A Novel Method for Unsupervised Multiple-Change Detection in Hyperspectral Images Based on Binary Spectral Change Vectors

Daniele Marinelli
Francesca Bovolo
Lorenzo Bruzzone

E-mail: daniele.marinelli@unitn.it
Web page: rslab.disi.unitn.it
Outline

1. Introduction to Change Detection in Hyperspectral Data
2. Aim of the Work
3. Change Detection Method based on Binary Spectral Change Vectors
4. Experimental Results
5. Conclusion and Future Developments
Change Detection (CD) methods for optical/passive multitemporal data have mainly been developed for Multispectral (MS) data, and demonstrated to be less effective for hyperspectral multitemporal images.

The dense sampling of spectrum of Hyperspectral (HS) sensors allow for the detection of changes that differ only in small portions of the spectrum.

In recent times, ad-hoc techniques for CD in HS data that are not fully automatic and perform lossy compression of change information in a 2D feature space have been developed.

However, the high dimensionality of HS data can be better exploited to effectively extract more change information from HS data.
Unsupervised change detection in passive sensor multitemporal images is commonly based on the analysis of the Spectral Change Vectors (SCVs) in: $I_D = I_2 - I_1$

- Major changes show large differences in spectral change signatures with respect to each others.
- Subtle changes have a spectral change signature similar to the one of a major change with significant difference only in a small portion of the spectrum.
- Small differences can be captured while working with hyperspectral data.
Aim of the Work

✓ Define a method for **change detection** in multitemporal HS images that:
  • separates both **major and subtle changes**;
  • handles the **high dimensionality** of HS data;
  • is **unsupervised**.

✓ The proposed method:
  • **moves from the real-valued space** of the SCVs to a **simpler discrete binary space**.
  • **preserves** the **high dimensionality** of the data while reducing data volume.
  • uses the discrete representation of the SCVs to define an **hierarchical tree structure** that identifies the different kinds of changes.
  • exploits the tree structure to highlight the relationship between **both major and subtle changes**.

✓ Validate the proposed method on a data set of real multitemporal hyperspectral images.
Proposed Method: Block Scheme

\[ \Omega = \{ \Omega_C, \omega_u \} \]

Spectral Change Vector binarization

Quantization \rightarrow Coding \rightarrow Compression

\{ p_{n1}^N \}_{n=1} \rightarrow \{ p_{n2}^N \}_{n=1}

CBSCVs

\{ c_{p1}^N \}_{n=1} \rightarrow \{ c_{p2}^N \}_{n=1}

Binary CD Map

\{ s_u \}_{u=1} \in \omega_u

Multiple CD Map

Hierarchical representation of changes

\[ \Omega_C = \{ \omega_1, \omega_2, ..., \omega_C \} \]
Given the difference image $I_D = I_2 - I_1$ we analyze the magnitude image $I_\rho = \sum_{b=1}^B I_{D,b}$.

In $I_\rho$ unchanged pixels have low magnitude whereas changed pixels have high magnitude values.

The pixels are labelled as unchanged samples $\{s_u\}_{u=1}^U$ and changed samples $\{s_n\}_{n=1}^N$ using threshold $T_\rho$.

Aim: to quantize the real-valued SCVs \( \{s_n\}_{n=1}^N \in \Omega_C \).

- Divide the spectral change vector component \( \{s_{n,b}\}_{n=1}^N \) \((b=1,\ldots,B)\) into a positive and a negative set;
- Adaptively divide each set into two (obtaining 4 groups) by thresholding \( \{s_{n,b}\}_{n=1}^N \) probability density functions [2].

Coding converts each real-valued SCVs \( \{s_n\}_{n=1}^{N} \) into discrete SCVs by using a band-based binary representation. The resulting SCVs are referred to as Binary SCVs (BSCVs) and contain redundant information.

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SCVs Binarization: Compression

- The sets of most ($\{p^1_{n, n=1}\}$) and least ($\{p^2_{n, n=1}\}$) have redundant information, i.e., large groups of SCVs share the same values over multiple contiguous bands.

- To reduce redundancy we compute the Hamming distance between adjacent bands:

$$d^i(b + 1, b) = \sum_{n=1}^{N} ||p^i_{n, b+1} - p^i_{n, b}||, i = 1, 2$$

![Diagram showing SCV-wise majority rule and compressed BSCVs (CBSCVs) with most significant bit ($cp^1_{n}$.)]
### SCVs Binarization: Compression

#### BSCVs (non-compressed)

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#### Compressed BSCVs

- \( p_3^1 = \{1,1,0,1,1,0,0,1\} \)
- \( cp_3^1 = \{1,0,1\} \)
- \( p_3^2 = \{0,0,1,1,0,1,1,0\} \)
- \( cp_3^2 = \{0,1,0,1,1\} \)

| \( cp_1^1 \) | 1 | 0 | 1 |
| \( cp_2^1 \) | 1 | 0 | 1 |
| \( cp_3^1 \) | 1 | 0 | 1 |
| \( cp_3^2 \) | 1 | 0 | 1 |
| \( cp_5^1 \) | 1 | 0 | 1 |

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Most significant bit

Least significant bit

---

105 05 05 1
Proposed Method: Block Scheme

\[
\Omega = \{\Omega_C, \omega_u\}
\]

\[
{s_n}_n=1^N \in \Omega_C
\]

\[
{c}_n=1^N \in \omega_u
\]

\[
\Omega = \{\Omega_C, \omega_u\}
\]

Binary CD

Quantization → Coding → Compression

\[
{p_n}_n=1^N \}
\]

Spectral Change Vector binarization

\[
{cp}_n=1^N\}
\]

CBSCVs

\[
{cp}_n=2^N\}
\]

CBSCV analysis

Multiple CD Map

Hierarchical representation of changes

\[
\Omega_C = \{\omega_1, \omega_2, ..., \omega_C\}
\]

\[
\omega
\]

\[
{\omega}_u=1^U\in \omega_u
\]
To divide CBSCVs among kinds of change, the two sets of CBSCVs \( \{c_{p_n^1}\}_{n=1}^{N} \) and \( \{c_{p_n^2}\}_{n=1}^{N} \) are used to define a two-level tree:

1. The first level represents CBSCVs \( \{c_{p_n^1}\}_{n=1}^{N} \) of most significant bits (major changes);
2. The second level represents CBSCVs \( \{c_{p_n^2}\}_{n=1}^{N} \) of least significant bits (subtle changes).

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### CBSCVs Analysis: Tree Definition

<table>
<thead>
<tr>
<th>CBSCV</th>
<th># of samples</th>
</tr>
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<tbody>
<tr>
<td>000</td>
<td>150</td>
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<tr>
<td>100</td>
<td>225</td>
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<tr>
<td>101</td>
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<td>01011</td>
<td>5</td>
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<tr>
<td>11101</td>
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<tr>
<td>01010</td>
<td>55</td>
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<tr>
<td>11111</td>
<td>3</td>
</tr>
</tbody>
</table>

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\( \Omega_C (498) \)
Hypothesis: Leaves (i.e., subtle changes) with a low number of CBSCVs are likely to be outliers.

Aim: for each major change node remove subtle change nodes (children) that are statistically irrelevant (i.e., they have less than the 5% of samples with respect to the parent node).
CBSCVs Analysis: Clustering

✓ CBSCVs in statistically irrelevant clusters (e.g., sample with $cp^1_n = \{1,0,1\}$ and $cp^2_n = \{1,1,1,1,1\}$) are reassigned to the leaf with the most similar $cp^2_n$ under the same first level $cp^1_n$ node according to the Hamming distance.

✓ Each leaf of the resulting tree is a kind of change in $\Omega_C = \{\omega_1, \omega_2, ..., \omega_C\}$.
Experimental Results

Dataset: two multitemporal hyperspectral images acquired by Hyperion sensor in 2004 and 2007, Oregon, US.
Size: 211 × 396 pixels
Number of spectral bands: 159 out of 242.

False color composition of the difference image

R: 579.45 nm, G: 972.99 nm, B: 1780.09 nm

Changes

No Change
Experimental Results

Compressed Binary signatures after clustering

Reference signatures of each kind of change

Hierarchical tree

\[ \Omega_C (12256) \]

Level of major changes \( \{ c_p^1 \}_{n=1}^N \)

Level of subtle changes \( \{ c_p^2 \}_{n=1}^N \)

\[ T_b^+ \]
\[ T_0 \]
\[ T_b^- \]

Change classes
Bit “0”
Bit “1”
Thresholds

\[ 887 \]
\[ 121 \]
\[ 188 \ 62 \ 516 \]

University of Trento, Italy
D. Marinelli, F. Bovolo, L. Bruzzone

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Experimental Results

Proposed method

State of the art method [3]

✓ A method has been presented for **unsupervised detection of multiple changes** in multitemporal hyperspectral images based on binary SCVs.

✓ The method **converts the real valued SCVs into binary compressed SCVs** and identifies multiple changes in a **simpler discrete space** while **preserving the high dimensionality of data**.

✓ The binary compressed SCVs are used to define a **tree structure where leaves represent the different classes of change**. The hierarchical structure of the tree highlights the relationship among changes.

✓ The proposed method showed promising results in identifying the multiple changes.
Future Developments

✓ Perform a **quantitative analysis** of method performance.

✓ Perform a **sensibility analysis** and improve the binarization process by:
  - making the number of **quantization levels adaptive** among the different bands;
  - using a **more accurate** method for the definition of the **quantization levels**.

✓ Reduce the **over clustering** problem in the hierarchical tree.

✓ Test the method on other datasets.