Linear Row and Column Predictors for the Analysis of Resized Images

12th ACM Workshop on Multimedia and Security
MM&Sec 2010

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Rome, Italy, 2010/09/09
Resampling Detection

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

\[ s(x) = \sum_{\chi=-\infty}^{\infty} h(x - \chi) s(\chi) \quad (x \in \mathbb{R}, \chi \in \mathbb{Z}) \]

- interpolation weights \( h(x - \chi) \) depend on the relative position \( \delta_x = x - \lfloor x \rfloor \), which is a periodic function: \( \delta_x = \delta_{x+1} \)
Interpolation of 1D Signals

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scaling / resizing: \( x = \omega \chi' \)

\[ \omega = \frac{2}{3} \]

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- \( \omega = \frac{q}{p} \) with \( p \perp q \) \( \implies \delta_{\omega \chi'} = \delta_{\omega (\chi'+p)} \)

- Interpolation weights are periodic with \( p \)
Interpolation of 1D Signals

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scaling / resizing: \( x = \omega \chi' \)

scaling factor: \( \omega^{-1} \)

\[
\begin{align*}
s_3' &= 1s_2 \\
s_4' &= \frac{1}{3}s_2 + \frac{2}{3}s_3 \\
s_5' &= \frac{2}{3}s_3 + \frac{1}{3}s_4 \\
s_6' &= 1s_4 \\
s_7' &= \frac{1}{3}s_4 + \frac{2}{3}s_5
\end{align*}
\]

linear dependencies between neighboring samples

\( \omega = 2/3 \)
state-of-the-art resampling detection relies on **linear predictor residue**

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

samples are modeled as linear combination of their neighbors

large absolute prediction errors indicate minor degree of linear dependence

interpolation causes **periodic artifacts in the residue signal** \( e_i \)
Analysis of Resampled Signals

- state-of-the-art resampling detection relies on **linear predictor residue**
  
  \[ e_i = s_i' - \sum_{|k| \leq K} \alpha_k s_{i+k} \]
  
  (EM estimate or pre-set)

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linear dependencies between neighboring samples

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Analysis of Resampled Signals

- fixed predictor coefficients $\alpha$ are not ideal to model interpolated signals

\[
\begin{align*}
  s_3' &= \frac{1}{2} s_0' - \frac{3}{2} s_1' + \frac{3}{2} s_2' + \frac{3}{2} s_4' - \frac{3}{2} s_5' + \frac{1}{2} s_6' \\
  s_4' &= \frac{1}{3} s_3' + \frac{2}{3} s_5' - \frac{1}{3} s_6' \\
  s_5' &= -\frac{1}{3} s_3' + s_4' + \frac{1}{3} s_6' \\
  s_6' &= \frac{1}{2} s_3' - \frac{3}{2} s_4' + \frac{3}{2} s_5' + \frac{3}{2} s_7' - \frac{3}{2} s_8' + \frac{1}{2} s_9' \\
  s_7' &= \frac{1}{3} s_6' + s_8' - \frac{1}{3} s_9'
\end{align*}
\]

"average" correlation
A Refined Model

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

\[
s'_i = \sum_{|k| \leq K} \alpha^{(i)}_k s'_{i+k} + e_i
\]

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

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

upsampling: $\forall i \exists \alpha^{(i)} \in \mathbb{R}$ (for suitable neighborhood sizes $K$)
A Refined Model

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

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

- scaling/resizing with scaling factor $\omega^{-1} = p/q$: $\alpha^{(i)} = \alpha^{(i+lp)}$
- upsampling: $\forall i \exists \alpha^{(i)} e_i = 0$ (for suitable neighborhood sizes $K$)
- downsampling: model error depends on interpolation kernel and scaling factor (never vanishes for linear interpolation kernel)
A Refined Model

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

\[ s'_i - \eta_i = \sum_{|k| \leq K, k \neq 0} \alpha^{(i)}_k (s'_{i+k} - \eta_{i+k}) + e_i \]

quantization/rounding noise

- scaling/resizing with scaling factor $\omega^{-1} = p/q$: $\alpha^{(i)} = \alpha^{(i+lp)}$
- upsampling: $\forall i \exists \alpha^{(i)} e_i = 0$ (for suitable neighborhood sizes $K$)
- downsampling: model error depends on interpolation kernel and scaling factor (never vanishes for linear interpolation kernel)

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

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Resizing of Digital Images

- assumption: **separable interpolation kernel**
- effects of resizing can be analyzed for each row/column independently
Resizing of Digital Images

▶ assumption: **separable interpolation kernel**

- effects of resizing can be analyzed for each row/column independently
- all pixels within one row/column are equally correlated with their vertical/horizontal neighbors

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Resizing of Digital Images

- **assumption:** **separable interpolation kernel**
  - effects of resizing can be analyzed for each row/column independently
  - all pixels within one row/column are equally correlated with their vertical/horizontal neighbors

\[
\begin{align*}
r(i-3) & \quad r(i-2) & \quad r(i-1) & \quad r(i) & \quad r(i+1) & \quad r(i+2) & \quad r(i+3) \\
\end{align*}
\]

- linear regression model to estimate ‘tailored’ predictor coefficients

\[
\begin{align*}
r(i) - \eta(i) &= \sum_{|k| \leq K, k \neq 0} \alpha_k^{(i)} \left( r(i-k) - \eta(i-k) \right) + e^{(i)} \\
&= (R^{(i)} - N^{(i)}) \cdot \alpha^{(i)} + e^{(i)}
\end{align*}
\]

- one regression per row/column
Estimation of Predictor Coefficients

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

$$r^{(i)} - \eta^{(i)} = \left( R^{(i)} - N^{(i)} \right) \cdot \alpha^{(i)}$$
Estimation of Predictor Coefficients

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

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

measurement errors on both sides

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

$$ \hat{r}^{(i)} = \hat{R}^{(i)} \cdot \hat{\alpha}^{(i)} \quad \text{such that} \quad \left\| \begin{bmatrix} R^{(i)} & r^{(i)} \end{bmatrix} - \begin{bmatrix} \hat{R}^{(i)} & \hat{r}^{(i)} \end{bmatrix} \right\|_F \to \min $$
Estimation of Predictor Coefficients

**ideal case:** vanishing model error $e(i)$ (e.g. for upsampling)

$$r(i) - \eta(i) = (R(i) - N(i)) \cdot \alpha(i)$$

measurement errors on both sides

**total least squares (TLS) estimate** $\hat{\alpha}(i)$

$$\hat{r}(i) = \hat{R}(i) \cdot \hat{\alpha}(i)$$

such that $\| [R(i), r(i)] - [\hat{R}(i), \hat{r}(i)] \|_F \rightarrow \min$
Estimation of Predictor Coefficients

- **ideal case:** vanishing model error $e^{(i)}$ (e.g. for upsampling)
  \[ r^{(i)} - \eta^{(i)} = \left( R^{(i)} - N^{(i)} \right) \cdot \alpha^{(i)} \]

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

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

![Graph showing estimated coefficients]

- theoretical coefficients
  \[
  \hat{\alpha}_1^{(i)} = \frac{3}{2}, \quad 1, \quad \frac{1}{3}
  \]
  \[
  \hat{\alpha}_2^{(i)} = -\frac{3}{2}, \quad -\frac{1}{3}, \quad 0
  \]
  \[
  \hat{\alpha}_3^{(i)} = \frac{1}{2}, \quad 0, \quad 0
  \]

row index $i$
Estimation of Predictor Coefficients

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

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Example: estimates for 150 % bilinear upsampling ($\omega = \frac{2}{3}, K = 3$)

- periodic artifacts in predictor coefficients can be exploited for detection of resizing
- ‘direct’ analysis instead of implicit measurement via the predictor residue
Estimation of Predictor Coefficients

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

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

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

- ideal world hardly ever matches reality; model error is negligible only if
  - interpolation parameters permit a complete model
  - neighborhood size is chosen correctly

- TLS estimates may become unstable

- but: resampling detection does not require *exact* knowledge of $\alpha$
Estimation of Predictor Coefficients

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

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

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▶ ideal world hardly ever matches reality; model error is negligible only if

▶ interpolation parameters permit a complete model $\rightarrow$ downsampling?

▶ neighborhood size is chosen correctly $\rightarrow$ unknown!
Estimation of Predictor Coefficients

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

\[ r^{(i)} - \eta^{(i)} = \left( R^{(i)} - N^{(i)} \right) \cdot \alpha^{(i)} \]

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

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▶ interpolation parameters permit a complete model

▶ neighborhood size is chosen correctly

→ downsampling? → unknown!

▶ large model error violates homoscedasticity assumption

\[ r^{(i)} - \left( \eta^{(i)} + e^{(i)} \right) = \left( R^{(i)} - N^{(i)} \right) \cdot \alpha^{(i)} \]

▶ TLS estimates may become instable
Estimation of Predictor Coefficients

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

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

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- ideal world hardly ever matches reality; model error is negligible only if
  - interpolation parameters permit a complete model → downampling?
  - neighborhood size is chosen correctly → unknown!

- large model error violates homoscedasticity assumption

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

- TLS estimates may become unstable

- **but:** resampling detection does not require *exact* knowledge of $\alpha$
A Simplified Model

\[ s_0' = s_0 \]
\[ s_1' = \frac{3}{4} s_1 + \frac{1}{4} s_2 \]
\[ s_2' = \frac{1}{2} s_2 + \frac{1}{2} s_3 \]
\[ s_3' = \frac{1}{4} s_3 + \frac{3}{4} s_4 \]
\[ s_4' = s_5 \]

linear dependencies, but no perfect model
A Simplified Model

\[ \omega = \frac{5}{4} \]

\[ s'_0 = s_0 \]
\[ s'_1 = \frac{3}{4} s_1 + \frac{1}{4} s_2 \]
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\[ s'_3 = \frac{1}{4} s_3 + \frac{3}{4} s_4 \]
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A Simplified Model

- bias towards left and right neighbors gradually varies

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A Simplified Model

- bias towards left and right neighbors gradually varies

- simplified predictor model: \( r^{(i)} = R^{(i)} \cdot \beta^{(i)} + \epsilon^{(i)} \)
A Simplified Model

- bias towards left and right neighbors gradually varies

simplified predictor model:

\[ r^{(i)} = R^{(i)} \cdot \beta^{(i)} + \varepsilon^{(i)} \]

weight least squares (WLS) estimate \( \hat{\beta}^{(i)} \)

\[ \hat{r}^{(i)} = R^{(i)} \cdot \hat{\beta}^{(i)} \] such that

\[ \left\| \left( r^{(i)} - \hat{r}^{(i)} \right) w^{(i)} \right\| \rightarrow \text{min} \]
A Simplified Model

- Bias towards left and right neighbors gradually varies

- Simplified predictor model: \( r^{(i)} = R^{(i)} \cdot \beta^{(i)} + \varepsilon^{(i)} \)

- Weighted least squares (WLS) estimate \( \hat{\beta}^{(i)} \)

\[
\hat{r}^{(i)} = R^{(i)} \cdot \hat{\beta}^{(i)} \quad \text{such that} \quad \left\| \left( r^{(i)} - \hat{r}^{(i)} \right) w^{(i)} \right\| \to \text{min}
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A Simplified Model

- bias towards left and right neighbors gradually varies

- simplified predictor model: \( r^{(i)} = R^{(i)} \cdot \beta^{(i)} + \epsilon^{(i)} \)
  - weighted least squares (WLS) estimate \( \hat{\beta}^{(i)} \)

- one possible (very coarse) analysis: \( d_i = \hat{\beta}_{-1}^{(i)} - \hat{\beta}_1^{(i)} \)
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]

$$S_{\rho}(f) = \sum_{l=-L}^{L} \rho(l) \exp(-2\pi i fl)$$
Spectral Analysis

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

\[
\begin{align*}
\text{differences } d_i \\
\text{robust density estimate } S'_\rho
\end{align*}
\]
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
- Analysis of the center 512 × 512 region, neighborhood size \( K = 3 \)

Decision criterion

\[
\rho = \frac{\text{max } S_\varrho}{\text{median } S_\varrho}
\]
Results for Downsampling


Detection rate at 1% false acceptance rate ($TP_{0.01}$), area under the ROC curve (AUC)

Interpolation kernels
- Bilinear

Detection method
- row/column
- Popescu & Farid
Results for Downsampling


- detection rate at 1% false acceptance rate ($TP_{0.01}$), area under the ROC curve (AUC)

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

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

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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**but** overall results for kernels beyond bilinear interpolation leave room for improvements
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**limitation**

- no straight-forward extension to general geometric transformations
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**future work**
- distinguish upsampled from downsampled images
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**future work**

- distinguish upsampled from downsampled images

\[ \omega = \frac{4}{3} \]
Concluding Remarks

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  - one linear regression per row/column
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**future work**
- distinguish upsampled from downsampled images
- incorporate image models
Thanks for your attention

Questions?

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Matthias Kirchner gratefully receives a doctorate scholarship from Deutsche Telekom Stiftung, Bonn, Germany.