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Hybrid CNN-LSTM Model for CSI Compression and Reconstruction in Dynamic Wireless Channels

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Abstract:

CSI is representing the channel states information of the new module. It has been shown that CSI feedback stress increases as the numbers of antennas, and this stress is clearly and demonstrably proportional. This research addresses the problem of CSI reconstruction using (CNN) and (LSTM). The underlying architecture of the efficient network (referred to the symbols of convolutional neutral network). This theoretical proposed methods utilizes a network with the single stages instead of multiple -stage network, employing a number of training parameters. The computer and simulation results showed a reduction in the burden of feedback on canal status information with clear effectiveness, and with outstanding and better performance in terms of multiple aspects such as accuracy, compression and recovery of canal status information compared to other available methods in the fields under current and past studies.

Keyword: Hybrid CNN-LSTM Model, CSI Compression , Reconstruction, Dynamic Wireless Channels.

1 Introduction:

Network (LSTM) is used to compress and reconstruct channel state information in dynamic wireless channels. This hybrid model, combining CNN and LSTM, offers an advanced solution for reducing the size of feedback data in wireless communication networks. The CNN extracts the spatial characteristics of the channel, while the LSTM simulates temporal

changes in dynamic channels, ensuring highly accurate reconstruction of channel state information's denoted by (CSI).

Model operates according to the following sequential software steps:

1. Compression of the convolutional neural network (encoder). The encoder on the operating device (UE) converts the high-dimensional CSI information matrix into a compressed, low-dimensional "code." The convolutional network exploits spatial correlation and frequency characteristics to significantly reduce data size and transmit it over the feed channel.

2. A data retrieval process using LSTM (time) at the base station. The model processes the compressed data using LSTM layers. This network analyzes and infers the time correlation of channel information across time frames in predefined dynamic channels.

3. Reconstruction then occurs by passing the LSTM outputs to the decoded layers within the base network, thus reconstructing the original channel state with high accuracy and minimal information loss.

The methods directly explain how the efficiently utilize and performs reverse transformation. This reverse transformation is non-recurrent and significantly faster than iterative algorithms. Method does not calculate account for variation of the time spent of channel when reconstructing channels state information (CSI). Researchers have expanded upon this by using multiple parallel networks, which has led to more accurate correction and reconstruction of low-compression channel state information.

Vectors applicaton model:

The model using the following relation :

$$yn, t = h\mathrm{T}_{n,}\, tvn, txn, t + zn, t, \qquad (1)$$

where hn, t ∈ ℂN × 1 and the frequency ranges ; $xn, t \in \mathbb{C}$, $zn, t \in \mathbb{C}$, $and\, \nu n, t \in \mathbb{C}$

At any time, t, the matrix represent as :

$$\mathbf{Ht = [[h1, t, ..., h_{Nc}, t]^{T} \in \mathbb{C}^{N}c \times N,} \qquad \mathbf{(2)}$$

The using of mathematical expression of the theory of Fourier transform, then expression can be defined:

$H_t' = F_d H_t F_a,$ (3)

The CSI method with the reconstruction refer to Figure (1). Three modules appear CNN, so LSTM and the attentions. LSTM network and its several units represent by figure (2).

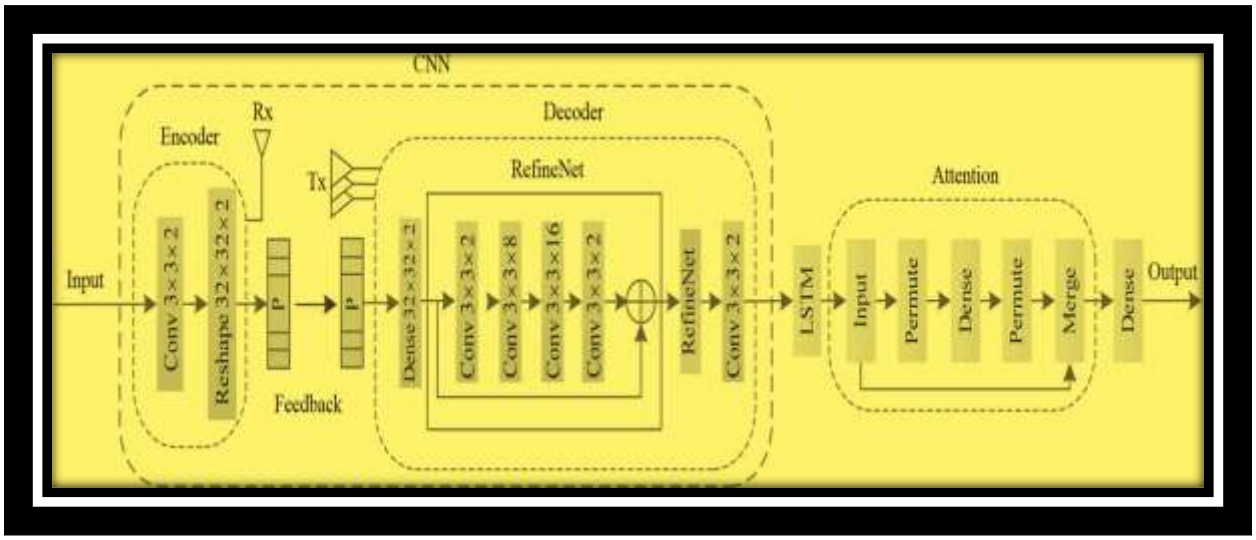


Figure (1): REPRESENTAION OF CNN-LSTM-A

The coherence of the time calculated as:

$$\Delta t = C/2v\ f_0 \qquad (4)$$

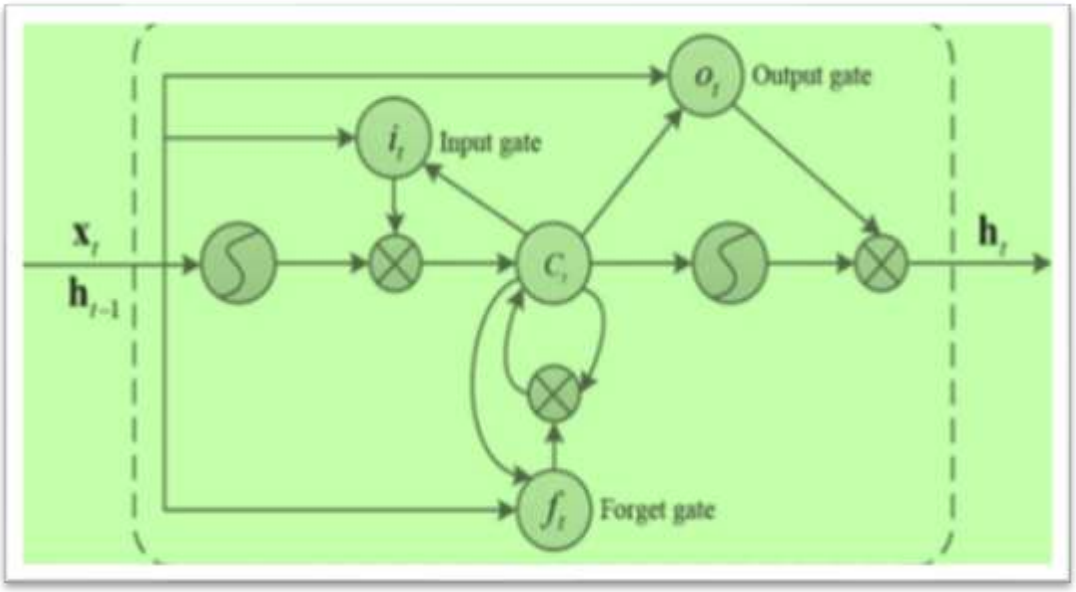
The mathematical description of the LSTM can be expressed:

$$\begin{aligned} it &= \sigma(Wixxt + Wihht-1 + Wicct-1 + bi), \\ ft &= \sigma(Wf\,xxt + Wf\,hht-1 + Wf\,cct-1 + bf), \\ ct &= ft \odot ct-1 + it \odot \phi(Wcxxt + Wchh-1 + bc), \\ ot &= \sigma(Woxxt + Wohht-1 + Wocct + bo), \end{aligned} \qquad (5)$$

$$ht = ot \odot \phi(ct),$$

The newest LSTM unit can be written :

$$ht = \text{LSTM}(ht - 1, xt, \theta), \quad (6)$$



Figure(2): Framework of LSTM

The mechanism of the Attention:

The relation can be set as :

$$xi = \phi(W^T s_i + b), \quad (7)$$

The normalization softmax function of each score vector.

The expression of the function is:

$a_i = \text{softmax}(x_i) = \exp(x_i) / \Sigma i \exp(x_i)$. (8)

The product of the eigenvector and its normalized fraction is the final output of attenuations represent of symbole o:

$o = \Sigma_{i=1}^{n} a_i * s_i$. (9)

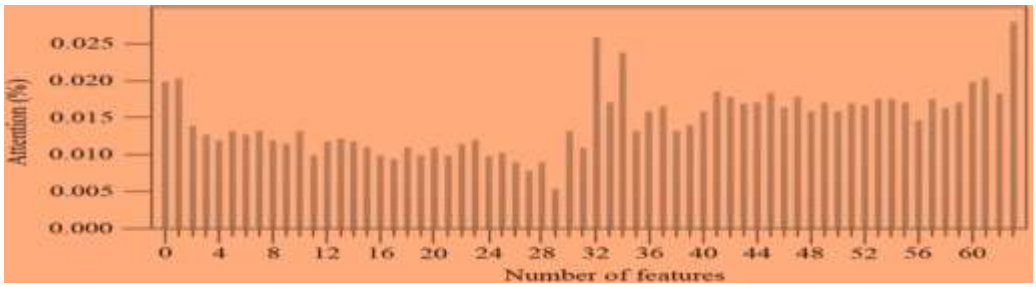


Fig. 3 The attention mechanism of the Weight assignment .

Table(1): Many parameters using .

Environment	Indoor	Outdoor
Scenarios	5.1 GHz	310 MHz
Subcarriers number	1064	1064
Antennas number of	32	32
Ratio compression	1/4, 1/16, 1/32, 1/64	1/4, 1/16, 1/32, 1/64

Training real process :

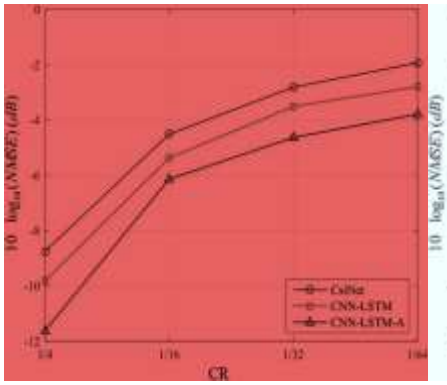
ADAM can represent and utilized:

The final results with respect to the losing functions for the end to end is represents as below:

$$NMSE = E\left[1/L\Sigma_{l=1} \quad {}^{L}\| H_t'' - H_t'' \|_2 {}^2 / \| Ht'' \|^2 {}_2 \right] \quad (10)$$

Simulation results:

The simulation can be expressed as shown in figure 4 and 5



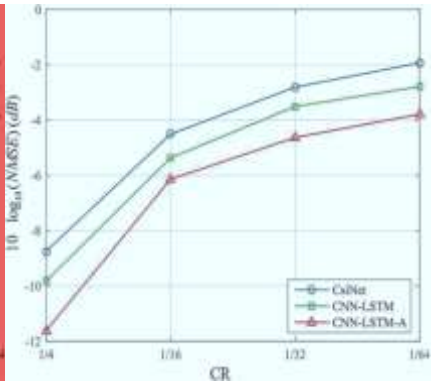
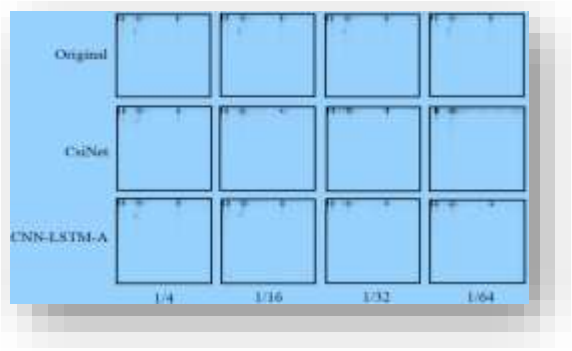


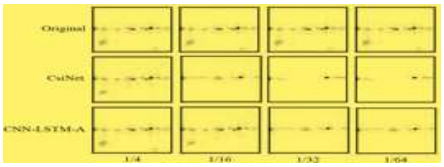
Figure (4): Different CRs in with NMSE indoor environment

Figure(5): NMSE with different CRs in outdoor environment

Figure(6) and also figure(7)explains several samples by four CRs with respect to the corresponded of situations of of H_t'' for the two states of this theoretical studies .



Figure(6): Reconstruction with different CRs in indoor environment



Figure(7): Reconstruction with different CRs in outdoor environment

The LSTM network can maintain this real-world correlation with the presence of an internal memory units.

Table (2) shows the many parameters in the various methods. Figure (8) shows the time associated with running the three hypothetical structures under investigation.

Table 2, and the inter-comparison of the cases under investigation compared to CsiNet-LSTM, clearly demonstrate the significant reduction in the data output of this network. This is due to replacing the parallel, multi-level LSTM with a single-stage long short-term memory and reducing the number of hidden long short-term memory units through the trial and noted errors.

Table (2): different methods of Parameter settings.

CR CsiNet [16]	CsiNet-LSTM	CNN-LSTM-A
1/16 530656	102009892	625472
1/32 268448	101354404	363264
1/64 137344	101026660	232160

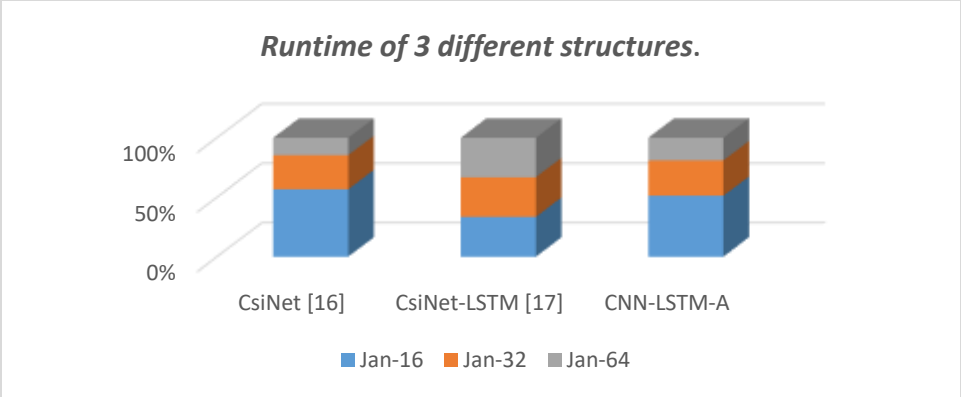


Figure (8): Runtime of three type structures .

Conclusions:

This study (referred to as CNN-LSTM-A), which incorporates a (CNN), a network (LSTM), and an attention with to mechanism, aims to address channel state (CSI) information reconstruction problems in various large systems. The study demonstrates that CNN-LSTM-A achieves a good balance and Compartions the performance, accuracy and complexity, significantly reducing the numbers of training and repeating the parameters by using a LSTM advanced a better determination. All the Simulations were achieves conducted to validate this special method, comparing it with the latest scientifically and practically available methods, particularly in future studies, to ensure clear performance and development, thus enabling its application.

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