Third International Workshop on Context Based Affect Recognition
CBAR 2015

Person-specific behavioural features for automatic stress detection

Jonathan Aigrain - Séverine Dubuisson
Marcin Detyniecki - Mohamed Chetouani

May 4, 2015

Introduction

Understanding nonverbal cues and social signals is one of the key elements in human-human interaction

- Nonverbal communication conveys an important part of the meaning
- Interpretation of these signals is person and context dependent

Context: stressful situations
Objective: Automatically detect stress in an unobtrusive way by studying the body language

Stress definition

Definition proposed by Lazarus [4] with the conditions regarding the stimulus proposed by Koolhaas et al. [3]

- Stress is the result of a transaction between a person and her environment
- This transaction includes:
    - A stimulus considered as uncontrollable and/or unpredictable
    - An evaluation of the situation and the conclusion of the presence of a threat
    - Coping processes
    - Several effects on mind and body

Related works

Automatic stress detection techniques are mainly using:

- Speech signals
- Physiological signals

Few works address stress detection using body language:

- Giakoumis et al.[2] enhanced the performance of stress detection systems with behavioural features
- Soury [7] used postural features in a multimodal fusion model
- Lefter [5] used visual features such as HOG and HOF to predict intermediate level variables, which are then used to predict stress

Presentation outline

- Data collection
- Feature extraction
- Person-specific normalization
- Stress detection
- Conclusions

Data collection

According to Dickerson and Kemeny [1], there are 4 main classes of stressors:

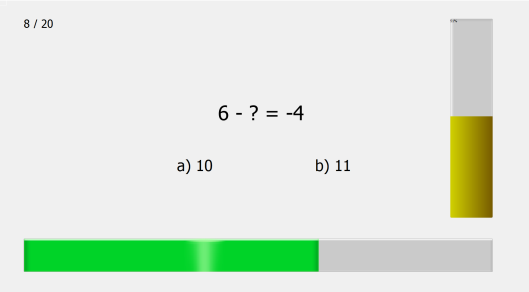
- Cognitive tasks
- Public speaking
- Noise exposure
- Emotion induction

Experiments which combine public speaking and cognitive tasks are considered the most effective

Stress induction procedure

The experiment used is an evaluated time-constrained mental arithmetic test:

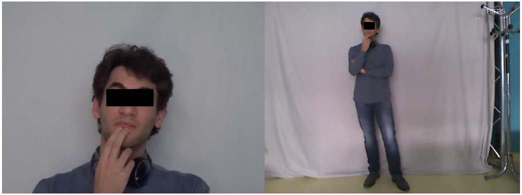
- 6 steps of increasing difficulty
- Performed in front of two people
- Biased performance feedback



Acquired data

For each of the 14 partipants, for each of the 6 steps:

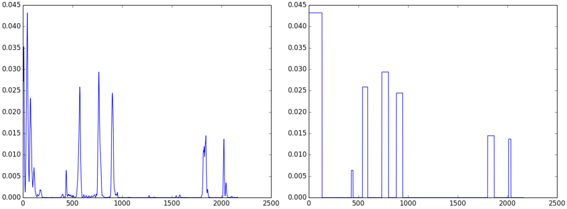
- Video of the whole body in 640 x 480 from the Kinect
- Skeleton from the Kinect
- Video of the face in 1440 x 1080 from the HD camera
- Self-assessed stress level using a Likert-scale (1-5)



Feature extraction

Body language features

- Quantity of Movement
  - Computed from the skeleton and from the image
  - Skeleton QoM computed for the head
  - FFT applied on the image QoM, divided in 10 bins
- Detection of periods of high activity
  - Using the peaks of the QoM

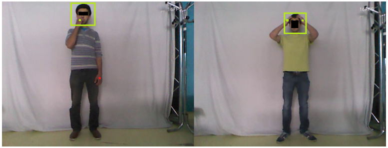


Feature extraction

Body language features

- Detection of posture changes

- Detection of self-touching
  - Self-touching in the region of the head
  - Fingers rubbing



25 features

Feature extraction

Facial features

- Activation level of 12 Action Units
  - AU are presented by Ekman in the Facial Action Coding System
  - Extracted using the method of Nicolle et al. [6]
  - Average and standard deviation used as features

24 features

Person-specific normalization

Objective : Reducing the impact of interindividual differences
Hypothesis : Stress is easier to detect if we look at the evolution of one's behaviour

$$\tilde{f_{ps}} = \frac{f_{ps} - f_{p1}}{f_{p1}}$$

with f_{ps} the vector of features for the person p on step s and $\tilde{f_{pj}}$ the normalized vector

Evaluation process

- Classification using SVM with three kernel functions
  - Linear
  - Radial Basis Function
  - Polynomial
- Each video is associated with a label
  - Stress (S) if self-assessed stress level > 3
  - Non-Stress (NS) otherwise
- Leave-One-Subject-Out cross-validation
- Mean accuracy over 10 runs

Results

kernel type	raw	normalized
Poly	$0.64 \pm \mathit{0.04}$	$0.77 \pm \mathit{0.02}$
RBF	$0.65 \pm \mathit{0.03}$	$0.76 \pm \mathit{0.02}$
Linear	$0.67 \pm \mathit{0.01}$	$0.77 \pm \mathit{0.01}$

- No significant difference between the 3 kernel functions
- Person-specific normalization improves accuracy:
  - Poly: +20%
  - RBF: +17%
  - Linear: +15%

Impact of the features set

features set	raw	normalized
All	0.67 ± *0.01*	0.77 ± *0.01*
Face	0.68 ± *0.01*	0.65 ± *0.03*
Body	0.63 ± *0.03*	0.80 ± *0.01*

- Results obtained with the linear kernel
- Person-specific normalization effective only on body features (+27%)
- Raw facial features give better results than raw body features
    - May be explained by less interindividual differences in facial expression

Performances of individual features

- Classification obtained with only one feature
- SVM with RBF kernel function
  - Allows several “split values” along the feature axis
- Leave-One-Subject-Out cross-validation
- Mean accuracy over 10 runs
- 5 best and 5 worst features are presented

Performances of individual raw features

feature	accuracy
PCC	0.73 ± *0.02*
AU9 - std	0.72 ± *0.01*
FFT2	0.72 ± *0.01*
AU4 - std	0.72 ± *0.01*
AU4 - mean	0.72 ± *0.01*
AU25 - mean	0.60 ± *0.03*
RHM	0.58 ± *0.01*
AU5 - std	0.58 ± *0.02*
AU9 - mean	0.56 ± *0.01*
HAPMD	0.55 ± *0.04*

- Better performances than the whole set of features (67%)
- Good results for posture changes (PCC) and brows activity (AU4 and AU9)
- Difficult to interpret what FFT2 means

Performances of individual normalized features

feature	accuracy
FFT1	0.76 ± 0.02
HAPC	0.74 ± 0.01
FFT7	0.73 ± 0.02
HAPMV	0.73 ± 0.02
PCC	0.73 ± 0.02
AU1 - std	0.49 ± 0.03
AU25 - mean	0.46 ± 0.02
AU26 - mean	0.45 ± 0.02
AU15 - mean	0.45 ± 0.03
AU17 - std	0.43 ± 0.04

- Similar performances than the whole set of features (77%)
- Normalization effective only on body features
- Good results for body activity (FFT1), periods of high activity (HAPC and HAPMV) and posture changes (PCC)
- Difficult to interpret what FFT7 means

Conclusions and possible improvements

Conclusions

- Unobtrusive solution for stress detection
- Person-specific normalization effective only on body language features
- Using only one feature can provide good classification accuracy
  - 73% for number of posture changes
  - 76% for normalized 1st bin of the FFT

Improvements

- Feature selection
- Using normalized body features and raw facial features

Thank you for your attention!

Bibliography

- S. S. Dickerson and M. E. Kemeny.
  Acute stressors and cortisol responses: a theoretical integration and synthesis of laboratory research.
  Psychological bulletin, 130(3):355–91, May 2004.
- D. Giakoumis, A. Drosou, P. Cipresso, D. Tzovaras, G. Hassapis, A. Gaggioli, and G. Riva.
  Using activity-related behavioural features towards more effective automatic stress detection.
  PloS one, 7(9):e43571, Jan. 2012.
- J. M. Koolhaas, a. Bartolomucci, B. Buwalda, S. F. de Boer, G. Flügge, S. M. Korte, P. Meerlo, R. Murison, B. Olivier, P. Palanza, G. Richter-Levin, a. Sgoifo, T. Steimer, O. Stiedl, G. van Dijk, M. Wöhr, and E. Fuchs.
  Stress revisited: a critical evaluation of the stress concept.
  Neuroscience and biobehavioral reviews, 35(5):1291–301, Apr. 2011.
- R. S. Lazarus.
  From psychological stress to the emotions: a history of changing outlooks.
  Annual review of psychology, 44:1–21, Jan. 1993.
- I. Lefter.
  Multimodal surveillance - Behavior analysis for recognizing stress and aggression.
  PhD thesis, 2014.
- J. Nicolle, K. Bailly, and M. Chetouani.
  Facial action unit intensity predicition via hard multi-task metric learning for kernel regression.
  IEEE International Conference and Workshops on Automatic Face and Gesture Recognition, 2015.
- M. Soury.
  Détection multimodale du stress pour la conception de logiciels de remédiation.
  PhD thesis, Université Paris-sud, 2014.