Spectral Reconstruction of the Pixels in a Satellite Image through Mixing Process

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Abstract

This research introduces a technique based on the spectral mixing i.e. something opposite to the well known unmixing technique. This is done by rearrangement and reconstruction of the pixels surface materials in order to make it spectrally look like some predefined pixels. The method is called Pixel MAKeup (PMAK). This means that it is tried to find a way to select materials where when spreading them out on the pixel surface, the resultant spectral reflectance of the pixel gets similar to some predefined surface covers.

The PMAK method was run for two subsets of one LISS-III P6 image in three bands where one of them is taken as the primary (the one that is intended to be reconstructed) and the other one is the secondary (the one that the reconstructed primary subset should be looked like). The RMSE between the secondary and PMAK output was found to be 0.0061, 0.0057 and 0.0035 for bands 2, 3 and 4 respectively. The number of materials used for this pixel reconstruction were as little as 3. Of course if we increase the number of bands, then the number of these materials may increase substantially. However the simple concepts of the PMAK method would make it applicable for any sensor with any number of bands.

Key words: unmixing, makeup, endmember, pixel, image

1. Introduction

For a long time a common problem in remote sensing was the presence of mixed pixels (mixels). The limited spatial resolution of the scanner may inevitably leads to mixels usually at class boundaries. That is, individual pixels may cover more than one ground cover type. This also may leads to the spectral response at a pixel be a mixture of the underlying pure classes what is called endmembers. In the best case if a standard single class per pixel classification is performed, then the accuracy might be compromised since a fraction of the pixel has been incorrectly classified (Rosin, 2001). In the worst case, mixing may produce a confusing spectral combination such that the pixel's classification might render totally incorrect. Another solution which may reduces these two sources of error is to model the spectral mixture and classify the proportions of each endmember classes at each pixel (Rosin, 2001). Finally the simplest, and most widely used approach could be the linear mixture model (Neville et al., 2003, Conghe, 2005; Bioucas-Dias and Nascimento, 2008), in which one may model the mixture as a linear combination of the product of the proportion of endmembers in spectral reflectance in an appropriate band. Of course some imposed constraints should be satisfied. Assuming that the endmembers spectral signatures are not linearly dependent, the mixing fractions may be recovered from the data (Neville et al., 2003). Alternatively, one might pool together the measurements from a set of pixels and classify the whole set (Rosin, 2001).

It is most often assumed that the reflected radiances from the pure materials are combined linearly, i.e., the spectral radiance for the mixture is simply the sum of the radiances from each of the constituent materials. In one sense this might be always true, provided that the interaction with the atmosphere is excluded. Then radiance arriving at the sensor is the sum of the radiance components reflected from/ scattered by the individual elements of the target.

On the contrary to unmixing, no one yet worked on the mixing problem (as far as these authors know). This research deals with the reverse problem i. e. rearrangement and reconstructing the pixels surface materials in order to simulate it to look something different in the image what we call it Pixel MAKeup (PMAK) from now on. This means that we try to find a way to select materials than when spreading out on the surface the resultant spectral reflectance of the pixel gets similar to some predefined surface covers or pixels.

In remote sensing of land surfaces, occasionally we face with patterns and features that are not actually present in the scene. The reason for this is the presence of mixels with constituents different in spectral behaviors where their combinations may produce a spectral curve similar to something which is not really present in the scene. Any material as a substance present in a pixel may contribute to the reflectance of that pixel according to its share proportion. So the result of these shares and contributions may come up with a reflectance curve similar to some particular land cover e.g. vegetation, bare soil, deserts, etc. sometimes the effect of atmosphere and its constituents may worsen this phenomenon. To solve this problem and to retrieve the actual surface material by remote sensing technology, the unmixing technique as explained above, have so far been introduced and used. On the contrary sometimes we might be interested to do the reverse procedure i.e. mixing some materials to have a pixel look alike another pixel (PMAK). Different application may exist for this technique two of which is in the image processing and estimation of uncertainties involved with the extracted information, and image simulation.

2. Methodology

The principle of the method is based on the following equation:

$$\begin{aligned}
\alpha &= a\alpha_1 + b\alpha_2 + c\alpha_3 + d\alpha_4 \\
\beta &= a\beta_1 + b\beta_2 + c\beta_3 + d\beta_4 \\
\gamma &= a\gamma_1 + b\gamma_2 + c\gamma_3 + d\gamma_4 \\
a + b &+ c + d = 1
\end{aligned} \tag{1}$$

Where here α_i, β_i and γ_i are reflectance values introduced to the equation mostly from spectral libraries and α, β and γ are the same reflectance values but for the pixel that we desire to achieve after pixel rearrangement. Here the 4th equation is a constraint for the proportions of the materials in each mixel where a, b, c and d are these proportions. To solve Eq. 1 the least square method was used where for this the set of Eq. 1 was rearranged in the shape of matrix as is shown in Eq. 2.

$$\begin{bmatrix} \alpha \\ \beta \\ \gamma \\ 1 \end{bmatrix} = \begin{bmatrix} \alpha_1 & \alpha_2 & \alpha_3 & \alpha_4 \\ \beta_1 & \beta_2 & \beta_3 & \beta_4 \\ \gamma_1 & \gamma_2 & \gamma_3 & \gamma_4 \\ 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} \tag{2}$$

here the left hand side matrix (*L*) is the one that we intend to have (known) and the first in the right (*A*) is the reflectance of the material needed to be spread out on the surface in the pixel (determined by iteration) and the last matrix in the right (*X*) is the fraction of each material in the pixel.

$$L = AX \tag{3}$$

We solve Eq. 2 for *X*

$$X = \left(A^T A\right)^{-1} A^T L \tag{4}$$

The image we used in this research was from IRS-P6 LISS-III sensor products. The reason for this selection was i) the availability of the image on a routine basis ii) the limited number of bands in this sensor.

To select the proper material, the spectral library available in the ENVI software[1] was used. The selected materials are those that either is in access in the area or man-made material. On the other hand those 3 regions of the electromagnetic spectrum relevant to in the LISS-III bands were selected. Then to limit the number of materials, a criterion for the selection was adopted. This criterion consists of the following stages:

1- The correlation coefficients between the reflectance of each substance with the reflectance of every other substance were calculated. It is believed that the magnitude of these correlation coefficients is a representative of the degree of similarity between reflectance of each pairs of substance.
2- Those materials that have the least correlation are selected as candidates for pixel reflectance simulation.

Two lists were prepared in this regards. The 1st list consists of 7 substances with the highest priorities according to the criteria (Table 1), in the second list 13 substances that have the next priorities were grouped (Table 2).

Number	Materials
1	Copper Metal (Metal 0681UUUCOP)~~14
2	Construction Tar (Tar 0099UUUTAR)~~3
3	Olive green gloss paint (Paints 0385UUUPNT)~~4

[1] John Hopkins University spectral library for minerals, rocks, snow and ice, man-made materials, vegetation, and water from 2 - 25 microns

4	Aluminum Metal (Metal 0384UUUALM)~~3
5	Olive green paint (Paints 0407UUUPNT)~~6
6	Construction Concrete (Cement Cinderblock 0432UUUCNC)~~9
7	Reddish Asphalt roofing shingle (Shingle 0672UUUASP)~~12

Table 1. List of the first 7 materials having least correlations between their reflectance values.

Number	Materials
1	Dark reddish brown organic-rich silty loam (Cryohumod 87P4264)~~17
2	Dark grayish brown silty loam (Agialboll 85P5339)~~3
3	Gray silty clay (Haplaquoll 86P4603)~~6
4	Black paint (Paints 0406UUUPNT)~~5
5	Bare Red Brick (Bricks 0413UUUBRK)~~7
6	Gray/dark brown extremely stony coarse sandy (Cryumbrept 87P3855)~~16
7	Grayish brown loam (Haplustall 85P4569)~~2
8	Pine Wood (Woods 0404UUUWOD)~~5
9	Brown sandy loam (Paleustalf 87P2410)~~9
10	Construction Concrete (Paving Concretes)~~1
11	Brown to dark brown gravelly loam (Haploxeralf 87P313)~~10
12	Dark brown fine sandy loam (Haplumbrept 86P4561)~~5
13	Very dark grayish brown silty loam (Plaggept 85P3707)~~1

Table 2. List of the next 13 materials having least correlations between their reflectance values.

3. Model Execution

Before implementing this technique on real data, it was run on a set of simulated data. For this a 10 by 10 pixels were setup containing different proportions of the substances randomly selected from the spectral library. That is 100 pixels are considered each one having its own unique spectral reflectance in 3 bands (LISS-III bands). Then one of the materials in Table 1 was selected as the desired one (the one that we are going to makeup pixels to be looked like at the end). Eq. 1 was solved for these pixels. The RMSE between model findings and known values were calculated and found to be of the order of 9×10^{-14} which is very acceptable.

In practice and in the real world, it is not so simple and there involved some ambiguities. To test this technique for the satellite images, a subset of 98 by 133 pixels from a LISS_III P6 image were selected. The selected subset was from a very complex land cover in the urban area. The area that this subset must look like was an agricultural area selected from the same scene, with the same dimensions. This minimizes the effects of the atmosphere as is believed to be the same for these two subsets. The aim is to select few materials mainly from the Table 1 and in few cases from Table 2 in different proportions and virtually spread out these materials over the pixel somehow that the resultant of the mixed reflectance makes this pixel to spectrally behave like say a fully vegetated pixel.

The image used was acquired on APR-01-2007. Here we imposed a restriction of 4 substances at a time, i.e. 3 substances from the materials in the lists and the forth one be the pixel's content material. At this stage all combinations of substances from both lists plus the pixel material itself all for different proportions must be tested. These combinations were as follow:

- One substance from list 1 plus pixel content
- Two substance from list 1
- Two substance from list 1 plus pixel content
- Three substance from list 1
- Three substance from list 1 plus pixel content
- Four substance from list 1
- One substance from list 1, one substance from list 2 plus pixel content
- Two substance from list 1 plus one substance from list 2
- Two substance from list 1, one substance from list 2 plus pixel content
- Three substance from list 1 and one substance from list 2

Fig. 1. shows the selected primary and secondary subsets. The secondary subset is the one that the primary subset will finally turns to it after being covered by the materials selected in the mixing procedure.

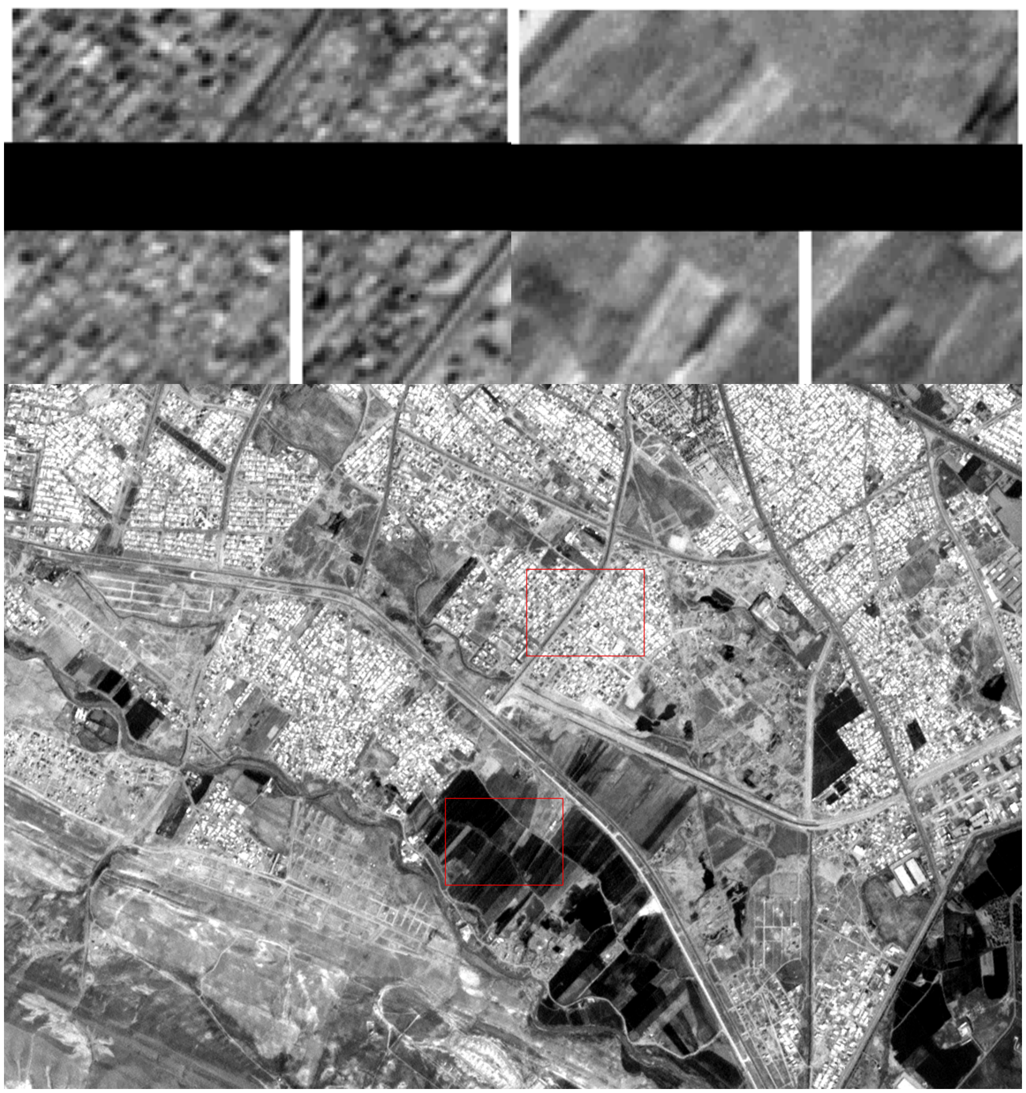

Fig 1: The selected LISS-III P6 image (lower), primary subset (upper left) and secondary subset (upper right). The primary subset is an urban area and the secondary subset is an agricultural area.

4. Results and Analysis

The technique was implemented, and the results were promising. The RMSE between the secondary subset and the technique output subset was found to be of the order of about 0.0051. The averaged RMSE in each band is shown in Table 3.

Bands	RMSE
Band 2	0.0061
Band 3	0.0057
Band 4	0.0035

Table 3. The RMSE between the secondary subset and the technique output subset in 3 bands

The technique output in band 1 is shown in Fig. 2. As can be seen this subset image is perfectly like the secondary subset at least visually.

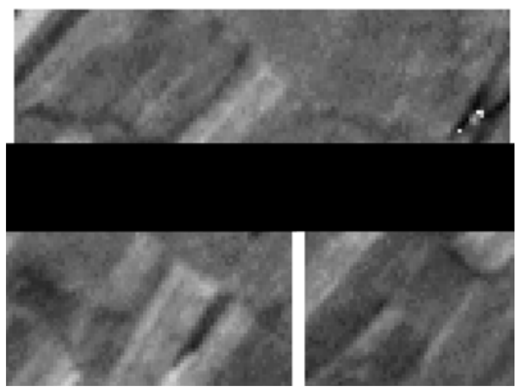

Fig 2: The technique output subset image in band 1. As can be seen it is visually similar to the secondary subset image in Fig. 1. (Upper-right).

The scatter plots between each band of the secondary subset and the corresponding technique outputs are shown in Fig. 3.

Fig 3: The scatter plots between each band of the secondary subset and the corresponding technique outputs, band2 (right), band3 (middle) and band4 (left).

Most of the points that have not laid on the line of the bisectors in this scatter plots are those pixels:

- That are in the shadow region having zero reflectance. The technique is not able to suggest the proper combination for these pixels
- That are in the boundaries where the change is abrupt and finding proper materials are practically difficult.

In the next attempt, an agricultural region was taken as primary subset image and it was tried to turn it to an urban area. This due to the ambiguities and complexities involved with city structures didn't produce satisfactory results compared to the previous one. This implies that the equations used in the previous one are not necessarily reversible. This is because it is not allowed to have negative coefficients in Eq. 1 where these coefficients are meant to be proportions of the material and substances used to cover the pixels. The subset image produced at this stage for converting agricultural subset to the urban is shown in figure 4.

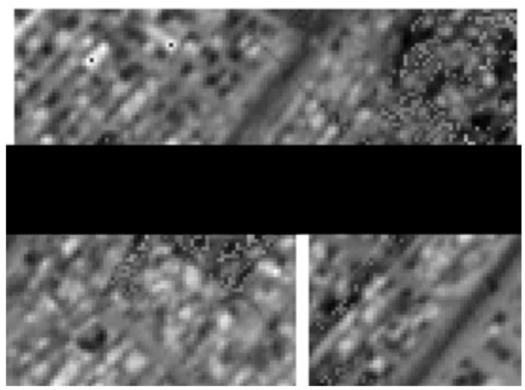

Fig 4: The output subset image for converting agriculture to urban.

It is worth noting that these images were not corrected for the atmospheric effects because it is presumed that the atmosphere was the same for both primary and secondary subsets and getting them to visually look alike was the main objective of this work. It is believed that the effects of the atmosphere are not usually so hard to change the geometry of the pixels except for the high values of optical thicknesses where in these circumstances nobody uses satellite images.

5. Conclusions

On the contrary of unmixing, the spectral mixing technique might be useful for many applications. This research dealt with the mixing problem i. e. rearrangement and reconstruction of the pixel's surface materials in order to make it to look something different in the scene what we call it Pixel MAKeup (PMAK). This means that it is tried to find a way to select materials where when spreading out on the surface of the pixel, the resultant spectral reflectance of the pixel gets similar to some predefined surface covers or pixels.

Any material as a substance present in a pixel may contribute to the reflectance of that pixel according to its sharing proportion. So the result of these shares and contributions may come up with a reflectance curve similar to some particular land cover. The PMAK method was run for two subsets from one LISS-III P6 image in three bands where one of them is taken as the primary (the one that is intended to be reconstructed) that was urban area and the other one is the secondary (the one that the reconstructed primary subset should be look liked) that was agricultural area. The RMSE between the secondary and PMAK output was found to be 0.0061, 0.0057 and 0.0035 for bands 2, 3 and 4 respectively. However in the reverse direction that is reconstructing an agricultural area to look like an urban region was not as good as previous one. This is mostly due to the presence of fully shadow pixel as well as abrupt change in the boundaries. The number of materials used for this pixel reconstruction were found to be as little as 3. Of course if we increase the number of bands, then the number of these materials may increase substantially.

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