Sea currents estimation during AUV navigation using Unscented Kalman Filter

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Abstract: An Unscented Kalman Filter (UKF) able to estimate the direction and the magnitude of a priori unknown marine currents is described in the paper; the currents estimation is performed during the navigation of an Autonomous Underwater Vehicle (AUV) together with the estimation of the vehicle navigation state. The filter here proposed is born augmenting the state of an UKF previously developed by the same authors. The proposed approach is validated offline exploiting the data of the onboard sensors of MARTA AUV (Marine Robotic Tool for Archaeology), collected during recent sea trials in La Spezia, Italy. In the near future the algorithm will be implemented onboard the vehicle to carry out an online estimation of the marine currents.

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Keywords: Underwater navigation, AUV, marine currents estimation, Unscented Kalman Filter, marine robotics.

1. INTRODUCTION

Nowadays many applications also in the civilian field, e.g. for underwater archaeology, biology or geology, started exploiting Autonomous Underwater Vehicles (AUVs) as a cost affordable technological solutions for different tasks. AUVs can be mainly considered as moving robots able to house payload sensors (e.g. cameras, sonars, multi-parametric probes, etc.) on a target area for data collection. Thus, having high precision self-localization systems to guarantee a good payload data geo-referencing is mandatory. AUVs can be equipped with quite expensive sensors (such as Doppler Velocity Logs and provided with efficient sensor fusion algorithms to reach good navigation capabilities. The authors worked in the recent past to the definition and the validation of an Unscented Kalman Filter (UKF) for AUV navigation state estimation, see Allotta et al. (2016b), based on a simplified dynamic model of the vehicle. In this research work, an improved version of the UKF navigation algorithm is proposed to allow the AUV to simultaneously estimate its state and sea currents (acting upon the vehicle), a priori unknown but assumed uniform. Sea currents deeply affect AUVs navigation performance, thus many current researches focus on its modeling and estimation, e.g. Batista et al. (2008), Bayat et al. (2016). In this work, the contribution of sea currents, uniform in an Earth-fixed frame and with null vertical component, has been included in the AUV dynamic model implemented inside the UKF prediction step. Moreover, the state vector dimension is augmented including the North and the East components of the current itself. The resulting algorithm has been validated offline exploiting the signals of MARTA AUV (Marine Robotic Tool for Archaeology) onboard sensors. MARTA AUV is a modular vehicle which was built by the University of Florence during the European ARROWS Project (2012-2015) and has onboard a Doppler Velocity Log - DVL, Attitude and Heading Reference System - AHRS, Pressure Sensor and Global Positioning System - GPS on the surface; the data used in this paper have been acquired during a mission performed in La Spezia, Italy during October 2016 (Fig. 1). The mission, performed within the activities of the SeaLab with the support of the Naval Experimentation and Support Centre (CSSN) of the Italian Navy, consists of a lawn-mower path executed at a constant depth of about 7m.

The approach is based only on vehicle navigation sensors trying to keep the overall cost of the sensor set limited; this is different with respect to other recent research works (e.g. Williams et al. (2016)) that exploit instead current measurements through onboard Acoustic Doppler Current Profiler (ADCP).

Section 2 introduces previous results about UKF-based navigation for AUVs. Section 3 describes the estimation
of the main parameters of the vehicle needed for a correct tuning of the onboard filter: the knowledge of the vehicle dynamics is mandatory to improve its navigation capabilities through the UKF and thus to evaluate the direction and the magnitude of the current acting upon the AUV. The proposed algorithm for the estimation of the marine currents is given in Section 4. The validation, based on data collected during a sea mission and processed offline, is proposed in Section 5. Finally, Section 6 summarizes the presented research, focusing on the main achieved results and on the developments for the near future.

2. UNSCENTED KALMAN FILTER FOR AUV NAVIGATION

AUVs, and generally speaking all Unmanned Underwater Vehicles (UUVs), require an accurate estimate of their navigation state. This way, surfacing in order to reacquire the GPS position can be avoided for longer times, and the georeferencing process of acquired payload data results more precise. Even if high performance sensors like DVL are mounted on the vehicle, or navigation is aided by acoustic positioning systems (Ultra Short BaseLine - USBL or Long BaseLine - LBL), e.g. see Allotta et al. (2015a), the adopted sensor fusion algorithm still constitutes a fundamental component of the navigation architecture of the whole AUV system. The most common approaches are based on Kalman Filtering; usually, since the dynamics of an AUV moving into the water is non-linear, the Extended Kalman Filter (EKF) is applied (see Fossen (1994), Antonelli (2006)). The non-linearity of the vehicle’s model is accentuated if a model of the propulsion system is taken into account. The authors derived an analytical expression for the model of the propulsion system in a previous work, based on the experimentally validated propeller behavior presented in Carlton (2007). According to (Allotta et al. (2016a)), the thrust $T_i$ generated by a propeller for given advance velocity $v_{a,i}$ (along the motor axis) and rotational speed $u_i$, is expressed by the following relation:

$$ T_i (v_{a,i}, u_i) = sgn(u_i) \left( k u_i^2 - k |u_i| g(sgn(u_i) v_{a,i}) \right) $$

where $g(\cdot)$ is a piecewise function defined as

$$ g(x) = \begin{cases} 0 & \text{for } x \leq 0 \\ |u_i| & \text{for } 0 < x \leq |u_i| p \\ |u_i| p & \text{for } x > |u_i| p \end{cases} $$

being $p$ the propeller pitch. Due to the non-linearity of the complete system, the authors decided to investigated alternative estimation solutions, focusing in particular on the Unscented Kalman Filter (UKF) (Kalman (1960), Julier and Uhlmann (2004)). Such filter is based on the Unscented Transform (UT), a deterministic sampling technique which allows the propagation of a Random Variable (RV) undergoing a generic non-linear transformation without requiring the computation of derivatives. The authors recently validated (offline) an UKF-based navigation state estimation algorithms for underwater vehicles, exploiting data collected during several sea test campaigns (Allotta et al. (2016a)). The work highlighted the benefits of the UKF with respect to the EKF for AUV navigation, which increase as the number of available sensors is reduced and the navigation algorithm relies more on the model-based prediction step, see Allotta et al. (2016b).

The system model used by the authors constitute a trade-off between kinematic and dynamic AUV model proposed in Fossen (1994), Antonelli (2006). In particular, a kinematic only model simplifies too much the real behavior of the vehicle and thus is unsuitable to accurately describe the evolution of its navigation state; on the other hand, a complete dynamic model, including all the physical phenomena acting on a rigid body moving in water, depends on a very high number of parameters, which are often difficult to identify; hence, uncertainty on such parameters would negatively affect the performance of any navigation filter. Then, a mixed kinematic and dynamic model has been used; the propagation of the state variables is as follows:

$$ \begin{bmatrix} \eta_{1, k+1} \\ \nu_{1, k+1} \end{bmatrix} = \begin{bmatrix} \eta_{1, k} \\ \nu_{1, k} \end{bmatrix} + \Delta T \cdot \begin{bmatrix} R \nu_{1, k} + m \tau_x (\nu_{1, k}, u_k) + F_x (\nu_{1, k}) \\ 0 \\ 0 \end{bmatrix} + w_k \tag{3} $$

where $\eta_{1, k}$ and $\nu_{1, k}$ are, according to Fossen (1994) and Antonelli (2006), respectively the position with respect to a North-East-Down (NED) fixed frame and the linear velocity expressed within a local frame (body frame) fixed with respect to the vehicle; $\Delta T$ is the working period of the filter; $m$ is the mass of the vehicle; $R$ is the rotation matrix that represents the orientation of the body frame with respect to the NED one, its estimation is obtained through an independent filter aimed at determining the orientation, see Mahony et al. (2008) and Costanzi et al. (2016): $\tau_x$ is the force exerted on the vehicle by a set of propellers, each of them providing a thrust computed as in (1); $F_x$ is the force resulted of the propeller(s) acting on the longitudinal degree of freedom. Additive white process noise $w_k$ has been taken into account to model uncertainty. With the state vector defined in (3), and considering that the available sensors (GPS, DVL, Depth Sensor, Acoustic Positioning Sensors) provide a direct measurements of its components, the observation function is affine.
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