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APPLICATION OF MULTIMODAL TECHNIQUES IN ANALYSIS OF NBI ENDOSCOPIC IMAGES

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ABSTRACT

The paper presents a proposition and possibility of application of multimodal images methods to segmentation of NBI endoscopic images. NBI endoscopic technology (Olympus NBI) in endoscopic examinations applies the filtration of white light into two bandwidths: blue and green and combine new image with original white light illumination. The endoscopic NBI images can be considered as multimodal images and for these images the segmentation using some clustering techniques were performed. The final results appear interesting and give new perspective to use multimodal techniques in NBI endoscopic image segmentation.

INTRODUCTION

Segmentation is one of a basic stage of medical image analysis and it gives a possibility of estimation of geometrical and morphological parameters of the objects on an image. The segmentation can be a first step before more complex analysis like recognition and classification and it can also improve the diagnosis by giving to the physician images easier to interpretation. In medical diagnosis many kinds of medical image analysis are applied. Together with such methodologies like CT, MRI, PET and SPECT the endoscopy became one of the most important diagnostic techniques. In standard endoscopy procedure the white light is used. This way one can see all the images as the reflection from only mucosal. The solution to this limitation is to replace white light to a bandwidth light for the wavelengths which eliminate distortion and can enhance the contrast of vessels. Because of the fact that hemoglobin has an increased absorption rate for light at wavelength of green and blue color a new image in this bandwidth improves the visual contrast. Next step is to decide whether the created image is good enough or any possibility to enhance the contrast exists [1]. In NBI endoscopic images we obtain two or more images giving the picture of the same part of mucosal, where each of images represents the different properties of the tissue. This gives the possibility of using multimodal methods to perform the segmentation for obtaining better images from diagnostic point of view. In the scientific literature have appeared many articles about NBI technique in endoscopy. Most of them present diagnostics based on classic endoscopic NBI images [2,3]. The paper presents the new approach in which we perform a segmentation basing on multimodal techniques which can be performed for NBI image treated as one two modal image. In multimodal image segmentation the important point is to use clustering techniques and to choose which of the clustering methods should be applied. There are many clustering techniques, from classical c-means algorithm, through statistical and fuzzy methods to some new techniques taking inspiration from statistical physics and artificial intelligence methods [4–6].

NBI ENDOSCOPY

In NBI endoscopy an interested area is illuminated by white light. This way the first image is created. Next the same area is illuminated by green and blue light (NBI) giving us the second image (see Figs. 1 and 2).

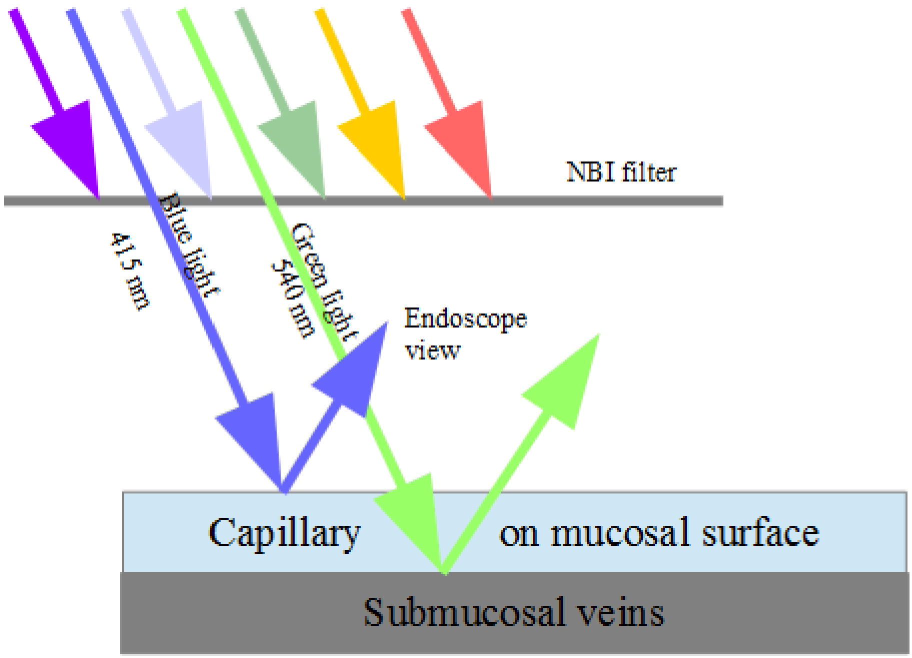
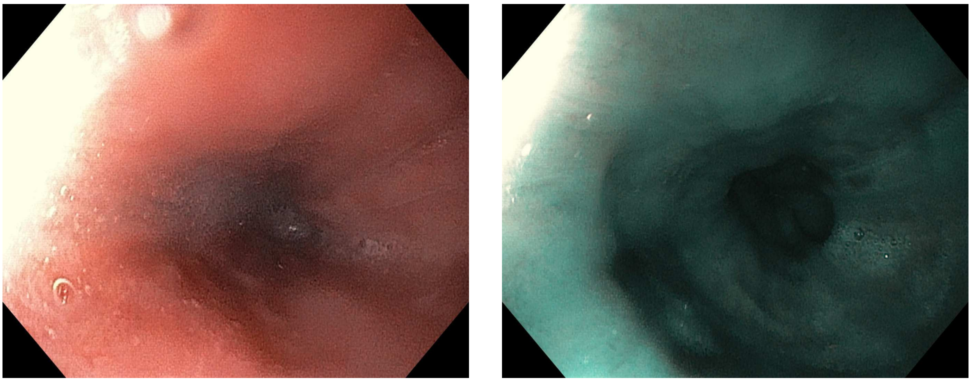


Figure 1. The schema of narrow band imaging (NBI) endoscopy.

Figure 2 presents an example of NBI images. Comparison of these two images shows the differences between views of various illuminations and makes easier the diagnosis. Find that areas where are a bigger concentration of hemoglobin are darker. Some special producers are used to see more details in images. For example, Pentax and Fujinon use only white light and by post-processing image enhancement technology provide more contrast image.

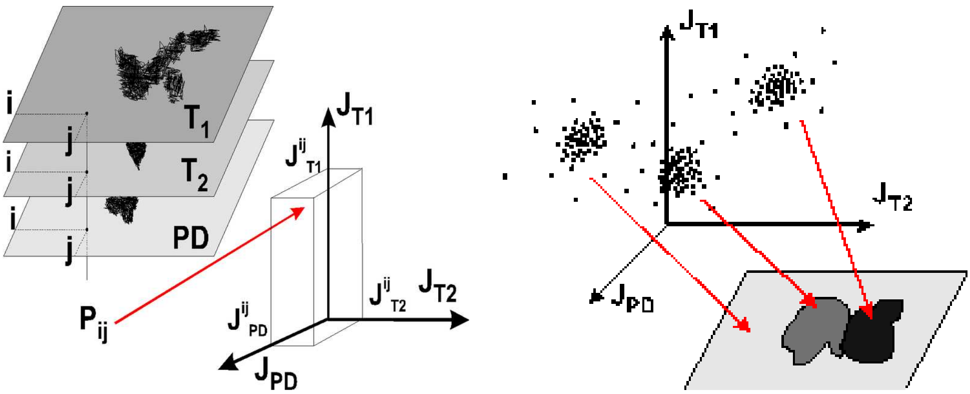
MULTIMODAL ANALYSIS

The multimodal medical imaging is an important technic is applied in medical imaging. The multimodal approach bases on imaging of the same anatomical area or section using different imaging methodologies where each image component presents different morphological, chemical and physical properties. The classic multimodal image is a MRI image where three corresponding images are obtained (T1, T2 and PD) [4, 5]. This way a pixel having the same coordinates has the different value on each image. This allows going to the feature space where the coordinates represent the pixel values. In this feature space there are as many points as pixels on an image. In the feature space the clustering is performed which gives resulted segmented image after labelling



(a) (b)

Figure 2. Example images for an area illuminated by white light (a) and NBI light (b).



(a) (b)

Figure 3. The schema of multimodal image analysis.

pixels belonging to the given cluster gives resulted segmented image. Instead of two or more multimodal images we obtain one segmented image containing the information from all multimodal images component (see Fig. 3) [4, 5].

The most important step in the presented analysis is clustering. Let us take n element set of data $\mathbb{X}$:

$$\mathbb{X} = \{x_1, x_2, \ldots, x_n\} \,, \tag{1}$$

The clustering of a set $\mathbb{X}$ is the division of $\mathbb{X}$ into c subsets where elements are similar to each other. The classic clustering algorithm is a "c-means clustering algorithm". In this approach having a data set $\mathbb{X}$ the c cluster centers $y_1, y_2, \ldots, y_c$ are chosen at the beginning. To which cluster (subset) the given element belongs, the distances of all element to all cluster centers are calculated. An element x_i will belong to this cluster i, for which the cluster center is placed as closed as possible to x_i. Next the new cluster centers are calculated taking into consideration only elements which were counted to the given cluster. This is next repeated till the cluster structure became stable [6]. The c-means clustering algorithm is equivalent to optimization of objective function in the form:

$$J = \sum_{i}^{n} \sum_{j=1}^{c} p_{ij} \left|x_i - y_j\right|^2 = \sum_{i}^{n} \sum_{j=1}^{c} p_{ij} d_{ij} \,, \tag{2}$$

where

$$p_{ij} = \begin{cases} 1 & \text{if} \quad x_i \quad \text{belong to cluster} \quad j \ , \\ 0 & \text{if} \quad x_i \quad \text{does not belong to cluster} \quad j \ . \end{cases} \tag{3}$$

Parameter p_{ij} is interpreted as a probability the point x_i belongs to cluster j. The optimization problem corresponding to c-means clustering algorithm falls often into local minima, what gives an impulse to improve and introduce new and better clustering algorithms. The most interesting direction is clustering methods based on statistical physics. In these methods the maximum entropy principle is used. The general approach was prepared by Jaynes [7], who used the information interpretation of Shannon entropy [8]. To apply the statistical physics methods in clustering [9–11] a set of data $\mathbb{X}$ (1) is introduced and a normalization condition on probabilities p_{ij} is assumed

$$\sum_{j=1}^{c} p_{ij} = 1 \ . \tag{4}$$

The corresponding entropy should take into account all groups and all data points

$$H(p_{11}, p_{12}, \ldots, p_{nc}) = -\sum_{i}^{n} \sum_{j=1}^{c} p_{ij} \ln p_{ij} \ , \tag{5}$$

while the mean energy of element x_i connection into cluster j is

$$\langle E \rangle_i = \sum_{j=1}^{c} p_{ij} E(x_i) \ , \tag{6}$$

and this allows presenting the full mean energy as

$$\langle E \rangle = \sum_{i}^{n} \langle E \rangle_i = \sum_{i}^{n} \sum_{j=1}^{c} p_{ij} E_{ij} \ . \tag{7}$$

After some manipulation as a result the Gibbs distribution is obtained

$$p_{ij} = \frac{\exp\left(-\beta E_{ij}\right)}{Z_i} \ , \tag{8}$$

where Z_i is a partial partition function

$$Z_i = \sum_{j=1}^{c} \exp\left(-\beta E_{ij}\right) \ . \tag{9}$$

The full partition function appear the product of Z_i components

$$Z = \prod_{i=1}^{n} Z_i \ , \tag{10}$$

The Lagrange multiplier β in statistical mechanics is interpreted as the reciprocal of temperature T

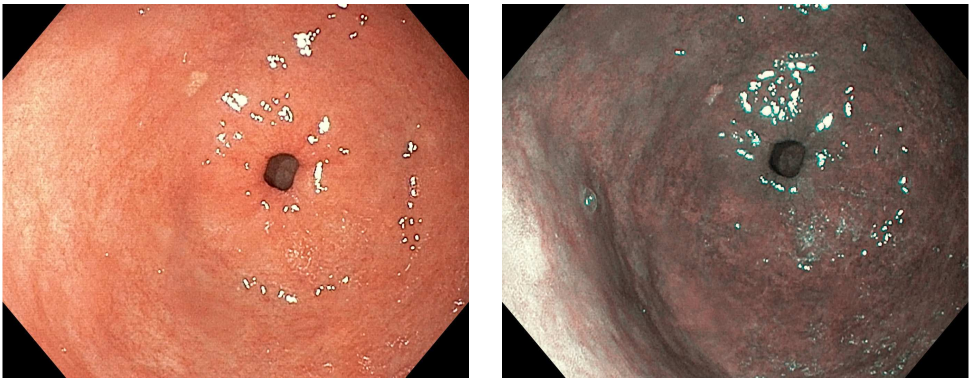
$$\beta = \frac{1}{T} \ . \tag{11}$$

Next the Variational Free Energy Minimization can be performed [12] what gives us a deterministic annealing schema [9–11]. Taking energy as a distance between x_i cluster center y_j

$$E_{ij} = d_{ij} = d(x_i, y_i) = |x_i - y_j|^2 \ , \tag{12}$$

finally we obtain

$$y_j = \frac{\sum_i^n p_{ij} x_i}{\sum_i^n p_{ij}} \ , \qquad \text{for all } j \ . \tag{13}$$



(a) (b)

Figure 4. Two example images obtained by NBI endoscopy (white light (a), NBI filter (b)).

Having an equation for cluster centers the deterministic annealing can be performed as minimization of free energy F while β goes to infinity

$$\lim_{\beta\to\infty} F = \langle E \rangle \; , \tag{14}$$

$$\lim_{\beta\to\infty} \left(\min_{Y} F \right) = \min_{Y} \langle E \rangle \; . \tag{15}$$

Changing β initially for $\beta = 0$ only one cluster is obtained but together with increasing of β value the new local minima appear.

The deterministic annealing schema can be presented as following:

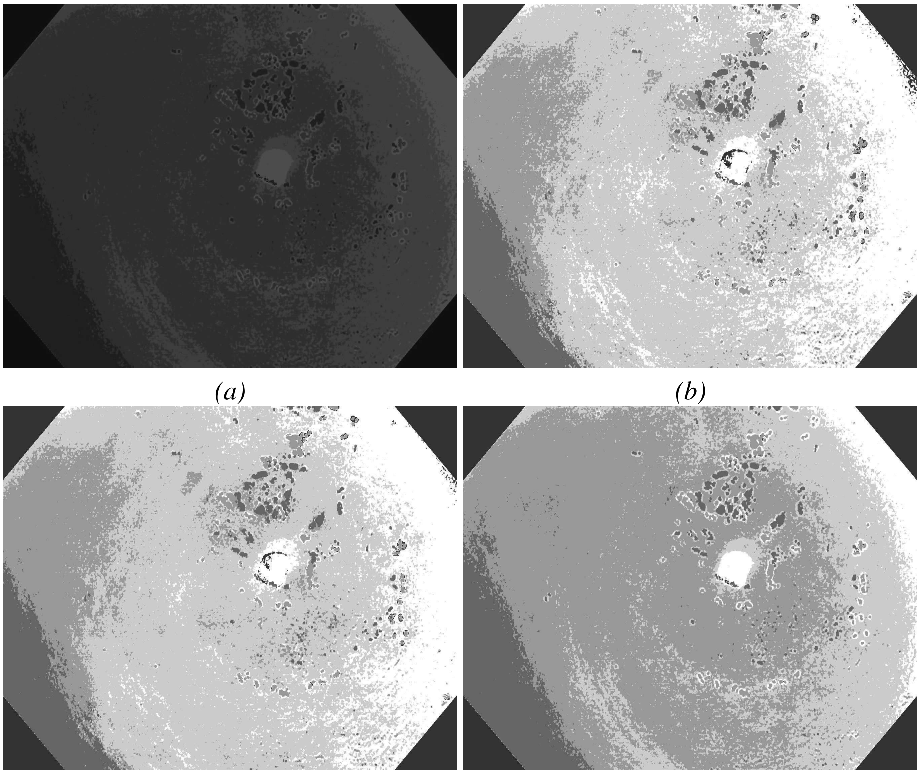
(1) Set $\beta = 0$.
(2) Chose any set of c cluster centers y_j.
(3) Perform iteration for y_j as to convergence using equation (2).
(4) Increase β.
(5) While $\beta < \beta_{\max}$ return into step 3.

Generally the above algorithm can be stopped in any moment and for any reason. The idea of this algorithm was taken from physics were the process of annealing consists of heat up of solid body into high temperature where it transits into liquid state and next slowly cooling what allow a particle to set up in low-energy states of crystal network.

RESULTS

The multimodal analysis was performed using in Matlab with using both types of images: white light illuminated images and NBI images. Together with segmentation some other experiments were also first performed on these images (e.g. image subtraction which is very often applied in medical image analyzers). Figure 4 presents two examples of NBI endoscopic images. For these images the segmentation using multimodal approach with application of clustering c-means algorithm was performed. The results are presented in Fig. 5.

In NBI endoscopy usually the picture on the right (NBI filter) is more legible (see Figs. 2 and 4). Find that NBI images differ with a lack or decrease amount of visible mucus what gives the impression of different tissue areas. In practice the mucus can be deleted and this way reflection can be reduced. But a general view of tissue is quite good. The full information image should be prepared with using bandwight light and compare it with standard picture. The problem is here that the endoscopic images are color images. It means that each image has three RGB components: red, green and blue and each pixel has not one but three values. Performing segmentation using



(a) *(b)*

(c) *(d)*

Figure 5. The result of segmentation for conversion to B&W case (a) and for consideration of three components separately: blue (b), green (c) and red (d).

multimodal schema gives a question — how to treat this color components. This question provokes the authors to perform this segmentation in two ways.

First way is to convert each image into grey scale B&W (black and white) where the pixel will have one value and next to perform segmentation for such two component images. It can be done but the results are not interesting (see Fig 5(a)). The really better results are obtained where three color components RGB are considered individually and the segmentation is performed for each color component separately (see Figs. 5(b),(c),(d)). In this case the good emphasizes segments can be seen what gives the bigger usefulness of these images for any next image analysis.

CONCLUSIONS

The researches demonstrated in the paper are showing the usefulness of application of multimodal techniques for segmentation of NBI endoscopic images. The NBI endoscopy by using of the bandwave light gives more data which can create multimodal images. Simple algorithms enable to visualize interesting parts of mucosal, get more contrast of image and mark distinguishing areas. The NBI endoscopy enables to see the vascular system of mucosal and bright places where blood is gathered. In this approach there is a problem of a speed of image analysis. Post-processing requires some time to prepare data from full HD image. Powerful image processors and special algorithms are needed to display neutral and post-process image at the same time.

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