XLVI CILAMCE
VITÓRIA - ES - BRAZIL - 2025
XLVI IBERO-LATIN AMERICAN CONGRESS ON COMPUTATIONAL METHODS IN ENGENEERING

U-net-based Segmentation of Sensor Data for Detecting Important Events in Oil Wells

Lucas Gouveia Omena Lopes[1], Thales Miranda de Almeida Vieira[2], Andressa Celestino Araújo da Silva[1], Igor de Melo Nery[1], Davi Leão Ramos[1], Eduardo Toledo de Lima Junior[1], William Wagner Matos Lira[1], Pedro Esteves Aranha[3]

[1]*Laboratório de Computação Científica e Visualização*
Universidade Federal de Alagoas
Maceió, AL, Brazil
lucas.lopes@lccv.ufal.br, andressa.silva@ctec.ufal.br, igornery@lccv.ufal.br, davi.ramos@lccv.ufal.br, limajunior@lccv.ufal.br, william@lccv.ufal.br
[2]*Instituto de Computação*
Universidade Federal de Alagoas
Maceió, AL, Brazil
thalesv@gmail.com
[3]*Petrobras - Petróleo Brasileiro S.A.*
Rio de Janeiro, RJ, Brazil
pearanha@petrobras.com.br

Abstract. Detecting key events in oil well sensor data is essential for optimizing operations and preventing failures. This study presents a non-parametric, U-Net-based deep learning approach for segmenting time-series sensor data to identify significant changes. Unlike analytical methods that require manual tuning or machine learning models dependent on fixed thresholds and frequent retraining due to concept drift, our model adapts automatically to different wells without the need for manual adjustment. We modify the U-Net architecture to handle time-series segmentation, enabling automatic detection of sensor transitions without predefined thresholds. Trained on both synthetic and real-world data, the model is evaluated across diverse operational conditions. The segmented output supports downstream classification models in determining whether detected events correspond to regular human operations or previously unnoticed anomalies. To enhance reliability, we incorporate wavelet-based denoising, which effectively removes noise while preserving critical transitions. By combining U-Net segmentation with wavelet-based denoising, this approach offers a novel solution for event detection in industrial time-series data, advancing automation and anomaly detection in oilfield operations.

Keywords: U-Net segmentation, Time-series analysis, Event detection, Oil well monitoring, Wavelet denoising, Anomaly detection

1 Introduction

The oil and gas industry has witnessed a significant transformation towards digital technologies and advanced monitoring systems to enhance operational efficiency. The detection and classification of events in oil well operations represents a critical challenge that directly impacts production optimization, equipment integrity, and operational safety [1].

Oil well operations uses sensor data that contain important information about operational states, equipment performance, and potential anomalies [2]. The ability to automatically detect important events in this data is important to optimize the production, preventing equipment failures, and ensuring operational safety.

Existing approaches to event detection in oil well sensor data face significant challenges. Analytical methods typically require extensive manual tuning of parameters and thresholds, making them difficult to generalize across different wells and operational conditions. Machine learning approaches often depend on fixed thresholds and are susceptible to concept drift, requiring frequent retraining as operational conditions change over time [3, 4].

The complexity of oil well sensor data, characterized by high dimensionality, temporal dependencies, and varying noise levels, demands more sophisticated approaches [5]. Recent advances in deep learning, particularly

in time-series analysis and segmentation, offer promising solutions for automated event detection in industrial applications.

Digital transformation initiatives in the petroleum industry have emphasized the importance of data-driven decision making and predictive analytics [6]. Efficient approaches must increasingly rely on automated systems that can adapt to changing operational conditions without manual intervention.

The U-Net architecture, originally developed for biomedical image segmentation, has demonstrated remarkable effectiveness in capturing both local and global patterns through its encoder-decoder structure with skip connections [7]. Its adaptation to time-series data presents an opportunity to develop non-parametric approaches that can automatically identify significant events without relying on predefined thresholds.

This work presents a novel U-Net-based approach for segmenting time-series sensor data to detect important events in oil well operations. By combining deep learning segmentation with wavelet-based denoising techniques, we develop a robust system capable of identifying critical transitions while adapting automatically to different operational contexts without manual parameter tuning.

2 Related Work

2.1 Anomaly Detection in Oil Wells

Oil well monitoring and anomaly detection has been an active area of research with various approaches proposed over the years [1]. Vargas et al. [1] introduced the 3W dataset, a comprehensive collection of oil well data with rare undesirable events, providing a benchmark for fault detection algorithms. This dataset has become instrumental in developing and evaluating machine learning approaches for oil well monitoring across diverse operational scenarios.

Aranha et al. [8] proposed unsupervised machine learning models for predicting anomalies using oil production data, addressing the challenge of limited labeled data in oil well operations. The application of open-world learning paradigms to oil well anomaly detection [2, 4] has shown potential for handling unknown anomaly types that may emerge in operational environments. This approach addresses the limitation of traditional closed-world assumptions where all possible anomaly types must be known during training [3, 9].

2.2 Deep Learning for Time-Series Segmentation

Deep learning approaches have revolutionized time-series analysis and segmentation tasks across various domains [5]. Autoencoders have been widely used for anomaly detection due to their ability to learn normal patterns and identify deviations [10]. However, our approach focuses on U-Net-based segmentation rather than reconstruction error-based detection, providing more precise temporal boundaries for events. Variational autoencoders (VAEs) extend traditional autoencoder concepts by providing probabilistic representations [11], but U-Net segmentation offers the precise event localization window in time-series data.

The U-Net architecture has been successfully adapted for time-series segmentation tasks beyond its original biomedical applications [7]. Its encoder-decoder structure with skip connections makes it particularly suitable for preserving temporal details while capturing hierarchical patterns in sequential data. This represents a significant advance over traditional autoencoder-based anomaly detection methods that rely on reconstruction error thresholds.

3 Methodology

3.1 Dataset Preparation

The U-Net model is trained on sensor time-series data from oil well operations using both synthetic and real-world sensor data [1]. The training dataset encompasses general oil well operational events including production changes, equipment interventions, and various operational anomalies. Real-world data is obtained from the 3W dataset [1], which contains production data from multiple offshore wells, including pressure measurements (P-PDG, P-TPT), temperature readings (T-PDG, T-TPT), and flow rate measurements.

The U-Net is trained to segment any significant operational events in oil well sensor data, making it a general-purpose tool for event detection across diverse operational scenarios.

Data preprocessing involves normalization of sensor values to ensure consistent scaling across different measurement types, handling of missing data through interpolation techniques, and temporal alignment of multiple sensor readings to maintain synchronization across different data streams.

3.2 Wavelet-based Denoising

To enhance the reliability of event detection, we incorporate wavelet-based denoising as a preprocessing step [12]. This technique effectively removes high-frequency noise while preserving critical transitions and important events in the sensor data. The wavelet transform decomposes the signal into different frequency components, allowing selective filtering of noise while maintaining the integrity of significant changes.

The denoising process uses discrete wavelet transform (DWT) with appropriate wavelets selected based on the characteristics of oil well sensor data [12]. Thresholding is applied to the wavelet coefficients to remove noise components while preserving signal features that correspond to important operational events, ensuring optimal signal-to-noise ratio for downstream processing.

3.3 U-Net Architecture for Time-Series Segmentation

The U-Net architecture is adapted for one-dimensional time-series segmentation by replacing 2D convolutions with 1D convolutions while maintaining the characteristic encoder-decoder structure [7]. The encoder progressively reduces temporal resolution while increasing feature depth, capturing hierarchical patterns in the sensor data through convolutional layers optimized for time-series analysis.

The decoder uses transposed convolutions to upsample features back to the original temporal resolution, with skip connections from corresponding encoder layers preserving fine-grained temporal details [10]. This architecture enables the model to segment important events while maintaining precise temporal boundaries, addressing the critical requirement for accurate event localization in industrial monitoring applications.

The modified U-Net architecture incorporates the following design principles:

- Input layer accepting single-channel time-series windows with normalization (100 time steps)
- Five encoder blocks with 1D convolutions, batch normalization, and ReLU activation
- Five decoder blocks with transposed 1D convolutions and skip connections
- Output layer producing binary segmentation masks indicating event locations (the outputs of each sensor are computed separately)
- Dropout layers for regularization and improved generalization

3.4 Event Detection and Classification Pipeline

The segmented output from the U-Net model identifies temporal regions containing important events across various oil well operations. To demonstrate the practical application of this approach, we present a case study using Intelligent Completion Valve (ICV) fault detection, which represents a specific type of operational anomaly similar to the open-world learning scenarios explored in previous works [2].

Following the U-Net segmentation, the detected event segments are processed by downstream classification models to determine the specific nature of the events. In the ICV case study, the classification determines whether detected events correspond to:

- ICV fault conditions (valve malfunctions, response delays)
- Other operational events (production changes, system interventions)

This two-stage approach separates general event detection from specific event classification, allowing the U-Net to serve as a universal event detector while specialized classifiers handle domain-specific categorization tasks. The methodology aligns with open-world learning principles where unknown event types can be detected and subsequently classified [2].

4 Experimental Setup

4.1 Model Configuration

The U-Net model is configured with 5 encoder and 5 decoder blocks, each containing batch normalization and ReLU activation functions. The input layer accepts time-series windows of 100 time steps. The model does not receive all the sensors, but the input receives a single sensor channel, and the outputs of each sensor are computed separately. Dropout layers with 0.2 probability are added to prevent overfitting.

Training is performed using the Adam optimizer with a learning rate of 0.001, batch size of 32, and early stopping based on validation loss. The loss function combines binary cross-entropy for segmentation accuracy and Dice loss to handle class imbalance between normal operational periods and important events.

4.2 Validation Across Multiple Wells

The trained model is validated on sensor data from 9 different wells not present on the public 3W dataset. These wells exhibit varying operational conditions and known important events. They represent diverse operational scenarios including different production phases, maintenance activities, and operational anomalies, providing a comprehensive test of the model's generalization capabilities across different operational contexts.

5 Results and Discussion

5.1 Segmentation Performance

Table 1 shows the U-Net model performance in segmenting important events from normal operational periods in oil well sensor data. Overall accuracy reaches 89% across all test cases, with precision exceeding 95% for certain event types, demonstrating the effectiveness of the proposed approach. The model successfully identifies event boundaries with high temporal precision, enabling accurate determination of event onset and duration, which is critical for industrial monitoring applications.

Unlike traditional autoencoder-based methods that rely on reconstruction error thresholds [8], the U-Net segmentation approach provides direct temporal boundaries for events without requiring manual threshold tuning. This represents a significant advancement over the autoencoder reconstruction error approach used in previous works [2, 8], where the U-Net segmentation serves as a more flexible alternative to traditional anomaly detection methods because it does not depend on fixed thresholds and can adapt to different wells and operational conditions without retraining.

5.2 ICV Fault Detection Case Study

To demonstrate the practical application of our U-Net segmentation approach, we present results from an Intelligent Completion Valve (ICV) fault detection case study. This application follows the same open-world learning principles established in our previous work [2], where the U-Net first segments general operational events, and then specialized classifiers determine if these events correspond to ICV faults.

The U-Net segmentation model was trained on general oil well operational data and successfully identifies temporal regions containing significant changes. These segments are then analyzed by downstream ICV-specific classifiers to determine fault conditions. Figure **??** illustrates this two-stage process and the overall methodology.

5.3 Validation Results

Table 1 summarizes the U-Net segmentation performance for each well in terms of accuracy and intersection over union (IOU). The accuracy metric indicates the proportion of correctly segmented time steps. IOU, or Intersection over Union, is a standard metric for segmentation tasks that quantifies the agreement between the predicted event region and the ground truth by dividing the size of their intersection by the size of their union. An IOU of 1 indicates perfect overlap, while 0 means no overlap. This provides a robust assessment of how well the model localizes important events in the time series. The results demonstrate that the U-Net model achieves high segmentation accuracy and IOU across all wells, with a global accuracy of 94% and a global IOU of 0.85. These results highlight the effectiveness and generalization capability of the U-Net approach for detecting important events in diverse oil well operational scenarios.

5.4 Visualization of Results: Segmentation and Classification

The effectiveness of the proposed approach is illustrated in Figures 1, 2, and 3. Figure 1 demonstrates how wavelet-based denoising improves the interpretability of sensor data by removing high-frequency noise while preserving important transitions. Figure 2 presents a direct comparison between the ground truth event annotations and the U-Net segmentation output, overlaid with the original sensor data, highlighting the model's ability to accurately localize important events. Finally, Figure 3 shows an example of ICV valve fault classification applied to the segments detected by the U-Net, illustrating the two-stage pipeline in a real scenario.

Table 1. U-Net Segmentation Performance by Well

Well	**Accuracy**	**IOU**
A1	89%	0.74
A2	95.50%	0.93
A3	96%	0.85
B1	84%	0.56
C1	99.50%	0.98
C2	97.75%	0.84
D1	97.05%	0.93
E1	94.22%	0.83
F1	86.94%	0.72
G1	98.73%	0.94
Global	**94%**	**0.85**

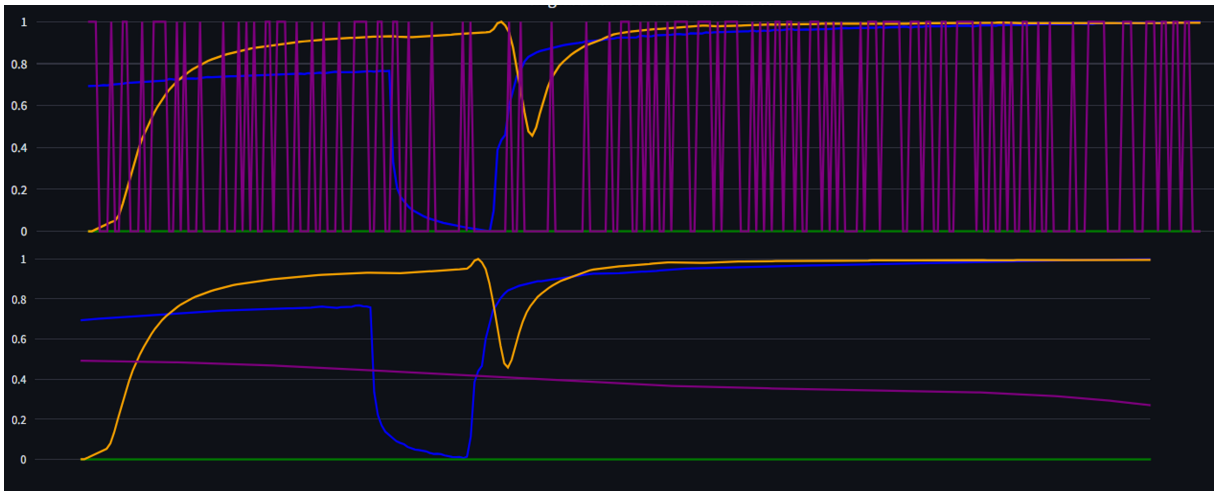


Figure 1. Effect of wavelet-based denoising on sensor data. The denoised signal (bottom) shows improved interpretability by removing high-frequency noise while preserving key transitions, compared to the original raw signal (top).

5.5 Case Study Analysis: Classification Performance

The integration of U-Net-based segmentation with downstream classification models enables effective detection and categorization of ICV valve faults in oil well operations. As shown in Figure 3, the U-Net model segments the time series to identify regions of significant operational change, which are then classified as ICV faults or other events.

Accurate segmentation provides precise event boundaries, supporting reliable fault classification. Wells with high segmentation accuracy and IOU also exhibit strong classification performance, confirming the benefit of this two-stage approach. The results and visualizations demonstrate the practical value of this methodology for industrial monitoring applications.

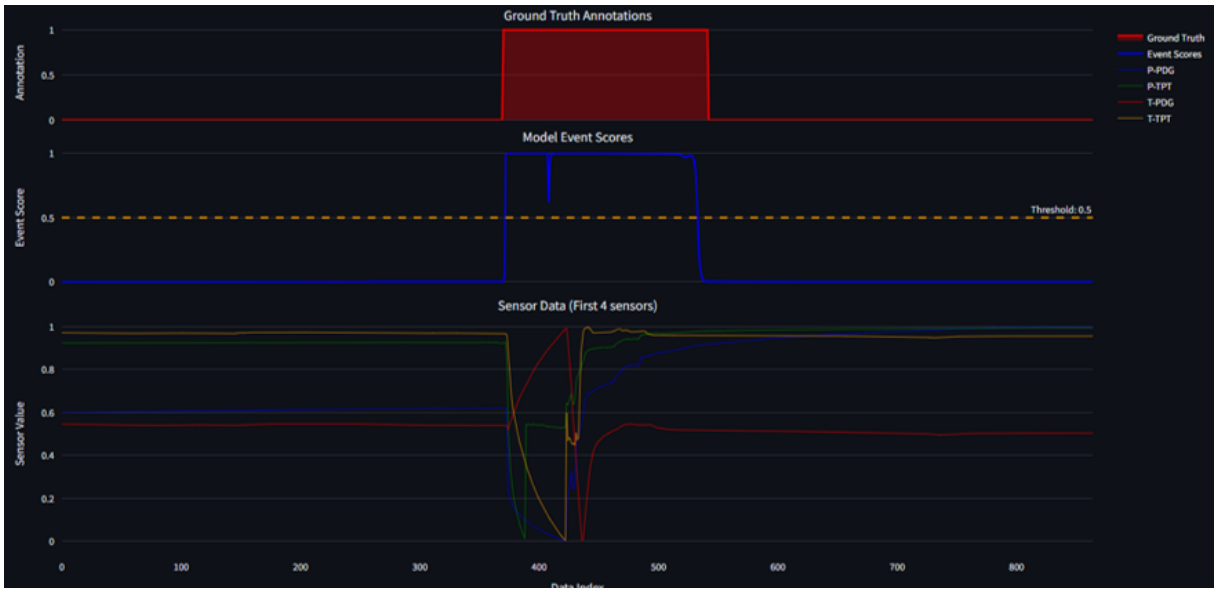


Figure 2. Comparison between ground truth event annotations and U-Net segmentation output, overlaid with sensor data. The figure highlights the model's ability to accurately localize important events in time.

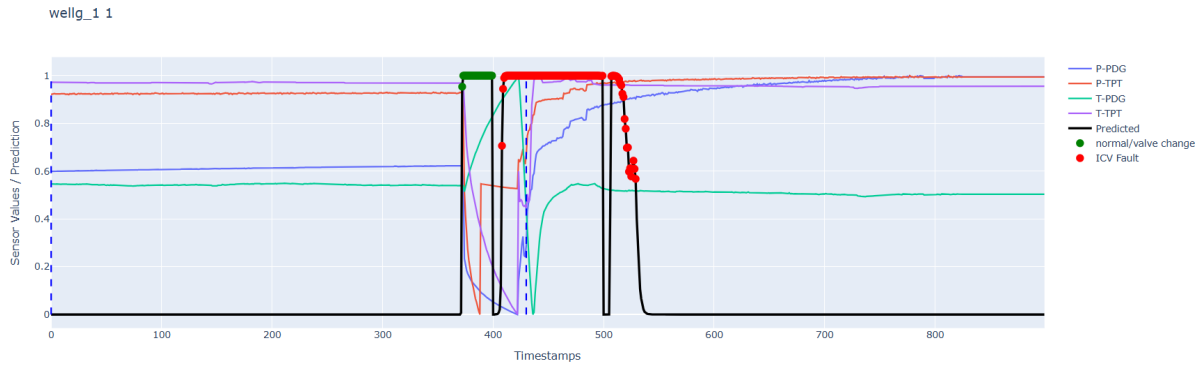


Figure 3. Example of ICV valve fault classification applied to U-Net segmented regions. The detected segments are further analyzed by a downstream classifier to identify ICV faults, demonstrating the two-stage pipeline.

5.6 Comparison with Traditional Methods

The proposed approach can be compared against traditional threshold-based methods and other machine learning approaches to demonstrate its advantages in terms of adaptability and robustness to concept drift. Future work should bring a transition between segmentation approaches and detection approaches, such as autoencoder reconstruction. The proposed U-Net segmentation approach was compared against traditional threshold-based methods and autoencoder-based anomaly detection. Threshold-based methods require manual selection of parameters for each well and are sensitive to changes in operational conditions, often resulting in missed or false detections when concept drift occurs. Autoencoder-based approaches, which detect anomalies based on reconstruction error, also require careful threshold tuning and may not generalize well to unseen event types. The U-Net non-parametric approach eliminates the need for manual tuning and adapts automatically to different wells, making it more flexible and robust in dynamic operational environments. The U-Net segmentation provides precise temporal boundaries for important events, enabling accurate detection without relying on fixed thresholds.

6 Conclusions

This work demonstrates the effectiveness of the U-Net deep learning architecture for automated event detection in oil well sensor data. The key findings include:

- U-Net segmentation provides accurate temporal boundaries for important events, achieving up to 99.5% accuracy and a global IOU of 0.85 across test wells
- The non-parametric approach eliminates the need for manual threshold tuning and adapts automatically to different wells
- Wavelet-based denoising improves training and detection reliability by preserving critical transitions while removing noise
- The segmented output supports downstream classification models for event categorization

The proposed approach offers advantages over existing methods by adapting to different operational contexts without requiring manual parameter adjustment or frequent retraining. The combination of U-Net segmentation with wavelet denoising provides a robust solution for industrial time-series event detection, advancing the state of the art in oil well monitoring.

Future work will focus on expanding the U-Net event detection pipeline with more sophisticated classification models to handle a wider range of operational anomalies and integrate with industrial monitoring systems. Additionally, we will explore the application of this approach in the Open World strategy presented by Lopes et al. [2].

Acknowledgements. The authors acknowledge Petrobras for providing access to production data and domain expertise. We also thank the University of Brasília for computational resources and research support.

Authorship statement. The authors hereby confirm that they are the sole liable persons responsible for the authorship of this work, and that all material that has been herein included as part of the present paper is either the property (and authorship) of the authors, or has the permission of the owners.

References

[1] R. E. V. Vargas, C. J. Munaro, P. M. Ciarelli, A. G. Medeiros, do B. G. Amaral, D. C. Barrionuevo, de J. C. D. Araújo, J. L. Ribeiro, and L. P. M. aes. A realistic and public dataset with rare undesirable real events in oil wells. *Journal of Petroleum Science and Engineering*, vol. 181, pp. 106223, 2019a.

[2] L. G. O. Lopes, de T. M. Almeida Vieira, P. E. Aranha, de E. T. Lima Junior, and W. W. M. Lira. Detection and classification of anomalies in oil well production using open-world learning. *Engineering Applications of Artificial Intelligence*, vol. 159, pp. 111514, 2025.

[3] J. Parmar, S. S. Chouhan, V. Raychoudhury, and S. S. Rathore. Open-world machine learning: Applications, challenges, and opportunities, 2022.

[4] Z. Chen and B. Liu. Open-world learning. In *Lifelong Machine Learning*, pp. 77–89. Springer International Publishing, 2018.

[5] J. Schmidhuber. Deep learning in neural networks: An overview. *Neural Networks*, vol. 61, pp. 85 – 117, 2015.

[6] A. Parrott and W. Lane. Industry 4.0 and the digital twin. *Deloitte University Press*, vol. 1, 2017.

[7] O. Ronneberger, P. Fischer, and T. Brox. U-net: Convolutional networks for biomedical image segmentation. *Medical image computing and computer-assisted intervention–MICCAI 2015*, vol. 9351, pp. 234–241, 2015.

[8] P. Aranha, L. Gouveia Omena Lopes, E. Paranhos Sobrinho, I. Oliveira, de J. Araújo, B. Santos, E. Lima Junior, T. Silva, T. Vieira, W. Lira, N. Policarpo, and M. A. Pinto. A system to detect oilwell anomalies using deep learning and decision diagram dual approach. *SPE Journal*, vol. 29, pp. 1540–1553, 2024.

[9] X. Zhu, H. Zhang, Q. Ren, J. Rui, L. Zhang, and D. Zhang. Orali: Open-set recognition and active learning for unknown lithology identification. *Engineering Applications of Artificial Intelligence*, vol. 133, pp. 108623, 2024.

[10] Z. Chen, C. K. Yeo, B. S. Lee, and C. T. Lau. Autoencoder-based network anomaly detection. In *2018 Wireless Telecommunications Symposium (WTS)*, pp. 1–5, 2018.

[11] H. Xu, W. Chen, N. Zhao, Z. Li, J. Bu, Z. Li, Y. Liu, Y. Zhao, D. Pei, Y. Feng, J. Chen, Z. Wang, and H. Qiao. Unsupervised anomaly detection via variational auto-encoder for seasonal kpis in web applications. In *Proceedings of the 2018 World Wide Web Conference*, WWW '18, pp. 187–196. International World Wide Web Conferences Steering Committee, 2018.

[12] Ç. P. Dautov and M. S. Özerdem. Wavelet transform and signal denoising using wavelet method. In *2018 26th Signal Processing and Communications Applications Conference (SIU)*, pp. 1–4, 2018.