# BCI 시스템의 성능 개선을 위한 병렬 모델 특징 추출

# Parallel Model Feature Extraction to Improve Performance of a BCI System

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**Abstract:** It is well knowns that based on the CSP (Common Spatial Pattern) algorithm, the linear projection of an EEG (Electroencephalography) signal can be made to spaces that optimize the discriminant between two patterns. Sharing disadvantages from linear time invariant systems, CSP suffers from the non-stationary nature of EEGs causing the performance of the classification in a BCI (Brain-Computer Interface) system to drop significantly when comparing the training data and test data. The author has suggested a simple idea based on the parallel model of CSP filters to improve the performance of BCI systems. The model was tested with a simple CSP algorithm (without any elaborate regularizing methods) and a perceptron learning algorithm as a classifier to determine the improvement of the system. The simulation showed that the parallel model could improve classification performance by over 10% compared to conventional CSP methods.

**Keywords:** parallel model, common spatial pattern, perceptron learning algorithm, electroencephalography, brain-computer interface

## I. INTRODUCTION

By attaching multiple electrodes on the head of human, measuring electrical potential from those electrodes keep changing and create the pattern that nowadays technology could find and identify those pattern and regard them as intentions of human to control wheelchair, robot or even surfing the web. These are the key point of brain-computer interface technology based on EEG (electroencephalography) signal [1][7].

This technology benefit to specially to patient who suffers from neurological disease such as ALS (Amyotrophic Lateral Sclerosis), spin cord injury, stroke and other case like condition impairment. Using machine learning algorithm, pattern could be identified and new coming EEG signal could be decided to one of the library of pattern from user intention and make it to control output application that help for those patient.

But, understand those pattern is not that easy. Researchers, nowadays, struggle in find new way to identify people intention using those EEG signals in reliable system and could be in realtime[8].

The famous method using in current BCI based EEG is called common spatial pattern. It is a spatial filtering technique that takes advantage of time-invariant transformation of an EEG signal into the same spatial-temporal space with constraining in optimizes the discriminant between two states of EEG signal patterns [2].

As other methods of time-invariant transformation technique, CSP algorithm could optimize it performance if only if the input signal is stationary by nature. In probabilistic sense, CSP algorithm bases on the estimated variables by assuming that those estimate variables are unchanged by any circumstance. In contrast to those assumption, natural characteristic of EEG signal is non-stationary sources. The characteristic of distribution density function of an EEG signal keep changing from time to time, session to session, between one subject to another. This problem cause the stationary model of EEG to performance poorly especially during the testing set were applied to estimate system performance.

To handle this problem, some method like RCSP (Regularize Common Spatial Pattern) were introduced by adding the panelty term to the objective function of CSP or in the estimate covariance term of CSP algorithm. By adding the panelty term, a CSP model with more constraint was created. Those constrains try to extract, within constraint information, to over come the sensitvity of CSP to noise and overfitting problem and specially to non-stationary character of CSP. In [3], authors had

unified the theory over the RCSP algorithm and proposed news fours RCSP algorithm. The simulation using 17 data sets showed the improvement over the classification accuracy rate and also enable performed effectively for subject-subejct transfer problem. Another use of regularize CSP algorithm is to solve the problem of non-stationary problem directly by regularize CSP towards stationary subspace and showed it could increase the classification accuracy of classifier. It is also enable for subjects that hardly control a BCI system to do use this system better than traditional CSP algorithm.

In this paper, authors tackled the problem of non-stationary EEG model by different mean. Using the subspace model of parallel CSPs, the non-stationary source of EEG could be suppressed, and performance of classifier could take benefit from this solution. By doing so, it leads to problem of model selection of optimal sub-parallel space and the specific number of spatial information of output of each sub-space as we increased number of features. The detail of method will introduce in third part of paper.

## II. RELATED WORKS

### 1. CSP (Common Spatial Pattern)

CSP is a orthogonal transformation of a segment of EEG signal with constraint of maximizing the discriminant of spatial information (energy of electrodes) between two patterns for instance: the imagination of right hand and right foot movement. By letting $X \in R^{C \times T}$ is the segment of EEG signal with of C electrodes and T time sample that is already filtered and centering. The next step of CSP algorithm is to calculate the covariance matrix as in (1).

$$\Sigma^{(c)} = \frac{1}{|I_c|} \sum_{i \in I_c} X_i X_i^T, c = \{+,-\} \tag{1}$$

Where $I_c$ is set of trial belongs to pattern $c = \{+\}$ corresponds to imagination of right hand and $c = \{-\}$ corresponds to imagination of right foot. Then the objective function of CSP can be taken as in (2), where $J(W)$ is in (3).

$$\arg\max_W J(W) \tag{2}$$

$$J(W) = \frac{W^T S_d W}{W^T S_c W} \tag{3}$$

Where $S_d = \Sigma^{(+)} - \Sigma^{(-)}$ is the discriminant activity EEG of pattern $\{+\}$ and $\{-\}$ and $S_c = \Sigma^{(+)} + \Sigma^{(-)}$ is the common activity of EEG patterns. As notice, $J(kW) = J(W)$, for any arbitrary value k. This means that we could scale the value if W to any value without

changing value of discriminant function $J(W)$. By letting $W^T S_c W = 1$, the maximization of objective function in (3) could be regard as maximizing problem with constraint.

$$\arg\max_W W^T S_d W,$$
$$constraint: W^T S_c W = 1 \tag{4}$$

Using Lagrange's multiplier technique, the maximizing problem can be done as in (5) and (6), where $\lambda$ is Lagrange multiplier coefficient and need to be found.

$$\arg\max_W L(\lambda, W) \tag{5}$$

$$L(\lambda, W) = W^T S_d W - \lambda W^T S_c W \tag{6}$$

The quadratic form of (6) makes it easy to find the solution of as $L(\lambda, W)$ is maximum when partial differential of $L(W)$ respects to $W$ is equal to zero. Then solution, the value of $W$ can be found as:

$$W^T S_d = \lambda W^T S_c \tag{7}$$

Here, the solution can be interprets as generalize eigenvalues and eigenvectors decomposition of matrix $S_d$ and $S_c$. $W = [w_1, ..., w_C]$ is matrix where its column vector is eigenvectors $w_i$ corresponding to eigenvalue $\lambda_i \in \lambda$.

In the spatial filtering sense, CSP algorithm could increase the performance of classifier by keeping only the most informative spatial information ones and reject the lesser information. By reducing the spatial information from total number of channel of C to $K \leq C$, the effectiveness of feature group could be enhanced, so increasing performance of classifier or at lease keeping the same level of performance as too many feature could lead to curse of dimension problem. As the spatial filtering concept, CSP acts as the transformation of an EEG signal

$X \in R^{C \times T}$ to $Y \in R^{K \times T}$, where $K \leq C$.
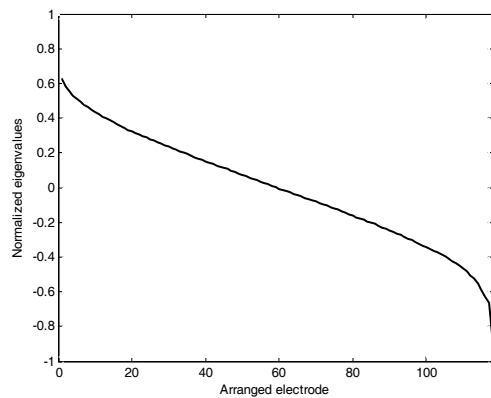
$$Y = W^T X \tag{8}$$



그림 1. 고유값의 차수 변화에 따른 계획된 뇌파 전극의 수.
Fig. 1. Arranged electrodes in the descending order of its eigenvalue.

Where $W \in R^{C \times K}$ obtains by concatenating $K$ number eigenvector $w_i$ from the pool of eigenvectors $[w_1,...,w_C]$. In [1], authors suggested by selecting 6 out of total eigenvectors where the first 3 are eigenvectors that correspond to 3 first largest eigenvalues that arranged in descending order as demonstrated in Fig. 1 and other 3 have the smallest eigenvalues.

In this paper, author used the model selection to determine number $K$ of spatial output. In order to select author proposed the algorithm bellow, where $W = [w_1,...,w_C]$ is arranging in the descending order of it eigenvalues $\lambda = [\lambda_1,...,\lambda_C]$.

1. Initial:
   - $\widehat{W} = [\,]$ set of selected eigenvectors
   - $W = [w_1,...,w_C]$; pool eigenvectors
2. For $i = 1,2,...,C$
   - If $i$ is odd, then $w_{select} = w_{first}$, else $w_{select} = w_{last}$.
   - Add $w_{select}$ to $\widehat{W}$
   - Remove $w_{select}$ from $W$
   - Calculate model fitness using $\widehat{W}$
3. Select the best model.

Feature extracts by CSP algorithm can be calculated using (9), where log(.) is logarithm operator and $var(.)$ is variance of filtered signal Y in time sample dimension.

$$z = \log(var(Y)) \tag{9}$$

## 2. PLA (Perceptron Learning Algorithm)

The simplicity and with non pre-assumption of feature probabilistic density function of PLA makes it simple and easy to use as the classifier in this paper. PLA with linear model and gradient descending rule for updating weight classifier for of EEG could use features extracted using equation (9). The linear model of PLA takes the simple form as in (10), where $x$ is feature vector with $\phi(x_0) = 1$ and $w$ is weight vector with $w_0$ is called bias. Function $f(.)$ is a step operator defined as in equation (11). The target value (+1) can be defined as imagination of right hand movement and (-1) is imagination of right foot movement.

$$y(x) = f(w^T \phi(x)) \tag{10}$$

$$f(a) = \begin{cases} +1, a \geq 0 \\ -1, a < 0 \end{cases} \tag{11}$$

The convergences of PLA can be observed through estimation over error of classified by PLA defined as in (12), where $(x_n, t_n)$ is pair of training feature and training target class $(t_n \in \{+1,-1\})$. $M$ is set of miss classification samples. $|M|$ denotes size of set $M$. Using partial deferential of $E(w)$ respect to $w$, the gradient value of $E(w)$ can be found as in (13).

$$E(w) = -\frac{1}{|M|} \sum_{n \in M} w^T \phi(x_n) t_n \tag{12}$$

$$\Delta E(w) = -\frac{1}{M} \sum_{n \in M} \phi(x_n) t_n \tag{13}$$

In case of feature space is not linear separable, PLA would not find the convergences value $(E(w) = 0)$. To avoid such scenario, PLA with pocket algorithm could help PLA to accept certain value of error even though PLA could not converge. The updating rule of PLA using gradient descending and pocket algorithm is given bellow, where $\eta$ is learning rate parameter for PLA.

1. Initiate: $w(t=0), E(w(t=0)) = 1$
2. For t = 0, 1, ..., $t_{max}$, do the following:
   - Compute gradient: $\Delta E(w(t))$
   - Update weight: $w(t+1) = w(t) - \eta \Delta E(w(t))$
   - Compute Error rate: $E(w(t+1))$
   - If $E(w(t+1)) < E(w(t))$, then set:
     $\widehat{w} = w(t+1)$.
   - Iterate next step: $t = t+1$
3. Return $\widehat{w}$

## III. PARALLEL MODEL OF CSP

### 1. Parallel model

In this paper, we investigated two model of parallel temporal subspace models as showing in Fig. 2. Both parallel models undergoes the same preprocessing method: band pass filtering and sub-segmenting of filtered EEG. Band pass filter is designed with IIR filter using windowing technique. Filtering window is practical Hamming window of 1 second length. Pass band frequency range is selecting at 7-30Hz which is the most active frequency rhythm related to motor movement and imagination of movement [5]. Subject specific frequency band was selecting in this paper as frequency range at 7-30Hz has the generalization sense to all BCI subjects.

Sub-segment EEG, then, is created using rectangular window of size $T = 1s$ with overlapping size from each window to another at $\Delta t$. To find the fittest value of $\Delta t$, it values is selecting from 0.1s to 1s with 0.1s increasing step. At value $\Delta t = 1s$, it means that all subspace windows are not overlapping each other at all.

In voting classifier parallel model, Fig. 2(a), EEG signal of N subspace are filtered with different spatial filter using CSP method and then extracted features using equation (9) are classified with $N$ different PLAs classifiers, where $N$ is number of sub-segment EEG. The
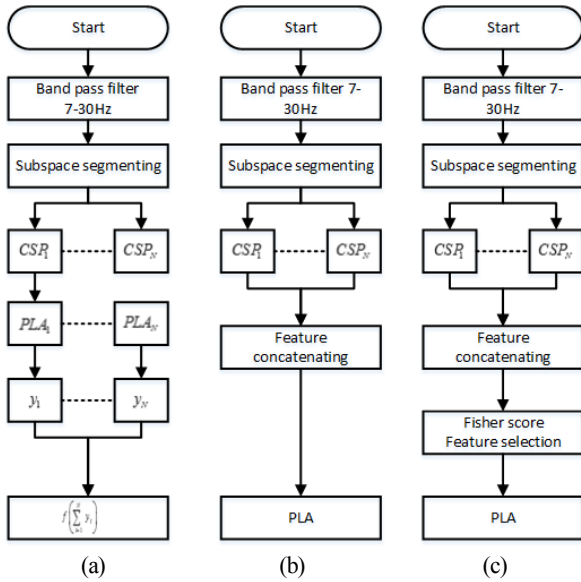
그림 2. 제안한 병렬 subspace 모델들. (a) CSPs와 PLAs(PCSP-a)
의 병렬모델 (b) PCSP-b1의 특징 추출없이 단일 분류기
를 이용한 CSPs의 병렬모델, (c) 특징 추출방법을 이용
한 단일 분류기를 CSPs의 병렬모델.

Fig. 2. Proposed parallel subspace models. (a) is parallel in both
CSPs and classifier PLAs (PCSP-a). (b) is parallel model
of CSPs with single classifier without feature selection
method (PCSP-b1). (c) is parallel model of CSPs with
single classifier with feature selection method (PCSP-b2).

final result could be obtained through voting the result for
majority as in (14), where $y_i \in \{+1, -1\}, i = 1, ..., N$ is the
result of individual classifier, N is the number of subspace
and $f(.)$ is a step function as in (11). We called this
method PLCSP-a.

$$y_{final} = f(\sum_{i=1}^{N} y_i) \qquad (14)$$

For signal classifier model, Fig. 2(b), the feature created
from N individual CSPs are concatenated into single
feature vector and then are classified by single PLA. As
the result, feature classified by single PLA has dimension
N times larger that classifier in the parallel model. The
output from PLA is the final result of this model as
showing in Fig. 2(b-1). Since the feature of this parallel
mode is large, we integrated feature selection base on
Fisher score to reduce size of feature created a model as
in Fig. 2(b-2). Fisher score could be understand as in
(15), where $\mu_k^j$ and $\sigma_k^j$ are mean and standard deviation of
feature $x^j$ in class pattern $k$. $\mu^j$ and $\sigma^j$ are mean and
standard deviation of feature $j^{th}$ of all class patterns.

$$F(x^j) = \frac{\sum_{k=1}^{c} n_k (\mu_k^j - \mu^j)}{(\sigma^j)^2} \qquad (15)$$

$$(\sigma^j)^2 = \sum_{k=1}^{c} n_k (\sigma_k^j)^2 \qquad (16)$$

We called parallel model of CSP with single classifier
without feature selection "PCSP-b1" and a model with
feature selection is called "PCSP-b2".

## 2. Model selection

In proposed parallel subspace model, there are two
parameters concerning in optimizing the performance of
system: number of sub-segment space causing by change
value of overlapping size $\Delta t = 0.1, 0.2, ..., T$ and
$K = \{1, ..., C\}$ number of spatial information output from
CSP algorithm where $C$ is total input number of electrode
before CSP and $T = 1s$ is length of sub-segment window
size. To obtained the optimal model, best value of $\Delta t$
and $K$ need to be selected from its corresponding set
based on the fitness value in (17). The coefficients
$a_1 = 0.6, a_2 = 0.2, a_3 = 0.1$ are fitness parameter weights.
The square on the component in fitness related $\Delta t$ and
$K$ are to ensure the smoothness of fitness function.
$Kappa$ is Cohen's coefficient (Kappa coefficient) of
model with as parameter of $\Delta t$ and $K$. Kappa coefficient
is closely related classification accuracy rate [6]. Kappa
coefficient can be found using (18), where $\Pr(o)$ is an
observe agreement probability, $\Pr(e)$ is expected
agreement probability.

$$g(\Delta t, K) = \frac{a_1 \times Kappa - a_2 \times \left(\frac{\Delta t}{T}\right)^2 - a_3 \times \left(\frac{K}{C}\right)^2}{a_1 + a_2 + a_3} \qquad (17)$$

$$Kappa = \frac{\Pr(o) - \Pr(e)}{1 - \Pr(e)} \qquad (18)$$

## IV. EXPERIMENT AND RESULT

### 1. Experimental data

EEG signal obtained from BCI competition III. Here we
analysis for subject independent system using dataset IVa
of the competition data set. This data set was recorded
from 5 healthy subjects using visual stimuli with 118
electrodes EEG equipment. Fig. 3 shows time scheme of
experiment during recording EEG signal. Each trial
conducted by indicating visual cue for 3.5s follow by 1
of 3 motor imageries that subject should perform: left
hand, right hand and foot. The target cues were
intermitted by period of random length, 1.75 to 2.25s, in
which subject could relax [6]. The BCI III data set IVa
released for public use contain 2 classes (right hand and
foot). Each subjects have totally 280 trails with sampling
frequency of 100Hz.

In this study, 150 trials of total data were randomly
pick for training and validation, the rest of data were
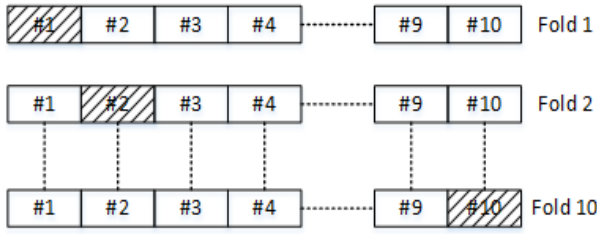treated as test set. With 150 training samples, data were

그림 3. 10 fold-cross validation 스키마를 표현. 각각의 블록은 데이터의 파티션 영역이다. 각각의 영역들은 트레인 모델과 데이터 사용되어진 unhatched 블록들로 구성된다. 마지막 결과는 모든 folds의 validation 집합의 평균 결과 값이다.

Fig. 3. Schema represent 10 fold-cross validation scheme. Each rectangular represent block partitioning of data. For each fold, data in unhatched blocks are used to train model and data in hatched block is used to validate model. Final result is averaging result of in validation set of all folds.
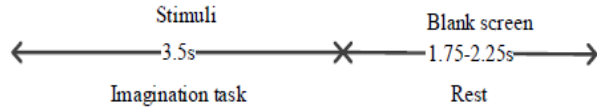


그림 4. BCI competition III 데이터 셋 IVa의 뇌파 실험 패러다임 타임라인.

Fig. 4. Time scheme of experiment paradigm of BCI competition III data set IVa.

divided using 10 fold cross-validation as showing in Fig. 4 and evaluation the fitness function in (17) of each model of $(\Delta t, K)$ using validation data block. With $N = 10$ is number of cross validation, the final fitness value is the averaging fitness across all fold as in (19), where $g_i$ is the fitness of fold $i^{th}$. The best model to select is using maximizing criteria as in (20). The best value of $(\Delta t_{best}, K_{best})$, the, are used in to evaluate the performance of test set.

$$\overline{g} = \frac{1}{N}\sum_{i=1}^{N} g_i(\Delta t, K) \qquad (19)$$

$$(\Delta t_{best}, K_{best}) = \arg\max_{(\Delta t, K)} \overline{g} \qquad (20)$$

The result of each method was repeated 100 times, while each time, the training set data were picked by random. This random separation and repetition of process are to ensure the generalization result of method according to the law of large number. The single evaluation using with partitioning data set could lead to fault conclusion of result. The final result obtained in this paper is the averaging of all repetitions

2. Simulation results

Models selected by proposed methods and CSP method are summarized in Table 1-4. In table 1-4, K is number

표 1. Cross-validation 집합에서 최적의 피트니스 값을 위한 PCSP-a 방법의 선택된 모델. K는 전극의 수이고, $\Delta t$는 오버랩 윈도우 사이즈의 크기이다.

Table 1. Selected model of PCSP-a method for the best fitness values in cross-validation set. K is number of electrodes, $\Delta t$ is overlapping size of sub-window parameter.

| Subject | $K$ | $\Delta t$ | Kappa | Fitness |
|---------|-----|------------|-------|---------|
| aa | 14 | 0.7s | 0.94 | 0.66 |
| al | 22 | 0.7s | 0.96 | 0.66 |
| av | 31 | 0.7s | 0.84 | 0.65 |
| aw | 7 | 0.7s | 0.97 | 0.66 |
| ay | 13 | 0.7s | 0.95 | 0.66 |

표 2. Cross-validation 집합에서 최적의 피트니스 값을 위한 PCSP-b1 방법의 선택된 모델. K는 전극의 수이고, $\Delta t$는 오버랩 윈도우 사이즈의 크기이다.

Table 2. Selected model of PCSP-b1 method for the best fitness values in cross-validation set. K is number of electrodes, $\Delta t$ is overlapping size of sub-window parameter.

| Subject | $K$ | $\Delta t$ | Kappa | Fitness |
|---------|-----|------------|-------|---------|
| aa | 12 | 0.7s | 0.99 | 0.66 |
| al | 7 | 0.7s | 1.00 | 0.66 |
| av | 20 | 0.7s | 0.94 | 0.66 |
| aw | 5 | 0.7s | 1.00 | 0.66 |
| ay | 6 | 0.7s | 1.00 | 0.66 |

표 3. Cross-validation 집합에서 최적의 피트니스 값을 위한 PCSP-b2 방법의 선택된 모델. K는 전극의 수이고, $\Delta t$는 오버랩 윈도우 사이즈의 크기이다.

Table 3. Selected model of PCSP-b2 method for the best fitness values in cross-validation set. K is number of electrodes, $\Delta t$ is overlapping size of sub-window parameter.

| Subject | $K$ | $\Delta t$ | Kappa | Fitness |
|---------|-----|------------|-------|---------|
| aa | 10 | 0.7s | 0.87 | 0.66 |
| al | 10 | 0.7s | 0.92 | 0.65 |
| av | 9 | 0.7s | 0.88 | 0.59 |
| aw | 9 | 0.7s | 0.99 | 0.66 |
| ay | 9 | 0.7s | 0.95 | 0.65 |

of electrodes output of optimal CSP model, $\Delta t$ is overlapping size of sub-window of parallel subspaces. The measurement of performance of model are measured by Kappa value in equation (18) and fitness assigned in equation (17). Comparing number of electrode required for achieve the maximum fitness value in equation (20), all proposed parallel models based CSP selected less number of electrodes (K) than conventional CSP method. The minimum electrode selected by all 3 parallel model are 7, 5, 9 for PCSP-a, PCSP-b1, PCSP-b2 respectively. While for CSP method, the minimum electrodes selected is $K = 25$ electrodes. The maximum number of selected electrodes

표　　4. Cross-validation 집합에서 최적의 피트니스 값을 위한 CSP 방법의 선택된 모델. *K*는 전극의 수 이다.

Table 4. Selected model of CSP method for the best fitness values in cross-validation set. *K* is number of electrodes.

| Subject | *K* | Kappa |
|---------|-----|-------|
| aa | 47 | 0.97 |
| al | 44 | 0.88 |
| av | 61 | 0.91 |
| aw | 25 | 0.80 |
| ay | 37 | 0.88 |

표　　5. 3개의 제안한 방법과 CSP 모델의 Kappa 값을 비교한 표. 가장 큰 kappa 값을 진하게 마크하였다.

Table 5. Comparing Kappa values with test data set of 3 proposed methods and conventional model of CSP. The highest Kappa value of each subject are marked by bold font.

| Subject | PCSP-a | PCSP-b1 | PCSP-b2 | CSP |
|---------|--------|---------|---------|-----|
| aa | 0.46 | **0.48** | 0.23 | 0.03 |
| al | 0.91 | **0.97** | 0.95 | 0.21 |
| av | 0.24 | **0.28** | 0.15 | -0.04 |
| aw | 0.65 | **0.75** | 0.61 | 0.12 |
| ay | 0.78 | **0.89** | 0.88 | 0.08 |

are 31, 20, 10, 61 for PCSP-a, PCSP-b1, PCSP-b2 and CSP method respectively. Notice that for PCSP-b2 number of selected electrodes of all subject are almost the same. For parallel models, parameter for sub-segmenting window is the same, $\Delta t = 0.7s$.

Table 5 shows Kappa values of each methods in test data set after applied the selected model (with corresponding K and $\delta t$ values). It is clear that parallel model with single classifier (PCSP-b1) performs better than other method as its Kappa values evaluation are higher than other parallel models and CSP method. PCSP-b1 also shows its robustness in subject variation problem as it still standout over other methods with all data from different subject. In classification accuracy sense, Fig. 5 shows that PCSP-b1 model achieve accuracy 98.5% for subject al and improve performance over than 10% comparing to CSP method. While PCSP-a method stands in second place of best classification performance.

In common sense, there are always trading off between training model and testing model as the testing performance never bound outside performance in training model. Measuring this value could help us know that while method has a good generalization using the training data than others. Table 6 gives correct classification accuracy trading off (CCATO) of all 3 proposed model and CSP method. Once again, the result in table 6 shows that PCSP-b1 model has a lowest CCATO than other methods. CSP method has highest CCATO which mean

표　　6. 트레이닝 데이터와 테스팅 데이터의 분류 정확도를 비교.가장 작은 trade off를 나타낸 항목에 진하게 표시하였다.

Table 6. Comparing correct classification accuracy trading off between training model and testing model. The lowest trading off performance (%) are marked by bold font.

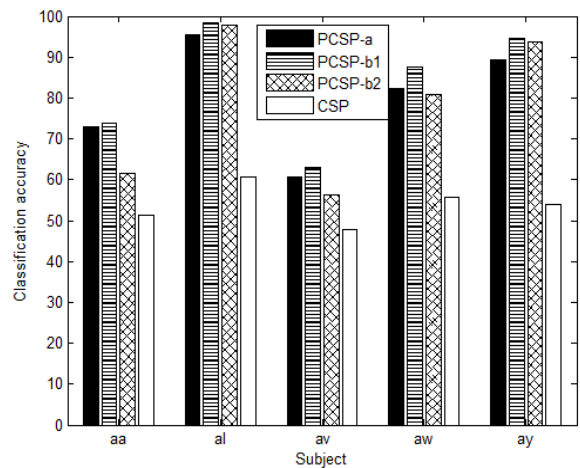| Subject | PCSP-a | PCSP-b1 | PCSP-b2 | CSP |
|---------|--------|---------|---------|-----|
| aa | 26.92 | **26.15** | 38.6 | 42.64 |
| al | 4.62 | **1.54** | 2.31 | 32.18 |
| av | 39.23 | **26.92** | 43.85 | 51.27 |
| aw | 17.69 | **12.31** | 19.23 | 28.05 |
| ay | 10.77 | **5.38** | 6.15 | 40.93 |



그림 5. 제안한 병령 모델들의 분류 성능 비교: PCSP-a, PCSP-b1, PCSP-b2, conventional CSP 방법.

Fig. 5. Comparing classification performance of proposed parallel models: PCSP-a, PCSP-b1, PCSP-b2, with conventional CSP method.

that this method is so sensitive to noise, artifact and non-stationary data such as EEG. While PCSP-b1 method is more robust to noise and non-stationary signal.

## V. CONCLUSION

In this work, 3 parallel models extending from CSP method were proposed. Using real EEG data, the simulation result show parallel model CSP with single classifier outperforms other method and especially the conventional CSP method. The proposed parallel model proved to be able to boost classification performance and is much more robust to noise, artifact and non-stationary signal than conventional CSP method. Parallel model CSP also reduce that number of electrode selected by spatial filter significantly which gave the advantage to extract other feature like time-frequency based like short time Fourier transformation or wavelet transformation that could be give a BCI system more useful to interpretation of EEG pattern.

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