Predicción de la posición correcta de disparo con una pistola basada en un modelo MANFIS

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Prediction of the Correct Firing Position with a Pistol Based on a MANFIS Model.

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Abstract. Simulator systems are intended to facilitate access to practice in different test environments through a closed environment using computer vision. In this paper, a MANFIS model is implemented to improve the position of a trainee through positioning practice, which is responsible for detecting and displaying the errors that the trainee has when adopting the shooting position in real time. This environment qualifies, evaluates the pistol shooting position in a closed environment, analyzes, compares, and discusses the results obtained to determine the best option for evaluating the shooting position where the integrity and safety of the practitioner are paramount. The programs are adjusted to the process of identification and evaluation by Computer Vision using algorithms and processing methods. The evaluation reached an overall efficiency 89.59 ± 3.36%, for 12 participants, determining the virtual simulator as adequate for training practices of the correct firing position.

Keywords: Computer Vision, MANFIS, Virtual Simulator, Firing Position, Pose Estimation.

1 Introduction

The posture a shooter adopts on the practice range becomes critical because it can affect the accuracy and speed of the shot, where the moving parts of the body, muscles, and bones (such as the legs, back, and arms) are involved [1, 2]. Proper shooter's posture helps to maintain balance, if the shooter does not control his posture during practice, it will increase body fatigue, which affects his physical condition, concentration, and shooting efficiency [3-5].

In the teaching-learning process, constant practice and correction of errors help to improve posture, accuracy, and performance on the shooting range through a continuous evaluation whose results allow a significant improvement in the functional capacity of the practitioner [6, 7]. Once this stage has been completed, technical and postural corrections are difficult to make again, an aspect that is evident in the sample studied in this work, as part of a preliminary diagnosis of the level of influence of the position of the body in front of the target. With the use of weaponry (see Sect. 2), the technical focus of the preparation lies in identifying specific alterations that may affect the shooter's postural control and consequently his performance [8, 9].

This article proposes the integration of technologies oriented to the use of immersive virtual reality, using an adaptive neural-fuzzy inference system for the prediction of the correct shooting position. The proposed model has been tested and compared with real cases of correct position evaluation in shooting ranges. The evaluation allows the student to develop his skills, abilities, and professional training. At the end of the practical exercises, a joints analysis of the results obtained on the position simulator is presented for experienced and inexperienced trainees.

2 System Desing

Virtual reality now allows for the visualization of biomechanical agents in shooting position simulators during conflict situations [10], offering potential training enhancements [11, 12]. Fig. 1 displays the system's design, highlighting key components: a) trainee positioning capture, b) recording and playback, c) a projection showcasing trainee silhouettes, and d) 3D representations in the projection area, supported by e) equipment rack, i) computer with connections, and ii) the projection area.

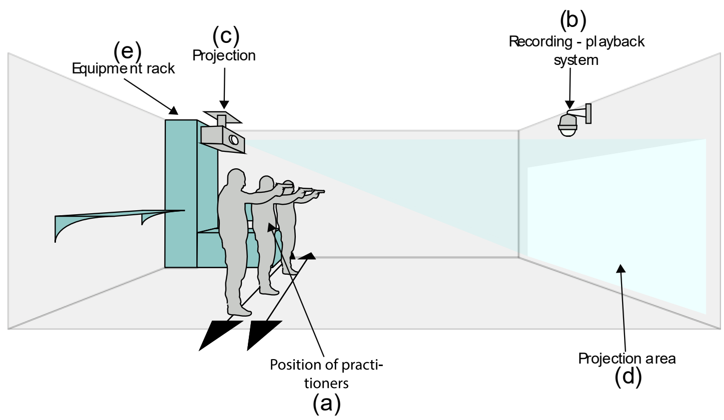


Fig. 1. Main components of system.

The virtual simulator uses a Computer Vision technique present in the Kinect sensor to detect the position of the practitioner [10, 11], and 4 Adaptive Neural-Fuzzy Inference System of Mamdani (MANFIS) techniques to evaluate the correct shooting position [13, 14]. To validate the results, we propose the creation of a scenario that visualizes the position with a 3D representation and the silhouette of the biomechanical agents of the practitioner (see Sect. 4.1), which facilitates the control of the evaluation [15].

3 Functional Scheme of the Firing Range Simulator

Using the Unity3D platform, a simulator was developed to teach the correct firing position by analyzing biomechanical agents. The collected data is stored adaptively [15]. Fig. 2 shows the functional schematic of the simulator with two modules: 1) User interaction, which places practitioners in a shooting position, and 2) Dialogue flow, which processes the practitioner's position and provides feedback. The reasoning is applied through the instructor's Knowledge Base (see Sect. 4) The final result shows both the firing posture and the percentage of positioning achieved using a 2D silhouette.

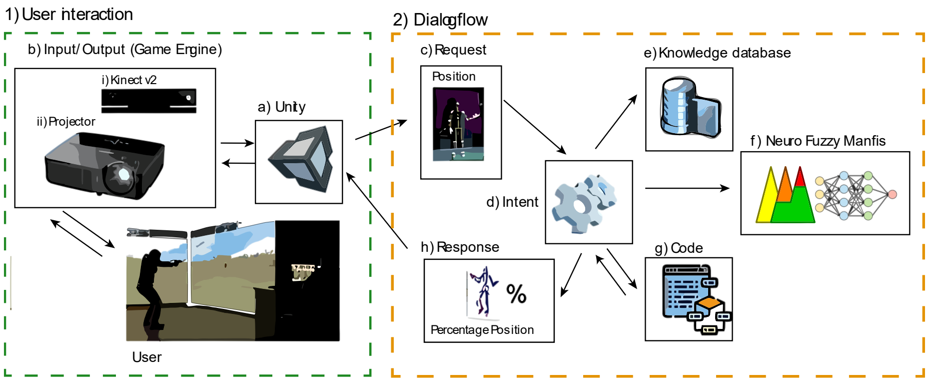


Fig. 2. Functional scheme of the proposed application: 1) User Interaction for communication with the simulator, 2) Dialog Flow receives inputs, processes them, and returns them as outputs.

The graphics engine, a) Unity 3D, was used to build the virtual and simulation environments (Unity SDK, Kinect 2 SDK). Blender and multimedia resources from the Unity Asset Store. b) The inputs and outputs of the system are realized by operating i) the Kinect 2 integrated motion sensor to obtain c) request or position information to be processed by f) MANFIS (see Sect. 4), and e) the knowledge database (see Table 2) and g) code return the percentage of correct firing position where the data visualization is obtained through the ii) projection of the scenario.

4 Adaptive Neural-Fuzzy Inference System of Mamdani (MANFIS)

Biomechanics applies mechanical principles to study human body movement, especially in shooting sports [7, 16]. Despite extensive research on licensed weapons and shooting psychology, there's a gap in technical and mechanical studies [17]. Biomechanical indicators (parts of a body) from shooters are pivotal for technical control [18, 19]. The Kinect 2 sensor enhances this analysis by a) tracking the human body and identifying the joints being studied by b) shooter position using parameters and shooter biomechanics to obtain c) Euclidean distances and angles to be used as input data in d) the Mamdani neuro-fuzzy system, uses membership functions and a neural network for defuzzification, with fully connected backpropagation learning (see Fig. 3).

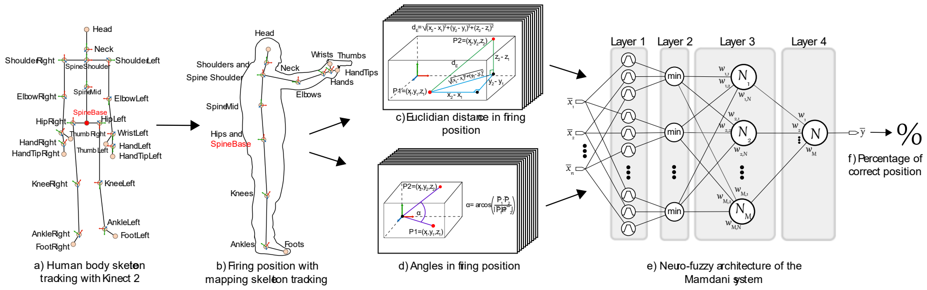


Fig. 3. Human body biomechanical agents tracking with Kinect 2 and correct position evaluation with a basic neuro-fuzzy architecture of the Mamdani system [17]

The tracking of a) human body skeleton is provided by the Kinect 2 through the integrated SDK, which uses human motion capture based on the Shotton algorithm using Support Vector Machine (SVM) for body part classification based on depth and RGB data and Randomized Decision Forests for precise joints position prediction, revolutionizing human motion capture [18, 19]. With this technology, the human motion of up to 6 people is tracked simultaneously, identifying 25 joints [19]. Fig. 3 shows the tracking of the human body to capture its motion, where b) the shooter's position given by Sect. 4.1. The biomechanics of the shooter is used to obtain c) the distances and d) the angles of its biomechanical agents using parameters of the membership functions. These parameters are the input of the neural network that will be introduced in the fuzzy logic system, to be integrated into e) the MANFIS in charge of predicting f) the percentage of the correct firing position.

4.1 Biomechanics of the Shooter

Biomechanics studies the movement of the human body using mechanical principles [7, 20]. In shooting sports, a general technique is integrated with other scientific disciplines [2, 6]. Some factors can influence the assessment of athlete performance [21, 22]. During training, instructors evaluate posture and weapon grip [6, 7]. Initially, shooters are taught correct positioning, but post-training technical corrections are rare. This neglect becomes evident in posture studies [8, 9]. Improper posture can cause increased fatigue, affecting a shooter's concentration and performance. Proper postural control is vital for maintaining balance and shooting efficiency [3-5].

The standard position for firing a weapon, as shown in Fig. 3, section b), has the arm extended, the sights oriented approximately 90° towards the feet and shoulders, to counterbalance the weight of the weapon [10]. However, this is not universal; factors such as posture, body composition, and height influence arm angle. Shorter shooters may raise their arms more, while taller shooters may aim lower [11]. The standard shooting position involves facing the target with feet shoulder-width apart, knees slightly bent, and aligned hips, back, shoulders, and head.

The body should lean forward slightly, forming an "isosceles triangle" with extended arms and straight shoulders. This stance ensures optimal balance, minimizes muscle strain, and offers comfort [11] (refer to Fig. 3). Angles refer to the degrees of rotation or flexion at specific joints, while distances indicate the spatial separation between body parts (see Table 1). Their measurement helps to correct the firing position. This study aims to analyze biomechanical indicators in firearm action by quantifying physical traits and comparing results from various practices.

4.2 Fuzzy Logic and Training

A Mamdani-type fuzzy system [21] can be represented by a multilayer architecture similar to a neural network [23]. This neuro-fuzzy architecture has as its first layer the calculation of the angle between two vectors in a 3D plane (see Equation 1), Fig 3 and the Euclidean distances between two points (see Equation 2), of the biomechanical agents of the shooter in a 3D environment, according to Sect. 4 and Table 1, evaluated in the membership functions, which gives me an idea to improve the firing position.

$$\alpha = arcos\left(\frac{P_1 \cdot P_2}{|P_1| \cdot |P_2|}\right) \tag{1}$$

$$d_E(P_1 \cdot P_2) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2} \tag{2}$$

In the second layer, the Cartesian product or minimum function is performed, where there are N results given by the number of IF-THEN fuzzy rules. The last two layers are responsible for defuzzification by the centroid method, constrained by fuzzy inference. However, this can be represented by a neural network [23, 24], so that various defuzzification formulas can be substituted as a function of the training samples, which constitute a learning sequence [25-28]. This process represents a fuzzy system modeling approach [29] for detecting the correct firing position with defuzzification using a neural network with backpropagation learning. In the following, the terms of the fuzzy system are defined:

- The Universe of Discourse: for the angles is between -180 to +180 and in distance between 0 to 2 meters.
- The Crisp set: the correct position of the practitioner is determined by comparing the angles between the centre of mass and the limbs of the body. This is considered accurate when it aligns with the shooter's biomechanics (see Sect. 4.1).
- The Fuzzy set: the Head and Trunk angles are 90º and the left and right arms 40º according to[20, 24]; However, these elements belong to a classical set therefore, a representation with adjustment to a fuzzy set given by Table 1 is proposed taking into account the instructor's indications and the noise generated by the Kinect 2 sensor.
- The Membership function: appropriate ranks in the fuzzy set are identified using specific membership functions [29]. These functions use Gamma (Γ) (see Equation 3), Lambda (Λ) (see Equation 4) for triangular shapes, and Pi (Π) (see Equation 5)

for trapezoidal shapes themselves to represent fuzzy sets Table 1 designates a membership function for each biomechanical agent within a category based fuzzy set.

$$\mu(x) = \begin{cases} 0 & si\ x \leq a \\ \frac{x-a}{m-a} & si\ a < x < m \\ 1 & s\ x \geq m \end{cases} \tag{3}$$

$$\mu(x) = \begin{cases} 0 & si\ x \leq a \\ \frac{x-a}{m-a} & si\ a < x \leq m \\ \frac{b-x}{b-m} & si\ m < x \leq b \\ 0 & si\ x \geq b \end{cases} \tag{4}$$

$$\mu(x) = \begin{cases} 0 & si\ x \leq a \\ \frac{x-a}{b-a} & si\ a < x \leq b \\ 1 & si\ a < x \leq c \\ \frac{d-x}{b-c} & si\ c < x \leq d \\ 0 & si\ x > d \end{cases} \tag{5}$$

Angle measures include head (H), trunk (T), left arm (LA), right arm (RA), left knee (LK), and right knee (RK). On the other hand, distance measurements comprise the arms (DAR), knees (DK) and ankles (DAN). These abbreviations simplify the identification and categorization of measurements, as angles represent joints positions and distances quantify spatial relationships.

Table 1. Membership functions on the fuzzy sets of the pistol shooting position.

Element	Membership function in the fuzzy set														
	Bad					Regular					Good				
	a	b	c	d	F	a	b	c	d	F	a	b	c	d	F
H (º)	105	120	-	-	Γ	115	130	145	155	Π	150	180	-	-	Λ
T (º)	105	120	-	-	Γ	115	130	145	155	Π	150	180	-	-	Λ
LA (º)	0	40	-	-	Λ	30	35	40	55	Π	40	65	85	105	Π
	130	180	-	-	Γ	95	105	120	135	Π					
RA (º)	0	40	-	-	Λ	30	35	40	55	Π	40	65	85	105	Π
	130	180	-	-	Γ	95	105	120	135	Π					
LK (º)	85	100	-	-	Γ	95	110	125	135	Π	130	180	-	-	Λ
RK (º)	85	100	-	-	Γ	95	110	125	135	Π	130	180	-	-	Λ
DAR (cm)	50	100	-	-	Γ	20	40	50	70	Π	0	25	-	-	Λ
DK (cm)	75	150	-	-	Γ	40	55	65	80	Π	0	50	-	-	Λ
DAN (cm)	30	100	-	-	Γ	25	30	40	55	Π	0	40	-	-	Λ

Table 1 provides an overview of the membership functions for a fuzzy set, where each element represents a biomechanical agent, complete with units of measurement. The descriptors "Bad", "Regular", and "Good" describe the acceptable features of the position, which are associated with upper and lower bounds, represented in columns a, b, c, and d. The Gamma, Lambda, and Pi functions assign these limits, denoted by x, and are described in Sect. 4.1 using specific letter representations. Essentially, Table 1 categorizes body measurements, such as the angle of the head or the distance between arms, into fuzzy sets using these membership functions. These parameters shape the functions and offer a structured framework for understanding and categorizing biomechanical measurements.

The defuzzification method employs a backpropagation neural network for training, using various inputs and their classifications [30]. This network takes its input from the results of the Mamdani table-based fuzzy rules [31] in the second layer of the MANFIS system. Table 2 shows an approach for modeling a backpropagation neural network, belonging to a MANFIS system, showing each biomechanical agent (see Sect. 4.1) in their respective units (degrees or centimeters) along with their percentages of correct position (see Fig. 3).

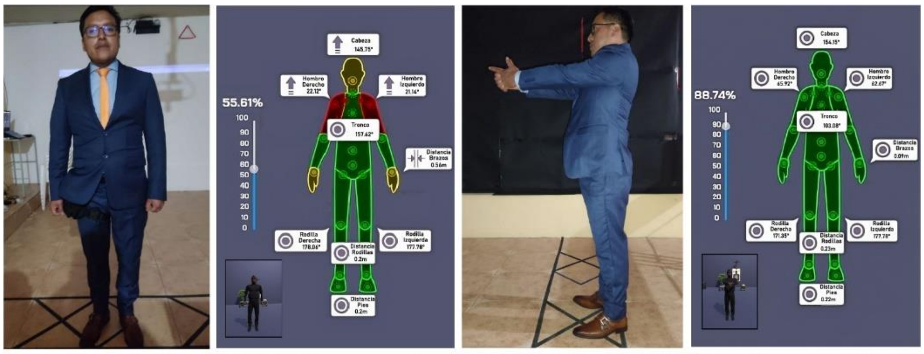
Table 2. The training data set used in this study for the correct position of fire obtained by sensor Kinect 2 and instructor.

#	0	1	2	3	4	…	6	…	299	300
H (°)	167	116	159	151	122	…	174	…	141	114
T (°)	160	106	168	154	149	…	173	…	140	119
LA (°)	43	16	99	42	47	…	104	…	120	142
RA (°)	72	27	48	39	36	…	101	…	54	33
LK (°)	166	119	169	146	150	…	156	…	146	112
RK (°)	157	111	151	132	135	…	154	…	137	112
DAR (cm)	9	66	5	30	32	…	22	…	21	126
DK (cm)	49	81	44	54	78	…	20	…	77	100
DAN (cm)	28	107	37	45	29	…	31	…	26	141
Percentage	71	27	75	73	51	…	96	…	55	21

Table 2 is a structured data set for training a neural network. The inputs are the biomechanical agents, while the percentage is the output data indicating the quality of the posture (rows), and the number of records used is 300 (columns) [25-28]. Using this data set in the training of a neural network, a model capable of predicting the percentage quality of the pistol shooting stance from the input values was developed. This predictive capability can be used in various contexts, such as postural control applications, virtual exercise assistants, or postural correction systems [30]. With the use of this dataset and a trained neural network model, a system capable of assessing and providing information about the quality of a person's posture can be obtained, which can contribute to improving health and prevent possible injuries related to incorrect posture.

5 Execution of the Practice

The simulator displays a 3D virtual environment in which the correct position of a character is displayed. To improve training results, practitioners must address and rectify positional faults. The simulation system evaluates the user's biometrics in real time, scoring them from 0 to 100 based on the distances and angles of the biomechanical agents (see Table 1). A score above 70 indicates optimal positioning, which directly influences the accuracy of the shot [31, 32].



a) Practitioner Position b) Initial Representation c) Firing Position d) Practitioner Qualification

Fig. 4. Scene 1, position training practice

The scene is designed to detect the biomechanical components of the practitioner. It starts with a) the practitioner's initial position in front of the Kinect, leading to b) a real-time representation of the practitioner's silhouette. The white boxes represent biomechanical angle inputs. The colors (red, yellow, and green) indicate the good position of each joint. The box at the bottom right projects the practitioner's movements in real-time, the process continues with c) the adoption of the shooting position and concludes with d) the evaluation of the practitioner's correct position, represented by a 0-100 score bar on the right side of the figure.

6 Simulation Cases and Results

This section presents the results of 12 simulation cases performed by trainee security officers on the range simulator. This function makes it possible to evaluate and obtain real-time information on the shooter's position. By providing immediate data on the shooting position, the system allows for quick analysis and adjustment, improving training and performance evaluation. The methodology of this research focuses on applied research with a descriptive scope and its design is quasi-experimental. The data are not manipulated, but the situation of the trainee's position at a given time is evaluated. The target population is the students of the private security training center Taurhus CIA. LTDA, between 18 and 48 years of age. As the population is a group of students made up of 9 males and 3 females, the study will be applied to the entire universe.

In this type of simulation, a brief induction on the scenario operation is carried out (see Fig. 4), where the final objective is to determine the relevance of adopting a good firing position. The rating metric establishes that a rating above 70% is determined as good and a rating above 90% is considered as a correct shooting position.

Table 3. Positioning practices on the virtual simulator.

Practitioner	Iteraction					
	first	second	third	fourth	fifth	average
1	87,23	94,12	78,34	83,23	93,12	87,208
2	73,12	71,23	85,23	87,34	89,23	81,23
3	89.04	87	91,4	87,34	91,5	89,31
4	78.6	89,4	78,23	91	89,23	86,965
5	89,45	93,12	93,5	89,23	95	92,06
6	92	94,23	93,45	93,6	95,34	93,724
7	87.56	89,2	94,23	98,23	92,45	93,5275
8	85,23	88	89,34	93,65	91,23	89,49
9	89,23	93,23	94,2	89,56	96,2	92,484
10	89	92,23	94,23	87,2	94,2	91,372
11	88,3	90	94,2	87,23	89,34	89,814
12	84,23	85,34	87	93,2	90	87,954

Table 3 shows the positional results of 5 interactions in 25 seconds and ending with an individualized average, for 12 pupils. The instructors of the CIA Taurhus. LTDA. instructors consider that this time is sufficient to adopt a correct shooting position. After an introduction to the virtual simulation system, the trainees adjust their positions with real-time feedback. During the exercise, it is observed that in each interaction, the trainees obtain good scores thanks to the real-time evaluation of the system, which proves its effectiveness and is approved by the instructors of CIA Taurhus. LTDA.

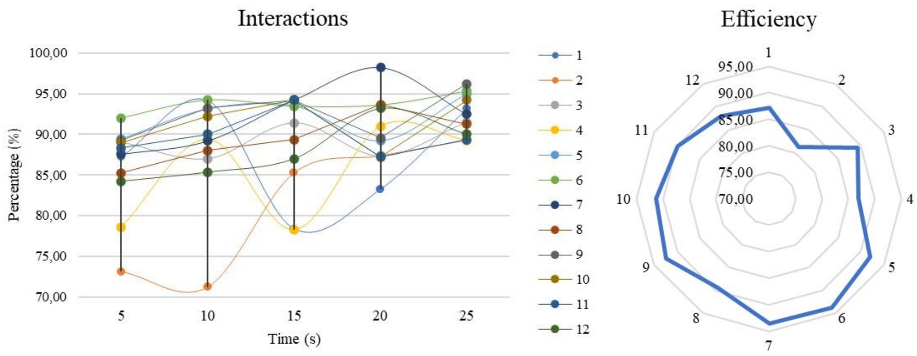


Fig. 5. Comparison of results of five interaction and efficiency by practitioner

Fig. 5 Interactions: shows that the score of the group of participants is above 70 out of 100 points. Each participant takes the shooting position for 5 seconds and at the end of the cycle, a new practice begins, thus obtaining individual results that are used for a more efficient analysis. For 25 seconds, spread over 5 interactions, it is observed that the overall trajectory decreases with each practice. With repeated use of the system, the results become more linear. Efficiency is calculated from 0 to 100, showing that constant interaction with the system leads to an improvement that can be visualized from the first practice to the last. In the first iteration, the practitioners' correct position score ranged from a minimum of 73.12% to a maximum of 92%. In the last iteration, the score ranged from a minimum of 89.23% to a maximum of 96.20%, indicating an alleged progressive improvement see Fig. 5. first and last interaction. Real-time evaluation allows immediate adjustment of the score without the need for constant intervention by the instructor.

7 Conclusions and Future Work

The research highlighted the effectiveness of the MANFIS model in the assessment of shooting posture as a valuable tool for handling complex data. The virtual simulator of this research met the expectations and the participants showed great interest. Through this simulator, trainees observe their virtualization in 3D and 2D formats (see figure 3). This immersive experience, coupled with real-time feedback, facilitates the adoption of an optimal shooting posture. Trainees experience a reduction in body fatigue (see section 1) and an increase in concentration, improving shooter efficiency. The importance of correct posture for safe shooting was emphasized. Despite research in the field of shooting, biomechanics, particularly in MANFIS, is an under-explored area. This study helps to fill this gap and suggests that MANFIS should be incorporated into training programs. Finally, the success of the model suggests its potential use in other areas of shooting and related sports.

This simulator plays a crucial role in helping shooters perfect their shooting position. With 300 postural records obtained by the instructors (see Table 2), the system's effectiveness is constantly monitored. The evaluation is carried out with inexperienced participants on a shooting range. The most remarkable result is an efficacy rate of 89.59 ± 3.36%, thanks to the proposed tool that guides the shooters to perfect their posture and achieve an appropriate position. This drastically improves shooting accuracy and efficiency, providing a competitive advantage.

Shooters can view real-time scores on the simulator, allowing instant adjustments and improved techniques (see Fig. 4). While accuracy in virtual simulators can vary based on various factors, experienced shooters usually achieve around 90% accuracy in physical practice [20]. Tests with the proposed simulator, mainly with new shooters, indicate its potential for high performance and alignment with traditional training.

Future research will broaden the study of shooting positions to cover all body biomechanics and adapt to various weapons. There's a plan to develop virtual shooting training programs that evaluate a practitioner's shooting traits and accuracy. Based on the results, a proficiency report will be produced, confirming the effectiveness of the shooting simulator training.

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