Ambulatory systems for monitoring physical activity: Technological issues in fall prevention in the elderly

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Outline

- Introduction: Ageing population
- Relevance of BFS for measuring human function
- Ambulatory monitoring: hardware and software
- Physical activity monitoring: algorithms and application to ageing
- Gait analysis: algorithm and application to ageing
- Fall detection
- Perspectives
Introduction: Ageing population

- Fall in elderly
  - 30% of persons older than 65 fall each year
  - 30% of falls lead to injuries and risk of death

- Fall consequences
  - Lose of confidence and Fear of falling
  - Physical activity avoidance
  - De-conditioning and lack of performance

Factors leading to disability

Pathology musculoskel, neurologic, etc.

muscle weakness
De-conditioning

Gait & balance impairment

Activity Avoidance

Disability

Fear of falling

?
Fall prevention in EU

- **ProFaNE**
  - Prevention of fall network Europe
  - Monitoring function before, during and after intervention
  - Prevent loss of function abilities
  - [www.profane.eu.org](http://www.profane.eu.org)

- **Mobex**
  - Mobility and exercises in elderly
Why Body-fixed sensors?

Fail in sampling rare events

Fail to measure natural activity

Cannot capture the long-term variation

Physical activity organization, history of fall

In Lab

fall, fall related tasks
Why Body-fixed sensors?

Ambulatory systems

- Long-term monitoring
- Natural environment
- No marker hiding
- Higher sampling rate
- Consistent with human sensory system
- Quality
- Quantity
Consistency with human sensory system

<table>
<thead>
<tr>
<th>Human receptors</th>
<th>Body-fixed sensors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Otolith</td>
<td>Inclinometer</td>
</tr>
<tr>
<td>Semi-circular channel</td>
<td>Triaxial acceleration</td>
</tr>
<tr>
<td>Tendon (Golgi)</td>
<td>Strain-gage</td>
</tr>
<tr>
<td>Neuromuscular spindle</td>
<td>Tactile sensors</td>
</tr>
<tr>
<td>thermoreceptor, pain</td>
<td></td>
</tr>
<tr>
<td>(nocireceptors)</td>
<td></td>
</tr>
</tbody>
</table>
Accelerometry

- Energy expenditure (actimeter)
- Gait Analysis: temporal parameters
- Gait speed
- Joint angles
- Balance control analysis
- Inverse dynamics
- Body posture allocation
- Physical activity classification
- Jump
Gyroscope

- Gait analysis: temporal-spatial
- Joint kinematics
- Walking classification (climbing-level)
- Balance control analysis
- Tremor and dyskinesia analysis
Examples of BFS fusion

- **Gyroscope-accelerometer**
  - Trunk position \((\text{Najafi et al.}, 2003)\)
  - Foot position \((\text{Sabatini et al.}, 2005)\)
  - 2D Knee angle \((\text{Williamson et al. 2001, Dejnabadi et al. 2005})\)
  - Hip abduction moment \((\text{Ziljstra et al. 2004})\)

- **Gyroscope-Magnetic compass**
  - Segment orientation \((\text{Haid et al. 2004})\)

- **Gyroscope-Accelerometer-magnetic Compass**
  - Body segment orientation \((\text{Luinge et al., 2004, Bachmann et al. 2003})\)
  - Lumbar spine motion \((\text{Lee et al. 2003})\)

- **Gyroscope-foot pressure sensor**
  - Foot angle \((\text{Pappas et al., 2001})\)
Ambulatory monitoring: hardware

- Sensors configuration
  - Type, number, position, attachment
- Datalogging configuration
  - Connection, recording, RT transmission
- Size
- Weight
- Robustness
- Power consumption
- Memory size
- A/D resolution
- Number of channels
- Bandwidth
- Sampling rate
Example: Physiolog®

- Record data on memory card
- Wireless communication with PC
- Small sensors

Parameters

Memory card

PC
Example: ASUR

- No cable
- High number of sensors
- Sensor module weight

Sensor modules → parameters

PC

Accelerometers

Gyroscope

Batteries
Signal processing and modeling

- Noise and artifacts
  - Movement artifacts: skin movement
  - Interference: temperature, impact, gravity, EM
  - Electronic noise and drift
- Non stationary signals
  - Posture transition
  - Walking with varied velocity
- Pattern recognition
  - Cyclic and non cyclic activity: gait, sit-stand
- Feature extraction
  - Spatio-temporal gait parameters, Joint’s ROM
Signal processing and modeling

- Biomechanical modeling
  - Biomechanical constraints: gait stance, free fall (jump)
  - Rotation and translation: stride length due to rotations
  - Mobile and fixed reference: sensor reference, room reference
  - Segment orientation: vertical absolute axis (gravity)

- Signal enhancing
  - Kalman filtering
  - Sensor fusion using biomechanical constraints
Physical activity monitoring

- Therapy Objectification
Daily Physical Activity classification

- Lying
- Back
- Side
- Sitting
- Leaning
- Transition
- Standing
- Static
- Dynamic
- Walking
- Fast
- Slow
- Descent
- Ascent
- Flat
- Turning
- Running
- Fall
- Tilting
- Fast
- Low activity
- High activity
Actimetry and EE estimation

- Generally triaxial accelerometer
- Algorithm:
  - Estimation of norm (or absolute value)
    \[ a = \sqrt{a_x^2 + a_y^2 + a_z^2} \]
  - Find the integral over a fixed period
  - Calibrate with EE (O₂ consumption)

FIGURE 2—Analytical processing of the acceleration data. 1. Raw: a 60-s window of a digitized raw signal collected at 32 Hz and using a 8-bit A/D conversion. 2. Rectification: all negative signal from (1) was turned into positive. 3. Integration: 15-s epochs.

KY. CHEN et al, MSSE, Nov 2005,
Limitation of actimetry

- Accelerometer output exhibited a high correlation with \( VO_2 \) and speed when data were analyzed separately for each incline.

- High error occurred when calibration based on level walking was used to estimate EE of inline walking.

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<table>
<thead>
<tr>
<th>Incline (%)</th>
<th>Predicted ( VO_2 ) (ml/min(^{-1}\cdot\text{kg}^{-1} ))</th>
<th>Measured ( VO_2 ) (ml/min(^{-1}\cdot\text{kg}^{-1} ))</th>
<th>Absolute error (ml/min(^{-1}\cdot\text{kg}^{-1} ))</th>
<th>Relative error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>–15</td>
<td>15.8</td>
<td>10.2</td>
<td>5.6</td>
<td>55.3</td>
</tr>
<tr>
<td>–10</td>
<td>15.1</td>
<td>9.7</td>
<td>5.4</td>
<td>55.7</td>
</tr>
<tr>
<td>–4</td>
<td>14.4</td>
<td>10.9</td>
<td>3.5</td>
<td>32.2</td>
</tr>
<tr>
<td>–5</td>
<td>12.6</td>
<td>17.4</td>
<td>–4.8</td>
<td>–27.8</td>
</tr>
<tr>
<td>+10</td>
<td>12.0</td>
<td>21.2</td>
<td>–9.2</td>
<td>–43.3</td>
</tr>
<tr>
<td>+15</td>
<td>11.7</td>
<td>24.8</td>
<td>–13.1</td>
<td>–52.9</td>
</tr>
</tbody>
</table>

Activity monitoring: segment orientation

- Algorithm: comparison of segment orientation
  - Rest or low acceleration
  - Limitation: threshold level, number of sensors

\[ a_c [g] = 1 \]
\[ a_t [g] = 1 \]

\begin{array}{cccc}
  & 1 & 0 & 1 \pm \text{acc}(c) \\
  \text{Sitting} & 1 & 0 & 1,0,-1 & 0 \pm \text{acc}(t) \\
  \text{Standing} & 0 & 1,0,-1 & \text{Lying} & \text{Dynamic}
\end{array}

Aminian et al., Med Biol Eng Computing, 1999
Comparison with video

**Physilog** vs. **video**

<table>
<thead>
<tr>
<th>Dy</th>
<th>Ot</th>
<th>Ly</th>
<th>St</th>
<th>Si</th>
</tr>
</thead>
</table>

![Graph showing comparison between Physilog and video]

- **Physilog** data:
  - Dy: 13 min, 13.2 sec
  - Ot: 5.8 min, 5.7 sec
  - Ly: 11.8 min, 12.8 sec
  - St: 0.5 min, 1.3 sec
  - Si: 28.8 min, 27 sec

- **Video** data:
  - Dy: 13 min, 13.2 sec
  - Ot: 5.8 min, 5.7 sec
  - Ly: 11.8 min, 12.8 sec
  - St: 0.5 min, 1.3 sec
  - Si: 28.8 min, 27 sec
Activity monitoring: posture transition

- Sit-stand patterns

![Graph showing sit-stand patterns with time and displacement axes.](image)
Activity monitoring: posture transition

- Algorithm
  - Transition pattern

- Transition pattern
  - Vertical displacement
  - Vertical acceleration
  - Vertical displacement
  - Vertical acceleration

- Stand-sit
- Sit-stand

\[\sin(\theta)\]
Posture transitions

- Using digital wavelet transform (DWT) to enhance acceleration pattern

Nafafi et al., IEEE TBME, 2003
Posture transitions features

\[ \hat{\theta}_g \quad \hat{\theta}_\text{trunk} \]

\[ \text{Min}(\hat{\theta}_\text{trunk}) \quad \text{Max}(\hat{\theta}_\text{trunk}) \]

\[ t\{\text{Max}(\hat{a}_\text{trunk})\} \quad t\{\text{Min}(\hat{a}_\text{trunk})\} \]

Salarian et al., IEEE TBME submitted
Posture transitions: thigh signal

- Thigh frontal acceleration and its derivative

*Paraschiv-Ionescu et al. Gait and Posture, 2004,*
Posture transitions: thigh and trunk signal

Paraschiv-Ionescu et al. Gait and Posture, 2004,
Physical activity during 12 hours

<table>
<thead>
<tr>
<th>Activity</th>
<th>Time, min</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sitting</td>
<td>200</td>
</tr>
<tr>
<td>Standing</td>
<td>400</td>
</tr>
<tr>
<td>Walking</td>
<td>600</td>
</tr>
<tr>
<td>Lying</td>
<td></td>
</tr>
<tr>
<td>Back</td>
<td></td>
</tr>
<tr>
<td>Sides</td>
<td></td>
</tr>
</tbody>
</table>
Physical activity monitoring: video
Main assemblies for physical activity monitoring

- Orientation based
  - acceleration

- Transition based
  - Gyro/acceleration

Ng J, et al., Comput Cardiol, 2000
Aminian et al., Med Biol Eng Computing, 1999

Nafafi et al., IEEE TBME, 2003
Paraschiv-Ionescu et al., Gait and Posture, 2004,
Salarian et al., IEEE TBME, submitted
### Comparison between some existing systems

<table>
<thead>
<tr>
<th>System</th>
<th>Fixation sites</th>
<th>Sub./hours</th>
<th>Sensitivity, %</th>
<th>Specificity, %</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Sitting</td>
<td>Standing</td>
</tr>
<tr>
<td>Salarian et al. IEEE, TBME, submitted</td>
<td>3</td>
<td>10/8 (h)</td>
<td>99.5</td>
<td>96.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>20/15 (p)</td>
<td>86.3</td>
<td>83.6</td>
</tr>
<tr>
<td>Paraschiv et. al. Gait &amp;Posture, 2004</td>
<td>2</td>
<td>21/61</td>
<td>98.2</td>
<td>98.0</td>
</tr>
<tr>
<td>Najafi et al. IEEE, TBME, 2003</td>
<td>1</td>
<td>15/30</td>
<td>87.0</td>
<td>87.6</td>
</tr>
<tr>
<td>Bussman et al. Pain 1998;</td>
<td>3</td>
<td>8/8</td>
<td>94</td>
<td>84</td>
</tr>
<tr>
<td>Ng et al. Comput.Cardiol., 2000</td>
<td>2</td>
<td>5/5 (h)</td>
<td>98.8</td>
<td>95.8</td>
</tr>
<tr>
<td></td>
<td></td>
<td>20/20 (p)</td>
<td>80.6</td>
<td>94.6</td>
</tr>
</tbody>
</table>

\[
\text{Sensitivity} = P(\text{test}^+ \mid \text{ref}^+) \\
\text{Specificity} = P(\text{test}^- \mid \text{ref}^-) \\
p: \text{patient, h: healthy subjects}
\]
Applications in Ageing

- Use duration of posture transition to classify faller and non-faller

- Use duration of posture transition to estimate physical activity of elderly with fear of fall
Fall risk score vs. Postural transition

- Clinical score, 11 patients

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Balance disorders</td>
<td>No = 0 / Discrete = 1 / Marked = 2</td>
</tr>
<tr>
<td>Gait disorders</td>
<td>No = 0 / Discrete = 1 / Marked = 2</td>
</tr>
<tr>
<td>History of falls in the preceding year</td>
<td>No = 0 / Yes = 2</td>
</tr>
<tr>
<td>Visual disorders</td>
<td>No = 0 / Discrete = 1 / Marked = 2</td>
</tr>
<tr>
<td>Cognitive disorders</td>
<td>No = 0 / Discrete = 1 / Marked = 2</td>
</tr>
<tr>
<td>Depressive disorders</td>
<td>No = 0 / Discrete = 1 / Marked = 2</td>
</tr>
<tr>
<td><strong>Fall-risk score</strong></td>
<td><strong>Summation of the above scores (0 to 12)</strong></td>
</tr>
</tbody>
</table>

* Based on Tinetti score

- Objective score obtained during 6 sit-stand-sit transitions:
  - M_TD, Δ_TD: meab and SD of transition duration
  - S_Trs: number of successive fail transition

Najafi et al., IEEE TMBE, 2002
## Classification of high fall-risk patients

<table>
<thead>
<tr>
<th>Subject</th>
<th>$M_{TD}, s$</th>
<th>$\Delta TD, s$</th>
<th>$S_{Trs}$</th>
<th>Fall-risk Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low fall-risk</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>2.94</td>
<td>0.729</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>3.24</td>
<td>0.593</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>2.96</td>
<td>0.576</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>3.14</td>
<td>0.959</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>2.52</td>
<td>0.371</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>6</td>
<td>2.92</td>
<td>0.549</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Average</td>
<td><strong>2.95</strong></td>
<td><strong>0.630</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High fall-risk</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>3.17</td>
<td>0.930</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>8</td>
<td>3.27</td>
<td>1.018</td>
<td>5</td>
<td>7</td>
</tr>
<tr>
<td>9</td>
<td>4.16</td>
<td>1.262</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>10</td>
<td>3.85</td>
<td>1.343</td>
<td>14</td>
<td>8</td>
</tr>
<tr>
<td>11</td>
<td>4.97</td>
<td>1.665</td>
<td>5</td>
<td>8</td>
</tr>
<tr>
<td>Average</td>
<td><strong>3.88</strong></td>
<td><strong>1.244</strong></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Quantification of everyday motor function in a geriatric population

- Postural allocations monitoring, 11 subjects
  - 2 consecutive weekdays (2 x 11-hours measurement)
  - One of these days of the subsequent week (11-hour)
  - Duration of each sit-stand and stand-sit transition

- Falls Efficacy Scale (FES), a 10-item rating scale, to assess confidence in performing daily activities without falling;
  - Each item is rated: 1 = extreme confidence 10 = no confidence at all
Physical activity: typical results

Week 1 - Day 1

- Sitting: 9%
- Standing: 48%
- Walking: 7%
- Lying: 36%
- Lying back: 9%
FES scores vs. Sit-stand mean duration

- 22 hours
- 11 subjects
- Day-day variability
- Perform several days of recording

Mean time for the SiSt transition (s)

Falls Efficacy Scale

\[ R = 0.707 \]
Gait Analysis

- Effect of age on spatio-temporal parameters
  - Decrease of: cadence, stride length and velocity

<table>
<thead>
<tr>
<th>References</th>
<th>Young</th>
<th>Old</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Age (years)</td>
<td>Velocity (m/s)</td>
</tr>
<tr>
<td><strong>Women</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Öberg et al. [72]</td>
<td>20–29</td>
<td>1.24</td>
</tr>
<tr>
<td>Hageman [92]</td>
<td>23.9</td>
<td>1.59</td>
</tr>
<tr>
<td>Finley [91]</td>
<td>29.9</td>
<td>0.84</td>
</tr>
<tr>
<td>Waters et al. [53]</td>
<td>40.1</td>
<td>1.28</td>
</tr>
<tr>
<td><strong>Men</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Öberg et al. [72]</td>
<td>20–29</td>
<td>1.23</td>
</tr>
<tr>
<td>Blanke and Hageman [77]</td>
<td>24.5</td>
<td>1.32</td>
</tr>
<tr>
<td>Waters et al. [53]</td>
<td>38.5</td>
<td>1.36</td>
</tr>
<tr>
<td><strong>Mixed</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elble et al. [66]</td>
<td>30</td>
<td>1.18</td>
</tr>
<tr>
<td>Cummings [22]</td>
<td>24.6</td>
<td>1.39</td>
</tr>
<tr>
<td>Winter et al. [76]</td>
<td>24.6</td>
<td>1.43</td>
</tr>
<tr>
<td>Ostrosky et al. [81]</td>
<td>28.2</td>
<td>1.38</td>
</tr>
<tr>
<td>Gabell et al. [78]</td>
<td>21–47</td>
<td>1.37</td>
</tr>
</tbody>
</table>

Prince et al., Gait and Posture, 1997
Temporal gait analysis

- **Gyroscope***
  - Angular velocity of lower limbs ($\alpha_{\text{shank}}, \dot{\beta}_{\text{thigh}}$)
  - Wavelet Transform

- **Other technique: footswitches**, accelerometers***

* Aminian et al., J. Biomechanics, 2002  
** Hausdorff et al, J. Biomechanics, 1995  
*** Aminian et al., Med Biol Eng Comput, 1999
Spatial gait analysis: double pendulum model

$$d_3(k) = \sqrt{(l_1 + M_2(k))^2 + (l_1 + M_1(k))^2 - (l_1 + M_2(k))(l_1 + M_1(k)) \cos \alpha(k)},$$

$$\alpha = \int \dot{\alpha}_{\text{thigh}}(t) \cdot dt \quad \beta = \int \dot{\beta}_{\text{shank}}(t) \cdot dt$$

Aminian et al., J. Biomechanics, 2002
Gait and fear of falling in elderly

Data collection:
- Fear of falling (FES*) (Tinetti, 1994)
- Gait parameters
- Age, Gender, Depressive Sx**, physical activity

* Validated french version (Büla C et al., GSA, Boston 2002)
** Assessed through two questions (Whooley 1997)
Percentage of evolution in Gait Speed

- Stratified in 2 groups by subject’s baseline FES
  - **Confident** (N=21): FES score higher than average (> 100)
  - **Fearful** (N=22): FES score lower than average (< 100)

![Graph showing percentage of evolution in gait speed](chart)

**Differences:**
- * Non significant
- ‡‡ p<0.01

Repetition: 100
Confident: 114
Fearful: 108
All: 104

*Stratified in 2 groups by subject’s baseline FES*

Confident (N=21): FES score higher than average (> 100)
Fearful (N=22): FES score lower than average (< 100)
Gait speed improvement (%) according to fear of falling status

% improving Gait speed

76.2%  

52.4%  

Fearfull  Confident  

‡‡ p<0.05
Gait Variability

- Spatio-temporal variability

Gait Velocity, m/s

Irregular, High variability
Regular, low variability
Same mean velocity

Measured by Coefficient of variation, $CV, \% = \frac{SD}{Mean}$
Gait variability in fallers

- Young subjects (22)
- Elderly-nonFaller (17)
- Elderly-Faller (18)

Fallers have significantly higher variability than non fallers

Hausdorff et al., Arch Phys Med Rehabil, 2001
Pattern variability

Knee flexion-extension

% Gait cycle

mean±SD

Stance
Gait Variability: trunk acceleration

\[ A_{\text{unbiased}} = \frac{1}{N - |m|} \sum_{i=1}^{N-|m|} x_i x_{i+m}. \]

Moe-Nilssen et al., J. Biomechanics, 2004
Gait Variability

- Trunk variability: vertical trunk acceleration
  - Ad1: step regularity, Ad2: stride regularity

Moe-Nilssen et al., J. Biomechanics, 2004
Gait variability in frail and fit elderly

- The frail group had lower mediolateral but higher vertical and anteroposterior trunk variability than the fit group.

- Trunk variability classified 80% of the subjects correctly into their respective group.

- Mediolateral interstride trunk variability represents a different aspect of motor control than variability in the direction of propulsion.
Dual task walking

☐ Walking is an automatic process controlled by sub-cortical brain region

☐ Cognitive resources are required under:
  ■ Challenging conditions
  ■ Lack of automatic process: pathology, inactivity, etc..

☐ Fall can occur when attention needs to be divided between tasks
  ■ “stops walking when talking”*

☐ Dual task assessment paradigm
  ■ Primary task: motor
  ■ Secondary task: cognitive
  ■ Fall risk: inability to divide attention between both tasks

*Ludin-Olsson, Lancet, 1997
## Gait variability in dual task

<table>
<thead>
<tr>
<th></th>
<th>Walking alone</th>
<th>Walking while Backward counting</th>
<th>P-Value*</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Young subjects (n = 12)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stride length CV (%)</td>
<td>2.3 ± 0.8</td>
<td>2.7 ± 1.2</td>
<td>0.308</td>
</tr>
<tr>
<td>Stride velocity CV (%)</td>
<td>3.2 ± 1.3</td>
<td>3.5 ± 1.8</td>
<td>0.638</td>
</tr>
<tr>
<td><strong>Old subjects (n = 12)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stride length CV (%)</td>
<td>3.9 ± 1.6</td>
<td>10.2 ± 9.3</td>
<td>0.023</td>
</tr>
<tr>
<td>Stride velocity CV (%)</td>
<td>5.6 ± 2.2</td>
<td>12.5 ± 9.2</td>
<td>0.015</td>
</tr>
</tbody>
</table>

* Based on Wilcoxon rank-sum test.

CV = coefficient of variation.
Fall detection

- No external support
- Loss of consciousness
- Lack of report

- Initial Fall
  - Fear of falling
  - Reduced mobility
  - Reduced confidence
  - Lower quality of life

- Second fall
  - Rapid Intervention
  - Fewer aftereffects
  - Return home
  - Smaller cost

- Placement in institution
  - Elderly people
  - No external support
  - Loss of consciousness
  - Lack of report
Example of Algorithm

- Fall detector behind the ear
- Sum-vector of acceleration in the transvers-plane higher than 2g
- Sum-vector of velocity of all spatial components before the impact higher than 0.7m/s
- Sum-vector of acceleration of all spatial components higher than 6g

Lindemann et al. Med Biol Eng Comput 2005
Gait and posture monitoring

- **Posture**
  - Sitting
  - Standing
  - Lying
  - walking

- **Gait**
  - Swing
  - Stance
  - Cadence
  - Angle
  - Velocity
  - Distance

**Summary:**
Gait and posture monitoring techniques are crucial for Neuro Motor assessment and rehabilitation.
Perspective

- Ubiquitous monitoring of elderly
  - Wearable technology
  - Embedded intelligence
  - Sensors networking
  - Autonomous energy

- Fall prevention
  - Real fall detection
  - Real fall condition
  - Fall mechanism
Perspective

☐ Optimal solution for sensor configuration and signal processing
  ■ Simple or fused sensors
  ■ Real time monitoring (needed for fall detection)

☐ Introducing new clinical practice
  ■ Improving diagnosis (fall risk)
  ■ Improving treatment (rehab program)
  ■ More development in evidence-based applications