MULTIPLE PIXEL CLASSIFIER COMBINATION FOR BRONCHIAL TUMORS IMAGE SEGMENTATION

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Abstract : The combination of classifiers has been proposed as a method allowing to improve the quality and the hardiness of recognition systems as compared to a single classifier. This paper describes a new segmentation scheme based on a combination of pixel classifications. The aim of this paper is to show the influence of the neighborhood information and of the number of classifiers used in the combination process. In the first part, we detail the ground of our study for an application. Then, we name the different steps of the new segmentation scheme. In the third part, we detail the classifiers combination step. In the next part, we present the different classifications results obtained on color microscopic images. Finally, we draw a conclusion on the improvement of the quality of the segmentation at the end of treatment.

Keywords : Pixel classifier combination, Segmentation, Pixel classification, Color, Microscopy.

1 Introduction

Image analysis in the field of lung cancer is a diagnosis tool for cytopathology. The quantitative analysis of form and structure of nuclei coming from microscopic color images brings to the pathologist information valuable for diagnosis assistance. This analysis can only be performed from perfectly segmented objects. The segmentation of the bronchial cells is a difficult task because the mucus present in the background has the same aspect as some cells (cytoplasm, nucleus) in the setting of the international coloration of Papanicolaou.

Our last works [7, 6] showed that an unsupervised or supervised pixel classification brings satisfactory results but that a combination of pixel classifications might improve our segmentation. Several studies [3, 10, 2, 8, 4] show that this technique has became more and more used to improve the quality of recognition systems in several applications and notably in medical [1]. The difficulty to affirm the superiority of a classifier in relation to another brings us to couple several classifiers simultaneously. It enables to use their complementarity and to increase the quality of recognition of our segmentation system.

To this aim, we propose an automatic segmentation scheme based on combination of pixel classifications. It is given in six steps : a simplification step to reduce the noise, pixel classifications to obtain three classes (background, cytoplasm and nucleus) in all images, a combination of pixel classifications, a marker extraction by using an operation of mathematical morphology and a color watershed growing to correctly segment the objects.

The paper is organized as follows : in section 2, we describe the color segmentation scheme. In section 3, we detail the combination of pixel classifications step. In section 4, we give experimental results on the combination of pixel classifications with an evaluation method adapted to microscopic images. Finally we draw a conclusion on the quality of the segmentation.

2 The segmentation scheme

The segmentation scheme is given in six steps [7, 6] :

❶ Image simplification: the simplification step consists in a pre-treatment phase with the aim of smoothing the initial image to reduce the importance of noise. The produced image is used to compute the gradient needed in the color watershed step. The growing quality depends greatly on the gradient image. This smoothed image is also used as input to the pixel classification step in order to reduce the classifier sensitivity to the presence of noise (see in [9] for more details).

❷ Pixel classification: the classification step consists in determining for each pixel of the image, a class among background, cytoplasm or nucleus. To realize this classification, we have used several unsupervised classifiers using a Hierarchical Ascendant Classification (K-means, Fisher) [7] and supervised classifiers (Bayes, kNN, SVM, MLP) using a learning data base that was built from four images segmented by an expert in cytopathology [6].

❸ Combination of pixel classifications: this step permits to increase the recognition of objects. To this aim, we use the complementarity which can exists between several classifiers. We combine by different methods the pixel classifications produced in the previous step. In this paper, we give a detailed description of this step by presenting the strategy of combination and the neighborhood information in the combination process.

❹ Marker extraction: with the image produced in the previous step, a pixel subset is recognized as belonging to the cytoplasm or the nucleus, this subset corresponds to true markers. The marker extraction is based on mathematical morphology operations which consists in a variable number of erosions on the level of the boundaries according to the marker type.

❺ Color watershed: from the markers previously extracted and the smoothed image, a watershed performs a growing using image color information. The obtained regions correspond to the cytoplasms and nuclei [5].

❻ Evaluation: our evaluation method is based on an improved classification rate and is adapted to our study. The proposed method uses a reference manual segmentation provided by an expert and provides a recognition quality index of the cytoplasm ($IdCytoplasm$) and of the nucleus ($IdNucleus$) [6].

3 Combination of pixel classifications

3.1 Definition of classifier

A classifier usually designates a recognition tool that provides class memberships information for an vector received in input. This tool can be described by a function e that with a feature vector x of the object to recognize, assign to x the class C_i among k possible ones :

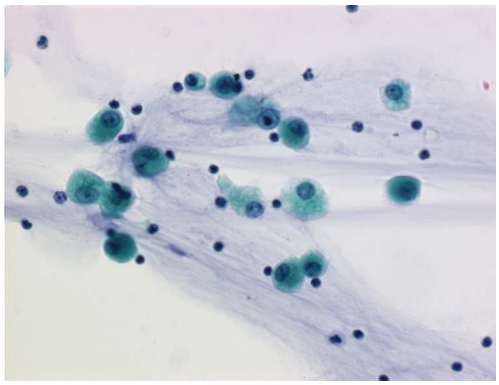
$$e : x \in R^n \rightarrow K \qquad \text{with } K = \{C_1, ..., C_k\} \tag{1}$$

Answers provided by the classifier can be classified in three categories [2] :

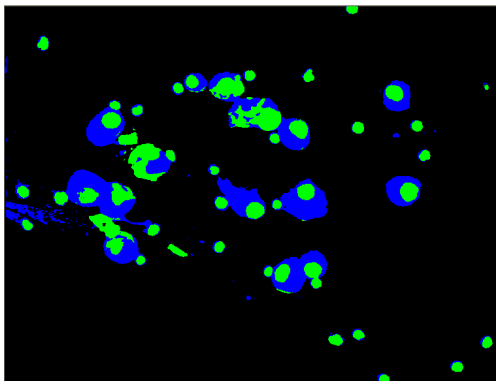
- Class type : $e(x) = C_i (i \in [\![1, k]\!])$, indicates that the classifier assigned the class C_i to x,
- Rank type : $e(x) = [\![r_1^j, ..., r_k^j]\!]$ where r_i^j is the assigned rank to the class i by the classifier,
- Measure type : $e(x) = [m_1^j, ..., m_k^j]$ where m_i^j is the measure assigned to the class i by the classifier.

3.2 Importance to the combination step

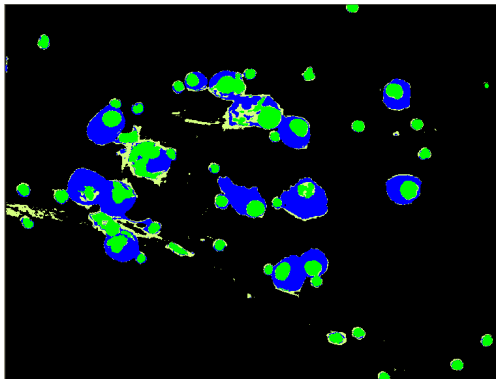
Since it is difficult to claim the superiority of classifiers one to another, a combination of classifier decisions is necessary. The classifiers having not the same opinion of the class to be allotted to the same pixel, we were brought to carry out a combination of pixel classifications. The answer provided directly by the pixel classification is of class type. But this type of output being the one that brings the less information, we coupled it to a confidence index to perform the combination of pixel classifications. The Figure 1(a) presents an initial image to segment and the Figure 1(b) gives the pixel classification result obtained by the SVM algorithm. The Figure 1(c) shows the result of all pixel classifications obtained previously. On this figure, the background is presented in black, the cytoplasm in blue, the nucleus in green, and "not-coherence"



(a) Initial image.



(b) Classified image by SVM algorithm.



(c) "Not-coherence" zones between the different classifiers (yellow).

Figure 1: Pixel classification results.

zones in yellow. These "not-coherence" zones show the pixels where all the classifiers do not give identical opinions on the class to be allotted to a same pixel.

3.3 Confidence index

A testing data base was built from four images containing objects with a wide variability and have been manually segmented by an expert in cytopathology[1]. We evaluate every classifier compared to this testing data base (the testing data base is different to the learning data base). We obtain for every classifier, like describes it the following relation, a confidence index $index_i$. This index represents the classification quality of the classifier to the class i (with $i \in [\![1, k]\!]$). For a $j \in [\![1, n]\!]$ classifier, we define :

$$index_j = \begin{pmatrix} index_j^0 \\ ... \\ index_j^k \end{pmatrix} \quad (2)$$

It is evaluated by a novel pixel classification quality index adapted to microscopic images (see in [6] for more details).

3.4 Combination scheme

A lot of different combination methods can be found in the literature [4, 3, 8, 2]. They usually combine several decisions coming from several classifiers. Each classifier providing a class membership. In the case of pixel classification, this is directly applicable and one can combine the different outputs of the classifiers one to another. However, dealing with images, the spatial information involved in the pixel connectivity is not taken into account while combining several classifications for one pixel. It is therefore interesting to use not only one single value to describe the output of a classification method but several ones corresponding to all the classifications obtained for pixels neighbors to the central one considered. For a neighborhood of size i, the size of the feature vector associated to one classifier is of $(8i + 1)$ (with $i = 0$ one recovers the simplest case of only one classification per pixel). The combination methods [4]

[1]The authors would like to thank Mr Michel Lecluse and the pathological anatomy and cytology department of the Louis Pasteur Hospital Center of Cherbourg for providing the ground truth reference images.

that we use are methods without training which can be described as follows :

If E the set of n classifiers used, we have $E = \{e_1, ..., e_n\}$. Every classifier associates a class C_i to an input vector x. We can thus define $E_{C_i}(x)$ as the set of classifiers which all associate to an input vector x the class C_i :

$$E_{C_i}(x) = \{e_j \in E | e_j(x) = C_i\} \quad (3)$$

We have clearly $\cup \{E_{C_i}(x)\} = E$ since a classifier takes only one decision of class type. With every $E_{C_i}(x)$ set with $i \in [\![1, k]\!]$, one can associate the set of confidence indexes for every classifier $e_j \in E_{C_i}(x)$. Each index corresponds to the confidence given to the classification carried out by the e_j classifier when it associates to x the class C_i. Let $I_{C_i}(x)$ denotes the set of these indexes :

$$I_{C_i}(x) = \{index_j^{C_i} | e_j \in E_{C_i}(x)\} \quad (4)$$

The set $I_{C_i}(x)$ corresponds to the respective confidence indexes of the classifiers who classify the input x as being of class C_i. From these sets, we can compute the membership probability of x to the class C_i by the following relation.

$$P(C_i|x) = g(I_{C_i}(x)) \quad (5)$$

where g is a combination rule among the followings : majority vote (MV), minimum (MIN), maximum (MAX), sum (SUM), average (AV), product (PDT).

We then assign to the pixel p the class C_k such as:

$$P(C_k|x) = \underset{l}{argmax} \quad P(C_l|x) \quad (6)$$

4 Experiments results

The images on which we work are microscopic cytology images of bronchial tumours acquired by a standardized platform. We provided the results of pixel classifications combination obtained on four cytological 24 bits color images of size 752×574 pixels, each one containing hundreds of cells and all segmented manually by an expert in cytopathology. Our treatment was developed in C++.

In table 1, we present in order of merit the results of single pixel classifications obtained with the best color space to further justify the importance of the combination step. The segmentation of nuclei bringing more information to the experts, we privilege the recognition quality index of the nucleus in relation to the cytoplasm. One can see that the best results are obtained SVM supervised classification.

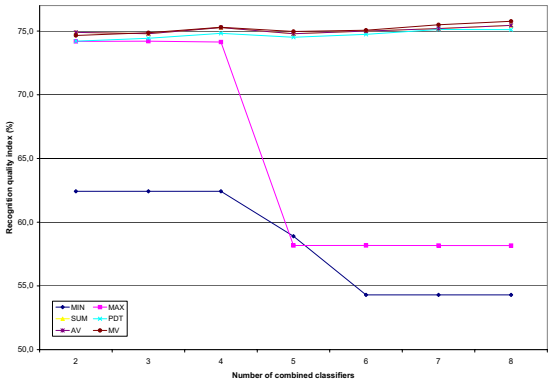
Classifier	Space	IdCytoplasm	IdNucleus
SVM	YCh_1Ch_2	77.4 %	74.2 %
Bayes	YCh_1Ch_2	72.4 %	74.6 %
k-means	YCh_1Ch_2	69.5 %	74.4 %
MLP	YC_bC_r	56.9 %	73 %
Fisher 1	RGB	50.8 %	72.3 %
kNN	HSL	79.9 %	70 %
Fisher 0	$I1I2I3$	57.3 %	71.9 %
Fisher 2	HSL	59.9 %	69.8 %

Table 1: Pixel classifications results with the best color space before the combination step.

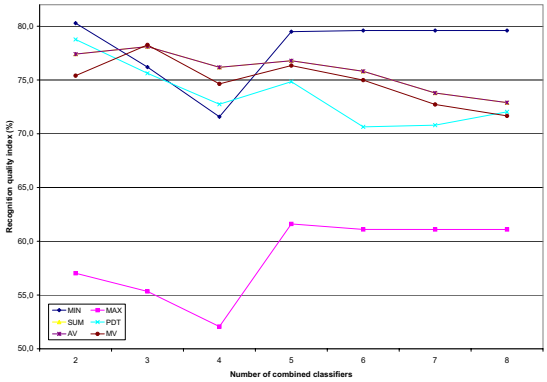
Figures 2(a) and 2(b) present the different combination rules according to the number of combined classifiers. The majority vote (MV), and sum (SUM) are the methods which gave the best results for the whole cell (cytoplasm and nucleus). In the following, we comment our combination results only with these two methods. For the nucleus recognition, the indexes slightly increase with the growth of the number combined classifiers. For the cytoplasm recognition, a maxima of the indexes is obtained for 3 combined classifiers. We conclude that the best recognition of the whole cell is obtained with 3 combined classifiers.

Figures 3(a) and 3(b) present the neighborhood influence in the combination process according to the number of classifiers. We show that the nucleus recognition is increased by using 8 or 16 neighbors. The cytoplasm recognition is increased or decreased with 8 neighbors according to the combination rule used. Beyond this, the nucleus and cytoplasm recognition decreases. We conclude that the best recognition of the whole cell is obtained with 8 neighbors.

The table 2 and figure 4 present the quality index of segmentation obtained with the end of treatment. We show

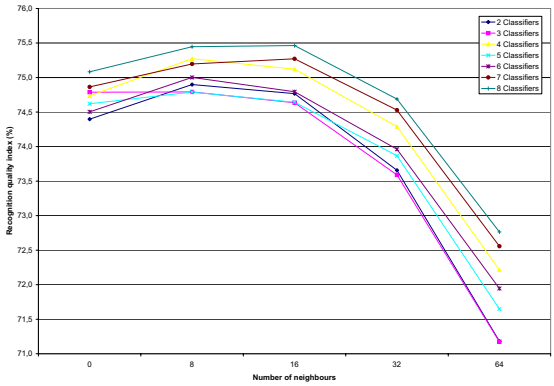


(a) Recognition quality index of the nucleus.

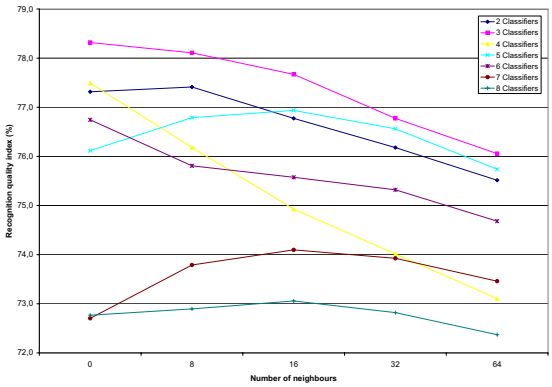


(b) Recognition quality index of the cytoplasm.

Figure 2: Influence of combination rules according to the number merged classifiers.



(a) Recognition quality index of the nucleus.



(b) Recognition quality index of the cytoplasm.

Figure 3: Influence of neighborhood information.

that the combination step increases the segmentation quality of the whole compared to a segmentation with a single pixel classification taken alone (k-means or SVM algoritms).

5 Conclusion

When using multiple classifiers, combination problems arise since conflicting predictions between classifiers are possible and one has to arbiter among them. Combining multiple pixel classification (obtained from several inducers) can provide better results than a single pixel classification taken alone. This is why we propose a segmentation scheme of color images based on a combination of pixel classification. This paper shows the improvement of the results by the use of a pixel classifications combination and of the neighborhood information. The best combination for our application in microscopic imagery consists in using a combination of the 3 better classifiers with the information of neighborhood (8 neighbors).

Our method is suitable for the segmentation of color images in a noisy environment and more particularly to the segmentation of cellular objects (Figure 4 and table 2). We improve the quality of our segmentation by the

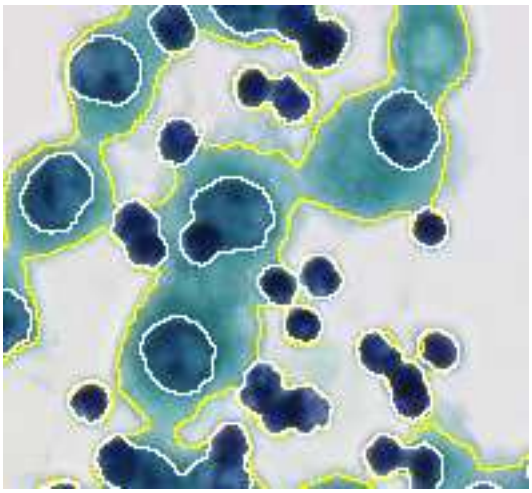


Figure 4: Segmented image.

	IdCytoplasm	IdNucleus
k-means	72.8 %	76.2 %
SVM	73.2 %	75.8 %
Combination	**74.4 %**	**76.4 %**

Table 2: The best segmentations.

addition of this combination step: quality index of 76.2 % for the nucleus and 72.8 % for the cytoplasm with the best single classifier and 76.4 % for the nucleus and 74.4 % for the cytoplasm with the best combination.

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