WP4: Joint Bi-Modal Authentication and Model Adaptation

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Presented by John Haddon

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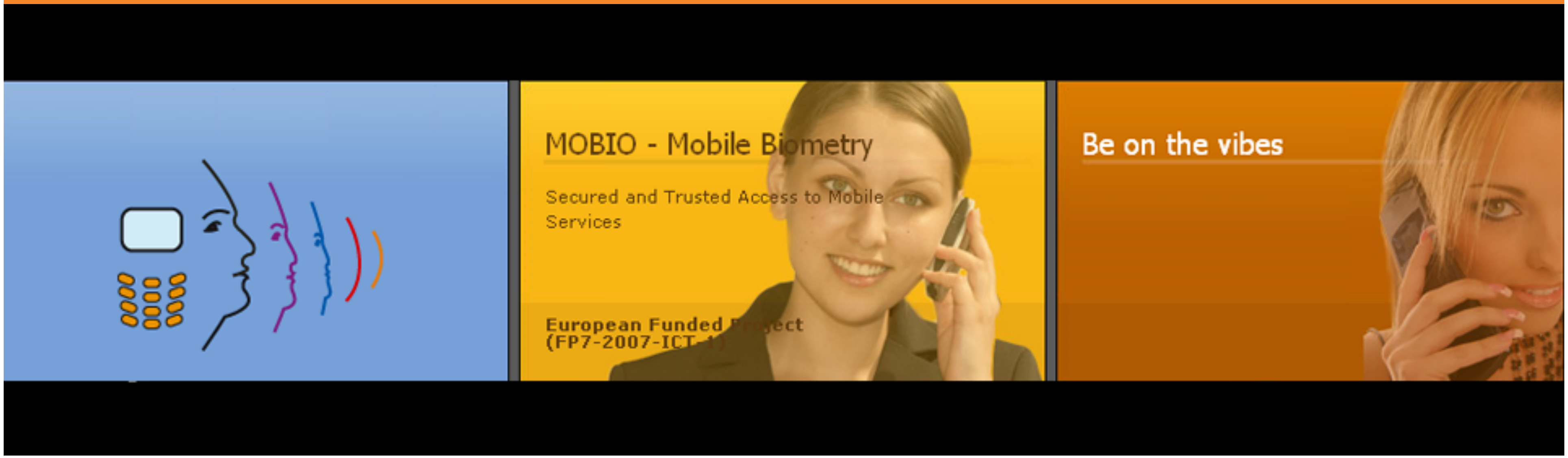
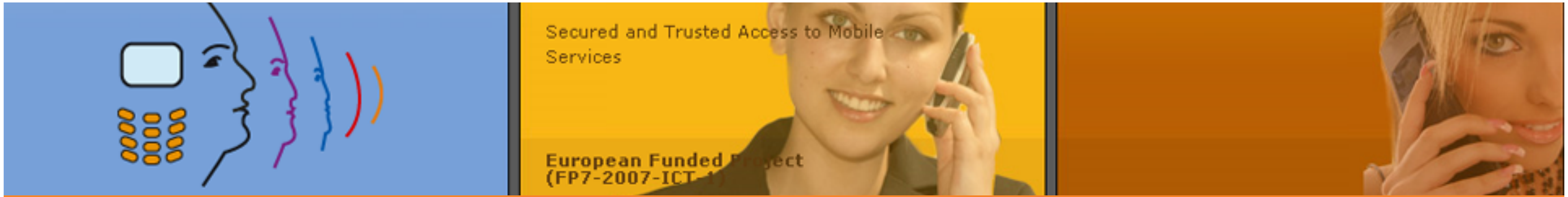
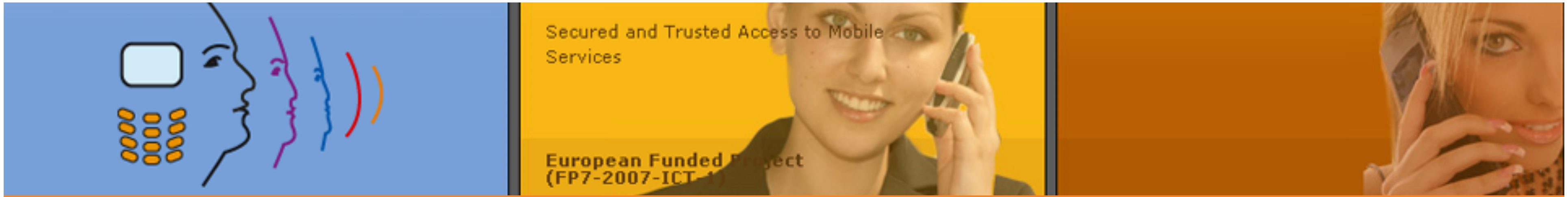
EyePmedia – 1020 Renens





Project management

- Overview
  - develop novel joint face and speaker authentication techniques and to investigate model adaptation techniques
- Project Status:
  - Delivered:
    - D4.1 & D4.2: Baseline Bimodal Authentication
    - D4.5 & D4.6: Baseline Model Adaptation Systems
  - To complete
    - D4.3 & D4.4: Advanced Bimodal Authentication
    - D4.7 & D4.8: Advanced Model Adaptation Systems
    - Both on m30

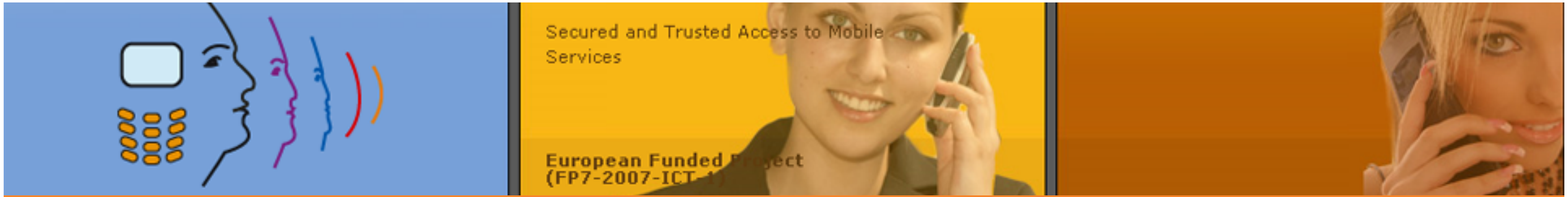


D4.1 & D4.2: Baseline Bimodal Authentication

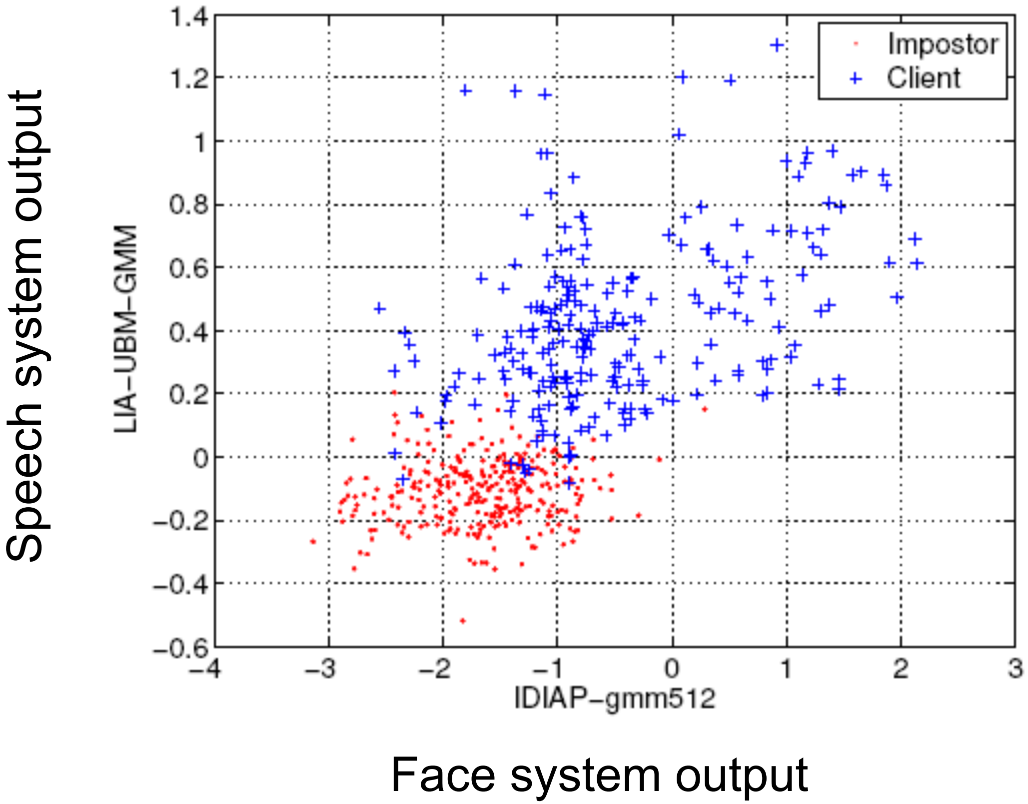
BANCA Bimodal Database

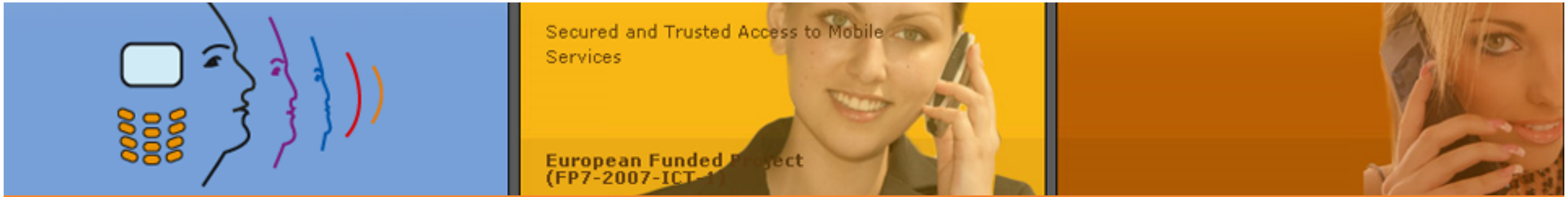
(a) Controlled (b) Adverse (c) Degraded

- Controlled – good lighting/exposure, clean background.
- Adverse – ‘natural’ setting, cluttered background etc.
- Degraded – as adverse but with lower quality camera, eg. Webcam.

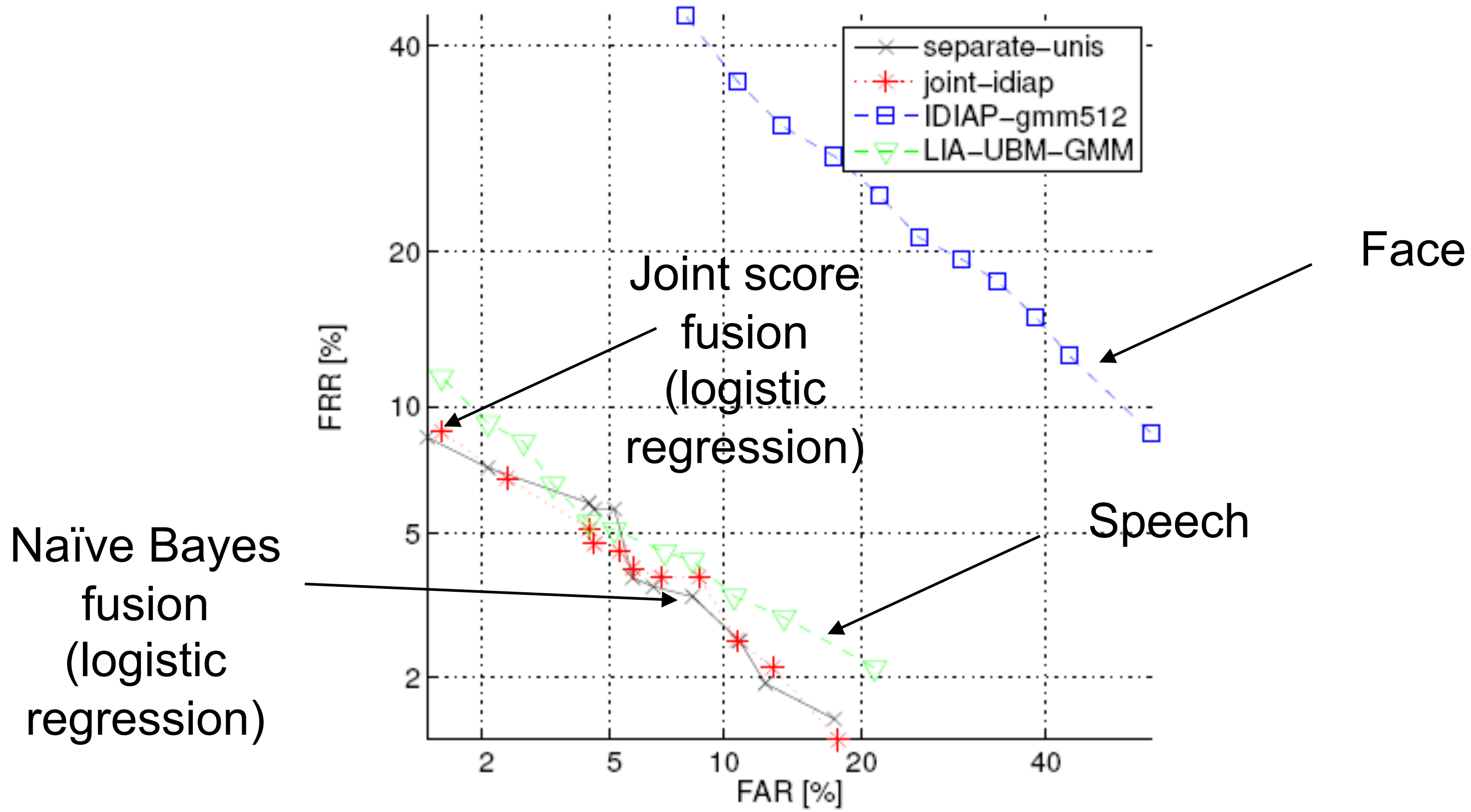


Combination of face and speech scores

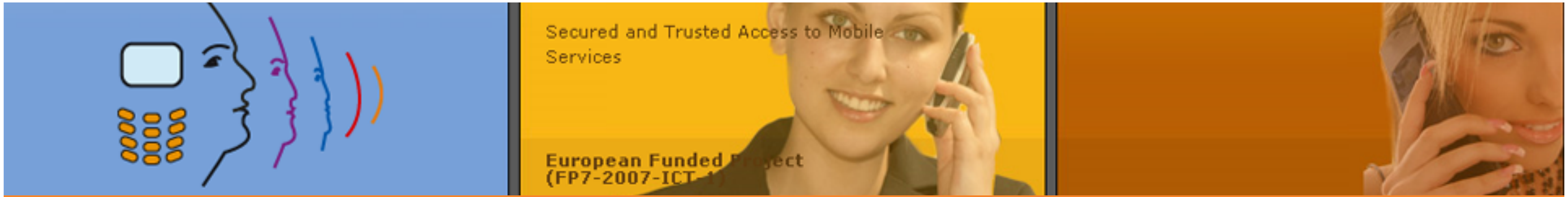




Results

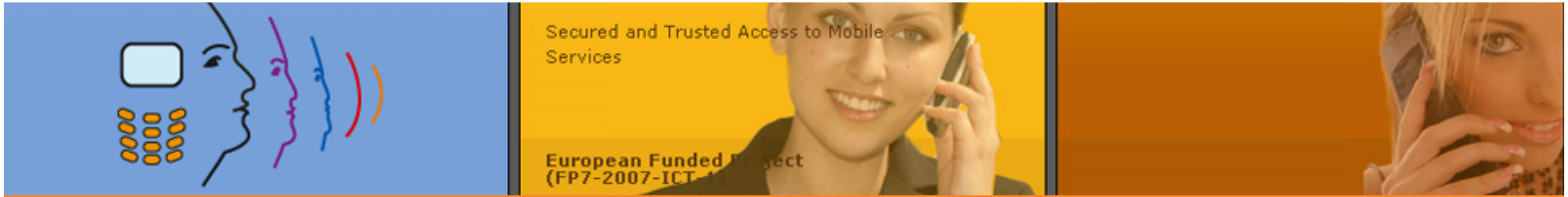


The combined system is better than any single modality



D4.5 & D4.6: Baseline Model Adaptation Systems

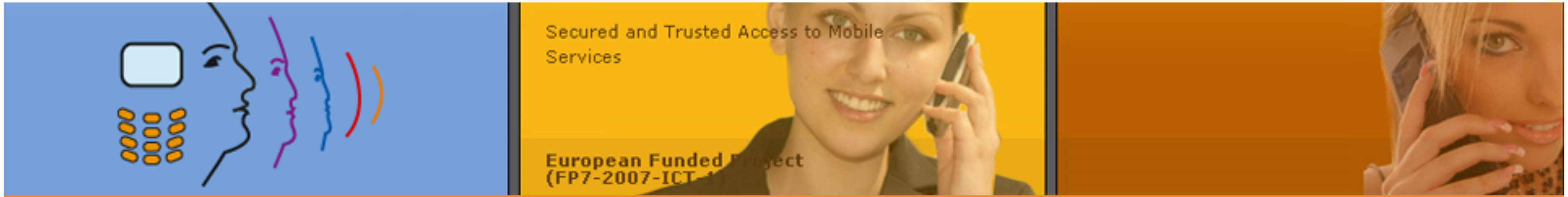
- Objective: Adaptive systems
  - To guard against the change of the quality of biometric samples, in particular, as a result of changing
    - acquisition environment
    - acquisition devices
      - i.e., matching between enrollment and query samples collected using different devices
- Two types of adaptation:
  - Model-level adaptation
    - Supervised adaptation (reference model contains the test conditions)
  - Score-level adaptation
    - Unsupervised (reference model was built in controlled conditions only)
    - Relying on additional operational data (made available at the training phase)



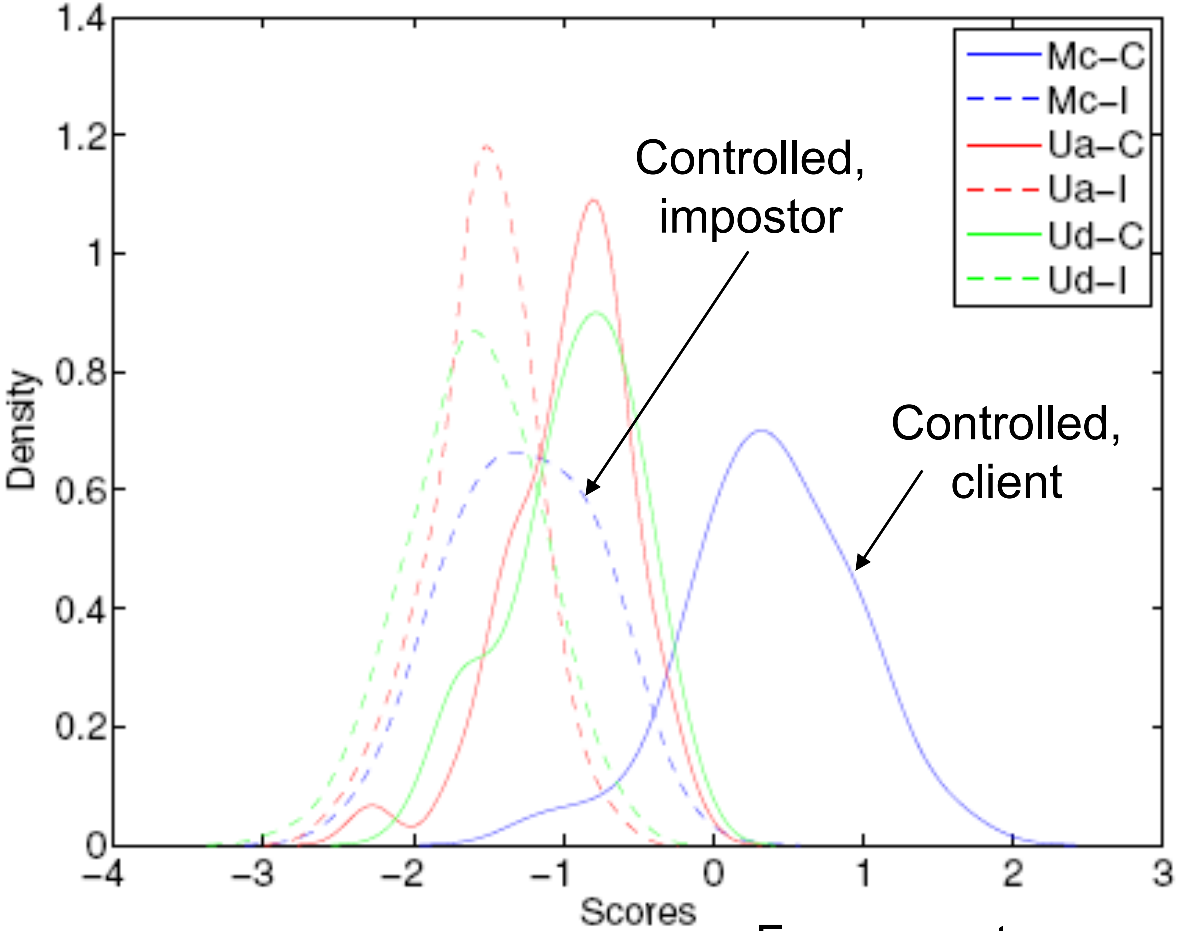
The Three Conditions (Recall)

BANCA Bimodal Database

(a) Controlled (b) Adverse (c) Degraded



Condition-Dependent Distributions (Image)

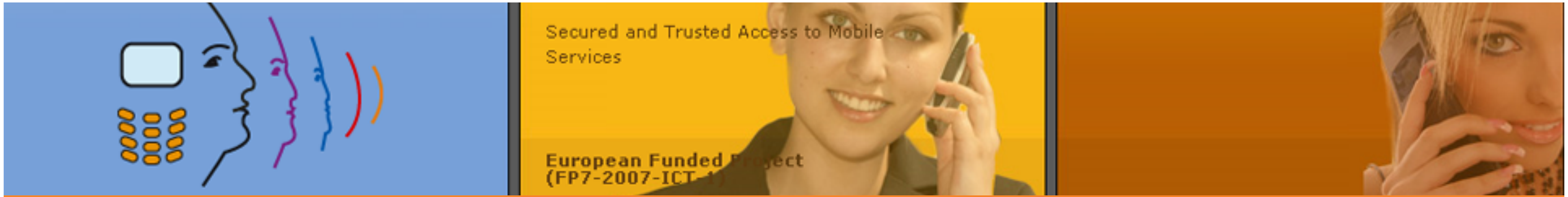


Face expert

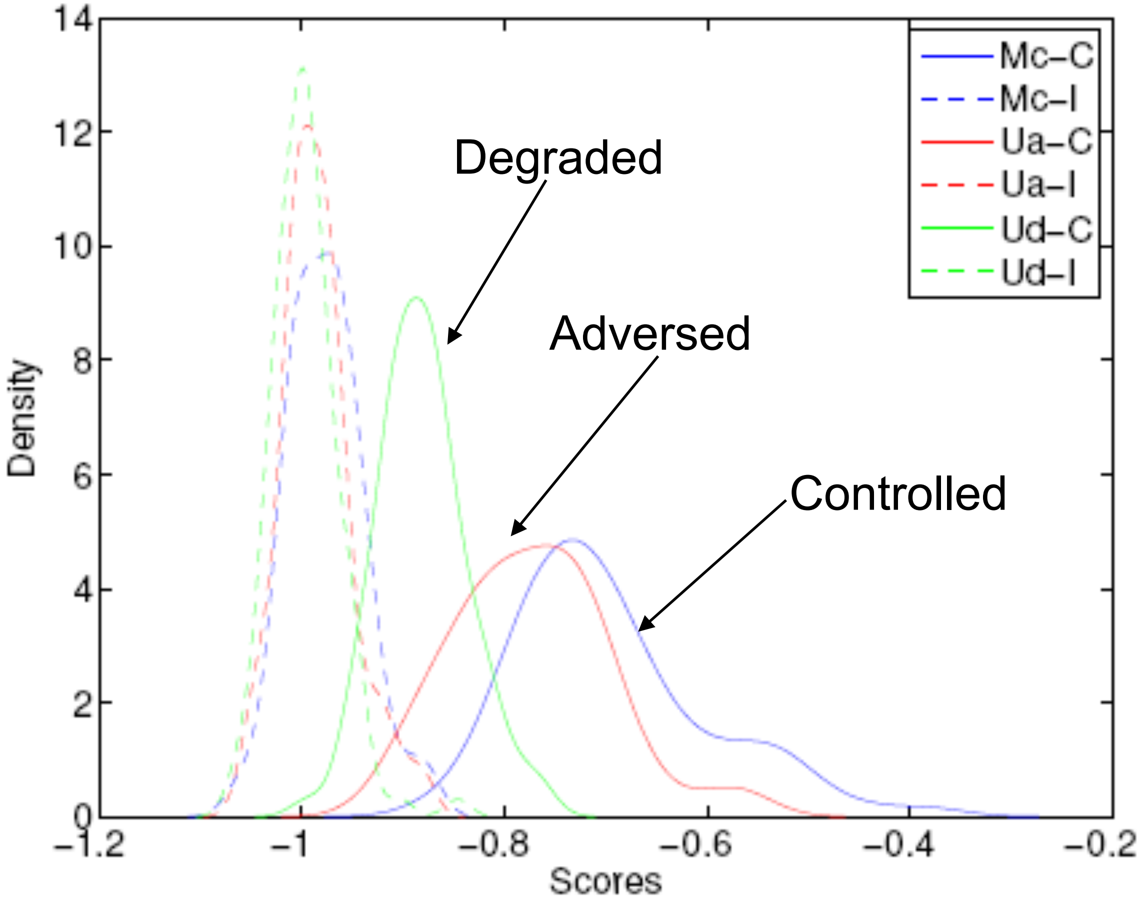
Controlled	Solid:	client
	Dashed:	Imposter
Adverse		
Degraded		

- The controlled client (solid blue) and imposter (dashed) curves are better separated than other pairs.
- Degradation and adverse conditions reduce the client/imposter separation.
- Imposter curves change a little as imaging conditions change.

SEVENTH FRAMEWORK PROGRAMME

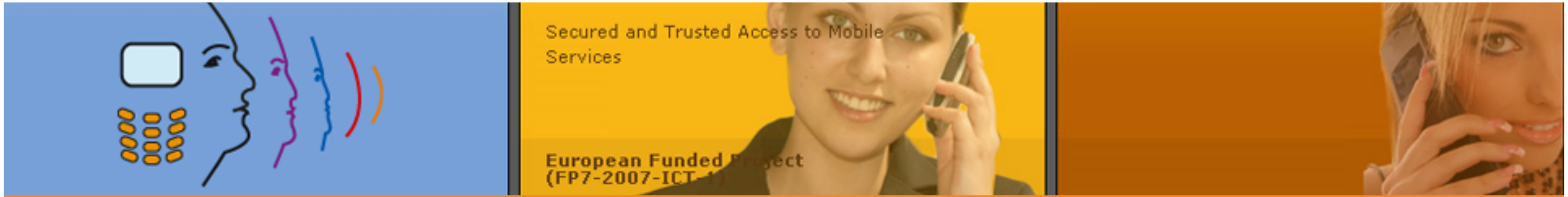


Condition-Dependent Distributions (Sound)



Speech expert

- As recording conditions change (to adverse and then degraded), the client likelihood scores decrease in value, moving closer to the impostor scores.
- Imposter scores do not change in line with recording conditions.
- Leads to graceful degradation in performance.



Score adaptation strategy

- Intuitively, one applies a normalization for each condition.
- Formally, we applied logistic regression as a normalization procedure:

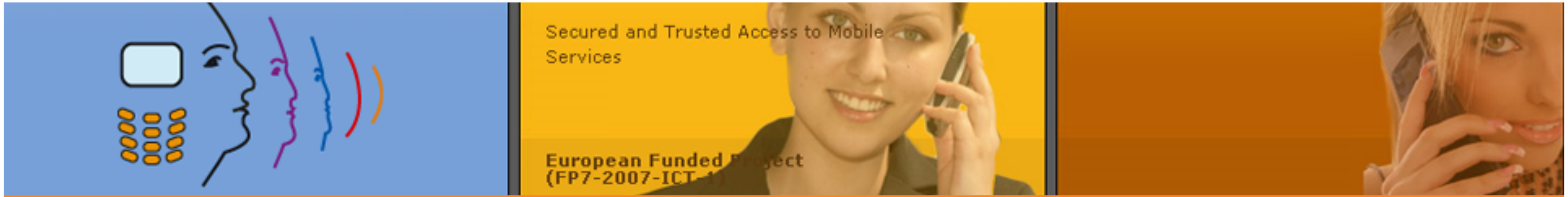
$$P(\mathtt{G}|y,Q) = \frac{1}{1+\exp\left(-(g_Q(y))\right)}$$

where $$g_Q(y) = w_1^{(Q)} y + w_0^{(Q)}$$

Scaling factor　　shift

Both are dependent on the condition, *Q*

Can extend to unknown condition easily: $P(\mathtt{G}|y,q) = \sum_Q p(\mathtt{G}|y,Q)P(Q|q)$



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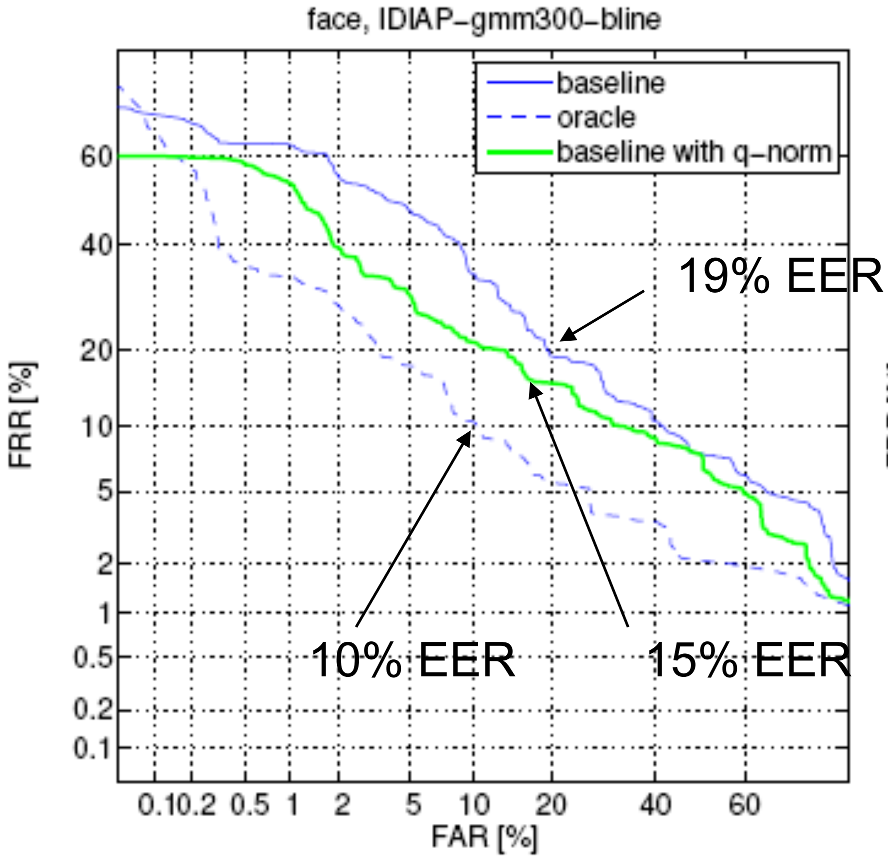
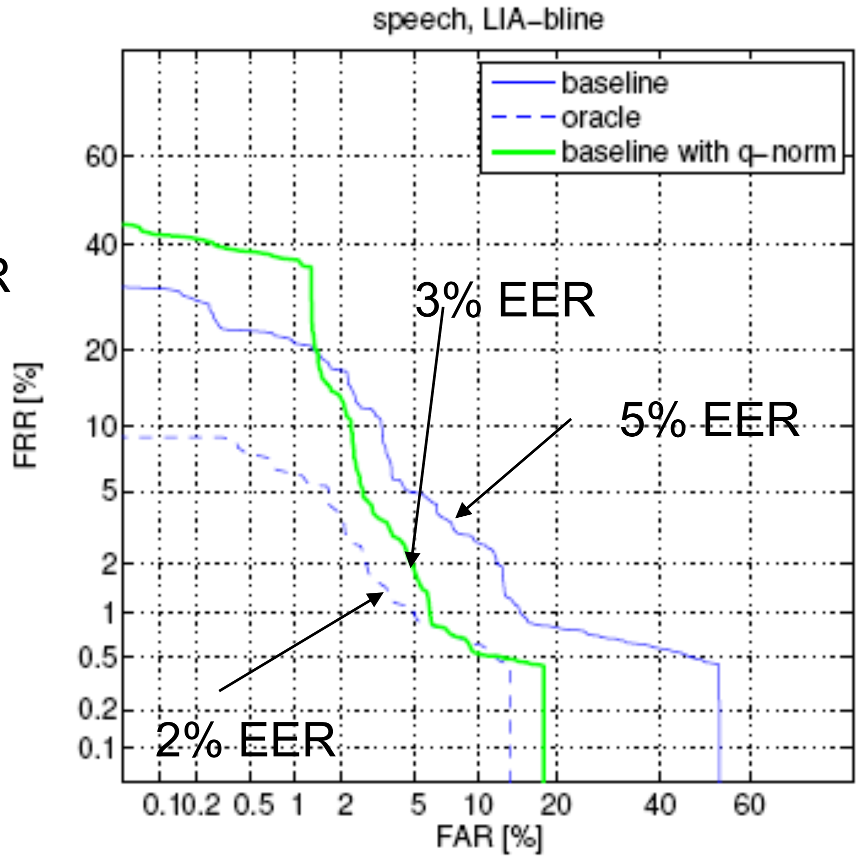
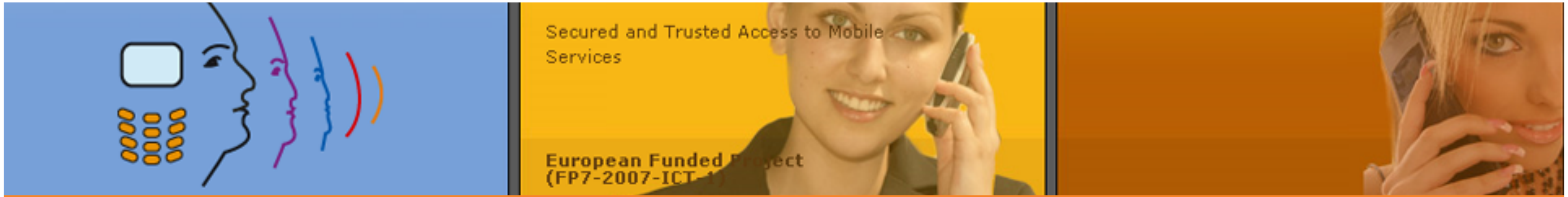


(a) Face

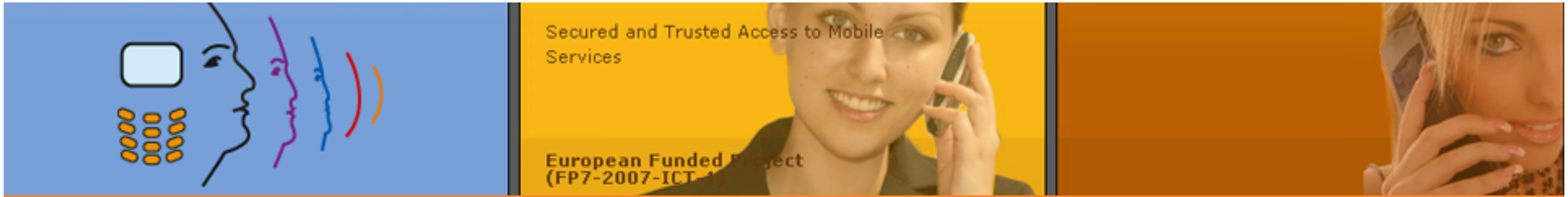


(b) Speech



Summary

- Supervised model adaptation performs the best
  - But this is the most optimistic scenario
    - Not achievable in practice
- Score-level adaptation is promising
  - Baseline models unchanged
  - Only requires operational data
  - In an experimental setting, the acquisition conditions are known; for unknown conditions, they can be inferred probabilistically (extension)



Thank you for your attention