Theoretical Issues in Ergonomics Science, Vol. X, No. X, Month 2006, xxx–xxx

Running heads (verso) *W. Shebilske* et al.
(recto) *Optimizing instructional strategies: BEST*

Optimizing Instructional Strategies: A Benchmarked Experiential System for Training (BEST)

WAYNE SHEBILSKE†, KEVIN GILDEA§, JARED FREEMAN*§,
AND GEORGIY LEVCHUK§

† Wright State University, 3640 Colonel Glenn Hwy., Dayton, OH 45435
§ Aptima, Inc., 12 Gill Street, Suite 1400, Woburn, MA 01801

Correspondence: *Jared Freeman. Email: freeman@aptima.com

Contact information:

Wayne Shebilske: Department of Psychology, Wright State University, 3640 Colonel Glenn Hwy., Dayton, OH 45435-2399,937-775-2399, Fax: 937-775-3347, wayne.shebilske@wright.edu

Kevin Gildea: Aptima; 12 Gill Street, Suite 1400, Woburn, MA 01801; 781-935-3966; Fax: 781-935-4385; kgildea@aptima.com

Jared Freeman: Aptima; 1726 M Street, NW, Suite 900, Washington, DC 20036; 202-842-1548 x316; Fax: 202-842-2630; freeman@aptima.com

Georgiy Levchuk: Aptima; 12 Gill Street, Suite 1400, Woburn, MA 01801; 781-935-3966; Fax: 781-935-4385; georgiy@aptima.com

Abstract

We address the problem of developing and delivering feedback concerning teamwork in ill-defined domains. We combine three strategies to train using feedback. (1) We leverage mathematical optimization techniques to rapidly devise solutions to the complex problems of asset selection and scheduling in military mission planning and execution, and we use those optimized solutions as feedback. (2) We focus trainee attention on specific principles that humans can learn from these optimized solutions. (3) We leverage the profound human capability to go beyond what is told and to learn from observation. We report an experiment that assessed the impact of these strategies on human learning in a team command and control task, and we state implications for simulation-based training.

Keywords: Instructional strategy; Training; Teams

1.0 Introduction

1.1 The training challenge

Expertise is a function of the amount of deliberate practice plus feedback. This simple formula derives from research concerning the genesis of expertise in exotic and everyday domains – from chess, music, and medicine to typing (Ericsson *et al.* 1993, Ericsson 2002, 2004), and it guides the design of training systems in three ways. First, *training systems should be highly accessible*, to promote frequent practice. Thus, training simulations should be delivered on the most portable, commonly available platform on which the targeted knowledge and skills can be trained. *Second, practice scenarios in simulations should be systematically structured and focused on training objectives*, to promote deliberate practice. *Third, performance assessments should be relevant to training objectives, and systematically delivered* to train and maintain competencies through feedback.

A large body of literature from cognitive and instructional psychology supports this approach and lends valuable nuance (e.g. Piorolli and Anderson, 1985; Schmidt and Bjork, 1982). Much of this literature, however, concerns tasks that are well-defined (e.g. mathematics) and that are executed mainly by individuals. We are concerned with human performance in domains that are ill-defined (e.g. command and control of complex operations) and that are executed by teams

In this paper, we address the problem of developing and delivering feedback concerning teamwork in ill-defined domains. We describe a solution – called the Benchmarked Experiential System for Training (BEST) – that implements three strategies, (a) using mathematical optimization techniques to optimize problem solutions for feedback (c.f. Bohil and Maddox, 2003); (b) focusing attention on principles in these optimized solutions; and (c) leveraging observational learning. Below, we discuss these strategies in some detail, a domain to which we applied this strategy, and an experimental test of its effects on learning.

1.2 Optimization of Problem Solutions for Feedback

Skilled personnel in command and control (C^2) settings assign capable assets to tasks, and create efficient schedules with which assets execute those tasks. Mathematical optimization techniques can solve such asset allocation and scheduling problems. We applied these techniques to develop assignment and schedule solutions for an air defense C^2 task in a moderate fidelity simulator, and we used these solutions as training feedback.

The simulation required participants to defend a no-fly zone from enemy intrusion by taking one of three actions against enemy aircraft to maximize team scores: *(a) attacking* the enemy when it entered the no-fly zone (which yielded the training team a reward of 50 points less penalties for time spent in the no-fly zones); (b) *preemptively* attacking the enemy before it entered the no-fly zone (which was penalized because it violated the Rules of Engagement); or (c) *ignoring* the enemy, so that the target completed its intended path (which accumulated penalty points for the entire time the target spent in the no-fly zone).

We developed near-optimal solutions to this task assignment and scheduling problem to use as feedback to teams. The optimization problem was tractable because: (a) each asset could strike only one enemy target before returning to base for reload/refuel; (b) each target could be attacked by only one asset (i.e. coordinating multiple assets to simultaneously attack a target was outside the scope of the problem); (c) complete target path parameters were known *a priori.*

The optimization algorithm has several interdependent phases. In Phase I, we find the *allocation of targets to assets*. Initially, each target is assigned to the closest asset whose capabilities are adequate to prosecute the target.

In Phase II, we obtain a *target sequence* – the order in which the targets will be attacked. When the sequence of targets is fixed, we can apply efficient algorithms to obtain a final schedule for the targets. The availability of multiple assets and hence feasible parallelism in task execution can introduce considerable complexity to the solution process. However, only a limited number of task sequences were feasible because of the timing with which tasks appeared and disappeared in this simulation.

In Phase III, we find a *task schedule* – the exact times when the tasks will be prosecuted by assets, and specific actions taken by assets against the tasks (detection, identification, attack, etc.). One of the primary decisions in this step is to determine when to launch an asset to intercept the targets. A fixed task execution sequence found in Phase II limits the number of alternative launch options. The objective is then to consider each asset as a separate entity and schedule its launches over time to minimize the penalty from target maneuvers and maximize the reward from target execution. The algorithm to find the optimal task times and associated launch schedule of the asset is based on a dynamic programming problem and accounts for influences of each task allocation on the execution of consecutive tasks in the task sequence. All information provided to the BEST model about the tasks' timing and identification was accurate.

The generic task schedule optimization solution is intractable: no polynomial time algorithm exists to solve this problem. The decomposition of schedule optimization in the phases described above is performed to reduce the complexity of the solution, but it sacrifices the optimality of the obtained schedule. The task sequence found in Phase II impacts the task time schedule (Phase III). The task-to-asset allocation (Phase I) also affects how and when the tasks can be executed. Therefore, we use a feedback among Phases I through III to iteratively improve the task schedule until a near-optimal solution is reached. When the schedule is obtained in Phase III and rewards and penalties for the schedules are calculated, we utilize an annealing approach to modify the allocation of the tasks to assets (Phase I) and then repeat Phases II and III to reliably raise the score of the schedule.

1.3 Focusing attention

In the experiment described below, we supplemented optimized problem solutions with guidance concerning C^2 principles. This was intended to focus novices on and help them understand the functional structure of the C^2 domain as experts do (Gillan *et al.* 1992, Chase and Simon, 1973).

Three methods focused attention on C^2 principles. First, instruction concerning this C^2 domain was given to all participants prior to the first training mission. Second, all participants engaged in a planning session preceding mission execution, which included a review of general strategies of asset allocation. Finally, feedback for all participants addressed strategies. The treatment group saw BEST, near-optimal solutions during debriefing. For each trial, one solution was presented as an animated visualization (see Figure 1), accompanied by a voice-over that explained the principles underlying the expert strategies illustrated by this solution. Participants in the control condition received the same preparation, opportunity for planning, and time during debrief, but feedback consisted of only a general list of strategies. Thus, preparation, planning, and feedback focused trainee attention on the structure of the domain and strategies for effectively leveraging that structure.

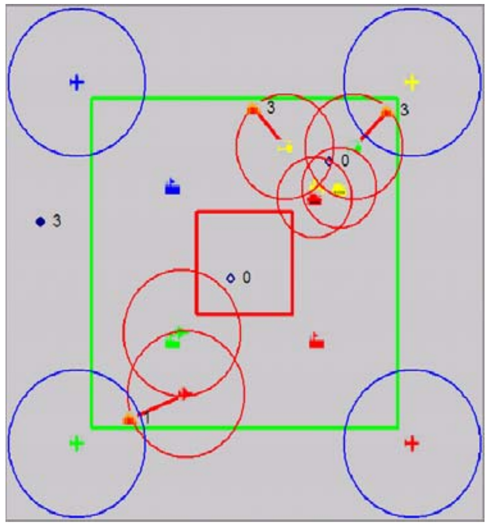

Figure 1: Animated feedback of an optimized problem solution

1.4 Observational learning

Our use of animated, near-optimal scenarios was intended to exploit both explicit strategic instruction and the potential complementary role of observational learning. Observational learning theory (Bandura 1986, Bandura *et al.* 1961, 1963) defines a method of enhancing learning (Ioerger *et al.* 2002; Shebilske *et al.* 1999), near transfer, and far transfer (Bandura 1986, Shebilske *et al.* 1998) by observing the performance of others. It engages four processes; (1) attention, (2) retention, (3) reproduction, and (4) motivation. The observer must first attend to a behavior that is being demonstrated either by a human or an artificial agent. Retention is aided by various learning strategies such as organizing material and mental rehearsal. Reproducing the observed behavior allows the learner to fine-tune the learned response. Motivation drives the learner to exercise the learned behavior. The experimental training supported each of these behaviors, respectively, by presenting (1) the animated solution, (2) strategic guidance, and (3) practice in (4) a game-like, scored task.

In sum, we combined three strategies to accelerate learning through feedback in a complex C2 task: generation of near-optimal solutions for feedback; focusing trainee attention on principles and strategies humans can learn from these solutions; and presentation of optimized solutions as animations to promote observational learning.

2.0 A representative command and control problem

We tested the impact of the BEST feedback strategy using a task that was exemplary of command and control in actual military settings. This degree of ecological validity improved the odds that the findings would generalize to the operational environment. The C^2 'node' emulated was an Airborne Warning and Control System (AWACS) team. Cognitive task analyses of AWACS in operational settings (Fahey *et al.* 2000) guided the simulation's design.The AWACS team operates on board an E-3 Sentry aircraft (Elliott *et al.* 1999) equipped with a radar system that is capable of detecting airborne targets in excess of 200 miles. The crew usually has at least a Mission Crew Commander (MCC), Senior Director (SD), and several Air Weapons Controllers (AWC) (Formerly known as Weapons Directors or WD; Fahey *et al.* 2000). The AWCs have the primary responsibility for directing friendly aircraft. Each AWC may have oversight of a particular location, or 'lane,' or they may be assigned specific functions such as controlling High Value Assets (HVAs) such as intelligence gathering aircraft. The MCC and SD leave decisions in the AWC's hands and intervene only if there appears to be an oversight. Working under high workload, these teams make decisions in current, military operations that take or spare the lives of enemies as well as preserve the lives of our own warfighters and non-combatants.

3.0 Method

3.1 Participants

One hundred twenty undergraduate college students (38 women and 82 men, mean age = 20.4 years) volunteered to participate. They were paid $6.75 per hour, and they were treated in accordance with the 'Ethical principles of Psychologists and Code of Conduct' (American Psychological Association 1992).

3.2 Materials

Office dividers separated 16 work stations in four rows of four. Teams of four sat in the rows. Each station had an IBM compatible PC with a 17 in. monitor, a mouse for all inputs, and a headset linked with an Aardvark sound system audio net that enabled open and recorded communication within teams and isolation of sounds between teams.

The teams defended two no-fly zones in a command and control task implemented on the Dynamic Distributed Decision Making (DDD) simulation (see Figure 2). Each team member, or decision maker (DM), controlled a base centered within one of four quadrants and four other assets, an AWACS, jet, helicopter, and tank. The bases were inside the corners of a green no-fly zone and outside the corners of a red critical no-fly zone. Six boxes in a blue report area displayed offensive scores (top three boxes) and defensive scores (bottom three boxes). The left, middle, and right boxes displayed scores for individual; groups for the North or South regions; and teams, the total score of all four DMs, respectively. The defensive scores dropped at the rate of one point per second for each enemy target in the green no-fly zone and two points per second for each enemy in the red critical no-fly zone. The offensive scores increased for every successful attack on an enemy target in the no-fly zones (individual + 5, group + 10, team + 25). The offensive scores decrease by 25 points each when an enemy target was destroyed outside the no-fly zones or when a friendly asset was destroyed anywhere. All these scores were displayed, but only the Team Defensive score, which started at 50,000, was used in the present analysis of team mission performance, because this score relates to the most important part of the mission, defending the no-fly zones.

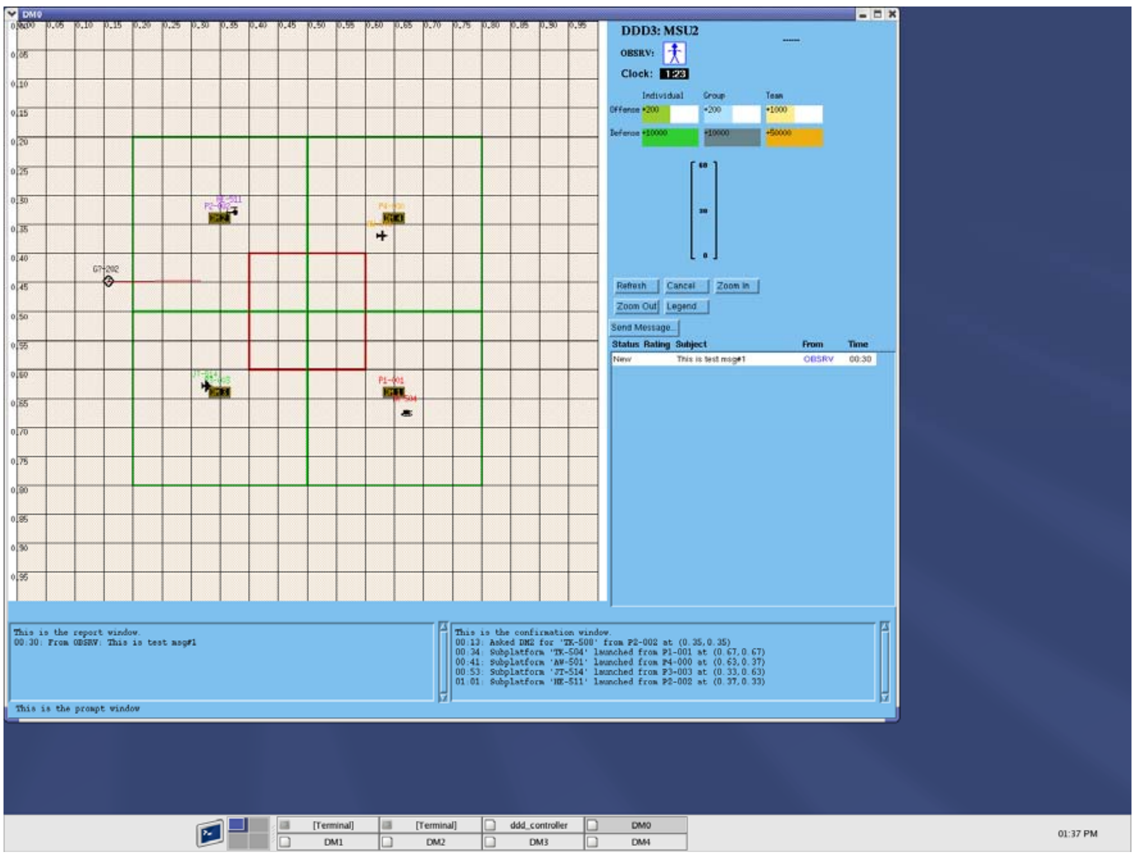

Figure 2: User interface to BEST scenarios on the DDD

All vehicles and the base had a black outer detection ring and a blue inner identification ring. All of the vehicles except the AWACS also had a red attack ring that was between the black and blue rings. Detection rings were progressively smaller and the speeds were progressively higher for the AWACS, jet, helicopter, and tank. The inner ring sizes changed proportionally with the outer ring size. Tracks were not visible unless they were within the detection ring. New tracks were labeled with a sequentially assigned number.

DMs launched vehicles one at a time from the base by right clicking the base and selecting ‘Info on Asset’ from a pop-up menu. Before another vehicle could be launched, a several second delay was marked by the base changing from a rectangle to an X, and a ‘busy signal’ appearing in the report area along with a strip display indicating the time left until the selected vehicle was clear of the base. The launched vehicle appeared next to the base at the end of the delay. DMs moved vehicles by right clicking them, selecting ‘Move (fast),’ ‘Move (medium),’ or ‘Move (slow)’ from a pop-up menu, moving the cursor to the vehicle destination, and left clicking to initiate the action. DMs identified a target as friendly or enemy and determined the power of the vehicle by putting the track in a blue identification ring and then right clicking on the track and selecting ‘identify’ from a pop-up menu. DMs attacked a target by moving such that the track was within the attack ring, right clicking on the attack vehicle, selecting ‘attack’ from a pop-up menu, moving the cursor to the target, left clicking and confirming the attack. A target track could be destroyed only if the DM’s attacking vehicle was of equal or greater power than the target (AWACS = 0, jet = 1, helicopter = 3, tank = 5). Enemy tracks had powers of one, three, or five. Friendly tracks were assigned a power of zero. All tracks could be attacked whether they were identified or not.

Missions were preceded by a planning session and followed by a debrief session. Planning and debrief checklists were analogous to those used by AWACS crews in operational settings (Elliott *et al.* 1999) During planning sessions, a Computer-based Intelligence Report displayed information about enemy tracks' expected distribution, speed, and power. The expected distribution included information about the expected arrival time and the expected quadrant in which the enemy would appear. This information was displayed on each teammate's computer monitor during the planning session, and during the mission in an easy to perceive format. An Interactive Mission Planner enabled teams to plan placements of their vehicles to defend against the expected attack pattern. The placement plan was limited to plans for the quadrant in which vehicles would be placed and included neither the specific planned placement location within a quadrant nor the time of arrival of the vehicle. These details had to be specified during the mission. The team's placement plan was displayed next to the intelligence report during the mission.

During missions, a Task Assignment Panel (TAP) enabled DMs to assign one another to attack specific enemy tracks. The TAP took advantage of DMs being color coded in the DDD AWACS simulation. After identifying a track as an enemy, a DM clicked on the enemy track and then clicked on a color coded drop down panel of DMs. This action turned the enemy track to the assigned DM's color indicating that the color coded DM is assigned to attack the track. Natural language, which could also be used to make assignments, has the advantage of making and understanding assignments more easily, but the disadvantage of requiring DMs to remember their assignments. The TAP reduces the memory burden by enabling DMs to pick up assignments easily anytime after they have been made. DMs typically used both natural language and the TAP to make assignments, which might include assignments to themselves.

During debrief, a video with a voiceover emphasizing the application of strategies at critical events enabled the BEST group to see and hear a near optimal execution of the preceding mission. The BEST model generated several near optimal executions. Similarly, two human expert teams who practiced for over 100 hours each developed two different strategies. Both of these human expert strategies were among the BEST near optimal solutions. This validated that (1) BEST can generate human-like scenario solutions and (2) promises to reduce the cost of generating such model solutions by enabling SMEs merely to select among automatically generated scenarios (and not requiring them to generate those solutions themselves). One of the two human-like strategies was selected for the video. The selected BEST strategy emphasized helping behavior. Specifically, in both the BEST strategy and in the human expert strategy, all DMs sent vehicles to the quadrant with the highest load. The video demonstrated the specific vehicles sent and used in the BEST execution.

3.3 Design and Procedure

The independent variable was the debrief treatment. The BEST experimental group received the BEST audio/video during debrief (described above). The Control group received a list of general strategies. The two groups had equal time to review these debriefing materials and reflect on the previous mission during debriefing. The groups were treated the same in all other respects. Subjects were randomly assigned to teams, which were randomly assigned to the groups. The dependent variable was the Team

Defensive score. There were three kinds of trials, Baseline (B), Practice (P), and Assessment (A). Each trial had a 5-min. Planning session, a 15-min. Mission, and a 5-min. Debrief session. The sequence of events for about 8 hr was: instructions (2.5 hr), B, P, A, P, A, P, A (about 3 hr), transitions between sessions and breaks, including a provided lunch (about 2.5 hr). All trials were the same except that trainees were told to emphasize learning during Practice, and they were told to perform as well as they could during Baseline and Assessment.

4.0 Results

BEST feedback improved both the Team Offensive score and Team Defensive score. On the Team Offensive score, the BEST and Control groups were similar at baseline, but the BEST group performed significantly better throughout training ($F(1,28) = 6.47$, $p < .05$) with the final Offensive score being 1108 for the Control Group and 1177 for the BEST group.

A similar pattern is shown in Figure 3 for the Team defensive score on the mission assessments: 0 (Baseline) and 1, 2, and 3 for the BEST and Control groups. (We focus her on the scores for defending the no-fly zones, because it is the essential function of this type of mission.) The Team Defensive score results were analyzed with a split-plot ANOVA, with training protocol (BEST versus Control) as the between-participant variable and mission as the within-participant variable. There was a significant main effect of mission, F (3, 84) = 389.75, $p<.01$, and a significant interaction between protocol and mission, F (3, 84) = 7.27, $p<.05$. Planned comparisons showed that the BEST group performed about the same as the Control group on the baseline before training (F (1, 29) = .18, $p>.05$) and then performed consistently better on Assessment missions 1 (F (1, 29) = 3.08, p<.05), 2 (F (1, 29) = 7.55, p<.01), and 3 (F (1, 29) = 4.21, p<.05). The effect size in terms of the percentage of variance accounted for as measured by partial eta squared (η_p^2) for assessments 1, 2, and 3 were .10, .21, and .13. In practical terms, the best score an expert team with 100 hours of training has achieved is 48,000. If the trend in Figure 3 continued, this optimum would be reached at 7 trials for the BEST group (R2=.97) and at 14 trails for Control group (R2=.98).

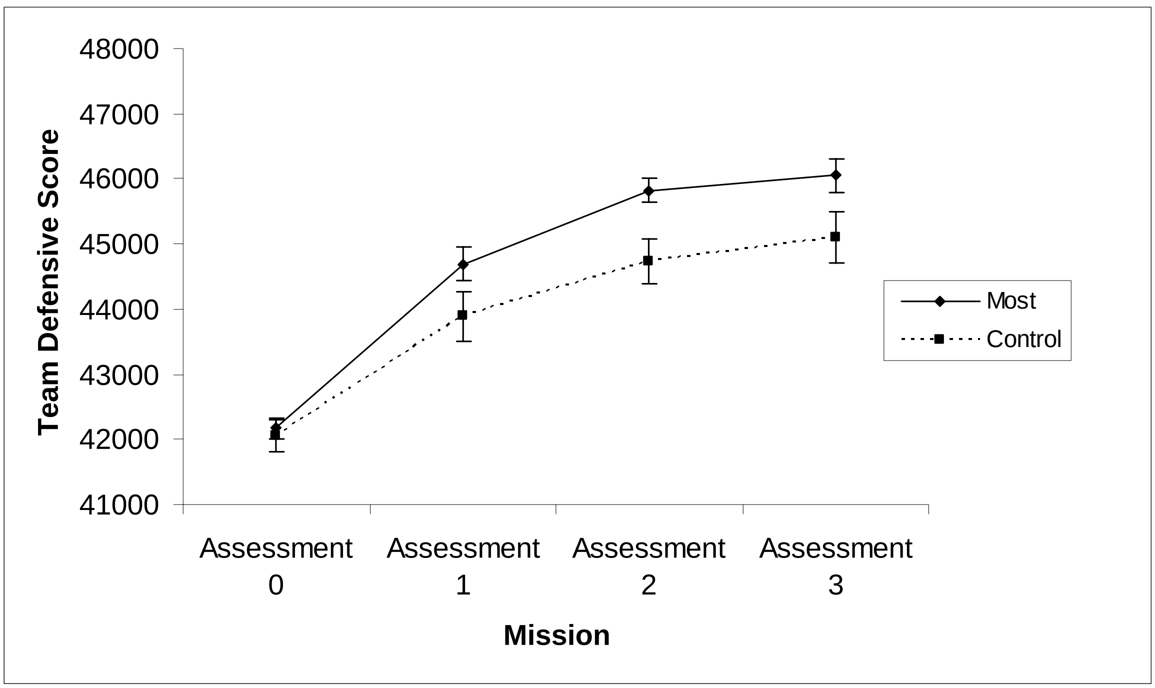

Figure 3: Performance effects of BEST group vs. control group

5.0 Discussion

Methods of optimization and theories of expertise and observational learning inspired a three pronged approach to training feedback in the BEST system. We used the techniques of mathematical optimization to devise near-optimal solutions, presentation of expert strategies to focus attention on aspects of these solutions, and demonstrations of the solutions to promote observational learning. These three perspectives complement one another. The mathematical perspective has the strength of objectively specifying near-optimal solutions in great detail, but these solutions do not make explicit the aspects that are relevant (invariant, deep structural characteristics) and irrelevant to learners. Providing expert strategies or principles reveals the deep structure of the domain as human experts perceive it, but does not illustrate how these principles apply to a given problem nor indicate whether the principles produce a near optimal solution. Observational learning leverages human discovery and recognition of complex patterns that cannot easily be explicated, though it requires the practice opportunity provided in the DDD to hone recognition and production of near optimal performance.

The experimental results illustrate that integrating these strategies can be effective. Based on an extrapolation of the learning curves, we hypothesize that BEST feedback has the potential to cut training time by as much as half. Future research will test this hypothesis by empirically determining training time to BEST and Control optima.

We also hypothesize that the present results will generalize to other C^2 domains in which asset tasking and scheduling are essential activities. Among these are JSTARS and E-2C operations. This hypothesis needs to be tested within the AWACS domain from the DDD to the operational weapons systems, and between domains.

We draw conclusions from these results at two levels: those concerning future directions for training optimization using BEST, and broader conclusions concerning virtual environments.

5.1 Future Research in Optimization of Training Strategies

Future research might follow several paths to optimize training strategies. The first is to have the BEST model include probabilistic (not 100% accurate) information. The second is to implement adaptive feedback, in which BEST would customize feedback based on specific errors from each training mission. Adaptive feedback would focus attention on specific parts of the mission based on the relationship between team performance and BEST execution on specific parts of the task. A third and related path is adaptive coaching, in which, BEST would monitor performance as the training mission unfolds and customize the content of real-time coaching. The same algorithms that examine the battlespace and determine optimal solutions might be made to function in real time: monitoring the current state of the trainee's solution, generating optimal next steps, comparing the distance between this optimal move and the student's actual move, and presenting relevant coaching to close the gap.

Another opportunity is to optimize the selection and composition of practice scenarios, much as a human tutor selects lessons that exercise and extend the student's current capabilities. We are currently exploring this path with an approach to optimizing training that uses Partially Observable Markov Decision Process models to generate or select training scenarios, and to do so in ways that exploit the hierarchical relationship between procedural skill and strategic knowledge.

Future research should also investigate which skills, in particular, the team is learning from the explication of domain structure and observation of optimized solutions. For example the Team Adaptation and Coordination Training protocol (TACT) (Serfaty *et al.* 1998) and the cross-training protocol (Blickensderfer *et al.* 1998) set goals of facilitating the learning of reciprocal relationships among individual actions, collective (team) actions, task dynamics, situation, and environment. BEST feedback is designed to promote observational learning of some of these reciprocal relationships by illustrating them in the context of a near optimal solution. BEST feedback is given as a part of debriefing so that processing resources used during missions are available to learn critical relationships. The present research indicates that BEST feedback alone can improve training performance. Future studies will have to determine the extent to which this improvement is mediated by learning the targeted reciprocal relationships in particular.

5.2 Broader Implications

Engineers, scientists, and trainers can use these results to develop not only learning theories and teamwork training in ill-defined domains, but also virtual technologies. Previous research and applications have shown that, with respect to training in operational settings, simulations are safer and can save millions of dollars (e.g. Ness *et al.* 2004). The present experiment documents another potential advantage: virtual environments can be highly effective for training when supported by computational models and sound instructional strategy.

To realize this potential benefit, we see the need for virtual technology that is scalable with respect to the physical, cognitive, and operational fidelity(c.f. Johnston et al., 1995; Driskel and Johnson, 1998). We are currently testing adaptive BEST feedback with physical, cognitive, and operational fidelity scaled up to be more representative of the complexity and workload of field settings. We are finding that the scaling process promotes synergistic development of learning theories, teamwork training methods, and virtual technologies.

Acknowledgements

The authors would like to thank the Air Force Office of Scientific Research, particularly Dr. Jerome Busemeyer and his predecessor Dr. Robert Sorkin, for orienting and funding this effort. We thank the participants in the study for aiding in this inquiry. Finally, we thank colleagues David Clark and Bruce Skarin of Aptima for their modeling efforts and for implementing the optimal feedback, and Ganesh Alakke and Shruti Narakesari of Wright State University for managing the data collection. The opinions expressed here are not necessarily those of the Air Force Office of Scientific Research or the Department of Defense.

References

AMERICAN PSYCHOLOGICAL ASSOCIATION, 1992, Ethical principles of Psychologists and Code of Conduct. *American Psychologist*, **47**, pp. 1597-1611.

BANDURA, A., 1986, *Social foundations of thought and action: A social cognitive theory.* (Englewood Cliffs, N.J.: Prentice-Hall).

BANDURA, A., ROSS, D., AND ROSS, S. A., 1961, Transmission of aggression through imitation of aggressive models. *Journal of Abnormal & Social Psychology*, **63**, pp. 575-582.

BANDURA, A., ROSS, D., AND ROSS, S.A., 1963, Vicarious reinforcement and imitative learning. *Journal of Abnormal & Social Psychology*, **67**, pp. 601-607.

BLICKENSDERFER, E., CANNON-BOWERS, J.A., AND SALAS, E., 2002, Cross-training and team performance. In *Making Decisions Under Stress: Implications for Individual* *and Team Training*, J.A, Cannon-Bowers and E. Salas (Eds.), pp. 191-217 (Washington, DC: American Psychological Association, 2002).

BOHIL, C.J. AND MADDOX, W.T., 2003, On the generality of optimal versus objective classifier feedback effects on decision criterion learning in perceptual categorization. *Memory & Cognition*, **31**, pp. 181-198.

CHASE, W.G. AND SIMON, H.A., 1973, Perception in chess. *Cognitive Psychology*, **4**, pp. 55-81.

CLARK, A., 1997, *Being There: Putting Brain, Body, and World Together Again.* (Cambridge, MA: MIT Press).

DRISKELL, J.E. AND JOHNSTON, J.H., 1998, Stress exposure training. In *Making Decisions Under Stress: Implications for Individual and Team Training* J.A Cannon-Bowers and E. Salas (Eds.), pp. 191-217 (Washington, DC: American Psychological Association, 1998).

ELLIOTT, L.R., CARDENAS, R., AND SCHIFLETT, S.G., 1999, Measurement of AWACS team performance in distributed mission scenarios. Available online at: http://www.dodccrp.org/1999CCRTS/pdf_files/track_3/013ellio.pdf (accessed 28 August 2003).

ERICSSON, K.A., 2002, Attaining excellence through deliberate practice: Insights from the study of expert performance. In *The Pursuit of Excellence Through Education*, M. Ferrari (Ed.), (Mahwah, NJ: Lawrence Erlbaum Associates, 2002).

ERICSSON, K.A., 2004, Deliberate practice and the acquisition and maintenance of expert performance in medicine and related domains. *Academic Medicine*, **79**, pp. S70-81.

ERICSSON, K.A., KRAMPE, R. TH., AND TESCH-ROMER, C., 1993, The role of deliberate practice in the acquisition of expert performance. *Psychological Review*, **700**, p. 379 and p. 384.

FAHEY, R.P., ROWE, A.L., DUNLAP, K.L., AND DEBOOM, D.O., 2000, *Synthetic task design (1): Preliminary cognitive task analysis of AWACS weapons director teams.* Technical Report. Brooks AFB, TX: Armstrong Laboratory.

GILLAN, D.J., BREEDIN, S.D., AND COOKE, N.J., 1992, Network and multidimensional representations of the declarative knowledge of human-computer interface design experts. *International Journal of Man-Machine Studies*, **36**, pp. 587-615.

HOGAN, J. AND LESSER, M., 1996, Selection of personnel for hazardous performance. In *Stress and Human Performance*, J.E. Driskell and E. Salas (Eds.), pp. 195-222 (Mahwah, NJ: Erlbaum, 1996).

IOERGER, T.R., SIMS, J., VOLZ, R.A., WORKMAN, J., AND SHEBILSKE, W.L., 2002, On the use of intelligent agents as partners in training systems for complex tasks. Available online at: http://faculty.cs.tamu.edu/ioerger/pasf.pdf (accessed 26 August 2003).

JOHNSON, S. (2001). *Emergence: The Connected Lives of Ants, Brains, Cities, and Software.* (New York: Scribner).

JOHNSTON, A.N., REGIAN, J.W., AND SHEBILSKE, W.L., 1995, Observational learning and training of complex skills in laboratory and applied settings. In *Aviation Psychology Training and Selection*, N. Johnston, R. Fuller, and N. McDonald (Eds.), pp. 316-323.

JUARRERO, A., 2002, *Dynamics in Action: Intentional Behavior as a Complex System.* (Cambridge, MA: MIT Press).

NESS, J.W., TEPE, V., AND RITZER, D.R., 2004, *The Science and Simulation of Human Performance*. (Boston: Elsiver).

PIOROLLI, PETER L. AND ANDERSON, J.R., 1985, The role of practice in fact retrieval. *Journal of experimental psychology: Learning, memory, and cognition*, **11**, pp. 136-53.

RASMUSSEN, J., PEJTERSEN, A.M., AND GOODSTEIN, L.P., 1994, *Cognitive Systems Engineering*, (New York: Wiley).

SCHMIDT, R.A., AND BJORK, R.B., 1992, New conceptualizations of practice: Common principles in three paradigms suggest new concepts for training. *Psychological Science*, **4**, pp. 207-217.

SERFATY, D, ENTIN, E.E., AND JOHNSTON, J.H., 1998, Team coordination training. In *Making Decisions Under Stress: Implications for Individual and Team Training* J.A Cannon-Bowers and E. Salas (Eds.), pp. 191-217 (Washington, DC: American Psychological Association, 1998).

SHEBILSKE, W.L., GOETTL, B., AND REGIAN, J.W., 1999, Executive control and automatic processes as complex skills develop in laboratory and applied settings. In *Attention* *and Performance XVII: Cognitive regulation of performance: interaction of theory and application,* D. Gopher and A. Koriat (Eds.), pp. 401-426 (Hillsdale, NJ: Erlbaum, 1999).

SHEBILSKE, W.L., JORDAN, J.A., GOETTL, B.P., AND PAULUS, L.E, 1998, Observation versus hands-on practice of complex skills in dyadic, triadic, and tetradic training-teams. *Human Factors*, **40**, pp. 525-540.

THELEN, E., AND SMITH, L., 1994, *A Dynamic Systems Approach to the Development of Cognition and Action.* (Cambridge, MA: MIT Press).

VYGOTSKY, L.S., 1978, *Mind and Society: The Development of Higher Mental Processes*. (Cambridge, MA: Harvard University Press).

WICKENS, C.D., 1996, Designing for stress. In *Stress and Human Performance*, J.E. Driskell and E. Salas (Eds.), pp. 257-277 (Mahwah, NJ: Erlbaum, 1996).

Author Biographies

Wayne Shebilske has taught at University of Virginia, Texas A&M University, and Wright State University. He has worked closely with government, military, and private agencies identifying critical issues for study in many areas including design and development of aerospace systems, visual display equipment, medical devices, standards for pilots and drivers, automated instruction for complex skills, and virtual reality systems.

Kevin Gildea is a Human Factors Psychologist at Aptima. Dr. Gildea has extensive experience developing and testing training protocols for complex skill acquisition including training with artificial partner agents and adaptive training protocols. Dr. Gildea works on developing training systems for Command and Control environments and military Senior Leadership.

Jared Freeman is Vice President for Research at Aptima. Dr. Freeman's work concerns problem solving and decision making in real-world settings and the design of assessment and training systems to support these activities. He also has served as principal investigator on projects to define and support collaborative critical thinking; automate the analysis of voice communications; automate the analysis of written usability documents; and model the fit between human cognitive abilities, decision support systems, and mission requirements.

Georgiy Levchuk is a Simulation and Optimization Engineer in the Cognitive Systems Group at Aptima. His research interests include global, multi-objective optimization and its applications in the areas of organizational design and adaptation, and network optimization. At Aptima, Dr. Levchuk is responsible for designing the mathematical engines for several of the company's simulation products.

Figure captions:

Figure 1. Expert solution demonstration screen. The icons within the square and surrounded by circles represent the resources and their associated attack or detection radii. Lines emanating from these circles are attacks that terminate at enemy targets in flame. The AWACS planes at the corners of the square are encircled by the blue rings. These large blue circles represent their detection radii.

Figure 2. The DDD task screen includes a white grid, which simulates a radar screen, and a blue report area to the right. The text explains the information in both parts.

Figure 3. Team Defensive Score for the BEST and Control groups on Assessment missions 0 (Baseline), 1, 2, and 3. Error bars equal one standard error.