Human Biomechanics as a Digital Twin & Real-time Motion Capture in Unity 3D Game Engine

By: Ian Abeyta, MPH PhD Student; Jason Weinstein, Student Research Assistant at DVXR Lab, UNT; Steve McDermott, Academic Lab Coordinator, UT Arlington.

Advisors: Dr. Sharad Sharma, Professor of Data Science & Director of the Data Visualization and Extreme Reality Lab (DVXR) Lab | Dr. Heejun Kim, Assistant Professor of Health Informatics

Abstract

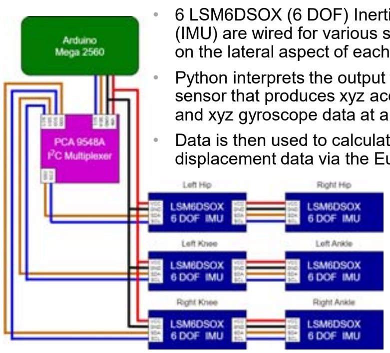
- Motion capture gives researchers the insights to analyze human movement.
- This can be used in many ways, such as to improve athletic performance or to create digital avatars for movies.
- Typically, motion capture is limited by line-of-sight
  - Subjects must wear a special suit that has numerous visual sensors fixed at various parts of the body.
  - Cameras monitor these sensors in 2 dimensions, until they lose line-of-sight.
  - Therefore, multiple cameras are used at various angles.
  - Computer software then compiles the combination of 2-dimensional camera/video feeds to reproduce a 3-dimensional representation of the subject in the digital space.
  - The current methods are expensive, difficult to set-up and do not produce viable information for additional applications such as fitness, physical therapy and entertainment.

Introduction

Purpose: To make human biomechanics more accessible for a wider audience through the use of Unity for data visualization.

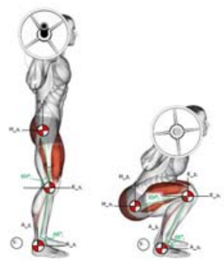
- Numerous sensors are still being used, however these sensors do not require cameras.
- This radically improves their utility for populations that cannot dedicate the space and funding to video motion capture endeavors.

Device for Motion Capture

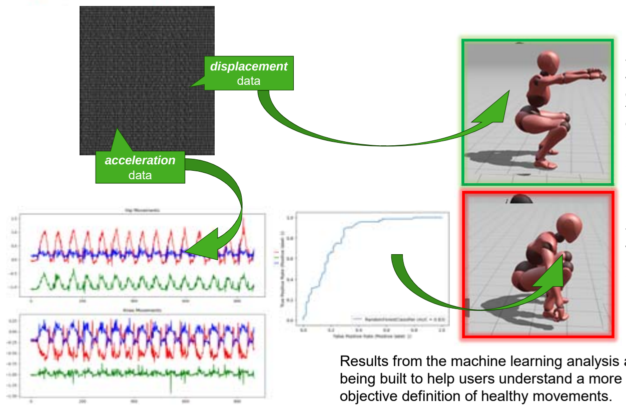


- An Arduino Mega 2560 Microcontroller is programmed with C++ to receive sensor data via a PCA 9548A I²C Multiplexer.
- 6 LSM6DSOX (6 DOF) Inertial Mass Units (IMU) are wired for various segments to rest on the lateral aspect of each leg.
- Python interprets the output from each sensor that produces xyz acceleration data and xyz gyroscope data at a rate of 40 hertz,
- Data is then used to calculate xyz displacement data via the Euler method.

Overview



- **Data collection**: Multiple IMUs are integrated through a single microcontroller.
- **Data Analysis**: Machine Learning with Python
  - Supervised Machine learning, random forest classification, and support vector machines
  - Unsupervised machine learning, cluster analysis.
- **Data visualization**: Unity will produce a digital twin based on motion capture data from the multiple sensors placed on the user.
- ☆ Unity **shows** us our movement,
- ☆ Machine learning will tell us **how well** we move.



Post-processing = good
The machine learning model will classify movements based on a known exercise. Although future models will also determine:
- Proper technique
- Healthy movement
- Good posture

Post-processing = bad
The machine learning model will classify a bad movement:
- Improper technique
- Unhealthy movement
- poor posture

Results from the machine learning analysis are being built to help users understand a more objective definition of healthy movements.

Data Collection

All data was captured from the primary researcher.

Warm-up:
- Prior to any physical activity, it is essential to perform light calisthenics across multiple muscle groups.
- This increases blood flow to the musculature and helps to prevent injury from more rigorous movements.

Securing the Sensors:
- Sensors are attached to the legs via an external pocket sewn to a pair of elastic straps and 5/8" plastic parachute buckles.

Motion Capture:
- Python script was initiated that begins the data collection process
- Data is displayed in the terminal on the connected laptop computer.
- Upon code termination, a comma separated version file is created with a unique timestamp for data analysis.

Practical Applications

Physical Therapy & Fitness
- Face-to-face: 'Proper' technique can be evaluated and shared through personal training or one-on-on client interactions
- Telemedicine: Patients are not required to be at PT office for each meeting
- Patient Adherence: PTs can evaluate patient rehabilitation
- Improvements to achieve better movements

Movement as Explicit Knowledge
- Martial Arts: study new skills through an avatar or against an opponent
- Dance: learn new moves inside of a ghost or in an ensemble

Entertainment
- Movies: Computer-generated imagery for fictional characters and safer stunts
- Video Games: multiplayer competitions such as races or battle royal

Conclusions

Human movement is saturated with numerous imperfections, however that does not overwhelm us to the point of sedentary confinement. We are active beings that enjoy running and jumping. Nor does that overwhelm machine learning when assigned for biomechanical analysis. Through the work of creating a digital twin using augmented reality software, we hope to understand these imperfections and develop new standards for explicit knowledge in human movement.

Among the most important lessons learned, we found that simplicity is essential for understanding complex data. On numerous occasions, we found ourselves stumbling on imperfect data or a faulty connection to the device. Although, through systematic testing, we were able to render a digital twin that is representative of human biomechanics.

Unity and machine learning can be used to identify different poses and movements based on the users distinct body type. Additionally, machine learning can then be used to assist various populations achieve higher goals associated with health and safety.

Acknowledgments

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References

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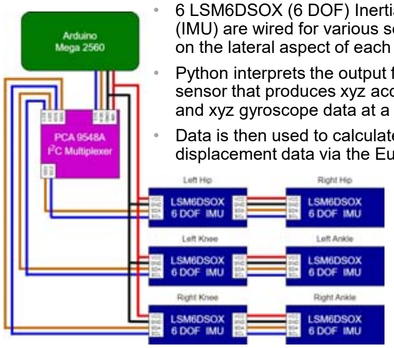

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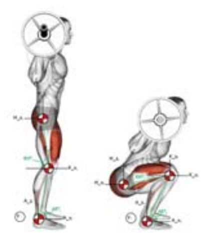

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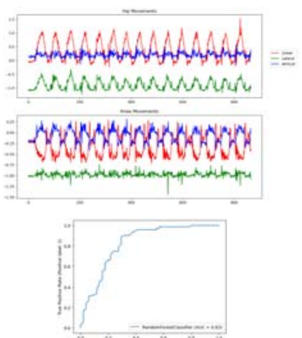

- **Data visualization**: Unity will produce a digital twin based on motion capture data from the multiple sensors placed on the user.
  - Accelerometer data is converted to displacement data for direct input into Unity
  - Results from the machine learning model will provide feedback to the system to define integrity of movements

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