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Adaptive Modulation and Coding Using Neural Network Based SNR Estimation

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ABSTRACT In this paper, we propose a novel Adaptive Modulation and Coding (AMC) scheme enabled by Artificial Neural Network (ANN) aided Signal-to-Noise power Ratio (SNR) estimation. The Power Spectral Density (PSD) values are trained for SNR classification and it is mapped to respective Modulation and Coding Scheme (MCS) sets. Once trained, optimal MCS can be determined in low calculation complexity. The proposed approach is robust especially in high mobility environment since the PSD appearance is hardly influenced by the Doppler shift. Its effectiveness in terms of throughput is presented through computer simulations compared to the existing Error Vector Magnitude (EVM) based link adaptation scheme.

INDEX TERMS SNR estimation, artificial neural network, adaptive modulation and coding.

I. INTRODUCTION

The next generation mobile radio communication systems, 5G and beyond 5G, require realizations of large capacity, massive connectivity and low latency [1], [2]. Link adaptation schemes such as Adaptive Modulation and Coding (AMC) and Transmit Power Control (TPC) are truly essential to maximize the throughput performance for wireless communication wherein propagation environments drastically fluctuate [3]–[7]. It can be rephrased that AMC is very sensitive to changes in Signal-to-Noise power Ratio (SNR) to maximize the spectral efficiency. Channel condition and the received SNR are varied from the instant of estimation due to the mobility of user terminal or surrounding objects such as vehicles. In order to track the dynamics of SNR, frequent SNR estimation and feedback should be performed. It imposes heavy computation complexity and feedback overhead. The modulation and coding schemes (MCS) are determined based on the SNR estimated at the receiver and is fed-back to the transmitter side. AMC is effective not only in the flat fading environment, but also in the frequency selective fading environment. In this case, MCS parameters should be optimally associated to SNR according to the channel condition on which error rate performance depend. In order to fully exploit channel capacity, lots of MCS parameters should be prepared with fine granularity of SNR [8]–[10] and its estimate values should be highly accurate. Complicated SNR estimation process for high accuracy may cause feedback delay and it could depress the throughput performance. Well investigated approaches are Error Vector Magnitude (EVM) [11] or time domain analysis [12]. In addition to the above concern, they are substantially based on the complex signal processing which may be affected by the Doppler shift in high mobility environment. Such fluctuation in time domain could impact to the SNR estimation accuracy.

In order to address the above issue, this paper proposes a novel SNR estimation method using an Artificial Neural Network (ANN) with supervised learning. ANN is composed of a plurality of neurons made by imitating the human brain function [13]–[18]. It has a high problem solving ability by changing synaptic connections according to learning results. Neural network design is roughly classified into supervised learning and unsupervised learning. Supervised learning extracts feature quantities using the pair of input training signals and output teacher signals. Resultant function can solve regression problems and identification problems. However, supervised learning, requires enormous teacher data sets that may be difficult to collect depending on an object of interest. On the other hand, unsupervised learning attempts to divide input signals into clusters having common factors and to extract frequent patterns, without giving correct solutions. Once learned, ANN can derive the result with simple calculation. It is extremely effective in the environment where

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computation resources and memory are limited or when the strictly low processing latency is imposed.

The proposed method estimates SNR using ANN exploiting power spectral density (PSD) values of the received signal. Since the estimator of the proposed method requires only PSD values, it can implement with a simple configuration. It is also a point that it is easy to acquire data set of PSD value and teacher signal of SNR value. Thus, this estimation method easily realizes a high accuracy and low computational complexity by extracting features such as noise power from the PSD. In addition, the proposed method is hardly affected by the Doppler shift since it focuses on only the power-domain which excludes the phase offset impact. SNR estimation accuracy can be kept even in the high mobility environment. Its robustness and maximized throughput performance are valuably disclosed through computer simulations.

The reminder of this paper is organized as follows. Section II reviews related works and validates our contribution. The system model is described in Section III. Section IV introduces the proposed method that estimates SNR using ANN for AMC scheme. Section V presents the simulation results from various viewpoints. Section VI concludes this paper.

II. RELATED WORKS

At present, an application of machine learning to the wireless communication field has attracted a great deal of attention and research has been actively conducted [19]. Particularly, modulation recognition (MR) [20]–[25] and channel estimation by using a neural network [26], [27] have been extensively studied. Modulation recognition (MR) is a pioneering technology that fully exploits the potentiality of ANN. MR aims at implementation of correct demodulation in the receiver side and is an essential technique to improve the communication performance especially in the cognitive radio environment. Literature claims that MR is fundamental for AMC, however, MR and AMC is substantially different techniques. AMC requires information about channel quality such as SNR at the receiver side and it is fed-back to the transmitter side. Our proposal introduces ANN to accurately estimate SNR using PSD. MR is to improve the signal reception performance even at lower SNR situation, but not to estimate SNR itself. On the other hand, the neural network based channel estimation can also improve the estimation accuracy as well as communication performance. The common objective of using neural networks among these approaches including our proposal is to simplify the complicated calculation processing for a high-speed and a high reliable communication. The proposed approach focused on frequency-domain real-valued signals which can be easily obtained by Fourier transform of specified signal samples and can reduce the burden on the receiver. In terms of learning neural network, a data set of PSD can be acquired not only by signal processing but also commercial measurement instruments such as a spectrum analyzer; captured images can also be acceptable. Once the learning process is conducted, only the resultant optimized function should be installed to the transceiver. Therefore, the proposed AMC works in a simplified manner and can be applied to small transceivers being driven with limited power. Furthermore, in the link adaptation such as AMC, FBI for control is essential. The computation complexity for SNR estimation and the amount of FBI itself are factors of the feedback delay. The neural network aided proposed method can also alleviate it, since these features, the proposed approach can contribute to the massive connectivity and low latency applications such as mission critical IoT and vehicle-to-vehicle communication.

III. SYSTEM MODEL

A. CHANNEL MODEL

This section explains the time-varying multipath fading channel that we assumed as the propagation model in this paper [28], [29]. In the case that the transmission bandwidth is larger than the channel coherence bandwidth, the frequency components of the transmission signal exceeding the coherent frequency bandwidth have different phase transitions and gains. This channel is called frequency selective channel [30]. Its discrete expression can be written as follows:

$$h(t;\tau) = \sum_{k=1}^{K} h_k(t)\delta(t - \frac{k}{W}) \tag{1}$$

$$h_k(t) = \frac{g_k}{\sqrt{K}} \sum_{k=1}^{K} exp\left[j\left(2\pi f_d t \; cos\alpha_k + \phi_k\right)\right] \tag{2}$$

where K is the number of discrete multipaths, and h_k represents the channel complex gain of the kth multipath component. $\delta(t)$ denotes the Dirac's delta function, W is the transmission signal bandwidth, g_k indicates the k-th path amplitude. f_d denotes the Doppler frequency, α_k and ϕ_k indicate the angle of arrival (AoA) of the kth incoming wave and its initial phase, respectively. We constructed a time-varying channel based on Jakes' model. $\sum_{k=1}^{K} E\left[\left|h_k^2\right|\right] = 1$ where $E[\cdot]$ indicates the ensemble-average operation. Then, the frequency response $H(t;f)$ is obtained by the discrete Fourier transform (DFT) of $h(t;\tau)$ expressed as follows:

$$\begin{aligned} H(t;f) &= \int_{-\infty}^{\infty} h(t;\tau) exp\left(-j2\pi f\tau\right) d\tau \\ &= \sum_{k=1}^{K} h_k(t) exp\left(-j2\pi f \frac{k}{W}\right). \end{aligned} \tag{3}$$

In regards to K, the following relationship holds,

$$K = \lfloor WT_{ms} \rfloor + 1, \tag{4}$$

where T_{ms} represents the spread of multipath. From (4), since $K > 1$, the frequency response of channel is not immutable due to the variation of each channel gains. Such a fading environment is called frequency selective. The Doppler power spectra can be written as follows:

$$D_k(\lambda) = \int_{-\infty}^{\infty} E\left[\frac{1}{2} h_k^*(t) h_k(t+\tau)\right] \cdot exp\left(-j2\pi\lambda\tau\right) d\tau, \quad \text{for } k = 1, 2, 3, \ldots, K. \tag{5}$$

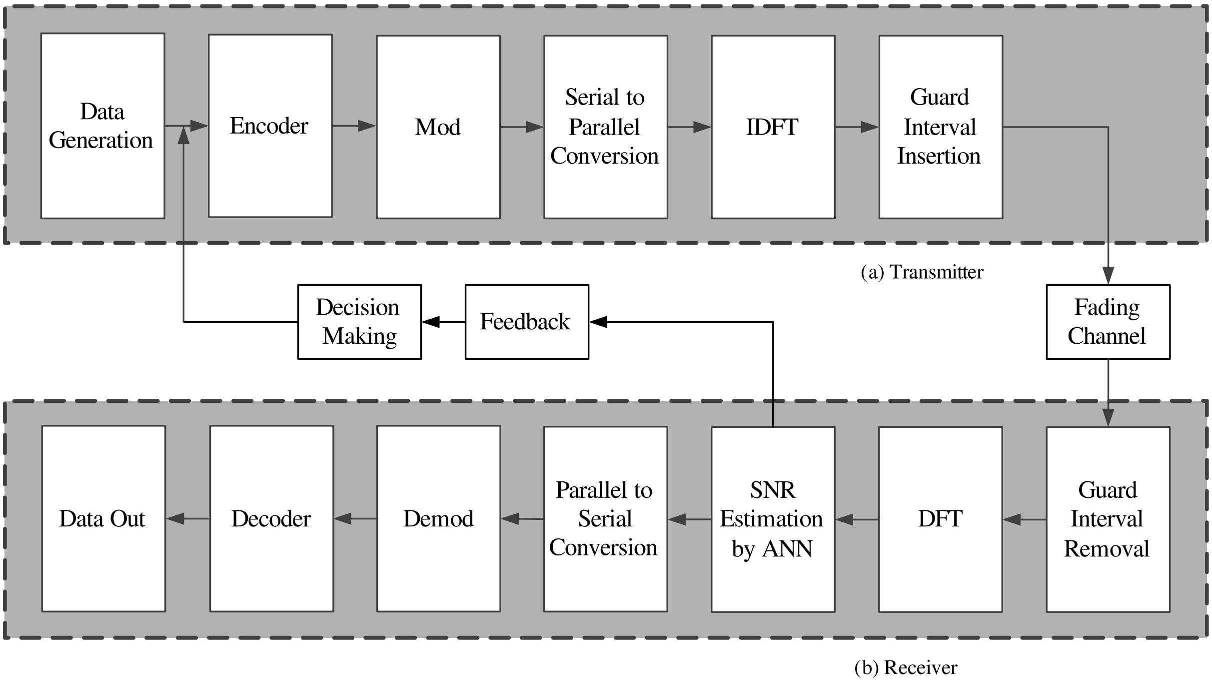


FIGURE 1. **Block diagram of the proposed system.**

As can be seen from the above equation, multipath can be modeled using Doppler spread and power spectra, and it is greatly affected by Doppler frequency representing moving speed of the transceiver. The influence of multipath phase changes in OFDM signals that degrade channel tracking performance depends on Doppler frequency. Thus, in the case of high Doppler frequency, channel estimation accuracy deteriorates and detection performance also deteriorates.

B. TRANSMITTER STRUCTURE

The transmitter structure is shown in Fig.1(a). The time domain transmission signal is represented as follows:

$$s(t) = \sum_{n=-\infty}^{\infty} \sqrt{\frac{2P}{N_c}} \cdot p(t-nT) \cdot \left[\sum_{m=1}^{N_c} d(m,n) \cdot exp\left(\frac{j2\pi m(t-nT)}{T_s}\right) \right] \quad (6)$$

where P is the average transmission power, N_c denotes the number of subcarriers and $d(m,n)$ is the m-th subcarrier of the n-th modulated symbol. Here, $d(m,n)$ satisfies $E\left[|d(m,n)|\right] = 1$. T is the symbol length of OFDM signal, T_s indicates the effective symbol length of OFDM signal not including guard interval (GI). It is assumed that GI length is T_g and T_g is a value that satisfies $T = T_s + T_g$. The frequency interval between adjacent orthogonalized OFDM subcarriers is $1/T_s$. $p(t)$ is the transmission pulse, and expressed as

$$p(t) = \begin{cases} 1 & -T_g \le t \le T_s \\ 0 & \text{otherwise.} \end{cases} \quad (7)$$

C. RECEIVER STRUCTURE

The receiver structure is shown in Fig.1(b). After removing the GI and performing serial to parallel conversion, the received signal that passed through the multipath fading channel is expressed as follows:

$$r(t) = \int_{-\infty}^{\infty} h(t;\tau)s(t-\tau)d\tau + z(t) \quad (8)$$

where $z(t)$ is the additive white Gaussian noise (AWGN) which has power spectral density of Z_0. The received signal after fast Fourier transform is given by

$$\begin{aligned} r(m,n) &= \frac{1}{T_s}\int_{nT}^{T_s+nT} r(t)\exp\left(\frac{-j2\pi m(t-nT)}{T_s}\right)dt \\ &= \sqrt{\frac{2P}{N_c}}\sum_{a=1}^{N_c} d(a,n)\cdot\frac{1}{T_s}\int_0^{T_s}\exp\left(\frac{j2\pi(a-m)t}{T_s}\right) \\ &\quad \cdot\left\{\int_{-\infty}^{\infty} h(\tau, t+nT)p(t-\tau) \right. \\ &\quad \left. \cdot\exp\left(\frac{-j2\pi a\tau}{T_s}\right)d\tau\right\}dt + z(m,n) \end{aligned} \quad (9)$$

where $z(m,n)$ is AWGN having variance of $2Z_0/T_s$ with zero-mean. Suppose the maximum chromatic dispersion between subcarriers is smaller than T_g, the integral with respect to τ can be expressed as

$$\begin{aligned} &\sum_{a=1}^{N_c}\left\{\int_{-\infty}^{\infty} h(\tau,t+nT)p(t-\tau)\exp\left(\frac{-j2\pi a\tau}{T_s}\right)d\tau\right\} \\ &= \sum_{a=1}^{N_c}\int_0^{T_s} h(\tau,t+nT)\exp\left(\frac{-j2\pi a\tau}{T_s}\right)d\tau \\ &= H(m,t+nT). \end{aligned} \quad (10)$$

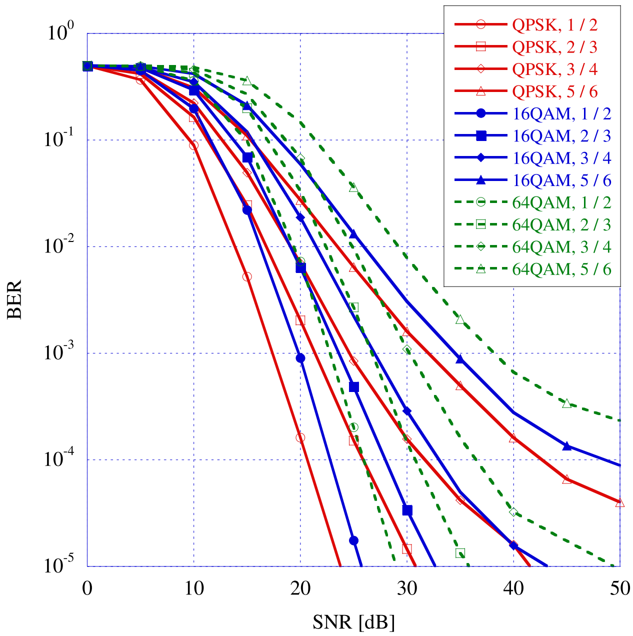


FIGURE 2. BER of various coding rate and modulation level at Doppler frequency of 10 Hz.

Here, under the assumption that the channel state remains nearly flat over the symbol duration T,

$$H\,(m, t+nT) \;\approx\; H\,(m, n) \quad for\ 0 \leqq t \leqq T. \tag{11}$$

Thus, (9) can be rewritten as

$$\begin{aligned}\tilde{r}(m,n) \;&\approx\; \frac{1}{T_s}\sqrt{\frac{2P}{N_c}}\sum_{a=1}^{N_c} d(a,n)\cdot\int_0^{T_s}\exp\left(\frac{j2\pi(a-m)t}{T_s}\right)\\ &\quad\cdot\left\{\int_{-\infty}^{\infty} h(\tau, t+nT)p(t-\tau)\right.\\ &\quad\left.\cdot\exp\left(\frac{-j2\pi a\tau}{T_s}\right)d\tau\right\}dt + z(m,n)\\ &= \sqrt{\frac{2P}{N_c}}H\,(m,n)\,d(m,n) + z(m,n). \end{aligned}\tag{12}$$

Observing (12), the received signal is affected by frequency selective fading. In addition, channel coefficient $H\,(m, n)$ is varied with the time progress. With the pilot-based channel estimation, a channel estimation accuracy is degraded for the latter part of transmission frame. Therefore, it indicates that the change in Doppler frequency between the transmitter and receiver greatly affects the channel estimation methods in terms of channel fluctuation tracking ability.

D. AMC

AMC is generally performed by FBI of estimated SNR [10]. The modulation levels and coding rates are selected according to the estimated SNR such that it satisfies the predetermined Bit Error Rate (BER). Fig.2 shows the BER performance of various coding rates at Doppler frequency of 10 Hz. Here, we use a convolutional code as an FEC and the modulation level as QPSK, 16QAM and 64QAM. Detailed simulation assumptions are presented in Section V.A. Suppose the target BER for switching is set to 10^{-3}, switching threshold can be determined as shown in Table 1 [31], [32]. Based on this setup, this paper examines the fundamental effectiveness of the proposed approach.

TABLE 1. Switching threshold parameters.

Threshold	Modulation	Coding rate	bit/symbol
SNR < 20.0dB	QPSK	1/2	1
20.0dB ≤ SNR < 23.0dB	16QAM	1/2	2
23.0dB ≤ SNR < 26.6dB	64QAM	1/2	3
26.6dB ≤ SNR < 30.3dB	64QAM	2/3	4
30.3dB ≤ SNR < 38.0dB	64QAM	3/4	4.5
38.0dB ≤ SNR	64QAM	5/6	5

E. SNR ESTIMATION WITH EVM

In this paper, SNR estimation using Error Vector Magnitude (EVM) was used as the conventional method [33]–[36]. EVM compares the reference constellation point with that of the received signal and then estimates SNR from these difference. Its SNR calculation formula can be expressed as follows,

$$SNR_{EVM} = 10\log 10\left(\frac{\frac{1}{N}\sum_{n=1}^{N}\left(I_{r(m,n)}^2 + Q_{r(m,n)}^2\right)}{Y_{r(m,n)}}\right), \tag{13}$$

where N is the number of received signal symbol. $I_{r(m,n)}$ and $Q_{r(m,n)}$ represent the m-th subcarrier ideal constellation points in inphase and quadrature phases, respectively. Here, $Y_{r(m,n)}$ is given by

$$Y_{r(m,n)} \;=\; (I_{r(m,n)} - \tilde{I}_{r(m,n)})^2 + (Q_{r(m,n)} - \tilde{Q}_{r(m,n)})^2, \tag{14}$$

where $\tilde{I}_{r(m,n)}$ and $\tilde{Q}_{r(m,n)}$ are measured in-phase and quadrature components from the received signal, respectively. EVM-based SNR estimation utilizes time-domain samples to suppress the AWGN effect. As above mentioned, in the mobility environment, the recovered IQ data contains error components due to the Doppler shift which would degrade the SNR estimation accuracy.

IV. PROPOSED METHOD

A. SNR ESTIMATION BY ANN

The ANN used in the proposed system is 3 layered neural network which is exemplified in Fig.3. Based on the back propagation algorithm [37]–[39], the input signal of the u-th neuron in the c-th ($c = 1, \ldots, C$) layer is expressed as follows:

$$x_u^c = \sum_{v=1}^{V} w_{u,v}^c y_v^{c-1} + b_u^c, \tag{15}$$

where $w_{u,v}^c$ represents the weight for connection of the v-th neuron in the $(c-1)$-th layer to the u-th neuron in the c-th layer and b_u^c indicates the bias for input of the u-th neuron

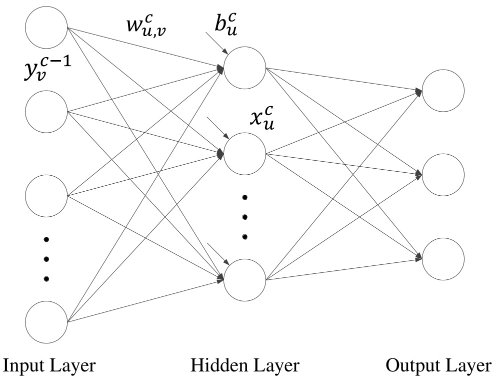
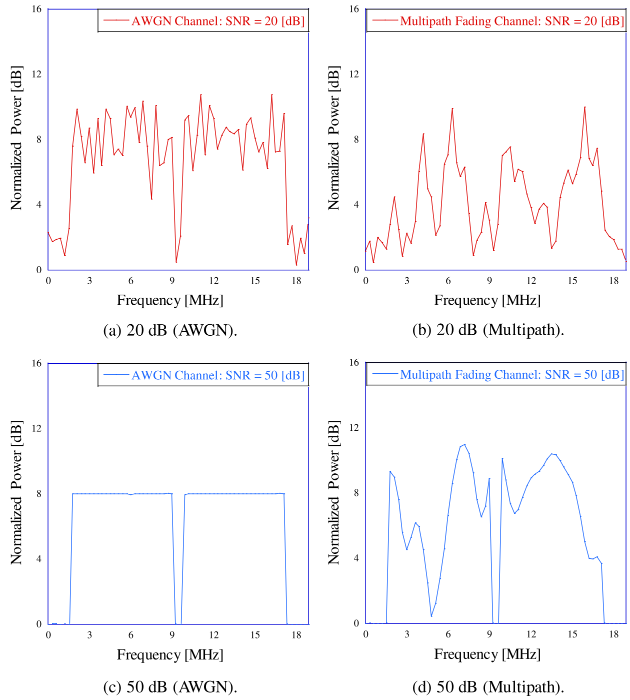


FIGURE 3. **Structure of a multilayer feed forward neural network.**



(a) 20 dB (AWGN). (b) 20 dB (Multipath). (c) 50 dB (AWGN). (d) 50 dB (Multipath).

FIGURE 4. **The power spectrum of the received signal according to SNR level.**

in the c-th layer, respectively. Here, y_v^{c-1} indicates the output signal of the v-th neuron in the $(c-1)$-th layer and the output signal of the u-th neuron in the c-th layer is represented as

$$y_u^c = f^c\left(x_u^c\right) = f^c\left(\sum_{v=1}^{V} w_{u,v}^c y_v^{c-1} + b_u^c\right), \tag{16}$$

where f is the activation function, and various differentiable functions are used depending on the application. From (16), it can be rewritten as follows:

$$y^c = f^c\left(w^c y^{c-1} + b^c\right). \tag{17}$$

The initial value of the input signal is the received signal given by (12) and expressed as follows:

$$y^0 = [\tilde{r}(1)^T, \tilde{r}(2)^T, \ldots, \tilde{r}(n)^T]^T, \tag{18}$$

where $\tilde{r}(n)$ indicates the n-th received symbol. Here, the number of neurons in the first layer is equal to the number of the received signal. Assuming that the combination of the teacher signal and the input signal is $[t, y^0]$, the output of the network is represented by

$$y^C = f^C\left(w^C y^{C-1} + b^C\right). \tag{19}$$

Supposing that the cost function is a square error function, the evaluation index of the network $\boldsymbol{\xi}$ is expressed as

$$\begin{aligned}\boldsymbol{\xi} &= \frac{1}{2}\left(t - y^C\right)^T\left(t - y^C\right) \\ &= \frac{1}{2}\left\|t - f^C\left(w^C y^{C-1} + b^C\right)\right\|^2.\end{aligned} \tag{20}$$

In back propagation algorithm, the steepest descent method is generally used. The gradient of the weight and the bias are expressed as follows,

$$\Delta w_{uv}^c = -\eta \frac{\partial \boldsymbol{\xi}}{\partial w_{u,v}^c} \tag{21}$$

$$\Delta b_u^c = -\eta \frac{\partial \boldsymbol{\xi}}{\partial b_u^c}, \tag{22}$$

where η represents the learning rate. As described above, the weights and biases are sequentially updated from the error between the teacher signal and the output signal, so that the output signal approaches to the teacher signal.

The proposed method estimates SNR from the PSD values of received signal as shown in Fig.4. From Fig.4(a), (c), the PSD under only AWGN channel has a large feature according to SNR level. Thus, it is possible to estimate coarse SNR level from these spectrum image in human eyes. Meanwhile, as shown in Fig.4(b), (d), the PSD under frequency selective fading channel shows intense fluctuation, and it seems difficult to extract the features in terms of SNR at a glance. It is expected to be possible to determine the SNR by extracting these complicated features using the neural network. Furthermore, the feature quantities involved in SNR estimation that obtained by the PSD value are not affected by Doppler frequency, because the effect of Doppler frequency appears as a rotation of the received signals' phase components; its effect can be excluded on the power spectrum. Although the PSD value is the key point in the proposed method, acquisition of this value can be easily acquired via simple signal processing or measurement instruments such as a spectrum analyzer. Captured images can also be acceptable to learn the network. In this case, the burden on the receiving side can be significantly reduced.

B. APPLICATION OF SNR ESTIMATION BY ANN TO AMC

In the proposed method, the estimator learns in advance using PSD values and corresponding SNR values. It enables simplification of the signal processing for the operation period. If channel environment was changed, newly trained neural network can be simultaneously updated to a large number of user terminals via software-based means. After that, substituting the PSD value of the received signal to the learned estimator as an input signal, estimated SNR can be obtained. AMC parameters the determined according to SNR estimated value. The above simplified mechanism is expected to contribute to light-weight signal processing with lower latency.

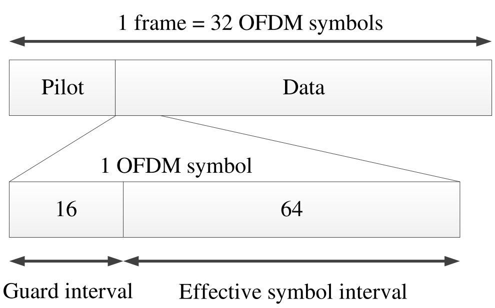


FIGURE 5. Frame structure.

TABLE 2. Simulation parameters.

Transmission scheme	OFDM
Bandwidth	20 MHz
Fading	15 path Rayleigh fading
Doppler frequency	10 Hz, 100 Hz
GI length	16 sample times
Data Modulation	QPSK, 16QAM, 64QAM
Number of subcarriers	52
FFT size	64
Frame size	32 symbols (N_p=2,N_d=30)
FEC	Convolutional code (R = 1/2, 2/3, 3/4, 5/6)
Layer size	C = 3
Learning rate	η = 0.01

V. COMPUTER SIMULATION

A. SIMULATION PARAMETERS

The frame structure is based on wide spread OFDM as shown in Fig.5. One frame consists of 2 pilot symbols and 30 data symbols where one OFDM symbol consists of 52 subcarriers and 16 guard interval samples. These parameters are selected based on the great majority of legacy wireless LAN standard. The duration of effective symbol is 3.2 μs and the guard interval duration is 0.8 μs. Table 2 summarizes detailed simulation parameters. The bandwidth of transmission signal is 20 MHz. Rayleigh fading channel consists of 15 multipaths with the interval of 50 ns. Max Doppler frequencies were set to 10 and 100 Hz representing low and high mobilities, respectively. As for the error correction code, the convolutional code with rates of 1/2, 2/3, 3/4 and 5/6 was applied. If the effectiveness of the proposed method is demonstrated with these basic parameters, other FEC codes, such as Turbo code, LDPC and Polar code, can also be effective as same.

The ANN structure used in the proposed method consists of $C = 3$ layers, an input layer, a hidden layer, and an output layer, respectively. The hidden layer is composed of 55 neurons and the learning rate η is set to 0.01. 10000 sets of PSD values and SNR values were used for each SNR as a data set. Sigmoid function is employed as the activation function given by

$$y = \frac{1}{1 + e^{-x}}. \tag{23}$$

PSD data sets are generated using MATLAB. The training network is designed using MATLAB Deep Learning Toolbox. Operating environment for training and testing the network is NVIDIA Quadro GV100 GPU.

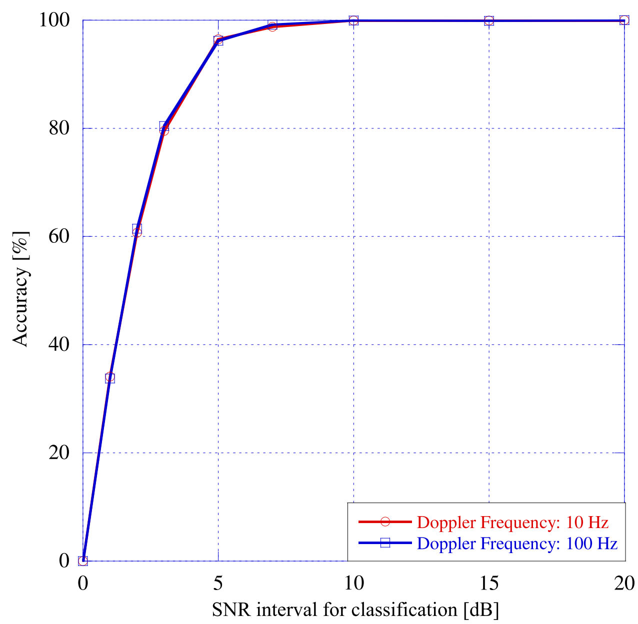


FIGURE 6. SNR estimation accuracy by ANN.

B. SIMULATION RESULTS

Fig. 6 shows the accuracy of estimated SNR with various SNR intervals to be classified. When the interval is small, the accuracy of SNR estimation is low. For this reason, in the case of small interval, the spectra of adjacent SNR values are very similar. Therefore it is difficult to extract different feature quantities by ANN; erroneous judgment increases. Meanwhile, increasing SNR interval to 3 dB, its accuracy exceeds 80%. Thus, the proposed method can demonstrate sufficient AMC performance by setting the interval of SNR threshold to 3 dB or more.

Fig. 7 compares estimated SNR and actual SNR for EVM. The accuracy of the estimated value by EVM deteriorates as the Doppler frequency increases. Since the EVM estimates SNR from the difference between the received IQ symbols and the reference one, it is largely influenced by the Doppler

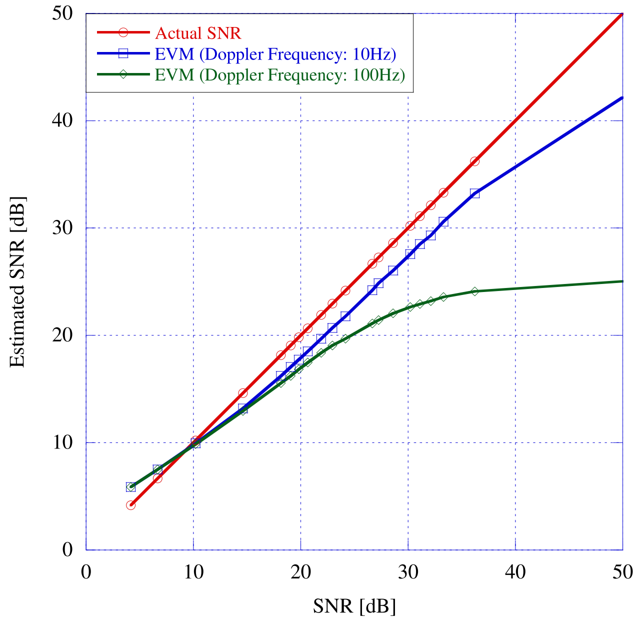


FIGURE 7. Estimated SNR by EVM versus actual SNR.

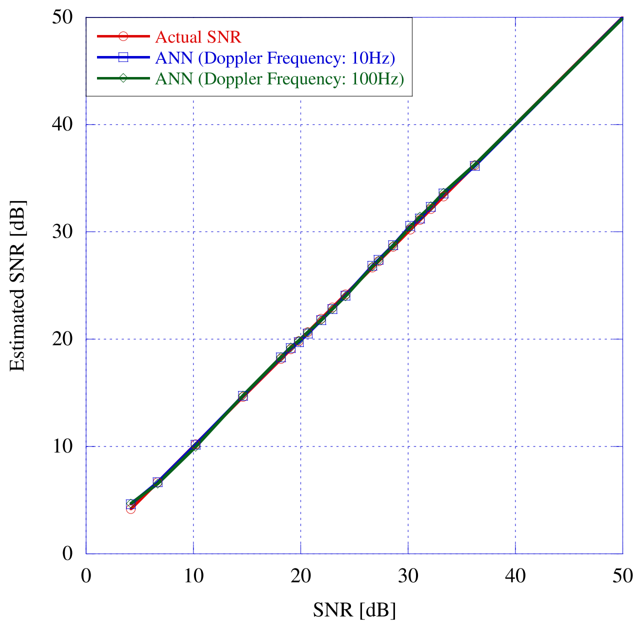


FIGURE 8. Estimated SNR by ANN versus actual SNR.

shift. Its impact becomes non-negligible as the Doppler frequency becomes higher.

Fig. 8 then compares estimated SNR and actual SNR for ANN case. Compared with Fig 7, it can be seen that SNR estimation using ANN is not affected by the Doppler shift. The measured value and the actual one completely coincides. This notable feature can be brought by the proposed method which exploits power-domain transformed signals. It successfully excluded the residual phase compensation error due to the Doppler shift. Therefore, in the method of estimating SNR from the spectral image using ANN, it is possible to minimize the influence of Doppler frequency and improve the AMC performance.

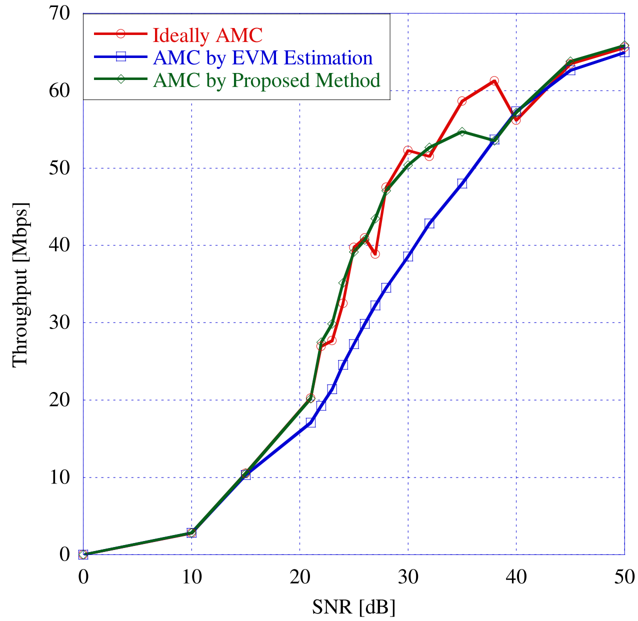


FIGURE 9. Throughput performance at Doppler frequency 10 Hz.

Fig. 9 plots the throughput performance with SNR at Doppler frequency of 10 Hz. It compares that of ideal AMC, AMC by EVM based SNR estimation and AMC by ANN based estimation. Applied MCS set is QPSK, 16QAM and 64QAM with coding rate 1/2, 2/3, 3/4 and 5/6 for convolutional code. Note that the BER-based AMC cannot always show the optimal throughput performance; it fluctuates with SNR especially in the ideal AMC case. From Fig. 9, The proposed method exhibits approaching throughput performance to the ideal AMC case and is better than the conventional EVM method. Focusing on the thresholds of SNR = 20.0, 23.0, 26.6, 30.3 and 38.0 dB, the conventional method can not keep up with this switching, while the proposed method can appropriately follow this switching boundary.

Fig. 10 shows the throughput performance at Doppler frequency of 100 Hz. In the case of high mobility, overall throughput performance deteriorates their maximum values are also saturated. That of the conventional scheme is further limited due to the degradation of SNR estimation accuracy as shown in Fig. 7. On the other hand, it can be confirmed that the proposed method can follow the ideal AMC almost perfectly. From this fact, the proposed method is a quite effective even under the high mobility environment where forces the intensive Doppler shift.

C. COMPUTATION COMPLEXITY

Here presents the effectiveness of the proposed method in terms of the computational complexity. Let ANN learn in advance, SNR can be estimated with reduced calculation cost. In the conventional method, calculation of (13) and (14) is required for SNR estimation. That for the proposed method is derived from only (15). From these equations, the computational complexity by the EVM is given by

$$\Gamma_{EVM} = 2(N_{sym}+1)(N_{sub}\times N_{sym})^2 + N_{sym}, \quad (24)$$

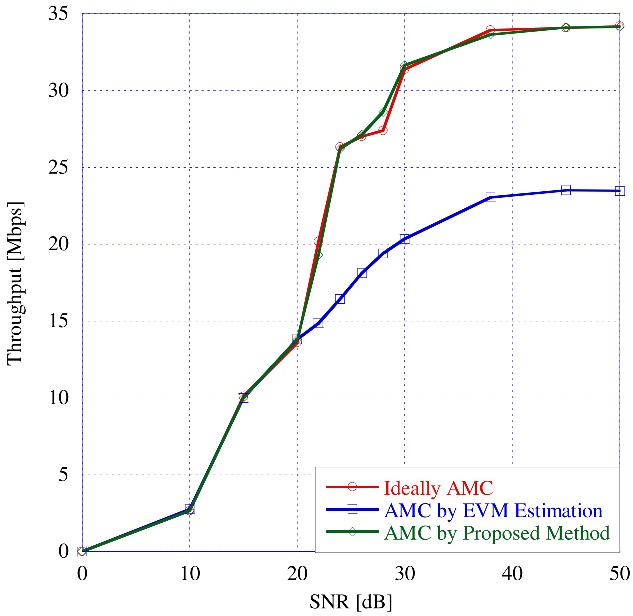


FIGURE 10. Throughput performance at Doppler frequency 100 Hz.

where N_{sym} is the number of symbols and N_{sub} is the number of subcarriers. From (24), Γ_{EVM} is significantly affected by the number of received symbols. On the other hand, the computational complexity by the proposed system is expressed as follows,

$$\Gamma_{prop} = \left(N_u^c \times N_v^c + 1\right)^{C-1}, \tag{25}$$

where C indicates the number of layers, N_u^c and N_v^c represent the number of neuron in the c-th layer and the $(c-1)$-th layer, respectively. From (25), Γ_{prop} is greatly affected by the number of layers. In the proposed system, $C = 3$ is sufficient for highly accurate SNR estimation, therefore the calculation complexity is lower than the EVM method. Substituting the parameters shown in Table2 results in $\Gamma_{EVM} = 228, 556, 830$ and $\Gamma_{prop} = 5, 808, 056$. Thus the proposed method can reduce significantly the computational complexity by 97.5%. The above assessment revealed overall advantage of the proposed AMC method based on ANN, which can achieve improved throughput performance as well as reduced computation complexity.

VI. CONCLUSION

This paper proposed the novel SNR estimation method by using ANN in AMC to improve the throughput performance in high mobility environment. The SNR estimation function was learned by using power spectral density values in a supervised manner. Once estimation function was learned, it can be installed to the communication terminals; required operation is only SNR classification based on the obtained PSD values. It can alleviate the computation burden on the receiver side. Simulation results revealed that the proposed SNR estimation method has high estimation accuracy being hardly influenced by the Doppler shift. Furthermore, we confirmed that the proposed method contributes to not only improving the throughput performance, but also reducing the computational complexity better than the conventional EVM based method.

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