

Effects of Equipment on Model Development for Adaptive Marksmanship Trainers

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ABSTRACT

Basic rifle marksmanship (BRM) involves the execution of fundamental procedures to consistently strike a target in a manner that can be replicated over multiple trials. The Engagement Skills Trainer (EST) is a simulated firing range designed as a cost-saving solution for deliberate practice of BRM fundamentals. In an effort to enhance the EST to support tailored instruction, work has started on integrating adaptive training technologies that enable real-time performance diagnosis for triggering objective-based guidance and remediation (Goldberg et. al., 2014). This involves the development of models to support a psychomotor-based training event, both from an expert performance perspective that designates what criteria to score trainee interaction against and a pedagogical perspective that designates how best to instruct when errors in execution are recognized.

In conceptualizing the role an expert model plays in a psychomotor-based use case, a question that arises is what impact do environmental factors have on behavior representations? In the instance of the EST, one environmental factor of particular interest is equipment. Specifically, we are interested in the effect variations in equipment have on behavior and performance outcomes, and to determine if the effect is large enough to warrant varying expert models based on equipment setups. In this paper, we present the results of a study comparing behavior and performance data across a set of experts from the U.S. Army Marksmanship Unit. Each expert performed BRM related tasks on the EST across two distinct uniform conditions: (1) wearing just the standard Army Combat Uniform consisting of jacket, trouser, t-shirt and Army Combat Boots; and (2) wearing combat equipment including helmet and body armor. Results will inform expert model implementation and future experimentation for an adaptive marksmanship capability, and may inform more realistic models of soldier representation across training domains.

ABOUT THE AUTHORS

Mr. Charles R. Amburn is the Senior Instructional Systems Specialist for the Advanced Modeling & Simulation Branch (AMSB) of the U.S. Army Research Laboratory's (ARL) Human Research and Engineering Directorate (HRED) in Orlando, FL. After obtaining both a Film degree and a Master's degree in Instructional Systems Design from the University of Central Florida, he began his DOD civilian career at the Naval Air Warfare Center Training Systems Division (NAWCTSD) where he worked on special projects for the Navy and Marine Corps for 10 years. He then became the Lead Instructional Designer for the Army's Engagement Skills Trainer (EST) program where Mr. Amburn was responsible for several innovations in the way immersive training scenarios were created, experienced and assessed. This drive to push the boundaries of what's possible in simulations and training is what led him to ARL's Advanced Training & Simulation Division (ATSD) in 2011. Since joining ARL, Mr. Amburn's award-winning research has spanned various domains including augmented reality, terrain visualization, and adaptive training systems.

Dr. Benjamin Goldberg is a member of the Learning in Intelligent Tutoring Environments (LITE) Lab at the U.S. Army Research Laboratory's (ARL) Human Research and Engineering Directorate (HRED) in Orlando, FL. He has been conducting research in the Modeling & Simulation community for the past eight years with a focus on adaptive learning in simulation-based environments and how to leverage Artificial Intelligence tools and methods to create personalized learning experiences. Currently, he is the LITE Lab's lead scientist on instructional management research within adaptive training environments and is a co-creator of the Generalized Intelligent Framework for Tutoring (GIFT). Dr. Goldberg is a Ph.D. graduate from the University of Central Florida in the program of Modeling & Simulation. His work has been published across several well-known conferences, with recent contributions to the

Human Factors and Ergonomics Society (HFES), Artificial Intelligence in Education and Intelligent Tutoring Systems (ITS) proceedings. Dr. Goldberg has also recently contributed to the journal *Computers in Human Behavior* and to the *Journal of Cognitive Technology*.

Mr. Dar-Wei Chen is a Presidential Fellowship PhD candidate in the engineering psychology program at the Georgia Institute of Technology, where he works in the Problem Solving and Educational Technology (PSET) Laboratory. He holds a master's degree from Georgia Tech in the same field and a bachelor's degree in industrial engineering from the University of Michigan (Ann Arbor). His research interests include instructional design, user experience, multimedia, and interface design. In the summer of 2016, he worked in the Learning in Intelligent Tutoring Environments (LITE) Laboratory at the U.S. Army Research Laboratory's Human Research and Engineering Directorate (ARL HRED), where he contributed to the present paper.

Mr. Charles Ragusa is a senior software engineer at Dignitas Technologies with over fifteen years of software development experience. After graduating from University of Central Florida with a B.S. in computer science, Mr. Ragusa spent several years at Science Applications International Corporation (SAIC) working on a variety of research and development (R&D) projects in roles ranging from software engineer and technical/integration lead to project manager. Noteworthy projects include the 2006 Defense Advanced Research Project Agency (DARPA) Grand Challenge as an embedded engineer with the Carnegie Mellon Red Team, program manager of the SAIC Common Driver Trainer/Mine-Resistant Ambush-Protected (MRAP) Independent R&D (IR&D) project, and lead engineer for Psychosocial Performance Factors in Space Dwelling Groups. Since joining Dignitas Technologies in 2009, he has held technical leadership roles on multiple projects, including principal investigator for the Generalized Intelligent Framework for Tutoring (GIFT). Mr. Ragusa is currently the lead engineer for the Adaptive Marksmanship project.

Dr. Michael W. Boyce is a Postdoctoral Research Associate supporting the Learning in Intelligent Tutoring Environments (LITE) Laboratory and the Advanced Modeling and Simulation Branch within the US Army Research Laboratory (ARL). As a part of his postdoctoral fellowship at ARL, Dr. Boyce conducts empirical studies to help support the development of user interfaces for the prototype Augmented Reality Sandtable (ARES). Dr. Boyce has his doctorate from the University of Central Florida, Applied / Experimental Human Factors Psychology Program.

Mr. Paul Shorter is currently assigned to the Army Research Laboratory Human Research and Engineering Directorate (ARL HRED) Advanced Modeling & Simulation Branch in support of the Adaptive Marksmanship and Augmented Reality Sandtable (ARES) programs. Prior to this assignment, he worked in the ARL Dismounted Warrior Branch where he undertook research pertaining to the interaction of individual anthropometrics and other factors on marksmanship performance. Mr. Shorter has a BS degree in Mathematical Sciences, Virginia Commonwealth University, 1988, and has been employed as an Operations Research Analyst by the Department of the Army (DA) since 1989, which has primarily entailed modeling & simulation and data analysis. Prior to reporting to ARL HRED in 2005, Mr. Shorter worked for the Army Materiel Systems Analysis Activity and the Army Test and Evaluation Command where he was assigned to conduct independent evaluations on various acquisition programs.

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INTRODUCTION

Basic Rifle Marksmanship (BRM) skills are deemed to be of the highest priority for the U.S. Army (Ranes, Lawson, King, & Dailey, 2014) and are assessed annually as a part of a soldier's evaluation (Department of the Army, 2012). To support this priority the Army Research Laboratory, Advanced Training and Simulation Division (ARL ATSD) has developed an adaptive marksmanship training system (Amburn, Goldberg & Brawner, 2014) leveraging expert models in an intelligent tutoring framework known as GIFT (Sottolare, Brawner, Goldberg & Holden, 2012).

The adaptive training system was built to collect and act on trainee data from a marksmanship simulator such as the Engagement Skills Trainer (EST). The EST has been shown to increase performance while minimizing cost and risk to the soldier (Powers, 2008) and is used throughout the Army alongside classroom instruction and live fire practice. During EST usage, a trainee's behavioral data (e.g. trigger pull, weapon orientation) and performance data (e.g. consistency, accuracy of shots) can be reviewed by an instructor who determines what, if any, feedback to provide. As James and Dyer (2011) point out, human instructors can have varying competency levels leading to mixed results. In contrast, the adaptive marksmanship training system developed in this research is intended to diagnose shooter errors and prescribe corrective feedback more efficiently and more accurately. However, in order to diagnose trainee behaviors, the intelligent tutoring system needs to know what "correct" or "incorrect" behaviors are.

Expert models for performance were developed, supported by GIFT, which collected data from members of the U.S. Army Marksmanship Unit (AMU) across several variables related to BRM (Goldberg, Amburn, Brawner and Westphal, 2014). These models would serve as the "gold standard" by which trainees could be compared by the adaptive system. Expert Models are typically used to help an individual learner understand where improvement can be made respective to the task at hand. One example is within the domain of music where Dannenberg, Sanchez, Joseph, Joseph, Saul, & Capell (1993) built a piano tutor to assess performance and give feedback. By tailoring the task level based on student performance the expert model works to isolate the area of difficulty. This same type of strategy can be leveraged in marksmanship, assessing performance and driving feedback (Goldberg et al., 2014).

While developing expert models, environmental factors which could alter behaviors must also be considered. For example, different soldiers wear different equipment (clothing, weaponry, armor, etc.) for different roles they serve. If this equipment setup affects marksmanship behaviors then shouldn't expert models used to evaluate marksmanship trainees reflect that? To determine if the "equipment effect" is large enough to warrant varying expert models, we conducted a study comparing the behavior and performance data of AMU experts who performed BRM tasks while wearing two different sets of equipment. In this paper we briefly discuss the marksmanship literature related to equipment, or soldier load, then present and analyze the results of the study.

Impact of Soldier System Equipment on Marksmanship

The Army Science Board (ASB) has recognized that the load associated with a soldier must be analyzed and organized to maximize efficiency, which led to the development of the Program Executive Office for Soldier systems (PEO Soldier). The goal, following the guidance of the Army Training and Doctrine Command (TRADOC) Pamphlet 525-97 (Jones, 2006), is to conceptualize a soldier as a system (SaaS) which encompasses an integrated model of soldier performance, includes soldier physiology and defines the considerations for variables such as soldier equipment (PEO Soldier, 2015). As a part of this effort, PEO Soldier has developed standardized soldier system baselines of dismounted, mounted and air which helps to approach experimentation in a repeatable, consistent manner.

Existing research has shown reduced accuracy and longer latency during marksmanship with increased equipment weight (Palmer, Bigelow & Van Emmerik, 2013). Research has also shown that equipment can impact the marksmanship of soldiers while moving. It was found that loads that were near 45% of the soldiers body weight caused an increase in task completion time and shot variability as well as a decrease in shooting precision (Jaworski, Jensen, Niederberger, Congalton, & Kelly, 2015). The equipment, especially when heavy, prevents adaptability to environmental changes (Palmer et al., 2013).

Related research also shows that the marksmanship benefit due to supportive clothing is about 20 percent compared to normal clothing, but is much less than the relative differences between experienced shooters and the control group, which ranged from 30 percent to 70 percent. Therefore, the difference between experienced and inexperienced shooters can be attributed to factors other than clothing (Era, Kontinen, Mehto, Saarela, & Lyytinen, 1996). These other factors may be explained by research taking an ecological approach to goal oriented task analysis that suggests a coupling between the participant and environment. The addition of combat equipment may adversely affect the neuromuscular fields required for regulating inertial and interaction forces during movement, prohibiting variability in the movement necessary to effectively perform the goal oriented task (Palmer, 2012).

Research Objective

The objective of this experimental laboratory study was to measure expert performance in the context of basic rifle marksmanship. The overall research objective was to build models of expert performance on the fundamentals of marksmanship for inclusion in the development of an adaptive marksmanship training system embedded with intelligent tutoring functionality. Models were built on sensor technologies that monitor variables linked to: (1) aim trace; (2) trigger pressure; and (3) breathing rate. Data was collected across a sample of expert marksmen, which was used to examine the efficacy of developing a generalized expert model based on trends and correlations present in the data output. Resulting models are being transitioned into ARL's Generalized Intelligent Framework for Tutoring (GIFT; Sottolare et al., 2012) for the purpose of conducting follow-on experimentation assessing their use in an operational context. Models were also built to account for environmental variables that can affect behavior and performance. This study examined the impact that variations in equipment setup have on the execution of fundamental marksmanship procedures. Two different equipment setups (standard Army Combat Uniform (ACU) vs. ACU with combat equipment) were examined, with expert models being developed across each.

Hypotheses

Sensor and behavior data collected during interaction with a simulated marksmanship training system will be significantly impacted by variations in uniform and equipment setups.

- Prediction 1: Application of trigger displacement as gauged from the mounted sensor will be significantly different across the two equipment setups.
- Prediction 2: Breathing rates and patterns as monitored by a breathing strap sensor will be significantly different across the two equipment setups.
- Prediction 3: A weapon's aim trace as measured from the mounted sensor will be significantly different across the two equipment setups.

METHODOLOGY

Apparatus

The experimental setup consists of hardware and software components associated with Meggitt's Fire Arms Training System (FATS) M100 Advanced Reality Simulator. Similar to the Army's EST, this apparatus includes a simulated M4 weapon with embedded sensor technologies for monitoring variables the hypotheses are defined around. In addition, physiological sensors were incorporated to collect data that associates with breathing patterns that are not inherently captured by the FATS M100. Each component will be described in detail below.

Meggitt FATS M100

The FATS M100 is a simulated marksmanship training environment that supports individual and collective training events across a full range of weapons. The system is composed of four components: (1) a computer hard-drive containing all simulation software components; (2) a projection system to visualize marksmanship ranges in both 2D and 3D formats; (2) a hit detect camera used to locate shot placements; and (4) the simulated weapons.

The system operates through an electronic optical sensor that is mounted directly within the barrel of the simulated rifle. The shooter aims at digital targets projected on the M100's screen. The system logs the point of aim in real-time as measured through the optical sensor. When the weapons trigger is activated, the point of impact is recorded. All data is logged in GIFT for post-hoc analysis and model development.

Meggitt Fully-Sensored M4 Rifle

The weapon used for this experiment is the fully-sensored Meggitt M-4 assault rifle that is laser aligned and assembled specifically for simulator use. It is designed to have the form, fit, and function of an actual standard issue M-4 used for BRM periods of live instruction. The weapon is designed with embedded sensors that provide real-time data capture, including: point of aim through an infrared laser mounted in the barrel at a 6 Hz sampling rate; trigger displacement leading up to a shot; butt-stock pressure; and the weapon's cant angle. All sensors are built within the form of the weapon, and are not noticeable unless pointed out. Each sensor stream was logged separately and used as the primary inputs in model development.

Zephyr Technology BioHarness BT

The BioHarness BT is a compact electronics module that attaches to a lightweight fabric strap which incorporates Electrocardiogram and breathing detection sensors. The sensor wears like a heart rate monitor avid runners use when exercising and is completely wireless. For this experiment, the data of interest are the breathing metrics the device provides. This information is used to monitor a participant's breathing pattern while executing shot groupings.

The Generalized Intelligent Framework for Tutoring (GIFT)

GIFT is an evolving architecture-based project intended to provide the tools and methods for authoring and delivering adaptive training in a variety of instructional domains (Sottolare et al., 2012). This generalized approach enables system developers to quickly construct intelligent tutoring capabilities through a set of standardized tools and messaging schemas. For this study, GIFT provided the architecture required to create a unified marksmanship system from which data was collected and logged while subjects interacted with the FATS M100. Modules in GIFT were authored to enable communication protocols for the collection of the FATS M100 performance information, the FATS M100 sensor embedded rifle data, and metrics collected from the BioHarness wearable sensor.

Participants

The expert marksmen for this study were recruited from the AMU Service Rifle Team, Fort Benning, GA. Based on the opinion of a leading researcher in the field of expert model development at the University of Central Florida, Dr. Avelino Gonzalez, the sample size selected was eight. This number allows for exploratory analyses to determine if a generalized model of expert performance can be constructed that takes into account all subject data. Of the eight experts recruited, six were male and two were female, with an average age of 26 across all participants. Several members were repeat national champions in service rifle competitions, and majority were recognized as being one of the top one-hundred shooters in the country, having received the President's Hundred Tab. Subjects were volunteers and received no compensation. Superiors had no influence over subordinates in determining their participation nor were they present during data collection. All involved will remain anonymous.

Independent Measures

There are two Independent Variables (IVs) for this study: firing stance and equipment setup (see Figure 1). The firing stance IV consists of two positions: (1) prone unsupported; and (2) kneeling. The second IV, equipment setup, consisted of two variations of uniform/equipment arrangements: (1) wearing just the standard Army Combat Uniform (ACU) consisting of jacket, trouser, t-shirt and Army Combat Boots; and (2) wearing combat equipment consisting of helmet and body armor. As the goal of the study is to build models of expert performance, the IVs will distinguish marksmanship behaviors to assess if differences are observable across the two firing conditions. To support model development, correlations and trends will be examined with relation to the collected Dependent Variables and how they measure up with performance for the associated interaction mode.

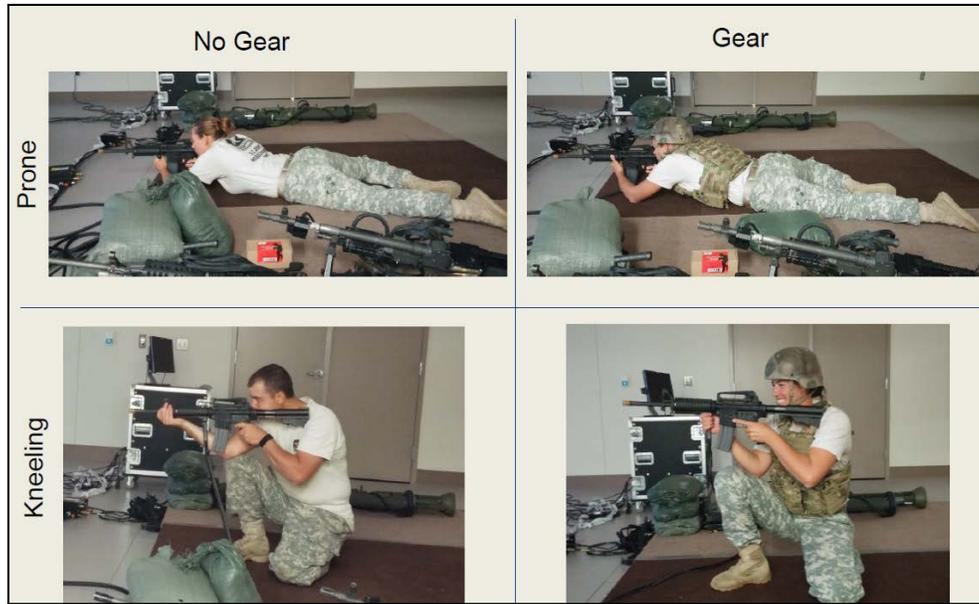


Figure 1. Resulting experimental conditions

Dependent Measures

Table 1. Description of Associated Dependent Measures

Category	Measure Type	Description	Data Source	Expert Model
Performance	Shot Grouping Distance	<ul style="list-style-type: none"> Measure computed by averaging the distance of each shot to the designated center point of each 5-shot cluster Used to gauge consistency across shots 	FATS M100 Shot Group Algorithm	Used to define expert performing groups
Behavior	Respiration Rate	<ul style="list-style-type: none"> Provides real-time monitoring of respiration patterns during execution of a shot 	BioHarness BT Breathing Strap	Breath Control
	Aim Trace	<ul style="list-style-type: none"> Provides real-time capture of optical sensor reading in relation to the FATS M100. Used to monitor stability and control of the weapon leading up to the execution of a single shot. 	FATS M100 Optical Sensor	Body Stability
	Trigger Displacement	<ul style="list-style-type: none"> Provides real-time monitoring of the distance displacement of the rifle's trigger during the execution of a shot 	FATS M100 Trigger Sensor	Trigger Pressure

Dependent measures are associated with two distinct categories. There are measures linked to performance outcomes that dictate the quality of a firing event, and there are measures linked to operator behaviors that occur during the execution of a shot. Behavior metrics are used to observe how an expert functions during a firing event and to determine if experts consistently do the same things across each trial. The measures were selected based on their relationship to the recognized four fundamentals of BRM (Army, 20011). Table 1, above, describes the measure being collected and their relationship in the process of expert model development.

Procedure

Upon arrival, participants received a brief overview of the study and were asked to fill out an informed consent. Next, subjects were fitted with the BioHarness breathing strap, and the sensors were then synced to GIFT for time-synced data logging. This process took approximately 10-15 minutes. Participants then filled out a Demographics Questionnaire covering experience in the Army Marksmanship Unit and the various awards they won throughout their career.

Following, participants were presented a short PowerPoint slideshow that reviewed the purpose of the study and went over in detail the experimental equipment. They then received information on the FATS M100 simulator and all the sensors that collected data during task execution. Next, participants were given the opportunity for familiarization

training with the system. They were instructed on tasks procedures, and then practiced with the weapon for a short time period. Following 5 minutes of practice, subjects were prepped for the main data collection window, where they were asked to produce shot groupings consisting of five rounds with the goal to get all shots as close to center of target as possible. There is no set limit for collection of shot groupings. All subjects were given 20-minutes for each condition, with self-regulated breaks administered when needed. Upon completion of data collection with the FATS M100, participants completed a post-experiment survey. This was followed by a short debrief where the subject was allowed to ask questions regarding the experiment and the next phases of the research.

Data Analysis

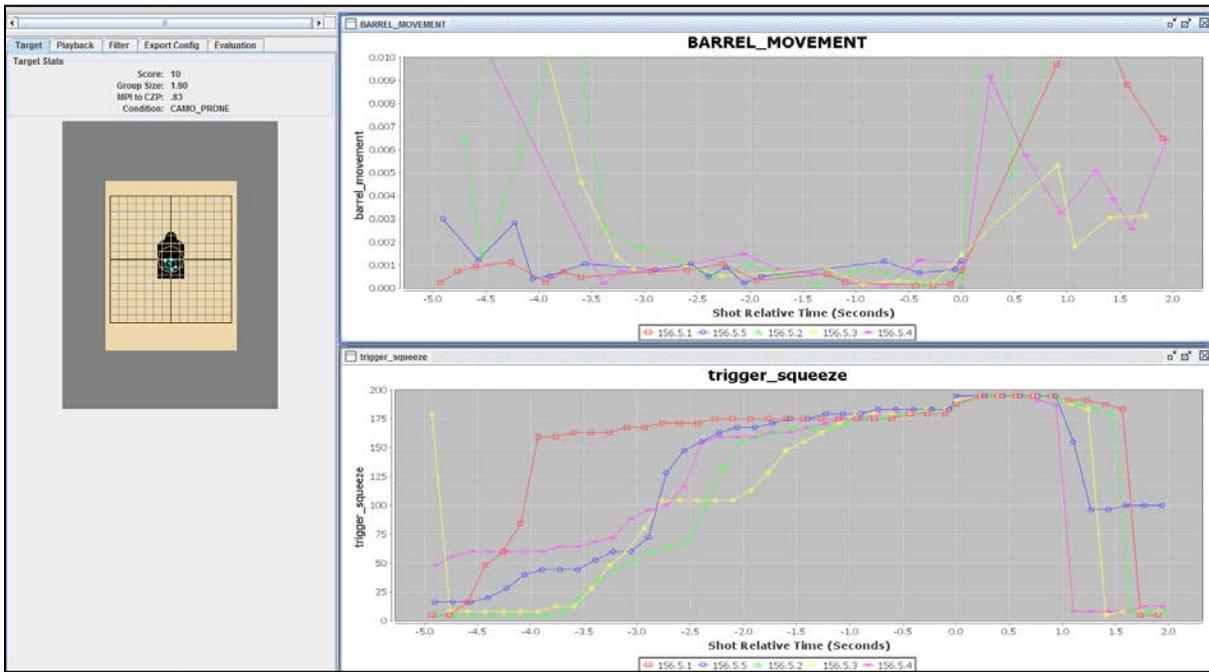


Figure 2. GIFT's Marksmanship Data Viewer (MDV) with Trigger Squeeze and Barrel Movement Data Across a 5-Shot Group

All data was logged within GIFT's file structure during all shot grouping exercises. Following data collection efforts, GIFT's Event Reporting Tool (ERT) was used to merge all data sources for a single experimental session into a Comma Separated Values (CSV) file, with each row defining data for all unique time stamps. These files were then loaded into the Marksmanship Data Viewer (MDV), a tool developed specifically for viewing and manipulating marksmanship data exported from the GIFT ERT (see Figure 2). The MDV has the ability to load multiple CSV files, allowing batch operations across multiple domain sessions.

Time Series Data

The system generated several sets of time series data as they associate with each registered shot. These are referred to as raw time series and include trigger displacement, aim X coordinate, aim Y coordinate, and breathing waveform. To support model development we found it useful to generate transformed time series representations. To quantify barrel movement we combined the x and y coordinates of consecutive aim points using a distance formula. At each time step the distance is the distance (in normalized screen coordinates) that the aim point moved since the last time step:

$$distance_t = \sqrt{(\Delta x_t)^2 + (\Delta y_t)^2} \quad (1)$$

The raw trigger squeeze data received by GIFT from the Meggitt system was a value in the range of zero to 200, with values at or near zero indicative of no trigger displacement, and values near 200 indicative of full trigger displacement. For modeling purposes, we normalized the values in the range of 0.0 to 1.0 by mapping the minimum signal value to 0.0 and the maximum signal value to 1.0. All other intermediate values were scaled to fit into range.

In accordance with good marksmanship breathing technique per the Army Field Manual (Army, 2011) our primary objective in analyzing the breathing waveform was to determine whether breathing was “quiet” (or not) during the time immediately preceding when a shot was fired. Observation of a live feed of the BioHarness breathing waveform indicated that the signal reliably increases during an inhale, reliably decreases during an exhale, and reliably flattens out (albeit with some drift) when the breath is held. Furthermore, we observed from both live data as well as recorded data that the absolute value of the signal varies too much to be directly useful. For these reasons, we decided that the best approach was to focus on the magnitude of the “deltas” (i.e., the first derivative of the breathing waveform). Thus, at each time step the first derivative was computed by subtracting the signal value of the preceding time step.

Data Reduction and Export using the MDV

As mentioned previously, each shot generates several sets of time series data. For each fundamental, we sought to distill the time series data for each shot into a single value reflecting the performance on that fundamental. Doing so would provide two benefits. The first is that it would create a simple and easy to understand measure for each fundamental that can be assessed simply by comparing a shooter's runtime value against a threshold value established by the expert model. The second is that it allows us to condense the multi-dimensional raw data set into a manageable data set amenable to straightforward statistical analysis.

To implement this approach we started with subjective human analysis guided by an understanding of the fundamentals of marksmanship and augmented by the visualization capability of the MDV. In particular, we used the time-series overlay capability of the MDV to contrast and compare numerous sets of shot data to identify noteworthy behavior, especially in the period of time immediately surrounding the time of the trigger squeeze. After viewing just a few graph overlays, several observations were made. First, the barrel movement (as evidenced by the aim trace data) invariably reduced to a minimum in the vicinity of the time the shot was fired. Second, as evidenced by the flatness of the breathing waveforms, the experts consistently quieted their breathing before, during and slightly after their shot. Finally, all but one of the shooters had an extended trigger squeeze that often started a second or more before the actual moment the shot was fired. Very commonly the trigger was squeezed up close to the breaking point and held for a period of time before finally squeezing enough to fire the weapon.

These observations, together with our desire to reduce the data set for each shot to a single value for each fundamental, led us to a common approach across each of the fundamentals. The approach was to select a time interval in the vicinity of the trigger break and integrate the signal (either raw or derived) over that interval, effectively making an area under the curve (AUC) calculation. For both breathing and barrel movement a smaller AUC was viewed as desirable in accord with the generally accepted ideas that minimizing barrel movement and quieting the breath during aiming and firing contribute to improved performance.

Once the integration approach was established for each metric the final step was to select an integration interval and integration step size. The intervals were chosen based upon visual inspection of relevant time series data using the MDV. For trigger squeeze and barrel movement we chose the interval from 1.5 seconds prior to the shot, up until the shot was fired (i.e. from $t = -1.5$ to $t = 0.0$). For breathing the interval also started at $t = -1.5$, but extended to $t = +0.5$, reflecting our observation that the experts typically kept their breath still for a full half second after firing.

RESULTS

Analyses of the collected data were performed using IBM SPSS Statistics 19 and a statistical significance threshold of 0.05. Statistical tests were performed on each behavioral metric to determine if there are observable differences between conditions as they relate to the shooter's stance and equipment setup.

Fundamental #1: Breath Control

T-tests were used to measure the main effects of firing stance (prone, kneeling) and equipment setup (camo, full equipment) on participants' steadiness of breathing. In terms of firing stance, the analysis indicated that participants in prone position ($M = 0.144$, $SD = 0.107$) breathed significantly more steadily than those in kneeling position ($M = 0.220$, $SD = 0.232$), $t(993) = 8.056$, $p < 0.001$. The manipulation of equipment also produced significant breathing differences, as participants wearing just camo ($M = 0.127$, $SD = 0.133$) were steadier than their counterparts who wore full equipment ($M = 0.226$, $SD = 0.203$), $t(1444) = 11.456$, $p < 0.001$.

A two-way Analysis of Variance (ANOVA) further revealed an interaction effect between firing stance and equipment setup, $F(1, 1552) = 45.925$, $p < 0.001$, and this interaction was explored with tests of simple main effects. When prone, participants wearing just camo ($M = 0.123$, $SD = 0.097$) were found to breathe significantly more steadily than those wearing full equipment ($M = 0.165$, $SD = 0.111$), $t(819) = 5.741$, $p < 0.001$. In kneeling conditions, the results were of a similar nature, but the extent to which camo participants ($M = 0.132$, $SD = 0.167$) breathed more steadily than participants in full equipment ($M = 0.290$, $SD = 0.252$) was even larger, $t(704) = 10.102$, $p < 0.001$ (see Figure 3 for a visual representation of breath control across each condition).

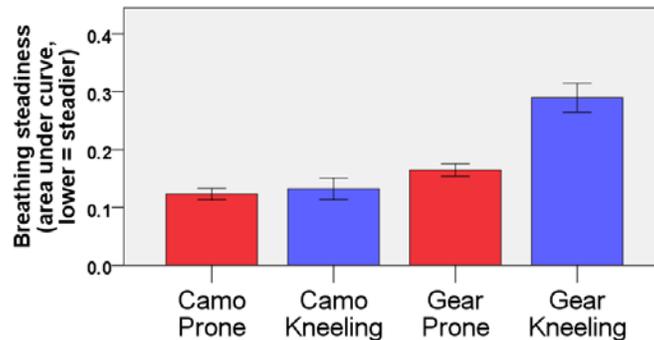


Figure 3. Breathing steadiness across all four stance-equipment conditions

Fundamental #2: Body Stability Inferred through Barrel Movement

According to t-tests, firing stance produced significant effects on gun barrel movement, as participants in prone position ($M = 0.001$, $SD = 0.001$) were significantly steadier holding their rifles than their counterparts in kneeling position ($M = 0.003$, $SD = 0.002$), $t(1255) = 27.031$, $p < 0.001$. Equipment type produced no such effects; whether a participant wore just camo ($M = 0.002$, $SD = 0.002$) or full equipment ($M = 0.002$, $SD = 0.002$), barrel movement amounts were not significantly different, $t(1487) = 0.291$, $p = 0.771$.

However, a significant interaction between firing stance and equipment setup was revealed through a two-way ANOVA, which provides some context to the above results, $F(1, 1552) = 4.134$, $p = 0.042$. That is, when prone, participants in camo ($M = 0.001315$, $SD = 0.001098$) and full equipment ($M = 0.001388$, $SD = 0.00099$) were similar in barrel movement amounts, $t(825) = 1.002$, $p = 0.316$, but when kneeling, the participants wearing just camo ($M = 0.003293$, $SD = 0.00158$) were less steady than those wearing full equipment ($M = 0.003097$, $SD = 0.00151$) at a level approaching statistical significance, $t(727) = 1.714$, $p = 0.087$ (see Figure 4 for a visual representation of barrel movement).

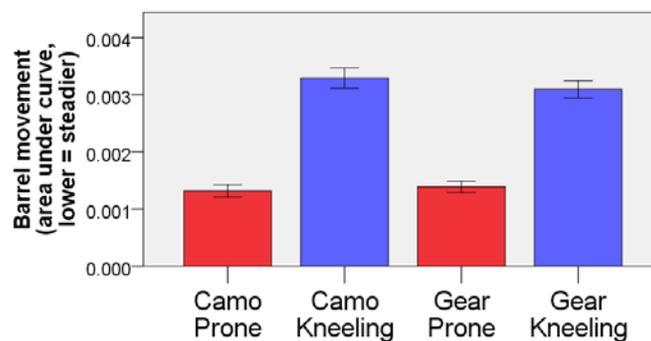


Figure 4. Body stability across all four stance-equipment conditions

Fundamental #3: Trigger Control

T-tests revealed that firing stance and equipment setup were both important factors of trigger control fundamentals. Although at just a “trending” significance level, prone participants ($M = 1.042$, $SD = 0.407$) were significantly more able to control the rifle trigger than their kneeling counterparts ($M = 0.999$, $SD = 0.470$), as measured by the amount of trigger slack a participant could clear before the shot, as well as how long that slack was cleared (higher numbers indicating less slack from 1.5 seconds prior to the shot), $t(1451) = 1.925$, $p = 0.054$. The main effect of equipment setup was a bit more pronounced, as participants wearing camo ($M = 1.056$, $SD = 0.403$) exhibited better trigger control than those wearing full equipment ($M = 0.992$, $SD = 0.465$), $t(1554) = 2.900$, $p < 0.01$.

A statistically-significant stance-equipment interaction in trigger control was revealed through an ANOVA, $F(1, 1552) = 13.062$, $p < 0.001$. When prone, participants in camo ($M = 1.113$, $SD = 0.302$) performed significantly better than those in full equipment ($M = 0.976$, $SD = 0.477$), $t(723) = 4.893$, $p < 0.001$; however, camo ($M = 0.986$, $SD = 0.492$) and full equipment ($M = 1.010$, $SD = 0.451$) were not statistically different when participants were kneeling, $t(664) = 0.666$, $p = 0.506$ (see Figure 5 for a visual representation of trigger displacement across each condition).

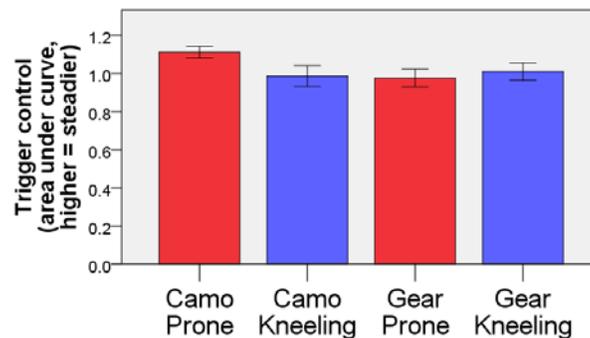


Figure 5. Trigger control across all four stance-equipment conditions

DISCUSSION

In this study, the effects of equipment setup on three fundamental marksmanship-related behaviors were measured, and interactions between equipment and firing stance were examined. As expected, barrel movement was significantly steadier when participants were in prone position than when kneeling. When prone, the shooter is able to relax most of his or her muscles allowing the bones - not the muscles - to support the rifle (Army, 2011). However, according to the data, barrel movement was not significantly affected by equipment, as those wearing just camo and those wearing battle equipment exhibited relatively equal stability. Although this result is not necessarily intuitive, it does align with some previous findings on soldiers' equipment. Effects of equipment in inhibiting performance have been found to be most pronounced during movement-oriented exercises (Palmer, 2012), but relatively minor in activities with less movement. Therefore, it is foreseeable that wearing full equipment does not adversely affect barrel movement when stationary shooters are firing at relatively static targets. In fact, during these conditions, the extra weight and rigidity may have a stabilizing effect.

A stance-equipment interaction effect was also found for trigger control, although it is hypothesized that its existence is likely an artifact of the experimental procedure, and not because of actual stance and equipment effects. Specifically, the main effects of stance and equipment, as well as the stance-equipment interaction, seem to be wholly driven by the relatively good trigger control in the “camo prone” condition, which was the first condition experienced by all participants during their trials; the trigger control behaviors during all three of the other conditions were relatively similar, which could indicate that the trigger control performance in the “camo prone” condition was anomalous (see Figure 5). It is hypothesized that an order effect occurred during the trials, with participants, at the start, generally paying more attention to procedural details and/or behaving more deliberately while familiarizing themselves with the weapon, both of which could manifest itself in better trigger control at the start. This hypothesis

is supported by findings that cognitive processes are not particularly influential on expert shooters' performances after some practice (Ranes et al., 2014), likely because of the automaticity of the activity (Kerick, Douglass, & Hatfield, 2004). Stance and equipment likely did not impact trigger control performance in this experiment, but future iterations of marksmanship experiments would benefit from a counter-balanced order of conditions.

Perhaps the most interesting behavioral finding relates to breathing, with results indicating that in kneeling conditions, participants wearing full equipment were less steady with their breathing than those wearing just camo. Existing research has already demonstrated the considerable extent to which external weights can create additional physical workload that impacts heart rates (Jaworski et al., 2015); extending that finding to breathing impacts appears logical. Increased breathing is generally thought to decrease marksmanship performance, whether due to fatigue (Chung et al., 2011), anxiety (Torre, Maxey, & Piper, 1987), or other factors. However, in this particular study, during conditions involving kneeling, participants wearing full equipment ($M = 4.457$, $SD = 2.713$) shot significantly smaller group sizes than those wearing camo ($M = 4.857$, $SD = 1.593$), despite not breathing as steadily, $t(727) = 2.35$, $p = 0.019$. This result could conflict with the notion that steadiness of breath is one of the four fundamentals of marksmanship (Army, 2011). Additionally, during prone conditions, camo participants ($M = 2.639$, $SD = 2.521$) and full-equipment participants ($M = 2.629$, $SD = 2.521$) were not significantly different in their group sizes, $t(496) = 0.076$, $p = 0.939$, despite camo participants again having a relative advantage in breathing steadiness, further corroborating the notion that breathing might not have as much an impact on shot performance as previously thought.

FUTURE WORK

Determining if models that account for equipment variations should be incorporated into an adaptive marksmanship training environment requires further exploration. The current research presented behavioral differences across a set of experts, with a goal of defining a required set of expert model representations to support assessment logic. One limitation of this study is the fact that the equipment conditions were relatively limited, covering just two possible configurations of many possible ones. Incorporating other types of equipment (e.g., gloves, backpacks, eye-protection, etc.) would require testing before determining how much, and what type of, equipment will influence model development.

Understanding the behavioral relationships of marksmanship with respect to performance outcomes must also be investigated. Current analyses are being performed to explore the effects the three behavioral metrics have on performance outcomes (i.e., shot group size). It is worth noting that these behaviors are all listed as fundamentals of marksmanship, but the nature of their effects on performance is still open for debate. An additional avenue of research that needs to be explored involves modeling novice behavior trends to identify common errors and misconceptions exhibited when learning how to operate a rifle. This can potentially extend the assessment space in GIFT to support misconception libraries to determine a specific causal error, rather than identifying a fundamental that is being violated through comparative analyses against expert profiles. In addition, examining the relationship of emotions and affect when learning marksmanship can provide valuable information in determining how best to coach and what causal factors influenced assessment outcomes (i.e., a trainee exhibited quick abrupt behaviors as a result of boredom). Wearable sensors can further be investigated to determine how physiological variables such as galvanic skin response and heart rate variability can map to affective states experienced during skill development phases.

CONCLUSION

The experiment presented within examined equipment effects on marksmanship behaviors to determine if an adaptive training solution needs to incorporate assessment models that account for environmental variables that may dictate how a task is executed. When constructing expert models for psychomotor tutoring systems, environmental/external factors, such as worn equipment, should be considered early on. Even if the factors are only relevant in particular settings, like in this experiment, it seems to be worthwhile to examine how experts vary their behaviors based on task features and external factors. Through this approach, one can determine how best to associate environmental information into models so that trainees can always learn what is most relevant under specific scenario settings.

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