AUV Positioning Model Employing Acoustic and Visual Data Processing

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***Abstract*— This paper describes a positioning model of an autonomous underwater vehicle attaining an underwater target equipped with an acoustic buoy. The model combines acoustic and vision-based navigation principles. The acoustic guidance assumes a one-way asynchronous signal exchanging mode. A vision-based positioning employs log-polar transformations of camera images. A PID controller is used to change the vehicle position and course. The corresponding control and error functions are given.**

The model was implemented in a programm code and thereafter a number of numerical tests were carried out. The tests confirmed an reliability of the developed algorithms.

I. Introduction

The World Ocean is the richest and at the same time the least researched source of natural resources. This inspires extensive investigations in the field of underwater vehicle development over the last decades. Existing underwater vehicles and robots are usually classified into [1] *deep submersible vehicles* (DSV), which are small diving manned submarines, *remotely operated vehicles* (ROV), which are controlled by a remote operator from a supporting ship, and *autonomous underwater vehicles* (AUV), which are self-floating robots operating without a direct human control. Clearly, due to autonomy the AUVs are preferable for a broad range of scientific, military, and commercial applications.

Positioning, navigation, and guidance of an autonomous vehicle are dominant challenges in order to attain true autonomous operating. Positioning and navigation systems can be divided into the following groups.

- *GPS systems* provide a true three-dimensional navigation capability. Since a penetration depth of radio-waves into sea water is only of 80 cm [2], an underwater vehicle equipped with a GPS receiver must float to the sea surface periodically to identify its location [3].
- *Relative positioning systems* consist of a Doppler velocity log [4], allowing for velocity estimations relative to the seafloor, and an inertial measurement unit [5] providing information concerning the vehicle linear acceleration and angular velocity. The measured data are used to estimate the current vehicle position. With the course of the time a position estimation error increases limitless. Therefore, the relative positioning systems are typically used in a combination with the GPS systems.
- A *terrain-based navigation* employs a map of sea bottom. The map is not usually available a priori, but it can be constructed on-line using simultaneous localization and mapping algorithms [6].
- *Acoustic navigation systems* utilize the concept of time-of-flight (TOF) measurements for sound waves propagating between a stationary buoy (or a set of buoys) and a hydrophon installed on the underwater vehicle [7], [8].
- A *vision-based guidance* uses a series of frames produced by an optical camera attached to an underwater vehicle [9], [10].

The operating range of the acoustic systems is typically of $\mathcal{O}$(10m – 10km), while underwater optical systems are able to work in the range of centimeters [11]. The combination of acoustic and vision-based principles can be profitable for the construction of a real navigation system.

In this paper we propose a navigation/positioning model that exploits a combination of acoustic and visual-based navigation principles. This paper is organized as follows: Section II introduces the navigation problem formally. In Section III an acoustic signal registration problem is considered. A vision-based guidance is discussed in Section IV. Section V summarizes simulation results which apply the proposed model.

II. Problem statement

Consider a torpedo-shaped autonomous underwater vehicle equipped with engines that are able to change its direction (course) $\phi \in [-\pi, \pi]$ and velocity $v \in [-v_{\max}, v_{\max}]$ in the forward direction. In order to avoid Doppler effect we assume that $v_{\max}$ is much less than sound speed v_s in sea water. The vehicle owns a hydrophone and an optical camera that is pointed along the main axis downwards. The AUV mission is formulated as follows. Starting from an arbitrary position the AUV should arrive a certain location and take a requested direction. Both parameters are defined unambiguously by an *underwater target* that is a two-dimensional *billboard* fixed on seabed and equipped with an acoustic buoy. Thus, the aim of AUV's mission is to localize the target location and justify

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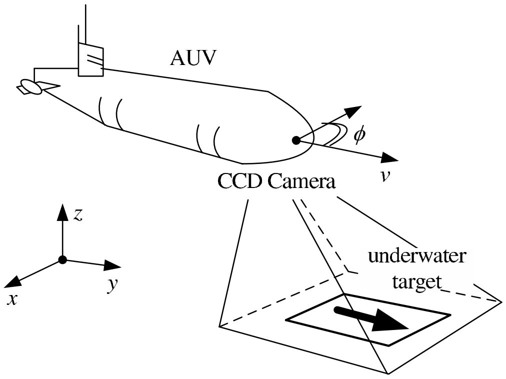

Fig. 1. Model configuration.

its course. The sketch of the model configuration is shown in Fig. 1.

In our model the positioning consists of two logical steps which are called a *long-distant* and *near-distant* guidance, respectively. During the first step an AUV makes a series of TOF measurements to attain an approximate target location. Capturing the target by a vision system the vehicle starts a near-distant guidance in order to improve its location and change its course in accordance to the direction defined by the underwater target.

III. ACOUSTIC NAVIGATION

Conventional acoustic navigation systems utilize the concept of TOF measurements for sound waves propagating in sea water. Depending on a data exchange mode three different scenarios can be distinguished, see Fig. 2.

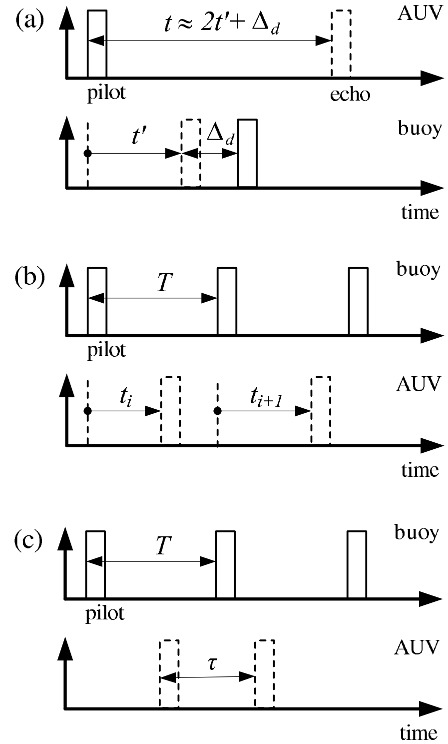

Fig. 2. Signal exchange modes: (a) two-way; (b) one-way synchronous; (c) one-way asynchronous.

Two-way transmission. The AUV transmits a pilot signal which is replicated by the buoy after a fixed delay Δ_d and is registered back on the AUV side. The resulting time-of-flight t is proportional to a doubled AUV-buoy distance.

One-way synchronous transmission. In this case, the acoustic buoy is used as a transmitter and AUV operates in a salient mode, *i.e.* it receives acoustic signals only. Both, the transmitter and transducer are synchronized so that an AUV equipment knows exactly the sending time of the pilot signals and their replication period T. Consequently, the time span t between the synchronization and registration moments defines the AUV-buoy distance.

One-way asynchronous transmission. In comparison to the previous mode the transmitter and transducer are not synchronized, *i.e.* on the AUV side it is known only the period T, but not the exact moment the signal was sent. Let denote τ the time span between two subsequent signal registration moments. Having $\tau < T$ the vehicle moves in the buoy direction. In the case $\tau = T$ the AUV does not change its relative position to the buoy.

Comparing pros and cons of the above modes one usually notices that the two-way transmission is simpler in implementation. On the other hand, it takes twice longer for a single TOF measurement than another modes and utilizes the channel inefficiently. For a far-distant data transmission a real channel has a narrow acoustic bandwidth [12]. In the case of multiple underwater vehicles accessing the common channel one is limited to use either a *time-* or *code-division multiple access* principles [13]. Thus, it is necessary to develop a complex data exchange protocol minimizing a number of *collisions*, *i.e.* simultaneous signal transmissions initiated by different AUVs. Consequently, over three mentioned modes the one-way asynchronous transmission is preferable.

In general, the far-distant guidance can be viewed as a TOF minimization problem, *i.e.* AUV should move to the buoy as close as possible. The problem splits into two subproblems: (i) implementation of a robust and an accurate TOF measurement and (ii) translation of the measurements into engine control signals changing the vehicle position and course.

The TOF estimation is a challenging task in a real environment. There are a lot of sources leading to erroneous estimations: an intensity transmission loss, a muti-path wave propagation implying inter-symbol and inter-carrier interferences [14], the Doppler effect, acoustic noises etc. Clearly, a reliable acoustic guidance requires the accurate registration of navigation signals by an underwater vehicle even in the presence of acoustic data noises. A conventional method for the detection of a transmitted signal in a noisy channel is the computation of the correlation function of an input signal with a mask (which is a series of discrete samples of a transmitted signal) [15]:

$$C_k = \sum_{i=0}^{N-1} u_{k+i} \cdot m_i \quad ,$$

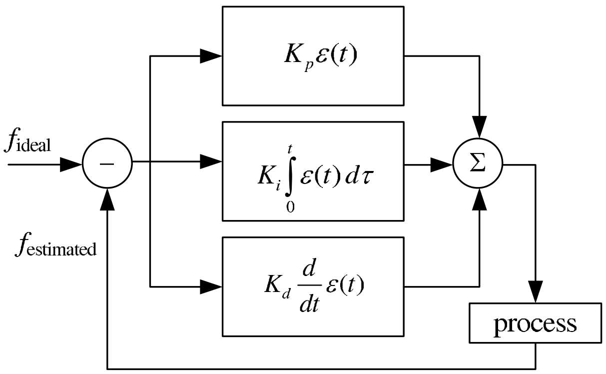

Fig. 3. PID controller.

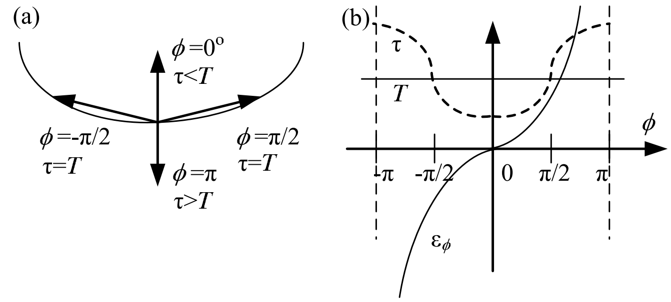

Fig. 4. (a) Dependence of the vehicle course ϕ and period of registered signals τ; (b) error course function ε_ϕ.

where u_k are samples of the digitized input signal, m_i are the discrete samples of the mask, and N is the number of samples to be processed (window size). In ref. [16] we described a hardware implementation of a modified correlation method which employs phase-manipulated M-sequences for acoustic signal registration. The advantages of the method are a high accuracy of TOF measurements (a potential distance error is below 1 m) and a high noise resistance (the method produces reliable estimations even for low SNR values; thus, the AUV-buoy distance can be of many kilometers).

The translation of TOF measurements into engine control signals can be implemented by a *proportional-integral-derivative* (PID) controller [17] given by

$$g(t) = K_p\varepsilon(t) + K_i\int_0^t \varepsilon(\tau)d\tau + K_d\frac{d}{dt}\varepsilon(t) \quad . \tag{1}$$

Here K_p, K_i, K_d are scale parameters for proportional, integral, and derivative parts, $g(t)$ is a control/impact function, error $\varepsilon(t)$ is a difference between measured and requested values. The PID controller works as follows, see Fig.3. The input for the controller is the difference between a measured $f_{\text{estimated}}$ and an ideal characteristics f_{ideal} of a chosen process. Changing the control function $g(t)$ according to eq. (1) one minimizes the difference denoted as $\varepsilon(t)$.

In our model the vehicle motion is controlled by the PID control functions g_ϕ and g_v, which adjust its course ϕ and velocity v, respectively. In the following we derive the corresponding orientation ε_ϕ and velocity ε_v error functions, which are dependent on the TOF measurements only. We assume that the AUV floats with a non-zero velocity and $\phi = 0°$ corresponds to the case that the vehicle is directed towards the acoustic buoy, see Fig. 4(a). Clearly, if $\phi \in (-\pi/2, \pi/2)$ the AUV approaches the buoy and, consequently, the period of registered signals τ is less than an actual period T. For $\phi = \pi/2$ and $\phi = -\pi/2$ the vehicle moves equidistantly around the buoy ($\tau = T$). Otherwise, it moves away from the buoy location, thus $\phi \in (-\pi, -\pi/2) \cup (\pi/2, \pi)$ and $\tau > T$. Let A be a constant and $\varsigma = \delta\tau/\delta t$ denote the rate of temporal changes in τ, we define the course error function as

$$\varepsilon_\phi = \begin{cases} \varsigma & \tau - T < 0 \\ \text{sign}(\varsigma)\cdot A - \varsigma & \text{otherwise} \end{cases} \tag{2}$$

shown in Fig. 4(b). The corresponding control function forces the vehicle to adjust its course in the direction of the buoy, *i.e.* where τ takes a minimal value. The velocity error function is of form

$$\varepsilon_v = B \cdot \tau \quad , \tag{3}$$

where B is a scale factor. The choice of the function ensures that the error grows while the vehicle moves in the direction opposite to the buoy and vice versa.

Please note that the asynchronous one-way acoustic guidance is possible only if an AUV is constantly moving. For a stationary vehicle τ coincides with the period T and, thus, there is no information concerning the relative position of the vehicle and buoy. The acoustic guidance finishes when a vision system captures an underwater target and the further positioning is continued based on a series of images produced by the on-board CCD camera.

IV. Vision-based positioning

The near-distant guidance aims to improve the position of the AUV and to justify its course in accordance to an underwater target. For a given picture I obtained by a digital camera and stored in a memory target pattern I_p an image processing algorithm computes a translation $(\Delta x, \Delta y)$ of I respectively I_p, a corresponding angular difference θ', and a scaling factor σ'.

In literature the problem is consider under different angles. The positioning of an underwater vehicle through image mosaicking is discussed in [18]. Estimations of vehicle motion parameters from an image series during a pipe inspection is shown in [19]. An underwater docking procedure for an AUV equipped with a charge-coupled device (CCD) camera was presented in [20]. Alternatively, one can use an acoustic camera for the object recognition [21].

The core of each vision-based positioning system is an image processing methods that extracts unknown parameters of camera motion from a single frame or an entire image series. In computer vision the problem is solved by *pattern matching* algorithms. The basic method uses a convolution of the original and pattern images [22]. If there is no rotation or scaling the correlation maximum corresponds to the lateral shift between the images. More sophisticated algorithms employ the polar Fourier transform [23], [24]. The methods are based on the properties of the Fourier domain: (i) an amplitude spectrum is invariant to the translation in the spatial domain; (ii) rotation in the spatial domain corresponds to the translation in the polar Fourier domain. Another large group of the algorithms deals with the sets of interest points extracted from the original and pattern images [25], [26]. The point extraction is followed by the computation of an optimal affine transformation of the sets.

In general the algorithms have a high computational complexity. Thus, they are not optimal for the implementation in the AUV hardware. In our work for the parameter extraction we use a modified log-polar transformation algorithm originally described in [27]. The algorithms includes the following computational stages. The image is convolved with a Gaussian kernel in order to reduce an image noise and to filter out insignificant image details. A normalized gradient image is computed and binarized according to a predefined threshold. Let us assume that an underwater target is captured by an AUV camera. In the resulting binary image I_b a center of the target is found estimating the center of mass

$$x_0 = \sum_{x \in I_b} x/N, \quad y_0 = \sum_{y \in I_b} y/N \quad .$$

Orientation θ' and scale factor σ' are computed by a *log-polar transformation* [28]. This transformation maps the point (x, y) of a cartesian plane to the point (θ, σ) in a log-polar plane. New coordinates are computed as

$$\sigma = \log(\sqrt{(x - x_0)^2 + (y - y_0)^2}),$$

$$\theta = \arctan((y - y_0)/(x - x_0)),$$

where (x_0, y_0) is the origin of the log-polar plane. An example of the transformation is shown in Fig. 5. Our algorithm converts the original image to the (σ, θ)-space. As the origin we use the center of mass computed in the previous step. Further, the algorithm convolves the converted image with a log-polar transform of the pattern. A maximum in the output image gives the estimate of parameters σ' and θ', and the lateral offset of I and I_p is computed as

$$(\Delta x, \Delta y) = (x_0 - x_{p0}, y_0 - y_{p0}),$$

where (x_{p0}, y_{p0}) is the center of mass in the pattern image. For the input images of size $M \times N$ pixels the total computational complexity of the algorithm is $\mathcal{O}(MN \log(\max(M, N)))$.

As it is shown in the previous section, the PID controller is used to manipulate the position and orientation of the vehicle. The corresponding error functions are of form

$$\varepsilon_\phi = \theta \text{ and } \varepsilon_v = \cos(\theta)\sqrt{\Delta x^2 + \Delta y^2} \quad .$$

Parameter σ' can be used to justify a vertical distance between the AUV and underwater target.

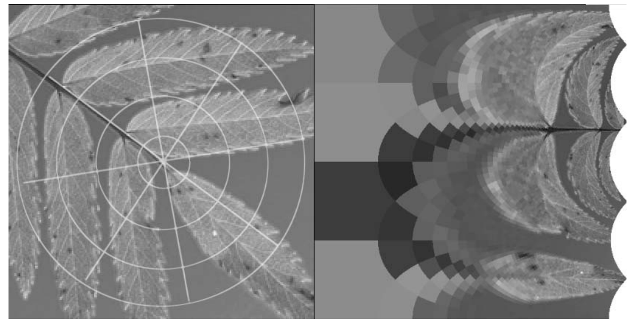

Fig. 5. Example of log-polar transformations.

V. Experiments and discussion

In order to implement the described model a continuous time line is represented by a set of discrete moments t_i. Let denote the position and course of the AUV at t_i by $[x_i, y_i]^T$ and ϕ_i, respectively. We organize a programm loop where on each iteration the parameters are recomputed in accordance with the derived control functions g_ϕ and g_v, namely

$$\begin{bmatrix} x_{i+1} \\ y_{i+1} \end{bmatrix} = \begin{bmatrix} x_i \\ y_i \end{bmatrix} + g_v(t_i) \begin{bmatrix} \cos(\phi_i) \\ \sin(\phi_i) \end{bmatrix}$$

and

$$\phi_{i+1} = \phi_i + g_\phi(t_i) \quad .$$

Starting the AUV mission, the acoustic guidance is performed, *i.e.* the error functions (2), (3) are used. As the AUV approaches the underwater target, the model switches to the vision-based positioning algorithm. We apply a small AUV-buoy distance to be the switching criteria. Alternatively, a correlation function of a camera and pattern images can be used. As soon as the convolution maximum exceeds a predefined threshold the camera captures the pattern. The vision-based positioning runs until the angular difference θ' and lateral offset $(\Delta x, \Delta y)$ minimize.

The developed algorithms are implemented and combined in a small 3D simulator. The 3D scene consists of an underwater vehicle, target, and artificial seabed. The shape of the virtual AUV was borrowed from a real underwater vehicle MMT-3000 [29] (Fig. 6). The vehicle is equipped with a hydrophone and an CCD camera.

The numeric results of the far-distant guidance are summarized by Fig. 7. Upper plot depicts four AUV trajectories started from different locations and at different courses. Regardless of the initial parameters the vehicle reaches the buoy (marked with a circle) in all instances. The velocity on the path grows, attains a maximal value, and then decreases slowly as shown in the bottom chart.

Simulations for the vision-based positioning stage reveal that the choice of the target pattern is of a high importance since it must define a certain orientation in space unambiguously. One of the proper patterns is shown in Fig. 6(b). Numerical experiments confirm a high accuracy and robustness of the presented algorithms (angular error does not exceed 5^o, lateral offset was in the range of centimeters).

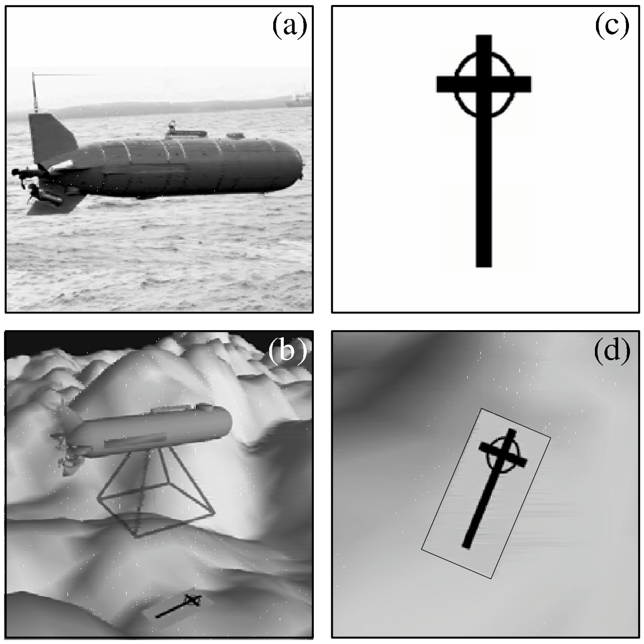

Fig. 6. (a) MMT-3000; (b) virtual 3D scene; (c) sample pattern image for the underwater target; (d) one frame from the AUV camera.

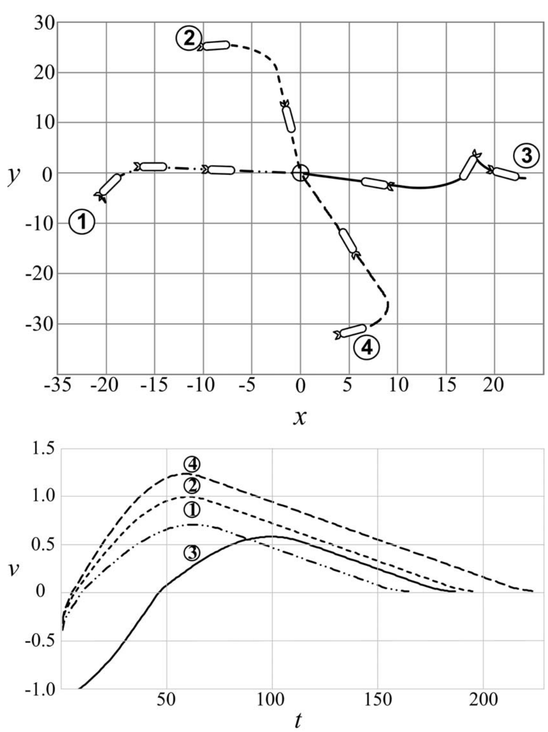

Fig. 7. Numeric simulations of the far-distant guidance algorithm: (upper) trajectories and (bottom) corresponding velocity curves.

VI. Conclusion

The paper addresses the AUV navigation problem. Here we propose a model which combines acoustic and vision-based guidance principles. The former is used on large AUV-target distances, the latter allows one to justify the vehicle course and improve its location with respect to an underwater target. The acoustic guidance is based on the TOF measurements. Among the different signal exchanging modes, the salient one-way asynchronous scheme fits the requirements of autonomy at the best. For the vision-based positioning we propose an image processing algorithm utilizing the log-polar transformations. A PID controller is used to change the vehicle position and course. The corresponding control and error functions are given. A series of numerical experiments confirms the reliability and accuracy of the developed algorithms. The goal of the future work is to examine the robustness of the algorithms against noise in acoustic and image data.

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