Sparse Deep Predictive Coding to model visual object recognition

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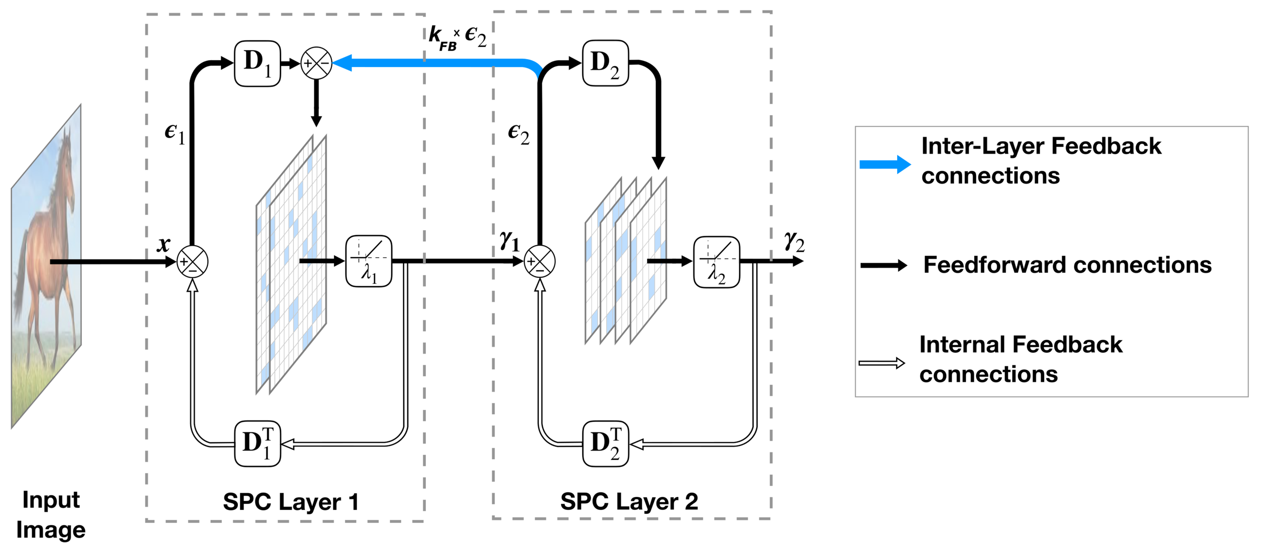
presentation number : 490.02

Introduction

The brain has to solve inverse problems to correctly interpret sensory data and infer the set of causes that generated the sensory inputs. To solve such a problem we use the Sparse Deep Predictive Coding (SDPC) algorithm, which combines Predictive Coding (PC) [3] and Sparse Coding (SC). PC governs interactions between layers. It suggests that feedforward connections transmit prediction error, and feedback connections carry the prediction of the lower level activity. SC is used to model local processing [2]. SDPC minimizes at at each layer the following loss function:

$$\mathcal{L} = \frac{1}{2}\|\gamma_{i-1} - \mathbf{D}_i^T\gamma_i\|_2^2 + \frac{k_{FB}}{2}\|\gamma_i - \mathbf{D}_{i+1}^T\gamma_{i+1}\|_2^2 + \lambda_i\|\gamma_i\|_1 \quad (1)$$

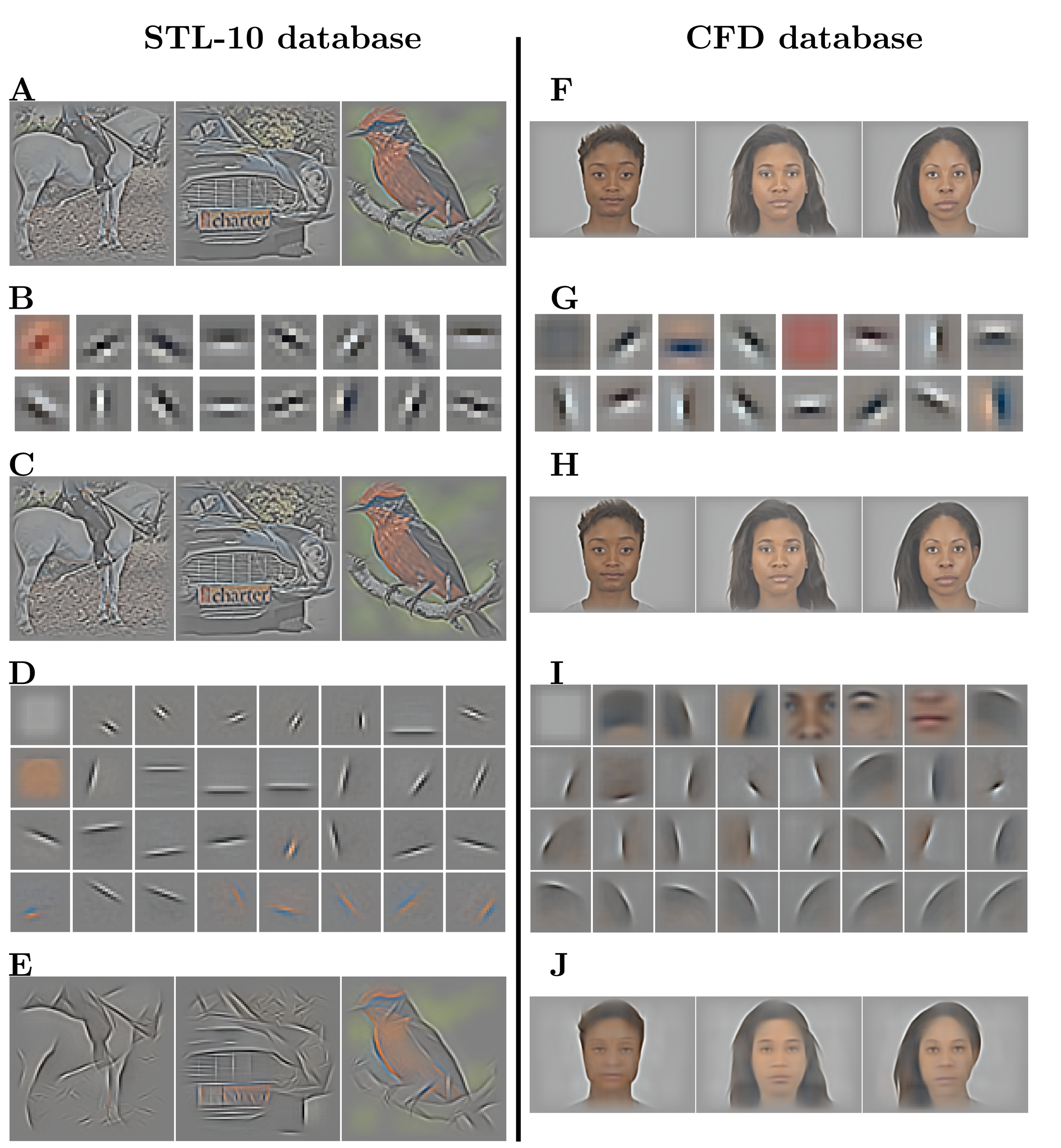
Method



Architecture of a 2-layered SDPC model. In this model γ_i represents the neural activity and ϵ_i is the prediction error at layer i. The synaptic weights are denoted D_i. The level of sparseness is tuned with the soft thresholding parameter λ_i. k_{FB} control the strength of the feedback connection represented with a blue arrow.

Results of the training

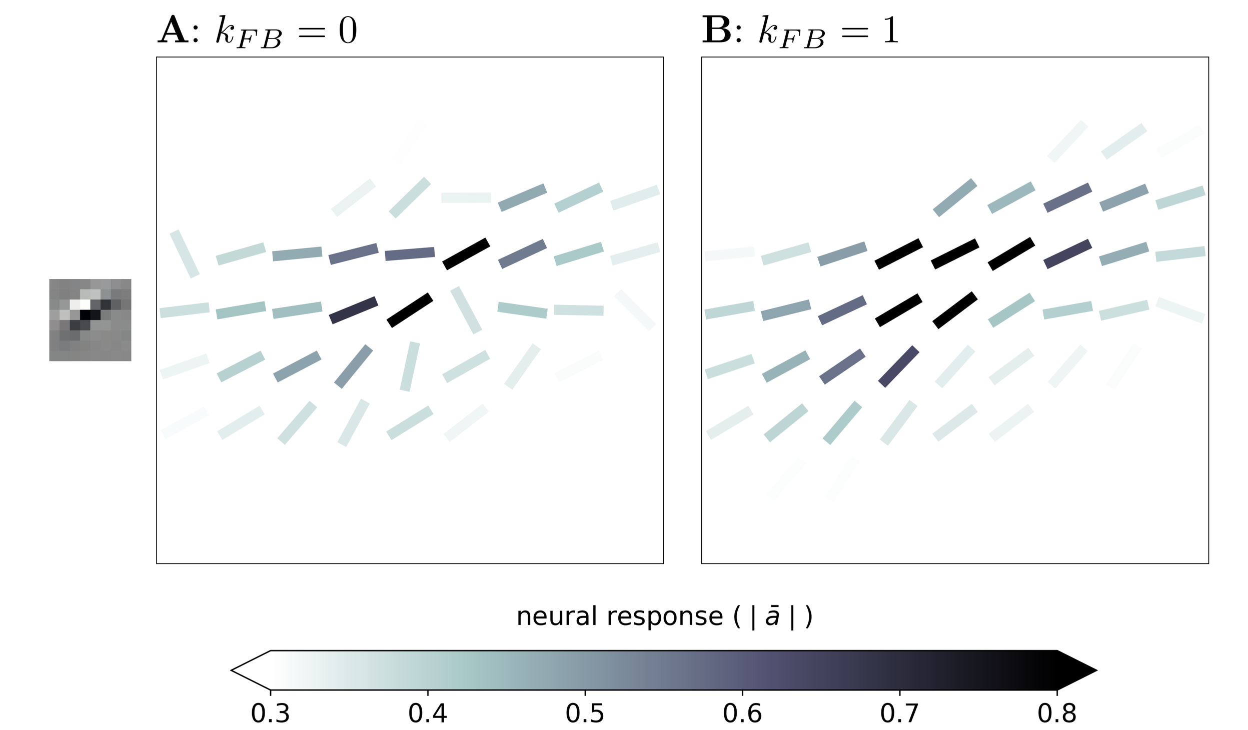
SPDC learns edge-like oriented filters



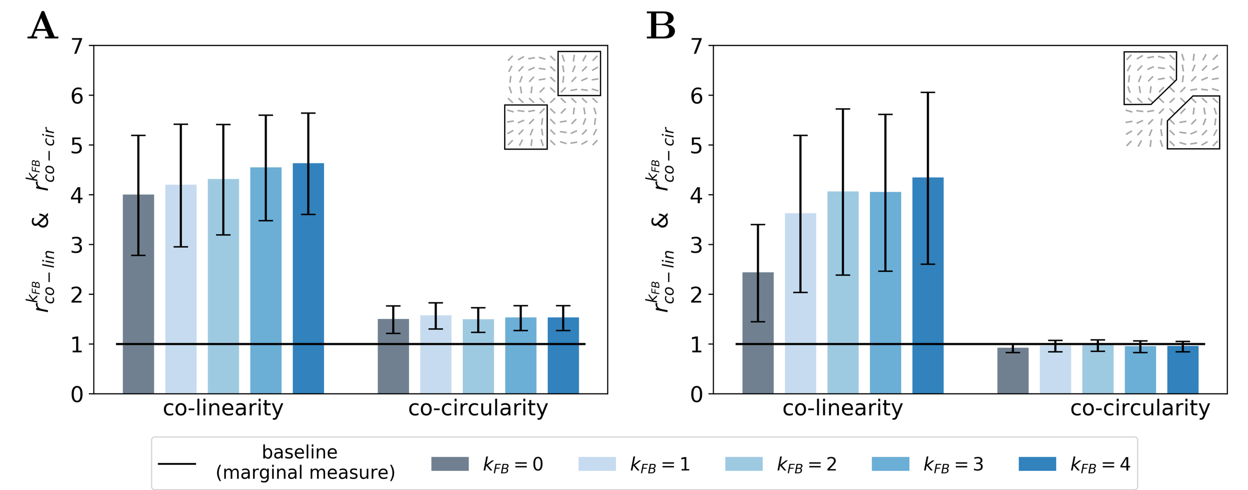
Results of the SDPC training on the STL-10 database (right block) and on the CFD database (left block) with a feedback strength $k_{FB} = 1$. **(A)** & **(F)**: Randomly selected input images. **(B)** & **(G)**: 1^{st} layer RFs of size is 8×8 px on the STL-10 database **(B)** and 9×9 px on the CFD database **(G)**. **(C)** & **(H)**: 1^{st} layer reconstruction. **(D)** & **(I)**: 2^{nd} layer RFs of size 22×22 px on the STL-10 database **(D)** and 33×33 px on the CFD database **(I)**. **(E)** & **(J)**: 2^{nd} layer reconstruction.

SDPC feedback - neural level (1)

SDPC feedback signal reorganizes the V1 interaction map

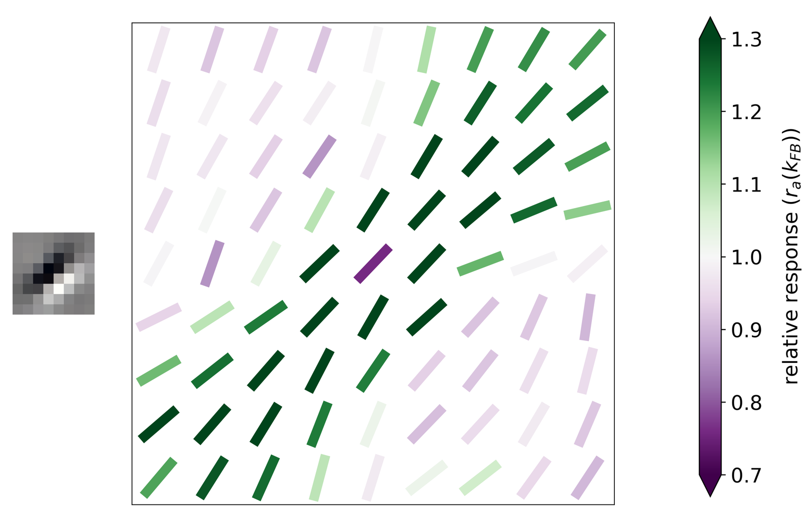


Example of a V1 interaction map centered on neurons strongly responding to a central preferred orientation of 30°. **(A)** With a $k_{FB} = 0$. **(B)** With a $k_{FB} = 1$. The SDPC is trained on STL-10. The color scale being saturated toward both maximum and minimum activity, all the activities above 0.8 or below 0.3 have the same dark green or white color, respectively.

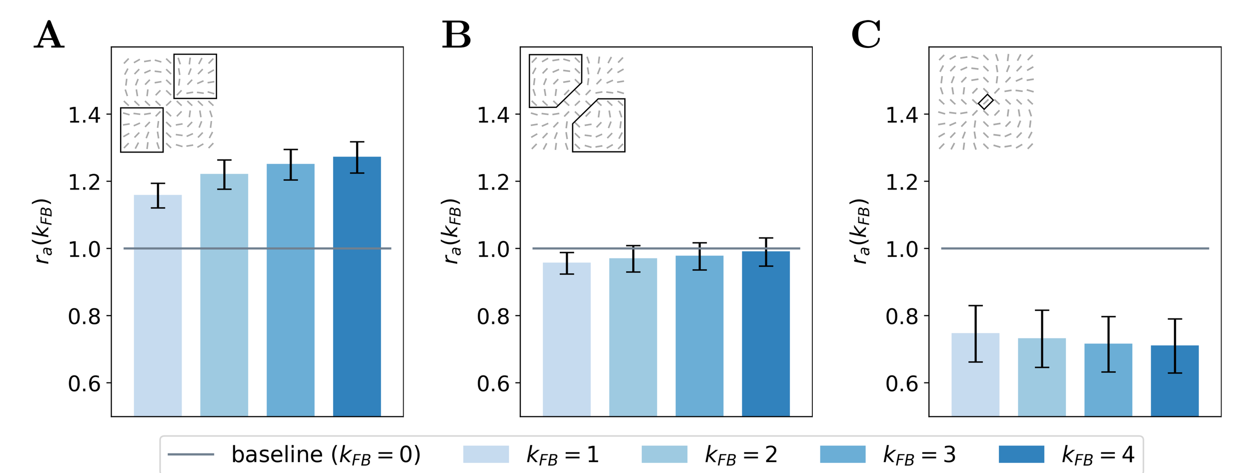


Relative co-linearity and co-circularity of the V1 interaction map w.r.t. marginal co-linearity/co-circularity. **(A)** In the end-zone. **(B)** In the side-zone. Bars' heights represent the median over all the orientations, and error bar are computed as the Median Absolute Deviation. The baseline represents the co-linearity and co-circularity without feedback.

SDPC feedback signals modulate the interaction map activity

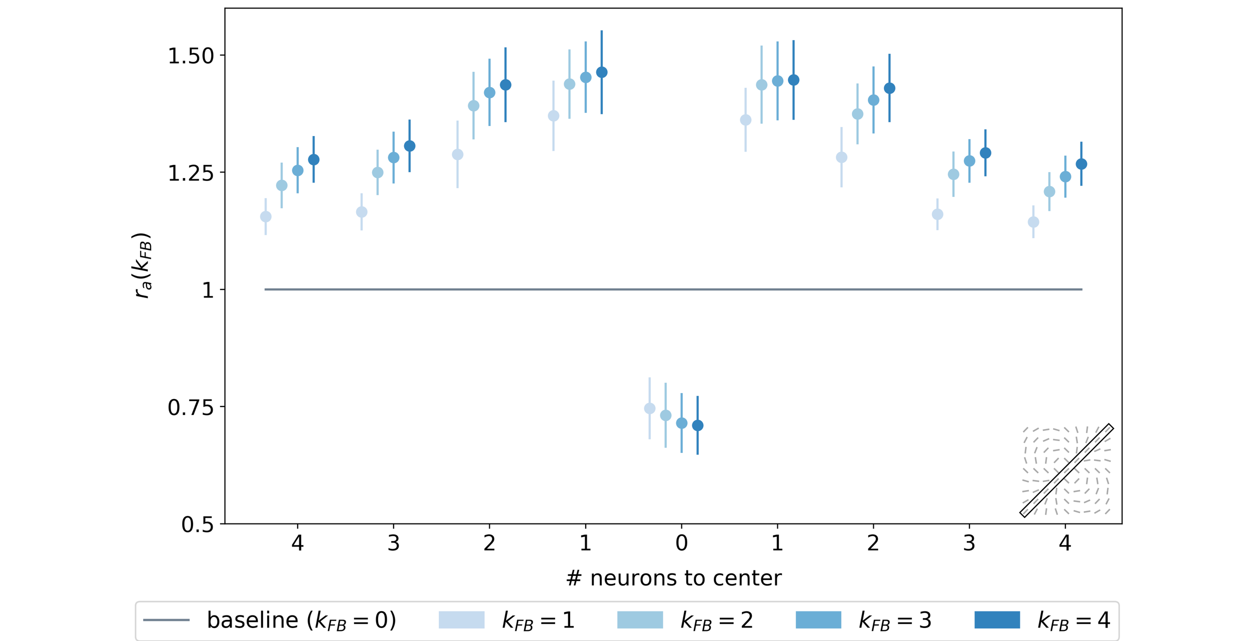


Example of a V1 interaction map centered on neurons strongly responding to a central preferred orientation of 45°, **and colored with the relative response w.r.t. no feedback.** The SDPC is trained on STL-10 and $k_{FB} = 1$. The color scale being saturated toward both maximum and minimum activity, all the activities above 1.3 or below 0.5 have the same dark green or dark purple color, respectively.



Relative response of V1 interaction map w.r.t. no feedback for all central preferred orientations. **(A)** In the end-zone. **(B)** In the side-zone. **(C)** In the center. Bars' height represent the median over all the central preferred orientation, and error bar are computed as the Median Absolute Deviation. The baseline represents the relative response without feedback.

SDPC feedback - neural level (2)



Relative response w.r.t. no feedback along the axis of the central preferred orientation of V1 interaction map. Each point represents the median over all the orientation, and error bar are computed as the Median Absolute Deviation. The x-axis represent the distance, in number of neurons, to the center of the interaction map. The baseline represents the relative response without feedback.

Technical details on interaction map

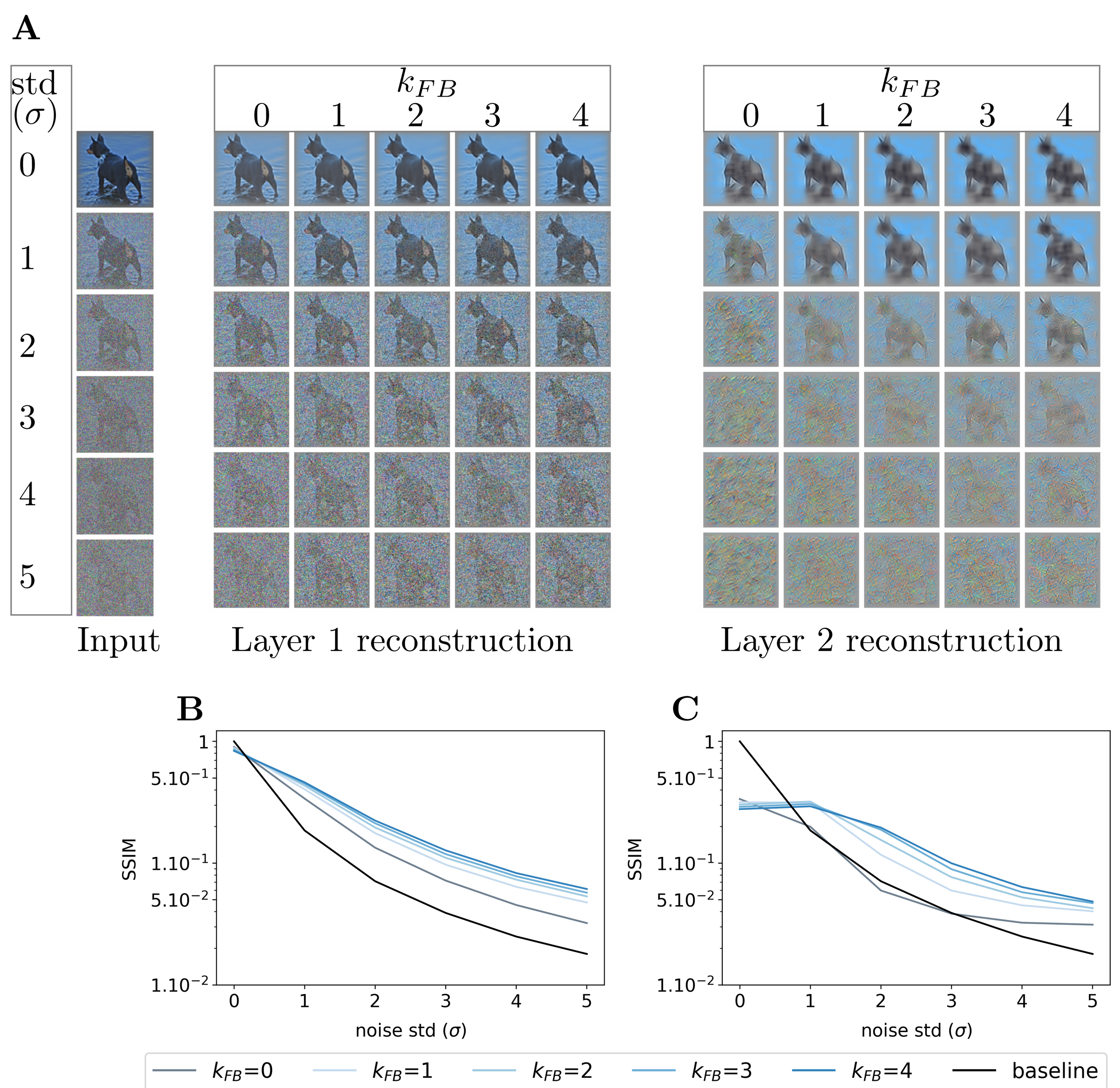
$$\gamma_1 \equiv \gamma_1[\theta, x, y]\, e^{j\theta} \text{and} \quad \mathbf{a}[\theta, x_c, y_c] = \frac{\gamma_1[\theta, x_c, y_c] - \gamma_1[\theta, x_{\sim c}, y_{\sim c}]}{\gamma_1[\theta, x_{\sim c}, y_{\sim c}]}$$

$$\bar{\theta}[x_c, y_c] = atan2\Big(\frac{1}{n}\sum_{\theta=\theta_1}^{\theta_n} \mathbf{a}[\theta, x_c, y_c]sin(\theta), \frac{1}{n}\sum_{\theta=\theta_1}^{\theta_n} \mathbf{a}[\theta, x_c, y_c]cos(\theta)\Big)$$

$$|\bar{\mathbf{a}}[x_c, y_c]| = \frac{1}{n}\sqrt{\Big(\sum_{\theta=\theta_1}^{\theta_n} \mathbf{a}[\theta, x_c, y_c]cos(\theta)\Big)^2 + \Big(\sum_{\theta=\theta_1}^{\theta_n} \mathbf{a}[\theta, x_c, y_c]sin(\theta)\Big)^2}$$

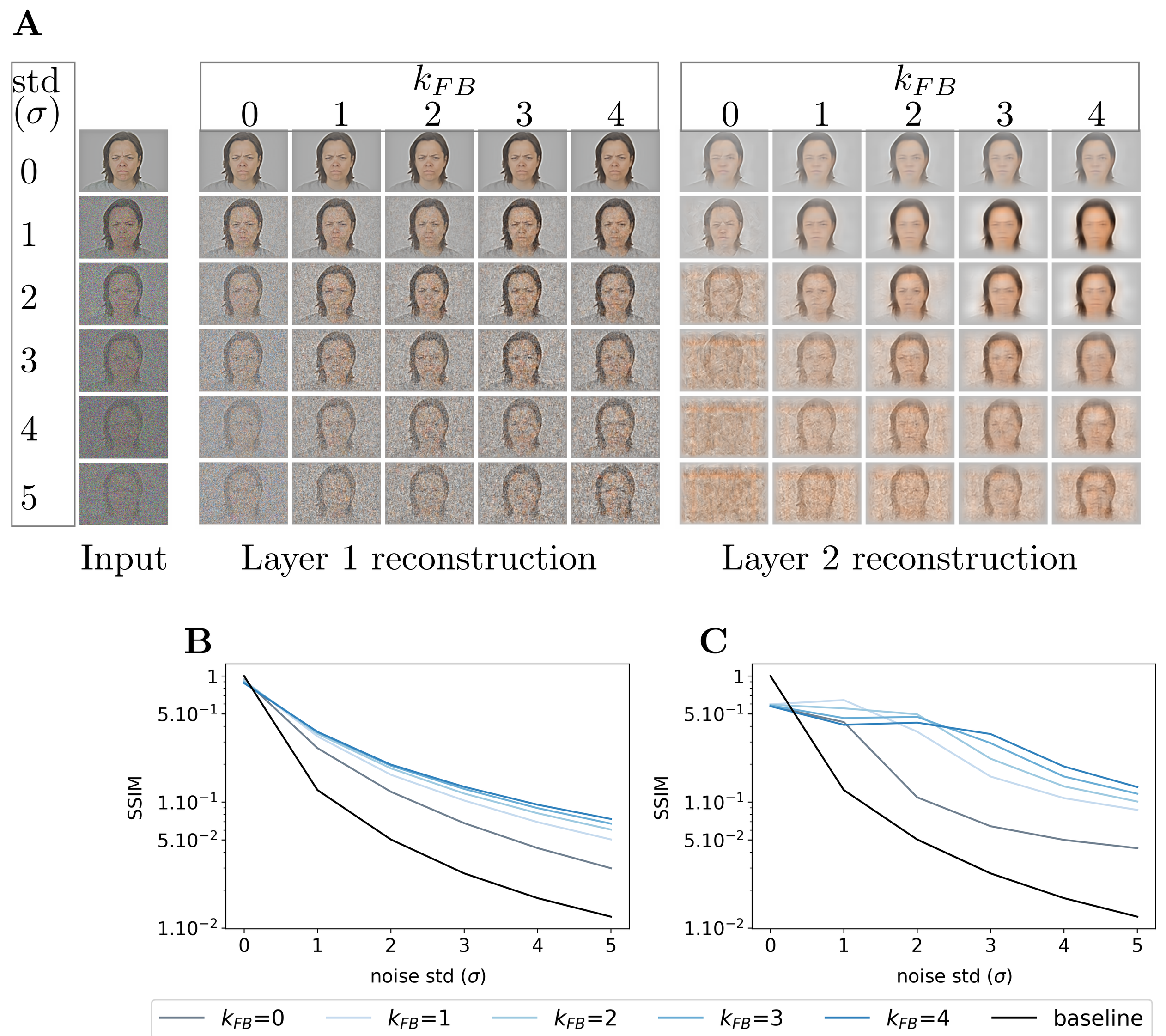
SDPC feedback - representational level (1)

SDPC feedback signal accounts for input denoising



Effect of the feedback strength on blurred images from STL-10 database. (A) In the left block, one image is blurred by Gaussian noise of mean 0 and standard deviation (σ) varying from 0 to 5. The central block exhibits the representations made by the first layer (γ_1^{eff}), and the right-hand block the representations made by the second layer (γ_2^{eff}). Within each of these blocks the feedback strength (k_{FB}) is ranging horizontally from 0 to 4. **(B)** exhibits the SSIM index between non-blurred images and their representations by the first layer of the SDPC. **(C)** exhibits the SSIM index between non-blurred images and their representations by the second layer of the SDPC. All curves represent the median SSIM over 1200 samples and present a logarithmic scale on the y axis. The color code corresponds to the feedback strength, from grey for $k_{FB} = 0$ to darker blue for higher feedback strength. The black line is the baseline, it is the SSIM between blurred and non-blurred input image.

SDPC feedback - representational level (2)



Effect of the feedback strength on blurred images from CFD database. (A) In the left block, one image is blurred by Gaussian noise of mean 0 and standard deviation (σ) varying from 0 to 5. The central block exibits the representations made by the first layer (γ_1^{eff}), and the right-hand block the representations made by the second layer (γ_2^{eff}). Within each of these blocks the feedback strength (k_{FB}) is ranging horizontally from 0 to 4. **(B)** exhibits the SSIM index between non-blurred images and their representations by the first layer of the SDPC. **(C)** exhibits the SSIM index between non-blurred images and their representations by the second layer of the SDPC. All curves represent the median SSIM over 400 samples and present a logarithmic scale on the y axis. The color code corresponds to the feedback strength, from grey for $k_{FB} = 0$ to darker blue for higher feedback strength. The black line is the baseline, it is the SSIM between blurred and non-blurred input image.

Conclusion

- **Neural level**: The SDPC interaction map are very similar to the association field defined by [1]. The SDPC feedback signal increases activity in the end-zone and decreases the activity in the center and in the side-zone of the interaction map. **SDPC feedback signals accounts for contour integration and association field representation in V1.**
- **Representational level**: SDPC feedback signal has the ability to denoise blurred image. **SDPC models models the crucial role of recurrent processing in recognition of degraded object**

THE SDPC ACCOUNTS FOR TWO LEVELS OF ANALYSIS

related article: www.arxiv.com/...

References

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Acknowledgment

This research received funding from the European Union's H2020 programme under the Marie Skłodowska-Curie grant agreement n°713750 and by the Regional Council of Provence-Alpes-Côte d'Azur, A*MIDEX (n°ANR-11-IDEX-0001-02).

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