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Deep Neural Network Enhanced Compressive Sensing and Kalman Filtering for 5G Channel Estimation

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Abstract: Massive MIMO systems operating at mmWave frequencies (mmWave) constitute one of the applications of 5G communication, which provides high data rate and spectral efficiency. Nevertheless, the channel estimation and tracking is still a problem because of high channel variations and sparse propagation. In this paper, I am going to suggest a joint architecture that would combine Compressive Sensing (CS), Long Short-Term Memory (LSTM) and Kalman Filtering (KF) to effectively estimate channels. CS is employed in order to recover sparsely-spread channel information with a reduced number of pilot signals. The LSTM corrects the errors and removes noise in the estimated channel. KF monitors the change in channel across the time, and maintains the accuracy. The given approach is more precise in estimations, decreases the rate of errors, and has a higher spectral efficiency than the traditional approaches.

Keywords: 5G Communication, mmWave Massive MIMO, Compressive Sensing, Deep Neural Network, Kalman Filter, Channel Estimation

I. INTRODUCTION

Due to the rapid evolution of the technology used in the field of wireless communication, the demand for high data rates, low latency, and high reliability is growing. Due to this, the development of the next generation of communication technology, referred to as the fifth generation (5G), is being pursued. It is designed to support the deployment of different applications such as infrastructure related to the smart city concept, vehicles related to the Internet of Things, and the Internet of Things. One of the enabling technologies being pursued for the development of the 5G communication technology is the deployment of the millimeter wave communication technology with Massive Multiple Input Multiple Output. Massive MIMO technology involves the deployment of many antennas to achieve high spectral efficiency with the aim of supporting high data transmission rates. It is evident that the performance of the Massive MIMO technology depends on the channel estimation. It is important to note that channel estimation is still a challenging task, especially considering the unique characteristics of the millimeter wave channel. In the context of the Massive MIMO technology, the channel is sparse, which means that only a few paths contribute to the transmission of the signal.

Moreover, the channel is time-varying. These factors affect the channel estimation. It is evident that the deployment of the Least Squares (LS) and Minimum Mean Square Error (MMSE) channel estimation techniques is not effective. In order to resolve these problems, many techniques of advanced signal processing and machine learning have been considered. One such technique is Compressive Sensing (CS), which has been found to be efficient in utilizing sparsity in the channel. With the help of this technique, channel estimation can be performed even with fewer samples. However, this technique has not been found efficient in handling noisy and changing channels. Hence, in order to improve the accuracy of channel estimation, another technique of machine learning, namely Long Short-Term Memory (LSTM), has been considered.

This technique of machine learning has been found to be efficient in handling time-varying systems. The ability of this technique to learn and memorize over a period of time improves the accuracy of channel estimation. In addition to this, another technique, namely Kalman Filter (KF), has also been considered to improve the accuracy of channel estimation. This technique has been found to be efficient in handling changing channels in real time. The combined technique of CS, LSTM, and KF has been found to be highly efficient in improving the accuracy of channel estimation and reducing error rates. Hence, this technique can be considered highly efficient and can be used in modern 5G communication systems.

II. PROBLEM STATEMENT

The main challenge in the accurate channel estimation and tracking in the context of the massive MIMO technology using the mmWave frequency band is related to the characteristics of the channel. It is sparse because fewer paths

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contribute to the transmission of the signal. Moreover, the channel is time-varying because of the movement of the users and the environment, as well as the blockages caused by the signal. These factors pose challenges in the accurate channel state information. The Least Squares (LS) method and the Minimum Mean Square Error (MMSE) method are not effective in this context because these methods require the transmission of a large number of pilot signals. Compressive Sensing (CS) is more effective in the context of channel estimation. It takes into account the sparse nature of the channel. Nevertheless, this method is highly affected by noise. Moreover, it is not effective in the context of time-varying channels. The Kalman Filtering (KF) method is more effective in channel estimation. Nevertheless, this method requires accurate channel models. Moreover, the basic deep learning techniques such as the neural networks cannot be considered effective in the context of channel estimation.

III. RELATED WORK

The channel estimation techniques in the context of the mmWave massive MIMO system have been studied. Various channel estimation techniques have been proposed in order to mitigate the challenges associated with the massive MIMO system. The challenges associated with the massive MIMO system occur because of the high dimensionality of the channel in the context of the massive MIMO system. The traditional channel estimation techniques such as LS and MMSE are some of the first channel estimation techniques proposed to be used in the context of the massive MIMO system. The traditional channel estimation techniques are based on linear channel estimation techniques. The traditional channel estimation techniques are simple in nature. However, these techniques require a high number of pilot signals to be transmitted in the context of the massive MIMO system. Moreover, these techniques are not effective in the context of sparse channel estimation techniques. Moreover, these techniques have a low level of accuracy in the context of traditional channel estimation techniques. In order to avoid the disadvantages associated with traditional channel estimation techniques, various sparse channel estimation techniques such as Compressive Sensing (CS) have been proposed in recent times in the context of massive MIMO system technology. The CS channel estimation technique is based on sparse channel estimation techniques in the context of massive MIMO system technology. The channel is sparse in nature in the context of massive MIMO system technology. Moreover, these techniques can estimate the channels by transmitting a low number of pilot signals in the context of massive MIMO system technology. However, these techniques are highly vulnerable to noise in the context of massive MIMO system technology. Moreover, these techniques are associated with several disadvantages such as grid mismatch.

With the introduction of artificial intelligence technology, the techniques of learning-based methods have acquired more importance in the past few years. Neural networks were used in modeling complex channels, where accurate results were obtained in channel estimation problems. However, the neural networks were not efficient in handling time-varying data, as the neural networks were not capable of learning time-varying patterns in the data. In order to obtain accurate results in time-varying channels, a new class of neural networks based on LSTM was introduced in the past few years. This type of neural network was highly efficient in handling time-varying data, as the neural networks were capable of learning the sequential patterns in the data.

IV. LITERATURE REVIEW

In recent times, the research in the field of mmWave massive MIMO channel estimation techniques has focused on improving their accuracy and computational efficiency. Moreover, there are studies that have focused on improving these techniques by incorporating signal processing techniques along with machine learning techniques to overcome the disadvantages of the above techniques. For instance, deep learning techniques are proposed to enhance the existing channel estimation techniques.

The techniques show promising results in terms of their performance in comparison with the performance of the Least Squares method. For instance, techniques such as using Extended Kalman Filters with learning-based techniques are proposed to enhance the performance of channel estimation techniques in the context of MIMO OFDM systems. Another significant work in this regard is the use of Compressive Sensing techniques with advanced antenna technologies such as Lens Array technology. Moreover, Adaptive Compressive Sensing techniques are proposed to overcome the disadvantages of the above techniques. The techniques enhance the accuracy of channel estimation techniques by avoiding grid mismatch effects. Furthermore, techniques such as Compressive Sensing with Kalman Filter techniques are proposed to enhance the performance of channel estimation techniques.

Even though the techniques show promising results in terms of their performance in comparison with other techniques, there are still disadvantages in the context of using these techniques in a dynamic environment. In recent times, LSTM techniques are proposed to enhance the performance of channel estimation techniques. The techniques show promising

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results in terms of their performance in comparison with other techniques in the context of channel estimation techniques. Moreover, these techniques are effectively used to enhance the performance of Compressive Sensing techniques with Kalman Filter techniques.

These recent advances have also attempted to investigate the integration of the proposed model of recurrent learning with signal processing techniques in order to further improve the performance of channel estimation. For example, the hybrid model of using the Long Short-Term Memory (LSTM) networks in combination with the application of the filtering techniques has been investigated. It has been observed that the application of these techniques has resulted in the impressive performance of channel estimation. It is because these techniques can effectively address the time-varying nature of the channel as well as the noise. Furthermore, the recent advances in channel estimation using machine learning techniques have attempted to investigate the application of the data-driven techniques in order to reduce the overhead associated with the pilot in channel estimation.

V. SYSTEM MODEL

The system model used in this work is based on a mmWave massive MIMO communication system model, which includes a transmitter, a wireless propagation channel, and a receiver. In the transmitter part, a hybrid precoding method is used for efficient transmission of pilot signals. This method combines analog and digital precoding, which makes the system efficient in terms of its performance and complexity. The transmitted signals are sent through a wireless propagation channel, which is characterized as a sparse channel and time-varying. The mmWave propagation channel has a number of dominant propagation paths, and these paths are time-varying due to the movement of users. Estimating this type of channel is a complex task. In the receiver part, a hybrid combining method is used to improve system performance.

The method used in this work for channel estimation is a complex process, which involves a number of steps. In the first step, a Compressive Sensing method is used for efficient estimation of channel information. The second step is to improve this information using an LSTM method, which helps in learning the pattern in the channel information and eliminates noise and errors in the estimation of the channel. The use of Compressive Sensing, LSTM, and Kalman Filter in the system model used in this work makes this system efficient in terms of its performance in mmWave massive MIMO systems.

VI. FLOW CHART OF THE SYSTEM

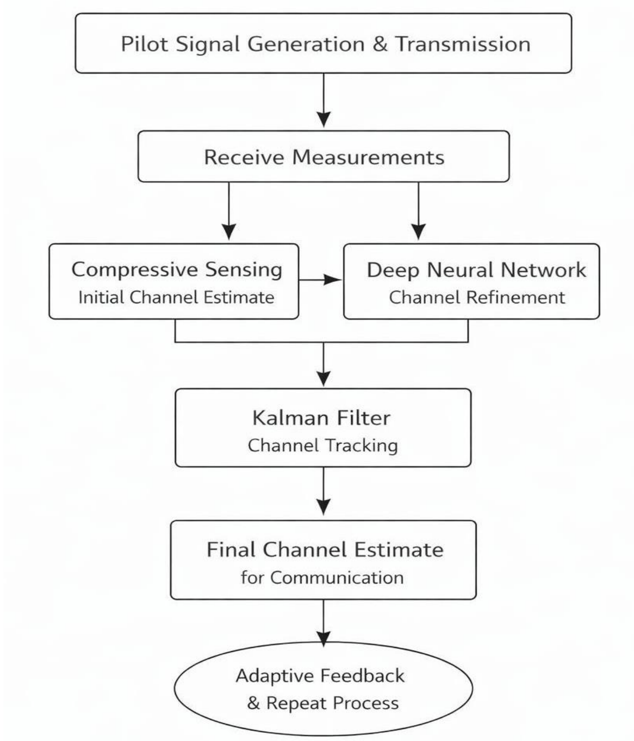

Fig 1 Flow chart of the system

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The algorithm of the CS -DNN -KF based system outlines the step-wise process of channel estimation and tracking to provide efficient and correct communication in mmWave massive MIMO systems. This algorithm is a blend of Compressive Sensing, Deep Neural Network, and Kalman Filters functionalities into a single workflow that can be used continuously during the process of communication. The communication starts at the transmitter where pilot signals are created and ready to be sent. These pilot signals are common predefined sequences, which are utilized in particular channel estimation. The signals are then precoded digitally and then analog beamformed before transmission which concentrates the energy to certain space directions. Such a step is necessary in mmWave systems to obtain high path loss and become an efficient signal propagation. After transmission, the signals are transmitted in the wireless channel that makes them suffer through different effects like attenuation, phase shift, and multipath propagation. The analog combiners and digital processing units captures the incoming signals in multi-antennas and processes them at the receiver. The receiver measures the values of the pilot signals sent by the transmitter that is the input to the channel estimation process. The former phase of estimation consists of using Compressive Sensing on the measurements received. The algorithm is used to reconstruct a sparse version of the channel by addressing an underdetermined system of equations. This operation gives a rough idea on the channel which has less pilot overhead. This estimate can be noisy and inaccurate even though it is efficient because of the limitations of measurements and the environment.

In order to enhance the quality of the estimate, the Deep Neural Network receives the output of the CS stage. The DNN takes the input and works on it with several layers and then applies learnt transformations to enhance the channel estimate. This step is useful in minimizing noise, reconstruction errors and improving the accuracy of the estimation. The refined output is much nearer to the actual channel conditions than the original CS estimate was. The fined down estimate is then transferred to the Kalman Filter which does channel tracking. The KF is a recursive algorithm, which initiates with an estimate of the current channel state using previous ones. It then corrects this forecast using new observation of the DNN output. The iterative process provides the channel estimate to be accurate with time, even when the variations are fast-varying. The channel estimate that is ultimately received by the Kalman Filter is channeled towards communication i.e. signal reception, channel decoding, and feedback to the transmitter. This estimate is important in enhancing the performance of this system in terms of data rate, reliability, and minimization of errors. The cycle is done repeatedly to enable the system to easily adjust to the changing channel conditions in real-time. On the whole, the algorithm guarantees effective system resources use, reduction in estimation errors, and strong performance in dynamic settings. It is practical because of its step-by-step framework that can easily be implemented in the 5G systems and beyond where the channel estimation should be precise and real-time to ensure high-quality communication.

VII. CHANNEL ESTIMATION METHODS

One of the major areas in reliable performance is channel estimation in mmWave massive MIMO technology. Various techniques have been introduced in channel estimation techniques. All these techniques have their own advantages and disadvantages. Least Squares estimation and Minimum Mean Square Error estimation are some of the techniques used in channel estimation techniques. These techniques are simple and can be easily implemented. However, these techniques require a large number of pilot signals. These techniques cannot be used in a dynamic environment. Compressive Sensing has been introduced in channel estimation techniques.

It has been observed that Compressive Sensing performs better than all other techniques in channel estimation techniques. Compressive Sensing is used based on the sparse nature of the mmWave channel. Thus, the efficiency of the channel can be improved by considering these dominant paths. However, the performance of Compressive Sensing is affected by noise as well. For reliable performance in channel estimation techniques, learning-based techniques are used. LSTM is also being used for the application of the learning-based methods for channel estimation. It is also seen that LSTM is able to learn the temporal dependencies for channel data.

Hence, the future state of the channel is better predicted by the use of LSTM for channel estimation. Therefore, this method is better suited for a dynamic environment. In a dynamic environment, the state of the channel is changing very fast. Kalman Filtering is another method that is being used for channel estimation. Kalman Filtering is also able to refine the state of the channel continuously. KF is better suited for a real-time environment. The above methods are also being combined for channel estimation. The combination of the methods is referred to as a hybrid method. Compressive Sensing is also being used for channel estimation. LSTM is being used for enhancing the accuracy of channel estimation. Kalman Filtering is being used for refining the accuracy of channel estimation. Hence, the performance of channel estimation is being enhanced for better accuracy, efficiency, and adaptability.

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VIII. RESULTS

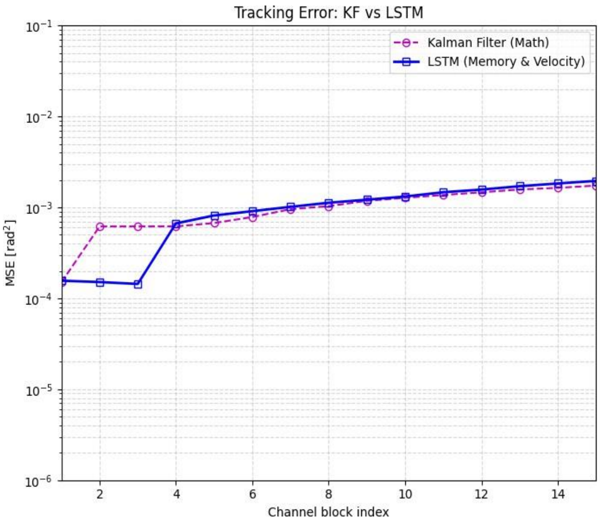

Fig 2 Channel Block Index Vs MSE

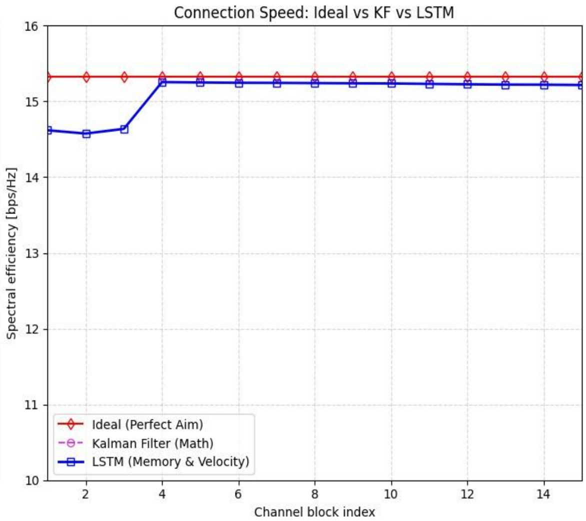

Fig 3 Channel Block Index Vs Spectral efficiency

The above left graph shows how Mean Square Error (MSE) is varying with channel block index, which represents how the error in channel estimation is varying over time. It can be noted from the above graph that in the initial stages, LSTM model is having a lower error rate compared to Kalman Filter (KF), which shows that LSTM model is effectively able to learn the channel in a short time using its capabilities. As channel block index increases, both KF and LSTM are having a steady increase in their respective error rates. This is due to the reason that a wireless system's channel is more dynamic in nature as time progresses, making it difficult to track the system's movement. It can also be noted from the above results of KF and LSTM that their results are very close to each other. From the above graph, it can be noted that LSTM is performing a little better in the initial stages, while both KF and LSTM are having comparable results in terms of tracking performance as time progresses, which shows that LSTM can replace traditional filtering techniques in a wireless system.

If the channel were at its highest theoretical capacity (spectral efficiency), the channel would have the exact same performance during each of its blocks (i.e. each block would have the same maximum performance). The Kalman Filter provides performance close to that of the ideal channel and therefore tracks variation in performance correctly, but provides less accurately than for ideal channel. At the begin of the analytic modeling, LSTM's performance was les than those of both the Ideal and Kalman Filter. In this modeling process the LSTM has yet to learn about the channel's behaviour and thus its performance was far from either of the other two. After a number of blocks, however, LSTM will have learned nearly enough such that its performance will be i.e. compared to the Ideal and Kalman Filter models.

IX. FUTURE SCOPE

The proposed hybrid framework based on Compressive Sensing, LSTM, and Kalman Filtering can be regarded as a promising framework to achieve the channel estimation with higher efficiency in the context of the proposed mmWave massive MIMO system. However, there are many possibilities to enhance the proposed framework and carry out further research in this context. For instance, more efficient frameworks based on LSTM, such as Bidirectional LSTM and Attention-based LSTM, can be proposed to enhance the learning capability to achieve complex temporal behaviours in the context of the proposed channel estimation framework. This can be carried out to enhance higher robustness in the context of sudden changes in the proposed channel. The other possibility to enhance the proposed framework can be regarded as optimizing the computational complexity associated with the proposed framework. For instance, the proposed framework based on LSTM can be regarded as a framework to enhance higher accuracy in achieving the channel estimation in the context of the proposed system. However, this framework can result in higher computational complexity to carry out the training and implementation of the proposed framework in a proper manner. Therefore, further research can be carried out in this context to propose more efficient frameworks based on LSTM and utilize techniques such as model compression, model pruning, and model quantization to carry out the same. The framework that has been proposed can also be integrated with other available technologies, such as 6G communication technology, intelligent reflecting surfaces, and edge computing technology. In these types of technology, the estimation of channels can also be considered another major problem, which should be addressed in a proper manner. In this context, the framework that has been

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proposed can be considered a more efficient framework. The use of online learning techniques by means of adaptive systems using LSTM can also be considered another major possibility in the context of developing the proposed system. The parameters of the proposed system can be updated in a more efficient manner by considering the new information related to the channels.

X. CONCLUSION

From the analysis of the tracking error and spectral efficiencies graphs, it is clear that a better understanding of the performance of different channel estimation methods in a time-variable mmWave massive MIMO channel is possible. The Kalman filter is clear in its tracking performance over the channel blocks due to its strong mathematics foundation and is thus able to track the channel variability with the inclusion of a controlled level of error (i.e., a reliable channel estimation is possible in a channel environment with a well-defined physical channel model).

However, different performance behaviors are seen for the Long-Short Term Memory (LSTM) compared to the Kalman filter because the LSTM is also an efficient channel estimation method and shows lower spectral efficiencies for small time intervals compared to the Kalman filter. Additionally, only small changes in tracking errors are seen for the LSTM for the initial few instances of receiving data regarding the channel. This is due to the nature of the LSTM that continues to teach itself regarding the channel characteristics by utilizing the channel data it is receiving and continues to improve its performance as a function of the channel data it is receiving.

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