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Neurotechnology to Accelerate Learning During Marksmanship Training

This article explores the psychophysiological metrics during expert and novice performances in marksmanship, combat deadly force judgment and decision making (DFJDM), and interactions of teams. Electroencephalography (EEG) and electrocardiography (ECG) are used to characterize the psychophysiological profiles within all categories. Closed-loop biofeedback was administered to accelerate learning during marksmanship training in which the results show a difference in groups that received feedback compared with the control. During known distance marksmanship and DFJDM scenarios, experts show superior ability to control physiology to meet the demands of the task. Expertise in teaming scenarios is characterized by higher levels of cohesiveness than those seen in novices.

Learning a novel task generally relies heavily on the conventional classroom instruction with qualitative assessment and observation. Integration of neuroscience-based evaluation and training techniques could significantly accelerate skill acquisition and provide quantitative and objective evidences of successful training. In a project supported by Defense Advanced Research Projects Agency's (DARPA) Accelerated Learning program, EEG (brain's electrical activity) and ECG (heart's electrical activity) techniques were used to assess expertise in marksmanship, combat DFJDM, and team neurodynamics.

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Accelerated Marksmanship Skill Learning

Marksmanship skill acquisition was accelerated by first modeling the psychophysiological characteristics of expertise and then developing sensor-based feedback to accelerate novice-to-expert transition. A preshot peak performance profile was identified in expert marksmen, characterized by an increase in theta and alpha power (derived from EEG) and a decrease in heart rate in the seconds leading up to a shot [1].

A recent study incorporated a novel device called the *adaptive peak performance trainer* (APPT) into a marksmanship training protocol with novice participants. The APPT provided real-time feedback of heart rate and EEG alpha power to the trainee. A haptic motor clipped to the collar vibrated in sync with the trainee's heart beat and stopped vibrating when alpha power was sufficiently elevated. The goal of the APPT was to indicate to the trainee when he is in the ideal state to fire the weapon. All participants completed eight trials of five shots each in a simulated indoor shooting range. The training protocol incorporated video-based coaching on the fundamentals of marksmanship by a qualified marksmanship coach. An instrumented weapon was developed using off-the-shelf sensing components and a demilitarized M16/A2 housing a pneumatic recoil system designed to approximate the weight, noise, and action of a real live fire weapon. Shots were directed against a scaled projection of a circular target simulating a 20-in diameter target at 200 yd. Marksmanship performance was measured as the average dispersion of five shots from the shot group center (inches), where lower dispersion represents a tighter shot grouping and better performance. Performance trajectories of novices trained with the APPT ($n = 37$) were 2.3 times greater than those of novices trained with an identical protocol without the APPT ($n = 17$) [1] (Figure 1). A one-way ANOVA revealed a control versus APPT difference in both final trials, $F(1,51) = 6.65$, $P < 0.05$, and percent improvement, $F(1,52) = 5.34$, $P < 0.05$.

Combat DFJDM

The decision of when to use deadly force is a complex skill to assess and train. Split-second life-or-death decisions require a delicate balance between restraint and aggression. The psychophysiology of DFJDM was evaluated using realistic video-based simulations to fully engage participants. Twelve experts (infantry with urban combat experience and police with ≥5 years patrol in active areas) and 12 novices (civilians with no military or police experience) participated in the study. All participants engaged in 24 DFJDM scenarios (approximately 70% justifying the use of deadly force). Scenarios were filmed using professional actors and represented characteristics of the most common deadly force situations encountered by law enforcement. When participants perceived a threat requiring deadly force, they responded by firing a simulated Glock 17 with a laser barrel insert. Between scenarios, participants were given a short rest (~2 min) to recover from the previous scenario and prepare for the next scenario. Participants were given a long rest (~40 min) after every three scenarios. EEG and ECG were measured throughout the day-long session (Figure 2).

Experts had significantly lower low-frequency heart rate variability (LF HRV) than novices during the scenarios [$t(22) = -2.79$, $P < 0.05$]. Lower LF HRV indicates less influence by

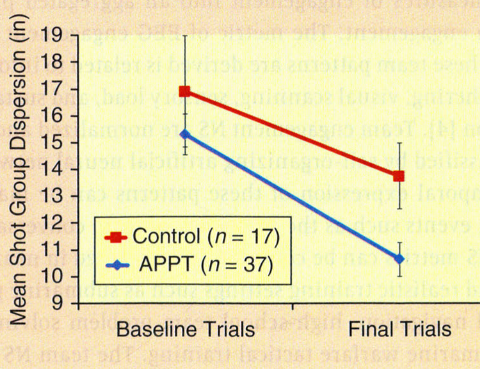

FIGURE 1 The performance trajectory for the APPT group is 2.3 times greater than the control group.

The psychophysiology of DFJDM was evaluated using realistic video-based simulations to fully engage participants.

the sympathetic nervous system, suggesting a lower state of stress [2]. Using a two-way ANOVA (group × task demands), experts showed greater suppression of right parietal EEG alpha power (8–12 Hz) during scenarios relative to rest periods, $F(3,44) = 3.84$, $P < 0.05$. Task-related alpha suppression is associated with increased attention demands, specifically, increased alertness and expectancy [3]. A greater change in alpha power between resting and scenario most likely indicates that experts are more efficient at matching their psychophysiological state (e.g., state of alertness) to task demands (scenario versus rest).

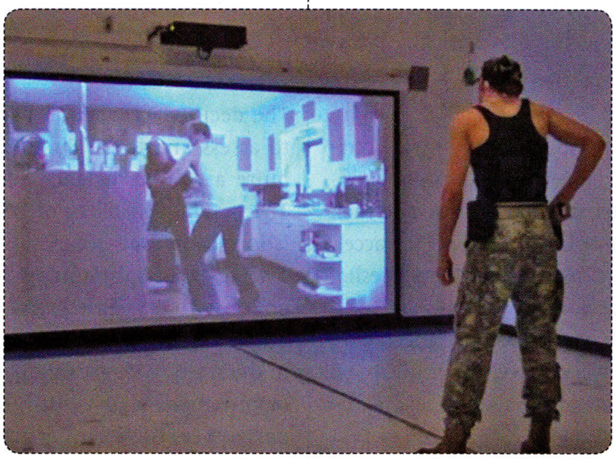

FIGURE 2 The DFJDM scenario conducted at Washington State University. (Photo courtesy of Scott L. Oplinger, Washington State University.)

Team Neurodynamics

Our goal for modeling team neurodynamics is to rapidly determine the functional status of a team to assess the quality of performance and decision with the potential to adaptively rearrange the team or task components to better optimize teamwork. Neurophysiologic synchronies (NS) are low-level data streams that combine individual team members' EEG-based measures of engagement into an aggregated profile of team engagement. The metric of EEG engagement from which these team patterns are derived is related to information gathering, visual scanning, sensory load, and sustained attention [4]. Team engagement NS are normalized and pattern classified by self-organizing artificial neural networks. The temporal expression of these patterns can be mapped to team events such as the frequency of team conversation. Team NS metrics can be collected and analyzed in near real time and realistic training settings such as submarine piloting and navigation, high-school team problem solving, or antisubmarine warfare tactical training. The team NS metrics that are expressed during team performance have been proven to provide insight into the dynamics of the team. For example, entropy, a measure of randomness or uncertainty of NSs expressed over a specified time period, was significantly higher for expert submarine piloting and navigation teams compared to less-experienced teams. Entropy increased as teams gained experience, approaching the level seen in experts. Transition matrices (a plot of the NS_E being expressed at time t versus that at time $t + 1$) showed that the expert teams use more of the available NS_E patterns available to them, possibly indicating a more flexible team and one that does not frequently get locked into a restricted pattern of engagement.

In Figure 3, the entropy metrics for two novices and one expert team are shown. Submarine Officer Advanced Course (SOAC) novice team 1 did not complete session 5, while novice team 2 had technical issues that resulted in session 1 being unavailable. However, the graphs in Figure 3(a) clearly demonstrate that novices increase in the entropy measure as they gain experience and plateau in sessions 3–5. Figure 3(b) compares the expert entropy to the novice entropy in sessions 1–2 versus 3–5. A significant difference is shown between experts' and novices' sessions 1–2.

NS expressions appear to be important constructs for studying team dynamics as

- they change rapidly in response to short- and long-term changes in the task [5]
- they relate to the task and some established aspects of team cognition such as speech [6]
- they can be rapidly reported for use by educators/trainers [7]
- they can distinguish some aspects of novice/expert performances
- they are sensitive to training effects.

Team engagement NS are normalized and pattern classified by self-organizing artificial neural networks.

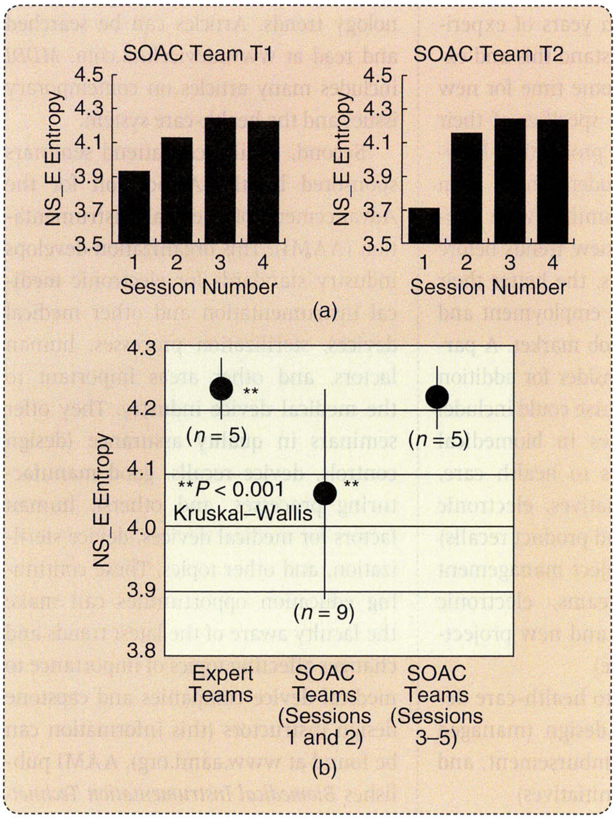

FIGURE 3 Entropy metric for two SOAC novice teams and one expert team: (a) the Shannon entropy levels for two SOAC teams that performed four SPAN simulations at different times during their nine-weeks training and (b) the mean (± S.D.) entropy levels for SPAN sessions performed by expert submarine navigation teams (Expert) and for SOAC teams on their first two SPAN performances (sessions 1 and 2) and subsequent performances (sessions 3–5).

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