An Iterative BP-CNN Architecture for Channel Decoding (Critical Review)

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Abstract

In this paper, I will discuss the system proposed by the authors for advances in error detection and code correction techniques along with the advantages and disadvantages of the proposed solution. Also, I'll discuss some update methods which can be helpful to make this system more robust.

1 Introduction

The paper discussed noise estimation and minimisation with collective measurements of Belief Propagation decoder(BP) and Convolutional Neural Network(CNN) which they collectively termed as BP-CNN. They have used CNN after BP decoder to estimate the noise associated with the system then it may be the noise occurring because of the system or it might be because of the environment. The noise is believed to follow a Gaussian distribution and some correlation. The correlation among the noise is considered as feature vector for noise estimation and further cancellation.

2 Summary

Belief propagation, also known as sum-product message passing, is a message-passing algorithm for performing inference on graphical models, such as Bayesian networks and Markov random fields. It calculates the marginal distribution for each unobserved node (or variable), conditional on any observed nodes (or variables). It mainly passes messages between neighboring nodes by joining the messages from all the neighbors except the receiving node. Where as in deep learning, a convolutional neural network (CNN, or ConvNet) is a class of deep neural networks, most commonly applied to analyzing visual imagery. CNN is used because of its strong capability to extract local features. As stated above, the correlation matrix is considered as feature for CNN. The weights initialisation at each stage is done by Xaviert Initialisation, this method helps to keep the variance same i.e. it keeps the signal exploding to high value or vanishing it to zero. The authors have focused their research on

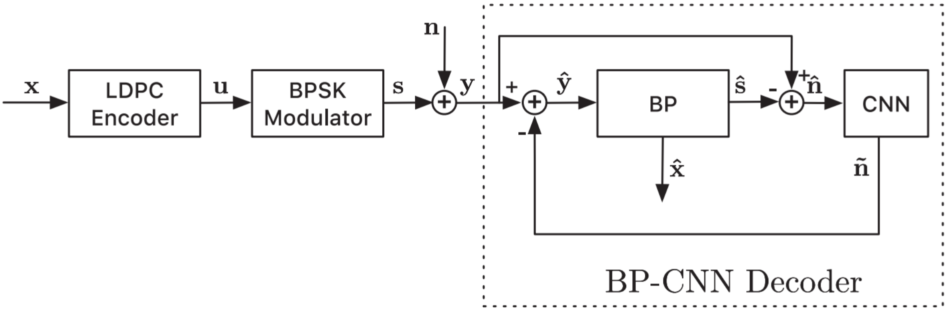

Figure 1: Block Diagram

finding out new loss function for accuracy in noise estimation and reducing Bit Error Rate for better results of Normality test, it basically checks to what rate the noise vector follows normal distribution. For optimisation, ADAM technique is used because of its high performance gains in terms of speed of training. The system gain gets improved as we increase the number of iterations.

Performance comparison of BP-CNN with standard BP decoding is done, and the results shows drastic improvement in the performance. Nearly same accuracy has been achieved with almost half number of iterations between BP and CNN. Results are shown in Figure 2.

Along with all these advantages, this system also has some limitations. The baseline CNN may not be optimal considering for AWGN channel and the residual noise may not necessarily follow a Gaussian distribution. Another drawback I came across was, for basic convolutional layers, pooling, dropout and fully connected layers being important components of ordinary CNN, authors have not considered or discussed the effect of those techniques in the proposed solution.

3 Update Method

Authors have considered only channel decoding phase and noise arriving till the decoding block for noise reduction, also, its not likely that the noise will always be correlated as the noise sources might get changed because of which the noise characteristics will also gets changed. So keeping these issues in mind, I have thought of the concept transfer learning.Transfer learning (TL) is a research problem in machine learning (ML) that focuses on storing knowledge gained while solving one problem and applying it to a different but related problem. It is mostly used when there is a shortage of the training dataset. Transfer learning is the fastest and easiest way to build a deep learning model by taking an available model off the shelf and adapting it to some other problem. It is done by chopping off the top layer of the already initialized model and replacing it with a randomly initialized one and then training the parameters of the top layer and keep all other fixed, especially for the models which have already trained on the data set. The top layer is the fully connected neural network and the rest layers are the feature extractors. Transfer learning is very helpful when there is a shortage of training data. The reference paper mentioned discusses an algorithm named DRCNet(Dense Residual Connection Network) along with some unconventional techniques of connection-finetuning(Transfer learning)i.e. Sparse Connection Dense Residual Connec-

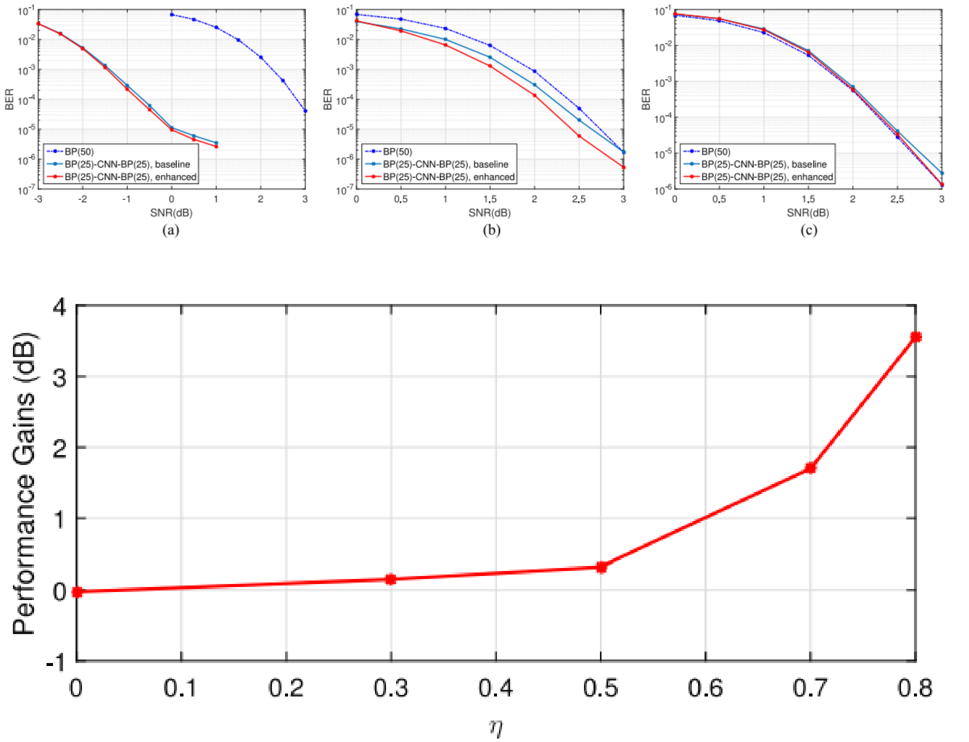

Figure 2: (a). 1(st) Figure shows Performance comparison of BP-CNN with the standard BP decoding. Only one iteration between CNN and BP decoder is executed. The numbers in the brackets denote the BP iterations. The SNRs corresponding to the Shannon capacities for eta = 0.8, 0.5, and 0 are 6.9 dB, 2.4 dB and 0.4 dB, respectively. (a) eta = 0.8, strong correlation. lambda = 0.1. (b) eta = 0.5, moderate correlation. lambda = 10. (c) eta= 0, no correlation. lambda = 10. (b). Performance gains of enhanced BP-CNN under different eta's. lambda = 10 for eta = 0, 0.3, 0.5 and lambda = 0.1 for eta = 0.7, 0.8.

tion Network(SC-DRCNet). [?] So, transfer learning can be used to train our model for removal of different types of noise coming from several sources. In ResNet the output of an intermediate-convolution layer is connected with immediately previous layer's output, it has skip connections as a baseline and in DenseNet, intermediate layers are connected densely to all the succeeding layers. In the provided solution SC-DRCNet, a connection fine tunning is done for DenseNet architecture to remove the redundant layer which does not have much importance to the output. The finetuning is done by providing the Connection Strength parameter to learn the importance of each connection.

4 Conclusion

Approach made for noise prediction and reduction is very much effective and robust as compared to the regular method and is very much appreciable as prediction of noise that too a random noise is extremely difficult task which this paper has somewhat able to achieve.

Also, the update method mentioned can be helpful if the suggested system is able to predict the noise accurately and can be reduced further from the actual signal.

References

[1] Pragya and Rohit. Dense residual connection finetuning. *IJCAI*, 2020.