This full text paper was peer-reviewed at the direction of IEEE Instrumentation and Measurement Society prior to the acceptance and publication.

2022 IEEE International Instrumentation and Measurement Technology Conference (I2MTC) | 978-1-6654-8360-5/22/$31.00 ©2022 IEEE | DOI: 10.1109/I2MTC48687.2022.9806696

Hierarchical Spectral-Temporal Feature Learning for Motor Task Recognition in Brain Computer Interfaces

Hamidreza Sadreazami †, Yaser Mohammad-Taheri ‡ and Marzieh Amini *
†Bioengineering Department, McGill University, Montreal, QC, Canada
‡Department of Electrical and Computer Engineering, Concordia University, Montreal, QC, Canada
*School of Information Technology, Carleton University, Ottawa, ON, Canada

***Abstract*—Feature extraction is an indispensable step in classification of electroencephalography (EEG) signals for motor task recognition. This paper proposes a novel method for motor imagery brain-computer interface (BCI) EEG signals classification based on spectral-temporal common spatial patterns feature extraction and deep convolutional neural network. Unlike other existing methods, the proposed method is built upon both frequency and time domain features of the EEG signals. These features are used as input to the proposed convolutional neural network for a higher level feature extraction and classification. The proposed network is comprised of convolutional and fully-connected layers to hierarchically learn the saliency in the signal. Several experiments are conducted on standard datasets taken from BCI competitions to assess the performance of the proposed method and to compare it with those of the other existing methods. The results exhibit a significant improvement in classification accuracy for a number of subjects when using the proposed method.**

***Index Terms*—Feature learning, convolutional neural network, task recognition, MI-BCI, EEG signal.**

I. Introduction

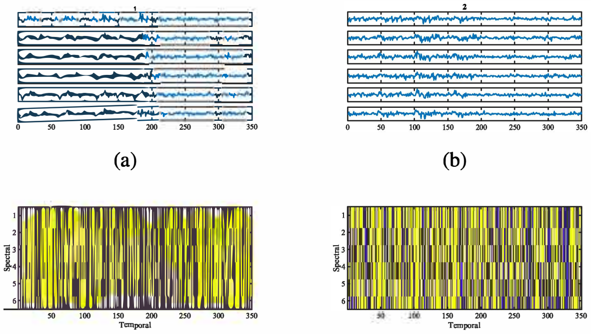
A motor imagery brain computer interface (MI-BCI) system points to the task of discriminating the motor imagery of different movements [1] such as moving a mouse cursor on a monitor to different directions, only by imagining hand movements. The goal of such system is to realize a patient-friendly neuro-rehabilitation [2] by establishing efficient and accurate algorithms to translate brain activities. The electroencephalogram (EEG) signals have commonly been used to analyze the brain activities in MI-BCI systems as these signals are able to detect changes in brain's electrical activities. To handle the poor spatial resolution of the EEG signals [3], many studies have investigated feature extraction techniques based on the common spatial patterns (CSP) [4], where the spectral characteristics of the EEG signals have been considered for class prediction. However, EEG signals are known to have complex patterns with high variability. Thus, manually extracting a limited number of features from EEG signals is not an optimal solution for detecting their salient patterns. In order to develop automated approaches and realize optimal feature extraction, deep learning based methods have widely been introduced [5], [6], to investigate if higher-level features from MI-BCI EEG signals can be learned via hierarchical nonlinear mappings. In [5]–[7], time or frequency domain features of the EEG signals were used as input to convolutional neural networks. In [8] and [9], the EEG signals in the time domain were analyzed using deep belief networks. In [10], a restricted Boltzmann machine was studied as an alternative to supervised approaches to cluster the EEG signals. In [11], an approach for EEG signal classification was proposed in the time domain using a long short-term memory network. In [12], a semi-supervised deep stacking network was proposed for EEG classification by incorporating the contrastive divergence algorithm with an adaptive learning rate. In [13], a residual network was proposed to classify EEG signals in the time-frequency domain. In [14], a capsule network was proposed to process EEG signals and distinguish different motor tasks. However, none of the above works have addressed the binary EEG classification problem through mapping the specially-filtered EEG signals into image representation and a convolutional neural network for hierarchical feature learning.

In view of this and to improve the recognition accuracy of the EEG signals in MI-BCI systems, a new method based on spectral-temporal common spatial patterns and convolutional neural network is proposed in this work. What differentiates the proposed method from the existing works is a joint feature extraction strategy. First, the proposed spectral-temporal common spatial patterns (STCSP) feature extraction captures the time-frequency information from EEG signals. In other words, unlike the existing CSP-based works where the log-variances of the filtered signals were used as input features to a classifier, the STCSP features are extracted from the EEG signals and converted into image representation by keeping their temporal resolution unchanged. Then, a customized convolutional neural network captures high-level features from the STCSP image representations. The proposed network leverages the convolutional neural network, which has demonstrated its advantages to capture complex mappings learned from labeled data, and fully-connected layers, which has smoothly conveyed the discriminative features to the output layer and captured the saliency in the EEG signals. Several experiments are conducted using the standard data sets taken from BCI competitions III and IV to validate the proposed method.

II. Proposed Method

In this work, motor task recognition from the EEG signals is studied. The EEG experiments set is denoted as $\mathbf{X}_i \in$

978-1-6654-8360-5/22/$31.00 ©2022 IEEE



(a) (b) (c) (d)

Fig. 1. (a)-(b) Two class samples of STCSP features obtained from AW subject in dataset 1 and (c)-(d) their corresponding image representations.

$\mathbb{R}^{N_{ch}\times N_t}$, for $(1 \leq i \leq N_{tr})$, where N_{tr} denotes the number of experiments; $\mathbb{R}$ represents the real domain, N_{ch} is the number of sensors, and N_t is the number of time samples collected from each sensor in an experiment. The training dataset is denoted by $\{(\mathbf{X}_i, l_i)\}$, for $(1 \leq i \leq N_{tr})$, where l_i represents the label corresponding to the ith trial.

Common spatial pattern identifies a linear subspace to maximize the variance of one class and minimize the variance of the other class [4], e.g., in the case of hand or foot movement recognition. In order to extract the STCSP features from the EEG signals, optimal spatial filters are first obtained through joint diagonalization of the two covariance matrices correspond to the two classes. The normalized covariance matrix $\mathbf{R}$ for each trial of the EEG signal $\mathbf{X}_i$, is determined as $\mathbf{R} = \frac{\mathbf{X}_i\mathbf{X}_i^T}{trace(\mathbf{X}_i\mathbf{X}_i^T)}$, where *trace* of a matrix gives the sum of the elements on the main diagonal. The covariance matrices $\mathbf{R}_a$ and $\mathbf{R}_b$ of the two classes a and b are summed up to a new covariance matrix $\mathbf{R}_c$. This matrix is then decomposed into a set of eigenvectors $\mathbf{B}_c$ and eigenvalues $\boldsymbol{\lambda}_c$, i.e., $\mathbf{R}_c = \mathbf{B}_c\boldsymbol{\lambda}_c\mathbf{B}^T$. This decomposition yields a whitening transform given by $\mathbf{W} = \boldsymbol{\lambda}_c^{-1/2}\mathbf{B}_c^T$, and used to transform $\mathbf{R}_a$ and $\mathbf{R}_b$ into a set of eigenvectors $\mathbf{U}$ and their corresponding diagonal matrices of eigenvalues $\boldsymbol{\psi}_a$ and $\boldsymbol{\psi}_b$. The eigenvectors $\mathbf{U} = (U_1, ..., U_{N_{ch}})$ are sorted in a descending order with respect to the eigenvalues in $\boldsymbol{\psi}_a = (\psi_{a,1}, \psi_{a,2}, ..., \psi_{a,N_{ch}})$, $\psi_{a,1} \geq ... \geq \psi_{a,N_{ch}}$ and in a ascending order with respect to $\boldsymbol{\psi}_b = (\psi_{b,1}, \psi_{b,2}, ..., \psi_{b,N_{ch}})$, $\psi_{b,1} \leq ... \leq \psi_{b,N_{ch}}$. It is noted that only $m = 3$ eigenvectors are selected to build the projection matrix, i.e., $\mathbf{U}^* = (U_1, ..., U_m; U_{N_{ch}-m+1}, ..., U_{N_{ch}})$, as suggested in [15]. The corresponding projection matrix is given by

$$\mathbf{P} = \mathbf{U}^*\mathbf{W}, \tag{1}$$

which is used to map each EEG trial $\mathbf{X}_i$ as $\mathbf{Z}_i = \mathbf{P}\mathbf{X}_i$. Unlike the commonly-used CSP techniques where the features are obtained by taking the logarithm of the variance of $\mathbf{Z}_i$, the proposed method is based on spectral and temporal CSP features of the EEG signals. In other words, the filtered EEG signals are projected onto image representation and the temporal resolution of $\mathbf{Z}_i$ are kept unchanged, shown in Fig. 1, resulting in STCSP features having both the frequency and time resolutions, i.e., the dimension of $\mathbf{Z}_i$ is $2m \times N_t$. Fig. 1 shows two examples of STCSP features and their corresponding images for right hand/right foot classes from AW subject in dataset 1, discussed in Section III. In the proposed MI-BCI EEG signal classification method, the convolutional neural network is applied to STCSP image representations to extract features from the filtered signals. Table I gives the configuration of the proposed network. The STCSP image representations $\mathbf{Z}$ are used as input to the proposed network. The feature map $\mathbf{Z}^{c_i}$ of each convolutional layer c_i is obtained as

TABLE I
CONFIGURATION OF THE PROPOSED DEEP NEURAL NETWORK.

Layer	Layer type	Filter shape	Output shape
0	Input	-	$[N_{tr}$, 6, 350, 1]
1	Convolutional	32×[2, 2]	$[N_{tr}$, 6, 350, 32]
2	Pooling	[2, 2]	$[N_{tr}$, 3, 175, 32]
3	Convolutional	64×[2, 2]	$[N_{tr}$, 3, 175, 64]
4	Pooling	[2, 2]	$[N_{tr}$, 2, 88, 64]
5	Deep-FC	-	[10]
6	Softmax	-	[2]

$$\mathbf{Z}^{c_i} = \text{ReLU}\left(\mathbf{Z}^{c_{i-1}} * \mathbf{K}^{c_i} + \mathbf{b}^{c_i}\right), \tag{2}$$

where $*$ is the convolutional operator, c denotes the layer index, $\mathbf{K}$ and $\mathbf{b}$ denote filters and biases, respectively, and rectified linear unit activation function (ReLU) is defined as $f(x) = \max(0, x)$. First, in convolutional layer c_1, 32 filters $\{k_j^{c_1}\}_{j=1}^{32}$ of size 2×2, are convolved with the input images with stride 1. After applying an activation function, the feature map is $\mathbf{Z}^{c_1}$ having a depth of 32. To lower the dimensionality of the convolved extracted features, a non-overlapping 2×2 max-pooling layer p_1 is employed after each convolution layer. The max-pooling operation is performed by obtaining the maximum value of features within a specified mask in the preceding layer. Next, in convolution layer c_2, the feature map of the previous pooling layer $\mathbf{Z}^{c_1}$, is convolved with 64 filters $\{k_j^{c_2}\}_{j=1}^{64}$ of size 2×2 with stride 1. Applying ReLU and max-pooling will result in $\mathbf{Z}^{c_2}$ feature map having a depth of 64. This feature map is flattened into a 1D vector and used as an input to the fully-connected layers having 1000, 300, 200, 50, 10 neurons to smoothly decrease the dimensionality of the feature maps, and one output layer for class prediction. The softmax function is used for classification of the bottleneck features. Having the true labels of the EEG signals l_i and probabilistic outcomes h_i^v, softmax cross-entropy cost function L is defined as [16], [17]

$$L = -\frac{1}{N_{tr}}\sum_{i=1}^{N_{tr}}\sum_{v=0}^{1} I(l_i = v)log(h_i^v), \tag{3}$$

where $I(.)$ is the indicator function. The optimal value for drop-out factor [18] was experimentally found to be $p = 0.7$, i.e., 70% of the neurons were randomly selected in each layer during training and the rest are discarded. Also, The Adam

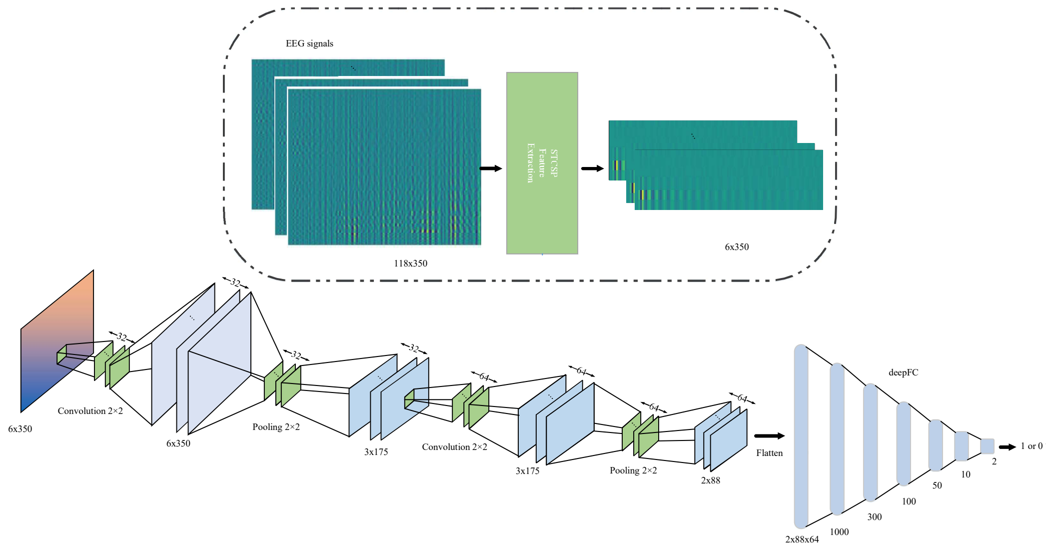


Fig. 2. Schematic of the proposed MI-BCI EEG signals classification method; STCSP feature extraction as well as deep neural network architecture.

TABLE II
DATA SETS UNDER STUDY FOR PERFORMANCE EVALUATION OF THE PROPOSED METHOD.

	Dataset 1					Dataset 2
Subject	AA	AL	AV	AW	AY	C1-C9
Trials	280	280	280	280	280	288
Training set	168	224	84	56	28	144
Testing set	112	56	196	224	252	144

optimizer [19] was used in the learning process and the batch normalization [20] was employed to normalize the data in all the mini-batches at each layer. These lead to a faster learning in the network and higher overall accuracy. Fig. 2 demonstrates the schematic of the proposed network for feature extraction and classification of the EEG signals.

III. RESULTS AND DISCUSSION

In this section, the results obtained using the proposed MI-BCI EEG signals classification method are presented.

Table II gives information about the subjects and the number of experiments. For comparison purpose, we used EEG signals from two publicly available data sets of BCI competitions. These data sets were collected when the subjects performed a classical MI, i.e., imagination of limbs movements, including:

1) *Data set IVa, BCI competition III*, which is comprised of EEG signals from 5 subjects, namely, AA, AL, AV, AW and AY, performing 280 experiments of right hand and right foot MIs. This dataset includes EEG recordings of 118 sensors.

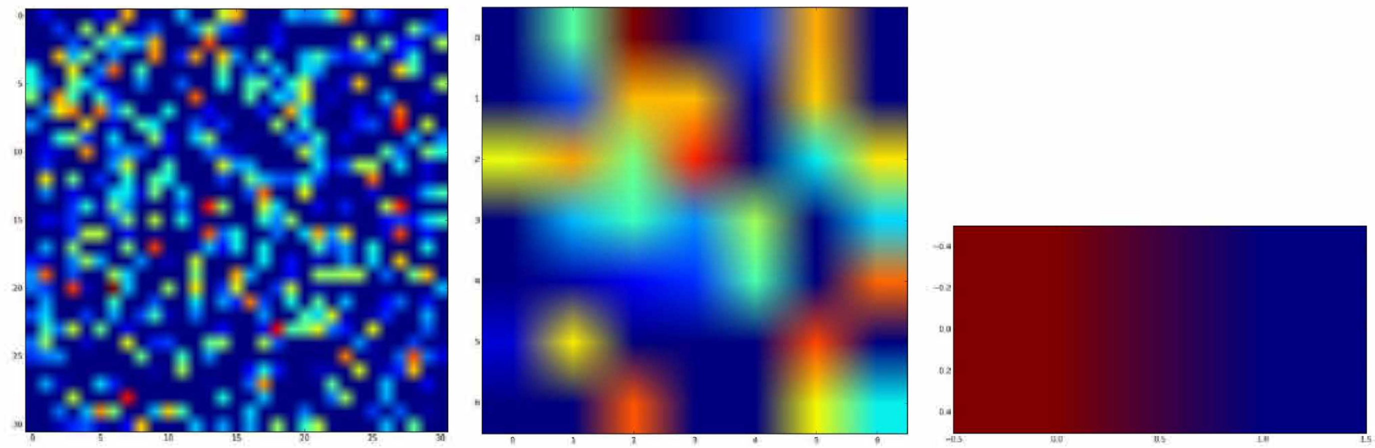
2) *Data set IIa, BCI competition IV*, which is comprised of EEG signals from 9 subjects, C1-C9, performing 288 experiments of left hand, right hand, foot and tongue MIs. This dataset includes EEG recordings of 22 sensors. In this work, only EEG signals corresponding to left and right hand MI were used.

TABLE III
CLASSIFICATION ACCURACY OBTAINED USING DIFFERENT METHOD ON DATASET 1. (BEST RESULTS ARE SHOWN IN BOLD AND THE SECOND BEST IN PARENTHESIS)

	AA	AL	AV	AW	AY
SCSP [3]	80.71	97.14	57.14	85	91.42
RCSP-Res [13]	**94.64**	(97.50)	**83.57**	89.64	(93.21)
DTMKL [21]	91.07	94.64	71.94	82.59	88.89
SBRCSP [22]	86.61	**98.21**	63.78	89.05	77.78
LRCSP [23]	79.46	**98.21**	72.45	87.95	87.7
DA-WNN [24]	86.7	90.8	(82.5)	78.3	87.5
SSRCSP [26]	70.54	96.43	53.57	71.88	75.39
SBCSP [27]	83.03	**98.21**	52.04	89.05	58.33
FBCSP [28]	83.93	96.43	63.26	72.32	54.37
LRDS [29]	80.4	94.6	50.0	(90.6)	83.3
Proposed	(92.85)	**98.21**	80.35	**94.64**	**96.42**

The proposed convolutional neural network realizes an automatic feature extraction and classification of the STCSP image representations. In order to understand how fully-connected layers evolve feature maps, the first and third fully-connected layers as well as the output layer are illustrated in Fig. 3. It is seen from this figure that through the layers the activations of STCSP signals become more abstract and carry less information about their visual contents and increasingly more information related to the class of the image.

The proposed STCSP based method is compared to some of the state-of-the-art methods in motor task recognition. Tables III and IV give classification accuracies of different methods, for subjects given in Table II, in a 5-fold cross-validation. It can be seen from these tables that the proposed method provides a



(a) (b) (c)

Fig. 3. Activations of (a)-(b) the first and third fully-connected layers, and (d) output layer, for one sample STCSP signal from AW subject in Dataset 1.

classification accuracy which is higher than the other methods on different datasets. This improved performance in motor task recognition is attributed to a two-stage feature extraction strategy, where the spectral and temporal domain features were first extracted and converted to an image representation, and then a hierarchical feature extraction was used based on the proposed convolutional neural network. From Table III, it is seen that the proposed method outperforms DTMKL [21], SBRCSP [22], LRCSP [23] and DA-WNN [24] on Dataset 1 with an average motor task recognition improvement of 7% over all the subjects. It is also seen that the proposed method provides classification accuracies higher than those of RCSP-Res [13] for AL, AW and AY subjects. In addition, on Dataset 2, the proposed method shows superior performance to other methods in most of the subjects under study. As compared to [25], [3], [12] and [11] with average classification accuracies of 79.89, 81.63, 83.54 and 76.49, respectively, the proposed MI-BCI EEG signal classification method provides an average classification accuracy of 84.55. It is noticeable that the SADSN [12] and AX-LSTM [11] perform considerably well on subjects C4-C6, while the proposed method provides a higher accuracy on the other subjects.

It is to be noted that more advanced CSP-based methods could be used in the first stage for extracting features. However, the work aimed to show that (1) how preserving time and frequency resolutions in CSP method can improve the recognition performance, and (2) the effectiveness of the proposed convolutional neural network for high-level feature extraction and classification. The classification accuracy may be further improved by careful choice of CSP-based filters for different time segments or frequency bands of the EEG trials.

In the case of drop-out, it was observed that for some subjects like AV and AA in Dataset 1, increasing the value of p, may result in higher recognition accuracies. However, for the sake of a fair comparison, subject-specific hyper-parameter selection was avoided and the experiments were conducted with fixed values.

TABLE IV
CLASSIFICATION ACCURACY OBTAINED USING DIFFERENT METHODS ON DATASET 2.

	C1	C2	C3	C4	C5	C6	C7	C8	C9
SCSP [3]	91.66	67.36	(97.91)	72.22	65.27	66.67	(84.72)	**97.22**	91.66
FDBN [10]	71.08	55.56	76.87	65.62	69.08	64.98	71.68	92.37	82.38
AX-LSTM [11]	75.12	**71.38**	72.24	72.91	(82.62)	69.64	**87.84**	80.28	75.05
SADSN [12]	77.14	68.57	72.43	**97.13**	**86.56**	**88.57**	78.57	(95.71)	87.19
TIS [25]	(95.3)	66	**98.2**	66	68.9	69.8	68.9	93.4	(92.5)
SSRCSP [26]	88.89	53.47	97.22	70.14	56.25	68.75	79.17	**97.22**	90.28
HSS-ELM [30]	81.14	49.86	78.02	63.33	44.03	49.44	81.11	81.49	81.38
FFTEM [31]	68.72	54.97	69.08	55.07	72.66	60.61	70.13	83.49	83.14
Proposed	**95.48**	(69.80)	**98.2**	(72.91)	71.53	(73.95)	**87.84**	**97.22**	**94.01**

IV. Conclusion

In this work, a new method for MI-BCI EEG signal classification was proposed. The proposed method was realized by developing two stages of feature extraction based on spectral-temporal common spatial patterns and convolutional neural network. In the first stage, discriminant spectral and temporal features were extracted from the EEG signals resulted in STCSP features. The STCSP features were obtained by preserving both the frequency and time domain features of the EEG signals and using them as input to the convolutional neural network for the second stage feature extraction and classification purposes. The proposed network was constructed by stacking convolutional and fully-connected layers to smooth the feature learning process and reduce the dimensionality of the feature map. It was shown that the proposed method provides a superior performance as compared to other existing methods in terms of recognition accuracy for a binary classification problem. The higher classification values of the proposed method can be attributed to the fact that unlike the other approaches, the proposed method constructs the STCSP features and relies on high-level feature extraction using convolutional neural network.

References

[1] G. Kalantar, H. Sadreazami, A. Mohammadi and A. Asif, "Adaptive dimensionality reduction method using graph-based spectral decomposition for motor imagery-based brain-computer interface," in *Proc. IEEE Global Conf. on Signal and Info. Process. (GlobalSIP),* pp. 990-994, 2017.

[2] S.-H. Park, D. Lee and S.-G. Lee,"Filter bank regularized common spatial pattern ensemble for small sample motor imagery classification," *IEEE Trans. on Neural Sys. and Rehab. Eng.,* vol. 26, no. 2, pp. 498-505, 2018.

[3] M. Arvaneh, C. Guan, K. K. Ang and C. Quek, "Optimizing the channel selection and classification accuracy in EEG-based BCI," *IEEE Trans. on Biomed. Eng.,* vol. 58, no. 6, pp. 1865-1873, 2011.

[4] H. Ramoser, J. Muller-Gerking and G. Pfurtscheller, "Optimal spatial filtering of single trial EEG during imagined hand movement", *IEEE Trans. on Rehab. Eng.*, vol. 8, no. 4, pp. 441-446, 2000.

[5] S. Sakhavi, C. Guan and Sh. Yan, "Learning temporal information for brain-computer interface using convolutional neural networks," to appear in *IEEE Trans. on Biomed. Eng.,* vol. 29, no. 11, pp. 5619-5629, 2018.

[6] P. Bashivan, I. Rish, M. Yeasin and N. Codella, "Learning representations from EEG with deep recurrent-convolutional neural networks," in *Proc. Int. Conf. on Learning Representations (ICLR),* 2016.

[7] V. J. Lawhern, A. J. Solon, N. R. Waytowich, S. M. Gordon, C. P. Hung and B. J. Lance, "EEGNet: A compact convolutional network for EEG-based BCIs," *J. of Neural Eng.,* vol. 15, no. 5, pp. 056013, 2018.

[8] D. F. Wulsin, J. R. Gupta, R. Mani, J. A. Blanco and B. Litt, "Modeling EEG waveforms with semi-supervised DBNs: fast classification and anomaly measurement," *J. of Neural Eng.,* vol. 8, no. 3, pp. 1-28, 2011.

[9] S. M. Plis, D. R. Hjelm, R. Salakhutdinov, E. A. Allen, H. J. Bockholt, J. D. Long, H. J. Johnson, J. S. Paulsen, J. A. Turner and V. D. Calhoun, "Deep learning for neuroimaging: a validation study," *Frontiers in Neuroscience,* vol. 8, pp. 1-11, 2014.

[10] N. Lu, T. Li, X. Ren and H. Miao, "A deep learning scheme for motor imagery classification based on restricted Boltzmann machines," *IEEE Trans. on Neural Sys. and Rehab. Eng.*, vol. 25, no. 6, pp. 566-576, 2017.

[11] P. Wang, A. Jiang, X. Liu, J. Shang and L. Zhang, "LSTM-based EEG classification in motor imagery tasks," *IEEE Trans. on Neural Systems and Rehab. Eng.,* vol. 26, no. 11, 2018.

[12] X. L. Tang, W. C. Ma, D. S. Kong and W. Li, "Semi-supervised deep stacking network with adaptive learning rate strategy for motor imagery EEG recognition," *Neural Comput.,* vol. 31, no. 5, pp. 919-942, 2019.

[13] H. Sadreazami, and G. D. Mitsis, "Motor task learning in brain computer interfaces using time-dependent regularized common spatial patterns and residual networks", in *Proc. IEEE International New Circuits and Systems Conference (NEWCAS)*, pp. 190-193, 2020.

[14] H. Sadreazami, M. Amini, M. Omair Ahmad and M. N. S. Swamy, "EEGCAPS: Brain activity recognition using modified common spatial patterns and capsule network", in *Proc. IEEE International Symposium on Circuits and Systems (ISCAS)*, pp. 1-4, 2021.

[15] B. Blankertz, R. Tomioka, S. Lemm, M. Kawanabe and K. Muller, "Optimizing spatial filters for robust EEG single-trial analysis", *IEEE Signal Process. Mag.*, vol. 25, no. 1, pp. 41-56, 2008.

[16] H. Sadreazami, M. Bolic and S. Rajan "Fall detection using standoff radar-based sensing and deep convolutional neural network", *IEEE Transactions on Circuits & Systems II: Express Briefs,* vol. 67, no. 1, pp. 197-201, 2019.

[17] H. Sadreazami, M. Bolic and S. Rajan "Contact-less fall detection using time-frequency analysis and deep neural network", *IEEE Transactions on Industrial Informatics,* vol. 17, no. 10, pp. 6842-6851, 2021.

[18] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever and R. Salakhutdinov, "Dropout: a simple way to prevent neural networks from overfitting," *Journal of Mach. Learn. Research,* vol. 15, no. 1, pp. 1929-1958, 2014.

[19] D. P. Kingma and J. L. Ba, "Adam: a method for stochastic optimization," in *Proc. Int. Conf. on Learn. Represent. (ICLR),* pp. 1-13, 2015.

[20] S. Ioffe and C. Szegedy, "Batch normalization: accelerating deep network training by reducing internal covariate shift," *arXiv:1502.03167v3,* pp. 1-11, 2015.

[21] M. Dai, S. Wang, D. Zheng, R. Na and S. Zhang, "Domain transfer multiple kernel boosting for classification of EEG motor imagery signals," *IEEE Access,* vol. 7, pp. 49951-49960, 2019.

[22] S.-H. Park and S.-G. Lee, "Small sample setting and frequency band selection problem solving using subband regularized common spatial pattern," *IEEE Sensors Journal,* vol. 17, no. 10, pp. 2977-2983, 2017.

[23] Y. Park and W. Chung, "Frequency-optimized local region common spatial pattern approach for motor imagery classification," *IEEE Trans. on Neural Systems and Rehab. Eng.,* vol. 27, no. 7, pp. 1378-1388, 2019.

[24] Z. Zhang, F. Duan, J. Sole-Casals, J. Dinares-Ferran, A. Cichochi, Z. Yang, and Z. Sun, "A novel deep learning approach with data augmentation to classify MI signals," *IEEE Access,* vol. 7, pp. 15945-15954, 2019.

[25] R. Soleymanpour and M. Arvaneh, "Entropy-based EEG time interval selection for improving motor imagery classification," in *Proc. Int. Conf. on Systems, Man, and Cybernetics (SMC),* pp. 1-6, 2016.

[26] F. Lotte and C. Guan, "Regularizing common spatial patterns to improve BCI designs: Unified theory and new algorithms," *IEEE Trans. on Biomedical Engineering,* vol. 58, no. 2, pp. 355-362, 2011.

[27] Q. Novi, "Subband common spatial pattern for brain-computer interface", in *Proc. IEEE/EMBS Int. Conf. on Neural Eng.,* pp. 204-207, 2007.

[28] K. K. Ang, Z. Y. Chin, H. Zhang and C. Guan, "Filter bank common spatial pattern (FBCSP) in braincomputer interface," in *Proc. IEEE Int. Joint Conf. on Neural Networks,* pp. 2390-2397, 2008.

[29] R. Tomioka and K. Aihara, "Classifying matrices with a spectral regularization," in *Proc. Int. Conf. on Mach. Learn. (ICML),* pp. 895-902, 2007.

[30] Q. She, B. Hu, Z. Luo, T. Nguyen and Y. Zhang, "A hierarchical semi-supervised extreme learning machine method for EEG classification," *Medical and Biological Eng. and Comput.,* vol. 57, pp. 147-157, 2019.

[31] T. Uktveris and V. Jusas, "Application of convolutional neural networks to four-class motor imagery classification problem," *Inf. Technol. Control,* vol. 46, no. 2, pp. 260-273, 2017.