FWO
AL 90 JAAR DE PERFECTE HABITAT VOOR KENNISMAKERS
IOT Sensors for Aging in Place

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Content

aging in place "the ability to live in one's own home and community safely, independently, and comfortably, regardless of age, income, or ability level".

• Physical function monitoring
  • Continues via video recordings

• Food intake monitoring
  • Bite detection via smart plate
Context – Physical functioning

• Available assessment tools:
  • Timed Get-Up-and-Go test,
  • 10 meter step test,
  • Tinneti test

• Shortcomings of this methodology:
  • Artificial setting
  • Test awareness
  • Administered infrequently => Snapshot
Context – gait speed / transfer time

- Gait speed primary predictor for:
  - hospitalization
  - decline in health
  - falls

- Aim: Can we automatically measure transfer time based with continuous video measurements?

Measurement

Start

Transfer zone

Stop

6
Approach

Person detection

Measure transfer times

Detect deviating trends
Person detection

- Approx. median fi
- NCC
- Erosion/dilation + Connected Components
- ROI = biggest object
Measuring Transfer Time
### Observational study: set-up

<table>
<thead>
<tr>
<th>Participant</th>
<th>Age</th>
<th>Sex</th>
<th>Home</th>
<th>Walking aid</th>
<th>Period</th>
<th>Events</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>75</td>
<td>F</td>
<td>Service flat</td>
<td>Walker, Cane, NA</td>
<td>12 weeks</td>
<td>444</td>
</tr>
<tr>
<td>B</td>
<td>80</td>
<td>F</td>
<td>Service flat</td>
<td>NA</td>
<td>12 weeks</td>
<td>197</td>
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<tr>
<td>C</td>
<td>95</td>
<td>F</td>
<td>Nursing home</td>
<td>Walker</td>
<td>8 weeks</td>
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<tr>
<td>D</td>
<td>75</td>
<td>M</td>
<td>Service flat</td>
<td>NA</td>
<td>12 weeks</td>
<td>368</td>
</tr>
</tbody>
</table>
Results – Real Life Data

• Real life measurements
• Recovery after stroke (Oct 15 to Dec 15)
• New stroke(s) and rapid decline in health (after Dec 15)
Observational study: results

• Healthy test subject:
  • Faster
  • Limited variability

• Unhealthy test subject:
  • Slower
  • Higher variability

Approach

Person detection

Measure transfer times

Detect deviating trends
Detection of deviating trends

- Review the measurements for each patient individually?
  - Time-consuming
  - Specialized knowledge needed
  - When to review the data?

Automatically detect changes in gait speed or transfer times.
Method

• Use Statistical Process Control (SPC) techniques to detect deviating trends
• SPC techniques:
  • Detect trends in the performance of a process
  • Trigger alerts when variations occur
• Evaluated techniques: Exponentially Weighted Moving Average (EWMA)
Real-life results

\[ z_i = \lambda x_i + (1 - \lambda) z_{i-1} \]

\[
UCL = \mu_0 + L\sigma \sqrt{\frac{\lambda}{2 - \lambda}}[1 - (1 - \lambda)^{2i}]
\]

\[
LCL = \mu_0 - L\sigma \sqrt{\frac{\lambda}{2 - \lambda}}[1 - (1 - \lambda)^{2i}]
\]

Greet Baldewijns et. al. “Developing a system that can automatically detect health changes using transfer times of older adults” *BMC Medical Research Methodology (2016)*
Discussion

• Transfer times can be extracted from video recordings
• Alarms can be extracted from monitoring the transfer times
• Split up transfer times with and without walking aid


• Replace video camera with other sensors
Content

• Physical function monitoring
  • Continues via video recordings

• Food intake monitoring
  • Bite detection via smart plate
Context: Malnutrition in the elderly

10-20% elderly malnourished

Monitoring happens manually:
- Questionnaires/food recall
- Manual data entry
- Contain mistakes / incomplete
- Work-intensive
Context: Hypothesis

Is it possible to automatically measure the daily food intake of an elderly person without the loss of comfort?

• Research goals:
  • Detection of food intake events => Chewing and Bites
Context: Universal eating monitor

Measure location and weight

- Pressure sensors in base
- Removable ‘dumb’ plate

+ One base / multiple plates
+ Simple hardware
+ Detect location / compartment
Location detection

Centre of Mass:

\[
R = \frac{1}{F_{tot}} \sum_{i=1}^{3} F_i r_i
\]
Location detection

Center of Mass:

\[ R = \frac{1}{F_{\text{tot}}} \sum_{i=1}^{3} F_i r_i \]

Bite location:

\[ x = \frac{1}{\Delta F_{\text{tot}}} \sum_{i=1}^{3} \Delta F_i x_i \]

\[ y = \frac{1}{\Delta F_{\text{tot}}} \sum_{i=1}^{3} \Delta F_i y_i \]
Test data

Lab
Controlled measurement
Slow eating
Minimum interaction with plate

Home
Uncontrolled
At own speed
No restrictions on how to eat

Weight per compartment measured with scale
before and after meal
Bite detection

Restricted eating:
eating:

Unrestricted
Annotation and pipeline

The diagram illustrates the process of stability detection, feature extraction, classification of bite/no bite, and compartment detection. The process starts with stability detection and iterates until a maximum number of stable regions. The chart below shows the total weight over time, highlighting intervals of interest.
Features for bite detection
Special case

Partial bite

(a) Utensils resting
(b) Zero bite
Results

- Leave One Person Out approach for training / testing
- Random Forest of classifier

<table>
<thead>
<tr>
<th></th>
<th>Predicted</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>bite</td>
<td>nobite</td>
</tr>
<tr>
<td>Real</td>
<td>bite</td>
<td>nobite</td>
</tr>
<tr>
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<td>602</td>
<td>133</td>
</tr>
<tr>
<td>nobite</td>
<td>173</td>
<td>282</td>
</tr>
</tbody>
</table>

- Accuracy: 74%
- Sensitivity: 82%
- PPV: 78%

![Box plot of error percentage]
Future work

• Extract ‘quality’ parameters


Conclusion

• Bites can be localized and detected

• Weight per compartment -> estimate calories (ongoing)

• Unobtrusive automatic food intake monitoring

• Portable
Thank you

- Acknowledgement
  - PhD students: Greet Baldewijns, Glen Debard, Gert Mertes
  - Medical partners: Koen Milisen and Jos Tournoy
  - Inhabitants of care home Edouard Remy (Zorg Leuven)