Non-periodic Noisy Signals Denoising Using Adaptive Neuro-Fuzzy Inference System (ANFIS)

I Santoso\textsuperscript{1,2}, A Warsito\textsuperscript{1}, T Prakoso\textsuperscript{1,2}, A Sofwan\textsuperscript{1}, A A Zahra\textsuperscript{1,2}, Y Christyono\textsuperscript{1,2}, M A Riyadi\textsuperscript{1}

\textsuperscript{1} Electrical Eng. Department, Diponegoro University, Tembalang, Semarang, 50275, Indonesia
\textsuperscript{2} Communication and Signal Processing Lab., Electrical Eng. Dept., Diponegoro University, Tembalang, Semarang, 50275, Indonesia

Abstract. Signal always occurs with noise. Since noise acts as an unwanted signal, we must clear or reduce it with some denoising method. It is relatively easy to denoise the normal distribution noise-contaminated the periodic signal. The problem ascends if a non-Gaussian noise intrudes into a non-periodic signal. The standard filter, such as DWT (discrete wavelet transforms), cannot overcome this directly and blindly. In this research, we proposed ANFIS (Adaptive Neuro-Fuzzy Inference System) as a non-periodic noisy signal denoising method. Foremost, the ANFIS trained to mimic or estimate the interfered noise, then this noise estimation used as a subtractive signal in a non-periodic noisy signal. As a result, the ANFIS can reduce the non-Gaussian noise in the various noisy non-periodic signals with minimum error better than standard DWT (Discrete Wavelet Transform).

1. Introduction
Any signal that we use usually contain noise. There are two primary types of noise with normal or Gaussian distribution and non-Gaussian distribution. Non-Gaussian noise such as impulsive noise, burst noise, or noise with different amplitudes and different duration. These kinds of noise may interfere the signal that we want to proceed or analyze in the next need. Denoising method must apply in order to have a more precise signal or signal with less unnecessary noise. However, for non-Gaussian noise, denoising must be modified to enhance its ability. The standard denoising method using classical Fourier Transform and Wavelet Transform. These methods can easily remove the noise if it can be perceived separately in a higher frequency range or at a certain decomposition level. Recently, many denoising methods for time-based signals have proposed. Many researchers used wavelets transform-based denoising method, whether it modified or standard DWT (discrete wavelet transform) such in [1-13], empirical mode decomposition (EMD) based denoising method [12], [14], and adaptive filter based [15]. There are also denoising using or implement ANFIS method for speech signal [16] [18], for vibration measurement signal [17], ECG and EMG signals [19], hybrid with the Wiener filter [20] and for EMG signal [21]. Typically the signal (in digital format) type to be diagnosed is biomedical signals, for example, ECG (Electrocardiogram) as in many researches [1], [4], [8], [12], [22], [23], [24] and EEG (Electroencephalogram) [11], [25], [26], ECG and EEG are semi-periodic signals. Other used non-periodic signals such as sunspot data [3], gas isotope ratio measurement signal
wavelet test signals (bumps, Doppler, heavy-sine, blocks), Tai-chi body-movement signal, and float-drift signal [7], [27], and quasi-periodic speech signal [7],[9],[10],[13],[28], partial discharge signal [29], and phonocardiogram [5]. According to those referred denoising, researchers commonly examine the Gaussian noise or AWGN (additive white Gaussian noise) form, with a mean equal to zero and certain variance value.

According to those references, it is rarely explored the ANFIS blindly denoising ability, especially for non-Gaussian noise that interferes with the non-periodic signal. Since the previous work mainly emphasis using wavelet-based denoising and Gaussian type noise. In this research, we proposed an adaptive artificial neural network-based fuzzy inference system or adaptive neuro-fuzzy inference system (ANFIS), in order to denoise the noisy non-periodic signals.

This paper contains five sections. First section is the introduction, while the second explain the theoretical background of signals, noise, and ANFIS. The third section states the research method or experimental setup, then the fourth describes and evaluates the research result. The last section yields some conclusions and recommends a future work.

2. Signal denoising

2.1. Signal and Noise

Noise, in general, denotes any erratic fluctuations that appear randomly on top of signals to be measured. It may corrupt the quality and the originality of the signal. So, it becomes unwanted and unnecessary information. We cannot delete the noise. It only can be reduced until it will be unnecessary. Noise can be classified based on the noise source and distribution function.

The most valuable noise performance use Signal to Noise Ratio or SNR. SNR indicates the level of signal and noise; level can be power or amplitude. Higher SNR value shown the less noise level, and lower SNR value shown a higher noise level. Factually we cannot separate the signal and noise based on SNR value. We can only take an estimation (noise estimation). Its noise estimation ability can show good denoising algorithm.

2.2. ANFIS

Adaptive Neuro-Fuzzy Inference System or ANFIS is a type of artificial intelligence method that combines fuzzy inference function and artificial neural network. By a learning method, ANFIS can map the input data value to a targeted output value, based on a training data in fuzzy rules form. Figure 1 shows a simple ANFIS architecture with two inputs, one output, and five layers.

![Diagram block of basic ANFIS using two inputs and one output.](image)

**Figure 1.** Diagram block of basic ANFIS using two inputs and one output.
First Layer is a fuzzification layer. The $\alpha$ and $\beta$ are fuzzy membership functions (FMF) with $x_1$ and $x_2$ are the input of each FMF.

$$y_{1,1i} = \mu_{\alpha_i}(x) = \frac{1}{1 + \left| \frac{x - p_{1,\alpha_i}}{p_{2,\alpha_i}} \right|^{2p_{3,\alpha_i}}}$$ (1)
$$y_{1,2i} = \mu_{\beta_i}(x) = \frac{1}{1 + \left| \frac{x - p_{1,\beta_i}}{p_{2,\beta_i}} \right|^{2p_{3,\beta_i}}}$$ (2)

The notations $p_{1,\alpha_i}$, $p_{2,\alpha_i}$, $p_{3,\alpha_i}$, $p_{1,\beta_i}$, $p_{2,\beta_i}$, $p_{3,\beta_i}$ are premise parameters.

Second Layer is the product layer. This layer multiplies the fuzzy membership value from $\alpha$ and $\beta$ according to the input of $x$ and $y$.

$$y_{2,i} = \omega_i = \mu_{\alpha_i}(x) \cdot \mu_{\beta_i}(x)$$ (3)

The third layer is the normalization layer. This layer normalizes the value of the product layer.

$$y_{3,i} = \bar{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2}$$ (4)

The fourth Layer is the defuzzification layer. This layer maps a fuzzy set from third layer to a crisp set by using first order of Takagi-Sugeno type fuzzy rules:

Rule 1: if $\alpha_1$ and $\beta_1$ then $f_1 = c_{11}x_1 + c_{21}x_2 + c_{31}$

Rule 2: if $\alpha_2$ and $\beta_2$ then $f_2 = c_{12}x_1 + c_{22}x_2 + c_{32}$

to determine the fourth layer output by

$$y_{4,i} = \bar{\omega}_i f_i$$ (5)

According to the rules, $c_{1i}$, $c_{2i}$, and $c_{3i}$ are consequent parameters with $i=1,2$.

The fifth layer is the final output layer. This layer provides a final decision based on the output of the defuzzification layer by using formula

$$y_s = \sum_i \bar{\omega}_i f_i$$ (6)

The ANFIS procedure starts with creating the fuzzy membership function (FMF) using a clustering method (i.e., grid partitioning) and based on a set of input-output data pairs. Then by using this created FMFs, the input data propagates its values from the first ANFIS layer until the fifth ANFIS layer and in the final layer, yields the output (decision) values. These ANFIS output values compare with target output values. If a difference or error, $e(k)$, occurs, the ANFIS learning procedure will activate.

The learning procedure is a hybrid process of least square estimate (LSE) and the gradient descent method. This hybrid learning procedure composed of a forward step in which the input signal propagates forward until the fourth layer, where the consequent parameters are attuned using the LSE of the error. Then, on the backward step, the error propagates back through the ANFIS system, and FMFs (premise parameters) in the first layer update by the gradient descent method. The learning process active until the error value equal to the early defined error threshold value ($\theta$) [30].

In order to have an ANFIS with denoising mechanism, back to the ANFIS idea, that the ANFIS inputs will try to mimic the target output. If the input is a Gaussian noise, then using ANFIS, it can mimic the output of non-Gaussian noise. As expected, the ANFIS output will yield an estimation of non-Gaussian noise $\eta(k)$ that interfered with a signal.

This non-Gaussian noise estimation then set as a subtractive signal to the target output data, $m(k)$, after subtraction we get the denoised version signal $r(k)$. The ANFIS denoising procedure shown in Figure 2.
3. Research Method

In this section, we describe our research method, which consists of three stages. The first stage is setting up the ANFIS input data or signal. The second stage is the ANFIS denoising process. The last one is the performance evaluation.

The data or signal set up has a role as training data for ANFIS, this include
- Generating a gaussian or normal distribution noise $\gamma(k)$
- Applying a non-linear function to $\gamma(k)$ in order to get a non-gaussian noise $\eta(k)$
- Generating a non-linear or non-periodic signal, we used six type signals for $x(k)$, namely as Blocks, Bumps, Heavy sine, Doppler, Quad-chirp, and Mishmash signal, refer to Figure 3.
- Creating an interfered noisy measured signal $m(k) = r(k) + \gamma(k)$, refer to Figure 4.

![Figure 2](image1.png)

**Figure 2.** Enhanced block diagram of ANFIS for signal denoising.

![Figure 3](image2.png)

**Figure 3.** Six original non-linear signals used in this signal denoising experiment as in [27].

![Figure 4](image3.png)

**Figure 4.** Generation of noisy measured signal $m(k)$. 

The primary ANFIS denoising process comprises
- Forming ANFIS training data, as input is $\gamma(k)$ and $\gamma(k-1)$ signals, and as output is $m(k)$ signal.
- Update the ANFIS parameters, i.e., premise and consequent parameters based on training data.
- The updated ANFIS parameters used to estimate the interferer noise signal $\hat{\eta}(k)$.
Then the denoising process for measured signal \( m(k) \) will be implemented using

\[
m(k) - \hat{y}(k) = \tilde{r}(k)
\]

The \( \tilde{r}(k) \) is a denoised version signal, refer to Figure 5.

Figure 5. The scheme of denoising of noisy measured signal \( m(k) \).

We use MSE (Mean Square Error), SNR (Signal to Noise Ratio), and Cross-correlation (CC) value in order to evaluate the denoised signal \( \tilde{s}(k) \). Besides that, two other denoising methods, DWT (Discrete Wavelet Transform) and MODWT (Maximal Overlap DWT), will also compare.

4. Result and Discussion

This research provides denoising results based on the performance metrics, refer to Table 1. In MSE, the lower value shown less error in the denoising process. Higher SNR value indicates the smaller noise level in the denoised signal. Cross-correlation (CC) has a maximum value of 1 or 100%. If the denoised signal and the original clean (without noise) signal have a small difference in pattern, it indicates the higher CC value.

Figure 6. The denoising result of the noisy measured signal; block signal (top left), bump signal (top right), heavy-sine signal (bottom left), and Quad-chirp signal (bottom right).
The bold numbers in Table 1 indicate the best performance of each signal type and metrics. According to Table 1, ANFIS and ANFIS & MODWT shown the first two methods that have superiority than DWT and MODWT.

The denoising using ANFIS alone gives the best performance metrics value, followed by the ANFIS & MODWT method. Especially for Quad-chirp and Mishmash signal, audio signal type, the DWT, and MODWT give a lousy performance, because it diminished the higher frequency component. Both denoised version signals have different pattern compare to the original signal.

For simplicity in Figure 6, we only show the denoising result of four type signals; block signal, bump signal, heavy-sine signal, and Quad-chirp signal. The Figure 6 shows the ANFIS denoising performance dominance against the other methods.

Table 1 The denoising performance metric for six types of non-periodic signals.

| Signal | Method | MSE* | SNR* (dB) | CC* | MSE** | SNR** (dB) | CC** |
|--------|--------|------|-----------|-----|-------|------------|------|
| Boc    | Noisy  | 0.93196 | 5.40388  | 0.78971 | 1.12215 | 4.59734 | 0.73896 |
|        | DWT    | 0.39543 | 9.12718  | 0.85164 | 0.48816 | 8.21225 | 0.81294 |
|        | MODWT  | 0.17391 | 12.69468 | 0.93783 | 0.19202 | 12.26433 | 0.93318 |
|        | ANFIS  | 0.01836 | 22.45814 | 0.99369 | 0.04585 | 18.48403 | 0.99255 |
|        | ANFIS & MODWT | 0.06827 | 16.75583 | 0.98161 | 0.09685 | 15.23693 | 0.97941 |
| Bum    | Noisy  | 1.02060 | 2.84947  | 0.75600 | 1.09607 | 7.80447 | 0.90376 |
|        | DWT    | 0.39910 | 6.92726  | 0.85590 | 0.82591 | 9.03351 | 0.91096 |
|        | MODWT  | 0.12012 | 12.14174 | 0.96661 | 0.26105 | 14.03560 | 0.97787 |
|        | ANFIS  | 0.01450 | 21.32360 | 0.99501 | 0.08904 | 18.70689 | 0.99589 |
|        | ANFIS & MODWT | 0.04560 | 16.34885 | 0.98959 | 0.20339 | 15.11948 | 0.98943 |
| Hvs    | Noisy  | 0.95289 | 2.12318  | 0.77983 | 1.10111 | 1.49531 | 0.75250 |
|        | DWT    | 0.03655 | 16.28490 | 0.98804 | 0.02972 | 17.18355 | 0.99037 |
|        | MODWT  | 0.02956 | 17.20721 | 0.99045 | 0.02947 | 17.22043 | 0.99036 |
|        | ANFIS  | 0.02395 | 18.12113 | 0.99592 | 0.02802 | 17.43852 | 0.99030 |
|        | ANFIS & MODWT | 0.01374 | 20.53295 | 0.99951 | 0.00327 | 26.76265 | 0.99896 |
| Dop    | Noisy  | 0.96347 | 1.86085  | 0.76466 | 0.96633 | 1.84802 | 0.77204 |
|        | DWT    | 0.18885 | 8.46029  | 0.92576 | 0.18885 | 8.93814 | 0.93304 |
|        | MODWT  | 0.06698 | 13.43993 | 0.97849 | 0.05565 | 14.24458 | 0.98082 |
|        | ANFIS  | 0.01355 | 20.37943 | 0.99533 | 0.03130 | 16.74367 | 0.98919 |
|        | ANFIS & MODWT | 0.00425 | 25.41277 | 0.99876 | 0.00833 | 22.49419 | 0.99729 |
| Qcr    | Noisy  | 0.96749 | 1.73995  | 0.76444 | 1.03392 | 1.45157 | 0.75556 |
|        | DWT    | 1.13103 | 1.06171  | 0.48158 | 1.24401 | 0.64821 | 0.64821 |
|        | MODWT  | 0.94910 | 1.82330  | 0.60519 | 1.00412 | 1.57856 | 0.57091 |
|        | ANFIS  | 0.01795 | 19.05590 | 0.99418 | 0.02592 | 17.45984 | 0.99245 |
|        | ANFIS & MODWT | 0.27049 | 7.27491  | 0.93433 | 0.31011 | 6.68124 | 0.92452 |
| Mim    | Noisy  | 1.05922 | 1.34584  | 0.76502 | 1.13677 | 1.03896 | 0.73133 |
|        | DWT    | 1.24063 | 0.65927  | 0.65927 | 1.23145 | 0.69153 | 0.39477 |
|        | MODWT  | 1.12363 | 1.08946  | 1.08946 | 1.11992 | 1.10381 | 0.48213 |
|        | ANFIS  | 0.02387 | 17.81647 | 0.99247 | 0.03956 | 15.62278 | 0.98626 |
|        | ANFIS & MODWT | 1.01111 | 1.54770  | 0.56539 | 1.02356 | 1.49455 | 0.55340 |

Note: * = gaussian noise, ** = non-gaussian noise, Boc = block signal, Bum = bump signal, Hvs = heavy-sine signal, Dop = doppler signal, Qcr = quad-chirp signal, Mim = mishmash signal.
5. Conclusion
This research result has shown that the ANFIS and combination of ANFIS and MODWT can denoise the Gaussian or non-Gaussian noise that interferes with the non-periodic signal. Lower MSE and higher correlation and SNR values indicate the better denoising ability compare to another method, such as alone DWT or MODWT.

The next research is enhancing the ANFIS denoising ability for challenging conditions that the signal level is too small than noise level.

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Acknowledgment

The authors give high appreciation to the Faculty of Engineering Diponegoro University for research fund support under the Strategic Research Grant project year 2019.