MULTISOURCE CLASSIFICATION BASED ON UNCERTAINTY MAPS

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ABSTRACT

A new methodology to perform classification of multisource data is proposed in this work. The technique takes into account the classification results (a classified image and an uncertainty map) derived from each data source in order to generate a new classified image. It is based on a region-based classifier which employs stochastic distances, statistical tests and reliability of the classification to produce a final classification. Images acquired from two distinct and independent data sources (optical and microwave sensors) were used to validate the proposed methodology. One LANDSAT5/TM image and one ALOS/PALSAR image from a region on Brazilian Amazon were classified, firstly individually and then using the proposed classification technique. The results showed that the individual classification results can be improved by the use of our multisource classification technique. It can be concluded that this new method to combine information derived from different data sources is strongly promising.

Index Terms— Multisource classification, statistical region-based classification, stochastic distances

1. INTRODUCTION

Earth surface mapping can improve understanding and management of natural resources. In remote sensing, a relevant tool to achieve this mapping is the digital image classification. There are several distinct protocols and models used in the image classification as, for instance, the region-based techniques.

A classical approach employed in region-based classification uses stochastic distances between the statistical distributions that model the regions (image's segments to be classified) and the classes (the samples to be assigned to each region). In most classifiers a multivariate Gaussian distribution is applied to data modeling. In Silva's work [1,2] is presented a region classifier based on stochastic distances, however, some improvements are added on it regarding to classical approach, such as: a) the class assignment to pixels of each image segment is done through a statistical test and not only by a simple distance; b) an uncertainty map is created based on the p-values associated with statistical test; and c) the classifier was developed to process radar as well as optical images, therefore, besides the multivariate Gaussian distribution it is possible to use others density probability functions, which model Synthetic Aperture Radar data (e.g., Wishart and Intensity Pair distributions).

Besides the classifier type an accurate classification is fundamental to produce good quality mapping. There are various methods to improve the classification accuracy. This improvement can be reached by using information derived from different sources, for instance, the jointly use of radar and optical data. The combined use (integration, fusion, etc) of optical and radar images aiming at better classification results can be found in [3-7]. In [3], it is also shown that there exist suitable ways to combine the information contained on these kind of data.

In this work it is proposed a methodology for composing the classification result of images derived from different data sources, called here as multisource classification. Our technique, differently than the multisource classification presented in [8], takes into account each classification result (a classified image and an uncertainty map) derived from each data source in order to generate a new classified image. This new classification result is generated using a mathematical function based on the p-values associated with statistical test employed in the region classifier developed in [2]. The new classification result is expected to present better classes' accuracies than those individual classification used to generate it.

2. REGION CLASSIFICATION BASED ON STATISTICAL TEST

Consider a image with r disjoint segments $C_1,...,C_r$, and random variables associated to the pixels belonging to these segments having a density probability function $f(x;\theta)$, where θ is its parameters vector. Consider also that for each segment C_i, $1 \le i \le r$, the parameters vector $\hat{\theta}_i$ is estimated by the maximum likelihood method. In the supervised classification k classes of interest are selected, from which the parameters $\hat{\theta}_\ell$, $1 \le \ell \le k$, are estimated. In order to verify the null hypothesis $H_0 : \hat{\theta}_i = \hat{\theta}_\ell$, r x k statistical tests are computed to each

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segment $1 \le i \le r$ and each class $1 \le \ell \le k$. The classification procedure using minimum statistical test values consists in assign the segment C_i to the t-th class if $S_\phi^h(\hat{\theta}_i, \hat{\theta}_t) < S_\phi^h(\hat{\theta}_i, \hat{\theta}_\ell),\ \forall t \ne \ell$. Since segment C_i was labeled with t class, the p-value associated to hypothesis test is computed by $p_{i,t} = \Pr(\chi_M^2 > s_\phi^h(\hat{\theta}_i, \hat{\theta}_t))$, where M is the number of estimated parameters of the density probability function. For instance, $M = q(q+3)/2$ when a q-multivariate Gaussian distribution is used to model the data and $M = 3$ when the data are modeled by a pair of intensity distribution. An uncertainty map is generated based on the p-values computed for each classified segment, where p represents reliability of the classification [2].

The region-based classifier developed in [2] employs several stochastic distances such as Bhattacharyya, Kullback-Liebler, Hellinger, Triangular, Rényi, and Chi-Square. In this work the Pair of Intensity distribution was used to model the SAR images while the optical images were modeled by the multivariate Gaussian distribution. For the classification process the Bhattacharyya distance was applied in both cases. Besides the classified image the classification procedure also generates an uncertainty map, which can be seen as a quality measure of the final classification. This uncertainty map indicates those segments for which the test null hypothesis was not rejected to a certain significance level.

3. DATA AND METHOD

The study area corresponds to Tapajos National Forest and its surroundings, which is located at Brazilian Amazon on Pará state. To perform the classification experiment, two images from this study site and acquired from distinct sensors, were selected: one from *Tematic Mapper* (TM) of LANDSAT5 satellite and one from *Phase Array L-Band Synthetic Aperture Radar* (PALSAR) onboard *Advanced Land Observing System* (ALOS). Both images were acquired on June 2010, the microwave on 21$^{\text{th}}$ and the optical on 29$^{\text{th}}$. The bands 2, 4 and 5 of the optical data and HH and HV polarizations in L-band of radar data were used after being pre-processed according to [9]. These images were orthoretified, producing images of 916 by 1996 pixels with pixel size of 15 meter. An unique segmented image, containing 17568 segments, was used to classify both type of data (optical and microwave). Training and test samples from Primary Forest (PF), Regeneration (RG), Bare Soil (BS), Pasture (PA) and Soybean (SO) classes were also selected to perform the classification procedure. The methodology employed in this work for composing classification results is described in detail below.

Consider a set A having Y different images that we have intention to classify into k classes. Consider also a unique segmentation for these images containing r segments (regions). For each image y, $y \in \{1,2,\ldots,Y\}$ and each region i, $i \in \{1,2,\ldots,r\}$ it is possible to compute an attribute vector $C_{ij}^y = C(p_{ij}^y, s_{ij}^y)$, $j \in \{1,2,\ldots,k\}$. The attributes p_{ij}^y (probability) and s_{ij}^y (statistics) indicate the uncertainty of the class j which was attributed to region i in the image y. Note that different classification results and uncertainty maps associated with image y can be created from functions of the elements of attribute vector C_{ij}^y. Each classification result is named here as scenario. In this work, the set A is composed by TM (T) and PALSAR (R) images $(A = \{T, R\})$ and they were classified according to the 5 abovementioned classes, the training samples and the segmented image. The C_{ij}^T and C_{ij}^R $i \in \{1,2,\ldots,17568\}$, $j \in \{1,2,\ldots,5\}$ represent the attribute vectors of the TM and PALSAR images, respectively. The following scenarios were defined:

Scenario I: It is only based on the TM image classification and its uncertainty map. For each region i is attributed to the class l that presents minimum value of s_{ij}^T, $j \in \{1,2,\ldots,5\}$. The uncertainty map is formed by uncertainties s_{il}^T values associated with the classification of region i in the class l.

Scenario II: It is relative only to PALSAR image classification and its uncertainty map. To each region i is attributed to the class v that contains the minimum value of s_{ij}^R, $j \in \{1,2,\ldots,5\}$. The uncertainty map is formed by uncertainties s_{iv}^R values associated with classification of region i in the class v.

Scenario III: It contains information from both classified images and their uncertainty maps. The attribute vector $C_{ij}^{TR} = C_{ij}^T + C_{ij}^R$ is then formed, where the symbol "+" indicates the sum of two vectors. For each region i is assigned to the class e for which the value of s_{ij}^{TR}, ($j \in \{1,2,\ldots,5\}$) is minimum. The uncertainty map is formed by s_{ie}^{TR} values associated with classification of region i in the class e.

It is possible to mathematically prove that using a region classifier based on stochastic distances and statistical tests, a proper way of combining the information of different sensors (considering independent sources) is the sum of their statistic values of the classes assigned to each region in each data source.

4. RESULTS AND DISCUSSION

The classified images for each scenario and their respective, uncertainty maps is shown in the Figure 1. The confusion matrices for all classification results is illustrated in Figure 2. Table 1 presents the classification accuracy per class and its error (commission and omission). The overall accuracy, the kappa values and their respective variances are presented in Table 2 for all scenarios of the classification.

The classification result using only TM data (scenario I) reaches high accuracy values (upper to 89%) with low misclassification rate. This data produced a classified image containing low values (around 10%) of commission and omission errors for all classes. The Primary Forest and Regeneration classes presented the lowest values of uncertainty.

On the other hand, the classification result for SAR data (scenario II) presents medium values of accuracy and misclassification rates, except for Bare Soil class which was very well classified (accuracy around 97%). The Soybean class presents the worst classification result, having an omission superior to 60%. In general, the scenario II presents smaller values of uncertainty than scenario I, as can be observed in Figure 1.

The proposed multisource classification (scenario III), in general, improves the classification results obtained on scenarios I and II. The percentage of correctly classified pixels is greater than or equal to 90% for all classes, in scenario III, showing very good classification results when information derived from different sources are properly used. It can also be observed that the commission and omission errors were reduced with the use of this classification technique. It was possible to improve the TM classification results for Pasture, Regeneration, and Bare Soil classes, increasing the accuracy of Bare Soil class in approximately 9%. The SAR classification results were enlarged for all classes, except for Bare Soil class and the classes' misclassification was reduced by using the proposed multisource classification. The scenario III presents a low rate of misclassification, being the Soybean the only class having a value superior to 10%.

From the index called quantitative improvement of classification ($QIC = [k_b - k_a]/[1-k_a]$) it is possible to evaluate how much the result of classification ***b*** could be improved relatively to the result of classification ***a***. Computing the *QIC* index using the kappa coefficient of the classification results, it can be observed that scenario III improves the classification results of the other scenarios. The scenario III presents, respectively, 16% and 83% of improvement possibility, in the quality of classification, when it is compared with scenario I and scenario II.

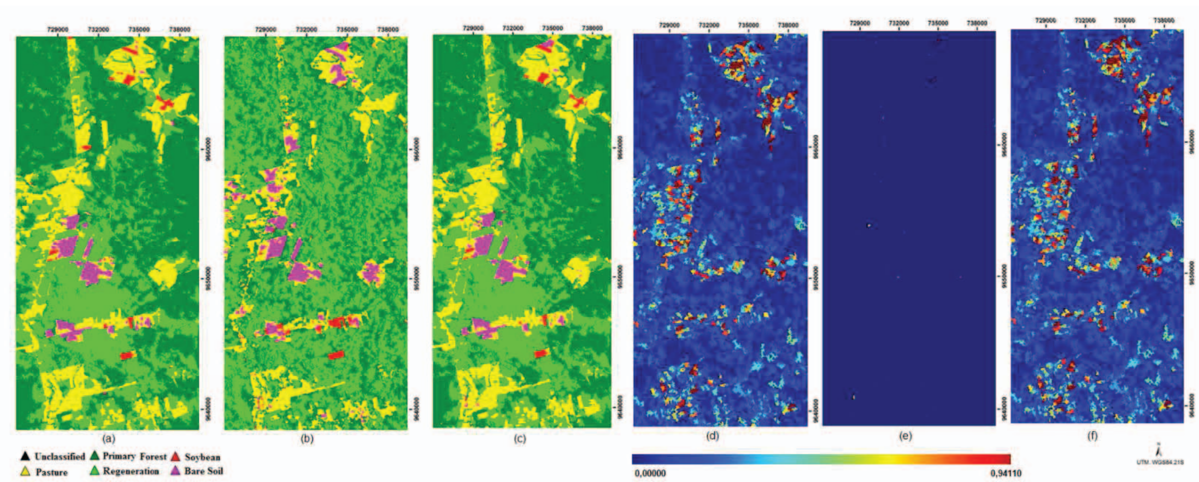

Figure 1: Classification of the scenarios and their uncertainty maps: (a) & (d) TM; (b) & (e) SAR; and (c) & (f) TM and SAR composition.

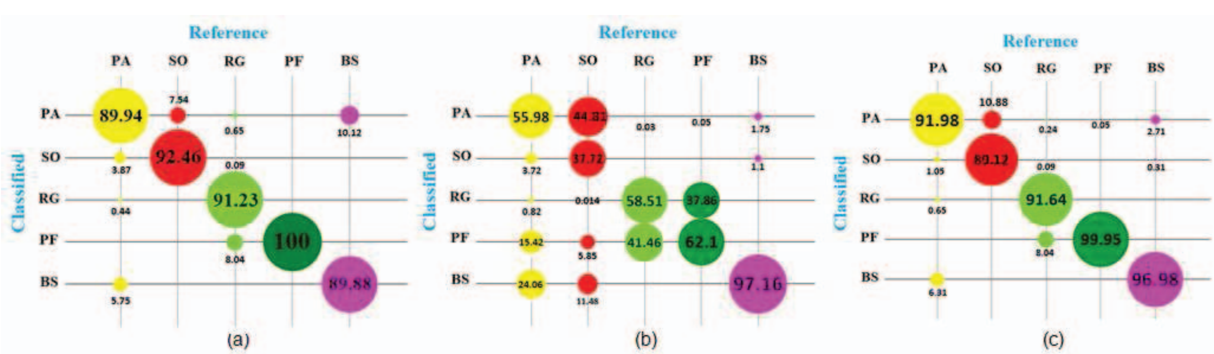

Figure 2: Confusion matrices of the scenarios: (a) TM; (b) SAR; and (c) TM and SAR composition.

Table 1: Classification accuracy per class (correctness and error rates) in percentage.

accuracy (A), commission error (C) and omission error (O)

%	Scenario I			Scenario II			Scenario III		
Class	A	C	O	A	C	O	A	C	O
PA	89.94	10.21	10.06	55.98	20.64	44.02	**91.98**	**5.74**	**8.02**
SO	**92.46**	12.99	**7.54**	37.72	28.07	62.28	89.12	**5.30**	10.88
RG	91.23	**0.17**	8.77	58.51	17.47	41.49	**91.64**	0.25	**8.36**
PF	**100.00**	**20.12**	**0.00**	62.10	70.59	37.90	99.95	20.13	0.05
BS	89.88	**9.51**	10.12	**97.16**	31.72	**2.84**	96.98	9.66	3.02

Table 2: *Kappa* coefficient and overall accuracy.

Classification	*Kappa*	*Kappa* variance	Overall Accuracy
Scenario I	0.89	2.93×10^{-4}	**0.92**
Scenario II	0.47	5.30×10^{-5}	0.62
Scenario III	**0.91**	3.48×10^{-4}	**0.93**

5. CONCLUSIONS

A methodology for combining multi-source information aiming at the improvement of land use and land cover classification was presented in this work. It employs a region classifier based on stochastic distances and statistical tests and it is assumed independent sources. It was observed that the proposed technique improves the classification results. Using this new technique the number of correctly classified and misclassified pixels were, respectively, increased and diminished when they are compared to those of individual classification results. Therefore, there is a strong indication of the possibility of generating classification results with a high degree of accuracy, when the information of distinct source are adequately combined. This study showed promising results that encourage us to continue studying this subject.

6. REFERENCES

[1] Silva, W.B. *Classificação de regiões de imagens utilizando testes de hipóteses baseados em distâncias estocásticas: aplicações a dados polarimétricos*. 2013. 143p. (sid.inpe.br/mtc-m19/2013/02.20.16-TDI). PhD. Thesis (Remote Sensing) - National Institute For Space Research (INPE), São José dos Campos. 2013. (in Portuguese).

[2] W.B. Silva, C.C. Freitas, S.J.S. Sant'Anna, and A.C. Frery, "Classification of segments in PolSAR imagery by minimum stochastic distances between Wishart distributions". *IEEE J-STARS*, v. 6, p. 1263-1273, 2013.

[3] L.O. Pereira, C. C. Freitas, S. J. S. Sant'Anna, D. Lu, and E.F Moran,. "Optical and radar data integration for land use and land cover mapping in the Brazilian Amazon," *GIScience and Remote Sensing*, v.50, p.301-321, 2013.

[4] P. Dusseux, T. Corpetti, L. Hubert-Moy, and S. Corgne, "Combined use of multi-temporal optical and radar satellite images for grassland monitoring," *Remote Sensing*, v.6, p.6163-6182, 2014.

[5] J. Reiche, C.M. Souza Jr., D.H. Hoekman, J. Verbesselt, H. Persaud, and M. Herold, " Feature Level fusion of multi-temporal ALOS PALSAR and Landsat data for mapping and monitoring of tropical deforestation and forest degradation," *IEEE J-STARS*, v.6, n.5, p. 2159-2173, 2013.

[6] G. Forkuor, C. Conrad, M. Thiel, T. Ullmann, and E. Zoungrana,"Integration of optical and synthetic aperture radar imagery for improving crop mapping in northwestern Benin, west Africa," *Remote Sensing*, n.6, p.6472-6499, 2014.

[7] L.F.A. Furtado, T.S.F. Silva, P.J.F. Fernandes, and E.M.L.M. Novo, "Land cover classification of Lago Grande de Curuai floodplain (Amazon, Brazil) using multi-sensor and image fusion techniques," *Acta Amazonia*, v.45, n.2, p.195-202, 2015.

[8] G. Moser, R. Gaetano, G. Poggi, G. Scarpa, and S.B. Serpico, "Contextual classification of multisensor optical-SAR remote sensing images,"*Handbook of Pattern Recognition and Computer Vision*, 4th ed, (Chapter 3.1), World Scientific Publishing, p.307-328, 2009.

[9] Reis, M. S. *Detecção de mudanças de uso e Cobertura da Terra utilizando dados óticos e de Micro-ondas em uma região da Amazônia Brasileira*. 2014. 331p. (sid.inpe.br/mtc-m21b/2014/06.30.19.09-TDI). M.S. Thesis (Remote Sensing) - National Institute For Space Research (INPE), São José dos Campos. 2014. (in Portuguese).