FACTORY2FIT

Potential of wearable devices for mental workload detection in different physiological activity conditions

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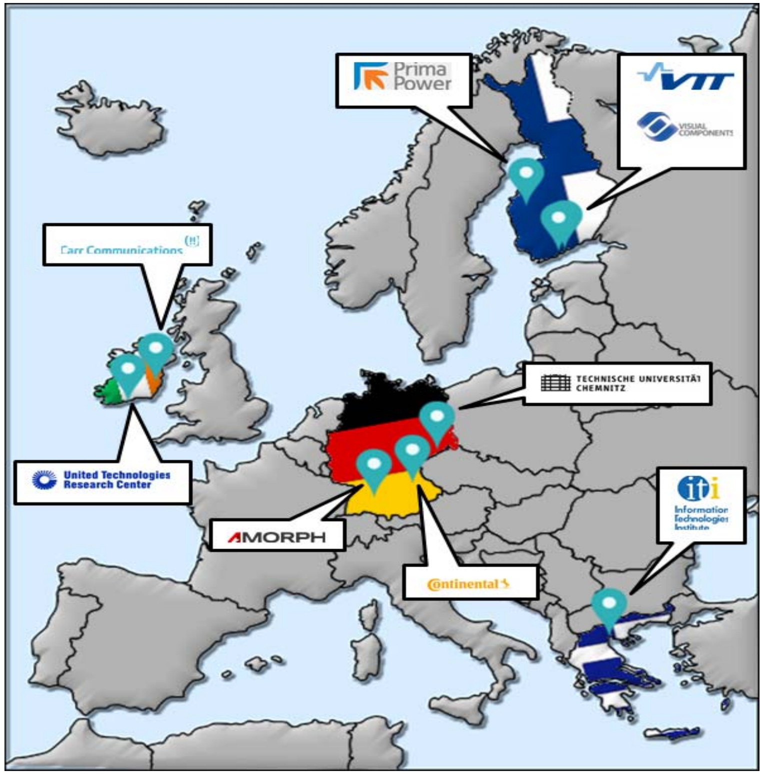
Rome, 29th September 2017

The research leading to these results has received funding from Horizon 2020, the European Union's Framework Programme for Research and Innovation (H2020/2014-2020) under grant agreement no 723277

Project

- Factory2Fit - Empowering and participatory adaptation of factory automation to fit for workers
- H2020 Factories of the Future, FoF-4 project
- 1.10.2016 – 30.9.2019
- 9 Partner
- EU funding 4,3 M€
- Coordinator Dr. Eija Kaasinen, VTT Technical Research Centre of Finland



www.factory2fit.eu

Mental Workload identification at work

Market success of wearable devices (IDC, 2017)

High potential for health monitoring (Marakhimov & Joo, 2017)

Some devices aim on identifying mental state

Wrist-worn devices at work, in the car…

To reduce mental workload and stress (e.g., Swan, 2012)

Can wearable devices help to **identify high mental** and **physical workload?**

Graph: http://www.freepik.com
Man: http://www.freeiconspng.com

Heart Rate parameters as indicators for workload

Workload and HR parameters

- increased **mental workload** and growing levels of **physical activity** are an **increase in Heart Rate** (HR) and **decrease in Heart Rate Variability** (HRV, Mulder, 1992; De Waard & Brookhuis, 1991)
- Higher mental workload reflects in HRV parameters when sitting, standing, cycling and walking (Sun et al., 2012)

Potential of Wearable Devices

- HR measures of different wearable devices (e.g., Mio Alpha, Microsoft Band, Fitbit Charge HR) **correlate highly** with the criterion measure and with each other, **even when people walk or run** (Stahl, An, Dinkel, Noble, & Lee, 2016)
- wearable devices proved satisfying HRV measurements for differentiation between high and low demanding cognitive tasks (Barber, Carter, Harris, & Reinerman-Jones, 2017)
- HRV parameters of wearables are too inaccurate for identifying increased mental workload (Reinerman-Jones, Harris & Watson, 2017)

→**H1:** HR increases and HRV parameter decrease when mental demand is increased

→**H2**: Higher physical demand should reflect in higher HR and lower HRV

Methods

Participants (*N* = 32)

- 31 (18 female) usable data sets
- 25 years old (*SD* = 5.5)
- 87% were right-handed

Design

- 2 (mental workload) x 4 (activity) factorial within-subject design
  - Mental workload: no additional task vs. arithmetic task (Meinel, 2013)
  - Physical activity: sit vs. stand vs. step vs. cycle

- DV: HR parameters (HR, IBI, SDNN, RMSSD, pNN50, LF, HF, LF/HF ratio)

Pics: www.freevector.co

Methods

Apparatus and material

HR measurement

- SUEmpathy® (SUE),
- Microsoft Band 2 (MB2),

Activity

- Step board
- Roller fix frame
- Metronome (Yixiang, 2015)

Questionnaires

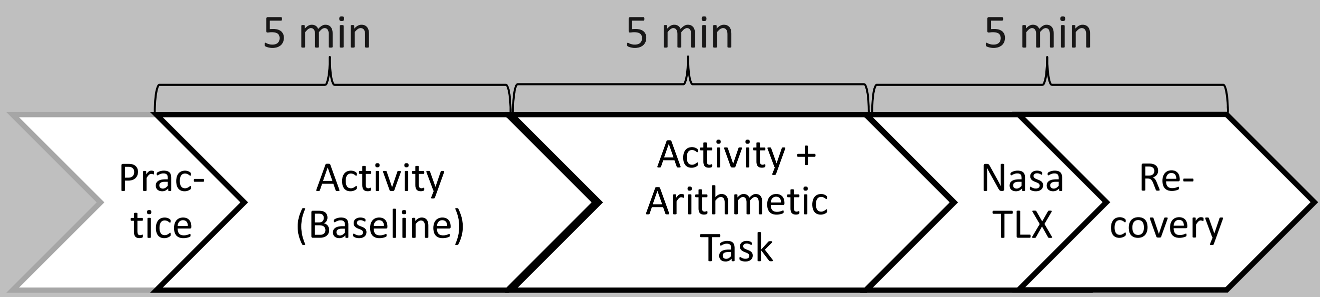
- NASA TLX (Hart & Staveland, 1988),
- Socio-demographic questionnaire

Methods

Procedure

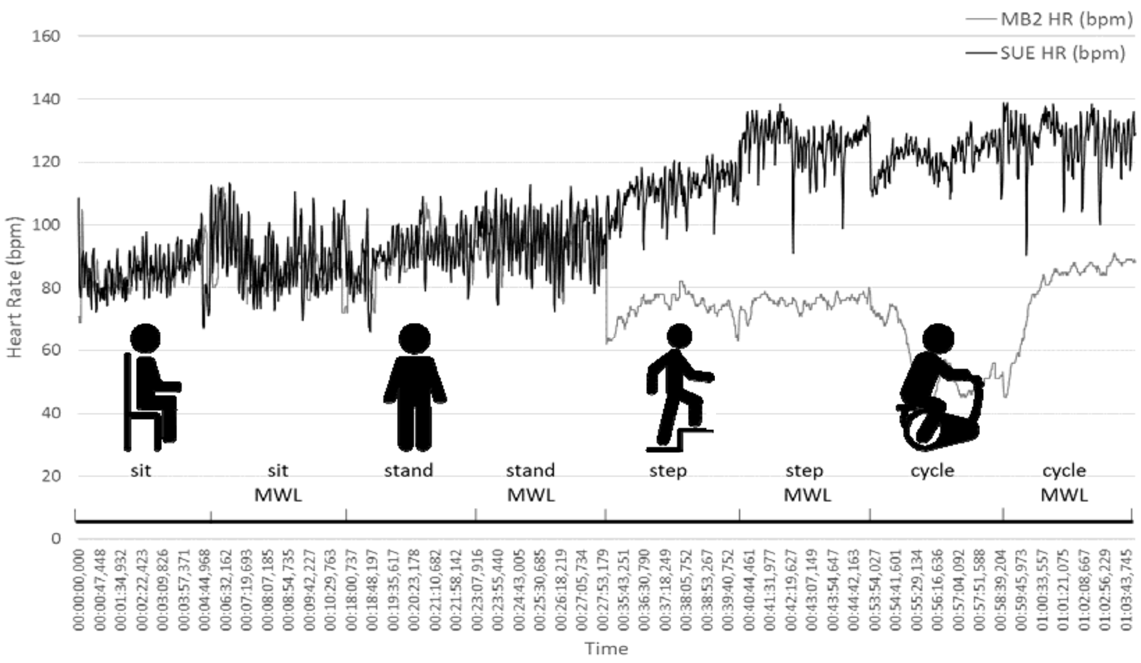
- 90 - 120 min
- Socio-demographic questionnaire, disqualification criteria, position devices
- Instructions via LabView, start of data and video recording
- Sequence of activities varied using Latin square

Procedure for every activity: sitting, standing, stepping, cycling (practice phase only for stepping and cycling)



Results – low accuracy of MB2 measurement

- SUEmpathy100 (SUE1-4.36j Scientific; SUESS Medizin-Technik Aue, 2009)
- Kubios (Version 3.0.2; Tarvainen, Niskanen, Lipponen, Ranta-Aho, & Karjalainen, 2014)
- Outlier Analysis (Grubbs, 1969)



Pics: www.freevector.co

Sit:	.83**	[0.58; 0.93]
Sit+MWL:	.70**	[0.24; 0.88]
Stand:	.86**	[0.65; 0.95]
Stand+MWL:	.66*	[0.13; 0.86]

→ Acceptable accuracy of HR only for sitting and standing condition

Results – hypotheses partly confirmed

IBI results (as example)

Physical workload ↑↑

Mean IBI ↓↓

F(3, 84) = 368.8, *p* = .000, η^2_p = .93

F(1.3, 23.7) = 17.9, *p* = .000, η^2_p = .19

Mental workload ↑↑

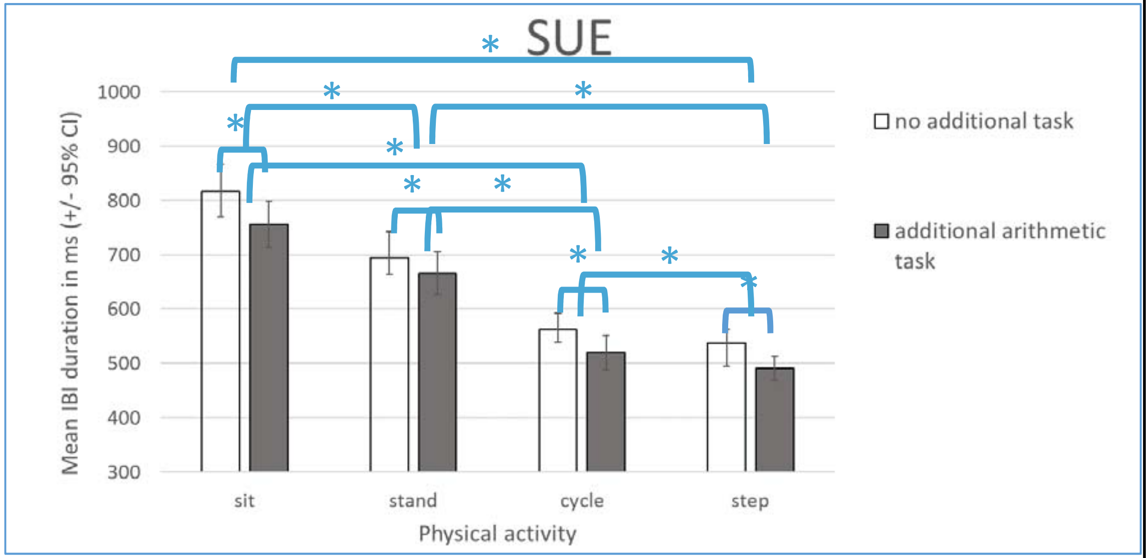
Mean IBI ↓→

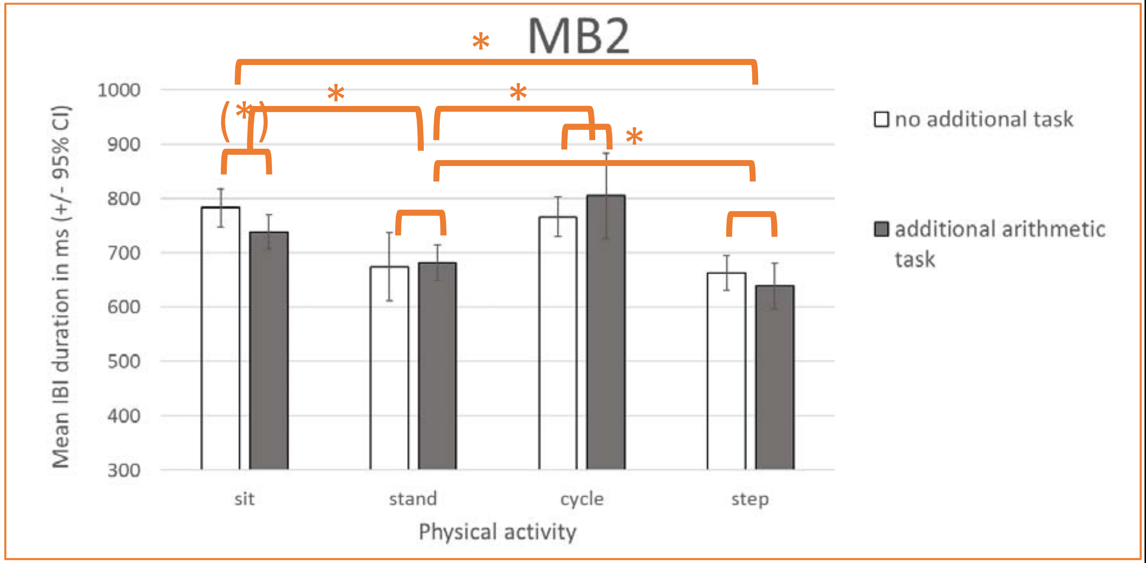
F(1, 28) = 68.8, *p* = .000, η^2_p = .71

F(1, 19) = 4.0, *p* = .060, η^2_p = .17

Significant interaction

F(2.4, 66.8) = 4.9, *p* = .007, η^2_p = .15

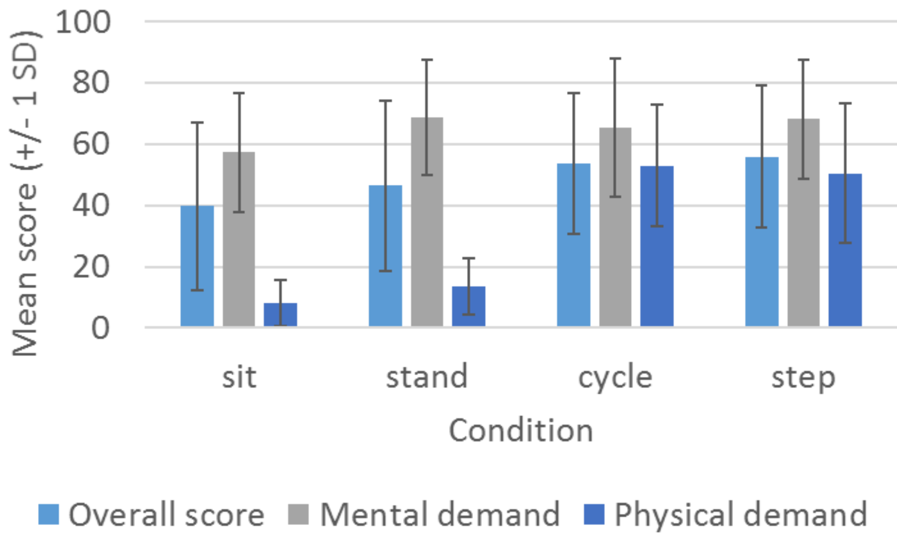




Results – other HR parameters and subjective workload

- **Main effect for physical workload** for all parameters and devices, but…
  - often no difference between cycling and stepping
  - less significant pairwise comparisons for MB2
- **Opposite direction** of **mental workload effect** for many other parameters
  - Higher mental workload was connected with higher values of SDNN, RMSSD (only MB2), LF and HF

- Higher (physical) workload reflected in higher NASA-TLX scores
  (overall: $F(1.99, 59.71) = 18.67$, $p = .000$, $\eta_p^2 = .384$
  (physical: $F(2.00, 60.13) = 82.72$, $p = .000$, $\eta_p^2 = .734$)
- Significant lower mental workload in sitting condition
  (mental: $F(2.34, 70.22) = 4.93$, $p = .007$, $\eta_p^2 = .141$)
- No significant correlations between subjective workload and HR parameters



Summary of results and implications

- Surprisingly low accuracy of MB2 data, inconsistent to earlier findings (Stahl et al., 2016)
  - real-time data assessment using the Microsoft SDK is only developed for reliable measurements when resting
  - even in the less active conditions reliability was not as high as in other studies (Barber et al., 2017)
- Hypotheses confirmed for physical workload, only HR and IBI measures of stationary device could support mental workload hypothesis
- Reverse effect of mental workload on HR parameters due to arithmetic task? (Schubert, 2009)

→Used wearable device with rather low potential for a fine-grained monitoring of physical and mental load at work

→Future research might concentrate on identifying rather long-term changes that indicate stress

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Thank you for your attention!

Any questions?

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