Image Fusion:
Principles, Methods, and Applications

Tutorial EUSIPCO 2007
Lecture Notes

Jan Flusser, Filip Šroubek, and Barbara Zitová
Institute of Information Theory and Automation
Academy of Sciences of the Czech Republic
Pod vodárenskou věží 4, 182 08 Prague 8, Czech Republic
E-mail: {flusser,sroubekf,zitova}@utia.cas.cz
Introduction

The term *fusion* means in general an approach to extraction of information acquired in several domains. The goal of *image fusion* (IF) is to integrate complementary multisensor, multitemporal and/or multiview information into one new image containing information the quality of which cannot be achieved otherwise. The term quality, its meaning and measurement depend on the particular application.

Image fusion has been used in many application areas. In remote sensing and in astronomy, multisensor fusion is used to achieve high spatial and spectral resolutions by combining images from two sensors, one of which has high spatial resolution and the other one high spectral resolution. Numerous fusion applications have appeared in medical imaging like simultaneous evaluation of CT, MRI, and/or PET images. Plenty of applications which use multisensor fusion of visible and infrared images have appeared in military, security, and surveillance areas. In the case of multiview fusion, a set of images of the same scene taken by the same sensor but from different viewpoints is fused to obtain an image with higher resolution than the sensor normally provides or to recover the 3D representation of the scene. The multitemporal approach recognizes two different aims. Images of the same scene are acquired at different times either to find and evaluate changes in the scene or to obtain a less degraded image of the scene. The former aim is common in medical imaging, especially in change detection of organs and tumors, and in remote sensing for monitoring land or forest exploitation. The acquisition period is usually months or years. The latter aim requires the different measurements to be much closer to each other, typically in the scale of seconds, and possibly under different conditions.

The list of applications mentioned above illustrates the diversity of problems we face when fusing images. It is impossible to design a universal method applicable to all image fusion tasks. Every method should take into account not only the fusion purpose and the characteristics of individual sensors, but also particular imaging conditions, imaging geometry, noise corruption, required accuracy and application-dependent data properties.

Tutorial structure

In this tutorial we categorize the IF methods according to the data entering the fusion and according to the fusion purpose. We distinguish the following categories.

- **Multiview fusion** of images from the same modality and taken at the same time but from different viewpoints.
- **Multimodal fusion** of images coming from different sensors (visible and infrared, CT and NMR, or panchromatic and multispectral satellite images).
- **Multitemporal fusion** of images taken at different times in order to detect changes between them or to synthesize realistic images of objects which were not photographed in a desired time.
- **Multifocus fusion** of images of a 3D scene taken repeatedly with various focal length.
- **Fusion for image restoration.** Fusion two or more images of the same scene and modality, each of them blurred and noisy, may lead to a deblurred and denoised image. Multichannel deconvolution is a typical representative of this category. This approach can be extended to superresolution fusion, where input blurred images of low spatial resolution are fused to provide us a high-resolution image.

In each category, the fusion consists of two basic stages: image registration, which brings the input images to spatial alignment, and combining the image functions (intensities, colors, etc) in the area of frame overlap. Image registration works usually in four steps.

- **Feature detection.** Salient and distinctive objects (corners, line intersections, edges, contours, closed-boundary regions, etc.) are manually or, preferably, automatically detected. For further processing, these features can be represented by their point representatives (distinctive points, line endings, centers of gravity), called in the literature control points.

- **Feature matching.** In this step, the correspondence between the features detected in the sensed image and those detected in the reference image is established. Various feature descriptors and similarity measures along with spatial relationships among the features are used for that purpose.
Transform model estimation. The type and parameters of the so-called mapping functions, aligning the sensed image with the reference image, are estimated. The parameters of the mapping functions are computed by means of the established feature correspondence.

Image resampling and transformation. The sensed image is transformed by means of the mapping functions. Image values in non-integer coordinates are estimated by an appropriate interpolation technique.

We present a survey of traditional and up-to-date registration and fusion methods and demonstrate their performance by practical experiments from various application areas.

Special attention is paid to fusion for image restoration, because this group is extremely important for producers and users of low-resolution imaging devices such as mobile phones, camcorders, web cameras, and security and surveillance cameras.

Supplementary reading


Handouts
Empirical observation

- One image is not enough
- We need
  - more images
  - the techniques how to combine them
**Image Fusion**

**Input:** Several images of the same scene

**Output:** One image of higher quality

The definition of “quality” depends on the particular application area

**Basic fusion strategy**

- Acquisition of different images
- Image-to-image registration
Basic fusion strategy

• Acquisition of different images
• Image-to-image registration
• The fusion itself (combining the images together)

The outline of the talk

• Fusion categories and methods (J. Flusser)
• Fusion for image restoration (F. Šroubek)
• Image registration methods (B. Zitová)
Fusion categories

• Multiview fusion
• Multimodal fusion
• Multitemporal fusion
• Multifocus fusion
• Fusion for image restoration

Multiview Fusion

• Images of the same modality, taken at the same time but from different places or under different conditions

• Goal: to supply complementary information from different views
Multiview fusion

Fusion categories

- Multiview fusion
- Multimodal fusion
- Multitemporal fusion
- Multifocus fusion
- Fusion for image restoration

Reprinted from R. Redondo et al.
Multimodal Fusion

- Images of different modalities: PET, CT, MRI, visible, infrared, ultraviolet, etc.
- **Goal**: to decrease the amount of data, to emphasize band-specific information

Common methods

- Weighted averaging pixel-wise
- Fusion in transform domains
- Object-level fusion
Medical imaging – pixel averaging

NMR + SPECT

Medical imaging – pixel averaging

PET + NMR
Visible + infrared

different modalities

VS

weighted average

IR

Reprinted from R. Blum et al.

Multispectral data – fusion by PCA
Fused image in pseudocolors

RGB = first 3 components

Multimodal fusion with different resolution

• One image with high spatial resolution, the other one with low spatial but higher spectral resolution.

• **Goal:** An image with high spatial and spectral resolution

• **Method:** Replacing bands in DWT
FUSED MS + OPT
replace
IWT
Fused image
FUSED MS + OPT
Challenge for the future: Object-level fusion

Fusion categories

- Multiview fusion
- Multimodal fusion
- **Multitemporal fusion**
- Multifocus fusion
- Fusion for image restoration
Multitemporal Fusion

• Images of the same scene taken at different times (usually of the same modality)

• Goal: Detection of changes

• Method: Subtraction

Digital subtraction angiography

Reprinted from Y. Bentoutou et al.
Fusion categories

• Multiview fusion
• Multimodal fusion
• Multitemporal fusion
• Multifocus fusion
• Fusion for image restoration

Multifocus fusion

• The original image can be divided into regions such that every region is in focus in at least one channel

• Goal: Image everywhere in focus

• Method: identify the regions in focus and combine them together
Multifocus fusion in wavelet domain

Input channels → Wavelet decompositions → Max-rule in highpass → Fused wavelet decomposition → Fused image

Artificial example

Images with different areas in focus
Regularized Decision Map

max rule

max rule with regularization

Microscopic images: fusion and 3D reconstruction
Fusion categories

- Multiview fusion
- Multimodal fusion
- Multitemporal fusion
- Multifocus fusion
- Fusion for image restoration

Realistic imaging

registration  image restoration
Fusion for image restoration

• **Idea**: Each image consists of “true” part and “degradation”, which can be removed by fusion

• **Types of degradation:**
  – additive noise: image denoising
  – convolution: blind deconvolution
  – resolution decimation: superresolution

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Denoising

• averaging over multiple realizations (averaging in time)
Denoising via time averaging

Before registration

After registration

Averaging

Blind deconvolution

• Ill-posed problem for one single image

• Solution:
  – strong prior knowledge of blurs and/or the original image
  – multiple acquisitions of the same object (multichannel blind deconvolution)
Realistic acquisition model (1)

\[
[u \ast h_k](x, y) + n_k(x, y) = z_k(x, y)
\]

MC Blind Deconvolution

- System of integral equations
  (ill-posed, underdetermined)
  \[
z_k(x) = (h_k \ast u)(x) + n_k(x)
\]
- Energy minimization problem (well-posed)
  \[
  E(u, \{h_i\}) = \frac{1}{2} \sum_{i=1}^{K} \|h_i \ast u - z_i\|^2 + \lambda Q(u) + \gamma R(\{h_i\})
  \]
Image Regularization

- $Q(u)$ captures local characteristics of the image $\Rightarrow$ Markov Random Fields

- Identity: $\int_{\Omega} |u|^2$
- Tichonov (GMRF): $\int_{\Omega} |\nabla u|^2$
- Variational integral: $\int_{\Omega} \phi(|\nabla u|)$
- Huber MRF, bilateral filters, …

PSF Regularization

$$z_1 = h_1 \ast u$$
$$z_1 \ast h_2 = u \ast h_1 \ast h_2$$
$$u \ast h_2 = z_2$$
$$h_2 \ast h_1 \ast u = h_1 \ast z_2$$

$$R(\{h_i\}) = \frac{1}{2} \sum_{1 \leq i, j \leq K} \|z_i \ast h_j - z_j \ast h_i\|^2$$

with one additional constraint $0 \leq h_i(x) \leq 1$, $\forall x, i$
AM Algorithm

- Alternating minimizations of $E(u,\{h_i\})$
  over $u$ and $h_i$
- input: blurred images and estimation of PSF size
- output: reconstructed image and PSFs

Vibrating Objects
Long-time exposure

Astronomical Imaging

degraded image
reconstructed image
**Superresolution**

**Goal:** Obtaining a high-res image from several low-res images

**Traditional superresolution**
Traditional superresolution

sub-pixel shift

pixel interpolation $\rightarrow$ superresolution

Realistic acquisition model (2)

original image $u(x, y) + n_k(x, y) + \text{noise}$

acquired images $z_k(x, y)$

\[ D\left( [u \ast h_k](x, y) \right) + n_k(x, y) = z_k(x, y) \]
SR & MBD

• Incorporating between-image shift

\[
[u * h_k](\tau_k(x,y)) + n_k(x,y) = z_k(x,y)
\]

\[
[u * g_k](x,y) + n_k(x,y) = z_k(x,y)
\]

• Incorporating downsampling operator \( D \)

\[
D[u * g_k](x, y) + n_k(x, y) = z_k(x, y)
\]

Superresolution: No blur, SRF = 2x
Superresolution with High Factor

Input
LR frames

interpolated
SR
Original frame

Superresolution and MBD

Scaled LR input images

MBD+SR
PSFs
Superresolution and MBD

Superresolved image (2x)
Optical zoom (ground truth)

Cell-phone images

LR input images

Scaled input image
Superresolved image (2x)
Webcam images

LR input frame
Superresolution image (2x)

Superresolution with noninteger factors

original image & PSFs
LR image SR=1.25x SR=1.75x
### Noninteger SR factors

<table>
<thead>
<tr>
<th>1x</th>
<th>1.25x</th>
<th>1.50x</th>
<th>1.75x</th>
<th>2.00x</th>
<th>2.50x</th>
<th>3.00x</th>
</tr>
</thead>
</table>

### Challenges

- 3D scene
- Objects with different motion
- Improving registration
- Space-variant deblurring
- Motion field
- Minimization over registration param.
IMAGE REGISTRATION

methodology

feature detection
feature matching
transform model estimation
image resampling and transformation
accuracy evaluation

trends and future
METHODOLOGY: IMAGE REGISTRATION

Overlaying two or more images of the same scene

Different imaging conditions

Geometric normalization of the image

Preprocessing of the images entering image analysis systems
METHODOLOGY: IMAGE REGISTRATION - TERMINOLOGY

**reference image**

**sensed image**

**features**

**transform function**

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METHODOLOGY: IMAGE REGISTRATION

**Main application categories**

1. Different viewpoints - multiview
2. Different times - multitemporal
3. Different modalities - multimodal
4. Scene to model registration
METHODOLOGY: IMAGE REGISTRATION

Four basic steps of image registration

1. Feature detection
2. Feature matching
3. Transform model estimation
4. Image resampling and transformation

FEATURE DETECTION
FEATURE DETECTION

Distinctive and detectable objects

Physical interpretability

Frequently spread over the image

Enough common elements in all images

Robust to degradations

FEATURE DETECTION

Area-based methods - windows

Feature-based methods (higher level info)

- distinctive points
- corners
- lines
- closed-boundary regions
- invariant regions
### FEATURE DETECTION POINTS AND CORNERS

<table>
<thead>
<tr>
<th>DISTINCTIVE POINTS</th>
<th>CORNERS</th>
</tr>
</thead>
<tbody>
<tr>
<td>- line intersections</td>
<td>- image derivatives</td>
</tr>
<tr>
<td>- max curvature points</td>
<td>(Kitchen-Rosenfeld, Harris)</td>
</tr>
<tr>
<td>- inflection points</td>
<td>- intuitive approaches (Smith-Brady)</td>
</tr>
<tr>
<td>- centers of gravity</td>
<td></td>
</tr>
<tr>
<td>- local extrema of wavelet transform</td>
<td></td>
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</tbody>
</table>

### FEATURE DETECTION LINES AND REGIONS

<table>
<thead>
<tr>
<th>LINES</th>
<th>REGIONS</th>
</tr>
</thead>
<tbody>
<tr>
<td>- line segments (roads, anatomic structures)</td>
<td>- closed- boundary objects (lakes, fields, shadows)</td>
</tr>
<tr>
<td>- contours</td>
<td>- level sets</td>
</tr>
<tr>
<td>- edge detectors (Canny, Maar, wavelets)</td>
<td>- segmentation methods</td>
</tr>
</tbody>
</table>

**Invariant regions with respect to assumed degradation**

<table>
<thead>
<tr>
<th>SCALE</th>
<th>AFFINE</th>
</tr>
</thead>
<tbody>
<tr>
<td>- virtual circles (Alhichri &amp; Kamel)</td>
<td>- based on Harris and edges (Tuytelaars &amp; V Gool)</td>
</tr>
<tr>
<td></td>
<td>- maximally stable extremal regions (Matas et al.)</td>
</tr>
</tbody>
</table>
FEATURE MATCHING

Area-based methods

similarity measures calculated directly from the image graylevels

image correlation, image differences
phase correlation, mutual information, …

Feature-based methods

symbolic description of the features matching in the feature space (classification)
FEATURE MATCHING                 CROSS-CORRELATION

\[ C(k,m) = \sum (I_{k,m} - \text{mean}(I_{k,m})) \cdot (W - \text{mean}(W)) \]
\[ \sqrt{\sum (I_{k,m} - \text{mean}(I_{k,m}))^2} \cdot \sqrt{\sum (W - \text{mean}(W))^2} \]

FEATURE MATCHING        CORRELATION-LIKE METODS

edge, vector correlation
extension to complex transformations
hardware correlation
SSDA  sequential similarity detection algorithm
various similarity measures
error functions
subpixel accuracy
FEATURE MATCHING        PYRAMIDAL REPRESENTATION

processing from coarse to fine level

wavelet transform

FEATURE MATCHING        PHASE CORRELATION

equivalent to standard correlation of “whitened” images

similar to correlation of edges

does not depend on actual image colors

multimodal registration
Fourier shift theorem

If $f(x)$ is shifted by $a$ to $f(x-a)$
- FT magnitude stays constant
- phase is shifted by $-2\pi a\omega$

Shift parameter – spectral comparison of images

SPOMF symmetric phase - only matched filter

Image $f$ window $w$

$$\frac{W \cdot F^*}{|W \cdot F|} = e^{-2\pi i (\omega a + \xi b)}$$

$$\text{IFT} \left(e^{-2\pi i (\omega a + \xi b)}\right) = \delta(x-a, y-b)$$
FEATURE MATCHING

PHASE CORRELATION

shift solved, what about rotation and change of scale?

log-polar transform

\[
polar \\
r = \sqrt{(x-x_c)^2 + (y-y_c)^2} \\
\theta = \tan^{-1}\left(\frac{y-y_c}{x-x_c}\right)
\]

\[
log \\
R = \frac{(n_r-1)\log(r/r_{min})}{\log(r_{max}/r_{min})} \\
W = n_w \theta / (2\pi)
\]
### FEATURE MATCHING

**RTS PHASE CORRELATION**

**Rotation, translation, change of scale**

\[
\begin{align*}
\mathcal{F}\{f(x-a)\}(\omega) &= \exp(-2\pi i a \omega) \mathcal{F}\{f(x)\}(\omega) \\
\mathcal{F}\{f_{\text{rotated}}\}(\omega) &= \mathcal{F}\{f\}_{\text{rotated}}(\omega) \\
\mathcal{F}\{f(ax)\}(\omega) &= |a|^{-1} \mathcal{F}\{f(x)\}(\omega/a)
\end{align*}
\]

\[
\mathcal{F} \rightarrow | \rightarrow \log\text{-polar} \rightarrow \mathcal{F} \rightarrow \text{phase correlation}
\]

\(\pi\) - amplitude periodicity -> 2 angles

dynamics - \(\log(\text{abs}(\mathcal{F})+1)\)

discrete problems

### FEATURE MATCHING

**MUTUAL INFORMATION**

**statistical measure of the dependence between two images**

often used for multimodal registration

popular in medical imaging
<table>
<thead>
<tr>
<th>FEATURE MATCHING</th>
<th>MUTUAL INFORMATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entropy function</td>
<td>$H(X) = - \sum_x p(x) \log p(x)$</td>
</tr>
<tr>
<td>Joint entropy</td>
<td>$H(X,Y) = - \sum_x \sum_y p(x,y) \log p(x,y)$</td>
</tr>
<tr>
<td>Mutual information</td>
<td>$I(X;Y) = H(X) + H(Y) - H(X,Y)$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>FEATURE MATCHING</th>
<th>MUTUAL INFORMATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entropy</td>
<td>measure of uncertainty</td>
</tr>
<tr>
<td>Mutual information</td>
<td>reduction in the uncertainty of X due to the knowledge of Y</td>
</tr>
<tr>
<td>Maximization of MI</td>
<td>measure <em>mutual agreement</em> between object models</td>
</tr>
</tbody>
</table>
## FEATURE MATCHING

### FEATURE-BASED METHODS

**Combinatorial matching**
- no feature description, global information
  - graph matching
  - parameter clustering
  - ICP (3D)

**Matching in the feature space**
- pattern classification, local information
  - invariance
  - feature descriptors

**Hybrid matching**
- combination, higher robustness

## COMBINATORIAL - GRAPH

Transformation parameters with highest score
FEATURE MATCHING

COMBINATORIAL - CLUSTER

Detected features - points, lines, regions

Invariants description
- intensity of close neighborhood
- geometrical descriptors (MBR, etc.)
- spatial distribution of other features
- angles of intersecting lines
- shape vectors
- moment invariants
- …

Combination of descriptors
maximum likelihood coefficients

<table>
<thead>
<tr>
<th></th>
<th>W1</th>
<th>W2</th>
<th>W3</th>
<th>W4</th>
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<tbody>
<tr>
<td>V1</td>
<td>Dist</td>
<td></td>
<td></td>
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<tr>
<td>V2</td>
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<tr>
<td>V3</td>
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<tr>
<td>V4</td>
<td></td>
<td></td>
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</tbody>
</table>

min (best / 2nd best)
<table>
<thead>
<tr>
<th>FEATURE MATCHING</th>
<th>FEATURE SPACE MATCHING</th>
</tr>
</thead>
<tbody>
<tr>
<td>relaxation methods – consistent labeling problem solution</td>
<td>iterative recomputation of matching score</td>
</tr>
<tr>
<td>based on match quality</td>
<td></td>
</tr>
<tr>
<td>- agreement with neighbors</td>
<td></td>
</tr>
<tr>
<td>- descriptors can be included</td>
<td></td>
</tr>
<tr>
<td>RANSAC</td>
<td>- random sample consensus algorithm</td>
</tr>
<tr>
<td>- robust fitting of models, many data outliers</td>
<td>- follows simpler distance matching</td>
</tr>
<tr>
<td>- follows simpler distance matching</td>
<td>- refinement of correspondences</td>
</tr>
</tbody>
</table>

**TRANSFORM MODEL ESTIMATION**

\[
x' = f(x,y) \\
y' = g(x,y)
\]

incorporation of *a priori* known information
removal of differences
TRANSFORM MODEL ESTIMATION

Global functions
similarity, affine, projective transform
low-order polynomials

Local functions
piecewise affine, piecewise cubic
thin-plate splines
radial basis functions
TRANSFORM MODEL ESTIMATION

Affine transform

\[ x' = a_0 + a_1x + a_2y \]
\[ y' = b_0 + b_1x + b_2y \]

Projective transform

\[ x' = \frac{a_0 + a_1x + a_2y}{1 + c_1x + c_2y} \]
\[ y' = \frac{b_0 + b_1x + b_2y}{1 + c_1x + c_2y} \]

TRANSFORM MODEL ESTIMATION - SIMILARITY TRANSFORM

translation \([\Delta x, \Delta y]\) rotation \(\phi\) uniform scaling \(s\)

\[ x' = s(x \cos \phi - y \sin \phi) + \Delta x \]
\[ y' = s(x \sin \phi + y \cos \phi) + \Delta y \]
\[ s \cos \phi = a, \quad s \sin \phi = b \]

\[ \min \left( \sum_{i=1}^{N} \left[ x_i' - (ax_i - by_i) - \Delta x \right]^2 + \left[ y_i' - (bx_i + ay_i) - \Delta y \right]^2 \right) \]

\[
\begin{vmatrix}
\Sigma(x_i^2 + y_i^2) & 0 & \Sigma x_i & \Sigma y_i \\
0 & \Sigma(x_i^2 + y_i^2) & -\Sigma y_i & \Sigma x_i \\
\Sigma x_i & -\Sigma y_i & N & 0 \\
\Sigma y_i & \Sigma x_i & 0 & N
\end{vmatrix}
= 
\begin{vmatrix}
a \\
b \\
\Sigma(x_i'x_i - y_i'y_i) \\
\Sigma(y_i'x_i - x_i'y_i)
\end{vmatrix}
= 
\begin{vmatrix}
\Sigma x_i \\
\Sigma y_i \\
\Delta x \\
\Delta y
\end{vmatrix}
\]
TRANSFORM MODEL ESTIMATION - PIECEWISE TRANSFORM

Pure interpolation – ill posed

Regularized approximation – well posed

\[ \min J(f) = a E(f) + b R(f) \]

- \( E(f) \) error term
- \( R(f) \) regularization term
- \( a,b \) weights
Choices for $\min J(f) = aE(f) + bR(f)$

$E(f) = \sum (x_i' - f(x_i, y_i))^2$

$R(f) \geq 0$

$||L(f)||$

$a \ll b$ least-square fit,

$f$ from the null-space of $L$

$a \gg b$ "smooth" interpolation

$R(f) = \int \int \left( \frac{\partial^2 f}{\partial x \partial x} \right)^2 + 2 \left( \frac{\partial^2 f}{\partial x \partial y} \right)^2 + \left( \frac{\partial^2 f}{\partial y \partial y} \right)^2 \, dx \, dy$

$f(x, y) = \alpha_1 + \alpha_2 x + \alpha_3 y + \sum_{i=1}^{N} a_i g_i(||x - x_i, y - y_i||)$

$TPS \quad g_i(t) = t^2 \log t$

another choice $G-RBF \quad g_i(t) = \exp \left( \frac{-t^2}{\sigma^2} \right)$
TRANSFORM MODEL ESTIMATION  OTHER REGISTRATIONS

Elastic registration
- not parametric models
- “rubber sheet” approach

Fluid registration
- viscous fluid model to control transformation
- reference image – thick fluid flowing to match

Diffusion-based registration

Optical flow registration

IMAGE RESAMPLING AND TRANSFORMATION

trade-off between accuracy and computational complexity
Interpolation nearest neighbor
   bilinear
   bicubic

Implementation 1-D convolution

\[ f(x_0, k) = \sum d(I, k) c(i - x_0) \]
\[ f(x_0, y_0) = \sum f(x_0, j) c(j - y_0) \]

ideal \( c(x) = k \cdot sinc(kx) \)
IMAGE RESAMPLING AND TRANSFORMATION

Interpolation mask \( c(\chi) \)

- closest neighbour
- linear
- smooth cubic

ACCURACY EVALUATION

Localization error - displacement of features
- due to detection method

Matching error - false matches
- ensured by robust matching (hybrid)
- consistency check, cross-validation

Alignment error - difference between model and reality
- mean square error
- test point error (excluded points)
- comparison (“gold standard”)

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TRENDS AND FUTURE

- complex local transforms
- multimodal data
- robust systems, based on combination of approaches
- 3D data sets
- expert systems

APPLICATIONS

- Different viewpoints
- Different times (change detection)
- Different sensors/modalities
- Scene to model registration
## PUBLICATIONS

### Papers

### Books
- A. Goshtasby, 2-D and 3-D Image Registration, Wiley Publishers, New York, April 2005
- J. Hajnal, D.Hawkes, and D. Hill, Medical Image registration, CRC Press, 2001
- J. Modersitzki, Numerical Methods for Image Registration, Oxford University Press, 2004