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## Introduction

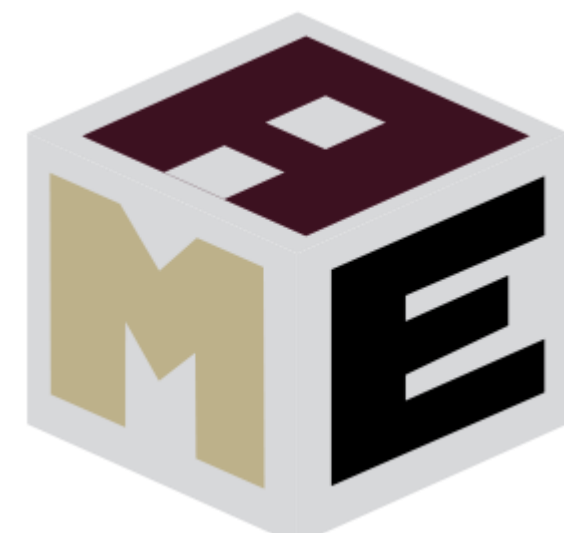
- This study explores a new way to predict when someone wants to walk faster or slower on a treadmill by analyzing their leg movements in real time.
- Using a motion-capture suit (Xsens), to track how a person's hip, knee, and ankle angles change as they walk a metric called the Mahalanobis distance can be used to determine the relevance of the recorded change in angle.
- The goal of our research is to create a personalized, responsive system that adapts to how people naturally move which could help improve treadmills for rehab, sports training, or everyday fitness.

## Mahalanobis distance

- Consider the equation:  
 $x(p, t) \sim N(\mu(p, t), \Sigma(p, t))$
- Where P is defined as:
- Preliminary results showed that dividing the gait cycle into these four phases resulted in greater accuracy and responsiveness than considering the whole gait cycle without phase divisions.
- t represents the number of time steps since that phase began, N symbolizes a Gaussian distribution,  $\mu$  is the mean vector of the distribution, and  $\Sigma$  is the covariance matrix of the distribution.
- To add data to the model one observation at a time, the mean and covariance estimates after the  $n$ th training observation are computed recursively via:  
$$\mu_n = \frac{(n-1)\mu_{n-1} + x_n}{n}$$
  
$$\Sigma_n = \frac{(n-1)\Sigma_{n-1} + (x_n - \mu_n)(x_n - \mu_n)^T}{n}$$
- The real-time intent identification algorithm begins with a single new measurement data point  $x_{new}$ . The current gait phase  $p$  and time step  $t$  for  $x_{new}$  are determined just as in model building. If this  $p$  and  $t$  combination exists in the model, the current data point  $x_{new}(p, t)$  is compared to that part of the model by assessing the Mahalanobis distance (MD) between it and the Gaussian distribution
- distribution

## Acknowledgements

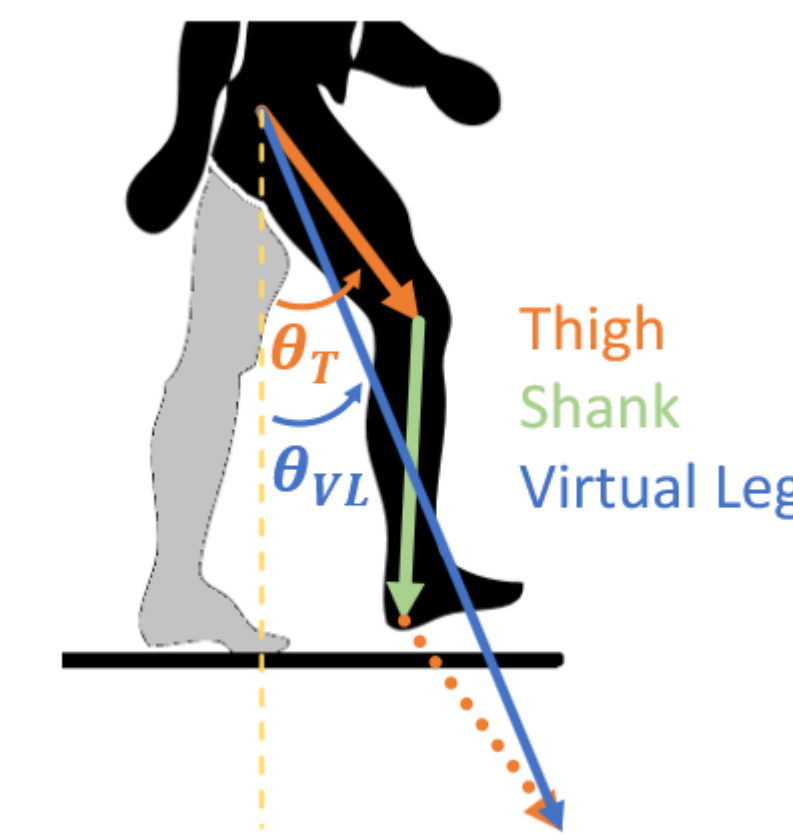
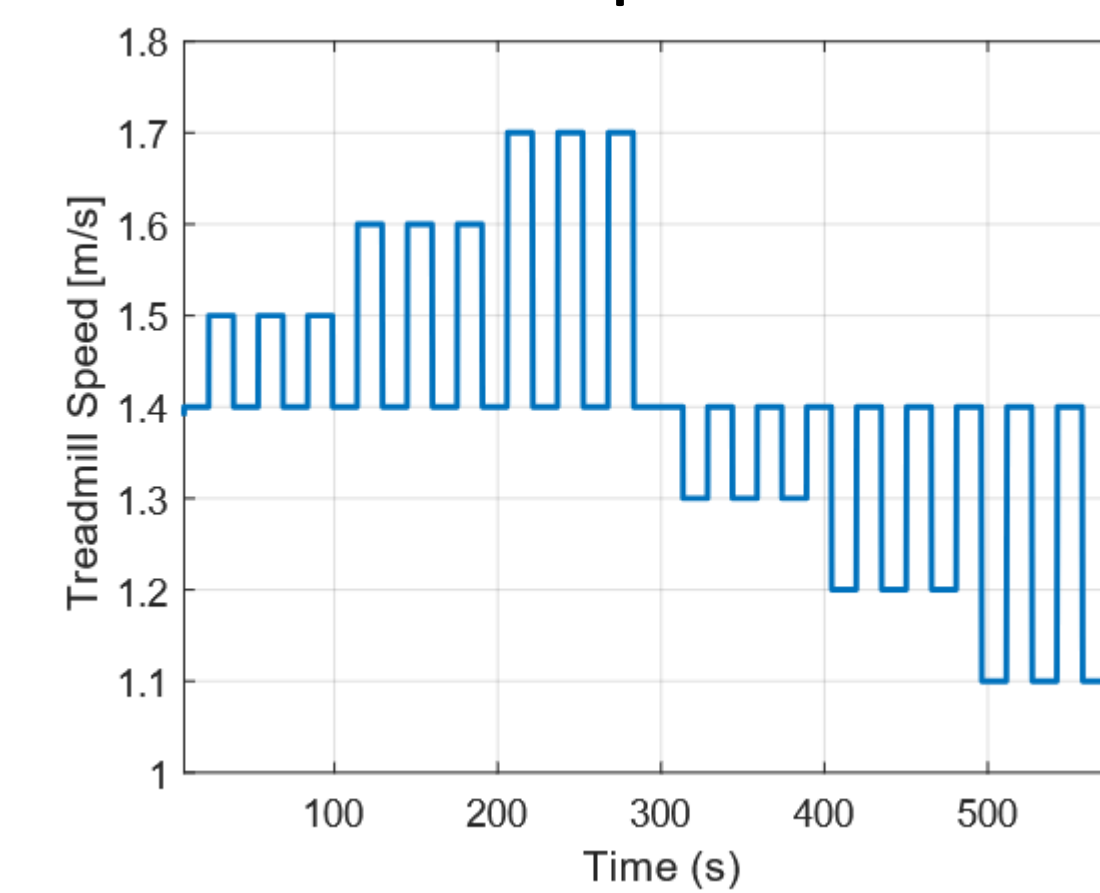
We would like to thank Dr. Taylor Higgins and our other research teams in the RTHM lab at the Aero-Propulsion, Mechatronics and Energy (AME) Center. We would also like to thank Florida State University for providing us with the funding necessary to continue pursuing our research.



## Methodology

- A subject is first asked to wear an Xsens mocap suit fitted with motion sensors on all major points of motion across the body.
- The lower body angle data received from a subject's Xsens suit are sent to a computer running MATLAB.
- The MATLAB program commands a Bertec treadmill to run a predetermined speed profile.
- During an initial training phase, the subject walks with a variable speed based on the predetermined speed profile.
- The joint angle data and corresponding speed changes are recorded and used to build a personalized model linking gait to intent.
- In the subsequent testing phases, the model will predict speed adjustments in real time based on incoming joint angle data.
- We then test the accuracy of the model's predictions by comparing the system's predictions to the treadmill's actual speed, measuring how closely they match.
- The study's dual-phase de-sign (training/testing) is intended to ensure generalization across individuals, offering a framework for personalized human-robot interaction.

Predetermined Bertec Treadmill Speed Profile



## Xsens



## What's next

- Our next steps will be to introduce a new set of participants as test subjects for an altered motion detection software.
- We hope to use this next group of test subjects to examine the same Mahalanobis distance when they are riding a unicycle instead of walking.
- We have other sets of teams working on creating an apparatus that send the orientation and speed data in conjunction with the motion intent data as well.

## Conclusion

- On average, the algorithm successfully detected the change in desired walking speed within one gait cycle and had a maximum of 87% accuracy at responding with the correct intent category of speed up, slow down, or no change.
- The findings also show that the accuracy of the algorithm improves with the magnitude of the speed change, and that speed increases were more easily detected than speed decreases.

## References

- Higgins, T. M., Bresingham, K. J., Schmiedeler, J. P., & Wensing, P. M. (2023). Data-efficient human walking speed intent identification. *Wearable Technologies*, 4. <https://doi.org/10.1017/wtc.2023.15>

