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# Effective Detection Method of Unstable Acoustic Signature Generated from Ship Radiated Noise

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**Abstract**

The unstable signature that is defined as frequency change with respect to the time or frequency modulation, is caused by the external loading variation in specific machinery component and Doppler shift etc. In this study, we analyze the generation mechanism of the unstable signature and apply the Extended Kalman filter (EKF) algorithm for its detection. The performance of Extended Kalman Filter is examined for numerical and measured signals and the results show its validity for unstable signature detection.

***Keywords*** *: Acoustic signature, Extended Kalman filter, Unstable signature, ASW*

## I. Introduction

In Anti Submarine Warfare (ASW), acoustic signatures of target ships are an important passive sonar parameter in target detection and classification. Among these signatures, an unstable signature such as unstable frequency that is defined as frequency change with respect to the time or frequency modulation, is due to the external loading variation in specific machinery component. The significant sources causing the unstable frequency are sea surface waves and medium turbulence effects on target ship. Also it is caused by Doppler shift. As an example, propeller blade frequency is measured as unstable signature and is considered as modulated signal by the propeller resistance to sea surface waves or current turbulence.

When a change rate of the unstable frequency with respect to the time is slow, the FFT algorithm can be applied to its detection with reasonable accuracy. But if it is fast, the FFT algorithm cannot be applied to its accurate detection to give a good frequency and time resolution. The real time technique which is crucial for early warning, is also required to detect unstable frequency of the high speed underwater targets such as a torpedo.

In this study, the Extended Kalman Filter (EKF) algorithm is applied to detect of the unstable signature such as frequency variation in time domain. To obtain better performance than existing similar technique, the generation mechanism of unstable frequency is analyzed. The Extended Kalman Filter is applied to numerical and measured signals and its validity is verified by these results.

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## II. Unstable signature model

The characteristics of unstable frequency is dependent on the wave spectrum of sea surface which is dominant in low frequency region and is not exactly low pass or band pass process. And the shape of wave spectrum in the ocean-depends on wind velocity, the duration of wind blowing, a fetch length and so on. In addition, the wave spectrum from moving ship's viewpoint is the function of ship's speed and direction relative to waves. And the autocorrelation function of wave spectrum cannot be described accurately. But it can be considered as a function that sample values of the process gradually become less and less correlated as the time separation between samples increases. Therefore the random process of wave spectrum which is primary source of causing an unstable frequency, is assumed to be the Gauss-Markov process $x(t)$[1].

The autocorrelation function $R_{xx}(\tau)$ of the Gauss-Markov process $x(t)$ is given to be

$$R_{xx}(\tau) = \sigma^2 e^{-\alpha|\tau|} \quad (1)$$

where $\sigma^2$ and are the mean-square value and bandwidth for the Gauss-Markov process $x(t)$, respectively ( $\alpha > 0$). Its spectral density function $S_x(s)$ is

$$S_x(s) = \frac{2\sigma^2 \alpha}{-s^2 + \alpha^2} \quad (2)$$

The integrated process $x_I(t)$ of the Gauss-Markov process $x(t)$ is defined as

$$x_1(t) = 2\pi \int^t x(\lambda) d\lambda \quad (3)$$

where the process $x_I(t)$ can be assumed to be the instantaneous phase of received signal in the underwater acoustic sensors. This integrated Gauss-Markov process is explained in Fig. 1[2].

The continuous state model of the integrated Gauss-Markov process shown in Fig. 1 is given as

$$\dot{X}(t) = F\ X(t) + G\ w(t) \quad (4)$$

$$X(t) = \begin{bmatrix} x_1(t) \\ x(t) \end{bmatrix}, F = \begin{bmatrix} 0 & 2\pi \\ 0 & -\alpha \end{bmatrix}, G = \begin{bmatrix} 0 \\ \sqrt{2\sigma^2 \alpha} \end{bmatrix}$$

where $X(t)$ is the state vector and $w(t)$ is a scalar zero-mean white Gaussian process with unity variance. The continuous measurement model is given by

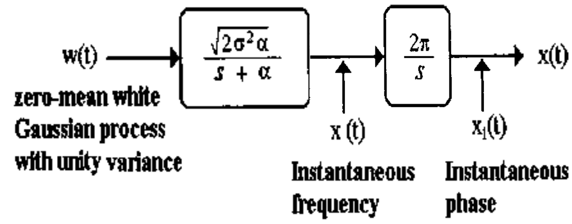


Fig. 1. Integrated Gauss-Markov process.

$$z(t) = A(t)\cos[2\pi f_0 t + x_1(t)] + v(t)$$
$$= h(X(t), t) + v(t) \quad (5)$$

where $A(t)$ is time-variant amplitude and $f_0$ is fundamental frequency of measurement signal and $v(t)$ is zero-mean white noise with constant variance parameter $\sigma_v^2$ and $h(x(t),t)$ is a nonlinear response function of the continuous measurement model.

## III. Unstable signature detection

The discrete state model may be derived by first writing the solution of (4), which is

$$X(k) = \Phi(k, k-1)X(k-1) + w(k) \quad (6)$$

where k is used to represent the discrete time instant $t_k$ and $\Phi(k, k\text{-}1)$ is the state transition matrix for the step from $t_{k-1}$ to $t_k$ and w(k) is the white noise sequence. In this discrete state model, the state transition matrix $\Phi(k, k\text{-}1)$ and the covariance matrix $Q(k)$ of $w(k)$ are given by [2]

$$\Phi(k, k-1) = L^{-1}[(sI - F)^{-1}]$$
$$= \begin{bmatrix} 1 & \frac{2\pi}{\alpha}(1 - e^{-\alpha T_s}) \\ 0 & e^{-\alpha T_s} \end{bmatrix} \quad (7)$$

$$Q(k) = E[w(k)w(k)^T] = \begin{bmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{bmatrix} \quad (8)$$

$$Q_{11} = \frac{8\pi^2\sigma^2}{\alpha}[T_s - \frac{2}{\alpha}(1 - e^{-\alpha T_s}) + \frac{1}{2\alpha}(1 - e^{-2\alpha T_s})]$$

$$Q_{12} = Q_{21} = 4\pi\sigma^2[\frac{1}{\alpha}(1 - e^{-\alpha T_s}) - \frac{1}{2\alpha}(1 - e^{-2\alpha T_s})]$$

$$Q_{22} = \sigma^2(1 - e^{-2\alpha T_s})$$

where $T_s$ is sampling interval.

The discrete measurement model can be written as

$$z(k) = A(k)\cos[2\pi f_0 kT_s + CX(k)] + v(k) \quad (9)$$
$$= h[X(k), k] + v(k)$$
$$C = [1 \quad 0]$$

where $z(k)$ is the measured sequence, $v(k)$ is zero- mean white Gaussian sequence with the covariance matrix obtained by $R(k) = E[v(k)v(k)^T]$ and $h[X(k),k]$ is the discrete nonlinear response function of the discrete measurement model.

Equation (9) is non-linear equation and the linear discrete measurement model can be obtained with Taylor's series expansions[2].

The actual state vector $X(k)$ may be written as

$$X(k) = X^*(k) + \Delta X(k) \quad (10)$$

where $X^*(k)$ is the nominal or reference state vector and $\Delta X(k)$ is the incremental state vector.

The linear discrete measurement model is obtained as

$$z(k) - h[X^*(k), k] = H(k) \cdot \Delta X(k) + v(k) \quad (11)$$

where the linear response vector H(k) is then

$$H(k) = [A(k)\sin(2\pi f_0 kT_s + CX^*(k)), 0] \quad (12)$$

The complete set of equations of the Extended Kalman filter algorithm for detecting the unstable signature with the discrete state and measurement model can be written as [3][4]

$$\Delta\hat{X}(k) = \Delta\hat{X}(k-1) + K(k)[z(k) - \hat{z}(k)]$$
$$\hat{F}(k) = f_0 + D[X^*(k) + \Delta\hat{X}(k)]$$
$$D = [0, 1]$$
$$K(k) = P(k)H(k)^T[H(k)P(k)H(k)^T + R(k)]^{-1}$$
$$\hat{z}(k) = h[X^*(k), k] + H(k)\Delta\hat{X}(k-1)$$
$$X^*(k+1) = \Phi(k+1, k)X^*(k)$$
$$P(k+1) = \Phi(k+1, k)[I - K(k)H(k)]P(k)$$
$$\cdot \Phi(k+1, k)^T + Q(k) \quad (13)$$

where the prior nominal state $X^*(1)$, incremental state $\Delta\hat{X}(0)$ and error covariance matrix $P(1)$ have to be given in $t_k$=0. The estimate vector $\hat{F}(k)$ is the detection of the unstable signature i.e. frequency.

In the equation (9), when $v(k)$ is zero, the mean value of $|z(k)|$ is $2|A(k)|/\pi$. The amplitude estimate $\hat{A}(k)$ of measurement signal applied in the measurement response function is obtained by [2][5][6]

$$\hat{A}(k) = \frac{\pi}{2} m(k) \quad (14)$$
$$m(0) = |z(0)|$$
$$m(k) = (1 - B)m(k-1) + B|z(k)| \quad (k > 0)$$

where is the time constant of first order recursive filter and sets 0.25 in this work.

## IV. Parameter Analysis

The fluctuation bandwidth caused by the sea surface roughness is as follow[7]

$$B_w = 2f_w \frac{4\pi f_0 \cos\theta_0}{c} h_w \quad (15)$$

where $w$ is wind speed in meter per sec[m/s], $f_w$=2/$w$ is the wave frequency in hertz, $h_w$=0.005$w^{5/2}$ is the wave height in meters, $f_0$ is a source frequency in hertz, $\theta_0$ is a normal incident grazing angle and $c$ is sound speed in

Table 1. Sea state and fluctuation bandwidth.

| Sea state | $w$[m/s] | $f_w$[Hz] | $h_w$[m] | $B_w$[Hz] |
|---|---|---|---|---|
| 1 | 2.572 | 0.778 | 0.053 | 0.042 |
| 2 | 4.630 | 0.432 | 0.230 | 0.100 |
| 3 | 6.688 | 0.299 | 0.578 | 0.174 |
| 4 | 8.746 | 0.229 | 1.131 | 0.260 |
| 5 | 10.803 | 0.185 | 1.918 | 0.357 |
| 6 | 12.861 | 0.156 | 2.966 | 0.464 |
| 7 | 14.919 | 0.134 | 4.298 | 0.579 |

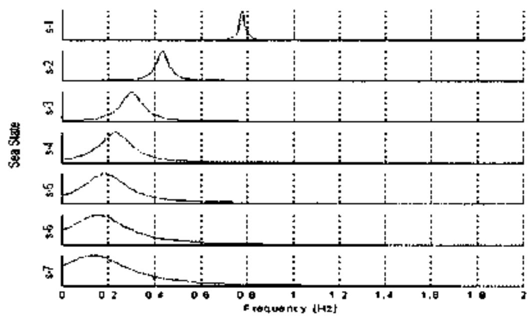


Fig. 2. Wave spectrum depending on the sea state.

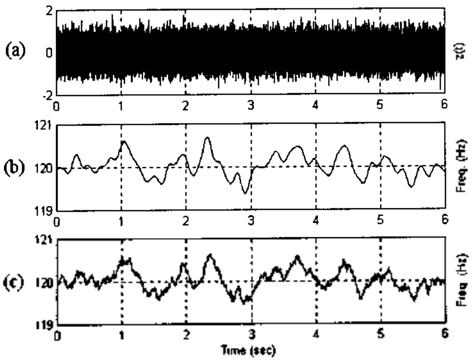


Fig. 3. Frequency detection results of FM signal.

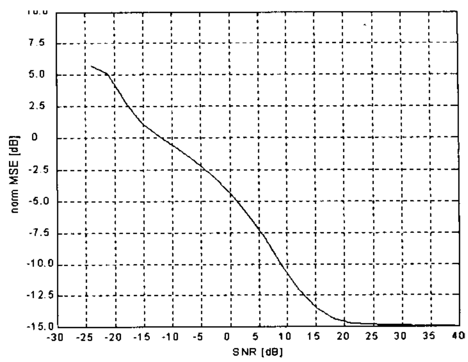


Fig. 4. The mean square error of EKF algorithm with respect to SNR.

meter per sec[m/s]. In each sea state we estimate the fluctuation bandwidth using (15) and $\alpha$ and $\sigma^2$ for the tracking model of unstable frequency in according to sea states even if loading variation parameter $\alpha$ and $\sigma^2$ are not directly functioned sea state fluctuation bandwidth.

Table 1 is shown a wind speed, a wave frequency, a mean wave height and a maximum fluctuation bandwidth calculated in each sea states when a normal incident grazing angle is zero and source frequency is 60 Hz.

A wave frequency is small and a maximum fluctuation bandwidth is large when sea state is high. Fig. 2 is shown the wave spectrum for the sea state.

The parameter bandwidth and variance $\sigma^2$ of the integrated Gauss-Markov process that is assumed as the generation model of the unstable frequency can be defined by sea states. When both parameter values set to small, fluctuations of the estimated frequency is decreased and the ability of EKF estimator to follow rapidly varying frequency changes deteriorates. When both set to large, its fluctuations is increased and EKF estimator is more robust toward frequency variations. In this work, both set as $\alpha = f_w + B_w/2$ and $\sigma^2 = h_w{}^2/2$ in each sea state.

## V. Simulation Results

To demonstrate and verify how the EKF algorithm detects the unstable signatures, it is applied to numerical signals such as FM modulation signal and Doppler shifted signal.

The Fig. 3 is the detection result of a frequency variation from the FM modulated numerical signal. This signal is characterized by the 120Hz carrier frequency, the band-limited message signal with 0.2Hz bandwidth and 0.3Hz center frequency and the 0.6 mean amplitude. In this case, the sea state is assumed as 3, fluctuation bandwidth is 0.2268Hz and wave height is 1.0668m approximately. Fig. 3 (a), (b) and (c) depict time waveform of the numerical FM modulated signal with 10dB SNR, an actual frequency variation and the estimated one with respect to the time, respectively. The figure (b) and (c) match well each other.

The Fig. 4 shows the normalized Mean square error (MSE) between the actual and estimated frequency in the case of Fig. 3 with respect to SNR. The normalized MSE is defined to evaluate the proposed method and as follow

$$norm\ \ MSE = 10\log_{10}\frac{E[\,(F(k) - \hat{F}(k))^2]}{E[F(k)^2]} \qquad (16)$$

where $F(k)$ is the actual frequency variation and $\hat{F}(k)$ is the estimated one using proposed method. In the Fig. 4, the norm MSE is less than -6dB when the SNR is approximately is larger than 3dB. The SNR is required to larger than 3dB in order to achieve the good detection of unstable frequency.

The Fig. 5 shows the frequency detection result from the Doppler shifted numerical signal. The source is assumed as the target passing by speed of 10knot with the fundamental frequency of 120Hz. In this case, CPA(Closest Point of Approach) and sea state is assumed as 3m and

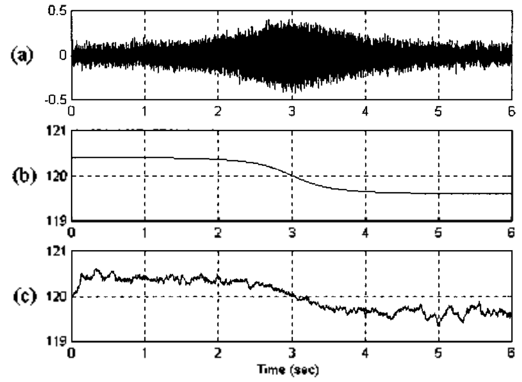


Fig. 5. Frequency detection results of Doppler shifted signal.

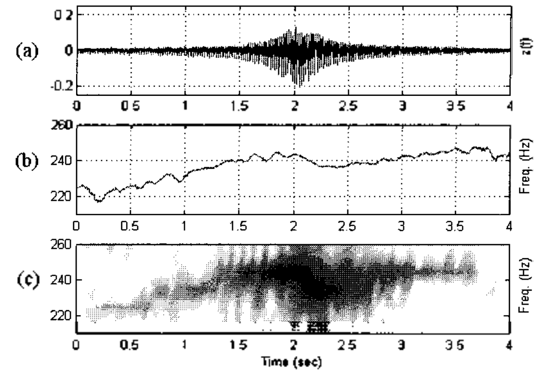


Fig. 7. Frequency detection results of the measured signal of moving motorcycle.

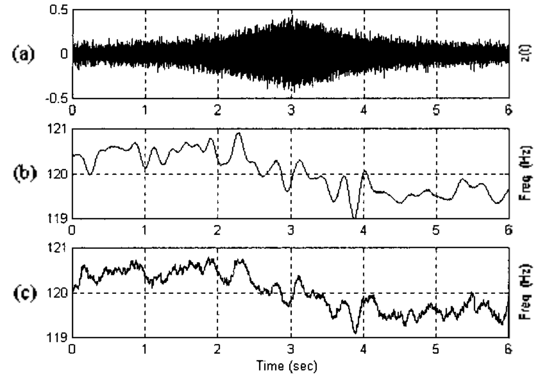


Fig. 6. Frequency detection results of FM modulated and Doppler shifted numerical signal.

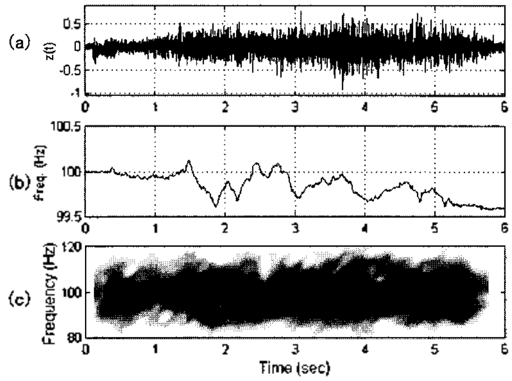


Fig. 8. Frequency detection results of the measured signal of moving ship.

0, respectively. Fig. 5 (a), (b) and (c) are time waveform of the Doppler shifted numerical signal with 10dB SNR, an actual frequency and the estimated frequency with respect to the time, respectively. The actual and estimated values match well each other.

The Fig. 6 shows the detection result of frequency variation when sea state is assumed as 3 and other condition is the same above case. Fig. 6 (a), (b) and (c) depict the numerical measurement signal, the actual and estimated frequency with respect to the time, respectively. The actual and estimated values coincide well each other. But it is important that the fundamental frequency $f_0$ of received signal is found out accurately.

## VI. Experimental Results

To verify the ability of the EKF algorithm to detect the frequency variations, it is applied to experiment data such as the radiated noise from moving motorcycle and ship. The experimental data obtained from measured signals in outdoor experiments. One of measured signals is the radiated engine noise from the motorcycle passing by average speed of about 11.1m/s and with speed-up condition. The closest range between a microphone and a motorcycle was 5m and the passing time was 2 sec approximately. The Fig. 7 shows the estimated result of frequency variation. The Fig. 7(a), (b) and (c) are the measured signal, the estimated unstable frequency using the EKF algorithm and the result of the spectrogram, respectively. In this result, the proposed method provides more accurate detection results of frequency variation from the measured data than one of the spectrogram.

The final result is unstable frequency detection from the measured signal in the sea. The received signal is the radiated noise from small ship passing by speed of about

20knot. CPA and sea state approximately were 10m and 2 respectively. The Fig. 8 shows the detection result of unstable frequency variation of this measured signal. The Fig. 8 (a), (b) and (c) are the measured signal, the estimated unstable frequency using the proposed method and spectrogram, respectively. This result indicates that the proposed method using EKF algorithm detects well the unstable frequency variations of received signal caused by Doppler effect and loading variation due to sea wave.

## VII. Conclusions

In this study, it is shown that the unstable signature which is defined as frequency change with respect to the time or the frequency modulation, can be detected using the Extended Kalman Filter (EKF) algorithm. The input parameters of EKF algorithm i.e. bandwidth $\alpha$ and variance $\sigma^2$ of the generation model that is the integrated Gauss-Markov process, is found to depend on sea state or wind speed. Therefore, the sea state wave spectra is modeled to increase the estimation accuracy of the parameters and the detection capability. It is also verified that the unstable signatures detection performance of proposed method depends on SNR. In order to obtain the reasonable detection accuracy, it's required that SNR be approximately larger than 3dB. Its other application which is shown in Doppler frequency tracking, is a moving target state estimation such as CPA or maneuvering state.


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## [Profile]


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