Hankel Matrix-Based Neural Network Model for Robust Signal Classification in ISAC Systems

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Abstract - *Integrated Sensing and Communication (ISAC) systems are becoming an important part of future wireless networks. These systems can send data and sense the environment at the same time. However, it's tough to classify the signals accurately because of things like noise, interference, and changing channel conditions. This project suggests a new way to classify signals using a neural network with a method called Hankelization, and it's built using MATLAB. The method takes the received time-based signals and turns them into structured Hankel matrices. These matrices help capture the time-based patterns and relationships in the signals better than normal feature extraction methods. Once these matrices are created, they are used to get important features that are then sent to a neural network to classify the signals. The model uses deep learning to tell apart different types of signals, even when the signal quality is not very good. MATLAB is used for running simulations, preparing the data, training the model, and checking how well it works. The system is tested with different signal datasets that represent various ways of sending signals and different communication situations. The model's performance is measured using things like accuracy, precision, recall, and confusion matrix analysis. The results show that using this Hankelization method greatly improves signal classification accuracy compared to older methods. It also makes the system more resistant to noise and signal problems.*

Key Words: ISAC, Signal Classification, Hankelization, Deep Learning, Neural Networks, MATLAB, Interference Handling.

1. INTRODUCTION

Integrated Sensing and Communication (ISAC) has become a key technology for next-generation wireless systems. It allows both data transmission and environmental sensing to happen at the same time within a single system. This ability improves how efficiently the system uses the radio spectrum and reduces the complexity of the hardware, which makes ISAC suitable for uses like self-driving cars, smart cities, and IoT networks [1], [3]. However, accurately classifying signals in ISAC environments is still difficult because of noise, interference, and constantly changing channel conditions. As artificial intelligence has advanced, deep learning methods have been widely used for signal processing tasks. Neural networks, especially deep ones, are good at learning complex patterns directly from raw signal data, and they perform better than traditional methods in signal classification [4], [5]. These models can automatically find important features without needing manual feature engineering, making them effective in dynamic wireless settings. Even with these benefits, traditional deep learning models often fail to capture the time-based connections and patterns found in time-series signals. To address this, structured signal transformation techniques like Hankelization have been introduced. By turning time-domain signals into Hankel matrices, this method captures time-based relationships and underlying signal behavior, which improves feature representation for classification tasks [1], [2].In addition to the challenge of feature extraction, ISAC systems must work reliably in tough conditions such as low signal-to-noise ratios and multi-user interference. Recent studies have explored advanced signal processing and learning-based methods to improve robustness and adaptability in these situations [6], [7]. These methods aim to make models better at handling different communication environments. An important part of this work is the integration of learning frameworks that can optimize both sensing and communication tasks together. Modern research focuses on combining signal transformation techniques with deep neural networks to build end-to-end systems that can manage complex signal changes [3], [6]. These hybrid approaches use both domain knowledge and data-driven learning to achieve better performance. Evaluating the performance of these models is important to test their effectiveness. Common metrics used include accuracy, precision, recall, and confusion matrix analysis. Recent studies show that using structured representations like Hankel matrices greatly improves classification accuracy and robustness compared to traditional approaches [1], [7].The availability of high-quality datasets and strong computational tools like MATLAB has helped speed up research in this area. Simulation environments allow for efficient data creation, preprocessing, model training, and validation, speeding up development and testing of new algorithms [6], [8].Despite progress, challenges still exist. Differences in signal characteristics, changing environmental conditions, and hardware limitations can affect model performance. Also, ensuring that deep learning models scale well and work in real-time for practical ISAC systems is still an open research question [3], [9].Current research trends focus on creating unified frameworks that combine signal transformation, feature extraction, and classification into one process. These methods aim to improve efficiency and accuracy while keeping models robust under tough conditions [1], [10]. These advancements are crucial for enabling reliable and smart wireless communication systems. Overall, using Hankelization-based feature extraction with deep learning offers a promising way to improve signal classification in ISAC systems. By effectively capturing time-based structures and boosting model learning, this approach helps in the development of next-generation intelligent communication technologies.

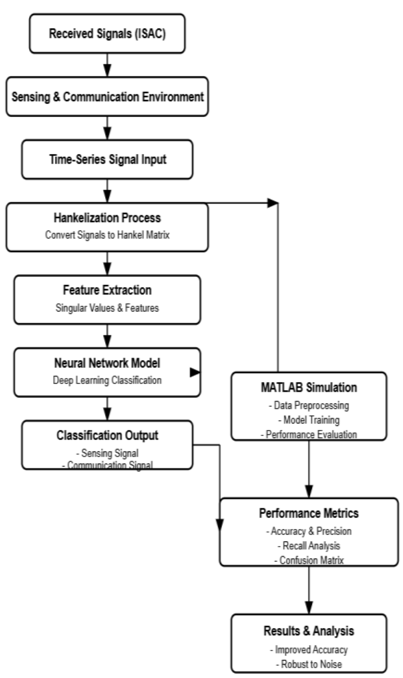

Fig-1: Block Diagram

2. METHODOLOGIES

The fig.1 shows the full process of the proposed signal classification system that uses a neural network along with Hankelization for Integrated Sensing and Communication (ISAC). The system starts by receiving signals from a place where sensing and communication happen together. These signals can come from radar systems, wireless devices, or mixed ISAC transmitters. Since sensing and communication use the same spectrum, it's hard to tell them apart. This architecture is built to process these signals well and accurately. It mixes signal processing and machine learning to make classification better. Each part of the diagram shows a specific step in the processing chain. The organized flow allows the system to manage complex and noisy signal environments. The first big step is time-series signal input. The received ISAC signals are treated as time-domain signals that have useful information and noise. These signals are collected and ready for more processing. Preprocessing includes things like normalizing and filtering to remove unwanted noise. MATLAB is used to handle getting and preparing the signals efficiently. This step makes the input data clean and ready for transformation. The quality of the input signals directly affects the performance of the classification model. So, careful preprocessing is important. This stage is the base for the whole system. The next step is the Hankelization process, which is a key part of the system. In this step, the time-series signal turns into a structured Hankel matrix. This transformation captures the time-based patterns and hidden features in the signal. By arranging overlapping parts of the signal into a matrix, the system gets a more detailed view of the signal's features. This structured view helps distinguish between sensing and communication signals. Unlike traditional methods, Hankelization doesn't need manual feature extraction. MATLAB's matrix operations are used to do this transformation efficiently. This stage improves the feature representation a lot. After Hankelization, feature extraction is done using Singular Value Decomposition (SVD).The Hankel matrix is broken down into singular values, which show the major parts of the signal. These values become feature vectors for the classification model. This step reduces the data size while keeping important information. It also helps remove noise by focusing on the main signal parts. The extracted features are normalized before going to the neural network. This ensures consistency and better model performance. The feature extraction stage is key to improving classification accuracy.The neural network model is the main part of the classification system. It takes the extracted features as input and goes through several layers to learn complex patterns. The model is trained with labeled data to tell sensing and communication signals apart. MATLAB's Neural Network Toolbox is used to build and train the model. The output is a classification result, usually in a one-hot encoded vector. The model can adapt to different signal conditions and environments. Its ability to learn nonlinear patterns enhances classification performance. This stage ensures accurate and reliable signal identification. The last part of the architecture is performance evaluation and result analysis. The system's performance is measured with metrics like accuracy, precision, recall, and confusion matrix. MATLAB has tools to calculate and show these metrics. The results show improved classification accuracy and better resistance to noise. The system works well under different Signal-to-Noise Ratio (SNR) conditions and in changing environments. This stage confirms the effectiveness of the proposed approach. It also gives insights for further improvement and optimization. Overall, the architecture provides a complete solution for efficient signal classification in ISAC systems.

2.1 Time-Series Signal Input Module

The Time-Series Signal Input Module is the first part of the system that takes in and prepares signals received in Integrated Sensing and Communication (ISAC) environments. These signals can include both sensing and communication data collected under different channel conditions. The module makes sure the raw signals are properly arranged and adjusted before they go through more processing. Since real-world signals often have noise, interference, and distortions, this step is important for keeping the data consistent. By organizing the input into a structured time-series format, the system sets up a solid base for the next steps. This helps make the signal classification process more reliable and effective.

2.2 Hankelization-Based Signal Transformation

The Hankelization-Based Signal Transformation Module is an important part of the system that helps turn raw time-series signals into a more organized format, making it easier to extract features and classify signals. In ISAC systems, signals often have complicated patterns over time that are hard to detect with regular methods. This module solves that problem by changing the input signal into a Hankel matrix. The process works by breaking the time-series signal into overlapping parts, creating a structured matrix where each row is a slightly shifted version of the original. This Hankel structure helps the system better understand the time-based connections and how the signal behaves. By keeping the order of the data, the model can get a better grasp of how the signal changes, which is key for accurate classification. This module also improves how well the system can represent the signal by making visible important patterns like repeating cycles, trends, and connections that might not be obvious in the original data. Because of this, the system can tell apart different types of signals more clearly, even when there is noise or interference. The organized output from this step is useful for the next part of feature extractin.

2.3 Feature Extraction

The Feature Extraction Module is important for finding the key features from the transformed Hankel matrix. Once the signal is organized into a structured format, this module identifies useful features like singular values and other statistical measures. These features help in distinguishing between different types of signals by capturing the essential details. By concentrating on the most relevant features, this module lowers the amount of data while keeping the important information. This makes the process more efficient and helps the neural network learn better. The features extracted offer a clear and detailed understanding of the signal, which improves the model's ability to classify signals accurately, even in tough situations.

2.3Neural Network Classification Module

The Neural Network Classification Module is the main part of the system that makes decisions. It uses the features that were extracted to sort signals into different groups. This part of the system uses deep learning methods to understand complex patterns and connections in the data. The neural network learns from datasets that have labels, so it can tell the difference between signals that are used for sensing and those used for communication.The model can adjust to changes in signal features and handles noise and interference well. Using deep learning helps this module achieve high accuracy and strong performance. The result from this step gives the final prediction, which is important for making smart decisions in ISAC systems.

2.4MATLAB Simulation

The MATLAB Simulation Module is used to build and check the proposed system in a controlled setting. MATLAB has strong tools for handling signals, showing data visually, and training models, which makes it a good choice for creating and testing the system. This part of the work includes tasks like preparing data, training the model, and checking if it works well.Simulating the system lets researchers try it out with different types of signals and situations without needing to use real-world equipment. It also helps in adjusting the model's settings and making

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the system perform better. Using MATLAB makes the whole development process faster and easier to adapt.

2.5Performance Evaluation

The Performance Evaluation Module checks how well the proposed system works by using standard ways to measure its performance. These include accuracy, precision, recall, and looking at a confusion matrix. These methods show how good the model is at recognizing different kinds of signals.This part of the process helps find out what the model does well and where it needs improvement.

By looking at the results, researchers can make sure the system meets the needed standards and is ready to be used in real situations.

RESULT & DISCUSSION

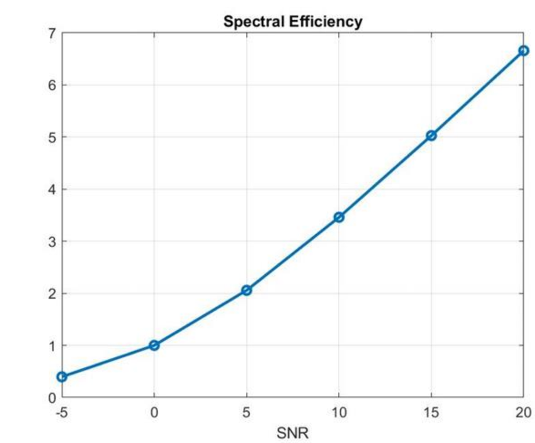

Fig.-2: Spectral Efficiency Vs SNR

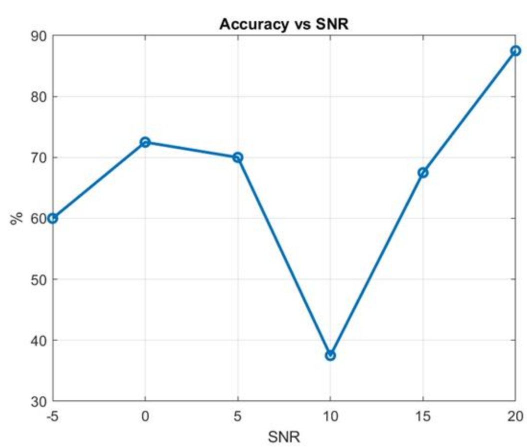

Fig-3: Accuracy Vs SNR

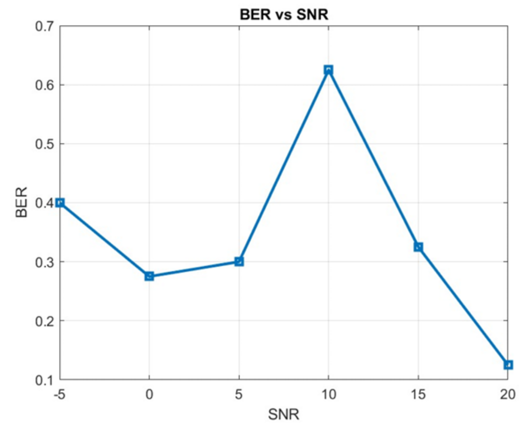

Fig-4: BER Vs SNR

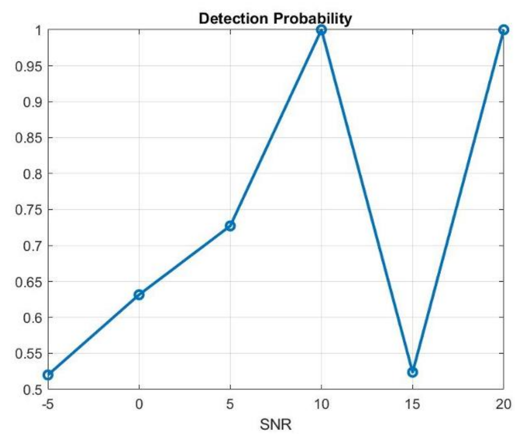

Fig-5: Detection Probability Vs SNR

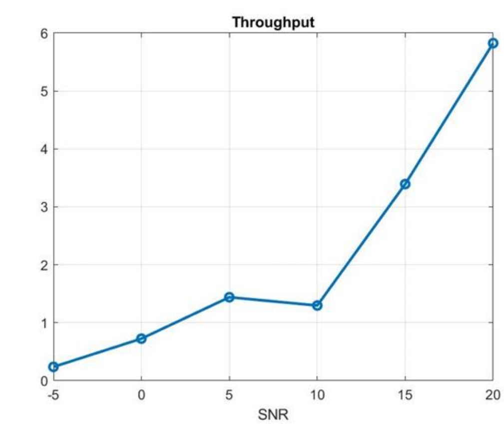

Fig-6: Throughput vs SNR

The experimental results show that the Hankelization-based deep learning model works well for signal classification in Integrated Sensing and Communication (ISAC) systems.Fig.2 (Spectral Efficiency vs SNR) shows that spectral efficiency goes up as the Signal-to-Noise Ratio

(SNR) increases.When the SNR is low, efficiency is low because of a lot of noise. But as the SNR gets better, the system uses the bandwidth more efficiently, reaching its highest efficiency at higher SNR levels. This shows the model helps improve communication performance when the channel conditions are good. Fig. 3 (Accuracy vs SNR) shows that classification accuracy improves as SNR increases. There is a small drop in accuracy at mid-level SNR (around 10 dB), but the model quickly bounces back and reaches maximum accuracy at higher SNR values. This means the model is strong and can deal with changes in noise in real-life situations. Fig.4 (BER vs SNR) shows how the Bit Error Rate changes with SNR.As SNR increases, the BER drops a lot, which is good for communication systems. At low SNR, the error rate is high because of noise, but as SNR increases, the BER becomes very low, showing that signals are transmitted reliably and accurately. Fig.5 (Detection Probability vs SNR) shows the sensing ability of the proposed ISAC system. As SNR goes up, the detection probability also increases and reaches a peak at higher SNR levels. This means the system can detect signals well under better conditions. There are some small ups and downs, but the overall trend shows strong sensing performance. Fig. 6 (Throughput vs SNR) shows that throughput increases a lot as SNR improves. At low SNR, throughput is limited because the signal is not strong. But as SNR rises, the system sends data faster, achieving maximum throughput at high SNR levels. This shows the system uses communication resources efficiently. Overall, the results show that the proposed system improves both sensing and communication performance. By combining Hankelization with deep learning, the system can better represent features, resulting in higher classification accuracy, fewer errors, and stronger resistance to noise. These findings prove that the approach is suitable for advanced ISAC applications.

CONCLUSION

This work introduces a new neural network framework that uses Hankelization for signal classification in ISAC systems. It changes time-based signals into structured Hankel matrices and uses SVD to extract important features. This helps the model better understand time-based patterns and remove noise. Using deep learning makes the model more accurate, even when conditions are tough like low signal quality or interference. Tests done in MATLAB show that this method is more accurate, dependable, and strong compared to traditional approaches. The system also works well with less training data, making it more flexible. Overall, this framework offers a good solution for future wireless communication systems and can be used in real-time setups and more complex designs in future research.

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