Activity recognition: Measuring human mobility using accelerometers
Why measuring human mobility?

- First attempt to analyze human motion was from the 5th century BC, by Aristotele
- Their model involved a musculoskeletal system with
  - Levers
  - Forces
  - Center of gravity
- Since then, the study of human motion has attracted a lot of attention
- Recently, with the advances and miniaturization of sensing devices
  new frontiers and application have been made possible
Importance of human motion

- Many efforts in our life are interrelated, and the lack of some of these may cause devastating effects in the quality of life.

Factors affecting quality of life [1]
Importance of human motion

- Specifically reduced motion may cause a vicious circle with devastating effects

Cascading effect of reduced motion [1]
Importance of human motion

- For these reasons, it is of primary importance to monitor the quality of human motion.
- For a long time, this has been done manually, by experts (e.g., doctors) in a controlled environment.
- Today the development of less intrusive sensing technologies can make this process automatic.
Measuring motions through accelerometers

- Accelerometers are the sensing devices used to measure human motions.
- Several types of technologies are available: piezoelectric, piezoresistive, differentiable capacitor, etc...
- The energy consumption of these devices is minimal = long lifetime.
- An accelerometer is in general able to measure the acceleration in one or more dimensions.
- The output of an accelerometer at a certain time $t$ is generally a triple $(a_x, a_y, a_z)$.
- The series of this triples generates a signal, that can be analyzed to infer the human activity.
General scheme of activity recognition approaches based on accelerometer data

- Signal collection
- Signal processing
- Machine learning
- Activity classification

Features selection
The (very) basics of signal processing (1)

- An (analog) signal is a function of time \( x(t) \)
- Signals are generally represented in the frequency domain using the **Fourier transform**
- Given a signal \( x(t) \), its Fourier transform \( X(\Omega) \) is the following, where \( \Omega \) is the frequency

\[
X(\Omega) = \int_{-\infty}^{\infty} x(t) e^{-j\Omega t} \, dt
\]

- This basically represents the signal as the (infinite) sum of sinusoidal functions thanks to Euler’s formula:

\[
e^{i\theta} = \cos \theta + i \sin \theta
\]

- The signal can be uniquely reconstructed by its functional representation

\[
x(t) = \int_{-\infty}^{\infty} X(\Omega) e^{j\Omega t} \, d\Omega / 2\pi
\]
An intuitive example is the following.

Note that here $f(t) = x(t)$ and $X(\Omega) = f^*(\xi)$.
The (very) basics of signal processing (2)

- Signals as in the case of the accelerometer are generally continuous functions that are sampled at each instant $nT$, with $n = 1, 2, 3, \ldots$
- $T$ is called the *sampling interval* (sec), $f_s = 1/T$ is the sampling rate (Hertz = 1/s)
- The sampling interval is very important, as it can significantly alter the representation of the original signal
- Intuitively, $T$ should be small enough to capture the variations occurring between samples, but not too small to cause too many samples to be processed
The (very) basics of signal processing (3)

- The Nyquist Theorem provides the sufficient conditions to accurately represent a signal $x(t)$
  
  - $x(t)$ must be bandlimited, i.e. it must contain frequencies up to a maximum value $f_{\text{max}}$
  
  - The sampling rate $f_s$ must be at least twice $f_{\text{max}}$, i.e., $f_s \geq 2f_{\text{max}}$
  
  - Typical rates for common applications are:

<table>
<thead>
<tr>
<th>application</th>
<th>$f_{\text{max}}$</th>
<th>$f_s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>geophysical</td>
<td>500 Hz</td>
<td>1 kHz</td>
</tr>
<tr>
<td>biomedical</td>
<td>1 kHz</td>
<td>2 kHz</td>
</tr>
<tr>
<td>mechanical speech</td>
<td>2 kHz</td>
<td>4 kHz</td>
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<tr>
<td>audio</td>
<td>20 kHz</td>
<td>40 kHz</td>
</tr>
<tr>
<td>video</td>
<td>4 MHz</td>
<td>8 MHz</td>
</tr>
</tbody>
</table>
The (very) basics of signal processing (4)

- Fourier transformation does not tell information regarding **when** certain frequencies occurred.
- This makes it appropriate for periodic signals, but not for signals that contain relevant changes over time.
- An alternative is to use sliding windows, e.g. \([t, t+K]\), and consider the Fourier transformation in the window only.
- The choice of \(K\) can however create resolution problems.
- In terms of human activity recognition, this translates in Fourier transformation being useful for static activities, and less suitable for dynamic activities.
- For dynamic activities, both the frequency and the time factors need to be taken into account.
- This is achieved usually through **Wavelet** transformation.

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**ACTIVITY RECOGNITION: MEASURING HUMAN MOBILITY USING ACCELEROMETERS**
The (very) basics of signal processing (5)

- The continuous wavelet transform (CWT) at a scale \( (a>0) \ a \in \mathbb{R} \) and translational value \( b \in \mathbb{R} \) is expressed by

\[
X_w(a, b) = \frac{1}{|a|^{1/2}} \int_{-\infty}^{\infty} x(t) \overline{\psi} \left( \frac{t - b}{a} \right) dt
\]

- where \( \psi() \) is the mother wavelet function (the bar stands for its complex conjugate)

- Also in this case the original signal can be reconstructed given the transformation
The (very) basics of signal processing (6)

- Signals can be **filtered** to remove some frequencies from the spectrum
- It is sometime useful to remove spurious frequencies resulting from erroneous sampling
- Several types of filters are available, for example

![Diagram of Low Pass Filter and High Pass Filter](image)

- There is much more to know about signal processing, if you are curious see [3]
Bibliography

