Visual Information Mining and Ranking using Graded Relevance Assessments in Satellite Image Databases

Adrian S. Barb and Chi-Ren Shyu

The large quantity of imagery generated by the geospatial domain constitutes a challenge for any system that manages, ranks, or classifies satellite images. Image analysts are able to evaluate only a fraction of this information and this trend is likely to increase in the future with the addition of new and higher resolution satellites and image modalities. In this setting, manual annotation of images becomes more and more difficult. It is a need for the community to develop algorithms and utilities that can automatically annotate images by their relevance to semantics before they are presented to analysts. Content-based techniques provide a wide variety of options for retrieving images based on their content. Such techniques map low-level features extracted from images into semantic classes of interest. Among these methods, associative classification methods [1][2][3][6] classify images by utilizing association rules while the approaches in [4][5] rank images by mathematically modeling of semantics. Associative methods are believed to achieve reasonably good classification accuracy [1] and ranking precision [5] while creating a model that is easier to understand. However, there are several differences between the traditional matching of items in a shopping basket for generic data mining tasks and matching visual patterns in an image for remote sensing applications [8]. Most of existent approaches use binary operations to evaluate the existence of patterns in databases – a visual pattern exists in an item or it does not exist [11].

In this paper, we developed a methodology for using graded ratings from user analysts when training the system which is shown to increase ranking precision [7]. Using graded assessments from analysts allows the system to differentiate among the relevance of visual patterns found in satellite images and subsequently change the order of ranking. Our approach uses kernel regression to map relevant feature subspaces into a parametric sigmoid function. The usage of the sigmoid function allows us to customize the semantic mapping to the individual preferences and increase the mean average precision of in ranking images by semantics for that specific remote sensing community member [6]. For example, considering that two image analysts assess differently the relevance of same image to the semantics called "Grassland," the system will customize their setting using different sigmoid parameters which will affect the ranking order in which the images will be presented. The equation of the sigmoid function *g* for a feature measure m is shown in Equation 1. It contains two half sigmoid functions (*L* - left and *R* - right) and it is controlled by three parameters: (a) the center of the function (λ^1), (b) the width (λ^2), and (3) the exponential factor (λ^3). For more information about the feature extraction algorithms, the reader is referred to [4].

$$g(m)=\begin{cases} \frac{2}{1+e^{\left((\lambda_L^1-m)/\lambda_L^2\right)^{\lambda_L^3}}} & for \quad m<\lambda_L^1 \\ 1 & for \quad m\in[\lambda_L^1,\lambda_{LR}^1] \\ \frac{2}{1+e^{\left((m-\lambda_L^1)/\lambda_L^2\right)^{\lambda_L^3}}} & for \quad m>\lambda_R^1 \end{cases} \tag{1}$$

This possibility distribution is shaped using the information in the training dataset. First, using kernel regression, we compute the normalized histogram of the distribution of data labeled with the target semantic ς over the feature interval ϑ. Kernel regression is a data-driven statistical method to determine the shape of the data distribution $y = f(y) + err$. It computes the predicted value $\hat{y}_i$ by performing a weighted sum of the observed values y. The weight of each observed value y is a decreasing function of the distances between the predictor values x_i from x_j with closer data points receiving more weight than more remote ones.

In the case of satellite images, we apply kernel regression to determine the non-parametrical distribution of relevance $\hat{\rho}\left(\mathrm{m}_{\mathrm{i}}^{\vartheta}\right)$ of a feature interval ϑ to a semantic s. In computing this distribution, we use the graded relevance ρ provided by image analysts. To compute $\hat{\rho}\left(\mathrm{m}_{\mathrm{i}}^{\vartheta}\right)$, we use a training data set $\left\{\left(\mathrm{m}_{\mathrm{i}}^{\vartheta}, \rho_s^j\right) | i \in [1, n]\right\}$ where $\mathrm{m}_{\mathrm{i}}^{\vartheta}$ is the feature value of image *i*, ρ is the relevance of image *i* to the semantic term *s.* This relevance is assigned by expert *j*. The potential is determined according to the following formula:

$$\hat{\rho}\left(\mathrm{m}_{\mathrm{i}}^{\mathrm{f}}\right) = \frac{\sum_{\mathrm{j}=1}^{\mathrm{n}} w(m_i, m_j, h) \rho_s^j}{\sum_{\mathrm{j}=1}^{\mathrm{n}} \epsilon_{\mathrm{j}}} \tag{2}$$

The weighting function, shown in Equation 2, is the probability density function of the normal distribution with the location at m_i and scale equal to the bandwidth h. The choice of bandwidth is data-driven. Its optimal value, shown in Equation 3, depends on the observed standard deviation σ and inter-quartile range (*IQR*) [9].

$$w\left(m_i, m_j, h\right) = \frac{1}{\sqrt{2\pi}h} e^{-\frac{(m_i - m_j)^2}{2h^2}} \tag{3}$$

$$h = 1.06157 \min\left(\sigma. IQR/1.34\right) n^{-1/5} \tag{4}$$

After the distribution of relevance $\left\{\hat{\rho}\left(\mathrm{m}_{\mathrm{i}}^{\vartheta}\right) \mid \mathrm{s} \in \mathrm{S}\right\}$ of feature subspace ϑ was computed for the semantic $s \in S$, we determine the sigmoid function g, using the algorithm described in [4] using a nonlinear least square fitting algorithm.

To evaluate our approach, we used a satellite image database, containing 443 high-resolution image tiles from three cities in Missouri, USA. Each image was generated by dividing 0.6–1.0-m pan-sharpened multispectral imagery high-resolution satellite images into 256 m x 256 m tiles. Further, for each image tile, a 227-dimensional feature vector was extracted [10]. Also, these images were labeled by image analysts to include one or multiple labels from the following set: *commercial* (CTRB), *construction* (CONST), *industrial* (INDS), *isolated road* (RD), *residential* (DEVH), *grassland* (GRSLD), *cropland* (FRM), or *forests* (FRST). Each image tile was assigned a degree of relevance to a semantic on a scale between 0 (non-relevant) and 1 (very relevant) with 0.1 increments. A total of 281 images in this dataset were assigned with multiple labels. We conducted two experiments: in the first experiment analyst ratings were transformed into binary rating—zero or one. In the second experiment we used the graded relevance provided by image analysts. For both experiments we computer the mean average precision and precision-recall. In this case, precision is the fraction of relevant images in the retrieved image set, while recall is the fraction of relevant images retrieved.

Table 1. Mean Average precision (MAP) for ranking geospatial images using crisp and graded image analyst rankings

	CONST	RD	INDS	GRSLD	FRST	FRM	DEVH	CTRB	**Average**
Graded	**0.753**	**0.477**	**0.811**	0.443	**0.743**	0.52	**0.754**	**0.62**	**0.64**
Crisp	0.385	**0.477**	0.793	**0.535**	0.462	**0.621**	0.586	0.474	0.542

Table 1 shows the mean average precision (MAP) for ranking geospatial images by each semantic as well as average results. As seen in this table, using graded rankings increases the MAP measure for five out of eight semantics. Detailed precision-recall data is shown in Figures Figure 1 and Figure 2.

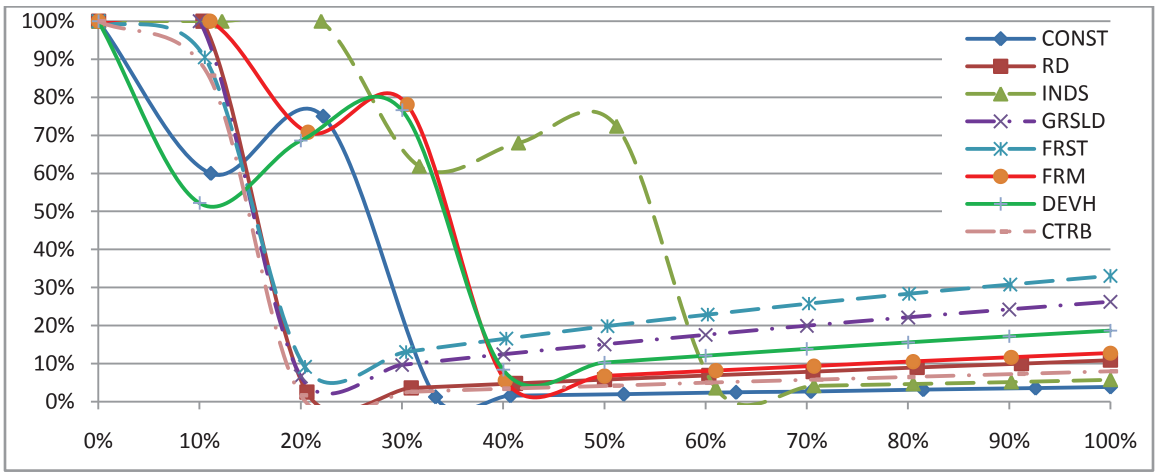

Figure 1. Precision-Recall chart for training the system using crisp image analyst ratings

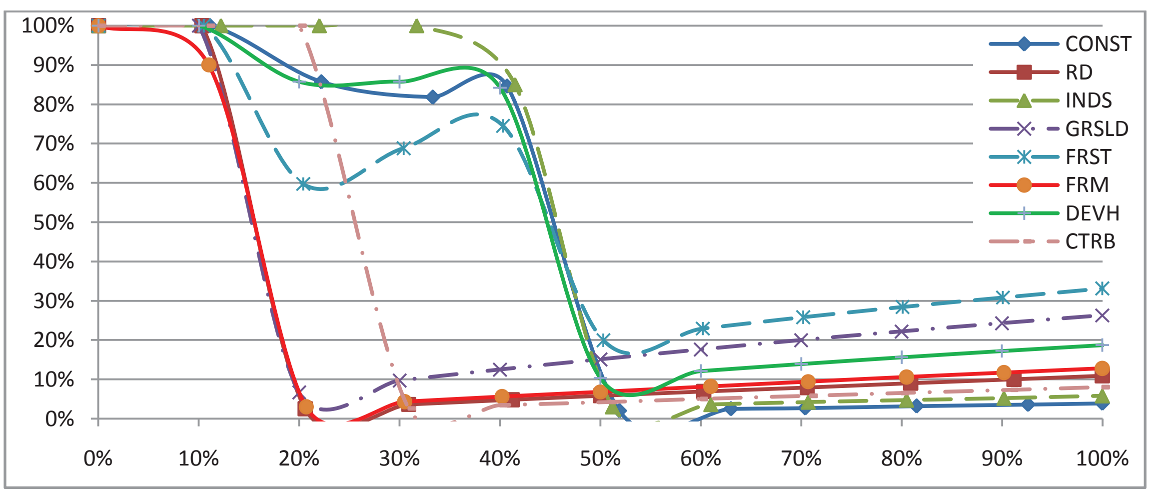

Figure 2. Precision-Recall chart for training the system using graded image analyst ratings

In this abstract, we briefly presented an inductive methodology to create flexible mappings of image features into semantics. More detailed explanations and comprehensive experimental results will be reported in the full paper. Our method uses kernel regression to evaluate the potential of feature subspaces and sigmoid functions to describe semantics using low-level features. Such an approach is relevant for systems that use large communities of contributors that analyze and share visual information in remote sensing applications. In conclusion, graded ratings combined with flexible parametric models of mapping feature subspaces into semantics can increase the retrieval precision for geospatial image communities and may result in quicker response to natural events.

Acknowledgement:

The image analysis part of this project was supported by the National Geospatial-Intelligence Agency under grant number HM1582-04-2028 and the visual knowledge understanding part is currently supported by the National Science Foundation under grant IIS-0812515.

Bibliography

1. B. Liu, W. Hsu, and Y.Ma, “Integrating classification and association rule mining,” in *Knowledge Discovery and Data Mining*, 1998, pp. 80–86.
2. W. Li, J. Han, and J. Pei, “CMAR: Accurate and Efficient Classification Based on Multiple Class-Association Rules,” in *Proceedings of the 2001 IEEE International Conference on Data Mining*, 2001, pp.369–376.
3. X.Yin and J.Han, “CPAR: Classification based on Predictive Association Rules,” in *Proceedings of the Third SIAM International Conference on Data Mining*, 2003.
4. A. S., Barb, C.-R., Shyu, and Y., Sethi, “Knowledge Representation and Sharing using Visual Semantic Modeling for Diagnostic Medical Image Databases," IEEE Transactions on Information Technology in Biomedicine, vol. 9, no. 4, pp. 538-553, 2005.
5. A.S. Barb, and C.-R. Shyu, " *Visual semantic modeling in content-based geospatial information retrieval using associative mining techniques*", in Geoscience and Remote Sensing Letters 2009;
6. A. Barb and C.-R. Shyu, “User-specific semantics for modeling content-based information in geospatial knowledge,” *in IEEE International Geoscience and Remote Sensing Symposium*, 2007.
7. K. Kekäläinen, Binary and graded relevance in IR evaluations: comparison of the effects on ranking of IR systems. Inf. Process. Manage. 41, 5, 1019-1033, 2005.
8. Santini, S. and Jain, R. 1997. Image Databases Are Not Databases with Images. In Proceedings of the 9th international Conference on Image Analysis and Processing-Volume II (September 17 - 19, 1997). A. D. Bimbo, Ed. Lecture Notes In Computer Science, vol. 1311. Springer-Verlag, London, 38-45.
9. B. W. Silverman, “Density Estimation for Statistics and Data Analysis”, Chapman&Hall/CRC, April 1986.
10. C.-R., Shyu, M., Klaric, G., Scott, A. S., Barb, C., Davis, and K., Palaniappan, “GeoIRIS: Geospatial Information Retrieval and Indexing System - Content Mining, Semantics Modeling, and omplex Queries," IEEE Transactions on Geoscience and Remote Sensing, Special Issue on Image Mining, vol. 45, pp. 839-852, 2007.
11. F. Thabthah, A review of associative classification mining, Knowl. Eng. Rev. 22, 1, 37-65, 2007.