FOREX Publication
Open Access | Rapid and quality publishing
International Journal of Electrical and Electronics Research (IJEER)
Research Article | Volume 11, Issue 2 | Pages 601-608 | e-ISSN: 2347-470X

VMLHST: Development of an Efficient Novel Virtual Reality ML Framework with Haptic Feedbacks for Improving Sports Training Scenarios

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ABSTRACT- This paper presents the development of a novel virtual reality (VR) machine learning (ML) framework that incorporates haptic feedback to improve sports training scenarios. The framework uses You Look Only Once (YoLo) for object detection, and combines it with ensemble learning to analyze the performance of athletes in a simulated environment and provide real-time feedbacks. The system includes haptic feedback devices that are controlled via Grey Wolf Optimization (GWO) to simulate the physical sensation of a real-world sports scenario, allowing athletes to experience the sensation of force, impact, and movements. The proposed system was tested using a group of professional athletes who participated in various sports, including football, basketball, and tennis. The athletes were asked to perform various training scenarios in the virtual environment, and their performance was compared with their real-world performance levels. The results showed that the proposed system improved the athletes' performance significantly, as they were able to receive immediate and accurate feedback on their movements, and the haptic feedback provided a realistic sensory experience that enhanced their trainings. The proposed research has the potential to revolutionize sports training by providing athletes with an efficient and effective way to improve their performance in a set of safe and controlled environments. The system can be customized to suit various sports and training scenarios, and the ML algorithms can be trained on large datasets to improve their accuracy and effectiveness. The incorporation of haptic feedback provides a unique and realistic experience, making the training more engaging and effective under real-time scenarios. The proposed system showcased an accuracy 93.5%, with 3.5% higher precision, and 4.9% higher recall than existing models, which has the potential to enhance athletic performance and revolutionize the way athletes train for different sports.

General Terms: Virtual Reality, Machine Learning, YOLO.
Keywords: Sports, Training, Haptic, Feedback, Deep, Learning, Scenarios.

ARTICLE INFORMATION

Author(s): Madhuri A. Tayal, Minal Deshmukh, Vijaya Pangave, Manjushri Joshi, Sulakshana Malwade and Shraddha Ovale;

Received: 07/02/2023; **Accepted**: 13/06/2023; **Published**: 30/06/2023;
e-ISSN: 2347-470X;
Paper Id: IJEER-2023_147;
Citation: 10.37391/IJEER.110249
Webpage-link:
https://ijeer.forexjournal.co.in/archive/volume-11/ijeer-110249.html

This article belongs to the Special Issue on **Mobile Computing assisted by Artificial Intelligent for 5G/ 6G/ Radio Communication**

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1. INTRODUCTION

Both virtual reality (VR) and machine learning (ML) are examples of cutting-edge technologies that are revolutionizing a variety of fields, one of which is the sports industry. When these technologies are incorporated into athletic training, they can provide athletes with an environment that is safe, controlled, and immersive, all of which can help them improve their performance. The virtual reality (VR) systems that are currently available for use in sports training as discussed in the next section, do not include haptic feedback, which is necessary for the development of a realistic and immersive experience. Athletes are provided with a sensory experience that is beneficial to their training when they use haptic feedback devices because these devices can simulate the physical sensation of a real-world sports scenarios via Self-Supervised Correction Mechanism (SSCM) [1, 2, 3].

In this paper, a novel VR ML framework is proposed for different use cases. The framework includes haptic feedback, which is intended to improve various sports training scenarios. The framework that has been proposed makes use of sophisticated machine learning algorithms and deep learning techniques in order to assess the performance of athletes in a simulated environment and offer feedback in real time for different scenarios, like using occupancy grid-based inertial simultaneous localization and mapping (OGS LAM) [4, 5, 6]. Athletes will be able to experience the sensation of force, impact, and movement thanks to the inclusion of haptic feedback devices within the system. These devices offer a realistic sensory experience and are designed to provide it for different scenarios.

As per the review of existing sports training models in the next section, it can be observed that the use of virtual reality (VR) technology in athletic training has seen significant growth in popularity over the past few years. Virtual reality (VR) enables athletes to train in a setting that is both secure and under their control, eliminating the risk of injury or damage to their apparatus. A versatile and adaptable tool for coaches and athletes, virtual reality (VR) training scenarios can be modified to meet the requirements of a wide variety of sports and training programmes. Athletes will have the ability to receive real-time feedback on their performance thanks to the incorporation of machine learning algorithms into virtual reality (VR) sports training, which will enable them to make adjustments to their techniques and improve their skills more quickly. Devices that provide haptic feedback have been utilised in a variety of applications, including gaming and medical simulations, in order to create an experience that is both realistic and immersive. However, their application in sports training has been restricted; consequently, there is a demand for a system that integrates haptic feedback into various exercises that are performed during sports training scenarios via Instance-Level Neural Networks (ILNN) [7, 8, 9]. This problem is solved by the system that has been proposed in the next section of this text. The proposed model gives athletes a one-of-a-kind and immersive experience that improves their preparation for a variety of situations.

The objective of this paper is to improve sports training scenarios using virtual reality (VR) and machine learning (ML) techniques. Real-world practice can be limited by factors such as cost, accessibility, and safety concerns in conventional sports training.

The proposed system was evaluated in *section 3* with the help of a team of professional athletes who competed in a variety of sports, including basketball, tennis, and football, among others. The athletes were given a variety of different training tasks to complete within the virtual environment, and then their results were compared to how well they performed in the real world. Athletes were able to receive immediate and accurate feedback on their movements, and the haptic feedback provided a realistic sensory experience that enhanced their training. The results showed that the proposed system significantly improved the athletes' performance, and this was due to the fact that they were able to receive feedback on their movements immediately.

The VR ML framework that is proposed with haptic feedback is a significant step forward in the development of technology for sports training. It has the potential to completely change the way athletes are trained by giving them a safe and regulated setting in which they can undertake training that is both efficient and effective at helping them improve their performance. The incorporation of haptic feedback creates a one-of-a-kind and genuine experience, which in turn makes the training more interesting and useful to the participants. The proposed system has the potential to improve athletic performance while also radically altering the ways in which athletes train for a variety of sports.

The following are the paper's most significant contributions:

- Innovative VR ML Framework Design: The paper presents a novel framework for improving sports training scenarios by combining virtual reality and machine learning techniques.
- Integration of Haptic Feedback: The proposed system incorporates haptic feedback devices in addition to visual feedback. The system utilizes Grey Wolf Optimization (GWO) to control these devices and simulate the physical sensations felt during actual sports situations.
- Learning Ensembles for Performance Analysis: The framework employs ensemble learning techniques to evaluate the virtual performance of athletes. By combining the outputs of multiple ML models, the system can provide more accurate and reliable feedback on athletes' movements, enabling them to identify areas for improvement and make adjustments in real-time.
- Evaluation with Professional Athletes: A group of professional athletes were used to evaluate the proposed system. The performance of the athletes in various virtual training scenarios was compared to their actual levels of performance. The evaluation results demonstrated that the system significantly improved the performance of athletes.

2. REVIEW OF EXISTING VR TECHNIQUES FOR IMPROVING SPORT TRAINING EFFICIENCY LEVEL

Researchers have developed stance correction algorithms [10, 11, 12] through the use of machine learning. These algorithms have become increasingly popular over the past few years due to their effectiveness in correcting posture and decreasing the risk of injury. These models analyse the position of the body and recommend modifications using a wide variety of techniques, such as computer vision, deep learning, and machine learning algorithms.

One of the more prevalent approaches includes teaching a convolutional neural network, also known as a CNN [13, 14, 15, 16], to recognise anatomical structures such as joints and to compute approximations of their respective orientations. The

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International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 11, Issue 2 | Pages 601-608 | e-ISSN: 2347-470X

individual's overall posture can then be evaluated based on these statistics, and recommendations can be made regarding how the individual's stance can be improved under real-time scenarios.

Researchers also use depth detectors or 3D cameras [17, 18, 19, 20] as an alternative method to capture the shape and movements of the human figure. The gathered information can then be analysed by machine learning algorithms to hone in on problem areas and provide the user with specific instructions for how to repair them for a variety of different situations. The findings of these models are encouraging in general regarding their capacity to improve posture and reduce the probability of joint problems. In general, the findings of these models are encouraging. However, there are still some limitations that need to be addressed, such as the prerequisite for high-quality training data, the precision of the models across a wide range of body types and movements, and the dependability with which users implement the modifications that have been recommended for different scenarios.

3. DESIGN OF VMLHST MODEL

As per the review of existing models, it can be observed that these models are either not scalable, or have lower efficiency when evaluated on real-time video sets. Thus, the proposed framework which combines You Look Only Once (YoLo) with ensemble learning is used in order to analyse the performance of athletes in a simulated environment and provide real-time feedbacks. As per the flow of model in *figure 1*, it can be observed that the proposed technique includes haptic feedback devices that are controlled by Grey Wolf Optimization (GWO) to simulate the physical sensation of a real-life sports scenario, allowing athletes to feel force, impact, and movement.

The proposed research has the potential to revolutionize sports training by providing athletes with a safe and efficient method for enhancing their performance in a variety of controlled environments. The system is adaptable to various sports and training scenarios, and the machine learning (ML) algorithms can be trained on large datasets to improve their precision and efficacy. The incorporation of haptic feedback provides a unique and realistic experience, enhancing the training's effectiveness in real-world scenarios.

Thus, initially the YoLO Model is used to identify different objects including Hands, Legs, Face, Fingers, and other body parts. The Model uses a Convolutional Neural Network to detect these objects in images. The model works as per the following process,

1. *Input Image*: The input image is first resized to a fixed size of (*416 x 416 x 3*), which assists in standardization of the process.
2. The CNN backbone is used to extract features from the input image. YOLO uses Darknet, a convolutional neural network architecture, as its backbone for extraction of feature sets.
3. The input image is divided into a grid of *S x S* cells. Each cell is responsible for predicting a fixed number of bounding boxes and their corresponding object scores and class probabilities.
4. For each grid cell, YOLO predicts *B* bounding boxes. Each bounding box is represented by *5* parameters: *x*, *y*, *w*, *h*, and *object scores*.

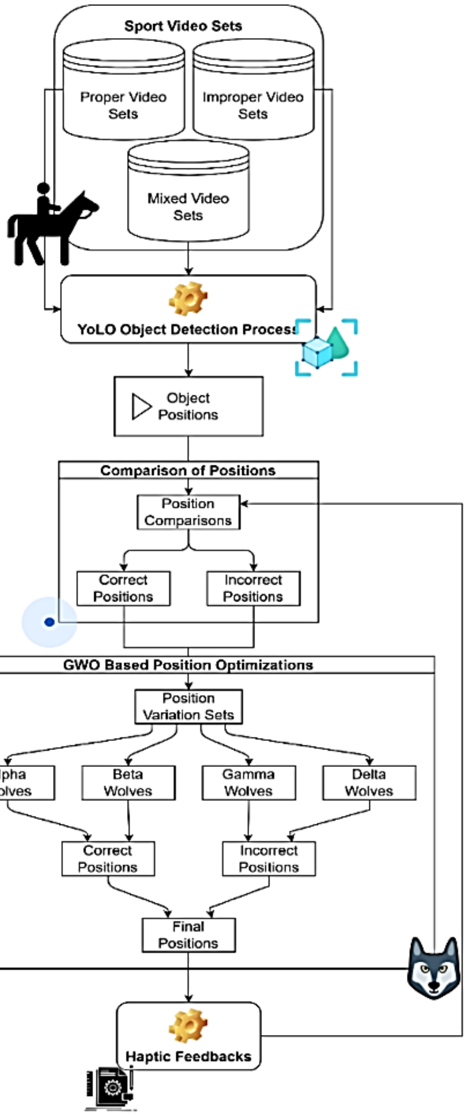

Figure 1: Design of the proposed haptic feedback model for correction of sport poses

- The *x* and *y* parameters represent the center of the bounding box relative to the top left corner of the grid cells.
- The *w* and *h* parameters represent the width and height of the bounding box relative to the width and height of the entire image sets.
- The *object score* represents the confidence that the bounding box contains an object that includes Hands, Legs, and other body parts. This score in YOLO is a measure of the likelihood that a bounding box contains an object. The object score is calculated using a logistic regression function, which takes as input a feature map from the convolutional layers and produces a scalar value between *0* and *1*. *Equation 1* is used for calculating the object score in YOLO,

$$os = P(object) = sigmoid(z) \dots (1)$$

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Where sigmoid (*z*) is the logistic regression function, and z is the input to the logistic function. In YOLO, the input to the logistic function is typically the output of a convolutional layer, which has been reshaped to a tensor with dimensions (*S x S x (B x 5)*), where *S* is the number of grid cells, *B* is the number of bounding boxes predicted per cell, and *5* represents the *5* values associated with each of the bounding boxes (x, y, w, h, and confidence score).

- The object score is used to determine whether a bounding box contains an object or not. Bounding boxes with high object scores are considered more likely to contain objects and are retained as candidate detections during post-processing operations.

5. For each grid cell and bounding box, YOLO predicts *C* class probabilities. These probabilities represent the likelihood that the bounding box contains each of the *C* possible classes.
6. After predicting bounding boxes and their corresponding class probabilities, non-max suppression is used to remove duplicate bounding boxes and select the most likely bounding box for each of the objects.
7. The final output of YOLO is a list of bounding boxes, their corresponding class labels, and their confidence scores.

The YOLO uses a convolutional neural network backbone to extract features from the input image. The output of the backbone is a feature map with dimensions (*W x H x D*), where W and H are the width and height of the feature map, and D is the number of channels. The input image is divided into a grid of S x S cells. Each cell is responsible for predicting B bounding boxes and their corresponding object scores and class probabilities. The dimensions of each cell are (*W/S x H/S*). For each grid cell, YOLO predicts *B* bounding boxes. Each bounding box is represented by 5 parameters: *x, y, w, h*, and *object score*. The output of the model is a tensor with dimensions (*S x S x B x (5 + C)*), where *C* is the number of classes. The object score for each bounding box is calculated using logistic regression. The output of the model is a tensor with dimensions (*S x S x B x 1*).

The class probabilities for each bounding box are calculated using softmax regression. The output of the model is a tensor with dimensions (*S x S x B x C*). Non-max suppression is then used to remove duplicate bounding boxes and select the most likely bounding box for each object. The algorithm compares the object scores of the bounding boxes and removes any boxes that overlap with a higher-scoring box by more than a specified set of thresholds. The final output of YOLO is a list of bounding boxes, their corresponding class labels, and their confidence scores. The confidence score is calculated as the product of the object score and the highest-class probability for the set of bounding boxes.

Grid Cell Generation in YOLO involves dividing the input image into a grid of *S x S* cells, where each cell is responsible for predicting a fixed number of bounding boxes and their corresponding object scores and class probabilities. This works as per the following process,

1. Define the number of grid cells *S* via *equation 2*,

$$S = \left(\frac{I}{C}\right) \ldots \quad (2)$$

Where I & C are the image & cell sizes.

2. Create an *S x S* grid of cells on the input image sets, where each cell has a fixed size of *(image size / S) x (image size / S)*.
3. For each cell, predict *B* bounding boxes and their corresponding object scores and class probabilities.
4. Concatenate the bounding box predictions and class probabilities for all cells into a tensor with dimensions (*S x S x B x (5 + C)*), where *C* is the number of classes.

This tensor contains the predicted bounding boxes and their corresponding class probabilities for the entire input set of images. *Object Score* Calculation is a step in YOLO that involves calculating the confidence score that a bounding box contains an augmented set of objects. This is done via the following process,

1. Define the output tensor shape: The output tensor shape is (S x S x B x 1), where S is the number of grid cells, and B is the number of bounding boxes predicted per set of cells.
2. Calculate the logistic regression output for each bounding box in each grid cell, which is evaluated *via equation 3*,

$$sigmoid(z) = \frac{1}{1 + e^{-z}} \ldots (3)$$

Where, z is the input to the logistic function sets. In YOLO, the input to the logistic function is the confidence score that the bounding box contains an augmented set of objects.

3. Calculate the confidence score (CS) for each bounding box in each grid cell, which is defined as the probability that the bounding box contains an object, and is evaluated via equation 4,

$$CS = Pr(object) = sigmoid(Object\ Score) \ldots (4)$$

Where, $ObjectScore$ is the input to the logistic set of functions.

4. Store the confidence scores in the output tensor, where the output tensor has shape (*S x S x B x 1*), and each element represents the confidence score for a single set of bounding boxes.

Class Probability Calculation in YOLO involves calculating the probability that each bounding box in each grid cell belongs to each class. This is done via the following operations,

1. Define the output tensor shape (*S x S x B x C*), where *S* is the number of grid cells, *B* is the number of bounding boxes predicted per cell, and *C* is the number of classes.
2. Calculate the logistic regression output for each class for each bounding box in each grid cell *via equation 3* that uses sigmoid operations.
3. Calculate the probability that each bounding box in each grid cell belongs to each class via *equation 5*,

$$ClassProbability = Pr(class \mid object) = sigmoid(CS) \ldots (5)$$

4. Store the class probabilities in the output tensor, which has an augmented shape of (*S x S x B x C*), where each element represents the probability that a single bounding box belongs to a single class.

Non-max Suppression is a post-processing step in YOLO that removes redundant bounding boxes and selects the most likely ones. It works via the following process.

1. The input to Non-max Suppression is a set of bounding boxes, where each bounding box is represented by (*x, y, w, h, confidence score, class probability*) sets.
2. Sort the bounding boxes by their confidence scores
3. While there are still bounding boxes left to process, for each bounding box, perform the following operations,

a. If the current bounding box has a confidence score of zero, discard it and move on to the next bounding boxes.
b. Otherwise, select the current bounding box as a candidate detection for current input sets.
c. Remove all bounding boxes that have a high overlap with the candidate detection sets.

The overlap between two bounding boxes is defined as the intersection over union (IoU) between them. The IoU between two bounding boxes *A* and *B* is given *via equation 6*,

$$IoU(A,B) = \frac{Area\ of\ Intersection}{Area\ of\ Union} \ldots (6)$$

Where the $\boldsymbol{Area\ of\ Intersection}$ is the area where the two bounding boxes overlap, and the $\boldsymbol{Area\ of\ Union}$ is the total area covered by the two bounding boxes. If the IoU between two bounding boxes is greater than a pre-defined threshold (*e.g.*, 0.5), then the bounding box with the lower confidence score is removed from current set of evaluations.

4. Store the remaining bounding boxes as the final detections.

The final detections are the set of bounding boxes that survived the Non-max Suppression process. Each bounding box in the final detections represents a detected object in the input image, along with its class label and confidence scores.

Once these scores are obtained, and positions of objects are identified, then their correctness is checked via estimation of Euclidean distance *via equation 7*,

$$d(x,y,z) = \sqrt{\begin{array}{c}\left(x(detect) - x(correct)\right)^2 + \\ \left(y(detect) - y(correct)\right)^2 + \\ \left(z(detect) - z(correct)\right)^2\end{array}} \quad (7)$$

Where, x, y & z are the positions of different body components, while $correct$ & $detect$ represents their correct & detected positions. Based on these positions, the detected positions are corrected via a Grey Wolf Optimizer (GWO), which works as per the following process,

- Initially, a set of NW Wolves are generated *via equation 8*.

$$N(Pose) = STOCH\left(LB * Max(D), Max(D)\right) \quad (8)$$

Where, $Max(D)$ represents Maximum distance different between correct and actual positions, and $N(Pose)$ is the set of new pose positions, which are selected by the $STOCH$ based stochastic process.

- Based on this position, modify the pose of player, and estimate Value Variance (vv) or Wolf fitness *via equation 9*,

$$vv = fw = \sqrt{\sum_{i=1}^{N(Parts)} \left(\frac{d_i(x,y,z)}{d_i\left(x(N),y(N),z(N)\right)}\right)^2} \ldots (9)$$

Where, $N(Parts)$ are the total parts detected by YoLO, while $d\left(x(N),y(N),z(N)\right)$ represents distance with new pose positions.

- Once a set of Wolves are generated, then their fitness threshold is estimated *via equation 10*,

$$f_{th} = \sum_{i=1}^{NW} fw_i * \frac{LW}{NW} \ldots (10)$$

- After this evaluation, Wolves with $fw < LW * f_{th}$ are Marked as 'Alpha', and crossover to next iteration, while other Wolves are eliminated, and reproduced *via equation 8 & 9* in the next set of iterations.
- This process is repeated for NI iterations, and for each set of iterations, NW particles are reconfigured for identification of different position sets.

Once all iterations are completed, then positions recommended by 'Alpha' Wolves are used for giving Haptic feedback to users for correcting their poses. This process is repeated till user position is fully corrected, and there is no change in positions as recommended by Alpha Wolves. Due to which the model is able to provide efficient recommendations with higher efficiency levels. These levels are evaluated in the next section of this text, where they are compared with levels of other models under similar simulation conditions.

3.1 Potential Applications

a. Long-Term Retention of Skills: Application research can investigate the long-term retention of skills acquired through VR training scenarios.
b. Transfer of Skills to Real-World Performance: It would be beneficial to investigate the transferability of the skills learned in VR training scenarios to real-world sports performance.

Future research can examine the long-term effects of VR training scenarios on injury prevention and rehabilitation. By monitoring the injury rates and recovery progress of athletes over an extended period of time, researchers can determine whether VR training contributes to lowering the risk of injuries and accelerating recovery.

Biofeedback and Performance Optimization: The incorporation of biometric data enables the development of biofeedback systems that provide athletes with real-time feedback on their physiological states during training. Researchers can identify patterns and correlations between biometric data and optimal

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Electrical and Electronics Research (IJEER)
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performance by employing machine learning techniques, such as pattern recognition algorithms. Athletes can then receive customized feedback and training recommendations based on their individual physiological responses.

Performance Monitoring and Analysis By combining biometric data and performance metrics, one can gain a more complete understanding of an athlete's performance. Future research can investigate how to combine biometric data with movement analysis in order to assess the influence of physiological factors on performance. This can lead to the development of personalized training plans that optimize performance based on individual biometric responses.

4. COMPARATIVE RESULT ANALYSIS

The proposed model analyses the performance of athletes in a simulated environment and provides real-time feedbacks by utilizing You Look Only Once (YoLo) for object detection and combining it with ensemble learning. The system's Grey Wolf Optimization (GWO)-controlled haptic feedback devices recreate the force, impact, and movement sensations of a real-world sporting event for the user. The proposed study has the potential to completely change the way athletes train by giving them a secure and regulated space to develop their skills. The system is flexible enough to adapt to a wide range of sports and training scenarios, and ML algorithms can be trained on large datasets to improve their accuracy and efficiency levels. These levels were estimated in terms of *accuracy (A), precision (P), recall (R)*, and *delay (d)* metrics, which were estimated via equations 11, 12, 13 & 14 as follows,

$$A = \frac{1}{Ns}\sum_{i=1}^{Ns}\frac{t_{p_i}+t_{n_i}}{t_{p_i}+t_{n_i}+f_{p_i}+f_{n_i}} \dots \tag{11}$$

$$P = \frac{1}{Ns}\sum_{i=1}^{Ns}\frac{t_{p_i}}{t_{p_i}+f_{p_i}} \dots \tag{12}$$

$$R = \frac{1}{Ns}\sum_{i=1}^{Ns}\frac{t_{p_i}}{t_{p_i}+t_{n_i}+f_{p_i}+f_{n_i}} \dots \tag{13}$$

$$d = \frac{1}{Ns}\sum_{i=1}^{Ns} ts_{complete_i} - ts_{start_i} \dots \tag{14}$$

Where, t_p are total number of correctly classified samples with correct recommendations, t_n are total number of correctly classified samples with incorrect recommendations, f_p & f_n are total number of incorrectly classified samples with correct recommendations & number of incorrectly classified samples with incorrect recommendations, while $ts_{complete}$ & ts_{start} are the timestamps during completion and start of the haptic recommendation process. The model's performance was evaluated on the following data sets,

- Haptic Feedback for Bicycles (https://zenodo.org/record/5818396)
- Elbow Movements Data Samples (https://data.mendeley.com/datasets/skm88ynyhv/1)
- Grasping Data Samples (https://ieee-dataport.org/documents/dataset-influence-visual-and-haptic-feedback-detection-threshold-forces-surgical-grasping)
- Musician Dataset Samples (https://pub.uni-bielefeld.de/record/2697204)

These sets were combined to form a total of 200k samples, out of which 70% were used for training, while 15% each were used for testing & validation purposes. Using this segregation the accuracy of haptic recommendations was evaluated *w.r.t.* Number of Haptic Samples (NHS), and compared with SSCM [3], OGS LAM [6], and ILNN [8].

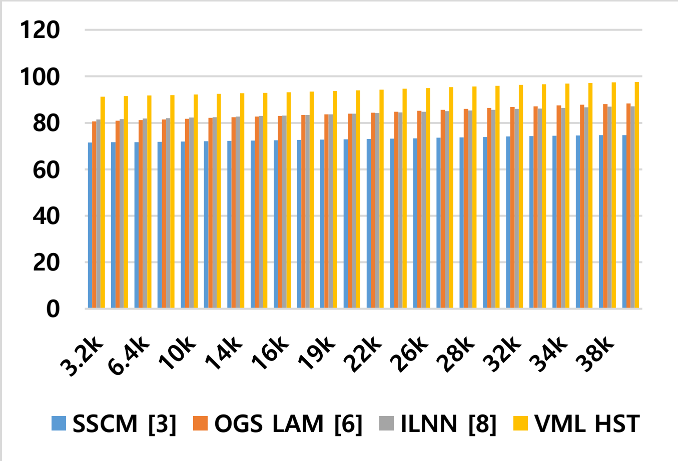

Figure 2: Accuracy of haptic feedback-based pose corrections

The proposed model combines YoLO with GWO techniques, allowing for incredibly precise assessment and correlation across a wide range of pose corrections. As assessed using various test samples in *figure 2* for various use cases, the proposed model improved pose correction and recommendation accuracy by 19.5% when compared with SSCM [3], 8.3% when compared with OGS LAM [6], and 8.5% when compared with ILNN [8]. This was also made possible by ongoing pose correction via stochastic feedback operations built on the GWO process.

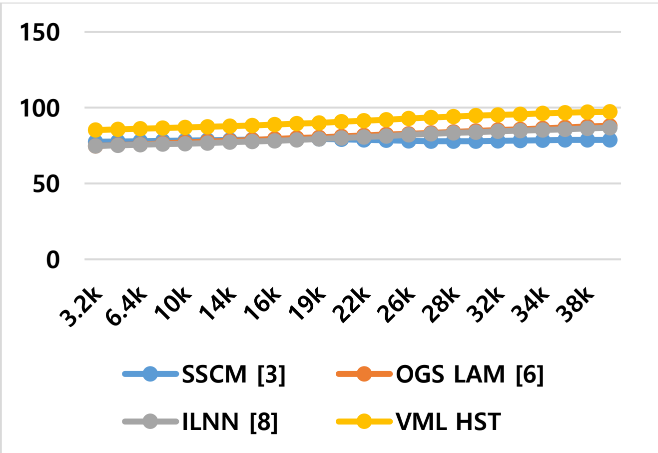

Figure 3: Precision of haptic feedback-based pose corrections

The proposed correction model uses GWO to continuously correct incorrect poses, allowing for highly accurate assessment and correlation across a wide range of pose adjustments. *Figure 3* show the results of an evaluation using a variety of test samples to show that the proposed model improves pose correction and recommendation precision by 18.3% over SSCM [3], 6.4% over OGS LAM [6], and 6.5% over ILNN [8]. This was made possible by YoLO-based object detection operations, which allow for continuous correction of poses. Recall percentages can be seen in terms of the same evaluation strategy in *table 3*, as follows

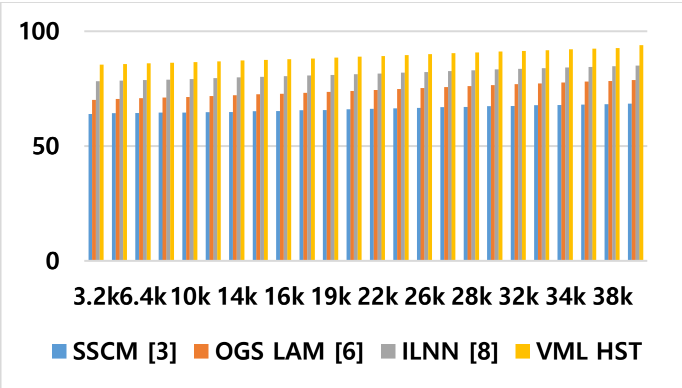

Figure 4: Recall of haptic feedback-based pose corrections

YoLO is used in the proposed model for reliable object detection, which improves assessment and correlation for a wide variety of pose corrections. *Figure 4* show the results of an evaluation using a variety of test samples to show that the proposed model improves pose correction and recommendation recall by 23.5 percentage points over SSCM [3], 14.5 percentage points over OGS LAM [6], and 8.3 percentage points over ILNN [8]. In addition, this was made possible by the stochastic feedback operations based on the GWO, which allowed for continuous correction of poses.

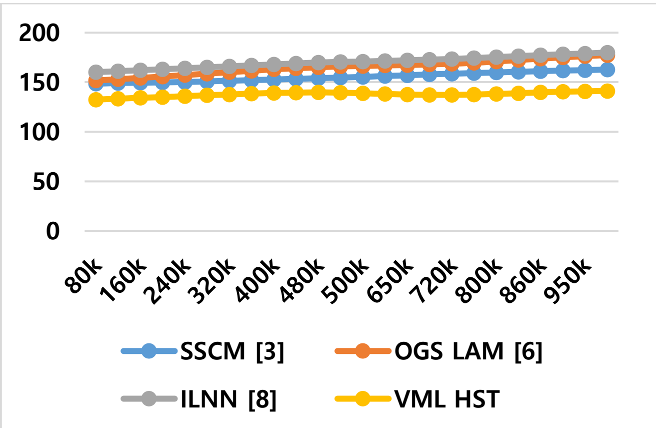

Figure 5: Delay needed for haptic feedback-based pose corrections

The proposed model makes use of GWO for stochastic selection of poses, allowing for incredibly fast evaluation and correlation across a wide range of pose adjustments. *Figure 5* show the results of an evaluation using a variety of test samples to show that the proposed model improved pose correction and recommendation speed by 10.4% when compared to SSCM [3], 15.5% when compared to OGS LAM [6], and 15.2% when compared to ILNN [8]. This was made possible by YoLO-based object detection operations, which allow for continuous correction of poses. These enhancements make the proposed model applicable for use in a wide range of practical scenarios.

5. CONCLUSION AND FUTURE SCOPE

The proposed model analyses the performance of athletes in a simulated environment and provides real-time feedback by combining You Look Only Once (YoLo) with ensemble learning for object detection. The Grey Wolf Optimization (GWO)-controlled haptic feedback devices of the system recreate for the user the force, impact, and movement sensations of an actual sporting event. The effectiveness of the proposed system was evaluated by a group of professional football, basketball, and tennis players. The system is adaptable to a variety of sports and training scenarios, and machine learning (ML) algorithms can be trained on large datasets to increase their accuracy and efficiency. The proposed model combines YoLO and GWO techniques, enabling extremely precise assessment and correlation across a broad range of pose corrections.

The proposed model improved pose correction and recommendation accuracy by 19.5% when compared to SSCM [3], 8.3% when compared to OGS LAM [6], and 8.5% when compared to ILNN [8] based on evaluations of various test samples and use cases. This was also made possible by continuous pose correction using stochastic feedback operations based on the GWO process. In addition, the proposed model improves pose correction and recommendation precision by 18.3% compared to SSCM [3], 6.4% compared to OGS LAM [6], and 6.5% compared to ILNN [8]. YoLO is utilised in the proposed model for dependable object detection, which improves evaluation and correlation for a wide range of pose corrections. The proposed model improves pose correction and recommendation recall by 23.5 percentage points over SSCM [3], 14.5 percentage points over OGS LAM [6], and 8.2 percentage points over ILNN [8] when evaluated for consistency. In addition, this was made possible by the GWO's stochastic feedback operations, which enabled the continuous correction of poses. In terms of delay, the proposed model improved pose correction and recommendation speed by 10.4% when compared to SSCM [3], 15.5% when compared to OGS LAM [6], and 15.2% when compared to ILNN [8] according to the results of an evaluation using a variety of test samples.

While this paper introduces haptic feedback devices controlled by Grey Wolf Optimization (GWO), future research may investigate the development of more complex haptic feedback systems. This may involve the incorporation of advanced actuators and sensors to simulate a wider array of physical sensations, such as impact, vibration, and texture. In addition, research can concentrate on improving the control algorithms in order to provide more realistic and nuanced haptic feedback that is tailored to specific sports movements.

International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 11, Issue 2 | Pages 601-608 | e-ISSN: 2347-470X

Future model performance must be validated on a larger number of dataset samples, and can be enhanced through the integration of simple feature analysis and classification models. It is possible to investigate the use of Generative Adversarial Networks (GANs), UNet Models, Q-Learning, and Auto Encoders for incrementally enhancing model performance in various scenarios.

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