# INTEGRATING MULTISCALE INFORMATION FOR URBAN VHR IMAGERY: VECTOR STACKING AND FUZZY APPROACHES

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**ABSTRACT**

In recent years, the processing techniques for very high resolution (VHR) imagery have received much attention since this data type can provide a large amount of detailed ground information. However, its availability poses challenges to image information extraction and classification due to the complex spectral attributes within each land cover class and between different classes. It is well known that exploitation of spatial information is an efficient way to address this issue. This study aims to 1) extract multiscale features from VHR urban imagery in order to fully exploit the rich spatial information, and 2) integrate the multiscale information using three SVM-based approaches.

The multiscale representations of an image are calculated using the following approaches:

(1) MPs and DMPs (Benediktsson *et al*. 2005) are constructed using the morphological operators OBR (opening-by-reconstruction) and CBR (closing-by-reconstruction). The multiscale features are obtained by using a series of structural element with different sizes.

(2) Multilevel FNEA approach (Bruzzone and Carlin, 2006) is carried out by using multiple scale parameters of the FNEA algorithm.

(3) Multiscale mean shift-based features can be obtained with different bandwidth (h) values (Huang *et al*. 2008; Huang *et al*. 2009).

Three information fusion approaches are proposed to integrate the extracted multiscale features: vector stacking (VS), fuzzy approach and the multi-classifier voting.

(1) The decision rule of VS fusion can be expressed as:

$$x \in k \Leftrightarrow k = \mathrm{Cla}(f(x)) \tag{1}$$

where $f(x) = \{f_1(x),...,f_s(x),...,f_S(x)\}$ is the multiscale representations of pixel $x$ in image $f$, and the SVM classifier is used for the VS fusion considering its insensitivity to the dimensionality of features.

(2) The fuzzy fusion exploits the output of multiclass SVMs, i.e. the discriminant function values for each class. The output of discriminant function for pixel $x$ with scale $s$ can be written as:

$$f_s(x)=\left\{f_s^1(x), f_s^2(x),\ldots, f_s^j(x),\ldots, f_s^c(x)\right\} \tag{2}$$

where $j$ ( $j \in \{1,2,\ldots c\}$) represents the label of an information class. Under the condition of single scale, the OAA-SVM decision rule can be expressed as:

$$x(s)=\arg\max_j\left(f_s^j(x)\right). \tag{3}$$

The discriminant function values ( $f_s^j(x)$) represent the distance between the sample points and the decision hyperplane. Therefore, we can construct a fuzzy set for each scale based on the multiclass discriminant function (Eq. (2)), and then the optimal scale is decided by comparing the uncertainties of different fuzzy sets. The fuzziness degree was calculated using α-quadratic entropy function (Pal and Bezdek, 1994; Fauvel *et al*. 2006). Consequently, the sing scale SVM decision in Eq. (3) is extended to the multiscale version:

$$x=\arg\max_{x(s)}\left(w(s)\cdot f_s^{x(s)}(x)\right) \tag{4}$$

where $w(s)$ denotes the fuzziness degree of the decision result of scale $s$. $w(s)$ is used as the weight of the discriminant function to favor the scale that is more reliable.

(3) The multi-classifier voting approach chooses the result having the largest votes as the optimal scale for each pixel:

$$x=x\left(\arg\max_s(\text{Vote}(s))\right) \tag{5}$$

where Vote($s$) is the number of votes for scale s.

In experiments, two VHR datasets are used for validation of the presented multiscale fusion schemes: ROSIS Pavia Centre and University datasets. Experiments showed that both vector-stacking and fuzzy approaches were able to give comparable or higher results than single scale approach in terms of accuracies. In most cases, the VS-SVM provided higher accuracies than the Fuzzy approach. Experimental results for the ROSIS University dataset are shown in Table1.

**Table 1.** The Results of Multiscale Fusion and Optimization In ROSIS University Dataset

| | Scale 1 | Scale 2 | Scale 3 | Scale 4 | VS-SVM | Fuzzy | Voting |
|---|---|---|---|---|---|---|---|
| MPs | 80.6 | 79.4 | 76.9 | 83.0 | 86.8 | 82.2 | 82.3 |
| DMPs | 80.1 | 77.6 | 79.9 | 84.3 | 89.3 | 83.5 | 84.3 |
| FNEA | 71.3 | 73.6 | 70.4 | 77.4 | 78.4 | 78.0 | 74.2 |
| MS | 71.3 | 71.2 | 83.2 | 80.5 | 83.4 | 80.8 | 80.8 |