ECE M202A Final Project

QVAR HOOPS

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BACKGROUND / MOTIVATION

- STMicroelectronics has recently developed a new class of sensor
  - QVAR: Charge (Q) Variation (VAR)
  - Can measure very small changes in electrostatic potential
- One application of this is to measure electric potential of the human body
  - EMG (Electromyography) : “[a signal] generated by the electrical activity of the muscle fibers active during a contraction” - IEEE
  - QVAR electrodes can be placed on the body and used to detect potential changes in certain muscles

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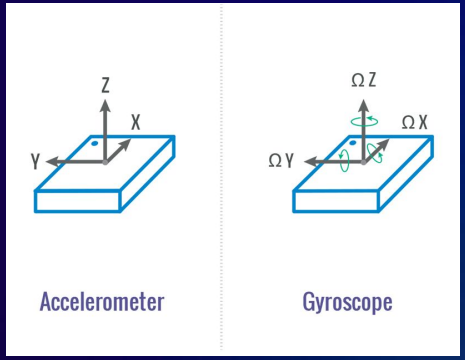
BACKGROUND / MOTIVATION



- Wanted to create a multimodal system
  - Combining QVAR with inertial (IMU) data
  - Measure movement in both the “micro” (Neuromuscular) and “macro” (Acceleration) domains
  - Detect both body part movement as well as muscular contraction during a specific action
- One field that has many of these “micro+macro” movements is sports
  - Always looking for new technological advancements to help improve player training/safety/data collection/etc.

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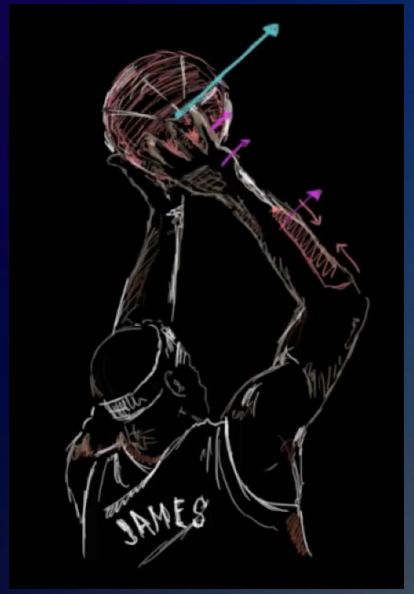
BACKGROUND / MOTIVATION

- One sports application in which this technology can be used to analyze motion is basketball
- Athletes are always training to improve the consistency of their shooting mechanics
  - Macro movement: acceleration of the arm/hand to propel the ball forward
  - Micro movement: contraction of the muscles in the forearm to shoot the ball



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GOALS & METRICS

Multimodal Data Collection

Collect clear, precise data from both the QVAR and IMU sensors that accurately represents the action taking place (Basketball Shot)

Data Consolidation/Processing

Combine all of the data from each sensor into one main “macro” and one main “micro” signal, from which conclusions can accurately be drawn

Meaningful Output

Code an algorithm that can take the macro and micro signals as inputs and output the number of shots taken as well as a metric of the consistency between shots

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PRIOR / RELATED WORK

- Current most advanced Basketball training technology - Homecourt AI
  - Machine vision-based smart shot tracking and training
  - Tracks certain visual statistics, but nothing else
- Current QVAR implementation example - Pison Technology
  - Use QVAR sensors to detect ENG (ElectroNeurography) signals
  - Detect minute hand gestures/movements from electrodes on the wrist and use them to help humans interface with technology (smart home, AR/VR, etc.)

PISON

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NOVELTY

01.

Data Collection

- Many basketball shot training methods exist, but none collect data from the athlete's neuromuscular system
- Data-driven training of muscle memory

02.

QVAR Technology

- This sensor technology is extremely new, and its possible use in sports applications hasn't previously been explored
- Can open up a whole new field of devices/implementations

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TECHNICAL METHOD

Data Collection

- IMU: Sensor chip attached to SensorTile.box Pro
- Initially placed sensor on back of hand, to get most precise acceleration data
- Sensor would detach during shot → Placed on upper forearm

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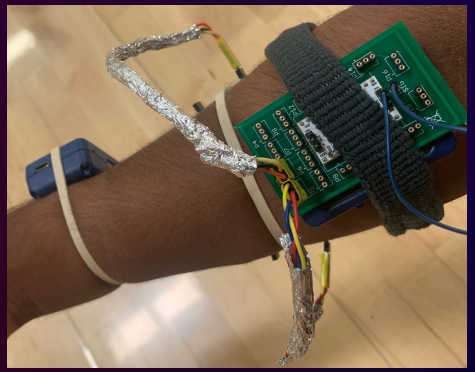
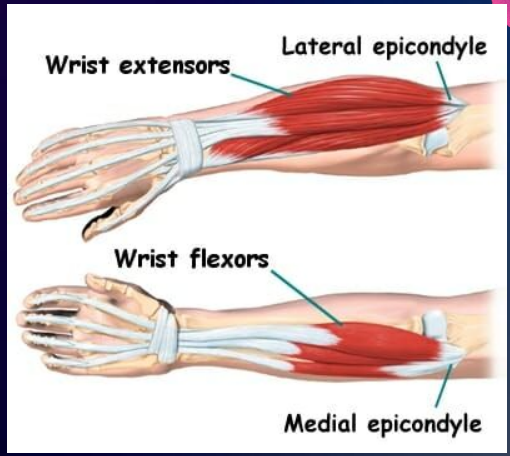
TECHNICAL METHOD

Data Collection

- QVAR: Sensor chip connected to multiplexer board, attached to SensorTile.box Pro
- Multiplexer board allows for multiple electrodes to be attached at the same time
- Attached two electrodes to the main forearm muscles





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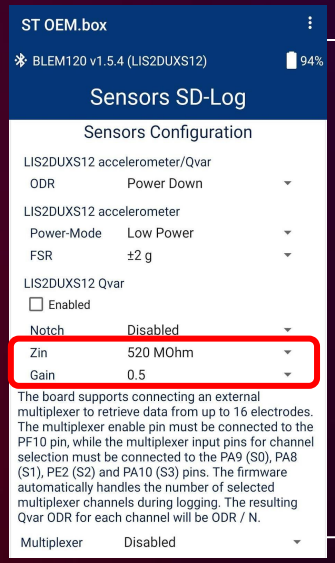
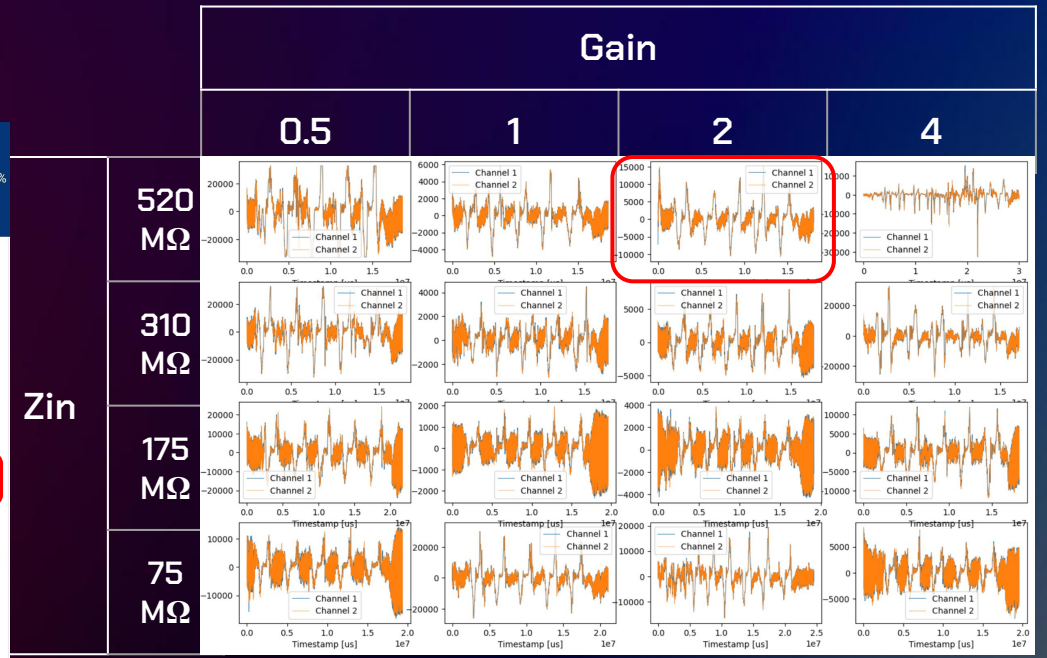
TECHNICAL METHOD

QVAR Calibration

- Choosing between Impedance (Zin) and Gain options for Qvar Sensing
  - ➢ 4 options for each
- Collected data for 5 shot movements with each possible parameter configuration, and chose the configuration with the most clear readings





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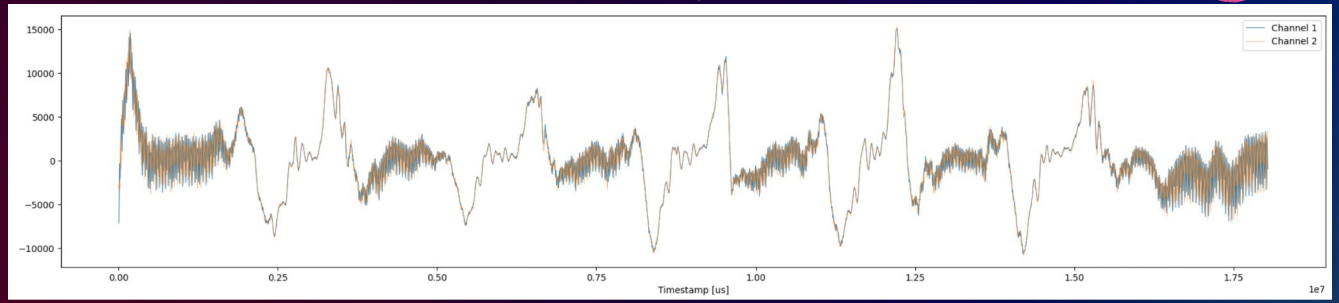
TECHNICAL METHOD

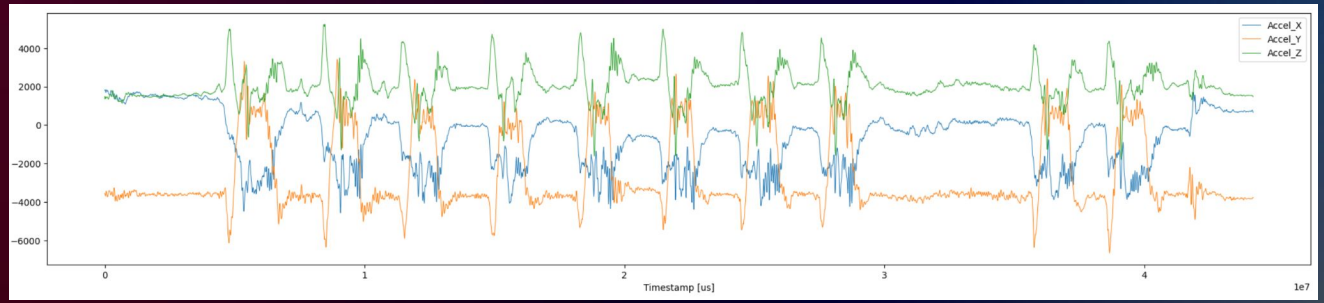
Data Consolidation

- For “Micro” signal, simply used one of the QVAR channel signals, as both channels were giving near identical readings
- For “Macro” signal, calculated magnitude of total acceleration data (using X, Y, and Z axes) and normalized it to zero mean

Micro (QVAR)



Macro (IMU)



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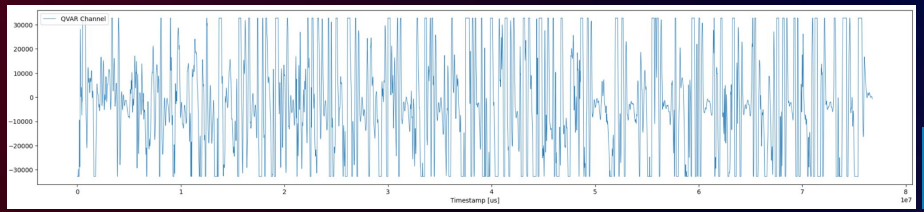
TECHNICAL METHOD

Data Noise Issues

- Initial Data collection procedure:
  - Shooting some shots on a regulation hoop and collecting both QVAR and IMU data from these shots
- Led to extremely noisy QVAR data - excess muscle movement, catching, etc



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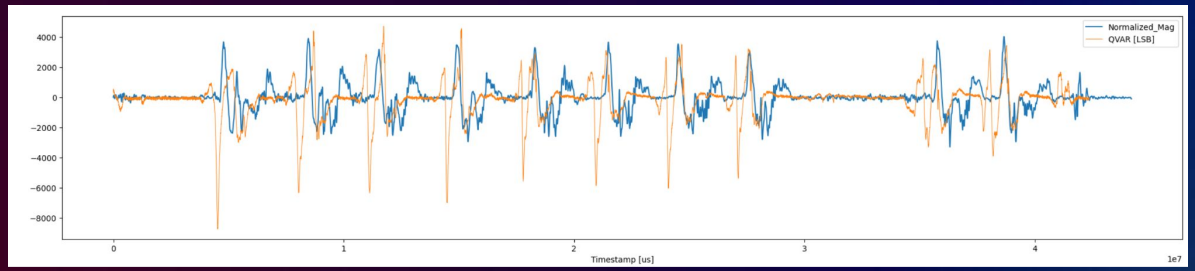
TECHNICAL METHOD

Data Noise Issues

- Updated data collection procedure:
  - Shooting some shots on a mini hoop at home, and only moving my arm to shoot
- Resulted in much clearer data collected from both QVAR and IMU sensors



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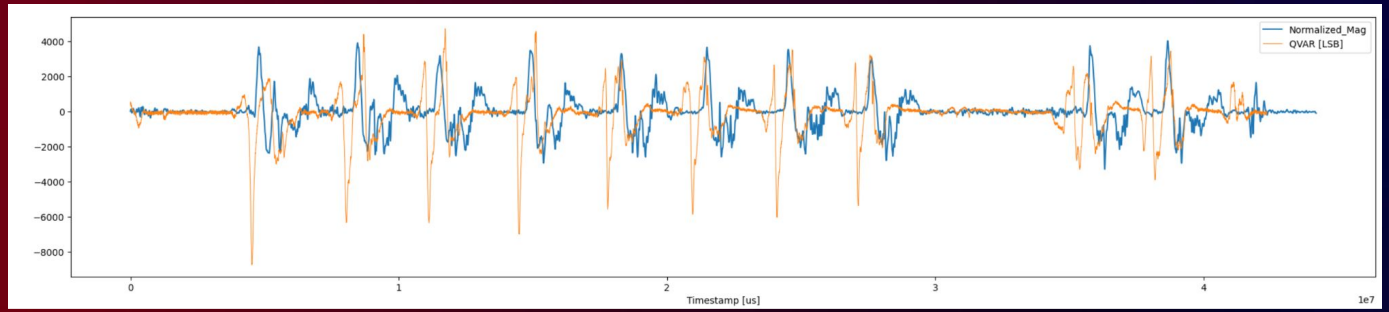
TECHNICAL METHOD

Current State

- Data collection and consolidation done
- Have clear “macro” (IMU) and “micro” (QVAR) signals that are characteristic of the 10 shots that were taken

Next Steps

- Data processing/analysis
- Implement some sort of algorithm that can detect how many shots were taken, and can also output some sort of similarity metric to show how consistent the shot mechanics were
- Making conclusions from the data



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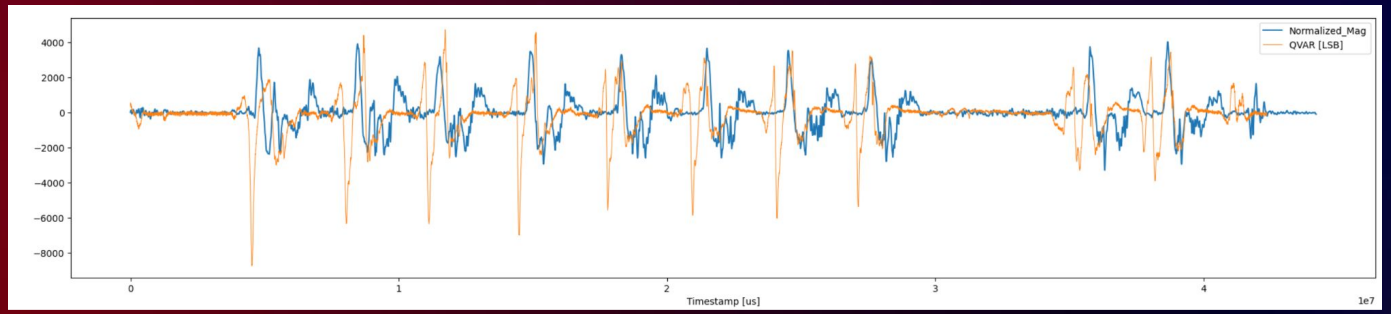
TECHNICAL METHOD

Data Processing/Analysis Method

- Requirements
  - Some sort of signal pattern recognition (for identifying each shot)
  - Some way to compare each identified shot and give a similarity metric between all shots
- Limitations
  - No lengthy training data to train a classifier or neural network



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TECHNICAL METHOD

Data Processing/Analysis Method

- Cosine Similarity
  - First converts each time series into a vector
  - Applies similarity function (Below) to the two vectors in question
  - A similarity value of 1 indicates perfect similarity, 0 indicates no similarity (orthogonality), and -1 indicates perfect dissimilarity
- Since there is no training data, must manually select a window containing one shot's data, and sweep that across the entire signal to find all instances with similarity above a certain threshold

$$similarity(A,B) = cos(\theta) = \frac{A \cdot B}{||A||\,||B||} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}.$$

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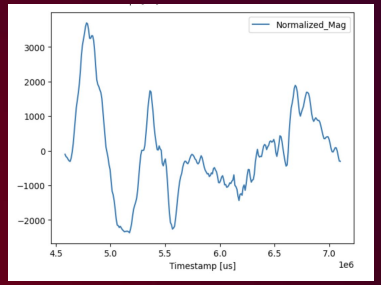
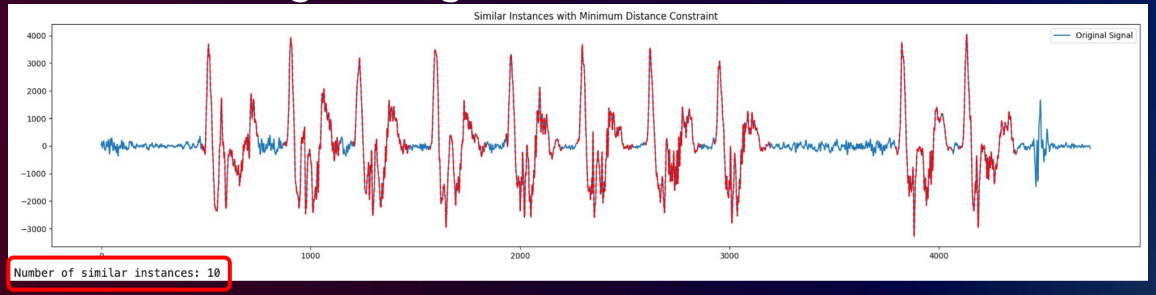
PROJECT RESULTS

Finding Similar Instances

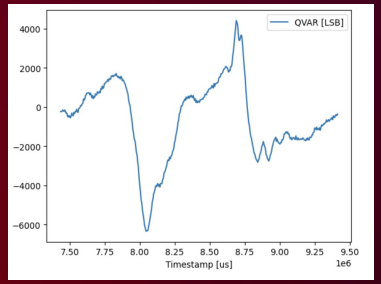
- With the selected window of one shot, use cosine similarity to identify all shots taken within the entire signal length

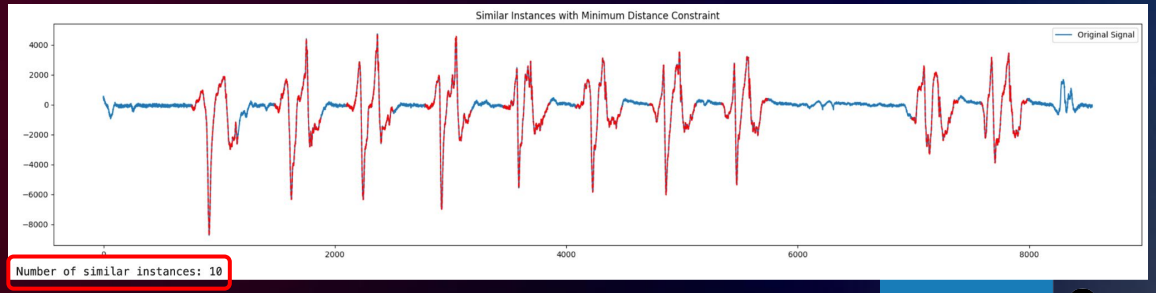
IMU





QVAR





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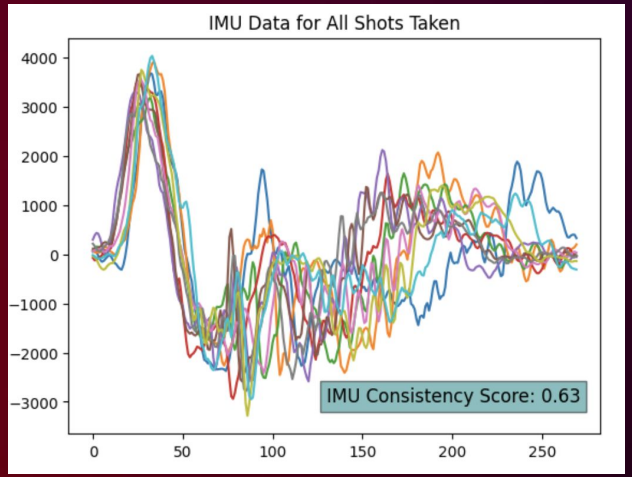
PROJECT RESULTS

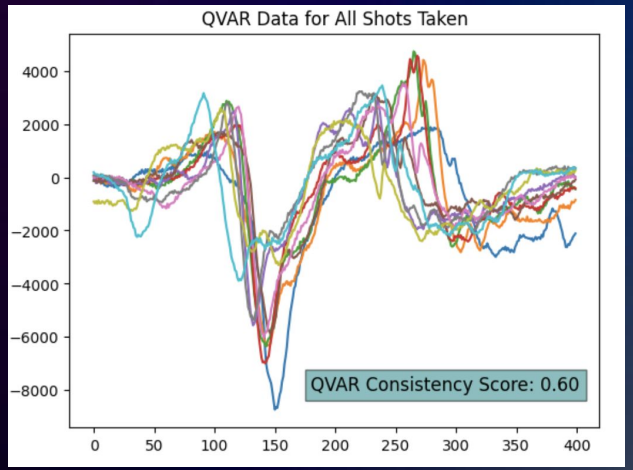
Finding Similarity/Consistency Metric

- Take all of the similar instances that were found by cosine similarity with the window, and calculate the average similarity between all of these instances to get a final metric for shot consistency

IMU



QVAR



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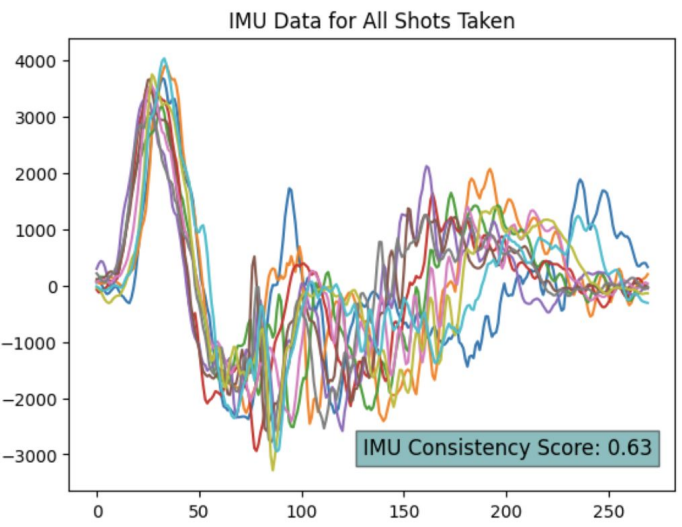

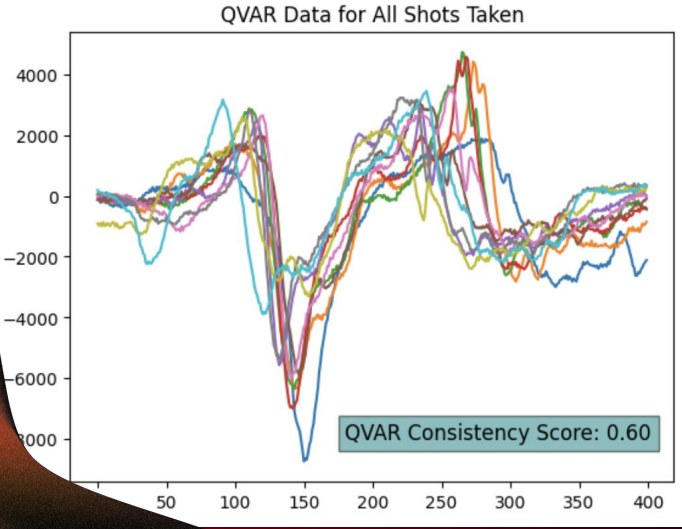

CONCLUSIONS

Data Determines Results

While these results are substantial and show promise for future directions using QVAR sensing technology, the main importance is in the accurate and precise collection of sensor data

New Training Options

Can use multimodal data collected from athletes' bodies to help optimize form and technique down to the neuromuscular level

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FUTURE DIRECTIONS

DATA COLLECTION OPTIMIZATION

Improve data collection system to be able to handle noisy data, so that the system can be used on a regulation basketball court

BRINGING QVAR TO OTHER SPORTS

This project's driving concept can be extrapolated and implemented in any other field in which there is both macro and micro movement and consistency is sought (ex. throwing a football, kicking a soccer ball, throwing a punch, etc.)

REAL TIME COMPUTING

The sensor chips are ML enabled, so the algorithm could also be implemented on the chip itself to be able to compute everything in real time

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SPECIAL THANKS:

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