A Theoretical Framework of Extrinsic Feedback Evaluation in Football Training Based on Motion Templates Using Motion Capture

Amir Irfan Mazian[1], Wan Rizhan[2], Normala Rahim[3], Muhammad D. Zakaria[4],
Mohd Sufian Mat Deris[5], Fadzli Syed Abdullah[6], Ahmad Rafi[7]
Faculty of Informatics and Computing, Universiti Sultan Zainal Abidin, Besut, Malaysia[1, 2, 3, 4, 5]
Faculty of Ocean Engineering Technology, Universiti Malaysia Terengganu, Kuala Nerus, Malaysia[6]
Faculty of Creative Multimedia, Multimedia University, Cyberjaya, Malaysia[7]

***Abstract*—Motion capture technology (MoCap) has emerged as a pivotal innovation, significantly impacting various sectors, including sports. In football training, MoCap is especially crucial for analyzing player movements with precision. Despite its potential, there remains a notable gap in the utilization of MoCap to create motion templates (MTs) that generate extrinsic feedback, particularly in football. This article proposes a comprehensive theoretical framework for evaluating extrinsic feedback in football training through MTs created using MoCap technology and Reverse-Gesture Description Language (R-GDL). The development of this framework involves several key steps: a literature review, acquaintance meetings, interviews, procedural approvals, experimentation, data conversion, MTs creation, and data evaluation. The framework integrates elements such as football players, MoCap systems, raw and processed data, MTs, evaluation processes, and extrinsic feedback models. The main purpose is to harness the full potential of MoCap technology, enhancing the evaluation and improvement of football training activities. By implementing this framework, we aim to revolutionize how football training is analyzed and optimized, providing coaches and players with invaluable insights and feedback.**

Keywords—Motion capture; motion templates; football; extrinsic feedback; reverse-gesture description language

I. Introduction

In the current era of rapid technology revolution, motion capture technology (MoCap) has emerged as an important innovation, profoundly impacting sectors such as sport [1], entertainment [2], healthcare [3] and martial arts [16]. This technology, which digitally records and analyzes movements for comprehensive examination, is distinguished into two types of techniques: marker-based and marker-less systems [3,4,17]. Marker-based systems, which involve attaching physical markers to an individual, excel in capturing movement with exceptional precision, making them invaluable for detailed analyses and the creation of animations, though they may limit natural movement. Conversely, marker-less systems rely on advanced computer vision algorithms to detect the body's natural features without additional equipment, offering a more unobtrusive and adaptable approach [5]. Despite facing challenges in accurately capturing intricate movements, the relentless pace of technological progress is continually improving the accuracy and reliability of both techniques.

The fascination and widespread appeal of football, transcending continents and cultures, significantly highlights its stature as a global sporting phenomenon. This sport, predicated on the principles of teamwork, strategic understanding, and peak physical conditioning, demands a holistic approach to player development, encompassing technical prowess, tactical knowledge, physical fitness, and mental fortitude [6]. Both marker-based and marker-less, play a pivotal role in football, especially in the analysis of player movements, thereby refining training methodologies. Marker-based systems, exemplified by Vicon [7], offer unparalleled precision in tracking athletes' movements within controlled environments, whereas marker-less systems such as OpenPose [8], excel in capturing motion in more organic settings. These technological advancements facilitate a comprehensive examination of player performance, enabling coaches and sports scientists to optimize training activities and enhance strategic execution, underscoring the symbiotic relationship between cutting-edge technology and the evolution of football training practices.

Moreover, a ground-breaking application of MoCap technology in football training is the use of MTs. These templates are engineered through detailed analysis of elite athletes' movements, captured via the MoCap system. They provide a standard for the ideal execution of specific sporting actions, such as kicking and passing, facilitating the accurate replication of optimal movement patterns. This methodology offers a dual advantage: a quantitative benchmark for evaluating performance and a visual aid for enhancing technical proficiency [9]. By setting side by side an athlete's movements with these predefined templates, coaches are empowered to pinpoint inaccuracies and provide bespoke corrective feedback. This tailored approach optimizes training efficiency by aligning with each athlete's unique biomechanical characteristics, thereby fostering a customized coaching paradigm.

Feedback can be classified into two types: extrinsic and intrinsic [10]. The confluence of extrinsic and intrinsic feedback mechanisms plays a quintessential role in football training. Extrinsic feedback, provided by external sources, offers invaluable insights into performance analytics and delineates areas ripe for improvement [18]. This is in harmonious complement to intrinsic feedback, which athletes derive from their own sensory experiences during the performance of an action. Together, these feedback modalities are indispensable in skill development, highlighting the critical importance of external inputs for learning and refining techniques. This synergy underscores a holistic approach to mastering skills, essential for the attainment of excellence in any sporting discipline.

However, there is a lack of MoCap technology usage to create MTs in sport that produce extrinsic feedback, especially in football. Therefore, the application of MoCap technology within football and additional sports disciplines marks a significant advancement in training methodologies and performance analytics. The integration of both marker-based and marker-less systems, supplemented by innovative solutions such as MTs, enables coaches and trainers to refine training regimens with unprecedented precision, efficiency, and customization. This technological evolution not only enhances the analysis and application of specific athletic movements but also paves the way for ground-breaking research and development within the field of sports science. Consequently, this promises to yield substantial enhancements in athlete performance and the refinement of training methodologies.

The research proposes a theoretical framework of extrinsic feedback in evaluating football training based MTs using MoCap. The next sections discuss the methods in Section III, the proposed framework in Section IV, the expected outcome in Section V and discussion and conclusion in Section VI.

II. Related Works

In MoCap technology, it has become a significant tool in football for analyzing player movement, medical evaluation and training improvement. In existing studies, the researchers have employed various techniques with different MoCap systems in football. For example, Yin et al. utilized a deep learning-assisted motion capture system (DL-MCS) in football training, which evaluates complexity, performance, latency and efficiency. This approach integrates deep learning to support training effectiveness, particularly by evaluating the accuracy of player movement [19]. Similarly, Della Villa et al. implemented a 2D video analysis scoring system to identify football players with a high knee abduction moment, which is a risk factor for ACL injuries. Their approach, which involved a stereophotogrammetric camera system and force platform, aimed to provide accurate health measurement to enhance injury prevention plan [20].

In marker-less MoCap, Bampouras and Thomas validated a Light Detection and Ranging (LiDAR)-based player tracking system for football-specific tasks, focusing on metrics such as velocity and acceleration. This technique evaluates the precision and responsiveness of marker-less system in capturing football player performance during fast-paced actions. By analyzing key performance indicators in real time, this study demonstrated the potential of marker-less MoCap system to provide relevant feedback, but with some limitation in data accuracy that affect the reliability of real-time extrinsic feedback [21].

Aughey et al. compared computer vision system with three-dimensional marker-based MoCap for tracking football players' movement in a stadium environment. Their evaluation, using root mean square deviation (RMSD) to calculate speed and accuracy, demonstrated how advance MoCap technology can capture dynamic football players' movement in large, open spaces, showing the adaptability of MoCap technology to diverse training activity condition. However, while computer vision systems support movement analysis, they still lack the precision needed for extrinsic feedback [22].

These studies highlight that while MoCap technologies have advanced considerably in capturing detailed player motion, the lack of extrinsic feedback remains a significant limitation. The integration of motion templates in MoCap system could bridge this gap, enabling real-time adjustment in training.

III. Method

To create MTs that enable effective extrinsic feedback in football training, benefiting coaches and experts, a systematic approach involving both formal and informal research methodology is essential. The approach to create a new framework was adapted [11], which has proven effective in generating MTs for folk dances but lacking for the dynamic requirements of football training. Incorporation of additional elements into approach is necessary to tailor it specifically to football's unique requirements. By refining this approach, acquisition of critical insights and development of MTs specifically designed for football training become possible. The refined approach, shown in Fig. 1, includes literature study, acquaintance meeting, interview, procedure and approval, experiment, data conversion, motion template creation, and data evaluation.

Fig. 1. New proposed approach for creating MTs in football training using MoCap.

A. Literature Study

Systematic Literature Review (SLR) is one of the methods in academic research, purposely to consolidate all existing evidence. The multifaceted process encompasses the formulation of a research question guided by specific keywords, the detailed selection of relevant studies, the evaluation of their quality, and the systematic extraction and analysis of data. The objective of SLR is to furnish an impartial, exhaustive overview of the evidence at hand [12] This method not only strengthens the foundation for evidence-based practices but also highlights gaps in current research. By being attached to established reporting guidelines like PRISMA, these reviews ensure transparency and reproducibility [13].

B. *Acquaintance Meeting*

The primary objective of the meeting is to collect critical information about football and its training. Hence, engaging with the State Football Club, recognized as one of football expertise, which involves the qualified coaching staff, becomes a vital initial step for accruing foundational information prior to progressing with the research. The anticipated outcomes from these introductory sessions include:

- Documentation of football and coaching, encompassing evaluation forms and training guidelines.
- Detailed accounts of the processes involved in football training and coaching.
- Proposal for conducting formal interviews with qualified coaches.

The insights obtained from these preliminary meetings are instrumental for advancing to the next phases of the research.

C. *Interview*

Conducting interviews serves as an essential method for obtaining comprehensive insights regarding football coaching directly from seasoned professionals. The structure of these discussions varies, encompassing formal interviews with predefined queries, semi-structured interviews with a mix of fixed and open-ended questions, and informal conversations that proceed naturally. To facilitate these discussions, a carefully curated set of questions will be prepared in advance. The frequency of these interviews is determined by the relevance and adequacy of the information collected in meeting specific goals and expectations. Furthermore, it is vital to communicate the purpose of the study to the coaches. This communication not only aids in clarifying the objectives of the research but also invites valuable contributions from the coaches regarding the selection of football training activities for the study.

D. *Procedure and Approval*

Further research on football training can be conducted by applying for and following the required legal procedures and obtaining the necessary approvals.

1) Letter of purpose for conducting the research: Obtaining approval and support from the appropriate authorities or organizations is important for conducting the research. This letter contains the purpose, needs and importance of research in football training. In addition to explaining the use of current technology which is MoCap that has potential to help improve football training through research.

2) Letter of invitation to interview session: This letter serves as an invitation to certified coaches for a formal interview session. The goal is to collect information related to football training activities that are suitable to, along with suggestions, input, and feedback from the qualified coaches to enhance the research. Essential details such as the names of the coaches, the specific date, time, and location of the interview will be included in the letter. This strategy ensures clarity and facilitates the effective participation of these professionals in the study.

3) Request for nomination of qualified football player: The purpose is to reach out to coaches, seeking their assistance in nominating skilled football players who exhibit diverse qualities, such as being adept with either their left or right leg. Given the coaches' deep familiarity with , their teamsensuring that the selected players are indeed the best fit. This approach leverages the coaches' expertise, ensuring that the chosen athletes truly reflect the required attributes, without any room for doubt or challenge regarding their suitability.

4) Letter of invitation for conducting the fieldwork: An invitation to certified coaches and selected football players to participate in the experiment. The goal is to record and collect the MoCap data of football players' movement doing football training activities that had been assigned by the coaches. Essential details such as the names of the coaches, the specific date, time, and location of the interview will be included in the letter.

5) Request for verification of motion template: The goal is to look for assistance from experts to confirm the MTs created with captured movement data. It is crucial to verify the data's authenticity. The request emphasizes the importance of having several experts available at a designated date, time, and place. This ensures a comprehensive evaluation and verification process.

E. *Experiment*

The main goal of the experiment is to gather detailed MoCap data of football players as they engage in specific training activities. These activities have been carefully selected based on recommendations from experienced coaches from the previous interview session, ensuring it is relevant to research. The experiment is set to take place in the natural environment of the players, which is outdoors on a football field. To record these movements, the proposed MoCap device is marker-based such as Perception Neuron 3, known for its accuracy and reliability in capturing even the most subtle movements.

Football players will be guided through a series of training activities planned by the coaches. These activities are designed to simulate common football scenarios and challenges, helping to gather a wide range of motion data. As the players perform, coaches will not only supervise but also evaluate their performance using a rubric score assessment form that is validated by the expert. The raw MoCap data collected will then be processed to create MTs. These templates aim to offer detailed data of the movements, serving as a valuable resource for further analysis.

F. Data Conversion

Understanding the need to convert raw data arises from a compatibility issue between the initial format provided by the Perception Neuron 3 MoCap device and the requirements of the Gesture Description Language (GDL) system. Unlike the GDL system, which was originally designed to work with the Xbox Kinect—a marker-less MoCap system. The Perception Neuron 3 relies on a marker-based approach to capture movements. This fundamental difference in technology means that the raw data produced by Perception Neuron 3 contain 59 sections of skeleton joints as shown in Table I [14] while the GDL system contains 25 sections of skeleton joints (Table II) that are available in SKL format. The data from Perception Neuron 3 are available in formats like FBX, BVH, CSV, and MBX, and cannot be directly used in a GDL system without first undergoing a conversion process to suit the SKL format.

TABLE I. SKELETAL JOINT GENERATED FROM PERCEPTION NEURON 3

Section Name	Logotype	Serial Number	Parent Node
Buttocks	Hips	0	Root Node
Right thigh	RightUpLeg	1	0
Right Calf	RightLeg	2	1
Right foot	Rightfoot	3	2
Left thigh	LeftUpLeg	4	0
Left calf	Leftleg	5	4
Left foot	LeftFoot	6	5
Lower Part of the Spine	Spine	7	0
Middle Spine section	Spine 1	8	7
Upper Spine section	Spine 2	9	8
Lower Neck section	Neck	10	9
Upper Neck section	Neck 1	11	10
Head	Head	12	11
Right Shoulder	RightShoulder	13	8
Right Arm	RightArm	14	13
Right Forearm	RightForeArm	15	14
Right Hand	RightHand	16	15
Right thumb finger	RightHandThumb1	17	16
Right thumb in the middle finger	RighthandThumb2	18	17
Right Thumb tip	RighthandThumb2	19	18
Right index metacarpal	RightInHandIndex	20	16
Right index finger root	RightHandIndex1	21	20
Middle finger of the right index finger	RightHandIndex2	22	21
Right index fingertip	RightHandIndex3	23	22
Right middle metacarpal	RightInHandMiddle	24	16
Right middle finger to the root	RightHandMiddle1	25	24
Right middle finger middle	RightHandMiddle2	26	25
Right middle fingertip	RightHandMiddle3	27	26
Right ring metacarpal	RightInHandRing	28	16
Right ring finger refers to the root	RightHandRing1	29	28
Right ring finger in the middle	RightHandRing2	30	29
Right ring fingertip	RightHandRing3	31	30
Right little finger metacarpal	RightInHandPinky	32	16
Right pinky finger root	RightHandPinky1	33	32
Right pinky finger in the middle	RightHandPinky2	34	33
Right pinky fingertip	RightHandPinky3	35	34
Left shoulder	LeftShoulder	36	8
Left upper arm	LeftArm	37	36
Left forearm	LeftForeArm	38	37
left hand	LeftHand	39	38
Left thumb finger root	LeftHandThumb1	40	39
Left thumb in the middle finger	LeftHandThumb2	41	40
Left thumb tip	LeftHandThumb3	42	41
Left index metacarpal bone	LeftInHandIndex	43	39
Left index finger root	LeftHandIndex1	44	43
Middle finger of the left index finger	LeftHandIndex2	45	44
Tip of the left index finger	LeftHandIndex3	46	45
Left middle metacarpal	LeftInHandMiddle	47	39
The left middle finger refers to the root	LeftHandMiddle1	48	47
The left middle finger is fingered in the middle	LeftHandMiddle2	49	48
Left middle fingertip	LeftHandMiddle3	50	49
Left ring metacarpal	LeftInHandRing	51	39
The left ring finger refers to the root	LeftHandRing1	52	51
Left ring finger in the middle	LeftHandRing2	53	52
Left ring fingertip	LeftHandRing3	54	53
Left little finger metacarpal bone	LeftInHandPinky	55	39
Left little finger finger root	LeftHandPinky1	56	55
Left little finger in the middle	LeftHandPinky2	57	56
Left little fingertip	LeftHandPinky3	58	57

TABLE II. SKELETAL JOINT GENERATED FROM GDL SYSTEM

No	Joint Name
1	Spine Base
2	Spine Mid
3	Neck
4	Head
5	Right Shoulder
6	Right Elbow
7	Right Wrist
8	Right Hand
9	Left Shoulder
10	Left Elbow
11	Left Wrist
12	Left Hand
13	Right Hip
14	Right Knee
15	Right Ankle
16	Right Foot
17	Left Hip
18	Left Knee
19	Left Ankle
20	Left Foot
21	Spine Shoulder
22	Right Thumb
23	Right Tip
24	Left Thumb
25	Left Tip

A series of steps outlined (see Fig. 2) are followed to transform the raw data into a format that the GDL system can understand and process. This conversion process results in the production of data in the SKL format, making it compatible for use with the GDL system. The conversion is not just a technical requirement but a bridge that enables the advanced MoCap dataset from Perception Neuron 3 to be utilized effectively in the GDL system environment, thereby enhancing the utility and applicability of MoCap data in various applications.

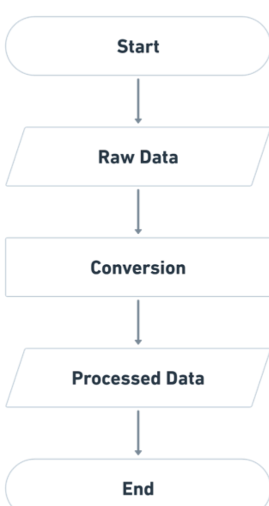

Fig. 2. Data conversion flowchart.

G. Motion Template Creation

R-GDL or Reverse-Gesture Description Language is an extension of the basic concept of GDL, focusing on a machine-learning approach for the recognition of full-body movements. R-GDL's methodology can be considered a form of reverse engineering compared to traditional GDL, as it starts with the outcome (recorded gestures) and works backward to infer the rules that define those gestures. Motion template will be developed by using R-GDL because this method has shown high accuracy in recognizing complex body movements, making it suitable for applications where precise motion detection is required, such as in physical therapy, sports analysis, and advanced human-computer interaction systems [15]. For creating the MTs, features in GDL will be used as shown below:

```
FEATURE angle(ShoulderRight.xyz[0] - ElbowRight.xyz[0],
WristRight.xyz[0] - ElbowRight.xyz[0]) AS RightElbow
FEATURE angle(ShoulderLeft.xyz[0] - ElbowLeft.xyz[0],
WristLeft.xyz[0] - ElbowLeft.xyz[0]) AS LeftElbow
FEATURE angle(ShoulderCenter.xyz[0] - ShoulderRight.xyz[0],
ElbowRight.xyz[0] - ShoulderRight.xyz[0]) AS RightShoulder
FEATURE angle(ShoulderCenter.xyz[0] - ShoulderLeft.xyz[0],
ElbowLeft.xyz[0] - ShoulderLeft.xyz[0]) AS LeftShoulder
FEATURE angle(HipRight.xyz[0] - KneeRight.xyz[0],
AnkleRight.xyz[0] - KneeRight.xyz[0]) AS RightKnee
FEATURE angle(HipLeft.xyz[0] - KneeLeft.xyz[0],
AnkleLeft.xyz[0] - KneeLeft.xyz[0]) AS LeftKnee
FEATURE angle(ShoulderRight.xyz[0] - ElbowRight.xyz[0],
ShoulderLeft.xyz[0] - ElbowLeft.xyz[0]) AS BetweenWrists
FEATURE angle(KneeLeft.xyz[0] - HipLeft.xyz[0],
KneeRight.xyz[0] - HipRight.xyz[0]) AS BetweenLeg
```

H. Data Evaluation

GDL are used for the recognition of user actions through the syntactic description of static body poses and movement sequences. It allows for representation of human movements in a way that computer systems can recognize and classify various gestures [15]. By using the GDL system, processed data will be evaluated with a motion template created previously and will produce the output of extrinsic feedback.

IV. PROPOSED FRAMEWORK

In this study, a theoretical framework of extrinsic feedback to evaluate football training has been proposed. Fig. 3 consists of several important models which are the football player, MoCap, raw data, processed data, motion template, evaluation and extrinsic feedback.

Fig. 3 shows the important models in phases of development, testing and evaluation. The development phase consists of football player, MoCap, raw data, processed data and motion template models while the testing phase contains football player, MoCap and raw data models. The evaluation phase consists of comparison and extrinsic feedback models.

A. Football Player

In the development phase of the proposed framework, a certified coach will select skilled and qualified players (Player A). The selection criteria are determined by the coach who also assigns specific football training activities to these players. While in the testing phase, another individual (Player B), who might be new to football or a novice player, participates alongside Player A in similar training activities. The coach will evaluate their progress using the approved score rubric assessment form.

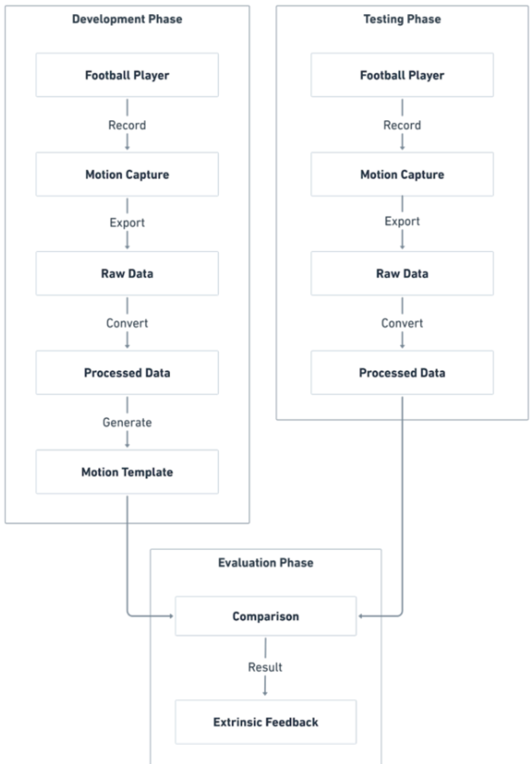

Fig. 3. Proposed framework.

B. *Motion Capture*

Both development and testing phases, the MoCap device from Perception Neuron with Axis Studio software, will be used on Player A and Player B. Each player will be recorded separately during the same training activities sessions. To ensure the highest quality of data, the actions of each player will be repeated several times per training activities. Specifically for Player A, the data will undergo review by the coach before it can be used as a motion template.

C. *Raw Data*

The training activities of both players will be digitally captured using the Perception Neuron via Axis Studio, and this data will be accessible in multiple file formats including FBX, BVH, CSV, and MBX that are provided in the software. The FBX and CSV format will be primarily used in the conversion process. This format is preferred because it is widely supported by most of the software, ensuring compatibility and ease of data handling.

D. *Processed Data*

To produce the processed data from raw data, several procedures in the conversion process (Fig. 2) are needed such as deleting the unused data and rearranging the data. Main purpose of conversion is to have the same attributes of data as the SKL format which is only suitable to use in the GDL system. Both players' data are compulsory to be processed before it can be analyzed.

E. *Motion Templates*

To create a motion template, the GDL system will be used. This process is exclusively for processed data from player A. As this data has previously received approval from the coach, it will serve as a reference for comparing other data collected from the same training activities by different players or individuals.

F. *Comparison*

Both motion template data of player A and processed data of player B will be used in the GDL system. To evaluate and get the result of the processed data of player B, the data will be compared to the validated motion template of player A. In the GDL system, it will determine the accuracy and score of the processed data of Player B compared to the motion template of Player A as the result.

The GDL classifier uses rules and features to recognize gestures from MoCap data in the GDL system. It processes MoCap data in several steps. First, it represents a sequence of MoCap data samples taken from ti time to tj, where each sample pta is a vector in R3.d, representing the three-dimensional coordinates (x, y, z) of the body joint.

$$P[ti..tj]=[pti, ...,ptj]$$

This raw data is then transformed into feature space, reducing dimensionality and making it invariant to the camera's position. The transformation is performed by a function F.

$$P[ti..tj]F\ ftj$$

The resulting sequence of feature vectors corresponds to the MoCap data samples over time.

$$F[ti..tj]=[fti, ...,ftj]$$

Next, the system evaluates whether specific rules are satisfied at each time step, creating a sequence of rule conclusions rta which can either be true or false.

$$rta \in \{true,false\}r$$

This sequence of rule conclusions over time is represented as

$$R[ti..tj]=[rti, ...,rtj]$$

The transformation function λ considers both the feature vectors and the previous rule conclusions to determine the current rule conclusions.

$$\{F[ti..tj],R[ti..tj-1]\} \rightarrow \lambda\ \ R[ti..tj]$$

Each time step's data, features, and rule conclusions are stored in a memory stack.

$$sta=\{pta,fta,r'ta\}$$

The entire sequence of MoCap data, feature vectors, and rule conclusions over the given time interval is stored in the GDL memory stack.

$$S[ti..tj]=[sti,...,stj]$$

The classifier uses this stack to apply rules and recognize gestures. When a sequence of rules corresponding to a gesture is satisfied, the gesture is recognized.

G. Extrinsic Feedback

By getting the result of processed data of player B from the GDL system, it can be compared to the previous score rubric assessment form that has the evaluation score from the coach. If the score has high similarity, the expert can verify that the model of motion template of player A can be used to evaluate other players' data because the GDL system produces the same result as the coach evaluation.

V. Expected Outcome

The proposed framework is to improve the way coaches execute and evaluate football training and the player's performance. By integrating MoCap devices, coaches are afforded a clearer picture of player performance. The technology not only assists in detailed analysis but also in decision-making processes and enhances the evaluation of players. Consequently, coaches can refine training methods, ensuring that players are not just practicing harder, but smarter. The immediacy with which feedback is provided to players allows for swift adjustments, fostering an environment of continuous improvement and growth.

Furthermore, MTs are not only an aid in training but a lasting resource that can be accessed, revisited, and utilized repeatedly without degradation or expiration. This aspect guarantees the preservation of data for future use, offering a foundation on which athletes can build and refine their skills over time. Players, therefore, are not just improving in the short term through practice with MoCap devices; they are investing in a resource that supports their long-term development. The reusable nature of these MTs means that both current and future athletes can benefit from a tailored, data-driven approach to skill enhancement, ensuring that the legacy of today's training methods extends far into the future.

VI. Conclusion

A theoretical framework of extrinsic feedback evaluation in football training has been presented in this paper based on MTs. This framework is designed to measure the success of technique execution during football training. To ensure the effectiveness of this study, an initial investigation into the development of MTs in football training, utilizing MoCap, is essential. This includes literature study, acquaintance meeting, procedures and approval, and interview.

In the experiments, the Perception Neuron 3, a marker-based MoCap device, was proposed for utilization due to its accuracy and reliability in capturing data, even for the most subtle movements in sports activities such as football. The data from the device can be used to create MTs, which facilitate the analysis of professional players' data and the preservation of their unique skill movements in digital form. Importantly, this technology is not limited to football but can be explored and applied to other sports activities, enhancing its versatility and value in various athletic disciplines. For futures works, this proposed will be utilized and tested for experimenting the football techniques such as freekick for both left and right footed football players.

Acknowledgment

The author would like to acknowledge the Ministry of Higher Education (MoHE) and Center for Research Excellence and Incubation Management (CREIM), Universiti Sultan Zainal Abidin. This research was supported by the Ministry of Higher Education (MoHE) through Fundamental Research Grant Scheme (Project Code: RR457, Ref. No: FRGS/1/2022/ICT03/UNISZA/02/1). We also want to thank the National Sports Institute of Malaysia and Terengganu Football Club for the shown interest and future collaboration in this study.

References

[1] He, Tianyu, and Qi Luo. 2019. "A Survey of Motion Capture Technology and Its Application in Sports." In *Advances in Intelligent Systems and Computing*, 876:854–59. Springer Verlag. https://doi.org/10.1007/978-3-030-02053-8_129.

[2] Bregler, C. (2007). Motion capture technology for entertainment [In the spotlight]. IEEE Signal Processing Magazine, 24(6), 160–158. https://doi.org/10.1109/msp.2007.906023

[3] Salisu, S., Ruhaiyem, N. I. R., Eisa, T. a. E., Nasser, M., Saeed, F., & Younis, H. A. (2023). Motion Capture Technologies for Ergonomics: A Systematic Literature Review. *Diagnostics*, *13*(15), 2593. https://doi.org/10.3390/diagnostics13152593

[4] Rizhan, Wan Idris, Ahmad Rafi, Azman Bidin, and Azrul Amri Jamal. 2018. "A Theoretical Framework of Extrinsic Feedback Based-Automated Evaluation System for Martial Arts." *International Journal of Engineering & Technology*. Vol. 7.

[5] Halser, Nils, Bodo Rosenhahn, Thorsten Thormahlen, Micheal Wand, Juergen Gall, and Hans-Pieter Siedel. 2009. *Computer Vision and Pattern Recognition, 2009, CVPR 2009, IEEE Conference on : Dates: 20-25 June 2009.* IEEE.

[6] Carling, Christopher, Jonathan Bloomfield, Lee Nelsen, and Thomas Reilly. 2008. "The Role of Motion Analysis in Elite Soccer Contemporary Performance Measurement Techniques and Work Rate Data." *Sports Med*. Vol. 38.

[7] Perrott, Margaret A., Tania Pizzari, Jill Cook, and Jodie A. McClelland. 2017. "Comparison of Lower Limb and Trunk Kinematics between Markerless and Marker-Based Motion Capture Systems." *Gait and Posture* 52 (February): 57–61. https://doi.org/10.1016/j.gaitpost.2016.10.020.

[8] Nakano, Nobuyasu, Tetsuro Sakura, Kazuhiro Ueda, Leon Omura, Arata Kimura, Yoichi Iino, Senshi Fukashiro, and Shinsuke Yoshioka. 2020. "Evaluation of 3D Markerless Motion Capture Accuracy Using OpenPose With Multiple Video Cameras." *Frontiers in Sports and Active Living* 2 (May). https://doi.org/10.3389/fspor.2020.00050.

[9] Polak, Ewa, Jerzy Kulasa, António VencesBrito, Maria António Castro, and Orlando Fernandes. 2016. "Motion Analysis Systems as Optimization Training Tools in Combat Sports and Martial Arts." *Revista de Artes Marciales Asiáticas* 10 (2): 105. https://doi.org/10.18002/rama.v10i2.1687.

[10] Vliet, Paulette van, and Gabriele Wulf. 2006. "Extrinsic Feedback for Motor Learning after Stroke: What Is the Evidence?" *Disability and Rehabilitation*. https://doi.org/10.1080/09638280500534937.

[11] Mazian, Amir Irfan, Wan Rizhan, Normala Rahim, Azrul Amri Jamal, Ismahafezi Ismail, and Syed Abdullah Fadzli. 2023. "A Theoretical Framework for Creating Folk Dance Motion Templates Using Motion Capture." *International Journal of Advanced Computer Science and Applications* 14 (5): 445–51. https://doi.org/10.14569/IJACSA.2023.0140547.

[12] Paez, Arsenio. 2017. "Grey Literature: An Important Resource in Systematic Reviews." *Journal of Evidence-Based Medicine*, December. https://doi.org/10.1111/jebm.12265.

[13] Moher, David, Alessandro Liberati, Jennifer Tetzlaff, and Douglas G. Altman. 2010. "Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement." *International Journal of Surgery* 8 (5): 336–41. https://doi.org/10.1016/j.ijsu.2010.02.007.

[14] Perception Neuron. (n.d.). MocapApi Calc type data in detail. Retrieved from https://support.neuronmocap.com/hc/en-us/articles/12275483246491-MocapApi-Calc-type-data-in-detail

[15] Hachaj, T., & Ogiela, M. (2015). Full body movements recognition - unsupervised learning approach with heuristic R-GDL method. Digital Signal Processing, 46, 239-252. https://doi.org/10.1016/j.dsp.2015.07.004

[16] Idris, W. M. R. W., Rafi, A., Bidin, A., & Jamal, A. A. (2019). Developing new robust motion templates of martial art techniques using R-GDL approach: a case study of SSCM. International Journal of Arts and Technology, 11(1), 36-79.

[17] Hisham, N. F. Z., Jamal, A. A., & Idris, W. M. R. W. Lower Limb Walking Gait Profiling Using Marker-less Motion Capture with GDL and R-GDL methods to Assist Physiotherapy Treatment.

[18] Wan Idris, W.M.R., Rafi, A., Bidin, A. et al. A systematic survey of martial art using motion capture technologies: the importance of extrinsic feedback. Multimed Tools Appl 78, 10113–10140 (2019). https://doi.org/10.1007/s11042-018-6624-y

[19] Yin, Xiaohui, C. Chandru Vignesh, and Thanjai Vadivel. 2022. "Motion Capture and Evaluation System of Football Special Teaching in Colleges and Universities Based on Deep Learning." International Journal of Systems Assurance Engineering and Management 13 (6): 3092–3107. https://doi.org/10.1007/s13198-021-01557-2.

[20] Della Villa, Francesco, Stefano Di Paolo, Dario Santagati, Edoardo Della Croce, N. Lopomo, Alberto Grassi, and Stefano Zaffagnini. 2021. "A 2D Video-Analysis Scoring System of 90° Change of Direction Technique Identifies Football Players with High Knee Abduction Moment." Knee Surgery, Sports Traumatology, Arthroscopy 30 (11): 3616–25. https://doi.org/10.1007/s00167-021-06571-2.

[21] Bampouras, Theodoros M., and Neil M. Thomas. 2022. "Validation of a LiDAR-Based Player Tracking System during Football-Specific Tasks." Sports Engineering 25 (1). https://doi.org/10.1007/s12283-022-00372-7.

[22] Aughey, Robert J., Kevin Ball, Sam Robertson, Grant M. Duthie, Fabio R. Serpiello, Nicolas Evans, Bartholomew Spencer, et al. 2022. "Comparison of a Computer Vision System against Three-Dimensional Motion Capture for Tracking Football Movements in a Stadium Environment." Sports Engineering 25 (1). https://doi.org/10.1007/s12283-021-00365-y.