On specific features of the endoscopic image processing

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Abstract. Main principles of endoscopic image processing are considered. Specific characteristics of such images and complexities in their classification are discussed. We suggest that several features may be regarded as specific signs that can be used to discriminate between benign and malignant loci. The methods of colour histograms, gradients and texture analysis are considered and discussed.

1. Introduction

Nowadays the prevalence of cancer continues to increase [1] despite the significant progress in medical science. The malignant process often originates from epithelial tissues, including mucous membranes. The detection of cancer is an important global issue since it can significantly improve survival rates and quality of life. For the early diagnosis of malignant tumours, various approaches are used: laboratory and instrumental. The second group includes endoscopic methods for visual assessing of the morphological changes. At the same time, in the vast majority of cases, the appropriate specialist evaluates the image. This leads to the fact that there is a non-zero probability of a false negative result of the assessment, which means the omission of the disease. It was previously shown in other fields of science, that the use of computer vision systems based on machine learning could significantly improve the efficiency in comparison with the cases of human work only [2-4]. Thus, the creation of a computer expert system for the analysis of diagnostic images is an urgent task that will improve the quality of medical care. Moreover, such a system can be used in difficult situations in the absence of qualified medical personnel.

Development of such systems is associated with the following problems:

- Images of tissues can vary significantly due to the contraction of the underlying muscle fibres.
- Differences in the hardware implementation of the various endoscopic devices.
- Structural diversity and heterogeneity of the studied images.
- A wide range of scales, sizes and angles during shooting.
- Blurring of images (due to the movement of the endoscopic device).
- Presence of glare.
- Topical application of the various solutions for contrasting the lesions.

These issues complicate the task of classification of the endoscopic images. Multicriteria classification is required to adequately represent the variety of types of such images. It is possible to
build a binary classifier, for example, based on the principles of “there is a malignancy” or “there is no malignancy”. Besides, with the use of computer vision and machine learning, it is possible to implement a computer expert system of diagnosis. Classification tasks require an extensive database of medical diagnostic images, including various pathologies and diseases, as well as images with defects and artefacts obtained on different equipment and with different resolutions. After the formation of the image database, it is possible to implement the actual classification tasks:

- Feature selection and extraction.
- Feature analysis in the classifier for making the decision (diagnosis).

A feature is a numerical characteristic that describes the properties of an object, in this case, an image. All features can be divided into natural and artificial. The first category includes features that can be obtained by analysing the image: brightness, light intensity in the red, blue and green optical bands, etc. Features of the second category are obtained by processing natural features. These features include:

- histogram of the image (the main features, which can be calculated by the histogram: mean value of brightness, variance)
- spectral-spatial feature;
- local Binary Patterns, LBP [5];
- key points features [6];
- Haar-like features [7,8];
- histogram of oriented gradients, HOG [9];
- convolutional features.

The purpose of this paper is an analysis of diagnostic images of endoscopy (colposcopy) to identify features, which can be used for the further building of a classifier. Colposcopy is a medical diagnostic procedure in which the vaginal part of the cervix is assessed visually using a special optical or video device – the colposcope. The colposcopy is utilised to diagnose cervical diseases, primarily malignant. At the first stage of our work that is discussed in the paper, we considered the creation of a classification system for a binary solution: “Cancer” or “non Cancer.”

2. Identification of special characteristic on diagnostic endoscopic images for the formation of features for further processing

Consider examples of diagnostic images of colposcopy. In fig. 1 images for the “not Cancer” class are presented. They are characterised by a smooth texture, without visual defects.

![Figure 1. Examples of the colposcopic images for class “non Cancer”.

In figure 2 images for the class "Cancer" are presented. As can be seen, these images are different from the previous class due to a more complex texture.
Figure 2. Examples of the colposcopic images for class “Cancer”.

The following methods may be taken into account as promising methods for identifying diagnostic features of images: colour histograms [10, 11, 12], gradients [10, 11, 12], texture [11, 12]. Let us consider the methods of calculating the features in the colposcopic images.

At the first stage, brightness histograms for image fragments were calculated. For the implementation of this method, the image fragments of 64x64 pixels in size were extracted. Examples of fragments for the classes “non Cancer” and “Cancer” are shown in figure 3.

Figure 3. Examples of diagnostic image fragments for the “non Cancer” (a) and “Cancer” (b) classes.

For obtained fragments, the histograms were calculated. The values of mean and dispersion were calculated and normalised by the image size. The scatterplot is presented in figure 4.
Figure 4. The scatterplot for two classes of image fragments.

This diagram shows that it is possible to build a binary classifier, but its efficiency is not enough because of the large number of overlapping decision-making areas.

The next method that we applied for processing of endoscopic images was a method of local binary patterns. Examples of images processing by local binary patterns are shown in figure 5.

Figure 5. Examples of local binary patterns for image fragments of “non Cancer” (a) and “Cancer” (b) classes.

As it can be seen from the presented data, the structure of processed images for the class “non Cancer” is more fine-grained (figure 5, a) due to the smooth surface without visual defects. This feature is essential and informative but also not enough for the full classification system.

Based on the analysis of state-of-the-art classification algorithms, the use of convolution networks for classification problems seems to be promising. Convolutional neural networks showed high results in the detection and classification of the objects [13-16] and may help to implement the localisation of the pathologic areas. The main advantage of the convolutional neural networks over other machine learning algorithms is the automatic formation of a set of features as a result of
learning. The following neural network architectures are supposed to be used as classifiers: AlexNet [17], VGGNet [18], DarkNet [16]. During the localisation phase, it is planned to use one or more of the following architectures: YOLO [14], YOLO2 [16], SSD [15], Mask-R-CNN [19], U-Net [20].

3. Conclusions

In the current article, we described the main features of endoscopic images and difficulties in classification. A number of diagnostic signs of the colposcopic images were revealed. We describe results of the implementation of methods of colour histograms, gradients, texture and local binary patterns for classification and analysis of the images. These methods revealed a number of critical diagnostic signs, but they are not sufficient for the creation of a well-trusted diagnostic classification system. We conclude that the most promising method of classification should be based on convolutional neural networks. The advantage of this approach is the automatic formation of a set of filters (features) as a result of algorithm training. Our further research will be devoted to the implementation of neural network architectures for the creation of intelligent classification system. Such an approach could significantly improve the efficiency of endoscopic diagnostics.

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