Inference in Nonlinear Dynamical Systems with Dynamic Stream Weights for Audiovisual Speaker Tracking

ICA 2019

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RUHR UNIVERSITÄT BOCHUM

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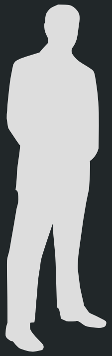
Audiovisual speaker tracking



Audiovisual speaker tracking

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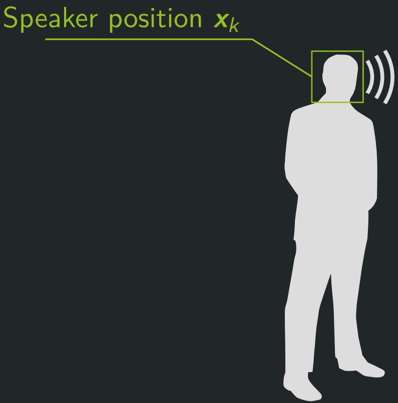

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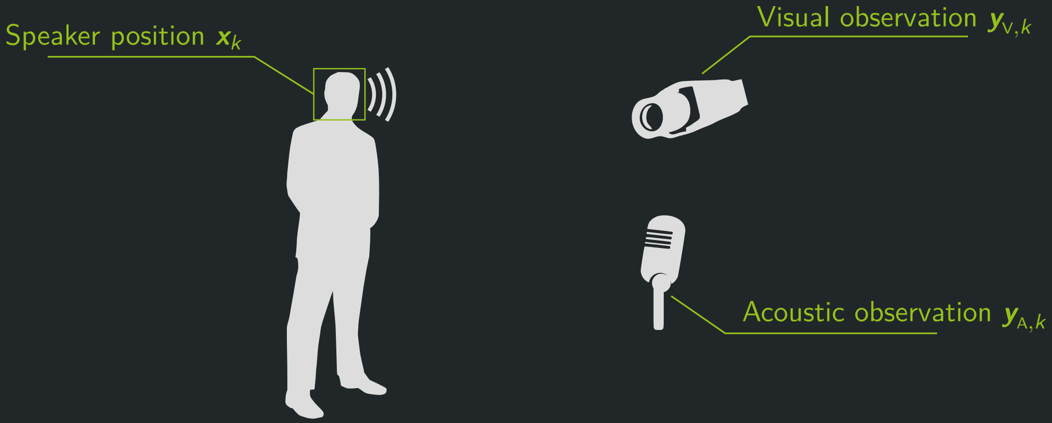

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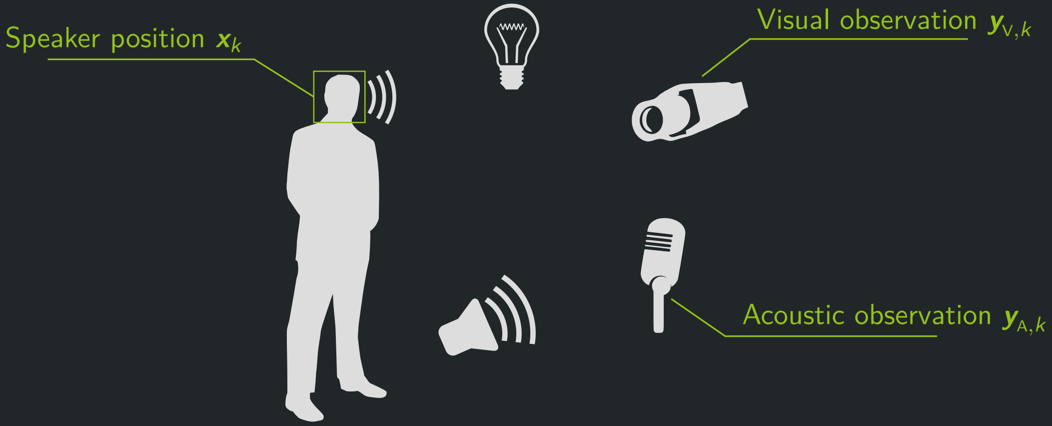

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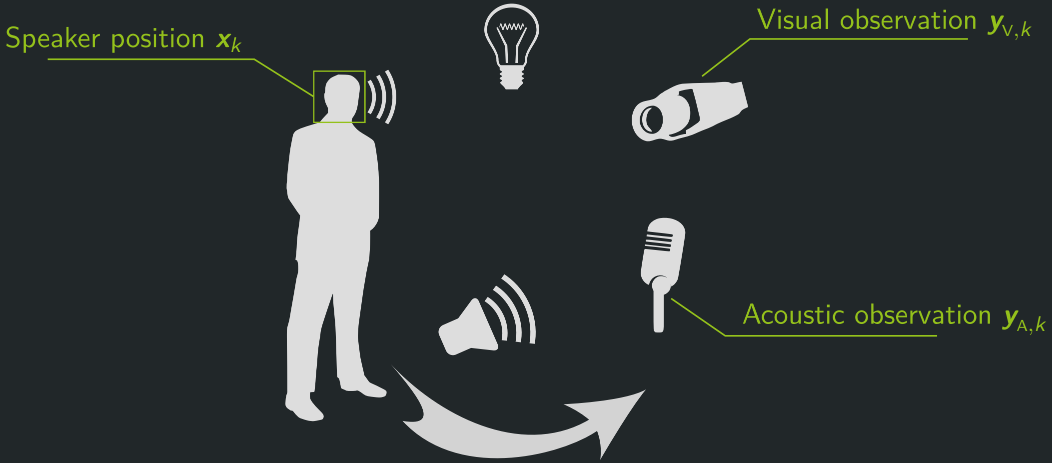
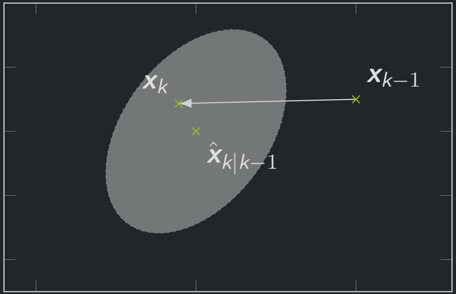


Audiovisual speaker tracking

Prediction step

System dynamics:

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



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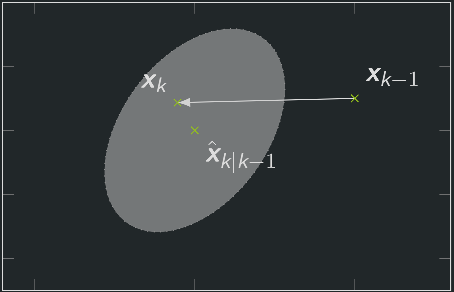

$$p(\boldsymbol{x}_k \,|\, \boldsymbol{Y}_{\mathrm{A},k-1},\, \boldsymbol{Y}_{\mathrm{V},k-1}) = \int \, p(\boldsymbol{x}_k \,|\, \boldsymbol{x}_{k-1}) \;\, p(\boldsymbol{x}_{k-1} \,|\, \boldsymbol{Y}_{\mathrm{A},k-1},\, \boldsymbol{Y}_{\mathrm{V},k-1}) \;\, d\boldsymbol{x}_{k-1}$$

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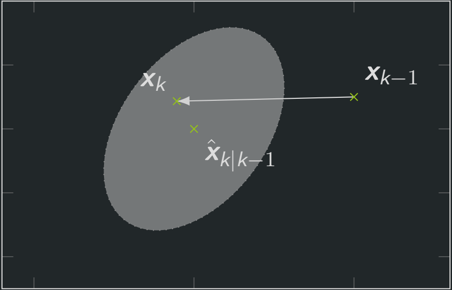


$$p(\boldsymbol{x}_k \mid \boldsymbol{Y}_{\mathrm{A},k-1},\ \boldsymbol{Y}_{\mathrm{V},k-1}) = \int \underbrace{p(\boldsymbol{x}_k \mid \boldsymbol{x}_{k-1})}_{\text{Dynamic model}} \underbrace{p(\boldsymbol{x}_{k-1} \mid \boldsymbol{Y}_{\mathrm{A},k-1},\ \boldsymbol{Y}_{\mathrm{V},k-1})}_{\text{Prior}}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

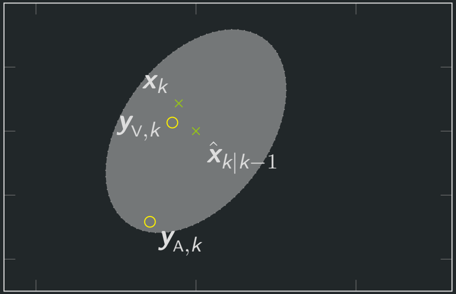
Audiovisual speaker tracking

Observation

Observation model:

$$\boldsymbol{y}_k = \begin{bmatrix}\boldsymbol{y}_{\mathrm{A},k} & \boldsymbol{y}_{\mathrm{V},k}\end{bmatrix}^{\mathsf{T}} = h\left(\boldsymbol{x}_k\right) + \boldsymbol{w}_k$$

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



Audiovisual speaker tracking

Update step (standard Kalman filter)

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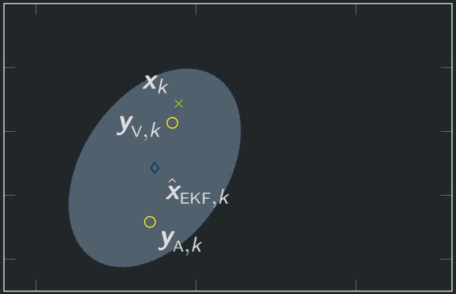

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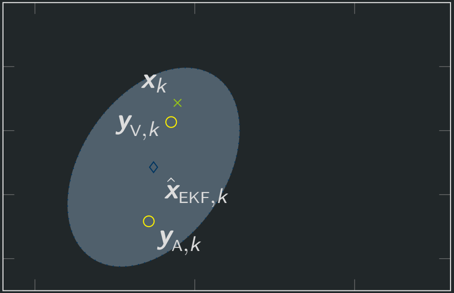

$$p(\boldsymbol{x}_k \,|\, \boldsymbol{Y}_{\mathrm{A},k},\ \boldsymbol{Y}_{\mathrm{V},k}) \propto p(\boldsymbol{x}_k \,|\, \boldsymbol{Y}_{\mathrm{A},k-1},\ \boldsymbol{Y}_{\mathrm{V},k-1})\, p(\boldsymbol{y}_{\mathrm{A},k},\ \boldsymbol{y}_{\mathrm{V},k} \,|\, \boldsymbol{x}_k)$$

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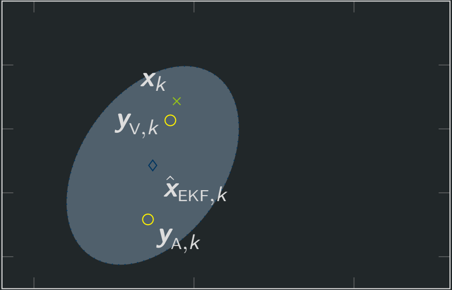

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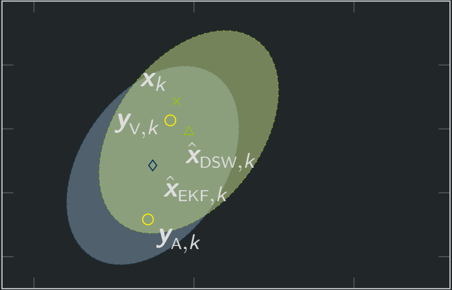
Audiovisual speaker tracking

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

Observation model:

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

$$\boldsymbol{y}_{\mathrm{V},k} = h_{\mathrm{V}}(\boldsymbol{x}_k) + \boldsymbol{w}_{\mathrm{V},k}, \quad \boldsymbol{w}_{\mathrm{V},k} = \mathcal{N}(0,\ \boldsymbol{R}_{\mathrm{VV}})$$



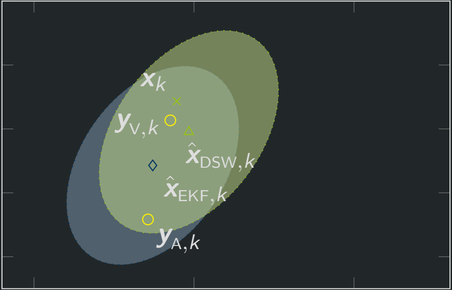
[1] C. Schymura et al.: *Extending linear dynamical systems with dynamic stream weights for audiovisual speaker localization*, IWAENC, 2018

Audiovisual speaker tracking

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

Observation model:

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



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

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Inference

Extended Kalman filter approach: first-order Taylor series expansion

$$f(\boldsymbol{x}_{k-1}) \approx f(\hat{\boldsymbol{x}}_{k-1}) + \boldsymbol{F}(\hat{\boldsymbol{x}}_{k-1})(\boldsymbol{x}_{k-1} - \hat{\boldsymbol{x}}_{k-1})$$

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$$\Rightarrow \quad p(\boldsymbol{x}_k \,|\, \boldsymbol{Y}_{\mathrm{A},k-1},\ \boldsymbol{Y}_{\mathrm{V},k-1}) = \mathcal{N}\left(\boldsymbol{x}_k \,|\, \hat{\boldsymbol{x}}_{k-1},\ \hat{\Sigma}_{k-1}\right)$$

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Prediction step (identical to standard EKF)

$$\hat{\boldsymbol{x}}_{k|k-1} = f(\hat{\boldsymbol{x}}_{k-1})$$

$$\hat{\boldsymbol{\Sigma}}_{k|k-1} = \boldsymbol{F}_{k-1}\hat{\boldsymbol{\Sigma}}_{k-1}\boldsymbol{F}_{k-1}^{\mathsf{T}} + \boldsymbol{Q}, \qquad \boldsymbol{F}_{k-1} \equiv \boldsymbol{F}(\hat{\boldsymbol{x}}_{k-1}) = \frac{\partial f(\boldsymbol{x}_{k-1})}{\partial \boldsymbol{x}_{k-1}}\Big|_{\boldsymbol{x}_{k-1}=\hat{\boldsymbol{x}}_{k-1}}$$

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Extended Kalman filter approach: first-order Taylor series expansion

$$h_{\{\mathrm{A,V}\}}(\boldsymbol{x}_k) \approx h_{\{\mathrm{A,V}\}}(\hat{\boldsymbol{x}}_k) + \boldsymbol{H}_{\{\mathrm{A,V}\},k}(\boldsymbol{x}_k - \hat{\boldsymbol{x}}_k), \quad \boldsymbol{H}_{\{\mathrm{A,V}\},k} \equiv \left.\frac{\partial h_{\{\mathrm{A,V}\}}(\boldsymbol{x}_k)}{\partial \boldsymbol{x}_k}\right|_{\boldsymbol{x}_k = \hat{\boldsymbol{x}}_k}$$

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$$\Rightarrow \qquad p(\boldsymbol{y}_{\{A,V\},k} \,|\, \boldsymbol{x}_k) = \mathcal{N}\Big(\boldsymbol{y}_{\{A,V\},k}, \,|\, h_{\{A,V\}}(\hat{\boldsymbol{x}}_k) + \boldsymbol{H}_{\{A,V\},k})(\boldsymbol{x}_k - \hat{\boldsymbol{x}}_k), \, \boldsymbol{R}_{\{A,V\}}\Big)$$

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Update step

$$\begin{bmatrix} \boldsymbol{K}_{A,k}^T \\ \boldsymbol{K}_{V,k}^T \end{bmatrix} = \begin{bmatrix} \boldsymbol{R}_A + \lambda_k \boldsymbol{H}_{A,k}\hat{\boldsymbol{\Sigma}}_{k|k-1}\boldsymbol{H}_{A,k}^T & (1-\lambda_k)\boldsymbol{H}_{A,k}\hat{\boldsymbol{\Sigma}}_{k|k-1}\boldsymbol{H}_{V,k}^T \\ \lambda_k \boldsymbol{H}_{V,k}\hat{\boldsymbol{\Sigma}}_{k|k-1}\boldsymbol{H}_{A,k}^T & \boldsymbol{R}_V + (1-\lambda_k)\boldsymbol{H}_{V,k}\hat{\boldsymbol{\Sigma}}_{k|k-1}\boldsymbol{H}_{V,k}^T \end{bmatrix}^{-1} \begin{bmatrix} \boldsymbol{H}_{A,k} \\ \boldsymbol{H}_{V,k} \end{bmatrix} \hat{\boldsymbol{\Sigma}}_{k|k-1} \tag{1}$$

$$\hat{\boldsymbol{x}}_k = \hat{\boldsymbol{x}}_{k|k-1} + \lambda_k \boldsymbol{K}_{A,k}\left(\boldsymbol{y}_{A,k} - h_A(\hat{\boldsymbol{x}}_k)\right) + (1-\lambda_k)\boldsymbol{K}_{V,k}\left(\boldsymbol{y}_{V,k} - h_V(\hat{\boldsymbol{x}}_k)\right)$$

$$\hat{\boldsymbol{\Sigma}}_{k|k-1} = \left(\boldsymbol{I} - \lambda_k \boldsymbol{K}_{A,k}\boldsymbol{H}_{A,k} - (1-\lambda_k)\boldsymbol{K}_{V,k}\boldsymbol{H}_{V,k}\right)\hat{\boldsymbol{\Sigma}}_{k|k-1}$$

Inference

The system of linear matrix equations in Eq. (1) can be expressed as

$$\begin{bmatrix} \boldsymbol{K}_{\mathrm{A},k}^{\mathsf{T}} & \boldsymbol{K}_{\mathrm{V},k}^{\mathsf{T}} \end{bmatrix}^{\mathsf{T}} = \begin{bmatrix} \boldsymbol{R} + \boldsymbol{U}_k \boldsymbol{W}_k \boldsymbol{U}_k^{\mathsf{T}} \end{bmatrix}^{-1} \begin{bmatrix} \boldsymbol{H}_{\mathrm{A},k} & \boldsymbol{H}_{\mathrm{V},k} \end{bmatrix}^{\mathsf{T}} \hat{\boldsymbol{\Sigma}}_{k|k-1}$$

$$\boldsymbol{R} = \mathrm{blkdiag}(\boldsymbol{R}_{\mathrm{A}},\ \boldsymbol{R}_{\mathrm{V}}),\ \ \boldsymbol{U}_k = \mathrm{blkdiag}(\boldsymbol{H}_{\mathrm{A},k},\ \boldsymbol{H}_{\mathrm{V},k}),\ \ \boldsymbol{W}_k = \begin{bmatrix} \lambda_k & 1-\lambda_k \\ \lambda_k & 1-\lambda_k \end{bmatrix} \otimes \hat{\boldsymbol{\Sigma}}_{k|k-1}$$

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Modified Kalman gain computation using the binomial inverse theorem[2]

$$\begin{bmatrix} \boldsymbol{K}_{\mathrm{A},k}^{\mathsf{T}} & \boldsymbol{K}_{\mathrm{V},k}^{\mathsf{T}} \end{bmatrix}^{\mathsf{T}} = \begin{bmatrix} \boldsymbol{R}^{-1} - \boldsymbol{R}^{-1} \boldsymbol{U}_k \boldsymbol{\Gamma}_k \boldsymbol{U}_k^{\mathsf{T}} \boldsymbol{R}^{-1} \end{bmatrix} \begin{bmatrix} \boldsymbol{H}_{\mathrm{A},k} & \boldsymbol{H}_{\mathrm{V},k} \end{bmatrix}^{\mathsf{T}} \hat{\boldsymbol{\Sigma}}_{k|k-1}, \quad \boldsymbol{\Gamma}_k = \boldsymbol{W}_k \left(\boldsymbol{I} + \boldsymbol{U}_k^{\mathsf{T}} \boldsymbol{R}^{-1} \boldsymbol{U}_k \boldsymbol{W}_k \right)^{-1}$$

[2] D. Harville: *Extension of the Gauss-Markov theorem to include the estimation of random effects*, Ann. Statist. vol.4, no. 2, 1976

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Complexity w.r.t. matrix inversions: $\mathcal{O}\left(8D_x^3\right)$ vs. $\mathcal{O}\left((D_{y_{\mathrm{A}}} + D_{y_{\mathrm{V}}})^3\right)$

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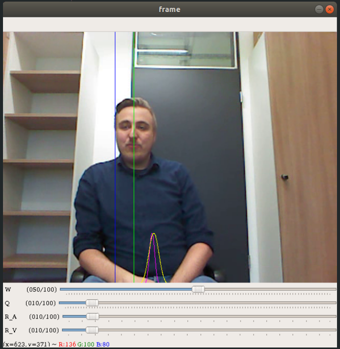
Evaluation

Experimental setup

- KAVTraC audiovisual dataset, recorded in an office room at RUB using the Kinect sensor (7 speakers, $T_{60} \approx 350\,\text{ms}$, 35 min. duration).



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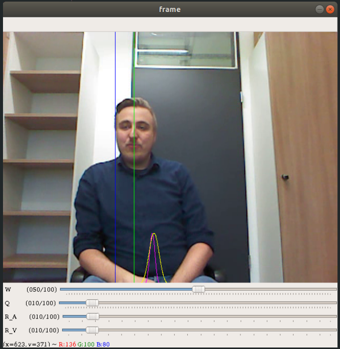

[3] C. Schymura et al.: *Audiovisual speaker tracking using nonlinear dynamical systems with dynamic stream weights*, arXiv, 2019

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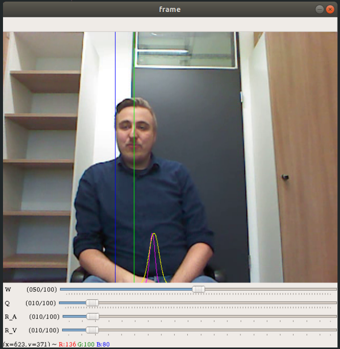
- Four baseline systems: standard EKF, one KF-based and two particle filter-based systems.
- Leave-one-out cross-validation paradigm.



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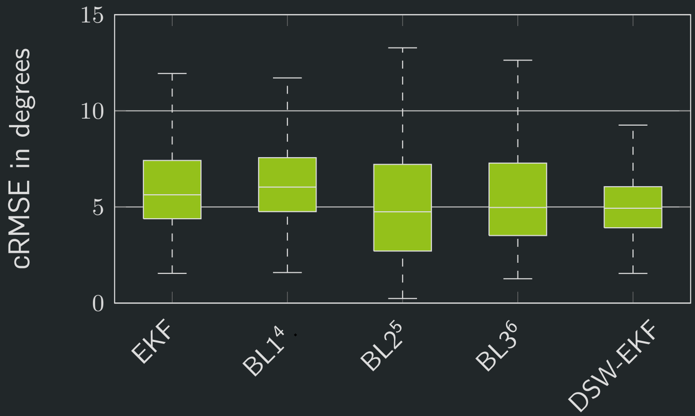
Results



[4] T. Gehrig et al.: *Kalman filters for audio-video source localization*, WASPAA, 2005

[5] S. Gerlach et al.: *2D audio-visual localization in home environments using a particle filter*, ITG Symp., 2012

[6] X. Qian et al.: *3D audio-visual speaker tracking with an adaptive particle filter*, ICASSP, 2017

Conclusions and outlook

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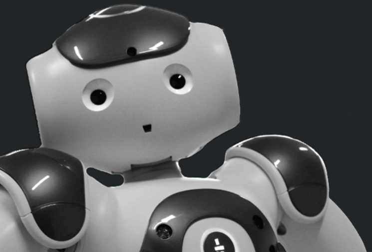
  - Joint optimization of model and DSW estimation in a deep learning framework.
  - Extension to multi-speaker scenarios.



Thank you for your attention!