TECHNISCHE UNIVERSITÄT DRESDEN

Faculty of Computer Science Institute of Systems Architecture, Privacy and Data Security Research Group

Linear Row and Column Predictors for the Analysis of Resized Images

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Technische Universität Dresden

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Resampling Detection

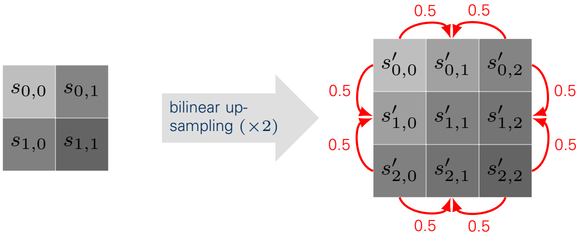
- resizing / scaling is a common digital image processing primitive
  - pre- or post-processing; or part of more complex manipulations

Andrea Sommer, Doc Baumann

Resampling Detection

- resizing / scaling is a common digital image processing primitive
  - pre- or post-processing; or part of more complex manipulations

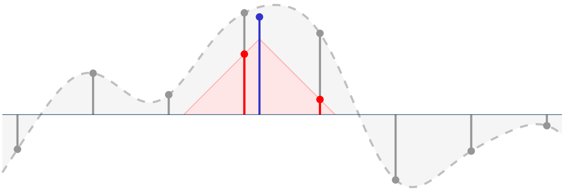
- **resampling** to a new image grid; involves an **interpolation** step
- interpolation introduces **periodic linear correlations** between neighboring pixels



- analysis and detection of interpolation artifacts is of interest in forensic settings, but also in steganalysis or digital watermarking

Interpolation of 1D Signals

$$s(x) = \sum_{\chi=-\infty}^{\infty} h(x-\chi)s(\chi) \qquad (x \in \mathbb{R}, \chi \in \mathbb{Z})$$



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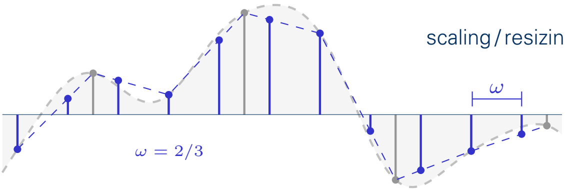
scaling / resizing: $x = \omega\chi'$



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  - $\omega = \frac{q}{p}$ with $p \perp q \quad \Longrightarrow \quad \delta_{\omega\chi'} = \delta_{\omega(\chi'+p)}$
  - interpolation weights are periodic with p

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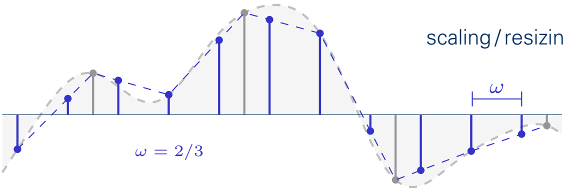

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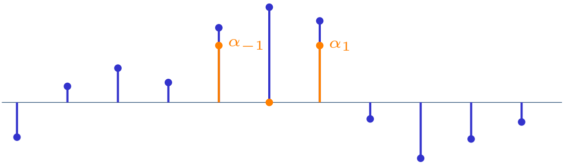
\end{aligned}\right\}$$

linear dependencies between neighboring samples

Analysis of Resampled Signals

- state-of-the-art resampling detection relies on **linear predictor residue**
  [Popescu & Farid, TSP 2005], [Kirchner, MMSec 2008]



- samples are modeled as linear combination of their neighbors

$$e_i = s'_i - \sum_{\substack{|k| \leq K \\ k \neq 0}} \alpha_k \, s'_{i+k}$$

- large absolute prediction errors indicate minor degree of linear dependence
- interpolation causes **periodic artifacts in the residue signal** e_i

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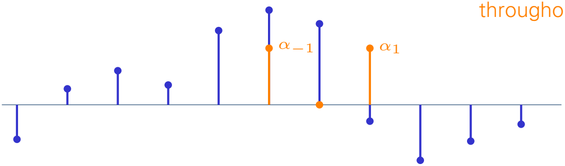

fixed predictor coefficients throughout the whole signal

(EM estimate or pre-set)

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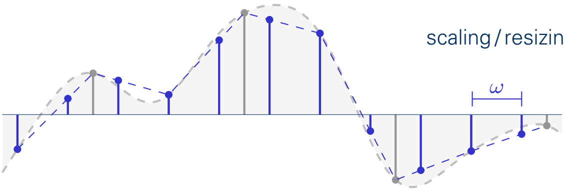

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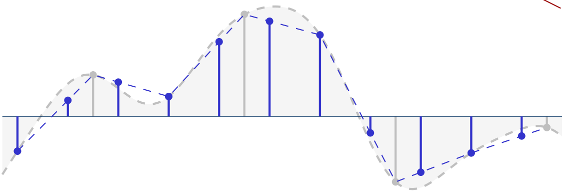
“average” correlation



$$
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$$

linear **periodic** (variable) dependencies between neighboring samples

A Refined Model

- fixed predictor coefficients $\boldsymbol{\alpha}$ are not ideal to **model** interpolated signals
- phase-dependent coefficients $\boldsymbol{\alpha}^{(i)}$ would better reflect the actual correlation for a specific sample s'_i

$$\boxed{s'_i = \sum_{\substack{|k| \leq K \\ k \neq 0}} \alpha_k^{(i)}\, s'_{i+k} + e_i}$$

- scaling / resizing with scaling factor $\omega^{-1} = p/q$: $\boldsymbol{\alpha}^{(i)} = \boldsymbol{\alpha}^{(i+lp)}$

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- downsampling: model error depends on interpolation kernel and scaling factor (never vanishes for linear interpolation kernel)

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$$\boxed{s'_i - \eta_i = \sum_{\substack{|k|\leq K \\ k\neq 0}} \alpha_k^{(i)} \left(s'_{i+k} - \eta_{i+k}\right) + e_i}$$

quantization / rounding noise

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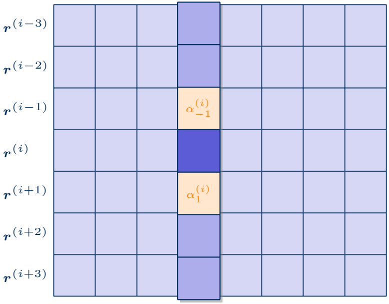
- explicit model for linear correlations in scaled / resized signals
- estimation of coefficients $\boldsymbol{\alpha}^{(i)}$?

Resizing of Digital Images

- ▶ assumption: **separable interpolation kernel**
  - ▷ effects of resizing can be analyzed for each row / column independently



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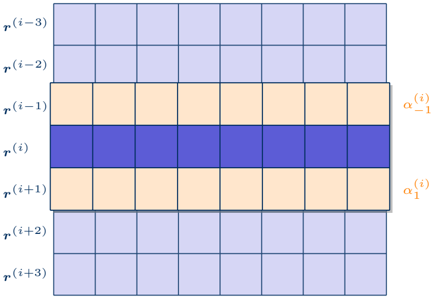

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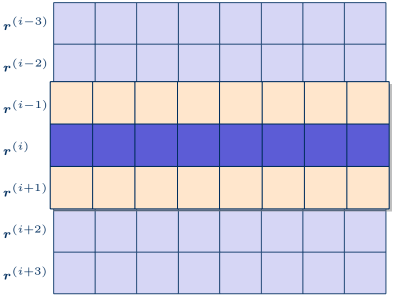

- linear regression model to estimate 'tailored' predictor coefficients

$$\boldsymbol{r}^{(i)} - \boldsymbol{\eta}^{(i)} = \sum_{\substack{|k| \leq K \\ k \neq 0}} \alpha_k^{(i)} \left(\boldsymbol{r}^{(i-k)} - \boldsymbol{\eta}^{(i-k)} \right) + \boldsymbol{e}^{(i)}$$

$$= \left(\mathbf{R}^{(i)} - \mathbf{N}^{(i)} \right) \cdot \boldsymbol{\alpha}^{(i)} + \boldsymbol{e}^{(i)}$$

- one regression per row / column

Estimation of Predictor Coefficients

- **ideal case:** vanishing model error $\boldsymbol{e}^{(i)}$ (e. g. for upsampling)

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measurement errors on both sides

- total least squares (TLS) estimate $\hat{\boldsymbol{\alpha}}^{(i)}$

$$\hat{\boldsymbol{r}}^{(i)} = \hat{\mathbf{R}}^{(i)} \cdot \hat{\boldsymbol{\alpha}}^{(i)} \quad \text{such that} \quad \left\| \left[\mathbf{R}^{(i)}, \boldsymbol{r}^{(i)}\right] - \left[\hat{\mathbf{R}}^{(i)}, \hat{\boldsymbol{r}}^{(i)}\right] \right\|_F \to \min$$

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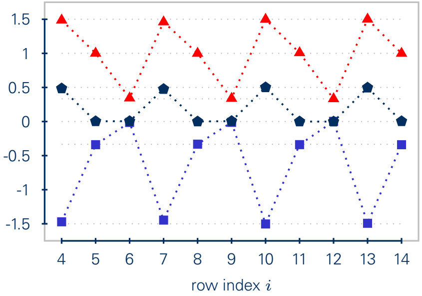
example: estimates for 150 % bilinear upsampling ($\omega = 2/3, K = 3$)



	theoretical coefficients		
$\hat{\alpha}_1^{(i)}$	$\frac{3}{2}$	1	$\frac{1}{3}$
$\hat{\alpha}_3^{(i)}$	$\frac{1}{2}$	0	0
$\hat{\alpha}_2^{(i)}$	$-\frac{3}{2}$	$-\frac{1}{3}$	0

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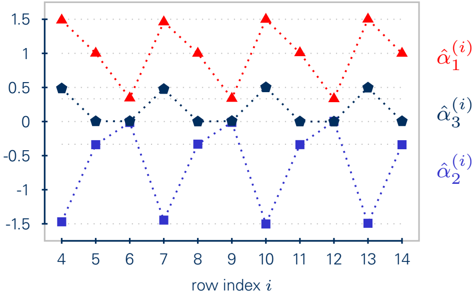

- periodic artifacts in predictor coefficients can be exploited for detection of resizing
- 'direct' analysis instead of implicit measurement via the predictor residue

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$$\boldsymbol{r}^{(i)} - \left(\boldsymbol{\eta}^{(i)} + \boldsymbol{e}^{(i)}\right) = \left(\mathbf{R}^{(i)} - \mathbf{N}^{(i)}\right) \cdot \boldsymbol{\alpha}^{(i)}$$

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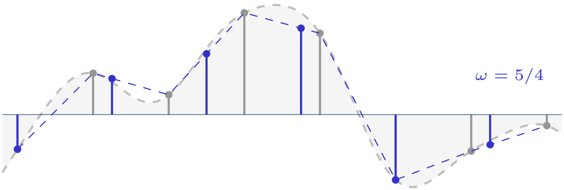
- TLS estimates may become instable
- **but:** resampling detection does not require *exact* knowledge of $\boldsymbol{\alpha}$

A Simplified Model



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linear dependencies, but no perfect model

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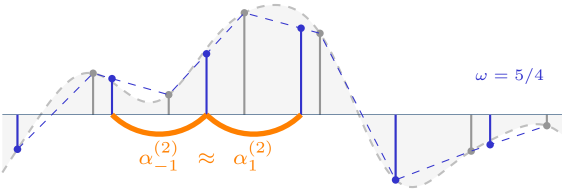

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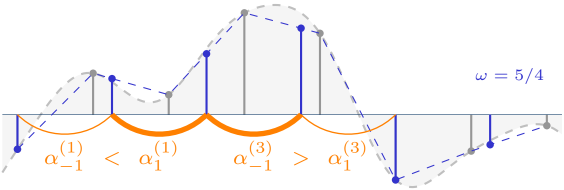
- bias towards left and right neighbors gradually varies



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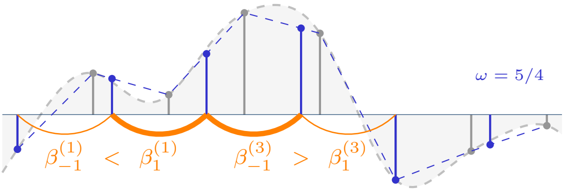

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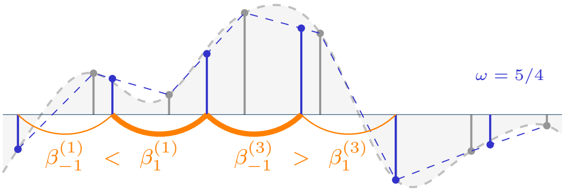

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  - weighted least squares (WLS) estimate $\hat{\boldsymbol{\beta}}^{(i)}$

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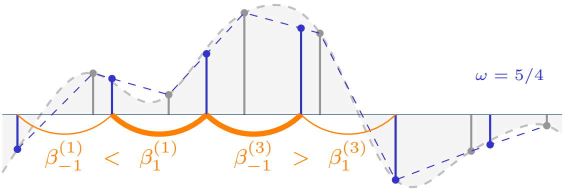

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$w_j^{(i)} \propto \left(const + \mathsf{localVar}\left(r_j^{(i)}\right)\right)^{-1}$

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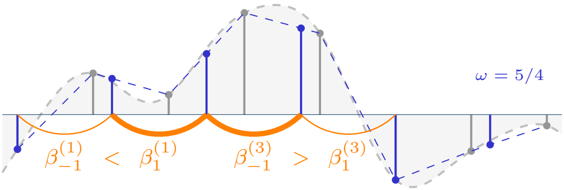

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- one possible (very coarse) analysis: $\boxed{d_i = \hat{\beta}_{-1}^{(i)} - \hat{\beta}_{1}^{(i)}}$

Spectral Analysis

- resizing causes periodic artifacts in the predictor coefficients, or their differences d_i
- typical detectors work in the frequency domain (Fourier spectrum)

but: estimated coefficients are error-prone and hardly exhibit a perfectly periodic behavior

▷ robust spectral density estimation

here: based on Spearman's rank correlation coefficient [Ahdesmäki et al., BMC Bioinf. 2005]

$$S_\varrho(f) = \sum_{l=-L}^{L} \varrho(l) \exp(-2\pi i f l)$$

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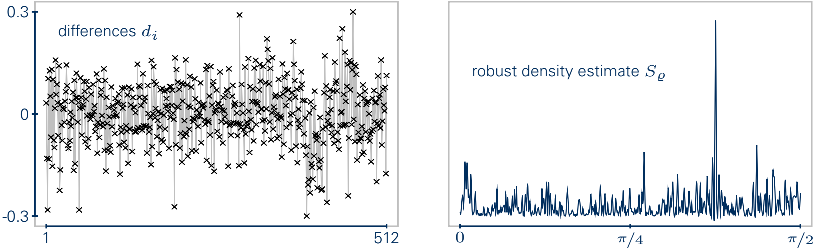
downsampling to 80 %, cubic spline interpolation, 512 × 512 image



Experimental Setup

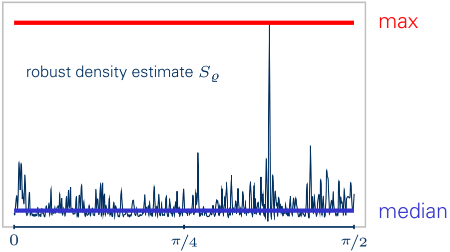
- test database of ≈1100 never-compressed images (five different camera models) from the **Dresden Image Database** [Gloe & Böhme, ACM SAC 2010]
- resizing of the green channel with ImageMagick's `convert`
  - four different interpolation kernels

	bilinear	bicubic	windowed sinc	cubic spline
`-filter`	`Triangle`	`Catrom`	`Lanczos`	`Cubic`

- analysis of the center 512×512 region, neighborhood size $K = 3$

decision criterion

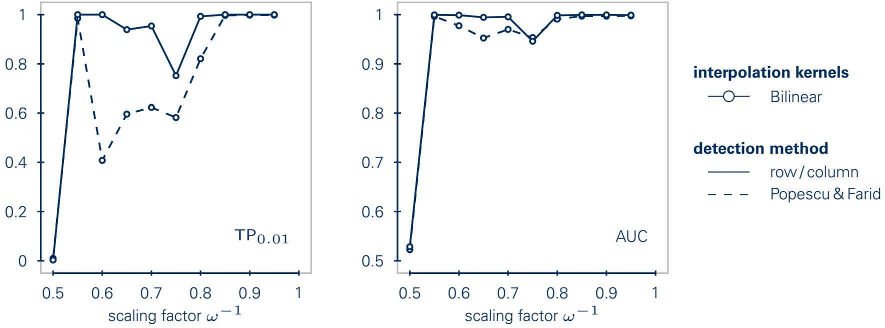
$$\rho = \frac{\max S_\varrho}{\text{median}\, S_\varrho}$$



Results for Downsampling

- benchmark detector: Popescu & Farid's EM-based global predictor [Popescu & Farid, 2005]

  detection rate at 1% false acceptance rate ($\text{TP}_{0.01}$), area under the ROC curve (AUC)



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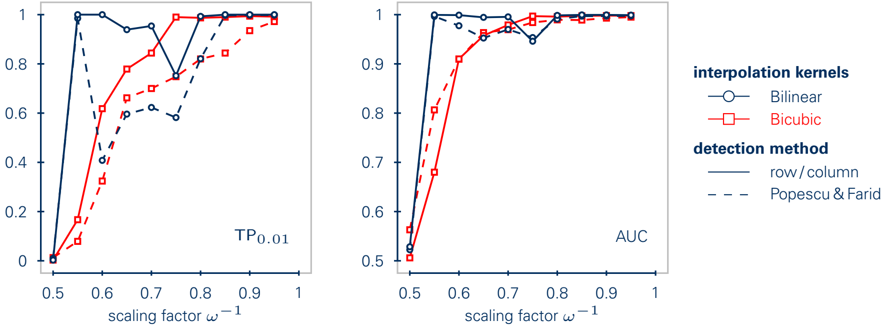

- superior (or at least comparable) detection results for row / column model

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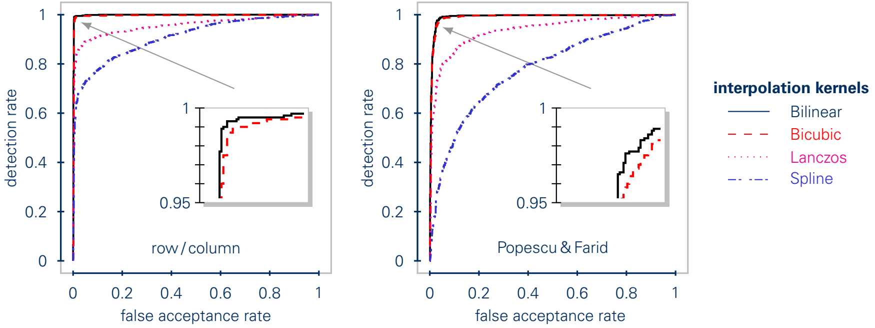
  ROC curves for downsampling to 80 %



- row / column model has strengths for more sophisticated kernels

Concluding Remarks

- characteristic structure of resized images suggests row / column predictors to analyze traces of interpolation
  - one linear regression per row / column
  - measure periodic artifacts in a series of predictor coefficients
- experiments show promising results compared to state-of-the-art

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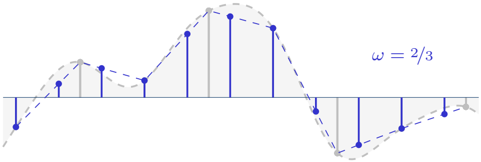

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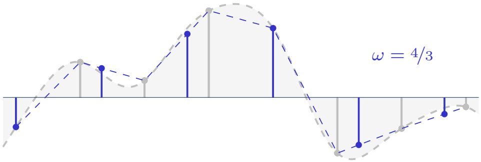

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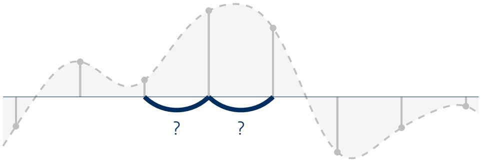

Thanks for your attention

Questions?

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Technische Universität Dresden

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