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Conference Article

# Reduction and Identification of Noise Signals Using Artificial Neural Networks with Various Activation Functions

**Panagiotis Kogias[1], Ivelina Balabanova[2], Michail Malamatoudis[1], Georgi Georgiev[2] and Stanimir Sadinov[2]**

[1]*Department of Electrical Engineering, Technological Educational Institute of Eastern Macedonia and Thrace Ag. Loukas, 65404 Kavala, Greece*
[2]*Department of Communications Equipment and Technologies, Technical University of Gabrovo, H. Dimitar St. 4, 5300 Gabrovo, Bulgaria*

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***Abstract***

The scientific paper examined options for reducing the levels of noisy signals and their identification using artificial neural structures. Single linear neurons were applied to sinusoidal signals with added Gaussian White Noise and Periodic Random noise. The changes of the Sum Squared Errors are monitored by selecting their minimum values, which achieve the lowest noise levels. Artificial neural structures were created to identify square waveforms with superimposed Uniform Gaussian Noise and Periodic Random Noise. Various types of activation functions and neuronal units were tested in the hidden layer of neural models by examining the metrics - Accuracy and Mean Squared Error. The highest accuracy of 94.00% achieved was obtained by hyperbolic tangent sigmoid activation function.

*Keywords:* Gaussian noise, Periodic random noise, linear neuron, transfer function, artificial neural network, noise identification.

## 1. Introduction

The prediction and processing of potential noise levels emitted by turbines and other components in airborne aircraft is one of the main areas of application of artificial neural networks related to the prevention of in-flight incidents [1]. A number of design developments performing high-quality qualitative and quantitative classifications of collected electrocardiogram signals through neural networks are directed to the field of medicine [2, 3].

A major part of scientific researches using artificial neural models are used for registration in speech sounds, processing and analysis of human speech by Deep Neural Networks [4]. There are studies which are focused in other fields of signal classification. That is given at the analysis of signals without / with a presence of Gaussian noise with application with Probabilistic Neural Networks (PNN) [5]. This example is an automatic noise recognition by PNN and Multilayer Perceptron (MLP) [5, 6].

The paper proposes an innovative approach for signal processing and analysis combining the stages of reduction of unwanted random background disturbances to signals of different shapes by artificial linear neurons. For the first time an identification of Gaussian and Periodic type of noises with the application of neural networks realized on the back-propagation algorithm is shown. Sine and rectangular signals were analyzed. Partial results are presented in this paper.

## 2. LABVIEW environment for simulation of signals and method

In LabVIEW software could be simulated Sine, Square, Triangle and Saw tooth signals and the following type of noises:

- Uniform White Noise (UWN) - generates a signal that contains a uniformly distributed;
- Gaussian White Noise (GWN) - generates a signal that contains a Gaussian-distributed;
- Periodic Random Noise (PRN) - generates a signal that contains periodic random noise;
- Gamma Noise (GN) - generates a signal that contains a pseudorandom pattern of values;
- Poisson Noise (PN) - generates a signal that contains a pseudorandom sequence of values;
- Binomial Noise (BinN) - generates a signal that contains a binomially distributed, pseudorandom pattern;
- Bernoulli Noise (BerN) - generates a signal that contains a pseudorandom pattern of ones and zeros;
- MLS sequence (MLS) - generates a signal that contains a maximum length sequence of ones and zeros;
- Inverse F Noise (IFN) – “1/f noise”.

On Fig. 1 are given all possible type of noises added into sine waveform.

*E-mail address: kogias@teiemt.gr
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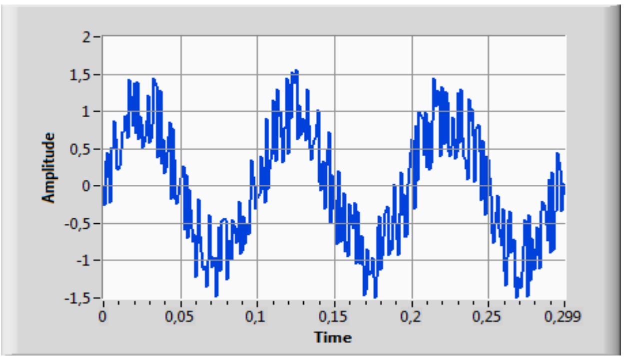


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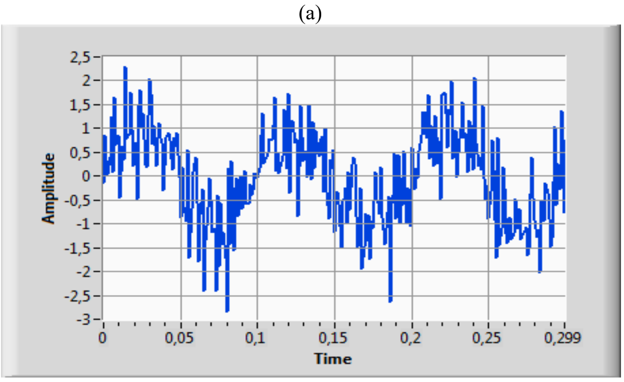


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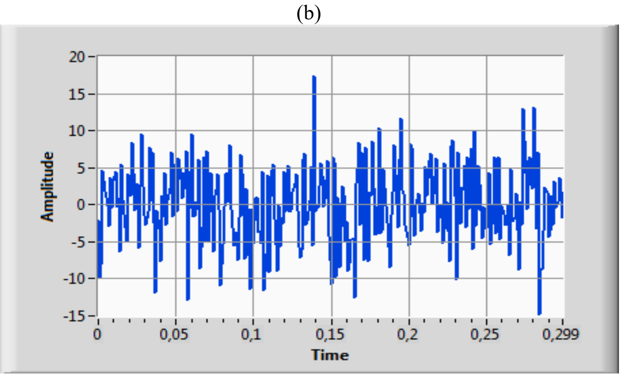


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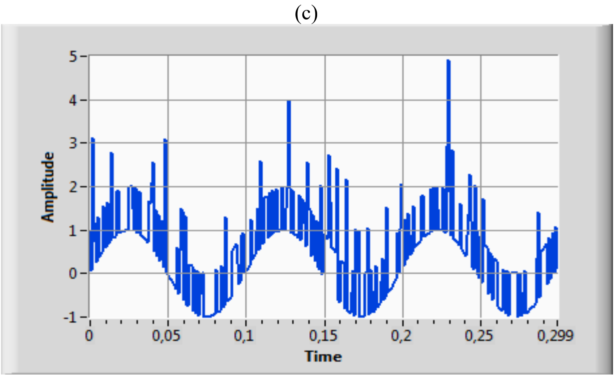


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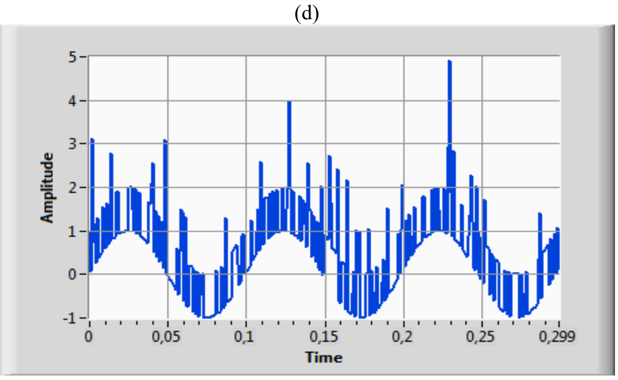


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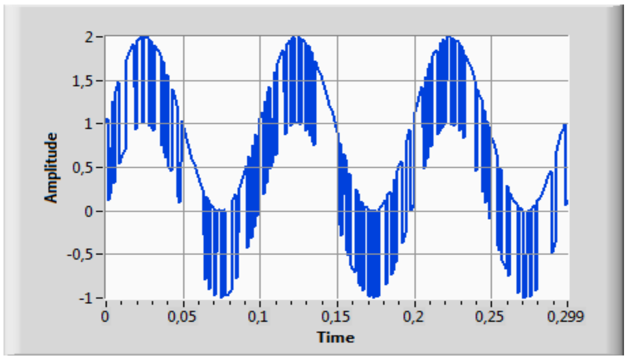


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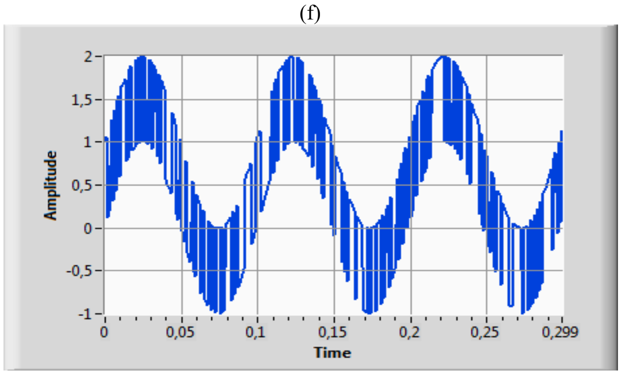


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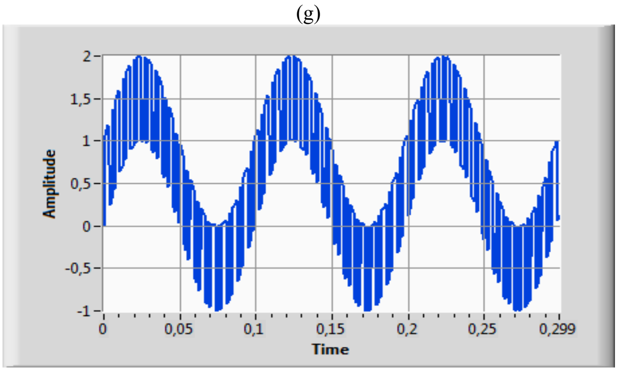


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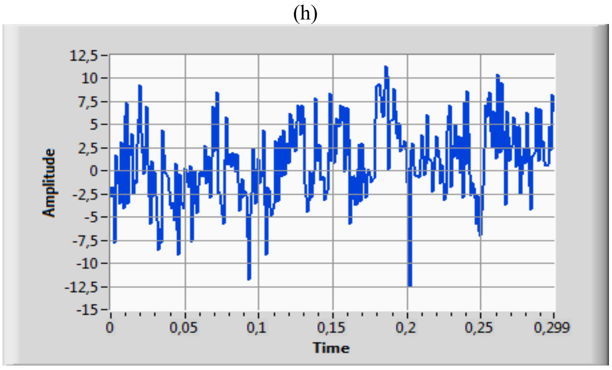



(i)

**Fig. 1** Sine waveforms with a) UWN, b) GWN, c) PRN, d) GN, e) PN, f) BinN, g) BerN, h) MLS and i) IFN.

### 3 Reducing the noise levels by applying neurons with linear activation function is subsection heading

The object of the study is a simulated sine waveforms, on which are superposed GWN and PRN. The signals are received in the LabVIEW product.

Initially, it performed a process of modeling of artificial neurons with a linear-type function in a MATLAB software environment. The Sum of Squared Errors (SSE) variations are examined against different values of the neural weights and biases ranging from the ranges in Fig. 2.

```
>> w_range = -1.0:0.1:1.0;
>> b_range = -1.0:0.1:1.0;
```

**Fig. 2** Ranges of weights "w" and biases "b".

Searching metric values W and B, in which is obtained the lowest SSEs. The values of the weights and displacements are subsequently used to create artificial neural structures with a linear activation function to reduce the level of the target input signals shown in Fig. 3.

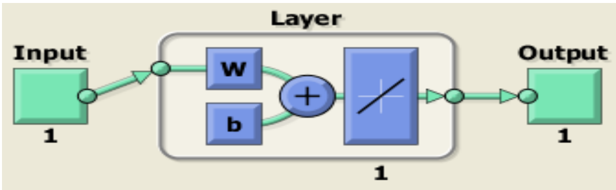



**Fig. 3** Linear neural model to reduce noise levels of sinusoidal signal with added Gaussian White and Periodic Random noises.

Simulation of the neural models and generation of a sinusoidal output signals with reduced noise levels is performed. The network errors are calculated. Their sums of squares (SSEs) are determined. On Fig. 4 are presented the surfaces and contour diagrams of the SSEs to which the best solutions have been added. It guarantees minimal SSEs and, respectively, the most complete reductions of noises.

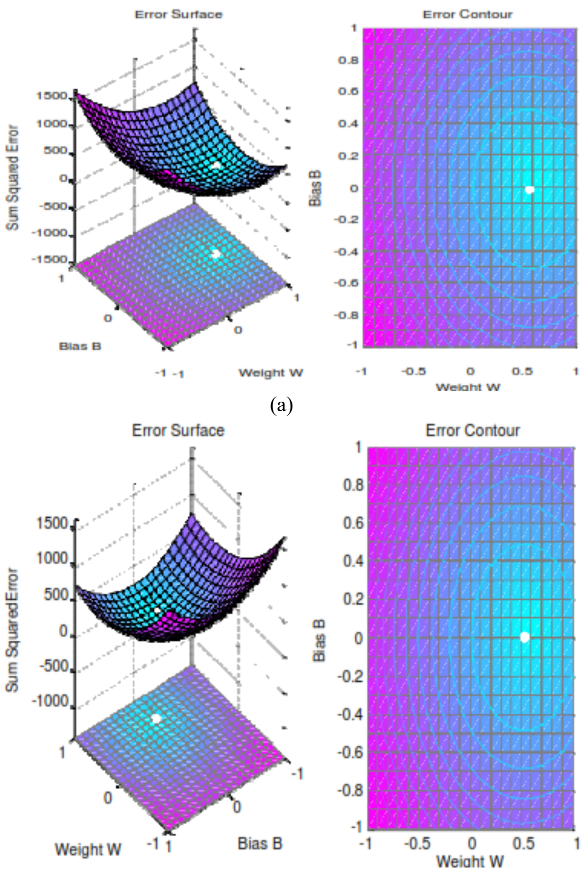



**Fig. 4** Decisions, guaranteeing minimum SSEs, to the surfaces and contour diagrams of SSEs at reducing of levels of a) GWN b) PRN.

The best numeral solutions, depicted in white, are located at the lowest points on the surfaces of the SSEs. The best W and B values are displayed (Fig. 5). At using of our selected linear neuron models with the best W and B the levels of noises will be maximum reducing.

The sine signals without and with reduced Gaussian White and Periodic Random noises versus time variations are given in Fig. 6. There are detected reduced noise levels, determining the successful applicability of the generated artificial linear.

```
>> best_w = net.iw{1,1}    >> best_b = net.b{1,1}

best_w =                   best_b =

    0.5688                    -0.0132
```

(a)

```
>> best_w = net.iw{1,1}     >> best_b = net.b{1,1}

best_w =                    best_b =

    0.5264                    5.8392e-04
```

(b)

**Fig. 5** Best weights W and biases B coefficients at reducing of levels of a) GWN and b) PRN

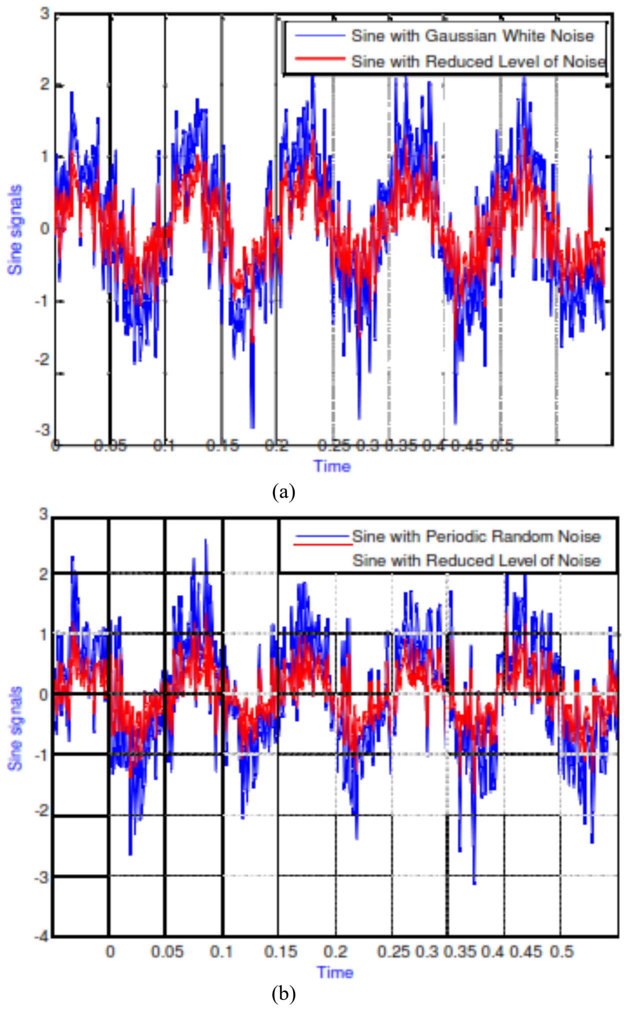
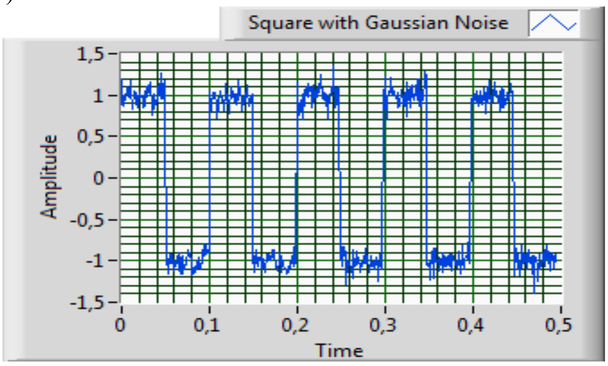


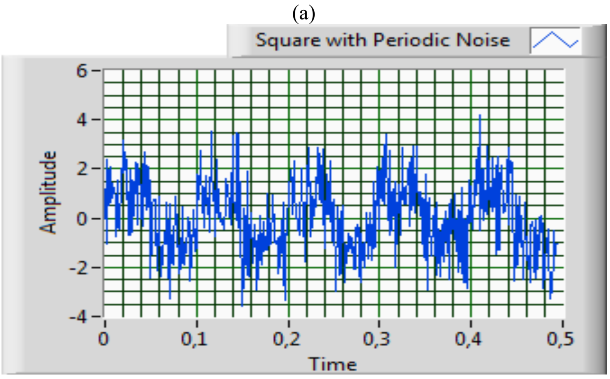

**Fig. 6** Sine signals without and with reduced levels of a) GWN and b) PRN neuron models

## 4 Identification of signals with overlaid noises using artificial neural networks with different types of activation functions

In the LabVIEW graphical environment are simulated Square Waveforms (SWs) are received, to which are added Uniform Gaussian Noise and Periodic Random Noise (Fig. 7).




(a)




(b)

**Fig. 7** LabVIEW simulated Square signals with a) UWN and b) PRN.

**Table 1.** Change of classification accuracy

| Hidden neurons | Accuracy, % | | |
|---|---|---|---|
| | purelin | tansig | logsig |
| 5 | 87.2 | 89.3 | 60.4 |
| 6 | 91.3 | 88.6 | 53.0 |
| 7 | **92.6** | 87.9 | 62.4 |
| 8 | 85.2 | 90.6 | 68.5 |
| 9 | 89.3 | 91.9 | 50.3 |
| 10 | 91.3 | **94.0** | 83.6 |
| 11 | 91.9 | 88.6 | 89.3 |
| 12 | 89.3 | 87.9 | 85.2 |
| 13 | 91.9 | 89.9 | 90.6 |
| 14 | 86.6 | 89.3 | **91.9** |
| 15 | 89.3 | 89.9 | 67.8 |

For their identification in MATLAB, a three-layer backpropagation neural networks (one input, one hidden and one output layers) with linear (purelin), tangent sigmoid (tansig) and logarithmic sigmoid (logsig) activation functions were created in the hidden network layers. The Levenberg- Marquardt algorithm is used for network training. The square waveforms (1000 samples – 500 samples for every signal) are applied to the network inputs (two inputs). The Encoding of the classification groups "SW with UGN" and "SW with PRN" was performed using separate output neurons (two output neurons) and discrete combinations "1 0" and "0 1" respectively for the first and second groups.

In the experiment the quantity of input data is divided, respectively - 60% for training, 20% for validation and 20% for the test procedures. The results of the study on Accuracy and Mean of Squared Errors (MSE) are presented in Table 1 and Table 2.

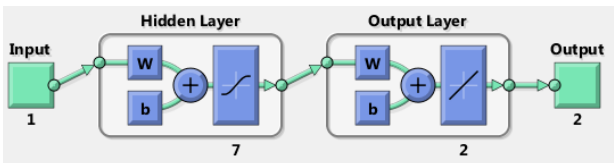
Relatively high classification precisions above 87.0% were observed for linear and tangential-sigmoidal activation functions in all neurons in the hidden layer. With logarithmic- sigmoidal function, there is a tendency of low accuracy ranging from 53.0% to 69.0%, respectively from 5 to 9 and 15 hidden neurons, while in other neuronal units the accuracy is above 83.0%. For this function, MSE levels significantly outstrip those of linear and tangential-sigmoidal functions.

**Table 2.** Change of mean squared error

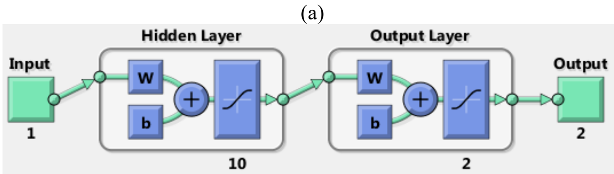
| Hidden neurons | purelin | Accuracy, % tansig | logsig |
|---|---|---|---|
| 5 | 0.1073 | 0.0778 | 0.2300 |
| 6 | 0.1013 | 0.0839 | 0.2021 |
| 7 | **0.0678** | 0.0924 | 0.1977 |
| 8 | 0.0999 | 0.0712 | 0.2240 |
| 9 | 0.0871 | 0.0621 | 0.3222 |
| 10 | 0.0704 | **0.0521** | 0.1746 |
| 11 | 0.0730 | 0.0951 | 0.1616 |
| 12 | 0.0923 | 0.0979 | 0.1747 |
| 13 | 0.0728 | 0.0849 | 0.1613 |
| 14 | 0.0970 | 0.0767 | **0.1600** |
| 15 | 0.0778 | 0.0848 | 0.1864 |

According to the presented results, the most suitable artificial neuronal structure for identifying target signals is the 10-neuron synthesized synthesis using a tangent sigmoid activation function in the exit layer (Fig. 8.b), where a maximum accuracy of 94.0% and a minimum MSE of 0.0521.

The obtained results for a linear function of activation function at 7 hidden neural units (Fig. 8.a) for which the highest accuracy and the lowest error, respectively - 92.6% and 0.0678, are also very good. Despite the maximum accuracy of 91.9% obtained at 14 hidden neurons, the structure with logarithmic sigmoid activation function (Fig. 8.c) was determined to be inappropriate due to the significant minimum MSE 0.1600.




(a)

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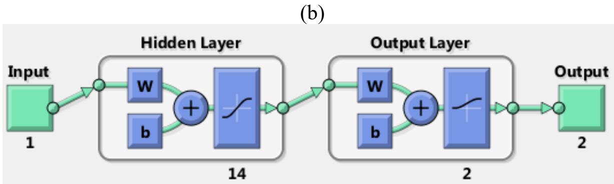


(c)

**Fig.8** Synthesized neural networks for noise identification with a) linear, b) tangent sigmoid and c) logarithmic sigmoid functions.

## 5. Conclusions

Synthesized artificial neural models can be successfully used in the field of the study of the quality of transmission of signals in telecommunications. The very good positive results achieved in the identification of signals with overlaid noises through artificial neural networks give reason to continue the research in the area under consideration. Future guidance is intended to increase the amount of input target signals and experiment with the number of hidden layers in neuronal structures under different activation functions. Also application of various types of pre-processing data such as component analysis, rapid Fourier transform, wavelet transformation, and more.



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## References

1. S. Yildirim, "Noise and performances analysis of commercial aircrafts using artificial neural networks", Recent Innovations in Mechatronics, vol. 2, pp. 1-2, 2015, DOI: 10.17667//riim.2015.1-2/9.
2. A. Ochoa, L. Mena, V. Felix, "Noise-tolerant neural network approach for electrocardiogram signal classification", Proceedings of 2017 International Conference on Compute and Data Analysis (ICCDA2017), Florida, United States, pp.277-282, May 2017, ISBN: 978-1-4503-5241-3.
3. A. Vishwakarma, "A new approach for Reducing Noise in ECG signal employing Gradient Descent Method by Artificial Neural Network", International Journal of Recent Research in Electrical and Electronics Engineering (IJRREEE), vol. 3, (2), pp.67-73, 2016, ISSN: 2349-7815.
4. Sh. Lin, Ch. Liu, Zh. Zhang, D. Wang, J. Tejedor, Th. Zheng, Y. Li, "Noisy training for deep neural networks in speech recognition", Springer, EURASIP Journal on Audio, Speech and music Processing, pp. 2-14, 2015, DOI: 0.1186/s13636-014-0047-0.
5. T. Santhanam, S. Radhica, "Probabilistic neural network – a better solution for noise classification", Journal of Theoretical and Applied Information Technology, vol. 27, №1, pp. 39-42, May 2011, ISSN: 1992- 8645.
6. R. Heghmaram, A. Aroudi, M. Aiagh, H. Veisi, "Automatic noise recognition based on neural networks using LPC and MFCC feature parameters", Proceedings of the Federal Conference on Computer Science and Information Systems, IEEE, pp. 69-73, 2012, ISBN: 798-83-60810-51-4.