Scattering features for multimodal gait recognition

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GlobalSIP 2017

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Introduction

Identification is a core component in many applications:

- Recommender systems,
- Online banking and commerce,
- Surveillance,
- Gaming,
- Administration etc.

Different biometrics: fingerprint, face, speech, retinal scan, *gait (this work)*...

Each comes with advantages and drawbacks, *e.g.* accuracy or intrusiveness.

Gait-based identification

Prior art - various modalities exploited:

- Video (silhouette) (1, 2): high accuracy, privacy issues.
- Mechanical force sensors (3, 4): high setup cost.
- Wearables (5, 6): instrusive.
- WiFi (7): limited accuracy and range.
- Sound (8, 9, 10, 11): (assuming VAD) privacy-preserving, wideband, widespread availability.
- Seismic (12): privacy-preserving, robust, secure, narrowband.

Complementary properties of sound and seismic cues indicate that a *bimodal* approach may be effective.

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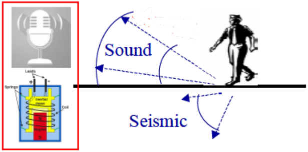

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Gait-based idetification

Open set identification:

1. Identify a person, if coming from a known set.
2. Otherwise, decide that the person is unknown.

Addressed through *GMM-UBM framework* (13).

Remaining challenges:

- No publicly available bimodal data.
- No generally acclaimed feature type.
- Seamless feature fusion?

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Remaining challenges:

- No publicly available bimodal data.
  - We recorded a small scale dataset (size precludes deep learning).
- No generally acclaimed feature type.
  - Tailored *scattering transform* (14) based features.
- Seamless feature fusion?
  - Surprisingly simple - stay tuned.

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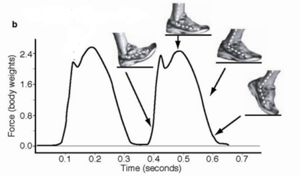
Gait signals



Particle velocity:

$$\hat{v}(\omega) = \mathcal{F}\left(v(\mathrm{t})\right) \propto \mathcal{F}\left(\int \vec{F}_{\mathsf{GRF}} dt\right)$$

Footfall ≈ 0.15s.
Period $\approx 2 \times 0.61$s. (15)

Acquired signals are band-passed and convoluted:

- Sound, *for* $200Hz \lesssim \omega \lesssim 20kHz$:

$$\hat{x}_{\mathsf{a}}(\omega, \vec{r}(\mathrm{t})) = \hat{h}_{\mathsf{a}}(\omega, \vec{r}(\mathrm{t}))\hat{v}(\omega) + \hat{e}_{\mathsf{a}}(\omega) = \hat{g}_{\mathsf{a}}(\omega, \vec{r}(\mathrm{t}))\frac{\hat{v}(\omega)}{\hat{z}(\omega)} + \hat{e}_{\mathsf{a}}(\omega)$$

- Seismic, *for* $20Hz \lesssim \omega \lesssim 300Hz$:

$$\hat{x}_{\mathsf{g}}(\omega, \vec{r}(\mathrm{t})) = \hat{h}_{\mathsf{g}}(\omega, \vec{r}(\mathrm{t}))\hat{v}(\omega) + \hat{e}_{\mathsf{g}}(\omega) = S_{\mathsf{g}}\hat{g}_{\mathsf{g}}(\omega, \vec{r}(\mathrm{t}))\hat{v}(\omega) + \hat{e}_{\mathsf{g}}(\omega).$$

Local stationarity assumption (LSA)

Within (short) temporal segment of duration τ:

$$\hat{g}_{\cdot}(\omega, \vec{r}(\mathrm{t}+\mathrm{t}')) \approx \hat{g}_{\cdot}(\omega, \vec{r}(\mathrm{t})), \text{ analogously } \hat{h}_{\cdot}(\omega, \vec{r}(\mathrm{t}+\mathrm{t}')) \approx \hat{h}_{\cdot}(\omega, \vec{r}(\mathrm{t})).$$

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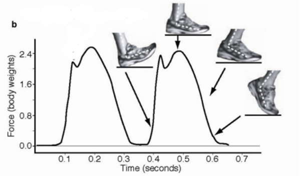

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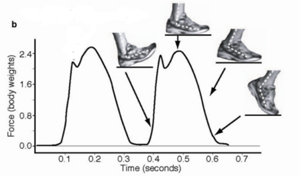

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Feature extraction

- Signals depend on impact velocity ☺ *and* relative position ☹
- Sound and seismic signals represent different physical quantities.
- To cope, we rely on a "CNN-like" scattering trnsform (16).

Feature extraction up to the *order* p:

0: $S_0(x) = \phi_T * x$,
1: $S_1^{\lambda_1}(x) = \phi_T * |\psi_{\lambda_1} * x|$,
2: $S_2^{\lambda_1,\lambda_2}(x) = \phi_T * |\psi_{\lambda_2} * |\psi_{\lambda_1} * x||$,
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$\phi_T := \phi_T(\mathrm{t})$ - a lowpass $(2\pi/T)$ filter, $\psi_\lambda := \psi_\lambda(\mathrm{t})$ - a complex wavelet at scale λ

Rule of thumb

1. Computational cost increases with T ("time-invariance").
2. $T \propto$ duration of a classified event (crucial for performance!).

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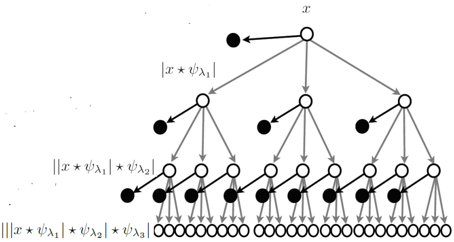

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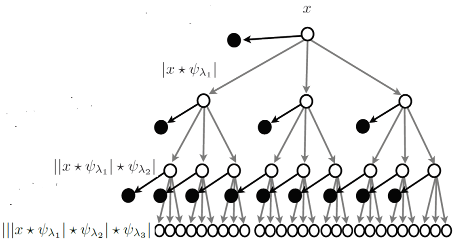

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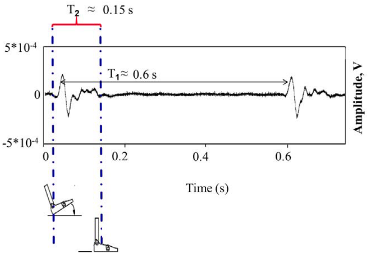
Competing requirements for T:

1. Short ($T \sim 0.15$s): characterizes only the footfall event, requires $\text{p} = 1$.
2. Large ($T \sim 1.22$s): captures also the temporal dynamics, but violates LSA and increases cost.

Can we avoid this tradeoff?



Visual comparison - two $\text{p} = 1$ scattering matrices (audio):

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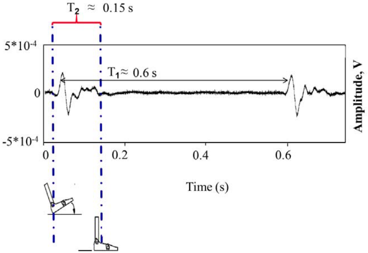

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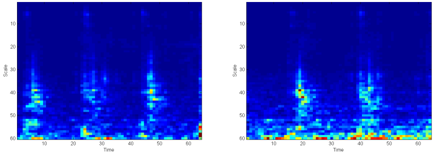

Invariances mostly due to a global temporal offset!

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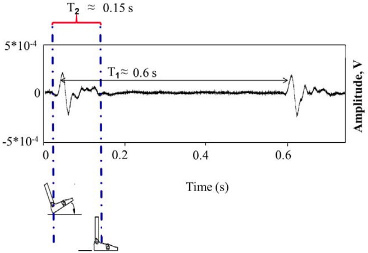

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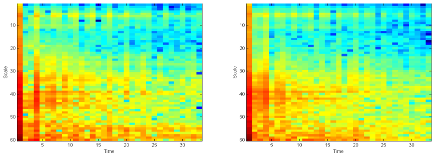

Remedy - compute Fourier modulus across rows (time).

Robust scattering features: normalized scattering

What about feature dependency on $\vec{r}$?

Normalized scattering

Under certain assumptions on $h := h(\mathrm{t})$, it can be shown:

$$S_{\mathrm{p}}^{\lambda_1,\dots\lambda_{\mathrm{p}}}(h * x) \approx |\hat{h}(\lambda_1)| S_{\mathrm{p}}^{\lambda_1,\dots\lambda_{\mathrm{p}}}(x),$$

then:

$$\tilde{S}_{\mathrm{p}}^{\lambda_1,\dots\lambda_{\mathrm{p}}}(h * x) := \frac{S_{\mathrm{p}}^{\lambda_1,\dots\lambda_{\mathrm{p}}}(h * x)}{S_{\mathrm{p}}^{\lambda_1,\dots\lambda_{\mathrm{p}-1}}(h * x)} \approx \tilde{S}_{\mathrm{p}}^{\lambda_1,\dots\lambda_{\mathrm{p}}}(x).$$

Consequence: if LSA holds, normalized scattering features depend *only* on $v(\mathrm{t})$!

A cheap channel normalization technique - “scattering CMS”.

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Feature fusion

What about fusion?

- Recall that $\hat{x}_{\text{a}}$ and $\hat{x}_{\text{g}}$ have (approx) complementary frequency range.
- Hence, $\tilde{S}_1^{\lambda_1}(x_{\text{a}}) > 0$ and $\tilde{S}_1^{\lambda_1}(x_{\text{g}}) > 0$ should be complementary as well.
- Due to channel normalization, $\tilde{S}_1^{\lambda_1}(x_{\text{a}})$ and $\tilde{S}_1^{\lambda_1}(x_{\text{g}})$ "live" in the same feature space, we can simply sum them up[1]:

$$\tilde{S}_{\text{fused}}^{\lambda_1} = \alpha_{\text{a}} \tilde{S}_1^{\lambda_1}(x_{\text{a}}) + \alpha_{\text{g}} \tilde{S}_1^{\lambda_1}(x_{\text{g}})$$

$\tilde{S}_0(x_{\text{a}})$ and $\tilde{S}_0(x_{\text{g}})$ are concatenated to $\tilde{S}_{\text{fused}}^{\lambda_1}$.

[1] $\alpha_{.}$ is a normalization constant

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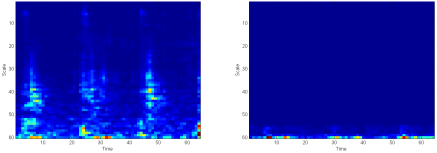

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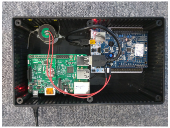
Experiments

Experimental setup (17):

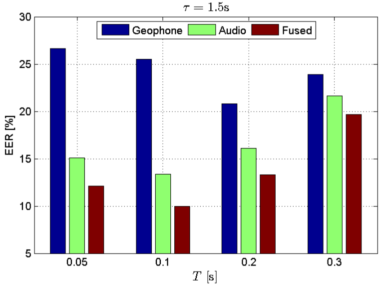
- Data collected internally, on a prototype dual sensor setup.
- 12 participants (8m and 4f), up to two types of shoes per person.
- (Low noise) recordings in a carpet-covered room, on 3 different days[2].
- 6 persons randomly chosen for training the UBM.
- From the remaining, randomly chosen 3 targets and 3 unknowns.
- Hyperparameters: τ, T, N (the number of retained coefficients after PCA).



[2] To avoid environmental effects: 2 days for training, 3rd day for evaluation.

Results

- Performance metric: *Equal Error Rate (EER)*, lower is better.
- Median results for the best-performing N, after 100 random partitions.



- "Optimal" hyperparameters agree with predictions:
  1. T on the order of the footfall impact duration.
  2. Larger τ degrades performance (violates LSA).
  3. "Richer" representations (*i.e.* audio and fused) favor larger N.

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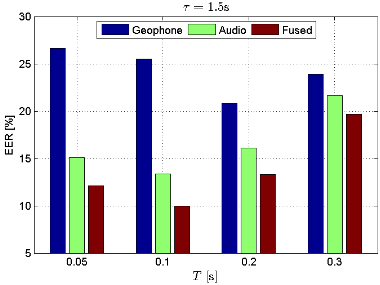

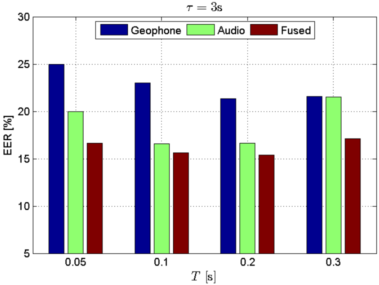

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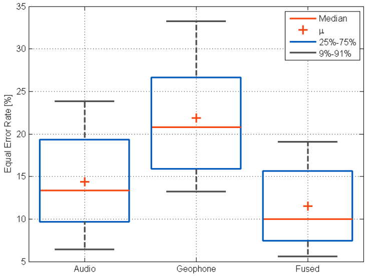
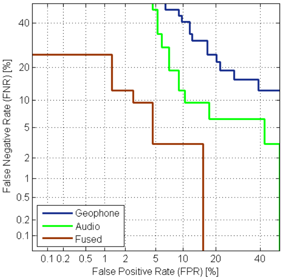


Best setting for each modality



Typical DET curves

Classification with fused features:

- exhibits the smallest variance,
- is the most robust wrt parameterization.

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Summary

Bimodal gait-based identification wrap-up:

- Confirmed identification by both sound and seismic observations.
- Performance gradation: fused $>$ sound $>$ seismic.
- Further research directions:
  - Recognition in noisy conditions and using cheap MEMS sensors.
  - "Walker diarization"?
  - Relevance of the shoe type, gender and/or environment.
  - A better way to fuse / extract features (new datasets), etc.

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