Learning Dynamic Stream Weights for Linear Dynamical Systems using Natural Evolution Strategies

ICASSP 2019

Christopher Schymura and Dorothea Kolossa

May 16th, 2019

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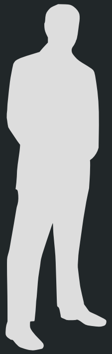
Audiovisual speaker tracking



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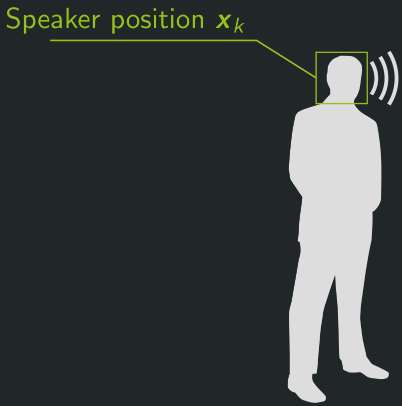

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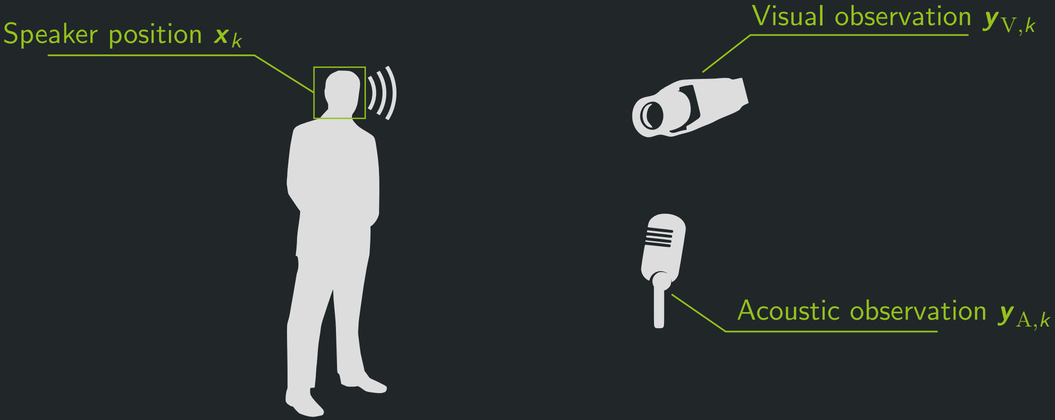

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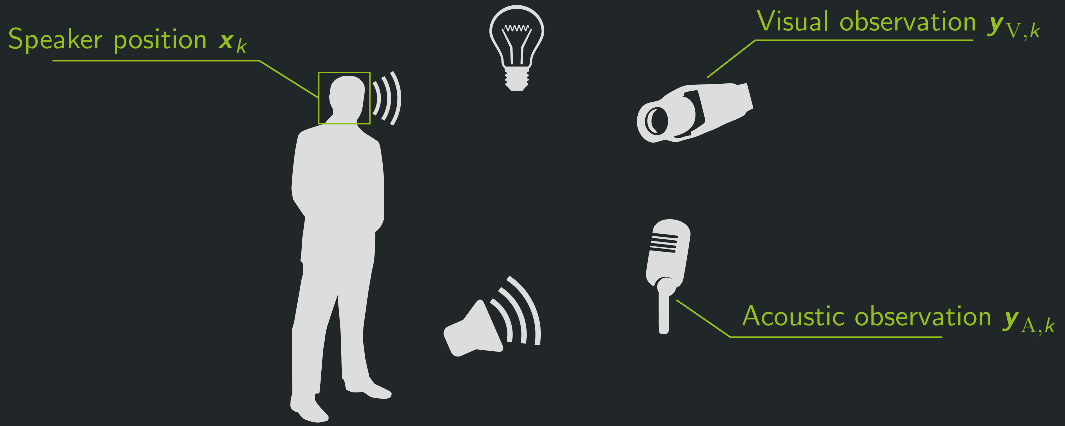

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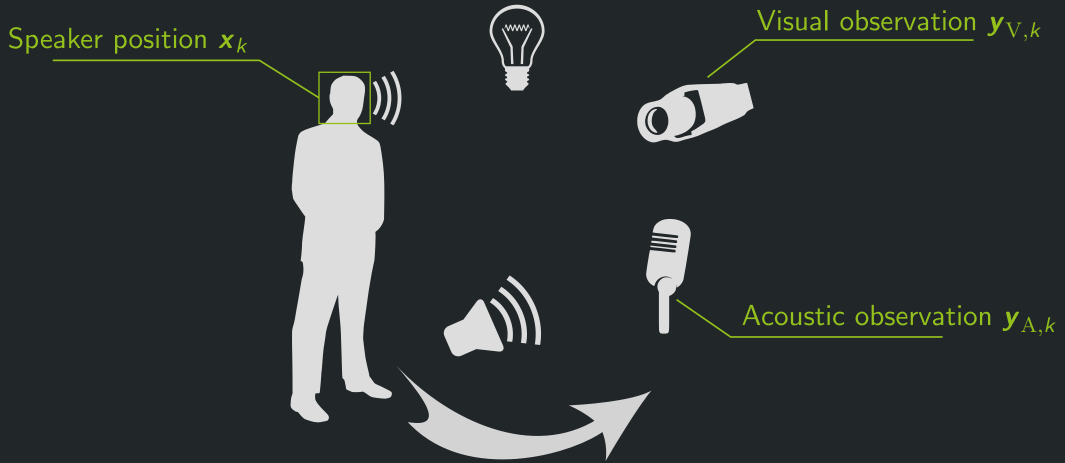
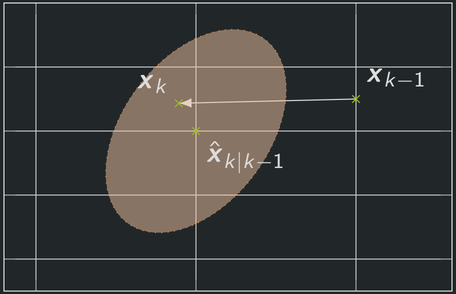


Audiovisual speaker tracking

Prediction step

System dynamics:

$$\boldsymbol{x}_k = \boldsymbol{A}\boldsymbol{x}_{k-1} + \boldsymbol{v}_k, \quad \boldsymbol{v}_k = \mathcal{N}(\boldsymbol{0}, \boldsymbol{Q})$$



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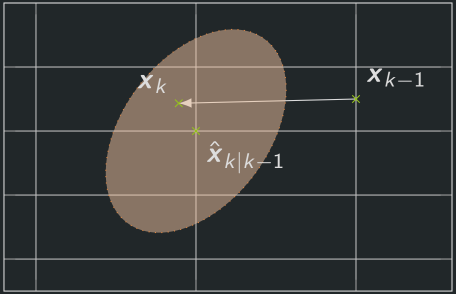

$$p(\boldsymbol{x}_k \mid \boldsymbol{Y}_{\mathrm{A},k-1},\ \boldsymbol{Y}_{\mathrm{V},k-1}) = \int p(\boldsymbol{x}_k \mid \boldsymbol{x}_{k-1})\ p(\boldsymbol{x}_{k-1} \mid \boldsymbol{Y}_{\mathrm{A},k-1},\ \boldsymbol{Y}_{\mathrm{V},k-1})\ d\boldsymbol{x}_{k-1}$$

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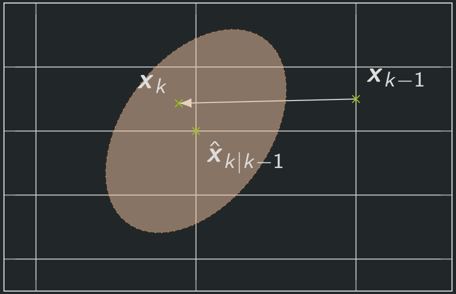


$$p(\boldsymbol{x}_k \mid \boldsymbol{Y}_{\mathrm{A},k-1}, \boldsymbol{Y}_{\mathrm{V},k-1}) = \int \underbrace{p(\boldsymbol{x}_k \mid \boldsymbol{x}_{k-1})}_{\text{Dynamic model}} \underbrace{p(\boldsymbol{x}_{k-1} \mid \boldsymbol{Y}_{\mathrm{A},k-1}, \boldsymbol{Y}_{\mathrm{V},k-1})}_{\text{Prior}} \, d\boldsymbol{x}_{k-1}$$

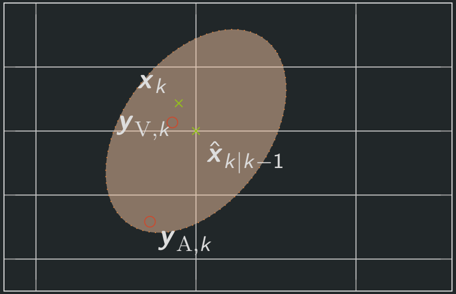
Audiovisual speaker tracking

Observation

Observation model:

$$\boldsymbol{y}_k = \begin{bmatrix} \boldsymbol{y}_{\mathrm{A},k} & \boldsymbol{y}_{\mathrm{V},k} \end{bmatrix}^{\mathrm{T}} = \boldsymbol{C}\boldsymbol{x}_k + \boldsymbol{w}_k$$

$$\boldsymbol{w}_k = \mathcal{N}(\mathbf{0},\ \boldsymbol{R}), \quad \boldsymbol{R} = \begin{bmatrix} \boldsymbol{R}_{\mathrm{AA}} & \boldsymbol{R}_{\mathrm{AV}} \\ \boldsymbol{R}_{\mathrm{VA}} & \boldsymbol{R}_{\mathrm{VV}} \end{bmatrix}$$



Audiovisual speaker tracking

Update step (standard Kalman filter)

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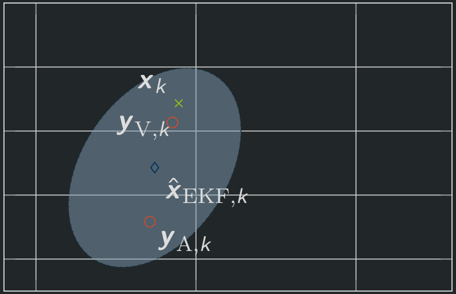

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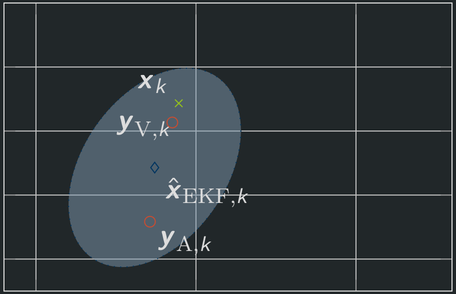

$$p(\boldsymbol{x}_k \,|\, \boldsymbol{Y}_{\mathrm{A},k},\ \boldsymbol{Y}_{\mathrm{V},k}) \propto p(\boldsymbol{x}_k \,|\, \boldsymbol{Y}_{\mathrm{A},k-1},\ \boldsymbol{Y}_{\mathrm{V},k-1})\, p(\boldsymbol{y}_{\mathrm{A},k},\ \boldsymbol{y}_{\mathrm{V},k} \,|\, \boldsymbol{x}_k)$$

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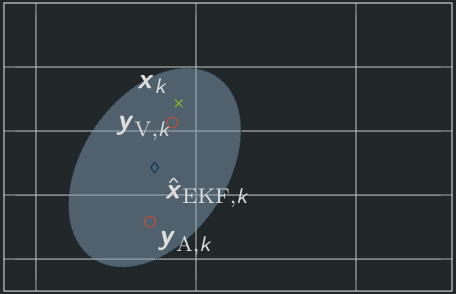

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Audiovisual speaker tracking

Update step (Kalman filter with dynamic stream weights[1])

Observation model:

$$\boldsymbol{y}_{\mathrm{A},k} = \boldsymbol{C}_{\mathrm{A}} \boldsymbol{x}_k + \boldsymbol{w}_{\mathrm{A},k}, \quad \boldsymbol{w}_{\mathrm{A},k} = \mathcal{N}(0, \boldsymbol{R}_{\mathrm{AA}})$$

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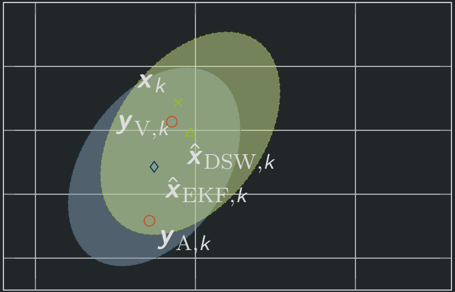

[1] C. Schymura, T. Isenberg, D. Kolossa: *Extending Linear Dynamical Systems with Dynamic Stream Weights for Audiovisual Speaker*

Audiovisual speaker tracking

Update step (Kalman filter with dynamic stream weights[1])

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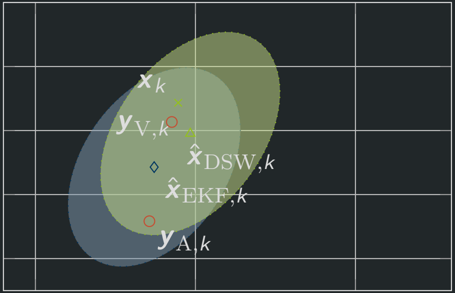

$$p(\boldsymbol{x}_k \,|\, \boldsymbol{Y}_{\mathrm{A},k}, \boldsymbol{Y}_{\mathrm{V},k}) \propto p(\boldsymbol{x}_k \,|\, \boldsymbol{Y}_{\mathrm{A},k-1}, \boldsymbol{Y}_{\mathrm{V},k-1}) \underbrace{p(\boldsymbol{y}_{\mathrm{A},k} \,|\, \boldsymbol{x}_k)^{\lambda_k}}_{\text{Acoustic model}} \underbrace{p(\boldsymbol{y}_{\mathrm{V},k} \,|\, \boldsymbol{x}_k)^{1-\lambda_k}}_{\text{Visual model}}$$

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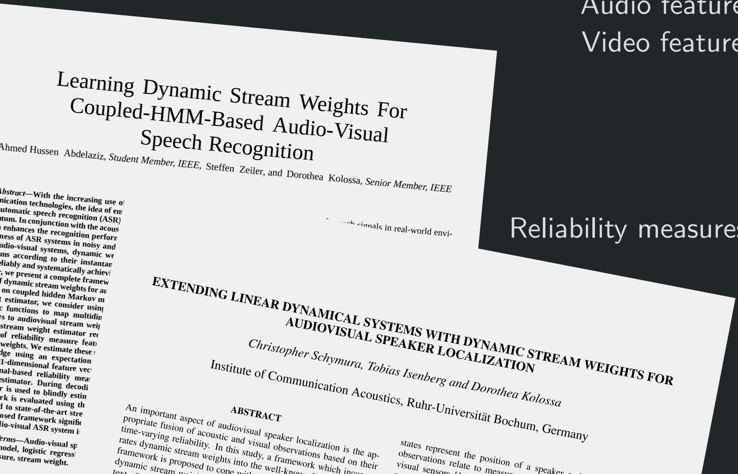
Learning dynamic stream weights

Standard approach: Supervised training with oracle dynamic stream weights


Learning Dynamic Stream Weights For Coupled-HMM-Based Audio-Visual Speech Recognition

Ahmed Hussen Abdelaziz, *Student Member, IEEE,* Steffen Zeiler, and Dorothea Kolossa, *Senior Member, IEEE*

EXTENDING LINEAR DYNAMICAL SYSTEMS WITH DYNAMIC STREAM WEIGHTS FOR AUDIOVISUAL SPEAKER LOCALIZATION

Christopher Schymura, Tobias Isenberg and Dorothea Kolossa

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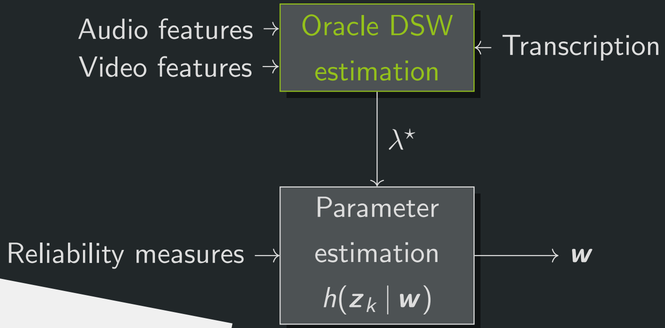
ABSTRACT



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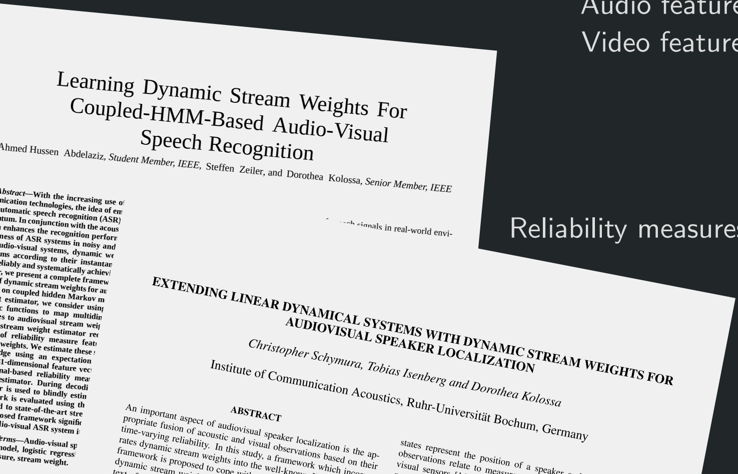
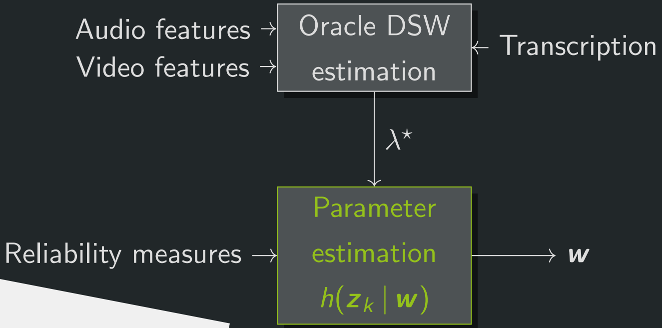




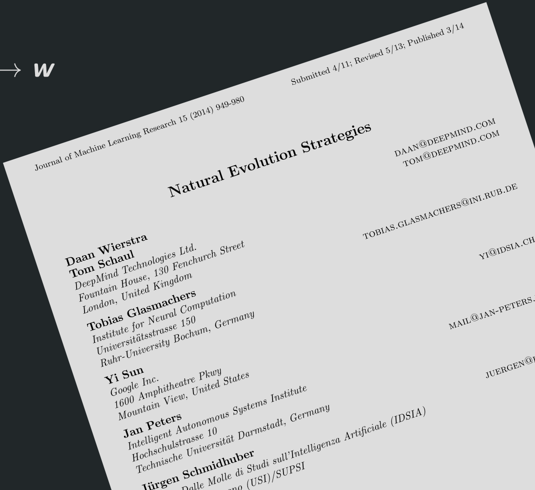
Learning dynamic stream weights

Proposed approach: Training with natural evolution strategies

Audio features →
Video features →
Speaker positions →
Realiability measures →

Black-box optimization $h(\boldsymbol{z}_k \mid \boldsymbol{w})$ → $\boldsymbol{w}$

- No oracle information required.
- Flexible choice of loss/fitness function.


Journal of Machine Learning Research 15 (2014) 949-980
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Natural Evolution Strategies

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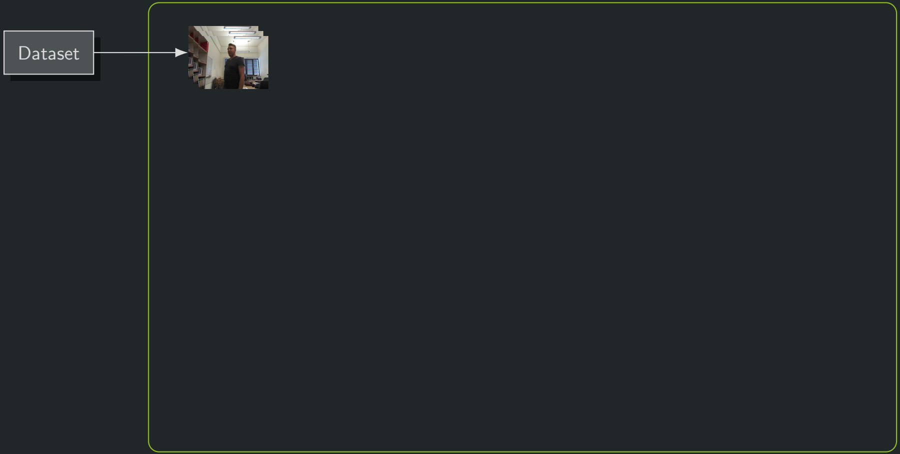
(USI)/SUPSI

Learning dynamic stream weights

Training procedure



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Training procedure

Dataset → 

$p(\boldsymbol{w} \mid \boldsymbol{\theta})$

Learning dynamic stream weights

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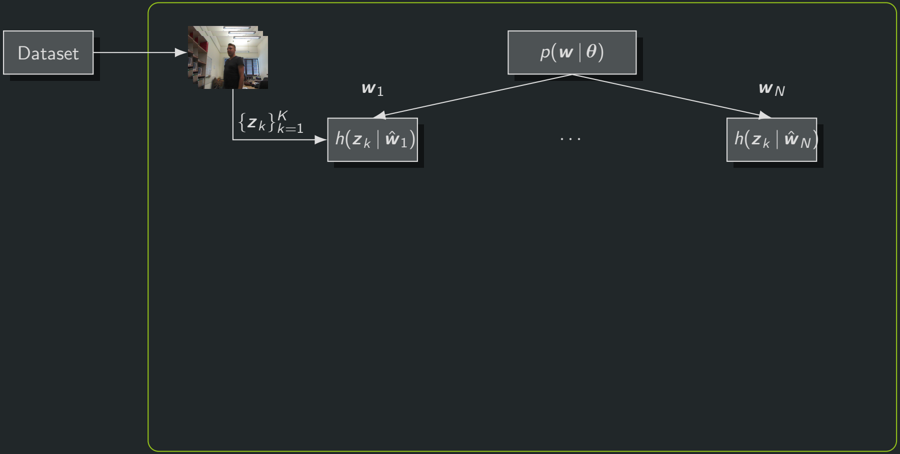

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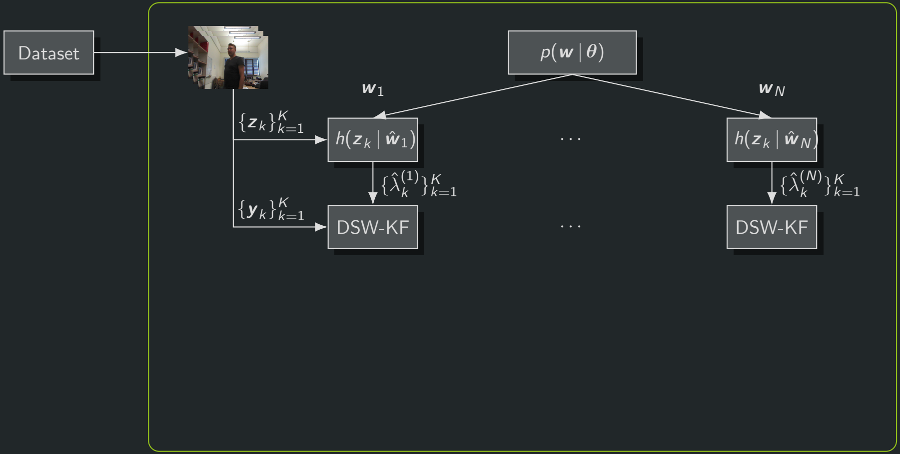

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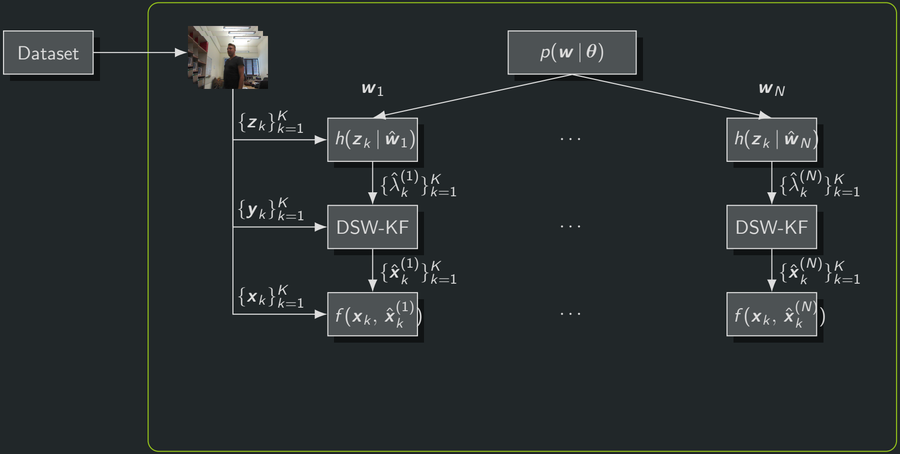

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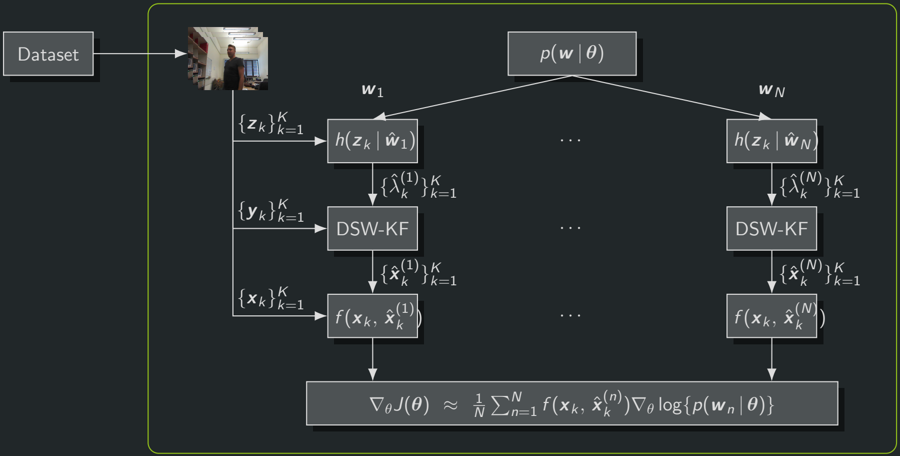

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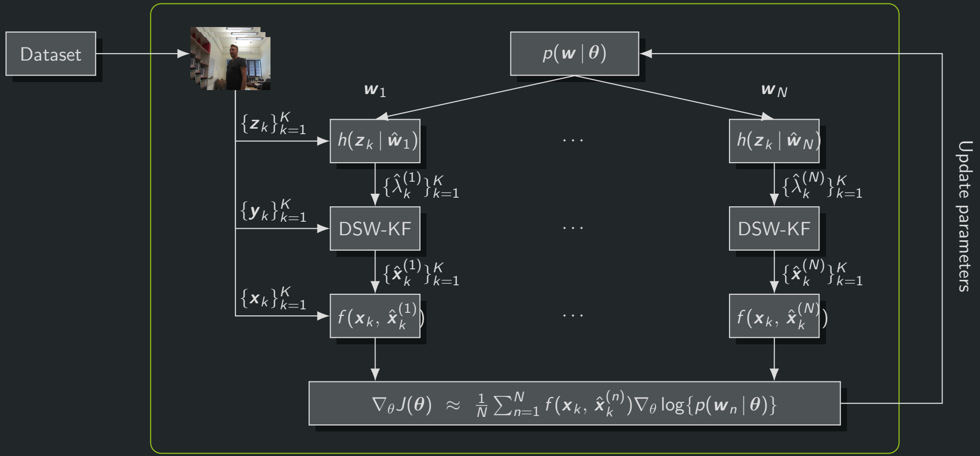

Learning dynamic stream weights

Implementation

- Reliability measures: instantaneous estimated a-priori SNR, acoustic and visual observation log-likelihoods[2].

[2] A. H. Abdelaziz, S. Zeiler, D. Kolossa: *Learning Dynamic Stream Weights for Coupled-HMM-Based Audio-Visual Speech Recognition*, 2015

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- Reliability measures: instantaneous estimated a-priori SNR, acoustic and visual observation log-likelihoods[2].
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- Separable natural evolution strategies (sNES) as optimizer:
  $p(\boldsymbol{w} \mid \boldsymbol{\theta}) = \mathcal{N}\left(\boldsymbol{w} \mid \boldsymbol{\mu}_{\boldsymbol{w}}, \operatorname{diag}(\boldsymbol{\sigma}_{\boldsymbol{w}})\right)$

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- Fitness function allowing direct optimization of instantaneous localization error:
  $f(\boldsymbol{w}) = -\frac{1}{M}\sum_{m=1}^{M}\frac{1}{K_m}\sum_{k=1}^{K_m}\left(\phi_k^{(m)} - \hat{\phi}_k^{(m)}(\boldsymbol{w})\right)^2$

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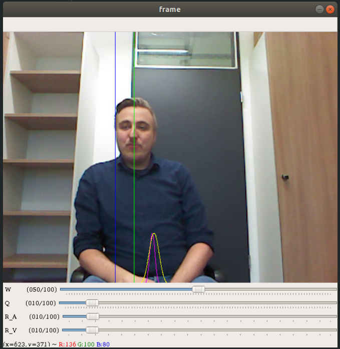
Evaluation

Experimental setup

- Front-end: DPD-MUSIC[3] for acoustic localization, Viola-Jones[4] algorithm for visual localization.



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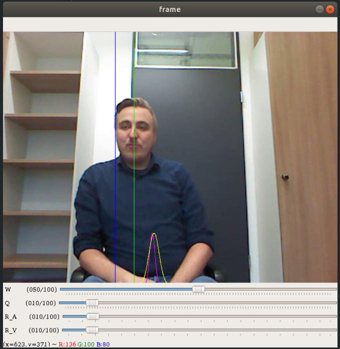

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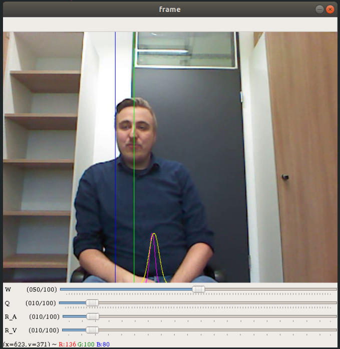

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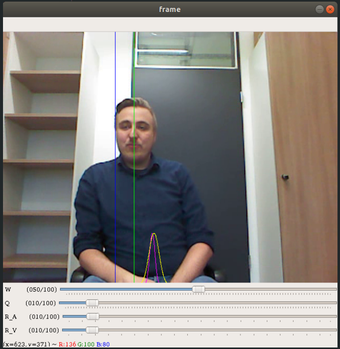
- Baseline: Stream weight prediction models trained on oracle DSWs with SGD (same architecture)



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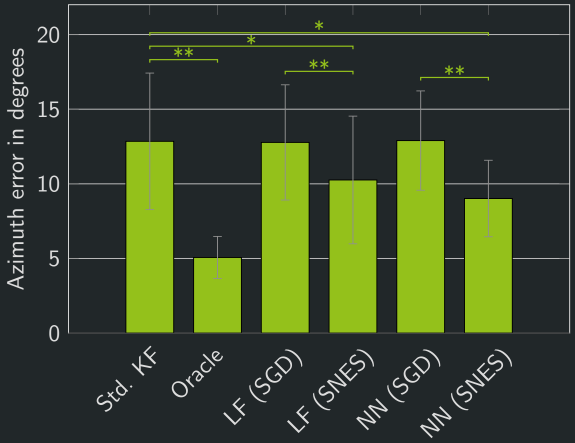
Results



Statistical significance: * for $p < 0.05$ and ** for $p < 0.01$

Conclusions and outlook

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Thank you for your attention!