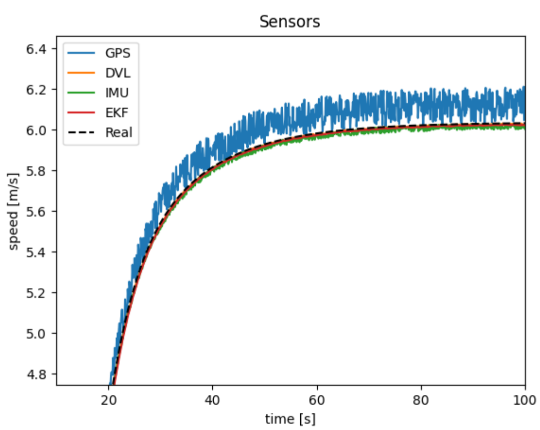

Fig. 14: Simulation for a speed setpoint of 6 m/s

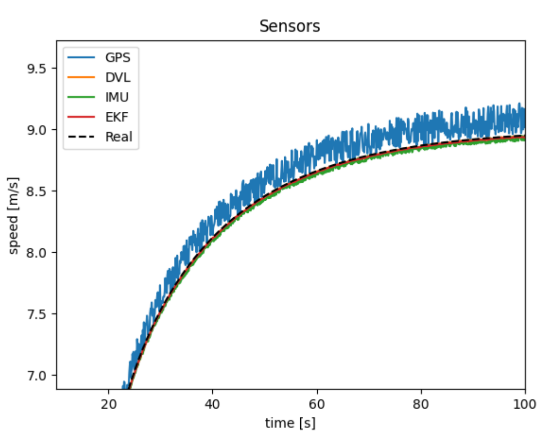

Fig. 15: Simulation for a speed setpoint of 9 m/s

VI. Conclusion

The controller was capable to lead the ASV speed to the desired final value in all the cases. the 2% settling time was almost the 40 seconds desired for the 3 m/s and the 6 m/s setpoints. For the 9 m/s setpoint the controller took more time to achieve the desired value. In all the cases, the value of the three estimated parameters, although not converging to the real value, ware limited, like expected after the stability analysis with the Lyapunov theory.

The EKF was able to make the sensor fusion, achieving rapidly a value close to the real speed, despite the error in the model and the noise in each sensor.

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