Optimum Design of Artificial Lateral Line Systems for Object Tracking under Uncertain Conditions

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Abstract This study develops a method for optimum design of an artificial lateral line system, which tracks underwater objects by using the extended Kalman Filter (EKF). Sensor noise and model uncertainty are considered for design optimization. Dependency of the optimum setting of the EKF and the design parameters on the amount of uncertainty is investigated as well.

Keywords: Extended Kalman filter; Underwater object tracking; Sensor placement

1. INTRODUCTION

An artificial lateral line (ALL) consists of a set of flow sensors arranged around a fish-like body, which can identify or track an underwater moving object and estimate its parameters including the size, shape, velocity and position by analyzing the measured local flow velocity at the sensors [1, 2, 3]. The uncertainty in the sensor measurements and the employed flow model, which is used to analyze the sensor measurements, challenges accuracy of the object tracking. Although several studies have been conducted on underwater tracking and estimation of moving objects using the ALL system [2], very few has addressed design of the optimal ALL, the one that provides the maximum tracking accuracy for an arbitrary moving object. A few studies developed a method for optimum design of an ALL for identification of spherical vibrating objects, called dipoles [4, 3]. In [5], the placement of flow sensors was optimized based on observability for the control purpose. The proposed estimation and optimization were performed in a uniform flow field, different from the tracking of a moving object.

Unlike most previous studies on ALLs, this article develops an evolutionary tool for optimum design of an ALL system, which dynamically tracks an arbitrary underwater moving object by applying the extended Kalman filter (EKF) strategy.

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2. PROBLEM FORMULATION

The ALL consists of a number of sensors, located in *xy* plane, with the sensor locations denoted as (x_i,y_i), $1 \le i \le N_{\text{sensor}}$. Each sensor provides a noisy measurement of the local flow velocity along its sensing direction, denoted by $M_i(t)$. $[x_s(t), y_s(t)]$ specifies the position of the center of the moving cylindrical shape at time *t*. The object is assumed to move at a constant speed of v_x along the *x* coordinate. This motion causes a disturbance and a flow field around the object which can be computed using a potential flow model:

$$M_i(\mathrm{t}) = f(\boldsymbol{\theta}(t), [x_i, y_i]), \boldsymbol{\theta} = [x_s, y_s, \lambda_s, v_s, R_s^2] \quad (1)$$

where $M_i(t)$ is the local flow velocity at the place of sensor *i* and $\boldsymbol{\theta}(t)$ represents parameters of the moving object including momentary position (x_s, y_s), shape (λ_s), velocity (v_s) and size (R_s) Function *f* is derived by the employed flow model (for details, please see [2]). Having the local flow velocity at the place of sensors ($\boldsymbol{M}(t)$=$M_1(t)$, $M_1(t)$, …, $M_{\text{Nsensor}}(t)$), $\boldsymbol{\theta}(t)$ can be determined, which means the moving object can be reliably tracked; however, due to presence of noise in the sensor measurements and the employed flow model, there is always a tracking error. The tracking error for an arbitrary moving object can be minimized by a proper selection of the ALL parameters, including, the shape, size, number and location of sensors on the body, which is the goal of this study.

3. OBJECT TRACKING METHOD

The extended Kalman filter (EKF) is employed in this study to track the object because of the nonlinearities in the system behavior. EKF employs an iterative process for which the initial estimate ($\underline{\boldsymbol{\theta}}_0$) and the initial values of matrices **C**, **P** and **Q** should be provided. For each state, the EKF is utilized to update the estimate of the parameters of the object. The tracking process starts from $\underline{x}_s = -10$ cm and continues to $\underline{x}_s = +10$ cm. The time interval of sampling is 0.01 second.

Figure 1 illustrates the tracking results for a sample object with $\underline{\boldsymbol{\theta}}_0$=[−10, 7, 1, 9, 5]. The EKF provides the estimate $\boldsymbol{\theta}_k$ which after some steps may converge to the actual object parameters. For a given $\boldsymbol{M}_k$, the tracking error is then defined as the difference between the actual and the predicted object:

$$e_k = \left\| \left[\frac{\underline{x_s} - x_s}{1\text{ cm}}, \frac{\underline{y_s} - y_s}{1\text{ cm}}, \frac{\underline{\lambda_1} - \lambda_1}{1\text{ cm}^2}, \frac{\underline{v_s} - v_s}{1\frac{\text{cm}}{\text{s}}}, \frac{\underline{R_s^2} - R_s^2}{1\text{ cm}^2} \right] \right\|_k \quad (2)$$

where the underlined parameters refer to the actual object.

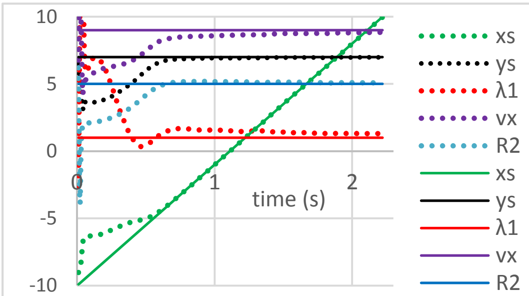


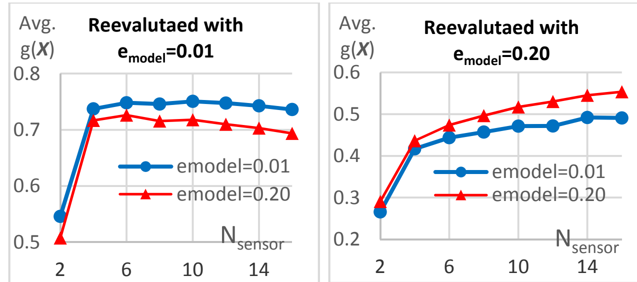
Figure 1. Tracking of a sample object a) Sample and the ALL and b) tracking estimate (dots) and the true values (continuous lines) for a typical cylindrical object

4. OPTIMIZATION RESULTS

It should be noted that in general, the cylinder may move anywhere in the predefined working area. Since considering all possible cases is not possible, the tracking problem is solved for a finite number (N_{cyl}) of cylinders. Considering different sources of uncertainties, a robust performance measure is strongly desired. Accordingly, a score for tracking accuracy in case of a single moving object is defined and the fitness is then computed as average of the scores for N_{cyl} sample cylinders.

We first searched for the best values of the Kalman filter by performing an optimization, which revealed that a priori set values were not optimum. We used these optimized parameters for object tracking and optimization of the ALL. We employed covariance matrix adaptation evolution strategy (CMA-ES) [6]. We set ε_{sensor}=0.0015 cm/s following the experimental results in [3] and considered two cases with different amount of model uncertainty (ε_{model}=0.01, 0.20). The ALL is optimized using CMA-ES given the optimum parameters of the EKF. The trade-off between the number of sensors and the accuracy of tacking is investigated by running CMA-ES for different values of the number of sensors (N_{sesnor}) independently. To check dependency of the final solutions on the ε_{model}, the final solutions for ε_{model}=0.01 and ε_{model}=0.20 are reevaluated in both conditions of ε_{model}=0.01 an ε_{model} =0.20 over a large number of sample objects. The reevaluated fitness ($g(\boldsymbol{X})$) is plotted in Figure 2. The obtained results reveal that:

- For the case with low uncertainty, increasing N_{sensor} is advantageous up to N_{sensor}=4 (Figure 2). After that, the extra sensors do not provide any contribution for tracking. In fact, the fitness of the optimized designs declines for $N_{sensor}\geq 12$. One reason for this odd observation can be the complexity in the problems with more number of sensors, e.g. more design parameters, which demands a more computation budget.
- For the case with high amount of uncertainty, increasing N_{sensor} continually improves the tracking accuracy. This means the contribution of extra sensors is significant in comparison with the increased problem complexity.
- The ALL optimized for ε_{model}=0.01 is not the optimal one for ε_{model}=0.20. This means the optimal design depends on the amount of uncertainty.



(a) (b)

Figure 2. Average fitness of the optimized designs for ε_{model}=0.01 and ε_{model}=0.20 reevaluated in different conditions

5. SUMMARY AND CONCLUSIONS

In this study, design of artificial lateral line system was optimized for maximizing the tracking accuracy for an arbitrary moving object by using the extend Kalman filter. The parameters of the filter were optimized first. Trade-off between the number of sensors and the tracking accuracy was also analyzed for different amount of uncertainties. Our numerical results revealed dependency of the optimum design on the amount of uncertainty. The obtained trade-off between the number of sensors and tracking accuracy can provide useful information to determine the number of sensors in the design. For our problem, the trade-off demonstrated that the contribution of extra sensors can be significant when the uncertainty is high, while it is negligible when the uncertainty is small.

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