da/sec BIOMETRICS AND INTERNET-SECURITY **RESEARCH GROUP** 



ANDREAS NAUTSCH\*

## Motivation

## **Research Questions**

- Q1: How do speaker sub-spaces accumulate by increasing sample duration?
- Q2: Can the biometric disrimination potential of i-vector feature spaces be measured?

While on score level cross-entropy analyses examine scalar speaker separation, feature space analyses place emphasis on e.g., i-vector distributions. By measuring the expected regularized Kullback-Leibler divergence between subjects, sub-space information is derived regarding:

- Collision probability of subjects, and
- Biometric uniqueness in given feature spaces

# Feature Space Entropy

## **Relative Entropy**

Biometric information addresses inter-subject distances of features x: measuring the Kullback-Leibler divergence of the intra-subject disctribution  $p(\mathbf{x})$ and the inter-subject distribution  $q(\mathbf{x})$ 



## Lower Bound by single Gaussians

# Entropy Analysis of i-vector Feature Spaces in Duration-sensitive Speaker Recognition

## CHRISTIAN RATHGEB\*

\* da/sec – Biometrics and Internet Security Research Group, Hochschule Darmstadt, Germany Department of Signal Processing and Acoustics, Aalto University, Finland andreas.nautsch@{cased|h-da}.de

Estimating KL-divergence	
Conventional Approach	Exp
Assuming, $p$ and $q$ follow a Gaussian distribution with $p(\mathbf{x}) \sim \mathcal{N}(\vec{\mu}_p, \mathbf{\Sigma}_p)$ and $q(\mathbf{x}) \sim \mathcal{N}(\vec{\mu}_q, \mathbf{\Sigma}_q)$ :	
$D(p  q) = k(\lambda + trace((\Sigma_p + \mathbf{T})\Sigma_q^{-1} - \mathcal{I})).$	
Where regularization is necessary, when feature spaces have more dimensions than samples are ob-served per subject.	Spea
Adler et al.: Towards a Measure of Biometric Information,	
1) Regularization for degenerated features	
• PCA transform by $q$ space scatter	732-
• Truncate low eigenvalues $< 10^{-10} [S_q]_1$	
2) Regularization for insufficient data	
• Ill-disposed $\mathbf{\Sigma}_P$ lead to $D(p  q)  ightarrow \infty$	Exp
$ullet$ Consider diag- $oldsymbol{\Sigma}_P$ as well	
• On $N_p$ samples of subject $p$ : non-diagonal $[\mathbf{\Sigma}_P]_{i,j} = 0, \qquad i,j \geq N_p$	
In our experiments, we extended 1 & 2 with: <b>3) Regularization for ill-conditioned PCA space</b>	
• Setting iteratively non-diagonal $[\mathbf{\Sigma}_P]_{i,j}$ to 0, until $ \mathbf{\Sigma}_P $ becomes positive	•
4) Regularization for insufficient samples	
<ul> <li>Minimum samples / subject: 10</li> </ul>	
Pros / Cons	
Metric: biometric ⇔ gross regularization uniqueness nsight: space behavior ⇔ lower bound metric	Con Spea i-vec
Perspective: 2-class $\Leftrightarrow$ subject-to-subject	atter

RAHIM SAEIDI<sup>†</sup>

CHRISTOPH BUSCH\*

## Results on I4U NIST SRE'12 train list

## erimental Set-Up

Pooled male/female I4U i-vectors	• 400-d
Pooled dev/eval files	• Proce
551 female & 425 male subjects (min. 10 samples)	<ul> <li>Analy</li> </ul>

## aker sub-space accumulation



## ected Relative Entropy

Duration		Entropy	(in bits)	)
group	$\mid \mu$	$\sigma$	min	max
full-5	127.2	24.0	71.5	226.6
full-10	124.3	28.1	65.0	254.8
full-20	135.5	35.3	63.2	319.0
full-40	155.0	43.1	71.1	421.9
full-full	182.1	50.0	88.7	471.6

• Collision probabilities diminish by duration:  $5 \times 10^{-10}$  on short duration to  $2 \times 10^{-55}$  on full

Cross-Modality Comparisons on Feature-Level: 2D-Face (56 bit), Fingerprint (85 bit), Iris (249 bit), and Password (128 bit)

## Iclusion

aker Recognition is viable for biometric recognition in either forensic or commercial applications. The ctor feature space conducts comparatively high subject discrimination, where current classifiers need more ntion towards robustness against probe sample duration variance.

## Comparison to performance metrics PLDA(400)





- lim i-vectors
- essing: whitening & length-norm
- ses regarding 5s, 10s, 20s, 40s, full samples