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AN OMNIBUS LIKELIHOOD RATIO TEST STATISTIC AND ITS FACTORIZATION FOR CHANGE DETECTION IN TIME SERIES OF POLARIMETRIC SAR DATA

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ABSTRACT

Based on an omnibus likelihood ratio test statistic for the equality of several variance-covariance matrices following the complex Wishart distribution with an associated \( p \)-value and a factorization of this test statistic, change analysis in a short sequence of multilook, polarimetric SAR data in the covariance matrix representation is carried out. The omnibus test statistic and its factorization detect if and when change(s) occur. Additionally, we gave examples on the application to change detection in truly multitemporal, full polarimetric SAR data. The test statistic and the associated \( p \)-value is determined if and when a difference occurs. Furthermore, we gave examples on the application to change detection in multilook, polarimetric synthetic aperture radar (SAR) data, see [5]. We also described a factorization of this test statistic, change analysis in a time series of multilook, polarimetric SAR data.

1. INTRODUCTION

In earlier publications we have described a test statistic for the equality of two variance-covariance matrices following the complex Wishart distribution with an associated \( p \)-value [1]. We showed their application to bitemporal change detection in truly multitemporal, full polarization SAR data, see [5] also. In [4] we focused on the block-diagonal case, we elaborated on some computer implementation issues, and we gave examples on the application to change detection in both full and dual polarization bitemporal, bifrequency, multilook SAR data.

In [5] we described an omnibus test statistic \( Q \) for the equality of \( k \geq 2 \) variance-covariance matrices following the complex Wishart distribution. We also described a factorization of \( Q = \prod_{j=2}^{k} R_{ij} \) where \( Q \) and \( R_{ij} \) determine if and when a difference occurs. Additionally, we gave \( p \)-values for \( Q \) and \( R_{ij} \). Finally, we demonstrated the use of \( Q \) and \( R_{ij} \) and the \( p \)-values to change detection in truly multitemporal, full polarization SAR data.

For more references to change detection in polarimetric SAR data, see [5].

The methods may be applied to other polarimetric SAR data also such as data from Sentinel-1, COSMO-SkyMed, TerraSAR-X, ALOS, and Radarsat-2 and also to single-pol data.

2. TEST STATISTICS AND THEIR DISTRIBUTIONS

This section gives the main results from [5]. The average covariance matrix for multilook polarimetric SAR is defined as [6]

\[
\langle C \rangle = \begin{bmatrix}
\langle S_{hh} \rangle & \langle S_{hh} S_{hv} \rangle & \langle S_{hh} S_{vv} \rangle \\
\langle S_{hv} S_{hh} \rangle & \langle S_{hv} \rangle & \langle S_{hv} S_{vv} \rangle \\
\langle S_{vv} S_{hh} \rangle & \langle S_{vv} \rangle & \langle S_{vv} S_{vv} \rangle
\end{bmatrix}
\]

where \( \langle \cdot \rangle \) denotes ensemble averaging and * denotes complex conjugation. \( S_{rt} \) denotes the complex scattering amplitude for receive and transmit polarization (\( r, t \in \{h, v\} \) for horizontal and vertical polarization).

2.1. Test for equality of several complex covariance matrices

To test whether a series of \( k \geq 2 \) complex covariance matrices \( \Sigma_i \) are equal, i.e., to test the null hypothesis

\( H_0 : \Sigma_1 = \Sigma_2 = \cdots = \Sigma_k \)

against all alternatives, we use the following omnibus test statistic (for the real case see [7]; for the case with two complex matrices see [1,2]; \( | \cdot | \) denotes the determinant)

\[
Q = \left\{ k^{pk} \prod_{i=1}^{k} \left| \frac{|X_i|}{|X|^k} \right| \right\}^n
\]

Here the \( \Sigma_i \) (and the \( X_i \)) are \( p \times p \) matrices for full pol data, \( p = 2 \) for dual pol data, and \( p = 1 \) for single channel power data), and the \( X_i = n \Sigma_i = n \langle C \rangle \) follow the complex Wishart distribution, i.e., \( X_i \sim W_C(p, n, \Sigma_i) \). \( n \) is the equivalent number of looks. Further, \( X = \sum_{i=1}^{k} X_i \sim W_C(p, nk, \Sigma) \). If the hypothesis is true (“under \( H_0 \)” in statistical parlance), \( \Sigma = X / (kn) \), \( Q \in [0,1] \) with \( Q = 1 \) for equality.
For the logarithm of the test statistic we get
\[ \ln Q = n \left\{ pk \ln k + \sum_{i=1}^{k} \ln |X_i| - k \ln |X| \right\}. \]

A simple expression for the probability of finding a smaller value of \(-2 \ln Q\) is
\[ P\{ -2 \ln Q \leq z \} \simeq P\{ \chi^2((k-1)p^2) \leq z \}. \]

A better approximation for \( P \) can be obtained. Setting
\[ f = (k-1)p^2, \]
\[ \rho = 1 - \frac{(2p^2-1)}{6(k-1)p} \left( \frac{k}{n} - \frac{1}{nk} \right), \]
\[ \omega_2 = \frac{p^2(p^2-1)}{24\rho^2} \left( \frac{k}{n^2} - \frac{1}{(nk)^2} \right) - \frac{p^2(k-1)}{4} \left( 1 - \frac{1}{\rho} \right)^2, \]
the probability of finding a smaller value of \(-2 \rho \ln Q\) is \( z = -2 \rho \ln q_{obs} \)
\[ P\{ -2 \rho \ln Q \leq z \} \simeq P\{ \chi^2(f) \leq z \} + \omega_2 P\{ \chi^2(f+4) \leq z \} - P\{ \chi^2(f) \leq z \}. \]

\( P\{ -2 \rho \ln Q \leq -2 \rho \ln q_{obs} \} = P\{ Q \geq q_{obs} \} \) is the change probability, \( 1 - P\{ -2 \rho \ln Q \leq -2 \rho \ln q_{obs} \} = P\{ Q < q_{obs} \} \) is the no-change probability.

2.2. Test for equality of first \( j < k \) complex covariance matrices

If the above test shows that we cannot reject the hypothesis of equality, no change has occurred over the time span covered by the data. If we can reject the hypothesis, change has occurred at some time point. To test whether the first \( j \) complex variance-covariance matrices \( \Sigma_i \) are equal, i.e., given that
\[ \Sigma_1 = \Sigma_2 = \cdots = \Sigma_{j-1} \]
then the likelihood ratio test statistic \( R_j \) for testing the hypothesis
\[ H_{0,j} : \Sigma_j = \Sigma_1 \text{ against } H_{1,j} : \Sigma_j \neq \Sigma_1 \]
is
\[ R_j = \left\{ \frac{\gamma_j^{jp} |X_1 + \cdots + X_{j+1}|^2}{(j-1)(j-1)p |X_1 + \cdots + X_j|^p} \right\}^n \]
Table 1. Part of the change analysis structure for an example with data from six time points.

<table>
<thead>
<tr>
<th>Time 1</th>
<th>Time 2</th>
<th>Time 3</th>
<th>Time 4</th>
<th>Time 5</th>
<th>Time 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Omnibus</td>
<td>t1 = t2</td>
<td>t2 = t3</td>
<td>t3 = t4</td>
<td>t4 = t5</td>
<td>t5 = t6</td>
</tr>
<tr>
<td>Q(1)</td>
<td>P(Q(1) &lt; qobs)</td>
<td>Q(2)</td>
<td>P(Q(2) &lt; qobs)</td>
<td>Q(3)</td>
<td>P(Q(3) &lt; qobs)</td>
</tr>
<tr>
<td>P(R(1) &lt; qobs)</td>
<td>P(R(1) &lt; qobs)</td>
<td>P(R(2) &lt; qobs)</td>
<td>P(R(2) &lt; qobs)</td>
<td>P(R(3) &lt; qobs)</td>
<td>P(R(3) &lt; qobs)</td>
</tr>
<tr>
<td>Q(4)</td>
<td>P(Q(4) &lt; qobs)</td>
<td>Q(5)</td>
<td>P(Q(5) &lt; qobs)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2. Average no-change probabilities for the grass field.

<table>
<thead>
<tr>
<th>Time 1</th>
<th>Time 2</th>
<th>Time 3</th>
<th>Time 4</th>
<th>Time 5</th>
<th>Time 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Omnibus</td>
<td>t1 = t2</td>
<td>t2 = t3</td>
<td>t3 = t4</td>
<td>t4 = t5</td>
<td>t5 = t6</td>
</tr>
<tr>
<td>0.0003</td>
<td>0.0010</td>
<td>0.0210</td>
<td>0.0653</td>
<td>0.0791</td>
<td></td>
</tr>
</tbody>
</table>

3. CHANGE VISUALIZATION EXAMPLES

To illustrate the above we use full polarimetry EMISAR [8,9] L-band data acquired in 1998 over a Danish agricultural test site on t1 = 21 March, t2 = 17 April, t3 = 20 May, t4 = 16 June, t5 = 15 July, and t6 = 16 August. Figure 1 shows the diagonal elements of the covariance matrix. \( \langle S_{hh}S_{hh}^* \rangle \) (red) is stretched linearly between –36 dB and –6 dB, \( \langle S_{hh}S_{vh} \rangle \) (green) between –30 dB and 0 dB, and \( \langle S_{vv}S_{vh}^* \rangle \) (blue) between –24 dB and 0 dB. The darker areas in the March and April images are bare surfaces corresponding to spring crops, and the very bright areas in all images are forest areas, primarily coniferous forest. The development of the crops during the growing season is clearly seen in the series of images from March to August.

Table 1 shows the change structure built (for each pixel) for an example with data from six time points. The first column indicates which tests are performed for the row in question. The second column shows Q(1) and P(Q(1) < qobs) (“Omnibus” row), or R(1) and P(R(1) < robs), \( j = 2, \ldots, 6 \) for all time points t1 through t6. The third column shows Q(2) and P(Q(2) < qobs) (“Omnibus” row), or R(2) and P(R(2) < robs), \( j = 2, \ldots, 5 \) for time points t2 through t6. The fourth column shows Q(3) and P(Q(3) < qobs) (“Omnibus” row), or R(3) and P(R(3) < robs), \( j = 2, \ldots, 4 \) for time points t3 through t6, etc. Remember, that for a test for R(\( i \)) to be valid, all previous tests for R(\( i-1 \)), \( i = 2, \ldots, j - 1 \) must show equality, see hypothesis H0,j in Section 2.2.

Note, that R(\( i \)) are the (marginal, non-omnibus) pairwise tests for equality.
Fig. 2. Test statistic (a) and $p$-value with grass field marked as black (b). Dark areas are no-change. $p$ is approximately 1 in the grass field.

3.1. Per pixel change visualization

As examples of per pixel change visualization, Figure 2 shows the quantity $-2p \ln Q$ and the corresponding $p$-value, i.e., the change probability. Figure 3 shows changes from $t_1$ to $t_2$ as blue, from $t_3$ to $t_4$ as green, and from $t_5$ to $t_6$ as red after applying a 3 by 3 mode filter. Black areas have not changed.

3.2. Per field change visualization

Table 2 shows the average no-change probabilities for the grass field shown in Figure 2. Table 2 shows that the pairwise tests reveal no change over time for the grass field ($p$-values are 0.2753, 0.0784, 0.2688, 0.1287 and 0.0791, respectively). The omnibus test statistic $Q$ indicates change at some time point between March and August ($P\{Q^{(1)} < q^{(1)}_{\text{obs}} \} = 0.0003$), and the $R_j$ show that the first change for this field occurs between April and May.

$P\{R^{(1)}_1 \leq r^{(1)}_{3,\text{obs}} \} = 0.0171$. The second and last change for this field occurs between June and July ($P\{Q^{(2)} < q^{(2)}_{\text{obs}} \} = 0.0010$ and $P\{R^{(2)}_4 \leq r^{(2)}_{4,\text{obs}} \} = 0.0048$).

4. REFERENCES


