Image smoothing of multispectral imagery based on the HNN and geo-statistics

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Abstract: A new method for image down-scaling using geostatistical interpolation or smoothing based on the Hopfield Neural Network (HNN) and zero semivariance value is introduced. The method utilises the smoothing effect of the semivariogram matching process to produce the smoothed sub-pixel multispectral (MS) image with smaller RMSEs in comparison with the bilinear interpolation. In fact, the zero semivariograms increase the spatial correlation between the adjacent sub-pixels of the super-resolution image. Containing higher spatial correlation, the resulting super-resolution MS image has smaller RMSEs compared with the original coarse image.

Key words: image smoothing, HNN, Geostatics

1 INTRODUCTION

The task of image super-resolution is to increase the spatial resolution of the imagery. In fact, image super-resolution commonly refers to the process of combining a set of coarse spatial resolution images of the same scene to obtain a single fine resolution image. There have been a large number of studies on super-resolution. Examples can be cited such as Elad and Feuer (1999), Freeman et al. (2002), and Tipping and Bishop (2003). Although widely applied in image processing, these approaches were hardly applicable for super-resolution of remotely sensed MS imagery because of the lack of a sequence of images in a scene at the same time. Amongst the remotely sensed data sources, the super-resolution approaches using image sequences are more applicable to hyperspectral imagery (Akgun, et al., 2005).

The spatial resolution of MS image can be increased using several methods such as Point Spread Function-derived convolution filter (Pinilla & Ariza, 2002) and the segmentation technique (Schneider & Steinwendner, 1999). The HNN is also used to downscale the spatial resolution of MS image based on the super-resolution mapping of unsupervised soft-classification land cover image (Nguyen, et al., 2009). However, the method used in that publication is only able to super-resolve the mixed pixels but not the pixels which is regarded as pure. This paper introduces a geostatistics-based approach to downscale MS imagery for pure pixels that cannot be super-resolved by HNN-based super-resolution mapping. This method does not aim to predict the MS image at the sub-pixel scale but produce the super-resolved and smoothed image for every adjacent pixel of different gray levels. The character of spatial variation in the reference image can be represented by the semivariogram (Atkinson & Tate, 2000). The new method employs the HNN and semivariance value of zero in form of a zero semivariance function to produce sub-pixel images.

2 IMAGE SMOOTHING USING THE HNN WITH SEMIVARIOGRAM MATCHING

2.1 General model

Fig. 1 shows the various steps in the method. The method can utilise the output image of the HNN super-resolution of a MS image together with the HNN super-resolution classification that was used to produce that MS image at sub-pixel scale (Tatem, et al., 2002, Nguyen, et al., 2006). Alternatively, coarse spatial resolution MS images can be used as input data, as long as the land cover classes corresponding to the MS image are already defined. The assumption is that information on the spatial distribution of these defined spectral classes is available. For example, if class A in the image is defined as cereal, then semivariograms of cereal can be extracted from other sources of available data such as air photographs or field surveying. The prior semivariograms and the input MS image (together with the associated classification) are then used in the HNN to produce

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In this HNN model, the input MS image is used to constrain the network in the form of a reflectance constraint. Semivariance functions are used to change the output values of neurons to match the available semivariograms. The method, therefore, amounts to semivariogram matching or pattern matching.

2.2 HNN structure

The structure of the HNN for semivariogram matching is depicted in Fig. 2. A pixel of the original image is divided into \((z \times z)\) sub-pixels in the super-resolution map (where \(z\) is the zoom factor). The coordinates of a sub-pixel \((m, n)\) are determined from the coordinates of the original pixel \((x, y)\), as in Fig. 2. Each sub-pixel in the super-resolution image is represented by a neuron in the HNN.

Thus, an image of \(2 \times 2\) pixels in the original image can be represented by a matrix of \(8 \times 8\) interconnected neurons in the HNN with the zoom factor \(z = 4\).

The HNN for semivariogram matching comprises a reflectance constraint and a number of semivariance functions. The HNN is initialised using the brightness values of the original image and it runs to a stable state in which the energy function is minimised and the output values of the nodes (sub-pixels) represent the brightness values of the semivariogram matching image. The energy function of the HNN is defined as

\[
E = -\sum_{i} \sum_{j} \left( k_{i} R_{i,j} + \sum_{m} k_{m} S_{m,i,j} \right),
\]

where \(R_{i,j}\) is the reflectance constraint of the neuron \((i, j)\), \(S_{m,i,j}\) is the semivariance function for the semivariance \(m\) of the neuron \((i, j)\), \(M\) is the number of prior semivariances, and \(k_{i}\) and \(k_{m}\) are the weighting constants.

The reflectance constraint retains the brightness values of the original image. This is based on the assumption that the reflectance of a pixel in the original image is an average of the reflectance of the corresponding sub-pixels (represented by the neurons in the HNN). The reflectance constraint of a neuron \((i, j)\) can be determined as

\[
\frac{dR_{i,j}}{dv_{0}} = \frac{1}{z} \sum_{m} \sum_{n} \frac{(v_{m,n}) - DN_{m,n}}{v_{0}},
\]

where \(v_{0}\) is the output of the neuron \((d, e)\) at time \(t\), \(z\) is the zoom factor, and \(brightness_{xy}\) is the brightness value of pixel \((x, y)\).

The semivariance function for neuron \((i, j)\) describes the semivariance calculated from the output of neuron \((i, j)\) for a lag \(h\) and must be matched with the prior semivariance \(\gamma_{m}\). In fact, the lag or vector \(h\) consists of a magnitude \(h\) and a direction. The prior semivariance for every lag \(h\) can be calculated as (Atkinson & Curran, 1995)

\[
\gamma_{m}(h) = \frac{1}{2N(h)} \sum_{m} [v_{m} - v_{0}]^{2},
\]

where \(N(h)\) is the number of neurons (representing sub-pixels) at lag \(h\) from the origin neuron \((i, j)\), and \(v_{m}\) is the output of the destination neuron \((i, j) + h\). From Eq. (3), the expected output value for the neuron \((i, j)\) can be derived as

\[
v_{i,j}^{predicted} = -\frac{b \pm \sqrt{b^{2} - 4ac}}{2a},
\]

where \(a = N(h), b = -2\sum_{i} v_{i,j} + c = \sum_{i} v_{i,j}^{2} - 2\gamma_{0}(h)\).
The value returned by the semivariance function can be calculated as

$$\frac{dS_{m,n}}{dy} = v_{m,n} \left( x, y+1 \right) - v_{m,n} \left( x, y \right)$$ \hspace{1cm} (5)

The idea of image smoothing using the HNN with semivariogram matching emerged from the analysis for semivariogram matching. From the semivariogram matching process, it can be seen that the prior semivariance values had an impact on the smoothness of the simulated image. If the values of the prior semivariances are smaller than those of the original image, then semivariogram matching generates a smoother simulated image. Accordingly, a smoothed simulated sub-pixel image can be obtained with semivariances of zero (the minimum value of semivariances).

The mechanism and effect of the image smoothing method using zero semivariogram matching for a single direction are demonstrated in Fig. 3 and Fig. 4. Since the prior semivariances are zero (i.e., the expected brightness values of the neighboring sub-pixels are the same as the central sub-pixel), a semivariance function for a separation \( h \) (Eq. (1)) will produce a positive value to increase the output of the neuron \((m,n)\) if the corresponding brightness value at separation \( h \) is greater than that of the neuron \((m,n)\). In case the brightness value at separation \( h \) is smaller, the semivariance function value will reduce the output of the centre neuron \((m,n)\). The semivariance function value is zero if the brightness values of the two neurons (representing the sub-pixels) are the same.

Considering the HNN neuron \((m,n)\) in Fig. 3, at the first iteration of the HNN optimisation process, the semivariance functions for separation \( h = 1 \) from the South and South-East directions increase the brightness value for neuron \((m,n)\) while the semivariance functions from the other directions produce zero values. In the next iteration, since the brightness value of the neuron \((m,n)\) increases, the reflectance constraint produces a negative gradient to retain the reflectance value of the original pixel. The output of neuron \((m,n)\) whereas the other semivariance functions produce semivariance functions for the South and South-East directions continue to increase gradient values to reduce it. The iteration is repeated until the HNN converges to a stable state in which the energy function (Eq. (1)) is minimised.

The resulting images for zoom factors of two and four are visually smoother than the original degraded images. In each original pixel, the spatial variation of the smoothed image was increased under the effect of the semivariogram functions with zero semivariance. Comparing with the bilinear interpolation images, the smoothness of the resulting (smoothed) images is visually similar. However, the statistics in Table 1 show that the results of the new smoothing method were closer to the reference image than those produced by bilinear interpolation. A comparison with the RMSE for the bilinear interpolation images.

3 RESULTS AND DISCUSSION

3.1 Smoothing of single MS image

An experiment was firstly tested on a single band of a QuickBird image in Fig. 5(a). The reason for applying the algorithm on a single image is that the feasibility of the method should be tested on a simple imagery before being applied wider with multi-band image. The input images were generated by degrading the reference image (Fig. 5(a)) by a factor of two to 5.2 m spatial resolution (Fig. 5(b)) and a factor of four to 10.04 m spatial resolution (Fig. 5(c)). The smoothed MS images are shown in Fig. 5(c) and Fig. 5(f). Bilinear interpolation was applied to the same images in order to provide a comparison for the new image smoothing method. The bilinear interpolation images produced from the degraded images are shown in Fig. 5(d) and Fig. 5(g).

The resulting images for zoom factors of two and four are visually smoother than the original degraded images. In each original pixel, the spatial variation of the smoothed image was increased under the effect of the semivariogram functions with zero semivariance. Comparing with the bilinear interpolation image, the smoothness of the resulting (smoothed) images is visually similar. However, the statistics in Table 1 show that the results of the new smoothing method were closer to the reference image than those produced by bilinear interpolation.
showed that the RMSE for the smoothed images using zoom factors of two and four were both smaller.

The steepness of the smoothing between two neighbouring pixels of the coarse spatial resolution image was controlled by the zoom factor $z$ and the number of lags $h$. When the zoom factor increased, the brightness values of the smoothed image using zero semivariance functions with lag $h = 1$ converged to the dotted line in Fig. 4. The effect of the increase of zoom factor from the value of 4 to the value of 8 can be seen in Fig. 5(f) and Fig. 5(h). However, if the semivariogram function with a larger number of lags were used for smoothing, the amount of smoothing (which is depicted by the shallowness of the local gradients of the dotted line in Fig. 4) would be increased by virtue of the increase in the spatial correlation between two separated sub-pixels. Consequently, the brightness values of more distant pairs of sub-pixels would become more similar. This suggests that the smoothing effect can be controlled by the values of the zoom factor and the number of lags. This finding is valuable because it makes the process more adjustable if other factors such as the point spread function are taken into account.

### 3.2 Smoothing of SPOT MS Image

In this experiment, the super-resolved images produced by the HNN and forward model were used as input data. The resulting smoothed images are reproduced in Fig. 6. The RMSE values of each band of the input super-resolved and smoothed image are given in Table 2. The smoothing process was applied only for the pure pixels which were not super-resolved by HNN super-resolution mapping using a forward model used by Nguyen, et al. (2009).

Statistical information in Table 2 shows that the RMSEs of the smoothed images were smaller in comparison with those of the input super-resolved images for all zoom factors of 2, 3, and 4. Although the decrease was small in each case, the RMSE values decreased for every spectral band. That means the smoothed images were more similar to the reference images than the input images. This suggests that the new method of image smoothing using zero semivariance is an appropriate technique for downscaling MS remotely sensed imagery.

### Table 2 RMSE of the super-resolved image using the HNN and smoothed SPOT images

<table>
<thead>
<tr>
<th>Degraded factor</th>
<th>Band</th>
<th>Super-resolved image</th>
<th>Smoothed image</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>Green</td>
<td>2.693319</td>
<td>2.688794</td>
</tr>
<tr>
<td></td>
<td>Red</td>
<td>2.765482</td>
<td>2.709012</td>
</tr>
<tr>
<td></td>
<td>NIR</td>
<td>5.909396</td>
<td>5.797107</td>
</tr>
<tr>
<td>$\Sigma$</td>
<td></td>
<td>11.36820</td>
<td>11.19491</td>
</tr>
<tr>
<td>3</td>
<td>Green</td>
<td>3.657465</td>
<td>3.648818</td>
</tr>
<tr>
<td></td>
<td>Red</td>
<td>3.887301</td>
<td>3.843548</td>
</tr>
<tr>
<td></td>
<td>NIR</td>
<td>8.140273</td>
<td>8.060652</td>
</tr>
<tr>
<td>$\Sigma$</td>
<td></td>
<td>15.68504</td>
<td>15.55302</td>
</tr>
<tr>
<td>4</td>
<td>Green</td>
<td>4.664462</td>
<td>4.6706206</td>
</tr>
<tr>
<td></td>
<td>Red</td>
<td>4.937389</td>
<td>4.925569</td>
</tr>
<tr>
<td></td>
<td>NIR</td>
<td>10.23934</td>
<td>10.199948</td>
</tr>
<tr>
<td>$\Sigma$</td>
<td></td>
<td>19.84119</td>
<td>19.796138</td>
</tr>
</tbody>
</table>
4 CONCLUSIONS

The semivariogram matching method required prior information on the per-class spatial variation in brightness at the sub-pixel spatial resolution. This information was provided in the form of discrete semivariogram functions to combine with the reflectance constraint in the HNN model. The method can be used to create a sub-pixel MS image with the spectral features of the original coarse spatial resolution MS image and the desired spatial character of variation at the sub-pixel spatial resolution. The design of algorithm aims to obtain a smooth image if the prior spatial variation at the sub-pixel resolution has a small value of variance, and increased the variance of image in case of value of prior spatial variation is high. That means the zero semivariance function produces the super-resolved and smoothed image.

The new algorithm using zero semivariance functions has been tested with QuickBird and SPOT imagery. The results showed that the super-resolved is more correlated with the original reference image. Using semivariance values of zero at a lag of one pixel, the HNN semivariogram matching model generated smoothed sub-pixel images with smaller RMSEs than those of the original degraded images, and also compared to the image obtained by downscaling using bilinear interpolation. This method can be used to smooth the resulting sub-pixel image from the HNN super-resolution with forward model.

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