Neural Network and Wavelet Transform For Classification and Object Detection

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Abstract: The practical utilization of object detection and classification, in high-performance structural mine detection or proximity fuses is somewhat impeded due to some complicated phenomena such as: existence of multiple wave modes, jamming, high susceptibility to diverse interferences, bulky sampled data, clutters and difficulty in signal interpretation. An intelligent signal processing approach using the wavelet transform and artificial neural network algorithms was developed; this was actualized in a signal processing package. The intelligent signal processing technique comprehensively functions as signal filtration, data compression and pattern recognition, capable of extracting essential features from acquired raw wave signals and further assisting in structural mine detection or proximity fuses evaluation. For validation, the algorithm was applied to the detection and classification of 10 different objects.
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1. Introduction

Signal processing and interpretation plays a pivotal role in a mine detection or proximity fuse system, dominating in deciding the precision that the system can offer and its feasibility. An effective signal processing and interpretation approach is expected to extract essential yet concise characteristics from acquired raw signals, and assist the decision-making unit in conducting a diagnosis or prognosis. In the past few decades, more challenging requirements from various industrial practices, such as real-time failure surveillance on aircraft, have increasingly motivated the research into developing viable Signal processing and interpretation techniques.

With the aid of the state-of-the-art advances in information processing and high-capacity computing devices, a diversity of novel and pragmatic signal processing and interpretation techniques have become available. Amongst these, methods using time-series analysis (Keilers, 1995), the fast Fourier spectrum (FFS) (Kim, 2001), the time–frequency distribution (the short-time Fourier transform (STFT) (Legendre, 2000), the wavelet transform (WT) (Legendre, 2000, Zheng, 2001) and blind de-convolution have been adopted. It's noticeable that Time-series analysis, FFS and STFT aren't suitable for time limited signals i.e. proposed magnetic sensor in this paper.

On the other hand, signal processing and interpretation have gained substantial acceptance from major engineering communities due to their good balance between desirable precision and versatile accessibility. However, several troublesome issues associated with the utilization of signal processing, are commonly noticed:

(1) In practice, the sensors may be operated in noisy or fluctuating environments, where the captured wave signals usually suffer from diverse disturbances or jamming signals.

(2) In experimental, the interferences from clutters, such as type of the soil in mine detection or clods in radar systems, may obscure the object-induced wave components in the signals.

(3) The use of high-resolution sampling can guarantee a precise identification, but it unavoidably leads to bulky data flow for serializing the scanning, burdening the signal processing to a certain extent.

All of these factors undoubtedly weaken the sensitivity of sensors to detecting and classifying objects and considerably lower the identification precision of a mine detection or proximity fuses system. With this motivation, an intelligent signal processing and pattern recognition technique for mine detection systems was developed, taking advantage of the wavelet transform and artificial neural algorithms, implemented by a signal processing package. The signal processing package is comprehensively includes units of signal filtration, data compression and pattern recognition. Validation of the algorithm was conducted by classifying the waves that acquired by the magnetic sensor proposed in (Birgé, 1997) for 10 different objects.

2. The Philosophy of Using Wavelet

In studies of vibrational signals in the early 1990s, found a clear advantage in singularity detection in signals. Nowadays, wavelet transform-based signal processing, covering signal purification, spectrographic analysis, clutters removing and signal/image compression. The output of magnetic sensor is time limited, thus the remarkable potential of the wavelet transform leads to powerful signal processing Technique for Clutter Reduction in detection problem.

During practical implementation, two forms of wavelet transform are available, the continuous wavelet transforms (CWT) and the discrete wavelet transforms (DWT).

Fundamentally, applied with a basic orthogonal wavelet transform function, $\Psi(t)$ a time-dependent wave signal, $f(t)$ acquired from a sensor is converted into a quadratic expression using the dual parameters scale, a , and time, b :

$$W(a,b)=\frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} f(t)\overline{\Psi}(\frac{t-b}{a})dt \quad (1)$$

The operation performed by equation (1) is defined as the CWT and W (a, b) is the CWT coefficient. $\overline{\Psi}(t)$ denotes the complex conjugate of $\Psi(t)$.

For simplicity, equation (1) is executed by calculating the wavelet coefficients only at discretized scale and time using dyadic variables m and n, contrastingly defined as the (DWT):

$$DWT(m,n)=a_0^{-m/2}\int f(t)\Psi(-a_0^{-m}t-nb_0)dt \quad (2)$$

$$a=a_0^m \qquad b=na_0^m b_0 \qquad m,n\in Z$$

where a_0 and b_0 are constants deciding the sampling intervals along the time and scale axes, respectively. Equation (2) decomposes signals into associated ranges of relatively higher and lower frequencies. The signal is represented hierarchically by a series of approximations (low-frequency components, denoted by A) (Figure 1) and details (high-frequency components, denoted by D). Inversely, reconstruction of the wave signal is discretely implemented via:

$$f(t)=c\sum_m\sum_m C_{m,n}(t)DWT(m,n) \quad (3)$$

$$C_{m,n}(t)=a_0^{-m/2}\Psi(a_0^{-m}t-nb_0)$$

This is the multi-resolution concept that is the base of signal de-noising or compression. The multi-resolution formulation is obviously designed to decompose signals into finer and finer details.

For the first step in object detection and classification, two approaches were used for signal purification: de-noising and scale selecting.

2.1. De-Noising

In this algorithm, at the first step, noise was removed from acquired signal; then the samples that are close to zero were removed (delay removing) and pure signal was remained. In the last step, correlations of pure signal with reference signals that are in database were computed in order to classify the proposed objects. In this way, input signal assigned to the class that lead to maximum correlation (Figure 2).

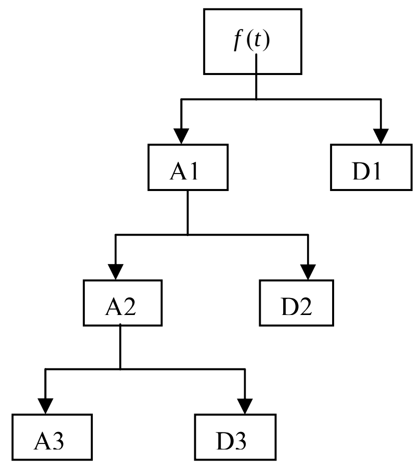

Figure 1. The hierarchical architecture for a three-level DWT decomposition.

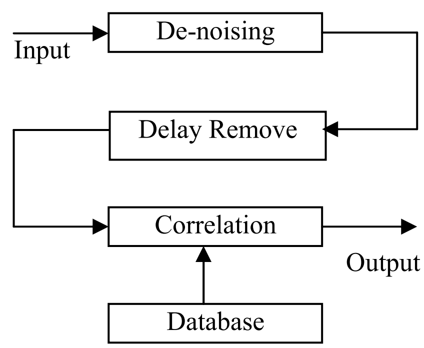

Figure 2. Classification by wavelet; De-noising method.

The underlying model for the noisy signal is basically of the following form:

$$s(n)=f(n)+\sigma e(n) \quad (4)$$

where time n is equally spaced. In the simplest model we suppose that $e(n)$ is a Gaussian white noise *N (0, 1)* and the noise level is supposed to be equal to 1. The main objective of de-noising is to suppress the noise part of the signal $s(t)$ and to recover $f(t)$. Use of wavelet for de-noising is efficient for families of functions $f(t)$ that have only a few nonzero wavelet coefficients or have a sparse wavelet representation (SU,2004). For example, a time limited function, has such a property and since the output of magnetic sensor is a time limited signal thus de-noising with wavelet was selected. From a statistical viewpoint, the model is a regression model over time and the method can be viewed as a nonparametric estimation of the function $f(t)$ using orthogonal basis.

The general de-noising procedure involves three steps:

(1) Decompose: Choose a wavelet and level N then compute the wavelet decomposition of the signal $s(t)$ at level N.

(2) Threshold detail coefficients: For each level from 1 to N, select a threshold and apply thresholding to the detail coefficients.

(3) Reconstruct: Compute wavelet re-construction using the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N.

According to the basic noise model, two threshold selection rules are implemented in the signal processing packet: *scarce* and *penalized*. These strategies are based on an approximation and de-noising result from Barge and Massart (Fausett, 1994).

2.1.1. Scarce Method

The scarce strategy is such that at level J the approximation is kept and for level j from 1 to J, the n_j largest coefficients are kept with:

$$n_j = \frac{M}{(J+2-j)^a} \tag{5}$$

where J is the level of the decomposition, M a positive constant and a a sparsely parameter ($a > 1$).

So, the strategy leads to select the highest coefficients in absolute value at each level. The numbers of kept coefficients grow scarcely with J-j. Typically, $a = 1.5$ for compression and $a = 3$ for de-noising. A natural default value for M is $L \le M \le 2L$ where L denotes the length of the coarsest approximation coefficients.

The rate of false alarm depends on a. Minimum of error (28%) obtain in $a = 2.2$. See Figure 3.

2.1.2. Penalized Method

This strategy can be viewed as a variant of the fixed form strategy of the wavelet shrinkage. The threshold *T* applied to the detail coefficients for the wavelet case or the wavelet packet coefficients for a given fixed *WP* tree is defined by:

$$T = \left| c(t^*) \right| \tag{6}$$

With:

$$t^* = \arg\min \left[-\sum_{k=1}^{t} c^2(k) + 2\upsilon t \left(a + \log(\frac{n}{t}) \right); t = 1, \ldots, n \right]$$

where $a > 1$, $c(k)$ are sorted in decreasing order of their absolute value υ is the noise variance.

Also, in this method, the rate of false alarm, depend on a (Figure 4).

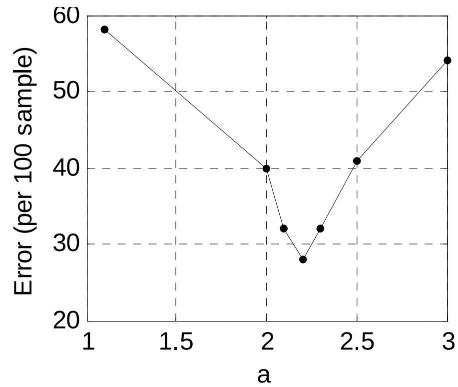

Figure 3. Scarce method

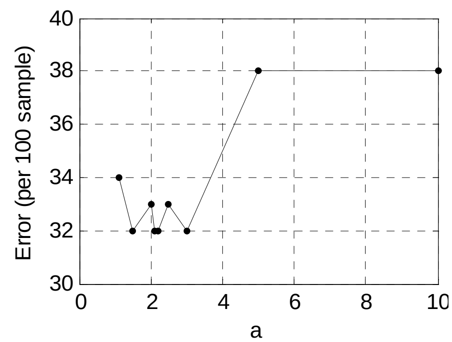

Figure 4. Penalized method

2.2. Scale Selecting

In this algorithm, at the first step, wavelet transform coefficients of acquired signal were computed; then the signal was reconstructed but some of coefficients for fine scales were removed. For example see Figure 5. This result would be clarified in the last section.

In the next step, samples that are close to zero were removed (delay removing) and pure signal was remained. In the last step, correlations of pure signal with reference signals that are in database were computed. Input signal assign to the class that lead to maximum correlation (Figure 6). In this method the amount of 7% error can be achieved.

3. The Philosophy of Using Neural Networks

Artificial neural networks are major tools for classification, especially in nonlinear systems (Kohonen, 1990). Because of nonlinearity nature of system such as magnetic field, communication channel and goal object, neural networks have been used to classify different objects. LVQ and MLP are supervised neural networks that have been used for object detection and classification.

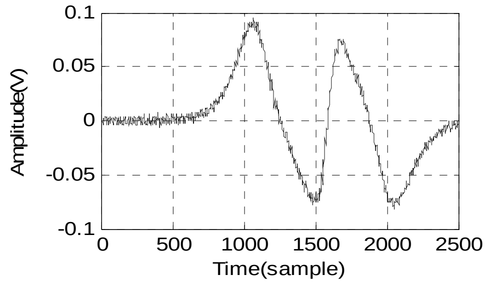

Figure 5. Amplitude vs. time of samples

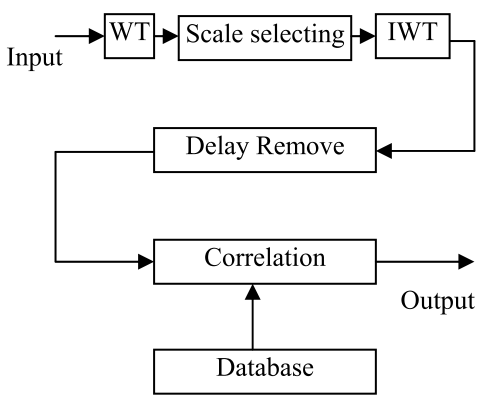

Figure 6. Classification by wavelet; Scale selecting method.

3.1. LVQ

Linear vector quantization (LVQ) (Mandelbrot, 1982) is a pattern classification method in which each output unit represents a particular class or category. The weight vector for an output unit is often referred to as a reference vector for the class that the unit represents. During training, the output units are positioned to approximate the decision surfaces of the theoretical base classifier. After training, an LVQ net classifies an input vector assigning it to the same class as the output unit that has its weights vector closed to the input vector. An LVQ network has a first competitive layer and a second linear layer. The competitive layer learns to classify input vectors in much the same way as the competitive layers of Self-Organizing. The linear layer transforms the competitive layer's classes into target classifications defined by the user. LVQ network training diagram have been shown in Figure 7. The network was trained in 7 epochs and 5.828 second by Intel 2.4MHz processor. Some of input vectors of each class have been used for initial values of weight vectors.

3.2. MLP

General purpose Multilayer Perceptron neural net, have been used for recognizing objects. A multi-layer feed-forward neural network, consisting of one input layer with α input elements, hidden layer with λ computing neurons and one output layer containing β output variables, was used. Where the variables α, β and λ are dependent on the actual application. Training diagram for MLP network with α, β and λ equal to 200, 16 and 8 respectively and 80 training vector have been showed in Figure 8. The network was trained in 603 epochs and 13.5 second by Intel 2.4MHz processor.

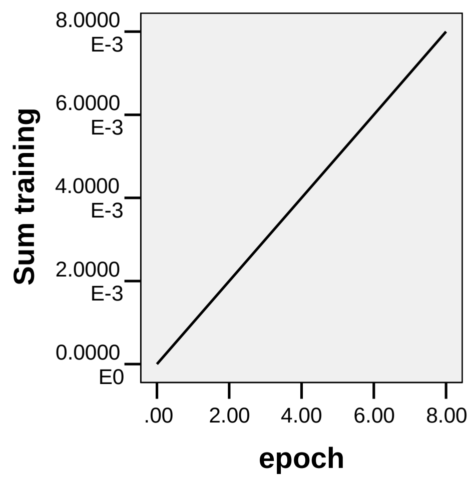

Figure 7. LVQ training diagram

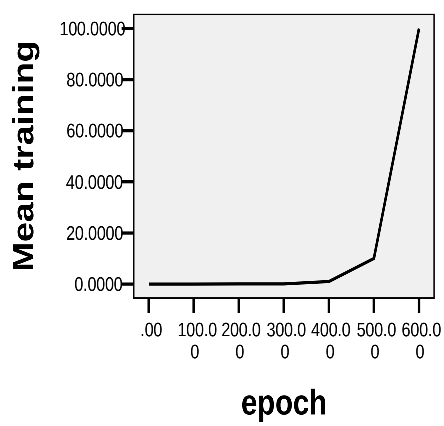

Figure 8. MLP training diagram.

4. The Philosophy of Combination of Neural Network and Wavelet

If the captured signals suffer with noise and clutter, the neural network can be unsuccessful to classify them correctly. Also, wavelet transform can be unsuccessful to classify captured signals from nonlinear systems (minimum 9% error in simulation results). Thus combination of wavelet transform and neural network has been used. Wavelet analysis and neural networks have been combined in numerous manners. We distinguish two categories of methods. In the first one, the wavelet part is essentially decoupled from learning. A signal is decomposed on some wavelet and the wavelet coefficients are furnished to a neural network. In the second category, wavelet theory and neural networks are combined into a single method. We limit the scope of this article to the first category.

The combination of neural network and wavelet algorithm procedure involves four steps (Figure 9):

(1) In the first step, wavelet transform coefficient of input signal was computed.
(2) In the second step some of scales were selected and coefficient of this scales furnished to a MLP neural network.
(3) Next, delay for stability emulated to signal.
(4) Finally, neural network classify inputs.

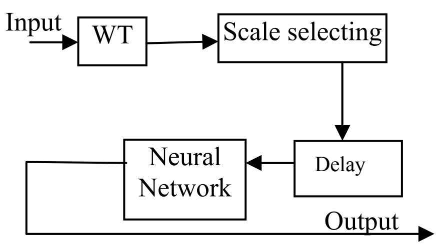

Figure 9. Classification by combination of Neural network and wavelet.

4.1. Selecting Scales

Details coefficients are independent random Gaussian realizations and coarse scales are object information. The multi-resolution analysis can be viewed as a bank of digital filters (low pass and high pass filters). Frequency bands correspond to wavelet analysis tree in Figure 1 was shown in Figure 10.

The maximum relative velocity of sensor and object is approximately 2 meters per second that should travel 10 centimeters. This travel consuming 0.05 seconds and lead to maximum 5 period of signal. The FFT of one of input signals was shown in

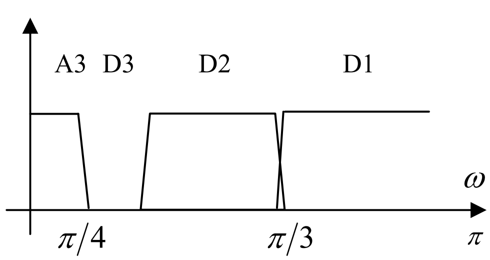

Figure 10. Classification by combination of neural network and wavelet.

Figure 11. The fastest component of acquired signals also confirms this bandwidth. Thus the bandwidth of input signals is approximately 100Hz. The sampling frequency of input signals is 5 KHz. Thus the filter bank idea leads to the selection of scales 6, 7 and 8.

This view also can be reasonable with Fractional Brownian motion (fBm). An fBm is a continuous-time Gaussian process depending on the Hurst parameter $0 < H < 1$. Versus fBm theory the fluctuation of signals depend on derivation of magnitude of wavelet transform coefficient (SU, 2004). Whatever fluctuation increases, the derivation of magnitude of wavelet transform coefficient would be close to zero and for completely random noise is equal to zero. For separating noise and object information from acquired signal, the 1-norm of wavelet transform coefficient of signal in each scale was computed. The logarithm of 1-norm versus scale was shown in Figure 12. It shows that derivation of 1-norm is close to zero for scales 1, 2, 3, 4 and 5, thus the detail of signal in these scales corresponds to noises and scales 6, 7 and 8 denote information. Coefficient of wavelet transform in scales 6, 7 and 8 furnished to neural network and would be classified. Wavelet transform remove noise and clutter and neural network classify objects. Also in this algorithm because some scale was selected, number of inputs to neural network would be decrease and training would be faster. Each acquired signal has 2500 samples. With this technique the input to neural network decreases to 87 samples.

5. Conclusion

With the motivation of some troublesome issues in the development mine detection, an intelligent signal processing and pattern recognition approach has been developed using the wavelet transform and artificial neural algorithms; this was actualized in a signal processing package. Its functionally consists of units of signal filtration, data compression and pattern recognition.

For validation, the signal processing package was applied to acquired wave signals from a magnetic sensor for 10 different objects. The results show that, taking advantage of the intelligent signal processing and pattern recognition technique, the procedure for mine detection effectiveness can be dramatically enhanced. The methodology presented in the current work can also be extended to other structural pattern recognition techniques with appropriate modifications.

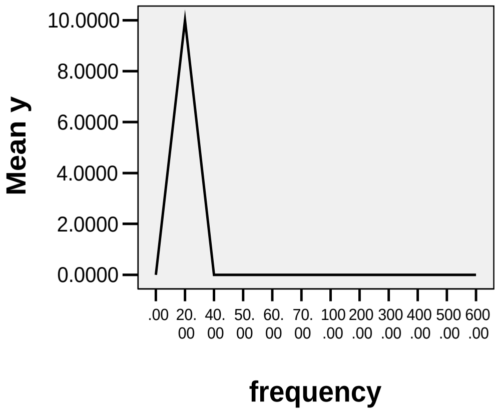

Figure 11. FFT of one of the input signal

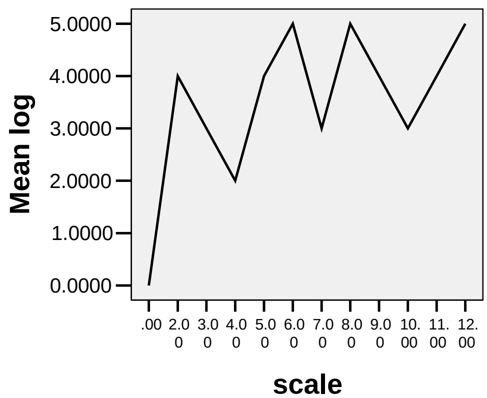

Figure 12. 1-norm of wavelet transform coefficient in each scales.

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