An Effective Noise Reduction Method for Wireless Sensor Network Signals using the ANFIS Algorithm

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Abstract: - This paper proposes an effective node-level noise reduction for Wireless Sensor Networks (WSNs) using an adaptive neuro-fuzzy inference system. The peak of the signal is masked when the WSNs are deployed in noisy areas, thereby making it difficult for the receiving module to detect the data signal. The sensor nodes deployed in the network gather the signal along with noise signal related to a certain desired parameter to be sensed. Traditionally, each sensor node in the network would transmit the signal containing the data it had acquired to a central processing unit. Here arises the chance for failure of the central processing unit, and to avoid this powerful processing unit may be required, which consumes a lot of power. The original signal collected by each sensor node contains too much noise, which makes the useful signal much more difficult to detect, so the noise has to be removed from the noisy data signal before information extraction. The purpose of cancellation of noise from the acquired signal is to remove the noise-corrupted version of the sensor signal, using the ANFIS algorithm implemented at the node level before it is transmitted to the neighbouring node. The proposed adaptive approach is a simple application for a wireless sensor network, which has the key advantages of guaranteed accuracy, less time consuming, greater flexibility, reduced bandwidth and decreases power usage which are desirable requirements for a wireless sensor network.

Key-Words: - Adaptive approach, Distributed Signal Processing, noise estimation, ANFIS algorithm, Signal to Noise, Mean Squared Error.

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1 Introduction

Recently, the research on wireless sensor networks is attaining popularity because of its unique features and it is used in various applications like military, environment, health and home etc. A wireless sensor network is a connected network of many self-powered sensor nodes deployed across a bounded geographic region that can detect unusual occurrences or gather data and transmit it to neighbouring nodes as radio signals. Sensing of data, processing the acquired information, and communication in a wireless fashion are the key functionalities in a sensor network, and when two or more sensors are combined, various applications like remote sensing, environmental monitoring, medical applications, precision agriculture, and battlefield surveillance can be developed. The goal of this research is to formulate a low complexity ANFIS-based adaptive signal processing algorithm for the mitigation of noise in each node. Generally, the sensors deployed in a wireless sensor network used for various applications are subjected to various sources of electromagnetic noise and interference, which are caused by closeness to electrical and communication devices. The sources of electromagnetic noise in the real world are microwave transmitters, radio and television transmitters, oscillators, transformers, generators, motors and motor starters, ac power lines, relays, electrical surges, etc. The reason for the interference is due to thermal noise in the measurement device, power line interference, or distortion through the transmission media. Generally, when the level of voltage or current is high, the sensor node is closer to the communication devices or electrical circuits,

this will increase the magnitude of the induced noise.

The noise imposed in WSN signals is usually a random signals of unknown frequency, which degrade the quality of the measured signal. In circumstances where the characteristic of interfering noise is unknown, the desired signal can be estimated only by using suitable adaptive algorithms for the reduction of noise by identification, estimation, and extraction. In the centralized approach, each sensor node transfers its signal to a central processor, and this method needs a powerful processor with a lot of signal conditioning and communication resources. As an alternative, each network node collaborates with nearby nodes to estimate the desired parameter using the local data that has been gathered. Therefore, in order to reduce the power consumption of wireless sensors deployed for real-time operation, adaptive algorithms on adaptive networks must be implemented to reduce communication complexity.

The signal processing experts working with sensor networks suggest that it offers more advantages when unwanted noise is reduced at the node level, [1]. Many approaches have also stressed reducing energy consumption in sensor networks previously mentioned in [1] and [2]. In network adaptive processing using the LMS algorithm in [3] and Distributed RLS for in- network adaptation presented in [4] have shown poor improvement in signal-to-noise ratio. Also, the performance evaluation [5] and the advantage of frequency estimation over distributed networks are explained in [6] and [7]. Random signal's distributed estimation and smoothing [8] and distributed estimation of deterministic signals [9] in WSN's is found to be the most suitable technique for WSN's. The sensor network can adjust for time changes in the signal statistics for each sensor using LMS-type adaptive filtering [10] and is not applicable for signals with nonlinear dynamic characteristics. Therefore, in signal processing applications, it is desirable to identify the narrowband noise or interference from recorded time series. The linear adaptive noise reduction method suggested in [11] can be applied to non-linear fields by using a non-linear adaptive system. The Adaptive Neuro-Fuzzy Inference System [12] is subsequently utilized to identify the unknown changing characteristics of the non-linear channel, transforming the unknown noise source into an interference source in a detected signal. The proposed methodology is proven to be more effective than frequency-selective filtering-based noise Reduction techniques because it is more difficult to distinguish the detected data signal in the frequency domain from the distorted noise signal when it overlaps the original signal. The ANFIS algorithm offers a learning method that can extract equivalent information. ie. fuzzy rule for the fuzzy modeling approach from the collected data samples. The learning process in ANFIS is similar to that of a neural network, and it can compute the ideal parameters efficiently for a fuzzy membership function, allowing each sensor's fuzzy inference system to accurately simulate an anticipated input-output relationship. Because of this, ANFIS can be an efficient modeling technique based on the data currently available.

2 Signal Processing in Wireless Sensor Networks

In this work, the smart devices measure the physical quantity and convert it into an equivalent readable signal which can be read by a man or analysed by an instrument. The sensors are classified based on their applications, e.g., seismic, magnetic sensing devices, passive infrared intrusion (PIR), acoustic microphone arrays, still video cameras, etc. A typical wireless sensor node used in our research for sensing the signal is a resource-constrained one consisting of four main units, namely, a sensor unit, processing unit, transmitter and receiver unit, and power supply unit, as shown in Figure 1. Each sensor in the network shares the data information with its neighbouring nodes and with the user via a data processing unit known as a sink, and a group of sensors can do some task or multiple tasks. And therefore, a group of sensors deployed to perform a specific task implemented as a network of sensors through wireless links is called a sensor network. The data is forwarded to a receiving node, which uses the data for local processing or transmits the data to other networks through a gateway. The sensor nodes can be moving or stationary depending upon the environment and the application. To ensure enough sensing coverage and connectivity, the sensors used to monitor physical quantities are either deployed individually or arranged in groups with a high enough density in relation to their communication ranges. This sensor network may be used in military applications, environmental monitoring, weather forecasting, health monitoring, security systems, energy monitoring, battlefield surveillance systems, etc.

The functionalities of a wireless sensor network include sensing activities, exchanging sensed information, aggregating data, reasoning in a local or distributed manner, raising alarms, activating

other sensors, etc. Sensing, processing, and communication are three key elements whose combination in one tiny device gives rise to a vast number of remote sensing applications, including environmental monitoring, precision agriculture, medical applications, and battlefield surveillance. WSN is mostly used in applications where running wires or cabling is usually impractical. Owing to the low energy consumption and low complexity of the device to prolong the lifetime of nodes, wireless sensor networks have become an area of current research over the last decade.

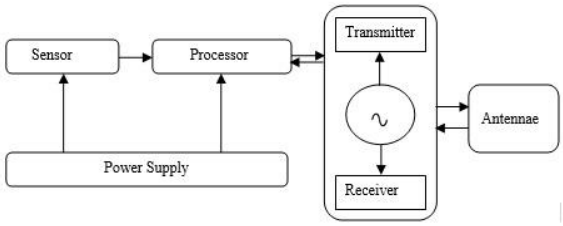

Fig. 1: Typical architecture of a simple wireless node
Source: created by the authors

3 Implementation of ANFIS for Noise Removal in WSN Signal

3.1 Noise Cancellation in WSN Signals

Since the signal being measured and transmitted is contaminated by noise, suitable noise Reduction must be done to retrieve the information contained in the signal by separating the noise. Small groups of sensors, which gather to form the sensor network's nodes, are physically connected to a central processing unit that performs all of the signal processing. In the method proposed here, the functionalities of the central processor are shared by each node in the network, with locally inbuilt signal processing abilities. In this work, the focus is on the Adaptive Noise Cancellation technique to reduce the undesirable background noise from useful data signals when it is buried in a noisy signal. Since the characteristics of the background noise changes time to time, the noise cancellation chosen must be an adaptive process suitable for a changing environment and conditions. Therefore, the objective of employing an effective denoising algorithm is to suppress the effect of noise, leaving the characteristics of the signal unchanged. And as mentioned above, the algorithm does need a priori knowledge about the characteristics of the data signal or the noise signal. The schematic diagram for ANFIS based filtering approach for adaptive noise cancellation is shown in Figure 2. The data sensed by the sensor node is transmitted to the neighbouring node, which performs adaptive noise cancellation and thereby making it easy for analysis of the received signal.

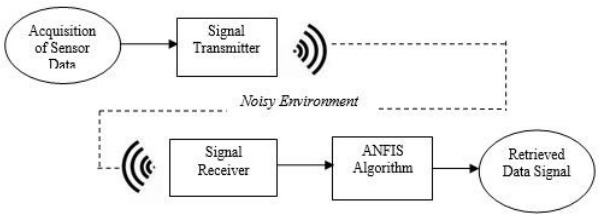

Fig. 2: Adaptive noise cancellation in WSN with ANFIS Algorithm
Source: created by the authors

3.2 Role of ANFIS

In this paper, we have presented a network that amalgamates fuzzy and neural network-based adaptive noise cancellation techniques. Hence, we have chosen ANFIS in our adaptive network, which serves as a fuzzy inference system (FIS), combining the advantages of a neural network and a fuzzy system. The outcomes of Jang's Adaptive Neuro-Fuzzy Inference System on a universal capable of approximating any real continuous function on a compact set to any degree have been extended in this work.

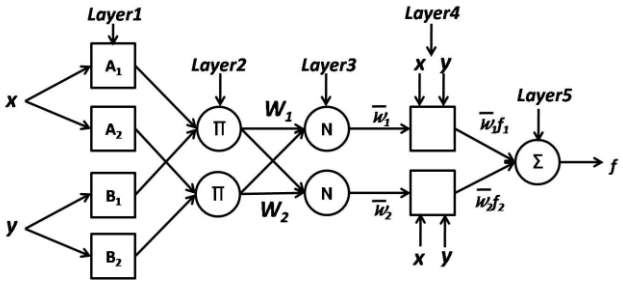

Fig. 3: ANFIS architecture using Sugeno fuzzy model
Source: Adapted from [21]

The ANFIS architecture using the Sugeno fuzzy model is shown in Figure 3, where nodes in each layer have identical roles, and two fuzzy if-then rules are taken into consideration in the first-order Sugeno model:

Rule1: If x and y are $A_1$and B_1 respectively
Then $f_1 = p_1 x + q_1 y + r_1$ (1)

Rule2: If x and y are $A_2$and B_2 respectively
then $f_2 = p_2 x + q_2 y + r_2$ (2)

where x, y are the input variables, A_i *and* $B_i$are the corresponding fuzzy sets ,$f_i$are the outputs specified

by the fuzzy rule within the fuzzy region, p_i , q_i, $r_i$are the subsequent parameter set that are obtained during the training process.
The nodes of each layers offer the following functions:

Layer 1: The membership grades of a linguistic label are generated by each node. Each node's output is given by

$$O_i^1 = \mu A_i(x) = \frac{1}{1+|\frac{x-c_i}{u_i}|^{2b_i}} \quad (3)$$

where x is the input to node i, A_i represents the linguistic label of the i_{th} node (e.g., very low, low, medium, large, very large, etc.), and a_i, b_i, c_i represents the parameter set that modifies the shapes of the membership function.

Layer 2: In layer 2 each node is fixed. The rule's firing strength is estimated by each node of this layer by multiplying the fuzzy sets A_i *and* B_i.

$$O_i^2 = W_i = \mu A_i(x)\mu B_i(y), i = 1,2 \quad (4)$$

Layer 3: Layer 3 is made up of fixed nodes that compute the firing strength ratio for the rules.

$$O_i^3 = \bar{W}_i = \frac{W_i}{W_{1+}W_2}, i=1,2 \quad (5)$$

Layer 4: In layer 4, the nodes are adaptable and carry out the consequent functions of the rules.

$$O_i^4 = \bar{W}_i f_i = \bar{W}(p_i x + q_i y + r_i), i=1,2 \quad (6)$$

Where $W_i$is the output obtained from layer 3, and the parameters evaluated in this layer are known as consequent parameters.

Layer 5: The final layer of the network is made up of a single converging node that calculates the overall output.

$$O_i^5 = Overall\ output = \sum \bar{W}_i f_i = \frac{\sum W_i f_i}{\sum_i W_i} \quad (7)$$

Given that the precise parameters are known, it is evident from the ANFIS architecture depicted in Figure 4 that the overall output f can be expressed as a linear combination of the evaluated consequent parameters.

$$f = \bar{W}_1 f_1 + \bar{W}_2 f_2 = (\bar{W}_1 x)p_1 + (\bar{W}_1 y)q_1 + (\bar{W}_1)r_1 + (\bar{W}_2 x)p_2 + (\bar{W}_2 y)q_2 + (\bar{W}_2)r_2 \quad (8)$$

3.3 How ANFIS Performs Noise Reduction

Figure 4 illustrates the adaptive noise cancelling method for a typical wireless sensor network. The input to Figure 5 comprises both noise signals that can be estimated and those that cannot be estimated. The signal becomes unmeasurable when it is combined with the unwanted distorted noise produced by the noise source with unknown non-linear dynamic properties. The current task is to extract the information signal *s(k)* from the noisy signal *y (k)*. From the mathematical equation, it can be found that the output signal *y(k)* comprises the information signal *s(k),* the distorted signal *b(k),* and the appropriate delay signals.

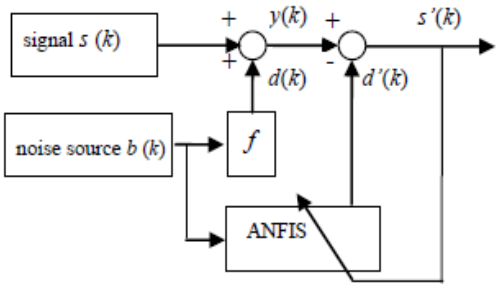

Fig. 4: Adaptive Noise Cancellation by ANFIS
Source: created by the authors

The expression for the detected signal is given by:

$$y(k) = s(k) + d(k) = s(k) + f(b(k), b(k\text{-}1), b(k\text{-}2), \ldots) \quad (9)$$

where $f(\cdot)$ describes the dynamic characteristics of the communication channel used for transmitting the noise signal. If $f(\cdot)$ is precisely known, it is simple to obtain the original data by directly subtracting $d(k)$ from $y(k)$.

However, because $f(\cdot)$ is unknown and changes with time, the commonly used frequency domain filtering technique cannot be applied to recover the data signal $s(k)$, which is buried in the spectrum of the noise signal $d(k)$. To estimate the distorted noise signal $d(k)$, we need to detect the clear noise signal $b(k)$ unrelated to the information signal. However, this cannot be directly achieved since the entire observable signal $y(k)$ also includes the distorted noise signal $d(k)$.

If the information signal $s(k)$ has a zero mean and is uncorrelated with the noise signal $b(k)$, we can still identify the signal $y(k)$ as the desired outcome of ANFIS training. ANFIS's learning rule attempts to reduce the error given by the equation:

$$\|u(k)\|^2 = \|y(k)\text{-}d'(k)\|^2 = \|s(k)+d(k)\text{-}d'(k)\|^2 = \|s(k)+d(k)\text{-}f'(b(k), b(k\text{-}1), b(k\text{-}2), \ldots)\|^2 \quad (10)$$

where f' is the function that was implemented using ANFIS. During the data fitting process, the information signal $s(k)$ is considered as an uncorrelated noise component, therefore until ANFIS detects the static trend of $s(k)$, it can do absolutely nothing for $s(k)$. However, ANFIS outperforms at reducing the error component that is correlated with $d(k)$ or $\| d(k)-f'(b(k), b(k-1),b(k-2),\ldots)\|^2$, which is basically the expected error measurement. And the error equation is expanded into.

$$\|u(k)\|^2=\|s(k)\|+\|d(k)-d'(k)\|^2+2s(k)d(k)-2s(k)d'(k) \quad (11)$$

If we apply mathematical expectation to both sides of (3) and observe that $s(k)$ is unrelated to $d'(k)$, we get:

$$U[u2] = U[s^2]+U[(d-d')^2]-2U[sd'] \quad (12)$$

If $s(k)$ is a random signal with zero mean, ANFIS is unable to formulate a model for it, and when $s(k)$ is infinite, $\frac{1}{m}\sum_k^1 s(k)d'(k)$ tends to zero, or $U[sd']=0$, we get

$U[u^2] = U[s^2]+U[(d-d')^2]$ where $U[s^2]$ will remain unchanged when ANFIS is tuned to minimize $U[u^2]$. Therefore, the total error minimized by ANFIS is the same as the minimized $U[(d-d')^2]$, making the ANFIS function $f'(\bullet)$ close to the dynamic characteristics.

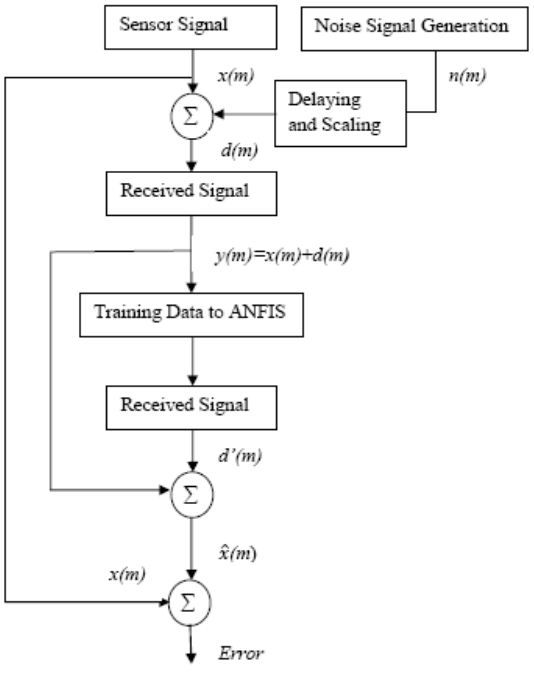

Fig. 5: Flow diagram for ANFIS Implementation of noise cancellation in WSN
Source: created by the authors

ANFIS is therefore used as adaptive filter for noise cancellation and therefore can be used for generation of reference signal in active noise cancellers in which the job of ANFIS will be to remove the noise component of the corrupted signal as shown in the flow diagram in Figure 5.

Hence, the suggested fuzzy inference system's rapid response and simplicity of implementation make it ideal for noise cancelling.

4 Results and Discussion

The simulation was performed using the existing functionalities of MATLAB. Considering one node as a transmitting node, which transmits a data signal that is received by the receiving node, is contaminated with various noises as discussed above. The signal taken is of frequency 1 KHz and a noise variance of 0.02. The following are the results obtained.

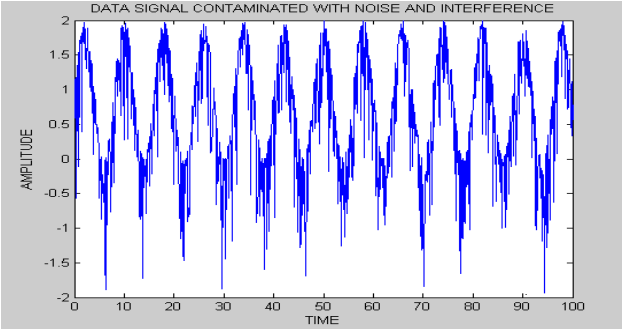

Fig. 6: Received Data Signal Corrupted with Noise and Interference
Source: created by the authors

Figure 6 shows that the received sensor data signal is buried in noise, which is difficult for the measurement system to detect the received signal.

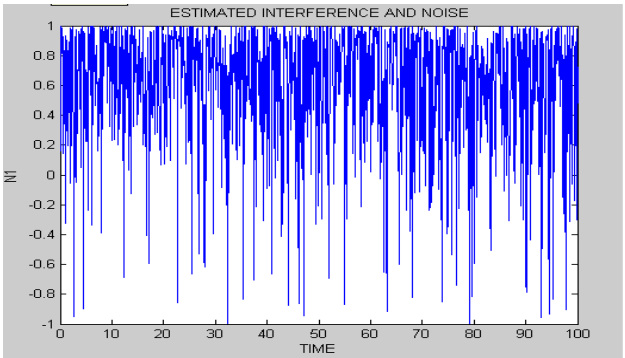

Fig. 7: Estimated Interference and Noise Signal
Source: created by the authors

Figure 7 gives the estimate of the interference signal obtained while performing simulation on the corrupted data signal.

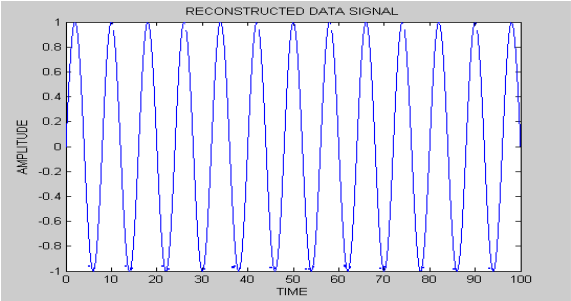

Fig. 8: Retrieved data Signal
Source: created by the authors

From the Figure 8, it is evident that noise is considerably removed from the contaminated signal, thereby reducing the communication overhead in terms of reduced bandwidth and power.

The performance parameters obtained from the experiments are tabulated below in Figure 9, and the results indicate that the strategy mentioned can effectively filter out the noise and provide the noise-free data signal.

Sl. No.	Algorithms	Frequency in KHz	SNR Improvement(dB)	Time Elapsed(ms)	MSE
1.	D-LMS	1	4.89	33.2	7.6×10^{-3}
		2	4.32	35.2	7.8×10^{-3}
		5	4.12	37.2	8.6×10^{-3}
		10	3.52	40.2	9.9×10^{-3}
2.	D-RLS	1	6.09	30.6	6.2×10^{-3}
		2	5.62	32.6	6.5×10^{-3}
		5	5.23	35.4	7.8×10^{-3}
		10	4.36	38.6	8.6×10^{-3}
3.	D-ANFIS	1	7.95	27.3	1.5×10^{-3}
		2	7.15	28.8	1.8×10^{-3}
		5	6.26	30.2	2.6×10^{-3}
		10	5.42	35.4	3.6×10^{-3}

Fig. 9: Comparison of performance parameters obtained from different adaptive algorithms.
Source: created by the authors

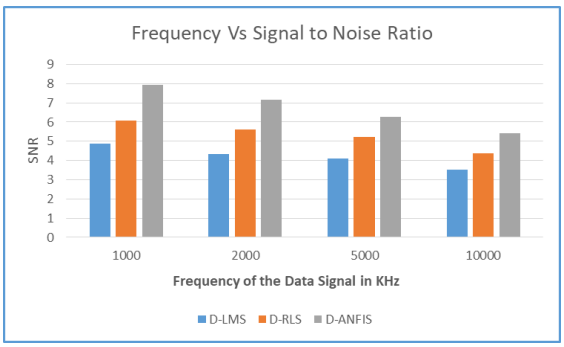

Fig. 10: Comparison of the performance of ANFIS with other algorithms
Source: created by the authors

To summarize, it has been discovered that ANFIS is more effective in eliminating the unknown distorted noise signal *d (k)* from the measured signal *y (k)*. Simulation, spectral analysis, and actual measurement have demonstrated that the use of an ANFIS network for noise cancellation can effectively extract the original information signal as shown in Figure 10. It also has a better advantage than traditional adaptive filtering techniques when the information signal substantially overlaps the distorted noise signal.

6 Conclusions and Future Directions

In this paper, an application of the ANFIS algorithm for adaptive noise reduction in Wireless Sensor Signals is presented. Fuzzy logic and neural networks are the foundation of the novel and intelligent real-time noise cancellation technique known as ANFIS. This approach has a quicker convergence time, minimal computational overhead, lesser memory requirements, and is more effective in removing noise for WSN signals. The algorithm also consumes less power by reducing the processing complexity that leads to a more reliable noise reduction method, and it is hoped that this method will be helpful to WSN sensor signals for various applications.

However, the choice of the adaptive algorithm to be chosen is a compromise between computational complexity and fast convergence, which has to be chosen based on the requirements of the sensor network and the environment where the sensor nodes are to be deployed. In future, researches can be extended to the area of the combination of signal processing and information fusion, as well as the combination of signal processing and network protocols.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the author(s) utilized artificial intelligence (AI) technologies solely for the purpose of linguistic refinement and grammatical correction. Following the application of these tools, the author(s) comprehensively reviewed, verified, and edited the resulting text. The author(s) maintain full accountability and responsibility for the accuracy, integrity, and final content of the publication.

References:

[1] Alessandro Depari, Alessandra Flammini, Daniele Marioli, Mauro Serpelloni, Emiliano Sisinni, and Andrea Taroni, "Efficient Sensor Signal Filtering for Autonomous Wireless Nodes," *IEEE Trans. Inst. and Measurement.*, vol. 59, no. 1, pp.229–237, Jan. 2010.doi: 10.1109/tim.2009.2023104.

[2] Federico S. Cattivelli, *Student Member, IEEE,* and Ali H. Sayed, *Fellow, IEEE*, "Diffusion LMS Strategies for Distributed Estimation," *IEEE Trans. Signal Process.*, vol. 58, no. 3, pp.1035–1048, Mar. 2010. doi: 10.1109/tsp.2009.2033729.

[3] I. D. Schizas, G. Mateos, and G. B. Giannakis, "Distributed LMS for consesus-based in-network adaptive processing," *IEEE Trans. Signal Process.*, vol. 57, no. 6, pp. 2365–2382, Jun. 2009. doi: 10.1109/tsp.2009.2016226.

[4] Gonzalo Mateos, Ioannis D. Schizas, and Georgios B. Giannakis, "Distributed Recursive Least-Squares for Consensus-Based In-Network Adaptive Estimation," *IEEE Trans. Signal Process.*, vol. 57, no. 11, pp.4583–4588, Nov. 2009. doi: 10.1109/tsp.2009.2024278.

[5] C. G. Lopes and A. H. Sayed, "Diffusion least-mean squares over adaptive networks: Formulation and performance analysis," *IEEE Trans.Signal Process.*, vol. 56, no. 7, pp. 3122–3136,Jul. 2008. doi: 10.1109/tsp.2008.917383.

[6] Miodrag D. Kusljevic," A Simple Recursive Algorithm for Simultaneous Magnitude and Frequency Estimation" *IEEE Transactions On Instrumentation And Measurement*, Vol. 57, NO. 6, June 2008. doi: 10.1109/tim.2007.913728.

[7] F. S. Cattivelli, C. G. Lopes, and A. H. Sayed, "Diffusion recursive least-squares for distributed estimation over adaptive networks," *IEEE Trans. Signal Process.*, vol. 56, no. 5, pp. 1865–1877, May 2008. doi: 10.1109/tsp.2007.913164.

[8] I. D. Schizas, G. B. Giannakis, A. Ribeiro, and S. I. Roumeliotis, "Consensus in ad hoc WSNs with noisy links—Part II: Distributed estimation and smoothing of random signals," *IEEE Trans. Signal Process.*,vol. 56, no. 4, pp. 1650–1666, Apr. 2008. doi: 10.1109/tsp.2007.908943.

[9] I. D. Schizas, A. Ribeiro, and G. B. Giannakis, "Consensus in ad hoc WSNs with noisy links—Part I: Distributed estimation of deterministic signals," *IEEE Trans. Signal Process.*, vol. 56, no. 1, pp. 350–364, Jan.2008. doi: 10.1109/tsp.2007.906734.

[10] C. G. Lopes and A. H. Sayed, "Incremental adaptive strategies over distributed networks," *IEEE Trans. Signal Process.*, vol. 55, no. 8, pp.4064–4077, Aug. 2007. doi: 10.1109/tsp.2007.896034.

[11] B.Widrow and D.S.teans. Adaptive signal processing. *Prentice Hall, Upper Saddle River, NJ*, 1995. Isbn: 0-13-004029-0.

[12] L.X.Wang and J.M.Mendel.Fuzzy adaptive filters with application to nonlinear chanel.*IEEE Transactions on Fuzy Systems*. 1(3):161-171,1993. doi: 10.1109/91.236549.

[13] Mohsen Mojiri, Masoud Karimi-Ghartemani, and Alireza Bakhshai, "Time-Domain Signal Analysis Using Adaptive Notch Filter", *IEEE Transactions on Signal Processing*, Vol. 55, No. 1, Jan 2007. doi: 10.1109/tsp.2006.885686.

[14] Mojiri and A. R. Bakhshai," An Adaptive Notch Filter for Frequency Estimation of a Periodic Signal", *IEEE Transactions on Automotive Control*, Vol.39, No.2, Feb. 2004. doi: 10.1109/tac.2003.821414.

[15] Lyndon J. Brown, *Member, IEEE,* and Qing Zhang, "Identification of Periodic Signals With Uncertain Frequency", *IEEE Transactions on Signal Processing*, 1538-1545, Vol. 51, No. 6, June 2003. doi: 10.1109/acc.2002.1023238.

[16] D. Estrin, G. Pottie and M. Srivastava. "Intrumenting the world with wireless sensor networks," *Proc. IEEE ICASSP*, pp. 2033-2036, Salt LakeCity, UT, USA, May2001. doi: 10.1109/icassp.2001.940390.

[17] S. Haykin, *Adaptive Filter Theory*. Upper Saddle River: Prentice Hall,1996.

[18] D. Srinath, P.K Rajasekaran, R.Viswanathan, "Introduction to Statistical Signal Processing with Applications" Pearson Education. ISBN: 978-0471044048.

[19] Raj Kumar Thenua and S.K. AGARWAL" Simulation and Performance Analyasis of Adaptive Filter in Noise Cancellation" *International Journal of Engineering Science and Technology*, Vol. 2(9), 2010, 4373-4378.

[20] Abdallah, A, Wolf, W., "Analysis of DistributedNoise Canceling", *Procedings of the 2nd International Conference* on Distributed Frameworks for Multimedia Applications, pp. 1-7. Pulau Pinang, Malaysia, May 2006, doi: 10.1109/dfma.2006.296890.

[21] Jyh-Shing Roger Jang, "ANFIS: Adaptive Network-Based Fuzzy Inference System", IEEE trans., on S ystems, Man and Cybernetics, Vol. 23, No. 3, May-June, 1993, pg. 665-685.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

In this study, both the authors D. Rene Dev and G. Beni contributed equally for Problem formulation, Solution and Analysis, Conceptualization, Review & Editing of the paper.

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The authors did not receive support from any organization for the submitted work.

Conflict of Interest

The authors have no conflict of interest to declare.

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