

AI-based Human Tracking for Remote Rehabilitation Progress Monitoring

Ameur Latreche^{1,2*}, Ridha Kelaiaia¹, Ahmed Chemori²

¹LGMM laboratory, University of Skikda, Algeria

²LIRMM laboratory, University of Montpellier, France

*Corresponding author's e-mail: am.latreche@univ-skikda.dz

ABSTRACT

Human movement analysis takes on great importance in the field of research related to artificial intelligence because it is used in many applications such as sports and rehabilitation. Human action analysis may be accomplished by anticipating the body's essential posture. The two most important parts of video-based human action analysis are recognizing actions and following the body. In this research paper, we present an effective model for tracking some human range of motion using artificial intelligence technology. A web application was developed to track the patient's rehabilitation progress at a distance.

Keywords: Pose estimation, MediaPipe, Telerehabilitation

1 Introduction

Human activity recognition, crucial in computer vision, aids in body tracking and injury prevention during physical exercise [1]. Telerehabilitation, particularly relevant in the era of COVID-19, offers cost-effective convenience. It is valuable for athletes, patients recovering from injuries or surgeries, and those with postural issues [2]- [8]. Traditional goniometers and inclinometers have limitations, with digital inclinometers being costlier. Inertial measurement units (IMUs), leveraging micro-electromechanical systems, provide remote tracking for rehabilitation and motion analysis, showing promise in accurately measuring joint angles [9]- [11]. While Kinect V1 and V2 have been used in telemedicine, they have accuracy and cost issues, especially for lower limb activities [12]- [14]. Developing cost-effective remote monitoring for physiotherapists is crucial [15]. Our aim is to employ cost-effective, cutting-edge technology for widespread use, focusing on pose estimation to measure limb joint motion in telerehabilitation.

The article is structured as follows: Section 2 covers body tracking in telerehabilitation, including movement analysis. Section 3 details ROM measurement methods with knee flexion/extension data from 25 volunteers. Section 4 assesses MediaPipe's reliability for knee motion. Section 5 focuses on patient validation, and Section 6 concludes.

2 Human Movement and Body Tracking

ML frameworks (TfLite, OpenPose, Pifpaf, Tfjs, BlazePose) improved fitness data [16]. A web app tracked patient rehab with Popper, Bootstrap, and JQuery. We assess pose detection for rehab movements in different camera positions. Position choice in front of the camera is vital for data accuracy. Avoiding obstructions is advised to prevent data fluctuations.

3 Methods and Data of measuring knee flexion/extension

25 participants aged 21-40 participated in a study at Skikda University. MediaPipe and a goniometer were used to measure four motions with three repetitions to assess reliability. The goniometer was employed once by the physiotherapist. Table 1 presents the statistical data for knee flexion/extension, which were collected using a universal Goniometer and MediaPipe.



Table 1: Data of knee flexion/extension obtained using universal Goniometer and MediaPipe

Movement	Meth	Mean	SE Mean	StDev	Min	Med	Max
Flexion	Go	20.40°	0.16°	0.81°	19°	21°	22°
	Med	20.00°	0.17°	0.86°	19°	20°	22°
Extension	Go	179.20°	0.18°	0.91°	178°	180°	180°
	Med	179.08°	0.18°	0.90°	177°	179°	180°

Table 2 shows excellent MediaPipe reliability (ICC: 0.81-1.0) for knee flexion and extension. Bland-Altman analysis [17] evaluated MediaPipe's validity against the goniometer.

Table 2: Reliability results of the MediaPipe based measurement system for knee movements

	ICC	StDev	SEM	MDC
Flexion	0.92	0.81°	0.23°	0.63°
Extension	0.87	0.91°	0.33°	0.91°

A 95% limit of agreement (LOA) amidst MediaPipe-based measurement and the universal goniometer is calculated:

As indicated in [18], the table 3, the MediaPipe is valid for using to measure the knee flexion extension in the telerehabilitation platform.

Table 3: Bland-Altman analysis results of knee flexion/extension data acquired using goniometer and MediaPipe

ROM	Goniometer vs MediaPipe	
	Mean bias	95% LOA
Flexion	0.40°	-0.98° to 1.78°
Extension	0.20°	-0.60° to 1.00°

4 Patients experimental validation

Three knee patients were studied, as shown in Table 4. Patient 1 reached 130° flexion, while Patients 2 and 3 achieved 125° and 142°, respectively. Patient 1 showed limited progress. Patient 2 and 3 improved from week 3. In week 6, all patients had slight gains. MediaPipe is effective for range of motion measurement and telerehabilitation.

Table 4: Data of range of motion in four records in four months

	Data 1	Data 2	Data 3	Data 4	Data 5	Data 6
Patient 1	130.00°	102.32°	95.86°	66.60°	67.83°	60.83°
Patient 2	125.49°	95.08°	59.52°	56.10°	46.62°	40.00°
Patient 3	142.26°	143.36°	88.60°	54.57°	42.93°	37.00°

5 Conclusion

A physiotherapist used clinical goniometer measurements, and participants' results were within normal averages. IBM SPSS Statistics version 26 was employed for statistical analysis. MediaPipe's reliability, assessed through the intraclass correlation coefficient (ICC), showed excellent results for knee flexion and extension (ICC values between 0.81 and 1.0). Validity of MediaPipe was evaluated using Bland-Altman analysis, including limits of agreement (LOA) and mean bias measurements, when compared to the goniometer. Our future project will develop a website and test and study the technique with different movements [19], [20].

6 Competing Interests

The authors declared that no conflict of interest exists in this work.

How to Cite

A. Latreche, R. Kelaiaia, A. Chemori, “AI-based Human Tracking for Remote Rehabilitation Progress Monitoring”, *AIJR Abstracts*, pp. 7–9, Feb. 2024.

References

- [1] Luvizon, D. C., Picard, D., & Tabia, H. (2018). 2d/3d pose estimation and action recognition using multitask deep learning. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 5137-5146).
- [2] Bazarevsky, V., Grishchenko, I., Raveendran, K., Zhu, T., Zhang, F., & Grundmann, M. (2020). BlazePose: On-device real-time body pose tracking. arXiv preprint arXiv:2006.10204.
- [3] Yadav, S. K., Singh, A., Gupta, A., & Raheja, J. L. (2019). Real-time Yoga recognition using deep learning. *Neural Computing and Applications*, 31, 9349-9361.
- [4] Sankai, Y. (2011). HAL: Hybrid assistive limb based on cybernics. In *Robotics Research: The 13th International Symposium ISRR* (pp. 25-34). Springer Berlin Heidelberg
- [5] Jezernik, S., Colombo, G., & Morari, M. (2004). Automatic gait-pattern adaptation algorithms for rehabilitation with a 4-DOF robotic orthosis. *IEEE Transactions on Robotics and Automation*, 20(3), 574-582.
- [6] Latreche, A., & Kelaiaia, R. (2021, November). Static and dynamic study of “Rééduc-Genou” a mechatronics prototype for knee rehabilitation. In *International Conference on Mechanical Sciences* (Vol. 15, p. 16).
- [7] Russo, M., & Ceccarelli, M. (2020). Analysis of a wearable robotic system for ankle rehabilitation. *Machines*, 8(3), 48.
- [8] Dollar, A. M., & Herr, H. (2008). Lower extremity exoskeletons and active orthoses: Challenges and state-of-the-art. *IEEE Transactions on robotics*, 24(1), 144-158.
- [9] Teufl, W., Miezal, M., Taetz, B., Fröhlich, M., & Bleser, G. (2019). Validity of inertial sensor based 3D joint kinematics of static and dynamic sport and physiotherapy specific movements. *PloS one*, 14(2), e0213064.
- [10] Cutti, A. G., Giovanardi, A., Rocchi, L., Davalli, A., & Sacchetti, R. (2008). Ambulatory measurement of shoulder and elbow kinematics through inertial and magnetic sensors. *Medical & biological engineering & computing*, 46, 169-178.
- [11] El-Gohary, M., & McNames, J. (2012). Shoulder and elbow joint angle tracking with inertial sensors. *IEEE Transactions on Biomedical Engineering*, 59(9), 2635-2641.
- [12] Ozturk, A., Tartar, A., Huseyinsinoglu, B. E., & Ertas, A. H. (2016). A clinically feasible kinematic assessment method of upper extremity motor function impairment after stroke. *Measurement*, 80, 207-216.
- [13] Perez-Medina, J. L., Jimenes-Vargas, K. B., Leconte, L., Villarreal, S., Rybarczyk, Y., & Vanderdonck, J. (2019). ePHoRt: towards a reference architecture for tele-rehabilitation systems. *IEEE Access*, 7, 97159-97176.
- [14] Sheng, B., Wang, X., Hou, M., Huang, J., Xiong, S., & Zhang, Y. (2020). An automated system for motor function assessment in stroke patients using motion sensing technology: A pilot study. *Measurement*, 161, 107896.
- [15] Naemabadi, M. R., Dinesen, B., Andersen, O. K., Najafi, S., & Hansen, J. (2018, January). Evaluating Accuracy and Usability of Microsoft Kinect Sensors and Wearable Sensor for Tele Knee Rehabilitation after Knee Operation. In *BIODEVICES* (pp. 128-135).
- [16] Ohri, A., Agrawal, S., & Chaudhary, G. S. (2021). On-device Realtime Pose Estimation & Correction. *International Journal of Advances in Engineering and Management (IJAEM)*, 3(7).
- [17] Stratford, P. W., Binkley, J. M., & Riddle, D. L. (1996). Health status measures: strategies and analytic methods for assessing change scores. *Physical therapy*, 76(10), 1109-1123.
- [18] Bland, J. M., & Altman, D. (1986). Statistical methods for assessing agreement between two methods of clinical measurement. *The lancet*, 327(8476), 307-310.
- [19] Latreche, A., Kelaiaia, R., Chemori, A., & Kerboua, A. (2023). Reliability and validity analysis of MediaPipe-based measurement system for some human rehabilitation motions. *Measurement*, 214, 112826.
- [20] Latreche, A., Kelaiaia, R., Chemori, A., & Kerboua, A. (2023). A New Home-Based Upper-and Lower-Limb Telerehabilitation Platform with Experimental Validation. *Arabian Journal for Science and Engineering*, 1-16.