UNIVERSITY OF BARCELONA

Centre de Visió per Computador

Dominance Detection in Dyadic Conversations

UNIVERSIDAD DE MÁLAGA

XI CONGRESO DE METODOLOGÍA DE LAS CIENCIAS SOCIALES Y DE LA SALUD

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Layout

- Dominance
- Motion-based features
- Dominance-based features
- Results
  - Observers inquiry
  - Manual evaluation
  - Automatic evaluation
- Conclusions and current work

Dominance

- Dominance in group interaction
  - Social signal processing
  - Social cognition
  - Social psychology
  - Communication

- Non-vebal communication
  - Formation, maintenance, and evolution of fundamental social constructs

- **Conversational patterns:**
- Addressing
  - Person at whom the speech is directed
- Turn-taking
  - "*Communication phases*"
- **States and personality:**
- Interest
  - "*Engagement*"
- Dominance

[Gaticao9] Daniel Gatica-Perez, "Automatic nonverbal analysis of social interaction in small groups: A review". Image and Vision Computing, 2009.

Dominance

- **Dominance:**
- "Personality characteristic" (a trait)
- "hierarchical position within a group" (a state)

"The ability to influence the behavior of another person"

[Dunbar05] N.E. Dunbar, J.K. Burgoon, "Perceptions of power and interactional dominance in interpersonal relationships", Journal of Social and Personal Relationships, vol. 22, issue 2, pp. 207-233, 2005.

Motion-based features

- Supose we have an environment from a face-to-face conversation
- Can we find an "objective" way to measure the dominant people?
- Can we model dominance be means of a combination of simple region-based motion features?
  - Motion-based features
  - Dominance-based features

Motion-based features

$S = \{s_1, .., s_e\}$ Frame sequence

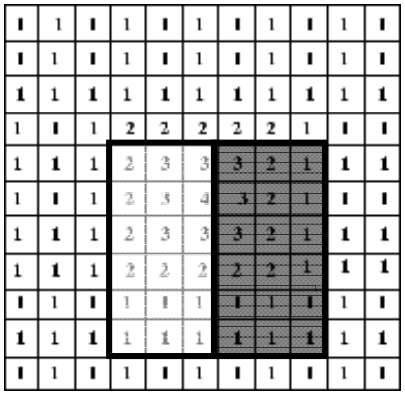
GM_{ij}, s_i and s_j Global movement

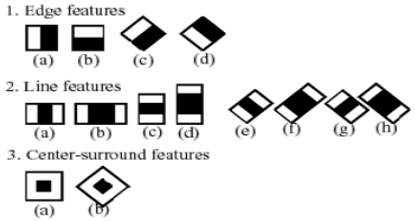
$FM_{ij} = \frac{1}{n \cdot m} \sum_k |F_{j,k} - F_{i,k}|, F_i, k \in \{1, .., n \cdot m\}$ Face movement

[Viola01] Paul Viola and Michael Jones, "Robust Real-time Object Detection", International Journal of Computer Vision, 2001.

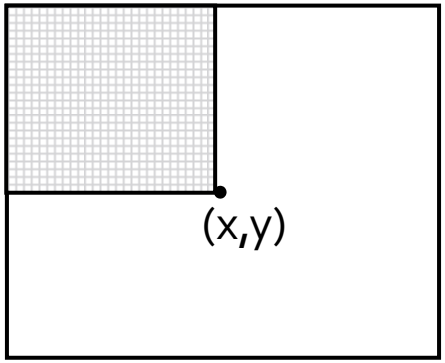
Motion-based features

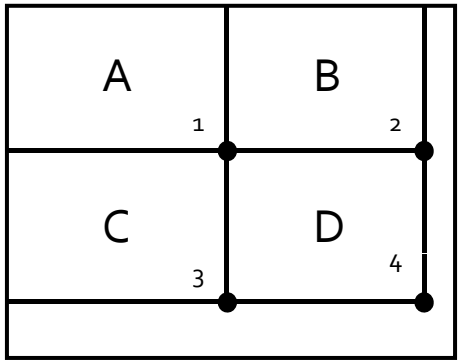
Haar-like





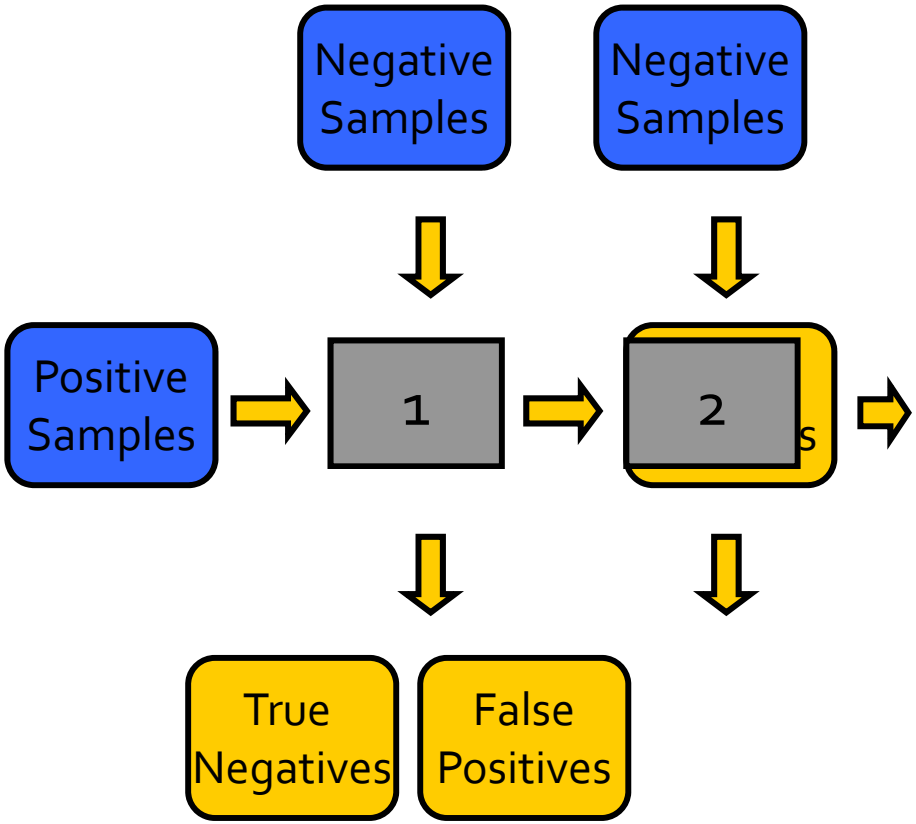
Integral image





$D = (4 + 1) - (2 + 3)$

Cascade of classifiers



[Viola01] Paul Viola and Michael Jones, "Robust Real-time Object Detection", International Journal of Computer Vision, 2001.

Motion-based features

Face tracking

Local body movement

Body movement historial

[Viola01] Paul Viola and Michael Jones, "Robust Real-time Object Detection", International Journal of Computer Vision, 2001.

Motion-based features

$S = \{s_1, .., s_e\}$ Frame sequence

GM_{ij}, s_i and s_j Global movement

$FM_{ij} = \frac{1}{n \cdot m} \sum_k |F_{j,k} - F_{i,k}|, F_i, k \in \{1, .., n \cdot m\}$ Face movement

$F_i \in \{0, .., 255\}^{n \times m}$ Face region

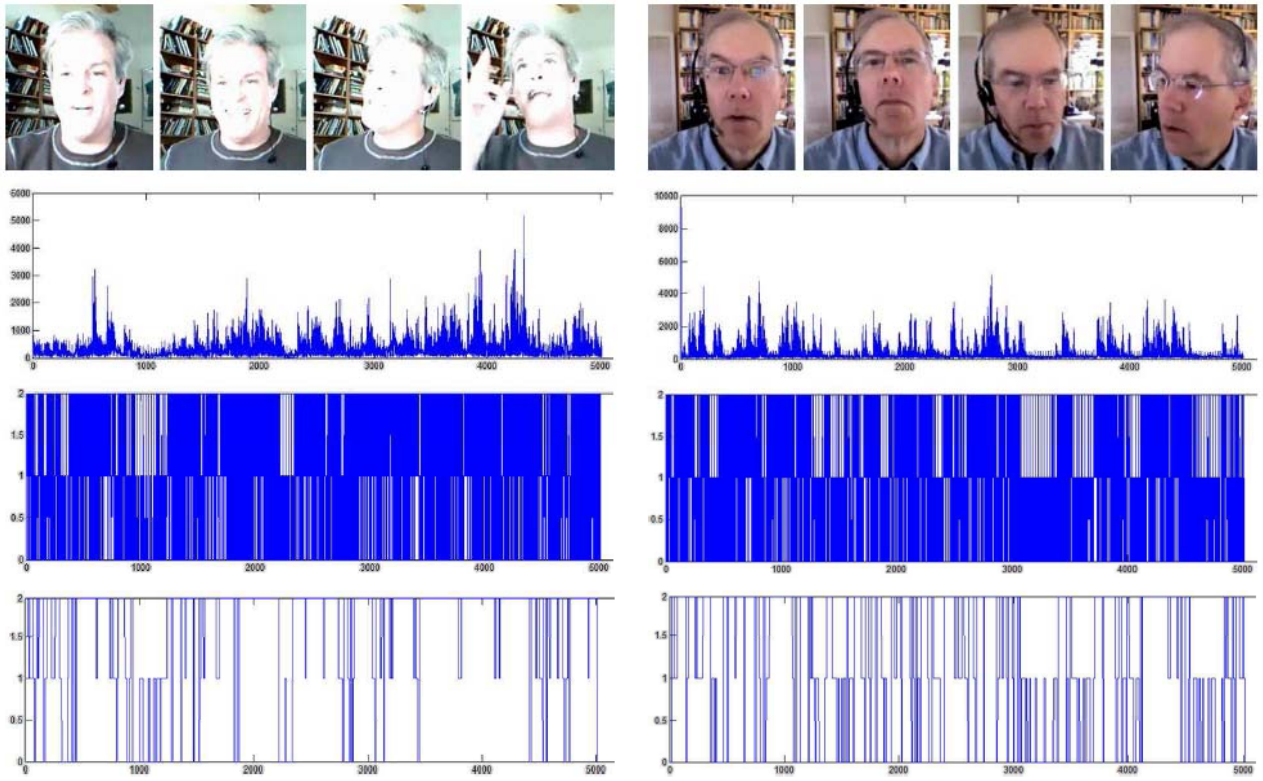
$M_i \in \{0, .., 255\}^{n/2 \times m/2}$ Mouth region

$MM_{il} = \frac{1}{n \cdot m/4} \sum_{j=i-l}^{i-1} \sum_k |M_{i,k} - M_{j,k}|$ Mouth movement

$M_i, k \in \{1, .., n \cdot m/4\}$

[Viola01] Paul Viola and Michael Jones, "Robust Real-time Object Detection", International Journal of Computer Vision, 2001.

Motion-based features



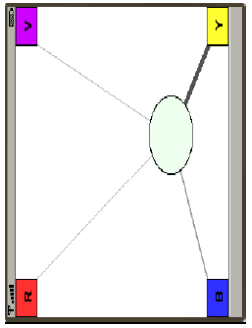
- Face movement vector
- 3-level Discretization

$$t_1 : \int_0^{t_1} P_{GM} = \frac{1}{3}, \quad t_2 : \int_0^{t_2} P_{GM} = \frac{2}{3}$$

- Filtering

Dominance-based features

- Which dominance features can we define from the previous motion-based features?
- Group conversations:
  - Adressing, turn-taking, etc.
  - Face-to-face conversations



•Speaking Time – ST

•The number of times the floor is grabbed by a participant – NOF

•The number of successful interruptions - NSI:

•The speaker gesticulation degree - SGD

[Pentland09] A. Pentland, Understanding Effects of Feedback on Group Collaboration, Human Behavior Modeling, AAAI Spring Symposium. Palo Alto, CA. March 2009.

Dominance-based features

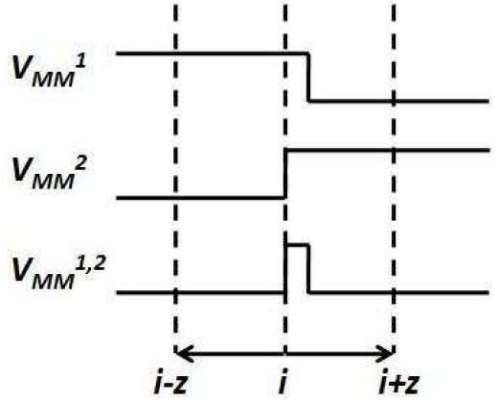
- **Speaking Time – ST**

$$ST^1 = \frac{\sum_{i=1}^{k} V_{MM_i}^1}{\max(\sum_{i=1}^{k} V_{MM_i}^1 + \sum_{i=1}^{k} V_{MM_i}^2, 1)}, \quad ST^2 = 1 - ST^1$$

- **The number of successful interruptions - NSI:**

$$V_{MM_{i-1}}^{1,2} = 0, \quad V_{MM_i}^{1,2} = 1, \sum_{j=i-z}^{i} V_{MM_j}^2 < \frac{z}{2},$$

$$\sum_{j=i}^{i+z} V_{MM_j}^2 > \frac{z}{2}, \quad \sum_{j=i-z}^{i} V_{MM_j}^1 > \frac{z}{2}, \quad \sum_{j=i}^{i+z} V_{MM_j}^1 < \frac{z}{2}$$



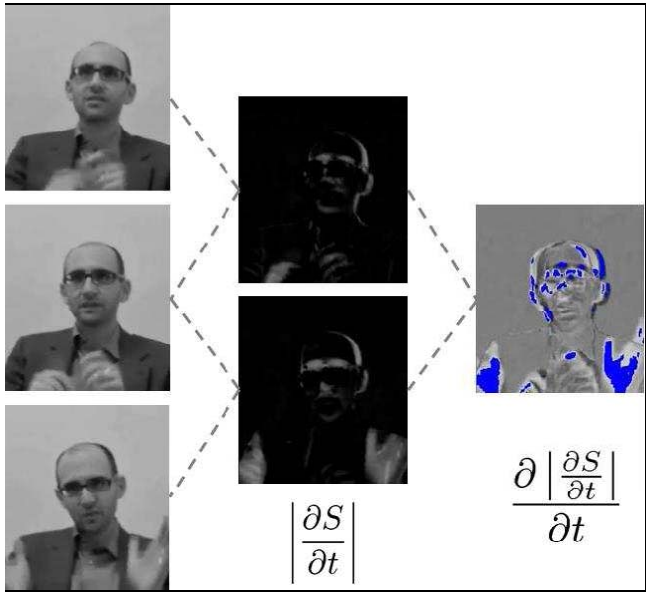
Interruption measurement

Dominance-based features

- **The number of successful interruptions - NSI:**

$$NSI^1 = \frac{|I^1|}{\max(|I^1| + |I^2|, 1)}, \quad NSI^2 = 1 - NSI^1$$

- **The number of times the floor is grabbed by a participant – NOF**



$$\sum \frac{\partial \left|\frac{\partial S}{\partial t}\right|}{\partial t}$$

$$NOF^1 = \frac{\sum_i VM_i^1}{\max(\sum_i VM_i^1 + \sum_i VM_i^2, 1)},$$

$$NOF^2 = 1 - NOF^1$$

Positive down directions
Negative up directions
Vertical movement VM

Dominance-based features

- **The speaker gesticulation degree - SGD**

$$\forall k \in \{1, .., e\}, V^i_{MM_k} := \min(1, V^i_{MM_k})$$

$$G = \left(V^i_{MM} \cdot V^i_{GM}\right) / \sum_k V^i_{MM_k}$$

$$SGD^1 = \frac{\sum_i G^1_i}{\max(\sum_i G^1_i + \sum_i G^2_i, 1)},$$

$$SGD^2 = 1 - SGD^1$$

Results - settings

- **Data**
  - Blogging heads New York Times opinion data base (http://video.nytimes.com/)
  - 7 video sequences
  - 5 min. 12 FPS : 2880 frames
- **Methods**
  - Gentle Adaboost (50 d. stumps)
  - Linear SVM (cv)
  - RBF SVM (cv)
  - FLDA (99.9% PCA)
  - NMC
- **Experiments**
  - Observers inquiry
  - Manual test
  - Automatic test


Video 1


Video 2


Video 3


Video 4


Video 5

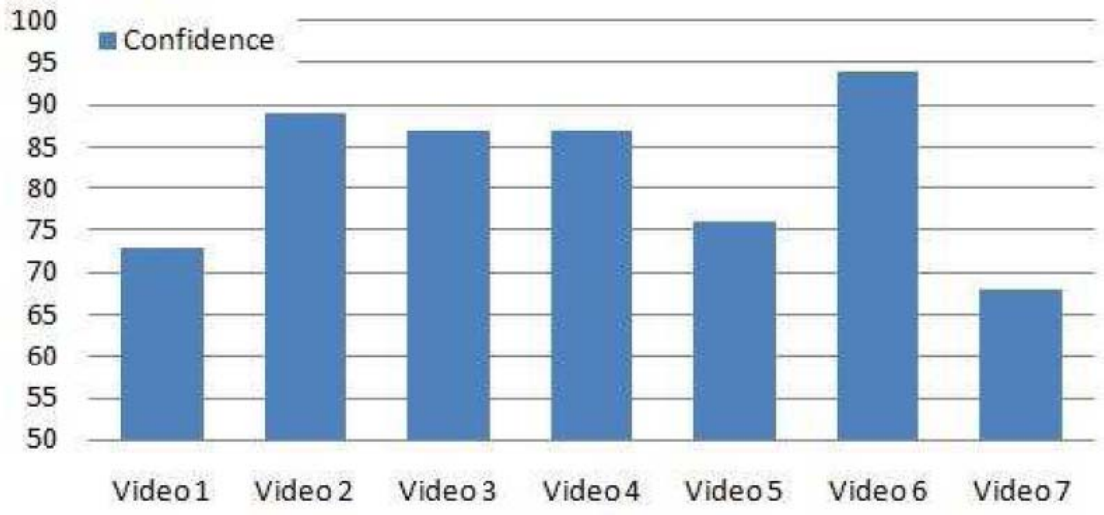

Video 6


Video 7

Results – observers inquiry

- 40 people (13 different nationalities)
- Dominance manual labeling (omitting audio)

- Confidence $P = 1 - \min(2 - C, C - 1)$



Observers correlation values.

Results – Manual dominance features

- Intervals of 10 seconds, 24 intervals for four indicators and two participants
- 192 values per video sequence, 1344 values for seven videos
- Indicators are activated if they appear in the interval (independently of duration)
- Three people for manual annotation, Majority voting
- Computing percentage of indicators

- Ground truth - Observers opinion
- Adaboost - leave-one-out
- One decission stump for each indicator

Indicator	Accuracy
Manual ST	100 %
Manual NSI	86 %
Manual NOF	71 %
Manual SGD	71 %

Results – Automatic dominance features

- 7 videos, 12FPS, 2880 frames, total 20160 analyzed frames
- Mouth accumulation of 10 frames

- Ground truth - Observers opinion
- Adaboost - leave-one-out
- One decission stump for each indicator

Indicator	Accuracy
Automatic ST	100 %
Automatic NSI	79 %
Automatic NOF	71 %
Automatic SGD	71 %

Indicator	Accuracy
Manual ST	100 %
Manual NSI	86 %
Manual NOF	71 %
Manual SGD	71 %

No critical differences with manual labeling!!!

Results – Automatic dominance features

- Binary problem using all indicators
- Different classifiers
- Leave-one-out
- Boostrap – 200 random sequences per video

1 2 4 3 6 4 5

2 5 3 3 3 4 6 -> (2,3,5,6) vs 1

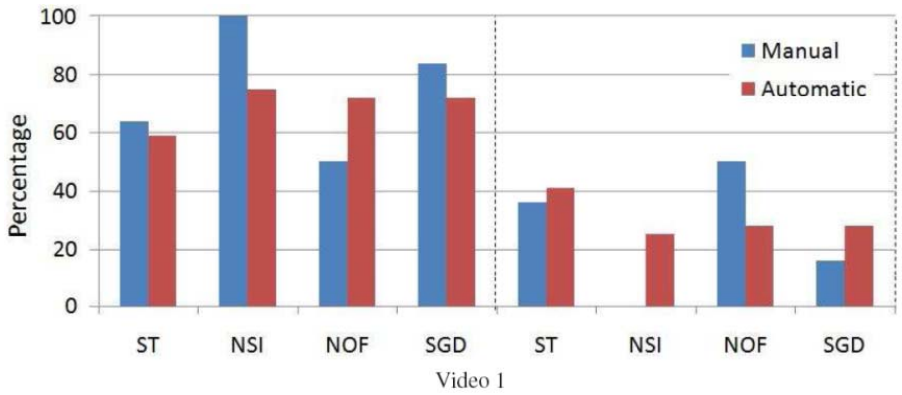
…

7 6 6 6 6 6 6 -> (6,7) vs 1

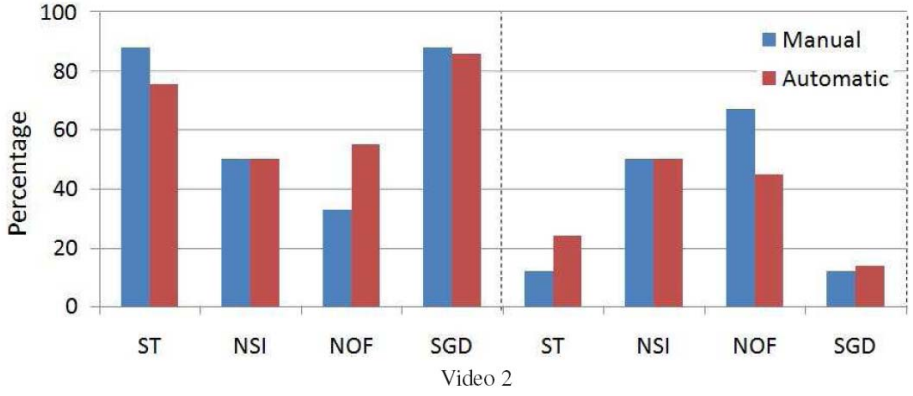
Learning strategy	Leave-one-out Accuracy	Boostrap Accuracy
Discrete Adaboost	100 %	93.62 %
Linear SVM	85.71 %	88.82 %
RBF SVM	100 %	86.83 %
FLDA	100 %	91.28 %
NMC	85.71 %	76.90 %

Results – Automatic dominance features

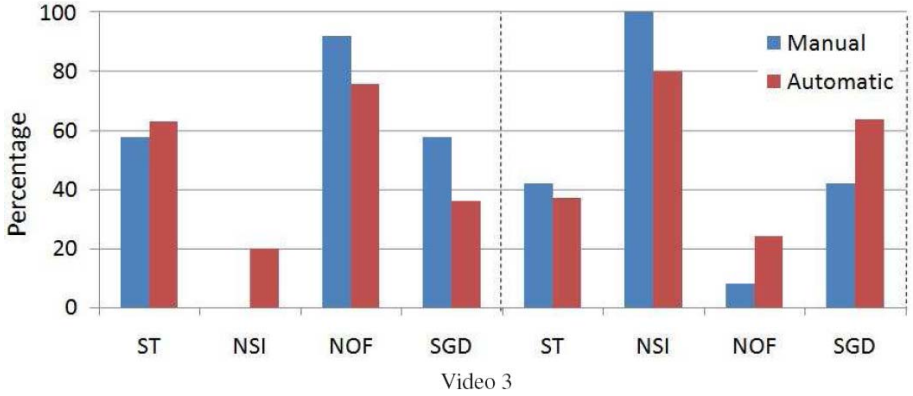
- Correlation of manual and automatic features



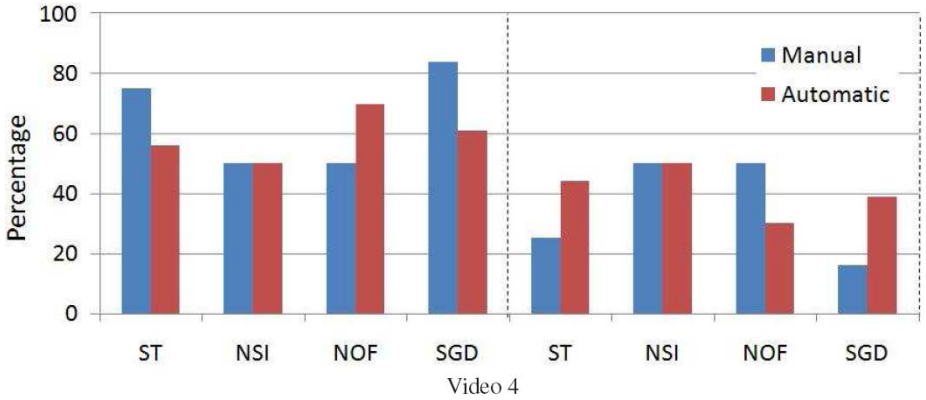
Video 1



Video 2



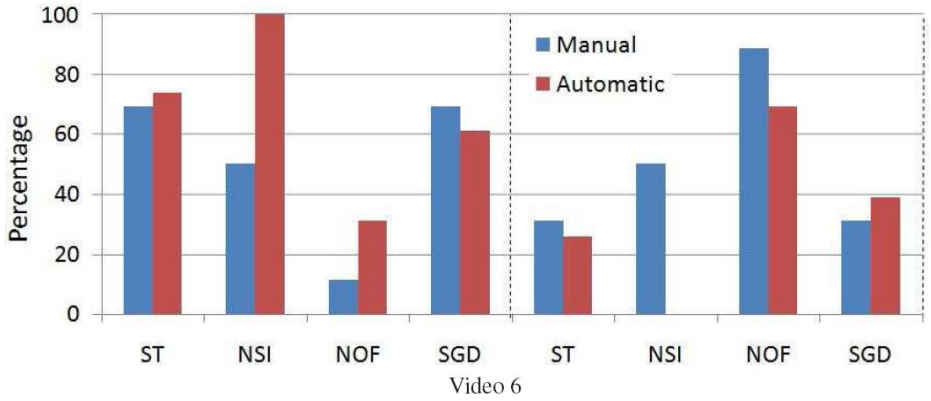
Video 3



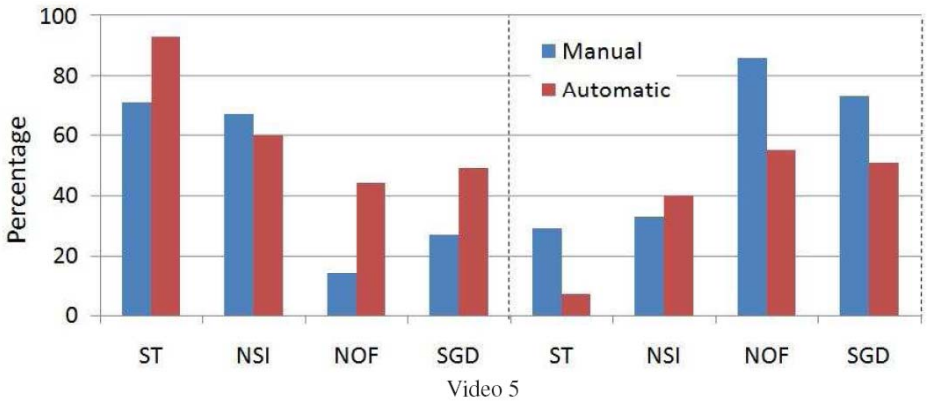
Video 4

Results – Automatic dominance features

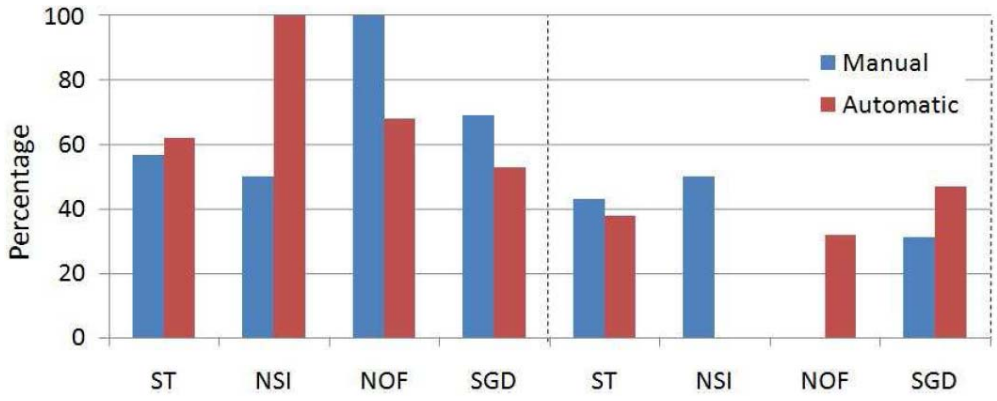
- Correlation of manual and automatic features



Video 6



Video 5



Video 7

Conclusions

- **Non-verbal cues for dominance detection** in face-to-face interactions
- **Observers correlation**
- **Manually labeled** indicators showed **high correlation** with observers opinion
- **Automatic approach** shows **similar correlation** to both observers and manual labeling
- **High dominance prediction** with **simple motion based features**
- Four **dominance indicators** are **high discriminative**

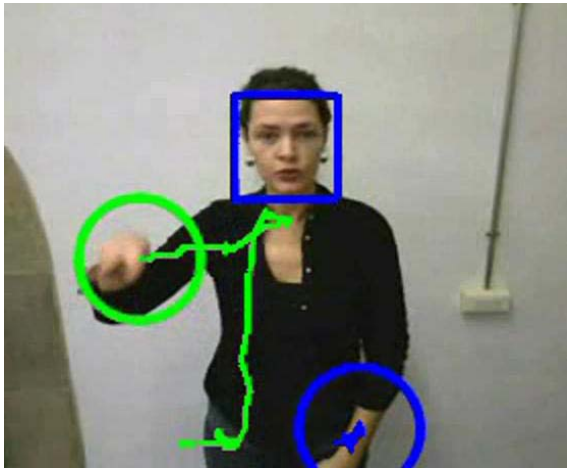
Open issues

- Complex video sequences
  - Non-controlled environments
- ST, NSI, NOF, SGD indicators require robust invariant descriptors
  - Face detector is not robust for non near frontal view
  - Extremity detection can be useful to avoid background moving objects
  - …
- Extend to group interactions
  - Analysis of alternative indicators
- Analysis of the thrid class: no clear dominant person

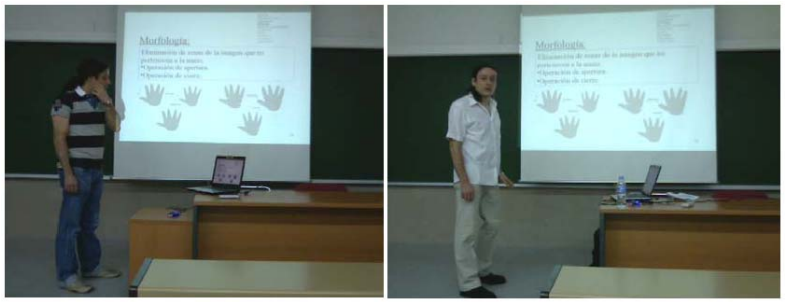
Current work on affective computint

Eyes and pose

Hands, face, and trajectories



Oral communication in EEES



TDAH Diagnosis

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Thank you!!
Questions?

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