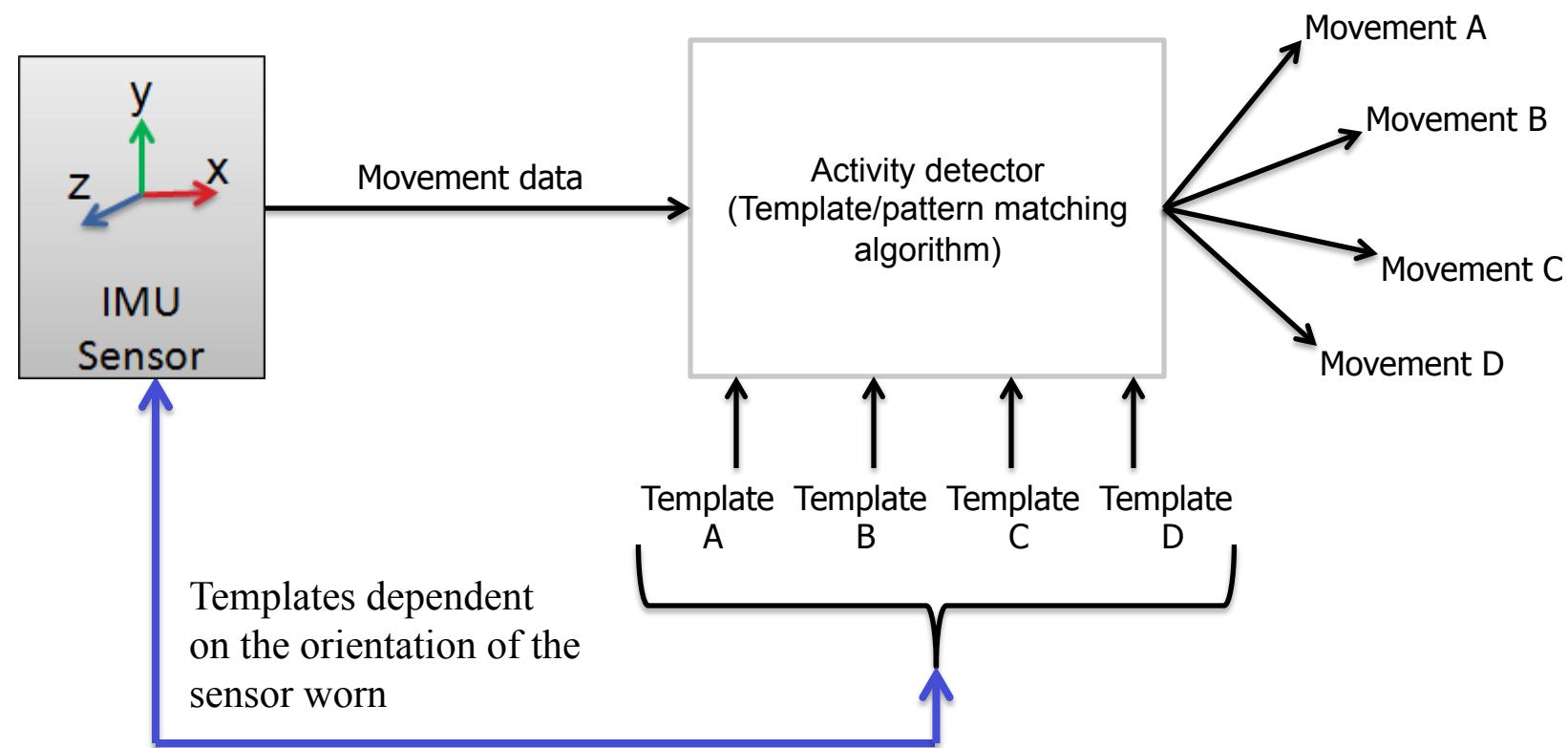


Motivation

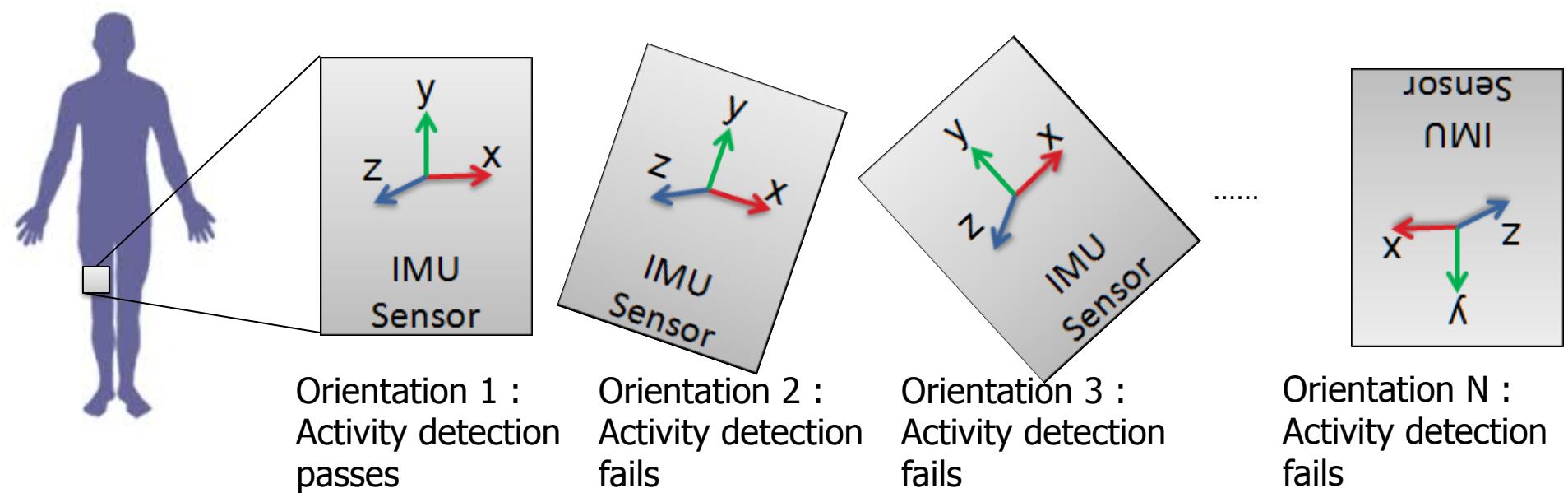
Build an energy efficient solution for robust activity detection, paving the way for a plethora of applications in healthcare and wellness monitoring

Background

- Wearable motion sensors have several applications in the area of health care, sports fitness and wellness assessment
- Data from sensors are valuable for both real-time activity monitoring as well as for longitudinal studies which uses recorded, long-term, non-reproducible data
- Several techniques have been shown that perform activity detection successfully
- Basic principle behind activity detection



Objectives



Limitation 1: the templates needed for activity recognition are only generated for one orientation of the sensor. The sensors have to be always worn in that orientation for effective activity recognition.

Limitation 2: templates cannot be generated or updated over time for changes in movement patterns that is caused by the variations in physical capabilities of the body due to age, progression of diseases, etc.

- The objective of our work is to address the limitations of the classical activity detection techniques in order to make it more robust
- The first limitation could be addressed by generating and retaining many templates for the same movement, but for different orientations of the sensor. However, this greatly slows activity recognition and requires significant computational and storage capabilities.
- Our proposed solution addresses this limitation by learning the orientation difference when a sensor is worn in a disparate orientation and transforming the sensor data to the required orientation
- This solution addresses the second limitation by enabling the notion of reuse of movement data independent of the orientation of the sensors.
- The notion of reuse enables many applications in healthcare such as meaningful study of longitudinal data, eliminating specific template training for every activity detector, etc.

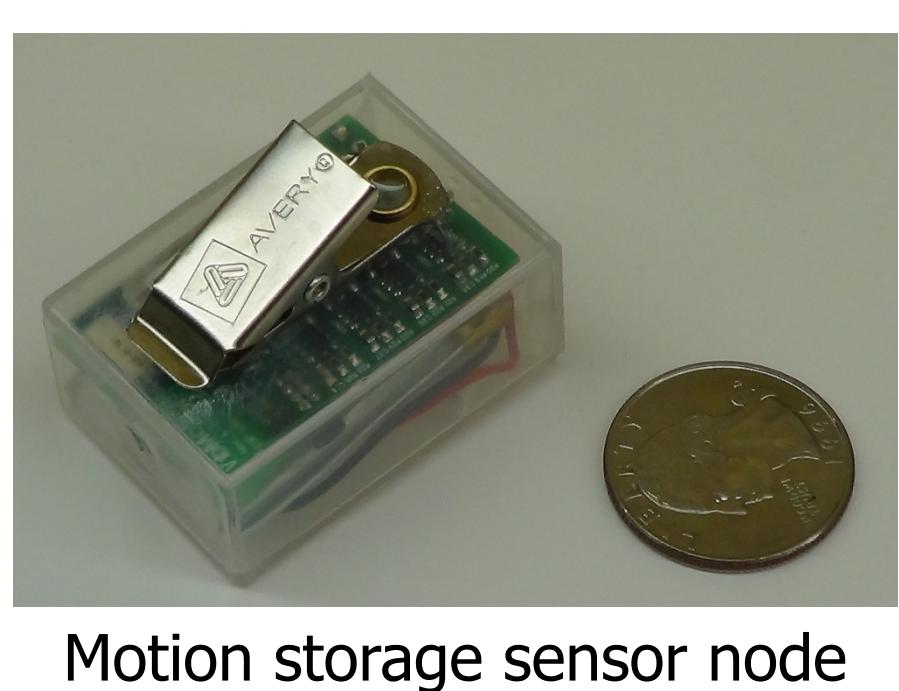
Proposed Solution

$$\begin{aligned}
& [X^{S1}_i \ Y^{S1}_i \ Z^{S1}_i] \text{ Representation of X,Y,Z axes of the inertial reference system in S1} \\
& [x_{S1} \ y_{S1} \ z_{S1}] \text{ X,Y,Z axes of the initial orientation (S1) axes system} \\
& [a^{S1}_1] \text{ gravity vector before movement represented in S1} \\
& [a^{S1}_2] \text{ gravity vector after movement represented in S1} \\
& Y^{S1}_i = Z^{S1}_i \times X^{S1}_i \\
& a^{S1}_2 = a^{S1}_1 \times a^{S1}_2 \\
& Z^{S1}_i = a^{S1}_1 \\
\\
& [X^{S2}_i \ Y^{S2}_i \ Z^{S2}_i] \text{ Representation of X,Y,Z axes of the inertial reference system in S2} \\
& [x_{S2} \ y_{S2} \ z_{S2}] \text{ X,Y,Z axes of the current orientation (S2) axes system} \\
& [a^{S2}_3] \text{ gravity vector before movement represented in S2} \\
& [a^{S2}_4] \text{ gravity vector after movement represented in S2} \\
& Y^{S2}_i = Z^{S2}_i \times X^{S2}_i \\
& a^{S2}_4 = a^{S2}_3 \times a^{S2}_4 \\
& Z^{S2}_i = a^{S2}_3 \\
\\
& R_i^{S1} = \begin{bmatrix} X_i^{S1} & Y_i^{S1} & Z_i^{S1} \end{bmatrix} R_i^{S1} = \begin{bmatrix} X_i \cdot X_{S1} & X_i \cdot Y_{S1} & X_i \cdot Z_{S1} \\ Y_i \cdot X_{S1} & Y_i \cdot Y_{S1} & Y_i \cdot Z_{S1} \\ Z_i \cdot X_{S1} & Z_i \cdot Y_{S1} & Z_i \cdot Z_{S1} \end{bmatrix} \quad R_i^{S2} = \begin{bmatrix} X_i^{S2} & Y_i^{S2} & Z_i^{S2} \end{bmatrix} R_i^{S2} = \begin{bmatrix} X_i \cdot X_{S2} & X_i \cdot Y_{S2} & X_i \cdot Z_{S2} \\ Y_i \cdot X_{S2} & Y_i \cdot Y_{S2} & Y_i \cdot Z_{S2} \\ Z_i \cdot X_{S2} & Z_i \cdot Y_{S2} & Z_i \cdot Z_{S2} \end{bmatrix} \\
& R_{S1}^{S2} = R_i^{S1'} * R_i^{S2}
\end{aligned}$$

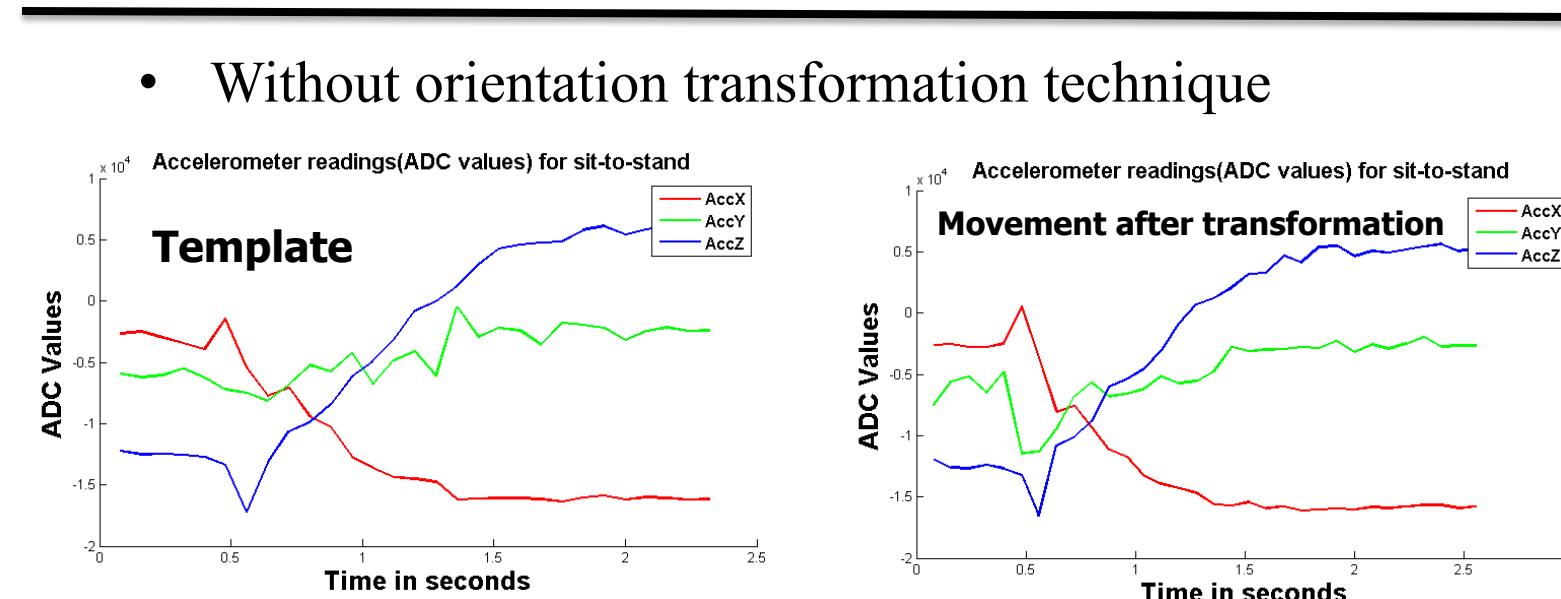
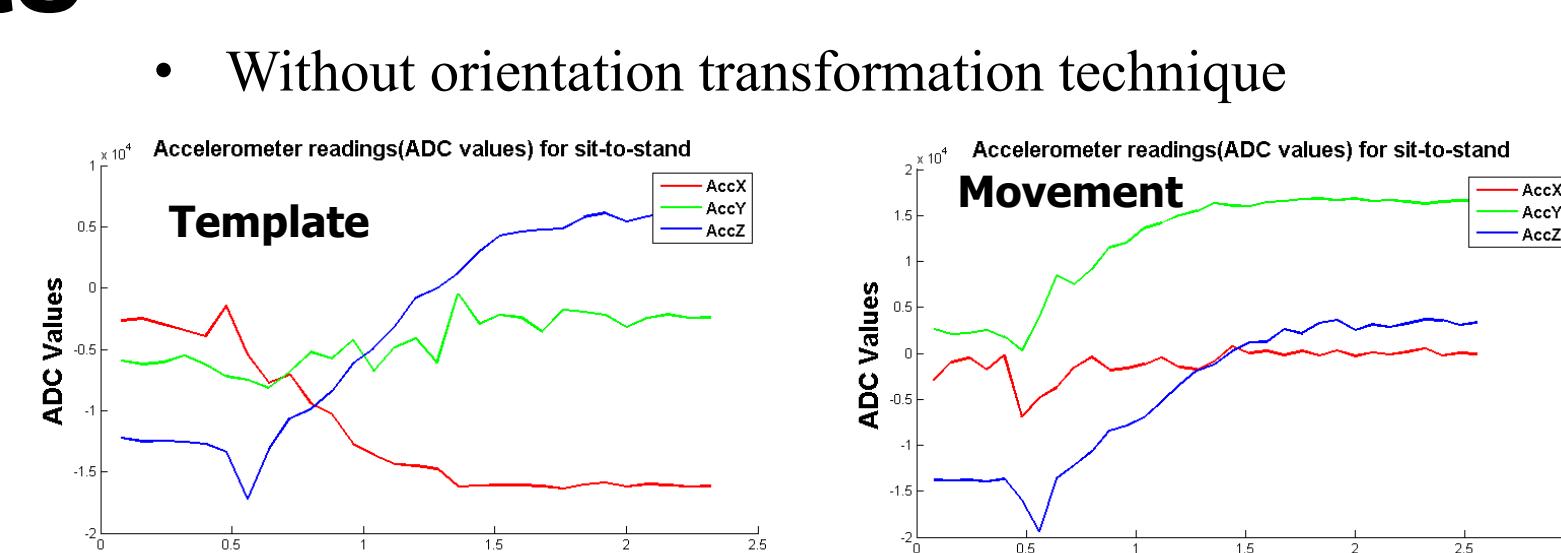
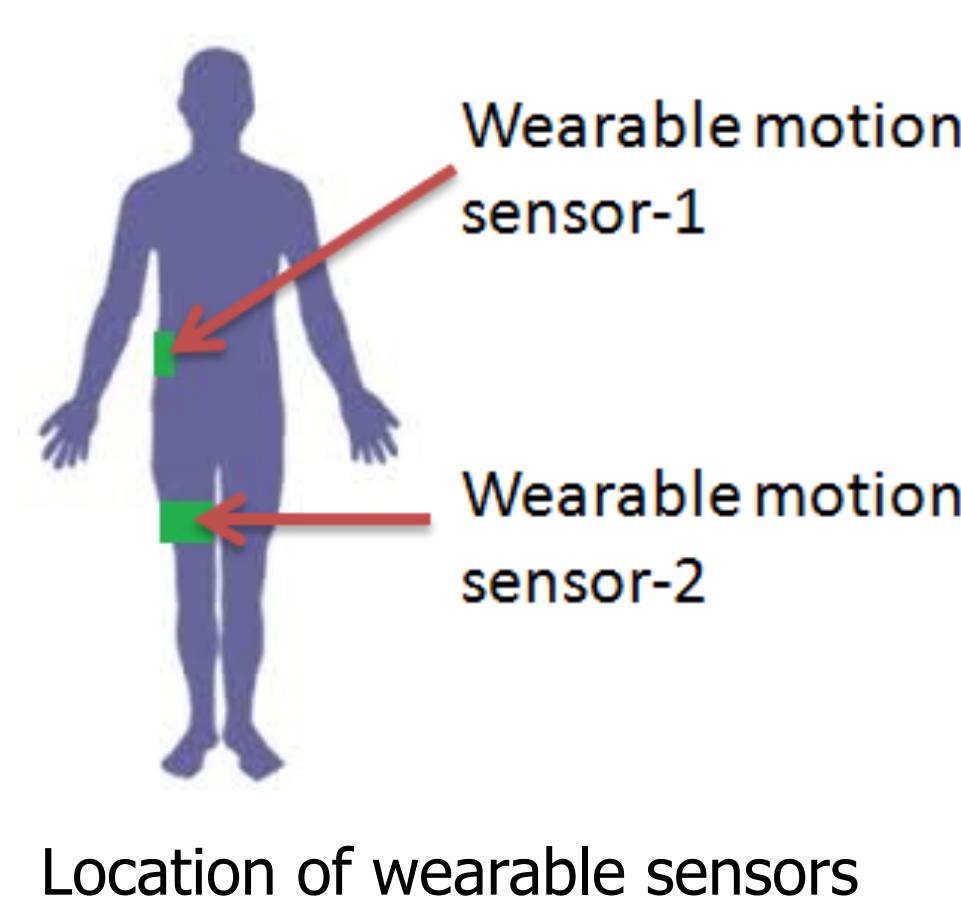
- To establish an orientation difference between two disparate sensor orientations, their individual orientations have to be known w.r.t. an inertial frame
- We use the gravity-vector representations from sensors during quiet (no activity) periods before and after a movement to derive the sensor orientation. Applying the two representations to our mathematical model we construct a common arbitrary inertial reference system
- This technique is applied to both the initial and current orientations of the sensor to derive rotation matrices describing each of their orientation differences w.r.t. the arbitrary inertial reference system and then finally w.r.t. each other
- This derived rotation matrix is used to transform the sensor data collected in the current orientation to an initial orientation enabling effective activity detection

Results

- The Motion-Storage unit designed in the ESP lab was used for the experiments. It consists of an IMU sensor composed of a 3-axis accelerometer, 3-axis gyroscope and 3-axis magnetometer
- 4 subjects wore two sensor units, one on the thigh and another on the waist in any random orientation
- With this setup a database of 4 target movements from the 4 subjects were collected. The target movements collected in this database were treated as templates
- A new user was then asked to perform the same movements with yet another new orientation for both sensors
- The proposed approach was used for data transformation
- The data transformation was followed by the classical DTW technique and all the target movements performed by the new user were identified to have minimum DTW distances with templates from the database and hence the movements were accurately detected



Motion storage sensor node



Num	Movement
1	Sit to stand
2	Stand to sit
3	Sit to lie
4	Lie to sit

Table of target movements

Summary

- From the results, it can be seen that orientation transformation is a potential technique that can lead to energy efficient activity detection independent the orientation of the sensors, paving way for a plethora of applications for better living

Future Work

- Realize the solution in a real-time environment
- Test the solution against for large sets of movements and with a large number of sensors to understand the complexity involved in a multi-sensor environment
- Incorporate the notion of cloud-based learning to match against movements that have been observed in the past.

Acknowledgments

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