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How is subject-to-subject transfer probable in motor imagery BCI?

Hohyun Cho[1], Sangtae Ahn[1], Sung Chan Jun[1*]

[1]*School of Information and Communications, Gwangju Institute of Science and Technology, Gwangju, Korea;*

*123 Cheomdangwagi-ro, Buk-gu, Gwangju 61005, Korea. E-mail: scjun@gist.ac.kr

Introduction: Subject-to-subject transfer is an ultimate goal of zero-training. We investigated how subject-to-subject transfer is probable in motor imagery (MI) brain computer interface (BCI) by comparing individual accuracies and subject-to-subject transfer rates for 156 subjects.

Materials and Methods: For this study, our team's left/right hand MI dataset of 52 subjects (100 trials for each class) [1] and open dataset of 104 subjects (about 20 trials for each class) [2-3] were used. Common spatial pattern (CSP) and linear discriminant analysis were applied. Individual accuracies were calculated by mean of cross-validations within each subject. For estimating of subject-to-subject transfer rate, 13-fold cross-validations on subjects were conducted. Each dataset were divided into training subjects (48 or 96 subjects) and testing subjects (4 or 8 subjects). For training filter and classifier, good subjects (individual accuracy > max{median accuracy, random chance level}) among training subjects were selected to use.

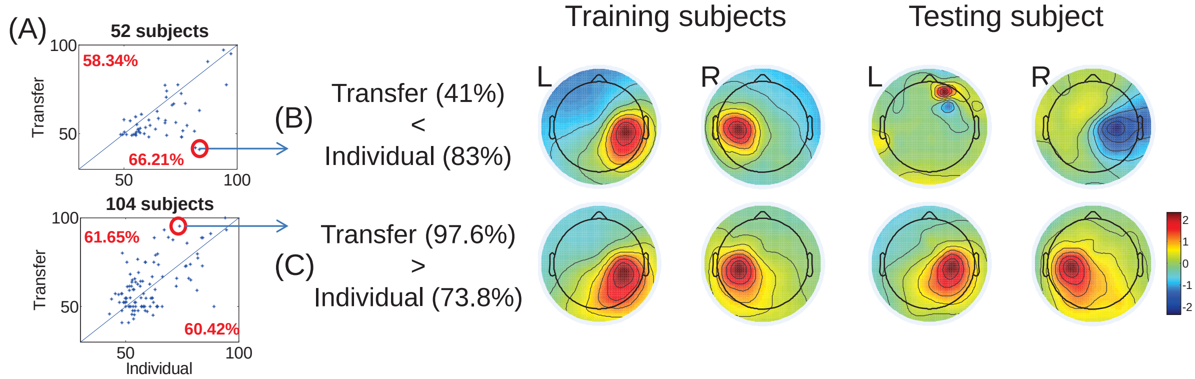

Figure 1 Individual accuracies and subject-to-subject transfer rates were compared on left/right hand motor imagery data and estimated source locations of MI by CSP filter. (A) Comparisons on 52 subjects (100 trials) and 104 subjects (20 trials). (B) a failure case of subject-to-subject transfer. (C) a successful case of subject transfer.

Results and Discussion: By the averaging effect, multi-subject data yielded quite fine CSP filter patterns as Figure 1(B-C). As Figure 1(A), mean of individual accuracies was higher than subject transfer rate on our team's MI data (52 subjects), however, individual accuracies and subject transfer rate were comparable on open MI data (104 subjects). It may be due to smaller number of trials (20 trials) in open MI data than in our team's MI data; weak individual information may produce low individual accuracy. It is found that when standard features extracted from multi-subjects are different from individual features of a subject, individual accuracy is likely higher than subject transfer rate. In such cases, estimated MI source locations extracted by CSP filters were far from somatosensory area, as depicted in Figure 1(B). It is quite doubtful if these are true MI features; it needs adaptive method. When individual features are similar to standard features, subject transfer rates are significantly higher (or at least comparable) than individual accuracies, as depicted in Figure 1(C).

Significance: There is tradeoff between generality and transfer rate [4]. Using fusion techniques [5], generality may be achieved, while subject transfer rate may be decreased. It is believed from this study that reasonable approaches for subject-to-subject transfer are neurofeedback method [6] (let user learn) and co-adaptive way [7] (let user and computer learn both).

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