# A pseudo-adaptive hum filter to suppress rotor noise in high-resolution airborne magnetic data

*Jianghai Xia,* Kansas Geological Survey; William E. Doll, Oak Ridge National Laboratory;*
*Richard D. Miller, Kansas Geological Survey; T. Jeffrey Gamey, Oak Ridge National Laboratory*

**Summary**

A unique filtering approach designed to eliminate helicopter rotor noise on aeromagnetic data without affecting the frequency content of signal provides a powerful harmonic noise suppression tool for data acquired with modern large dynamic range recording systems. This three-step approach—polynomial fitting, bandpass filtering, and rotor noise synthesis—significantly reduces the rotor noise and does not alter the spectra of signals. The approach to modeling the rotor noise is stable and efficient. Real data examples demonstrate this method can suppress rotor noise by more than 90% when implemented in an aeromagnetic data processing flow.

**Introduction**

Since 1998, Oak Ridge National Laboratory (ORNL) has been involved in development of high-resolution airborne systems for detection of unexploded ordnance (UXO) and other small metallic objects that are the targets of environmental surveys (Gamey et al., 2002; Doll et al., 2001; Gamey et al., 2000). These differ significantly from conventional helicopter systems designed for mineral surveys in which sensors are placed in a bird that is suspended 30-50m below the helicopter (e.g., Doll et al., 2000). The Oak Ridge Airborne Geophysical System – Arrowhead (ORAGS-Arrowhead; see Doll et al., this volume) uses eight Scintrex CS-2 cesium vapor magnetometers at 1.75m spacing in booms that attach directly to the helicopter. A RT-DGPS navigation system is used to guide the pilot in acquiring data on prescribed lines, and post-processed DGPS is used to provide sub-meter accuracy for mapping purposes. By placing the sensors in helicopter-mounted booms instead of in a bird suspended below the helicopter, it is possible to acquire data within 1.5m of the surface. Test data demonstrate that these systems are capable of detecting objects having a mass of less than 4 kg and can cover 250-400 acres/day.

Low altitude operation is key to the sensitivity of the ORAGS system. The minimum altitude for bird-mounted systems is on the order of 10m because of line-of-sight limitations on the helicopter pilot. The increase in noise that results from positioning sensors in proximity to the helicopter is more than compensated by the increase in signal strength that results from the lower altitude operation. The dominant source of noise in the ORAGS data is associated with the magnetization of the rotor at about 6.4 Hz. This noise typically has a root-mean-square amplitude of 0.4 nT. The amplitude of this signal varies as a function of sensor position. Noise measurements around a stationary helicopter (see Doll et al., this volume) demonstrate that the noise is largely symmetric about the rotor, so that the sensors that are furthest from the rotor have the lowest amplitude noise. In flight, the frequency of the rotor noise varies a few tenths of 1 Hz, perhaps as a function of throttle speed, and there is a component of the noise amplitude that varies slightly with time.

The rotor noise overlaps a portion of the spectrum where signal occurs. Thus it is important to develop signal processing techniques that reduce the rotor noise with a minimal effect on the signal components recorded at the same frequency. Application of a notch filter generally results in a sawtooth shaped spectrum with dropouts around the notch frequency. Notch filters can be effective in reducing the rotor noise, but remove part of the signal as well. The most appropriate filter for the rotor noise is one that preserves the signal by subtracting the rotor noise (a sinusoid) from the raw data with the frequency, amplitude, and phase of the sinusoid determined from the data itself.

The hum filter (Xia and Miller, 2000) was designed to suppress power-line noise possessing single or multiple frequencies in seismic data. Amplitude and phase of each frequency harmonic were treated as unknowns, and frequency was assumed to be constant. The filter was determined using "pure" power-line noise from a time window before the first break (on set of first source generated seismic energy). The problem differs from the rotor noise problem in that the seismic noise can be assumed constant in amplitude, phase, and with a known frequency for each trace, whereas the rotor noise is known to vary slightly in amplitude, phase, and frequency. A small change in frequency will cause a significant error in the corrected data, especially towards the end of a record (Butler and Russell, 1993). Moreover, power-line noise can be acquired in the time window before the first break of the seismic data, but the time window is not normally available during acquisition of aeromagnetic data. Aeromagnetic data collected at high altitude provides a measure of "pure" noise, but because the frequency, amplitude, and/or phase of the harmonic noise changes slightly with time, it cannot be used for filtering purposes. Our algorithm, therefore, was developed based on a dynamic filtering concept where the hum filter removes the rotor noise segment by segment along each recorded data channel until reaching the end of the line. A segment length is normally in the range of 100 to 1000 data points depending on uniformity of frequency, amplitude, and phase of data. The amplitude, phase, and frequency of the rotor noise within a segment can be treated as unknown constants. Because the filter is adaptive segment-by-segment rather than point-by-point, we called it a *pseudo-adaptive hum filter*.

**Algorithm Structure**

We formulated a three-step algorithm to eliminate the rotor noise for each segment of data. First, a polynomial, normally of degree less than eight, is employed to fit the input data in a least-square sense. Then the polynomial is removed from the data. Second, a bandpass filter designed around the frequency of the rotor noise is applied to the polynomial-removed data to obtain approximated rotor noise signature. Finally, a sinusoid function model is fitted to the approximated rotor noise to determine the frequency, phase, and amplitude of the rotor noise. The first step which ensures that a sinusoid function can successfully model the rotor noise is critical because the average value of a sinusoid function over a given period is zero. The bandpass filtering in the second step removes non-rotor noise or signals, making the sinusoid modeling of the rotor noise stable and accurate.

The rotor noise is synthesized from approximated rotor noise. The rotor noise and its multiples will be thought of as a summation of sinusoid functions with different frequencies, amplitudes, and phases.

$$P(\vec{x}, t) = \sum_{i=1}^{n} A_i \sin(2\pi f_i t + \Phi_i), \tag{1}$$

where $P$ is a rotor noise model; $t$ is time; $f_i$, $A_i$ and $\Phi_i$ are the frequency, amplitude, and phase of the rotor noise; $n$ is the number of sinusoid functions that are needed to model the rotor noise and its multiples ($n$ is equal to one in most case because the multiples are normally too weak to be noticed); and the vector $\vec{x}$ represents the parameters of the rotor noise model ($\vec{x}$ = $[f_1, A_1, \Phi_1, f_2, A_2, \Phi_2, ..., f_n, A_n, \Phi_n]^T$). The total number of parameters in the model is $3\times n$ (the parameters for each sinusoid are the frequency, amplitude, and phase). Similarly, the approximated rotor noise obtained by a bandpass filtering can be represented as the vector $\underline{\vec{b}}$ of length $m$, $\underline{\vec{b}}$ = $[\underline{b}_1, \underline{b}_2, \underline{b}_3, ..., \underline{b}_m]^T$, where $m$ is the number of data points of one segment. We employ the objective function shown as follows to determine the rotor noise model.

$$\Psi = \left\| \mathbf{J}\,\Delta\vec{x} - \vec{b} \right\|_2^2 + \lambda \left\| \Delta\vec{x} \right\|_2^2, \tag{2}$$

where $\lambda$ is a damping factor, $\vec{b} = \underline{\vec{b}} - P(\vec{x}_0)$, $\vec{x}_0$ is an initial estimate of parameters of the rotor noise model, $P(\vec{x}_0)$ is calculated by Eq. 1, $\Delta\vec{x}$ is modification to initial estimate $\vec{x}_0$, and $\mathbf{J}$ is the Jacobian matrix consisting of $m$ rows and $3\times n$ columns. The elements of the Jacobian matrix are the first order partial derivatives of $P$ with respect to parameters of the rotor noise model at each sampling time. Elements of the Jacobian matrix are sine and cosine functions and can be easily calculated from Eq. 1.

The Levenberg-Marquardt (L-M) method (Marquardt, 1965) is used to iteratively find the minimum point of the objective function $\Psi$ (Eq. 2) therefore determining frequencies, amplitudes, and phases of the sinusoid model (functions of the rotor noise). Good initial estimates of frequency, amplitude, and phase are required by the L-M method. Based on our experience, initial frequencies determined by a spectral analysis are good enough to guarantee convergence of the L-M method. Initial amplitudes of sinusoids are determined in the frequency domain by the fast Fourier transform (FFT) method and initial phases by a time-domain correlation (Xia and Miller, 2000). Calculation efficiency of the L-M method is achieved by using singular value decomposition techniques (Golub and Reinsch, 1970) so the solution to Eq. 2 is given by

$$\Delta\vec{x} = \mathbf{V}(\Lambda^2 + \lambda\mathbf{I})^{-1}\Lambda\,\mathbf{U}^T\vec{b}, \tag{3}$$

where $\mathbf{V} = [\vec{v}_1, \vec{v}_2, \vec{v}_3, ..., \vec{v}_{3n}]$, $\vec{v}_i$ ($i$ = 1, 2, ..., $3\times n$) are eigenvectors of matrix $\mathbf{A}^T\mathbf{A}$, $\Lambda$ = diag $(\sqrt{\lambda_1}, \sqrt{\lambda_2}, ..., \sqrt{\lambda_{3n}})$, $\Lambda$ has elements that are the square roots of the eigenvalues of $\mathbf{A}^T\mathbf{A}$, $\mathbf{U} = [\vec{u}_1, \vec{u}_2, \vec{u}_3, ..., \vec{u}_{3n}]$, $\vec{u}_i = \mathbf{A}\vec{v}_i/\lambda_i$ ($i$ = 1, 2, ..., $3\times n$), and $\mathbf{I}$ is the unit matrix. After determining $\Delta\vec{x}$, the initial frequency, amplitude and phase estimates are modified by

$$\vec{x}^k = \vec{x}^{k-1} + \Delta\vec{x}. \tag{4}$$

Normally it takes about ten to twenty iterations requiring only a fraction of a second to determine the rotor noise model (sinusoids) of a segment. Finally, the rotor noise model is subtracted from the original data.

## Examples

“Pure” rotor noise data was acquired during a test flight at high altitude with no particular line direction. The line contained over 5,700 measurement points. The first portion is shown in Figure 1a. The rotor noise frequency is approximately 6.4 Hz (Figure 1b). The hum filter was applied to the data with a segment length chosen as 500 points. After hum filtering (Figure 1c), the rotor noise appears to be completely filtered out and signals around frequency 6.4 Hz are not altered (Figure 1d).

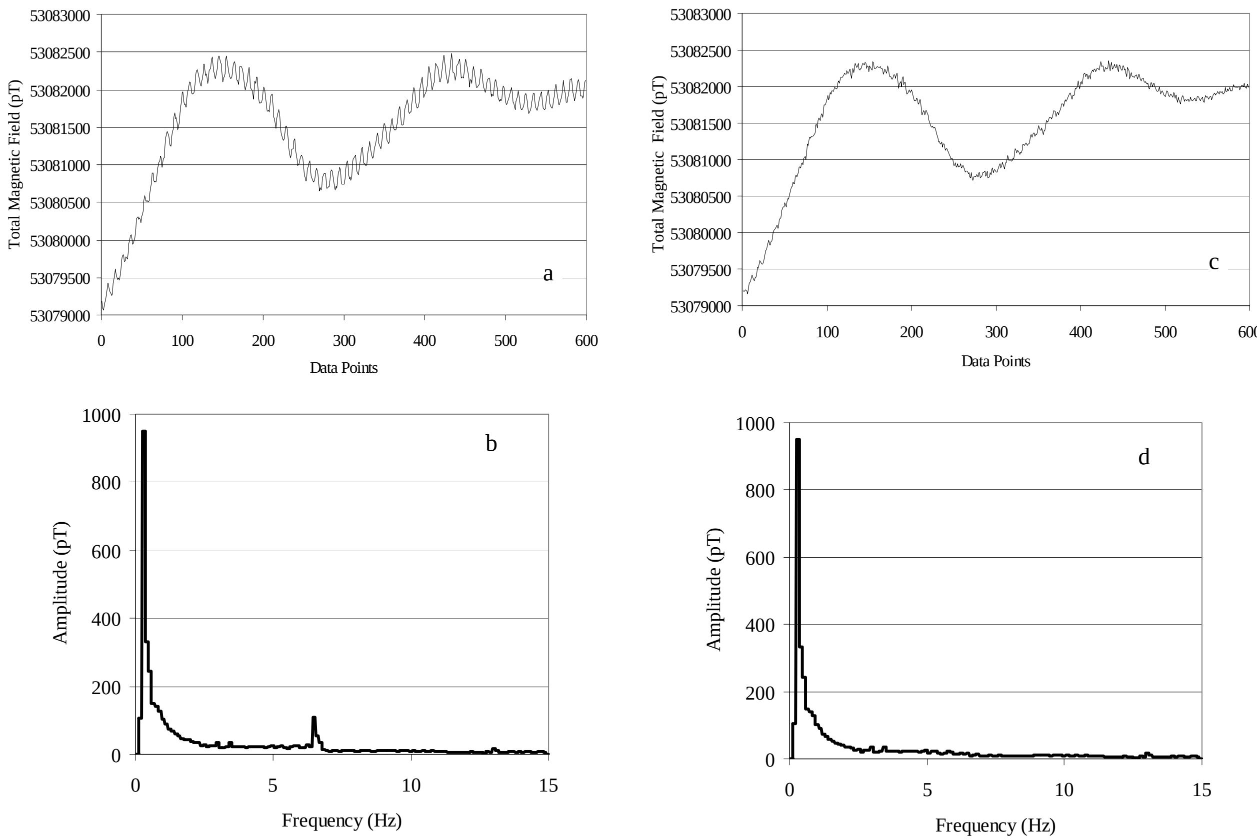


Figure 1. “Pure” rotor noise (a) and its spectrum (b). Data after the hum filtering (c) and its spectrum (d).

Figure 2 shows processed results from a data set acquired at or near a test site in which ordnance and scrap metal were buried at known locations at the Badlands Bombing Range (Doll et al., 2001). The top portion of Figure 2 consists of 48 seconds (2,860 measurement points) of unfiltered data that were acquired with the helicopter flying about 2m above the ground. A polynomial of degree six was used to remove non-harmonic components in the data. A segment of 360 points (1/8 of the portion of the data set) was chosen to dynamically filter the rotor noise. After hum filtering, we found that frequencies and amplitudes of the rotor noise were in the ranges of 6.43 to 6.48 Hz and 0.183 to 0.267 nT, respectively. More than 90% of the rotor noise was removed, based on the spectral analysis (the bottom portion of Figure 2). The noise around points 1,750 and 2,500 possess frequencies that are not rotor noise frequency (6.4 Hz) based on the spectral analysis.

## Conclusions

A pseudo-adaptive hum filter eliminates rotor noise in high-resolution airborne magnetic data. Rotor noise can be suppressed more than 90% without harming signals. The filter is theoretically not limited to aeromagnetic data. It can be applied to any geophysical data with sinusoidal noise properties.

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## References

Butler, K.E., and Russell, R.D., 1993, Subtraction of powerline harmonics from geophysical records: Geophysics, 58, 898-903.

Doll, W.E., Beard, L.P., and Gamey, T.J., this volume, An advanced airborne magnetic system for high-resolution mapping: Extended abstracts, 2002 Annual Meeting of the Society of Exploration Geophysicists, Salt Lake City, UT.

Doll, W.E., Nyquist, J.E., Beard, L.P., and Gamey, T.J., 2000, Airborne geophysical surveying for hazardous waste site characterization on the Oak Ridge Reservation, Tennessee: Geophysics, 65, 1372-1387.

Doll, W.E., Gamey, T.J., and Holladay, J.S., 2001, Current research into airborne UXO detection: Proceedings of the 2001 Symposium on the Application of Geophysics to Environmental and Engineering Problems, 16pp., available on CD-ROM.

Gamey, T.J., Doll, W.E., Bell, D.T., Duffy, A., and Millhouse, S.D., 2000, Evaluation of improved airborne techniques for detection of UXO: Proceedings of the 2000 Symposium on the Application of Geophysics to Environmental and Engineering Problems, p. 57-66.

Gamey, T.J., Doll, W.E., Beard, L.P., and Bell, D.T., 2002, Airborne vertical magnetic gradient for UXO detection: Proceedings of the 2002 Symposium on the Application of Geophysics to Environmental and Engineering Problems, 11pp., available on CD-ROM.

Golub, G.H., and Reinsch, C., 1970, Singular value decomposition and least-squares solution: Numerical Mathematics, 14, 403-420.

Marquardt, D.W., 1965, An algorithm for least squares estimation of nonlinear parameters: Journal of the Society for Industrial and Applied Mathematics, 2, 431-441.

Xia, J., and Miller, R.D., 2000, Design of a hum filter for suppressing power-line noise in seismic data: Journal of Environmental and Engineering Geophysics, v. 5(2) 31-38.

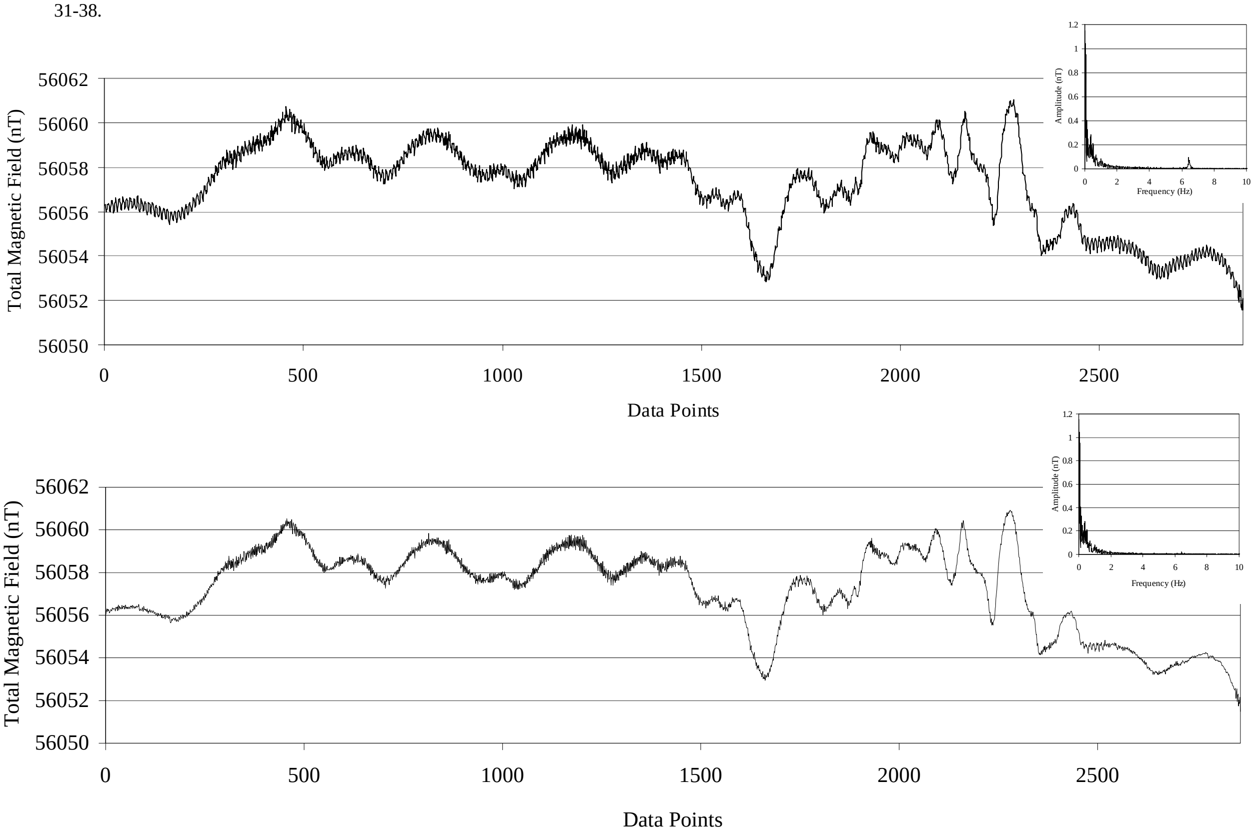


Figure 2. The first portion of a real data set before (top) and after hum filtering (bottom) with their spectra on the upper right corners.