Online multi-resolution image fusion: an application for water mapping

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Abstract

Fresh water is a vital resource for all aspects of agricultural and industrial production. Monitoring the variation of surface water level allows resource managers to detect perturbations, predict long-term trends in water availability, and set consumption guidelines accordingly. Satellite imaging data has been increasingly used to map surface water at global scales. Improving the performance of current water mapping strategies requires high-resolution image data with low revisit times. However, imaging devices on board of existing satellites face a trade-off between their spatial resolution and revisit period, which limits the applicability of those methods. In this work, a multimodal image fusion methodology is developed for water mapping. By combining data from multiple instruments, high-resolution image sequences with low revisit times are generated, leading to improved water mapping results. The proposed methodology was based on Bayesian filtering and smoothing theory, and is able to combine each observed images recursively for a reduced computation complexity. Experiments with real data acquired by Sentinel and Landsat instruments showed that the proposed strategy can lead to significant improvements in water mapping results with compared to competing methodologies.
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Session H43F: Remote Sensing of Rivers, Lakes, Reservoirs, and Wetlands III Oral

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Background

Fresh water is a vital resource for agricultural and industrial productions. Monitoring the variation of surface water level allows resource managers to predict long-term trends in water availability, and set consumption guidelines accordingly. Satellite imaging data has been increasingly used to map surface water at global scales. Improving the performance of current water mapping strategies requires high-resolution image data with high revisiting rate. However, fundamental limitations of multi-band imaging instruments and large sensor-to-target distances impose a trade-off between spatial and temporal resolutions of satellite image sequences.
Motivation

Popular methods for image fusion:

- weighted fusion;
- unmixing-based;
- learning-based;
- Bayesian approaches.

Our goal is to generate high-resolution image sequences at higher revisiting rates by leveraging the spatial relationship between images at multiple modalities.
Basic measurement model

\[ y_{k,\ell}^m = \mathcal{H}_\ell^m(S_k)c_{\ell}^m + r_{k,\ell}^m, \quad \ell = 1, \ldots, L_m, \quad (1) \]

- \( k \) is acquisition time index, \( m \) is the modalities, \( \ell \) shows \( \ell \)-th band;
- \( y_{k,\ell}^m \) represents observed image, either LandSat or MODIS;
- \( S_k \in \mathbb{R}^{N_H \times L_H} \) is Landsat image estimation;
- \( \mathcal{H}_\ell^m \) is a linear operator, either identity matrix multiplication or convolution.
- \( c_{\ell}^m \in \mathbb{R}^{L_H} \) denotes a spectral transformation vector, mapping all bands in \( S_k \) to the \( \ell \)-th measured band at modality \( m \);
- \( r_{k,\ell}^m \) represents the measurement Gaussian noise.
Outlier mitigation

\[ \tilde{y}_{k,\ell}^m = D_k^m \mathcal{H}_\ell^m (S_k) c_{\ell}^m + \tilde{r}_{k,\ell}^m, \quad (2) \]

- \( \tilde{y}_{k,\ell}^m = D_k^m y_{k,\ell}^m \) is the measured image band in which the outlier values have been removed;
- \( \tilde{y}_{k,\ell}^m = D_k^m r_{k,\ell}^m \) is the corresponding measurement noise.
Dynamic evolution model

\[ s_{k+1} = F_k s_k + q_k , \]  \hspace{1cm} (3)

- \( F_k \) is an identity matrix;
- \( q_k \sim \mathcal{N}(0, Q_k) \)

\( Q_k \) estimation

\[ \ell^* = \arg \min_{\ell \in \mathcal{I}_{D_k}} \mathcal{L}(\hat{y}^{m \in \Omega H}_{k-\tau}, [D_k]_\ell) , \]  \hspace{1cm} (4)

\[ q^2_{k,j} = \max \left( \text{var}([D_k]_{\ell^*:\ell^*+d}^j), \varepsilon^2 \right) , \]  \hspace{1cm} (5)
Kalman filter algorithm

Time update phase:

\[ s_{k|k-1} = F_{k-1} s_{k-1|k-1} \]  \hspace{1cm} (6)

\[ P_{k|k-1} = F_{k-1} P_{k-1|k-1} F_{k-1}^T + Q_k \]  \hspace{1cm} (7)

Measurement update phase:

\[ v^m_k = \tilde{y}^m_k - \tilde{H}^m_k s_{k|k-1} \]  \hspace{1cm} (8)

\[ T^m_k = \tilde{H}^m_k P_{k|k-1} (\tilde{H}^m_k)^T + \tilde{R}^m_k \]  \hspace{1cm} (9)

\[ K^m_k = P_{k|k-1} (\tilde{H}^m_k)^T (T^m_k)^{-1} \]  \hspace{1cm} (10)

\[ s_{k|k} = s_{k|k-1} + K^m_k v^m_k \]  \hspace{1cm} (11)

\[ P_{k|k} = P_{k|k-1} - K^m_k T^m_k (K^m_k)^T \]  \hspace{1cm} (12)
Smooother algorithm

\[
\begin{align*}
    s_{k+1|k} &= F_k s_{k|k} \\
    P_{k+1|k} &= F_k P_{k|k} F_k^T + Q_k
\end{align*}
\] (13)

\[
G_k = P_{k|k} F_k^T P_{k+1|k}^{-1}
\] (15)

\[
\begin{align*}
    s_{k|K} &= s_{k|k} + G_k (s_{k+1|K} - s_{k+1|k}) \\
    P_{k|K} &= P_k + G_k (P_{k+1|K} - P_{k+1|k}) G_k^T
\end{align*}
\] (16) (17)

Simulation

Figure: Oroville dam. The red box delimits the specific study area used in our experiments.
Fused images in red band (MODIS and Landsat)
Average NRMSE between the true and estimated Landsat images

Normalized Rooted Mean Square Error (NRMSE):

$$\text{NRMSE}(s, \hat{s}) = \sqrt{\frac{\| s - \hat{s} \|^2}{\| s \|^2}}$$  \hspace{1cm} (18)

<table>
<thead>
<tr>
<th>Method</th>
<th>KFQ</th>
<th>SMQ</th>
<th>ESTARFM</th>
<th>KF</th>
<th>SM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image (07/19)</td>
<td>0.3672</td>
<td>0.3815</td>
<td>0.2905</td>
<td>0.4157</td>
<td>0.4269</td>
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<tr>
<td>Image (08/20)</td>
<td>0.5071</td>
<td>0.4049</td>
<td>0.5517</td>
<td>0.5355</td>
<td>0.4611</td>
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<tr>
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<td>0.3426</td>
<td>0.5775</td>
<td>0.4794</td>
<td>0.3371</td>
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<tr>
<td>Image (09/21)</td>
<td>0.4940</td>
<td>0.1466</td>
<td>0.6125</td>
<td>0.4914</td>
<td>0.2200</td>
</tr>
<tr>
<td>Average</td>
<td>0.4675</td>
<td>0.3189</td>
<td>0.5081</td>
<td>0.4805</td>
<td>0.3613</td>
</tr>
</tbody>
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## Water map

<table>
<thead>
<tr>
<th>Date</th>
<th>Dataset</th>
<th>K Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>07/19</td>
<td>Landsat</td>
<td>k = 4</td>
</tr>
<tr>
<td>08/20</td>
<td>KFQ</td>
<td>k = 10</td>
</tr>
<tr>
<td>09/05</td>
<td>SMQ</td>
<td>k = 13</td>
</tr>
<tr>
<td>09/21</td>
<td>ESTARFM</td>
<td>k = 16</td>
</tr>
<tr>
<td>07/19</td>
<td>KF</td>
<td></td>
</tr>
<tr>
<td>08/20</td>
<td>SM</td>
<td></td>
</tr>
</tbody>
</table>

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## Percentage of mis-classified pixel

<table>
<thead>
<tr>
<th>Method</th>
<th>KFQ</th>
<th>SMQ</th>
<th>ESTARFM</th>
<th>KF</th>
<th>SM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image (07/19)</td>
<td>6.1423</td>
<td>5.4260</td>
<td>5.4870</td>
<td>8.0171</td>
<td>9.4041</td>
</tr>
<tr>
<td>Image (08/20)</td>
<td>10.0899</td>
<td>7.0416</td>
<td>18.3051</td>
<td>16.4761</td>
<td>13.6717</td>
</tr>
<tr>
<td>Image (09/05)</td>
<td>12.0408</td>
<td>7.5446</td>
<td>22.7404</td>
<td>18.1375</td>
<td>8.1390</td>
</tr>
<tr>
<td>Image (09/21)</td>
<td>9.8461</td>
<td>1.7528</td>
<td>26.3374</td>
<td>18.9605</td>
<td>2.3777</td>
</tr>
<tr>
<td>Average</td>
<td>9.5298</td>
<td>5.4412</td>
<td>18.2175</td>
<td>15.3978</td>
<td>8.3981</td>
</tr>
</tbody>
</table>
Water flow trend

Figure: Percentage of water pixels in the estimated images over image index (time) and the reservoir volume in $m^3$ (hydrograph). High resolution Landsat images were observed at index $k \in \{1, 17\}$. We observe that KFQ and SMQ match the hydrograph curve much more closely than the other algorithms.
In conclusion, an online Bayesian approach for fusing multi-resolution space-borne multispectral images was proposed. By formulating the image acquisition process as a linear and Gaussian measurement model, the proposed method leveraged the Kalman filter and smoother to perform image fusion by estimating the latent high resolution image from the different observed modalities. Moreover, a classification-based strategy is also proposed to define an informative time-varying dynamical image model by leveraging historical data, which leads to a better localization of changes occurring in the high-resolution image even in intervals where only coarse resolution observations are available.

Experimental results indicate that the proposed strategy can lead to considerable improvements compared to both the use of noninformative models, and to widely used image fusion algorithms.
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