OPTICAL TRACKING IN AWAKE BRAIN SURGERY: UNDERSTANDING SOURCES OF POSITIONAL ERRORS AND LIMITATIONS IN ACCURACY

Jerry Cai

A THESIS

in

The Department of Neuroscience

Presented to the Faculties of the University of Pennsylvania

in

Partial Fulfillment of the Requirements for the

Degree of Bachelor of Arts

2024

Thesis Supervisor:

Iahn Cajigas-Gonzalez, MD, PhD

Assistant Professor of Neurosurgery

University of Pennsylvania School of Medicine

Senior Thesis Director:

Judith McLean, PhD

Department of Neuroscience

Abstract

Nearly one million patients in the United States suffer from movement disorders, often undergoing awake brain surgeries where surgeons need to track upper arm movements using optical trackers. These surgeries pose challenges due to the operating room environment and the complexity of calibrating multiple sensor systems together, which can introduce sensor errors. This study compares error differences in optical tracking when using different sensor configurations and under various experimental conditions such as tracker mode, arm velocity, and tremor presence. Results indicate that combining different sensors increases errors, and certain experimental configurations prevent high positional measurement accuracy needed in behavioral tasks. Our findings suggest that for optimal position tracking in surgical settings, decreased movement velocity and upper extremity tremor seem to minimize optical sensor positional errors.

Introduction

Background in the Neural Correlates of Movement

The human brain and the neural correlates of limb movement are complex biological mechanisms that underpin human health, mobility and state-of-the-art robotics technology. Nearly one million patients in the USA suffer from movement disorders, often undergoing awake brain surgeries where surgeons need to track upper arm movements using optical trackers. These efforts often utilize clinical translational studies that integrate experimental neurosurgery with novel brain-computer interface (BCI) technologies in early stages of development. The challenge lies in the need for extremely precise acquisition of both neural and kinematic data—accurate positional tracking of both the target and the subject's arm is critical to these studies. Currently, existing kinematic tracking technology is not yet optimized for the nuanced and complex environment of the surgical operating room, and the complexity of calibrating multiple sensor systems together inevitably introduces sensor errors. The precision of data collection is compromised by the calibration requirements of combining different sensor modalities that measure the positions of the target and the subject's arm, highlighting a significant hurdle in advancing these important translational studies. Existing motion capture systems in biomechanical and robotics research use multimodal sensors for posturing analysis. Common sensor modalities include inertial measurement unit (IMU), optical tracking, piezoelectric gloves and external jointed robotic arm frames to precisely measure the absolute location in space of a subject's forearm and finger position. In this study, I aim to explore the intricate considerations of utilizing optical tracking sensors in the surgical environment by identifying specific experimental sources of positional errors and quantifying the sensor's positional accuracy.

Current Optical Tracking Sensor Systems

The HTC Vive system is a consumer-grade motion capture system typically used in virtual reality applications - the system consists of a headset, auxiliary sensors and external lighthouse cameras called base stations. The base stations emit synchronized light sweeps, and trackers that use photodiodes to measure light pulse timings as a proxy for estimating the horizontal and vertical angles to lighthouses. The trackers fuse angle measurements from a bundle of rigid photodiodes together to estimate the pose using a technique similar to Angle-of-Arrival. The tracker also has access to motion data from an incorporated Inertial Measurement Unit (IMU) to maintain a smooth and continuous trajectory. The IMU is a small stand-alone device that integrates different multiaxial sensors (i.e., accelerometer, gyroscope, and magnetometer). The raw data collected by each integrated sensor are complemented via real-time sensor-fusion algorithms to achieve a complete description in terms of motion, rotation, and heading with respect to the sensor's own reference frame. IMUs can address different body parts to enable direct determination of kinematics, providing data of angular acceleration, velocity, and spatial orientation.

Environmental Challenges Affecting Sensors in the Operating Room

Environmental factors such as tracker placement, beacon angle, electromagnetic interference, physical visual occlusion in the operating room will affect the effectiveness of sensor tracking, along with positional accuracy. Multiple trials will be conducted assessing manipulation of such environmental variables and its effect on sensor reliability. Statistical analyses will be conducted to examine deviation from a ground truth, which will be established from baseline recordings established from the HTC Vive and visual base station system Given the difficulty of obtaining positional ground truth in the operating room environment, the error difference between kinematically constrained and unconstrained calibration serves as a proxy to indicate reliability of measurements and whether significant positional errors are introduced during a procedure. During our experiment where neural signals and physical kinematic movements are recorded, obtaining precise kinematic data is essential. To ensure reliable data collection within a minimal margin of error, kinematic error differences will be checked throughout recording sessions. Efforts to maintain measurement reliability may result in limiting patient recruitment based on a criterion of permissible tremor and range of motion.

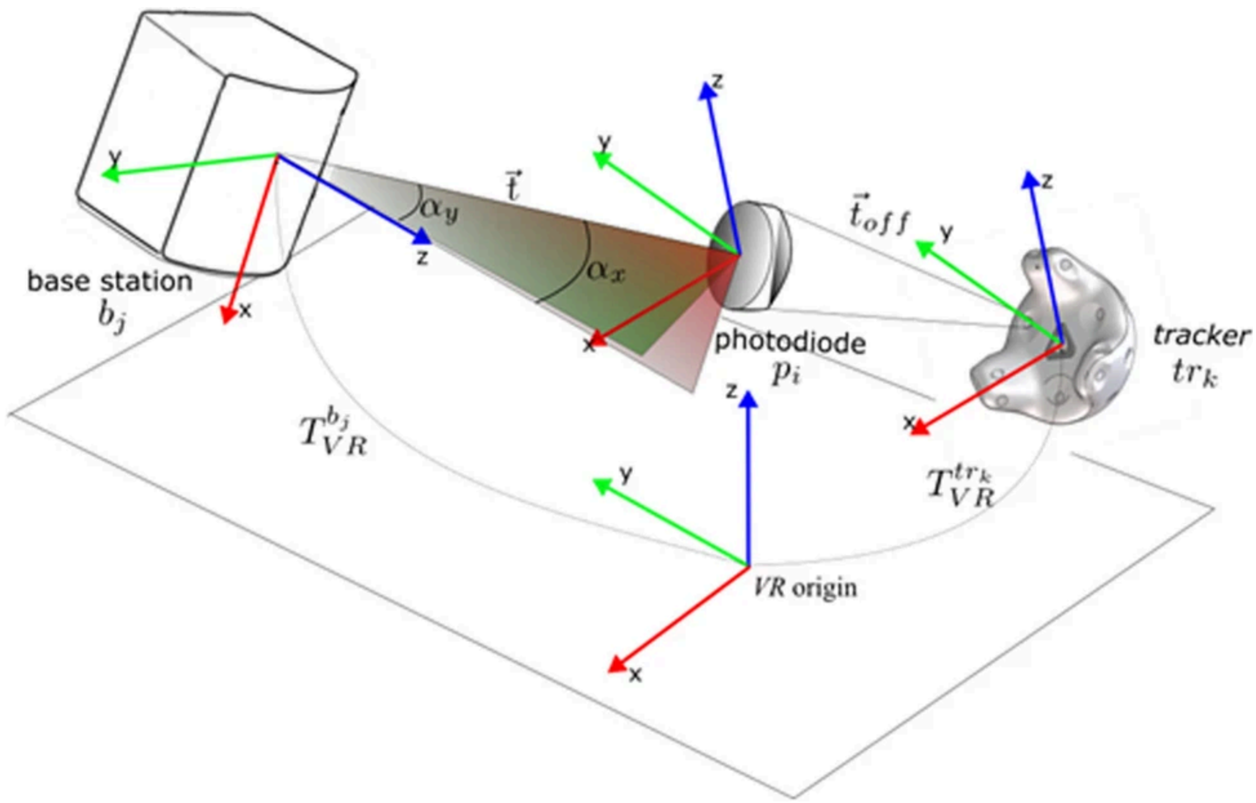


Figure 1: The hardware configuration of HTC Vive optical trackers (Borges, 2018)

Motivation and Research Question

There is a lack of analysis in tracking performance of the Vive tracker under dynamic movement in complex environments, as well as the accuracy improvements that could be achieved by fusing other sensors at the component level. Similar to studies by Barclay (2023), Borges (2018) and Weber (2023), we integrate both IMU sensors with optical trackers to quantify human upper extremity movements in behavioral tasks.We seek to identify how error differences can be minimized and which factors—such as base station components, movement speed, and calibration sequences—affect the magnitude of error in positional data. We are further extending research into the viability of specifically HTC VIVE optical trackers as i) a source of ground truth in the absolute coordinate space and ii) its utility as a separate moving target for reach tasks. By measuring the absolute error introduced through several reach tasks and analyzing movement features, we hypothesize that base station movement, increased velocity and tremor presence in reach movements will lead to a rise in total observed error, underscoring the need for meticulous calibration and setup in experimental designs.

Methods

I used the following equipment to execute experimental trials and collect data: Movella Xsens inertial sensor kit, 2 HTC VIVE optical trackers, 2 HTC VIVE base stations, 2 StretchSense gloves. For each movement recording, we recorded through the Movella Xsens software and SteamVR Brekel viewer.

HTC Vive Sensor Setup

The Vive VR system was used to create and immerse the participants in the virtual environment. HTC Base stations were set up approximately 2 meters away from each other facing straight forward. Calibration involved using a HTC Vive sensor being placed halfway between both base stations at ground level to establish an absolute spatial origin. The subject then stands approximately 6 feet away, sitting on a mock platform simulating the surgical operating table. Each HTC Vive sensor is secured onto a predetermined location along the subject’s forearms using a screw-on mount, with the photodiode antennae facing outwards to be visible for the base stations.

Xsens Movella IMU Calibration and Integration

UE movement data were recorded using the Xsens MTw Awinda System (MVN version 2020.0.0, Enschede, Netherlands). The system included 17 IMUs placed on the head, arms, and legs according to the Xsens MVN User Manual. Body measurements were taken with a measuring tape and inserted into the software to create an appropriately sized motion capture model. A brief calibration was then completed to ensure the accuracy of the model. Each participant was asked to stand in a neutral position with both arms straight to the side and head facing forward (N-Pose). Alternative calibration configurations include the T-Pose, where the subject has arms extended outwards along the body axis to form a T-shape. Participants then walked in a straight line, turning around when the software indicated. (Barclay, 2018)

Calibration of the Xsens system integrates both the optical tracker (HTC Vive) and IMU (Xsens Movella) sensor modalities. Subsequent adjustments to achieve satisfactory calibration quality included the 'Axis Reset' and 'Ground Reset', in which the subject must additionally move their upper arms in various positions and orientations to correctly align axes and establish the correct height of the subject from the ground. Reach forward, to the sides, and upwards. Repeat for 10 Seconds. Hold T-pose again for 10 seconds for final calibration and processing.

Satisfactory calibration is indicated by a 'Calibration Quality: Good', as qualitatively determined relative to the Xsens algorithm quality. We did not measure the exact metrics used by Xsens in distinguishing a 'Good' calibration from 'Poor'. The subject was positioned in a semi-fowler's position to simulate patient positioning during a neurosurgical operation.

Experimental Design Setup

The reach tasks assessed in each recording trial were the following: The left arm remained static, while the right arm reached forward towards a target approximately arm-length away. Starting from resting position, the right arm extended to grasp the target before returning back to position. A 4 total of 4 positions were assessed: low-elevation versus high-elevation, contralateral versus ipsilateral reach.

Experiment 1: To measure the effect of base station movement on tracker position vector difference, the aforementioned sequence of behavioral tasks was executed to completion for Trial 1. Then, the Vive base stations were unplugged, completely powered down and transferred across the room and reset to simulate the patient being transferred from preoperative room to the operating room. The aforementioned sequence of behavioral tasks were repeated afterwards.

Experiment 2: To measure the effect of movement velocity and tremor on system position error and difference-difference error, the aforementioned sequence of behavioral tasks was executed but with variable movement characteristics. To assess movement velocity, 2 experimental conditions were implemented to simulate faster (approximately 1 m/s) and slower (approximately 0.5 m/s) reach speeds. To assess tremor, the subject presented slight shakiness in their arm across the duration of the experimental sequence.

Data Types and Relevant Metrics

Absolute position x, y and z coordinates based on a global coordinate system were collected via Blender from both the independent sensor (Brekel) and integrated sensor systems. integrated sensor systems (Movella).

Data Type or Metric	Description
Position data (x, y, z)	Over 4000 frames (60-70 second recording) for 2 tracker systems: independent sensor (Brekel) and integrated sensor systems (Movella). Raw data was formatted as <Time/Frame, x, y, z> position defined by conventions of the FBX file format when imported into 3D visual editing environments. (Blender)
System Vector Differences	System Vector Differences: Position vector between 2 trackers within the same system. The vector difference between the optical trackers placed on the right and left arm is calculated as the difference of tracker positions. (Experiment 2)
Difference of System Vector Differences	The difference between the independent sensor and integrated sensor system position vectors is calculated to determine the relative amount of error offset between the 2 systems. (Experiment 2)

Coordinate Axes Alignment

There is the challenge of differing coordinate axes between independent optical trackers and Movella-integrated optical trackers, necessitating the alignment of vectors in coordinate axes space to accurately compare the difference of differences, which serves as a proxy for the net error deviation from ground truth. Additionally, the systems differ in their definition of local origin points: the independent sensor system, Brekel, centers its origin at the subject's hip position, whereas the integrated sensor system, Movella, establishes its origin at the position of the closest HTC Vive Base Station. These disparities highlight the critical need for precise calibration and alignment to ensure reliable position measurements across different tracking systems.

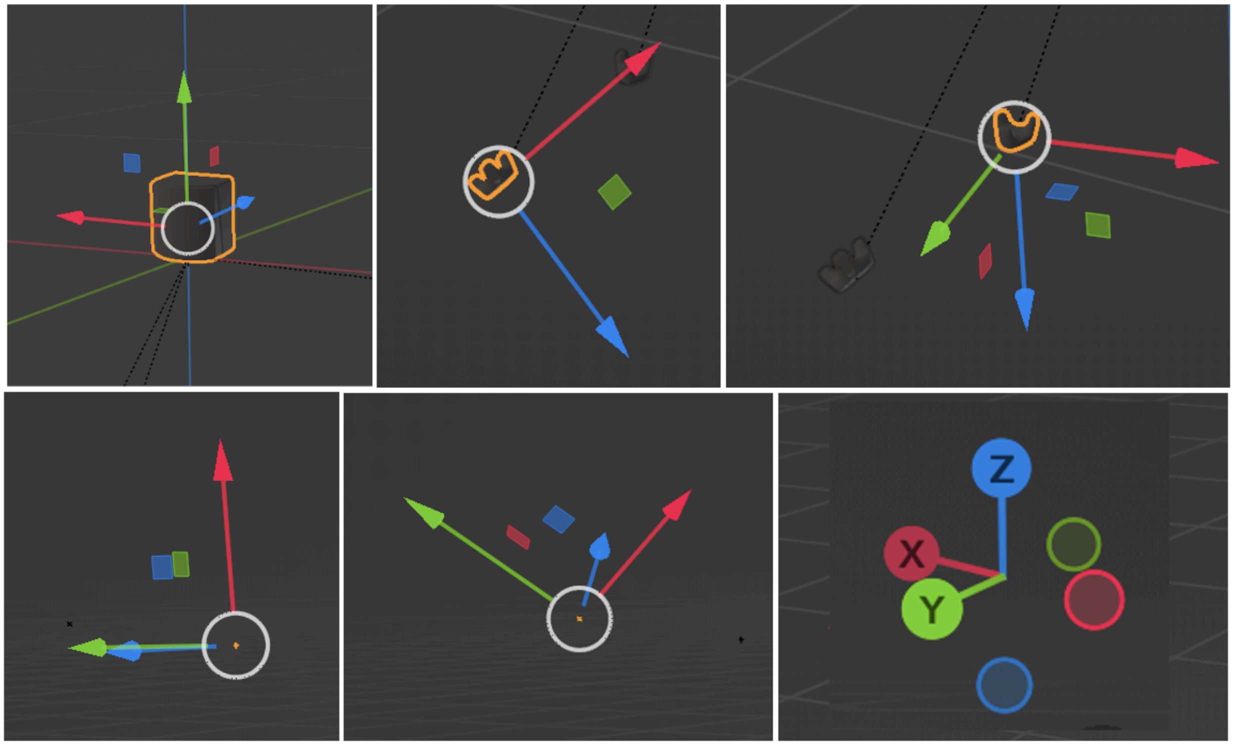


Figure: Each sensor component has a unique local coordinate system. (Blender)

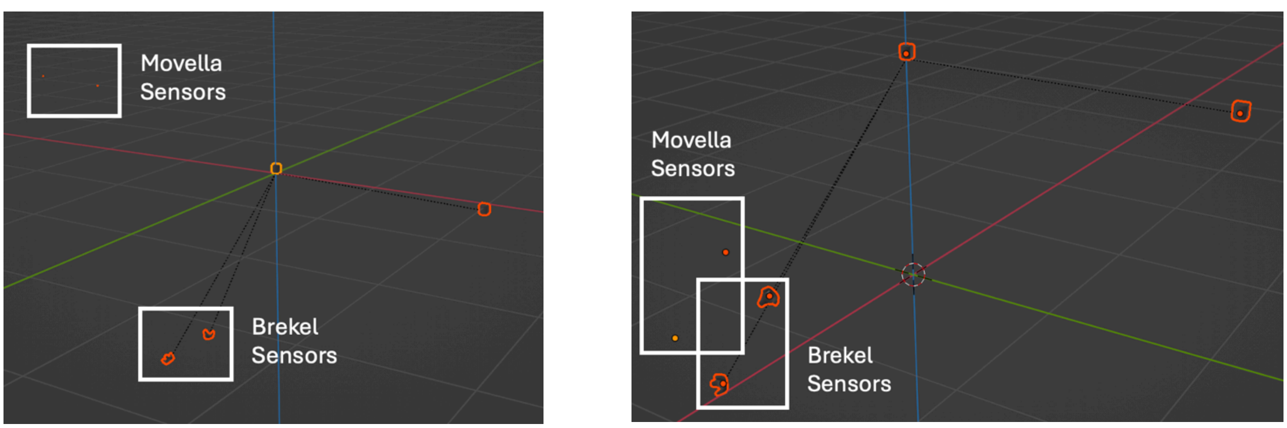


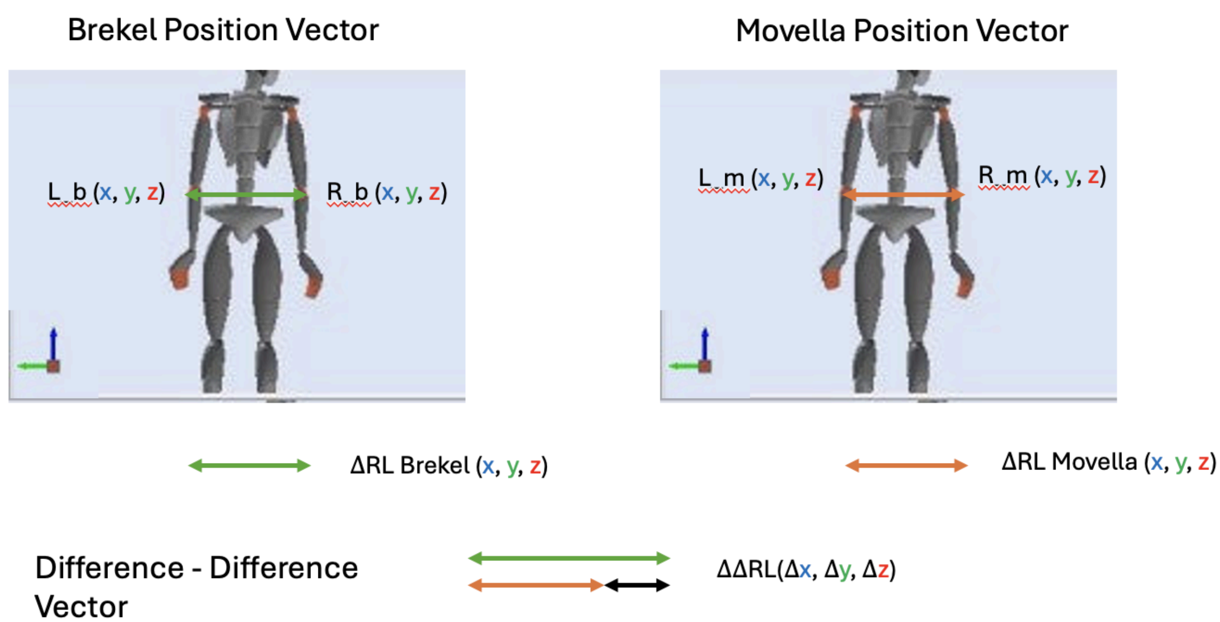
Figure: Before and after correcting for coordinate axes alignment. (Blender)

$$R\_t1 = \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$R\_t2 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & 1 & 0 \end{bmatrix}$$

$$R\_t3 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Figure: The following transformation matrix was applied.



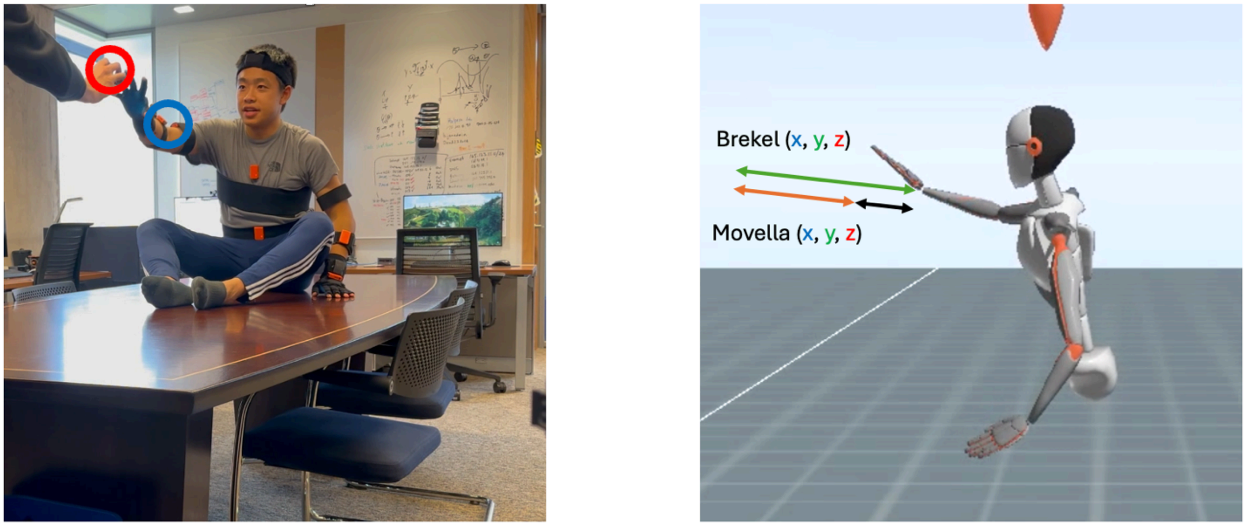
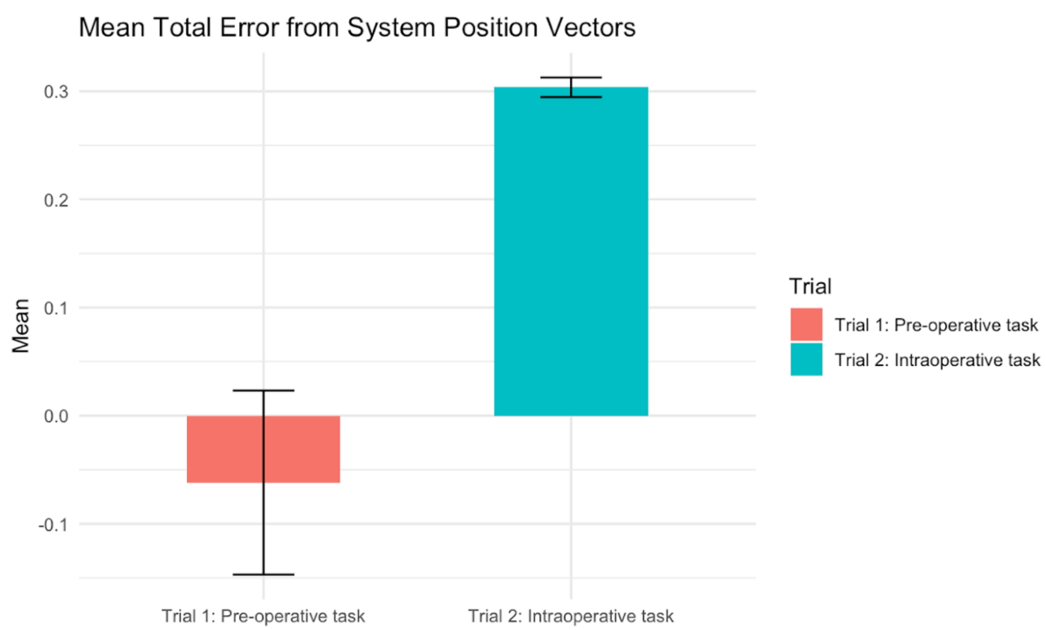


Figure: Position vectors of a given sensor position between 2 different systems.

Results

Analysis 1: Effect of Base Station Movement on Tracker Position Vector Difference

Statistic	**Trial 1: Preoperative Task**	**Trial 2: Intraoperative Task**
Mean (cm)	-0.0618	0.304
Standard Deviation (cm)	4.255	0.454
N	2500	2500
Standard Error	0.08507	0.00908



Analysis 2: Effect of Velocity and Tremor on System Position Error and Difference-Difference

Trial	Velocity	Tremor	Total Error (cm)	X Mean Error (cm)	Y Mean Error (cm)	Z Mean Error (cm)
1	Fast	None	1.794	-1.361	0.891	0.757
2	Slow	None	0.866	0.632	0.576	-0.135
3	Fast	Present	9.855	-7.768	5.700	-2.073
4	Slow	Present	9.162	-8.6944	0.0114	2.889

$$\text{systemErrorDifference} = \beta_0 + \beta_1 \times \text{velocity} + \beta_2 \times \text{tremor} + \epsilon$$

In the regression analysis conducted, the model's residuals were closely clustered around zero, indicating a well-fitting model with minimal deviation from predicted values. The coefficients revealed significant predictors within the model: tremor had a considerable impact on the dependent variable with an estimate of 8.1785 and was highly significant ($p = 0.00915$), suggesting robust evidence for its effect. Velocity also appeared influential with an estimate of 0.8106, though its p-value of 0.09171 suggests marginal significance. The model exhibited an exceptionally high goodness of fit, with a multiple R-squared value of 0.9998 and an adjusted R-squared of 0.9994, indicating that nearly all variability in the dependent variable could be explained by the model. The overall model was statistically significant as reflected by an F-statistic of 2442 on 2 and 1 degrees of freedom, with a p-value of 0.01431, confirming the predictive power of the included factors.

$$\text{systemErrorDifference} = 0.925 + 0.811 \times \text{velocity} + 8.179 \times \text{tremor} + 0.0588$$

Discussion

Results and analyses seem to confirm the significance of base station movement, increased velocity and tremor presence on increasing positional error introduced. Such findings support our initial hypothesis that variables unique to the operating room environment (base station movement, increased velocity and tremor presence) cause significant error and would limit the applications integrated optical tracker systems to less precise behavioral tasks. The total error computed for various experimental conditions ranged from 0.866 cm to 9.855, in which tremor greatly introduced positional error. Assuming that subjects present minimal tremor, the amount of error introduced would still be within the acceptable margin of approximately 2-3 cm.

There are several limitations with the experimental design that could impact the validity of the findings. The use of the Difference of Difference method to measure total error effectively eliminates linear translation effects, but it may not adequately capture mean error variations. Additionally, the experimental setup included only a small number of trials, with just two trials in Experiment 1 and four in Experiment 2, potentially limiting the statistical power and robustness of the conclusions. Furthermore, the accuracy of replicating the base station's Vive position and orientation relied heavily on visual inspection, introducing subjectivity and potential inaccuracy into the experimental results.

Future research could enhance the accuracy and relevance of findings by adopting more sophisticated pattern classification approaches to examine the signal features, aiming to more precisely correlate specific movement sequences with spikes in error offset. This could help better characterize the effects of large spikes in error offset caused by optical tracker occlusion or interference. Additionally, investigating the direct difference vector between Brekel and Movella sensor positions rather than using the difference of differences might provide a clearer representation of absolute ground truth deviation by directly measuring the distance between sensors. Applying consistent experimental conditions across all variables (base station movement, increased reach velocity, and tremor presence) will standardize the data collection process. Finally, addressing the sensor drift observed 30 seconds into recordings with tremor is critical - further understanding and optimization of software algorithms used during sensor fusion could mitigate total error deviation and improve overall experimental accuracy.

Contributions

Katie Wingel, Qasim Qureshi, Jarl Haggerty, Agrita Dubey, PhD, Iahn Cajigas, MD, PhD, Bijan Pesaran, PhD

References

Angel, R. W., Alston, W., & Higgins, J. R. (1970). Control of movement in Parkinson's disease. Brain, 93(1), 1-14.

Bachmann, E. R., et al. (1999). Orientation tracking for humans and robots using inertial sensors. In Proceedings of the 1999 IEEE International Symposium on Computational Intelligence in Robotics and Automation (CIRA'99) (Cat. No. 99EX375). IEEE.

Barclay, S. A., et al. (2023). Characterization of Upper Extremity Kinematics Using Virtual Reality Movement Tasks and Wearable IMU Technology. Sensors, 24(1), 233. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10781219/

Boon, L. I., et al. (2019). A systematic review of MEG-based studies in Parkinson's disease: The motor system and beyond. Human Brain Mapping, 40(9), 2827-2848.

Borges, M., et al. (2018). HTC vive: Analysis and accuracy improvement. In 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE. Retrieved from https://longhorizon.org/trey/papers/borges18_htc_vive.pdf and GitHub: https://github.com/asymingt/deepdive

Bonifati, P., et al. (2023). A Multi-Modal Under-Sensorized Wearable System for Optimal Kinematic and Muscular Tracking of Human Upper Limb Motion. Sensors, 23(7), 3716. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10098930/

Braak, H., et al. (2000). Parkinson's disease: affection of brain stem nuclei controlling premotor and motor neurons of the somatomotor system. Acta Neuropathologica, 99, 489-495.

Cajigas, I., et al. (2023). Brain-Computer interface control of stepping from invasive electrocorticography upper-limb motor imagery in a patient with quadriplegia. Frontiers in Human Neuroscience, 16, 1077416.

Cerfoglio, S., et al. (2023). Evaluation of Upper Body and Lower Limbs Kinematics through an IMU-Based Medical System: A Comparative Study with the Optoelectronic System. Sensors, 23(13), 6156. Retrieved from https://www.mdpi.com/1424-8220/23/13/6156

Gallagher, A., Matsuoka, Y., & Ang, W.-T. (2004). An efficient real-time human posture tracking algorithm using low-cost inertial and magnetic sensors. In 2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (IEEE Cat. No. 04CH37566) (Vol. 3). IEEE.

Karatsidis, A., et al. (2018). Validation of wearable visual feedback for retraining foot progression angle using inertial sensors and an augmented reality headset. Journal of Neuroengineering and Rehabilitation, 15(1), 1-12.

Martínez-Cagigal, V., et al. (2020). Non-linear online low-frequency EEG decoding of arm movements during a pursuit tracking task. In 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). IEEE.

Mazzoni, P., Shabbott, B., & Cortés, J. C. (2012). Motor control abnormalities in Parkinson's disease. Cold Spring Harbor Perspectives in Medicine, 2(6).

Myn, U., Link, M., & Awinda, M. (2015). Xsens mvn user manual. Xsens Motion Technologies BV: Enschede, The Netherlands.

Niehorster, D. C., Li, L., & Lappe, M. (2017). The Accuracy and Precision of Position and Orientation Tracking in the HTC Vive Virtual Reality System for Scientific Research. Iperception, 8(3), 2041669517708205. https://doi.org/10.1177/2041669517708205. PMID: 28567271; PMCID: PMC5439658. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5439658/

Piña-Fuentes, D., et al. (2019). Direct comparison of oscillatory activity in the motor system of Parkinson's disease and dystonia: a review of the literature and meta-analysis. Clinical Neurophysiology, 130(6), 917-924.