Towards Improved AUV Control Through Learning of Periodic Signals

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***Abstract*—Designing a high-performance controller for an Autonomous Underwater Vehicle (AUV) is a challenging task. There are often numerous requirements, sometimes contradicting, such as speed, precision, robustness, and energy-efficiency. In this paper, we propose a theoretical concept for improving the performance of AUV controllers based on the ability to learn periodic signals. The proposed learning approach is based on adaptive oscillators that are able to learn online the frequency, amplitude and phase of zero-mean periodic signals. Such signals occur naturally in open water due to waves, currents, and gravity, but can also be caused by the dynamics and hydrodynamics of the AUV itself. We formulate the theoretical basis of the approach, and demonstrate its abilities on synthetic input signals. Further evaluation is conducted in simulation with a dynamic model of the Girona 500 AUV on a hovering task.**

I. INTRODUCTION

A major obstacle for wider adoption of Autonomous Underwater Vehicles (AUVs) is their limited autonomy at many levels: limited energy autonomy, limited cognitive capacity, limited adaptability to changes, etc. Improving the level of autonomy of AUVs in all these different aspects is crucial for increasing their utility. The ultimate goal would be to have AUVs working fully autonomously over extended periods of time and in challenging underwater missions, which is also the main goal of the European project PANDORA [1].

In addition to the compulsory navigation and trajectory following tasks, there is an ever-increasing demand for complex task to be executed by AUVs. Examples include autonomous inspection of sub-sea structures in an unknown area, autonomous image mosaicing using vision and sonar, or even more demanding object manipulation tasks, such as autonomous valve turning [2].

In the existing literature, there are many extensions of the standard underwater vehicle modeling and control approaches [3]. For instance, robust control approaches for non-linear trajectory following [4], and also underactuated underwater vehicle disturbance rejection methods [5]. An alternative approach to manually-engineered controllers is to use some form of machine learning, such as reinforcement learning, to directly search for optimal behavior given a cost/reward function to optimize [6].

In this paper, we propose a novel approach for improving the performance of the AUV controller based on the ability to learn to predict input signals. The proposed learning approach is based on the theory of synchronization and uses adaptive oscillators to learn online the frequency, amplitude and phase of periodic signals. Such signals occur naturally in open water due to the waves, currents, and gravity, but also can be caused by the dynamics and hydrodynamics of the AUV itself. The approach is tested on a *hovering* tasks, using a dynamic model of the Girona 500 AUV (shown in Fig. 1).

Fig. 1. The Girona 500 hover-capable AUV getting disturbed by waves in open water. A dynamic model of this AUV, obtained through system identification [8], is used for the simulated experiments described in this paper.

In addition, we address the problem of energy efficiency from the following perspective: how to improve the energy efficiency of already existing AUVs by improving the design of their controllers. The proposed solution is based on the theory of synchronization [7], and more specifically on the so-called *adaptive oscillators*. To the best of our knowledge, this is the first time adaptive oscillators are being applied in the domain of marine robotics. Until now, their primary field of application has been to legged robots or walking assistance devices.

II. PROPOSED THEORETICAL CONCEPT

Let us consider some input signal to the AUV controller (e.g. coming from an onboard sensor such as an IMU, DVL or GPS sensor). This signal is usually affected by external disturbances applied to the AUV. We assume that these disturbances can be represented with a single variable force $F_{ext}(t)$ acting on the center of mass (CoM) of the AUV. We define an external disturbance $G(t)$ to be a *zero-mean periodic disturbance* if the following holds true:

$$\exists T > 0 \quad \forall t_0 \int_{t_0}^{t_0+T} G(t)\, dt = 0, \tag{1}$$

considering only non-trivial solutions (i.e. $G(t) \not\equiv 0$), and limiting the period T to a specific range $T \in [T_0, T_1]$. The interesting property of such zero-mean periodic disturbances is that their net effect on the state of the AUV over longer periods of time ($\gg T$) is negligible. Thus, they could potentially be ignored by the AUV controller without affecting the long-term macro-scale tracking precision. This is where the theoretic potential for energy saving is found – by ignoring certain disturbances, instead of trying to actively counteract them, the AUV controller could save energy at the micro-scale level without compromising the overall macro-scale performance.

Typical examples for such zero-mean periodic disturbances are the sea waves. Their effect can easily go as deep as tens of meters underwater. Another example is gravity, causing pendulum-like oscillations to AUVs with low CoM and positive buoyancy of the upper part (which is commonly used, to prevent excessive roll or pitch of the AUV). Yet another example is hydrodynamic oscillation at higher speed due to turbulent water flow around the AUV. Most of these disturbances could potentially be ignored (either completely or partially) by the controller in order to save energy.

However, finding such zero-mean periodic disturbances hidden within the noisy total external disturbance $F_{ext}(t)$ is not a trivial task. A simple Fourier analysis is not enough to identify reliably and track smoothly the non-stationary spectrum of the zero-mean periodic disturbances, due to artifacts caused by the sliding window and signal enveloping. Moreover, the spectrum of real-world disturbances is non-stationary, i.e. it evolves over time. Even if the spectrum was stationary, the perceived disturbance by the AUV would still vary in time due to the Doppler effect caused by the motion of the AUV itself.

The *instantaneous* total external disturbance $F_{ext}(t)$ can be represented as: $F_{ext}(t) = \sum_{i=1}^{N} G_i(t) + H(t) + c$, where $G_i(t)$ are zero-mean periodic functions, $H(t)$ is a non-periodic function which can include also random noise, and c is a scalar offset.

Following this formulation, the problem is to identify as many G_i components as possible and as accurately as possible, while simultaneously tracking their evolution over time. In order to make this hard problem more tractable, we restrict the class of zero-mean periodic functions to harmonic oscillations, i.e. having the following form: $G_i(t) = \alpha_i \cos(w_i t + \phi_i)$. The proposed solution is to create individual oscillators – one for each G_i component that needs to be tracked – and synchronize them gradually with the input signal. Then, taking advantage of the dynamic consistency of the oscillators, they maintain synchrony with the harmonic components G_i thus providing smooth output (and accurate predictions) to be used by the AUV controller.

We propose to use an extended version of the simple Hopf oscillator called *Adaptive Hopf Oscillator* (AHO). It is based on the concept of dynamic Hebbian learning in adaptive frequency oscillators as described in the work of Righetti *et al.* [9][10]. It gives the AHO the ability to dynamically adapt both its frequency and amplitude to any periodic signal. The AHO embeds the learning process directly into the dynamics of the oscillator itself. The equations governing the dynamics of the adaptive oscillator are as follows:

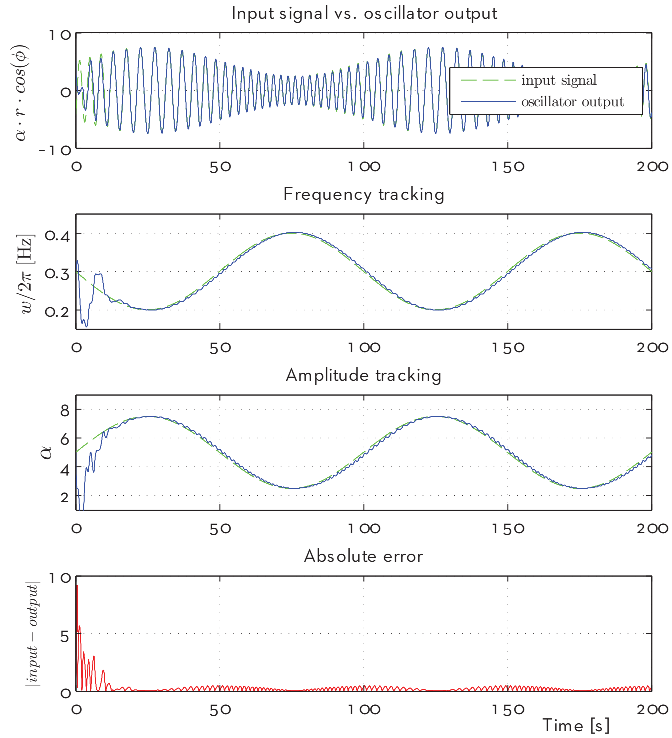

Fig. 2. An adaptive oscillator tracking a non-stationary input signal whose frequency and amplitude both vary over time.

$$\begin{cases} \dot{r}(t) = \gamma(\mu - r(t)^2)r(t) + \epsilon F(t) \cdot \cos(\phi(t)) \\ \dot{\phi}(t) = w(t) - \dfrac{\epsilon}{r(t)} F(t) \cdot \sin(\phi(t)) \\ \dot{w}(t) = -\epsilon F(t) \cdot \sin(\phi(t)) \\ \dot{\alpha}(t) = \eta F(t) \cdot \cos(\phi(t)) \cdot r(t), \end{cases} \tag{2}$$

where $F(t)$ is the input (driving) signal and $\alpha(t)$ is the amplitude of the oscillation. The output of the system is redefined as $G(t) = \alpha(t) \cdot r(t) \cdot \cos(\phi(t))$. In the case of non-stationary input, the adaptive oscillator is able to smoothly track the changes of the input frequency and amplitude, as demonstrated in Fig. 2. This tracking ability is very important since the perceived external disturbance by the AUV is influenced by its self-motion (e.g. Doppler shift).

As explained in [11], it is possible to construct a system capable of dynamical frequency analysis using adaptive oscillators as basic units. This is done by constructing a pool of N such oscillators. The proposed architecture for integrating the developed dynamical frequency analysis part with the AUV controller is illustrated in Fig. 3.

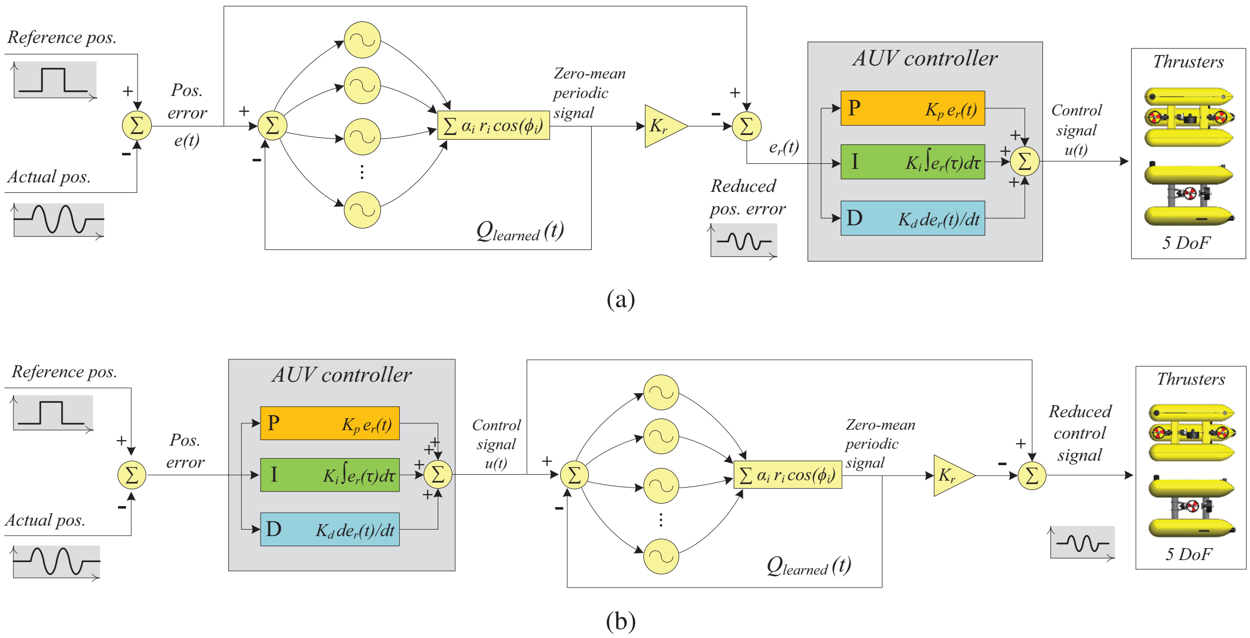

Fig. 3. Integration of the proposed approach with the AUV controller. Two possibilities for integration are shown here. In both, the learning part is based on a pool of multiple adaptive oscillators. The two alternatives are: (a) The learning takes as input the positional error signal, learns the zero-mean periodic part of it, and subtracts it from the original error, in order to produce the reduced positional error; (b) The learning takes as input the control signal computed by the controller, learns the zero-mean periodic part of it, and subtracts it from the original signal, in order to produce the reduced control signal.

III. EXPERIMENTAL EVALUATION

For the experimental evaluation we used the specialized *UnderWater SIMulator*[1] (UWSim). In the experiment we used an AUV dynamic model whose parameters were previously estimated for the Girona 500 AUV using system identification. Here we give a brief overview of the AUV kinematic and dynamic model used in the experimental evaluation.

We consider an underwater vehicle modeled as a rigid body and subject to external forces and torques. According to the standard underwater vehicle modeling properties [3], the dynamic model equations in matrix-vector form are as follows:

$$\begin{cases} M\dot{\mathbf{v}} + C(\mathbf{v})\,\mathbf{v} + D(\mathbf{v})\,\mathbf{v} + g(\eta) = \tau \\ \dot{\eta} = J(\eta)\,\mathbf{v}\,, \end{cases} \tag{3}$$

where:

- $\eta = [x\ y\ z\ \phi\ \theta\ \psi]^T$ is the AUV pose (position and orientation) vector;
- $\mathbf{v} = [u\ v\ w\ p\ q\ r]^T$ is the AUV velocity vector;
- M is the AUV rigid body inertia matrix;
- $C(\mathbf{v})$ is the rigid body Coriolis and centripetal matrix;
- $D(\mathbf{v}) = D_{quad}(\mathbf{v}) + D_{lin}(\mathbf{v})$ is the quadratic and linear drag matrix respectively;
- $g(\eta)$ is the hydrostatic restoring force vector;
- $J(\eta)$ is the Jacobian matrix transforming the velocities from the body-fixed to Earth-fixed frame;
- τ is the input (force/torque) vector.

[1] UWSim – an UnderWater SIMulator for marine robotics research and development, `http://www.irs.uji.es/uwsim/`.

The parameters of the dynamic model were previously estimated for the Girona 500 AUV using well-known system identification methods [12], [13]. The technical specification of Girona 500 is available in [14].

For modeling the water motion due to surface waves we use the following equations for deep-water waves [15]:

$$\begin{cases} \dot{x}(t) = \dfrac{kga}{w} \cdot \dfrac{\cosh(kz(t)+kd)}{\cosh(kd)} \cdot \cos(kx(t) - wt) \\ \dot{z}(t) = \dfrac{kga}{w} \cdot \dfrac{\sinh(kz(t)+kd)}{\cosh(kd)} \cdot \sin(kx(t) - wt). \end{cases} \tag{4}$$

The experimental results from the simulated *hovering task* are shown in Fig. 4. After the initial 10-20 seconds of tuning, the adaptive oscillator converges to the frequency, amplitude and phase of the signal, and exhibits stable behavior. After 25-30 seconds the proposed approach shows significant energy-saving capabilities while at the same time maintaining high controller gains. In Fig. 4, the bottom subplot shows that the steady state power consumption is successfully reduced from 300 to only 190 W, which is a significant reduction. Further experimental results with focus on improving the AUV energy efficiency can be found in [16].

IV. CONCLUSIONS

The original contributions of this paper include: introduction of synchronization methods in the field of marine robotics; novel concept for energy saving of underwater vehicles; first use of adaptive oscillators to learn to predict periodic external disturbances; a mechanism for integration of a PID position controller with dynamical frequency analysis based on adaptive oscillators.

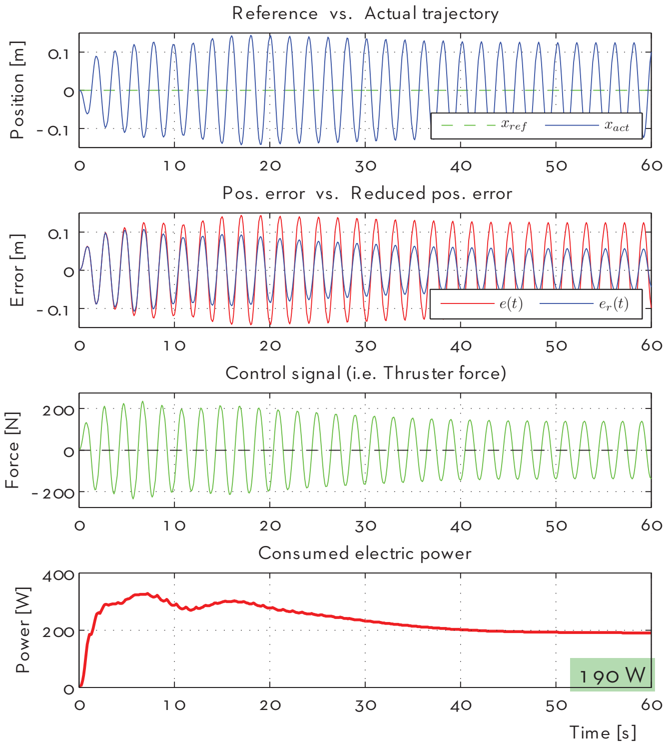

Fig. 4. Hovering experiment - hovering at a fixed position while being perturbed by a wave. ($K_r = 0.5$)

The proposed approach has numerous advantages that make it suitable for solving the posed problem: (i) it is dynamically consistent; (ii) it is computationally cheap; (iii) it makes accurate predictions.

In the future, depending on funding and resources, we plan to conduct real-world experiments with the proposed approach in open water.

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