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A De-noising Algorithm for PIND Signals Based on Kalman Filter

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Abstract. *The Particle Impact Noise Detection (PIND) is a screening test that is required before aerospace relays delivery. The weak remainder signal is easily submerged by several kinds of noise, and hard to extract or identify. In this paper, the sources and characteristics of the noise are analyzed. A self-adaption de-noising algorithm is presented for ambient noise based on Kalman filter. The signal model and its parameters are received using Linear Prediction Coefficients and iterative algorithm. An attenuation coefficient is defined to distinguish if the Kalman input is remainder signal or the noise. The experiment demonstrates that the de-noising algorithm is effective to improve the ratio of signal to noise.*
Keywords: Aerospace relay, PIND, weak signal, kalman filter

1. **Introduction.** The aerospace sealed relays, which are widely used in the man-made satellites, missiles, airplanes and radars, are the necessary base elements in the defense electronic systems. They are important in the subsystems such as the automatic control, navigation and signal transmission [1]. For examples, there are 354 relays in a launch vehicle, and at least one thousand in the Chinese No.4 SHEN ZHOU airship. Therefore, the reliability of the aerospace relays will influence their defense electronic system greatly [2, 3].

The remainders will be produced and remained in a sealed relay during the processes such as manufacture, seal and use. They are excited and dissociated at the extreme mechanic condition. They moved with a random motion, leading to the system failure. In the 75 relays invalid accident, the percent caused by the remainders is 22.67%. Several aerospace accidents have happened because of the remainders in the relays, resulting in the immeasurable loss.

Up to now, several methods are used to detect the remainders, including microscopic observation, X ray photography, Matrah detecting and Particle Impact Noise Detection (PIND). PIND is widely applied because of its fastness, convenient, low cost and high sensitivity [4, 5].

PIND is first proposed by NASA as a non-destructive examination to filter the remainders in the military electronic components. The remainders are excited according to the lashing and shock by the vibrator, then it impact with the cavity wall. The acoustic emission sensor transfer the impact energy to the voltage signal and export, differentiating if the remainders exist [4, 5].

Several researchers studied PIND during its application. However, as the designs and producing technology were improved, the remainders were effectively controlled in USA after 1970s. Therefore, few researches about PIND were carried out in USA now. Few about PIND were done in European, Russia and Japan because of their relative small market. Nearly no researches were explored in the other countries except for China.

From 1990s, as the aerospace market expanded, the Chinese researchers have realized the importance of remainders and have laid down a criterion on the remainder detection in the sealed electronic components [6, 7]. Zhang X.S. et al. extracted small mass remainder information by wavelet transforms to improve the detecting sensitivity [8]. Li H.F. et al. studied the detecting method for the remainders in the aerospace electric relays systematically. He proposed the evaluating characteristic of the signal period based on the autocorrelation coeficient and waveform geometric centroid, together with the power characteristic spectrum based on statistical theory [9]. Zheng S.C. et al. presented to distinguish component signal period based on the PIND machine [10]. Gao H.L., et al. detected the remainder with various mass of large, small and tiny, by crest coefficient method, wavelet de-noinsing and complex wavelet phase detection, respectively [11, 12, 13]. However, the completeness of algorithm needs to be improved. Wang S.C. et al. proposed stochastic resonance detecting method of tiny mass remainder, but the preconditions of the method were harsh and the application was limited [14, 15].

Up to now, though PIND can detect if the remainder exist, the signal of tiny mass such as lower than 0.02 mg is very weak, which can be easily submerged by the background noise, and is hardly detected. There are no reported have been presented for the tiny mass remainder. For the normal PIND test, when the mass of the detected remainder is small, the erroneous judgments often happened as the acoustic emission sensor background noise and the signals of the remainder are quite similar.

2. **Analysis of Remainder Signals.** The detection of the remainders in the aerospace relays was realized by analyzing the acoustic emission signal by PIND. Therefore, to filter the noise and detect the weak signals, it is necessary to study the constitution and characteristic of the acoustic emission signal. The PIND signals come from the remainders, the components, background noise, ambient noise and impulsive interference. The characteristic of these signals and the causes were listed in Table 1.

Of the 5 kind signals, the remainder signals is the PIND detecting target and the others are the interference signals. For the most of sealed electronic components, the signals are nearly undetectable, and the impulsive interferences are rapidly decreased further when the isolation transformer are introduced, so the influence of component are discarded. The background noises are the foreign random noises coupling from acoustic emission sensors. As the acoustic emission sensors work with resonance principle, they appear as a kind of narrowband random noises with fixed carrier frequency and random low-frequency envelope component. The ambient noise come from PIND detecting circuit, ambient condition and power sources. It was constitute of thermal noise, ground coupled interference and power harmonic interference. The thermal noise was made up with the ambient couple with electromagnetic field and the electronic component.

The ground coupling interference came from the different power circuit according to the mixed circuit with analog and digital circuit. The ground coupling and thermal noise appear to broadband random noise, nearly to white noise. The power harmonic interference came from sub harmonic and power frequency electromagnetic field. The frequency of these interferences is fixed at 50 Hz and its integral multiple. The amplitude is relative low.

Table 1. The constitutions of acoustics emission signals

Constitution	Cause	Signal characteristics
Signals of remainders	The remainder collide with the relay component and cavity wall	A series of random spike pulses with large amplitude variation and frequency range of 100kHz160kHz
Signals of components	Collide by the moving component during the vibration	Periodic spike pulses
Background noises	Random narrowband signal coupling from sensors	Narrowband noises with smaller amplitude and frequency range of 50kHz160kHz
Ambient noises	Noises cause by electronic circuit thermal noise, space electromagnetic interference, and so on	Broadband random noises with smaller amplitude, like white noise
Impulsive interferences	Signals saltus step cause by external power shock or environmental electromagnetic shock	Signals with smaller amplitude and shorter duration

3. **Ambient Noise Suppression Based On Kalman Filter.** The ambient noise was mainly constituted of power line interference with small amplitude and broadband random noise. These can be simplified and equivalent to white noise. The experience of speech enhancement, which was to extract pure voice from voice signal with noise, can be drew to remove the white noise from the remainder signals.

Kalman filter, estimate the extracted signals and noises from the testing results using measuring results and priori information,. Both speech signal and noise models are referred. So the non-stationary signals can be dealt with and the results contained little noise. The Kalman filter is applied to remove the ambient noise from the PIND signals here.

3.1. **All pole models and parameter estimation for the signals of the remainders.** During the remainder detecting processes, no matter whether the remainder collides with the cavity wall, colliding position and time appear a randomized procedure, the remainder signal is a typical random signal. Therefore, the remainder signal can be expressed by the randomized procedure as equation (1). Here, P is the autoregressive factorial, including e with lagged variable weighting and Gauss white noise $\{\omega(n)\}$

$$x(n) = \sum_{j=1}^{P} a_j x(n-j) + \omega(n) \tag{1}$$

Pure remainder signals can be expressed by autoregressive model, while that with noise can be expressed by

$$s(n) = x(n) + v(n) \tag{2}$$

Where $\{v(n)\}$ is Gauss noise, which its amplitude cannot be measured every time. Then the extractions of weak remainder signals were transferred to calculate the optimum $\{\hat{x}(n)\}$ and background noise by PIND after wavelet de-noising. After filtering background noise of PIND with wavelet, the noise in the signal of remainder is Gauss type. Then the standard Kalman filter algorithm can be used to detect the weak remainder signal mentioned above.

When $\{v(n)\}$ is Gauss white noise, Eq. (1) can be transferred to regulatory state space matrix equation

$$\boldsymbol{X}(n) = \boldsymbol{F}\boldsymbol{X}(n-1) + \boldsymbol{G}\boldsymbol{W}(n) \tag{3}$$

$$\boldsymbol{S}(n) = \boldsymbol{H}^{\mathrm{T}}\boldsymbol{X}(n) + v(n) \tag{4}$$

Here

$$\boldsymbol{X}^{\mathrm{T}}(n) = [x(n-P+1) \quad x(n-P+2) \quad \cdots \quad x(n)]$$

$$\boldsymbol{F} = \begin{bmatrix} 0 & 1 & 0 & \dots & 0 & 0 \\ 0 & 0 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & & \vdots & \vdots \\ 0 & 0 & 0 & \dots & 0 & 1 \\ a_P & a_{P-1} & a_{P-2} & \dots & a_2 & a_1 \end{bmatrix}$$

In state equation (3), the driving term $\{\omega(n)\}$ is the white noise with the average value zero and the variance σ_ω^2. The parameters of $X(n)$ state vector was estimated by Kalman recursion optimal estimation theory.

$$\hat{\boldsymbol{X}}(n) = \boldsymbol{F}\hat{\boldsymbol{X}}(n-1) + \boldsymbol{K}(n)[\boldsymbol{S}(n) - \boldsymbol{H}^{\mathrm{T}}\boldsymbol{F}\hat{\boldsymbol{X}}(n-1)] \tag{5}$$

Here, $K(n)$ is Kalman filter gain.

$$\boldsymbol{K}(n) = \boldsymbol{P}(n \mid n-1)\boldsymbol{H}\left[\boldsymbol{R} + \boldsymbol{H}^{\mathrm{T}}\boldsymbol{P}(n \mid n-1)\boldsymbol{H}\right]^{-1} \tag{6}$$

$P(n \mid n-1)$ is the forecasting error matrix of covariance

$$\boldsymbol{P}(n \mid n-1) = \boldsymbol{F}\boldsymbol{P}(n-1)\boldsymbol{F}^{\mathrm{T}} + \boldsymbol{G}\boldsymbol{Q}\boldsymbol{G}^{\mathrm{T}} \tag{7}$$

$$\boldsymbol{P}(n) = \left[\boldsymbol{I} - \boldsymbol{K}(n)\boldsymbol{H}^{\mathrm{T}}\right]\boldsymbol{P}(n \mid n-1) \tag{8}$$

Here, $P(n)$ is the estimation of error for matrix of covariance $\boldsymbol{R} = \sigma_v^2\boldsymbol{I}$, $\boldsymbol{Q} = \sigma_\omega^2\boldsymbol{I}$.

From equation (5) to (8), if $\hat{\boldsymbol{X}}(0)$ and $P(0)$ have initial value, then the final $S(n)$ value with noise can be calculated according to the equation

$$\hat{x}(n) = \boldsymbol{H}^{\mathrm{T}}\hat{\boldsymbol{X}}(n) \tag{9}$$

When $\{v(n)\}$ is Gauss white noise. The state vector equation can be improved by adding variance. Similar to the AR model for signal of pure remainder, it is possible to modeling time serials of $\{v(n)\}$. The AR model

$$v(n) = \sum_{j=1}^{q} b_j v(n-j) + \eta(n) \tag{10}$$

Where the order of the model is q and $\{\eta(n)\}$ is Gauss white noise. Equation (7) was transferred to regulatory state space matrix equation.

$$\boldsymbol{V}(n) = \boldsymbol{F}_v\boldsymbol{V}(n-1) + \boldsymbol{G}_v\eta(n) \tag{11}$$

$$v(n) = \boldsymbol{H}_v^{\mathrm{T}}\boldsymbol{V}(n) \tag{12}$$

Here

$$\boldsymbol{V}(n) = [v(n-q+1) \quad v(n-q+2) \quad \dots \quad v(n)]^{\mathrm{T}}$$

$$\boldsymbol{F}_v = \begin{bmatrix} 0 & 1 & 0 & \dots & 0 & 0 \\ 0 & 0 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & & \vdots & \vdots \\ 0 & 0 & 0 & \dots & 0 & 1 \\ b_q & b_{q-1} & b_{q-2} & \dots & b_2 & b_1 \end{bmatrix}$$

$$\boldsymbol{G}_v = \boldsymbol{H}_v = \begin{bmatrix} 0 & 0 & 0 & \dots & 0 & 1 \end{bmatrix}^{\mathrm{T}}$$

Combining equation (3), (4), (11), (12) to do vector operation. Then

$$\bar{\boldsymbol{X}}(n) = \bar{\boldsymbol{F}}\bar{X}(n-1) + \bar{\boldsymbol{G}}\bar{W}(n) \tag{13}$$

$$\boldsymbol{S}(n) = \bar{\boldsymbol{H}}^{\mathrm{T}}\bar{\boldsymbol{X}}(n) \tag{14}$$

Here

$$\bar{\boldsymbol{X}}(n) = \begin{bmatrix} \boldsymbol{X}(n) \\ \boldsymbol{V}(n) \end{bmatrix} \bar{\boldsymbol{F}} = \begin{bmatrix} \boldsymbol{F} & 0 \\ 0 & \boldsymbol{F}_v \end{bmatrix}$$

$$\bar{\boldsymbol{G}} = \begin{bmatrix} \boldsymbol{G} & 0 \\ 0 & \boldsymbol{G}_v \end{bmatrix} \bar{\boldsymbol{W}}(n) = \begin{bmatrix} \omega(n) \\ \eta(n) \end{bmatrix}$$

$$\bar{\boldsymbol{H}}^{\mathrm{T}} = \begin{bmatrix} \boldsymbol{H}^{\mathrm{T}} & \boldsymbol{H}_v^{\mathrm{T}} \end{bmatrix}$$

Combining equation (13) and equation (5)∼(8):

$$\hat{\bar{\boldsymbol{X}}}(n) = \bar{\boldsymbol{F}}\hat{\bar{X}}(n-1) + \boldsymbol{K}(n)\left[\boldsymbol{S}(n) - \bar{\boldsymbol{H}}^{\mathrm{T}}\boldsymbol{F}\hat{\bar{\boldsymbol{X}}}(n-1)\right] \tag{15}$$

$$\boldsymbol{K}(n) = \boldsymbol{P}(n \mid n-1)\bar{\boldsymbol{H}}\left[\bar{\boldsymbol{H}}^{\mathrm{T}}\boldsymbol{P}(n \mid n-1)\bar{\boldsymbol{H}}\right]^{-1} \tag{16}$$

$$\boldsymbol{P}(n \mid n-1) = \bar{\boldsymbol{F}}P(n-1)\bar{\boldsymbol{F}}^{\mathrm{T}} + \bar{\boldsymbol{G}}Q^{*}\bar{\boldsymbol{G}}^{\mathrm{T}} \tag{17}$$

$$\boldsymbol{P}(n) = \left[I - \boldsymbol{K}(n)\bar{\boldsymbol{H}}^{\mathrm{T}}\right]\boldsymbol{P}(n \mid n-1) \tag{18}$$

Here,

$$\boldsymbol{Q}^{*} = \boldsymbol{E}\left[\bar{\boldsymbol{W}}(n)\bar{\boldsymbol{W}}^{\mathrm{T}}(n)\right] = \begin{bmatrix} \sigma_\omega^2 & 0 \\ 0 & \sigma_\eta^2 \end{bmatrix} \tag{19}$$

So, when the noise of matrix for covariance $\boldsymbol{Q}^{*}$ is known, if the initial value $\hat{\bar{X}}(0) = 0$ and $P(0) = 0$, then the optimal estimation of $\hat{\bar{\boldsymbol{X}}}(n)$ and $\hat{\bar{x}}(n)$ could be calculated at the time of n. The final estimation

$$\hat{\bar{x}}(n) = \left[\boldsymbol{H}^{\mathrm{T}} \quad 0\right]\hat{\bar{\boldsymbol{X}}}(n) \tag{20}$$

3.2. **Processes of kalman filter.** According to the Kalman filter theory, before gaining the algorithm of suppressing the ambient noise in the weak remainder signals, it is necessary to receive the signal model and its parameters. In the light of the speech enhancement, the noise model

$v(n) = \sum\limits_{j=1}^{q} b_j v(n-j) + \eta(n)$, q is 6. That is 6 orders for the AR model of noise.

Before starting PIND experiment, the noise with no load was obtained, then the initial value of the parameter b and σ_η^2 can be received to the noise model. These values can be used as the initial value for the iterative procedure.

For the remainder signal model $x(n) = \sum\limits_{j=1}^{P} a_j x(n-j) + \omega(n)$, the simulation results were received at different P. When P is 10, it is the most similar to the real remainder signals; therefore, the order of the AR model for the remainder signal is 10. Combining the noise mode parameter, the parameter for the remainder signal can be calculated.

As F or $\bar{F}$ is the function of time, it is a time varying system. To estimate the signal with more accuracy, the adjustment of the noise model and its parameters are necessary. So a self-adaption Kalman filter system is built as Fig. 1.

Before detecting the remainder experiment, the signals were firstly collected without samples as background noise. Then the σ_v^2 was obtained with statistical method under white noise. Or b and σ_η^2 will be received using Linear Prediction Coefficients under colored noise.

The remainder signals cannot be received according to the experiment, but it work to iterative algorithm to receive model parameters a and σ_ω^2. The mixed signals with remainder and noise of $\hat{a}$ and $\hat{\sigma}_\omega^2$ were firstly calculated by LPC algorithm. The results were filtered by Kalman filter, calculated by LPC algorithm. The new results $\hat{a}$ and $\hat{\sigma}_\omega^2$ were input the Kalman filter again, and round it. The residual errors of the remainder signal model were carried out with each iterative step. When the residual error was lower than the threshold value e, stop the iterative step.

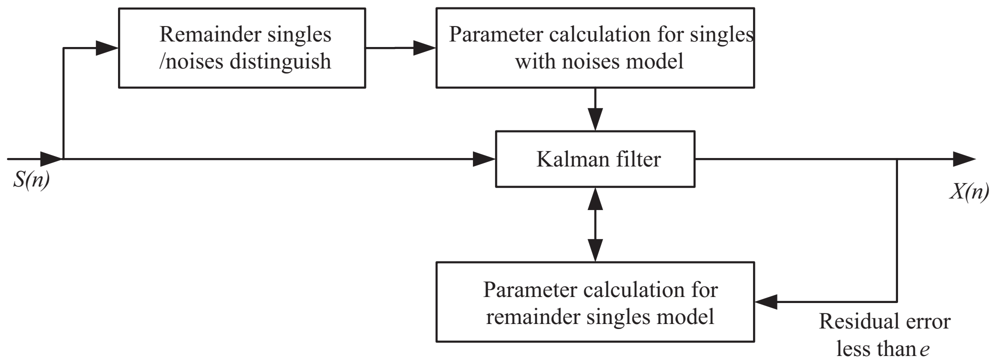


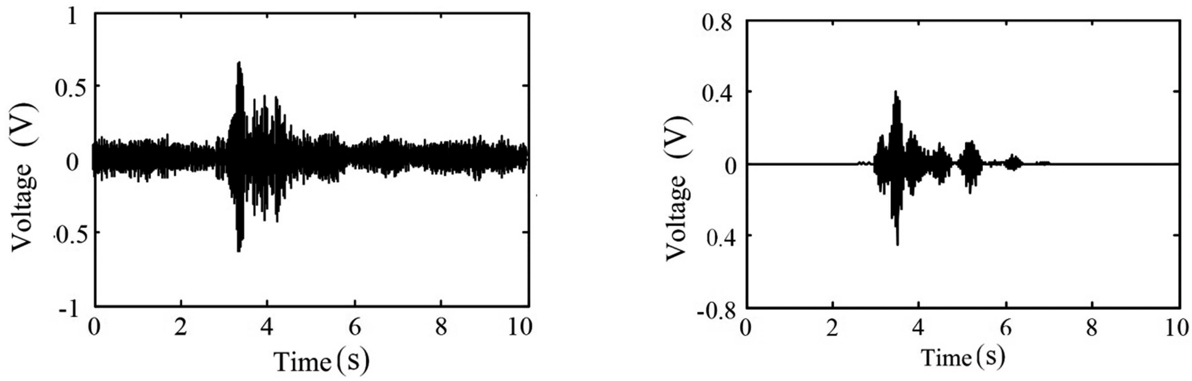
Figure 1. Adaptive Kalman filtering system

As the collision between the remainder and the cavity wall does not happen at every time during the detection, the Kalman input sometimes is the signal with noise, and sometimes is only the noise. So before starting the iterative procedure, the input should be confirmed. If both the remainder signal and the noise are filtered, the energy changes have a great difference between these two. So the attenuation coefficient is defined as the following

$$D = \frac{\frac{1}{N}\sum_{j=1}^{N} S^2(j)}{\frac{1}{N}\sum_{j=1}^{N} \hat{S}^2(j)} \tag{21}$$

As filtering the ambient noise, not the remainder signal, the energy of the ambient noise is decayed rapidly. Its attenuation coefficient D is much larger than that of the signal with noise. Based on the PIND results, only if the D threshold is ascertained, it is easy to distinguish if the Kalman input is remainder signal or the noise. When the input is noise, the parameters of the noise model b and σ_η^2 can be calculated. This can lead the system adapt its input during the PIND experiment, achieving its self-adaption.

4. **Experimental Confirmation.** The PIND detecting power was offered by linear power supply with ripple lower than 20 mV and isolation transformer under electromagnetic screen to make sure that no impulsive interference noise exists in the detecting results. A 0.02 mg lead - tin alloy as remainder was embedded into the aerospace relay.



a) The signals with noise

b) The signals after Kalman filter

FIGURE 2. The result after Kalman filtering

After wavelet de-noising, the signal with noise was shown in Fig. 2a). The result after Kalman filtering was shown in Fig. 2b).

It can be seen that the background noise with signal was decreased obviously after Kalman filtering, but some useful signal was also lost. The reason was probably that the model of remainder signal and noise are not very accurate, or the threshold is not rational. Later work will be focused on this.

5. **Conclusion.** The de noising of the PIND with ambient interference was successfully realized by Kalman filter. The characteristics of acoustic emission and PIND signals were analyzed, explicating the noise source. A suitable de-noising algorithm was presented based on Kalman filter. The test results demonstrated that it is effective to de noise by the algorithm.

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