From Novice to Expert: Developing Shooter Performance Models

Amanda E. van Lamsweerde, Katlin M. Anglin, Jennifer S. Murphy

Quantum Improvements Consulting

Corresponding Author:
Amanda E. van Lamsweerde
12124 High Tech Ave. Ste 165
Orlando, FL 32817
(407) 603-5939
avanlamsweerde@quantumimprovements.net

Abstract

Marksmanship skills are critically important to the Armed Forces but are expensive and time-consuming to train. To alleviate the burden on marksmanship training, data about rifle position prior to the shot can potentially be used to provide diagnostic information to shooters and instructors. Models of marksmanship are in an early stage of development; this project provides insight into the novice and expert patterns of behavior. Novice and expert shooters in the U.S. Marine Corps provided 10 shots in four different shooting positions (prone, sitting, kneeling, and standing) with weapons-mounted sensors attached to their rifles to determine whether shooters could be reliably categorized based on pre-shot behavior (aim, hold, and trigger control). Novices and experts could be reliably categorized based on a combination of all three skills and classification accuracy increased as shooting position became less stable. Furthermore, on each individual skill, scores were generally better for experts than novices. For both experts and novices, scores skill behavior decreased as shooting position became less stable. This has several important implications for the development of training technology that evaluates shooter behavior to provide diagnostic feedback.

Keywords: Marksmanship; Performance; Training; Modeling; Expert

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Developing and maintaining superior marksmanship skills critically impacts members of the U.S. Armed Forces. To maximize training effectiveness while reducing costs, training technology has been developed that provide practice opportunities without the need for live range time and ammunition (e.g., shooting simulators, weapons-mounted sensors, etc.). Another advantage to these technologies is that they capture a rich dataset about shooter behavior. This behavior data can serve many purposes, depending on training goals and system capabilities. A relatively simple use of this data is to display the aim trace on top of a simulated target. This type of visualization is computationally simple and does not require the system to make any judgement, although it may be difficult for the user to interpret. A more difficult, but potentially more informative, use of weapons sensor data would be to evaluate performance and provide feedback about skill level. This diagnostic information may be used by an instructor who provides remediation strategies, or via an intelligent tutoring system that provides remediation strategies in the absence of an instructor. However, to provide evaluation, the captured data must adequately diagnose shooter performance. The purpose of this project was to determine whether the data from a weapons-mounted sensor system to differentiate between expert and novice shooters.

While existing literature on this topic is limited, there have been previous attempts to model marksmanship behavior using sensor data (Goldberg, Amburn, Brawner, & Westphal, 2014; Nagashima, Chung, Espinosa, & Berka, 2009). Some of these efforts center around creating a model of expert marksmanship performance. Goldberg, et al. (2014), for example, developed models of expert behavior on marksmanship skills including trigger pressure, cant/angle of the weapon's orientation, and breath control. In this study, eight U.S. Army expert shooters shot in the prone-unsupported and kneeling positions. A pressure sensitive trigger, Weapon Orientation Module (WOM), and Zephyr bio-harness were used to collect behavior data. Leave-one-out cross-fold validation was used to create models of behavior (which established mean scores and standard deviations), and the remaining experts were compared to these models. Across measures of trigger squeeze, breathing, and weapon orientation, data from most participants fell in the score distribution generated from the data from other experts. This demonstrates that there is a reasonable range of behavior that can be used to judge the overall skill level of a shooter. Similarly, Goldberg, Amburn, Ragusa, & Chen (2018) measured breathing, barrel movement, and trigger control measurements from shots taken by experts. Using a leave-one-out cross validation technique they found 90-100% of the shots taken by each expert fell within an ‘expert’ range. These efforts to characterize expert-like behavior can be useful for the purpose of developing an ‘ideal’ to which shooter behavior can be compared.

Nagashima et al. (2009a and 2009b), using a combination of breath control measures (breath location, breath duration, and shot-percent breath) and trigger control (trigger duration) collected from a respiratory belt and a force-pressure sensor attached to the trigger, developed a model to classify shots as being taken by a novice (civilian) or an expert (active duty military) based on shots taken in the kneeling position. The model was able to correctly identify 67.5% of shots taken by experts and 96% of shots taken by novices in one study (Nagashima et al., 2009a) and 54.3% of all expert shots and 92% novice shots in another (Nagashima et al., 2009b).

In this project, weapons sensor data was collected from expert and novice shooters to evaluate whether shooter expertise (novice, expert) could be predicted from shooter behavior. However, in this project, a portable weapons-mounted system (Fabrique National, FN, America’s FN Expert™) was used that calculates three fundamental marksmanship skills (aim, hold, and trigger control) from a single data stream (weapon movement; explanations the calculations made to these data to estimate these skills are provided in the Methods section). The sensor has several properties that make it useful for training: it is portable and mounts directly to any rifle, so a trainee could mount the device directly to their standard-issue rifle and practice at any time, or with an instructor in a classroom, in dry-fire with a reflective target. The device can also be used in live fire, by using reflective prisms. The companion software operates on any windows-based tablet and calculates three fundamental skills (aim, hold, and trigger control) to evaluate behavior. The approach used in this study builds upon previous research by including novice and expert shooters from the same population (members of the U.S. Marine Corps) and by testing all shooting positions used by this population during training (prone, sitting, kneeling, standing). Two questions formed the focus of the project: 1) can data from the weapons-mounted sensors adequately differentiate between experts and novices and 2) how do expertise and shooting position affect skill (aim, hold, trigger control) scores? This second question is important because one of the goals of this training system is to evaluate skill level. If shooter expertise and shooting position substantially effect the skill scores, these variables need to be considered when providing evaluation (e.g., good, moderate, or poor) of a specific skill.

To address these questions novice and expert shooters from the U.S. Marine Corps (USMC) took 10 shots in all four shooting positions while their aim trace was monitored by the weapons-mounted sensor. Broadly, these data reveal that novices and experts were classified above chance (with up to 100% accuracy) on a combination of these three skills in each shooting position. Furthermore, for each individual skill, experts performed better than novices most of the time (these differences were always significant in the kneeling and standing positions) and behavior for both novices and experts when transitioning from sitting to kneeling, and again from kneeling to standing.

Method

Participants

Participants were U.S. Marines stationed at Quantico, VA. Participation was voluntary and information that links participant identity to data is maintained on a secure server. Participants were selected based on their level of marksmanship expertise (novice or expert), as identified by Marine Corp Weapons Battalion leaders. Experts were members of the U.S. Marine Corps Shooting Team, a competitive shooting team and novices were new recruits who had recently completed initial entry training (with the exception of one novice had 3 years of military experience). Sample size was estimated by reviewing previous literature that has attempted to create models of expert marksmanship (e.g., Nagashima et al., 2006). Twenty participants (10 novices and 10 experts) completed the study. However, four participants were excluded because data files were incomplete and one participant was excluded because of a software zero malfunction. Therefore, a total of seven experts and eight novice participants were included in the final analyses. Participants completed a questionnaire to gather demographic information which asked for their age, gender, number of years of service, education, and self-reports (on a 1 to 5 scale) of their familiarity with rifles, shotguns, and handguns.

Experts. Experts (n = 7) were selected as experts by leadership and have served as members of the Marine Corps Shooting Teams. Experts ranged from 24 to 36 years old (*M* =29.14, *SD* = 4.53), all male. Military experience ranged from five to 18 years (*M* = 9.43, *SD* = 4.24). Three experts (42.86%) had a high school-level education, and the remaining four (57.14%) had some college-level education. All but one expert was right-handed, and all experts were right-eye dominant. Experts were highly familiar with rifles, (*M* = 5, SD = 0), shotguns (*M* = 4.43 *SD* = .98), and handguns (*M* = 4.86, *SD* = .38).

Novices. Novice shooters (n = 8) were selected by instructors and ranged from 19 to 21 years old (*M* =19.25, *SD* = .89; seven male, one female). Novices ranged from one-half to three years of military experience (*M* = .94, *SD* = .81). Six novices (75%) had a high school-level education, and two (25%) had some college level education. All novices were right-handed, and all but one participant was right-eye dominant. Novices reported moderate familiarity with rifles, (M = 3.25, SD = 1.39) and moderately low familiarity with shotguns (*M* = 2.13, *SD* = 1.18) and handguns (*M* = 2.13, *SD* = 1.46).

Equipment

Data collection was conducted using Fabrique National (FN) America's FN Expert™. The FN Expert™ is a commercially available training system composed of rifle-mounted sensor which collects data about the shooter's aim trace (see Figure 1) and software, which evaluates and displays aim trace and skill evaluation. The FN Expert™ mounts on the rifle barrel or picatinny rail and uses an eye-safe IR LED that reflects off the target to track aim trace and final shot point at a sampling rate of 66 Hz. The data are collected on tablet by software that displays aim data for each shot as well as shooter diagnostics. The current research used the FN Expert ™ indoors during dry fire drills on a Marine standard rifle.

- Figure 1 Here -

Procedure

All data were collected in a large indoor room. Researchers set up four shooting stations (one for each shooting position). Each shooting station contained a dry-fire reflective target displayed 10 meters away from the shooting line. These reflective targets are smaller than targets used on a live fire range, such that a distance of 10 meters simulates a shooting distance of 200 yards. The researcher attached the FN Expert™ to each Marine's standard issue rifle.

A researcher provided an overview of the system and explained the procedure to each participant. At every station (prone, sitting, kneeling, standing), the FN Expert™ device was calibrated through a procedure called "software zeroing." To software zero, the participant takes three shots at the target and the system adjusts the center of the target to the center of the shot groupings. Once participants finished software zeroing, each participant took 10 shots in each shooting position, for a total of 40 shots each. Participants shot at their own pace and took breaks between shots as needed. Four shooting 'lanes' were set up in a classroom, one for each shooting position (target height was adjusted for each position) and software zero was completed each time a shooter changed lanes. Because of the need to minimize time constraints on the Marines, shooters progressed through the shooting lanes in different orders, depending on the availability of the lane. Once the participant completed all shooting positions, they were then thanked for their time and dismissed.

Results

There were two primary goals to this study. The first goal was to determine whether experts and novices could be reliably classified based on skill scores calculated from the sensor data. The second goal was to determine how expertise level and shooting position affect individual skill scores. To accomplish these goals, the (x,y) coordinates from the FN Experts™ were used to calculate scores on three fundamental marksmanship scores: aim, hold, and trigger control. To determine whether experts and novices could be reliably differentiated, linear discriminant analysis (LDA) was conducted on mean skill scores using a leave-one-out cross validation technique. Finally, to test the effect of expertise and shooting position on skill scores, mean skills cores were bootstrapped and confidence intervals were calculated. All data analysis was conducted with custom created scripts written in Matlab® and the Statistics and Machine Learning Toolbox™ for Matlab® was used to conduct bootstrapping and LDA procedures.

Skill Calculation

Marksmanship fundamental skill scores for each shot were first calculated using the formulas within the FN Expert™ software. The software data output include the x,y coordinates for the entire aim trace in a json file, which were loaded into Matlab for all analyses. For all three marksmanship scores, lower scores indicate better skill proficiency (i.e., less weapon movement). A brief description for each of these skills is described below.

Aim represents the position of the weapon prior to trigger pull. Aim is represented by the difference between the center of gravity of the aim point and the center of the target (X_0 , Y_0).

Hold represents how steady the shooter holds the rifle prior to shooting the weapon and is therefore represented as the variability of the aim coordinates over the final 1.5 seconds of the shot.

Trigger control represents the manipulation of the trigger, which influences the position of the weapon and shot accuracy. It is calculated as the distance between the aim point 250ms prior to shot termination and the final aim trace point.

Linear Discriminant Analysis (LDA)

To determine whether experts and novices could be reliably differentiated, linear discriminant analysis (LDA) was conducted that factored in scores on all three fundamental skills. LDA is a technique that enables categorization of data into distinct groups (e.g., novice or expert) based on multiple input variables (e.g., aim, hold, and trigger control). The LDA model is trained based on one set of data with known category labels to generate parameter estimates; test data is then compared to this model to predict category membership. Because of the small sample size in this study, it was not possible to have entirely separate training and test data. Therefore, a leave-one-out cross validation technique was used. With this technique, model parameters are created for all subjects except one and classification of the remaining participant was then tested. This process was repeated until all participants are left out once. Model prediction accuracy was averaged across all subjects to calculate overall model classification accuracy. Four separate models were created, one for each shooting position (prone, sitting, kneeling, standing). Model classification accuracy was high across all shooting positions (prone $M = .73$, sitting $M = .73$, kneeling $M = .80$, standing $M = 1$).

To determine whether the classification is more accurate than would be expected by chance, the classification rate was compared to a chance model using random permutation tests (Phipson & Smyth, 2010). With this method, random models were created with the same leave-one-out procedure as the test model, except that the expert and novice labels were shuffled prior to conducting the LDA. These chance models should, on average, classify the remaining participant at a rate of 50% accuracy. This random model creation process was completed 1000 times to generate a *null* distribution of classification accuracy (see Figure 2). The proportion of the null distribution that classifies shooters as accurately as the test model (adding one to both the numerator and denominator; Phipson & Smyth, 2010) represents the *p*-value (in Figure 2, the p-value is .02).

- Figure 2 Here -

Chance models accurately classified shooters on average 50% of the time (prone $M = .50$, sitting, $M = .50$, kneeling $M = .50$, standing $M = .50$) All models accurately classified shooter membership at a rate greater than chance (prone, $p = .03$; sitting, $p = .04$; kneeling, $p = .02$, standing, $p < .001$). Therefore, experts and novices were reliably differentiated by their behavior data, although classification accuracy were greater with less stable shooting positions (specifically, standing).

Individual Skill Data Analysis

To determine how novices and experts compared on each individual skill, non-parametric bootstrap distributions were generated from novice and expert skill scores (aim, hold, and trigger control) in each shooting position to calculate sample means. Bootstrapping is a method of resampling data with replacement that is particularly valuable for estimating distribution parameters, including descriptive statistics such as means and estimates of variance (Efron, 1979; Zoubir & Iskander, 2007) as well as inferential confidence intervals as an alternative to null hypothesis testing (Wood, 2005). To create non-parametric bootstrap distributions, scores were randomly drawn with replacement from the possible set of scores to create a new sample that is the same size as the original sample; this process is completed many times (in this case, 5000) to mimic the process of sampling data from a population. Confidence intervals were calculated using the bias accelerated method (Efron, 1987) using the statistics and machine learning toolbox for Matlab to correct for skewness. Mean skill scores and confidence intervals are shown in Figure 3.

- Figure 3 Here -

Individual Skill Results: Novices vs Experts

Overall, expert shooters had substantially better (lower = better) scores than novices (See Figure 1). For the *aim* skill, this difference was significant for all but the kneeling position (see Table 1a). For the *hold* skill, this difference was significant across all shooting positions (Table

1b). For the *trigger control* skill, this difference was significant in the kneeling and standing positions (Table 1c).

- Table 1 Here -

Individual Skill Results: Shooting Positions

For both experts and novices, there was no change in behavior from the prone to sitting positions in any skill (see Table 1a-c). In the hold skill, skills scores were better in the prone/sitting position than kneeling for both experts and novices (Table 1b) and scores were better in the kneeling than standing position. Novice trigger control decreased from prone/sitting to kneeling, and again from kneeling to standing (Table 1c). Experts, on the other hand, showed a smaller change when transitioning from kneeling standing in the hold and trigger control positions (Table 1b-c), while in the aim skill, standing scores were better than prone and sitting scores (Table 1a).

Discussion

Overall, shooters were reliably classified as novices or experts based on a combination of aim, hold, and trigger control. However, differences between experts and novices were not found most consistently in the less stable shooting positions. For aim and trigger control, differences between novices and experts were found only in the kneeling and standing positions. Hold (which represents steadiness of the rifle) was the only skill that reliably distinguished between novices and experts and novices across all shooting positions. However, behavior was impaired for both novices and experts when moving to less stable shooting positions. These data suggest several important implications for the use of sensor data in marksmanship training technology and future research.

The use of senor data to evaluate skills may enable easier identification of the source of skill deficiencies for novice shooters; this in turn could increase training efficiency and reduce costs. For example, U.S. Marine Corps instructors in the Weapons Training Battalion rely on their expertise to diagnose the cause of a shooter's problems from typical characteristics of problems in their shot point and may vary from instructor to instructor. Furthermore, it may be difficult to determine the source of shooter problems, and shooters go through multiple rounds of remediation with several different instructors and coaches (personal communication with instructors of the Weapons Training Battalion, October 2017). For these cases, it would be especially useful for instructors to have guidance about what the shooters are doing wrong (e.g., poor trigger control), so they know what kind of remediation strategies to offer.

The results that shooting position and expertise both affect individual skill scores suggest that, when using sensor data to *evaluate* shooter behavior in this way, the effectiveness of this evaluation can be maximized by considering the shooting position and overall shooter skill level. For example, if the goal of evaluation is to diagnose shooter skill deficiencies, it may be desirable to create cutoff scores to determine whether that skill (e.g., trigger control) is 'good', 'moderate', or 'bad.' The scores from a shooter using the training tool can be compared to these cutoff scores, and feedback can be provided to the shooter about skill competency. However, an *expert* model alone may not sufficiently diagnose novice shooter performance. When compared to an expert, novices will often appear 'bad' as they will often have substantially different performance from experts. Therefore, comparing novices to experts alone may make it difficult distinguish which shooters have true deficiencies. A novice model, on the other hand, can provide insight into whether a novice performs well for their relative skill level. This is true of shooting positions as well: a prone cutoff score would be different from a standing score, for example, as behavior is very different across these positions.

The use of a training device that could evaluate performance could also be helpful for standardizing instruction and remediation. While some instructors train based on U.S. Marine Corps doctrine, others also train based on experience, which may result in transfer of bad habits from one shooter to another (personal communication with instructors of the Weapons Training Battalion, October 2017). Early standardization issues can be mitigated with technology that provides both diagnostic capabilities and individualized feedback. For example, an expert model of performance can be used to determine the difference between current shooter behavior and standard behavior based on an expert model and training doctrine. This difference can be used to provide individual feedback correct behavior in a standardized way (Goldberg et al., 2018).

There are several directions that future research can advance the effectiveness of weapons sensor use in training. Although the goal of this project was to determine whether the sensor data can be used to classify the shooter as expert or novice, another goal for sensor technology might be to predict how a novice shooter will qualify at a qualification event. This would require a prediction model, rather than the classification model used here; however, such a tool could be useful for identifying which shooters require additional training.

In addition, given that evaluating the progression of skill over time has been noted as a remaining gap in marksmanship literature (Chung et al., 2006), replication of this study to include shooters of more moderate skill will be highly useful for developing a model of marksmanship skill progression over time. Furthermore, in these data, the effects of any improvement over time throughout a training session were not measured. Shooters took only ten shots per position and did not receive any visual feedback regarding their performance; therefore, there was minimal opportunity for improvement over the course of the data collection session. However, the goal of a training session would be to improve performance. In this case, it might be expected that behavioral measures captured from sensor data (and performance outcomes such as accuracy) would improve throughout a typical training session. Future research could model this change within a training session and determine whether there are characteristics that predict improvement within a session.

Another line of future research could be to evaluate the effect of systematic shooting position changes on behavior. In this study, participants did not change shooting positions in the same order. Therefore, the effects of shooting position (e.g., poorer skills in less stable positions) are independent of order. However, if shooters systematically change positions (e.g., prone to sitting to kneeing to standing) throughout training, it might be expected that fatigue, practice, or carryover effects might be systematically observed in some shooting positions. Therefore, changes in position may be modeled in future research.

Skill decay may also affect the expected behavior scores, which could be useful for developing training programs. For example, it could be useful to know decay rate to create a time table for refresher training. Alternately, skill behavior can be assessed at regular intervals and compared to expected decay rates to personalize training regimens.

Additionally, replication of this study in a live fire event would be useful to determine whether separate models are required for live or dry fire training. While the sensor that was used in the current study can be used in both live and dry fire, the models were developed in dry fire only. Furthermore, dry fire is used in simulators. It would be useful to know how the models developed in a dry fire condition transfer to life fire behavior (and vice versa).

Finally, models of performance may be most efficient if developed based on the target training population. These data suggest that skill scores vary based on the expertise and shooting position; the population of interest (e.g., Army, police, etc.) may also influence expected behavioral scores, as these groups may differ in training strategies and weapons used.

Despite the importance of training fundamental marksmanship skills in the armed forces, there is little research that models performance on these skills and monitors their development over time. The data presented here demonstrates that it is possible to differentiate experts and novices based on a combination of aim, hold, and trigger control measured from pre-shot data. This information can be used to improve training by automatically diagnosing trouble shooters and potentially offering remediation suggestions, which can reduce training time and cost.

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Table 1. Means, standard deviations, and confidence intervals for individual skills.

1a Aim

	Prone	Sitting	Kneeling	Standing
Expert	*M*= 88.74 *SD*= 8.69 *CI*= [67.25, 103.16]	*M*= 92.81 *SD*= 2.19 *CI*= [73.18, 124.4]	*M*=129.84 *SD*=18.49 *CI*= [99.63, 177.46]	*M*=156.63 *SD*=14.74 *CI*= [130.32,187.32]
Novice	*M*= 157.4 *SD*= 18.69 *CI*= [118.66,192.77]	*M*= 149.62 *SD*= 10.84 *CI*= [131.57, 173.62]	*M*= 195.99 *SD*=13.15 *CI*= [162.98,217.53]	*M*= 326.44 *SD*= 19.59 *CI*= [290.89, 367.47]

1b Hold

	Prone	Sitting	Kneeling	Standing
Expert	*M*= 42.67 *SD*= 6.63 *CI*= [33.52, 63.22]	*M*= 47.73 *SD*= 4.71 *CI*= [40.16, 59.93]	*M*= 81.33 *SD*= 8.81 *CI*= [65.4, 98.32]	*M*= 145.82 *SD*= 12.14 *CI*= [125.72,176.06]
Novice	*M*= 78.83 *SD*= 6.56 *CI*= [67.34, 93.4]	*M*= 77.38 *SD*= 10.52 *CI*= [62.36, 107.66]	*M*= 145.45 *SD*= 17.91 *CI*= [120.82,201.23]	*M*= 301.48 *SD*= 18.2 *CI*= [273.72,347.17]

1c Trigger Control

	Prone	Sitting	Kneeling	Standing
Expert	*M*= 45.88 *SD*= 14.86 *CI*= [28.77, 98.6]	*M*= 58.01 *SD*= 7.13 *CI*= [45.74, 75.67]	*M*= 86.32 *SD*= 10.41 *CI*= [68.08, 108.32]	*M*= 168.74 *SD*= 11.13 *CI*= [149.31, 191.99]
Novice	*M*= 83.72 *SD*= 10.34 *CI*= [62.27, 102.78]	*M*= 87.87 *SD*= 8.77 *CI*= [73.55, 107.14]	*M*= 143.38 *SD*= 20.85 *CI*= [113.06, 201.12]	*M*= 326.94 *SD*= 26.84 *CI*= [278.86, 385.19]

Figure 1. FN Expert device mounted to rifle picatinny rail.

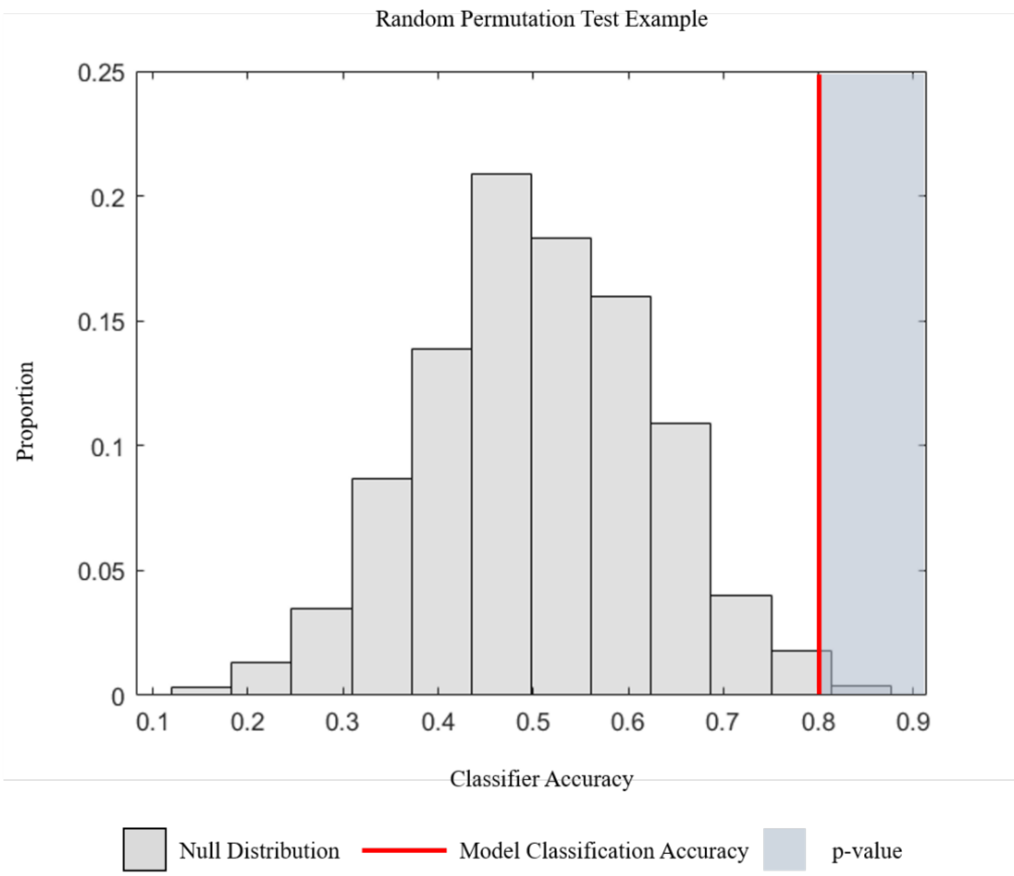

Figure 2. Example of p-value generation from random permutation test. In this example, the null distribution has a mean classification accuracy of 0.50 and the test model has a classification accuracy of 0.80. The p-value in this case is .02, which represents proportion of the null distribution with accuracy of .80 or greater.

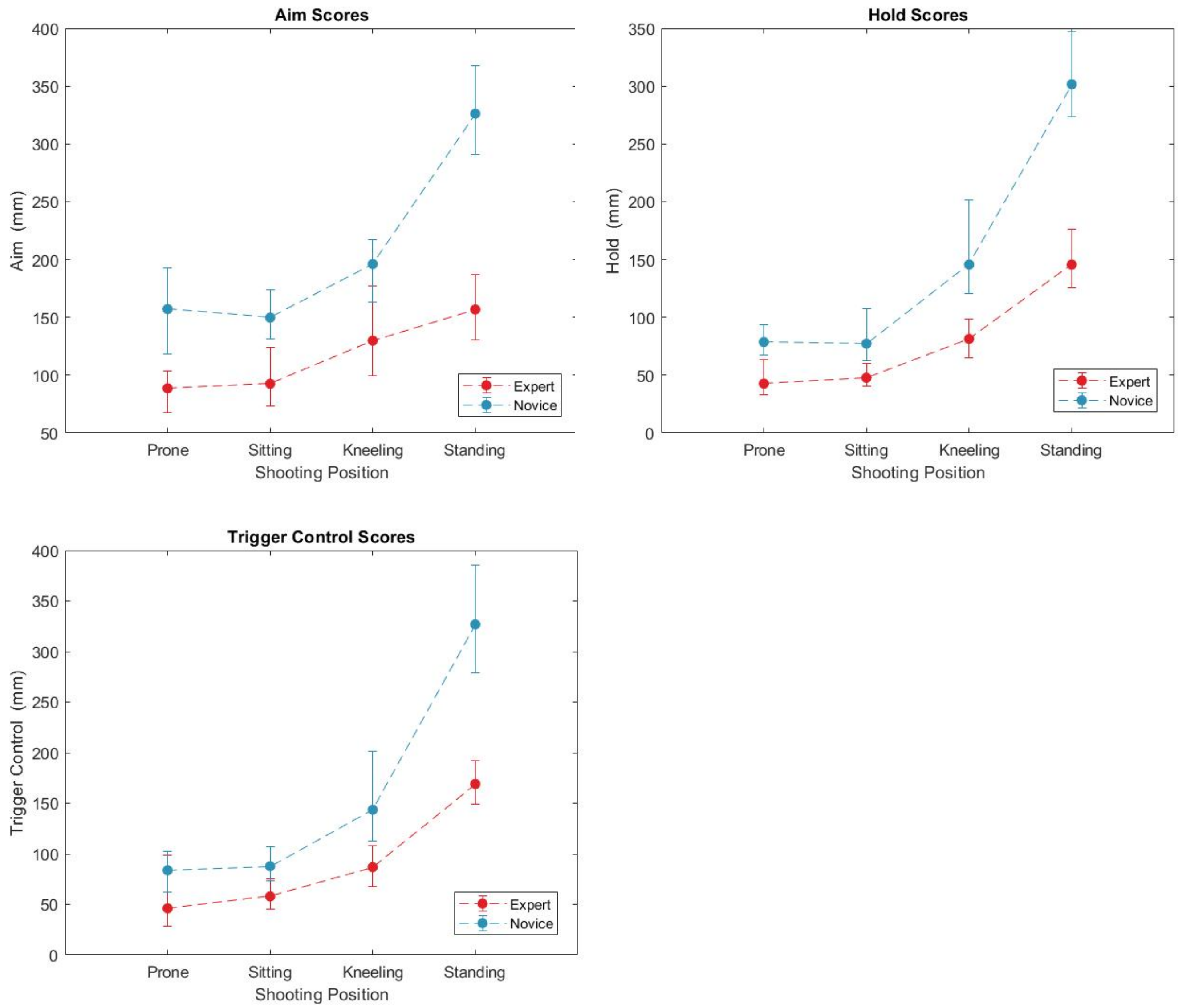

Figure 3. Means and confidence intervals for individual marksmanship scores. Lower scores indicate better performance.