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Meta-learning for Adaptive Image Segmentation

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ICIAR 2014: Notice of Acceptance (270)

ICIAR 2014 <iciar14@aimiconf.org> 26 juin 2014 05:52
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À : Yasmina Jaâfra <yasmina.jaafra@gmail.com>

Dear Yasmina Jaãfra,

On behalf of the ICIAR 2014 Program Committee members, we are pleased to inform you that your paper (270), entitled:

"Meta-learning For Adaptive Image Segmentation"
Yasmina Jaãfra, Aymen Sellaouti, Atef Hamouda

has been accepted for publication in the conference proceedings, which will be published by Springer as a volume in the "Lecture Notes in Computer Science" (LNCS) series.

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Congratulations again on having your paper accepted!

We look forward to seeing you in Vilamoura, Algarve, Portugal.

Sincerely,

Aurelio Campilho
Mohamed Kamel

ICIAR 2014 Co-chairs
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Meta-learning for Adaptive Image Segmentation

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Abstract. Most image segmentations require control parameters setting that depends on the variability of processed images characteristics. This paper introduces a meta-learning system using stacked generalization to adjust segmentation parameters within an object-based analysis of very high resolution urban satellite images. The starting point of our system is the construction of the knowledge database from the concatenation of images characterization and their correct segmentation parameters. Meta-knowledge database is then built from the integration of base-learners performance evaluated by cross-validation. It will allow knowledge transfer to second-level learning and the generation of the meta-classifier that will predict new image segmentation parameters. An experimental study on a satellite image covering the urban area of Strasbourg region enabled us to evaluate the effectiveness of the adopted approach.

Keywords: Object-based analysis · Segmentation · Very high resolution satellite image · Meta-learning · Stacked generalization

1 Introduction

The object-based image analysis (OBIA) [1] has grown in importance with the advent of the very high resolution (VHR) satellite imagery as pixels considered individually no longer capture the characteristics of classified targets. The initial step in OBIA approaches is segmentation which defines thematic image objects by clustering adjacent pixels with similar characteristics. Inserting a segmentation step prior to classification has demonstrated its effectiveness in the case of VHR remote sensing images [2]. Despite the various developed segmentation techniques, no general methods have been stated to process efficiently the wide diversity of images in real world applications. Most of these techniques require control parameters setting that depends on the variability of processed images characteristics. This variability is caused by weather and lighting conditions, imaging devices, clouds, etc [3]. However, segmentation parameters selection is problematic because the user is forced to adopt an exhausting trial-and-error procedure to achieve an acceptable quality of segmentation. Indeed, default

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parameters settings identified by algorithms designers lose effectiveness when the conditions under which they have been designed are changed. Furthermore, the impact and interaction of parameters are complex and can't be modeled in a rule-based framework [4].

Various machine learning techniques have been proposed for the adjustment of segmentation parameters. Derivaux et al. [5] apply a genetic algorithm to generate the elevation map of the Watershed transform and tune segmentation parameters. Bhanu et al. [3] propose connectionist reinforcement learning techniques to adjust the four most critical parameters of Phoenix segmentation algorithm. The selection of the most appropriate learning method to solve a specific problem is not an easy task. In fact, according to " No Free Lunch " theorems there is no algorithm better than all others on all tasks [6]. The solution specifying the optimal learning model in a given context has been defined within the discipline of machine learning as meta-learning. It refers to the ability of a learning system to increase its effectiveness and ability to learn how to learn through experience. It is differentiated from conventional base-learning by the extent of its adaptation level. While the latter has a fixed bias a priori, meta-learning selects dynamically its bias according to the context of study [7].

Although numerous learning models have been applied to the setting of segmentation parameters, no meta-learning approach was proposed to solve this problem. In this paper, our main goal is to provide the segmentation process with the ability to adapt to image characteristics variations. A meta-learning strategy using stacked generalization is assigned to adjust Watershed segmentation parameters according to combined predictions provided by a set of learning algorithms. Our approach aims at achieving a better performance of image interpretation than the one obtained with conventional learning. Although several studies have been conducted in the field of image analysis with machine learning, to our knowledge, no one of them has implemented a stacking approach in setting segmentation parameters.

In the remainder of this paper, we present in Section 2 the details of used segmentation algorithm and related parameters. Section 3 describes the stacking approach implementation. Section 4 exposes experimental results. The last section is dedicated to findings and conclusions discussion.

2 Watershed Segmentation Parameters

Watershed segmentation presented in [8] belongs to the family of edge-based algorithms and is considered as the main method of mathematical morphology segmentation. The Watershed transform is a well-known segmentation method that has been widely used and tested. It considers the image as a topographic surface where the gradient function is used to attribute a gray level corresponding to the height of each pixel. An immersion procedure is applied to this surface that is flooded from its minima generating different growing catchment basins. Watershed lines are built to avoid merging water from two different basins.

The Watershed algorithm is characterized by its tendency to generate over-segmented images where each object of interest is represented by several regions.

Different solutions were proposed in the literature to reduce over-segmentation. In our study, it consists in integrating three parameters in Watershed algorithm that will define thresholding controls for segments construction [9]:

- Gradient threshold: Once the topographic surface is created, any pixel p with a gradient value $G(p)$ below a certain threshold h_{min} is set to zero. Thus, small variations belonging to homogeneous areas, which correspond to low values of the gradient, are removed.

$$G_{h_{min}}(p) = \begin{cases} G(p) & if\ G(p) > h_{min} \\ 0 & otherwise \end{cases} \tag{1}$$

- Basin dynamic: A catchment basin r_i will be separated from another by a watershed line if its dynamic d_i is greater than a given threshold d_{min}. Indeed, small dynamic basins are filled during immersion stage.

$$keep(r_i) = \begin{cases} True & if\ d_i > d_{min} \\ False & otherwise \end{cases} \tag{2}$$

- Regions merging: This technique is based on the idea that similar related areas should be merged. If the Euclidian distance between the spectral averages of each band b for two neighboring regions r_i and r_j is below a threshold m_{min}, these two regions are merged.

$$neighbor(r_i, r_j) = \begin{cases} True & if\ p_i \in r_i, p_j \in r_j |\ p_i\ and\ p_j\ are\ adjacent \\ False & otherwise \end{cases} \tag{3}$$

$$dissimilarity(r_i, r_j) = \sqrt{\sum_{b=1}^{B} (avg(r_i, b) - avg(r_j, b))^2} \tag{4}$$

$$merge(r_i, r_j) = \begin{cases} True & if\ neighbor(r_i, r_j) = true\ and \\ & dissimilarity(r_i, r_j) < m_{min} \\ False & otherwise \end{cases} \tag{5}$$

Dealing with the over-segmentation effects of Watershed segmentation requires the adjustment of parameters h_{min}, d_{min} and m_{min}. We propose a stacked generalization approach to solve this problem. As part of our experiment, we will define 3 classes P_1, P_2 and P_3 representing different combinations of parameters h_{min}, d_{min} and m_{min}. Each image from our test database is segmented using these combinations. The best parameterization assigned to the processed image is determined according to the evaluation of the corresponding classification.

3 Stacking for Watershed Parameters Selection

We aim at establishing a meta-learning strategy using stacked generalization to adjust Watershed segmentation parameters. This adaptation is performed according to the variability of processed satellite images features caused mainly by environmental conditions. Our adaptive Watershed segmentation approach set in the stacking framework is structured around the following main phases, illustrated in Figure 1:

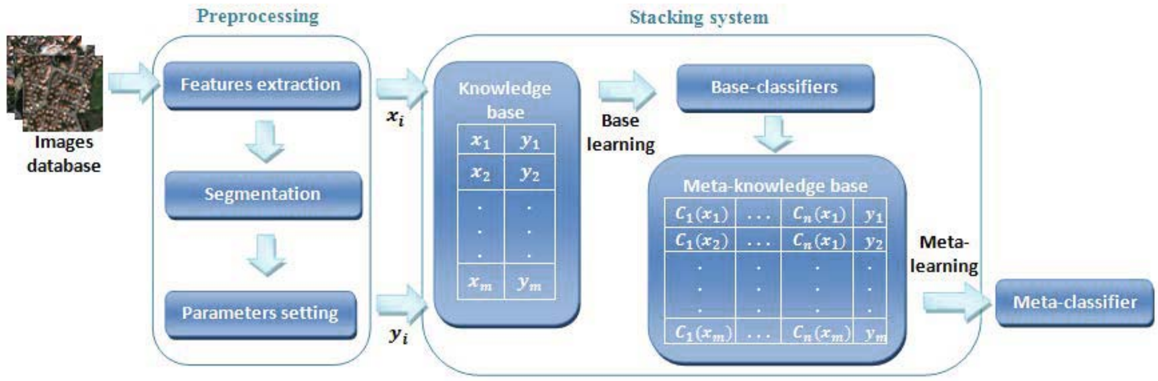

Fig. 1. Stacking approach for adaptive image segmentation

– Preprocessing: The objective of this step is to construct knowledge database where each instance is the concatenation of image characteristics and its correct segmentation parameters class.
– First level or base-learning: Base learners are applied to knowledge database in order to infer base-classifiers. Meta-knowledge database is generated from the integration of base-classifiers predictions into the representation of instances original features.
– Second level or meta-learning: This step consists in applying a meta-learner to the new meta-knowledge database to induce prediction rules of the appropriate segmentation class for new received cases.

3.1 Preprocessing

This phase leads to the realization of knowledge database D which is the starting point of our stacking approach. First, images are characterized in order to identify the group of images that need the same processing parameters achieving the best segmentation results. Attig et al. [10] study the impact of four different image descriptions on the determination of appropriate segmentation parameters and confirm the relevance of texture characteristics. We determine for each image a vector x_i of four texture characteristics that are contrast, energy, homogeneity, and sum variance. These criteria have been selected among those defined by Haralick [11] using a descriptive discriminant analysis.

We assign thereafter to each image its correct parameters class y_i. We set the range of testing parameters to three combinations P_1, P_2 and P_3 of variables h_{min}, d_{min} and m_{min} estimated through a manual trial-and-error procedure operated on a sample of images selected from different areas of the original image. Identifying a good measure for segmentation quality is a known complex problem since the criteria of a good segmentation are generally hard to explicitly define. Nevertheless, segmentation algorithm is used as a preprocessing step within an OBIA, therefore it is natural to use the overall performance of image interpretation to evaluate the segmentation quality. In our approach, the evaluation of the segmentation performed with the three sets of parameters for each image consists in estimating the accuracy of the classification applied to these segmentations [5]. The OBIA used in this study is the hierarchical classification based on a region growing approach introduced by Sellaouti et al. [12] that establishes a collaborative interaction between object segmentation and classification.

Every image is attributed the best segmentation parameters setting among P_1, P_2 or P_3. The classification is evaluated through quantitative comparisons between classification result and image benchmarks using a confusion matrix. The evaluation criteria are precision, recall and F-measure computed from this matrix [13]. Three benchmarks of classes (road, building and vegetation) are constructed for every image on the basis of its corresponding ground-truth. The set of used ground-truths are extracted from a digital map of Strasbourg city[1]. Figure 2 presents an example of a classified image and its related benchmarks.

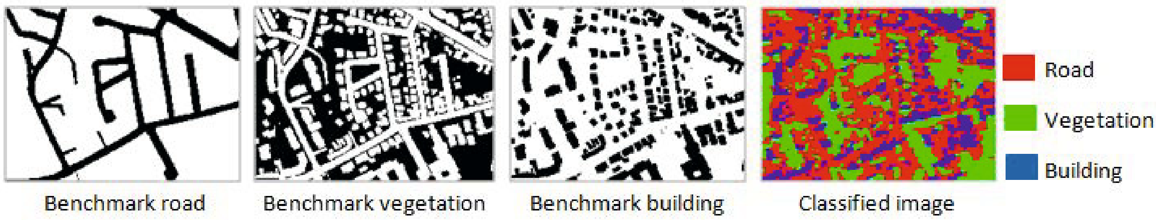

Fig. 2. Classified image and related benchmarks

The construction of the knowledge database D is completed by assigning the appropriate correct segmentation parameters y_i among P_1, P_2 and P_3 to test images that were characterized previously with their textural properties vector x_i. It will serve as an entry point to the meta-learning system.

3.2 Stacking System

Meta-learning main focus is to learn about the learning task itself. It employs a meta-classifier that takes as input the space of results from base-level classifiers and generalizes over them. The main meta-learning tasks that have been considered within literature are learning to select the best learner, to dynamically select an appropriate bias, and to combine predictions of base-level classifiers [7]. Stacked generalization [14] is a meta-leaning scheme that aims at learning a meta-level classifier to combine the predictions of multiple base-level classifiers. It differs from the conventional meta-learning strategy of selecting the best classifier by exploiting the diversity in the predictions of base-level classifiers and therefore predicting with higher accuracy at meta-level [15].

[1] http://www.carto.strasbourg.eu/

The proposed stacking method is a two-layer structure. At the first level, learning algorithms take as input the initial training data to generate the base-level classifiers. The second layer takes as input the predictions of the previous one and a meta-learner combines them to provide the final meta-classifier. One of the advantages to use stacking is that the transfer of knowledge between levels allows the meta-classifier to learn the base-classifiers errors.

More precisely, the input to the stacking system consists of the knowledge database D. In the base level of learning, a set of classifiers $C_1, ..., C_n$ is generated by using different learning algorithms $L_1, ..., L_n$ on dataset D where $C_i = L_i(D)$ and D consists of examples $e_i = (x_i, y_i)$, i.e., pairs of feature vectors x_i and their parameters classes y_i. To generate meta-knowledge database, a J-fold cross-validation procedure is applied. D is randomly split into disjoint and equal parts $D^1, ..., D^J$. At each j^{th}-fold, $j = 1..J$, the $L_1, ..., L_n$ learning algorithms are applied to the training dataset part $D - D^j$ inducing classifiers $C_1, ..., C_n$ which are then applied to the test part D^j. The predictions of the base-classifiers on each feature vector x_i in D^j are concatenated with the original segmentation parameters class to generate a new set MD^j of meta-feature vectors.

By the end of the entire cross-validation procedure, the meta-knowledge database is constituted from the union $MD = \bigcup MD^j$, $j = 1..J$ and used for applying a learning algorithm L_M and inferring the meta-classifier C_M. Finally, the base-learning algorithms are applied to the entire knowledge database D inducing the final base-classifiers $C_1, ..., C_n$ to be used at the execution of the stacking approach. In order to determine the appropriate segmentation parameters of a new image, the latter is first attributed the base-classifiers predictions vector, then assigned the appropriate parameters class by the meta-classifier C_M. Algorithm 1 presents an algorithmic description of the stacking framework dedicated to adaptive image segmentation approach.

4 Experiment and Results

The empirical evaluation of our approach is conducted on 50 VHR Quickbird images covering the urban area of Strasbourg. A sample from used images dataset is presented in Figure 3:

Fig. 3. A sample of test images

The choice of learners is not restricted and considered as " black art " issue in stacked generalization systems in the sense that there are no specific recommendations in this regard [14]. We built our choice on the findings of Seewald [16] which affirms that stacked generalization works better with a small number of diversified base-learners and those of Skalak [17] who confirms the effectiveness of decision tree as meta-learner. Learning algorithms selected for our experiment are support vector machine (SVM) and discriminant analysis used as base learners while decision tree fills the role of both base and meta-learner [18].

Algorithm 1: Stacking for adaptive image segmentation

Input: Knowledge database D, base-learners $L_1, ..., L_n$, meta-learner L_M, J, new image I

Output: Final prediction of segmentation parameters

Begin
- $MD = \emptyset$
- **for** $j = 1$ *to* J **do**
  - $MD^j = \emptyset$
  - **for** $i = 1$ *to* n **do**
    - $C_i = L_i(D - D^j)$
    - $Pred_i(j) = C_i(D^j)$ // prediction of base-classifier i
    - $MD^j = MD^j \bigcup Pred_i(j)$
  - **endfor**
  - $MD = MD \bigcup MD^j$
- **endfor**
- // end of cross-validation procedure
- $C_M = L_M(MD)$ // training of meta-classifier
- **for** $i = 1$ *to* n **do**
  - $C_i = L_i(D)$ /* training of base-classifier i to entire knowledge database D */
- **endfor**
- // new image execution
- $x_I = extract - features(I)$ // construct new image features vector
- **for** $i = 1$ *to* n **do**
  - $Pred_i(I) = C_i(x_I)$ // prediction of base-classifier i
  - $VPred = VPred \bigcup Pred_i(I)$ /* construct new image meta-features vector */
- **endfor**
- $y_I = C_M(VPred)$ // final prediction of segmentation parameters

End

Base-classifiers are inferred by running 25-fold cross-validation resulting in the attribution of three predictions of parameters to each image. Despite cross-validation may be computationally expensive for large J, it is generally considered reliable [19]. This database transformation by integrating information on base-classifiers predictions allows us to switch to the second level of learning. The meta-learner L_M is trained on the meta-knowledge database in order to induce the meta-classifier C_M that will be used in predicting the appropriate segmentation parameters for new images. Figure 4 illustrates the impact of learned Watershed segmentation parameters on image interpretation result.

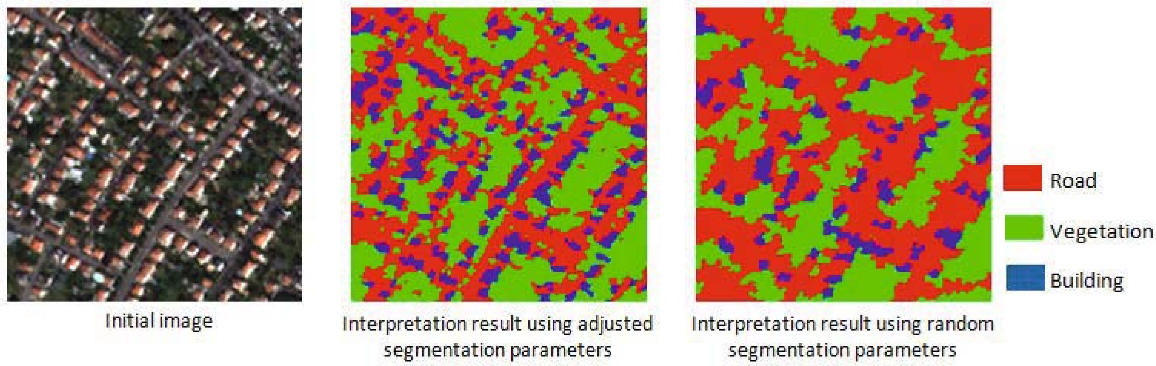

Fig. 4. Impact of Watershed parameters adjustment on image interpretation

Stacking approach global performance is evaluated using a cross-validation technique in order to increase training data for the applied meta-learner and lead therefore to more accurate predictions [15]. We use a " leave-one-out " cross-validation where each instance is a fold itself to maximize meta-learner training data. Table 1 presents segmentation parameters predictions produced by base-classifiers and stacking system for a sample of images. The contribution of our system is brought out when the base-classifiers predictions diverge (cases 2 and 6) or when they are all incorrect (case 7), however the stacking system is able to predict the correct parameterization class.

Table 1. A comparison between stacking system and base-classifiers predictions

	Decision Tree	SVM	Discriminant Analysis	Stacking	Correct Class
Case 1	1	1	1	1	1
Case 2	2	3	1	3	3
Case 3	2	2	2	2	2
Case 4	3	1	1	1	1
Case 5	2	2	1	2	2
Case 6	1	2	3	1	1
Case 7	1	2	2	3	3
Case 8	1	3	3	1	1
Case 9	3	1	1	1	2
Case 10	2	1	1	2	3

The overall performance of our meta-learning approach is measured by the percentage of correct predictions commonly used in learning problems and also called success rate ratio [20]:

$$SRR = \frac{Number\ of\ correct\ predictions}{Number\ of\ total\ predictions} \times 100$$

We need to ensure that the stacking system is more efficient than base-learning in predicting the best segmentation parameters and therefore achieves a more efficient image analysis. In the assessment of their stacking approaches, Fan et al. [15] compared the performance of meta-learning system to the base-learners one applied individually. We present in Figure 5 a comparison of stacking SRR to those of base-learners applied separately. The stacked generalization, with a SRR of 64%, exceeds significantly the performance of decision tree, SVM and discriminant analysis algorithms whose SRR reached respectively 52%, 50% and 42%.

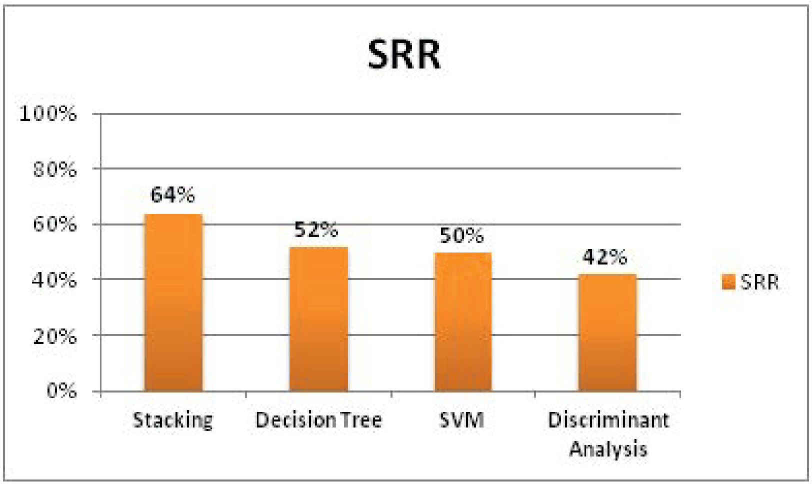

Fig. 5. Comparison between stacking system and base-classifiers performances

The results of the experiment described above confirms the hypothesis that meta-learning increases the efficiency of a learning task (OBIA in our case) through knowledge transfer from the first to the second learning level.

5 Conclusions and Future Work

In this paper we have presented a meta-learning system using stacked generalization to adjust Watershed segmentation parameters. The empirical evaluation of our approach is conducted on VHR satellite images covering the urban area of Strasbourg. The results show that the performance of stacked generalization system exceeds significantly base-learners applied individually. These findings confirm the assumption that meta-learning increases the efficiency of OBIA task.

In future work, we plan to use base-learners that produce class probabilities instead of class predictions. Indeed, some studies state that this type of learners enhances the performance of stacked generalization approach [21].

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