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lti-spectral Texture Characterisation for Remote Sensing Image Segmentation

Filiberto Pla[1], Gema Gracia[1], Pedro García-Sevilla[1],
Majid Mirmehdi[2], and Xianghua Xie[3]

t. Llenguatges i Sistemes Informàtics, University Jaume I, 12071 Castellón, Spain
{pla,ggracia,pgarcia}@lsi.uji.es
[2] Dept. of Computer Science, University of Bristol, Bristol BS8 1UB, UK
majid@compsci.bristol.ac.uk
[3] Dept. of Computer Science, University of Swansea, Swansea SA2 8PP, UK
x.xie@swansea.ac.uk

stract. A multi-spectral texture characterisation model is proposed, the lti-spectral Local Differences Texem – MLDT, as an affordable approach to used in multi-spectral images that may contain large number of bands. The DT is based on the Texem model. Using an inter-scale post-fusion strategy image segmentation, framed in a multi-resolution approach, we produce un- ervised multi-spectral image segmentations. Preliminary results on several ote sensing multi-spectral images exhibit a promising performance by the DT approach, with further improvements possible to model more complex tures and add some other features, like invariance to spectral intensity.

ywords: Texture analysis, multispectral images, Texems.

oduction

hyperspectral sensors acquire information in several spectral bands, which yperspectral data in high dimensional spaces. These systems have tradition- used to perform tasks in remote sensing, and are being introduced and in other application fields like medical imaging or product quality assess- ltispectral image data are used in order to estimate and analyze the presence f vegetation, land, water and other man made objects, or to assess the quan- bstances, chemical compounds, or physical parameters, e.g. temperature, a qualitative and quantitative evaluation of those features.

rd multispectral image interpretation techniques barely exploit the spectral- ationships in the image. The multi-spectral image data is basically treated as dependent spectral measurements at each pixel location, without taking into heir spatial relations. In order to exploit hyper-spectral imagery in applica- iring high spatial resolution, e.g., urban land-cover mapping, crops and best of our knowledge, there are no texture characterisation methods for ral images with high number of bands. Such methods are unaffordable d directly in gray level and colour images due to the increase of dimen- in texture characterisation. Multi-band images techniques have been lly restricted to three-band colour images, by processing each channel ently, taking into account spatial interactions only within each channel approaches decompose the colour image into luminance and chromatic extracting texture features from the luminance channel [4]. There are t try to combine spatial interaction within each channel and interaction spectral channels, applying gray level texture techniques to each channel ently [5], or using 3D colour histograms as a way to combine informa- all colour channels [6].

r group of techniques try to extract correlation features between the for colour texture analysis, like in [7], where spatial and spectral interac- simultaneously handled. Such techniques assume the image to be a col- f epitomic primitives, and the neighbourhood of a central pixel to be ly conditionally independent. A more recent approach based on these is the Texem model [8], consisting of a Gaussian mixture model repre- for colour images using conditional dependency in neighbouring and nnels information. The gray level Texem model assumes spatial condi- pendency within the pixel neighbourhood. The Texem model will be the he work presented in this paper for texture characterisation in multispec- es.

Texem Model

m model [8] is a texture characterisation method that models the image as a process where a set of image primitives generate the image by superposi- age patches from a number of texture exemplars, Texems.

enerative model uses a Gaussian mixture to obtain the Texems that have an image. The Texems are derived from image patches that may be of any hape. In this work, square image patches of size *N=n x n* have been consid- image $\boldsymbol{I}$ is decomposed as a set of $\boldsymbol{Z}=\{\boldsymbol{Z}_i\}_{i=1}^{P}$ patches, each one belonging *K* possible Texems, $\boldsymbol{T}=\{\boldsymbol{t}_k\}_{k=1}^{K}$. A patch vector at a central pixel location *i* is $\boldsymbol{Z}_i=(g_{i1},...g_{iN})$, with the gray level values $g_{ij}=\boldsymbol{I}(x_{ij},y_{ij})$ at pixel locations N in the patch grid. Each Texem is modelled as a Gaussian distribution, given the *k*th Texem $\boldsymbol{t}_k$, the likelihood of a patch $\boldsymbol{Z}_i$ is expressed as a stribution

$$p(\boldsymbol{Z}_i \mid \boldsymbol{t}_k,\theta_k)=G(\boldsymbol{Z}_i;\mu_k,\Sigma_k) \quad (1)$$

$=(\alpha_k,\mu_k,\Sigma_k)$ is the parameter set defining the Gaussian in a mixture, with the a set of sample patches extracted from an image, the generative Gaussian nodel of the *K* Texems that generated that image can be estimated by the on Maximisation (EM) algorithm [9]. Thus, the probability density function age patch $\boldsymbol{Z}_i$ will be given by the Gaussian mixture model,

$$p(\boldsymbol{Z}_i \mid \alpha) = \sum_{m=1}^{K} \alpha_m \, p(\boldsymbol{Z}_i \mid \boldsymbol{t}_m, \theta_m) \quad (2)$$

ghtforward way to extend the gray level Texem model to colour images consider instead of the image patch $\boldsymbol{Z}_i = (g_{i1}, \ldots g_{iN})$ of *N* pixel values in a ome image, an image patch at pixel *i* in a three band colour image, e.g. an ge, as $\boldsymbol{Z}_i = (g^R_{i1}, \ldots g^R_{iN}, g^G_{i1}, \ldots g^G_{iN}, g^B_{i1}, \ldots g^B_{iN})$. This increases the feature patch nality in a proportional way with respect the number of bands. In order to increase in dimensionality of the generative Texem model for colour im- pixels *i=1,...,N* within the patch are assumed to be statistically independ- the Texem, with each pixel value following a Gaussian distribution in the ace [8]. Thus, now the likelihood of a patch $\boldsymbol{Z}_i$ given the *k*th Texem $\boldsymbol{t}_k$ is as a joint likelihood of the *N* pixels belonging to the patch, that is,

$$p(\boldsymbol{Z}_i \mid \boldsymbol{t}_k, \theta_k) = \prod_{j=1}^{N} G(\boldsymbol{Z}_{j,i}; \mu_{j,k}, \Sigma_{j,k}) \quad (3)$$

v the *k*th Texem parameters $\theta_k = (\mu_{1,k}, \Sigma_{1,k}, \ldots, \mu_{N,k}, \Sigma_{N,k})$ are the mean $\mu_{j,k}$ and e $\Sigma_{j,k}$ of the *j=1,...,N* pixels in the Texem grid. The mean $\mu_{j,k}$ and the co- $\Sigma_{j,k}$ of each pixel are now defined in the colour space.

nentation with Inter-scale Post-fusion

l, to model the texture features of an image appropriately, several Texem needed. Alternatively, instead of using different Texem sizes to character- of patches that may generate an image, the same Texem size can be used iresolution scheme, assuming each resolution level is generated from a t independently [10]. However, applying multi-resolution to image seg- needs a fusion process in order to integrate the information across the image resolution levels, from coarser to finer levels. We follow this ap- this paper.

i-spectral Local Difference Texems - MLDT

ur Texem model described in section 2.2 can be easily extended from col- es, usually represented by 3 bands, to any number of bands B. However, hyper-spectral images may contain order of hundred bands to represent dimensional spaces, involving more computational complexity issues and called curse of dimensionality, when having a limited number of samples e the Gaussian mixtures. In order to cope with such a high dimensionality each image patch $\boldsymbol{Z}_i$ at a pixel location i in a multi-spectral image I with vill be defined as follows,

$$\boldsymbol{Z}_i = (\overline{g}_{i1},...\overline{g}_{iB}, d(\boldsymbol{g}_{i1},\overline{\boldsymbol{g}}),...,d(\boldsymbol{g}_{iN},\overline{\boldsymbol{g}})) \tag{4}$$

is defined as

$$\overline{g}_{ib} = \frac{1}{N}\sum_{j=1}^{N} g_{ijb}; \quad b = 1,...,B$$

the mean value of the N pixels in the image patch grid for each band and

$$d(\boldsymbol{g}_{ij},\overline{\boldsymbol{g}}_i) = \frac{1}{B}\sum_{b=1}^{B} |\,\overline{g}_{ib} - g_{ijb}\,|; \quad j = 1,...,N$$

norm of the spectral differences between pixels $j=1,\ldots N$ in the image patch l location i and the mean spectrum $\overline{\boldsymbol{g}}_i = (\overline{g}_{i1},...\overline{g}_{iB})$ in the image patch $\boldsymbol{Z}_i$. In t work, *L1* norm has been used, which would represent in a continuous epresentation the area between two spectral power spectra, although other spectral difference measures could be used. Analogously, instead of the an $\overline{\boldsymbol{g}}_i$ as the patch spectral reference, other possible spectral image patch tives could be used, e.g. the median spectral pixel or the spectrum of the xel in the patch.

patch $\boldsymbol{Z}_i$ is then a $B+N$ dimensional vector, with B the number of bands number of pixels in the image patch grid. Note that given a patch size y spectral number of bands B, the dimensionality of the texture feature s always a fixed part size of N difference terms, and only the mean spec- increases linearly as the number of bands B increases. This is a desirable of the texture characterisation in the multi-spectral domain, since the ty of the Texem model is controlled, keeping dimensionality to an af- way. In addition, if a band reduction technique is used as a previous step Texem dimensionality can even be kept at a more reduced and affordable

LDT characterisation captures in a compact way the difference patterns image patch in a multi-spectral image, and is thus able to represent the l spatial and spectral information in a single representation. Using the tch representation expressed in (8) will enable the use of the gray level odel in section 2.1 directly, keeping spectral and spatial dependencies in

erimental Data

o test the validity of the proposed MLDT characterisation, it has been ap- set of three hyper-spectral remote sensing images captured with different

EX099 project provides useful aerial images about the study of the variabil- the reflectance of different natural surfaces. This source of data, referred as ap in figures, corresponds to a spectral image of 700×670 pixels and 7 es of identified crops and other unknown land use class, acquired with the ands HyMap spectrometer during the DAISEX-99 campaign /io.uv.es/projects/daisex/). In this case, 126 bands were used, discarding the SNR bands (0, 64). Figure 1 (left) represents a pseudo-colour image com- l from three of the 126 bands.

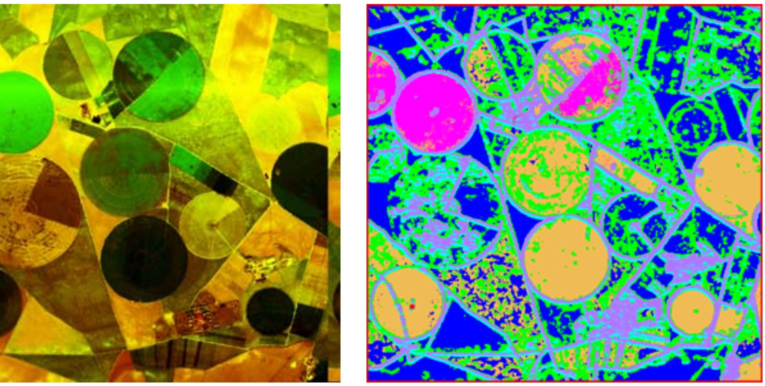
ite PROBA has a positional spectra-radiometric system (CHRIS) that ures the spectral radiance. The images used in this study come from the IS-PROBA mode that operates on an area of 15×15 km, with a spatial reso- of 34m obtaining a set of 62 spectral bands that range from 400 to 1050 541×617 pixels and 9 classes of identified crop types and other unknown use classes. In this case, 52 bands were used, discarding the lower SNR (25, 33, 36-37, 41-43, 47, 50, 53). Figure 2 (left) represents a pseudo- r image composed from three of the 52 bands.

rd multi-spectral image of seven spectral bands and 512×512 pixels, ob- l from LandSat-7 of an area around the Kilauea Volcano, in Hawaii. This e will be referred as LandSat-7. Figure 3 (left) represents a pseudo-colour e composed from three of the 7 bands.

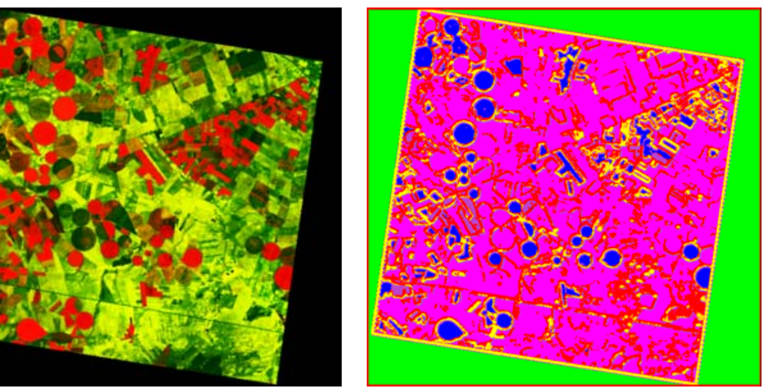
ering multi-spectral images can contain a huge amount of information with mber of bands, and taking into account that most of these bands are very [11], it seems logical that the dimensionality reduction problem in multi- mages has to be linked with the texture characterisation problem, since try- nbine correlations simultaneously in the spectral and spatial domain can be onally expensive.

r to exploit inter-band correlation to reduce the multi-spectral band repre- the unsupervised band reduction technique by [11] has been used to reduce of HyMap and CHRIS to the seven most relevant bands. This band reduc- ique exploits inter-band correlation to reduce the multi-spectral band repre- by means of theoretic information concepts. The seven bands selected by the ction algorithm for HyMap images have been bands (1, 28, 41, 52, 79, 107, for CHRIS image, bands (0, 9, 20, 30, 40, 46, 59).

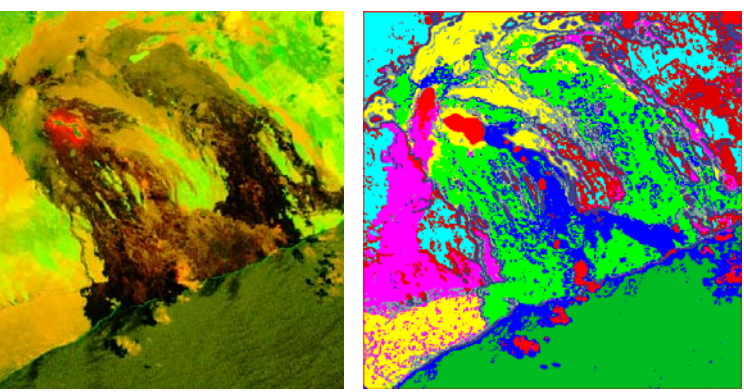
ne selected bands for every image of this dataset, an unsupervised image ion algorithm has been applied, based on an EM algorithm for a Gaussian nodel, fixing the number of Texems as input parameter, and the inter-scale n strategy pointed out in section 3. The results are discussed in the next



1. HyMap pseudo-colour image (left) and its MLDT-based segmentation (right)



2. CHRIS pseudo-colour image (left) and its MLDT-based segmentation (right)



LandSat 7 pseudo-colour image (left) and its MLDT-based segmentation (right)

lts

right) shows the result of the proposed method to the HyMap multispectral ing the selected 7 image bands, with L=3 multi-resolution levels, K=12 nd N=7×7=49 image patch size. The Texem model was trained with 3000 nage patches in each level. Note how the MLDT multi-spectral characterisa- nter-scale post-fusion segmentation has been able to identify the most im- xture types in the image, grouping them in a satisfactory way. Note how the xems found model most of the structures of the image, finding the main orresponding to the different crop and land uses in the image.

ously, Figure 2 (right) shows the result of the algorithm for the CHRIS mul- image, using the selected 7 image bands, with L=3 multi-resolution levels, ems and N=7×7=49 image patch size. The Texem model was trained with om image patches in each level. In this case, the Texems found correspond n three types of land uses. Note how it is also modelled the different types nd borders, where we can distinguish fairly well at least two different border modelled by their corresponding Texems.

, Figure 3 (right) shows the result of the algorithm for the LandSat-7 multis- age, using the 7 image bands, with L=2 multi-resolution levels, K=10 Tex- /=3×3=9 image patch size. The Texem model was trained with 3000 random ches in each level. The results on this image show how well the different water types have been extracted, being able to discriminate even distinct iments levels. Another important detail is how the spectral information has able to detect the area covered by the smoke from the volcano, which can- ually appreciated very well from the pseudo-colour composition, only near o, but the MLDT characterisation has been able to represent.

orth noting that when using 7 image bands an a 49 pixel patch size, the ctor has 7+49=56 dimensions, and the Texem model in this case is defined e Gaussian of 56 dimensions in a Gaussian mixture model. In the case of a 9 h size, Texem dimensionality reduces to 7+9=16 dimensions. If the multi- nage had 50 dimensions, the Texem dimensionality for a 3×3=9 patch size 50+9=59, which is still affordable.

clusions

remark, the basis for a multi-spectral texture characterisation technique has , with promising results and affordable complexity to deal with the huge f data a multi-spectral image may contain, capturing the essential properties tial and spectral relationships.

e improvements and variations of the proposed MLDT characterisation can n several areas, for instance, if the mean spectra of image patches are the MLDT vector then reduces considerably and for a given image patch

ally, more tests should also be directed to model Texems as several Gaus-
ponents, as pointed out in [10], exploring some hierarchical clustering struc-
[12], to merge Gaussian modes to form clusters.

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