

## Signatures of team performance in the brain

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### Introduction:

Real-world tasks and military missions often require the coordinated efforts of many team members for successful completion. Understanding how expertise develops within a team and identifying the relevant variables that determine how an expert team operates is a prerequisite for training to be directed. Recently, we have developed a new approach for the study of team dynamics from behavioral data [1]. Here we extend the methods used in [1] to the neural domain to distinguish expert teams from novice teams on the basis of their brain dynamics measured by simultaneous EEG from the team members. The experimental setting consisted in a scenario that has been developed to simulate a realistic and challenging combat situation, intentionally structured so that it necessitates extensive coordination and communication between the team members.

### Methods:

High density EEG data (256 channels) with a sampling rate of 250 Hz was acquired simultaneously from the two team members of four teams (two novice teams, two expert teams) in a simulated combat scenario where the subjects were coordinating to accomplish a common goal. Data from 14 trials were acquired for each team. Each trial lasted about 20 minutes and comprised a time point ("turning point") after which simulated hostilities occurred. Our goal here was to characterize differences between team levels and differences before and after the turning point.

Along with more traditional methods such as time-frequency analysis, we build on our approach in previous work on team dynamics [1] where we characterized the behavior of the expert team over time mathematically by a manifold in phase space spanned by the task variables. Although this phase space is high-dimensional (one dimension for each task variable of each team member, which corresponds to  $2 \times 256 = 512$  dimensions in this experiment), constraints imposed by the task itself as

well as by the coordination between the team members leads to the manifold having a lower dimension. In [1] it has been shown that the manifolds are descriptive of the expertise level of the teams and of the level of team coordination. Here we assess the expert and novice manifolds by performing singular value decomposition (SVD) of the joint data of subjects 1 and 2 using a sliding window (length 10s). For each time window the eigenvectors of the SVD span a local subspace (tangent space to the manifold) of the phase space in which the team data is evolving. The evolution of the subspaces may reflect temporal or spatial modulation in the brain [3]. Local dimensionality of the manifold was determined from the local subspaces. Here we show results from the local dimensionality analysis of the team manifolds (Figs. 1, 2) and from time frequency analysis (Figs. 3, 4). Prior to the analyses artifacts were reduced by an in-house program.

### **Results:**

We found that the mean local dimensionality of the team manifolds was higher for the novice teams than for the expert teams and this result was highly consistent over trials (Fig. 1). This indicates that the joint brain dynamics of expert teams is much more constrained than that of the novice teams.

In addition in the experts the mean local dimensionality was slightly higher after the turning point than before the turning point (Fig. 2), indicating a slight increase in local dimensionality with task demand. This effect was less pronounced in the novices. The overall effect is small, and to assess significance we determined the number of trials in which the effect occurred. A significance value was computed by using the binomial distribution with a 50% probability which would occur if the effect were absent. In addition we assessed whether the effect was consistently found in both single subject data and joint data of the same trials. According to this measure the experts had significant increases in the mean local dimensionality after the turning point ( $p < 0.001$  for subject 2 and joint data,  $p < 0.011$  for subject 1), which furthermore were consistent for the majority of trials. In the novices significant increases occurred in subject 2 ( $p < 0.005$ ) and the joint data ( $p < 0.03$ ), but not in subject 1. In addition the increases were inconsistent for the majority of trials in the novice teams. This indicates that both subjects in the expert teams react to the increased task demand with an increase in dimensionality of their brain dynamics, while in novices the two subjects react inconsistently with each other.

Time-frequency analysis was performed using a Gaussian window of length 960 ms. The Fourier transformed data of each window was averaged over electrodes and its power was computed. We found that in novices power occurs mostly in the alpha range (around 10 Hz, cf. Fig. 3) while experts tend to show some power in the beta range (20–30 Hz, cf. Fig. 4).

### **Conclusions:**

Novice and expert teams exhibit different characteristics in their brain dynamics

as measured by simultaneous EEG when performing a highly nontrivial ongoing task. In particular the local dimensionality of the joint data was smaller in the expert teams, consistent with a higher coordination than in the novice teams. Increased task demand such as the onset of hostilities after the turning point was associated with a slight but consistent higher local dimensionality in the expert team. The presented results are the first steps in extending the approach for analyzing team dynamics from behavioral data used in [1] to analyzing brain dynamics in teams. In further work we will analyze the team manifolds in terms of their tangent spaces representing locally dominant spatial patterns of the joint EEG data of both subjects. We will assess signatures of team coordination in the brain by comparing team manifolds from real teams to team manifolds from surrogate teams without team coordination.

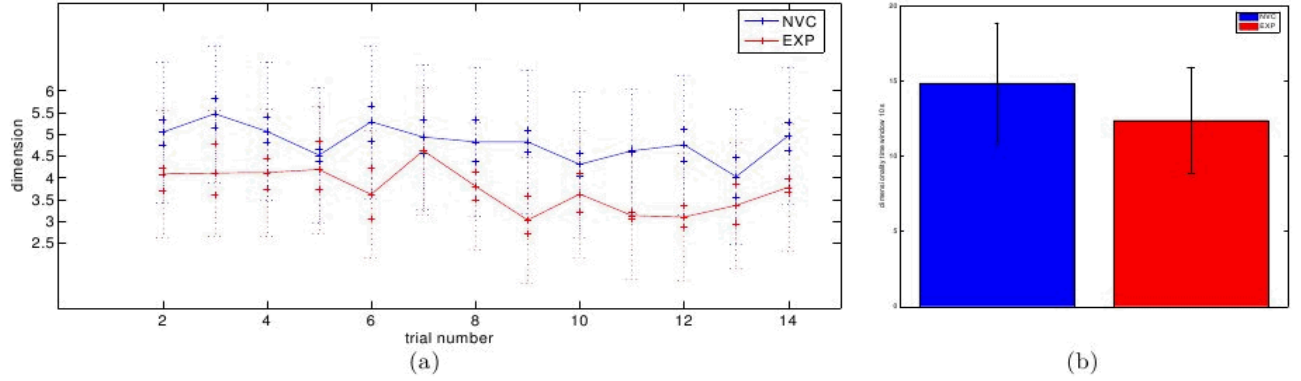


Figure 1: Dimensionality over trials of joint subjects. Blue: novices, red: experts. Solid lines: Mean dimensionality over both teams of the same team level, dotted lines: standard deviation. Isolated crosses: mean dimensionality over the single teams of the same team level.

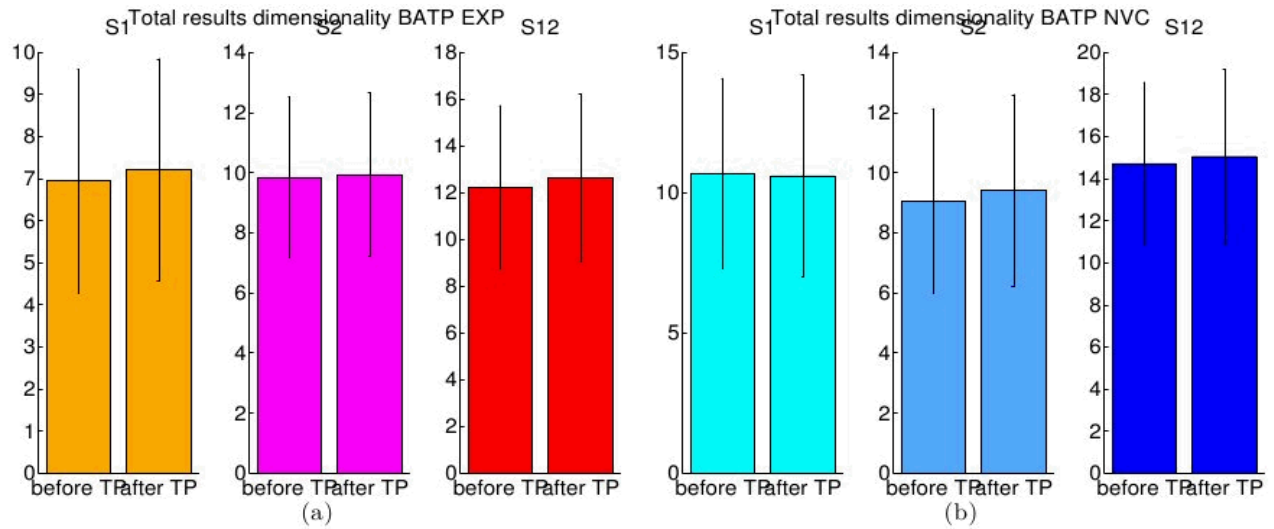


Figure 2: Mean local dimensionality over all trials before and after turning point. Error bars: Standard deviation. (a) Expert teams. Orange: subject 1, magenta: subject 2, red: joint data of both subjects. (b) Novice teams. Cyan: subject 1, light blue: subject 2, blue: joint data of both subjects.

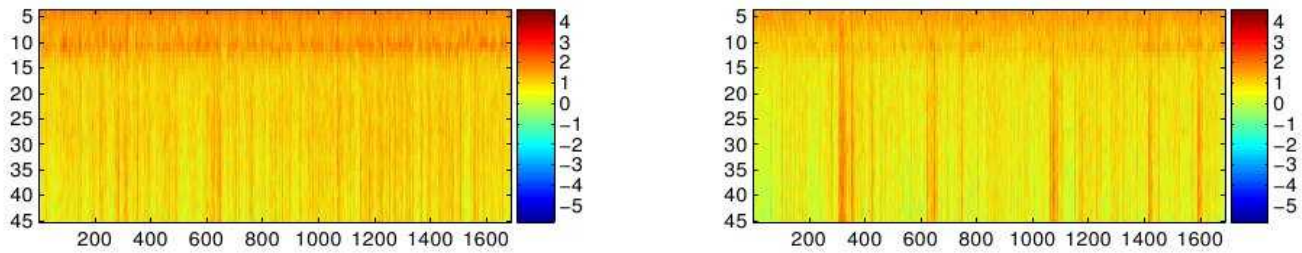


Figure 3: Average power over all electrodes over time in the two subjects of a novice team in the same trial (left: subject 1, right: subject 2). Color code: Log scale. Length of time windows: 960 ms. Frequency range: 4-45 Hz. Time units: seconds.

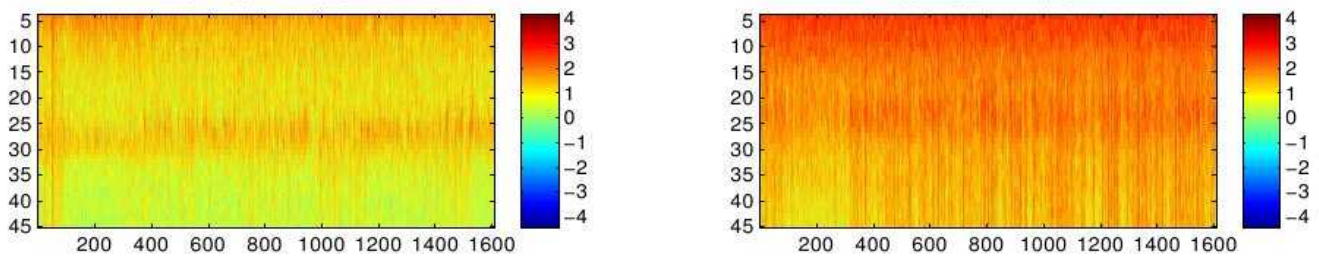


Figure 4: Average power over all electrodes over time in the two subjects of an expert team in the same trial (left: subject 1, right: subject 2). Color code: Log scale. Length of time windows: 960 ms. Frequency range: 4-45 Hz. Time units: seconds.

## References:

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#### Categories

- Reasoning and Problem Solving (Cognition and Attention)
- Social Behavior (Emotion and Motivation)
- EEG (Imaging Techniques and Contrast Mechanism)
- Multivariate Modeling, PCA and ICA (Modeling and Analysis)
- Multisensory and Crossmodal (Sensory Systems)