

# CSE 162 Mobile Computing

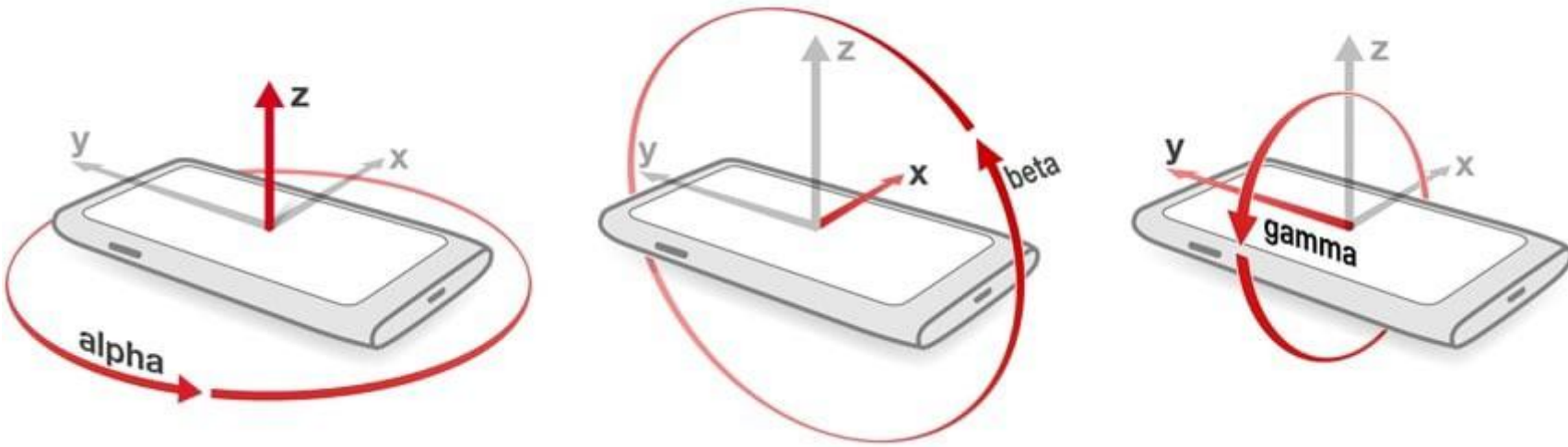
## Orientation and Step Counting

Hua Huang

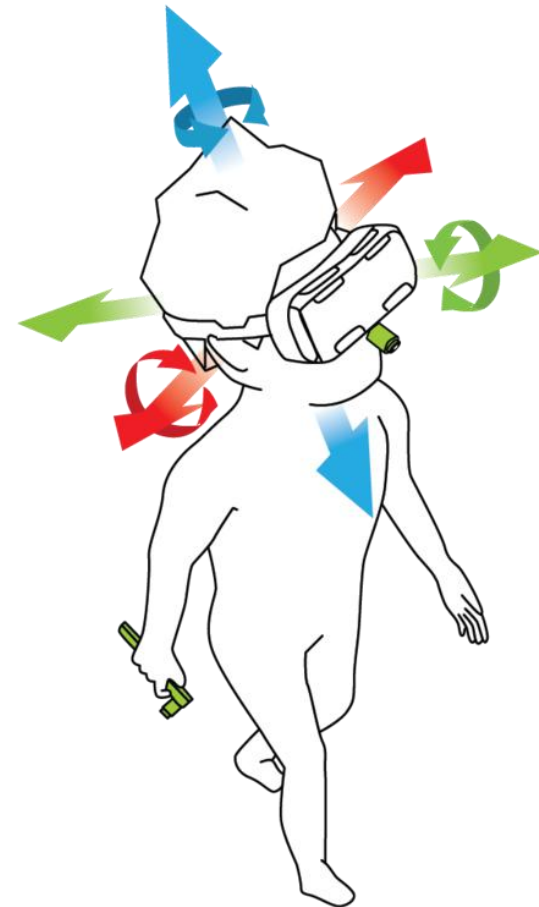
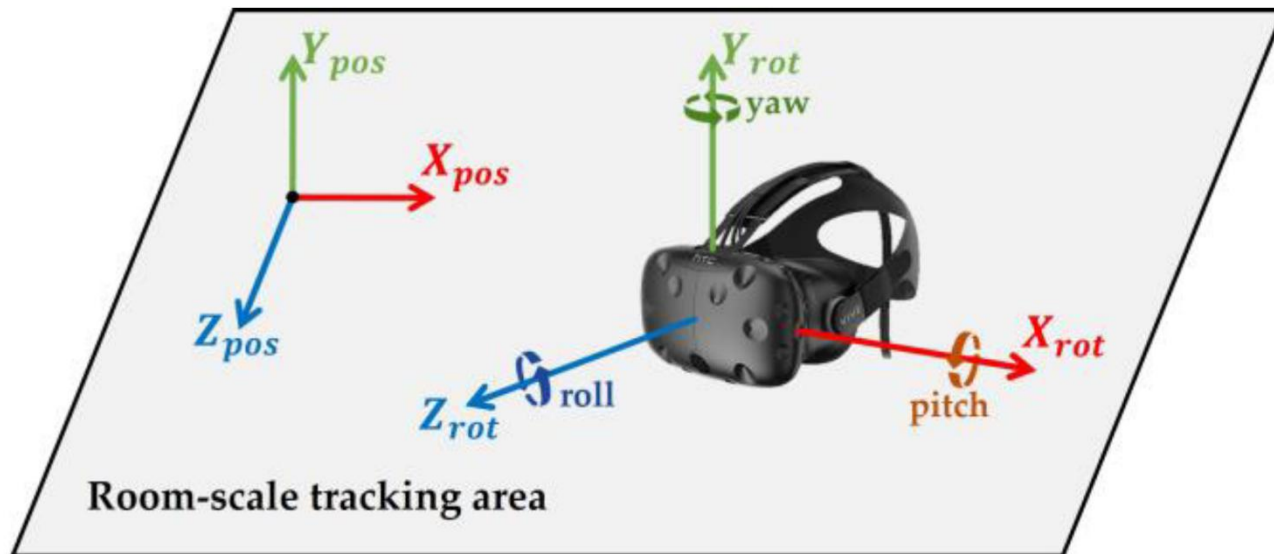
# Virtual Sensor: 3D Orientation

Question:

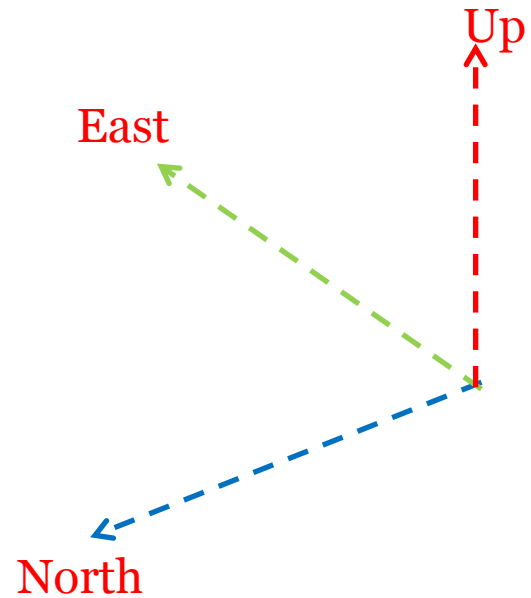
How do we know the orientation of the phone?



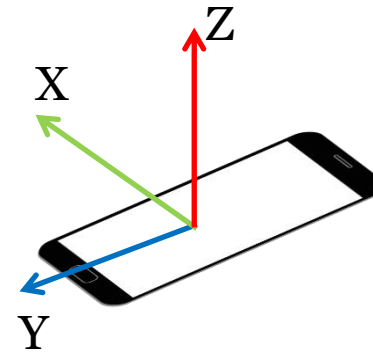
- Orientations of the VR goggle?



# Coordinate frames

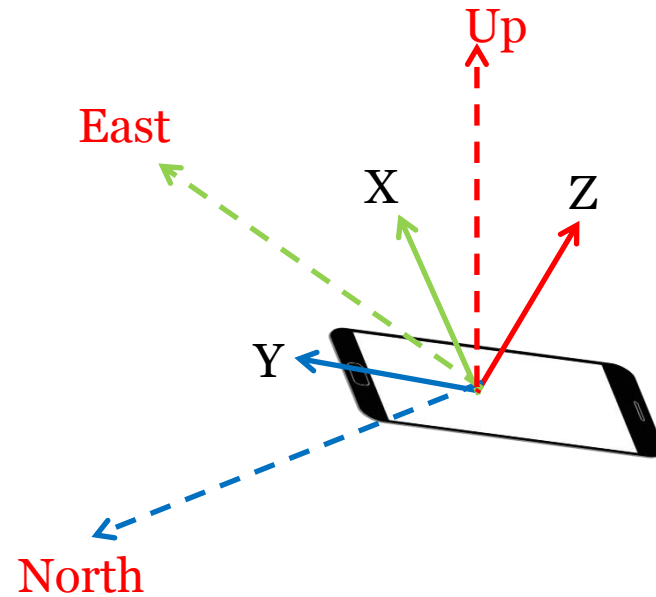


Global Frame



Local Frame

# Consider a phone in a random orientation

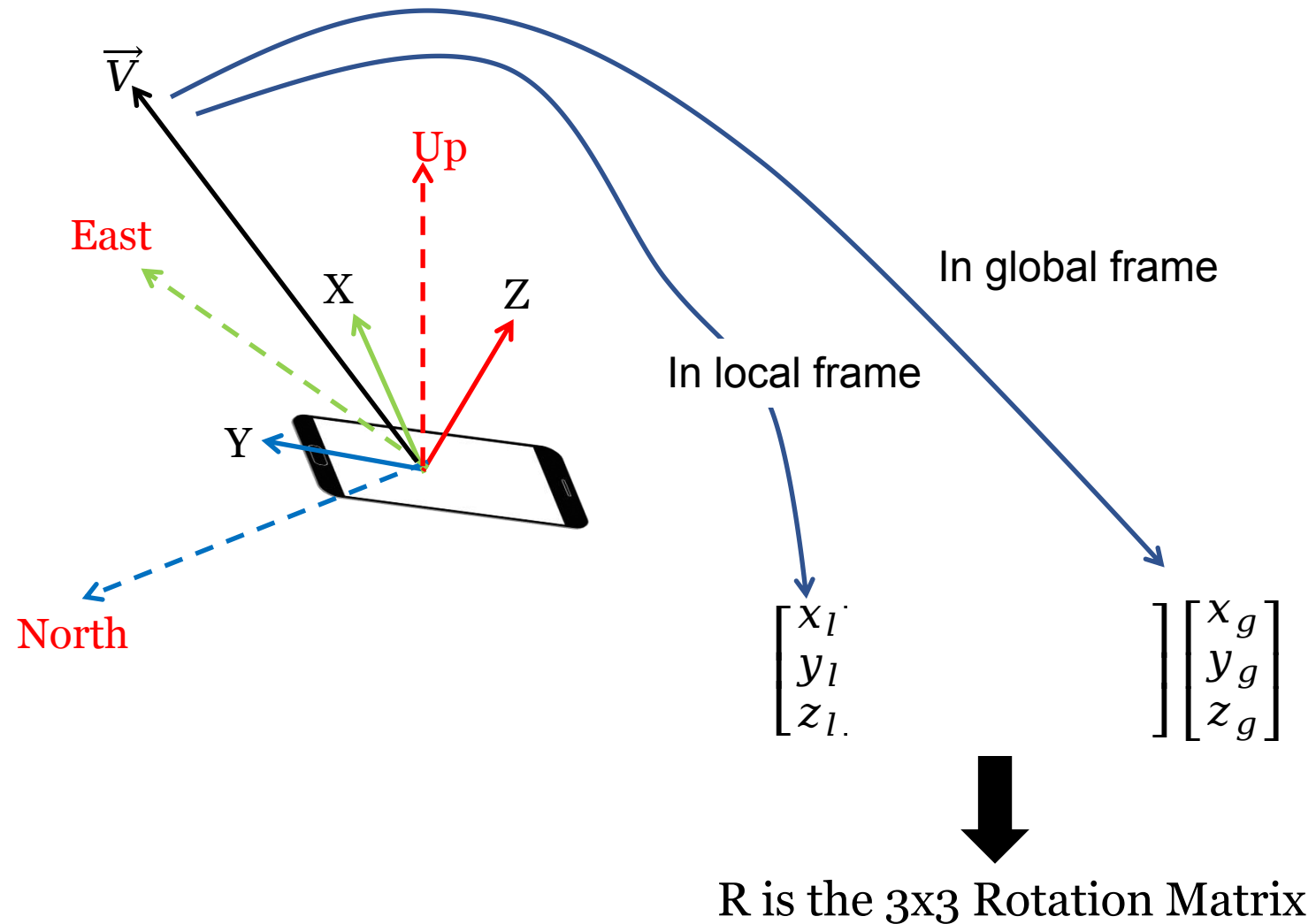


3D Orientation captures the **misalignment** between **global** and **local** frames

# Gravity Sensor

- A virtual sensor
- Calculated using accelerometer
- Always points to the earth

# Rotation Matrix



**3x3 Rotation matrix captures the full 3D orientation**



# How can we estimate rotation matrix?

Key idea     use globally known reference vectors

which can also be measured in the local frame of reference

- Gravity
- Magnetic North

# Gravity equation

Gravity globally known, measurable in local frame with gravity sensor

$$\begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ -g \end{bmatrix}$$

$$\begin{bmatrix} m_x \\ m_y \\ m_z \end{bmatrix} = \begin{bmatrix} 0 \\ M \\ 0 \end{bmatrix}$$

Magnetic north, globally known, measurable in local frame with magnetometer

6 equations and 9 unknowns (3x3 rotation matrix) can we solve ?

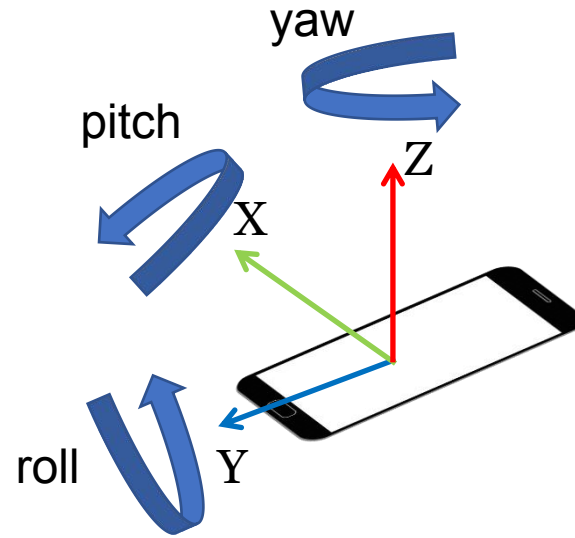
Yes, these 9 unknowns are all not independent (rotation matrix satisfies special properties)

- It does not change length of a vector
- Columns are orthogonal unit vectors

The above 6 equations are sufficient to solve the rotation matrix

Gravity Sensor and Magnetometer can be used to determine the rotation matrix (3D orientation)

# Decomposing the rotation matrix



$$\begin{bmatrix} \text{3x3 Rotation Matrix R} \end{bmatrix} = \begin{bmatrix} \cos(\text{pitch}) & 0 & -\sin(\text{pitch}) \\ 0 & 1 & 0 \\ \sin(\text{pitch}) & 0 & \cos(\text{pitch}) \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\text{roll}) & \sin(\text{roll}) \\ 0 & -\sin(\text{roll}) & \cos(\text{roll}) \end{bmatrix} \begin{bmatrix} \cos(\text{yaw}) & -\sin(\text{yaw}) \\ \sin(\text{yaw}) & \cos(\text{yaw}) \\ 0 & 0 & 1 \end{bmatrix}$$

Orientation can be represented as 3D yaw, pitch, roll

Estimating yaw, pitch, roll will determine the orientation

# Gravity equation

$$\begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix} = \begin{bmatrix} \text{Rotation} \\ \text{Matrix R} \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ g \end{bmatrix}$$

$$\begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix} = \begin{bmatrix} \cos(pitch) & 0 & -\sin(pitch) \\ 0 & 1 & 0 \\ \sin(pitch) & 0 & \cos(pitch) \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(roll) & \sin(roll) \\ 0 & -\sin(roll) & \cos(roll) \end{bmatrix} \begin{bmatrix} \cos(yaw) & -\sin(yaw) \\ \sin(yaw) & \cos(yaw) \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ -g \end{bmatrix}$$

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**Gravity output does not depend on yaw!**

**Hence, yaw cannot be estimated using gravity**

# Accelerometer equation

$$\begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix} = \begin{bmatrix} \text{Rotation} \\ \text{Matrix R} \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ -g \end{bmatrix}$$

$$\begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix} = \begin{bmatrix} -\sin(\text{pitch}) \cdot \cos(\text{roll}) \\ -\sin(\text{roll}) \\ -\cos(\text{pitch}) \cdot \cos(\text{roll}) \end{bmatrix} \cdot g$$

**The above equations estimate pitch and roll**

# Magnetometer equation

$$\begin{bmatrix} m_x \\ m_y \\ m_z \end{bmatrix} = \begin{bmatrix} \text{Rotation} \\ \text{Matrix R} \end{bmatrix} \begin{bmatrix} 0 \\ M \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} m_x \\ m_y \\ m_z \end{bmatrix} = \begin{bmatrix} \cos(pitch) & 0 & -\sin(pitch) \\ 0 & 1 & 0 \\ \sin(pitch) & 0 & \cos(pitch) \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(roll) & \sin(roll) \\ 0 & -\sin(roll) & \cos(roll) \end{bmatrix} \begin{bmatrix} \cos(yaw) & -\sin(yaw) \\ \sin(yaw) & \cos(yaw) \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 0 \\ M \\ 0 \end{bmatrix}$$

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Pitch, roll known from accelerometer

Unknown yaw can be determined from above equations

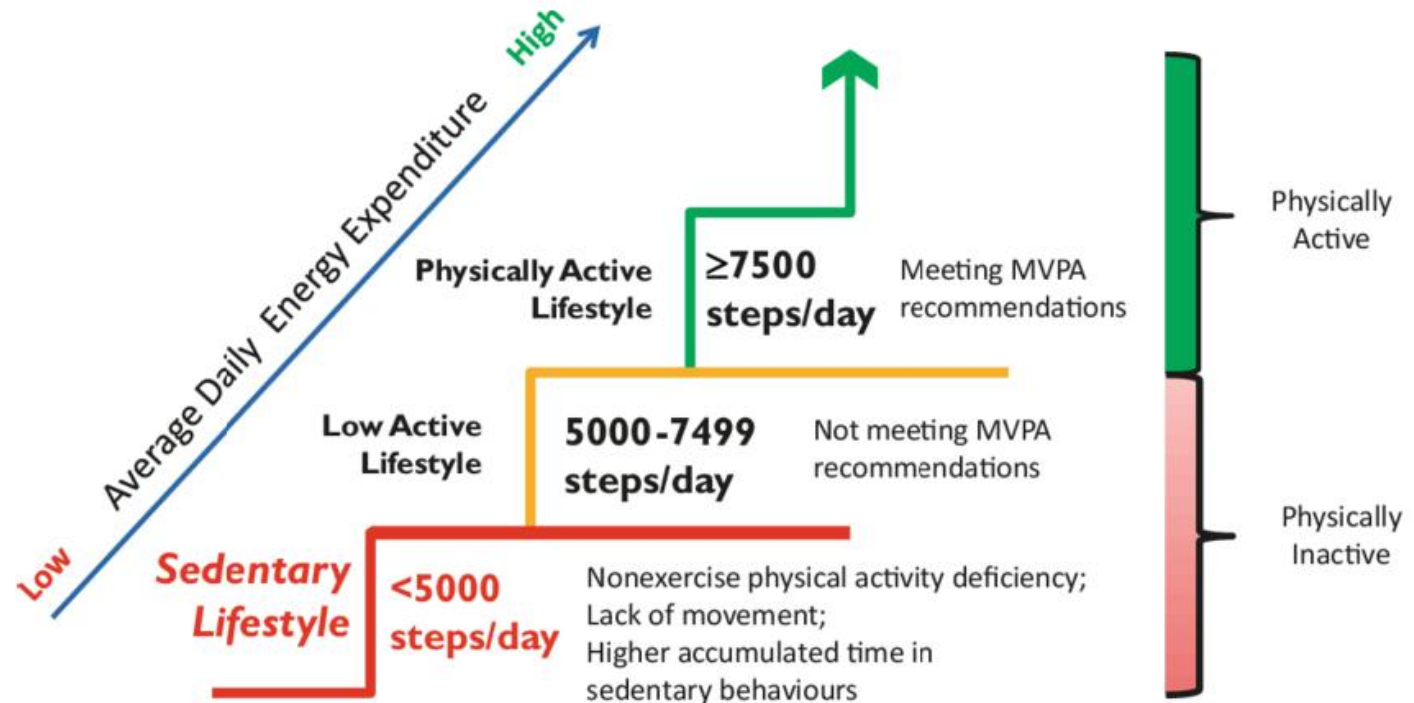
**yaw, pitch, roll together determine the rotation matrix (3D orientation) of a system**



# Virtual Sensor: Step Counting

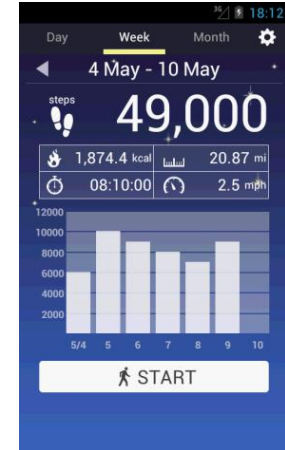
# Sedentary Lifestyle

- Sedentary lifestyle
  - Increases risk of diabetes, heart disease, dying earlier, etc
  - Kills more than smoking!!
- Categorization of sedentary lifestyle based on step count:
  - “A step-defined sedentary lifestyle index: < 5000 steps/day” (2013)



# Step Count Mania

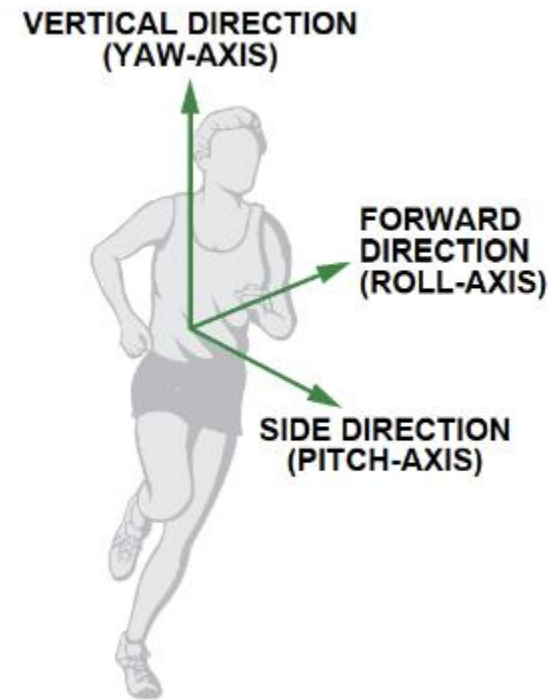
- Everyone is crazy about step count these days
- Pedometer apps, pedometers, fitness trackers, etc
- Tracking makes user aware of activity levels, motivates them to exercise more



# Benefits mobile step counters

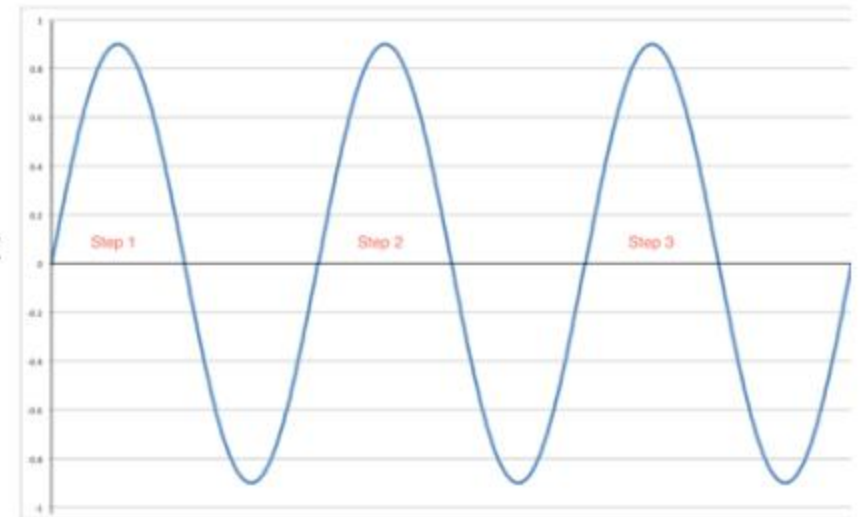
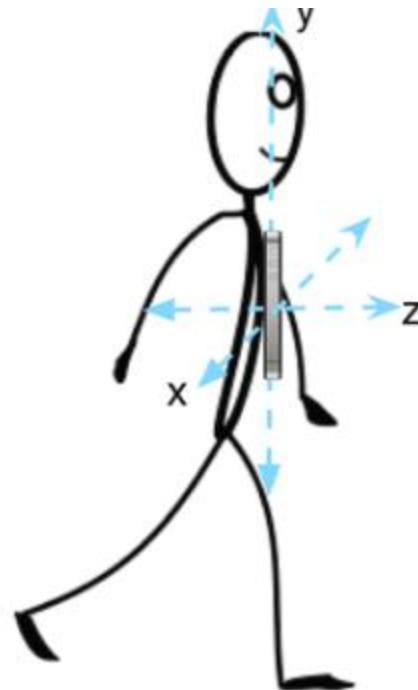
- Always on. Everywhere. Continuous monitoring.
- Low-cost
- Better privacy than computer vision

# *Definition of each axis*



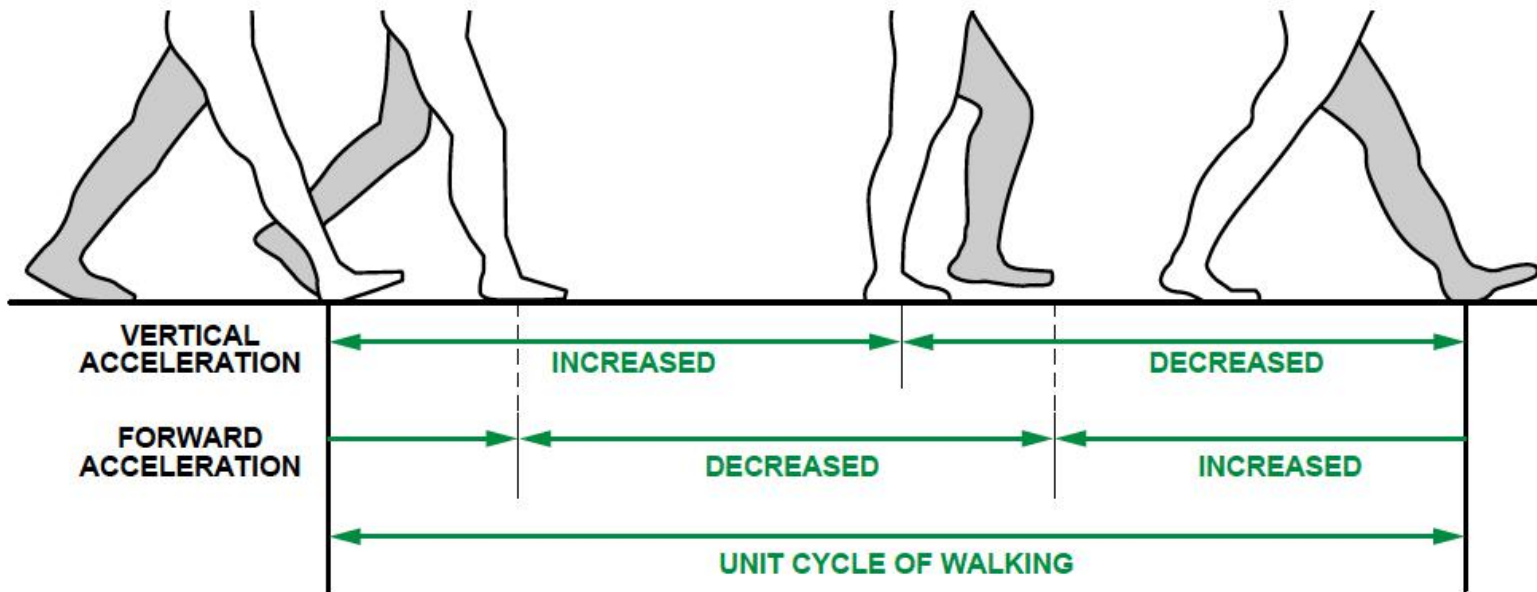
# Ideal sensor data

- In an ideal situation, you would like to see a signal like this.
  - One of the axes of the phone is along the direction of gravity, and the steps can be clearly observed in the signal.
- But in practice, the data often deviates from the ideal case



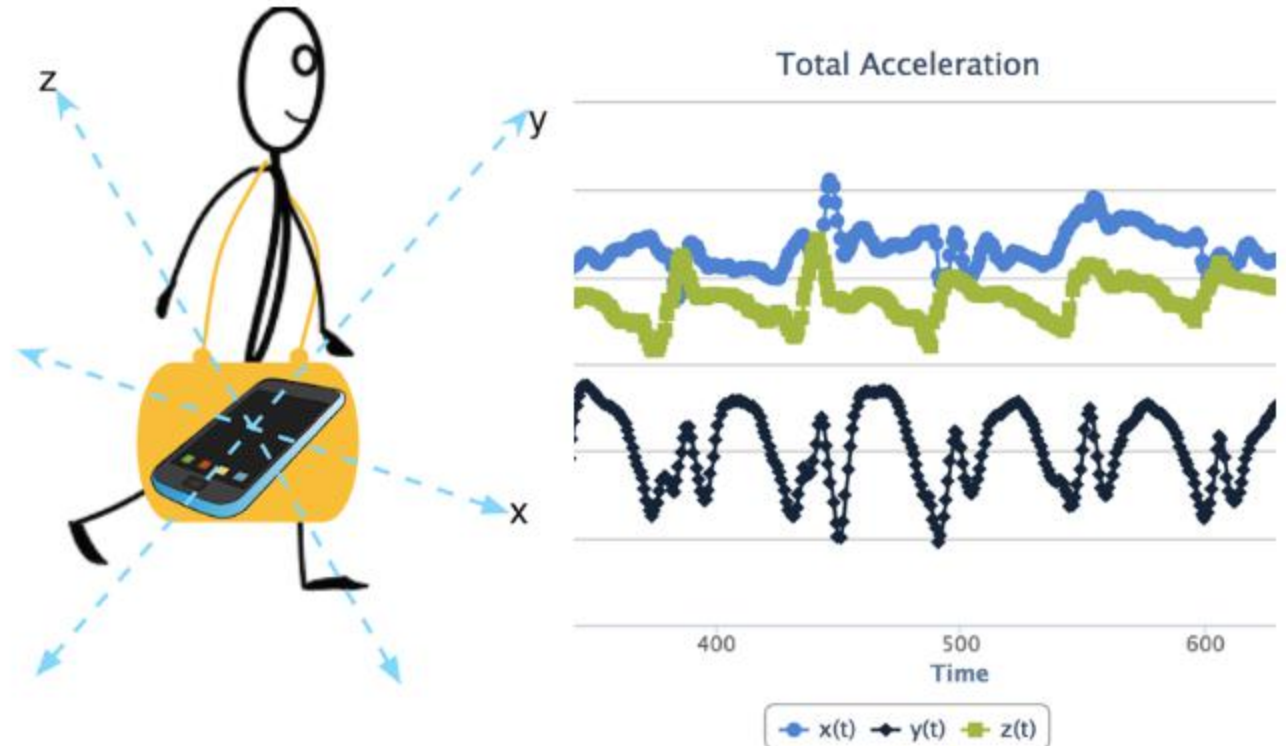
# The Nature of Walking

- Vertical and forward acceleration increases/decreases during different phases of walking
- Walking causes a large periodic spike in one of the accelerometer axes
- Which axes (x, y or z) and magnitude depends on phone orientation



# Accelerometer signal in a real-world situation

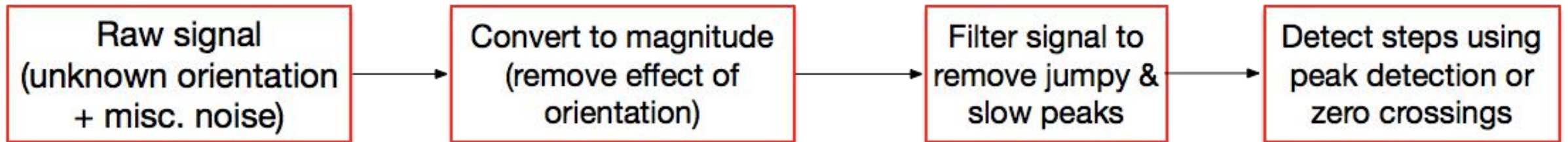
- A more realistic signal is shown
  - some component of the user acceleration and gravity is present along all three axes.
  - The measurements are influenced by the phone orientation
- we need to design an *orientation-independent* algorithm to detect steps.





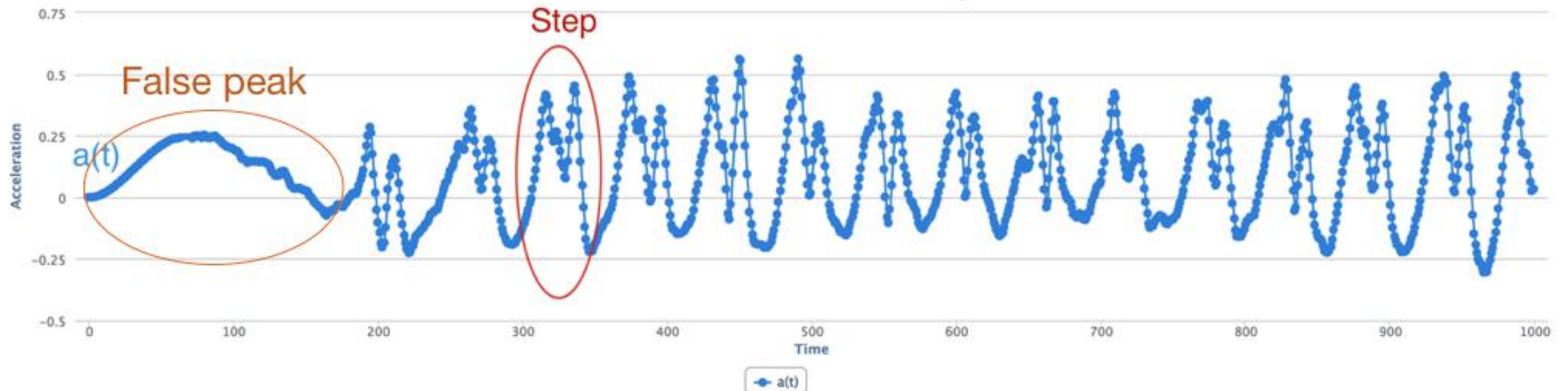
# Step Detection Algorithm

- The key insight in our method is to convert the 3-axis signal into a one axis magnitude signal, and then extract steps from this signal.



# Step 1: Extract Signal Magnitude

- take the magnitude of the entire acceleration vector i.e.  $\sqrt{x^2 + y^2 + z^2}$ , where x, y, and z are the readings of the accelerometer along the three axes.
- The signal is not dependent on phone orientation now



# Step 2: Filter the signal to remove noise

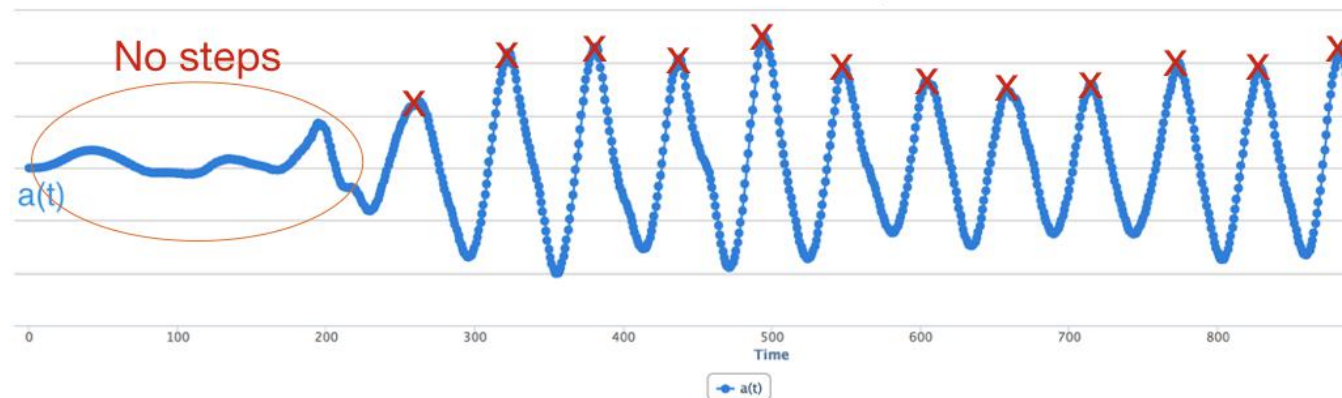
- What noises exist in the data?
  - **Jumpy peaks:** Since the phone is often carried in a pocket/purse, it can jiggle a little with each step. Also, some users have a bounce in their step, so even though they are taking a single step, the phone can bounce multiple times within this step.
  - **Short peaks:** Small peaks can occur when a user is using a phone (e.g. making a call or using an app).
  - **Slow peaks:** Slow peaks can occur when the phone is moved or due to movements of the leg while sitting (if the phone is in the pant pocket)

# Filtering

- To remove these sources of noise, we are going to use frequency-domain noise removal.
- Notice that we need to remove high frequency variations like jumpy peaks and low frequency variations like slow peaks.
- A simple solution is to use a filter that keeps only frequencies relating to walking and removes the rest.

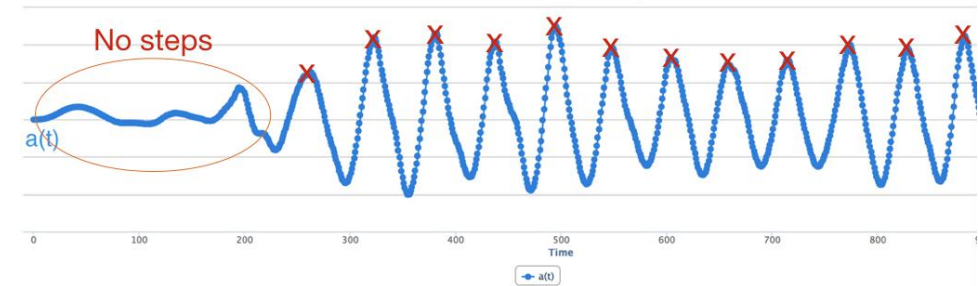
# Filtering

- Typical walking pace may be under three steps a second (3 Hz) and over half step a second (0.5Hz), so we remove all frequencies above 5 Hz and below 0.5 Hz (just to give some margin for error)
- Even after we remove low and high frequency peaks, we may be left with some short peaks.
  - A simple way to deal with this is to look only for large peaks and ignore small peaks.

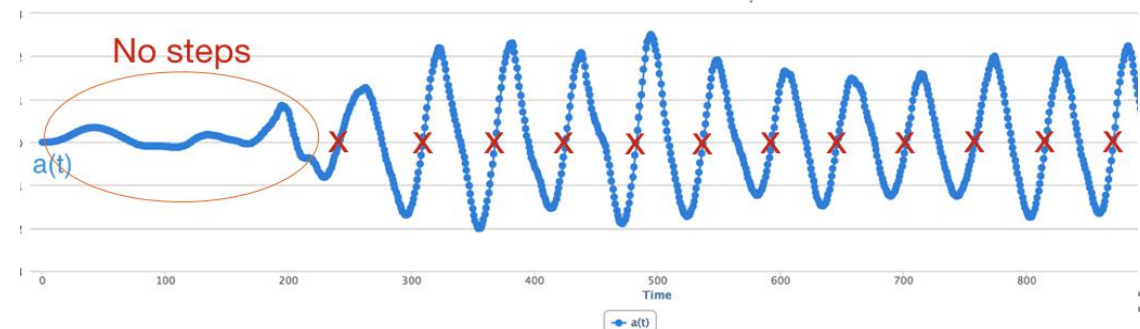


# Step 3: Detect Steps

- Approach 1: Find signal peaks

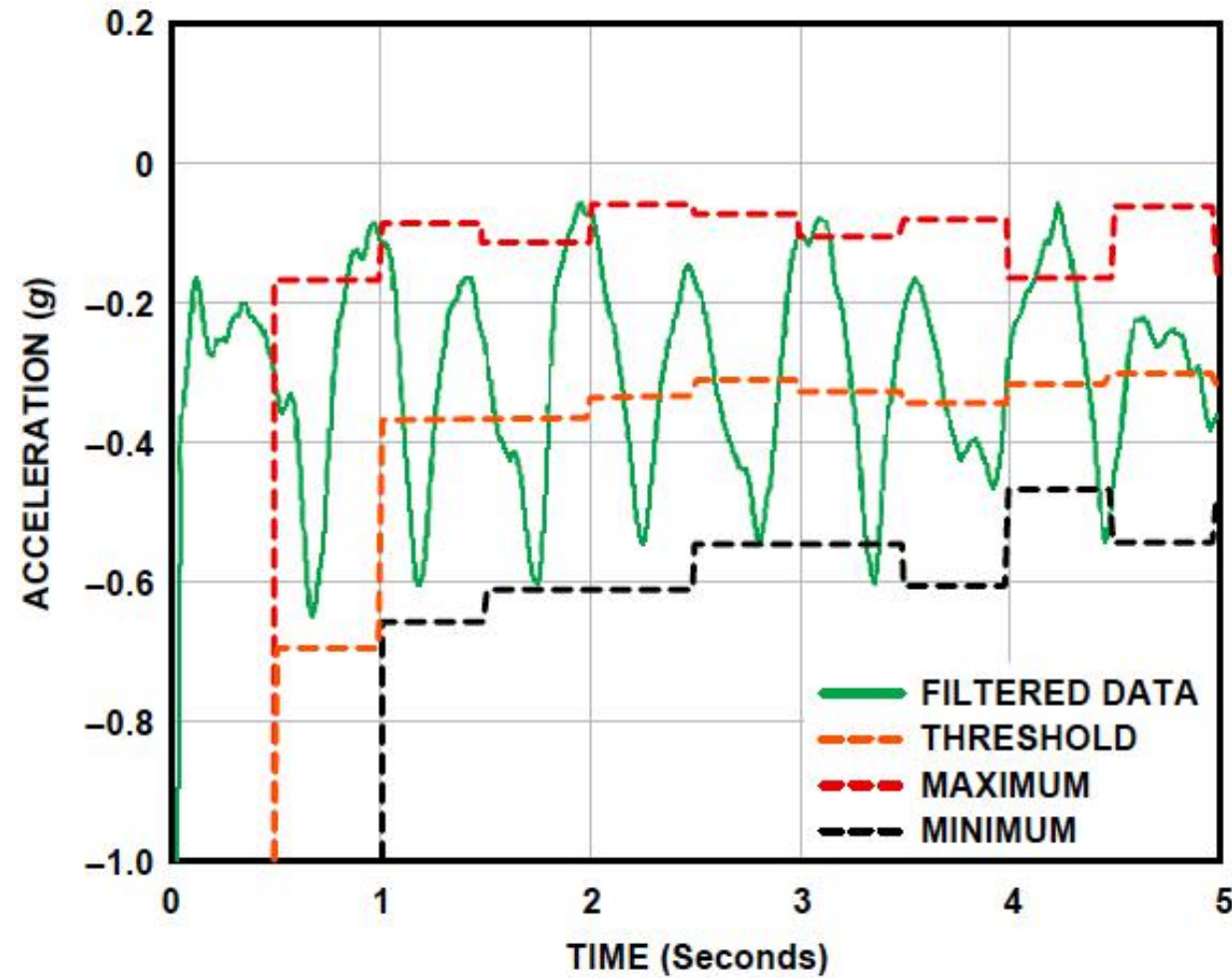


- Approach 2: Zero crossing:
  - Subtract the mean for each window and look at zero crossings i.e. times when the signal crosses from the negative to positive in the upward direction



# Dynamic Threshold-based Step Detection

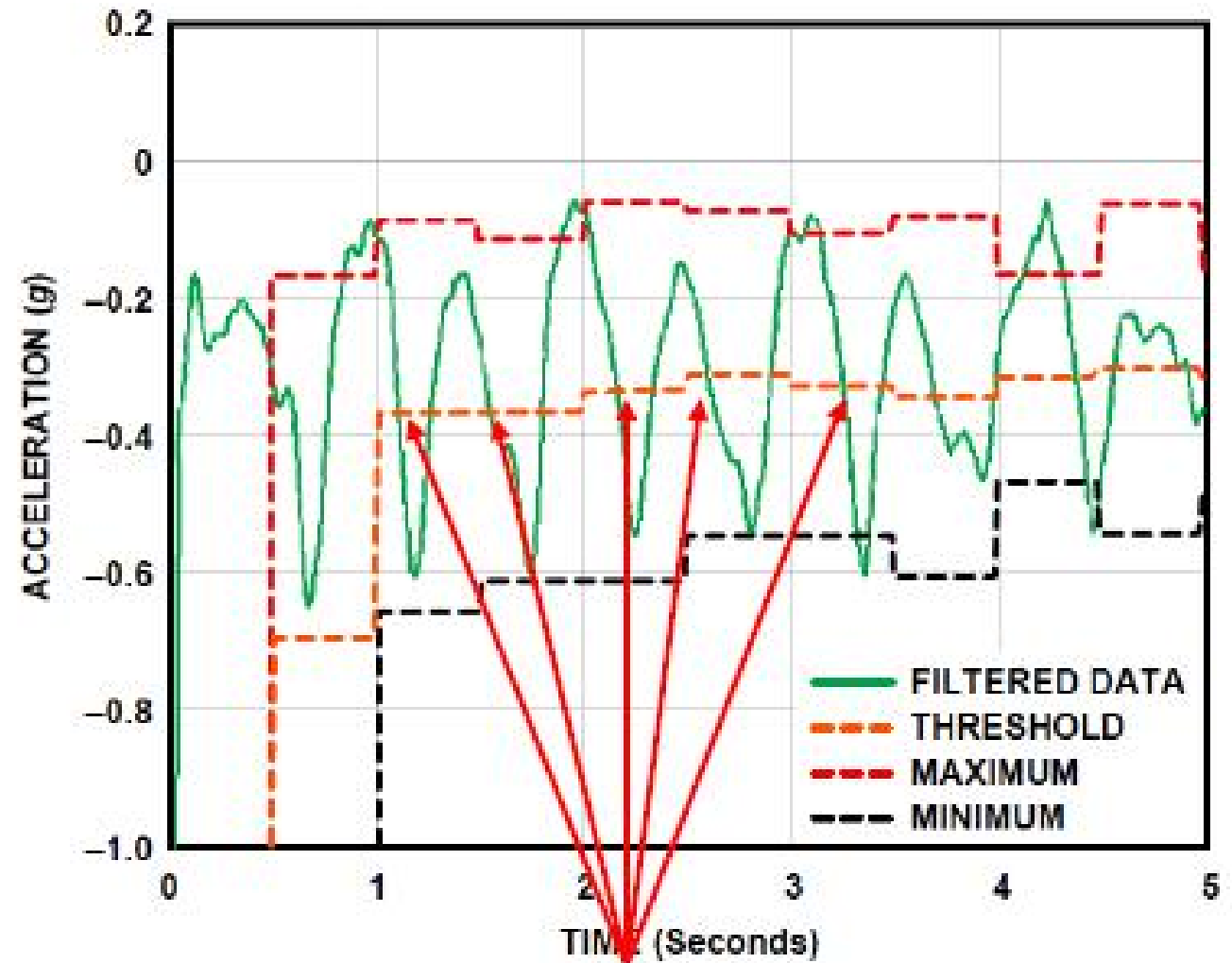
- Focus on accelerometer axis with largest peak
- Would like a threshold such that each crossing is a step
- Track min, max values observed every 50 samples
- Compute ***dynamic threshold:  $(Max + Min)/2$***



# Step Detection Algorithm

A step is

- Indicated by crossings of dynamic threshold
- Defined as negative slope ( $\text{sample\_new} < \text{sample\_old}$ ) when smoothed waveform crosses dynamic threshold



Steps



# Distance Estimation

- Calculate distance covered based on number of steps taken
  - *Distance = number of steps × distance per step*
- Distance per step (stride) depends on user's height (taller people, longer strides), and step frequency
- Using person's height, can estimate their stride, then number of steps taken per 2 seconds

Steps per 2 s	Stride (m/s)
0~2	Height/5
2~3	Height/4
3~4	Height/3
4~5	Height/2
5~6	Height/1.2
6~8	Height
>=8	1.2 × Height

# Calorie Estimation

- To estimate speed, remember that  $\text{speed} = \text{distance}/\text{time}$ . Thus,
  - $\text{Speed (in m/s)} = (\text{no. steps per 2 s} \times \text{stride (in meters)})/2\text{s}$
- Calorie expenditure, which depends on many factors
  - Body weight, workout intensity, fitness level, etc
- Empirical simplified equation:
  - $\text{Calories (C/kg/h)} = 1.25 \times \text{speed (m/s)} \times 3600/1000 = 4.5 \times \text{speed (m/s)}$

# Limitations and Future Work

- Strong assumptions on how the users walk.
  - What about short-interval, high intensity exercise?
  - What about the other calorie expenditures? Standing vs sitting
- Currently, dedicated system for each activities. General activity recognition is still under research.

