**Motion Tracking Technology in Kinesiology**

**Background**

Kinesiology is rooted in the study of the human body and physical activity, and has been a growing area of research for decades (Hamill et al., 2021). One sub-discipline of Kinesiology that has grown in interest and scope, thanks to continual improvements in technological capacity, is the study of biomechanics. Since the 1970’s, researchers have leveraged available technology in attempts to quantify human movement and improve understanding of the nature of locomotion (Andriacchi & Alexander, 2000). Early movement research relied on single-frame film analysis, but continually improving technological advancements, software algorithms and computing capacity, have led to the point where researchers and enthusiasts alike can measure complex, dynamic movements with ever increasing precision via technology that is becoming accessible to nearly everyone (Hamill et al., 2021; Mündermann et al., 2006).

Tools used to measure biomechanics and human movement range from optoelectronic measurement systems (OMS), inertial measurement units, and image processing systems (van der Kruk & Reijne, 2018). Each system tracks movement mechanics differently, and the focus of this paper will be on the advancement of OMS marker-based systems to markerless motion tracking and its implications for health and performance.

**Optoelectronic Measurement Systems**

OMS is considered the gold standard in motion capture technology (Corazza et al., 2010). It requires multiple fixed cameras that detect light from markers affixed to areas of interest on the body which a program can then triangulate to determine limb locations and interactions between body segments (van der Kruk & Reijne, 2018). Modern motion capture systems have sampling rates upwards of 60Hz, measurement resolution within tenths of a millimeter, and measurement errors within one millimeter; although some systems may be far less accurate (Topley & Richards, 2020). This enables OMS to record very high-quality data within 3D space, giving insights into biomechanics of interests and the ability to estimate joint torques, power and velocity associated with different movements (Gauffin et al., 1990). OMS can use active or passive markers to track body positioning, with active capture utilizing markers which emit their own infrared light frequencies while passive capture uses simple reflective markers (Richards, 1999). Active capture is more accurate and robust than passive capture, but is also more cumbersome, requiring extra cables and batteries to function thereby restricting participant mobility (van der Kruk & Reijne, 2018). This limits active capture systems to use within controlled lab settings with limited space for dynamic movements, whereas passive systems, while less accurate, can be used in both lab and real-world environments to capture complex movements (Mündermann et al., 2006). This ability to record complex, dynamic movements has broadened research into biomechanics, and its utility has been implemented in movies and video games to enhance the life-like nature of CGI. In more recent years, there has been a shift towards markerless tracking which broadens the scope of motion tracking even more.

**Markerless Tracking**

Improvements in software, deep learning, and computer processing have led to the development of markerless tracking systems which are more accessible and easier to deploy in real-world settings, while sharing many similarities with OMS. High quality setups, like OMS, will still employ multiple stationary cameras to capture movement data, but there is a much heavier reliance on body pose models and deep learning training to accurately track limb positions in 3D space (Zhang et al., 2011). This makes the development of tracking algorithms and accurate 3D human models critical for success. Earlier versions of markerless tracking relied upon rigid body modeling with low degrees of freedom, resulting in poor tracking accuracy and large measurement error (Corazza et al., 2010). Advancements in modeling techniques and a proliferation of tracking algorithms – including constraint propagation, optical flow, silhouette contours and annealed particle filtering (Mündermann et al., 2006) – have significantly improved performance, but it is large-scale data use with convolutional neural networks and deep learning which have greatly enhanced human pose estimation (Desmarais et al., 2021). Some markerless systems can now achieve joint detection rates upwards of 90% reducing manual user input to properly highlight relevant joints on the human model thereby improving its utility (Newell et al., 2016). Despite these advancements, markless tracking still suffers from drawbacks.

Compared to OMS, markerless systems have higher tracking errors and struggle to consistently track body joints and frame-by-frame accuracy due to occlusions caused by clothing and lack of contrast between the subject and the background (Cheng et al., 2020; Desmarais et al., 2021). For the best results, markerless tracking still requires multiple cameras set up in fixed locations to cross-reference data and generate the models with minimal errors (Zhang et al., 2011). This doesn’t make markerless technology more accessible to the average person, though, which is a limitation of its utility; although, strides within monocular tracking are showing increased robustness which is beginning to provide utility in sports performance and health care (Hamill et al., 2021).

**Future of Markerless Tracking**

Monocular tracking is not a new technology, but improvements in deep learning algorithms, the ability to extrapolate 3D models from 2D images, higher quality cameras and improved computing capacity has elevated monocular tracking to the point where it is increasingly accessible to the average person from their smartphone (Fan et al., 2022). Data processing times have also improved significantly which means motion tracking occurs in near-real-time allowing for instant, relatively accurate feedback for users (Šajina & Ivašić-Kos, 2022). In an athletic setting, this means it’s possible for a coach to quantitatively assess an athlete’s technique, provide feedback to their athlete, and continue video analysis without any need to process the data. Similarly, in healthcare settings, physiotherapy and medical clinics can use monocular tracking on a simple tablet to assess a patient’s gait, squat, jump and other biomechanics to determine root causes of injuries and pathologies. This positions consumer-accessible monocular tracking as a powerful diagnostic tool with the potential to improve patient quality of life.

The future of monocular tracking lies in the fusion of deep learning methods with AI models to further optimize motion tracking accuracy while minimizing measurement errors in real-time (Rondao et al., 2024; Zollhöfer et al., 2018). Integration of AI will not only improve tacking, but also help diagnose movement patterns providing a powerful tool for clinicians seeking instantaneous feedback of client movement patterns.

**References**

Andriacchi, T. P., & Alexander, E. J. (2000). Studies of human locomotion: Past, present and future. *Journal of Biomechanics*, *33*(10), 1217–1224. https://doi.org/10.1016/S0021-9290(00)00061-0

Azhand, A., Rabe, S., Müller, S., Sattler, I., & Heimann-Steinert, A. (2021). Algorithm based on one monocular video delivers highly valid and reliable gait parameters. *Scientific Reports*, *11*(1), 14065. https://doi.org/10.1038/s41598-021-93530-z

Cheng, Y., Yang, B., Wang, B., & Tan, R. T. (2020). 3D Human Pose Estimation Using Spatio-Temporal Networks with Explicit Occlusion Training. *Proceedings of the AAAI Conference on Artificial Intelligence*, *34*(07), 10631–10638. https://doi.org/10.1609/aaai.v34i07.6689

Corazza, S., Mündermann, L., Gambaretto, E., Ferrigno, G., & Andriacchi, T. P. (2010). Markerless Motion Capture through Visual Hull, Articulated ICP and Subject Specific Model Generation. *International Journal of Computer Vision*, *87*(1), 156–169. https://doi.org/10.1007/s11263-009-0284-3

Desmarais, Y., Mottet, D., Slangen, P., & Montesinos, P. (2021). A review of 3D human pose estimation algorithms for markerless motion capture. *Computer Vision and Image Understanding*, *212*, 103275. https://doi.org/10.1016/j.cviu.2021.103275

Fan, Z., Zhu, Y., He, Y., Sun, Q., Liu, H., & He, J. (2022). Deep Learning on Monocular Object Pose Detection and Tracking: A Comprehensive Overview. *ACM Comput. Surv.*, *55*(4), 81:1-81:40. https://doi.org/10.1145/3524496

Gauffin, H., Jarenmark, R., & Tropp, H. (1990). Implementation of a two-dimensional biomechanical model i n an opto-electronic motion analysis system. *Clinical Biomechanics*, *5*(2), 108–116. https://doi.org/10.1016/0268-0033(90)90045-8

Hamill, J., Knutzen, K. M., & Derrick, T. R. (2021). Biomechanics: 40 Years On. *Kinesiology Review*, *10*(3), 228–237. https://doi.org/10.1123/kr.2021-0015

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

Newell, A., Yang, K., & Deng, J. (2016). Stacked Hourglass Networks for Human Pose Estimation. *Computer Vision – ECCV 2016*, 483–499. https://doi.org/10.1007/978-3-319-46484-8\_29

Richards, J. G. (1999). The measurement of human motion: A comparison of commercially available systems. *Human Movement Science*, *18*(5), 589–602. https://doi.org/10.1016/S0167-9457(99)00023-8

Rondao, D., He, L., & Aouf, N. (2024). AI-based monocular pose estimation for autonomous space refuelling. *Acta Astronautica*, *220*, 126–140. https://doi.org/10.1016/j.actaastro.2024.04.003

Šajina, R., & Ivašić-Kos, M. (2022). 3D Pose Estimation and Tracking in Handball Actions Using a Monocular Camera. *Journal of Imaging*, *8*(11), 308. https://doi.org/10.3390/jimaging8110308

Topley, M., & Richards, J. G. (2020). A comparison of currently available optoelectronic motion capture systems. *Journal of Biomechanics*, *106*, 109820. https://doi.org/10.1016/j.jbiomech.2020.109820

van der Kruk, E., & Reijne, M. M. (2018). Accuracy of human motion capture systems for sport applications; state-of-the-art review. *European Journal of Sport Science*, *18*(6), 806–819. https://doi.org/10.1080/17461391.2018.1463397

Zhang, Z., Seah, H. S., Quah, C. K., & Sun, J. (2011). A markerless motion capture system with automatic subject-specific body model acquisition and robust pose tracking from 3D data. *2011 18th IEEE International Conference on Image Processing*, 525–528. https://doi.org/10.1109/ICIP.2011.6116397

Zollhöfer, M., Thies, J., Garrido, P., Bradley, D., Beeler, T., Pérez, P., Stamminger, M., Nießner, M., & Theobalt, C. (2018). State of the Art on Monocular 3D Face Reconstruction, Tracking, and Applications. *Computer Graphics Forum*, *37*(2), 523–550. https://doi.org/10.1111/cgf.13382