

DETERMINISTIC DECOUPLING OF GLOBAL FEATURES AND ITS APPLICATION TO DATA ANALYSIS, M. González

Joint work with:

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-] IO-CSIC.

MOTIVATION: TEXTURES



Visual textures in nature

- Portilla-Simoncelli (2000): statistical model for the description of texture images
- Problems: classification, synthesis, transfer,...

MOMENTS IN STATISTICS:

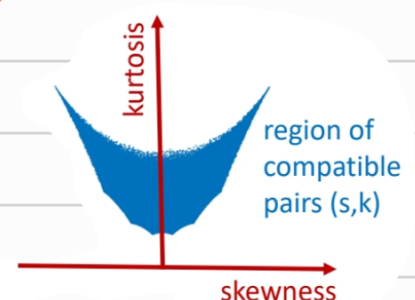
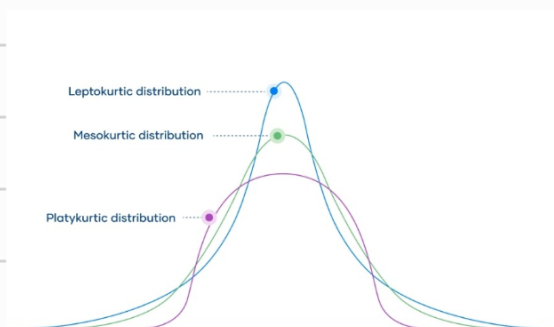
- Mean
- Variance



• Skewness

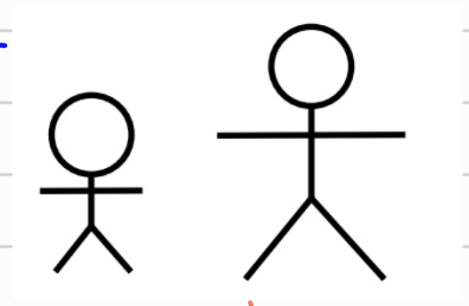
heavily coupled!

• Kurtosis



MAIN OBJECTIVE: DECOUPLING

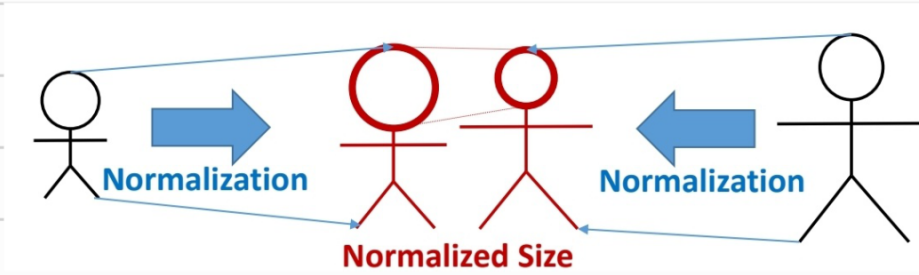
Two measurements: $\begin{cases} \nearrow \text{total size} \\ \searrow \text{head size} \end{cases}$



coupled!

New measurement: heads' relative size

↑ decoupled from total size



equalization

Back to (standardized) moments:

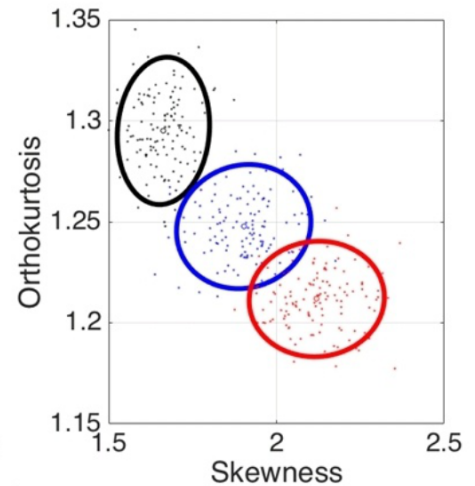
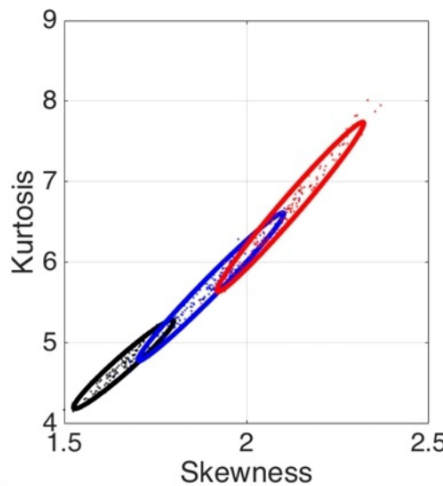
- Mean
- Variance
- Skewness
- Kurtosis

gradients are orthogonal everywhere!

→ gradient is not orthogonal

New:

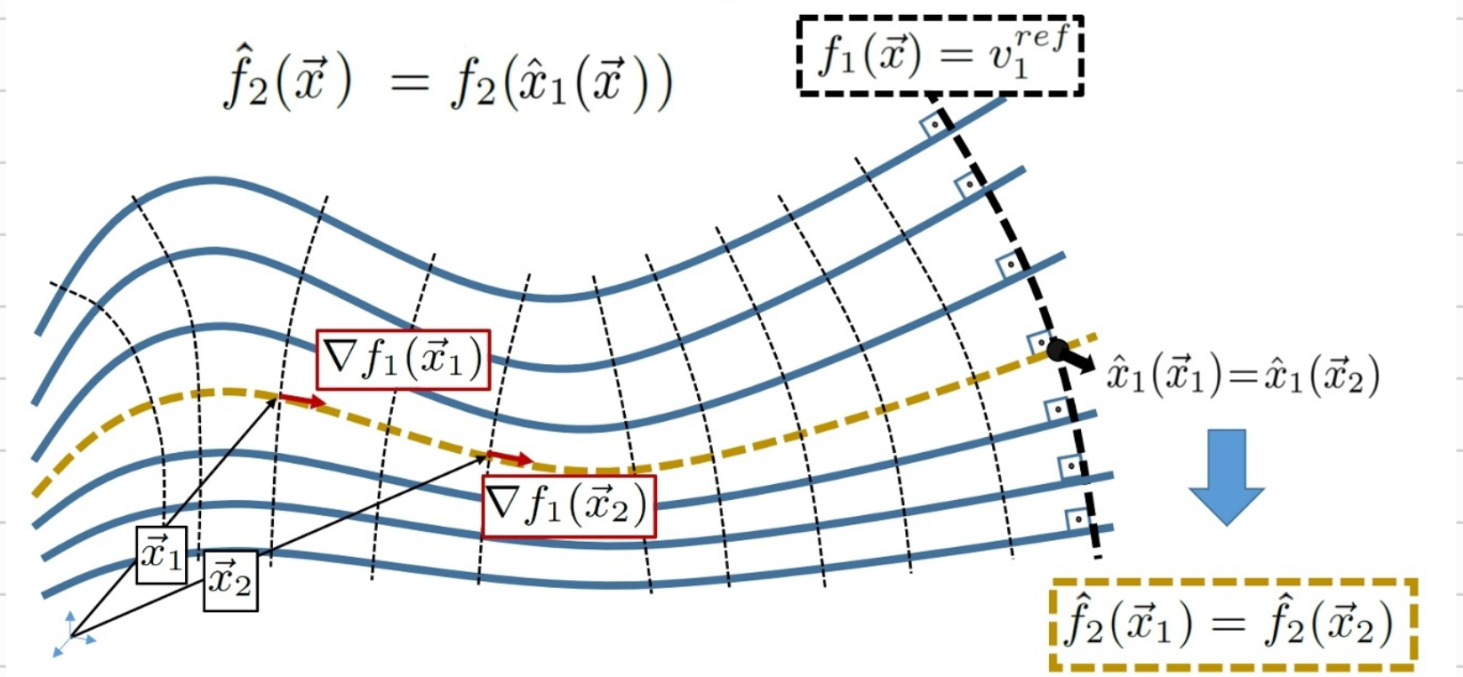
orthokurtosis



DECOUPLING VIA NORMALIZATION

- feature: $f: \mathbb{R}^N \rightarrow \mathbb{R}$
- f_i and f_j are decoupled if $\nabla f_i \perp \nabla f_j$

NAIVE IDEA: surfing invariance manifolds

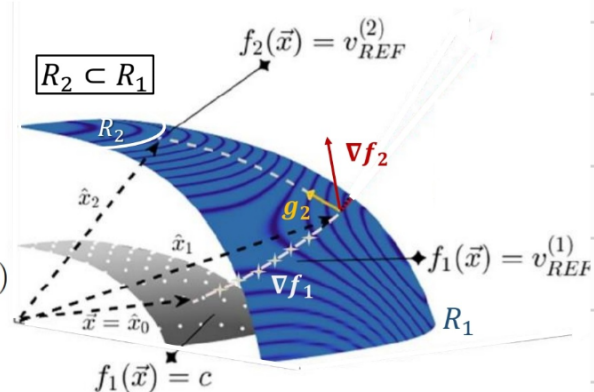


SOME IDEAS OF THE ALGORITHM: $\{f_1, \dots, f_k\}$

- Nested normalization
- Move along the invariance manifold of $\{f_1, \dots, f_k\}$ until we cross the reference manifold.
- Frobenius theorem !!
- Algorithm: $\begin{cases} \rightarrow \text{Narrow path} \\ \rightarrow \text{Broad path} \end{cases} \rightarrow \text{approximate decoupling}$

Require: $\mathbf{x} \in \Omega \setminus \Lambda$, $\{f_j, v_j^{ref}, j = 1, \dots, M\}$

- 1: **Initialization:** $\hat{f}_1 = f_1$; $\mathcal{R}_0 = \Omega \setminus \Lambda$; $\hat{\mathbf{x}}_0(\mathbf{x}) = \mathbf{x}$
- 2: **for** $k = 1$ to $k = M - 1$ **do**
- 3: Compute $\mathbf{g}_k = P_{\mathcal{R}_{k-1}}(\nabla f_k)$
- 4: $\mathbf{y}_k(0) = \hat{\mathbf{x}}_{k-1}(\mathbf{x})$
- 5: Follow \mathbf{g}_k until $f_k(\mathbf{y}_k(t)) = v_k^{ref}$
- 6: $\hat{\mathbf{x}}_k(\mathbf{x}; v_k^{ref}) = \mathbf{y}_k(t)$
- 7: $\hat{f}_{k+1}(\mathbf{x}) = f_{k+1}(\hat{\mathbf{x}}_k)$
- 8: **end for**
- 9: **return** $\{\hat{f}_j(\mathbf{x}), j = 1, \dots, M\}, \hat{\mathbf{x}}_{M-1}(\mathbf{x})$



APPLICATIONS: Style transfer

- Canham - Martín - Bertalmio - Portilla
Use higher moments



- Portilla + UV + UJS. Convolutional networks for image recognition.

