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A fast and efficient segmentation scheme for cell microscopic image

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1 Introduction

In recent years, computer-aided image processing and analysis systems have played a significant part in quantitative pathology. Image analysis in the field of cancer screening is a significant tool for cytopathology. Two principal reasons can be highlighted. Firstly, the quantitative analysis of shape and structure of nuclei coming from microscopic color images brings to the pathologist information valuable for assistance diagnosis. Secondly, the quantity of information that the patologists must deal with is more and more gigantic, in particular when the number of cancer screening increase. For this reason, segmentation schemes for microscopic cellular imaging must be efficient for the analysis and fast in order to process huge quantity of images.

Several studies showed that segmentation schemes combining color pixel classification and morphological operations are efficient with microscopic cellular images [2, 3]. Cells staining with international coloration of Papanicolaou makes it possible to classify the color pixels among the three classes: background, cytoplasm or nucleus, but this classification cannot be perfect. Indeed, a fraction of nucleus pixels are the same color as cytoplames pixels because of the variability of the nucleus according to the types of cells and the chromatin distribution. Moreover, for some cytophathology, the mucus present in the background has the same color as some cells (cytoplasm and nucleus). Then morphological operations, like regions growing, which take into account neighborhood relations from the spacial repartition of pixels on cells and nucleus, improve the quality of the segmentation.

The studies mentioned before only focus on improving segmentation quality, thus that can lead to build a powerful classifier of pixels but the computing times of this one are intractable for a real application. So at first, a new learning method [1] is proposed to build Support Vector Machine (SVM) decision function of reduced complexity, efficient generalisation. Moreover each decision function uses an adapted hybrid color space [4]. The aim is to build a fast and efficient SVM classifier of pixels.

There is another problem for the design of segmentation schemes. It is how the quality of a segmentation is evaluated. Indeed, almost segmentation schemes have some parameters. Human observation highlight that the values chosen for these parameters are significant for the quality of the segmentation. However, for an automatic selection of the optimal parameter values, the quality of a segmentation must be automatilly evaluated. There are some criteria: LUI and BORSOTTI, VINET, classification rate and other statistical measures, but all of them have drawbacks and are not well designed for the evaluation of cell image segmentation quality. A new quality criterion is proposed for this quality evaluation. It takes into account that different experts cannot make exactly the same pixel segmentation, nevertheless the differences are only for pixels near the edges of the shapes. So our new quality criterion weighting all pixel classification error in function of its nearer distance from edge shapes of a manual expert segmentation. It also is critical that the segmentation losts the least possible cells and nucleus presents in the expert segmentation. In the same way, it is as significant as the number of artifacts produced by the segmentation as small as possible. Our new criterion also takes into account of this effect by counting the number of false or lost objects in the automatic segmentation compared to the expert segmentation.

2 Fast and efficient pixel classification

SVMs are powerfull classifier having high generalisation abilities, but the Decision Function (DF) provided by SVMs has a complexity which increases with size of training set (pixel database). Therefore using SVMs for pixel classification is not directly tractable.

To this aim we propose a new learning method which uses the vector quantization to simplify the training set and thus permits to reduce the complexity of the DF built by SVMs. For each DF an adapted hybrid color space also is chosen. A new criterion is defined to estimate the Quality of a Decision Function (QDF). This QDF criterion takes into account the recognition rate but also the time complexity of the DF. Tabu search metaheuristic is used to select SVM hyperparameters, level of simplification and hybrid color space in order to optimize the QDF. This method also uses PLATT algorithm to map SVM outputs into posterior probabilities.

This learning method has produced pixel classification of microscopic bronchial tumors images (fig. 1(a)) with good pixel recognition rate (background: 96.4%, cytoplasm: 85.0%, nucleus: 90.1%). Moreover, process time has only taken approximately 1 second per image for computing classification image (fig. 1(g)) and posterior probabilities associated (fig. 1(b), 1(c), 1(d)).

3 New segmentation quality criterion

This new quality criterion q_{seg} must take into account the good adequacy q_{shape} between the shape of the objects produced by the automatic segmentation I_a and those produced by the expert segmentation I_e . This criterion must also take into account the number of lost objects n_{lost} and the number of artifact objects $n_{artifact}$.

$$q_{\text{seg}} = q_{\text{shape}} + \lambda n_{\text{lost}} + (1 - \lambda) n_{\text{artifact}} \quad \lambda \in [0, 1]$$
(1)

The constant λ makes it possible to favorise a segmentation which limits the number of lost objects compared to the number of artifact objects and vice versa. For example, in the case of the segmentation of cells, it is essential that none cell is lost, even if that forces to keep artifacts like bronchial carbon remains, so we have chosen $\lambda = 0.9$. The good shape adequacy q_{shape} is defined as following:

$$q_{\text{shape}} = \frac{1}{|I_a|} \sum_{\substack{p \in I_a \\ I_a(p) \neq I_e(p)}} \min\left(d_{\text{edge}}(p, I_e), d_{\max}\right)^2 \quad (2)$$

where $d_{\text{edge}}(p, I_e)$ corresponds to the distance between the pixel p and the nearest pixel of p belonging to the shape edges in I_e . Figure 1(f) illustrates where the errors of classifications are the least serious in function of expert segmentation (fig. 1(e)).

4 The segmentation scheme

The segmentation scheme is given in five steps:

- ①: Pixel classification and associated posterior probabilities
- ②: Smoothing pixel image probabilites (gaussian filter)

③: Marker extraction (pixels with sufficient high probabilities are selected)

④: Removal of false markers (erosions followed by dilatations)⑤: Watershed using probability images.

All parameters in this scheme are chosen by a tabu search method which optimizes the segmentation quality criterion as defined in section 3.

References

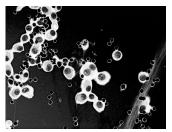
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(b) background pixel probabilities.

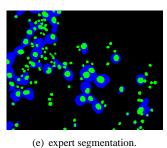
(a) microscopic image.

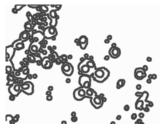


(c) cytoplasm pixel probabilities.

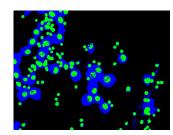


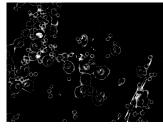
(d) nucleus pixel probabilities.





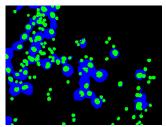
(f) pixel errors map.





errors

(g) pixel classification. (h) pixel classification $(q_{\text{shape}}=0.769).$





(i) automatic segmentation.

(j) pixel segmentation errors $(q_{\text{shape}}=0.492)$.

Figure 1. images illustrating various steps of the segmentation scheme.