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Classification characteristics of fine motor experts based on electroencephalographic and force tracking data

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ABSTRACT

The application of machine learning techniques provides a data-driven approach for a deeper understanding of the development and expressions of expertise. In extension to the common procedure of comparing experts' and novices' performances in expertise-domain-related tasks we applied conventional classification algorithms. We distinguished between tasks for each participant and between groups, i.e., experts or novices, based on electroencephalographic (EEG) activity patterns and force output variables during four different force modulation tasks. The tasks under investigation involved sinusoidal and steady force tracking tasks, which were performed with the left and right hand. Classification of tasks based on EEG patterns as well as force output was possible with high accuracy in novices and experts, whereas classification of group membership, i.e., experts or novices, was at chance level. In follow-up analyses, we found a high degree of individuality in the EEG patterns of the experts, implying the long-term development of specialized central processing during fine motor tasks in fine motor experts. Taken together, the results suggest that continuous practice in the work context leads to the development of a highly individual and task-specific central control pattern.

1. Introduction

Many years of professional experience in the work context contribute to the development of an outstanding and highly automatized performance level, i.e., expertise in domain-specific areas (Ericsson et al., 2006). A common approach to assess expertise-related differences is to compare experts' and novices' performances in expertise-domain-related laboratory tasks. In this context, fine motor experts have often been studied because their respective domains can be represented under laboratory conditions. Experts' compared to novices' behavioral performance was observed to be more precise and executed faster in precision mechanics (Vieluf et al., 2012; Vieluf et al., 2013; Vieluf et al., 2018), musicians (Krampe and Ericsson, 1996; Krampe, 2002) and surgeons (Law et al., 2004) when the task under investigation corresponds to the experts' domain. Moreover, experts' performance was less variable in terms of intra- and intertrial variability and more complex (Komar et al., 2015; Vieluf et al., 2018). On the neuronal level a comparison of experts and novices shows manifold differences in both structure and function of certain brain areas and their complex interaction, i.e., network behavior, pointing to more efficient information processing (Binder et al., 2017; Gölz et al., 2018; Vieluf et al., 2018).

Assessing differences of central processing and behavior, experts and novices can be classified by using machine learning techniques. Such data-driven approaches allow us to build models based solely on

Abbreviations: CSP, common spatial patterns; dev, mean deviation; DMD, dynamic mode decomposition; ICA, independent component analysis; int var, intertrial variability; LDA, linear discriminant analysis; LH, left hand; MVC, maximum voluntary contraction; RH, right hand; SVM, support vector machine; UMAP, uniform manifold approximation and projection; var, absolute variability.

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measurements and to learn general principles (Brunton and Beyeler, 2019; Bzdok and Yeo, 2017). Machine learning, thus, complements the characterization of expertise-related differences using classical statistical approaches by automatically extracting generalizable components from the complex interaction of features. Such models find practical application in the automatic classification of individual performance states. In a previous study, we used EEG data to classify fine motor tasks. We found differences in classification performance between different age groups that were associated with neurophysiological differences between the groups (Goelz et al., 2021). Building upon this, decoding expertise on a group level as well as decoding fine motor tasks using machine learning methods could provide information about expertise and task-related characteristics of central information processing. Previous classification of experts was done based on different types of data and in different expertise contexts. Using support vector machines, experts and novices were classified based on their hand movements during a simulated surgical procedure (Watson, 2014). Likewise, it was possible to classify the level of expertise of neurosurgeons based on force application and acceleration of the instruments used during a neurosurgical procedure in virtual reality (Winkler-Schwartz et al., 2019). Artists and non-artists could be classified using the periodicity in the frequency spectra of EEG data recorded during visual observation and mental imagery of paintings (Shourie, 2016). In addition, three stages of expertise of goalkeepers in soccer could be classified with a high accuracy based on gaze behavior (Hosp et al., 2021). Moreover, classification was used to show individuality of finger movement patterns in expert flute players (Albrecht et al., 2014) as well as in timing and movement variability in pianists (Caramiaux et al., 2018).

It remains unclear whether such a classification can also be performed successfully using a task that reflects more generalized functions or skills related to specific fields of expertise such as fine motor skills. To the best of our knowledge, no study so far investigated whether differences in classification of fine motor tasks are also evident for groups with different expertise levels. A deeper understanding of this would help to better characterize expertise-related differences in fine motor tasks and has practical implications for areas where data-driven models are used to automatically diagnose performance levels or classify tasks at the individual level.

In this study, novices and fine motor experts performed force tracking tasks, i.e., sine and steady force tracking with the left and right hand, while their brain activity was recorded with EEG. We classified the type of task based on behavioral and EEG parameters and investigated group differences in classification performance. Furthermore, we aimed to classify the level of expertise, i.e., membership in the group of experts or novices. Based on our previous results in groups of different ages, we expected to gain insight into neurophysiological characteristics of fine motor expert performance.

2. Results

2.1. Group differences in force tracking and EEG activity

Results of the force tracking performance of the sine and steady target forces (see Fig. 1A) with the right and left hands are summarized in Fig. 1C and Table 1. For simplicity, the tasks are referred to as steady right, sine right, steady left, and steady left. Performance of experts was more accurate (lower mean absolute deviation from target force level) in steady left compared to novices. There was no significant difference in mean deviation for steady right, sine left, or sine right. Variability within trials was smaller in experts compared to novices in steady left but not in steady right, sine right, or sine left. Intertrial variability was lower in experts in steady left (see Table 1).

Similar to our previous studies (Gölz et al., 2018; Vieluf et al., 2018), we used dynamic mode decomposition (DMD) to calculate EEG markers representing brain network characteristics (Brunton et al., 2016) and extracted DMD mean modes per task and frequency band (θ, α, β_1 and β_2) from the EEG. Group differences in EEG activity are displayed in Fig. 1D as statistical t-maps. There were no group differences on EEG level

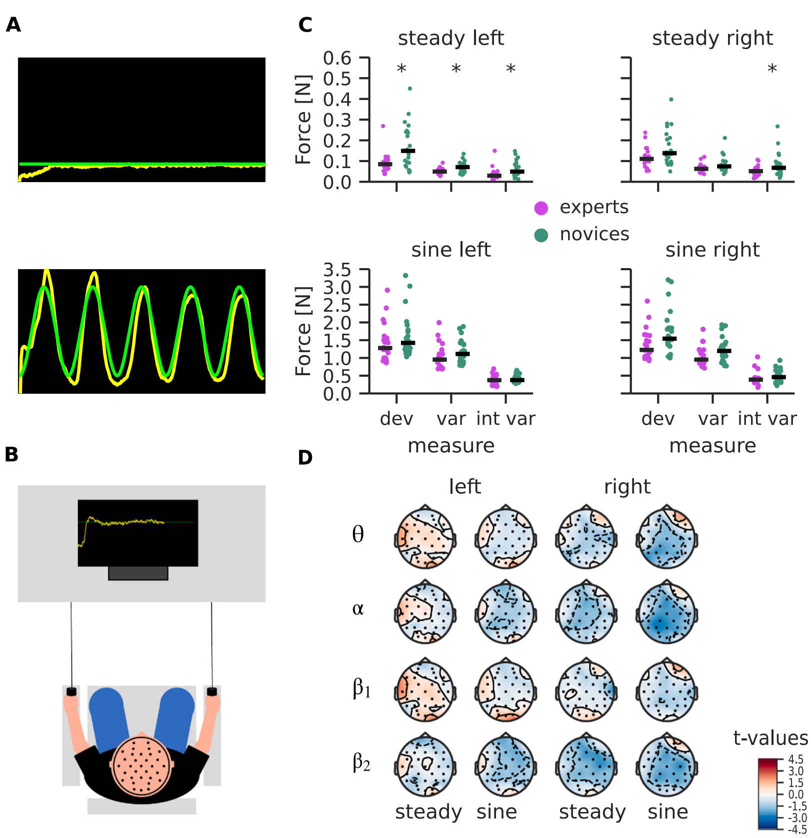

Fig. 1. A: Target force (green) and exemplary applied force (yellow). B: Experimental setup. C: Force tracking performance per group (dev: mean deviation, var: absolute variability, int var: intertrial variability). Each dot corresponds to one participant. Black bars reflect the median value. * indicates a p-value < 0.05. D: Statistical t-maps of the group comparison of fine motor experts vs. novices. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Group differences in force tracking. dev: mean deviation, var: absolute variability, int var: intertrial variability, Mdn: median, IQR: interquartile range, M: mean, SD: standard deviation, U: test statistic of the Mann-Whitney-*U* test (in case of not normally distributed data), t: test statistic of the *t*-test (in case of normally distributed data), p: probability value.

		Experts	Novices	Statistical values
dev [N]	**Steady right**	Mdn = 0.110 IQR = 0.128	Mdn = 0.138 IQR = 0.225	U = 158.000, p = 0.117
	Sine right	Mdn = 1.226 IQR = 1.632	Mdn = 1.542 IQR = 1.844	U = 154.000, p = 0.108
	Steady left	Mdn = 0.085 IQR = 0.104	Mdn = 0.149 IQR = 0.240	U = 112.000, p = 0.028*
	Sine left	Mdn = 1.279 IQR = 1.556	Mdn = 1.424 IQR = 1.775	U = 165.000, p = 0.122
var [N]	**Steady right**	Mdn = 0.062 IQR = 0.020	Mdn = 0.074 IQR = 0.031	U = 151.000, p = 0.107
	Sine right	Mdn = 0.953 IQR = 0.355	Mdn = 1.197 IQR = 0.403	U = 151.000, p = 0.107
	Steady left	M = 0.049 SD = 0.025	M = 0.071 SD = 0.037	t(41) = -2.990, p = 0.028*
	Sine left	Mdn = 0.954 IQR = 0.396	Mdn = 1.112 IQR = 0.447	U = 163.000, p = 0.121
int var [N]	**Steady right**	Mdn = 0.051 IQR = 0.038	Mdn = 0.067 IQR = 0.045	U = 139.000, p = 0.079
	Sine right	Mdn = 0.389 IQR = 0.123	Mdn = 0.459 IQR = 0.195	U = 163.000, p = 0.121
	Steady left	Mdn = 0.029 IQR = 0.016	Mdn = 0.049 IQR = 0.046	U = 121.000, p = 0.031*
	Sine left	Mdn = 0.374 IQR = 0.224	Mdn = 0.376 IQR = 0.101	U = 214.000, p = 0.689

comparing DMD mean mode magnitude between the groups in all force tracking tasks and frequency bands.

2.2. Task classification

For task classification we trained and tested a machine learning model for each participant individually. Results are displayed in Fig. 2 as confusion matrices and Table 2 including accuracy, F1, precision and recall for each group as mean over folds and group (see supplementary material Table S4 for individual results). Classification of tasks based on EEG features was above chance level in all individuals of both groups (chance level ~ 0.25). The same was true for classification based on force tracking. Neither classification based on EEG features nor based on force tracking features differed between the groups (see Table 2 for statistical values).

Besides models for each participant, we trained a model for task classification at group level for experts and novices respectively and tested it on participants not used during model training to test if generalizable patterns can be learned. Results are displayed in Table 2 including accuracy, F1, precision and recall as mean over folds. The performance of these models based on EEG data tended strongly towards chance (chance level ~ 0.25). The model trained and tested on data from the novices showed a slightly higher classification performance. Classification performance based on force tracking parameters decreased. Here, a better classification performance was found for experts compared to novices (see Table 2 for statistical values).

2.3. Classification of group membership

Model training and testing for group classification followed the same principle as the group level task classification, i.e., a model was trained for classification of group membership and tested on participants not used during model training. As with the classification of tasks, Fig. 3 and Table 3 summarize the performance of models for group membership classification as confusion matrices and by the metrics accuracy, F1, precision, and recall. Classification based on EEG features did not perform above chance (chance level ~ 0.5). The same was true for the classification based on force tracking features. Only classification based on force tracking features of steady left was slightly above chance. Here, the classifier performed more accurately in classifying experts than novices. Combining features of both levels as well as different classifiers and features did not improve classification performance (see supplementary material Table S3).

2.4. Feature space characteristics

To examine the EEG feature space, we used uniform mani fold approximation and projection (UMAP) (McInnes et al., 2018). Visualization of EEG feature space revealed patterns of individual characteristics in both groups. As shown in Fig. 4A and 4C, the EEG characteristics of each trial formed a cluster structure that can be assigned to individual participants. Comparing this individuality between the groups of experts and novices, it was more pronounced in the experts. This is illustrated by considering the distances of the cluster centroids as shown in Fig. 4B and 4D. What was striking here is an overall larger distance of the clusters in relation to each other which was present in a larger mean distance of the cluster centroids to each other in experts (see Fig. 4F). In addition, we compared the mean cluster size between the groups and found a smaller cluster size, i.e., more compact clusters, within the experts (see Fig. 4E). On the behavioral level, however, we did not find such a structure.

3. Discussion

In this study we gained insights into central and behavioral aspects of experts' fine motor performance by using machine learning techniques. Classification of different tasks at the individual level in both groups could be performed with high accuracy, indicating that indeed task-relevant features were chosen for classification. In contrast, the classification of group membership was at chance level. Follow-up analyses suggest that experts' brain activation patterns were characterized by higher individuality than those of novices. Overall, the results support the assumption that continuous practice in the work context results in the development of a highly individual and task-specific central control pattern.

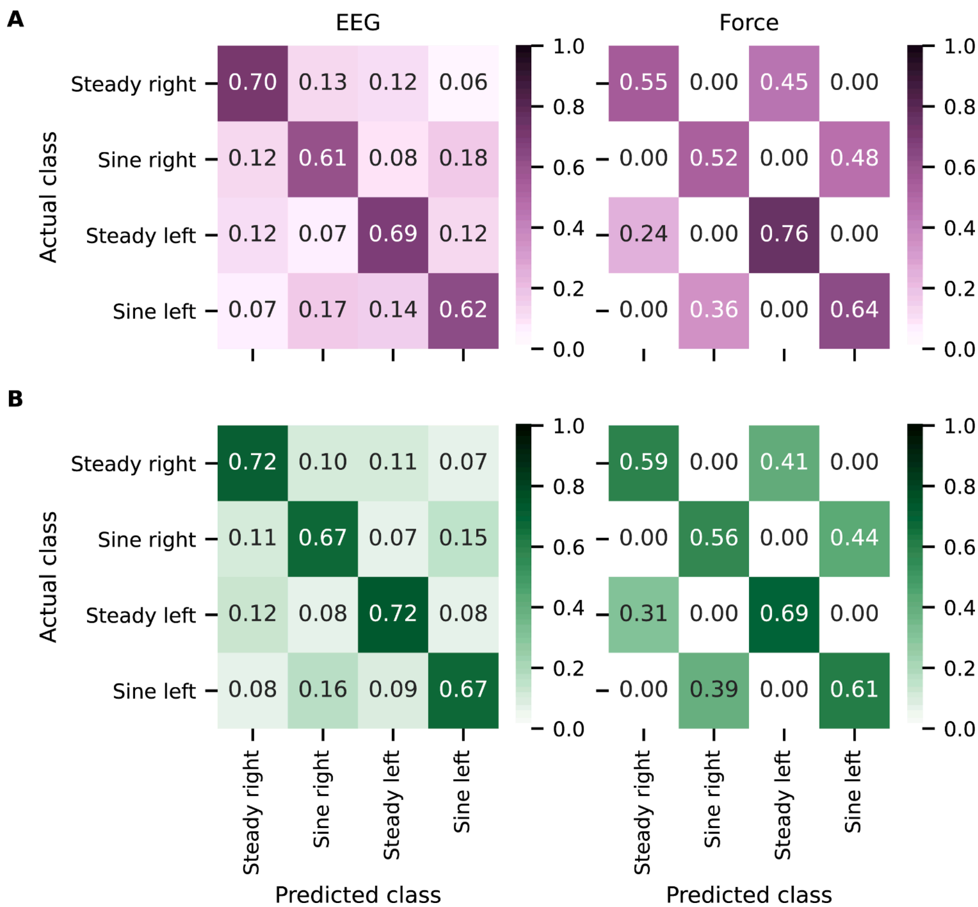

Fig. 2. Confusion matrices of task classification of fine motor experts (A) and novices (B) based on EEG features (left) and force tracking features (right). Mean over all participants.

3.1. Expertise-related differences in force tracking and EEG characteristics

Similar to our previous studies (Gölz et al., 2018; Vieluf et al., 2012; Vieluf et al., 2013; Vieluf et al., 2018), we found differences in force tracking performance between experts and novices. Experts' force tracking performance was more precise and less variable within the steady left task. Intertrial variability between trials of the steady left and steady right tasks was lower in experts. Although we did not see this effect consistently across all tasks, a general pattern of higher performance levels among the expert group emerged. Based on previous results using the same cohort and an experimental procedure with longer trials, we assume that this pattern would become more pronounced with longer task execution (Gölz et al., 2018; Vieluf et al., 2018). Likewise, we did not observe differences in DMD mean mode magnitudes. This result may at first seem to be inconsistent with previous results (Gölz et al., 2018; Vieluf et al., 2018). However, the task context studied here is rather characterized by short trials with breaks in between. This could have had a different requirement profile than longer trials, so that the participants likely fatigued less quickly. Furthermore, it must be considered that the participants performed numerous iterations of the steady and sine force tracking tasks in previous experimental sessions within the framework of the Bremen-Hand-Study@Jacobs. However, we may exclude the possibility that faster adaptation processes may have taken place in the experts. Furthermore, as in our previous paper, we did not consider task-related values or electrode preselection in the expert-novice comparison to ensure automatic pattern recognition by the classifiers.

3.2. Classification of tasks in experts and novices

Following our previous study (Goelz et al., 2021) in which we found differences in decoding tasks between age groups, we examined the classification of different tasks based on EEG and force tracking at the individual level, i.e., training and testing a model for each participant. Classification performance at the EEG level was comparable to previous results based on the same tasks. While we found differences in the classification performance in different age groups in our previous study which might point to dedifferentiated and compensatory brain network activation, we couldn't detect any in the task decoding between novices and experts at the individual level. This could indicate that the groups do not differ in the task representations. However, it could be that expertise-related differences are more related to efficiency of information processing (Binder et al., 2017; Gölz et al., 2018; Vieluf et al., 2018).

Besides task classification based on EEG, we added force tracking features here as an additional feature set, since we observed expertise effects mainly at the behavioral level. Again, we did not find any differences in classification performance between the groups for individual models. Descriptively, a worse performance of the machine learning models based on the force tracking features can be observed in comparison to models based on EEG features. However, it should be considered that the classification with force tracking features was based only on the mean deviation and the variability of the deviation between applied and target force. Furthermore, almost perfect classification (~100%) was observed in the classification of steady vs sine tracking, whereas the classification of the hand used for force tracking was not accurate, especially for the steady task. An extension of the force tracking feature set further increased the performance of the classifiers regarding the used hand (see supplementary material Figure S1).

Table 2
Overview of task classification results at individual and group level. Mdn: median, IQR: interquartile range, M: mean, SD: standard deviation, U: test statistic of the Mann-Whitney-*U* test (in case of not normally distributed data), t: test statistic of the *t*-test (in case of normally distributed data), p: probability value.

			Experts	Novices	Statistical values
Individual level	**Accuracy**	**EEG**	M = 0.658 SD = 0.156	M = 0.696 SD = 0.097	t(41) = 0.955, p = 0.345
		Force	M = 0.617 SD = 0.074	M = 0.614 SD = 0.077	t(41) = -0.163, p = 0.872
	F1	**EEG**	M = 0.652 SD = 0.159	M = 0.689 SD = 0.101	t(41) = 0.913, p = 0.367
		Force	M = 0.590 SD = 0.091	M = 0.588 SD = 0.091	t(41) = -0.055, p = 0.956
	Precision	**EEG**	M = 0.675 SD = 0.158	M = 0.708 SD = 0.100	t(41) = 0.913, p = 0.415
		Force	M = 0.615 SD = 0.086	M = 0.611 SD = 0.097	t(41) = -0.139, p = 0.890
	Recall	**EEG**	M = 0.658 SD = 0.156	M = 0.695 SD = 0.097	t(41) = 0.936, p = 0.355
		Force	M = 0.617 SD = 0.074	M = 0.614 SD = 0.077	t(41) = -0.138, p = 0.891
Group level	**Accuracy**	**EEG**	M = 0.306 SD = 0.034	M = 0.352 SD = 0.021	t(18) = -3.597, p = 0.002*
		Force	Mdn = 0.517 IQR = 0.024	Mdn = 0.503 IQR = 0.017	U = 77.000, p = 0.045*
	F1	**EEG**	M = 0.298 SD = 0.031	M = 0.348 SD = 0.023	t(18) = -4.095, p < 0.001*
		Force	M = 0.490 SD = 0.028	M = 0.418 SD = 0.044	t(18) = 4.403, p < 0.001*
	Precision	**EEG**	M = 0.308 SD = 0.032	M = 0.359 SD = 0.021	t(18) = -4.198, p < 0.001*
		Force	Mdn = 0.520 IQR = 0.059	Mdn = 0.455 IQR = 0.099	U = 78.000, p = 0.040*
	Recall	**EEG**	M = 0.306 SD = 0.034	M = 0.352 SD = 0.021	t(18) = -3.568, p = 0.002*
		Force	Mdn = 0.516 IQR = 0.024	Mdn = 0.504 IQR = 0.016	U = 75.000, p = 0.064

However, such maximization and benchmarking at this level was not the final goal of this study and the use of this enlarged feature set did not increase classification performance (see supplementary material Table S3).

To compare the generalizability of task classification between experts and novices, we also trained a classification model for each group at group level and compared their performance on participants not used during model training. Here, we found a drop in classification performance presumably caused by individuality due to differing physical and mental conditions across participants, as it is described in the literature for subject-transfer decoding (Morioka et al., 2015). While the reduction in classification performance was higher for experts for the model based on EEG data, it was the opposite for the model based on force tracking data. This could indicate higher individuality in EEG data of experts while the force tracking performance was more similar between experts. This was also reflected in the statistical comparison of force tracking performance.

In summary, the high accuracy in the classification of tasks at the individual level supports our decision on feature selection. We found no differences between experts and novices in classification performance at individual level as we found for different age groups (Goelz et al., 2021), which could indicate that the specificity of the task representation on central level is not different between experts and novices. Generalizability is different between groups and might be related to different levels of variability between participants. Subsequent studies in other contexts would be valuable, especially in areas where the effect of machine learning models is crucial, such as neurofeedback or brain-computer-interface (BCI) systems.

3.3. Classification of group membership

Classification of group membership was not above chance level. This was true for both feature levels and level combination (EEG and force tracking features). The best classification performance was achieved using the force tracking features of the steady left task, which is in line with the results of the group comparison at behavioral level. We additionally applied various other classifiers including random forest, linear discriminant analysis and automatic machine learning techniques (Feurer et al., 2019; see supplementary material Table S1 for an overview of tested models) and used different feature sets (see supplementary material Table S2 for an overview of tested models). Taken together, the results of all models were comparable. The most promising results were achieved with random forest and combined EEG and force tracking features using the force tracking of the steady left task (see supplementary material Table S3).

These results differ from the studies presented in the introduction, in which it was possible to successfully classify experts and novices (Hosp et al., 2021; Shourie, 2016; Watson, 2014; Winkler-Schwartz et al., 2019). It is striking that all these studies used tasks in the exact expertise context for classification. The expertise level of surgeons during simulated or virtual operations could be classified with a high accuracy of 83% and 84% (Watson, 2014; Winkler-Schwartz et al., 2019). Artistic expertise was successfully classified with an accuracy of 97.5% based on spectral features of EEG during observation and mental imagery of paintings (Shourie, 2016). Classification of different expertise levels of goalkeepers in soccer observing game scenes was possible as well with high accuracy (Hosp et al., 2021). Compared to these studies, the professional context of the fine motor experts (including opticians, watchmakers etc.) analyzed in this study was rather broad and the chosen force tracking tasks were only a rough estimate of the expertise context. Although this experimental set-up had the advantage of controlled laboratory conditions, it might have been at the expense of an exact expertise context. Consequently, the expertise context could be a crucial component in classifying experts and novices. This could also be reflected in the fact that we achieved the best classification performance for the steady left tracking task. Holding objects statically with the left hand could be a fundamental part of the work context of the experts studied here. In addition, a larger data pool could help to build more accurate ML models (e.g., using deep learning) that are able to capture even subtle expertise-related differences in indistinct representations of

Fig. 3. Mean confusion matrices of group membership classification over all folds based on EEG features (A) and force tracking performance features (B). Exp.: experts, nov.: novices.

Table 3
Overview of group membership classification results. Mean (M) and standard deviation (SD) over all folds.

	Task	Accuracy	F1	Precision	Recall
EEG	**All**	M = 0.531	M = 0.517	M = 0.552	M = 0.550
		SD = 0.068	SD = 0.077	SD = 0.091	SD = 0.089
	Steady left	M = 0.556	M = 0.530	M = 0.561	M = 0.563
		SD = 0.067	SD = 0.058	SD = 0.061	SD = 0.062
	Sine left	M = 0.558	M = 0.539	M = 0.572	M = 0.570
		SD = 0.078	SD = 0.094	SD = 0.096	SD = 0.106
	Steady right	M = 0.461	M = 0.446	M = 0.495	M = 0.482
		SD = 0.073	SD = 0.084	SD = 0.111	SD = 0.104
	Sine right	M = 0.545	M = 0.535	M = 0.569	M = 0.569
		SD = 0.094	SD = 0.099	SD = 0.092	SD = 0.099
Force	**All**	M = 0.434	M = 0.421	M = 0.509	M = 0.535
		SD = 0.161	SD = 0.165	SD = 0.122	SD = 0.051
	Steady left	M = 0.618	M = 0.604	M = 0.673	M = 0.681
		SD = 0.114	SD = 0.130	SD = 0.097	SD = 0.088
	Sine left	M = 0.489	M = 0.482	M = 0.551	M = 0.545
		SD = 0.117	SD = 0.117	SD = 0.092	SD = 0.082
	Steady right	M = 0.473	M = 0.454	M = 0.549	M = 0.575
		SD = 0.180	SD = 0.183	SD = 0.200	SD = 0.078
	Sine right	M = 0.522	M = 0.517	M = 0.590	M = 0.594
		SD = 0.145	SD = 0.147	SD = 0.100	SD = 0.097

the expertise context.

Future studies could further exploit research questions targeting the context dependency of classification performance. Furthermore, the high degree of individuality described above plays a major role, influencing classification performance also in the classification of group membership. A deeper understanding would further advance the use and development of technologies based on machine learning. Such technologies could be applied in areas where it is of interest to predict the performance state of individuals. These include, for example, rehabilitative or professional contexts. Other possible fields of application could be talent acquisition or adaptive systems.

3.4. Feature space characteristics

Given the low generalizability of the machine learning models in classifying group membership in combination with good decoding performance of force tracking tasks at the individual level, we further investigated the feature space of the EEG features (see Fig. 4A and 4C). Studying the UMAP visualization, a clear assignment of trial-specific EEG features to individual subjects is possible. For both groups, there is a clustered structure with clearly assignable clusters. This structure suggests a large individuality of the EEG markers, which could partly explain the poor classification performance of the tasks and group membership at the group level. However, we found good classification performance of the tasks within participants. Considered together, this could suggest an individual structure and representation of the tasks in each participant that is not transferable to other participants. This phenomenon is also known from the field of BCI research. Here it has been observed that the models used are poorly transferable to other participants or sessions, thus the development of generalizable models is a current field of research (Morioka et al., 2015; Xu et al., 2020).

Comparing the structure of EEG features between the groups of experts and novices the clustered structure of UMAP embedded EEG features is more prominent in the group of experts. Indeed, the distances of the cluster centroids in the UMAP embedding of the feature representation are higher in experts compared to novices (see Fig. 4B and 4D). However, we do not observe this individuality in all experts in the same way, so it would be conceivable that different expertise levels are represented in our dataset. To the best of our knowledge, individuality of brain activity states in the context of expertise research has not been explored yet. However, a high degree of individuality can be found in the movement patterns of musicians. For example, flute players and pianists showed individuality in their movements and playing, which is skill-dependent (Albrecht et al., 2014; Caramiaux et al., 2018). Likewise, high individuality of muscle synergies was found in trained powerlifters, which was related to specific neural strategies in trained athletes (Kristiansen et al., 2015). Similarly, our data suggests a specialization of brain activation during fine motor tasks. In addition, we also observed a lower dispersion of UMAP embedded EEG patterns per trial in experts (see Fig. 4E). This was reflected in a smaller cluster size per subject for experts.

This high individuality, especially in experts, could have applications for the development of generalizable algorithms in the context of BCI. In this context, the training state of users could have an influence on the transfer of BCI systems to different users.

3.5. Methodological considerations

First and foremost, we had a limited amount of data. However, the size of our dataset was not smaller than that of comparable articles mentioned previously. These studies used data of 20–50 participants and significantly fewer samples due to fewer task repetitions to classify experts and novices with conventional machine learning methods comparable to those we used (Hosp et al., 2021; Winkler-Schwartz et al., 2019). Machine learning models are generally considered to be rather data-hungry and benefit from higher data volumes, which make it

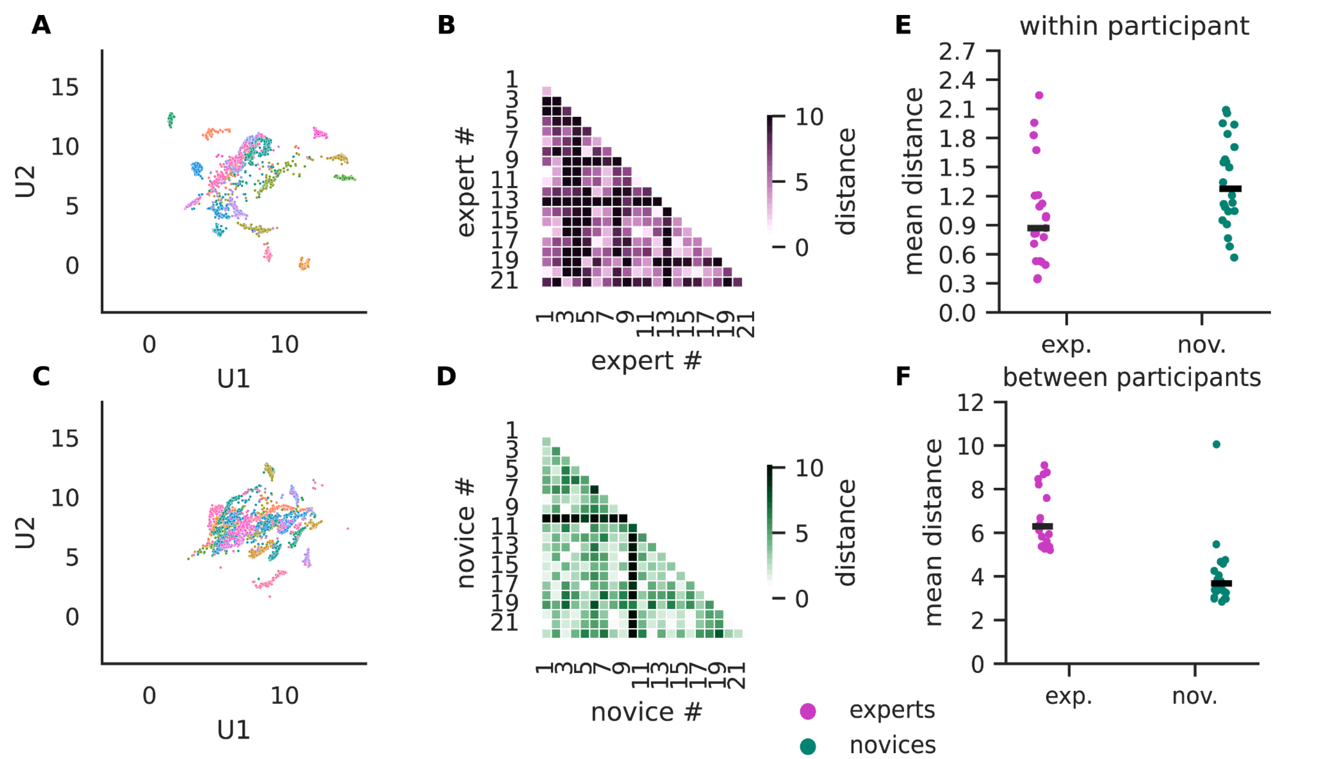

Fig. 4. A & C: UMAP embedding of EEG feature space of fine motor experts (A) and novices (C). Each color corresponds to one participant, each dot corresponds to one trial. B & D: Distance matrices of centroids of each participant cluster in UMAP embedding of experts (B) and novices (D). E: Mean distance of trials within each participant. F: Mean distance of between centroids of each participant cluster. Exp.: experts, nov.: novices. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

possible to detect even subtle differences. However, to compensate for this in terms of a data augmentation approach, we classified at the trial level. In addition, we chose conventional machine learning models that can be applied to smaller datasets. We did not use other methods like deep learning because of their suitability for much larger amounts of data. In the process of group membership classification, feature reductions were not performed to obtain a result based on the entire set of variables and ensure automatic pattern recognition by the classifiers. However, such an approach involves the risk of overfitting, since it is possible that the model is not transferable to new data as it might include redundant features (Hawkins, 2004). We therefore decided to use support vector machines (SVMs) which are effective in high dimensional space.

Using alternative machine learning approaches might result in different performance metrics. For comparison, we used various other classifiers and feature sets (see supplementary material Table S1 and Table S2) without being able to achieve significant improvement in classification. All machine learning methods used are dependent on the features selected. We decided not to use end-to-end decoding and to use features that have shown expertise-related differences in previous studies. As such the analysis of electrophysiological data was performed with DMD. This method was applied successfully in our previous work detecting expertise-related differences (Gölz et al., 2018; Vieluf et al., 2018). In addition, DMD has already proven to be a valuable method for feature extraction (Rahul-Vigneswaran et al., 2019) as well as classifying fine motor movements (Shiraishi et al., 2020). On the one hand, we did not have to make assumptions by using DMD, as the decomposition step adheres to mathematical optimization principles. On the other hand, we selected DMD modes that belong to certain frequency bands. However, a large part of the spectrum, i.e., θ-, α-, β_1 and β_2- band, was represented and thus this assumption should not affect the analysis greatly. Finally, we would like to point out that the high individuality might reflect amplitude effects that were influenced by measurement conditions. Since the experiments were performed by several people, we exclude that this explains the observed effect completely. Furthermore, we obtain satisfactory results in the classification of the tasks on an individual level, so that we assume that the EEG reflects the task effects sufficiently.

4. Conclusion

In this study, we used machine learning to gain data-driven insights into expressions of expertise. We found that classification of group membership based on tasks that roughly reflect the expertise context is not possible with high accuracy. In contrast to positive reports from the literature, we assume a high importance of the expertise context in classification. Furthermore, the classification of tasks is possible with high accuracy within novices and experts at individual level. By examining a low-dimensional representation of the feature space, we found a more pronounced individuality of EEG patterns in experts, suggesting more specialized neural mechanisms in fine motor experts during task performance. In addition to providing data-driven insights, these results could be relevant to the application of machine learning in the context of expertise classification as well as the generalizability of such algorithms in the context of BCI research.

5. Methods

5.1. Participants

The sample was recruited in the context of the Bremen-Hand-Study@Jacobs (Voelcker-Rehage et al., 2013) via flyers, newspaper announcements and telephone calls. Participation was voluntary and each participant provided informed consent. Participants got 8 € per hour compensation. The study was conducted in accordance with the Declarations of Helsinki. The Ethics Committee of the German Society of

Psychology approved the study.

All participants were healthy, without neurological abnormalities and had normal or corrected to normal vision and hearing. In line with their self-report, the Edinburgh Handedness Inventory (Oldfield, 1971) identified all participants as right-handed. Exclusion criteria included hobbies that require the skilled use of hands, such as playing a musical instrument or sewing. Participants were asked about their demographic and educational background, weekly working hours, daily hand use and health related conditions. Experts should have at least 10 years professional experience in a field that requires the skillful and dexterous use of hands such as precision mechanics, e.g., opticians or watchmakers, (Ericsson et al., 2006). Novices were defined as participants whose daily work does not involve extensive use of their hands, such as office or service workers. The sample consisted of 21 experts and 22 novices. Both groups were comparable in age (experts: Mdn = 54.00, IQR: 16.25; novices: Mdn = 55.50, IQR = 18.00) and gender (experts: 10 female / 11 male, novices: 13 female / 9 male). Left hand maximum voluntary contraction (MVC) did not differ between the two groups. Experts had higher MVC in the precision grip with the right hand and a higher frequency of daily hand use (see Table 4 for group values and statistical values).

5.2. Experimental procedure

The experimental setup has been described previously (Goelz et al., 2021). The experiment comprised various force tracking tasks. The task was to track a given target force as precisely as possible. The target force matched either a constant (steady) or a sinusoidal (sine) force level, which was presented as a green line on a screen (19′’, 60 Hz frame rate) 80 cm away from the participants (see Fig. 1A and 1B). The steady line was fixed at 2 N and the sine wave ranged from 2 N to 12 N with a frequency of 1 Hz. The time axis (x-axis) corresponded to 5 s and the force axis (y-axis) to a scale from 0 N to 14 N. Participants manipulated a force curve displayed on the screen by pressing a force transducer with thumb and index finger in precision grip with left or right hand. The inactive hand rested either on the armrest or in the participant's lap. The force transducers (Mini-40 Model, ATI Industrial Automation, Garmer, NC, USA) were attached to the armrests of a chair on which the participants were sitting. The experiment took place in four blocks of 40 trials with 5 s each and 5–7 s break in between. The first two blocks involved tracking the constant target force with the right hand (steady right) followed by the sinusoidal curve (sine right) with the same hand. The participants then performed the following two blocks with the left hand in the same order (steady left, sine left).

The applied force trajectory was recorded at a sampling rate of 120 Hz with 0.06 N resolution. EEG was recorded with a 32 active channel system (ActiveTwo, BioSemi, Amsterdam, Netherlands). Electrodes were placed according to the international 10–20 system (Jasper, 1958). Two additional electrodes, active Common Mode Sense and Driven Right Leg were used as reference and ground electrodes and fixed next to Cz. Furthermore, six additional electrodes recorded vertical and horizontal eye movements as well as mastoid potential. The sampling rate of the signal was set to 2048 Hz and an online band-pass filter between 0.16 Hz and 100 Hz was used.

5.3. Data analysis

For the data analysis we used *Python* version 3.7.6 (Python Software Foundation, Wilmington, DE, USA) with *MNE Python* version 0.20.7 (Gramfort et al., 2013) to analyze and visualize the EEG and *umap-learn* version 0.5.1 (McInnes et al., 2018) to examine the EEG feature space. The machine learning pipelines were implemented with *scikit-learn* version 0.24.2 (Pedregosa et al., 2011). For each participant we classified which task, i.e., steady right, sine right, steady left or sine left, was performed. In addition, we classified experts vs. novices on a group level. For all classifiers we tuned the hyperparameters using grid search, i.e., we searched for the best hyperparameters among a predefined grid of values. An overview of the hyperparameter grid used can be found in Table S1 in the supplementary material. Consequently, hyperparameters were chosen that resulted in the highest classification accuracy.

5.3.1. Preprocessing

5.3.1.1. Force tracking data. First, we filtered the data of the force trajectory with a fourth order Butterworth filter with a cut-off at 30 Hz (Gölz et al., 2018; Vieluf et al., 2012; Vieluf et al., 2015; Vieluf et al., 2018). Next, for each trial we calculated the mean deviation representing the mean absolute difference between target and applied force for each participant. Furthermore, we extracted the absolute variability represented by the standard deviation of the difference between target and applied force. To automatically detect outliers in the force data, we used the statistical Z-values of the mean accuracy of the individual results. Trials with $Z > 3$ were excluded from further analyses as we assumed these to be incorrectly executed.

5.3.1.2. EEG data. EEG data was resampled to 200 Hz and re-referenced to the linked mastoids. The default zero-phase FIR filter in MNE-Python was used to filter the signals between 4 and 30 Hz. We corrected ocular artifacts using independent component analysis (ICA) with the FastICA Algorithm (Hyvärinen, 1999). The resulting independent components whose source signal correlated with the signal of the electrooculography channel were automatically marked and removed. This resulted in the rejection of one component in 17 experts / 18 novices and two components in 4 experts / 4 novices. Next, we created data segments starting at the one second and ending at the four seconds after trial onset mark. Trial segments that contained artifacts were identified and removed automatically using the Autoreject pipeline (Jas et al., 2017). Moreover, we excluded all trial segments marked as

Table 4
Group characteristics - MVC: Maximum voluntary contraction, RH: right hand, LH: left hand, Mdn: median, IQR: interquartile range, M: mean, SD: standard deviation, U: test statistic of the Mann-Whitney-*U* test (in case of not normally distributed data), t: test statistic of the *t*-test (in case of normally distributed data), p: probability value.

		Experts (n = 21, female: 10)	Novices (n = 22, female: 13)	Statistical values
Age [years]		Mdn = 54.000 IQR = 16.250	Mdn = 55.500 IQR = 18.000	U = 204.000, p = 0.635
MVC [N]	**LH**	Mdn = 46.455 IQR = 24.519	Mdn = 42.627 IQR = 27.757	U = 204.000, p = 0.520
	RH	Mdn = 56.000 IQR = 28.386	Mdn = 48.614 IQR = 13.243	U = 147.000, p = 0.043*
Daily use of hands[1]		M = 37.381 SD = 5.536	M = 18.381 SD = 5.670	t(41) = 10.988, p < 0.001*
# of trials after preprocessing		Mdn = 156 IQR = 1	Mdn = 156 IQR = 2	U = 274.000 p = 0.296

1: Maximum value = 45; A higher value corresponds to a higher frequency of hand use.

incorrectly executed. Each three second segment was decomposed using DMD (Brunton et al., 2016). For this step we analysed windows of 0.5 s with 0.25 s overlap to account for data nonstationarities and each segment was embedded by stacking and shifting the data four times, as described in previous work (Goelz et al., 2021). The optimum of these parameters (stacking depth, window size, and overlap) were determined by an error analysis of data from five randomly chosen subjects.

5.3.2. Classification of tasks

To show that we are using task-relevant features for group membership classification and to detect any group differences, we classified the tasks based on EEG as well as behavioral measurements, i.e., force tracking. EEG feature extraction as well as classification followed strictly the procedure described in previous work (Goelz et al., 2021). The absolute DMD mode magnitudes in each frequency band and trial were projected onto the common spatial pattern (CSP) space and the logarithmic variance of the projected DMD mode magnitudes of all time windows per trial were calculated as features. To be consistent with our previous work, we used linear discriminant analysis (LDA) for the classification based on EEG. The force tracking features included the mean deviation and variability per trial. For classification based on force tracking we used support vector machines (SVMs).

For each participant, we built and evaluated a machine learning model using 10-fold nested cross-validation. In each fold the data was divided into 80% (i.e., maximum 128 trials) for training and 20% (i.e., maximum 32 trials) for testing. Due to exclusion of trials because of incorrect execution or artifacts in corresponding EEG segments the exact number of trials varied between participants but was comparable between groups (see Table 4 and supplementary material Table S4).

To test the generalizability of the models between participants, we also built and evaluated a model at the group level for experts and novices. For this we used 10-fold nested cross-validation. In each fold we used all trials of 80% of the subjects (experts: 17 / novices: 18) per group for training and the 20% of the subjects (experts: 4 / novices: 4) for testing.

Hyperparameters of SVM or LDA classifiers were tuned in each fold using ten-fold cross-validation on the training data using a grid search procedure (see supplementary material Table S1 for the hyperparameter grid used).

5.3.3. Classification of group membership

To increase the data size for the classification of group membership, we performed the classification on all force tracking trials rather than the mean values of an entire force tracking block. All force tracking tasks were used collectively as well as each force tracking task individually. For that, we used either only EEG features, only force tracking features or a combination thereof in separate iterations. The EEG features consisted of the absolute DMD mean modes per frequency band and trial assuming that expertise relevant information is detectable in spatially and temporally coherent EEG patterns, as we have shown in previous studies (Gölz et al., 2018; Vieluf et al., 2018). We averaged DMD modes corresponding to the frequency bands θ- (4 to $<$ 8 Hz), α- (8 to $<$ 12 Hz), β_1- (12 to $<$ 16 Hz) and β_2- (16 to $<$ 30 Hz) per trial for each participant to obtain the DMD mean mode for each frequency band and trial. As force tracking features the mean deviation and variability per trial for each participant as described above were used.

To classify group membership based on EEG data and force tracking performance, we used SVMs. The model was trained and tested using 10-fold nested cross-validation. Therefore, we divided the dataset ten times into a training and test set using all trials of 80% of participants (i.e., 35 participants) for training and all trials of 20% of participants (i.e., 8 participants) to test the generalization of the classifier to unseen participants (see supplementary material Table S3). In each data partition hyperparameters of the SVM classifier were tuned dividing the training dataset again 10 times with the same procedure (see supplementary material Table S1 for the hyperparameter grid used).

5.3.4. Extraction of feature space characteristics

To visually examine the EEG feature space, we used uniform manifold approximation and projection (UMAP) (McInnes et al., 2018) and reduced the dimensionality to two dimensions. To quantify the clustering structure in the UMAP embedding, we calculated the Euclidean distance of trials within each participant. In addition, the centroids of all trials per participant were calculated and the Euclidean distance between these centroids was determined.

5.3.5. Statistical analysis

For statistical analyses, we used *scipy* version 1.6.2 (Virtanen et al., 2020), *statsmodels* version 0.12.2 (Seabold and Perktold, 2010) and *permute* version 0.2 (Millman, 2015). To compare the groups in basic characteristics as well as in their force tracking performance, we conducted t-tests and Mann-Whitney-U tests, in case of violation of normality assumption. Force tracking performance of each participant was quantified as mean over all trials in measures described above (mean deviation and variability). Intertrial variability was calculated as standard deviation over all trials of the mean tracking accuracy.

To test for group differences in EEG activity, we averaged the DMD mean mode magnitudes in each frequency band over all trials per force tracking task and participant. Next, we conducted permutation t-tests to compare DMD mean mode magnitudes between the groups. This statistic was chosen as a non-parametric alternative suitable for high dimensional data like EEG data (Maris and Oostenveld, 2007). For this we determined all possible values of the test statistics under the null hypothesis with a 10,000-fold random reordering of the data.

To evaluate the machine learning models, we calculated the proportion of correct predictions of the model (accuracy) as well as (macro average) F1, precision and recall values and report the mean over all folds. We conducted t-tests and Mann-Whitney-U tests, in case of violation of normality assumption, to compare performance of task classification between the groups. For all tests the alpha level was set to 0.05 and false discovery rate (Benjamini and Hochberg, 1995) was used to account for type I errors.

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Code availability

Python source code that supports the results is available from: https://github.com/christiangoelz/FME_classification.

CRediT authorship contribution statement

R. Gaidai: Software, Formal analysis, Writing – original draft. **C. Goelz:** Software, Formal analysis, Writing – original draft. **K. Mora:** Software, Formal analysis, Writing – review & editing. **J. Rudisch:** Writing – review & editing. **E. Reuter:** Conceptualization, Investigation, Writing – review & editing. **B. Godde:** Conceptualization, Supervision, Writing – review & editing. **C. Reinsberger:** Writing – review & editing. **C. Voelcker-Rehage:** Conceptualization, Supervision, Writing – review & editing. **S. Vieluf:** Conceptualization, Investigation, Supervision, Project administration, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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