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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 \( p \)-values to change detection in truly multitemporal, full polarimetric SAR data, see [5].

1. INTRODUCTION
In earlier publications we have described a test statistic for the equality of two variance-covariance matrices following the complex Wishart distribution [1]. We showed their application to bitemporal change detection and to edge detection in multilook, polarimetric synthetic aperture radar (SAR) data [2]. In [4] we focused on the block-diagonal covariance matrix for multilook polarimetric SAR. We also described a factorization of this test statistic, change analysis in a short sequence of multilook, polarimetric SAR data in the covariance matrix representation [3]. In this section we give the main results from [5]. The average covariance matrix for multilook polarimetric SAR data, see [6], is

\[
(\Sigma) = \begin{bmatrix}
(S_{hh}S_{hh}^*) & (S_{hh}S_{hv}^*) & (S_{hh}S_{vv}^*) \\
(S_{hv}S_{hh}^*) & (S_{hv}S_{hv}^*) & (S_{hv}S_{vv}^*) \\
(S_{vv}S_{hh}^*) & (S_{vv}S_{hv}^*) & (S_{vv}S_{vv}^*)
\end{bmatrix}
\]

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

2. TEST STATISTICS AND THEIR DISTRIBUTIONS
This section gives the main results from [5]. The average covariance matrix for multilook polarimetric SAR data is defined as [6]

\[
(\Sigma) = \begin{bmatrix}
(S_{hh}S_{hh}^*) & (S_{hh}S_{hv}^*) & (S_{hh}S_{vv}^*) \\
(S_{hv}S_{hh}^*) & (S_{hv}S_{hv}^*) & (S_{hv}S_{vv}^*) \\
(S_{vv}S_{hh}^*) & (S_{vv}S_{hv}^*) & (S_{vv}S_{vv}^*)
\end{bmatrix}
\]

where \( (\cdot) \) denotes ensemble averaging and \( * \) denotes complex conjugation. \( S_{rt} \) denotes the complex scattering amplitude of 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-variance 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)

\[
Q = k^p \prod_{i=1}^{k} |X_i|^{n} \left( \sum_{i=1}^{k} |X_i|^{n/k} \right)^n
\]

Here the \( \Sigma_i \) (and the \( X_i \)) are \( p \) by \( p \) (\( p = 3 \) for full pol data, \( p = 2 \) for dual pol data, and \( p = 1 \) for single channel power data), and the \( X_i = n\Sigma_i = n(\Sigma)_i \) follow the complex Wishart distribution, i.e., \( X_i \sim W_C(p, n, \Sigma_i) \). \( n \) is the equivalent number of looks. Further, \( X = \sum_{i=1}^{k} X_i = W_C(p, nk, \Sigma) \). If the hypothesis is true (“under \( H_0 \)” in statistical parlance), \( \Sigma = X/(kn) \). \( Q \in [0, 1] \) with \( Q = 1 \) for equality.
Fig. 1. RGB images of diagonal elements of the L-band data March, April, May (top row, left to right), June, July, August (bottom row, left to right).

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

$$f = (k-1)p^2$$

$$\rho = 1 - \frac{2p^2 - 1}{6(k-1)p} \left( \frac{k}{n} - \frac{1}{nk} \right)$$

$$\omega_2 = p^2 \left( \frac{p^2 - 1}{24\rho^2} \left( k^2 - \frac{1}{(nk)^2} \right) \right) - \frac{p^2(k-1)}{4} \left( 1 - \frac{1}{\rho} \right)^2$$

the probability of finding a smaller value of $$−2\rho \ln Q$$ is

$$P\{-2\rho \ln Q \leq z\} \simeq P\{\chi^2(f) \leq z\}$$

$$+ \omega_2 \left[ P\{\chi^2(f+4) \leq z\} - P\{\chi^2(f) \leq z\} \right].$$

$$P\{-2\rho \ln Q \leq -2\rho \ln q_{obs}\} = P\{Q \geq q_{obs}\}$$ 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

$$H_{0,j} : \Sigma_j = \Sigma_1$$ against $$H_{1,j} : \Sigma_j \neq \Sigma_1$$

is

$$R_j = \left\{ \frac{j^p \prod_{i=1}^{j-1} |X_{i+1} + \cdots + X_{j-1}| |X_j|}{(j-1)^{(j-1)p} |X_1 + \cdots + X_j|^p} \right\}^n$$
Table 1. Part of the change analysis structure for an example with data from six time points.

<table>
<thead>
<tr>
<th>Omnibus</th>
<th>$t_1 = \cdots = t_6$</th>
<th>$t_2 = \cdots = t_6$</th>
<th>$t_3 = \cdots = t_6$</th>
<th>$t_4 = \cdots = t_6$</th>
<th>$t_5 = t_6$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t_1 = t_2$</td>
<td>$Q(1): P(Q(1) &lt; q_{\text{obs}})$</td>
<td>$Q(2): P(Q(2) &lt; q_{\text{obs}})$</td>
<td>$Q(3): P(Q(3) &lt; q_{\text{obs}})$</td>
<td>$Q(4): P(Q(4) &lt; q_{\text{obs}})$</td>
<td>$Q(5): P(Q(5) &lt; q_{\text{obs}})$</td>
</tr>
<tr>
<td>$t_2 = t_3$</td>
<td>$Q(2); P(R(2) &lt; q_{\text{obs}})$</td>
<td>$Q(3): P(Q(3) &lt; q_{\text{obs}})$</td>
<td>$Q(4): P(Q(4) &lt; q_{\text{obs}})$</td>
<td>$Q(5): P(Q(5) &lt; q_{\text{obs}})$</td>
<td></td>
</tr>
<tr>
<td>$t_3 = t_4$</td>
<td>$Q(3); P(R(3) &lt; q_{\text{obs}})$</td>
<td>$Q(4); P(Q(4) &lt; q_{\text{obs}})$</td>
<td>$Q(5): P(Q(5) &lt; q_{\text{obs}})$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$t_4 = t_5$</td>
<td>$Q(4); P(Q(4) &lt; q_{\text{obs}})$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$t_5 = t_6$</td>
<td>$Q(5): P(Q(5) &lt; q_{\text{obs}})$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Omnibus</th>
<th>$t_1 = t_2$</th>
<th>$t_2 = t_3$</th>
<th>$t_3 = t_4$</th>
<th>$t_4 = t_5$</th>
<th>$t_5 = t_6$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t_1 = t_2$</td>
<td>0.0003</td>
<td>0.0100</td>
<td>0.0210</td>
<td>0.0653</td>
<td>0.0791</td>
</tr>
<tr>
<td>$t_2 = t_3$</td>
<td>0.2753</td>
<td>0.0171</td>
<td>0.0784</td>
<td>0.2688</td>
<td>0.1287</td>
</tr>
<tr>
<td>$t_3 = t_4$</td>
<td>0.0341</td>
<td>0.0048</td>
<td>0.0309</td>
<td>0.1521</td>
<td>0.0791</td>
</tr>
<tr>
<td>$t_4 = t_5$</td>
<td>0.0015</td>
<td>0.3565</td>
<td>0.3016</td>
<td>0.2184</td>
<td>0.1521</td>
</tr>
<tr>
<td>$t_5 = t_6$</td>
<td>0.3565</td>
<td>0.3016</td>
<td>0.2184</td>
<td>0.1521</td>
<td>0.0791</td>
</tr>
</tbody>
</table>

or

$$\ln R_j = n\{p(j \ln j - (j - 1) \ln(j - 1)) + (j - 1) \ln \sum_{i=1}^{j-1} X_i + \ln |X_j| - j \ln \sum_{i=1}^{j} X_i \} \]$$

Furthermore, the $R_j$ constitute a factorization of $Q$

$$Q = \prod_{j=2}^{k} R_j$$

or $Q = \sum_{j=2}^{k} \ln R_j$. If $H_0$ is true the $R_i$ are independent.

A simple expression for the probability of finding a smaller value of $-2 \ln R_j$ is $(z_j = -2 \ln r_{j,\text{obs}})$

$$P\{-2 \ln R_j \leq z_j\} \approx P\{\chi^2(p^2) \leq z_j\}.$$ 

A better approximation for $P$ can be obtained. Letting

$$f = p^2$$

$$\rho_j = 1 - \frac{2p^2 - 1}{6pn} \left(1 + \frac{1}{j(j-1)}\right)$$

$$\omega_{2j} = \frac{p^2}{4} \left(1 - \frac{1}{\rho_j}\right)^2 + \frac{1}{24n^2p^2(p^2 - 1)} \left(1 + \frac{2j - 1}{j(j-1)^2}\right) \frac{1}{\rho_j}$$

we get $(z_j = -2 \rho_j \ln r_{j,\text{obs}})$

$$P\{-2\rho_j \ln R_j \leq z_j\} \approx P\{\chi^2(f) \leq z_j\} + \omega_{2j}[P\{\chi^2(f + 4) \leq z_j\} - P\{\chi^2(f) \leq z_j\}].$$

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 $t_1 = 21$ March, $t_2 = 17$ April, $t_3 = 20$ May, $t_4 = 16$ June, $t_5 = 15$ July, and $t_6 = 16$ August. Figure 1 shows the diagonal elements of the covariance matrix. $\{S_{hh}, S_{hv}, S_{vv}\}$ (red) is stretched linearly between $-36$ dB and $-6$ dB, $\{S_{hh}, S_{hh}\}$ (green) between $-30$ dB and $0$ dB and $\{S_{vh}, S_{vv}\}$ (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 $P\{Q(1) < q_{\text{obs}}\}$ (“Omnibus” row), or $R(1) = P\{R(1) < r_{j,\text{obs}}\}$, $j = 2, \ldots, 6$ for all time points $t_1$ through $t_6$. The third column shows $Q(2)$ and $P\{Q(2) < q_{\text{obs}}\}$ (“Omnibus” row), or $R(2) = P\{R(2) < r_{j,\text{obs}}\}$, $j = 2, \ldots, 5$ for time points $t_2$ through $t_6$. The fourth column shows $Q(3)$ and $P\{Q(3) < q_{\text{obs}}\}$ (“Omnibus” row), or $R(3) = P\{R(3) < r_{j,\text{obs}}\}$, $j = 2, \ldots, 4$ for time points $t_2$ through $t_6$. Remember, that for a test for $R_{j}^{(i)}$ to be valid, all previous tests for $R_{j}^{(i)}$, $i = 2, \ldots, j - 1$ must show equality, see hypothesis $H_{0,j}$ in Section 2.2.

Note, that $R_{j}^{(i)}$ are the (marginal, non-omnibus) pairwise tests for equality.
3.1. Per pixel change visualization

As examples of per pixel change visualization, Figure 2 shows the quantity $-2\rho \ln Q$ 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.

Fig. 3. Shows changes from $t_1$ to $t_2$ as blue, from $t_3$ to $t_4$ as green, from $t_5$ to $t_6$ as red (after application of a 3 by 3 mode filter); change probability significance level is 99.99%.

$P(R_j^{(1)} \leq r_{3,\text{obs}}^{(1)}) = 0.0171$). The second and last change for this field occurs between June and July ($P(Q^{(2)} < q_{\text{obs}}^{(2)}) = 0.0010$ and $P(R_j^{(2)} \leq r_{4,\text{obs}}^{(2)}) = 0.0048$).

4. REFERENCES


