INCREASING AND EVALUATING THE RELIABILITY OF MULTIPLE ENDMEMBER SPECTRAL MIXTURE ANALYSIS (MESMA)

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ABSTRACT:
As more and more information extraction techniques emerge, there is a growing demand on addressing the reliability of the produced results. The prominent examples for initiatives addressing this issue are the CEOS CalVal activities, where calibration and validation of satellite imagery and related products is conducted by international space agencies. In the field of airborne hyperspectral remote sensing, the JRA2 initiative within the FP7 EUFAR project focuses on development and harmonization of quality indicators for pre-processed data and selected thematic products.
In this paper, examples are presented on how to address the reliability of a Multiple Endmember Spectral Mixture Analysis (MESMA) approach.

KEYWORDS: product quality, validation, spectral unmixing, MESMA

1. INTRODUCTION

Linear spectral unmixing provides highly accurate results if all end-members (EM) are known, and if the spectral variability of the EMs is included in the mixture model (e.g., GARCIA-HARO et al., 1999).

But in real life, not all EM are known, and, when using image-derived EMs, some EMs are already mixtures themselves. When applying recent EM derivation approaches like Sequential Maximum Angle Convex Cone (SMACC, see GRUNINGER et al., 2004) on synthetic test scenes, about ~70% of all EMs can be automatically retrieved, but also 1 in 10 EM is a mixed spectrum, or an erroneous pixel (e.g., saturated or affected by noise) (BACHMANN, 2007). Similar to supervised classification techniques, errors in the training data (i.e., the EMs) result in a significantly reduced accuracy of the final product.
Also some combinations of EMs result in an ill-conditioned mixing model.
A further general limitation arises from low local view angles (BACHMANN et al., 2007b).

As a result, the overall accuracy of spectral unmixing approaches is reduced, and the accuracy does vary over the scene. Thus to fulfill the requirements of CEOS as well as EUFAR JRA2, a general reliability measure as well as per-pixel quality indicators are valuable for the end-user.

2. THE µMESMA APPROACH

An improvement to a standard spectral unmixing are Multiple Endmember Spectral Mixture Analysis (MESMA) approaches. Since a large number of EMs and thus the spectral variability of materials can be included in the mixing model, the retrieved abundances are usually more accurate (see e.g., GARCIA-HARO et al., 2005, LOBELL et al., 2001, ROBERTS et al., 1998).

The μMESMA approach is an automated MESMA which was developed for the retrieval of subpixel ground cover fractions in semi-arid regions. Quantitative cover estimates are derived for photosynthetic active vegetation (PV), non-photosynthetic active vegetation (NPV) and bare soil. In the following, selected features of this approach which increase the reliability and address the quality of the data product are described. A full description of μMESMA is given in BACHMANN (2007).

2.1 Addressing numerical problems

The well-known basic equation of the linear mixture model can be formulated as

$$Ax = b$$

where A is the m*n EM-matrix, x is the abundance vector for n EMs, and b the measured spectrum in m bands.

For hyperspectral data where m >> n, solving for x is an overdetermined problem. This is usually solved in a least-squares approximation. E.g., as a simple case, by using the pseudo-inverse

$$x = A^{+}b \quad \text{with} \quad A^{+} = (A^{T}A)^{-1} A^{T}$$

Since this and other solving algorithms include matrix inversion, linear dependencies between spectrally similar classes often result in numerical problems, i.e. an ill-conditioned problem (e.g., BOARDMAN & GOETZ, 1991). This problem is even more prominent when increasing the number of EMs, since there is a higher probability of such cases with linear dependencies. Thus μMESMA includes a first check of the condition number κ of the EM-Matrix A:

$$\kappa = \|A\| \, \|A-1\|$$

where || denotes the Euclidean L2-norn.

Consequently all EM combinations which would result in an ill-conditioned problem are excluded, ensuring that the mathematical requirements for meaningful results are met.

2.2 Selecting reasonable mixture models

While other MESMA approaches select the EM-model with the lowest unmixing RMS error, the μMESMA approach uses a combined model selection criteria (see BACHMANN et al. (2004) for a more detailed description).

The approach includes a residual analysis (GILLESPIE et al., 1990) where spectral features in the residual spectra are automatically detected and identified using a knowledge-based approach. When diagnostic spectral features are still present in the residual, then a part of the signal can not be modelled with the current EMs. As consequences, the retrieved abundances are likely to be incorrect, and another EM model should be applied for unmixing.

Second, information from the spatial neighbourhood is also included in the unmixing process. Since the soil type –and thus the soil EM– is rather unlikely to change between adjacent pixels, a second unmixing iteration is conducted where the dominant soil EM within a spatial neighbourhood is used. If the unmixing error is not significantly increased, the mixing model with the dominant soil EM is used.

When using this methodology including information form the spatial neighbourhood, as well as a taking advantage of hyperspectral data for the identification of materials in the residual, the stability of unmixing results is significantly increased. This was found to be of high importance, especially when incorrect EMs are included in the EM model (BACHMANN, 2007).

2.3 Addressing view angle effects as general limitations

An often neglected source of uncertainty on estimated cover percentage is caused by local view angle effects, where parts of bare soil patches are not visible due to vegetation blocking the sensor line-of-sight (see Fig. 1).

When estimating the fractional cover of pixels far off-nadir or at slopes pointing away from the sensor, plant cover can be overestimated by more than 50%, seriously decreasing the accuracy. This problem is inherent when using wide field of view (FOV) sensors, or satellite sensors tilted off-nadir. This issue is addressed in more detail in BACHMANN et al. (2007b).

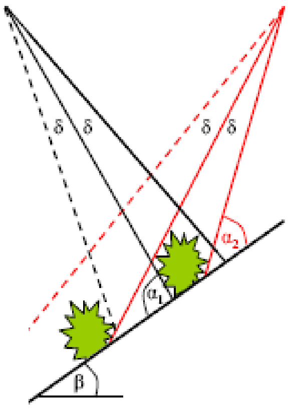

Figure 1: Schematic illustration of line-of-sight blocking. α denotes local incidence angle, β the slope, δ the instantaneous field of view of the sensor.

2.3 Reliability score and quality indicators

The first step required for estimating the reliability is the identification of error-prone pixels. The Linear spectral unmixing approach already offers a simple measure for "goodness of fit", i.e. the model RMSE. Since the RMSE is not always linked to the error in abundances (e.g., Garcia-Haro et al., 2005), an improved detection of pixels which are likely to be error-prone is included in μMESMA, which is formulated as a combined error score. This includes a residual analysis as described in section 3.2, as well as a weighted model RMSE.

Also the level of agreement between the unmixing-derived abundances and abundance values derived by empirical regression models is included. The baseline for this approach (similar to LOBELL et al., 2001) are band indices which parameterize diagnostic absorption features (e.g., clay absorption at 2.2 μm for soils, or holo-cellulose at 2.09 μm for dry and dead vegetation). Although the accuracy of these regression models is lower than spectral unmixing (R^2 values ranging from 0.5 for dry vegetation coverage to 0.7 for soil coverage for regression models), large discrepancies between both approaches indicate a lower confidence in the results.

In addition, critical local incidence angles are included in the score, as well as the per-pixel quality flags from the pre-processing (see BACHMANN et al., 2007a).
Equally important as the calculation of the quality indicators is the communication of a combined quality indicator in a user-friendly form. For this purpose, an additional data layer with a per-pixel quality flag is produced within μMESMA. An example is shown in Fig. 3.

3. RESULTS

In order to provide a "typical accuracy", a large number of simulations were calculated based on the field spectral libraries (e.g., PREISSLER et al., 1998, ELVIDGE, 1990, and various measurements by DLR in Spain and Namibia).
Depending on the scenarios used, the mean error of μMESMA was found to be in the range of 5% - 10% abundance absolute, with R^2 between 0.65 and 0.85 (significance $p < 0.0005$).
It is worth noting that similar to other MESMA approaches, about 50% of simulated models could be unmixed with an error of less then 3% abundance absolute, while single errors could range up to 60% abundance absolute. This variability emphasizes the need for a per-pixel reliability score.

For the real-world test case Capo de Gata (see BACHMANN et al., 2004), the mean error on ground cover estimates was 9.6% abundance absolute, with R^2 values between 0.76 and 0.86 (significance $p < 0.005$), and again with single errors up to 20% abundance absolute. Examples for abundance maps are shown in Fig. 2a, b & c.

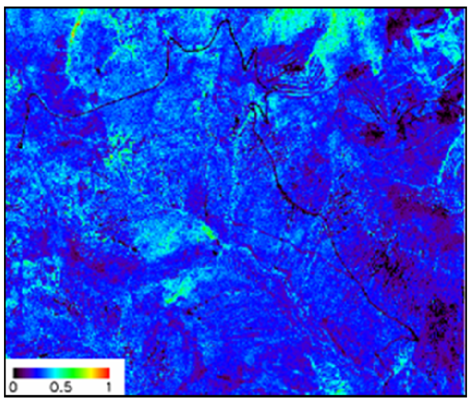

Figure 2a: Quantitative cover for PV [%].

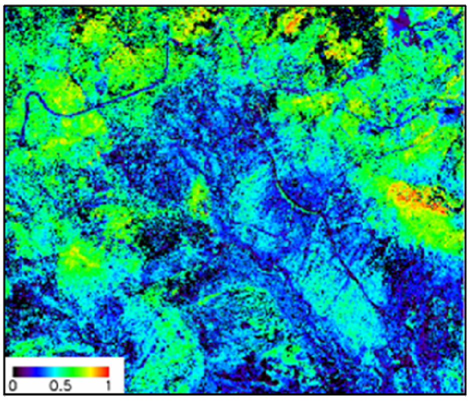

Figure 2b: Quantitative cover for NPV [%].

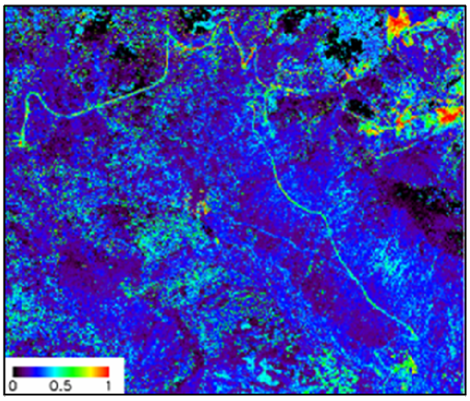

Figure 2c: Quantitative cover for soil [%].

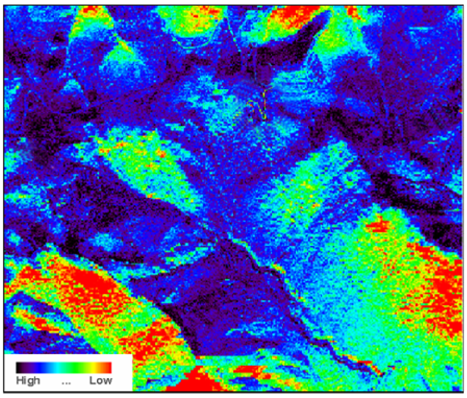

Figure 3: Reliability score image.

When investigating the influencing factors leading to these results, the most important was the usage of MESMA instead of simple linear unmixing. Thereby the mean error could be reduced by ~4% abundance absolute (30% - 50% relative). Also highly important are the appropriate selection of EMs (~4% abundance absolute, 20% - 40% relative, with significant larger values when wrong EMs are included), and the model selection criterion (~3% abundance absolute, 20% - 25% relative). The model selection criterion is of increased importance when not all EM were found. Additional factors are the choice of the solving algorithm, an empirical correction of local view angle effects, and improved approaches for including a shade component.

4. CONCLUSIONS

Summarizing, there is a need for quality indicators in pre-processing chains (as addressed in the EUFAR JRA2 task 2), as well as in thematic products (as in EUFAR JRA2 task 4 and CEOS CalVal). In order to fulfill such a demand, it is necessary to identify and –if possible– eliminate errors and sources of uncertainty. The remaining errors need to be quantified by providing typical accuracies. These errors and limitations have to be communicated to the end-user.
Within the µMESMA approach, effort was put in increasing the general unmixing accuracy, on providing typical accuracies for a wide range of scenarios, and on explicitly addressing the quality for each pixel by including a reliability score image. Thus the end user of the thematic abundance maps has a better insight in the quality

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