Superpixel Co-Occurrence for Quantitative Description of Biomedical Images

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Abstract: *With this study, a method for quantitative description of biomedical images based on splitting the target image into superpixels followed by categorization using pre-calculated superpixel dictionaries and calculation of co-occurrence matrices is proposed. The method has been tested on the classification of biomedical images of three types: lung CT images, histology images of ovary and thyroid tissues.*

Keywords**:** superpixel, co-occurrence, image, descriptor, biomedical

1. INTRODUCTION

Quantitative image description is considered to be one of the most important steps in image analysis tasks. The choice of a certain method of image description usually strongly influences the overall performance of pattern recognition algorithms, content-base image retrieval systems [1], CAD systems [2], etc. Recent studies suggest that the development of quantitative image description methods is of great importance for more accurate image classification and understanding [3]. One of the possible ways of this development is switching from straightforward utilizing of local image features based on pixel intensities and gradients to the description based on more complicated morphological and geometrical image primitives (visual words [4], patches [5], etc.).

Recently a concept of superpixel image representation has been emerged in a number of studies dedicated to object localization [6], skeletonization [7] and scene understanding [8]. However, in the most cases superpixels are used in various image segmentation solutions [9–11].

The purpose of this study is to present a method for quantitative description of biomedical images based on superpixel representation and utilizing a co-occurrence concept for more detailed description. To our best knowledge the potential of superpixel-based image description has not been completely researched yet [12].

2. MATERIALS

With this study, we used three different datasets to assess the efficiency of the proposed image description methods. Each dataset contained images of 2 classes.

CT image slices. Typical chest Computed Tomography (CT) image is a 3D digital image consisting of about 60–300 2D slices of 512×512 pixels resolution. From original CT images of 195 tuberculosis patients a total number of 270 2D image regions of 128×128 pixels in size were extracted. Among them there were 92 image regions corresponding to tuberculosis lesions (Fig.1, d), and the remaining 178 did not contain any visual signs of the disease (Fig.1, a).

Ovary (Fig.1, b,e) and *thyroid* (Fig.1, c,f) histological images. Each of the two histological datasets contained 200 images, 100 of them corresponding to normal cases (Fig 1, b,c) and the other 100 being images of cancerous tissue (Fig 1, e,f). All the 128×128 pixel images were transformed to gray-level as it was suggested in [13].

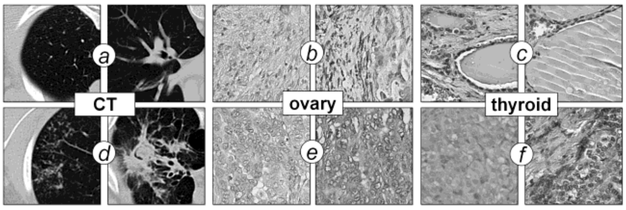

Fig.1 – The examples of dataset images (top row – normal, bottom row – malignant)

3. GENERAL SCHEME OF THE METHOD

The proposed biomedical image description method includes two major stages: (a) generating a superpixel dictionary and (b) describing the images using the obtained dictionary.

With this study, superpixel dictionaries were represented by the sets of features of the most typical superpixels occurring on the images of a given type. The *generating superpixel dictionary* stage included the following steps:

– selection of a certain number of representative images of given type;
– extraction of superpixels from the selected images;
– extraction of superpixels features;
– splitting the superpixel feature-space into *N* clusters;
– calculating cluster (class) centroids;
– composing the superpixel dictionary (set of centroids).

The *image description* stage was based on calculation of histograms and co-occurrence matrices of image superpixels categorized into *N* classes according to the previously obtained dictionary. This included the following:

– extraction of superpixels from the target image;
– extraction of superpixels features;
– categorization of each superpixel into one of *N* classes according to the pre-calculated dictionary;
– calculating a histogram and a co-occurrence matrix [10] of the categorized superpixels.

4. SUPERPIXEL DICTIONARIES

In [14] a set of 1708 superpixel features (color, texture, shape and location features) was used for the task of scene description. In our study, we used a set of 6 major superpixel features which basically describe texture and shape of a single superpixel:

– mean intensity of internal pixels;
– standard deviation of intensity;
– entropy of intensity;
– mean gradient magnitude;
– compactness (square root of superpixel area divided by its border length);

– “squareness” (how much the superpixel shape is similar to a square).

Superpixel dictionaries were generated separately for all three image datasets: CT image regions, histological ovary images and histological thyroid images. The superpixel generation algorithm [15] used with this study has two control parameters: superpixel size *Sz* and a regularization parameter *Reg*. The examples of generated superpixels are shown in Fig.2

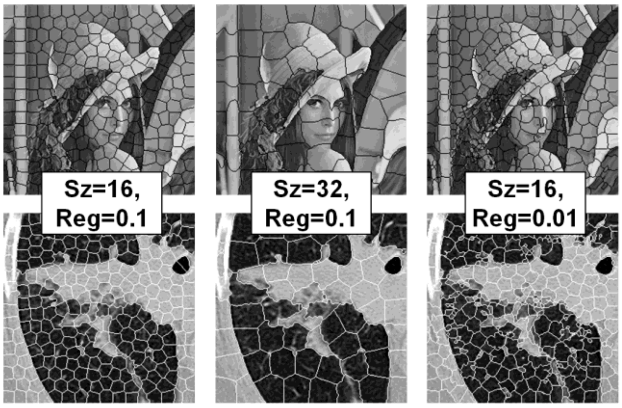

Fig.2 – Examples of generated superpixels.

Dictionaries were generated for each selected combination of parameters *Sz* and *Reg*. Superpixel clustering was performed using *k*-means algorithm, number of clusters being set to N = 16, 32, 64 and 128. Fig.3 illustrates sample superpixels extracted from CT image regions (*Sz* = 16, *Reg* = 0.1); each column corresponds to a certain superpixel class.

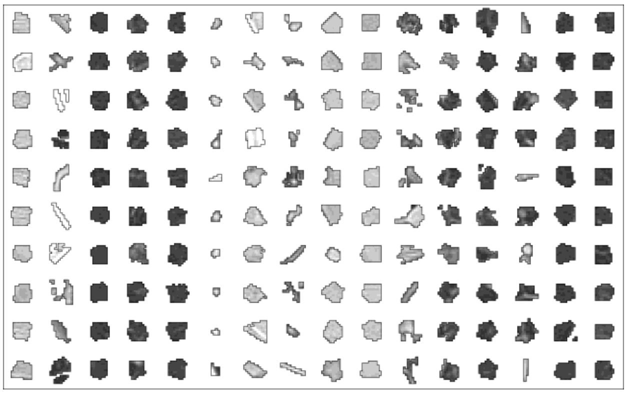

Fig.3 – Sample CT-image superpixels (per class).

5. IMAGE CLASSIFICATION

The main goal of this study was to assess the efficiency of the proposed image description method compared to conventional ones. Therefore image classification was performed with use of a rather simple *k*-nearest neighbors classifier (k = 5) and a city-block metrics for calculation of distances in feature-spcae. A cross-validation procedure was involved to exclude over-fitting. For more accurate assessing of algorithms performance a bootstrapping scheme was used. The overall image classification procedure was repeated 100 times on random subsets of image datasets, subset size being equal to 80% of the one of the original dataset. The resultant classification accuracy was averaged.

The assessing was performed for the following combinations of control parameters of superpixel extraction algorithm: *Sz* = 16, *Reg* = 0.1; *Sz* = 32, *Reg* = 0.1; *Sz* = 8, *Reg* = 0.1; *Sz* = 16, *Reg* = 0.3; *Sz* = 16, *Reg* = 0.03; *Sz* = 16, *Reg* = 0.01. The superpixel dictionary size N was set to 16, 32, 64 and 128. Four image description methods were tested and compared: conventional Local Binary Patterns (LBP), conventional Gray-Level Co-occurrence Matrices (GLCM), proposed Superpixel Histograms (SP-hist) and proposed Superpixel Co-occurrence Matrices (SPCM).

The classification accuracy acquired using various parameters is shown in Fig.4–6. For each dataset, only the best combination of *Sz* and *Reg* parameters are displayed. As we can see from the plots, the suggested image description method based on superpixel co-occurrence (SPCM) may provide comparable or better classification accuracy than the considered conventional image description methods.

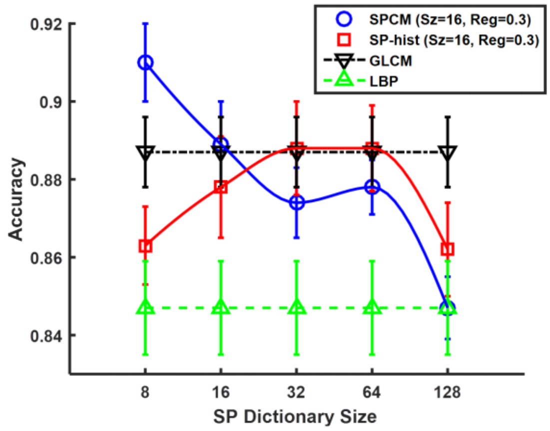

Fig.4 – Classification Accuracy vs Dictionary Size (CT slices).

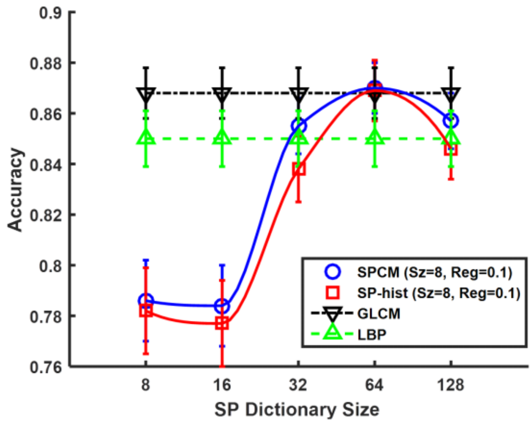

Fig.5 – Classification Accuracy vs Dictionary Size (ovary).

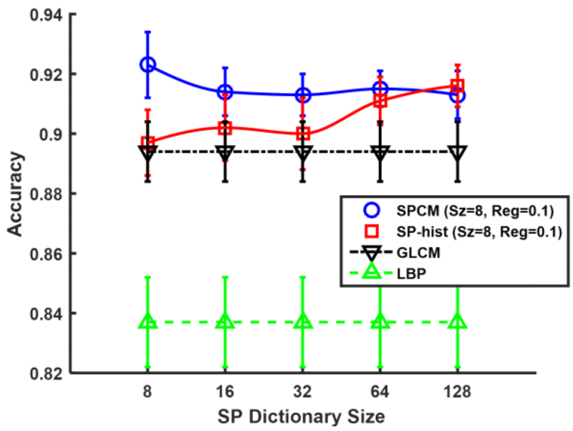

Fig.6 – Classification Accuracy vs Dictionary Size (thyroid).

6. CONCLUSION

With this study, a method for quantitative description of biomedical images is proposed. The method is based on splitting the target image into superpixels followed by categorization using pre-calculated superpixel dictionaries and calculation of co-occurrence matrices. It was shown that the suggested method may perform comparable or better results when applied to the task of biomedical image classification.

The suggested approach may be easily transformed for the case of 3D images to describe entire volumetric CT or MRI scans instead of treating those in a slice-by-slice manner.

6. REFERENCES

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