Multimodal recognition of mental states (emotions, dispositions, clinical conditions)

– Part 1 –

Prof. Dr. Harald C. Traue
Ulm University, Medical Psychology

Theoretical framework of mental states

CHAPTER 5

A Framework for Emotions and Dispositions in Man-Companion Interaction

Harald C. Traue, Frank Ohl, André Brechmann, Friedhelm Schwenker, Henrik Kessler, Kerstin Limbrecht, Holger Hoffmann, Stefan Scherer, Michael Kotzyba, Andreas Scheck and Steffen Walter

In Rojc, M. & Campbell, N. (Eds.) Coverbal Synchrony in Human-Machine Interaction. New Hampshire, USA: Science Publishers

Complexity of mental states in HCI and ist applications

- **User-related**
  - Emotions
  - Dispositions
  - Cognitions
  - Clinical conditions

- **Situation-related**
  - Communicators (Persons, devices, avatars)
  - Presence and proxemics
  - Mental and body activity

- **Interaction-related**
  - verbal Communication
  - Non-verbal Communication

Complexity of mental states in HCI and ist applications

- **User-related**
  - Emotions
  - Dispositions
  - Cognitions
  - Clinical conditions

Focus today

- **Situation-related**
  - Communicators (Persons, devices, avatars)
  - Presence and proxemics
  - Mental and body activity

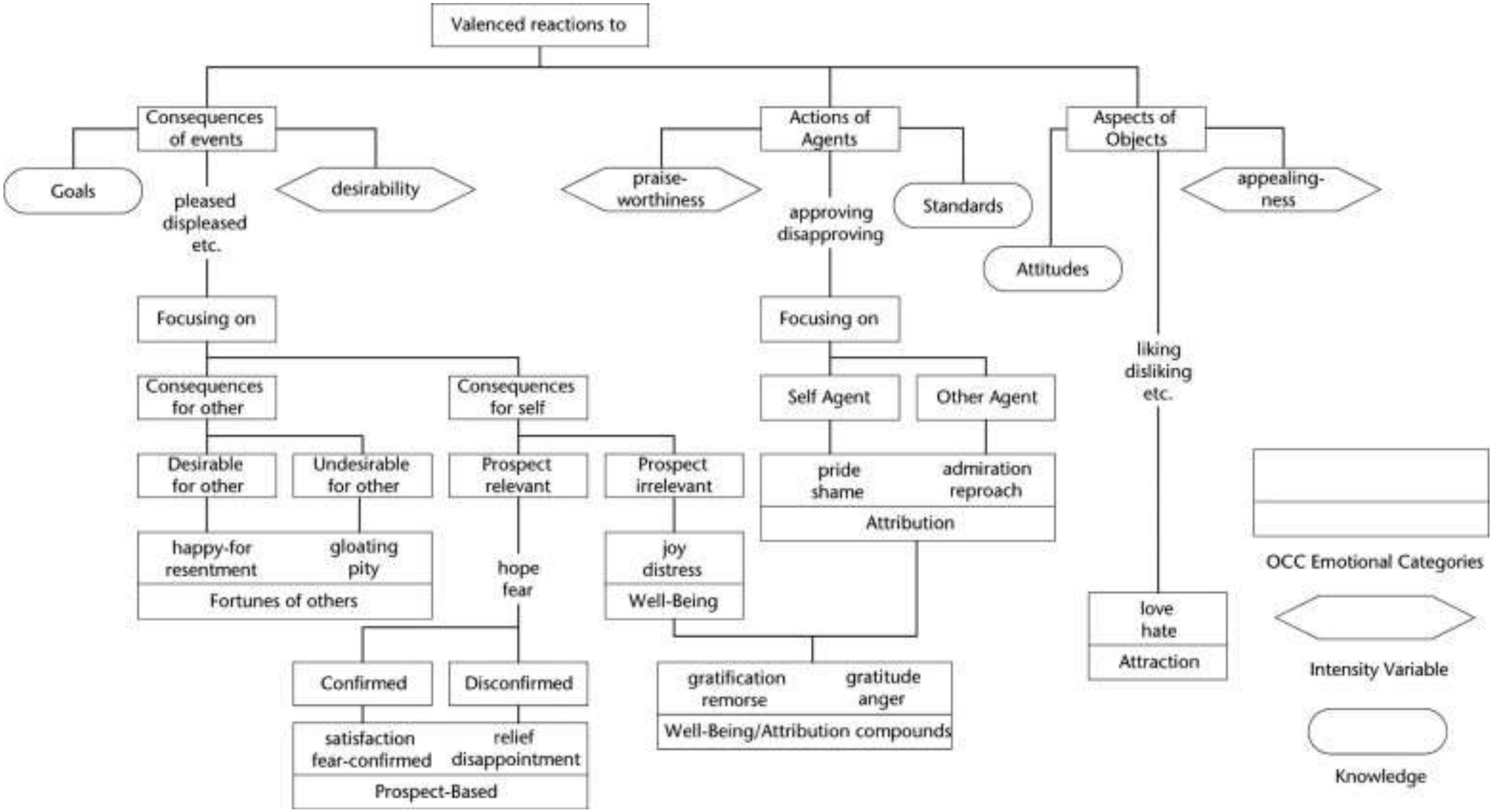
- **Interaction-related**
  - verbal Communication
  - Non-verbal Communication

User-related emotions

- Emotions
  - Mood
  - Emotion space (core affect)
  - discrete emotions
    - anger
    - happiness
    - Anxiety
    - Sadness
    - Stress, tension
    - Irritation
    - Etc.
  - Secundary emotions

→ (e.g. OCC-Categories)

The OCC-model



User-related emotions

- Emotions
  - Mood
  - Emotion space (core affect)
  - discrete emotions
    - anger
    - happiness
    - Anxiety
    - Sadness
    - Irritation
    - etc.
  - Secundary emotions (e.g. OCC-Categories)
    - Pride, success
    - disappointment
    - Failure (Mißerfolg)
    - Hope
    - Admiration
    - etc.
  - Clinical conditions)
    - Stress, tension
    - Depression
    - Pain
    - Compulsion
    - etc.
- Dispositions
- Cognitions

User-related dispositions

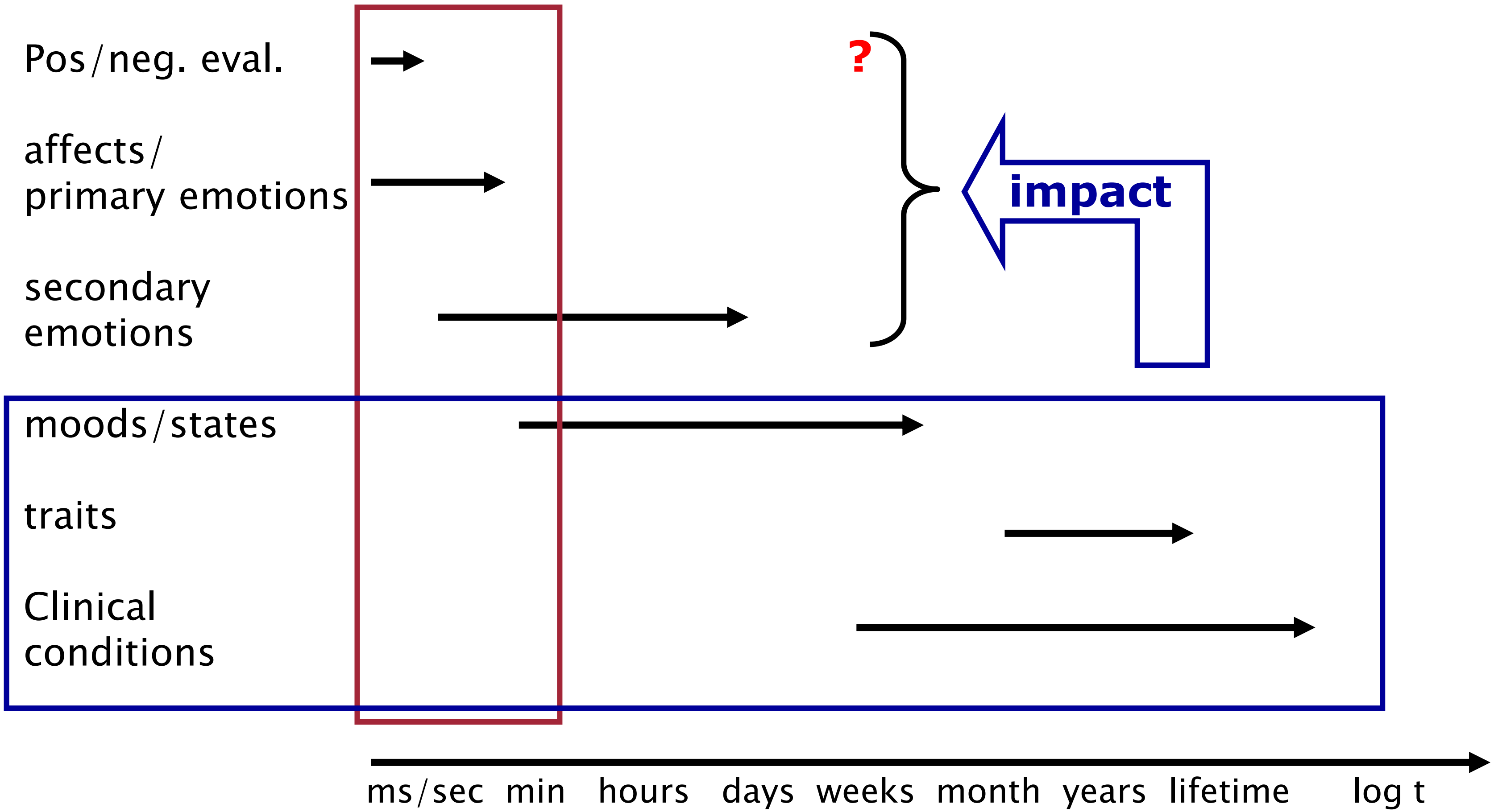
- Emotions

- Dispositions
  - Motivs (domain-specific)
    - Primary motives
    - social motives (status, dominance, the need to belong etc.)
    - Performance motives (Engagement, the willingness to xxx Anstrengungsbereitschaft und Beharrlichkeit)
  - Action readiness
    - vigilance
    - Selective Attention
    - Avoidance/Aproach
    - Frustration
    - Interest
    - Etc.
  - Personality
    - NEO-FFI
    - Optimism
    - Hardiness
    - Sense of coherence
    - etc.
- Cognitions

User related Cognitions

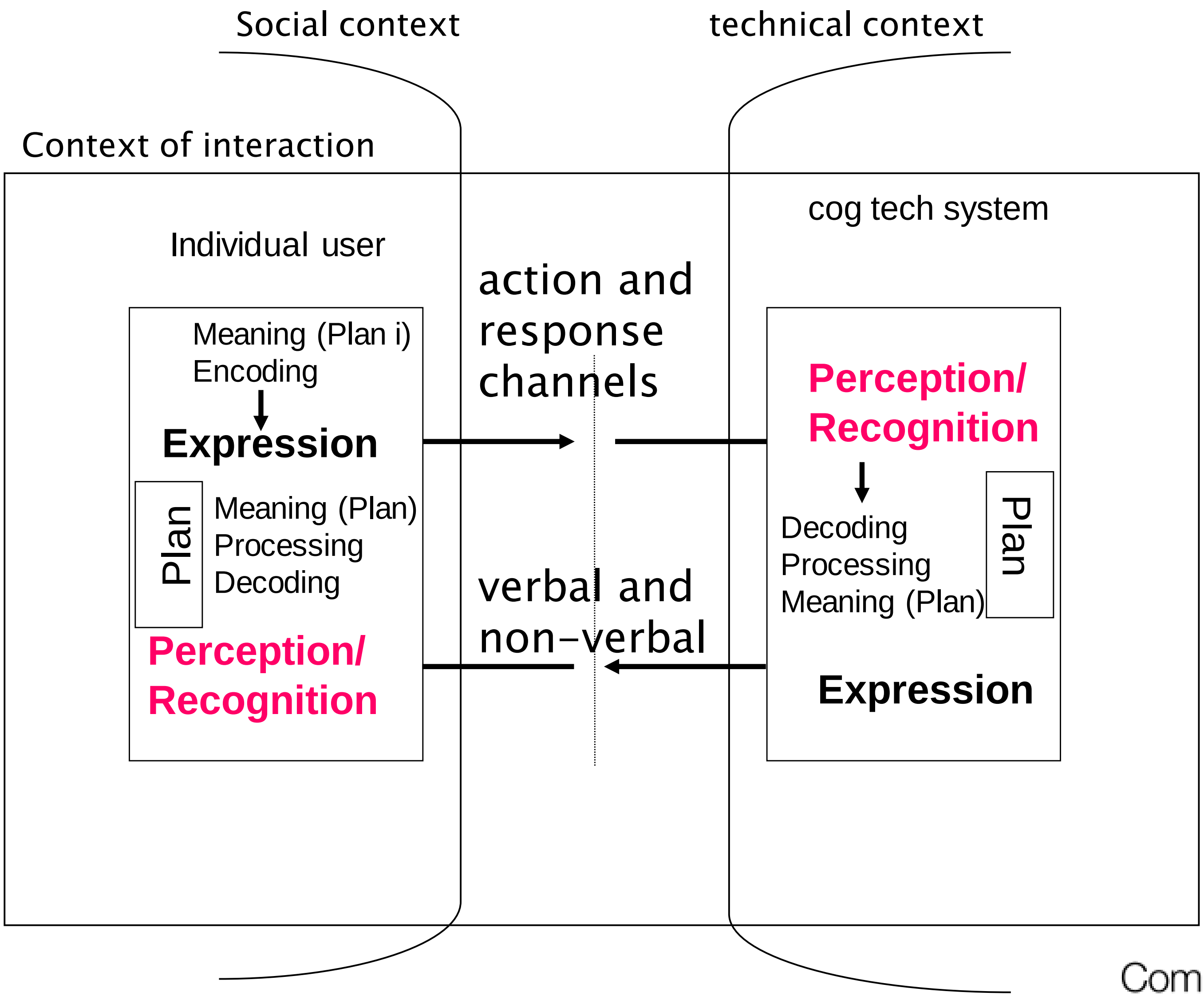
- Emotions
- Dispositions
- Cognitions
  - Relevance
    - Newness
    - Self-relevance
    - Goal relevance
    - etc.
  - Implications
    - Causal attributions
    - Outcome probability
    - etc.
  - Coping
    - Sense of control
    - Emotion regulation
    - Style of attribution
    - etc.

Temporal characteristics of emotions, dispositions and clinical conditions

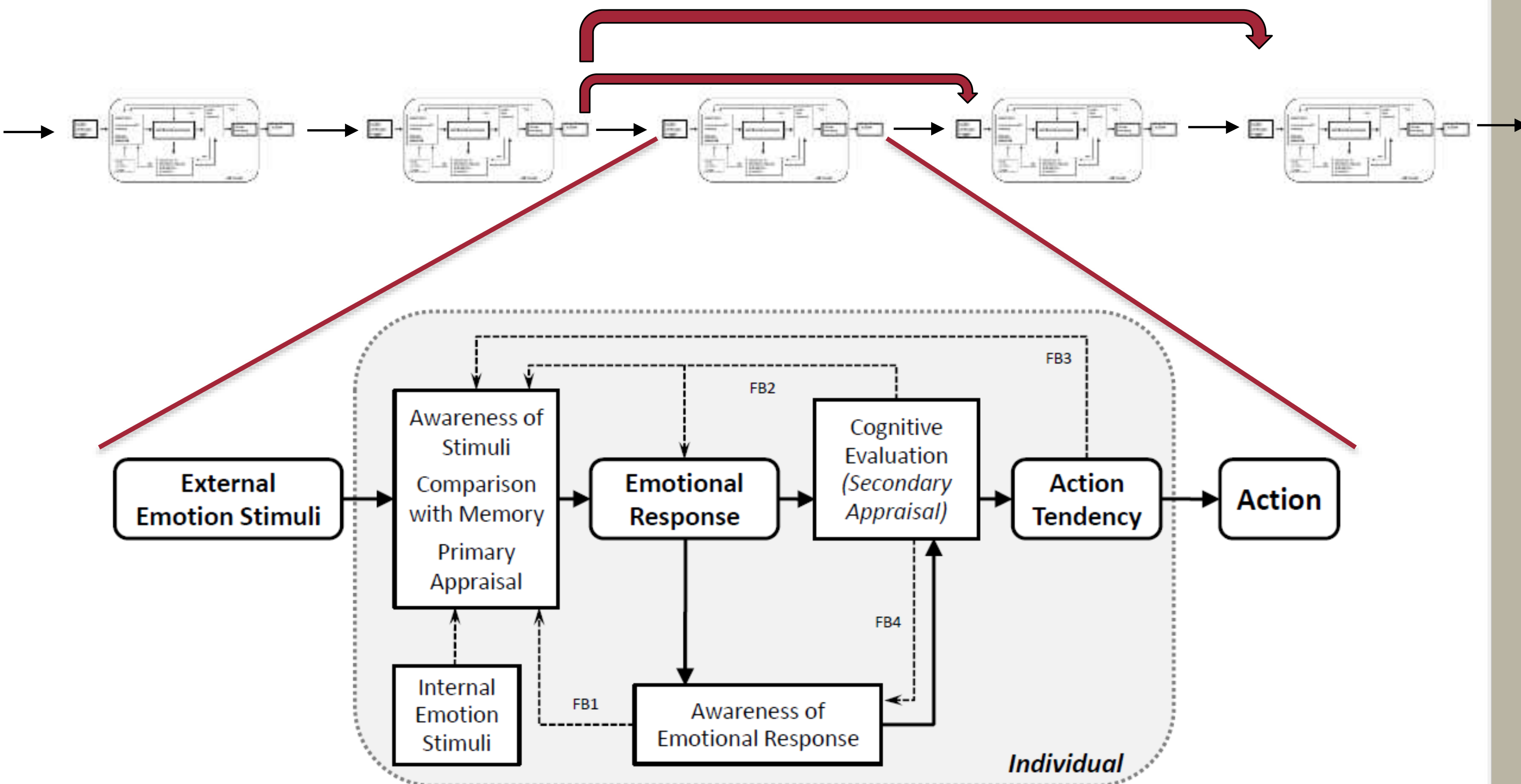


Adapted and extendet from K. Oatley and J.M. Jenkins, *Understanding Emotions.* Oxford, UK: Blackwell, 1996.

Simplified model of interaction (including emotional expressive behavior)



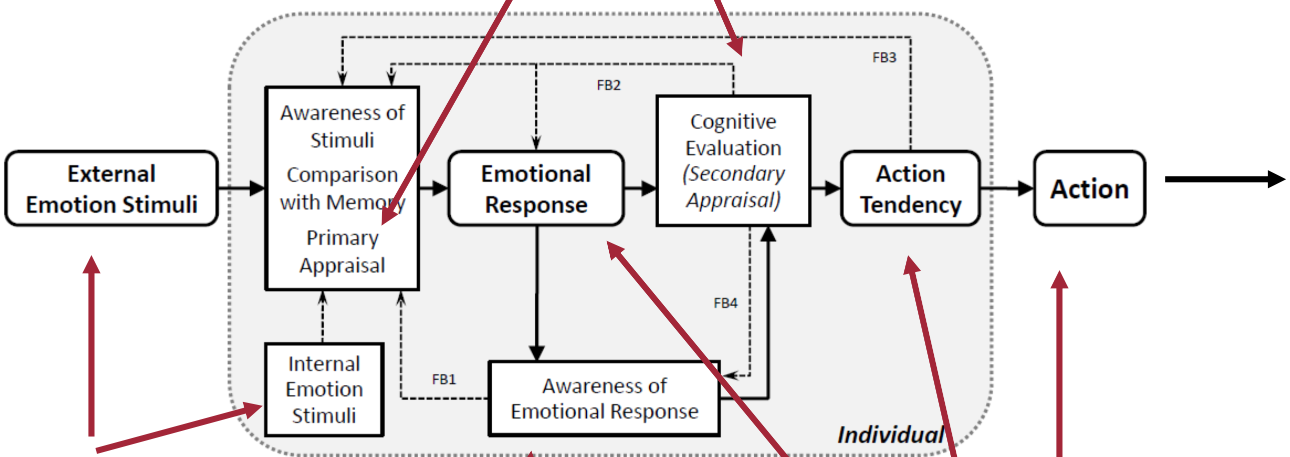
HCI chain: Modelling emotion structure and processes



Traue et al. (2013) A framework for emotions and dispositions in man-companion-interaction. In Rojc, M. & Campbell, N. (Eds.) Coverbal Synchrony in Human-Machine Interaction. New Hampshire, USA: Science Publishers

Methods and measuring of mental states

Logic & Audio (semantic content analysis, ratings)



Emotion-Elicitation by

- IAPS
- WOZ-Sequences
- Mental Load
- Psychomotor tasks
- thoughts, images…

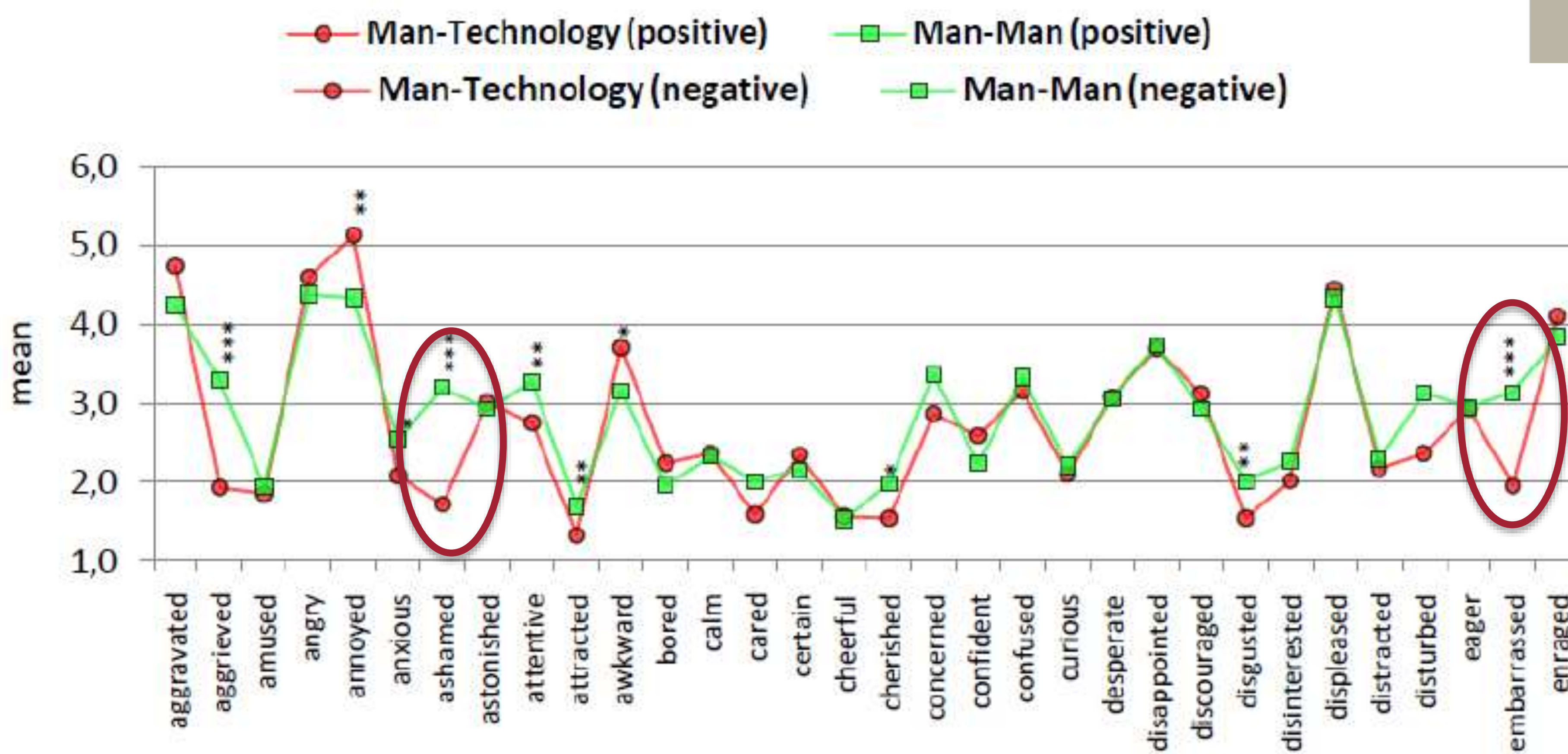
•Subjective ratings (e.g. SAM, content analysis)

- Psychobiology (ZNS, ANS, motor behavior)
- Audio (content analysis, prosody)
- Video (FACS, motor behavior, gestures etc.)

Please lean back for a moment and try remember an event within the past two weeks with a digital machinary (PC, tv, smartphone…cash counter)…

an events which had an emotional nature.

Recently we asked the same 145 subjects



Walter et al. (2014) Similarities and differences of emotions in human-machine and human-human interactions. Ergonomics (3):374-86.

Conclusion

- Emotional events with digital machinary in HCI happen
- they are similar to human–human encounter

Definitions are not easy…
so what is an emotion?

Everyone knows what an emotion is, until asked to give a definition. Then, it seems, no one knows.

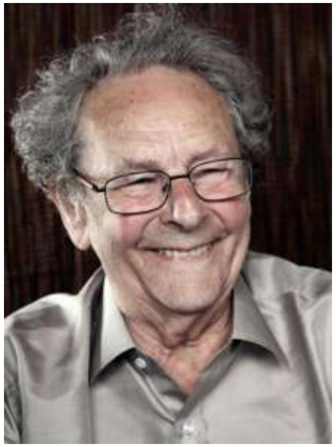
(Beverly Fehr und James A. Russell,1984)

Fehr, Beverley; Russell, James A. (1984) Concept of emotion viewed from a prototype perspective. Journal of Experimental Psychology: General, Vol 113(3), 464–486.

We all agree…

…something emotional happens here.

First concept of laws of emotion by N. Frijda 1988 (gest. am 1.4.2015)



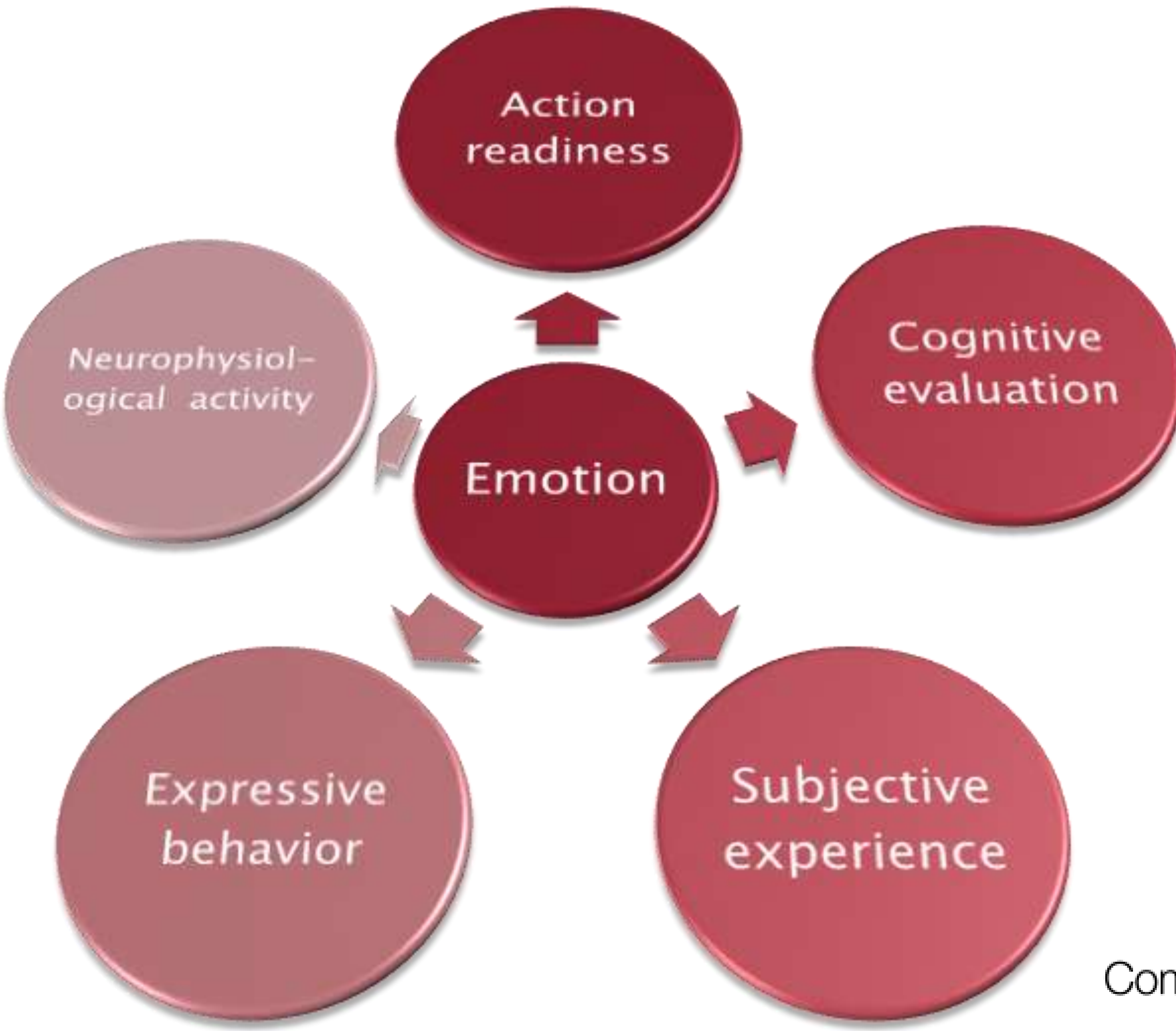
May 1988 • American Psychologist

Vol. 43, No. 5, 349–358

The Laws of Emotion

Nico H. Frijda *University of Amsterdam, The Netherlands*

Since then, there is a basic agreement on components of emotions



however Marvin Minsky – pioneering artificial intelligence – considers emotions…

…not especially different from the processes that we call ‘thinking’.

Minsky, Marvin (2007). *The Emotion Machine*. New York: Simon & Schuster.

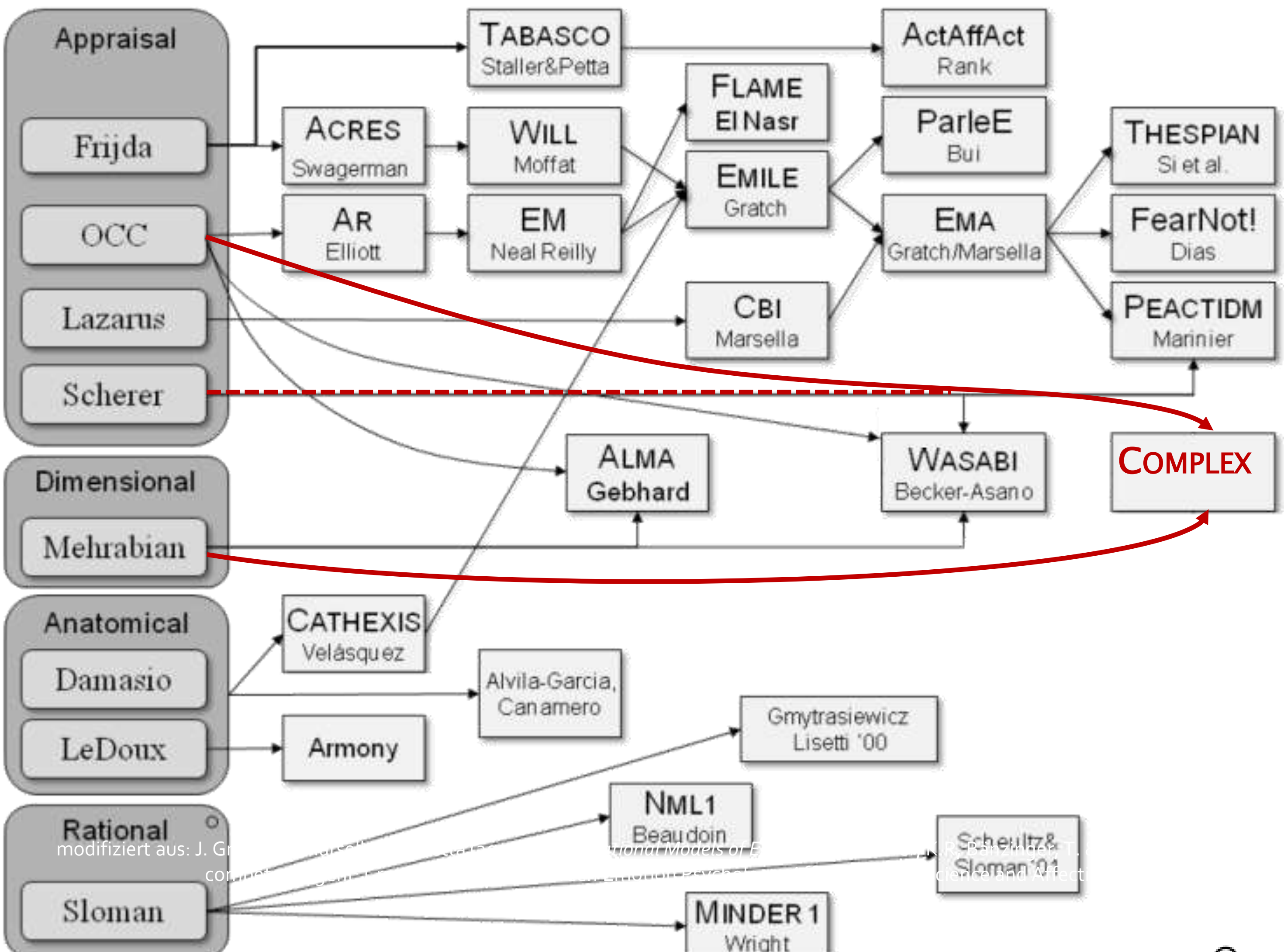
Emotion and dispositions in companions: Affective Computing

"*Affective Computing* is computing that relates to, arises from, or deliberately influences emotion…"

(Rosalind Picard, 1997)

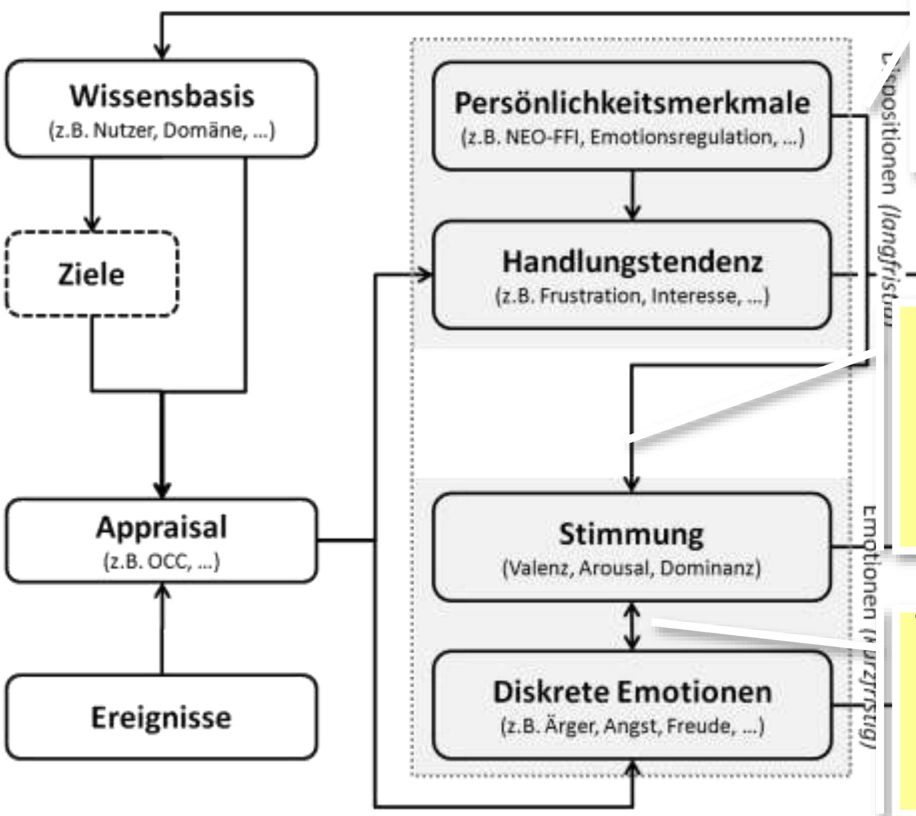
1. Enabling systems to recognise and understand user emotions and dispositions (e&d)
2. Enabling systeme to express e&d) (e.g. tone of voice, avatar)
3. Systems which use e&d for self and user regulation (e.g. by e&d controlled feedback
4. Maschine-Learning as main method.
5. Systems which have emotions ???

Affect computing introduced numerous concepts and models



modifiziert aus: J. Gr … K.R. Banzinger, T. …

COMPLEX (Companion's Personalized Emotion Experience)



Impact of personality on emotions and dispositions

Interaction between short-term (emotions) and long-term processes (dispositions)

Time course of emotions (mood, discrete emotions) and dispositions (load, attention etc.)

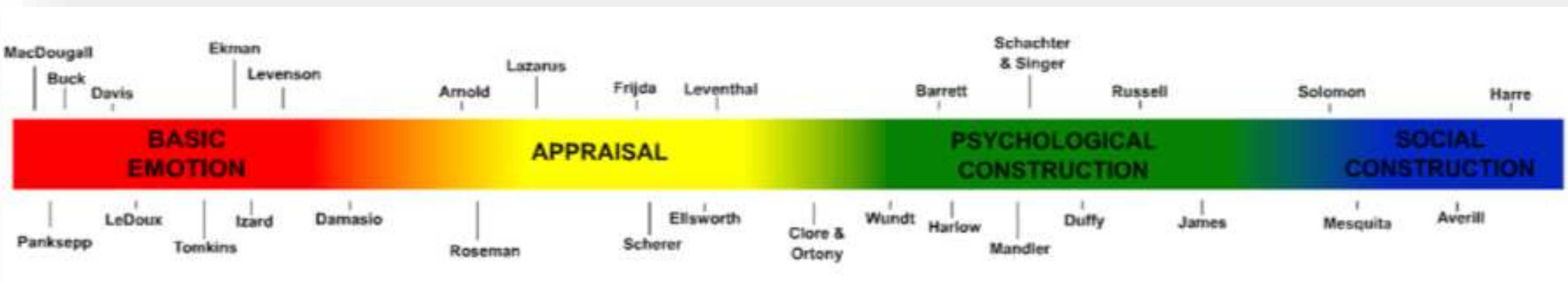
so the battle is going on, what are emotions and how can emotions be modelled.

The Hundred-Year Emotion War: Are Emotions Natural Kinds or Psychological Constructions? Comment on Lench, Flores, and Bench (2011)

Kristen A. Lindquist[1], Erika H. Siegel[2], Karen S. Quigley[2,3], and Lisa Feldman Barrett[2,4]

Psychol Bull. 2013 January ; 139(1): 255–263. doi:10.1037/a0029038.

Basically the battle is still between the left and the right side of model spectrum



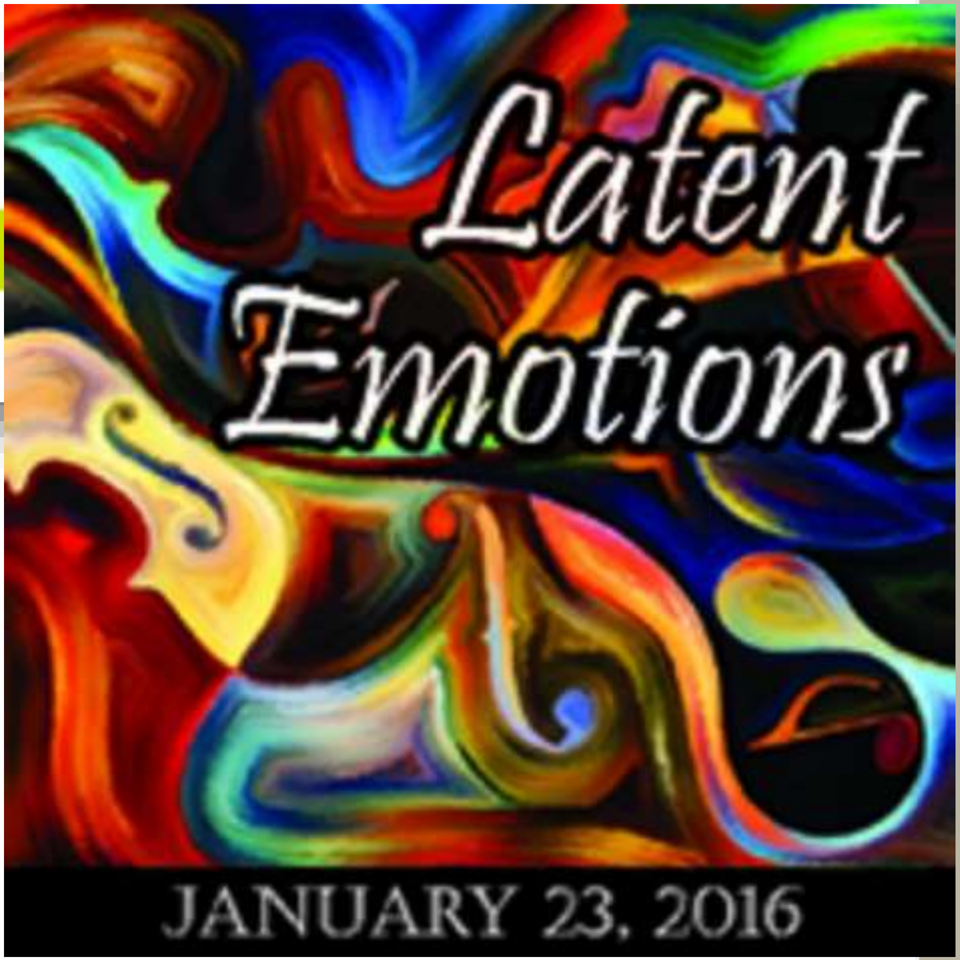
biologicaly driven entities

social & culturel constructs

Spanning over very different concepts

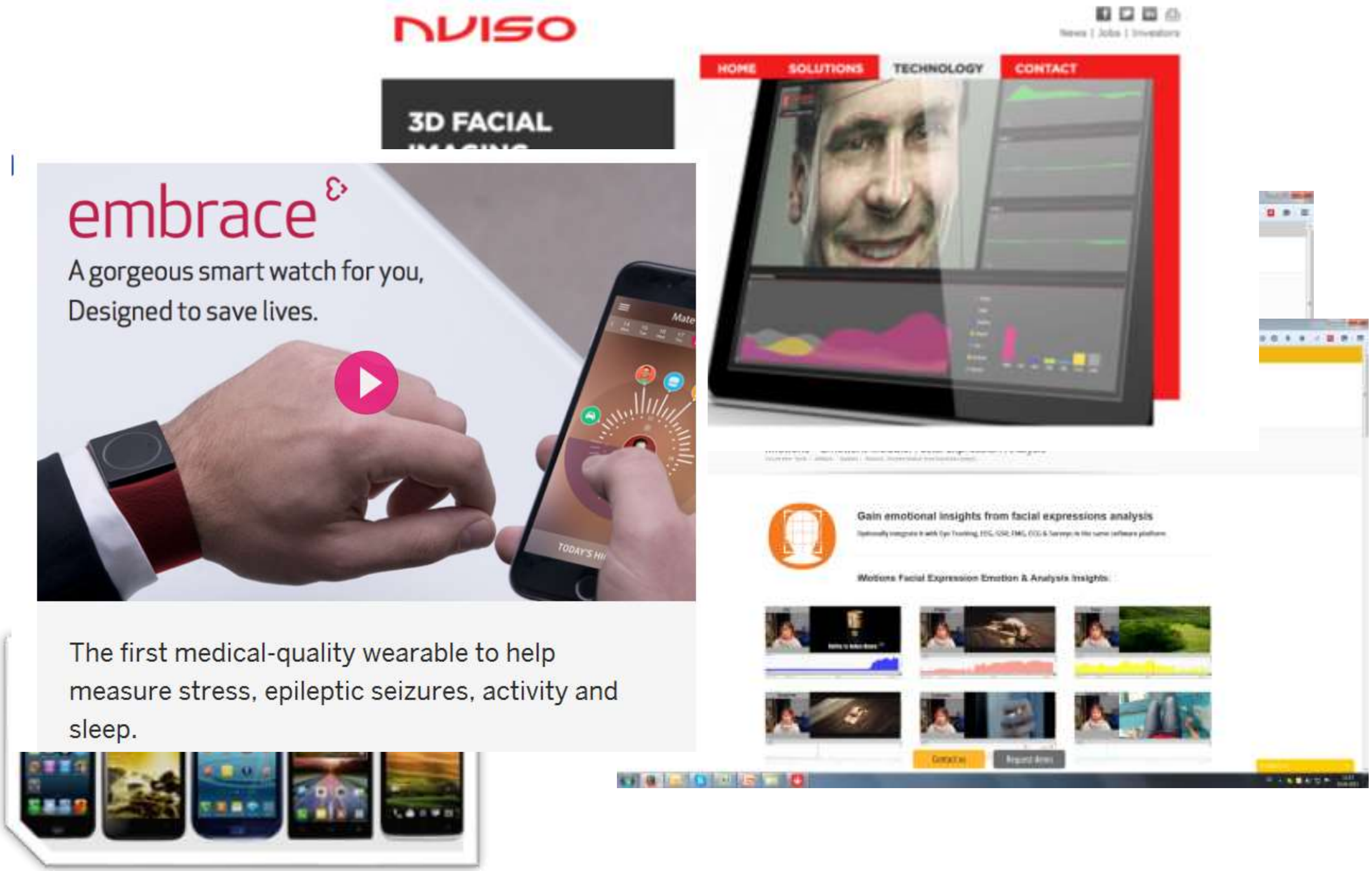
Basically the battle is still between the left and the right side of model spectrum

biologicaly driven entities



social & culturel constructs

Despite this ongoing battle affective computing became a major field of AI and commercial applications



… and diverse hardware

Market Research Reports (Amsterdam) forecast the affective computing market to grow from USD 9.35 billion in 2015 to USD 42.51 billion in 2020*

*www.asdreports.com/ASDR-216944 (**US$ 4,650**)

But there are no simple solutions. E.g. emotion recognition from facial expression


The Human Face
2003, pp 215-234

What Facial Activity Can and Ca[illegible]t Tell us About Emotions

Arvid Kappas

d Kappas,
3)

- Display rules

See also: Hoque E, Picard RW (2011) Acted vs. natural frustration and delight: Many people smile in natural frustration" *IEEE FG pp. 354-359*


© PA

e.g. emotion recognition from facial expression

The Human Face
2003, pp 215-234

What Facial Activity Can and Cannot Tell us About Emotions

Arvid Kappas

(Arvid Kappas, 2003)

- Display rules
- Systematic ambiguity
- Deception
- inhibition

See also: Hoque E, Picard RW (2011) Acted vs. natural frustration and delight: Many people smile in natural frustration" *IEEE FG pp. 354-359*

What are the challenges for emotion recognition in affective computing?

- Context-dependent situation interpretation
- Multimodality mimic, movement, speech, psychobiology)
- Modelling (discrete, dimensional or more complex)
- Reliability (across time and situations)
- Validity (ground truth if possible…)
- Observation of emotional events
  - Natural occurance
    - rare events
    - short duration
    - unstable
    - uncontrolled observation conditions
  - Experimental
    - elicitation methods
    - Problem with generalization

e.g. impact of elicitation methods

Table 4

Effect Sizes for Type of Emotion Elicitation for Each Emotion Comparison

Emotion comparison	No. of studies	Effect size (g)	95% CI
Happiness vs. sadness			
Film	106	0.88***	[0.76, 1.00]
Pictures	15	1.02***	[0.52, 1.53]
Prime	4	−0.07	[−0.31, 0.17]
Music	39	0.66***	[0.49, 0.85]
Velten	48		
Imagine	26		
Read text	7		
Behavior	11		
Real	19		
Recall	75		

IAPS Stimulus (contemporary)

Venus from Hohle Fels ~ 34000 years

Lench et al. (2011) Discrete emotions predict changes in cognition, judgment, experience, behavior, and physiology. Psychological Bulletin. 137:834-855.

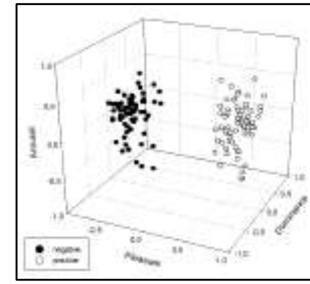
Modelling: Discrete emotions/dispositions or dimensions?

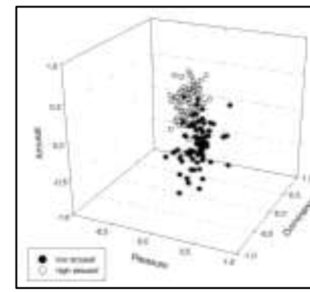
Lench et al. (2011) argued with her meta-analysis of 687 studies that discrete emotions and dimensional modelling is not contradictory: hybrid models

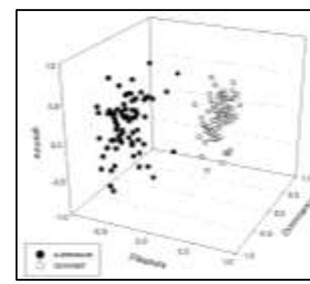
Mapping of discrete emotions into the VAD space

N=70 Vpn im Alter zwischen 18 und 30 Jahren (♀:♂ = 4:3)

Emotion	Valenz	Arousal	Dominanz	Oktand
jmdn. bewundern	,49 (,27)	–,19 (,42)	,05 (,50)	+P–A+D
schadenfroh sein	,08 (,47)	,11 (,45)	,44 (,50)	+P+A+D
Genugtuung	,39 (,43)	–,18 (,46)	,41 (,43)	+P–A+D
dankbar sein	,69 (,24)	–,09 (,58)	,05 (,55)	+P–A+D
sich für jmdn. freuen	,75 (,21)	,17 (,51)	,37 (,49)	+P+A+D
(auf etwas) hoffen	,22 (,33)	,28 (,52)	–,23 (,52)	+P+A–D
being happy	,82 (,18)	,43 (,54)	,55 (,43)	+P+A+D
Zuneigung	,80 (,22)	,14 (,58)	,30 (,52)	+P+A+D
stolz sein	,72 (,25)	,20 (,48)	,57 (,43)	+P+A+D
erleichtert sein	,73 (,21)	–,24 (,59)	,06 (,53)	+P–A+D
zufrieden (mit etw.) sein	,65 (,26)	–,42 (,47)	,35 (,47)	+P–A+D
being angry	–,62 (,23)	,59 (,38)	,23 (,58)	–P+A+D
enttäuscht sein	–,64 (,22)	–,17 (,54)	–,41 (,49)	–P–A–D
being unhappy	–,75 (,16)	–,31 (,52)	–,47 (,45)	–P–A–D
being frightend	–,74 (,19)	,47 (,56)	–,62 (,43)	–P+A–D
bestätigte Furcht	–,74 (,22)	,42 (,59)	–,52 (,48)	–P+A–D
Abneigung	–,52 (,26)	,00 (,45)	,28 (,45)	–P+A+D
jmdn. bemitleiden	–,27 (,29)	–,24 (,37)	,24 (,51)	–P–A+D
Reue	–,42 (,33)	–,01 (,54)	–,35 (,54)	–P–A–D
(jmdm. etw.) vorwerfen	–,41 (,28)	,47 (,38)	,50 (,45)	–P+A+D
(jmdm. etw.) misgönnen	–,52 (,26)	,00 (,51)	,03 (,49)	–P+A+D
sich schämen	–,66 (,22)	,05 (,55)	–,63 (,46)	–P+A–D

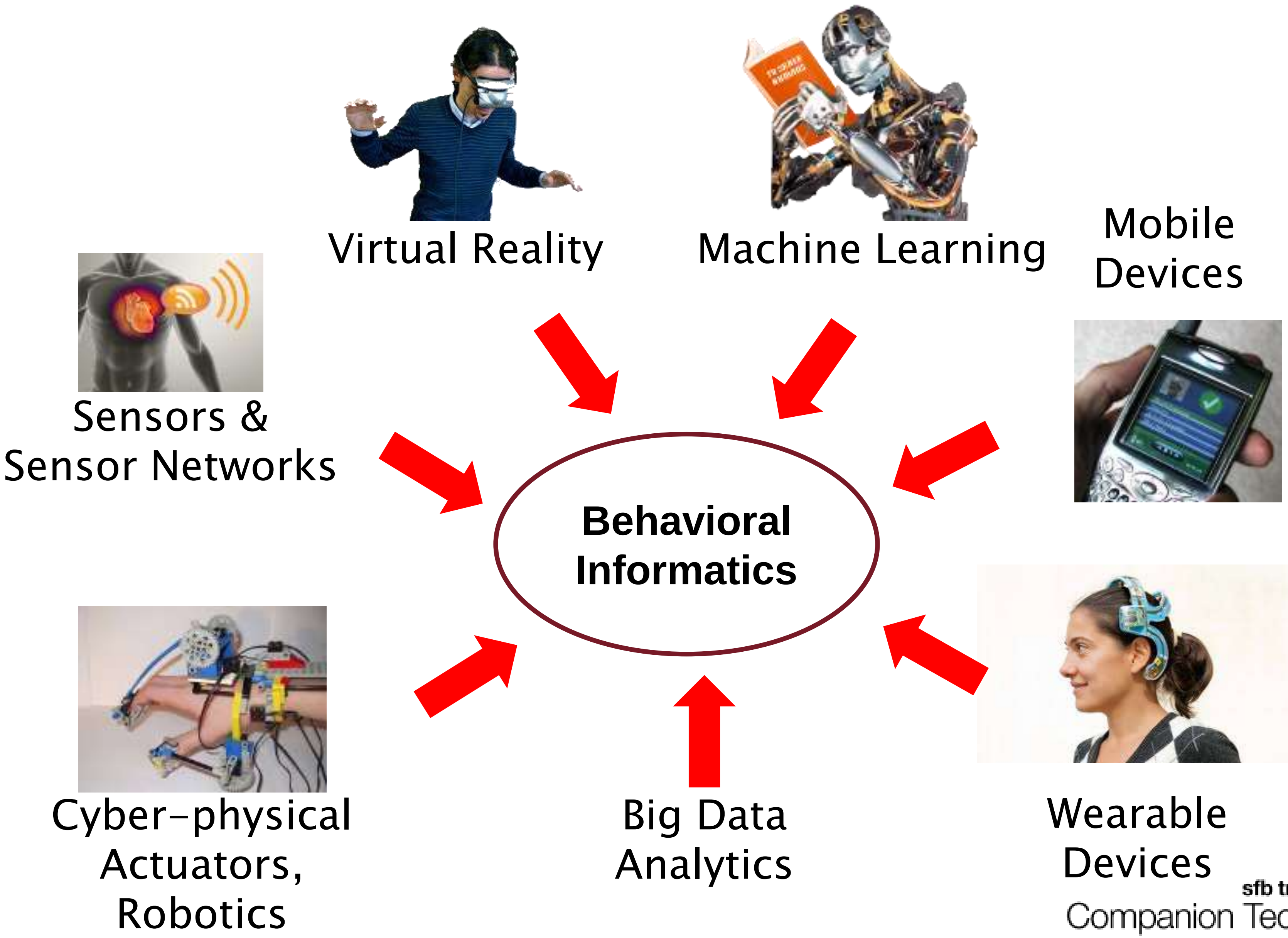




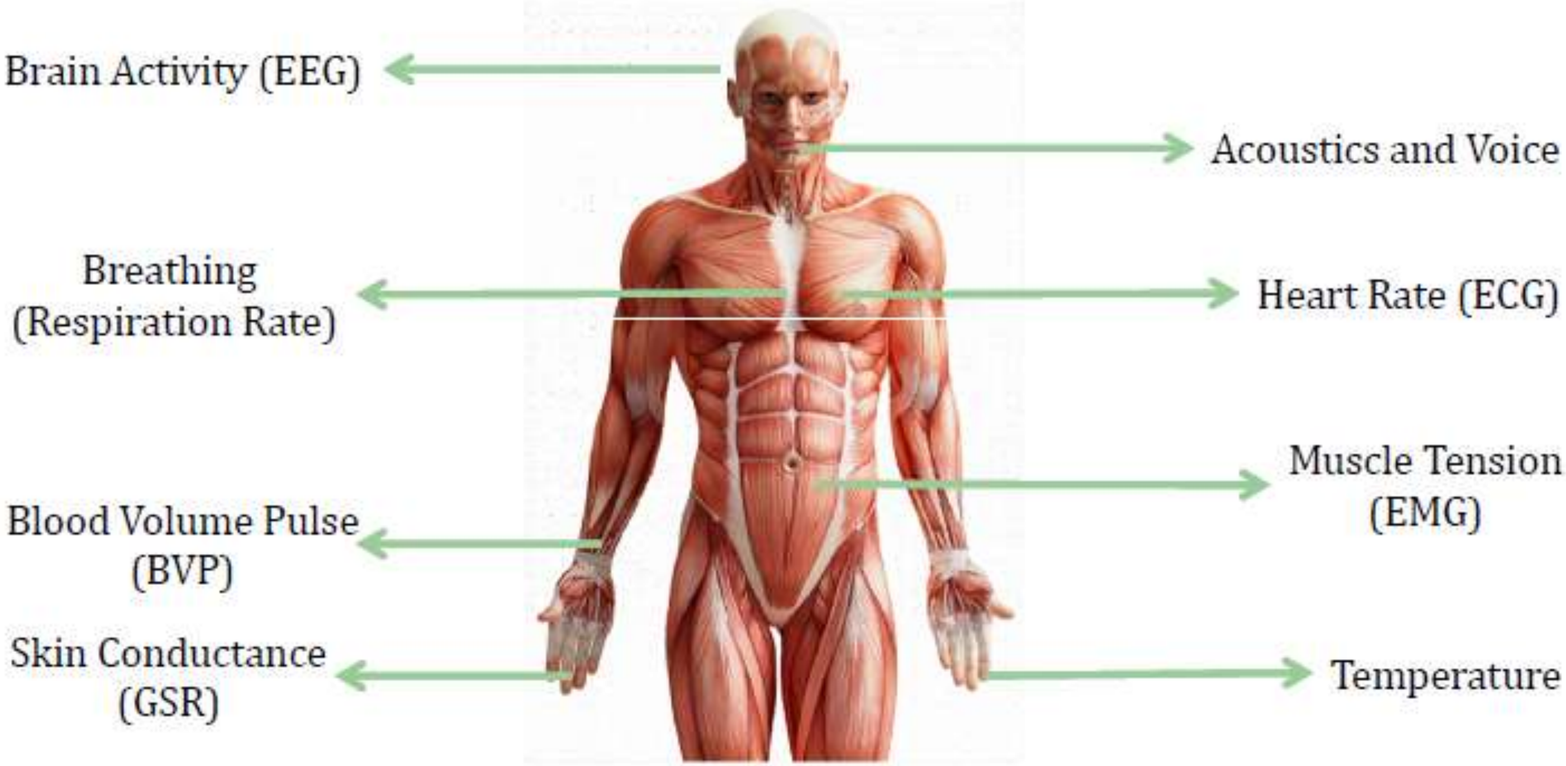


Hoffmann H, Scheck A, Schuster T, Walter S, Limbrecht K, Traue HC, Kessler H (2012) "Mapping discrete emotions into the dimensional space: An empirical approach" In *Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics (SMC 2012)* Seoul, Korea

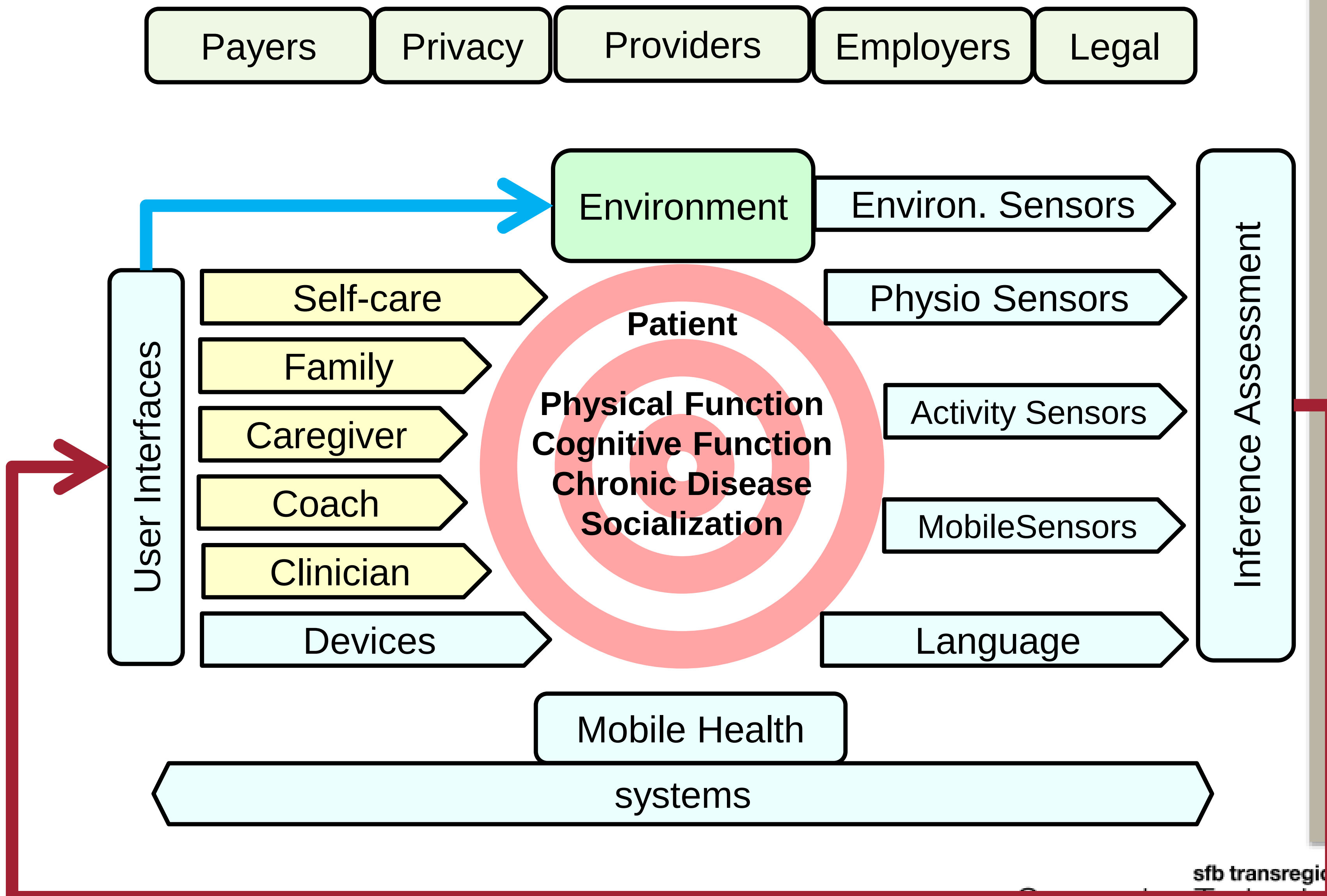
Affective Computing Technology Opportunity: Confluence of Sensors, Networking and Computation



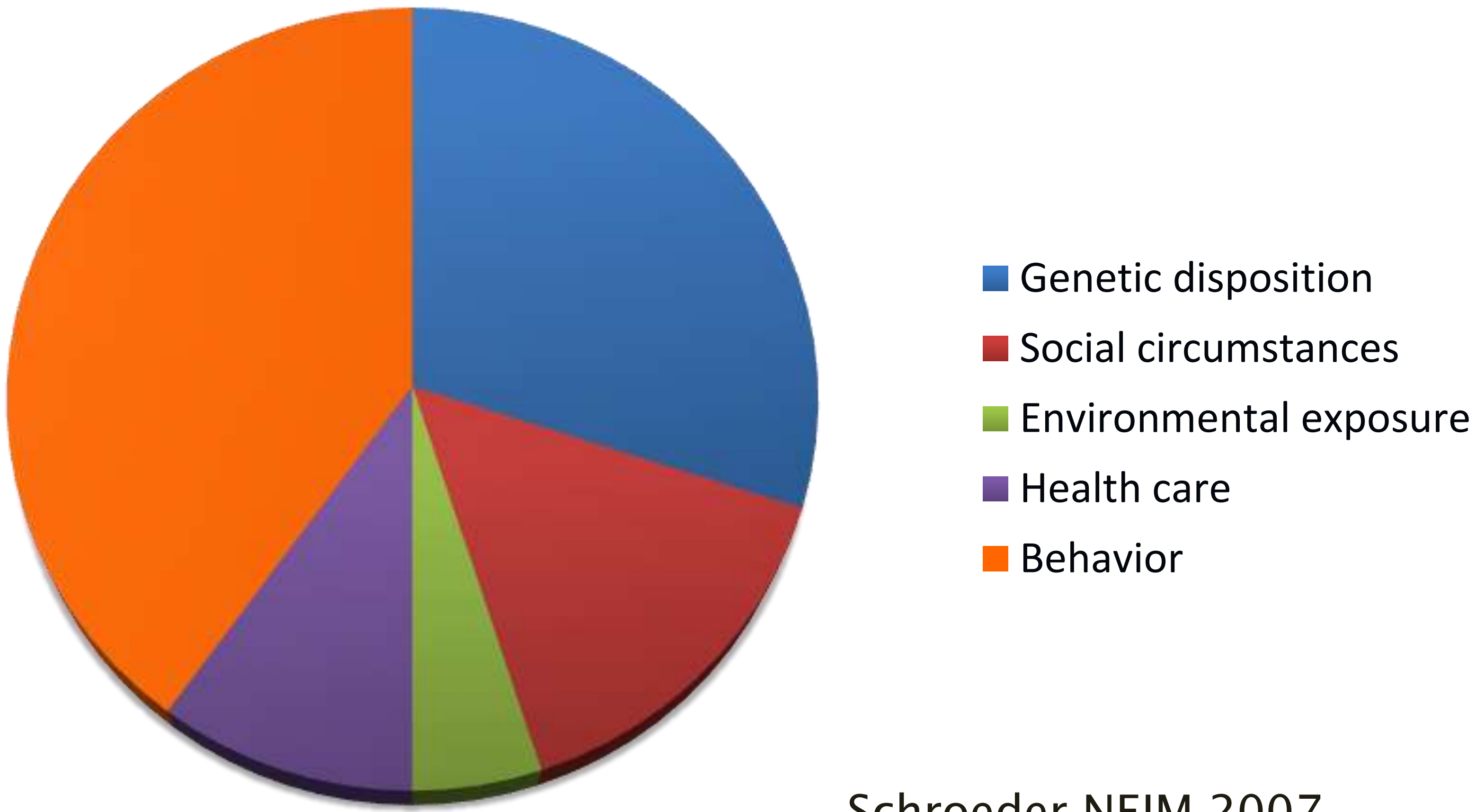
Body systems of interest for health care applications



Precision Healthcare: An Individual Citizen

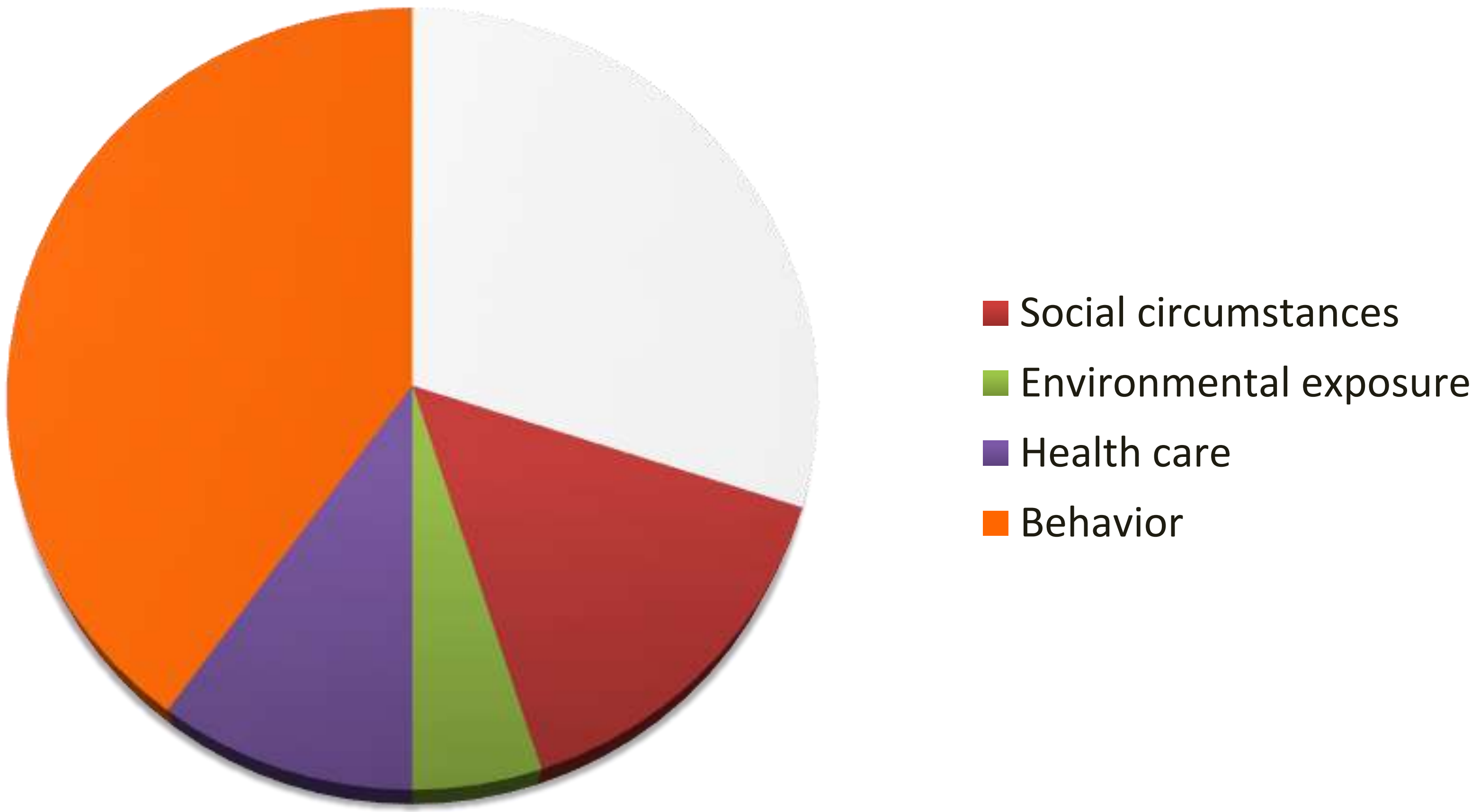


Proportional contribution to health problems



Schroeder NEJM 2007

This can be changed…



Domains for affective computing technology (Companion technology)

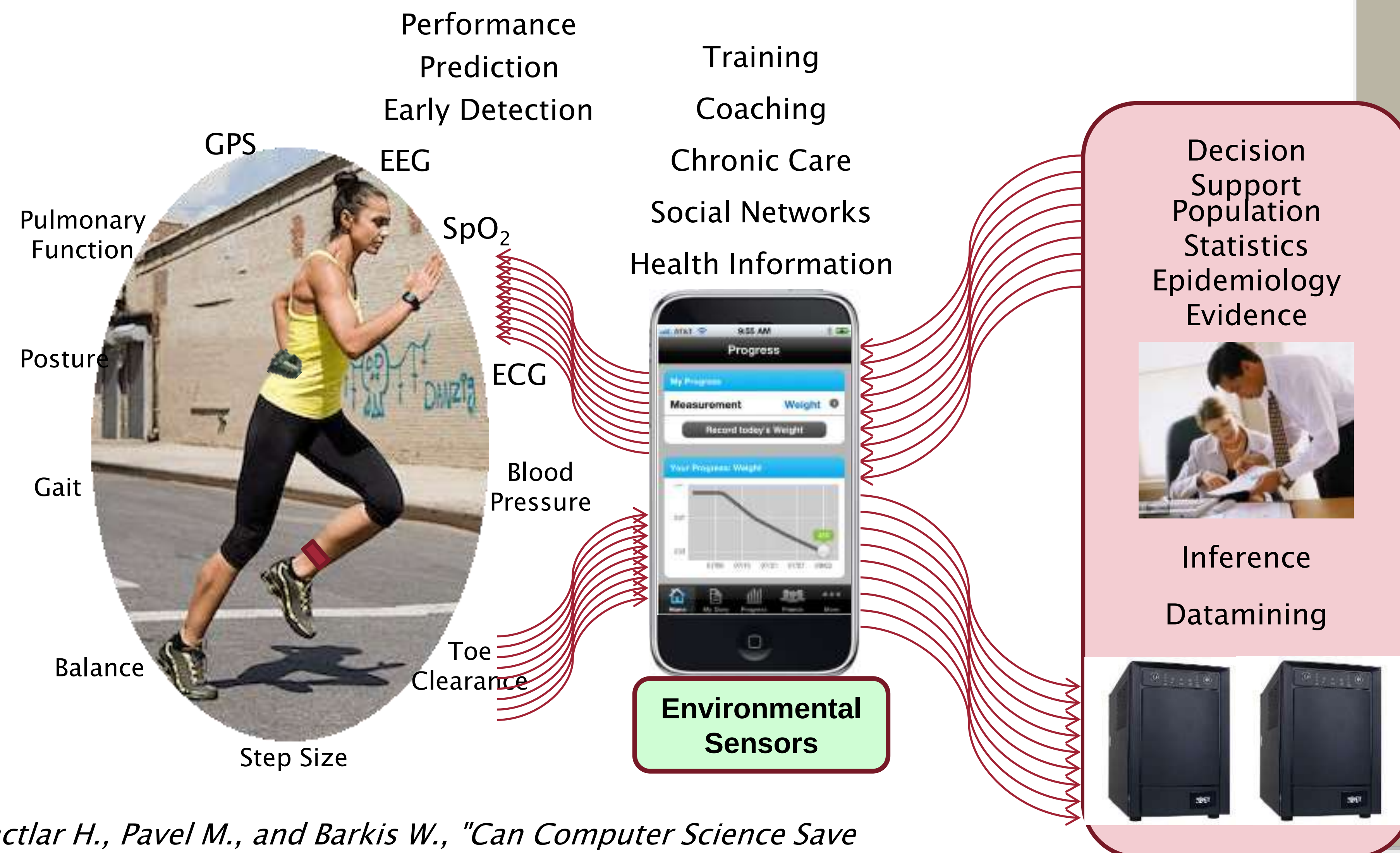
- Nutrition


- Physical Exercise


- Cognitive Exercise


- Sleep, Stress, etc.


Example: Companion Technology for Enhancing Health and Quality of Life



Wactlar H., Pavel M., and Barkis W., "Can Computer Science Save Healthcare?," Intelligent Systems, IEEE, vol. 26, pp. 79-83, Sept. 2011.

Applications functionality

- Behavior monitoring and assessment
- Inference, intervention based on system–theory
- Foundations for optimizing health behavior change
- Guiding technology to amplify the scalability and effectiveness of health interventions
- Tailoring to individuals
- Objective measurements whenever possible
- Just in time adaptive interventions

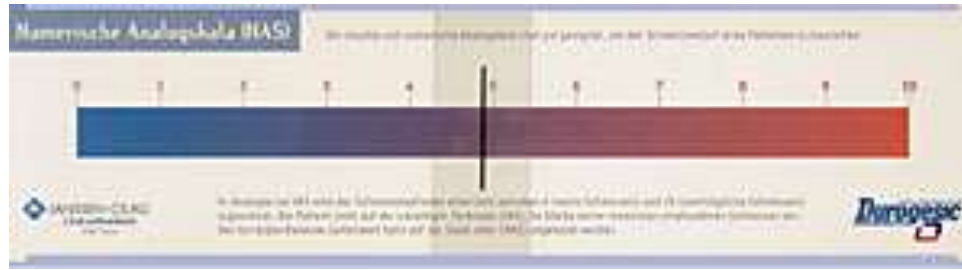
Case study: Automated detection of pain levels with autonomic and behavioral parameters

Contemporary clinical pain assessment

- Clinical interview
- Diaries
- Psychometric multi-dimensional subjective scales (pain experience, emotional an cognitive coping)
- Neurological diagnosis (reflexe, muscle tone, quantitative sensory testing etc.)

e.g. scales for clinical pain assessment

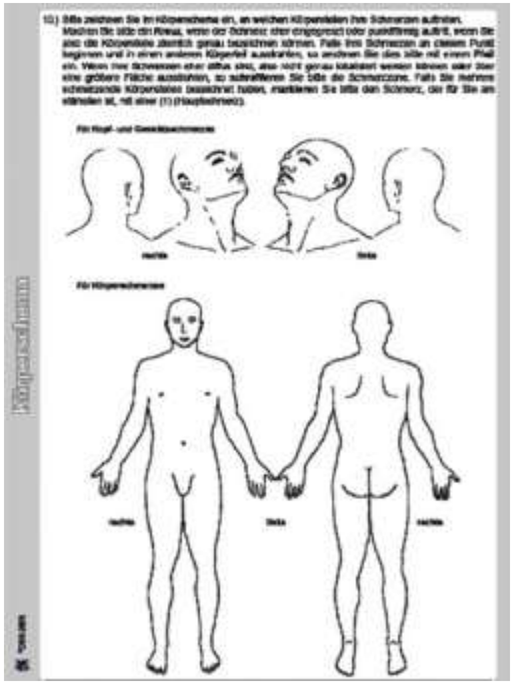
Lamche M et al. Journal für Urologie und Urogynäkologie 2002; 9 (3) (Ausgabe für Österreich): 24-26 ©

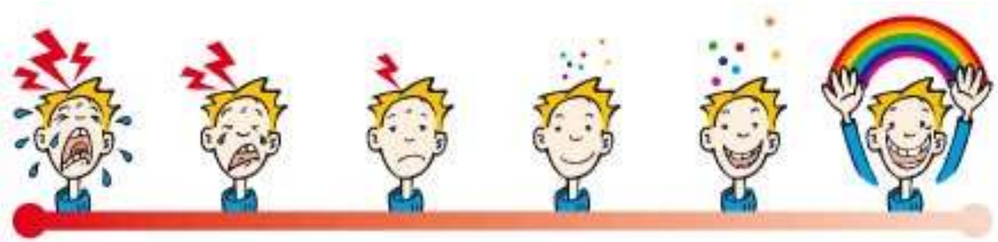


Schmerzempfindungs-Skala

psychische Empfindungen					physische Empfindungen				
mörderisch	❑	❑	❑	❑	schneidend	❑	❑	❑	❑
elend	❑	❑	❑	❑	klopfend	❑	❑	❑	❑
schauderhaft	❑	❑	❑	❑	brennend	❑	❑	❑	❑
scheußlich	❑	❑	❑	❑	reißend	❑	❑	❑	❑
schwer	❑	❑	❑	❑	pochend	❑	❑	❑	❑
entnervend	❑	❑	❑	❑	glühend	❑	❑	❑	❑
marternd	❑	❑	❑	❑	stechend	❑	❑	❑	❑
furchtbar	❑	❑	❑	❑	hämmernd	❑	❑	❑	❑
unerträglich	❑	❑	❑	❑	heiß	❑	❑	❑	❑
lähmend	❑	❑	❑	❑	durchstoßend	❑	❑	❑	❑

trifft genau zu ⟷ trifft nicht zu   trifft genau zu ⟷ trifft nicht zu





Zurich Observation Pain Assessment (ZOPA); (Handel, Gnass, Müller-Sanders & Sirsch, 2010)

Behavioral characteristics:

- Vocalization
- Facial expression
- Body language
- Physiological indicators
- Change of skin color

The Problem

• The conventional clinical assessment of pain are not sufficiently objective, reliable and valid - and it is time consuming!

<u>Special problems of pain diagnostic:</u>

- Not vigilant patient (especially in intensive car units)!
- Infants
- Demented patient
- Mentally disturbed persons
- **not sufficient temporal information density**

Aim of the Case-Study

- Optimize a **multimodal** technology system to detect **pain quantification** (stress) under a laboratory pain stimulation.

- To find features and **feature patterns** that contribute to the highest recognition rate for **pain quantification.**

… lot of commercial clinical interest, e.g. Medasens

Diese Seite ist Englisch. Soll sie mit der Google Toolbar übersetzt werden? Erfahren Sie mehr Nicht auf Englisch? Unterstützen Sie uns. Übersetzen Englisc

Home | Clinical Need | Technology | Market | About Us | Careers | News & Events | Contact

MEDASENSE
pain monitoring solutions

Follow

Technology

Medasense Biometrics developed a patented technology enabling objective assessment of changes in pain level. Information is collected through a finger-mounted probe that monitors changes in physiological parameters affected by pain and by analgesic medications. This information is analyzed using proprietary artificial intelligence algorithms, which convert the physiological data to a real-time Pain Index.

The information generated by Medasense monitors enables clinicians to improve patient management by properly and timely adjusting pain medications and minimizing adverse events. The technology can be implemented in standalone devices offered by the company or embedded in third-party systems intended to monitor patient's physical state.

Following five years of research, the company has demonstrated the feasibility of its technology to assess pain in alert and sedated patients, as well as the enhanced accuracy of its monitors compared to other methods currently available.

news & events

SEPTEMBER 2013

Medasense abstract entitled "Objective measurement of pain levels in patients with radicular pain treated by spinal cord stimulation" was accepted for presentation at the American Academy of Pain Medicine 30th Annual Meeting (March 6-9, 2014, Phoenix, AZ, USA).

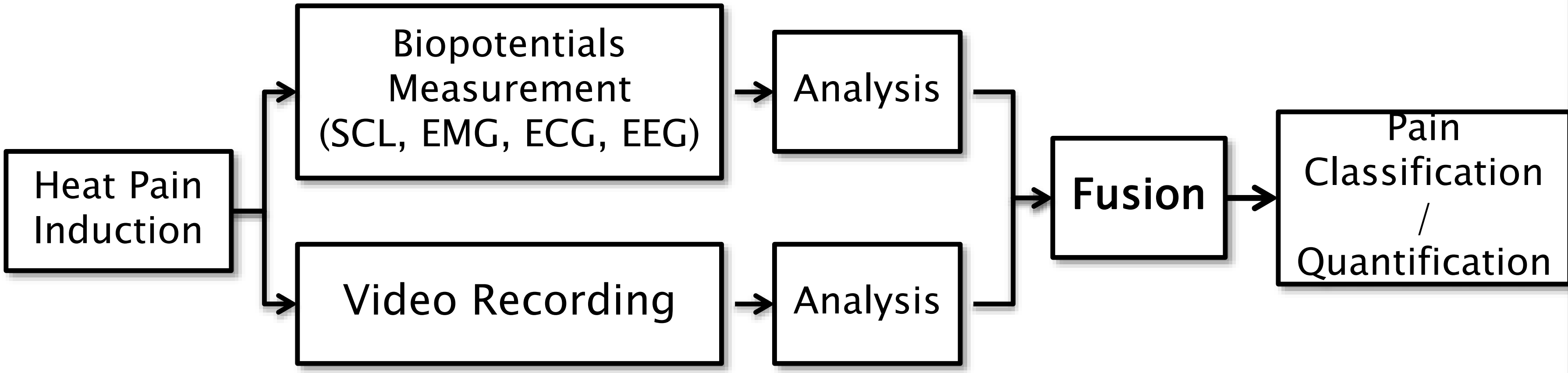
AUGUST 2013

Medasense Receives Patent Approval for Novel Pain-Monitoring System

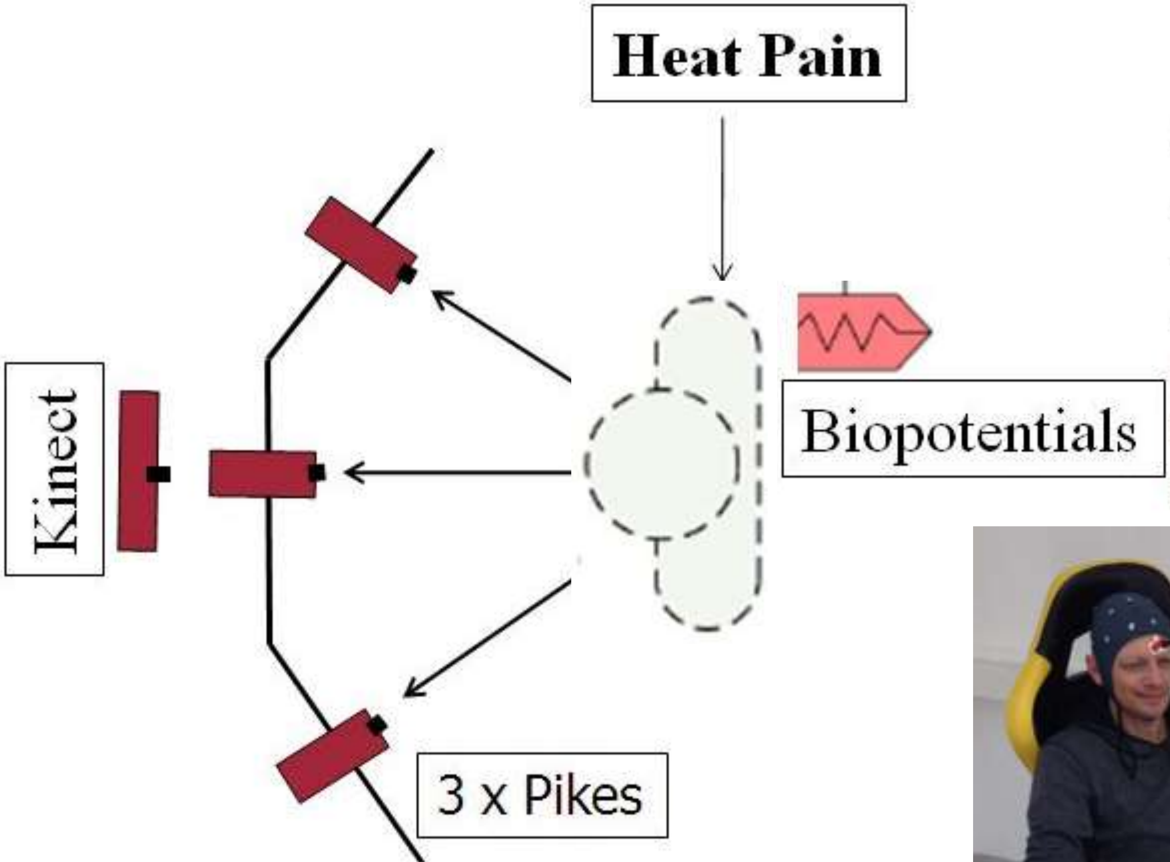
JULY 2013

Internet

General experimental protocol of the (multi modal) pain recognition



Multi Modal Design



- Electromyography (EMG)
  - Corrugator
  - Zygomaticus
  - Trapezius
- Skin Conductance Level (SCL)
- Electrocardiogram (ECG)
- Electroencephalography (EEG)

Technique of Pain Stimulation

- Medoc Pathway System (Peltier Element)
  - Quantitative Stimulation Testing (clinical setting)
  - Stimulus control for experiments
  - fMRT compatible
  - Trigger output
  - Heat 32°C – 55°C
  - Thermode size: 30x30mm (900 mm^2),
  - Ethical approval
  - CE-Certification

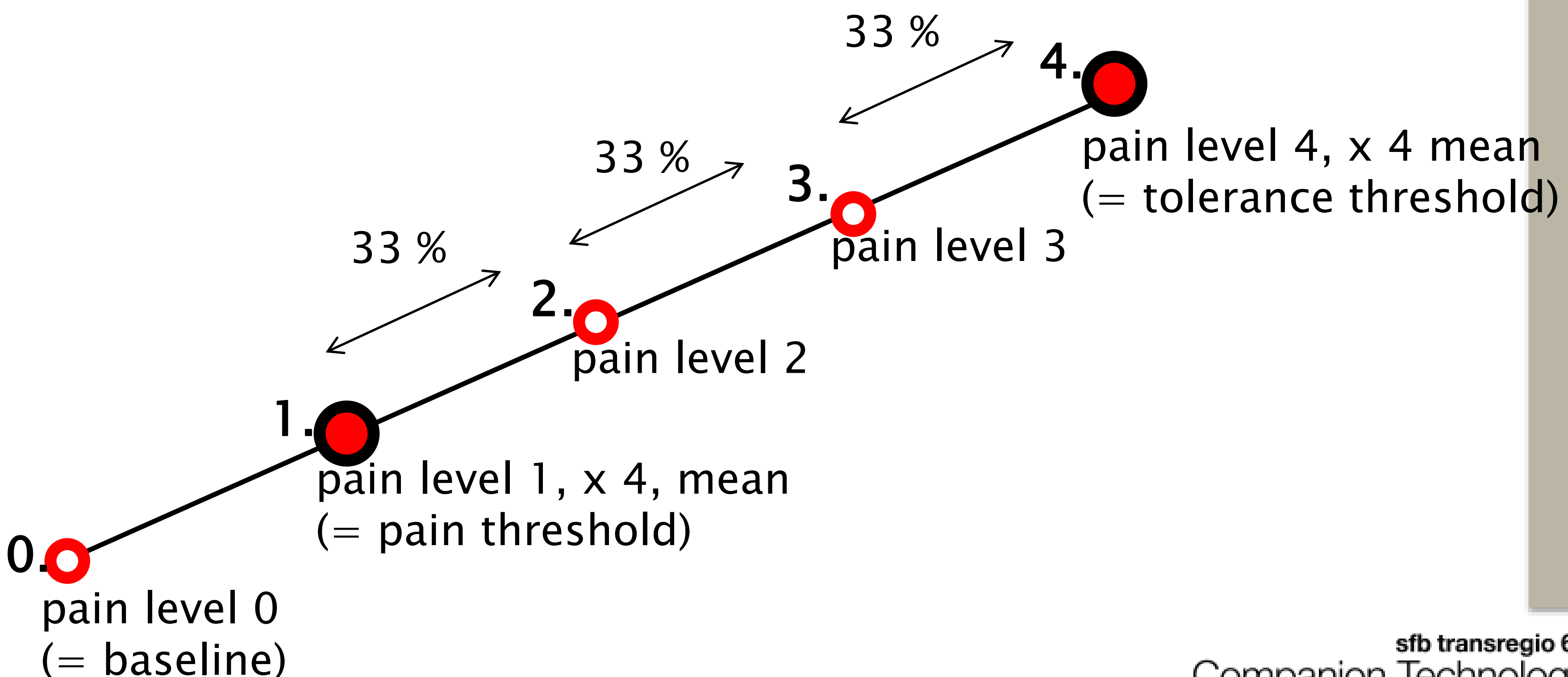
Instruction of Pain Calibration

Instruction pain threshold: Please immediately press the stop button when a feeling of burn, sting, drill or draw appears in addition to the feeling of heat.

Instruction tolerance threshold: Please immediately press the stop button when you cannot accept the heat regarding the burn, sting, drill or draw any more.

Pain Calibration

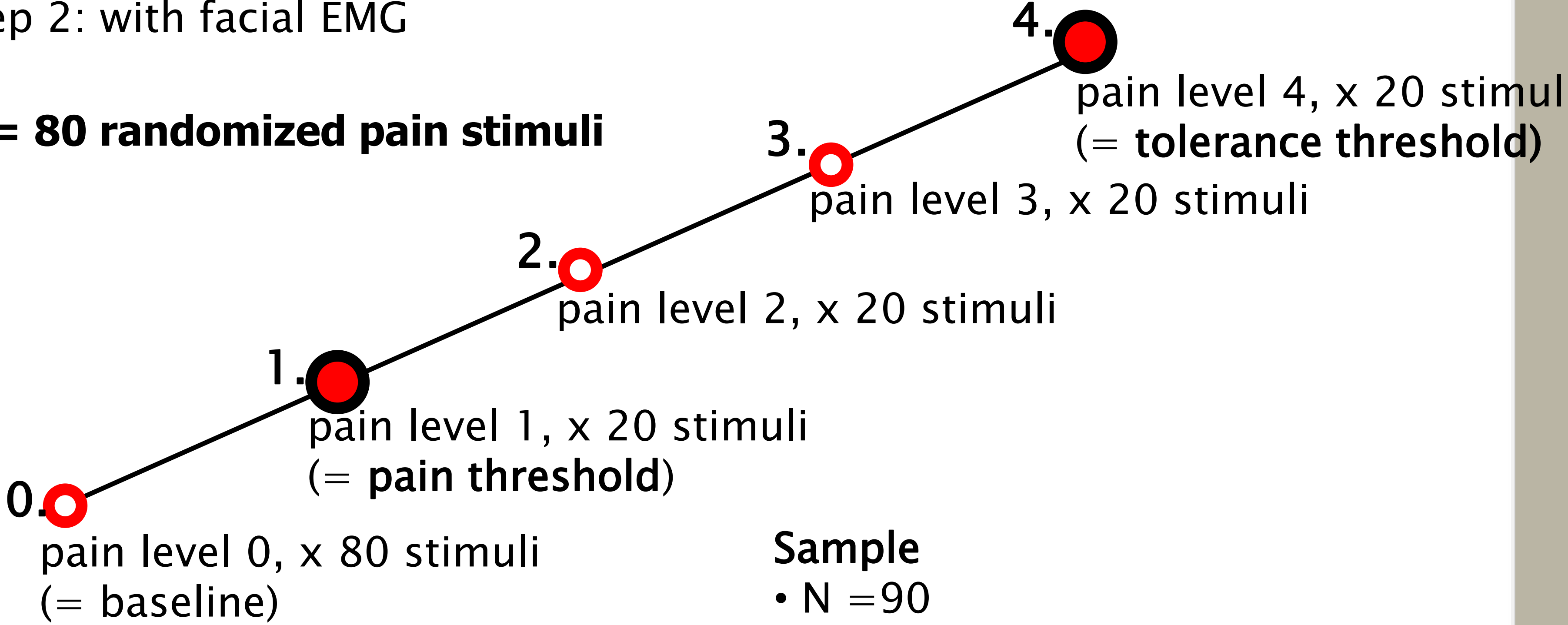
1. pain threshold
2. tolerance threshold (max. 50.5 °C, burn risk!)
3. two intermediate levels between the pain and tolerance threshold



Configuration of Pain Stimulation

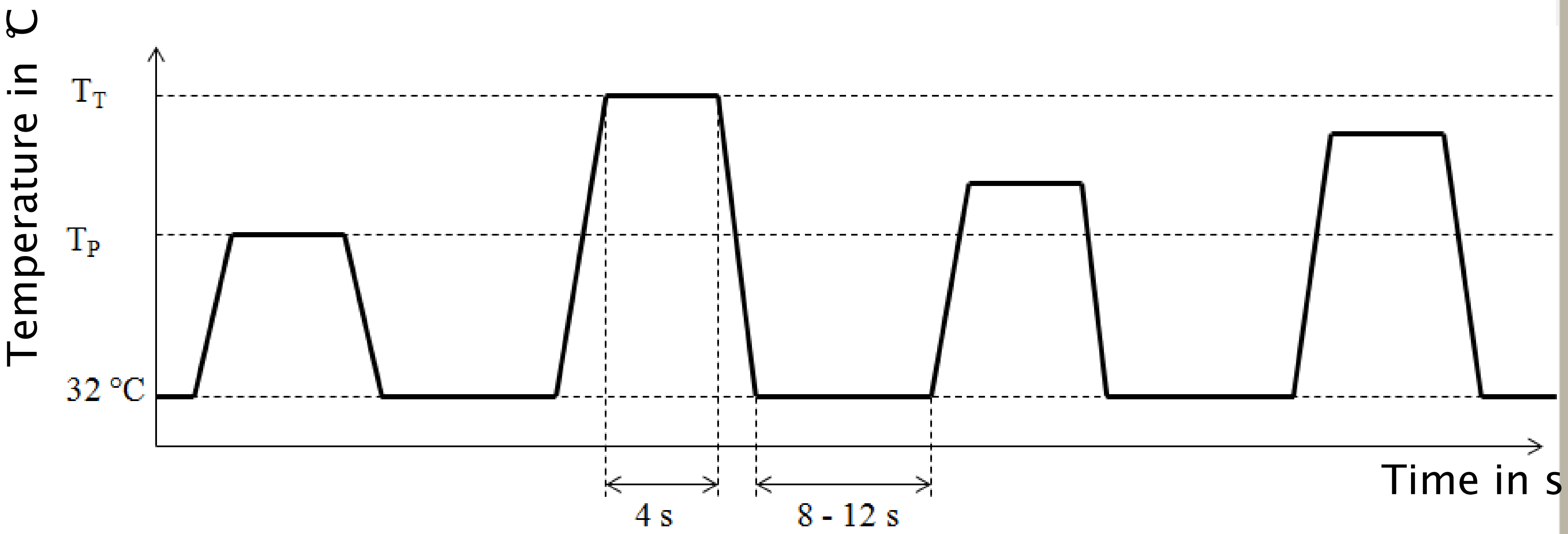
2 x ca. 25 minutes, ca. 1 h break
Step 1: without facial EMG
Step 2: with facial EMG

Σ = 80 randomized pain stimuli



Sample
- N =90
- 1. age group: 18–35 (N = 30)
- 2. age group: 36–50 (N = 30)
- 3. age group: 51–65 (N = 30)
- split half gender: women vs. man

Example of Randomized Pain Stimulation



Video Example: Baseline vs. Level 1 vs. Level 2 vs. Level 3 vs. Level 4

Baseline

Level 1

Level 2

Level 3

Level 4

Machine learning

1. Preprocessing:
✓ visualization,
✓ filtering,
✓ decompensation

2. Feature extraction (normalization?)

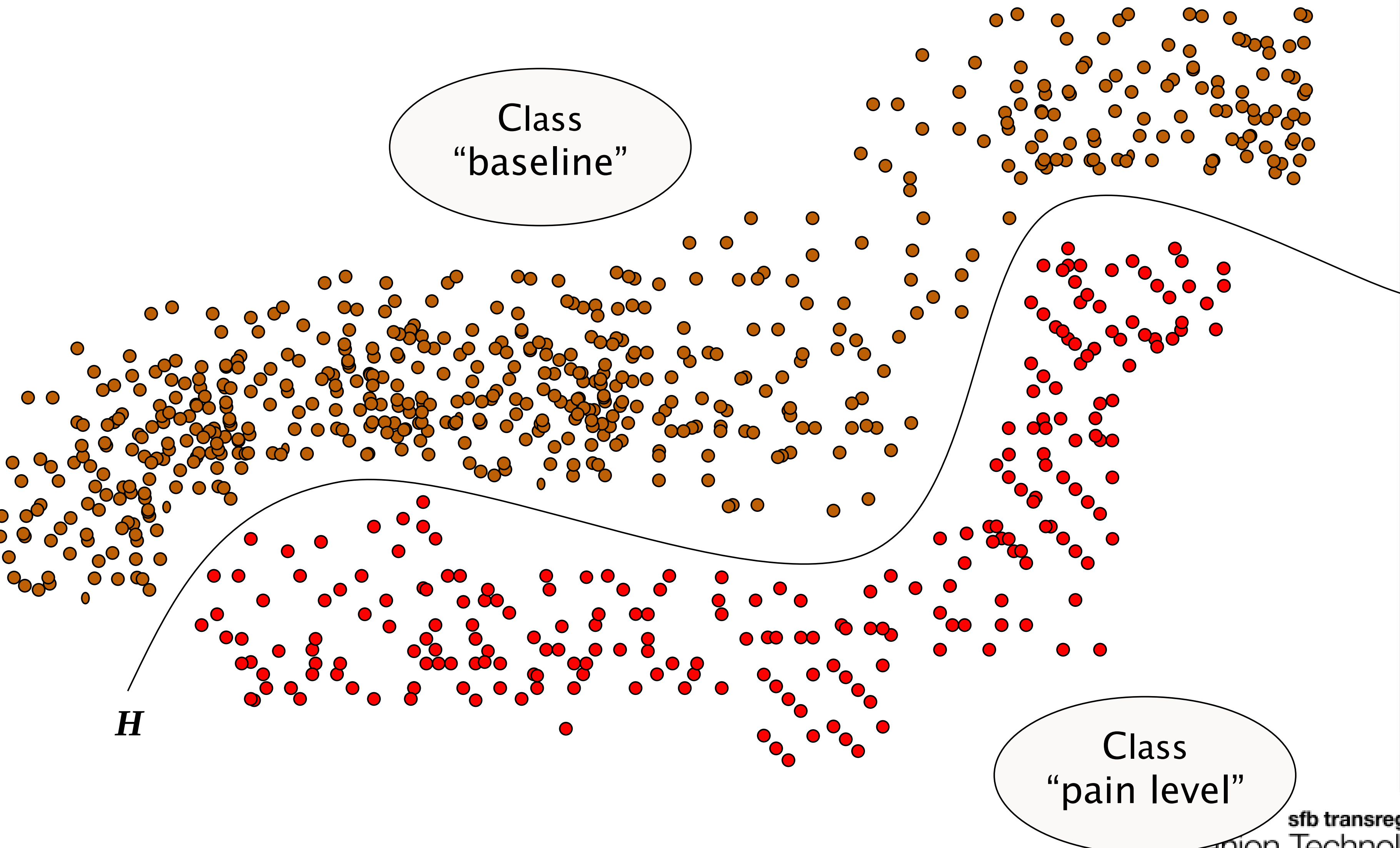
3. Feature selection

4. Fusion

↕

5. Classification

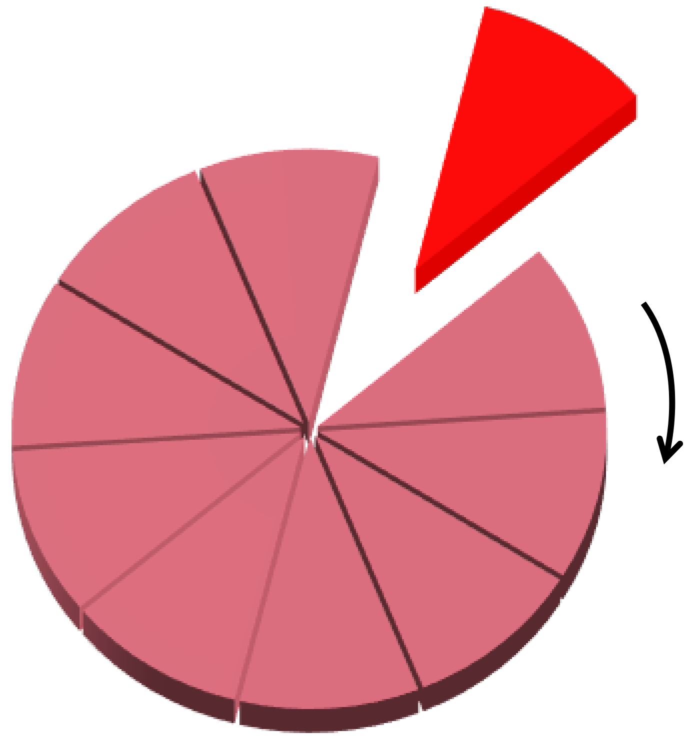
Support Vector Machine (SVM) – e.g. Pain Threshold Classification



1. Individual Feature Selection and Cross Validation - Model

k-te Iteration (1 participant)
recognition rate in %

Feature Selection



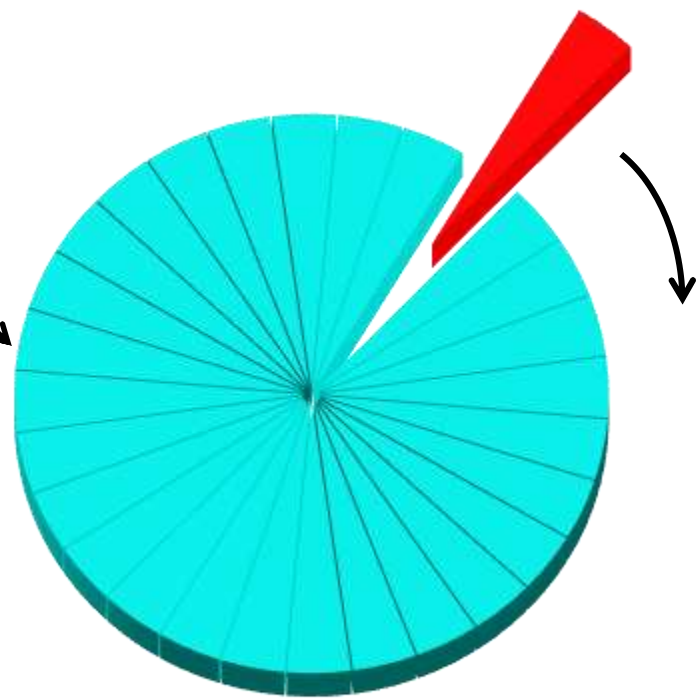
Training
Validation

mean personal recognition rate in %
mean generic recognition rate in %

2. Generic Feature Selection and Cross Validation - Model

k-te Iteration (1 participant)
recognition rate in %

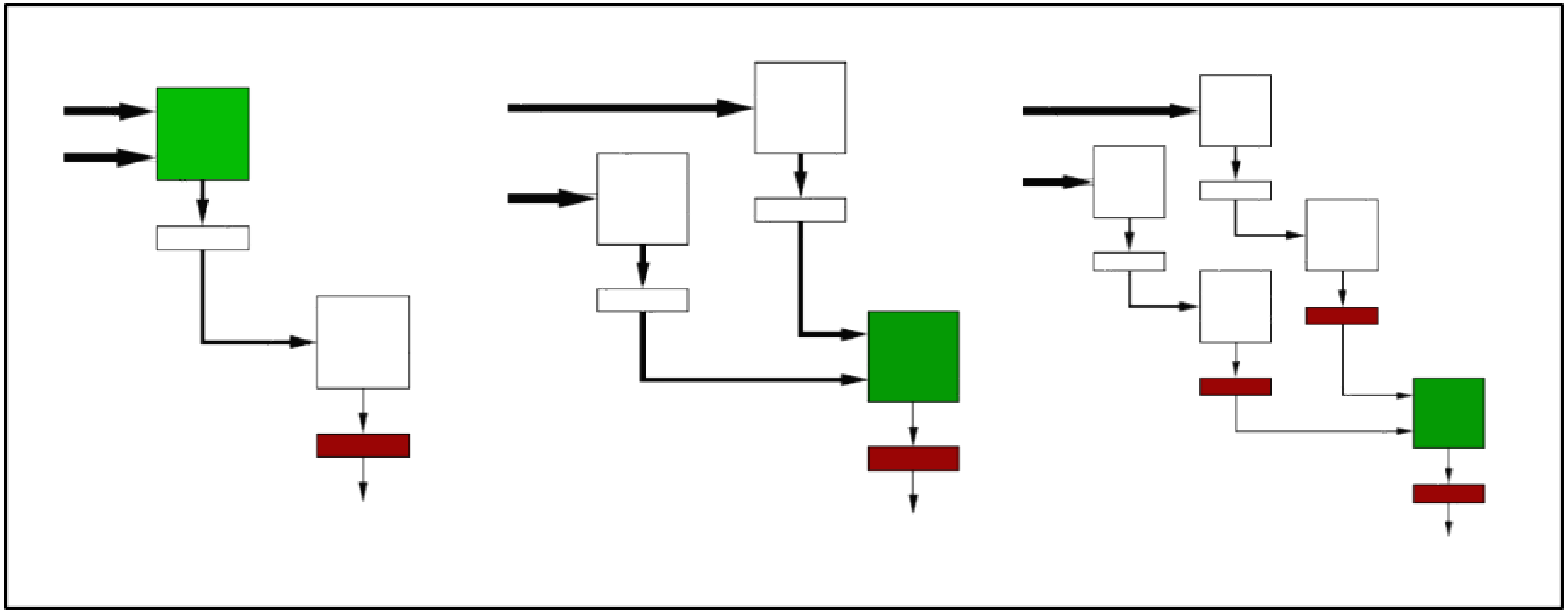
Feature Selection



Training
Validation

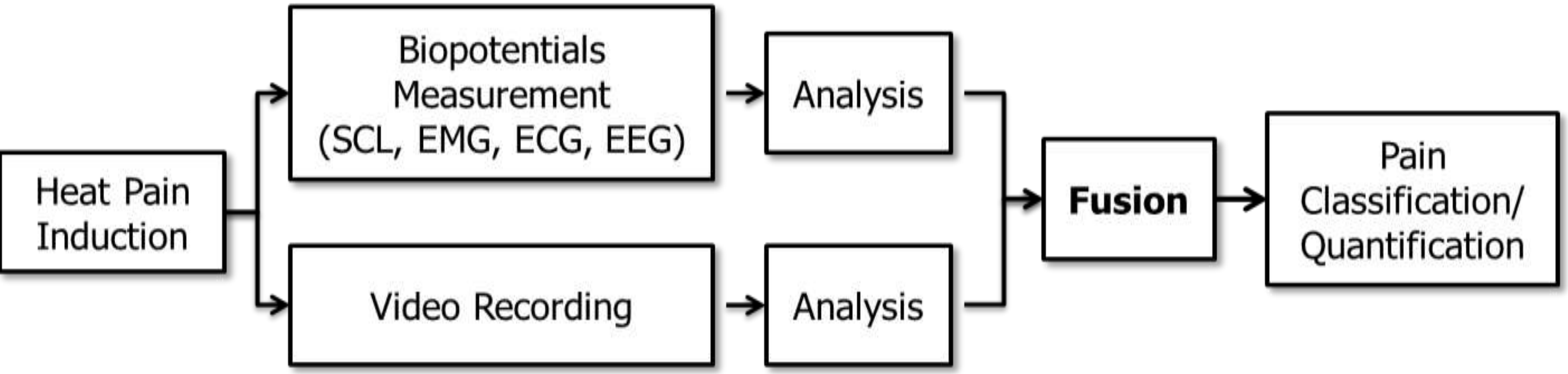
mean generic recognition rate in %

Data fusion: later more by Sascha Meudt



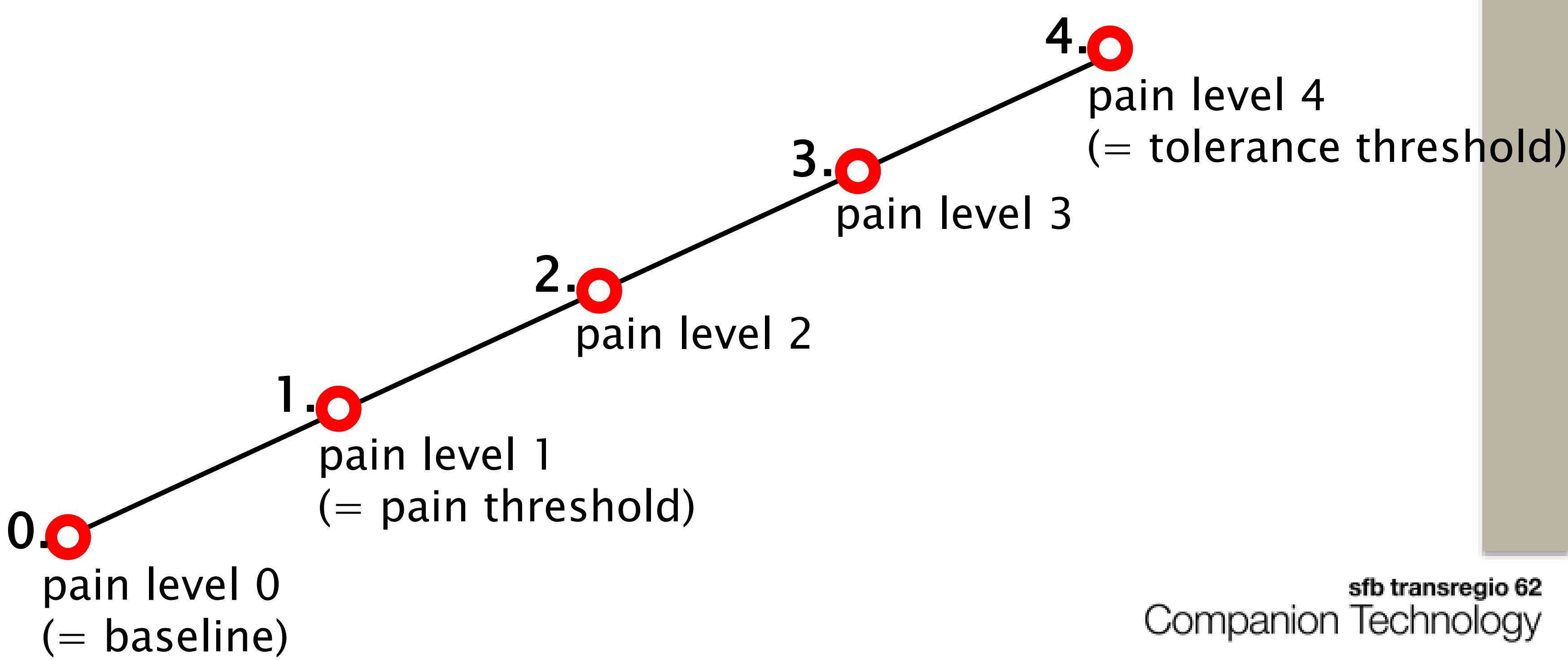
a. early fusion   b. inter mediate   c . late fusion

Multimodal data analysis

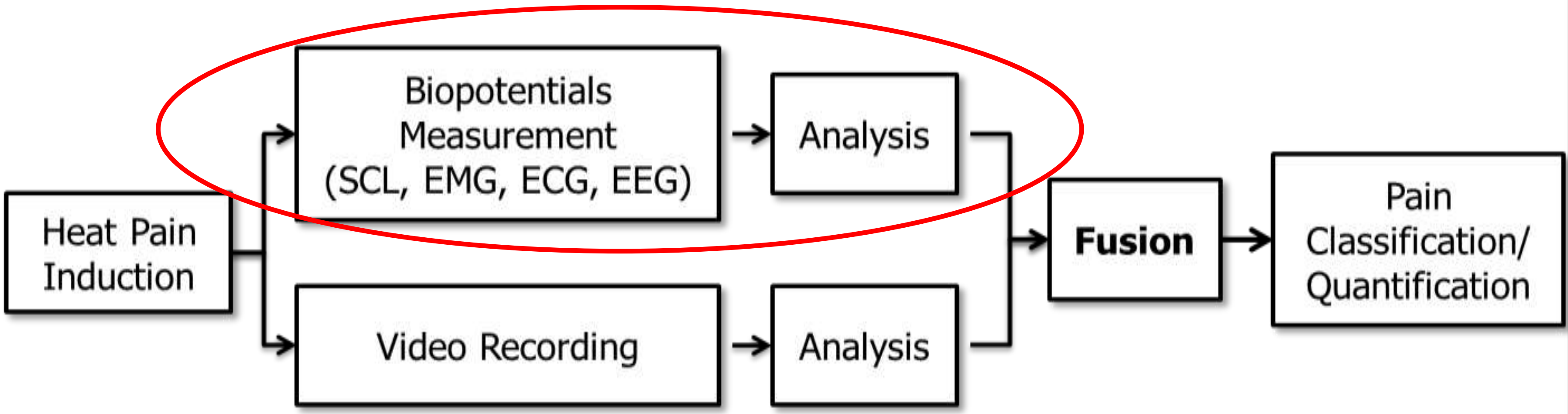


Procedure of Pain Quantification: Baseline vs. Level 1 vs. Level 2 vs. Level 3 vs. Level 4

- baseline 0 vs. pain level 4
- baseline 0 vs. pain level 1
- pain level 1 vs. pain level 2
- pain level 2 vs. pain level 3
- pain level 3 vs. pain level 4
- pain level 0 vs. pain level 1 vs. 2 vs. 3 vs. 4



Data analysis



Preprocessing of Biopotentials

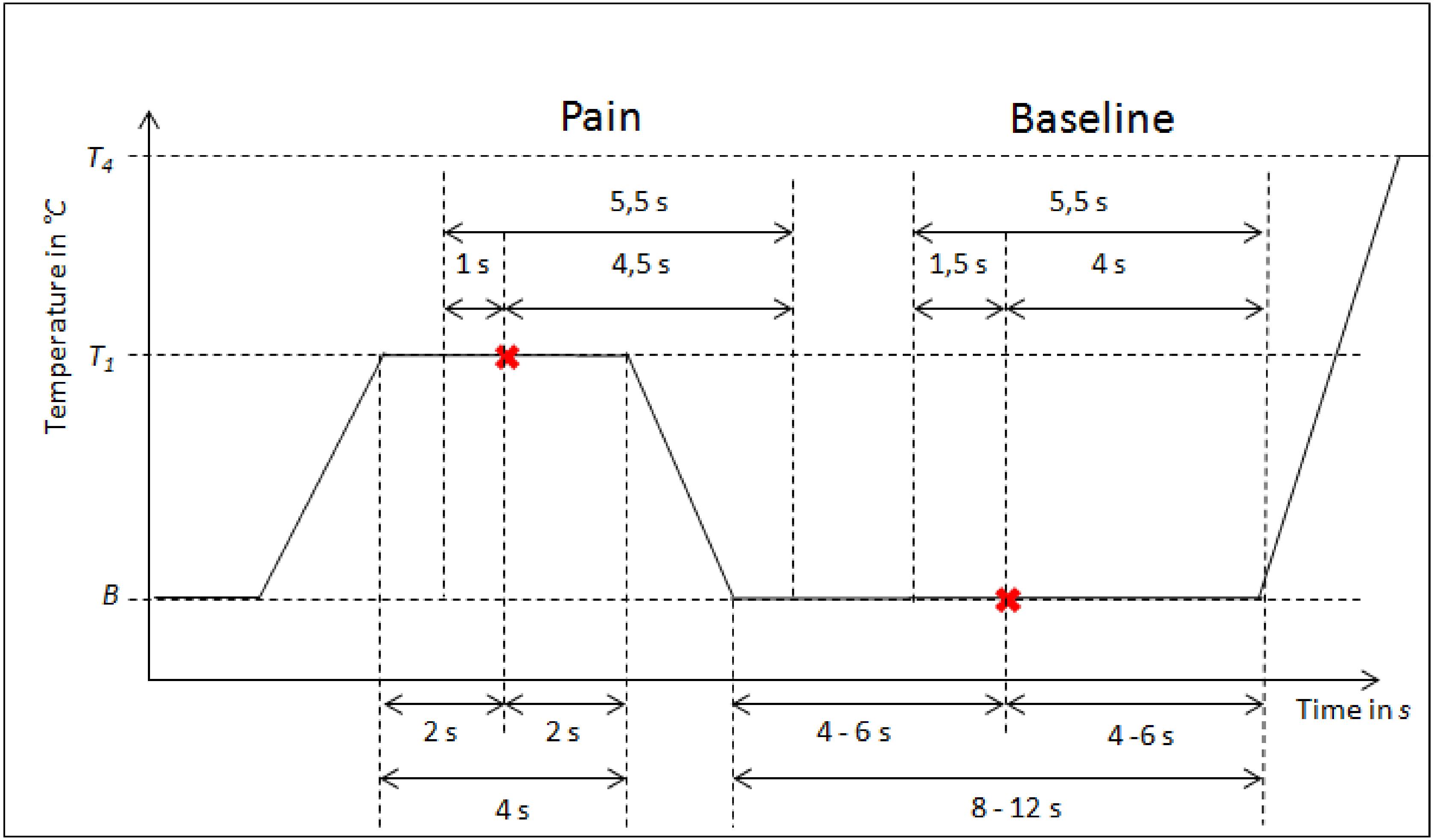
- We applied a Butterworth filter to the EMG (20 Hz - 250 Hz) and ECG (0.1 Hz - 250 Hz) signals.

- We also applied an additional filter using the Empirical Mode Decomposition technique.

- We detected bursts of activity via EMG using the Hilbert Spectrum.

- Z-transformation for all signal feature

Pain Quantification



Feature extraction (Σ = 135) Signals: EMG SCL, ECG

Amplitude (Σ 40)

Entropy (Σ 20)

Frequency (Σ 24)

Linearity (Σ 8)

Stationarity (Σ 24)

Variability (Σ 19)

Feature extraction (Σ = 69)
Signals: EMG (trapezius), SCL, ECG

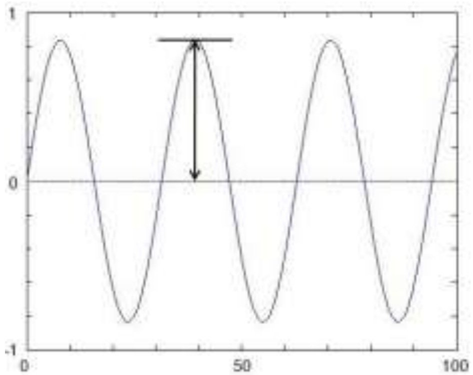
Amplitude (Σ 20)

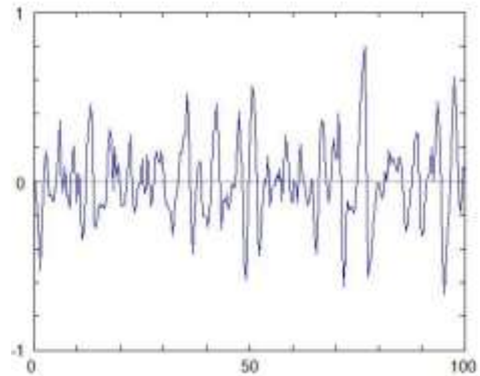
10 subgroups
e.g. peak, peak-to-peak, rms …

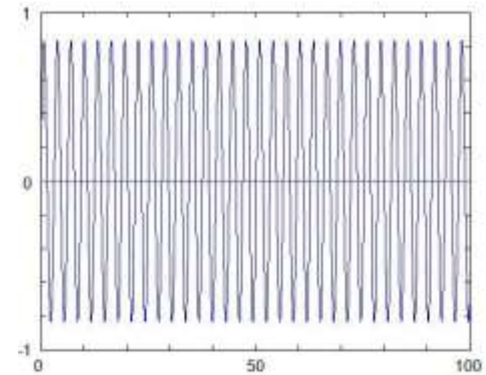
Entropy (Σ 10)

Frequency (Σ 12)

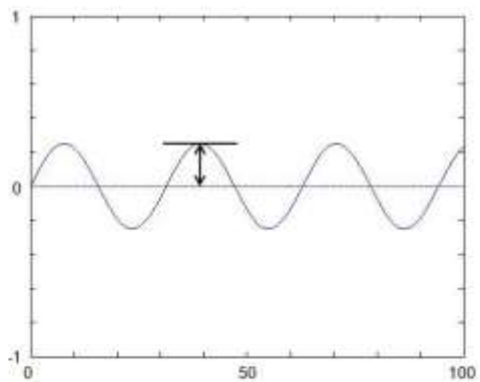
example high:

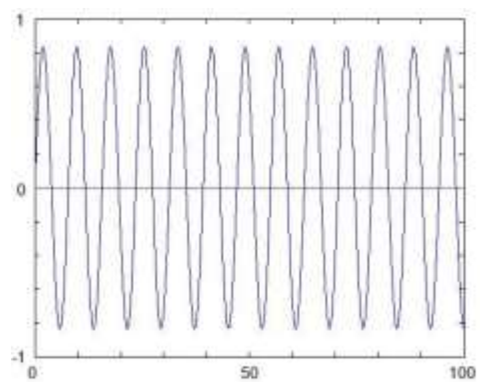


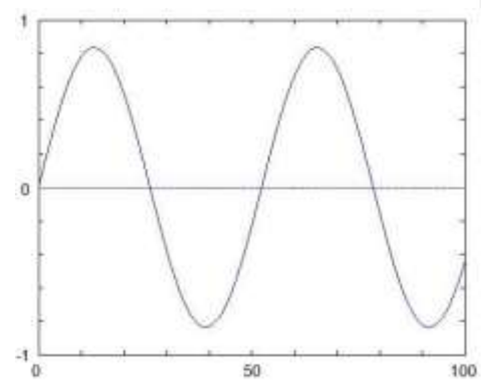




example low:



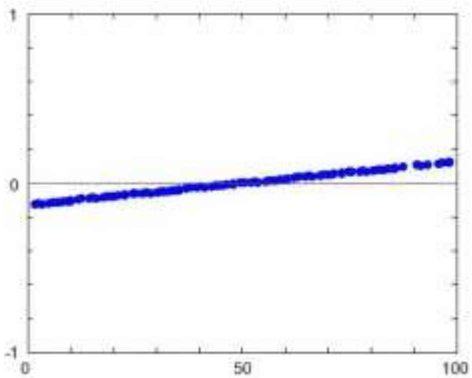


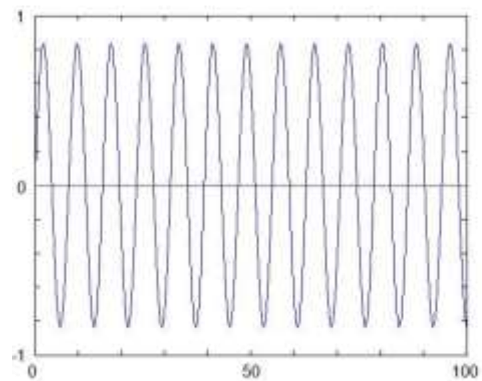


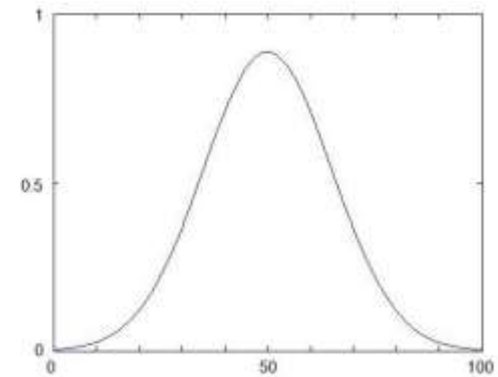
Feature extraction (Σ = 69)
Signals: EMG (trapezius), SCL, ECG

	Linearity (Σ 4)	Stationarity (Σ 12)	Variability (Σ 11)

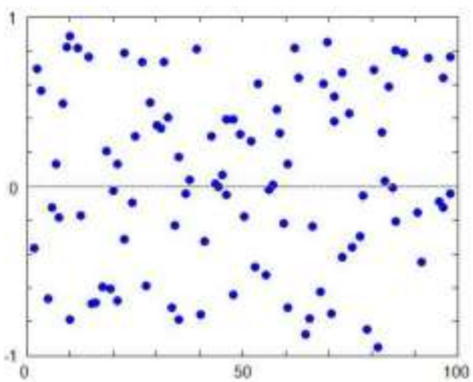
example high:

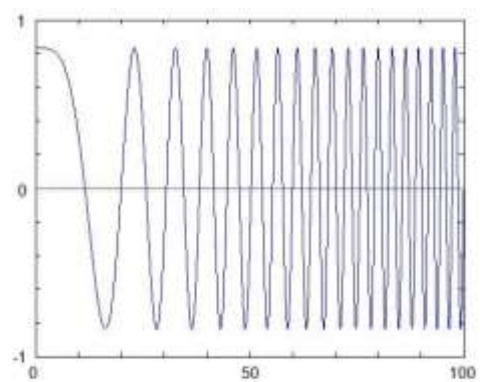


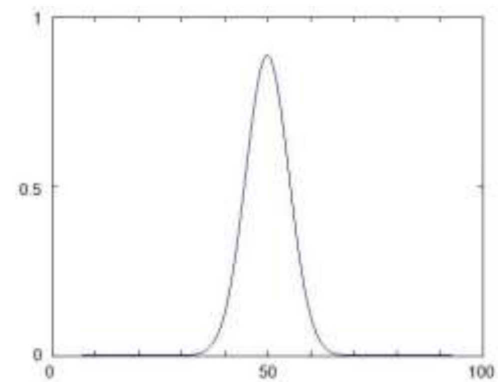




example low:

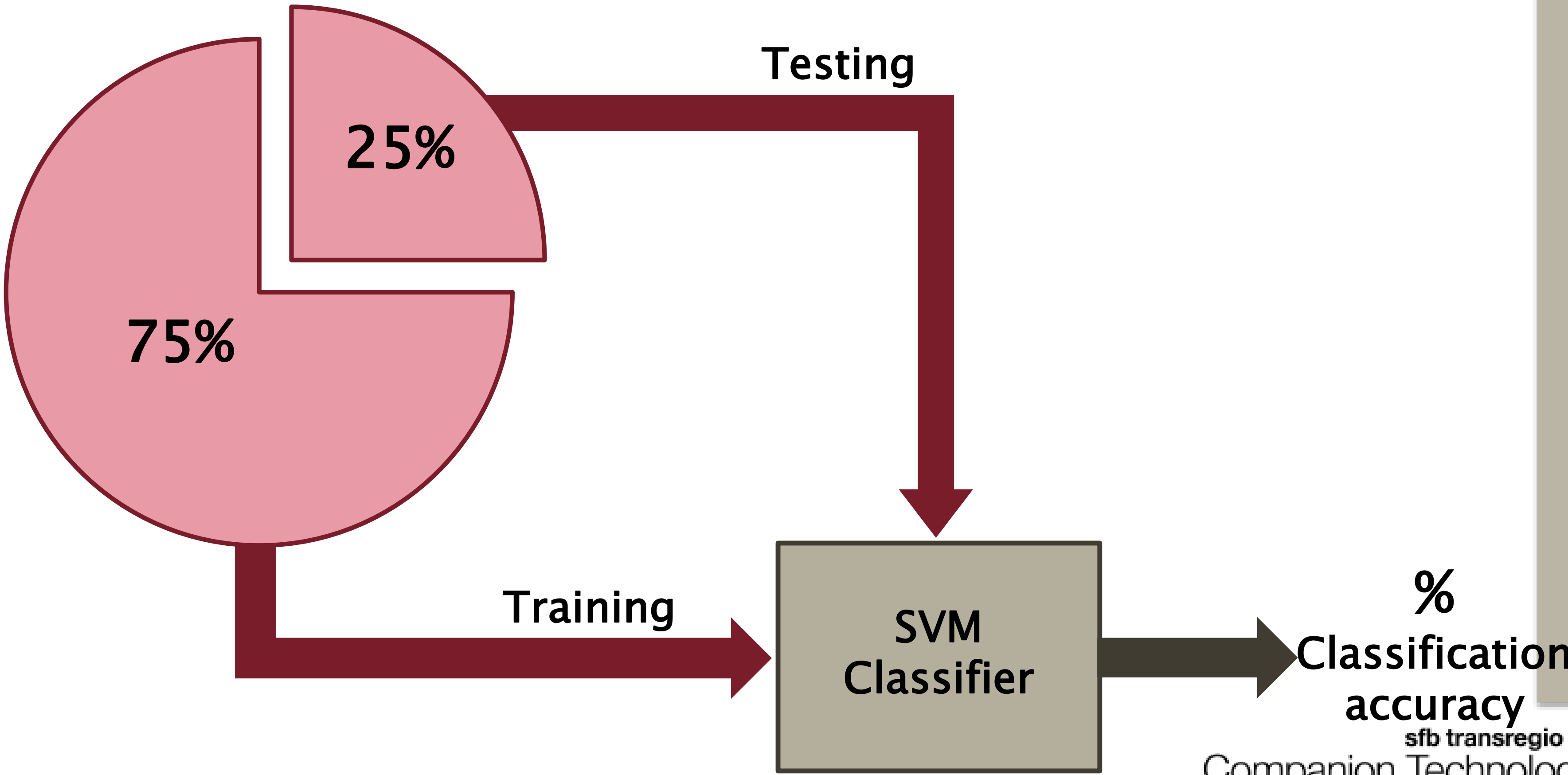




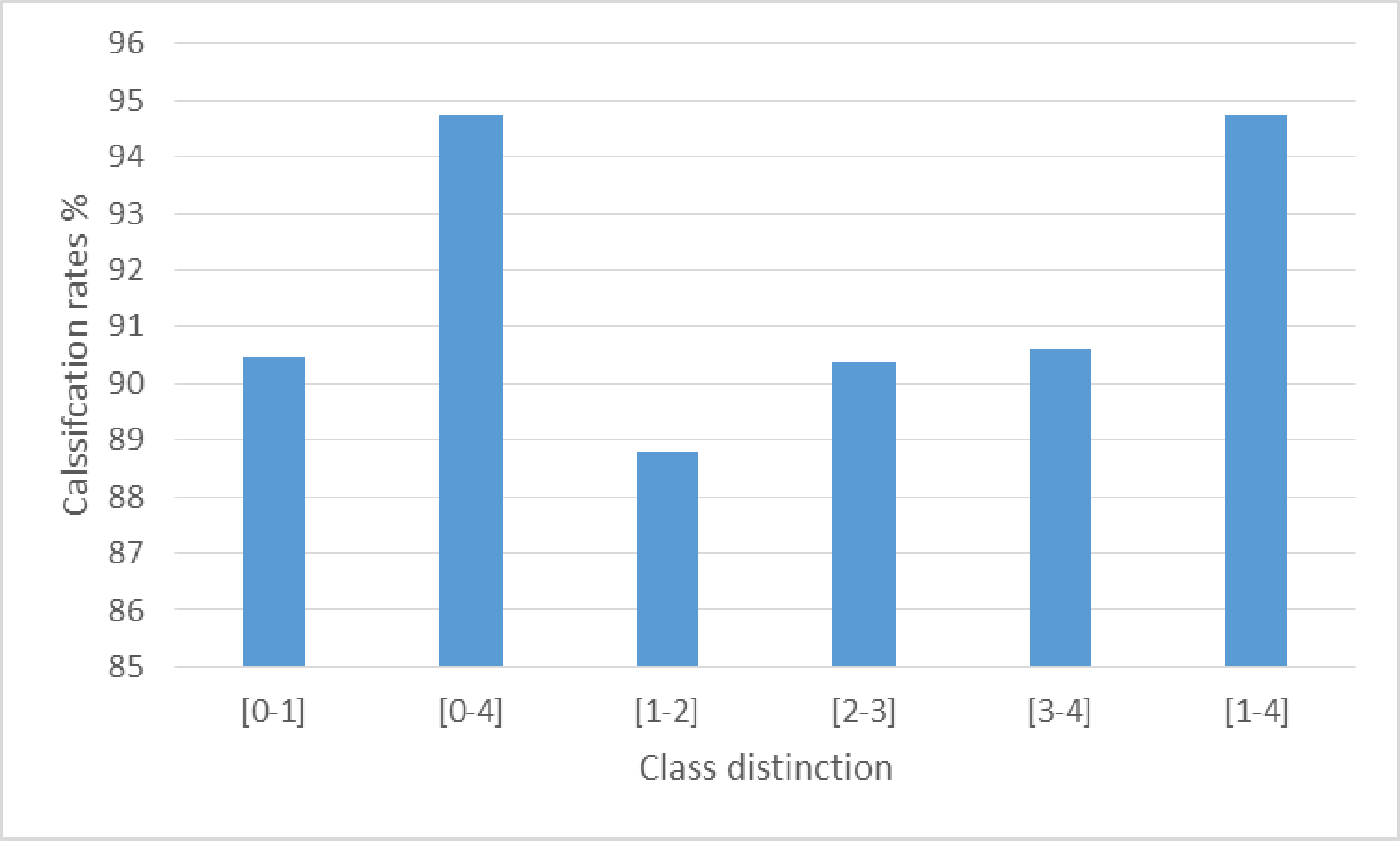


Generic Feature Selection 75 % of Sample Size and Testing 25 % Unsupervised

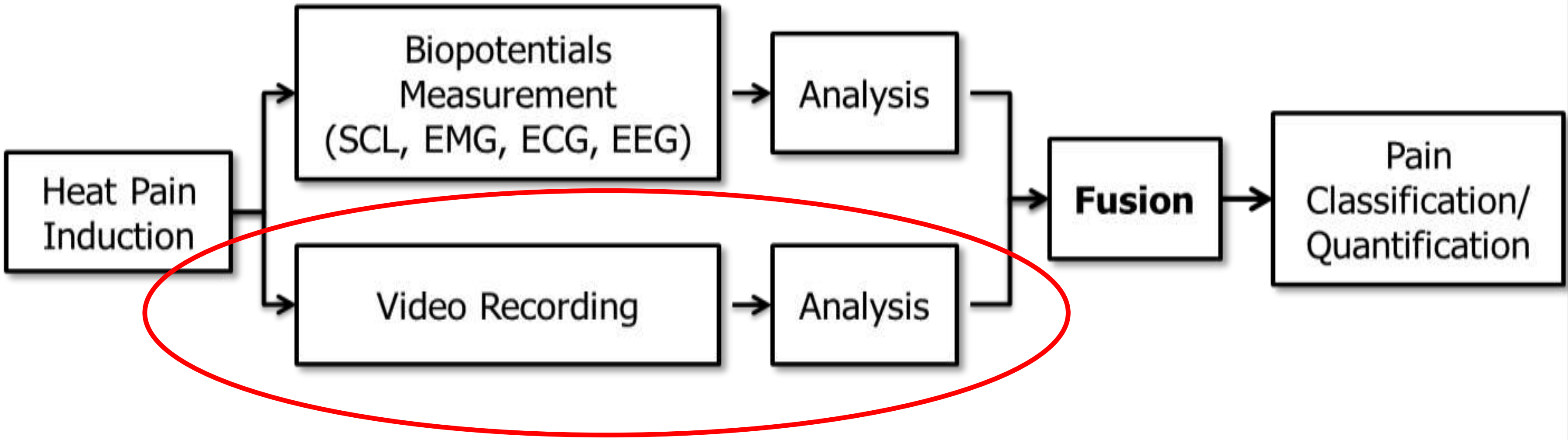
Step 1: Training support vector machine on 75% data
Step 2: Testing SVM with unsupervised 25% of data



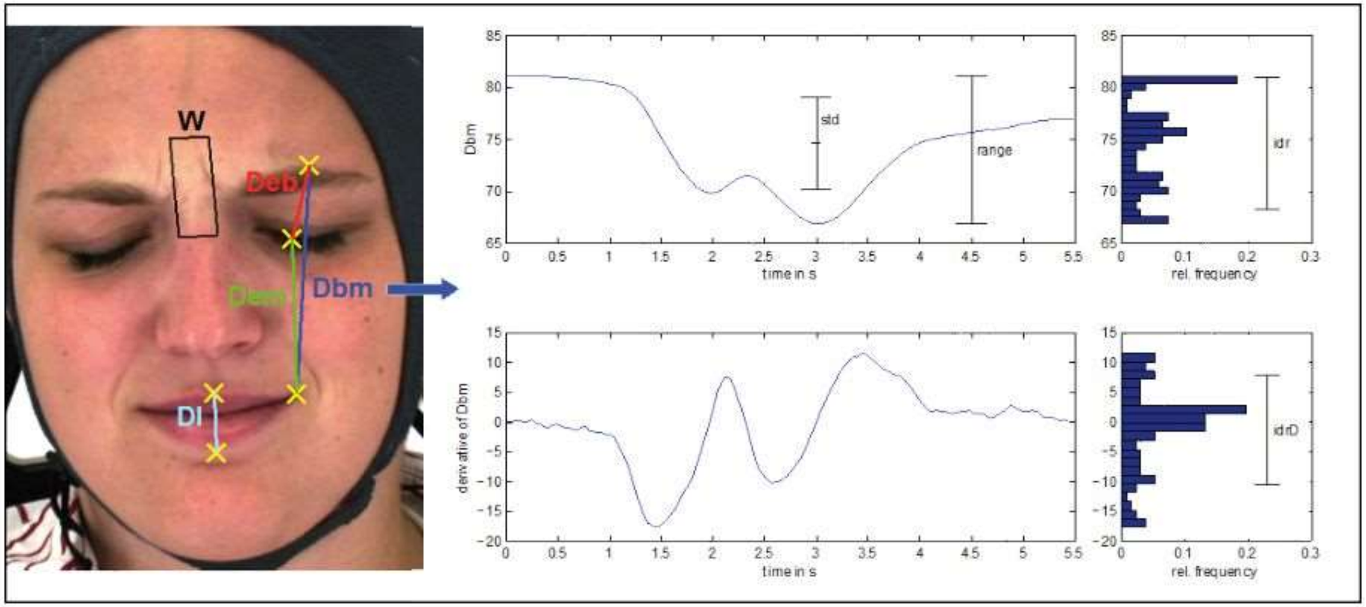
1. Individual Feature Selection and Testing with Cross Validation - Results



Data analysis

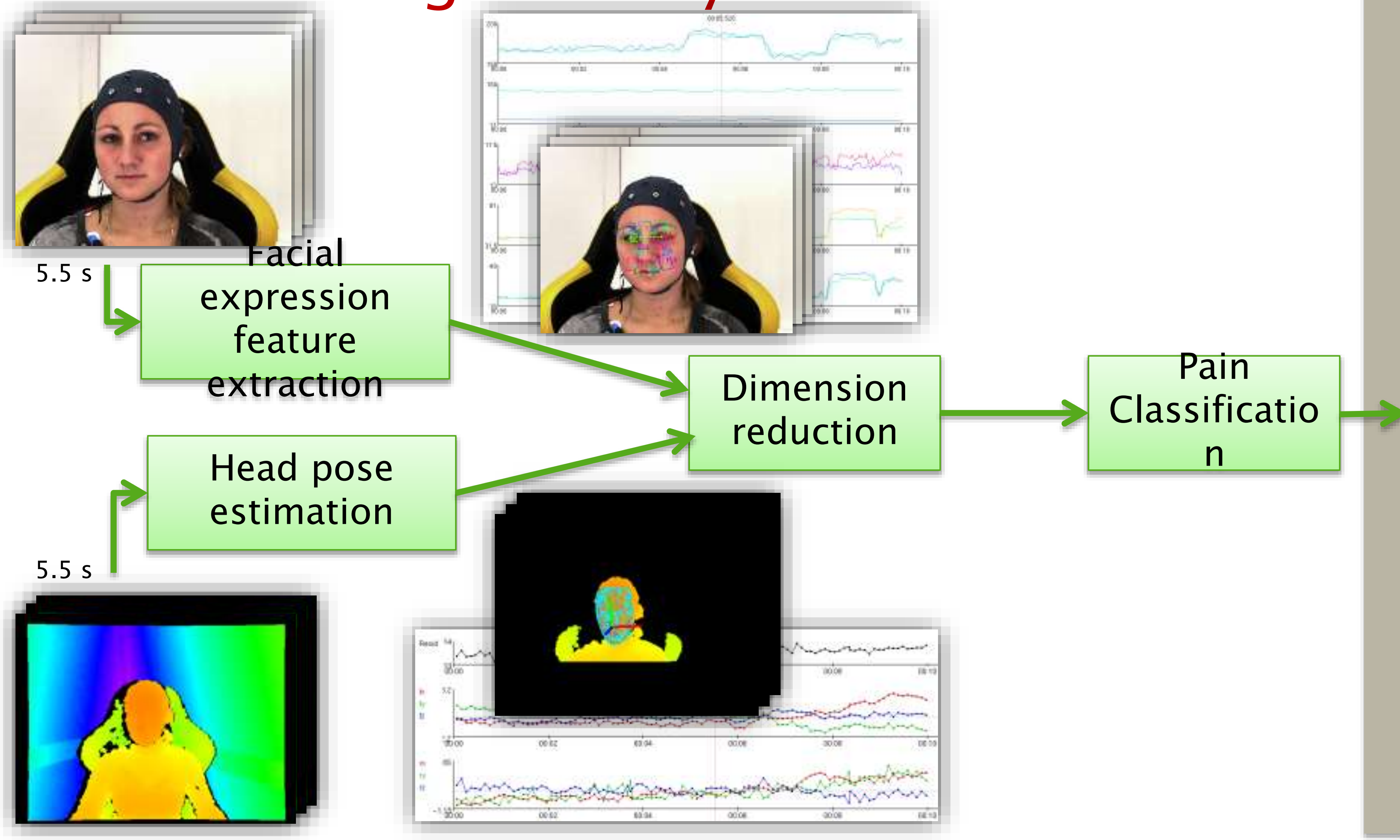


Video Feature Extraction ($\Sigma = 399$)



Signal	Meaning
Dbm	Distance between brow and mouth corner
Dem	Distance between eye and mouth corner
Deb	Distance between eye and brow
Dl	Distance between top upper lip and bottom of lower lip
W	Wrinkles on nasal root and between eyebrows
Feature	
std	Standard deviation of the signal
range	Range of the signal, i. e. the difference of maximum and minimum
idr	Interdecile range of the signal, i.e. the difference between the ninth decile and the first decile

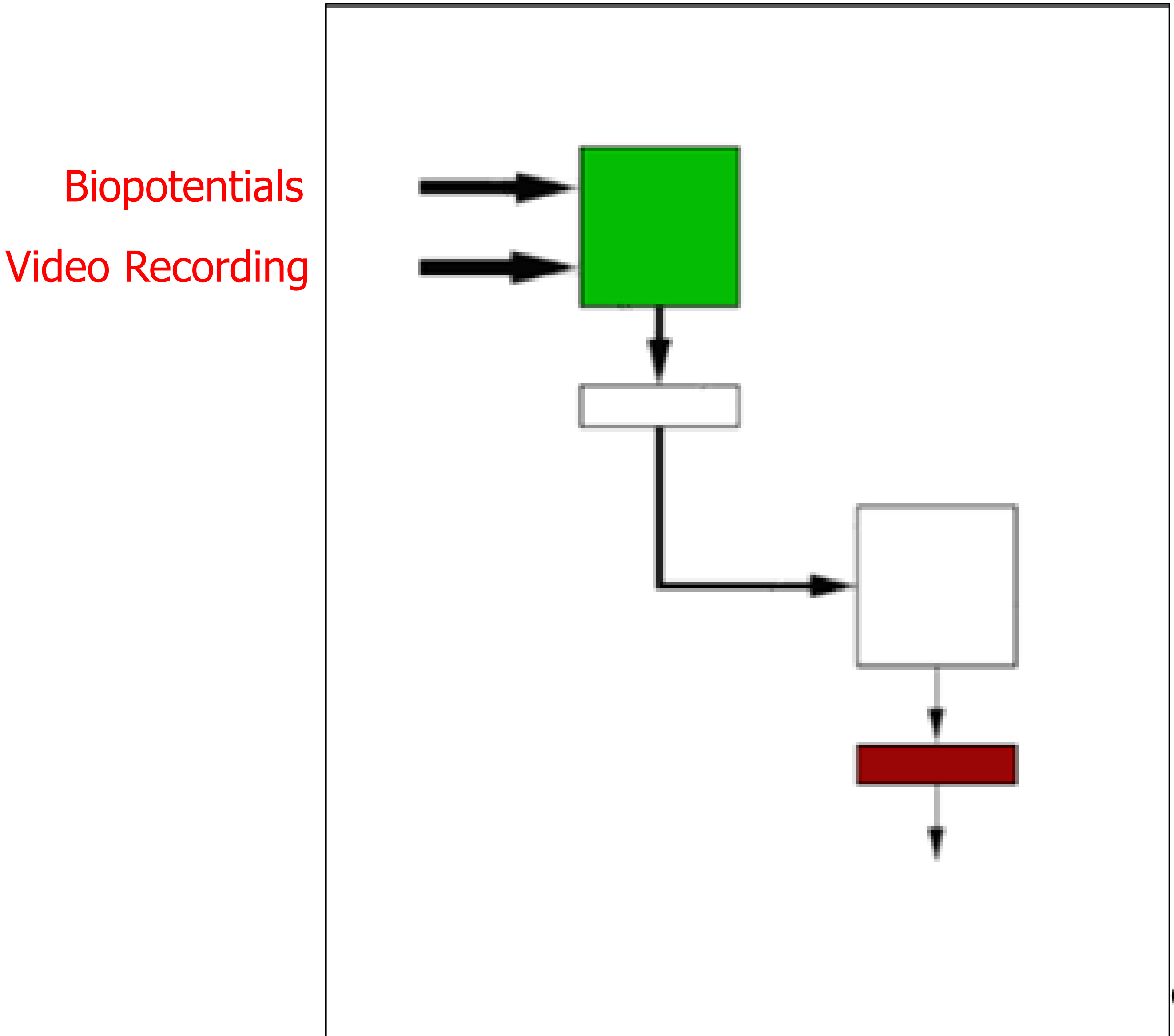
Video Recognition System



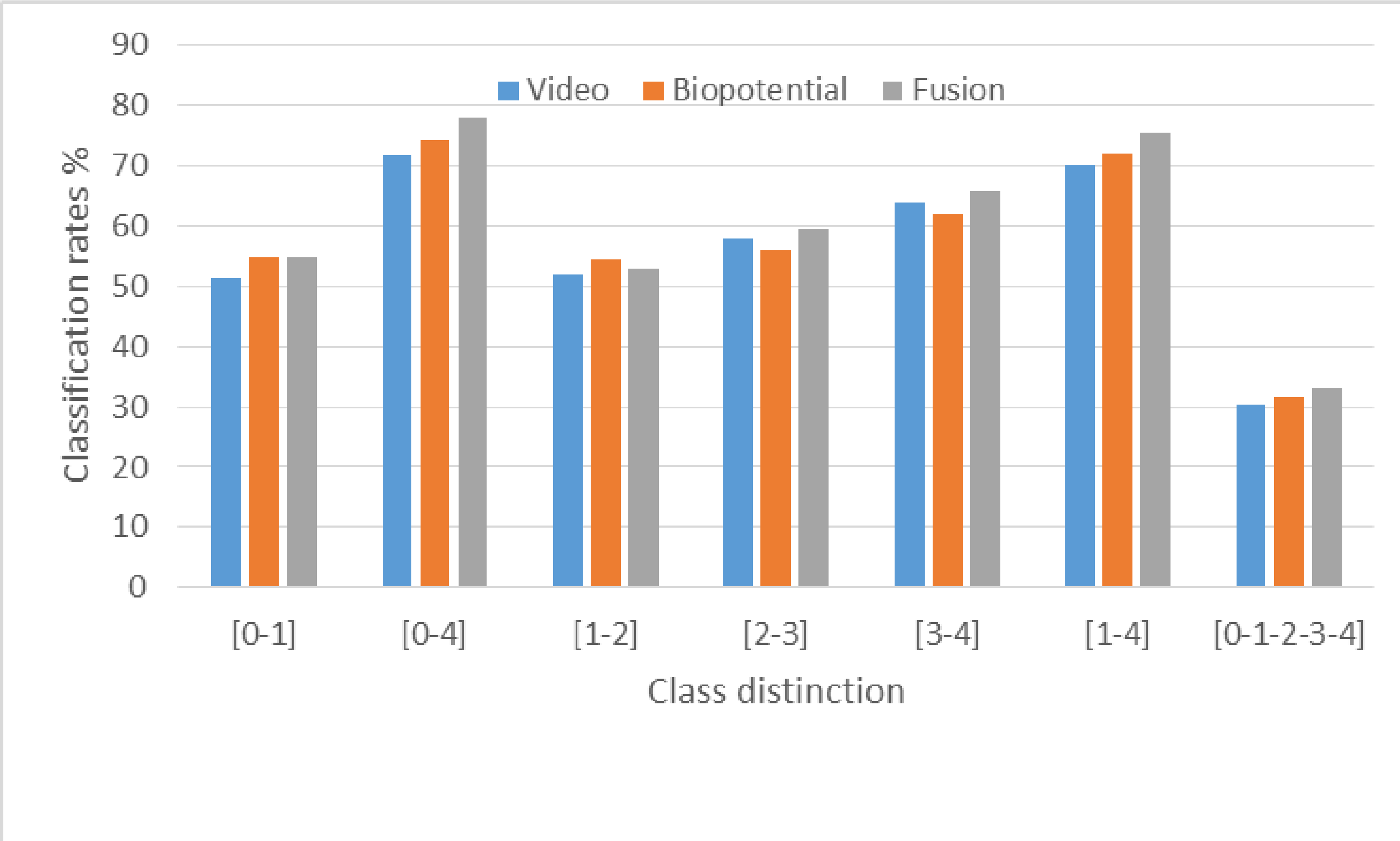
Fusion Results

Used features	B vs. T_4 i.	g.	B vs. T_3 i.	g.	B vs. T_2 i.	g.	B vs. T_1 i.	g.
Facial expression	74.9	70.8	67.1	62.1	57.1	53.7	49.3	50.7
Head movement	70.4	65.9	63.8	57.3	54.9	52.3	48.3	50.1
All video	75.7	71.2	68.0	61.8	57.4	53.9	49.4	51.5
SCL	71.9	73.8	64.0	65.9	57.9	60.2	49.4	51.4
EMG	63.1	57.9	55.9	52.7	51.3	49.6	47.6	55.4
ECG	64.0	62.0	60.0	56.5	54.5	51.6	49.6	48.7
All biopotential	75.6	74.1	65.5	65.0	58.7	59.2	49.1	54.9
All video + bio	**79.4**	**77.3**	**71.2**	**66.9**	**59.8**	59.5	49.6	54.4

Data Fusion (Early Fusion)



Data Generic Fusion



Most common feature

Biopotentials

1. SCL_amplitude_peak
2. Trapezius_amplitude_2peak
3. HRV_slopeRR

Video feature

1. Brow_to_mouth_corner_distance_std
2. Brow_to_mouth_corner_distance_range
3. Wrinkles_on_nasal_root_and_between_eyebrows_std

Summary

1. Individual automated recognition rate has a higher performance compare with generic machine learning models.

✓ **pain threshold: 90.46 %**

✓ **tolerance threshold: 94.73 %**

Calibration methods improves the recognition rate.

2. The fusion of video and biomedical signals performed better than the state-of-the-art approach.

✓ **pain threshold: 54.9 %**

✓ **tolerance threshold: 78 %**

References

- Gruss, S., Roi Treister, Philipp Werner, Harald C. Traue, Stephen Crawcour, Adriano Andrade & Steffen Walter (2015) Pain intensity recognition rates via biopotential feature patterns with support vector machines. PLOS ONE | DOI:10.1371/journal.pone.0140330
- Walter S., Gruss S., Limbrecht K., Traue H.C., Werner P., Al-Hamadi A., Diniz N., Moreira da Silva G., Andrade A.O. (2014) Automatic pain quantification using autonomic parameters. Psychology & Neuroscience, 7, 3, 363 – 380 DOI: 10.3922/j.psns.2014.041
- Werner, P., A. Al-Hamadi, R. Niese, S. Walter, S. Gruss, und H. C. Traue, „Towards Pain Monitoring: Facial Expression, Head Pose, a new Database, an Automatic System and Remaining Challenges“, in *Proceedings of the British Machine Vision Conference*, 2013, S. 119.1-119.13.
- Walter, S., P. Werner, S. Gruss, H. Ehleiter, J. Tan, H. C. Traue, A. Al-Hamadi, A. O. Andrade, G. Moreira da Silva, und S. Crawcour (2013) „The BioVid Heat Pain Database: Data for the Advancement and Systematic Validation of an Automated Pain Recognition System“, in *Cybernetics (CYBCONF), 2013 IEEE International Conference on*, S. 128-131.
- P. Werner, A. Al-Hamadi, R. Niese, S. Walter, S. Gruss, und H. C. Traue, (2014) “Automatic Pain Recognition from Video and Biomedical Signals”, in *IEEE International Conference on Pattern Recognition (ICPR)*, Stockholm, Sweden, S. 4582-4587
- P. Werner, A. Al-Hamadi, S. Walter, S. Gruss, und H. C. Traue (2014) Automatic Heart Rate Estimation from Painful Faces, in *IEEE International Conference on Image Processing (ICIP)*, Paris, France, Page 1947 – 1951

The End

Clinical single case study: preliminary results

In cooperation: University Hospital Clinic, Uberlândia, MG, Brazil; Lima, Zarus, Daibert, Walter, Pereira & Andrade, 2014

Participant

33 year old **man**, electrical burn injury for one week at the time of the commencement of the study **3 weeks of data acquisition**

Independent variable: **Wound Treatment** (P1) vs. **Physiotherapy** (P2) vs. **Analgesic** (3); VNS: **Verbal Numeric Scale**

Dependent variable: SBP: Systolic Blood Pressure, MAP: Mean Arterial Pressure, DBP: Diastolic Blood Pressure, SpO_2: Oximetry, HR: Heart Rate, RR: Respiration Rate, $p \leq .05^*$, $p \leq .01^{**}$

Clinical signal case study: preliminary results

	Mean of the biomedical signals								
	SBP	MAP	DBP	Pulse	SpO_2	HR	T	RR	VNS
Wound Treatment	134.17	105.26	90.97	104.02	94.37	103.57	32.64	13.64	4,54
Physiotherapy	131.49	99.28	82.94	126.04	94.15	125.39	35.00	16.60	4,11
Analgesic	129.09	97.98	83.58	105.23	94.14	105.91	35.50	18.89	2,95
Test:	p-level								
Chi2 Wald Test	.000	.000	.000	.000	.309	.000	.002	.000	.048
Post Hoc Test 1-2	.010	.000	.000	.000	.276	.000	.037	.000	.000
Post Hoc Test 1-3	.000	.738	.000	.067	.177	.009	.001	.000	.000
Post Hoc Test 2-3	.034	.176	.499	.000	.981	.000	.663	.001	.000
	Correlation r-level								
Correlation betweenVNS and Biomedical Signals for the protocol Analgesic	.412**	.507**	.513**	-.423**	.165*	-.502**	.511**	-.096	1

<u>Independent variable</u>: **Wound Treatment** (P1) vs. **Physiotherapy** (P2) vs. **Analgesic** (3); VNS: **Verbal Numeric Scale**

<u>Dependent variable</u>: SBP: Systolic Blood Pressure, MAP: Mean Arterial Pressure, DBP: Diastolic Blood Pressure, SpO_2: Oximetry, HR: Heart Rate, RR: Respiration Rate, $p \leq .05$*, $p \leq .01$**

Outlook via clinical design