UNIVERSITATEA DIN PETROȘANI
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Teză de doctorat

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Ing. **Arun Fabian PANAITE**

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Study regarding motion capture and identification

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CHAPTER 1: CURRENT TRENDS AND MOTION CAPTURE TEHCNOLOGIES – LITERATURE REVIEW

This chapter presents the state of the art of motion capture technologies with focus on wearable systems and methods to capture human motion. Wearable motion capture devices have been on the rise because of their mobility and simplicity in use and have a high recognition rate of human gestures through feature extraction and dimensionality reduction. These advancements have a lot of impact on the automation of industries and the validation studies of the users. However, problems like power supply constraints and sensor design issues are still present and the future work is devoted to the implementation of such systems into robotics and optimization of the sensor designs for further enhancement of real-time interactive systems and industrial applications.

Wearable biomarkers are also presented as effective means of monitoring the advancement of neurodegenerative diseases. It is possible to use machine learning to analyze the data obtained from the full-body motion capture suits to create digital biomarkers, which could potentially shorten the clinical trials period for the diseases that develop slowly. But there are still some issues, namely in the development of more effective methods for monitoring biomarkers and in the use of wearable biomarkers in clinical trials.

This chapter also includes the comparative studies that have shown that wearable sensor systems can capture gait cycle movements with high levels of accuracy, indicating their applicability for accurate gait assessment. However, issues like placement of sensors and the technologies which are currently available remain as some of the challenges, though current research focuses on the reduction of the number of sensors while trying to achieve high accuracy.

Besides the wearable devices, the document also discusses about the non-wearable sensor systems as well. New approaches have been proposed to improve the accuracy of motion capturing such as, automatic methods using depth and RGB data from Kinect sensors that can capture human movements even with occlusion. Optical motion capture has also been used to assess its applicability in intuitive robot programming and performance assessment of industrial tasks.

The incorporation of deep learning frameworks into motion capture systems has improved the estimation of human motion to a large extent. Such frameworks tend to be more effective than conventional methods since they apply probabilistic models that combine statistical inference and knowledge. Low-cost marker-based motion capture systems have also been proved to be effective in capturing human body movements and there are algorithms to reduce the impact of soft tissue artefact.

There are some benefits of marker-less motion capture systems as compared to traditional marker-based systems, these include the use of algorithms and deep learning for body position and orientation estimation. Such systems have been observed to provide accurate estimation of joint position and segment angles, thus being ideal for clinical and research purposes.

In general, the modern technologies of motion capture have expanded the opportunities to analyze human movements with higher accuracy and with less time consumption. Nevertheless, further studies are required to tackle the existing problems, to find new possibilities of the application of these systems, and to improve their stability and usability. The combination of motion capture technology with machine learning and artificial intelligence has a very promising future where new opportunities for real-time interactive systems, clinical trials, and industrial applications can be created.

CHAPTER 2: FOUNDATIONS AND METHODOLOGIES FOR GAIT MOTION CAPTURE USING ACCELLEROMETRIC SENSORS

Chapter 2 focuses on the development, execution, and evaluation of a gait motion capture system. This system, therefore, employing accelerometric sensors and an Arduino board, seeks to provide a cheap, transportable, and accurate approach to gait assessment, suitable for biomechanics, healthcare, sports science, and rehabilitation.

In the first section of the chapter, the authors describe the experimental setup and the system integration where the main objective was to create a working and precise gait capture system. This system combines 6-axis accelerometric sensors with an Arduino board to capture precise gait information with emphasis on factors such as stride length, stride time and the angles of the joints involved. Some of the hardware components which are incorporated include the Arduino Uno R3 board, a Serial Port Expander, while software components include MATLAB Simulink for real-time data processing and visualization. Accelerometers were attached to the pelvis, thighs, shins, and feet with the aim of obtaining full motion data of the lower limbs. In order to measure the walking speed, participants walked at a comfortable speed in a hall with no distractions, and trials were taken several times to ensure validity of the results.

The hardware was constructed in a very neat manner; the sensors were firmly strapped on the body and connected to the Arduino board through the Serial Port Expander. The Arduino board was programmed for the initial setup of the sensors, sensor reading and preprocessing of data and sending it to MATLAB Simulink for further processing and visualization. Static and dynamic calibration procedures were effectively performed to guarantee the reliability of the sensors. The experiment proved that the system is accurate, reliable, and easy to use by the participants expressing comfort during the use of the system.

The chapter also explains the hardware design where the accelerometric sensors are used for measuring linear acceleration as well as the angular velocity. The sensors were mounted on the body in a way that would allow capturing of key gait movements and the Serial Port Expander was important in handling data from several sensors. Correct wiring and connection were critical to data transmission and data security while frequent calibration was important for maintaining accuracy in the long run.

The IMU software design is described in detail including the integration of the sensors, data acquisition, processing and real-time analysis. MATLAB Simulink was selected based on the fact that it supports real-time data processing, is user-friendly and has numerous tools to help in the project. The design of the software entails effective data acquisition, noise reduction, calibration, and real time data display hence improving the system performance.

The chapter is concluded with the discussion on the experimental setting, where the focus is made on the integration of modern sensor technology with microcontrollers, the cost and portability of the system, and the potential for further development of gait analysis. The experiment proved that it is possible to use cheap and easily obtainable technology for high-level gait analysis with the future upgrades of the application likely to include machine learning for the automatic recognition of gait patterns. In conclusion, the system is a useful tool for the researchers, clinicians and other persons who are interested in gait analysis due to the modularity and scalability of the system and due to the possibility for further improvements.

CHAPTER 3: ADVANCED DATA MANIPULATION TECHNIQUES FOR OPTIMIZING IMAGE DATASETS IN NEURAL NETWORK TRAINING

Chapter 3 is the in-depth discussion of the image data manipulation methods focused on the image data sets for neural network training. This chapter discusses the extraction of frames from the video files all the way to the resizing of the images to a format that is suitable for training of the complicated neural networks such as ResNet-50 and GoogLeNet.

The chapter starts with the discussion of the fact that data manipulation is crucial in the training of a neural network. The main reasons include data harmonisation and standardisation, image quality, reduction in data redundancy, and robotic approaches that ease the process and reduce human interference.

The first process is frame extraction, which involves extracting different frames from video files using Python scripts that are supported by OpenCV. These frames are stored as PNG files and the script provides information on the extraction process and guarantees that all moments from the video are covered.

After that, the chapter explains color temperature adjustment, which is necessary for bringing images to a standard temperature of 6500K, which is most suitable for CNN training. The process includes working out the original temperature of each image, convert Kelvin values to RGB and using these values to correct the color balance.

Another technique explained is background blurring where the background of the image is blurred to make the foreground stand out or the human subjects. In this process, Mediapipe's segmentation model is used to generate masks for the human bodies and the background is blurred using Gaussian blur while the foreground is kept sharp to provide focus on the features important for neural network training.

Skeleton drawing with inverted colors and fringes is one of the techniques that can be applied to emphasize the outline of human body. In this step, human landmarks are detected, colour inversion is done on the skeleton and fringes are added to make the features more distinguishable to the neural network. This technique employs Mediapipe's pose estimation for the identification of landmarks and appends white, black, and red fringes to the skeletons.

The chapter also involves resizing images depending on object detection using YOLOv5, a model that detects and crops images around people, on the content of interest. This helps in preserving the relevant sections of the images and removing the unnecessary background besides aiding in the standardization of the dataset for neural networks.

The last resizing is done with the help of the Pillow library, which brings images to the necessary dimensions for neural networks (for example, 400×400 pixels). This step is important to make sure that the size of the inputs in the dataset is standardized to make training and evaluation easy.

The last step is redundancy removal where the Structural Similarity Index (SSIM) is used to compare images within a directory and delete the similar images based on a similarity index. This process helps to remove the similar images from the dataset and thus make the dataset more efficient and diverse.

The chapter ends with the brief recap of the whole data manipulation process starting from the frame extraction up to the final resizing and stressing on the role of each stage in building a solid dataset for the training of the neural network. It also points out the systematic way to guarantee that the images are of high quality, unified and prepared for more complex neural network architectures.

CHAPTER 4: COMPARATIVE ANALYSIS OF CURSIVE POSE ESTIMATION MODELS

Chapter 4 of the thesis aims at giving a comparative study of different pose estimation models with special emphasis on ResNet-50 and GoogLeNet. The first goal is to evaluate the performance of the given models in terms of the binary classification of poses as “CORRECT” or “INCORRECT”. The chapter also contains information about the approaches applied for training and testing of these models, the measures used for their comparison, as well as the conclusions made.

The models were trained in different configurations, namely single CPU, multiple CPUs, single GPU and multiple GPUs. In each of the configurations, the training process was observed based on accuracy, loss and time taken. The evaluation measures used were accuracy, precision, recall, F1 score and the confusion matrix.

Single CPU training for the ResNet-50 model was done, and it took about 81 minutes, with a high validation accuracy of 94. 53% with small overfitting. Multiple CPU training was further carried out to 86 minutes with validation accuracy of 92. 58%. Training with single GPU has further decreased the training time to 11 minutes with the validation accuracy of 97. 27%. The training with multiple GPU took about 14 minutes to train and the validation accuracy achieved was 96. 88%. The findings also pointed out that training with the GPU, particularly with multiple GPUs was the most efficient in terms of speed and accuracy.

The specifics of the analysis for ResNet-50 were presented by training curves, confusion matrices, and other metrics such as recall, precision, and F1 score. Single CPU training depicted a progressive rise in the training accuracy to 94. 53% with low and stable validation loss. From the confusion matrix, it was observed that the model had a perfect accuracy for the “CORRECT” class and high recall for the “INCORRECT” class. Same trends were observed with multiple CPU training, though it had slightly lower validation accuracy. The single GPU training provided the best and fastest learning rates with the highest validation accuracy and the best metrics consistency. Both multiple GPU training yielded high accuracy and fast training time, thus showing the benefits of parallelism.

Single CPU training of the GoogLeNet model was about 94 minutes and the validation accuracy was 92. 97%. Training on multiple CPU also did not differ much with stable training and validation metrics. With single GPU training, the time was brought down to 13 minutes with validation accuracy of 93. 36%. Multiple GPU training also took approximately 14 minutes while the validation accuracy was 92. 97%. The model's scalability was good across different configurations, though GPU-based training was much more time efficient.

The training process of GoogLeNet was illustrated by graphs of training process, confusion matrix, and performance. Single CPU training was observed to increase in accuracy and was relatively stable at 93-94%. The confusion matrix analysis showed high level of precision and recall especially for the "INCORRECT" class. The multiple CPU training kept the accuracy and loss curves at par with each other suggesting proper learning. Single GPU training showed fast learning and high validation accuracy and at the same time, multiple GPU training allowed for efficient training with high robustness.

In conclusion, Chapter 4 focuses on the necessity of computational resources in training the pose estimation models. The use of GPUs in training especially with multiple GPUs results in increased training speed and better model performance. It was also observed that both ResNet-50 and GoogLeNet models yielded high accuracy and were less sensitive to changes in the hyperparameters for binary classification tasks in the pose estimation. The chapter is useful in understanding how one can choose the right training methods depending on the resources available as well as the project's needs.

CHAPTER 5: CONCLUSIONS, CONTRIBUTIONS AND HILIGHTS

Chapter 5 is a summary of the thesis, discussing the developments and uses in motion capture technologies, and emphasizing the increased improvement in both wearable and non-wearable devices. Wearable motion capture devices, which are getting more appreciation for their high level of accuracy in human gesture recognition, are widely applicable in areas from user verification to industrial automation. Some of the challenges that have been identified include; power supply constraints and sensor design drawbacks, but further research is anticipated to counter these problems especially in the integration of these systems with robotics and improving their real-time interactivity. The thesis also focuses on the possibility of using wearable biomarkers for the diagnosis of neurodegenerative diseases, which will help to increase the accuracy of diagnostics and shorten the time of clinical trials.

Non-wearable sensor systems have also been developed to a significant level especially with the incorporation of depth and RGB data from Kinect sensors and the emergence of deep learning frameworks to predict human arm movements. These innovations offer better coverage and precision of motion tracking, including cases in which occlusions occur. The combination of IMUs with motion capture systems has enhanced the accuracy of these systems and they are used in areas such as robot teaching and industrial analysis.

It has been established that marker-based motion capture systems are affordable substitutes for commercial systems in capturing human movements from distinguishable markers and human body models. These systems are especially beneficial in clinical and sports medicine settings because of algorithms that are employed to reduce effects of soft tissue motion. On the other hand, markerless motion capture systems, which use sophisticated algorithms and deep learning algorithms, have the following advantages in terms of joint position and segment angles' measurement without using markers.

This thesis focuses on the fusion of motion capture technologies with artificial intelligence and machine learning; a field that has allowed for further understanding of intricate human movements with higher precision and in real-time. This integration is expected to change numerous fields such as healthcare, sports and entertainment by offering better understanding of human biomechanics and enhancing individualized approaches.

In industrial automation, motion capture technologies are poised to improve performance and safety by allowing robots to interpret and mimic human movements, which may decrease the time and skills needed for automation procedures. The use of these technologies in VR and AR is also promising since they provide more engaging experiences that are suitable especially in gaming, training, and remote collaboration.

In the medical field, the motion capture technologies can provide accurate and quantitative data of human motion, which can facilitate the diagnosis and treatment of musculoskeletal diseases and help the rehabilitation process. They are also useful in monitoring disease rates and the impact of interventions, which may help to shorten the duration of clinical trials and their expenses.

The thesis finishes with the call for further research on the motion capture technologies as these innovations can be applied in numerous fields such as manufacturing process automation, health care, etc. The use of motion capture system is expected to grow in the future because of advancement of sensor technologies that make them cheaper to use in future developments.

FUTURE ENHANCEMENTS

Future development of this technology is important to overcome some of the challenges that are facing the development of sensors today including; the design of the sensors, the energy source, and sensitivity. These challenges can be solved by creating more energy efficient sensors and incorporating more sensors to get more physiological data, expanding the usage in health care, sports and physical rehabilitation. The motion capture systems can be enhanced by extending the use of machine learning, especially through the use of RNNs algorithms for accurate classification of different motion patterns. These models could be fine-tuned with new data and would be more effective in different environments if trained continuously.

Applying motion capture technologies in AR/VR provides new opportunities for interaction, while improvement possibilities are aimed at developing less invasive systems that would increase the comfort of interaction. This could extend to the areas of entertainment, training and remote equipment operation. Future advancements in the medical industry may integrate motion capture with wearable biosensors to improve diagnostics and treatment evaluation, which may shorten the trials and improve patient-tailored treatment. To capture these benefits, it is necessary to standardize data acquisition and processing since the application of a common framework for image data preprocessing, detection, and analysis is beneficial for the data quality and homogeneity that is essential for machine learning model development and use.

REFERENCES

1. Abdel-Malek, K., & Arora, J. S. (2013). Human motion simulation: Predictive dynamics (1st ed.). Elsevier. https://doi.org/10.1016/C2012-0-06906-8
2. Abhayasinghe, N., Murray, I., & Sharif Bidabadi, S. (2019). Validation of thigh angle estimation using inertial measurement unit data against optical motion capture systems. Sensors, 19(3), 596. https://doi.org/10.3390/s19030596
3. Akhter, I., Simon, T., Khan, S., Matthews, I., & Sheikh, Y. (2012). Bilinear spatiotemporal basis models. ACM Transactions on Graphics, 31(2), Article 17. https://doi.org/10.1145/2159516.2159523
4. Alarcón-Aldana, A. C., Callejas-Cuervo, M., & Bo, A. P. L. (2020). Upper limb physical rehabilitation using serious videogames and motion capture systems: A systematic review. Sensors, 20(21), 5989. https://doi.org/10.3390/s20215989
5. Allen, B., Curless, B., & Popović, Z. (2003). The space of human body shapes: Reconstruction and parameterization from range scans. In ACM SIGGRAPH 2003 Papers (pp. 587-594). Association for Computing Machinery. https://doi.org/10.1145/1201775.882311
6. An, W. C., Ngali, M. Z., Kaharuddin, Z., & Khairu Razak, S. B. (2017). Performance of dual depth camera motion capture system for athletes' biomechanics analysis. MATEC Web of Conferences, 135, 00059. https://doi.org/10.1051/matecconf/201713500059
7. Arent, I., Schmidt, F. P., Botsch, M., & Dürr, V. (2021). Marker-less motion capture of insect locomotion with deep neural networks pre-trained on synthetic videos. Frontiers in Behavioral Neuroscience, 15, 637806. https://doi.org/10.3389/fnbeh.2021.637806
8. Arsenault, D., & Whitehead, A. (2015). Wearable sensor networks for motion capture. In SG EAI. https://doi.org/10.4108/icst.intetain.2015.259265
9. Arus, E., Ph.D. (2017). Biomechanics of human motion: Applications in the martial arts (2nd ed.). CRC Press. https://doi.org/10.1201/b22446
10. Banerjee, D., & Yu, K. (2019). Integrated test automation for evaluating a motion-based image capture system using a robotic arm. IEEE Access, 7, 1888-1896. https://doi.org/10.1109/ACCESS.2018.2886272
11. Beeler, T., Hahn, F., Bradley, D., Bickel, B., Beardsley, P., Gotsman, C., Sumner, R. W., & Gross, M. (2011). High-quality passive facial performance capture using anchor frames. ACM Transactions on Graphics, 30(4), 75. https://doi.org/10.1145/2010324.1964970
12. Bernardina, G. R. D., Cerveri, P., Barros, R. M. L., Marins, J. C. B., & Silvatti, A. P. (2016). Action sport cameras as an instrument to perform a 3D underwater motion analysis. PLoS ONE, 11(8), e0160490. https://doi.org/10.1371/journal.pone.0160490
13. Boddy, K. J., Marsh, J. A., Caravan, A., Lindley, K. E., Scheffey, J. O., & O'Connell, M. E. (2019). Exploring wearable sensors as an alternative to marker-based motion capture in the pitching delivery. PeerJ, 7, e6365. https://doi.org/10.7717/peerj.6365
14. Bosco, G., Delle Monache, S., Gravano, S., Indovina, I., La Scaleia, B., Maffei, V., Zago, M., & Lacquaniti, F. (2015). Filling gaps in visual motion for target capture. Frontiers in Integrative Neuroscience, 9, 13. https://doi.org/10.3389/fnint.2015.00013

15. Bravo, D. A., & Rengifo, C. F. R. (2015). Trajectory generation from motion capture for a planar biped robot in swing phase. Ingeniería Y Ciencia, 11(22), 25-47. https://doi.org/10.17230/ingciencia.11.22.2
16. Burger, B., & Toiviainen, P. (2013). MoCap Toolbox -- A Matlab toolbox for computational analysis of movement data. In R. Bresin (Ed.), Proceedings of the 10th Sound and Music Computing Conference (pp. 172-178). KTH Royal Institute of Technology.
17. Calderita, L. V., Bandera, J. P., Bustos, P., & Skiadopoulos, A. (2013). Model-based reinforcement of Kinect depth data for human motion capture applications. Sensors, 13(7), 8835-8855. https://doi.org/10.3390/s130708835
18. Canton-Ferrer, C., Casas, J. R., & Pardàs, M. (2010). Marker-based human motion capture in multiview sequences. EURASIP Journal on Advances in Signal Processing, 2010(1), 105476. https://doi.org/10.1155/2010/105476
19. Chanpimol, S., Seamon, B., Hernandez, H., Harris-Love, M., & Blackman, M. R. (2017). Using Xbox Kinect motion capture technology to improve clinical rehabilitation outcomes for balance and cardiovascular health in an individual with chronic TBI. Archives of Physiotherapy, 7(1). https://doi.org/10.1186/s40945-017-0033-9
20. Chatterton, G. J., Hansen, J. B., Kristiansen, N. H., Kunwald, N. P., Kersting, U. G., & Oliveira, A. S. (2022). Assessing kinematics and kinetics of high-speed running using inertial motion capture: A preliminary analysis. ISBS Proceedings Archive, 40(1), Article 29. Available at https://commons.nmu.edu/isbs/vol40/iss1/29
21. Chatzitofis, A., Zarpalas, D., Kollias, S., & Daras, P. (2019). DeepMoCap: Deep optical motion capture using multiple depth sensors and retro-reflectors. Sensors, 19(2), 282. https://doi.org/10.3390/s19020282
22. Chaumeil, A., Lahkar, B. K., Dumas, R., Muller, A., & Robert, T. (2022). Accuracy of a markerless motion capture system for balance related quantities. bioRxiv. https://doi.org/10.1101/2022.11.10.515951
23. Chen, H., Schall, M. C., & Fethke, N. B. (2020). Measuring upper arm elevation using an inertial measurement unit: An exploration of sensor fusion algorithms and gyroscope models. Applied Ergonomics, 89, 103187. https://doi.org/10.1016/j.apergo.
24. Chen, P., Kuang, Y., & Li, J. (2016). Human motion capture algorithm based on inertial sensors. Journal of Sensors, 2016(1), 4343797. https://doi.org/10.1155/2016/4343797
25. Chen, S., Zhao, X., Luo, B., & Sun, Z. (2020). Visual browse and exploration in motion capture data with phylogenetic tree of context-aware poses. Sensors, 20(18), 5224. https://doi.org/10.3390/s20185224
26. Cheng, X., Gu, Y., Chen, B., Zhang, Y., & Shi, J. (2019). Weighted multiple instance-based deep correlation filter for video tracking processing. IEEE Access, 7, 161220-161230. https://doi.org/10.1109/ACCESS.2019.2951600
27. Chèze, L. (2014). Kinematic analysis of human movement. John Wiley & Sons, Inc. https://doi.org/10.1002/9781119058144
28. Cler, J. (2016). Commentary on "Measuring Aksak Rhythm and Synchronization in Transylvanian Village Music by Using Motion Capture". Empirical Musicology Review, 10(4), 302-304. https://doi.org/10.18061/emr.v10i4.4960
29. Climent-Pérez, P., & Florez-Revuelta, F. (2021). Improved action recognition with separable spatio-temporal attention using alternative skeletal and video pre-processing. Sensors, 21(3), 1005. https://doi.org/10.3390/s21031005
30. Clouthier, A. L., Ross, G. B., Mavor, M. P., Coll, I., Boyle, A., & Graham, R. B. (2021). Development and validation of a deep learning algorithm and open-source platform for the automatic labelling of motion capture markers. IEEE Access, 9, 36444-36454. https://doi.org/10.1109/ACCESS.2021.3062748
31. Cotton, S., Vanoncini, M., Fraisse, P., Ramdani, N., Demircan, E., Murray, A. P., & Keller, T. (2011). Estimation of the centre of mass from motion capture and force plate recordings: A

study on the elderly. Applied Bionics and Biomechanics, 8(3-4), 123246. https://doi.org/10.3233/ABB-2011-0006

32. Cuadrado, J., Michaud, F., Lugrís, U., & Pérez Soto, M. (2021). Using accelerometer data to tune the parameters of an extended Kalman filter for optical motion capture: Preliminary application to gait analysis. Sensors, 21(2), 427. https://doi.org/10.3390/s21020427
33. Dahan, A., Noy, L., Hart, Y., Mayo, A., & Alon, U. (2016). Exit from synchrony in joint improvised motion. PLoS ONE, 11(10), e0160747. https://doi.org/10.1371/journal.pone.0160747
34. Das, K., de Paula Oliveira, T., & Newell, J. (2023). Comparison of markerless and marker-based motion capture systems using 95% functional limits of agreement in a linear mixed-effects modelling framework. Scientific Reports, 13, 22880. https://doi.org/10.1038/s41598-023-49360-2
35. De la Torre, J., Marin Bone, J., Ilarri, S., & Marin, J. (2020). Applying machine learning for healthcare: A case study on cervical pain assessment with motion capture. Applied Sciences, 10(17), 5942. https://doi.org/10.3390/app10175942
36. Delamare, M., Duval, F., & Boutteau, R. (2020). A new dataset of people flow in an industrial site with UWB and motion capture systems. Sensors, 20(16), 4511. https://doi.org/10.3390/s20164511
37. Dockstader, S. L., & Tekalp, A. M. (2002). A kinematic model for human motion and gait analysis. In Proceedings. Retrieved from https://api.semanticscholar.org/CorpusID:18322318
38. Dong, R., Cai, D., & Ikuno, S. (2020). Motion capture data analysis in the instantaneous frequency-domain using Hilbert-Huang transform. Sensors, 20(22), 6534. https://doi.org/10.3390/s20226534
39. Drapeaux, A., & Carlson, K. (2020). A comparison of inertial motion capture systems: DorsaVi and Xsens. International Journal of Kinesiology and Sports Science, 8(3), 24-27. https://doi.org/10.7575/aiac.ijkss.v.8n.3p.24
40. Dudzik, S. (2020). Application of the motion capture system to estimate the accuracy of a wheeled mobile robot localization. Energies, 13(23), 6437. https://doi.org/10.3390/en13236437
41. Dürsteler, M. R. (2014). A common framework for the analysis of complex motion? Standstill and capture illusions. Frontiers in Human Neuroscience, 8, 999. https://doi.org/10.3389/fnhum.2014.00999
42. Farella, E., Benini, L., Riccò, B., & Acquaviva, A. (2007). MOCA: A low-power, low-cost motion capture system based on integrated accelerometers. Advances in Multimedia, 2007(1), 082638. https://doi.org/10.1155/2007/82638
43. Fischer, G., Jermann, D., List, R., Reissner, L., & Calcagni, M. (2020). Development and application of a motion analysis protocol for the kinematic evaluation of basic and functional hand and finger movements using motion capture in a clinical setting—A repeatability study. Applied Sciences, 10(18), 6436. https://doi.org/10.3390/app10186436
44. Fleet, D. J. (2011). Motion models for people tracking. In T. B. Moeslund, A. Hilton, V. Krüger, & L. Sigal (Eds.), Visual analysis of humans: Looking at people (pp. 171-198). Springer London. https://doi.org/10.1007/978-0-85729-997-0_10
45. Fonk, R., Schneeweiss, S., Simon, U., & Engelhardt, L. (2021). Hand motion capture from a 3D Leap Motion controller for a musculoskeletal dynamic simulation. Sensors, 21(4), 1199. https://doi.org/10.3390/s21041199
46. Freire, S., Santos, G., Armondes, A., Meneses, E. A. L., & Wanderley, M. M. (2020). Evaluation of inertial sensor data by a comparison with optical motion capture data of guitar strumming gestures. Sensors, 20(19), 5722. https://doi.org/10.3390/s20195722
47. Fu, Q., Zhang, X., Xu, J., & Zhang, H. (2020). Capture of 3D human motion pose in virtual reality based on video recognition. Complexity, 2020(1), 8857748. https://doi.org/10.1155/2020/8857748

48. Furtado, S., Galna, B., Godfrey, A., Rochester, L., & Gerrand, C. (2024). Feasibility of using low-cost markerless motion capture for assessing functional outcomes after lower extremity musculoskeletal cancer surgery. PLoS ONE, 19(3), e0300351. https://doi.org/10.1371/journal.pone.0300351
49. Gamulescu, O. M., Rosca, S. D., Panaite, F., Costandoiu, A., & Riurean, S. (2020). Accident sites management using drones. MATEC Web of Conferences, 305, 00004. https://doi.org/10.1051/matecconf/202030500004
50. Ganguly, A., Rashidi, G., & Mombaur, K. (2021). Comparison of the performance of the Leap Motion Controller™ with a standard marker-based motion capture system. Sensors, 21(5), 1750. https://doi.org/10.3390/s21051750
51. Gao, Z., Yu, Y., Zhou, Y., & Du, S. (2015). Leveraging two Kinect sensors for accurate full-body motion capture. Sensors, 15(9), 24297-24317. https://doi.org/10.3390/s150924297
52. García-Pinillos, F., Jaén-Carrillo, D., Soto Hermoso, V., Latorre Román, P., Delgado, P., Martinez, C., Carton, A., & Roche Seruendo, L. (2020). Agreement between spatiotemporal gait parameters measured by a markerless motion capture system and two reference systems—a treadmill-based photoelectric cell and high-speed video analyses: Comparative study. JMIR Mhealth and Uhealth, 8(10), e19498. https://doi.org/10.2196/19498
53. Gasparutto, X., Wegrzyk, J., Rose-Dulcina, K., Hannouche, D., & Armand, S. (2020). Can the fusion of motion capture and 3D medical imaging reduce the extrinsic variability due to marker misplacements? PLOS ONE, 15(1), e0226648. https://doi.org/10.1371/journal.pone.0226648
54. Giarmatzis, G., Zacharaki, E. I., & Moustakas, K. (2020). Real-time prediction of joint forces by motion capture and machine learning. Sensors, 20(23), 6933. https://doi.org/10.3390/s20236933
55. Gleicher, M. (2002). Motion graphs. In Proceedings of the 29th annual conference on Computer graphics and interactive techniques - SIGGRAPH '02 (10 pages).
56. Grochow, K., Martin, S. L., Hertzmann, A., & Popović, Z. (2004). Style-based inverse kinematics. ACM Transactions on Graphics (Proc. SIGGRAPH'04). Retrieved from https://grail.cs.washington.edu/projects/styleik/styleik.pdf
57. Guo, H., & Sung, Y. (2020). Movement estimation using soft sensors based on Bi-LSTM and two-layer LSTM for human motion capture. Sensors, 20(6), 1801. https://doi.org/10.3390/s20061801
58. Guo, L., & Xiong, S. (2017). Accuracy of base of support using an inertial sensor based motion capture system. Sensors, 17(9), 2091. https://doi.org/10.3390/s17092091
59. Hafer, J. F., Mihy, J. A., Hunt, A., Zernicke, R. F., & Johnson, R. T. (2022). IMU-derived kinematics detect gait differences with age or knee osteoarthritis but differ from marker-derived inverse kinematics. medRxiv. https://doi.org/10.1101/2022.01.10.22269024
60. Halvorson, R. T., Castillo, F. T., Ahamed, F., Khattab, K., Scheffler, A., Matthew, R. P., et al. (2022). Point-of-care motion capture and biomechanical assessment improve clinical utility of dynamic balance testing for lower extremity osteoarthritis. PLOS Digital Health, 1(7), e0000068. https://doi.org/10.1371/journal.pdig.0000068
61. Hamill, J. (2010, July). Real-time measurement using EMG and motion capture systems. In XXVIII International Symposium of Biomechanics in Sports (pp. 78-81). Marquette, MI, USA. Url: https://ojs.ub.uni-konstanz.de/cpa/article/view/4385
62. Hamilton, L., Franklin, R. J. M., & Jeffery, N. D. (2007). Development of a universal measure of quadrupedal forelimb-hindlimb coordination using digital motion capture and computerised analysis. BMC Neuroscience, 8(1), 77. https://doi.org/10.1186/1471-2202-8-77
63. Harsted, S., Holsgaard-Larsen, A., Hestbæk, L., et al. (2019). Concurrent validity of lower extremity kinematics and jump characteristics captured in pre-school children by a markerless 3D motion capture system. Chiropractic & Manual Therapies, 27, 39. https://doi.org/10.1186/s12998-019-0261-z

64. Herda, L., Fua, P., Plankers, R., Boulic, R., & Thalmann, D. (2000). Skeleton-based motion capture for robust reconstruction of human motion. In Proceedings of Computer Animation 2000 (pp. 77-83). https://doi.org/10.1109/CA.2000.889046
65. Hindle, B. R., Keogh, J. W. L., & Lorimer, A. V. (2021). Inertial-based human motion capture: A technical summary of current processing methodologies for spatiotemporal and kinematic measures. Applied Bionics and Biomechanics, 2021(1), 6628320. https://doi.org/10.1155/2021/6628320
66. Hodgins, J. K., Wooten, W. L., Brogan, D. C., & O'Brien, J. F. (1995). Animating human athletics. In Proceedings of the 22nd Annual Conference on Computer Graphics and Interactive Techniques (pp. 71-78). Association for Computing Machinery. https://doi.org/10.1145/218380.218414
67. Hu, H., Cao, Z., Yang, X., Xiong, H., & Lou, Y. (2021). Performance evaluation of optical motion capture sensors for assembly motion capturing. IEEE Access, 9, 61444-61454. https://doi.org/10.1109/ACCESS.2021.3074260
68. Hu, S., Dai, M., Dong, T., & Liu, T. (2019). A textile sensor for long durations of human motion capture. Sensors, 19(10), 2369. https://doi.org/10.3390/s19102369
69. Hwang, J., Ishii, S., Kwon, T., & Oba, S. (2020). Modularized predictive coding-based online motion synthesis combining environmental constraints and motion-capture data. IEEE Access, 8, 202274-202285. https://doi.org/10.1109/ACCESS.2020.3036449
70. Iliyasu, A. M. (2013). Towards realising secure and efficient image and video processing applications on quantum computers. Entropy, 15(8), 2874-2974. https://doi.org/10.3390/e15082874
71. Imanullah, M., Yuniarno, E. M., & Sooai, A. G. (2019). A novel approach in low-cost motion capture system using color descriptor and stereo webcam. International Journal of Technology, 10(5), 291-319. https://doi.org/10.14716/ijtech.v10i5.2789
72. Jackson, B. E., Evangelista, D. J., Ray, D. D., & Hedrick, T. L. (2016). 3D for the people: Multi-camera motion capture in the field with consumer-grade cameras and open source software. Biology Open, 5(9), 1334-1342. https://doi.org/10.1242/bio.018713
73. Jaume-i-Capó, A., Varona, J., González-Hidalgo, M., & Perales, F. J. (2009). Adding image constraints to inverse kinematics for human motion capture. EURASIP Journal on Advances in Signal Processing, 2010, 142354. https://doi.org/10.1155/2010/142354
74. Jensen, G. W., van der Smagt, P., Heiss, E., Straka, H., & Kohl, T. (2020). SnakeStrike: A low-cost open-source high-speed multi-camera motion capture system. Frontiers in Behavioral Neuroscience, 14, 116. https://doi.org/10.3389/fnbeh.2020.00116
75. Jiao, C., Yang, J., Wang, X., & Liang, B. (2019). Adaptive coordinated motion control with variable forgetting factor for a dual-arm space robot in post-capture of a noncooperative target. International Journal of Advanced Robotic Systems, 16(5). https://doi.org/10.1177/1729881419872342
76. Johnson-Glenberg, M. C., & Megowan-Romanowicz, C. (2017). Embodied science and mixed reality: How gesture and motion capture affect physics education. Cognitive Research: Principles and Implications, 2(1), 24. https://doi.org/10.1186/s41235-017-0060-9
77. Kadirvelu, B., Gavriel, C., Nageshwaran, S., et al. (2023). A wearable motion capture suit and machine learning predict disease progression in Friedreich's ataxia. Nature Medicine, 29(1), 86-94. https://doi.org/10.1038/s41591-022-02159-6
78. Kanade, T., & Narayanan, P. J. (2007). Virtualized reality: Perspectives on 4D digitization of dynamic events. IEEE Computer Graphics and Applications, 27(3), 32-40. https://doi.org/10.1109/MCG.2007.72
79. Kang, J., Badi, B., Zhao, Y., & Wright, D. K. (n.d.). Human motion modeling and simulation by anatomical approach. Brunel University. Retrieved from http://ndl.ethernet.edu.et/bitstream/123456789/88742/1/2017_Book_FundamentalsOfBiomechanics.pdf

80. Kanko, R. M., Laende, E. K., Davis, E. M., Selbie, W. S., & Deluzio, K. J. (2021). Concurrent assessment of gait kinematics using marker-based and markerless motion capture. Journal of Biomechanics, 127, 110665. https://doi.org/10.1016/j.jbiomech.2021.110665
81. Karatsidis, A., Bellusci, G., Schepers, H. M., De Zee, M., Andersen, M. S., & Veltink, P. H. (2017). Estimation of ground reaction forces and moments during gait using only inertial motion capture. Sensors, 17(1), 75. https://doi.org/10.3390/s17010075
82. Keizer, M. N. J., & Otten, E. (2020). Technical note: Sensitivity analysis of the SCoRE and SARA methods for determining rotational axes during tibiofemoral movements using optical motion capture. Journal of Experimental Orthopaedics, 7, 6. https://doi.org/10.1186/s40634-020-0219-z
83. Kessler, S. E., Rainbow, M. J., Lichtwark, G. A., Cresswell, A. G., D'Andrea, S. E., Konow, N., & Kelly, L. A. (2019). A direct comparison of biplanar videoradiography and optical motion capture for foot and ankle kinematics. Frontiers in Bioengineering and Biotechnology, 7, 199. https://doi.org/10.3389/fbioe.2019.00199
84. Kim, Y. (2017). Dance motion capture and composition using multiple RGB and depth sensors. International Journal of Distributed Sensor Networks, 13(2). https://doi.org/10.1177/1550147717696083
85. Kim, S., & Nussbaum, M. A. (2014). Evaluation of two approaches for aligning data obtained from a motion capture system and an in-shoe pressure measurement system. Sensors, 14(9), 16994-17007. https://doi.org/10.3390/s140916994
86. Kim, B.-G. (2020). Digital signal, image and video processing for emerging multimedia technology. Electronics, 9(12), 2012. https://doi.org/10.3390/electronics9122012
87. Kita, Y., Gunji, A., Sakuma, R., Goto, T., Okumura, Y., & Inagaki, M. (2017). Training attention to the other's need improves helping behaviors in children with autism spectrum disorder: A behavioral analysis using a two-dimensional motion capture system. Frontiers in Education, 2. https://doi.org/10.3389/feduc.2017.00050
88. Kitzig, A., Demmer, J., Bolten, T., Naroska, E., Stockmanns, G., Viga, R., & Grabmaier, A. (2018). An HMM-based averaging approach for creating mean motion data from a full-body motion capture system to support the development of a biomechanical model. Current Directions in Biomedical Engineering, 4(1), 389-393. https://doi.org/10.1515/cdbme-2018-0093
89. Knight, J. (2008). Rotation points from motion capture data using a closed form solution. In Proceedings. https://api.semanticscholar.org/CorpusID:61197979
90. Knippenberg, E., Verbrugghe, J., Lamers, I., Palmaers, S., Timmermans, A., & Spooren, A. (2017). Markerless motion capture systems as training device in neurological rehabilitation: A systematic review of their use, application, target population and efficacy. Journal of NeuroEngineering and Rehabilitation, 14(1), 61. https://doi.org/10.1186/s12984-017-0270-x
91. Knyaz, V. A. (2015). SCALABLE PHOTOGRAMMETRIC MOTION CAPTURE SYSTEM "MOSCA": Development and application. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XL-5/W6, 43-49. https://doi.org/10.5194/isprsarchives-XL-5-W6-43-2015
92. Kokubu, T., Mifune, Y., Inui, A., Kuroda, R., & Kurosaka, M. (2016). Clinical outcome of arthroscopic fixation for glenoid fracture using a double threaded screw. Asia-Pacific Journal of Sports Medicine, Arthroscopy, Rehabilitation and Technology, 6, 34. https://doi.org/10.1016/j.asmart.2016.07.079
93. Kopf, M., Schulder, M., & Hanke, T. (2022). The Sign Language Dataset Compendium: Creating an overview of digital linguistic resources. In E. Efthimiou, S.-E. Fotinea, T. Hanke, J. A. Hochgesang, J. Kristoffersen, J. Mesch, & M. Schulder (Eds.), Proceedings of the LREC2022 10th Workshop on the Representation and Processing of Sign Languages: Multilingual Sign Language Resources (pp. 102-109). European Language Resources Association (ELRA). https://www.sign-lang.uni-hamburg.de/lrec/pub/22025.pdf

94. Kruglov, A., Chiryshev, A., & Shishko, E. (2016). Applying of the NVIDIA CUDA to the video processing in the task of the roundwood volume estimation. ITM Web of Conferences, 8, 01009. https://doi.org/10.1051/itmconf/20160801009
95. Kumar, K., Varghese, A., Reddy, P., Narendra, N., Swamy, P., Chandra, M., & Purushothaman, B. (2014). An improved tracking using IMU and vision fusion for mobile augmented reality applications. The International Journal of Multimedia & Its Applications, 6. https://doi.org/10.5121/ijma.2014.6502
96. Kurniati, N., Basuki, A., & Pramadihanto, D. (2016). Remo dance motion estimation with markerless motion capture using the optical flow method. EMITTER International Journal of Engineering Technology, 3(1), 1-18. https://doi.org/10.24003/emitter.v3i1.33
97. Kwon, T., & Hodgins, J. (2010). Control systems for human running using an inverted pendulum model and a reference motion capture sequence. In Z. Popovic & M. Otaduy (Eds.), Eurographics/ACM SIGGRAPH Symposium on Computer Animation (pp. 129-138). The Eurographics Association. https://doi.org/10.2312/SCA/SCA10/129-138
98. Lee, J. K., & Jung, W. C. (2018). Quaternion-based local frame alignment between an inertial measurement unit and a motion capture system. Sensors, 18(11), 4003. https://doi.org/10.3390/s18114003
99. Lewis, J. P., Cordner, M., & Fong, N. (2023). Pose space deformation: A unified approach to shape interpolation and skeleton-driven deformation (Doctoral dissertation). Association for Computing Machinery. https://doi.org/10.1145/3596711.3596796
100. Li, W., Zeng, Y., Zhang, Q., Wu, Y., & Chen, G. (2021). Human motion capture based on incremental dimension reduction and projection position optimization. Wireless Communications and Mobile Computing, 2021, 5589100. https://doi.org/10.1155/2021/5589100
101. Li, M., Zhou, Z., & Liu, X. (2020). 3D hypothesis clustering for cross-view matching in multi-person motion capture. Computational Visual Media, 6, 147-156. https://doi.org/10.1007/s41095-020-0171-y
102. Li, J., Zhang, J., Wang, Z., Shen, S., Wen, C., Ma, Y., Xu, L., Yu, J., & Wang, C. (2022). LiDARCap: Long-range markerless 3D human motion capture with LiDAR point clouds. In 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 20470-20480). https://doi.org/10.1109/CVPR52688.2022.01985
103. Li, C. (2020). Badminton motion capture with visual image detection of picking robotics. International Journal of Advanced Robotic Systems, 17(6). https://doi.org/10.1177/1729881420969072
104. Li, S., Cui, L., Zhu, C., Li, B., Zhao, N., & Zhu, T. (2016). Emotion recognition using Kinect motion capture data of human gaits. PeerJ, 4, e2364. https://doi.org/10.7717/peerj.2364
105. Li, J., Xiao, D., Li, K., & Li, J. (2021). Graph matching for marker labeling and missing marker reconstruction with bone constraint by LSTM in optical motion capture. IEEE Access, 9, 34868-34881. https://doi.org/10.1109/ACCESS.2021.3060385
106. Ligorio, G., & Sabatini, A. M. (2016). Dealing with magnetic disturbances in human motion capture: A survey of techniques. Micromachines, 7(3), 43. https://doi.org/10.3390/mi7030043
107. Long, J., & Jones, M. D. (2013). Reconstructing 3D tree models using motion capture and particle flow. International Journal of Computer Games Technology, 2013(1), 363160. https://doi.org/10.1155/2013/363160
108. Ma, H., Yan, W., Yang, Z., & Liu, H. (2019). Real-time foot-ground contact detection for inertial motion capture based on an adaptive weighted naive Bayes model. IEEE Access, 7, 130312-130326. https://doi.org/10.1109/ACCESS.2019.2939839
109. Maidhof, C., Pitkäniemi, A., & Tervaniemi, M. (2013). Predictive error detection in pianists: A combined ERP and motion capture study. Frontiers in Human Neuroscience, 7, 587. https://doi.org/10.3389/fnhum.2013.00587
110. Marin, J., Blanco, T., & Marin, J. J. (2017). Octopus: A design methodology for motion capture wearables. Sensors, 17(8), 1875. https://doi.org/10.3390/s17081875

111. Markova, K., Dovramadjiev, T., & Jecheva, G. (2017, December 28). Computer parametric designing in Blender software for creating 3D paper models. Annual Journal of Technical University of Varna, Bulgaria, 1(1), 77-84. https://doi.org/10.29114/ajtuv.vol1.iss1.44
112. Martinez, H. R., Garcia-Sarreon, A., Camara-Lemarroy, C., Salazar, F., & Guerrero-González, M. L. (2018). Accuracy of markerless 3D motion capture evaluation to differentiate between On/Off status in Parkinson's disease after deep brain stimulation. Parkinson's Disease, 2018, 5830364. https://doi.org/10.1155/2018/5830364
113. Masiero, A., Fissore, F., Antonello, R., Cenedese, A., & Vettore, A. (2019). A comparison of UWB and motion capture UAV indoor positioning. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLII-2/W13, 1695-1699. https://doi.org/10.5194/isprs-archives-XLII-2-W13-1695-2019
114. Maulana, G. G., Erdani, Y., Budiyarto, A., & Purnomo, W. (2018). Design and building motion capture system using transducer Microsoft Kinect to control robot humanoid. MATEC Web of Conferences, 197, 11007. https://doi.org/10.1051/matecconf/201819711007
115. Mazzarella, J., McNally, M., Richie, D., Chaudhari, A. M. W., Buford, J. A., Pan, X., & Heathcock, J. C. (2020). 3D motion capture may detect spatiotemporal changes in pre-reaching upper extremity movements with and without a real-time constraint condition in infants with perinatal stroke and cerebral palsy: A longitudinal case series. Sensors, 20(24), 7312. https://doi.org/10.3390/s20247312
116. Menolotto, M., Komaris, D.-S., Tedesco, S., O'Flynn, B., & Walsh, M. (2020). Motion capture technology in industrial applications: A systematic review. Sensors, 20(19), 5687. https://doi.org/10.3390/s20195687
117. Merino, E., Mannrich, G., Guimarães, B., Speck, G., Matos, D., Domenech, S., & Merino, G. (2018). Implementation of integrated instrumentation in assistive technology. In F. Rebelo & M. Soares (Eds.), Advances in Ergonomics in Design (pp. 549-560). Springer International Publishing. https://doi.org/10.1007/978-3-319-60582-1_55
118. Mihálik, A., Ďurikovič, R., & Sejč, M. (2018). Application of motion capture attributes to individual identification under corridor surveillance. Journal of Applied Mathematics, Statistics and Informatics, 14(1), 37-56. https://doi.org/10.2478/jamsi-2018-0004
119. Min, X., Sun, S., Wang, H., Zhang, X., Li, C., & Zhang, X. (2019). Motion capture research: 3D human pose recovery based on RGB video sequences. Applied Sciences, 9(17), 3613. https://doi.org/10.3390/app9173613
120. Moradzadeh, A., Mansour-Saatloo, A., Mohammadi-Ivatloo, B., & Anvari-Moghaddam, A. (2020). Performance evaluation of two machine learning techniques in heating and cooling loads forecasting of residential buildings. Applied Sciences, 10(11), 3829. https://doi.org/10.3390/app10113829
121. Mündermann, L., Corazza, S., & Andriacchi, T. P. (2006). The evolution of methods for the capture of human movement leading to markerless motion capture for biomechanical applications. Journal of NeuroEngineering and Rehabilitation, 3(1), 6. https://doi.org/10.1186/1743-0003-3-6
122. Naeemabadi, M., Dinesen, B., Andersen, O. K., & Hansen, J. (2018). Investigating the impact of a motion capture system on Microsoft Kinect v2 recordings: A caution for using the technologies together. PLOS ONE, 13(9), 1-17. https://doi.org/10.1371/journal.pone.0204052
123. Nakamura, T., Koga, H., Horie, M., Watanabe, T., Yagishita, K., Sekiya, I., & Muneta, T. (2016). Postoperative outcome is affected by an intraoperative combination of each graft tension change pattern in a double-bundle anterior cruciate ligament reconstruction. Asia-Pacific Journal of Sports Medicine, Arthroscopy, Rehabilitation and Technology, 6, 1-6. https://doi.org/10.1016/j.asmart.2016.08.002
124. Nakamura, T., Matsumoto, J., Nishimaru, H., Bretas, R. V., Takamura, Y., Hori, E., ... & Ono, T. (2016). A markerless 3D computerized motion capture system incorporating a skeleton model for monkeys. PLoS ONE, 11(11), e0166154. https://doi.org/10.1371/journal.pone.0166154

125. Nakano, N., Sakura, T., Ueda, K., Omura, L., Kimura, A., Iino, Y., Fukashiro, S., & Yoshioka, S. (2020). Evaluation of 3D markerless motion capture accuracy using OpenPose with multiple video cameras. Frontiers in Sports and Active Living, 2, 50. https://doi.org/10.3389/fspor.2020.00050
126. National Health and Nutrition Examination Survey (U.S.), National Center for Health Statistics (U.S.), & Westat. (1988, October). National Health and Nutrition Examination Survey III: Body measurements (anthropometry). https://stacks.cdc.gov/view/cdc/53134
127. Nicolella, D. P., Torres-Ronda, L., Saylor, K. J., & Schelling, X. (2018). Validity and reliability of an accelerometer-based player tracking device. PLoS ONE, 13(2), e0191823. https://doi.org/10.1371/journal.pone.0191823
128. Niu, J., Wang, X., Wang, D., & Ran, L. (2020). A novel method of human joint prediction in an occlusion scene by using low-cost motion capture technique. Sensors, 20(4), 1119. https://doi.org/10.3390/s20041119
129. O'Brien, J. F., Bodenheimer, R. E., Brostow, G. J., & Hodgins, J. K. (2000, May). Automatic joint parameter estimation from magnetic motion capture data. In Proceedings of Graphics Interface 2000 (pp. 53-60). Retrieved from http://graphics.cs.berkeley.edu/papers/Obrien-AJP-2000-05/
130. Olar, M. L., Risteiu, M., Panaite, A. F., Rebrisoreanu, M., & Musetoiu, O. (2020). Controlling a robotic arm with augmented reality. MATEC Web of Conferences, 305, 00022. https://doi.org/10.1051/matecconf/202030500022
131. Olar, M. L., Panaite, A. F., Leba, M., & Sibișanu, R. (2021). Stewart platform modified into a bio-inspirational device of the human shoulder. In Á. Rocha, H. Adeli, G. Dzemyda, F. Moreira, & A. M. Ramalho Correia (Eds.), Trends and Applications in Information Systems and Technologies (pp. 151-160). Springer International Publishing. https://doi.org/10.1007/978-3-030-72654-6_15
132. Ossendorff, R., Richter, J., Heijens, E., Schildberg, F., Haeder, G., & Salzmann, G. (2023). The validity of motion capture analysis system against the gold standard long-standing radiography in the measurement of lower extremity alignment. Journal of Clinical Medicine, 12(2), 567. https://doi.org/10.3390/jcm12020567
133. Ostrek, M., Rhodin, H., Fua, P., Müller, E., & Spörri, J. (2019). Are existing monocular computer vision-based 3D motion capture approaches ready for deployment? A methodological study on the example of alpine skiing. Sensors, 19(19), 4323. https://doi.org/10.3390/s19194323
134. Özkaya, N., Leger, D., Goldsheyder, D., & Nordin, M. (2017). Fundamentals of biomechanics: Equilibrium, motion, and deformation (4th ed.). Springer International Publishing. https://doi.org/10.1007/978-3-319-44738-4
135. Panaite, A. F., Leba, M., Olar, M. L., Sibisanu, R. C., & Pellegrini, L. (2021). Human arm motion capture using gyroscopic sensors. MATEC Web of Conferences, 343, 08007. https://doi.org/10.1051/matecconf/202134308007
136. Panaite, A. F., Rosca, S., & Sibişanu, R. (2021). Pose and motion capture technologies. MATEC Web of Conferences, 342, 05004. https://doi.org/10.1051/matecconf/202134205004
137. Panaite, A., Rîsteiu, M.-N., Olar, M., Leba, M., & Ionica, A. (2019). Hand rehabilitation - a gaming experience. IOP Conference Series: Materials Science and Engineering, 572, 012092. https://doi.org/10.1088/1757-899X/572/1/012092
138. Panaite, A. F., & Bogdanffy, L. (2019). Reimagining vision with infinity mirrors. MATEC Web of Conferences, 290, 01011. https://doi.org/10.1051/matecconf/201929001011
139. Park, H. S., Kim, J. Y., Kim, J. G., Choi, S. W., & Kim, Y. (2013). A new position measurement system using a motion-capture camera for wind tunnel tests. Sensors, 13(9), 12329-12344. https://doi.org/10.3390/s130912329
140. Petrosyan, T., Dunoyan, A., & Mkrtchyan, H. (2020). Application of motion capture systems in ergonomic analysis. Armenian Journal of Special Education, 4(2), 107-117. https://doi.org/10.24234/se.2020.1.1.157

141. Prameswari, S. J., Basori, & Wihidayat, E. S. (2019). The comparison between the use of Blender and 3DS Max application toward students' comprehension of 3D animation subject at vocational school in Surakarta. Indonesian Journal of Informatics Education, 3(2). https://doi.org/10.20961/ijie.v3i2.25200
142. Protopapadakis, E., Voulodimos, A., Doulamis, A., Camarinopoulos, S., Doulamis, N., & Miaoulis, G. (2018). Dance pose identification from motion capture data: A comparison of classifiers. Technologies, 6(1), 31. https://doi.org/10.3390/technologies6010031
143. Rallis, I., Protopapadakis, E., Voulodimos, A., Doulamis, N., Doulamis, A., & Bardis, G. (2019). Choreographic pattern analysis from heterogeneous motion capture systems using dynamic time warping. Technologies, 7(3), 56. https://doi.org/10.3390/technologies7030056
144. Rambely, A. S., & Fazrolrozi. (2012). A six-link kinematic chain model of human body using Kane's method. International Journal of Modern Physics: Conference Series, 9, 59-67. https://doi.org/10.1142/S2010194512005107
145. Reis, P. M. R., & Lochmann, M. (2015). Using a motion capture system for spatial localization of EEG electrodes. Frontiers in Neuroscience, 9, 130. https://doi.org/10.3389/fnins.2015.00130
146. Ren, T., Li, W., Jiang, Z., Li, X., Huang, Y., & Peng, J. (2020). Video-based human motion capture data retrieval via MotionSet Network. IEEE Access, 8, 186212-186221. https://doi.org/10.1109/ACCESS.2020.3030258
147. Reuter, A. S., & Schindler, M. (2023). Motion capture systems and their use in educational research: Insights from a systematic literature review. Education Sciences, 13(2), 167. https://doi.org/10.3390/educsci13020167
148. Riazati, S., McGuirk, T. E., Perry, E. S., Sihanath, W. B., & Patten, C. (2022). Absolute reliability of gait parameters acquired with markerless motion capture in living domains. Frontiers in Human Neuroscience, 16. https://doi.org/10.3389/fnhum.2022.867474
149. Ricci, L., Formica, D., Sparaci, L., Lasorsa, F. R., Taffoni, F., Tamilia, E., & Guglielmelli, E. (2014). A new calibration methodology for thorax and upper limbs motion capture in children using magneto and inertial sensors. Sensors, 14(1), 1057-1072. https://doi.org/10.3390/s140101057
150. Richter, C., Daniels, K. A. J., King, E., & Franklyn-Miller, A. (2020). Agreement between inertia and optical based motion capture during the VU-Return-to-Play field test. Sensors, 20(3), 831. https://doi.org/10.3390/s20030831
151. Rigoni, M., Gill, S., Babazadeh, S., Elsewaisy, O., Gillies, H., Nguyen, N., Pathirana, P. N., & Page, R. (2019). Assessment of shoulder range of motion using a wireless inertial motion capture device—A validation study. Sensors, 19(8), 1781. https://doi.org/10.3390/s19081781
152. Roberts, R., Lewis, J. P., Anjyo, K., et al. (2019). Optimal and interactive keyframe selection for motion capture. Computational Visual Media, 5(2), 171-191. https://doi.org/10.1007/s41095-019-0138-z
153. Rosca, S. D., Leba, M., & Panaite, A. F. (2020). Modelling and simulation of 3D human arm prosthesis. In Á. Rocha, H. Adeli, L. Reis, S. Costanzo, I. Orovic, & F. Moreira (Eds.), Trends and innovations in information systems and technologies. WorldCIST 2020. Advances in intelligent systems and computing (Vol. 1160). Springer, Cham. https://doi.org/10.1007/978-3-030-45691-7_73
154. Rosiak, O., Pietrzak, N., Szczęsna, A., et al. (2024). The effect of immersive virtual reality on balance: An exploratory study on the feasibility of head-mounted displays for balance evaluation. Scientific Reports, 14, 3481. https://doi.org/10.1038/s41598-024-54274-8
155. Safonova, A., Hodgins, J. K., & Pollard, N. S. (2004). Synthesizing physically realistic human motion in low-dimensional, behavior-specific spaces. ACM Transactions on Graphics, 23(3), 514-521. https://doi.org/10.1145/1015706.1015754
156. Saucier, D., Davarzani, S., Turner, A., Luczak, T., Nguyen, P., Carroll, W., Burch V, R. F., Ball, J. E., Smith, B. K., Chander, H., et al. (2019). Closing the wearable gap—Part IV: 3D

motion capture cameras versus soft robotic sensors comparison of gait movement assessment. Electronics, 8(12), 1382. https://doi.org/10.3390/electronics8121382
157. Scott, B., Seyres, M., Philp, F., Chadwick, E. K., & Blana, D. (2022). Healthcare applications of single camera markerless motion capture: A scoping review. PeerJ, 10, e13517. https://doi.org/10.7717/peerj.13517
158. Secco, E. L., Maereg, A. T., Reid, D., & Nagar, A. K. (2018). An integrated haptic system combining VR, a markerless motion capture system, and tactile actuators. EAI Endorsed Transactions on Ambient Systems, 5(17). https://doi.org/10.4108/eai.23-3-2018.154375
159. Sekiguchi, Y., Kokubun, T., Hanawa, H., Shono, H., Tsuruta, A., & Kanemura, N. (2020). Evaluation of the validity, reliability, and kinematic characteristics of multi-segment foot models in motion capture. Sensors, 20(16), 4415. https://doi.org/10.3390/s20164415
160. Sellers, W. I., & Hirasaki, E. (2014). Markerless 3D motion capture for animal locomotion studies. Biology Open, 3(7), 656-668. https://doi.org/10.1242/bio.20148086
161. Shakir, D. I., García-Peraza-Herrera, L. C., Daga, P., Doel, T., Clarkson, M. J., Ourselin, S., & Vercauteren, T. (2017). GIFT-Grab: Real-time C++ and Python multi-channel video capture, processing and encoding API. Journal of Open Research Software, 5(1), 27. https://doi.org/10.5334/jors.169
162. Shimada, S., Golyanik, V., Li, Z., Pérez, P., Xu, W., & Theobalt, C. (2022). HULC: 3D human motion capture with pose manifold sampling and dense contact guidance. In S. Avidan, G. Brostow, M. Cissé, G. M. Farinella, & T. Hassner (Eds.), Computer Vision - ECCV 2022. Lecture Notes in Computer Science (Vol. 13682). Springer, Cham. https://doi.org/10.1007/978-3-031-20047-2_30
163. Shotton, J., et al. (2011). Real-time human pose recognition in parts from single depth images. In CVPR 2011 (pp. 1297-1304). IEEE. https://doi.org/10.1109/CVPR.2011.5995316
164. Sila-Nowicka, K., & Thakuriah, P. (2019). Multi-sensor movement analysis for transport safety and health applications. PLOS ONE, 14(1), e0210090. https://doi.org/10.1371/journal.pone.0210090
165. Skublewska-Paszkowska, M., Montusiewicz, J., Łukasik, E., Pszczoła-Pasierbiewicz, I., Baran, K. R., Smołka, J., & Pueo, B. (2016). Motion capture as a modern technology for analysing ergometer rowing. Advances in Science and Technology Research Journal, 10(29), 132-140. https://doi.org/10.12913/22998624/61941
166. Skurowski, P., & Pawlyta, M. (2019). On the noise complexity in an optical motion capture facility. Sensors, 19, 4435. https://doi.org/10.3390/s19204435
167. Slipsager, J. M., Ellegaard, A. H., Glimberg, S. L., Paulsen, R. R., Tisdall, M. D., Wighton, P., et al. (2019). Markerless motion tracking and correction for PET, MRI, and simultaneous PET/MRI. PLoS ONE, 14(4), e0215524. https://doi.org/10.1371/journal.pone.0215524
168. Snoswell, A. J., Yamada, M., Kirby, G. T. S., Singh, S. P. N., & Prow, T. W. (2020). Motion capture quantification of user variation in topical microparticle application. Frontiers in Pharmacology, 11, 1343. https://doi.org/10.3389/fphar.2020.01343
169. Sun, C., Sun, P., & Wang, P. (2015). An improvement of pose measurement method using global control points calibration. PLoS ONE, 10(7), e0133905. https://doi.org/10.1371/journal.pone.0133905
170. Suzuki, Y., Inoue, T., & Nomura, T. (2018). A simple algorithm for assimilating marker-based motion capture data during periodic human movement into models of multi-rigid-body systems. Frontiers in Bioengineering and Biotechnology, 6, 141. https://doi.org/10.3389/fbioe.2018.00141
171. Szczęsna, A., Skurowski, P., Lach, E., Pruszowski, P., Pęszor, D., Paszkuta, M., Słupik, J., Lebek, K., Janiak, M., Polański, A., et al. (2017). Inertial motion capture costume design study. Sensors, 17(3), 612. https://doi.org/10.3390/s17030612
172. Szczęsna, A., Błaszczyszyn, M., & Pawlyta, M. (2021). Optical motion capture dataset of selected techniques in beginner and advanced Kyokushin karate athletes. Scientific Data, 8, 13. https://doi.org/10.1038/s41597-021-00801-5

173. Teramoto, K., Mukainakano, R., Watanabe, H., Hashizume, H., & Sugimoto, M. (2019). 3D tracking using smartphones for a marker-based optical motion capture system. International Conference on Indoor Positioning and Indoor Navigation. Available at https://ceur-ws.org/Vol-2498/short10.pdf
174. Teranishi, N. (2016). Analysis of subthreshold current reset noise in image sensors. Sensors, 16(5), 663. https://doi.org/10.3390/s16050663
175. Texas Instruments. (2010-2019). STEM activities with TI-Nspire. Retrieved from https://www.stem.org.uk/rxt82
176. Tien, R. N., Tekriwal, A., Calame, D. J., Platt, J. P., Baker, S., Seeberger, L. C., Kern, D. S., Person, A. L., Ojemann, S. G., Thompson, J. A., & Kramer, D. R. (2022). Deep learning based markerless motion tracking as a clinical tool for movement disorders: Utility, feasibility and early experience. Frontiers in Signal Processing, 2. https://doi.org/10.3389/frsip.2022.884384
177. Tits, M., Tilmanne, J., & Dutoit, T. (2018). Robust and automatic motion-capture data recovery using soft skeleton constraints and model averaging. PLoS ONE, 13(7), e0199744. https://doi.org/10.1371/journal.pone.0199744
178. Torresani, L., Hertzmann, A., & Bregler, C. (2008). Nonrigid structure-from-motion: Estimating shape and motion with hierarchical priors. IEEE Transactions on Pattern Analysis and Machine Intelligence, 30(5), 878-892. https://doi.org/10.1109/TPAMI.2007.70752
179. Tsilomitrou, O., Gkountas, K., Evangeliou, N., & Dermatas, E. (2021). Wireless motion capture system for upper limb rehabilitation. Applied System Innovation, 4(1), 14. https://doi.org/10.3390/asi4010014
180. Usami, T., Nishida, K., Iguchi, H., Okumura, T., Sakai, H., Ida, R., Horiba, M., Kashima, S., Sahashi, K., Asai, H., Nagaya, Y., Murakami, H., Ueki, Y., & Kuroyanagi, G. (2022). Evaluation of lower extremity gait analysis using Kinect V2® tracking system. SICOT-J, 8, 27. https://doi.org/10.1051/sicotj/2022027
181. Wang, P., Wang, J., Wei, X., Meng, J., & Xun, J. (2020). Motion recurring pattern analysis: A lossless representation for motion capture databases. IEEE Access, 8, 78932-78941. https://doi.org/10.1109/ACCESS.2020.2989430
182. Wang, J.-p., Wang, S.-h., Wang, Y.-q., Hu, H., Yu, J.-w., Zhao, X., Liu, J.-l., Chen, X., & Li, Y. (2021). A data process of human knee joint kinematics obtained by motion-capture measurement. BMC Medical Informatics and Decision Making, 21(1), 121. https://doi.org/10.1186/s12911-021-01483-0
183. Wang, Q., Kurillo, G., Ofli, F., & Bajcsy, R. (2015). Evaluation of pose tracking accuracy in the first and second generations of Microsoft Kinect. [Unpublished manuscript]. https://doi.org/10.13140/RG.2.1.4789.0009
184. Welch, G., & Foxlin, E. (2002). Motion tracking: No silver bullet, but a respectable arsenal. IEEE Computer Graphics and Applications, 22(6), 24-38. https://doi.org/10.1109/MCG.2002.1046626
185. Westlund, J. K., D'Mello, S. K., & Olney, A. M. (2015). Motion Tracker: Camera-based monitoring of bodily movements using motion silhouettes. PLoS ONE, 10(6), e0130293. https://doi.org/10.1371/journal.pone.0130293
186. Wu, B., Zhu, Y., Nishimura, S., & Jin, Q. (2020). Analyzing the effects of driving experience on prebraking behaviors based on data collected by motion capture devices. IEEE Access, 8, 197337-197351. https://doi.org/10.1109/ACCESS.2020.3034594
187. Yao, S., Queathem, E., Neville, D., & Kelty-Stephen, D. (2018). Teaching movement science with full-body motion capture in an undergraduate liberal arts psychology class. Research in Learning Technology, 26. https://doi.org/10.25304/rlt.v26.2119
188. Yin, K., Loken, K., & van de Panne, M. (2007). SIMBICON: Simple biped locomotion control. ACM SIGGRAPH 2007 Papers. https://www.cs.ubc.ca/~van/papers/2007-siggraph-simbicon.pdf

189. Yun, Q., & Leng, C. (2020). Intelligent control of urban lighting system based on video image processing technology. IEEE Access, 8, 155506-155518. https://doi.org/10.1109/ACCESS.2020.3019284
190. Yükseltürk, E., Erbay, H., & Kutlu, M. (2017). Motion capture technology in sports science: 3D virtual sports platform with Kinect. Turkish Journal of Sports Medicine, 52(4), 155-162. https://doi.org/10.5152/tjsm.2017.083
191. Zakhem, E., Murphy, S. V., Davis, M. L., Raghavan, S., & Lam, M. T. (2016). Image and video acquisition and processing for clinical application. Biomedical Engineering and Computational Biology, 7(s1). https://doi.org/10.4137/BECB.S40272
192. Zatsiorsky, V. M. (1998). Kinematics of human motion. Human Kinetics. Available at https://archive.org/details/kinematicsofhuma0000zats
193. Zhang, Q., Zhang, S., & Zhou, D. (2014). Keyframe extraction from human motion capture data based on a multiple population genetic algorithm. Symmetry, 6(4), 926-937. https://doi.org/10.3390/sym6040926
194. Zhu, Z., Li, X., Wang, Z., He, L., He, B., & Xia, S. (2020). Development and research of a multi-medium motion capture system for underwater intelligent agents. Applied Sciences, 10(18), 6237. https://doi.org/10.3390/app10186237
195. Zhu, L., Feng, M., Yin, X., Wang, S., & Yu, J. (2017). Kinematics analysis of cervical rotation-traction manipulation measured by a motion capture system. Evidence-Based Complementary and Alternative Medicine, 2017, 1-6. https://doi.org/10.1155/2017/5293916