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A Compressive Sensing-Based Automatic Sleep-Stage Classification System With Radial Basis Function Neural Network

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ABSTRACT This study presents an automatic sleep-stage classification system based on utilizing compressive sensing (CS) for data reduction. The amount of electroencephalogram (EEG) signal data required for sleep-stage classification can be significantly reduced by applying CS at the cost of distortion in the reconstructed EEG signal. A neural network trained on features extracted from the reconstructed EEG signal was implemented as a classifier to avoid compromising the accuracy of classification in the presence of distortion in the reconstructed EEG signal. A radial basis function (RBF) neural network that uses a simple Manhattan distance function instead of complicated computation, such as vector multiplication matrix (VMM), was selected to reduce the hardware complexity. A classification method that utilizes information from the previous sleep stage based on the unique nature of human sleep was also presented and implemented on the proposed RBF classifier for further improvement of the classification accuracy. The classification system has been evaluated using EEG data from eight subjects in the Cyclic Alternating Pattern (CAP) sleep dataset. The measurement results showed that the classification system achieved high classification accuracy comparable to the previously reported sleep-stage classifiers that do not utilize signal compression.

INDEX TERMS Compressive sensing, electroencephalogram, neural networks, radial basis function, sleep-stage classification.

I. INTRODUCTION

Presently, many people are suffering from various kinds of sleep disturbances attributed to mental stress, insomnia, and extreme work. The diagnosis and treatment of sleep disturbance require measurement of sleep stages [1], [2]. In general, polysomnography (PSG) is considered the gold standard for the classification of sleep stages. PSG is a subjective and time-consuming process because it is performed manually by experts [3], [4]. Recently, various automatic sleep-stage classification (ASSC) systems have been reported to address the subjectivity and time constraints of PSG [5]–[18]. However, ASSC systems need to acquire and process a significant amount of sleep data, including electroencephalograms (EEGs), electrooculograms (EOGs), and electromyograms (EMGs). In designing an ASSC system, the acquired data size needs to be reduced without compromising the classification accuracy.

Compressive sensing (CS) is an effective method to reduce the size of the acquired data because the original signals can be reconstructed from fewer samples than the Nyquist-rate samples by applying CS [19]–[22]. Bio-signals such as ECGs and EOGs, which are known as sparse signals, have been successfully reconstructed by CS [23], [24]. However, CS cannot be directly applied to ASSC systems, which mostly process EEG signals because of the significant difference between the original and reconstructed EEG signals owing to the lack of sparsity [25]–[27].

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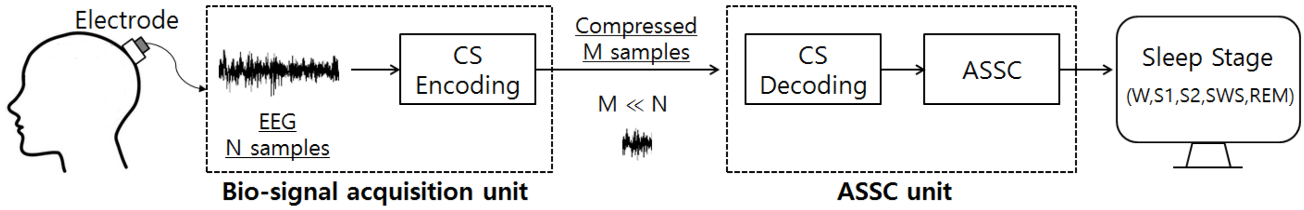

FIGURE 1. Block diagram of CS-based sleep-stage classification system.

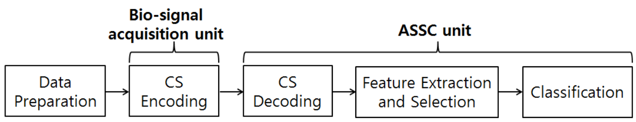

FIGURE 2. Data processing in CS-based sleep-stage classification system.

This paper presents a CS-based automatic sleep-stage classification system that utilizes a radial basis function (RBF) neural network. The proposed classification system reduces the size of the acquired EEG signals through CS and maintains the classification accuracy by employing an RBF neural network trained on features extracted from reconstructed EEG signals. To further improve the classification accuracy, a classification method that utilizes information from previously classified sleep stage is presented and its effectiveness is demonstrated through measurements.

The classification system was tested on a Cyclic Alternating Pattern (CAP) sleep dataset [28]. The test results show that the classification system achieved a classification accuracy comparable to that of the state-of-the-art classifiers [9], [11]–[13], [18], [29], [30] using only 40% of data in the dataset.

The rest of the paper is organized as follows. The proposed classification system is presented in Section II. Results are presented in Section III, and Discussion and Conclusions are presented in Section IV.

II. PROPOSED CLASSIFICATION SYSTEM

Fig. 1 shows the overall block diagram of the proposed CS-based automatic sleep-stage classification system. The system consists of two units: bio-signal acquisition and ASSC. A CS encoding block is included in the bio-signal acquisition unit. Depending on the compression ratio, this block allows reduction of EEG data transmitted to the ASSC unit. A simplified classification process implemented in this study is depicted in Fig. 2. The process involved the following steps. First, the CS encoding was performed on selected subjects from the sleep dataset. Given that CS performed signal acquisition and compression simultaneously, it reduced the number of the bio-signals transmitted from the bio-signal acquisition unit to the ASSC for classification. Next, the ASSC reconstructed the compressed bio-signals and extracted the energy features of the reconstructed bio-signals. Finally, the neural network was used for the sleep-stage classification of the subjects.

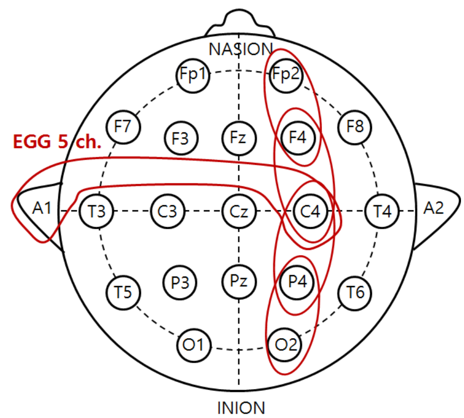

FIGURE 3. Electrode placements in ten to twenty systems for five EEG signals selected from the insomnia dataset.

A. SLEEP DATASET AND DATA PREPARATION

The CAP sleep dataset [28], which includes sleep data from people with and without diseases such as bruxism, insomnia, and narcolepsy was used to evaluate the proposed classification method. The data in the dataset, including bio-signals such as EEGs, EOGs, and EMGs, were divided into 30-s epochs. Each epoch was directly sampled from the dataset without any preprocessing and labeled as one of the seven stages (W, S1, S2, S3, S4, REM, and MT) based on the Rechtschaffen and Kales (R&K) rules.

The network for classification was trained and evaluated using data obtained from eight insomnia subjects, whose ages ranged from 47 to 82. Half of the subjects were male, and the other half were female. As shown in Fig. 3, data captured by five bipolar EEG channels (Fp2-F4, F4-C4, C4-P4, P4-O2, and C4-A1) were selected because those channels were used for all subjects. Seven sleep stages were sorted into five stages based on the American Academy of Sleep Medicine (AASM) rules. MT was excluded and S3 and S4 were merged to form slow wave sleep (SWS). Fig. 4 shows a hypnogram of the sleep cycle for the five sleep stages.

B. COMPRESSIVE SENSING: ENCODING AND DECODING

By applying CS, a sparse signal can be reconstructed from fewer signal samples than required by the Shannon–Nyquist

TABLE 1. Extracted time and frequency features.

Type	Features
Time domain	Mean, Minimum, Maximum, Variation, Standard deviation, Root mean square, Kurtosis, Skewness, Percentiles (75%)
Frequency domain	Slow delta (0.5–2Hz), Theta (3–7Hz), Alpha (7.5–12Hz), Beta1 (12–20Hz), Beta2 (20–50Hz), Sleep spindle (11.5–15Hz)

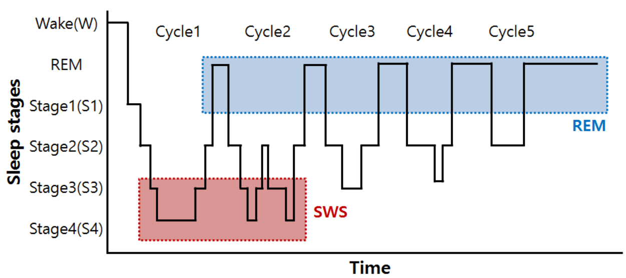

FIGURE 4. Hypnogram of sleep cycle for five stages.

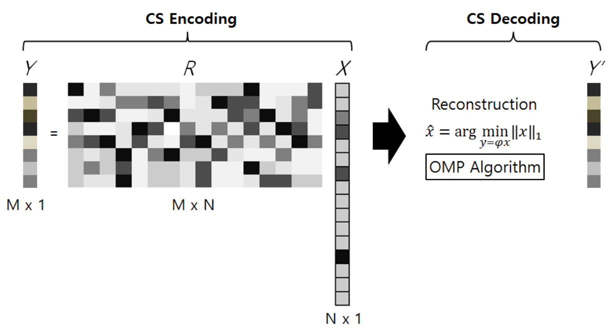

FIGURE 5. Compressive sensing encoding and decoding process.

sampling theorem. Most nonsparse signals are known to be transformed into sparse signals through various signal transformations, such as discrete wavelet transform (DWT) and discrete cosine transform (DCT). Therefore, CS can be applied to nonsparse signals provided that the sparsity of the transformed signal is guaranteed. However, owing to the lack of sparsity, a noticeable difference is reported between the original and reconstructed EEG signals [25], [27]. Although the reconstructed EEG signals cannot be directly used for signal processing, this study found that the erroneous reconstructed signal can be used for neural networks without compromising the accuracy of classification. This will be explained in the following subsections.

The CS encoding and decoding process is illustrated in Fig. 5. If the sizes of the input sample (X) and measurement matrix (R) are N and M $\times$ N, respectively, the encoded output (Y) can be obtained as follows:

$$Y = R \cdot X \tag{1}$$

In general, the size of Y (M) is smaller than that of the input (N). The compression ratio is determined as M/N. The reconstruction of Y can be performed using a reconstruction algorithm, such as orthogonal matching pursuit (OMP), L-1 norm minimization, or convex algorithms.

In this study, five-channel EEG signals (E_1, E_2, E_3, E_4, E_5) were processed by CS. Each EEG was divided into L subepochs, which were sampled at 256 Hz for 30 s. Fig. 6 illustrates the CS encoding process of one subepoch. First, a 1 $\times$ 7680 (30 $\times$ 256) subepoch (X_k) was transformed to an N $\times$ 7680/N matrix. Then, an M $\times$ N random measurement matrix (R) with binary entries (either 0 or 1) for reduction of computational load was determined. Finally, the encoded output (Y_k) was obtained by multiplying R with X_k. The size of Y_k becomes M $\times$ 7680/N. Given that input X_k with size N $\times$ 7680/N was encoded to output Y_k with size M $\times$ 7680/N, the compression ratio (CR) was determined as M/N. In this study, M and N were set to 51 and 128, respectively. Accordingly, CR was equal to 0.39.

C. FEATURE EXTRACTION AND SELECTION

Time and frequency domain features have been generally used for sleep-stage classification [31], [32]. Table 1 summarizes the time and frequency features that were initially extracted for this study. In the time domain, statistic features such as mean, minimum, maximum, variance, standard deviation, kurtosis, skewness, and percentile were extracted from each channel. In the frequency domain, the spectral power density (SPD) of each frequency band, such as delta (0.5–2 Hz), theta (3–7 Hz), alpha (7.5–12 Hz), beta1 (12–20 Hz), beta2 (20–50 Hz), and sleep spindle (11.5–15 Hz), was extracted using the Welch spectral estimation [6].

After feature extraction, the effective features for classification were identified and selected to reduce the computational burden of the classifier [33]. Sequential backward selection (SBS) [32] was used to select the features through network simulations. Based on simulation results for sleep-stage classification, 30 most effective features that are absolute and relative power spectrums for each frequency band were selected and used for classification.

D. CLASSIFICATION METHODOLOGY

Various types of neural networks, such as the Bayesian, hidden Markov model, and deep convolution, have been used for sleep-stage classification owing to their high classification accuracies. Among them, the RBF neural network [34], [35] was selected for this study because its hardware implementation is relatively simpler than that of other neural networks. Unlike most neural networks that require complicated computation, such as vector matrix multiplication (VMM),

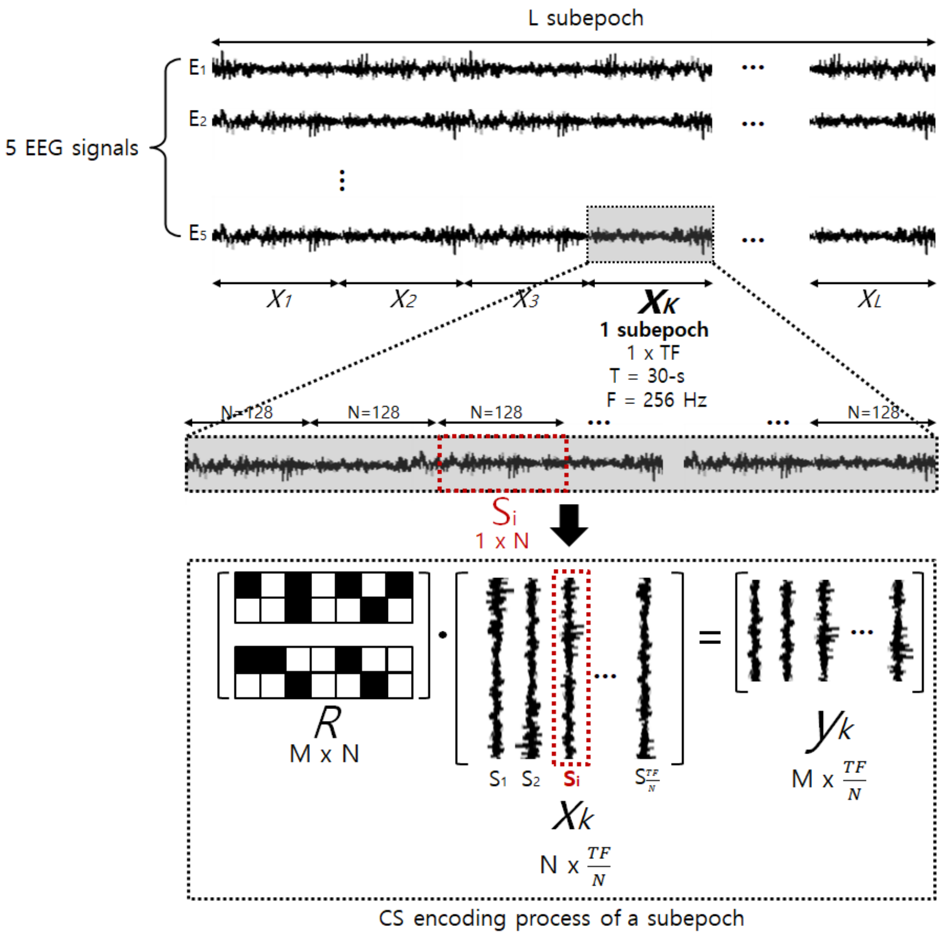

FIGURE 6. CS encoding process for a subepoch.

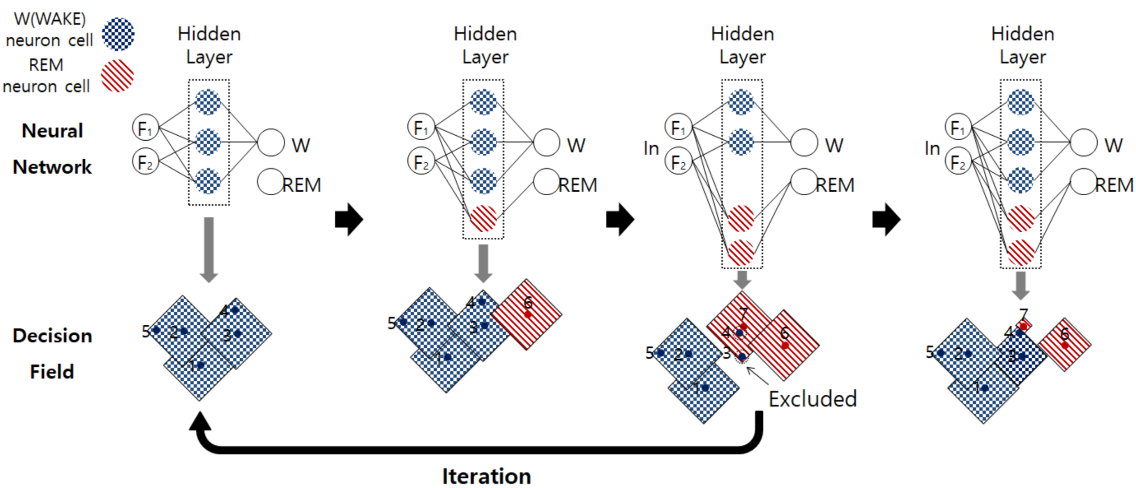

FIGURE 7. Example of simplified learning procedure of RBF neural network.

the Manhattan distance function requires only addition [36]. Hence, a significantly simplified hardware was used to determine a firing neuron in the RBF neural network.

The sleep-stage classification system was implemented with CM1K, which is similar to a field programmable gate array (FPGA) platform but only dedicated to the realization of the RBF neural network [37]. After CS encoding and decoding of EEG signals with a selected CR, one subepoch EEG was processed into 30 features through feature extraction and selection. The 30 features became an input vector for the RBF neural network, and supervised training of the network was performed using the classified sleep dataset.

The training of the RBF classifier can be explained using the example shown in Fig. 7. For simplicity, only two sleep stages (Wake and REM) are classified in the example. First, input vectors consisting of the 30 selected features were sequentially applied to the classifier and hidden neurons, which have an initial decision field, were generated. It is assumed that only 3 hidden neurons (denoted as 1, 2, and 3) were generated by the first 3 input vectors, and the 4th and 5th input vectors did not generate hidden neurons because their hidden neurons were placed inside the existing decision fields. When the 6th input vector was used to train the classifier for the other stage (REM), a hidden neuron was generated with the decision field (colored in red). A case existed where the decision fields for Wake and REM overlapped. In the example, the decision field for REM generated by the 7th input vector was overlapped by the decision fields for the 3rd and 4th input vectors. In this case, connections between the input vectors and the hidden neuron were reformed by disconnecting the 3rd and 4th input vectors and reconnecting the 7th input vector to the corresponding neuron. The training process proceeded until the final decision fields and connections were all determined by iterating the above process.

The training detail of each training iteration is illustrated in the flow chart shown in Fig. 8. Each input vector consists of 30 input neurons, clustering distance (λ_i), and sleep stage information. The value of λ_i determines the size of the decision field of a hidden neuron, and a diamond-shaped decision field is formed by using a Manhattan distance function for the sake of hardware simplicity. Initially, the first input vector generates a new hidden neuron and, starting from the second input vector, Manhattan distances (D_j) between the input vector and hidden neurons are calculated and compared with λ_i. When D_j is smaller than λ_i and the sleep stage from which the input vector is extracted is different from that of the hidden neuron, a new hidden neuron is generated, and the current hidden neuron is excluded from the hidden layer. On the contrary, a new hidden neuron is not generated when the input vector and hidden neuron belong to the same category of sleep stages. If D_j is equal to λ_i and the input vector and hidden neuron do not belong to the same sleep stage, a new hidden neuron is generated and λ_i is adjusted to be a smaller value. If D_j is larger than λ_i, a new hidden neuron is generated and the sleep stage for the new hidden neuron is specified as the sleep stage to which the input vector belongs. During network training, the number of hidden neurons continuously increased before becoming saturated, at which point the training process stopped. Fig. 9 shows a network of the classifier with its decision fields.

Notice that decision fields can be modified by being excluded and later reassigned as new ones. The centroids of

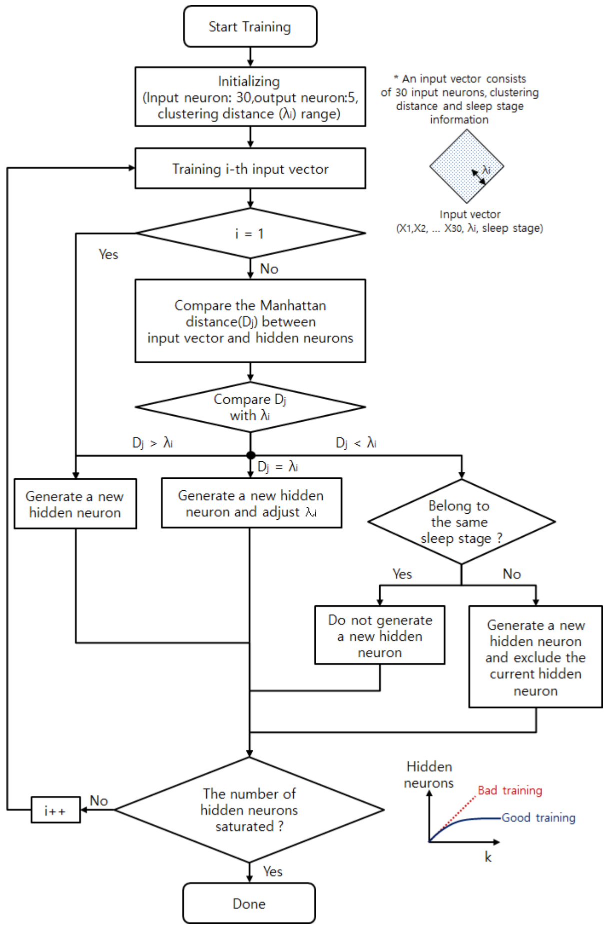

FIGURE 8. Flow chart of training process for the classifier.

the decision fields can be adjusted through this process during training iterations, as shown in Fig. 7. Once the centroids and sizes of decision fields were determined, the weights between the output and hidden neurons were calculated by the simple pseudo-inverse-matrix method [35], [36].

After the network was trained on training datasets, the decision field was formed. Next, the distance between the input vector and the center of each decision field was calculated as per the definition of the Manhattan distance. When the distance between the input vector and the trained vector was smaller than the reference distance, the corresponding neuron was fired and the sleep stage was determined based on the category of a specific neuron that had the smallest distance among the firing neurons.

To improve the accuracy of classification without increasing computational complexity, the following distinct feature of human sleep was exploited. In general, the sleep stage does not go through abrupt transition, which means that if a subject just entered the sleep stage, SWS, the subject stayed in SWS for a certain time and went up or down by one step, i.e., S2. As shown in Table 2, all subjects experienced abrupt sleep-stage transition less than 3% of the time duration while sleeping. Therefore, when the classifier calculates the distance

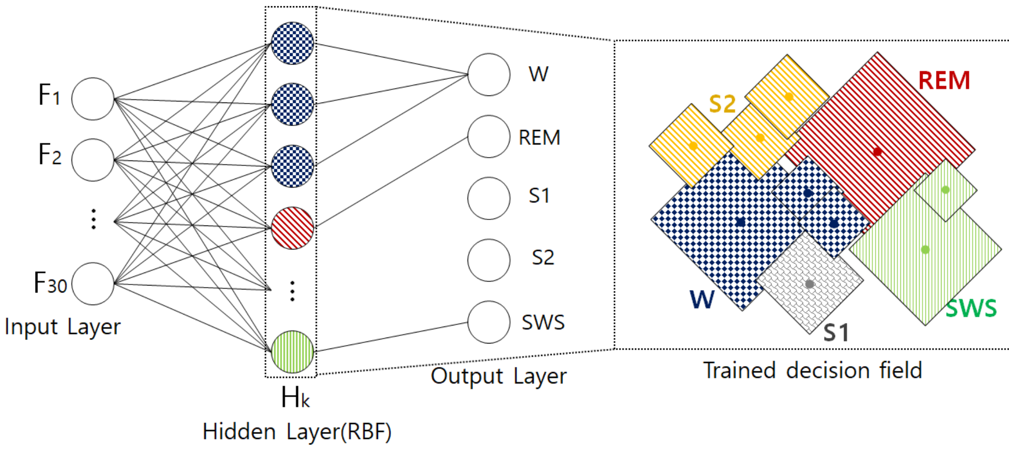

FIGURE 9. Trained decision field of sleep stages of the RBF classifier.

TABLE 2. Summary of sleep stage with abrupt transition.

	Subject1	Subject2	Subject3	Subject4	Subject5	Subject6	Subject7	Subject8
Number of epochs	1673	1673	1673	1719	1719	1719	1719	1719
Number of epochs with abrupt transition	25	33	39	29	31	21	48	25
Abrupt transition rate (%)	1.49	1.97	2.33	1.69	1.80	1.22	2.79	1.45
$\text{Abrupt transition rate} = \dfrac{\text{Number of all epochs}}{\text{Number of epochs with abrupt transition}} \times 100(\%)$								

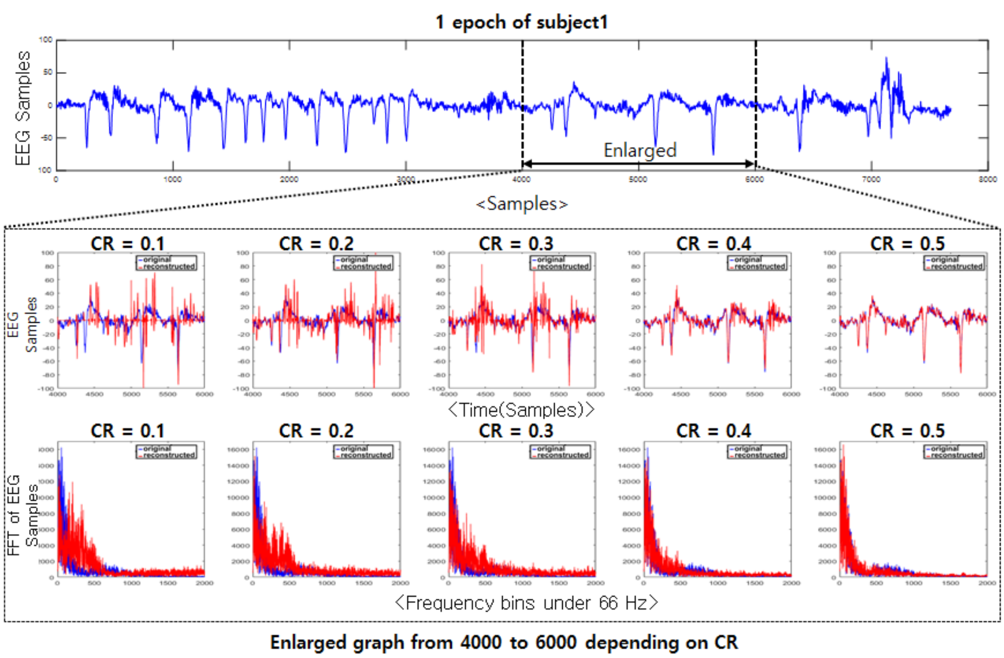

FIGURE 10. Original and reconstructed EEG signal with various CR values.

between neurons, it selects the next stage based on the current stage and calculates the distance only between the neurons belonging to the current and next stages. Furthermore, if a current neuron does not fire, i.e., it does not belong to any of the decision fields, it is considered to belong to the same stage as the previous neuron's stage. As a result, the classification

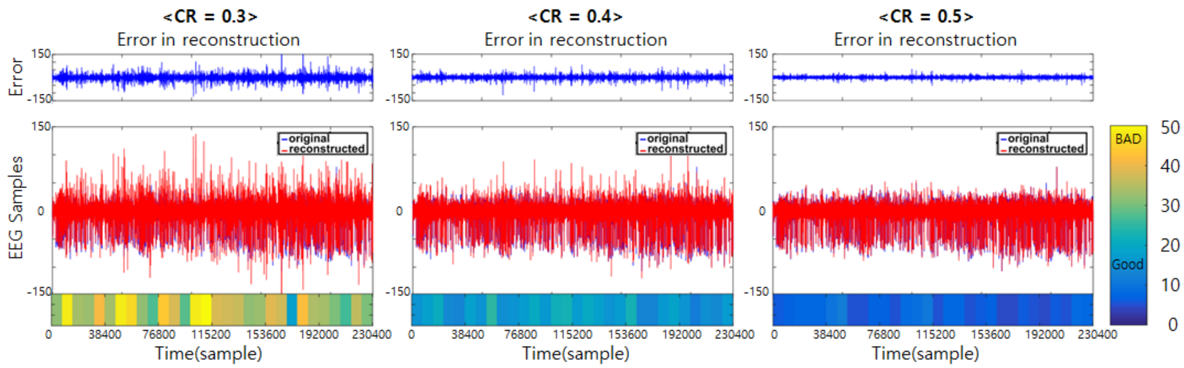

FIGURE 11. EEG samples (error) of 30 epoch and corresponding PRD for each window.

TABLE 3. Confusion matrix for the RBF classifier without using the proposed classification method.

	Wake	REM	S1	S2	SWS	Classification Acc. (%)
Wake	5429	43	3	13	1	98.91
REM	53	1407	45	10	0	92.87
S1	26	35	101	69	1	43.53
S2	5	21	74	2803	194	90.51
SWS	0	0	0	181	1182	86.72
Overall classification accuracy (%) : 79.33						

TABLE 4. Confusion matrix for the RBF classifier with using the proposed classification method.

	Wake	REM	S1	S2	SWS	Classification Acc. (%)
Wake	5813	50	19	58	10	97.70
REM	56	1729	43	45	1	92.26
S1	58	47	211	79	2	53.15
S2	36	34	102	3511	213	90.12
SWS	0	0	0	179	1318	88.04
Overall classification accuracy (%) : 92.42						

accuracy of the classifier improved by almost 13% without increasing computational complexity.

In this study, the evaluation of the RBF classifier was performed using the CAP sleep dataset. Datasets of each subject were divided into 10 groups to apply ten-fold cross-validation (CV). While one group was used to train the network, the other groups were used as test datasets, and the evaluation proceeded until all 10 groups changed their roles. The whole evaluation process was repeated multiple times with and without CS encoding and decoding of datasets. The evaluation results were presented in the Section III.

III. RESULTS

To evaluate the proposed classification method, which improves the classification accuracy by utilizing the previous sleep-stage information, the RBF classifier was tested with and without applying the proposed method. Tables 3 and 4

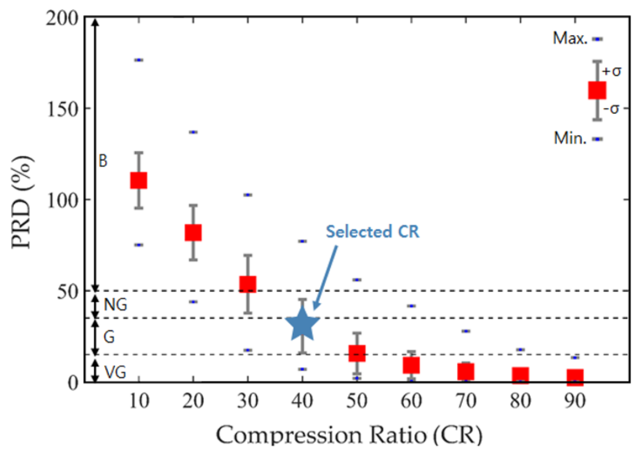

FIGURE 12. Output PRD for all subjects depending on CR after CS.

summarize the measurement results without and with using the proposed method, respectively. The tables show that classification accuracy improved by approximately 13% with the classification method.

In this study, a binary measurement matrix [38] and the OMP reconstruction method [39] were used for CS encoding and decoding, respectively. Fig. 10 shows the CS encoded and reconstructed EEG samples of subject 1. The distortion of the reconstructed signal becomes larger as CR decreases. To measure the quality of the reconstructed signal, the percentage root-mean-square difference (PRD) was calculated as follows:

$$PRD = \frac{||X - X'||2}{||X||2} \times 100 \tag{2}$$

where X and X' denote original and reconstructed signals, respectively. According to previous studies [24], [40], the quality of a reconstructed signal is often categorized based on PRD values. For example, reconstructed signals whose PRD values are less than 15, 15–35, 35–50, and greater than 50 can be considered as very good (VG), good (G), not good (NG), and bad (B), respectively [40]. Fig. 11 shows a comparison of the PRD of an EEG signal in the dataset depending on the CR. As the CR becomes smaller beyond 0.4, the reconstructed signal changes its state from G to B. Fig. 12

TABLE 5. Confusion matrix for the CS-based RBF classifier with a CR of 0.4.

	Wake	REM	S1	S2	SWS	Classification Acc. (%)
Wake	5584	66	257	42	1	93.85
REM	34	1659	106	74	1	88.53
S1	46	38	297	16	0	74.81
S2	95	234	218	3059	290	78.52
SWS	6	0	5	105	1381	92.25
Overall classification accuracy (%) : 88						

TABLE 6. Comparison of the proposed system with previously published sleep-stage classification systems.

Ref. Year	Signal Type	Stage No.	Feature No.	Method	Subject No.	Acc.(%)
2010 [29]	EEG + EOG + EMG	4	5	Genetic fuzzy classifier	4	84.6
2010 [12]	EEG + EOG + EMG	5	13	Discrete hidden Markov model	20	85.3
2013 [11]	1 EEG	5	6	Elman recurrent neural classifier	8	87.2
2016 [30]	1 EEG	6	8	Complex-valued neural networks	8	93.8
2018 [13]	EEG +FLOW +EMG	3	12	Bayesian neural network classifier	184	89.6
2018 [18]	1 EEG	5	30	HyCLASSS	198	85.6
2019 [9]	1 EEG	5	-	State-space model	-	92.3
Proposed	5 EEG	5	30	CS based RBF neural network	8	88

shows the averaged output PRD for all subjects depending on a CR. Based on network simulations, a CR of 0.4 was selected for the evaluation of the classifier because even when the classification accuracy dropped to less than 5% the classifier still achieved an overall classification accuracy comparable to those of the previous works [9], [11]–[13], [18], [29], [30].

Unlike bio-signals such as ECG and EOG, which maintain a small PRD after CS reconstruction, the PRD of an EEG signal is relatively large owing to the lack of signal sparsity. As discussed in the preceding section, the RBF classifier achieved a high classification accuracy through network training even with a high PRD signal. Tables 4 and 5 present the measured confusion matrix with and without CS decoding and encoding of EEG signals. The data in the tables show that the overall classification accuracy of the RBF classifier with a CR of 0.4 dropped from 92.42% to 88% only by approximately 4.42%. This accuracy is comparable to that of the previously published sleep-stage classifiers that do not utilize signal compression. Table 6 summarizes the previous works and compares their results with the results of this study.

TABLE 7. Comparison of performance parameters for various ASSC implementations.

Specifications	Software-based implementation (GPU/CPU) ([8], [18])	Hardware-based implementation	
		Without data compression or CS ([43], [44])	With CS (This study)
Energy efficiency	Low	Medium	High
Accuracy	High	Medium	Medium
Cost	High	Low	Low
Flexibility	High	Low	Low
Speed	Low	High	High

It is worth discussing that the degradation of the classification accuracy with CS is mainly caused by misclassification of S2. The main reason can be explained as follow. The distinct features of S2 are low-frequency activities and sigma oscillation whose frequency band ranges from 11.5 to 15 Hz, which are, respectively, known as sleep spindle and K-complex [41]. Although low-frequency components are well reconstructed from the original EEG signals, frequency components generated from the sleep spindle activity are severely distorted after CS reconstruction, as shown in Fig. 10. As a result, S2 is often misclassified as other sleep stages, which causes degradation of the overall classification accuracy.

Another noticeable difference between Tables 4 and 5 is an approximately 20% improvement in S1 classification accuracy. This can be partly explained by the fact that relatively low-frequency featured activities such as theta, slow-eye movement, and vertex sharp-wave of S1 are well maintained after CS reconstruction. However, the accuracy of S1 has little impact on the overall classification accuracy [42], because the total number of data epochs for S1 is approximately 5–10 times smaller than that of other stages.

IV. DISCUSSION AND CONCLUSION

An ASSC system utilizing CS encoding and decoding has been presented in this study. In the proposed system, the acquired EEG signals are reduced by applying CS encoding and later reconstructed for classification. The reconstructed EEG signal was shown to exhibit significant distortion, which depended on the CR. To avoid compromising the accuracy of classification in the presence of signal distortion, a neural network trained on features extracted from the reconstructed EEG signal was implemented as a classifier. An RBF neural network, which utilized a simple Manhattan distance function for firing neurons instead of complicated computation such as VMM, was used to reduce hardware complexity. To improve the classification accuracy further, a classification method that utilizes information from the previous sleep stage based on distinct features of human sleep has been proposed and implemented on the RBF classifier.

The classification system was tested with five-channel EEG signal data of eight subjects from the CAP sleep dataset. The measurement results show that the proposed classification system achieved high classification accuracy despite having a CR of 0.4, which is comparable to the state-of-the-art sleep-stage classifiers that do not utilize signal compression.

Table 7 shows a comparison of the existing ASSC implementations with that in this study in terms of performance specifications such as energy efficiency, accuracy, cost, flexibility, and speed. Although software-based implementations utilizing a graphic processing unit (GPU) or central processing unit (CPU) [8], [18] can achieve high classification accuracy and flexibility to be adapted to a variety of applications at the cost of classification speed and energy efficiency, the FPGA or application-specific integrated circuit (ASIC) implementations [43], [44] in this study are appropriate for high-speed and energy-efficient applications that require moderate classification accuracy. Furthermore, additional energy efficiency can be achieved by data compression used in this study.

The previous studies on CS implementations have mainly focused on how to increase the reconstruction rate. The studies on ASSC systems have tried to improve the classification accuracy by utilizing neural networks without considering the increased hardware complexity. The proposed method uses data reduction. Furthermore, the complexity of the system minimized by applying CS. It was proven that, instead of using system resources to improve the quality of reconstructed EEG signals, the classification accuracy can be maintained by training an RBF network on distorted EEG signals. The ASSC system can be used for basic science researches or an early examination of sleep disorder patients. Further improvement in the accuracy of classification, particularly for the S2 sleep stage, is required for the clinical use of the proposed method by experts. Because only the CAP sleep dataset was used for the evaluation of the ASSC, additional evaluation by other datasets might be helpful for improving the reliability of the test results [45], [46].

The hardware implementation of the ASSC system will need to be optimized so that system can be embedded in a handheld portable device. The feature extraction method needs to be further simplified, and the number of channels for EEG acquisition needs to be minimized without compromising the accuracy of classification [47]–[50]. Various feature-extraction methods together with CS reconstruction algorithms should be studied, including developing new ones, for this purpose.

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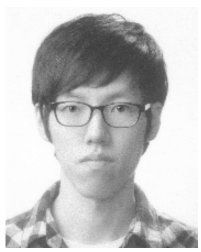

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