Adaptive Filter Design For Suppressing The Moving Surface Interferences In Optic-acoustic Remote Sensing

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***Abstract*—Optic-acoustic remote sensing has been proposed to detect underwater sound signal from the air, thus providing a new method for underwater communication and detection. It exploits the fact that acoustic pressure waves propagating within the water environment cause vibrations on an air-water interface and the particle velocities can be optically detected by observing the amplitude or phase characteristics of the reflected optical beam which is emanated from a laser interferometer. This paper studies an interesting phenomenon observed from our optic-acoustic remote sensing experiments. In the hydrodynamic surface condition, the air-water interface is in motion, thus the moving water surface is a strong interference source. We design some adaptive filters such as the least mean squares (LMS), recursive least squares (RLS) and Kalman filter to suppress this interference. The designed filters are applied to the experiment raw data, and the processing results show an obviously improved signal-to-interference ratio.**

***Keywords*: Optic-acoustic remote sensing; moving water interference; LMS; RLS; Kalman filter; signal-to-interference ratio**

I. Introduction

Ceramic-based hydrophones have long been used to detect underwater sound and form the basis of modern sonar systems. However, those sensors must be physically immersed in the water for efficient acoustic signal reception.

Optic-acoustic remote sensing has been proposed to detect underwater sound signals from the air [1], [2]. It exploits the fact that acoustic pressure waves propagating within the water environment cause vibrations on an air-water interface and the particle velocities can be optically detected by observing the amplitude or phase characteristics of the reflected optical beam which is emanated from a laser interferometer. Fig. 1 illustrates the concept of optic-acoustic underwater remote sensing. A laser pulse is used to generate an acoustic wave within the water (red beam in Fig. 1). Upon reflection from the sea floor (or an object), the returning acoustic wave perturbs the water surface and is optically detected with an interferometer (green beam in Fig. 1). Some experiments have been conducted under hydrostatic and hydrodynamic surface conditions to test the optic-acoustic sensing feasibility [3], [4]. From the experiments, it is known that the optic-acoustic

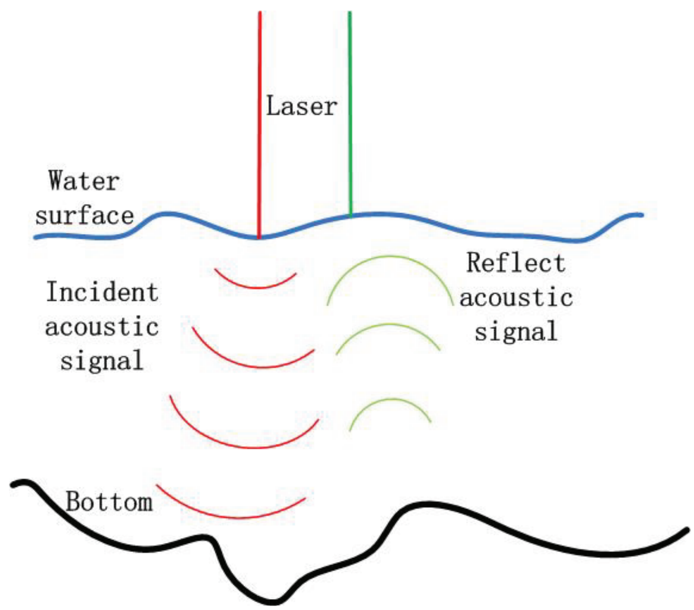

Fig. 1. Concept of acoustic-optic underwater remote sensing.

sensing can be used in the hydrostatic surface condition, but has some limitations in the hydrodynamic surface condition. In real environments, the air-water interface is rough and continually moving, and as a consequence, the optic-acoustic sensing performance can be seriously affected. Several key mechanisms affecting the performance have been identified, including signal dropout, sensing position uncertainty, acoustic signal distortion at the air-water interface, and the effect of in-water particulate reflectors located just beneath the surface [5].

Note that information on the underwater acoustic field is represented by the vibrations on the air-water interface. The vibrations modulate the incident optic beam, which then carries that information and returns to the laser interferometer. Demodulating the optic beam's amplitude or phase, one can get the original underwater acoustic signal. There are several demodulation schemes; on the whole, we can divide them

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into two catalogs: Heterodyne demodulation and Homodyne demodulation. The difference between them is whether or not the demodulation scheme uses a Heterodyne frequency.

In our experiment conducted in test tank and lake, we observed an interesting phenomenon: a continuous interference coexists with the designed sound wave signal. Via analysis, it is determined that the interference signal is not from the underwater sound signal itself, but from the experimental system setup and the surface wave vibration on the air-water interface, which cannot be properly handled by the current demodulation scheme.

In this paper, we resort to signal processing via designing some adaptive filters to suppress this interference. The rest of the paper is organized as follows: In Section II, we give a brief introduction of the basic principle of optic-acoustic sensing. In Section III, our experiment is introduced, along with some typical data. In Section IV, the designed filters are presented and applied to the experiment raw data, and the processing results are compared and discussed. Finally, some conclusions are made in Section V.

II. Principles of Optic-acoustic Sensing

The optic-acoustic sensing provides a method for detecting underwater sound by measuring the velocity of the water surface vibrations generated as the underwater acoustic waves reach the water surface. The relationship between underwater particle velocity u and acoustic pressure p is given by a time integral:

$$\overrightarrow{u} = -\frac{1}{\rho_{water}} \int \nabla p dt \tag{1}$$

where ρ_{water} is the density of water. Consider an acoustic plane wave of amplitude P_0 propagating in the water at an angle θ with respect to the normal to the water-air interface. The Laser Doppler Vibrometer (LDV) detects the normal component of the velocity at the air-water interface, where the acoustic pressure vanishes and the particle velocity doubles. Since the characteristic impedance ($\rho_{water}c_{water}$) of water is much greater than that of air, the air-water interface presents an impedance mismatch, leading to pressure release surface that vibrates in response to an impinging acoustic field. As a result, the acoustic pressure in the water, incident on and reflected from the air-water boundary, causes the surface to vibrate at the frequency of the acoustic pressure producing the vibrations. The amplitude of the normal component of the velocity $u(z,t)$ created by the acoustic plane wave is therefore given by

$$u(z,t) = \frac{2P_0}{\rho_{water}c_{water}} \cos kz \cdot e^{j\omega t} \tag{2}$$

where ω and k denotes the frequency and wavenumber of the incident laser, respectively. $u(0,t)$, which represent the velocity of the surface, is then given by

$$u(0,t) = \frac{2P_0}{\rho_{water}c_{water}} \cdot e^{j\omega t} = \frac{2P_i(t)\cos\theta}{\rho_{water}c_{water}} \tag{3}$$

where $P_i(t)$ denotes the incident laser beam.

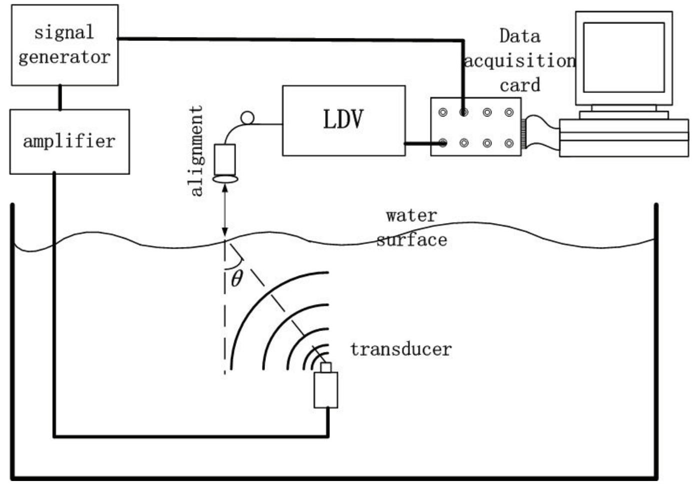


Fig. 2. Configuration of the acoustic-optic sensing experiment.

The vibration of air-water boundary causes the incident laser a Doppler frequency shift, and the acoustic field's information is then embedded into the reflected laser beam's phase. The Doppler frequency shift is given by

$$\Delta f = \frac{2}{\lambda_{laser}} u(0,t) = \frac{4P_i(t)\cos(\theta)}{\lambda_{laser}\rho_{water}c_{water}} \tag{4}$$

where λ_{laser} is the wavelength of the incident laser beam, and thus the phase change is

$$\Delta\phi = \int \Delta f dt. \tag{5}$$

No matter what type of demodulation scheme is used, the output voltage $V_{out}(t)$ from the interferometer is proportional to the surface velocity by applying the m/s per volt scale factor of the device, *C*:

$$V_{out}(t) = \frac{u(0,t)}{C}. \tag{6}$$

The relationship between the output voltage from interferometer and the vibration velocity is determined, thus the relationship between the output voltage and the acoustic field is clear. The LDV sensor presents a potentially wide bandwidth, covert sonar reception without the need for underwater instrumentation and can be combined with underwater acoustic transmitters or laser sound source for active operation.

III. Experimental Data Analysis

A lake test for investigating the performance of our optic-acoustic sensing equipment was conducted in Qiandao Lake. The experiment setup is shown in Fig. 2. The transducer is suspended $1m$ below the water surface; a continuous 6 KHz acoustic signal is generated from the signal generator and then amplified. When the acoustic signal propagates to the water surface and causes vibrations on an air-water interface, the vibrations are captured by the $1550nm$ wavelength laser which is emanated from an alignment $0.5m$ above the water surface. Then a data acquisition card is used to acquire the laser data,

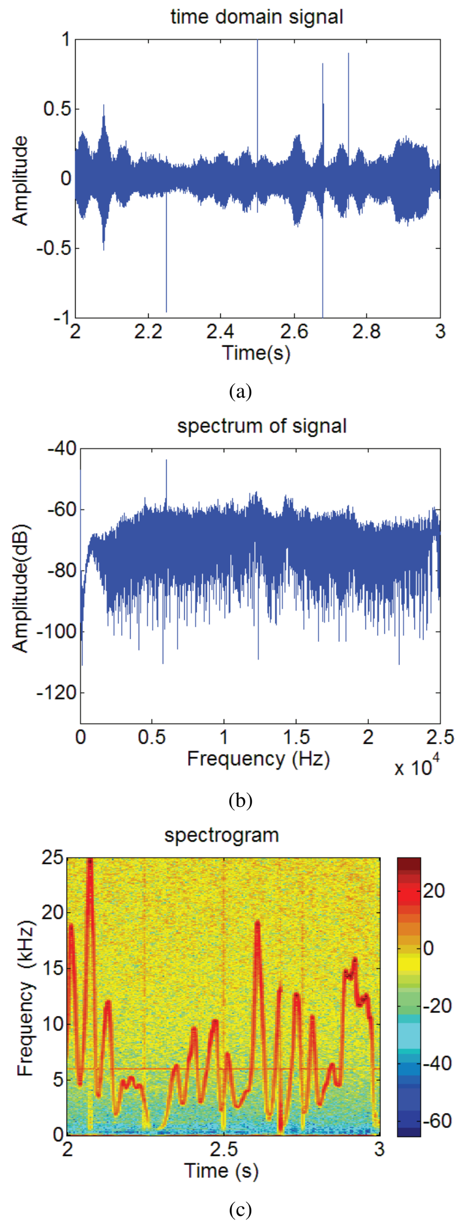


Fig. 3. Results of Qiandao Lake experimental data processing: (a) Time domain; (b) Frequency domain; (c) Spectrogram.

and the demodulation and processing are done off-line in the computer.

Without loss of generality, we take a segment of the demodulated data for analysis. Firstly, the data is filtered by a high-pass filter with 500Hz cut-off frequency and normalized. As we mention in Section I, optic-acoustic sensing has some limitation in the hydrodynamic surface condition. In our experiment in lake, we observe a interesting phenomenon, which were not mentioned in the existing literatures. As shown in Fig. 3, the demodulated signal is a superposition of the desired underwater signal, interferences and noise. The frequency of the interferences is continuously varying from zero to tens of kHz periodically. We also observe that the interferences' frequency can be even higher as the water surface becomes more turbulent.

Initially, we attribute this phenomenon to surface clutter. Because the radar has a similar problem in detecting target on the sea surface. However, we also observe this phenomenon in a contrast laboratory experiment. After some analysis, we exclude the possibility of surface clutter. The contrast laboratory experiment was conducted in a $10m \times 3m \times 1.5m$ acoustic tank facility; the experimental platform is the same as the lake experiment. The four side-walls of the tank is filled with sound-absorbing materials to reduce the reflection of acoustic signal. The bottom of the tank is covered with sands. The water surface wave is generated by disturbing the water.

Note that the demodulated signal is the response to vibration on the air-water interface. Given that the sound-pressure level just beneath the water surface is $195dB\ re\ 1\mu Pa$, the pressure just beneath the surface is 5623 Pa, the surface velocity is 7.5 mm/s, and the particle displacement at the surface is 1.7×10^{-7} m in amplitude. If the sound-pressure level is of $165dB\ re\ 1\mu Pa$, the pressure just beneath the water surface is 178 Pa, the surface velocity is 2.34×10^{-4} m/s, and the particle displacement is 5.46×10^{-9} m [6]. Hence compared to the water surface motion, the vibration caused by the acoustic field is quite small and may be masked. Even if we can detect the acoustic signal, the moving water surface also coexists as a strong interference.

The water surface's oscillation frequency is low, thus it can't reach such a high frequency as observed. The possible reasons are sampling frequency and demodulation scheme for by improving the sampling frequency the interferences' frequency becomes lower. Looking back to the Eqs. (4) and (5), the velocity of the water surface is much large than the wavelength of the laser, thus the doppler frequency Δf is large. If the sampling step dt is not small enough, $\Delta\phi$ can be more than 2π. Thus the laser's phase changes rapidly, and as a consequence, the demodulated signal's frequency may change to a higher value, which cannot be properly handled by the current demodulation scheme. In addition, the moving water changes the optic beam's strength periodically, which shall also be included in the demodulation scheme. Further experiments need to be done to test those assumptions.

IV. Adaptive Filter Design and Processing Results

The interferences coming from the moving water surface remarkably degrade the performance of optic-acoustic communication and detection. Although we may overcome it by improving the sampling frequency, the cost would be expensive. In order to get the Doppler information carried by the laser beam, the sampling frequency is already enough high. If we want to overcome the interference problem, the sampling frequency should be increased by thousands of times. In some applications, for example, active sonar, we could know some priori knowledge of the acoustic signal source, or communication, we could send some training sequence.

We can design some adaptive filter to suppress those interferences. In the discussions below, the least mean square (LMS), recursive least square (RLS) and Kalman adaptive filter are selected. Note that the acoustic signal source generates a single-frequency sinusoidal signal.

The demodulated signal $y(t)$ can be represented as

$$y(t) = x(t) + i(t) + n(t); \tag{7}$$

where $x(t)$ denotes the acoustic signal, $i(t)$ denotes the interferences coming from the moving water surface, $n(t)$ denotes the total other noise.

A. LMS algorithm

The LMS algorithm, introduced by Widrow and Hoff, is widely used in practice due to its simplicity, computational efficiency, and good performance under a variety of operating conditions [7]. The LMS algorithm can be summarized as

$$\begin{aligned} &\widehat{x}(n) = \mathbf{c}^H(n-1)\mathbf{y}(n) && filtering \\ &e(n) = x(n) - \widehat{x}(n) && error\ formation \\ &\mathbf{c}(n) = \mathbf{c}(n-1) + 2\mu\mathbf{y}(n)e^*(n) && coefficient\ updating \end{aligned} \tag{8}$$

where $\mathbf{y}(n)$ is the M-order input demodulated signal vector, $\mathbf{c}^H(n-1)$ is the preview coefficient of the filter, $\widehat{x}(n)$ is the estimation result of the acoustic signal, $x(n)$ is the desired acoustic signal of the form: $A\sin(2\pi ft + \theta)$, $\mathbf{c}(n)$ is the current coefficient vector of the filter and $e(n)$ is the priori error. μ is the adaptive step size, ensuring that the LMS algorithm converges in the mean-square sense, which must satisfy the condition: $0 \prec 2\mu \prec \frac{1}{\lambda_{\max}}$ with $\lambda_{\max}$ being the maximum eigenvalue of input covariance matrix $\mathbf{R}$. The filter's parameters and results are shown in Fig. 4.

B. RLS algorithm

RLS adaptive filters are designed so that the updating of the coefficients always attains the minimization of the total squared error from the time the filter initiates operation up to the current time [7]. Therefore, the filter coefficients at time index n are chosen to minimize the cost function:

$$E(n) = \sum_{j=0}^{n} \lambda^{n-j} \left|e(j)\right|^2 = \sum_{j=0}^{n} \lambda^{n-j} \left|x(j) - \mathbf{c}^H\mathbf{y}(j)\right|^2 \tag{9}$$

where $e(j)$ is the instantaneous error and the constant λ, $0 \prec \lambda \prec 1$, is the forgetting factor, typical values of which are between 0.99 and 1. The conventional RLS (CRLS) algorithm can be summarized as

$$\begin{aligned} &\widehat{x}(n) = \mathbf{c}^H(n-1)\mathbf{y}(n) && filtering \\ &e(n) = x(n) - \widehat{x}(n) && error\ formation \\ &\mathbf{c}(n) = \mathbf{c}(n-1) + 2\mathbf{g}(n)e^*(n) && coefficient\ updating \end{aligned} \tag{10}$$

The difference between the CRLS algorithm and the LMS algorithm is that it uses an adaptation gain vector $\mathbf{g}(n) = \widehat{\mathbf{R}}^{-1}(n)\mathbf{y}(n)$, instead of the adaptive step μ. The filter's parameters and results are shown in Fig. 5.

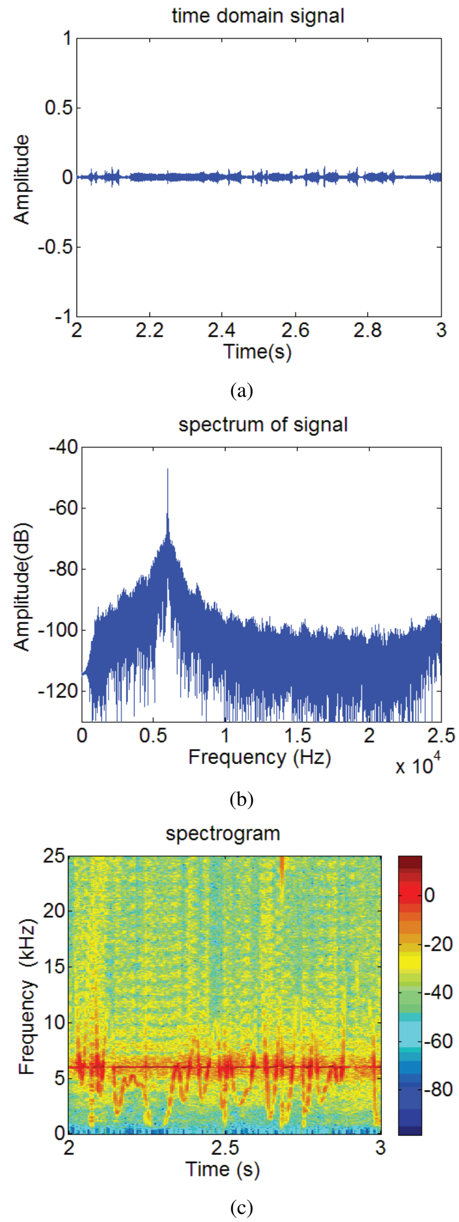


Fig. 4. LMS filtering results with μ=0.1, filter order M=40: (a) Time domain; (b) Frequency domain; (c) Spectrogram.

C. Kalman algorithm

In 1960, R. E. Kalman provided an alternative approach to formulating the MMSE linear filtering problem using dynamic models [8]. This "Kalman filter" technique was quickly hailed as a practical solution to a number of problems that were intractable using the more established Wiener methods. The two main features of the Kalman filter formulation and solution are the dynamic (or state-space) modeling of the random processes under consideration and the time-recursive processing of the input data. A typical dynamic system is described as

$$\begin{aligned} x_n &= f(\mathbf{x}_{n-1}, \mu_n) + w_n \\ y_n &= h(x_n) + v_n \end{aligned} \tag{11}$$

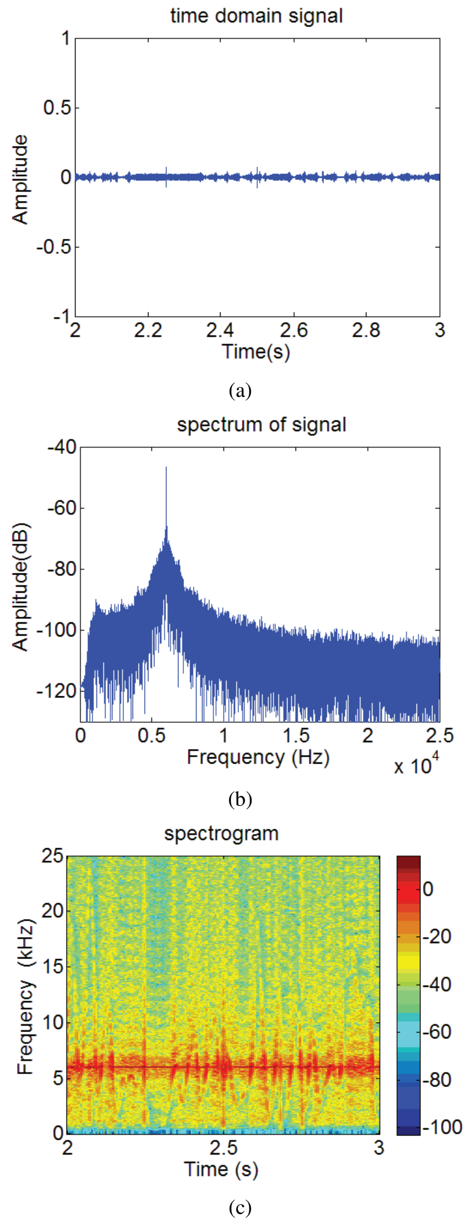


Fig. 5. RLS filtering results with λ=0.995, filter order M=40 : (a) Time domain; (b) Frequency domain; (c) Spectrogram.

where the measurable mapping f defines the state transition and h defines the evolution of the observation , $\mathbf{x}_{n-1} \triangleq [x_{n-1}, \cdots, x_{n-m}]^T$denotes the vector of the state history of length m, μ_n is the known input signal, y_n denotes the observable, w_n is the dynamic noise, and v_n is the measurement noise, all at discrete time n.

In many situations, we know little about the state transition function. We can use some data-based model such as the autoregressive (AR) model to formulate the transition function. A sequence can be modeled as an AR process should satisfy some conditions like zero-mean, stationary and normality [7] [9]. Through some stationary test method, we have the result that the acoustic signal is a stationary process while the interference is a non-stationary process. Hence the acoustic signal can be modeled as an M-th order AR process described as

$$x(n) = \sum_{i=1}^{M} a_i x(n-i) + b z_n \tag{12}$$

where the $a_i, i = 1, 2, 3..., M$ and b are the parameters of the AR process which can be calculated with LS estimation or Yule-Walker equation, and M is the order of AR process which can be decided with some criterion such as AIC, BIC, CAT [7]. The z_n is a white Gaussian process. As we know, the form of acoustic signal is $A\sin(2\pi f t + \theta)$, thus we can take a segment of data to compute the coefficients of AR model. Rewrite Eq. (11) as

$$\begin{aligned} \mathbf{x_n} &= \mathbf{A}\mathbf{x_{n-1}} + \mathbf{w_{n-1}} \\ y_n &= \mathbf{H}\mathbf{x}_n + \mathbf{v_n} \end{aligned} \tag{13}$$

where the $\mathbf{x_n}$ denotes the state vector which has the form of $\mathbf{x_n} = \left[\begin{array}{cccc} x_n & x_{n-1} & \cdots & x_{n-M+1} \end{array} \right]^T$, i.e., the current and passed M-1 time acoustic signal samples. The transform matrix $\mathbf{A}$ and the measurement matrix $\mathbf{H}$ have the following forms respectively.

$$\mathbf{A} = \begin{bmatrix} a_1 & a_2 & \cdots & a_M \\ 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix} \tag{14}$$

$$\mathbf{H} = \left[\begin{array}{cccc} 1 & 0 & \cdots & 0 \end{array} \right]^T \tag{15}$$

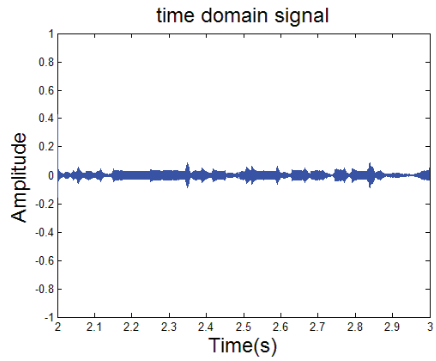
The random variables w_n and v_n are assumed to be independent (of each other), white Gaussian, with normal probability: $p(w) \sim N(0, Q)$, $p(v) \sim N(0, R)$, with Q being the process noise covariance and R the measurement noise covariance. Q and R are parameters of Kalman filter; R is usually measured prior to operation of the filter, while Q is generally difficult to determine. We can obtain a good filter performance (statistically speaking) by tuning the parameters Q and R. The Kalman filter's results are shown in Fig. 6 and the Kalman filter gains and estimation error variances are shown in Fig. 7.

D. Discussions

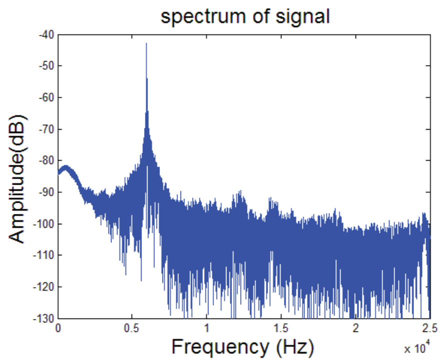
Compare Fig. 3 with Figs. 4, 5, and 6, we can see that the interferences have been suppressed and the signal-to-interference ratios have been improved in some degrees. The kalman filter has the best performance, for we can set up a more precise model to process the data.

V. Conclusion

A lake test for investigating the performance of a set of optic-acoustic sensing equipments for remotely detecting underwater sound was conducted in Qiandao Lake. It was observed that the demodulated signal is a superposition of acoustic source, interference and noise, and the frequency of the interference is continuously varying from zero to tens of



(a)



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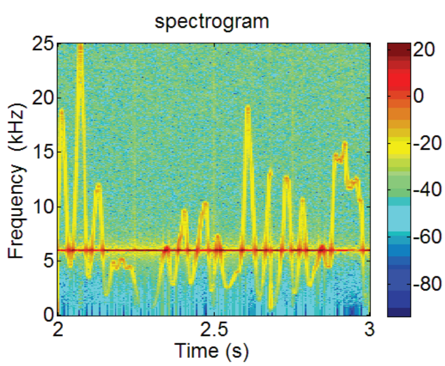

(c)

Fig. 6. The 55th order AR model kalman filter results: (a) Time domain; (b) Frequency domain; (c) Spectrogram.

kHz periodically. After a contrast laboratory experiment and some analysis, we infer that the interference comes from the moving water surface and system aliasing.

In this paper, we design some adaptive filter to suppress the moving surface interference. The designed filters are applied to the experimental raw data, and the processing results show that the interference have been suppressed and the signal-to-interference ratios have been improved in some degrees.

In practical situations, one has little knowledge of the acoustic signal, and it is also desired to maintain as much information of the acoustic source as possible. Further work would be to improve the hardware performance, or design some adaptive filter to track and estimate the moving surface interferences and then subtract it from the receiving signal, or

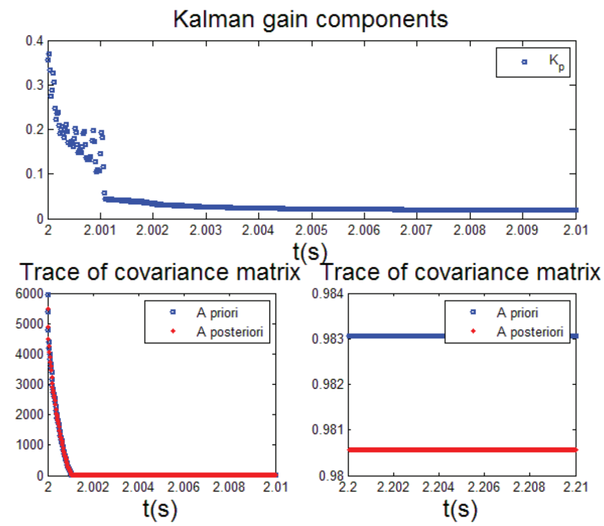

Fig. 7. Kalman filter gains and estimation error variances.

use multiple detection point technology to build up a laser array and take a time and space average to suppress the interferences.

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