Fusion of Multi Resolution Remote Sensing Data for Urban Sprawl Analysis

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Today’s Presentation

- Introduction
- Study area and Data
- Method
- Results and Discussion
- Conclusion
The urban population in India is growing at around 2.3% per annum.

An increased urban population in response to the growth in urban areas is mainly due to migration.

There are 35 urban cities having a population of more than one million in India (in 2001).
Urbanisation is the growth in response to many factors –

- Economic,
- Social,
- Political,
- Physical geography of an area, etc.
There are two forms of urbanisation:

- Planned in the form of townships.
- Unplanned or organic [Outskirts, Peri urban] – leads to sprawl

- Happens when two towns are connected through roads, infrastructure improvements, etc.,
Urban sprawl: Characteristics

- Dispersed development in the outskirts.
- Leads to land use and land cover change.
- Devoid of any infrastructure.
- Left out in Government surveys [e.g. national population census].

Understanding this kind of growth is very crucial for regional planning.

- Requires temporal and spatial data to understand the urban dynamics
  - Remote sensing data – provides spatial data on temporal scale (since 1970’s)
Remote sensing data (IKONOS, IRS, Landsat, MODIS) provides spatial data (on temporal scale).

These data are in multi-resolution
- Spatial (1m, 4m, 5.8m, 23.5 m, 30m, 250,m.....1Km)
- Spectral [B, G, R, NIR, Superspectral (MODIS), Hyperspectral (Hyperion)]
- Temporal (1 day, 8 days, 21 days, 24 days.....)

Analysis of these data (multi resolution) help in capturing urban dynamics.

Mapping landscapes on temporal scale provide an opportunity to inventory and also to understand changes.
Greater Bangalore, India-Study area

- Area - 741 sq. km.
- Grown spatially more than 10 times since 1949 to 2006 (from 69 km² ≈ 700 km²).
- Fifth largest metropolis in India.
Growth of Bangalore – Consequent land use changes (1973 - 2006)

<table>
<thead>
<tr>
<th>Year</th>
<th>Class</th>
<th>Built up</th>
<th>Vegetation</th>
<th>Water</th>
<th>Others</th>
</tr>
</thead>
<tbody>
<tr>
<td>1973</td>
<td>Ha</td>
<td>5448</td>
<td>46639</td>
<td>2324</td>
<td>13903</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>7.97</td>
<td>68.27</td>
<td>3.40</td>
<td>20.35</td>
</tr>
<tr>
<td>2006</td>
<td>Ha</td>
<td>29535</td>
<td>19696</td>
<td>1073</td>
<td>18017</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>43.23</td>
<td>28.83</td>
<td>1.57</td>
<td>26.37</td>
</tr>
</tbody>
</table>

- 466% increase in built up area from 1973 to 2006.
- 54% decline in area of water bodies.
- 65% decline in vegetation.
1973 – 2006 Land use change
- High Spatial resolution with low Spectral resolution (very expensive).

- Low Spatial resolution with high Spectral resolution (not expensive, some are in public domain as at GLCF website).

- Fusion of these data provide high spatial with high spectral resolution – economical.
Fusion permits identification of objects on the Earth’s surface,
- especially useful in urban areas because the characteristic of urban objects are determined not only by their spectra but also by their structure.

Objective: to optimise multi-resolution data through fusion
- to analyse and understand landscape dynamics in Greater Bangalore.
Data used

- Low spatial with Multispectral Data (4m)
  (MSS - IKONOS)

- High Spatial with Single Spectral Data (1m)
  (PANCHROMATIC - IKONOS)

- Ancillary Data
  - Landsat and IRS MSS bands
  - Google Earth images
  - Survey of India Toposheets
Method

- **Adoption of SFIM (Smoothing Filter-based Intensity Modulation) for fusion of co-registered multi-resolution images.**
- **SFIM (Liu, 2000) is a general spectral preserve image fusion technique applicable to co-registered multi-resolution images.**
  - based on a simplified solar radiation and land surface reflection model.

Solar radiation and land surface reflection model

\[
DN(\lambda) = r(\lambda) \ E(\lambda) \quad \ldots \ldots \ldots (1)
\]

where \(DN\) is digital number, \(\lambda\) – Band, \(E(\lambda)\) - irradiance, \(r(\lambda)\) - spectral reflectance.

Let

\[
DN(\lambda)_{\text{low}} - \text{DN value in a lower resolution image of spectral band } \lambda,
\]

\[
DN(\gamma)_{\text{high}} - \text{DN value of the corresponding pixel in a higher resolution image of spectral band } \gamma
\]

and the two images are taken in similar solar illumination conditions,

\[
DN(\lambda)_{\text{low}} = r(\lambda)_{\text{low}} \ E(\lambda)_{\text{low}} \quad \ldots \ldots \ldots (2)
\]

\[
DN(\gamma)_{\text{high}} = r(\gamma)_{\text{high}} \ E(\gamma)_{\text{high}} \quad \ldots \ldots \ldots (3)
\]
Technique - SFIM

Defined as,

\[
\text{DN(\lambda)_{sfim}} = \frac{\text{DN(\lambda)_{low} \; \text{DN(\gamma)_{high}}}}{\text{DN(\gamma)_{mean}}} \]

\[
= \frac{r(\gamma)_{low} \; E(\lambda)_{low} \; r(\gamma)_{high} \; E(\gamma)_{high}}{r(\gamma)_{low} \; E(\gamma)_{low}}
\]

If the two images are quantified to the same DN range and with no significant spectral variation within the neighbourhood, we can presume \(E(\lambda)_{low} \approx E(\gamma)_{low}\), \(r(\gamma)_{low} = r(\gamma)_{high}\), for any given resolution because the both vary with topography in the same way.

\[
= r(\lambda)_{low} \; E(\gamma)_{high} \quad \text{.......... (4)}
\]
- In General SFIM can be written as

\[ IMAGE_{SFIM} = \frac{IMAGE_{low} IMAGE_{high}}{IMAGE_{mean}} \]

where,

- \( IMAGE_{low} \) is a pixel of a lower resolution image co-registered to a higher resolution image of \( IMAGE_{high} \)
- \( IMAGE_{mean} \) a smoothed pixel of \( IMAGE_{high} \) using averaging filter over a neighbourhood equivalent to the actual resolution of \( IMAGE_{low} \)
RGB bands are transformed to HIS (Carper et al., 1990)

(hue – dominant or average wavelength of light contributing to a colour,
intensity – total brightness of the colour,
saturation – purity of colour relative to gray)

\[
\begin{bmatrix}
\frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\
-\frac{1}{\sqrt{6}} & -\frac{1}{\sqrt{6}} & \frac{2}{\sqrt{6}} \\
\frac{1}{\sqrt{6}} & -\frac{1}{\sqrt{6}} & 0
\end{bmatrix}
\begin{bmatrix}
DN^l_{PAN} \\
V_1 \\
V_2
\end{bmatrix}
= 
\begin{bmatrix}
DN^l_{MS1} \\
DN^l_{MS2} \\
DN^l_{MS3}
\end{bmatrix}
\]

where \(DN^l_{MS1}, DN^l_{MS2}, DN^l_{MS3}\) are the low resolution bands

\(V_1, V_2\) are the intermediate variables.

Technique – RGB-HIS

\[ I = D N^l_{P A N} \]
\[ H = \tan^{-1}\left(\frac{V_2}{V_1}\right) \]
\[ S = \sqrt{V_1^2 + V_2^2} \]

- \( I \) is replaced with high spatial resolution image – \( D N^h_{P A N} \) (contrast stretched to \( I \)) which is to be integrated.

\[ D N_{\text{new\_image}} = \frac{\sigma_{\text{ref}}}{\sigma_{\text{old}}} (D N_{\text{old}} - \mu_{\text{old}}) + \mu_{\text{ref}} \]

\[
\begin{pmatrix}
D N^h_{MS1} \\
D N^h_{MS2} \\
D N^h_{MS3}
\end{pmatrix} =
\begin{pmatrix}
1 & \frac{-1}{\sqrt{6}} & \frac{3}{\sqrt{6}} \\
\frac{-1}{\sqrt{6}} & \frac{-3}{\sqrt{6}} & \frac{3}{\sqrt{6}} \\
\frac{2}{\sqrt{6}} & 0 & 0
\end{pmatrix}
\begin{pmatrix}
D N^h_{P A N} \\
V_1 \\
V_2
\end{pmatrix}
\]

where \( D N^h_{MS1}, D N^h_{MS2}, D N^h_{MS3} \) are the fused high resolution multispectral bands.
**Technique – Brovey Transform**

(Pohl, 1996)

\[
\begin{bmatrix}
DN_{MS1}^h \\
DN_{MS2}^h \\
DN_{MS3}^h
\end{bmatrix} =
\begin{bmatrix}
DN_{MS1}^l \\
DN_{MS2}^l \\
DN_{MS3}^l
\end{bmatrix} + (DN_{PAN}^h - DN_{PAN}^l)
\]

\[
\begin{bmatrix}
DN_{MS1}^l \\
DN_{MS2}^l \\
DN_{MS3}^l
\end{bmatrix}
\]

where

\[
DN_{PAN}^l = (1/3)(DN_{MS1}^l + DN_{MS2}^l + DN_{MS3}^l)
\]

\(DN_{MS1}^l, DN_{MS2}^l, DN_{MS3}^l\) are the low resolution bands

\(DN_{MS1}^h, DN_{MS2}^h, DN_{MS3}^h\) are the fused high resolution multispectral bands

Results and Discussion

- **SFIM, RGB-HIS, Brovey Output -**
  - Based on the fusion of IKONOS MSS and PAN data
**Performance analysis**

- **Quantitatively - Correlation Coefficient.**

<table>
<thead>
<tr>
<th>Fusion techniques</th>
<th>Original Band 2</th>
<th>Original Band 3</th>
<th>Original Band 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>HIS</td>
<td>0.22</td>
<td>0.32</td>
<td>0.17</td>
</tr>
<tr>
<td>Brovey</td>
<td>0.99</td>
<td>0.98</td>
<td>0.67</td>
</tr>
<tr>
<td>SFIM</td>
<td>0.96</td>
<td>0.98</td>
<td>0.97</td>
</tr>
</tbody>
</table>

- **Universal Image Quality Index (UIQI)** (Wang et al., 2005)

  \[
  Q = \frac{\sigma_{AB}}{\sigma_A \sigma_B} \cdot \frac{2 \mu_A \mu_B}{\mu_A^2 + \mu_B^2} \cdot \frac{2 \sigma_A \sigma_B}{\sigma_A^2 + \sigma_B^2}
  \]

  The 1st component is the CC for A (original band) and B (fused). The 2nd component measures how close the mean DN of A and B is. The 3rd measures the similarity between A and B. Range is [-1, 1]. If two images are identical, Q = 1.

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</thead>
<tbody>
<tr>
<td>HIS</td>
<td>0.17</td>
<td>0.27</td>
<td>0.11</td>
</tr>
<tr>
<td>Brovey</td>
<td>1.00</td>
<td>0.97</td>
<td>0.63</td>
</tr>
<tr>
<td>SFIM</td>
<td>0.97</td>
<td>0.97</td>
<td>0.97</td>
</tr>
</tbody>
</table>

SFIM compared to HIS and Brovey transform fusion techniques - Improves spatial details with the fidelity to the image spectral properties and contrast.

This technique can be used to perform Image fusion for better visualisation of sprawl regions.

However, the SFIM is not applicable for fusing images that are fundamentally different in illumination conditions or physical properties (optical and radar images).
Acknowledgement

- Grateful to Geoeye Foundation, USA for providing the IKONOS spatial data.

- ISRO-IISc Space Technology Cell, Indian Institute of Science for the financial support.

- Department of Electrical Engineering, University Visvesvaraya College of Engineering, Bangalore facilitated this study.
E-version of this presentation and paper at
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