Image Fusion using ICA bases

Dr. Nikolaos Mitianoudis

Hellenic Open University
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OUTLINE

- Extraction of ICA / Topographic ICA bases.
- Introduction to Image Fusion.
- Image Fusion using ICA bases.
- Fusion Rules using ICA Fusion.
- Contrast Correction for Multi-modal ICA fusion
- Conclusions.
Receptive fields of simple cells in mammalian primary visual cortex can be characterized as spatially localized, oriented and bandpass. (Field 1996, Olshausen-Field @ Nature 1996)

Such filter responses should emerge from:

a) Unsupervised learning algorithms that estimate a factorial product of independent visual features. (Barlow 1989, Bell 1996)

The image $I(x, y)$ can be expressed as a linear combination of basis functions $b_i(x, y)$:

$$I(x, y) = \sum_i u_i b_i(x, y)$$

where $u_i$ are scaling coefficients, such that $u_i = \langle I(x, y), b_i(x, y) \rangle$.

The requested visual fields can be estimated either by:
- Maximising the sparseness of $u_i$.
- Maximising the statistical independence of $b_i(x, y)$.

Independent Component Analysis (ICA) can perform these two equivalent tasks, i.e. estimate analysis bases, resembling receptive fields of the visual cortex. (Lewicki-Sejnowski 2000, Hyvarinen-Hoyer-Oja 2001)
TRAINING LOCAL IMAGE ANALYSIS BASES

Assume image \( I(x, y) \) of size \( M_1 \times M_2 \) and window \( W \) of size \( N \times N \), centered around pixel \((x_0, y_0)\).

Express the observed patches:

\[
\begin{align*}
\underline{u}(t) &= AI_w(t) \quad (A \text{ analysis kernel}) \\
I_w(t) &= Bu(t) = A^{-1}u(t) \quad (B \text{ synthesis kernel})
\end{align*}
\]
Estimate the analysis kernel \( A = [a_1 \ a_2 \ \ldots \ a_N]^T \).

**Principal Component Analysis (PCA) bases:**

PCA can identify **uncorrelated vector bases**, given linear generative model.

Assuming **uncorrelatedness**, the analysis bases \( [a_1 \ a_2 \ \ldots \ a_N]^T \) are given by **eigenvectors** of **data correlation matrix** \( C = E \{ I_W I_W^T \} \), normalised by corresponding eigenvalues.

Dimensionality reduction is also possible, forming a \( K \times N^2 \) reduced orthonormal analysis kernel.

PCA bases, using **second-order statistics**, estimate **Gaussian-like localised bases.**
PCA bases trained using local $8 \times 8$ patches from natural images.

PCA bases does not estimate localised structures.
Independent Component Analysis (ICA) bases:

A stricter criterion is **statistical independence** between the transform coefficients.

Assuming **statistical independence**, the estimated analysis bases are **localised edge features**, resembling Gabor functions.

**Independent Component Analysis** can estimate the synthesis matrix $B$ of the following linear generative model:

$$I_w(t) = Bu(t)$$

Conditions:

- $B$ is a full rank matrix, i.e. redundancy has been removed by PCA.
  
  ($\text{rank}(B) = K$)
An interpretation of sparsity or statistical independence is non-Gaussianity. Enhance sparsity by maximizing non-Gaussianity => FastICA algorithm (Hyvarinen 1997)

Training using FastICA algorithm. PCA bases estimation is required. Reduced $K$ bases set also possible $Q = \begin{bmatrix} q_1 & q_2 & \ldots & q_K \end{bmatrix}^T$.

Estimation via iterating over a training set of patches:

$$q_i^+ \leftarrow E\{q_i \phi(q_i^T u_{PCA})\} - E\{\phi'(q_i^T u_{PCA})\}q_i \quad \forall \quad i = 1, \ldots, K$$

$$Q \leftarrow Q(Q^T Q)^{-0.5}$$

where $\phi(y) = -\partial G(y) / \partial y$ and $G(y)$ any non-quadratic function.
Topographic Independent Component Analysis (TopoICA) bases:

**Statistical independence** is a strong assumption.

Topographic ICA allows **spatial correlation** between neighbouring bases. PCA is again a prerequisite.

Estimation via iterating over a training set of patches:

\[
q_i^+ \leftarrow q_i + \eta E\{u_{PCA}(q_i^T u_{PCA})r_i\} \quad \forall \quad i = 1, \ldots, K
\]

\[
r_i \leftarrow \sum_{k=1}^{K} h(i, j) \phi\left(\sum_{j=1}^{K} h(j, k)(q_i^T u_{PCA})^2\right) \quad h(i, j) = \begin{cases} 1, & \text{if } |i - k| \leq L \\ 0, & \text{otherwise} \end{cases}
\]

\[
Q \leftarrow Q(Q^T Q)^{-0.5}
\]

where \(\eta\) is the learning rate, \(\phi(y) = -\frac{\partial G(y)}{\partial y}\) and \(L\) is the neighbourhood size.
The ICA and Topographic ICA bases are given by the product of respective ICA matrix $Q$ and PCA bases $A_{PCA}$.

$$A \leftarrow QA_{PCA}$$
ICA AND TOPOGRAPHICAL BASES

Trained ICA and Topographical ICA bases using $16 \times 16$ patches from natural images.

**Difference:** Topography, i.e. allowed spatial correlation.
TRAINING OF ICA AND TOPOGRAPHIC ICA BASES

Training strategy:

- Randomly select ~10000 8x8 patches from similar content images.
- Select 40-64 bases using PCA.
- Perform ICA or TopoICA to train corresponding bases.
- Store the analysis kernel.
DENOISING VIA SPARSE CODE SHRINKAGE

(Hyvarinen-Hoyer-Oja 2001)

Concept:

- Apply a sparse linear transform $T\{\cdot\}$ on the noisy image.
- In the sparse representation perform ML estimation using superGaussian priors (sparse code shrinkage).
- Move the “shrinked” data back to the original domain.

ML estimator assuming isotropic noise $C_N = \sigma^2 I$:

$$S(x, y) = A^{-1}g(AI(x, y))$$

Diagram:

- Noisy image $\xrightarrow{T\{\cdot\}}$ Sparse image $\xrightarrow{\text{Shrinked image}}$ $\xrightarrow{T^{-1}\{\cdot\}}$ Denoised image
Shrinkage Operators:

Assuming Laplacian priors:

\[ g(u) = \text{sgn}(u) \max(0, |u| - \sqrt{2\sigma^2}) \]
DENOISING VIA SPARSE CODE SHRINKAGE

(Hyvarinen-Hoyer-Oja 2001)

ICA bases

Topographic ICA bases

SNR=20.4156 dB

SNR=21.1336 dB
**IMAGE FUSION**

**Definition:** Image fusion is the process of combining information from different sensors that capture the same scene.

**Objective:** Enhance the **perception quality of the observed scene**, not achievable by a single sensor.

(a) Image Fusion usually performed in **transform domain**, i.e. highlight **image salient features**.

(b) Image fusion community usually employs the **Dual-Tree Wavelet Transform (DTWT)** [1] or **Pyramid Decomposition** [2].
Proposal:
Replace DTWT with ICA and Topographical ICA bases [3] trained on similar images.

Benefits:
(a) Better performance, (transform is tailored to application).
(b) More degrees of freedom than DTWT.
(c) Describe image features more accurately.

Drawbacks:
The bases are shift variant
No problem, if images are registered.
Sliding window to overcome problem, however computationally expensive.
IMAGE FUSION USING ICA AND TOPOGRAPHIC ICA

Transform estimation

Fusion

Input Images → Estimated Transform → Transformed images → Optional Denoising → Fusion rule → Fused Image

Image Patches → ICA/TopoICA → Transform Kernel → $T\{\}$

$u_k(t)$

(Information Fusion 2007)
Proposed fusion strategy:

8 x 8 patches are selected using 1-pixel overlap from input images.
Fusion rule = method to combine coefficient to form fused image.

**Fusion by “max-abs”**

Select the maximum in absolute value coefficient from all inputs.

\[ T\{I_f(t)\} = \text{sgn}(T\{I_k(t)\}) \max_k |T\{I_k(t)\}| \]

**Pros**

Enhances contribution of certain bases, i.e. localised features, therefore enhances edges.

**Cons**

Distorts constant background or light textural information.
**GENERAL FUSION RULES**

**Fusion by “mean”**

Select the mean of the corresponding input coefficients.

\[
T\{I_f(t)\} = \text{mean}(T\{I_k(t)\})
\]

**Pros**

Preserves constant background information.

**Cons**

Smoothes out edges, as averaging is a low-pass filtering process.

**Objective**

Find fusion rules that tackle the shortcomings of these approaches.
WEIGHTED - COMBINATION FUSION RULE

(Information Fusion 2007)

Combine the image patches $I_k(t)$ using an activity detector ($L_1$-norm):

$$E_k(t) = \| u_k(t) \|_1 \quad k = 1, \ldots, T$$

The “fused” image is constructed, as follows:

$$T\{I_f(t)\} = \sum_{k=1}^{T} w_k(t) T\{I_k(t)\}$$

where

$$w_k(t) = E_k(t) / \sum_{k=1}^{T} E_k(t)$$

As the ICA bases capture activity → large $E_k(t)$ represents larger activity.

The weighted combination emphasises patches with greater activity.
REGION-BASED FUSION RULE

Divide the image using activity detector $E_k(t)$ into two regions:

a) **active** regions (**salient features**)  
   if $E_k(t) \geq 2 \text{ mean}_t\{E_k(t)\}$

b) **non-active** regions (**constant background**)  
   if $E_k(t) < 2 \text{ mean}_t\{E_k(t)\}$

Fuse **active** regions with the **weighted combination** rule  
fuse **non-active** regions with the **mean** rule.

Segmentation map in two regions
**Objective:** Identify a self-adaptive fusion scheme emphasising local features in most fusion scenarios.

**Formulation:** \( \underline{u_f} = W_1 \underline{u_1} + W_2 \underline{u_2} + \ldots + W_T \underline{u_T} \)

**Problem:** Estimate \( \underline{w} = [w_1 \ w_2 \ \ldots \ w_T]^T \), so that local features are emphasised.

Assuming \( N \times N \) patches, we can define

\[ x(n) = [u_1(n) \ u_2(n) \ \ldots \ u_T(n)]^T, \ \forall \ n = 1, \ldots, N^2 \]

The fused image can be expressed, as follows:

\[ u_f(n) = \underline{w}^T x(n), \ \forall \ n = 1, \ldots, N^2 \]
Observation:

The actual non-distorted representation should be more sparse than the distorted or different sensor inputs.

Conclusion:

The fusion process should enhance sparsity in the ICA domain.

Approach:

Perform fusion using Maximum Likelihood (ML) estimation of $J(w)$, subject to several constraints:

$$
\max_{w} J(w) = \max_{w} E\{\log p(u_f)\}
$$

subject to

$$
\begin{bmatrix}
1 & 1 & \ldots & 1
\end{bmatrix}w = e^T w = 1
$$

$w \geq 0$
ADAPTIVE FUSION RULES (ICASSP 2006)

Sparse models:

Model sparsity

Laplacian distribution

\[ p(u) \propto e^{-\alpha |u|} \]

Verhulstian distribution

\[ p(u) \propto \frac{e^{-u/s}}{s(1+e^{-u/s})^2} \]

\[ a, s \text{ const} \]
ADAPTIVE FUSION RULES

Algorithm summary:

1. Initialise \( w = e / T \)

2. Update \( w \), as follows: 

   \[
   w^+ \leftarrow w + \eta \mathbb{E}\{\text{sgn}(w^T x)x\} \quad \text{Laplacian priors}
   \]

   or

   \[
   w^+ \leftarrow w + \eta \mathbb{E}\left\{\frac{1 - e^{-w^T x/s}}{1 + e^{-w^T x/s}} x \right\} \quad \text{Verhulstian priors}
   \]

3. Apply the constraints \( w^+ \leftarrow |w^+|/(e^T |w^+|) \)

4. Repeat 2,3 until convergence.
VARIOUS FUSION RULES FOR ICA-BASED FUSION

- **“Max-Abs” rule**
  The greatest coefficients in abs construct the fused image.

- **“Mean” rule**
  An average of the input coefficients constructs the fused image.

- **Weighted-Combination rule:**
  Input coefficients are weighted according to contribution of the total energy.

- **Regional Rule:**
  Segment scene into active/non-active areas and use different rules for each area.

- **Adaptive Rule:**
  Estimate optimal weights for the coefficients by ML-estimation for a sparse prior (e.g. Laplacian prior).
EXAMPLE  Fusion of out-of-focus images:

Input Image 1     Input Image 2     DT-WT (max-abs)     TopoICA (max-abs)

TopoICA (WC)     TopoICA (region)     TopoICA (Laplace)     TopoICA (Verhulst)

Tested Transforms  Tested fusion schemes
Dual-Tree Wavelet Transform (DTWT), ICA, Topographic ICA.  Max-abs, Weighted Combination (WC), Region-based (region), Adaptive (Laplacian).
**EXAMPLE** Fusion of *out-of-focus* images:

Performance comparison of several combinations of transforms and fusion rules for out-of-focus datasets, in terms of the Piella/Petrovic indexes.

<table>
<thead>
<tr>
<th></th>
<th>WP (Sym7)</th>
<th>DT-WT</th>
<th>ICA</th>
<th>TopoICA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Clocks dataset</td>
<td></td>
</tr>
<tr>
<td>Max-abs</td>
<td>0.8727/0.6080</td>
<td>0.8910/0.6445</td>
<td>0.8876/0.6530</td>
<td>0.8916/0.6505</td>
</tr>
<tr>
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<td>0.8747/0.5782</td>
<td>0.8747/0.5782</td>
<td>0.8523/0.5583</td>
<td>0.8560/0.5615</td>
</tr>
<tr>
<td>Weighted</td>
<td>–</td>
<td>–</td>
<td>0.8678/0.6339</td>
<td>0.8743/0.6347</td>
</tr>
<tr>
<td>Regional</td>
<td>–</td>
<td>–</td>
<td>0.8583/0.5995</td>
<td>0.8662/0.5954</td>
</tr>
<tr>
<td>Laplacian</td>
<td>–</td>
<td>–</td>
<td>0.8521/0.5598</td>
<td>0.8563/0.5624</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Disk dataset</td>
<td></td>
</tr>
<tr>
<td>Max-abs</td>
<td>0.8850/0.6069</td>
<td>0.8881/0.6284</td>
<td>0.9109/0.6521</td>
<td>0.9111/0.6477</td>
</tr>
<tr>
<td>Mean</td>
<td>0.8661/0.5500</td>
<td>0.8661/0.5500</td>
<td>0.8639/0.5470</td>
<td>0.8639/0.5459</td>
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<tr>
<td>Weighted</td>
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<td>0.9134/0.6426</td>
<td>0.9134/0.6381</td>
</tr>
<tr>
<td>Regional</td>
<td>–</td>
<td>–</td>
<td>0.9069/0.6105</td>
<td>0.9084/0.6068</td>
</tr>
<tr>
<td>Laplacian</td>
<td>–</td>
<td>–</td>
<td>0.8679/0.5541</td>
<td>0.8655/0.5489</td>
</tr>
</tbody>
</table>
Fusion of multi-modal images:

**Tested Transforms**
- Dual-Tree Wavelet Transform (DTWT)
- ICA
- Topographic ICA

**Tested fusion schemes**
- Max-abs
- Weighted Combination (WC)
- Region-based (region)
- Adaptive (Laplacian)
EXAMPLE Fusion of multi-modal images:

Tested Transforms: Dual-Tree Wavelet Transform (DTWT), ICA, Topographic ICA.

Tested fusion schemes: Max-abs, Weighted Combination (WC), Region-based (region), Adaptive (Laplacian).
**EXAMPLE** Fusion of surveillance images:

<table>
<thead>
<tr>
<th>Visual Sensor</th>
<th>Infrared sensor</th>
<th>DT-WT (max-abs)</th>
<th>TopoICA (max-abs)</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1" alt="Visual Sensor" /></td>
<td><img src="image2" alt="Infrared sensor" /></td>
<td><img src="image3" alt="DT-WT (max-abs)" /></td>
<td><img src="image4" alt="TopoICA (max-abs)" /></td>
</tr>
<tr>
<td>TopoICA (WC)</td>
<td>TopoICA (Region)</td>
<td>TopoICA (Laplace)</td>
<td>TopoICA (Verhulst)</td>
</tr>
<tr>
<td><img src="image5" alt="TopoICA (WC)" /></td>
<td><img src="image6" alt="TopoICA (Region)" /></td>
<td><img src="image7" alt="TopoICA (Laplace)" /></td>
<td><img src="image8" alt="TopoICA (Verhulst)" /></td>
</tr>
</tbody>
</table>

**Tested Transforms**
- Dual-Tree Wavelet Transform (DTWT), Topographic ICA.

**Tested fusion schemes**
- Max-abs, Weighted Combination (WC), Region-based (region), Adaptive (Laplacian - Verhulst).
EXAMPLE Fusion of surveillance images:

Tested Transforms: Dual-Tree Wavelet Transform (DTWT), Topographic ICA.
Tested fusion schemes: Max-abs, Weighted Combination (WC), Region-based (region), Adaptive (Laplacian - Verhulst).
Fusion of surveillance images:

Performance comparison of several combinations of transforms and fusion rules for multimodal datasets, in terms of the Piella/Petrovic indexes.

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<th>ICA</th>
<th>TopoICA</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Multimodal-1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Max-abs</td>
<td>0.6198/0.4163</td>
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</tr>
<tr>
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<td>0.6591/0.3965</td>
<td>0.6593/0.3967</td>
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<tr>
<td>Weighted</td>
<td>–</td>
<td>–</td>
<td>0.6832/0.4487</td>
<td>0.6861/0.4528</td>
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<tr>
<td>Regional</td>
<td>–</td>
<td>–</td>
<td>0.6523/0.3885</td>
<td>0.6566/0.3871</td>
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<tr>
<td>Laplacian</td>
<td>–</td>
<td>–</td>
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<td>0.6608/0.3983</td>
</tr>
<tr>
<td><strong>Multimodal-2</strong></td>
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<td></td>
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<tr>
<td>Max-abs</td>
<td>0.5170/0.4192</td>
<td>0.58022/0.4683</td>
<td>0.6081/0.4759</td>
<td>0.6092/0.4767</td>
</tr>
<tr>
<td>Mean</td>
<td>0.6028/0.420</td>
<td>0.6028/0.4207</td>
<td>0.6056/0.4265</td>
<td>0.6061/0.4274</td>
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<tr>
<td>Weighted</td>
<td>–</td>
<td>–</td>
<td>0.6252/0.4576</td>
<td>0.6286/0.4632</td>
</tr>
<tr>
<td>Regional</td>
<td>–</td>
<td>–</td>
<td>0.5989/0.4148</td>
<td>0.5992/0.4133</td>
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<tr>
<td>Laplacian</td>
<td>–</td>
<td>–</td>
<td>0.6071/0.4277</td>
<td>0.6068/0.4279</td>
</tr>
<tr>
<td><strong>‘UN Camp’</strong></td>
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<tr>
<td>Max-abs</td>
<td>0.6864/0.4488</td>
<td>0.7317/0.4780</td>
<td>0.7543/0.4906</td>
<td>0.7540/0.4921</td>
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<tr>
<td>Mean</td>
<td>0.7104/0.4443</td>
<td>0.7104/0.4443</td>
<td>0.7080/0.4459</td>
<td>0.7081/0.4459</td>
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<tr>
<td>Weighted</td>
<td>–</td>
<td>–</td>
<td>0.7361/0.4735</td>
<td>0.7429/0.4801</td>
</tr>
<tr>
<td>Regional</td>
<td>–</td>
<td>–</td>
<td>0.7263/0.4485</td>
<td>0.7321/0.4508</td>
</tr>
<tr>
<td>Laplacian</td>
<td>–</td>
<td>–</td>
<td>0.7101/0.4475</td>
<td>0.7094/0.4473</td>
</tr>
</tbody>
</table>
OPTIMAL CONTRAST FOR MULTI-MODAL ICA FUSION

Fact
The ICA-based fusion performs fusion of local-patches from the different sensor images. These patches need to be normalised to zero mean.

Question
How do we reconstruct the means of the fused image?

Previous Solution
The means were reconstructed using an average of the input sensor means.

Problems
- Correct solution in the case of out-of-focus examples.
- Might not be optimal in the case of multi-modal examples.
EXAMPLE OF MEANS CHOICE

Visual Sensor

IR Sensor

Means from Visual

Average Means

Means from IR

(IEEE Sensors Journal 2008 submitted)
A general cost function seeking to identify the weights of the means was formulated, based on a simplified Piella index.

\[ m_f = w_1 m_{x_1} + w_2 m_{x_2} + \ldots + w_T m_{x_T} \]

Piella’s index is based on the Wang and Bovik index:

\[ Q(x, f) = \frac{2\sigma_{xf}}{\sigma_x^2 + \sigma_f^2} \frac{2m_x m_f}{m_x^2 + m_f^2} \]

Wang and Bovik index is divided into a variance and means term:

\[ Q(x, f) = Q_\sigma(x, f) Q_m(x, f) = Q_\sigma(x, f) \frac{2m_x m_f}{m_x^2 + m_f^2} \]

constant
The term \( A_{\sigma x_i} = \lambda_i Q_{\sigma} (x_i, f) \) is not dependent on any mean change.

\[
Q_p (w_i) = \mathcal{E} \left\{ \sum_{i=1}^{T} A_{\sigma x_i} \frac{2m_{x_i}m_f}{m^2_{x_i} + m^2_f} \right\}
\]
A GENERALISED OPTIMAL CONTRAST SCHEME

Optimise the Piella Index in terms of \( \mathbf{w} = [w_1 \ w_2 \ \ldots \ w_N]^T \).

Gradient ascent on the cost function will give the following iterative update for the weights:

\[
\mathbf{w}^+ \leftarrow \mathbf{w} + \eta \mathcal{E} \left\{ \frac{m_x}{A_{\sigma x_i} m_{x_i}} \sum_{i=1}^{T} \frac{m^2_{x_i} - m^2_f}{(m^2_{x_i} + m^2_f)^2} \right\}
\]

To avoid unnecessary deviations, during the updates we can force the weights to sum up to 1.

\[
\mathbf{w}_i^+ \leftarrow \mathbf{w} / ([1 \ 1 \ \ldots \ 1] \mathbf{w})
\]
A GENERALISED OPTIMAL CONTRAST SCHEME

(IEEE Sensors Journal 2008 submitted)
A GENERALISED OPTIMAL CONTRAST SCHEME

(a) InfraRed Image  (b) Visual Image

(c) Equal Weights ($Q = 0.7920$)  (d) Optimised Weights ($Q = 0.7968$)  (e) DT-WT ($Q = 0.7758$)
## A Generalised Optimal Contrast Scheme

*(IEEE Sensors Journal 2008 submitted)*

<table>
<thead>
<tr>
<th>Method</th>
<th>&quot;Dune&quot;</th>
<th>&quot;Trees&quot;</th>
<th>&quot;Uncamp&quot;</th>
<th>Octet 1</th>
<th>Octet 2</th>
<th>Car Image</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICA - Equal Weights</td>
<td>0.7311</td>
<td>0.7770</td>
<td>0.7441</td>
<td>0.8251</td>
<td>0.8176</td>
<td>0.6822</td>
</tr>
<tr>
<td>ICA - Opt. Weights</td>
<td>0.7325</td>
<td>0.7814</td>
<td>0.7452</td>
<td>0.8354</td>
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<td>0.6857</td>
</tr>
<tr>
<td>DT-WT</td>
<td>0.7156</td>
<td>0.7595</td>
<td>0.7317</td>
<td>0.8254</td>
<td>0.8602</td>
<td>0.6392</td>
</tr>
</tbody>
</table>
CONCLUSIONS

- Proposed an alternative image fusion framework, based on trained ICA bases.

- Improved results compared to Dual-Tree Wavelets:
  - Transform is tailored to application.
  - More degrees of freedom than DTWT.

- Proposed different fusion rules and techniques for out-of-focus and multi-modal fusion.
REFERENCES


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