2Trax3: Raising Accessibility and Everyday Use of Automatic Motion Analysis in (Combat) Sports via ML Enhanced 2D to 3D Estimation Algorithms

Samir Duvelek[1], Dominik Hoelbling[1][a], René Baranyi[1][b], Roland Breiteneder[1], Karl Pinter[1][c] and Thomas Grechenig[1,2]

[1]*Research Group for Industrial Software (INSO), Vienna University of Technology, Vienna, Austria*

[2]*RISE Institute of Technology, Sri Sathya Sai District, Andhra Pradesh, India*

Keywords: Motion Capturing, Video Analysis, Kinematic, Martial Arts, Kicking Techniques, Artificial Intelligence.

Abstract: A sound technique forms the fundamental basis for many sports, particularly Martial Arts, as it often distinguishes between successful hits and being hit. However, the process of improving one's technique is highly intricate, often requiring expert feedback and expensive technology such as 3D motion capturing. The integration of automated technique analysis has the potential to streamline this process and make it more accessible. In this study, the aim is to democratize technique analysis by developing and evaluating a web application. This application allows users to upload 2D video recordings of themselves performing the double side kick technique and receive immediate feedback. To validate the analysis generated by the application, it was compared to a Vicon motion app 3D analysis of the same data from a preliminary study involving 44 participants. The results of Bland-Altman plot analysis demonstrated a highly significant agreement between the 3D and 2D performance indicators (Mean differences: relative phase duration: <0.04s; vector spreading angle: <15 degrees; relative body position <13%), indicating that the web application is a suitable tool for fast and effective motion analysis.

1 INTRODUCTION

High performance in sports particularly requires extensive technique skills among other abilities. Especially, in combat sports, technique execution does not solely serve to reach a biomechanical goal but rather has a tactical purpose (Hoelbling et al., 2021b). Studying your opponents and understanding their strengths and weaknesses in advance is also essential. Once the opponent's technique has been analysed correctly, a counter-strategy can be applied (Ouergui et al., 2021).

Furthermore it can also be used for self improvement, a technique analysis enables targeted training planning. Certain weaknesses, such as the execution of certain kicks, can be eliminated through analysis and subsequent targeted training.

The analysis of such sports techniques has been the focus of biomechanical and kinematic research for decades (Elliott, 1999). Even AI applications continually gain popularity in the field (Lapham and Bartlett, 1995).

Technique analysis in combat sports is based on a precise study of techniques, such as punches and kicks. Each technique requires accurate execution of sequential actions in combination with correct posture and precise targeting to achieve maximum effectiveness (Ambroży et al., 2020). Careful analysis and potential adaption can be greatly improve the skills and abilities of athletes by uncovering physical and coordinative weak spots, which can be compensated in the training process.

However, despite the multitude of advantages of technique analysis, it requires highly professionalized performers and is a very time-consuming task. Particularly, when it comes to complex motions, which are rapidly executed with quite little deviations leading to the distinction between success and failure in fighting situations, a complex multidimensional approach is necessary to comprehensively disclose the optimum and define the necessary adaptions (Lees, 2002).

[a] https://orcid.org/0000-0001-7099-2576
[b] https://orcid.org/0000-0002-0088-9140
[c] https://orcid.org/0000-0002-8930-1875

Duvelek, S., Hoelbling, D., Baranyi, R., Breiteneder, R., Pinter, K. and Grechenig, T.
2Trax3: Raising Accessibility and Everyday Use of Automatic Motion Analysis in (Combat) Sports via ML Enhanced 2D to 3D Estimation Algorithms.
DOI: 10.5220/0012165200003587
In *Proceedings of the 11th International Conference on Sport Sciences Research and Technology Support (icSPORTS 2023)*, pages 128-135
ISBN: 978-989-758-673-6; ISSN: 2184-3201

1.1 Double Side Kick

A number of current publications of the double side kick in pointfighting kickboxing (Yuncza, 2011) for example shows how complex this process really is and how many factors must be taken into account to model high performance (Hölbling et al., 2017). As a gold standard of this type of analysis researchers use i.e. Vicon 3D motion capturing systems (Barris and Button, 2008). Late research successfully defines a number of characteristics, strongly correlating with performance, measured by both, expert ratings and general competition success (Hölbling et al., 2020a) (Hoelbling et al., 2021b). However, extracting these variables is practically impossible for regular coaches, as it requires a very high skill set, very expensive 3D motion capturing technology and a sufficient amount of time. In addition, cameras can pick up more detailed characteristics than visible to the human eye (Barris and Button, 2008).

Some of the study's exploring the double side kick used 3D cameras to record various athletes performing the technique. The technique was then semi-automatically analysed using the 3D video recordings (Hölbling et al., 2020b). The performances were simultaneously recorded using 2D cameras.

1.2 Preexisting Dataset

A comprehensive data set from a preliminary study was provided as the foundation for this software application (Hölbling et al., 2017). The experiment recordings consisted of 3D Vicon motion capturing data with corresponding 2D videos of the double side kick executions of 44 athletes. All results of the 3D motion capturing, were extracted and published by previous researchers (Hölbling et al., 2017) (Hölbling et al., 2020a) (Hölbling et al., 2020a).

1.3 Automated Analysis Using 2D Video

Given the opportunity of existing scientifically proven performance characteristics in combination with current advancement in the field of AI expert systems (Zhang and Lu, 2021) and user-based development (Zorzetti et al., 2022) it appears possible to simplify this process in a way that regular coaches and athletes can easily track their performance status and progress. In particular, these components could be used to develop a system to automatically analyse such techniques with known performance characteristics using 2D videos, advanced motion capturing algorithms and a set of additional rules to significantly decrease analysis time effort and sophisticated equipment. There are already studies that compare the use of 3D and 2D motion capturing in other sports, such as cross-country running (Maykut et al., 2015) and youth baseball (DeFroda et al., 2021), but no research for automatic or semi-automatic analysis of Martial Arts techniques was found.

1.4 Aims

For the purpose of simplifying complex analysis and ultimately allow for integration of these methods into regular training, the aim of this study is to develop and evaluate a system for automatic analysis of 2D videos of the double side kick, based on performance characteristics defined in (Hölbling et al., 2017) (Hölbling et al., 2020a) (Hölbling et al., 2020b).

1.5 Hypothesis

Based on existing raw data from the fundamental publications, following hypothesis can be defined. There is a significant agreement between the following performance characteristics extracted in 2D (by the system) and 3D (by the fundamental research) kinematic analysis: (a) the duration of a specific segment of the technique execution relative to the total execution duration, (b) the vertical knee height at specific points of the technique execution relative to the height of the trochanter major in neutral standing position, (c) the distance between knee and frontal shoulder at specific points of the technique execution relative to the same distance in neutral standing position, (d) the angle created by the hip and knee of the standing leg with the vector connecting the knee and hip of the kicking leg at specific points of the technique execution, (e) the angle created by the hip and heel of the standing leg with the vector connecting the heel and hip of the kicking leg at specific points of the technique execution, (f) the velocity of the vertical knee elevation over the course of a specific segment of the technique execution, (g) the velocity of the kick leg over the course of a specific segment of the technique execution.

2 METHODS

Requirements Engineering: In a first step after literature research and qualitative dataset analysis, semi-structured interviews (Adams, 2015) with domain experts in pointfighting kickboxing and biomechanics were conducted and analysed via qualitative content analyses (Mayring et al., 2004), to extract essential requirements.

Table 1: Node and phases of the double side kick.

Nodes	Description
Node 1 - Initialisation (INI)	Defined as the moment when the kicking legs' foot loses contact with the ground
Phase 1 - Chambering 1 (CH1)	Consists of flexion of the knee as well as flexion and abduction of the hip joint of the kicking leg
Node 2 - Time of measurement 1 (MT1)	Defined as the highest elevation of the knee before the kicking legs' knee angle surpasses 110°
Phase 2 - Kicking phase 1 (KI1)	Mainly consists of extension of knee and hip joint with ankle flexion of the kick leg
Node 3 - Knee extension maximum 1 (KE1)	The first kick ends with the maximum extension of the kick leg's knee
Phase 3 - Chambering 2 (CH2)	Re-Chambering is similarly defined as CH1 and describes the preparation for the second kick
Node 4 - Time of measurement 2 (MT2)	Similarily defined as MT1, but after the first kick
Phase 4 - Kicking phase 2 (KI2)	Second kicking Phase, with the same definition as KI1
Node 5 - Knee extension maximum 2 (KE2)	Maximum extension of the kicking legs' knee and hip, leading to target contact

These requirements were later adapted and extended based on observations and comments throughout the development.

System Design and Implementation: Based on the extracted requirements a frontend and backend architecture was designed and an application was developed using the method of prototyping (Floyd, 1984). This procedure allowed practical demonstration of relevant parts of the system early on in the development process. Multiple iterations, incorporating expert feedback and trial and error processes were performed, to improve user experience and measurement accuracy.

Phase and Node Definition: The foundation for motion analysis is the segmentation (Meinel and Schnabel, 2007; Göhner, 1992) of the double side kick into six functional phases and seven nodes as defined by Hölbling et al. (Hölbling et al., 2017). Nodes are defined as the exact moments when one phase transitions into another, see table Table 1.

Variable Definition: After the definition and segmentation of the movement, the performance indicators had to be extracted and calculated at the nodes or within the phases, as described in (Hölbling et al., 2017). They are grouped into the following three categories: (a) the relative duration of the functional phases, (Hölbling et al., 2017) (b) the relative position of relevant body parts (kicking legs' knee height and distance between knee and front shoulder) , (c) the accumulated angles between the legs at the time of a node, (Hölbling et al., 2020a) and (d) the velocity of a body parts motion during a phase (Hölbling et al., 2020b), see table Table 2. The time-domain parameter values in the following text are the absolute duration given in seconds. The angles are given in degrees. And the distance parameter values are given as relative values without unit.

Phase Detection and Motion Analysis Algorithms: Based on the phase, node and performance indicator definitions, an advanced algorithm was developed, which solely relied on some anthropometric data and was able to automatically separate the phases and extract the variables. In an iterative process, the algorithm was then improved.

Statistical Evaluation: In a final step, the extracted data (from the 2D analysis) was statistically compared to the pre-existing data (from Vicon 3D motion capturing). Statistical analysis and plot generation was conducted using the Python programming language Python Software Foundation. Python Language Reference, version 3.9).The differences between 3D and 2D variables were checked for normal distribution by using Shapiro-Wilk tests. Similar to previous studies exploring the agreement between 3D and 2D measurements in kinematic analysis (Peebles et al., 2021; Schurr et al., 2017), Bland-Altman plots (Bland and Altman, 1986) were calculated for each of the dependent variables, in order to evaluate agreement between 3D and 2D analysis.

The y axis is constructed using the average mean difference, because the x displays a small concentra-

Table 2: Performance indicators.

Durations	Relative duration of each phase, normalized by the duration from the nodes INI to KE2
Distances	(i) The vertical height of the kick leg's knee normalized by trochanter major height in straight stance (KHK). (ii) The relative distance between the kick leg's knee and nearest shoulder normalized by their distance in neutral standing position. Both extracted at every node
Vector spreading Angle (VSA)	(i) The angle between the femur bones of both legs (vector connecting knee and hips' center of rotation). (ii) The angle between both legs (vector connecting hip and ankles' center of rotation)
Velocity	The mean velocity of the kick leg's knee vertical elevation during CH1 and CH2. And the mean velocity of the kick legs' foot in target direction during phase KI2

tion range (Bland and Altman, 1999). For 95% limits of agreement were used.

For the angle characteristics the a priori acceptable limits were set to 20°. This decision was made by consulting the results of similar studies where a subset of the results exceeds 20° (Schurr et al., 2017) or where an average of 20° agreement (Remedios and Fischer, 2021) was reported.

For the duration and distance characteristics there were no comparable studies found, therefore it has been decided to calculate an equivalent of the 20° limits of agreement taken from (Remedios and Fischer, 2021). It was decided to consider the minimum and maximum value for each of the individual characteristics and choose the 25 % value of the difference between minimum and maximum as the acceptable limit for that characteristic. This choice was made to ensure that in the case that, the 3D analysis measures a performer to be either in the top 25 % or bottom 25 % of a characteristic, the 2D analysis agrees with the 3D analysis in so far that it puts the performer into the top half or bottom half for that characteristic respectively. This is defined as the minimum viable case for a characteristic to be considered in the 2D analysis.

This means for the duration variables the limits are for CH1 (0.162s), KI1 (0.05s), CH2 (0.19s), KI2 (0.108s).

And for the distance variables: For KHK1 (22), KI1 (28.5), KHK2 (16.5), DKS1 (15.5), DKS2 (20)

3 RESULTS

The gathered results will be described in the following subsections.

3.1 Requirements List

The iterative requirements engineering process resulted in a set of requirements, which are categorized into the following three groups: (a) User instruction. The user shall be instructed in how to execute the technique and how to film the technique being performed. (b) User input. The user shall be enabled to upload the video of the performance and metadata that is necessary for the analysis. (c) Performance feedback. The user shall be presented with feedback about their performance.

3.2 Technical Design of the Application

The application is deployed inside of Microsoft's Azure cloud environment (Microsoft, 2023a) and uses Azure resources for storing data (Azure blob storage) and orchestrating the analysis (Azure container instances).

The two backend services that process the input video and calculate the analysis results are written in Python. This was chosen, because the initial processing of the input video is done using the Python version of the Openpose system (Cao et al., 2017).

Deployment: The chosen modular design of the architecture allowed for custom deployment strategies fitting the needs of the individual parts of the system (Salah et al., 2016).

The python services were deployed inside short-lived docker containers. This was done, because of the high hardware requirements for the Openpose system (Openpose, 2023), and this way the usage of the hardware is limited to the time the service is running.

3.3 User Instructions

Depicted in Figure 1 is the examplary analysis that is presented to the user when the application is first opened. This provides the user with an insight how the performance should be recorded and how the technique should be executed. The performer in the video is obfuscated and the analysis results are blurred due to data privacy and ethical reasons.

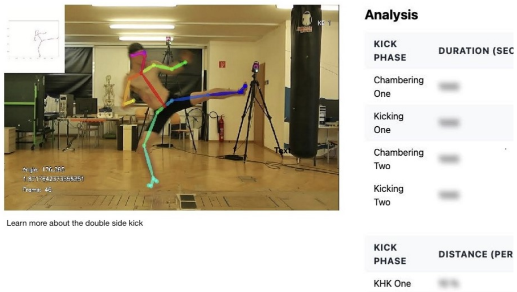

Figure 1: Analysis example presented to the user.

3.4 User Input

Figure 2 illustrates the interface where users can upload videos of performances. These videos capture a person executing the double side kick technique, recorded from a side view. Within the system, users have the capability to upload both the video itself and accompanying metadata regarding the performer. This metadata is crucial for analysis purposes and includes details such as the leg used by the performer for the kick and the performer's height in centimeters, as depicted in the video.

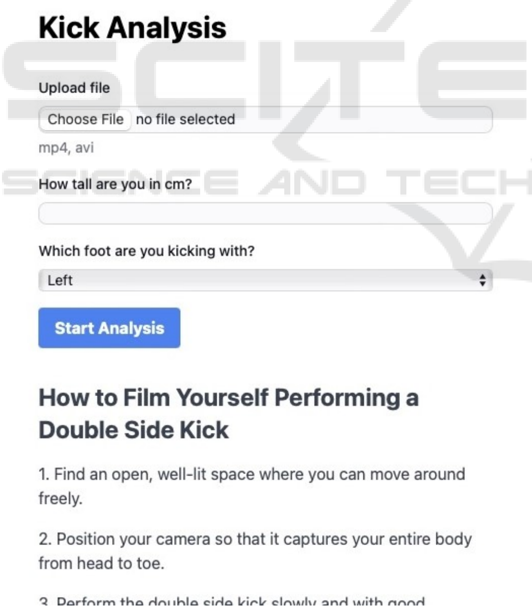

Figure 2: Upload of video including user metadata.

3.4.1 Analysis Algorithm

The analysis algorithm is a five-step process: (1) coordinates for keypoints of the performer's body are detected and extracted from every frame of the video, (2) the time series created by the set of coordinates are cleaned by running them through an anomaly detection, (3) 3D angles are calculated from the extracted keypoints, (4) the calculated angles are processed through an anomaly detection, (5) the cleaned coordinates and angles are used to generate the phases and nodes, as well as to extract and calculate the performance indicators.

Image Processing: The frames of the video are processed using the Openpose system (Cao et al., 2017). Openpose takes a single frame as input, detects the performer in the video and outputs coordinates for a set of keypoints. The pose detection model is trained on the COCO data set (Lin et al., 2014), which contains 250.000 images of people each labeled with 18 keypoints of the human body. The coordinates of the left and right shoulder, the left and right hip, the left and right knee, the left and right ankle and the nose of the performer are used in the following procedures.

Anomaly Detection: The anomaly detection comprises a set of predefined rules that marks output of the previous step as anomalies that are then not considered for the calculation. It uses a time series as input, created by either the x-coordinates (horizontal) or y-coordinates (vertical) of the kicking leg's ankle, knee or hip. In this context the coordinates refer to the position in the 2D image currently being processed. Two different type of errors occur in the output: (i) The body part cannot be detected in the frame and the coordinates are either missing or zero, (ii) the body part position is falsely detected and the coordinates are present but incorrect.

The first type of error is handled by using the average between the first preceding non-zero coordinate and the next non-zero coordinate to interpolate the missing value. The second type of error is handled by the rule set. A rule takes a consecutive sequence of coordinates as an input and returns a boolean indicating that sequence represent an anomaly or not. The rules check for differences in value between successive points in the sequence or check the monotony of the sequence.

Calculation Characteristics: The determination of knee angles involves an initial estimation of the missing depth coordinates, which are not available in the 2D analysis as compared to the 3D analysis. To obtain these coordinates, the distances between the knee and hip, as well as the knee and ankle of the kicking leg, are computed. These distances are then sorted in ascending order, and the upper value corresponding to the 95^{th} percentile of each set is selected as the "real" length of the knee and hip or knee and ankle. This estimation of the depth coordinate is calculated for each frame of the video analysis.

The obtained value is utilized to construct a right triangle, considering the detected positions of the knee and ankle, for instance. This enables the estimation of the depth coordinate. By doing so, a 3D vector is generated, representing the line connecting the knee to the ankle, as well as the line connecting the knee to the hip. Subsequently, the angles between these 3D vectors are calculated. Furthermore, the calculated angle values undergo anomaly detection, employing a specific set of rules designed for this purpose. The identified coordinates and calculated angles are employed to detect the nodes that signify the commencement and conclusion of distinct phases within the technique. To determine the INI node, the y-coordinates of the ankle of the kicking leg are examined, specifically by identifying the first monotonically increasing sequence of a predetermined length. Regarding the MT1 node, the previously described simple definition is utilized, involving the highest y-coordinate of the knee prior to the angle surpassing 110 degrees. For the KE1 node, the first monotonically decreasing sequence of angles subsequent to the MT1 node is considered. The same respective rules are applied for the detection of the MT2 and KE2 nodes.

To compute the velocity and distance characteristics, the distance between the nose and ankle is utilized. Similarly, the upper value of the 95^{th} percentile is employed to determine the true height of the performer, as provided by the user, and map it to the corresponding coordinates in the video. This allows for accurate estimation and calculation of the performer's velocity and distance metrics.

3.5 Statistical Evaluation

Only 26 of the full 44 videos from the preliminary study, were suitable (due to quality issues) for analysis.

The differences between 3D and 2D measurements were all prechecked for normal distribution by Shapiro-Wilk test using a significance level of $\alpha = 0.05$.

The Bland-Altman plots estimated the average mean difference agreement between the 3D and 2D analysis for the phase duration in CH1 (-0.04 s; LOA -0.15 to 0.06), KI1 (0.04 s; LOA -0.05 to 0.12), CH2 (-0.04 s; LOA -0.16 to 0.08), and KI2 (-0.01 s; LOA -0.13 to 0.12).

Agreement for the femur angles at the node MT1 (-0.59°; LOA -20.20 to 19.03), KE1 (4.92°; LOA -23.47 to 33.31), MT2 (4.13°; LOA -13.64 to 21.89), KE2 (-11.59°; LOA -43.94 to 20.77).

Agreement for the leg spreading angles at the node MT1 (4.25°; LOA -14.47 to 22.97), KE1 (6.84°; LOA -17.63 to 31.31), MT2 (-0.36°; LOA -16.04 to 15.33), KE2 (-7.08°; LOA -40.09 to 25.92).

Agreement for the relative knee height at KHK1 (-5.78; LOA -29.76 to 18.20), KI1 (-3.30; LOA -23.95 to 17.36), KHK2 (-2.04; LOA -32.06 to 27.99).

Agreement for the relative shoulder knee distance DSK 1(0.48; LOA -11.75 to 12.71), DSK 2 (1.41; LOA -21.46 to 24.27).

A positive value of the average mean difference indicates that the 2D analysis measured larger values for this characteristic, and a negative value indicates the 3D analysis has measured larger values compared to the 2D analysis. The limits of agreement represent the range within which approximately 95 % of the differences between the 2D and 3D measurements will fall.

4 DISCUSSION

Generally it can be stated, that the main functionality of the application is suitable for the purpose and includes all defined functional requirements. Furthermore, all non-functional requirements were met. However it must be noted, that not all videos could be analyzed due to quality issues of the recording, implying that the uploads must have a certain standard for further processing. Despite, these quality issues of the source material, which led to exclusion of 18 videos, the accuracy of the extracted data is rather high.

Furthermore based on the plots, the 2D measurements do not have any significant systematic bias for any of the characteristics compared to the 3D measurements.

In particular, based on the results of the Bland-Altman plots, the hypothesis can be accepted for performance indicators (i) Leg spreading vector at node MT2, (ii) phase duration of CH1 and CH2, (iii) relative should distance DSK1 and relative knee height KI1 but must be declined for the remaining distance, angle, duration performance indicators.

There are studies that report a higher accuracy in the kinematic analysis of 2D video (Schurr et al., 2017; Peebles et al., 2021). In those two studies however the performer in the video remains in the same position of the screen throughout the analysis. They are either performing a single-leg squat or running on a treadmill. The main challenge of the analysis in this study was the movement of the performer, particularly because of the missing depth parameters. There has been a study using the Kinect™ (Microsoft Corporation, Redmond, Washington, United States of America) 2D sensor for kinematic analysis (Pfister et al., 2014), but the results indicate that the measurements cannot reach the accuracy of a 3D motion capture system.

This study used only one type of camera and one viewing angle for the recordings, which is common in comparable 2D and 3D video investigations (Schurr et al., 2017; Peebles et al., 2021; Remedios and Fischer, 2021), although it would be interesting to examine the effect of different recording setups and different recording equipment on the analysis quality. Particularly because it would better resemble the real world environment, as athletes using the automated analysis in their day to day training will not always have the same recording quality and setup.

Besides effort and operation simplity, the cost factor is essential for integration of video analysis in regular training. The analysis in this study relies on hardware that has a graphics processing unit. This type of hardware is generally more expensive(Microsoft, 2023b). Similar analysis can be performed on cheaper hardware that only contains a central processing unit, however this leads to a much longer analysis duration (Liang et al., 2019), which would prevent providing instant feedback to the athletes.

Largely the challenges faced in this study are similar to other studies with same pose estimation software setup (Remedios and Fischer, 2021), which means 2D video pose estimation is not yet ready to replace more complex and expensive capturing systems, but serves well for performance estimations in everyday training.

4.1 Limitations

The videos used for validating the application, were recorded in 24 frames per second. A higher frame rate would allow for a higher accuracy in measuring the characteristics. In addition, the recording setup for all of the videos was similar. Only a subset of the test data was able to be used for validation, due to poor video quality of parts of the test data (recording equipment from approx. 2005). The use of different camera types, video quality and recording setups should be explored in a subsequent study.

5 CONCLUSIONS

Based on the current findings, it can be inferred that the system, although in a prototypic stage, demonstrates its suitability for automated analysis of 2D double side kick videos. Moreover, it offers a convenient and cost-effective means of technique analysis, catering to a wide range of users, helping to identify weaknesses for targeted innovative training (Hoelbling et al., 2021a) (Hoelbling et al., 2020). However, it should be noted that the system's effectiveness and accuracy heavily rely on scientifically established performance indicators, as well as the quality of the source material. In light of these considerations, it can be concluded that the system serves as a valuable tool for various applications.

REFERENCES

Adams, W. C. (2015). Conducting semi-structured interviews. *Handbook of practical program evaluation*, pages 492–505.

Ambroży, T., Rydzik, Ł., Kędra, A., Ambroży, D., Niewczas, M., Sobiło, E., and Czarny, W. (2020). The effectiveness of kickboxing techniques and its relation to fights won by knockout. *Archives of Budo*, 16.

Barris, S. and Button, C. (2008). A review of vision-based motion analysis in sport. *Sports Medicine*, 38:1025–1043.

Bland, J. M. and Altman, D. (1986). Statistical methods for assessing agreement between two methods of clinical measurement. *The lancet*, 327(8476):307–310.

Bland, J. M. and Altman, D. G. (1999). Measuring agreement in method comparison studies. *Statistical methods in medical research*, 8(2):135–160.

Cao, Z., Simon, T., Wei, S.-E., and Sheikh, Y. (2017). Realtime multi-person 2d pose estimation using part affinity fields. In *CVPR*.

DeFroda, S. F., Sugimoto, D., Staffa, S. J., Bae, D. S., Shanley, E., Thigpen, C. A., and Kriz, P. K. (2021). Reliability of an observational biomechanical analysis tool in adolescent baseball pitchers. *International Journal of Sports Physical Therapy*, 16(6):1523.

Elliott, B. (1999). Biomechanics: an integral part of sport science and sport medicine. *Journal of Science and Medicine in Sport*, 2(4):299–310.

Floyd, C. (1984). A systematic look at prototyping. In *Approaches to prototyping*, pages 1–18. Springer.

Göhner, U. (1992). Movement theory: Fundamental aspects. *Sport Science in Germany: An Interdisciplinary Anthology*, pages 191–200.

Hoelbling, D., Grafinger, M., Baca, A., and Dabnichki, P. (2020). The flexibility trainer: Feasibility analysis, prototype-and test station development for a sports device for hip-joint flexibility and strength enhancement. In *8th International Conference on Sport Sciences Research and Technology Support (ICSPORTS)*, pages 22–29.

Hoelbling, D., Grafinger, M., Smiech, M. M., Cizmic, D., Dabnichki, P., and Baca, A. (2021a). Acute response on general and sport specific hip joint flexibility to training with novel sport device. *Sports Biomechanics*, pages 1–16.

Hoelbling, D., Smiech, M. M., Cizmic, D., Baca, A., and Dabnichki, P. (2021b). Exploration of martial arts kick initiation actions and telegraphs. *International Journal of Performance Analysis in Sport*, 21(4):507–518.

Hölbling, D., Baca, A., and Dabnichki, P. (2020a). A kinematic model for assessment of hip joint range-of-motion in fast sport movements using spreading angles. *Sports Biomechanics*, pages 1–13.

Hölbling, D., Baca, A., and Dabnichki, P. (2020b). Sequential action, power generation and balance characteristics of a martial arts kick combination. *International Journal of Performance Analysis in Sport*, 20(5):766–781.

Hölbling, D., Preuschl, E., Hassmann, M., and Baca, A. (2017). Kinematic analysis of the double side kick in pointfighting, kickboxing. *Journal of sports sciences*, 35(4):317–324.

Lapham, A. and Bartlett, R. (1995). The use of artificial intelligence in the analysis of sports performance: A review of applications in human gait analysis and future directions for sports biomechanics. *Journal of Sports Sciences*, 13(3):229–237.

Lees, A. (2002). Technique analysis in sports: a critical review. *Journal of sports sciences*, 20(10):813–828.

Liang, X., Kapetanios, E., Woll, B., and Angelopoulou, A. (2019). Real time hand movement trajectory tracking for enhancing dementia screening in ageing deaf signers of british sign language. In *Machine Learning and Knowledge Extraction: Third IFIP TC 5, TC 12, WG 8.4, WG 8.9, WG 12.9 International Cross-Domain Conference, CD-MAKE 2019, Canterbury, UK, August 26–29, 2019, Proceedings 3*, pages 377–394. Springer.

Lin, T.-Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., Dollár, P., and Zitnick, C. L. (2014). Microsoft coco: Common objects in context. In *Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part V 13*, pages 740–755. Springer.

Maykut, J. N., Taylor-Haas, J. A., Paterno, M. V., DiCesare, C. A., and Ford, K. R. (2015). Concurrent validity and reliability of 2d kinematic analysis of frontal plane motion during running. *International journal of sports physical therapy*, 10(2):136.

Mayring, P. et al. (2004). Qualitative content analysis. *A companion to qualitative research*, 1(2):159–176.

Meinel, K. and Schnabel, G. (2007). *Bewegungslehre-Sportmotorik: Abriss einer Theorie der sportlichen Motorik unter pädagogischem Aspekt*. Meyer & Meyer Verlag.

Microsoft (2023a). Azure cloud computing services. https://azure.microsoft.com/en-gb/. Accessed: 2023-05-31.

Microsoft (2023b). Azure machine pricing. https://azure.microsoft.com/en-us/pricing/details/virtual-machines/windows/. Accessed: 2023-06-01.

Openpose (2023). Openpose hardware requirements. https://github.com/tramper2/openpose/blob/master/doc/installation.md. Accessed: 2023-06-01.

Ouergui, I., Delleli, S., Bouassida, A., Bouhlel, E., Chaabene, H., Ardigò, L. P., and Franchini, E. (2021). Technical-tactical analysis of small combat games in male kickboxers.

Peebles, A. T., Carroll, M. M., Socha, J. J., Schmitt, D., and Queen, R. M. (2021). Validity of using automated two-dimensional video analysis to measure continuous sagittal plane running kinematics. *Annals of biomedical engineering*, 49:455–468.

Pfister, A., West, A. M., Bronner, S., and Noah, J. A. (2014). Comparative abilities of microsoft kinect and vicon 3d motion capture for gait analysis. *Journal of medical engineering & technology*, 38(5):274–280.

Remedios, S. M. and Fischer, S. L. (2021). Towards the use of 2d video-based markerless motion capture to measure and parameterize movement during functional capacity evaluation. *Journal of Occupational Rehabilitation*, 31:754–767.

Salah, T., Zemerly, M. J., Yeun, C. Y., Al-Qutayri, M., and Al-Hammadi, Y. (2016). The evolution of distributed systems towards microservices architecture. In *2016 11th International Conference for Internet Technology and Secured Transactions (ICITST)*, pages 318–325. IEEE.

Schurr, S. A., Marshall, A. N., Resch, J. E., and Saliba, S. A. (2017). Two-dimensional video analysis is comparable to 3d motion capture in lower extremity movement assessment. *International journal of sports physical therapy*, 12(2):163.

Yuncza, E. (2011). *Sport karate point sparring: An essential guide to the point fighting method*. Indomitable Pub.

Zhang, C. and Lu, Y. (2021). Study on artificial intelligence: The state of the art and future prospects. *Journal of Industrial Information Integration*, 23:100224.

Zorzetti, M., Signoretti, I., Salerno, L., Marczak, S., and Bastos, R. (2022). Improving agile software development using user-centered design and lean startup. *Information and Software Technology*, 141:106718.