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SNR Classification Using Multiple CNNs

Thinh Ngo, Paul Rad, Brian Kelley

Abstract—Noise estimation is essential in today wireless systems for power control, adaptive modulation, interference suppression and quality of service. Deep learning (DL) has already been applied in the physical layer for modulation and signal classifications. Unacceptably low accuracy of less than 50% is found to undermine traditional application of DL classification for SNR prediction. In this paper, we use divide-and-conquer algorithm and classifier fusion method to simplify SNR classification and therefore enhances DL learning and prediction. Specifically, multiple CNNs are used for classification rather than a single CNN. Each CNN performs a binary classification of a single SNR with two labels: less than, greater than or equal. Together, multiple CNNs are combined to effectively classify over a range of SNR values from $-20 \leq SNR \leq 32$ dB. We use pre-trained CNNs to predict SNR over a wide range of joint channel parameters including multiple Doppler shifts $(0, 60,$ 120 Hz), power-delay profiles, and signal-modulation types (QPSK,16QAM,64-QAM). The approach achieves individual SNR prediction accuracy of 92%, composite accuracy of 70% and prediction convergence one order of magnitude faster than that of traditional estimation.

Keywords—Classification, classifier fusion, CNN, Deep Learning, prediction, SNR.

I. Introduction

TODAY, SNR plays an increasingly important role in wireless systems. Both accuracy and readiness are demanded for the quality of services of 5G generation and beyond. Conventional SNR estimation techniques from the 4G era which are knowledge-driven and rely on expert models [2], [14], [10], [19] faces new challenging requirements. Alternatively, DL classifications are data-driven approaches and based on learning from the data relationship not on modeling from the governing theory. The success of DL classification in many areas including wireless communication (i.e. RF signal and modulation classifications) [3]-[9], [12], [13], [17], [18] calls for continuous expansion of its applications. Moreover, DL classification using off-line training can produce predictions for every input data frame; whereas, estimation techniques typically requires 50 to hundreds frames [16], [1]. DL prediction time is at least an order of magnitude shorter than estimation time. This readiness can make a big difference in short-message services (e.g. M2M) where SNR estimation overhead uses a significant portion of message transmission resources. However, traditional application of DL classifications to predict SNR does not yield satisfactory accuracy (i.e. below 50%). One of the potential reason is that the classifier is overwhelmed by features governed the input output relationship (i.e. number of features). There are techniques to improve DL classification such as increasing size of the training dataset, selecting a better DL model in terms of architectures, number of layers, filter sizes, etc. In this paper, we use multiple CNN classifiers in a divide-and-conquer manner to reduce prediction uncertainty and increase the learning effectiveness. From Machine Learning perspective, we make use of classifier fusion [11], [15] to improve classification performance. Specifically, we split the classification scope from a range of SNRs for a single CNN classifier to individual SNRs for multiple CNN classifiers, each of which performs a binary classification of a single SNR (e.g. less than, greater than or equal). Additionally, our study demonstrates that the same CNN classification model can learn to predict SNR in various dynamic wireless environments including multiple modulation types, Doppler shifts and path delays (e.g. Rician fading). This flexibility is not typical of existing estimation techniques and would translate to small-footprint implementation.

Thinh Ngo is with The University of Texas at San Antonio, United States (e-mail: thinhngo11@gmail.coml).

II. Divide-and-Conquer Algorithm and Classifier Fusion

Divide-and-conquer algorithm is widely applied in many fields including mathematics, engineering, etc. This section describes the application of divide-and-conquer algorithm to CNN classification for SNR prediction. Historically, classifier fusion methods have been extensively researched to improve classification performance. Of the three levels of abstraction, namely, data-level fusion, feature-level fusion and classifier fusion, our approach is the third type. Specifically, multiple classifiers are used in a divide-and-conquer manner where individual classifier is dedicated to the binary classification - less than, greater than or equal to - a single label rather than strictly equal to a specific label of the entire range of labels for traditional classifier. Consequently, reduction of uncertainty is achieved and classification accuracy enhancement is expected. For example, an error occurs when a traditional classifier misclassifies a target label (i.e. 4 instead of 0); whereas, for binary classifier, an error occurs when it misclassifies a range of labels (i.e. [-20, -4] instead of [0, 32]).

Individual classifiers' outputs are combined in an union fashion to produce a predicted range. In effect, individual classifiers are combined to form a composite classifier. Performance of the composite classifier is less than those of binary classifiers and is expected to be better than the traditional multi-class classifier. In many applications, when composite classifier does not yield acceptable performance, range prediction from binary classification may have its own merit and potential usage for consideration. For instance, it is important to know when SNR is less than 0 and whether it is equal -4 or -8dB is good but practically of less added value.

For SNR classification, a range of SNRs [-20,32]dB is split into 14 individual SNR classifications [-20, -16, ..., 32].

A. *Traditional CNN Classifier for All SNRs*

Fig. 1 shows a traditional CNN classifier for SNR in the range [-20, 32]dB with a resolution of 4dB.

Fig. 1 Traditional SNR Classifier

B. *Multiple CNN Binary Classifiers for Individual SNRs*

Fig. 2 shows two individual SNR binary classifiers. There are total 14 individual classifiers corresponding to 14 SNRs in the range [-20, 32] with 4dB resolution. Test labels are modified to binary classification w.r.t. the target SNR of individual SNR classifiers. For instance, individual $SNR = 4$ classifier has $testlabel = 1$ for RF data with true $SNR < 4$ and $testlabel = -1$ otherwise.

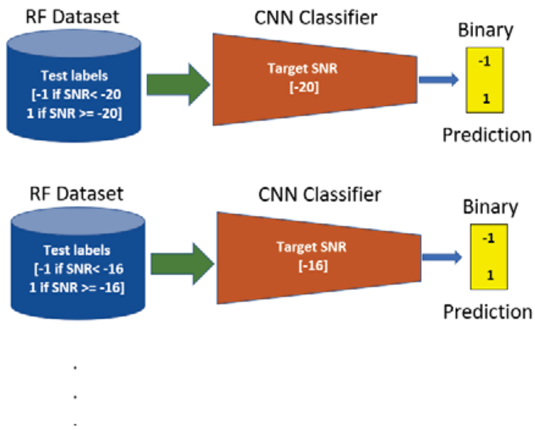

Fig. 2 Individual-SNR Classifiers

C. *Composite CNN Classifier for All SNRs*

Composite SNR classifiers can be used to predict a specific SNR range. The smallest SNR range is between two consecutive SNRs predicted by two individual SNR classifiers - one for the high limit SNR and other for the low limit. Effectively, all individual SNR classifiers are combined to form one composite SNR classifier over the entire SNR range. Fig. 3 shows the composite SNR classifier. After training individual SNR classifiers, we subject the same test data to all of these individual classifiers. Their outputs are examined for predictions switching from being greater than or equal to less than classifier SNRs. The identified SNRs form the range of predicted SNR. For example, when outputs of all classifiers for SNR from -20 to -4 are greater than and outputs of all classifiers for SNR from 0 to 30 are less than, the predicted SNR is in the range from -4 to 0 (see Fig. 4). It is possible to have more than such a switching since the prediction accuracy of individual classifiers are not perfect. We select the first switching which corresponds to union combination. Finally, we compare test labels to predicted range for prediction accuracy. Accuracy of the composite classifier is 70% which is less than those of binary classifiers (i.e. 92%) and is better than the traditional multi-class single CNN classifier (i.e. $< 50\%$).

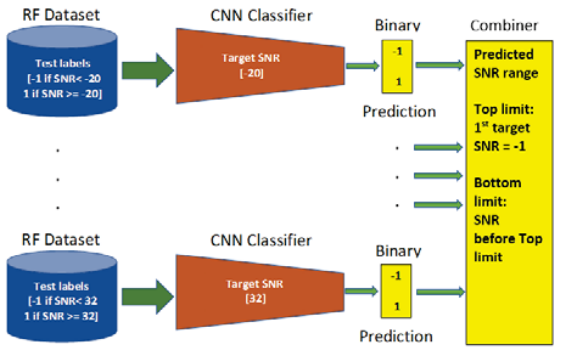

Fig. 3 Composite-SNR Classifier

Classifier	...	SNR=-4	SNR=0	SNR=4	...	SNR=28	Range	Test Label	Correct
Prediction	1	1	-1	-1	-1	-1	(-4, 0)	0	Y
Prediction	1	1	1	-1	-1	-1	(0, 4)	-4	N

Fig. 4 Samples of Composite-SNR Prediction

III. Simulation Framework

This section shows the simulation aspects applied to both the MATLAB and Python platforms. The concept is invariant to the computing platform with significant improvements illustrated.

A. *MATLAB Simulation Model*

Fig. 5 shows the simulated model adopted from MATLAB Modulation Classification example. The Transmitted Signal is modulated and fed into the Multi Path Channel which is parameterized by Sample Rate, Path Delay, Path gain, KFactor and Doppler Shift. The channel output signal is sampled and added with AWGN to produce the impaired complex-valued Received Signal which is fed into DL Prediction Model.

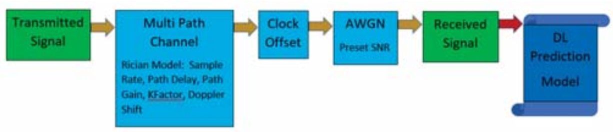

Fig. 5 MATLAB Simulated Model

1) RF DataSets: The Modulation Classification from MATLAB Deep Learning example is adopted for this work. A parameterized channel model and signal data generation are shown in Tables I and II respectively. Inputs comprise 378 sets of 3 modulation types, 3 Doppler shifts, 3 path delays and 14 SNRs. Each set has 100 frames of 128 data symbols each of which samples 8 times. Each frame is of

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TABLE I
CHANNEL MODEL

Parameter	Value
Model type	Rician
Path delays(uSec)	[0 0 0 0], [0 2 4 6], [0 5 10 15]
Path gains(dB)	[0 -3 -6 -9]
KFactor	3
Doppler Shift(Hz)	0, 60, 120
Clock offset(ppm)	5
Sampling frequency(Hz)	200e3
Center frequency(Hz)	900e6

TABLE II
DATA GENERATION

Parameter	Value
Input frames	37800
Input frames / Set	100
Data symbol / Input frame	128
Samples / Data symbol	8
Samples / Input frame	1024
Modulation Types	QPSK 16QAM 64QAM
SNR(dB)	[-20, -16, ..., 0, 4, ..., 32]

TABLE III
CNN ARCHITECTURE

Layer	Details
Input	2x1024
Convolution2D	FilterSize=1x32, numFilters=16
Activation	relu
MaxPooling2d	poolSize=strideSize=1x2
Convolution2D	FilterSize=1x32, numFilters=24
Activation	relu
MaxPooling2d	poolSize=strideSize=1x2
Convolution2D	FilterSize=1x32, numFilters=32
Activation	relu
MaxPooling2d	poolSize=strideSize=1x2
Convolution2D	FilterSize=1x32, numFilters=48
Activation	relu
MaxPooling2d	poolSize=strideSize=1x2
Convolution2D	FilterSize=1x32, numFilters=64
Activation	relu
MaxPooling2d	poolSize=strideSize=1x2
Convolution2D	FilterSize=1x32, numFilters=96
Activation	relu
MaxPooling2d	poolSize=strideSize=1x2
fullyConnected	
Activation	softmax

the same modulation, Doppler shift, path delays and SNR. Prediction of SNR is performed on one frame at a time.

2) Convolutional Neural Networks: The convolution neural network (CNN) is adopted from MATLAB Modulation Classification example with details in Table III. Input frame comprises 1024 complex-valued I and Q samples. Details of training and validation are shown in Table IV.

3) Results and Discussions: ML and DL prediction performance is typically reported using accuracy as shown in Equation 1.

$$Accuracy(\%) = 100 * Correct\#/Total\# \qquad (1)$$

TABLE IV
CNN TRAINING

Parameter	Value
Training percentage	80
Validation percentage	10
Test percentage	10
Mini-batch size	256
Max epoch	12
Training method	SDGM
Initial learning rate	2e-2
Learn rate schedule	piecewise
Learn rate drop period	9
Learn rate drop factor	0.1

Fig. 6 demonstrates the training with a low validation accuracy of about 46%. The confusion chart of Fig. 7 indicates wide spreading of predictions to neighboring classes. The bottom curve of Fig. 10 shows accuracy over the range of test SNRs with an average accuracy of 39%. This is the main challenge when using DL for SNR classification.

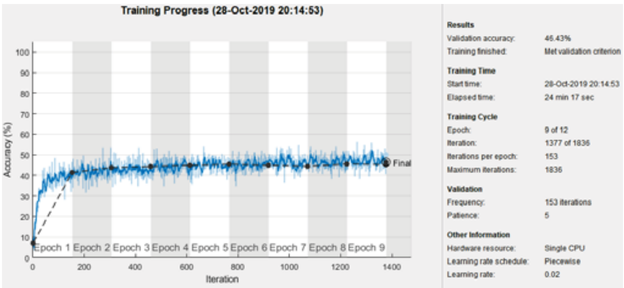

Fig. 6 Training of Traditional Classifier

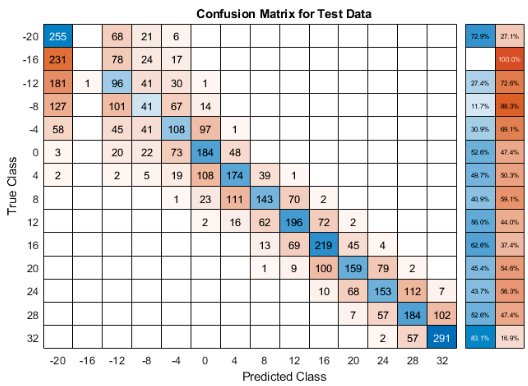

Fig. 7 Confusion Matrix of Traditional Classifier

Fig. 8 demonstrates the training of SNR=0 classifier with a validation accuracy of 92%. The confusion chart of Fig. 9 shows common True Positive, True Negative, False Positive and False Negative . The top curve of Fig. 10 shows accuracy of individual SNR classifiers over the range of test SNRs with an average accuracy of about 92%. This indicates that the DL model learns to classify single SNR (e.g. greater or less than) more effectively than a range of SNRs. What are the values and usages of these individual SNR classifiers? Individually, they can be used to determine if a UE is at the network edges where SNR is less than 0dB or if an opportunity exits to boost transmission rate (i.e. using more efficient modulation types) where SNR is greater than 20dB. Collectively, they help answer whether SNR is in a range (i.e. [0, 10]dB.) to keep the default transmission condition.

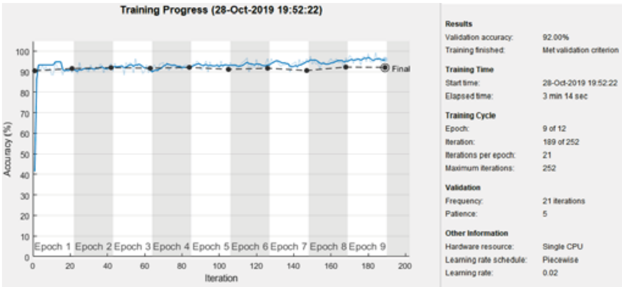

Fig. 8 Training of SNR=0 Classifier

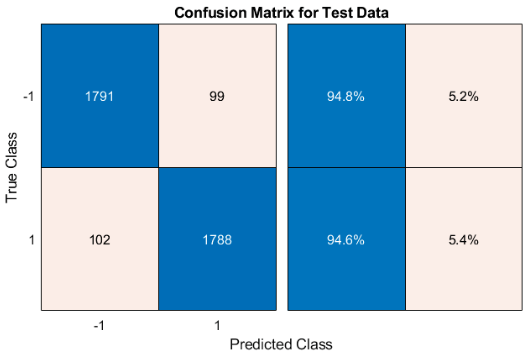

Fig. 9 Confusion Matrix of SNR=0 Classifier

Accuracy of the composite classifier is 70%. It is expected that tighter prediction resolution often leads to lower accuracy. The middle curve of Fig. 10 shows accuracy of the composite SNR classifier.

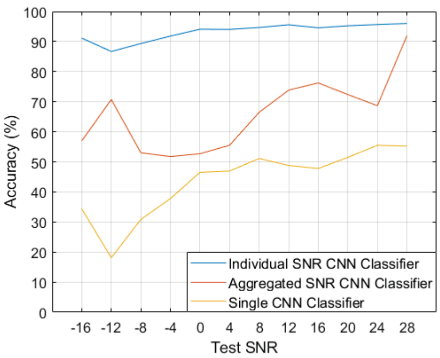

Fig. 10 Prediction Accuracy Comparison

B. Python Simulation

We use Python 2.7 with Tensorflow and Keras packages. We leverage the Python code with datasets R2016.10A made available by O'Shea and et al [8]. Specifically, we replace its CNN with the MATLAB custom CNN for comparison purpose. Moreover, we use SNRs as prediction labels instead of Modulation types. The dataset consists of about 220,000 examples (e.g. input frames) each of which comprises 128 samples. The examples are both synthetically generated and over-the-air recordings. Synthetic impairments include delay spreads, carrier frequency, phase, sampling frequency, etc [6]. We simulate at both SNR resolution = 2 and resolution = 4 where data in between are removed. Figs. 11 and 12 show prediction accuracy. In general, our idea of SNR prediction is confirmed well with Python platform and DeepSig dataset over the entire SNR range from -20dB to 16dB.

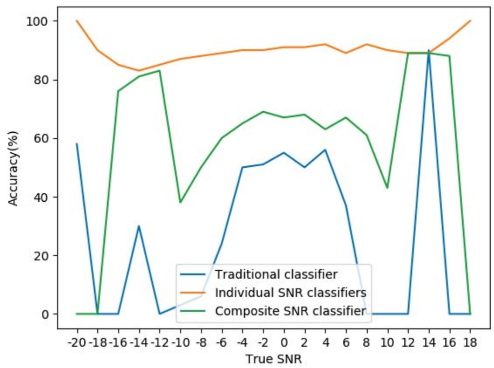

Fig. 11 Python platform: Accuracy @SNR resolution = 2

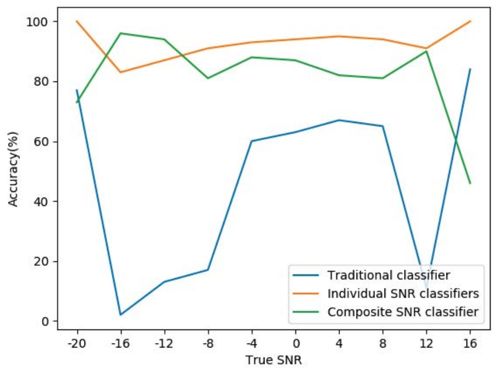

Fig. 12 Python platform: Accuracy @SNR resolution = 4

IV. Conclusion

Traditional SNR estimation methods have well served the 4G (e.g. LTE-Advanced and LTE-Advanced Pro). For 5G and beyond, the demand for accurate and immediate SNR assessment is even greater. Deep learning SNR prediction using multi-CNNs can collaborate with the conventional SNR estimation methods to meet this challenge. For comparison, deep learning SNR prediction accuracy is about the same as those of conventional SNR estimation methods. However, SNR prediction time is an order of magnitude faster. In addition, this paper demonstrates MATLAB as a viable engineering platform for Deep Learning investigation.

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Thinh Ngo received the BSEE degree from Oklahoma State University and the MSEE degree from Stanford University in 1984 and 1988 respectively. He is currently a doctoral candidate with focus on Wireless Communication at the University of Texas at San Antonio. His research interest is Machine Learning for Wireless Network PHY layer. His recent work was in design verification engineering. He published seven papers in design verification. He is a student member of the IEEE and a member of Eta Kappa Nu.

Brian Kelley received his BSEE from Cornell University's College of Electrical Engineering in Ithaca NY where he graduated Tau Beta Pi and Eta Kappa Nu. He received his MSEE and PhDEE from Georgia Tech in 1992 where he was an Office of Naval Research Fellow and a Georgia Tech Presidential Fellow with a research focus on communications, Signal Processing, and high performance computing architectures. He spent 10+ years in industry with both Motorola and Motorolas spinoff, Freescale. While there, he rose to Distinguished Member of the Technical Staff, developing Wi-Fi, HSPA, LTE platforms, radio link simulators, and traveled around the world as a representative to the 3GPP RAN4 (4G-LTE) standards body. Since 2007, Dr. Kelley has been an Associate Professor of Electrical and Computer Engineering at the University of Texas at San Antonio (UTSA). At UTSA, Dr. Kelley is Director of the Wireless Information and Next Generation Systems Laboratory (WINGS) with an emphasis on 5G Communications, Software Defined Radio (SDR), Cloud Radio Access Network (CRAN), IoT, Physical Layer Security, and Quantum Information Systems. Dr. Kelley has received over $2.6M in research funding from ONR, AFRL TECHLAV, DoE and consults extensively with cellular communications companies. He has numerous IEEE publications and holds 11 US patents. Dr. Kelley has been an IEEE 4G Technical Workshop Organizer, has served on the Technical Program Committee for IEEE Globecom, currently Chairs the IEEE Chapter of Communications and Signal Processing of San Antonio, and has been Associate Editor of the IEEE System Journal. From 2015-2016, Dr. Kelley was Sabbatical Employee of the Department of Defense in Washington D.C.; and in 2015 and 2017, he was a Summer Faculty Fellow at Oak Ridge National Laboratory (ORNL) in the Quantum Information System Group. At UTSA, Dr. Kelley instructs courses on 5G-New Radio Communications, Internet of Things (IoT), Software Defined Radio (SDR), Error Correction Codes, and Statistics, Random Signals and Noise.

Paul Rad received the Ph.D. degree in electrical and computer engineering on cyber analytics from the University of Texas at San Antonio, San Antonio, TX, USA. He is a co-founder and Associate Director of the Open Cloud Institute (OCI), and an Associate Professor with the information systems and cyber security (ISCS) from University of Texas at San Antonio. He has received his first B.S. degree from Sharif University of Technology in Computer Engineering in 1994, his 1st masters in artificial intelligence from the Tehran Polytechnic, the 2nd masters in computer science from the University of Texas at San Antonio (Magna Cum Laude) in December 1999, and the Ph.D. in electrical and computer engineering from the University of Texas at San Antonio. He was a recipient of the Most Outstanding Graduate Student in the College of Engineering, 2016, Achieving Rackspace Innovation Mentor Program Award for establishing Rackspace patent community board structure and mentoring employees, 2012, Achieving Dell Corporation Company Excellence (ACE) Award in Austin for exceptional performance and innovative product research and development contributions, 2007, and Dell Inventor Milestone Award, Top 3 Dell Inventor of the year, 2005. He holds 15 U.S. patents on cyber infrastructure, cloud computing, and big data analytics with over 300 product citations by top fortune 500 leading technology companies such as Amazon, Microsoft, IBM, Cisco, Amazon Technologies, HP, and VMware. He has advised over 200 companies on cloud computing and data analytics with over 50 keynote presentations. He serves on the advisory board for several startups, high performance cloud group chair at the Cloud Advisory Council (CAC), OpenStack Foundation Member, the #1 open source cloud software, San Antonio Tech Bloc Founding Member, Childrens Hospital of San Antonio Foundation board member.