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Algorithm for Estimating Rotation from Rigid Body Human Pose

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Abstract
Image analysis has become an important tool in sports science. Traditional sports research relies heavily on observation and measurement; however, these methods have limitations in speed of analysis of capturing movement details, such as applying reflective labels. The human pose estimation (HPE) and rigid rotation animation formation is important to coaches. They would know strength, flexibility, balance and aesthetics. Traditional observation methods are insufficient to fully grasp its complexity, while imaging science research can accurately capture the mechanical and aesthetic characteristics of movements, such as tumbling, jumping, and supporting. Through image analysis, researchers can not only break down movements and detect errors, but also establish standardized technical teaching and training procedure. From single photo human pose estimation, its hard to judge the human movement rotation. Thus, this study wants to design an algorithm for calculating rigid body human pose rotation from a video. The research result was that it proposed an algorithm to estimate rotation from rigid body human pose. The detail of human movement from video was more important than pure human key points from a single image.
Keywords: *Human pose estimation, human key points, human movement classification, rigid body, HPE.*

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I. INTRODUCTION

In digital times and artificial intelligence age, image analysis has become an important tool in sports science. Traditional sports research relies heavily on observation and measurement; however, these methods have limitations in speed of analysis of capturing movement details, such as applying reflective labels. The newer sports imaging techniques provides a more precise labelling of human pose and enabling the presentation of athletes' postures, movements, and performance in a multi-viewer perspective. This trend not only aligns with the global development direction of sports science but also responds to modern society's needs for health promotion and improved athletic performance.

In competitive sports, the value of imaging science is particularly prominent. Through high-speed photography, 3D motion capture, and image recognition technologies, sport scientist can deeply analyze athletes' technical details, assist coaches in developing more precise training plans, and effectively reduce the risk of injury. The scientific processing of image data means that improvements in athletic performance no longer rely solely on experience-based judgments, but are built on objective and quantifiable evidence.

The human pose estimation (HPE) and rigid rotation animation formation is important to coaches. They would know strength, flexibility, balance and aesthetics. Traditional observation methods are insufficient to fully grasp its complexity, while imaging science research can accurately capture the mechanical and aesthetic characteristics of movements, such as tumbling, jumping, and supporting. Through image analysis, researchers can not only break down movements and detect errors, but also establish standardized technical teaching and training procedure. From single photo human pose estimation, its hard to judge the human movement rotation. Thus, this study wants to design an algorithm for calculating rigid body human pose rotation from a video.

II. LITERATURE REVIEW

Nowadays, there were 181,316 above of human pose estimations academic papers within ScienceDirect database. If these would be limited into sport field, there were 8825 related papers. In this section, it would discuss below.

Huang et al. [1] studied real-time HPE for sports combining IoT and deep learning. The need to process large amounts of high-resolution image data quickly required significant computing resources. Exercise training was typically conducted in environments, changing lighting conditions and background disturbances, which further affected the accuracy and robustness of pose estimation. In their study, the proposed algorithm treated the lightweight and high-resolution networks.Ying et al. [2] proposed a HPE model based on few-shot learning. Experimental results showed that the proposed model can identify basic human key points (HKP) using only 10 support images, with a recognition rate of over 90%. Human skin color can include white, green, black, or various other skin tones, which can cause distortion in HKP of images. When a human body is moving at high speed, there may not be enough images available for prediction of HKP, which may lead to some errors.

Xiao et al. [3] studied HKP of HPE, especially in occlusion from object. The main method was to use prior human knowledge to ensure the physical plausibility of the reconstructed posture, and then use reasoning to determine the HKP. In their research, under complex lighting conditions, background noise image, self-obscuring of limb images were caused inaccurate HKP.Fassold [4] proposed LiveSkeleton, which can treat 25fps of 5 people HKP at the same time. It was based on Scaled-YOLOV4 HKP of HPE. Cabahug et al. [5] introduced smartphone application to examine gymnastics training. The system employed a four-layer architecture, deployed on an iPhone 15 Pro Max, which used multiple cameras and LiDAR sensing. The video recording was 30 frames per second (fps). The work demonstrated smartphone technology can serve as a motion capture systems in practical sports applications. Haq et al. [6] applied HKP of HPE to fast-paced sports. The precise body movements and techniques played a crucial role in success. In their paper, the 3D pose detection methods and focus on visualizing HKP data for badminton players. Martinelli et al. [7] customized YOLO Ver. 11 implementation for cross-view sphere detection and 2D HPE and 3D reconstruction was performed through geometric methods without fine-tuning the model for the human pose task. They provided a small set of labeled data containing dribbling actions in individual basketball.

Nayak et al. [8] stated that artificial intelligence and its applications have not only had a profound impact on academia and industry, but have also changed modern lifestyles, even extending to yoga and spirituality. By testing and correcting yoga postures, combining artificial intelligence with yoga, it can not only help preserve the ancient wisdom of yoga, but also facilitate more convenient learning. Li [9] used motion capture technologies to speed climbing. They developed a workflow that combines Kinovea's motion capture and intelligent analysis. The goal was to achieve convenient quantitative assessment of speed climbers' technical movements and immediate early warning of potential risks. Zhou et al. [10] stated stacking and occlusion complexed environment, HKP was hard to recognize. They used Yolo v11s-pose package to enhance edge feature extraction. Liu et al. [11] proposed a hybrid human fall detection method based on modified YOLOv8s and AlphaPose package. They used a modified YOLOv8s as the target detector, achieving a 4.30% improvement in accuracy compared to AlphaPose alone. Narrowing the target frame helped improve accuracy. Ray et al. [12] tried using OpenPose, AlphaPose, HRNet packages co-work to generate HKP. It would help improve accuracy and be stronger than one package. Ino et al. [13] used OpenPose-MA, involved 21 young and healthy adults, the knee valgus angle during a drop vertical jump task was calculated. The HKP was applied into sport science. Pattanapisont et al. [14] used HKP of HPE to psychological and emotional tasks. They deployed the multi-view gait databases for the experiment, called CASIA-B and OUMVLP-Pose. The features were separated into three parts: whole, upper and lower body features. It showed HKP could tell the body health.

Sun et al. [15] presented current mainstream target detection algorithms describe the target to be detected as a bounding box. Continuous motion sequence information put into HPE was not sufficient discussion in literature due to there were too many movements. In their research, the HPE can be summarized as HKP, feature extraction, and movements classification. Al-Harbi et al. [16] studied unintentional drowning. If the system can automatically detect human drowning movements and process them using advanced computer vision algorithms, it will improve the safety of swimming in swimming pools. Abid et al. [17] classified five-finger movements using machine learning algorithms. They included 20 healthy participants, and concluded 17 features based on kurtosis, variance, mean, skewness and others. They also used algorithms to aid classification, including Genetic Algorithm (GA), Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO). Husaina et al. [18] adapted the YOLO algorithm for HKP tracking to analyze movements during physical workouts such as squats and planks. Experimental results showed that the application can recognize body poses with high accuracy, thus improving the effectiveness and avoiding injury. Lu et al. [19] used Mediapipe framework to extract 14 HKP of the upper body. A table tennis racket swing action dataset was constructed, covering the standard actions of forehand and backhand attacking. This method not only improved the accuracy and timeliness of action classification, but also enhanced the visualization of feature importance. Zhao [20] used sensor fusion for physical exercises. Also used machine learning models to identify the correctness of squatting. The system required only 30 fps to achieve highly accurate classification without waiting for the complete movement to be executed. The data between 14th and 23rd frames of the sample had a higher impact on the classification decision of the model. It indicated that the temporal dynamics were essential in the classification of movements.

Ferguson et al. [21] measured multi-segment foot kinematics in ballet. The 3D kinematics of eight ballet movements (knee bend, toe point, leg lift, tiptoeing, single-leg tiptoeing, toe jump, tiptoeing, and posing) were measured. There were 12 Australian dancers included into this research. The markers were applied to camera reorganization. Their research aimed to prevent dance injuries. Oka et al. [22] analyzed of 52 normally developing Japanese children aged 4-6. It would calculate the rotations in gymnastics and ballet, and assess their stability. Each iteration lasted 30 seconds, and the total length of the trajectory and the area formed by the ellipse's circumference were calculated. The results found that each child's skills would vary depending on the level of training they received, resulting in different athletic performance. Swain et al. [23] included 22 participants and studied Polar Verity Sense magnetic, angular rate, and gravity (MARG) sensors on their chest and both wrists, thighs, and ankles, while performing exercise. Although they did not use optical detection, they wearied devices that can still determine the position of the limbs. Silva et al. [24] considered physical factors and adjusted players' maximum speed because physical exhaustion leads to poor control of the ball in the subsequent stages of the soccer game. Wang et al. [25] studied rope skipping movements, breaking down the movement and applied into analyze students' movements and provide correct guidance from video analysis. Wei et al. [26] discussed occlusion, depth blur, and changes in human proportions problems in image recognition. In their research, image recognition applied into classification, detection and HPE. The machine learning effects would rise the efficiency in HKP.

Based on above literatures, human movement categories were still fewer discussed. Most research focused on HKP of HPE; however, we did not know exactly how human proceed the movement from algorithms. Thus this study designed and discussed rigid body rotation estimation algorithm.

III. PROBLEM FORMULATION

In robotics and augmented reality (AR) applications, model-based 3-D tracking of rigid was applied into help HPE for increasing reliability and decrease jitter in total [27]. The state-space model of rigid body kinematics; in the theory, the state vector consists of six generalized coordinates and their first-order time derivatives [28].

Poom [29] studied three-dimensional rigid structure-from-motion (SFM). A rigid motion model described the direction of motion of a human body model, whether walking along a circular path or a straight line. What was its rotational speed? With the deviation from the initial circular or helical path, the rigid body provided a model description. Wesierski and Jezierska [30] focused on video-assisted surgery, using rigid body capture to assess appearance, analyzing key point data (HKP), and then performing two-dimensional pose estimation.

In this section, it would separate three sub parts to discuss.

3.1 Pseudocode of Estimating Rotation

In figure 1, this study proposed a rigid estimation of rotation algorithm. In this algorithm, a human pose video has to input to the software and rotation speed is desired answer. From images within video sequence, the software keep the memory knowing how *angle* changes from shoulder horizontal (or previous movement) line, and inferring the rotation speed w.

Input: A Human Pose Video
Output: *Rotation Speed*

Vector of Human Key Points (*HKP*)
(*Vector* means a normalization value, which is between zero to one.)

To identify left or right shoulder from ***Vector***
To **Calculate** *angle* of horizontal and shoulder
To **Record** clockwise or counterclockwise of rotation
To **Record** backward of *HKP*
From *frame number* to know the *timeline operations*
To **Calculate** *interval*

Output: *Rotation Speed* w

w = *identical HKP / interval*

Figure 1: Algorithm of Rigid Rotation Estimation

In this algorithm, memorized the history of movement is necessary. I find its very hard to know this from academic paper database. Most of them emphasize on machine learning recall rate or image recognition accuracy.

3.2 A Flowchart of Rigid Rotation Estimation

From the pseudocode of estimating rotation, in figure 2, it illustrated how proceed this algorithm. In the first, we put a video into the software. Then its to find HKP, calculating *angle*, keeping the memory, reconstructing the rigid rotation and finally output the rotation speed.

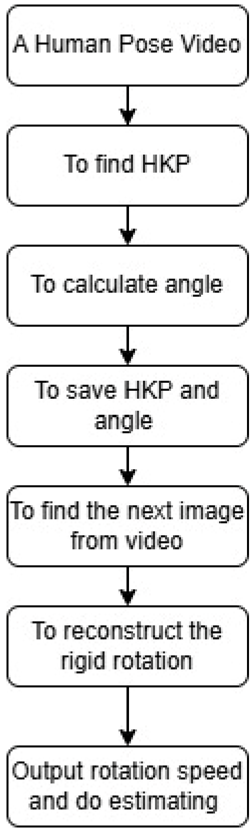

Figure 2: A Flowchart of Rigid Rotation Estimation

3.3 A Rigid Movement Decompose

In the main part of estimation, from a serious movements of HKP. We would know how it rotation. This study used Python computer language to draw the rigid body rotation.

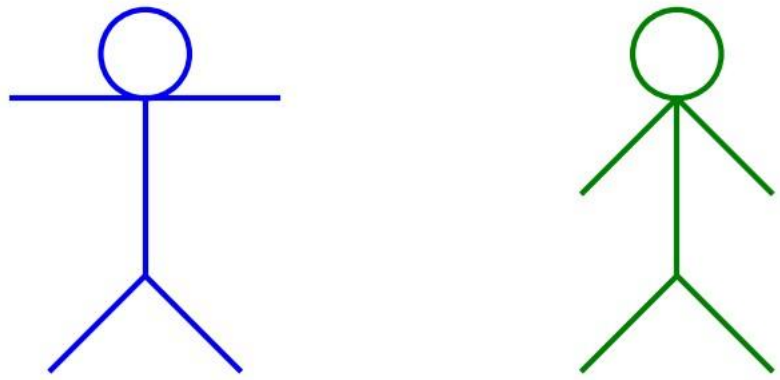

Figure 3: Rigid Body Rotation Python Draw

Based on these methods, *twin* techniques application promotion would turn into possible. The computer would know the human body language.

IV. CONCLUSION

Most of previous HPE focused on recall rate or image recognition accuracy. This study focused on algorithm for estimating rotation from rigid body human pose. Although its only the algorithm design, not related any really human videos. It offers a thought and maybe in the future study, the detail of human movement from video is more important than pure human key points from a single image.

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REFERENCES

[1]. Huang, R.B., B. Zhang, Z. X. Yao, B. J. Xie, J.Guo (2025), "DESNet: Real-time human pose estimation for sports applications combining IoT and deep learning" Alexandria Engineering Journal, Vol. 112, pp.293-306.

[2]. Ying, J. J. C., Y. H. Chen, J. Zhang (2025), " Few-shot learning-based human pose estimation model, Information Sciences" Information Sciences, Vol.717, No.122320, doi: 10.1016/j.ins.2025.122320.

[3]. Xiao, H. Y., H. He, Y. F. Xie, Y. Zheng (2025) , "Occluded human pose estimation based on part-aware discrete diffusion priors" Knowledge-Based Systems, Vol. 315, No. 13272, doi: 10.1016/j.knosys.2025.113272.

[4]. Fassold, H. (2024), "LiveSkeleton: High-quality real-time human tracking and pose estimation" 2024 International Symposium on Multimedia (ISM), 11-13 December, Tokyo, Japan, doi: 10.1109/ISM63611.2024.00054.

[5]. Cabahug, S. M., A. Maulidani, Y. H. Lin (2025) , "Mobile app for motion analysis in gymnastics" 2025 IEEE/IEIE International Conference on Consumer Electronics-Asia (ICCE-Asia), 27-29 October, Busan, Republic of Korea, doi: 10.1109/ICCE-Asia67487.2025.11263534.

[6]. Haq, M. A., N. Alamsyah, M. A. Haq, S. Riyadi (2025), "Pose analysis of amateur badminton players using transformer-based models" 2025 International Conference on Information Technology and Computing (ICITCOM), 06-07 August, Yogyakarta, Indonesia, doi: 10.1109/ICITCOM66635.2025.11265017.

[7]. Martinelli, G., N. Bisagno, N. Conci (2025), "Breaking the game: A low-cost system for 3D human and ball pose estimation in basketball" 2025 IEEE International Workshop on Sport, Technology and Research (STAR), 29-31 October, Trento, Italy, doi: 10.1109/STAR66750.2025.11264807.

[8]. Nayak, R. K., S. Waghdhare, G. Bargaley, S. Singh, S. Telang, S. Khandelwal (2025) , "A comparative study of classification AI models for yoga pose detection and correction" 12th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), 18-19 September, Noida NCR, India, doi: 10.1109/ICRITO66076.2025.11241748.

[9]. Li (2025), "Application of Kinovea-Based Motion Capture in Speed Climbing Training" 2025 International Conference on Computers, Information Processing and Advanced Education (CIPAE), 26-28 August, Ottawa, ON, Canada, doi: 10.1109/CIPAE66821.2025.00066.

[10]. Zhou, Z. G., Y. J. Lu, L. Lv (2025), "Unmanned forklift pallet positioning algorithm based on an improved human pose estimation model" Ann N Y Acad Sci, Vol. 1551, No. 1, pp.294-311.

[11]. Liu, L., Y. Sun, Y. Y. Li, Y. H. Liu (2025), "A hybrid human fall detection method based on modified YOLOv8s and AlphaPose" Sci Rep, Vol.15, No.1, P.2636, doi: 10.1038/s41598-025-86429-6.

[12]. Ray, A., M. Z. Uddin, K. Hasan, Z. R. Melody, P. K.Sarker, M. A. R. Ahad (2024), "Multi-Biometric Feature Extraction from Multiple Pose Estimation Algorithms for Cross-View Gait Recognition" Sensors (Basel), Vol. 24, No.23, P.7669, doi: 10.3390/s24237669.

[13]. Ino, T., M. Samukawa, T. Ishida, N. Wada, Y. Koshino, S. Kasahara, H. Tohyama (2024), "Validity and reliability of OpenPose-based motion analysis in measuring knee valgus during drop vertical jump test" J Sports Sci Med, Vol.23, No.1, pp. 515-525.

[14]. Pattanapisont, T., K. Kotani, P. Siritanawan, T. Kondo, J. Karnjana (2024), "Multi-view gait analysis by temporal geometric features of human body parts" J Imaging, Vol.10, No.4, P.8, doi: 10.3390/jimaging10040088.

[15]. Sun, L. F., N. Li, G. F. Zhao, G. Wang (2024), "A three-dimensional human motion pose recognition algorithm based on graph convolutional networks" Image and Vision Computing, Vol.146, No. 105009, doi: 10.1016/j.imavis.2024.105009.

[16]. Al-Harbi, R., L. Al-Mubarak,; L. Al-Tamimi, N. Al-Otaibi, Z. Sbai (2025), "Analysis of deep learning algorithms for automated drowning detection" 9th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT), 14-16 November, Ankara, Turkiye, doi: 10.1109/ISMSIT67332.2025.11267965.

[17]. Abid, U., O. Zulfiqar, H. Nazeer, N. Naseer, A. P. L. Bo, H. Khan (2025), "fNIRS based comparative study of classifiers and feature selection techniques for finger tapping" 47th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 14-18 July, Copenhagen, Denmark, doi:10.1109/EMBC58623.2025.11254285.

[18]. Husaina, L. A., R. Faradisa, P. Wibowo, G. Arifiyan P. (2025), "Development of a Real-Time Workout Validation and Repetition Counting Application Using YOLO-Based Human Pose Estimation" 2025 International Electronics Symposium (IES), 05-07 August, Surabaya, Indonesia, doi: 10.1109/IES67184.2025.11161135.

[19]. Lu, G., Y. Sun, Z. Qin, C. Wang, Q. Yin, Z. Li (2025), "Research on table tennis movement evaluation method based on human posture estimation" 40th Youth Academic Annual Conference of Chinese Association of Automation (YAC), 17-19 May, Zhengzhou, China, doi: 10.1109/YAC66630.2025.11149809.

[20]. Zhao, Y., S. Dill, A. Ahmadi, M. Grimmer, D. Haufe, L. Herrmann (2025), "Sensor fusion for physical exercises classification" IEEE Medical Measurements & Applications (MeMeA), 28-30 May, Chania, Greece, doi: 10.1109/MeMeA65319.2025.11067962.

[21]. Ferguson, H., J. Bonacci, R. M. J. Snipe, D. Condo, A. S. Fox (2026), "Can we accurately measure multi-segment foot kinematics in ballet pointe shoes using marker-based methods" J Biomech, Vol.194, No.113079, doi: 10.1016/j.jbiomech.2025.113079.

[22]. Oka, S., S. Tanaka, N. Hamachi, K. Nonaka, N. Harada, A. Kondo (2025), "Comparison of motor performance in typically developing children engaged in gymnastics and classical ballet" J Phys Ther Sci, Vol. 37, No.8, pp.403-407.

[23]. Swain,T. A., M. A. McNarry, S. Manzano-Carrasco, K. A. Mackintosh (2025), "Assessing real-world movements using consumer-grade wearable devices: Measuring segment orientations and movement quality" Wearable Technol, Vol.19, No.6, P.e54., doi: 10.1017/wtc.2025.10034.

[24]. Silva, M. F. d., Á. Novillo, A. Aleta, R. L. D. Campo, R. Resta, Y. Moreno, J. M. Buldú (2025), "The interplay between pitch control and top speed in soccer considering the stamina factor" Sci Rep, Vol.15, No.1, P. 38799, doi: 10.1038/s41598-025-22778-6.

[25]. Wang, Y., Y. C. Zhang, L. J. Shen, S. M. Wang (2021), "Analysis and research on human movement in sports scene" Comput Intell Neurosci, Vol.23, P.2376601, doi: 10.1155/2021/2376601.

[26]. Wei, J. N., B. Yu, T. J. Zou, Y. D. Zheng, X. Z. Qiu, M. Z. Hu, H. Yu, D. D. Xiao, Y. Yu, J. Liu (2025), "A review of transformer-based human pose estimation: Delving into the relation modeling" Neurocomputing, Vol.639, No.28, P. 130210, doi: 10.1016/j.neucom.2025.130210.

[27]. Gedik, O.S. and A A. Alatan (2013). "3-D rigid body tracking using vision and depth sensors" IEEE Trans Cybern, Vol.43, No.5, pp. 1395-1405.

[28]. Halvorsen, K., T. Söderström, V. Stokes, H. Lanshammar (2005), "Using an extended kalman filter for rigid body pose estimation" J Biomech Eng, Vol.127, No.3, pp.475-83.

[29]. Poom, L. (2025), "Dynamics of visual reversals from ambiguous spinning biological-motion and rigid structure-from-motion" Iperception, Vol.16, No.3, P. 20416695251342410, doi: 10.1177/20416695251342410.

[30]. Wesierski, D. and A. Jezierska (2018), "Instrument detection and pose estimation with rigid part mixtures model in video-assisted surgeries" Med Image Anal, Vol. 46, pp.244-265.