Sensor based gait characteristics: prediction models for falls

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Assess fall risk from gait in daily life – WHY?

Fall risk assessment in older adults (FARAO)

- Identify people at risk
- Targeted interventions

Current fall prediction models

- Relative low predictive power (AUC < .70)

(Gates et al. 2008, Scott, et al. 2007, Lee et al., 2013)

Gait

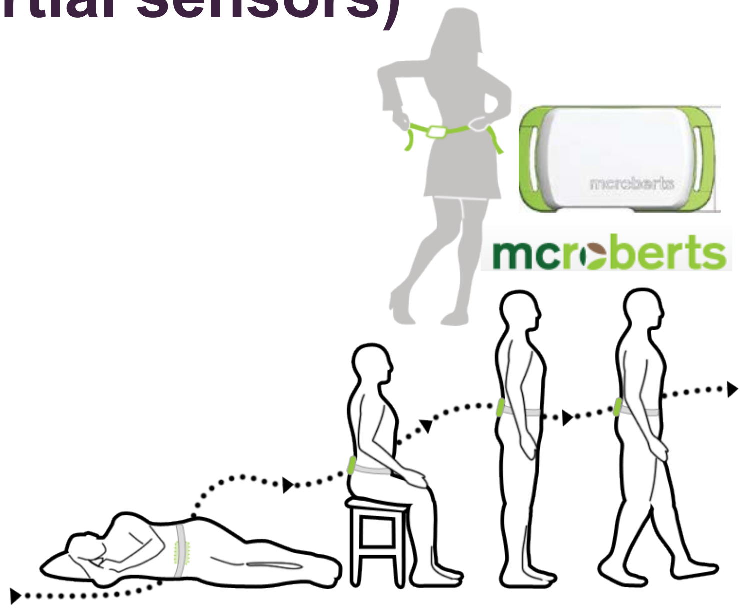
- Many falls during walking
- Gait stability measures

Daily life

- Quality of gait ~ intrinsic fall risk
- Amount of physical activity ~ exposure

Assess fall risk from gait in daily life – HOW?

Sensor based assessments (inertial sensors)



- **Amount of activities**
  - Number of steps
  - Total duration
  - Median duration
  - Maximum duration

- **Gait quality characteristics**
  - Stride time
  - Gait speed
  - Intensity (Range and standard deviation)
  - Variability (Autocorrelation, power and width of ground frequency in psd)
  - Symmetry (Harmonic ratio)
  - Smoothness (Index of harmonicity)
  - Sample entropy
  - Local divergence exponent (Lyapunov exponent)

Assess fall risk from gait in daily life – HOW?

Sensor based assessments (inertial sensors)

- Amount of gait
- Gait quality characteristics

Gait characteristics

- All gait episodes from 1 week acceleration data
- 10 sec windows
- Median of all walking periods
  - Extreme values (10th and 90th percentiles)

Prediction models

1. Fall prediction with median values of gait characteristics
2. Fall prediction with extreme values
3. PCA & survival analysis with 10-fold cross-validation

Data

Subjects (total N=313)
- 75 ± 6 years

Questionnaires
- Fall history
- Depression (GDS)
- LASA, FES, hand grip strength, TMT-A&B

Trunk accelerations 3D
- Continuously measured one week
- MoveMonitor (McRoberts, NL)

Fall incidence
- Six months follow-up
- 36% fallers (>= 1 fall)

Model 1: Fall prediction with median values

Additional value of daily-life accelerometry (amount and quality of gait) in fall risk prediction?

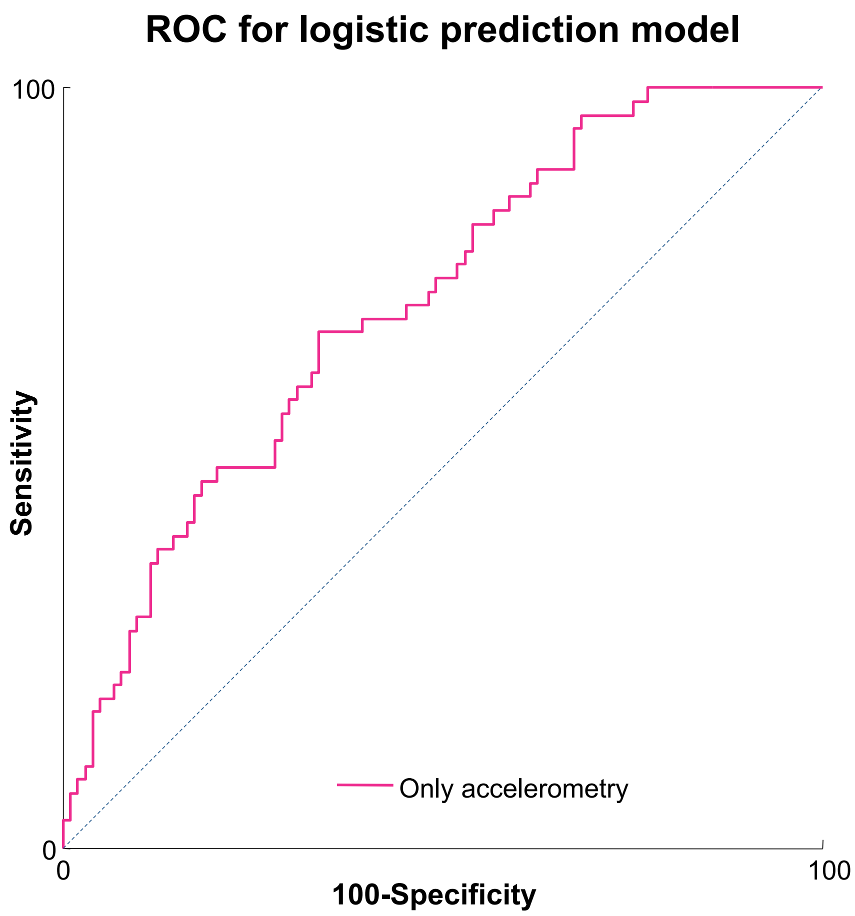
Evaluation

- N=169
- Forward stepwise regression model
- Compare AUC of models with either or both accelerometry and questionnaires

Model 1: Fall prediction with median values

Predictors accelerometry

- local divergence exponent AP
- intensity VT
- number of steps
- duration of lying
- intensity VT x number of steps



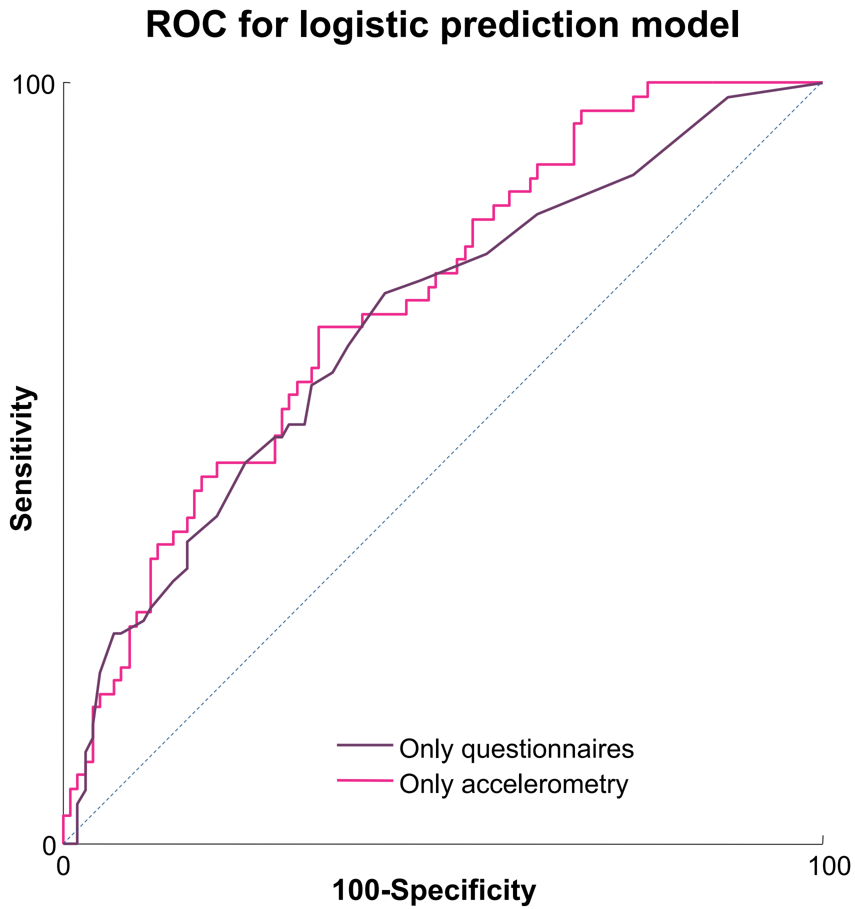
- AUC 0.71

(van Schooten et al., J. Gerontol 2015)

Model 1: Fall prediction with median values

Predictors from questionnaires

- 6-month history of falls
- geriatric depression scale



- AUC 0.68

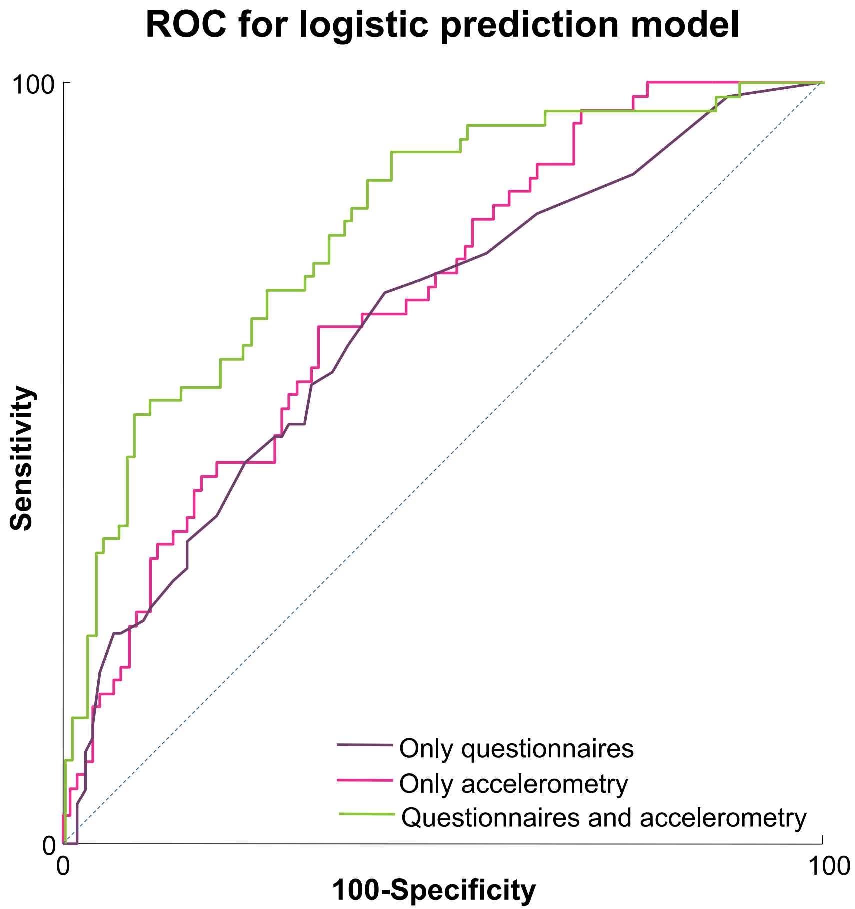
(van Schooten et al., J. Gerontol 2015)

Model 1: Fall prediction with median values

Added value of accelerometry

- 6-month history of falls
- local divergence exponent AP
- intensity VT
- number of strides
- geriatric depression scale
- smoothness ML
- sample entropy VT
- intensity VT x number of strides
- smoothness ML x number of strides

• AUC 0.82*



(van Schooten et al., J. Gerontol 2015)

Model 2: Fall prediction with *extreme* values

Additional value of extreme values (10^{th} and 90^{th}) of daily-life accelerometry in fall risk prediction?

Median vs high / low extremes

- Median value = Indication of most representative behavior
- Highest-risk episodes = worst-case environment (exposure to risky situations)
- Ideal situations = best-case environment (personal risk factors)

Evaluation

- N=202
- Compare univariate associations of median and extreme values
- Replace median with extreme (if stronger univariate association)

Model 2: Fall prediction with *extreme* values

Univariate associations of medians with falls

- Gait speed
- Stride frequency
- Sample entropy (VT)
- RMS (VT & AP)
- Stride regularity (VT & AP)
- Local divergence exponent (VT & AP)
- Low frequency percentage (VT & AP)
- High frequency percentage (ML)
- Symmetry (VT & AP)

Model 2: Fall prediction with *extreme* values

Stronger associations for extremes

- Low extremes
  - Variability of frequency (AP)
  - Local divergence exponent (AP)
  - Sample entropy (VT & AP)

- High extremes
  - Stride regularity (AP)
  - Symmetry (VT, AP & ML)

(Rispens et al., JMIR Res Protoc. 2015)

Model 2: Fall prediction with *extreme* values

Area under the ROC curve

- Questionnaires only
  AUC = 0.68
- Add activities and gait medians
  AUC = 0.78
- Use extremes if stronger associated
  AUC = 0.81

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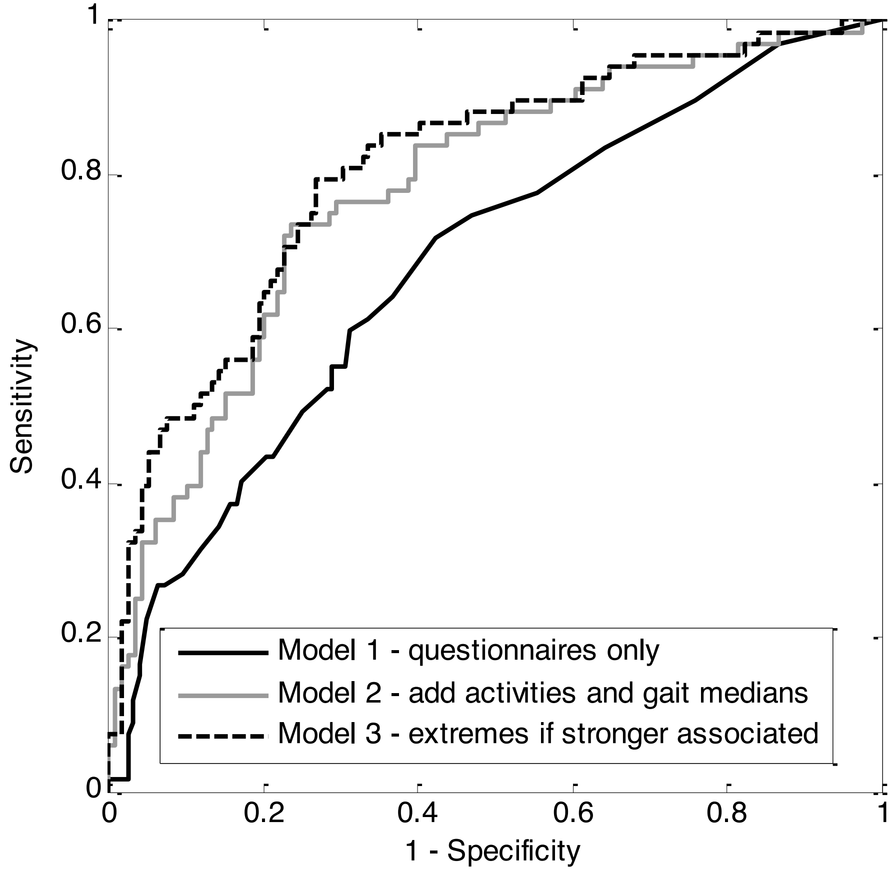

(Rispens et al., JMIR Res Protoc. 2015)

Model 3: Fall prediction with PCA and survival analyses with cross validation

How to get to a more consistent prediction model?

Evaluation

- N=313
- Large number of highly correlated variables
  → Principle component analyses
- Time to fall based on longer follow-up (6-12 months)
  → Survival analyses: time to 1st and 2nd fall
- Validation
  → 10-fold cross validation

Model 3: Fall prediction with PCA and survival analyses with cross validation

Preliminary results

- N=313
- First fall: AUC 0.64-0.67 PCA: fall history + fear/depression
  - Non-fallers: AUC 0.49-0.62 PCA: gait variability
  - Fallers; AUC 0.67-0.75 PCA: fear/depression + lying/sitting duration + gait intensity/strength + gait quality
- Second fall: AUC 0.69-0.78 PCA: fear/depression + history + gait quality

Conclusion

Sensor based gait characteristics contribute substantially to the prediction of falls

- Accelerometry contributes substantially to questionnaires
- Lower-risk extremes
  - Stronger associated with falls
  - Do not significantly improve the prediction model
- Mainly added value for prediction recurrent falls
- Future directions
  - Gait and other activity characteristics
  - Machine learning for phenotyping?
  - External validation

Thank you www.fbw.vu.nl/fallrisk

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