EXTRACTING FEATURE VECTORS OF BIOMEDICAL IMAGES

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Abstract - **We present few approaches for extracting feature vectors from biomedical images with cervical cancer. In the first case we using technique of statistical wavelet analysis. In the second case we using wavelet analysis in "Brute force" approach. In the third case we combine two above approaches. On the first step an image is subjected to discrete wavelet transformation. On the following step the wavelet analysis of transformation coefficients is carried out. After extracting of feature vectors we used neural net to classification biomedical images. Also we have compared approaches to find best feature vectors.**

I. INTRODUCTION

Cervical cancer is the third most common cancer in women worldwide [1-6]. The natural history of cervical cancer is well understood; lesions progress from dysplasia to carcinoma *in situ* to cancer. The cervix can be sampled cytologically by use of the Pap smear. Although never subjected to a randomized clinical trial, the Pap smear has decreased mortality in all countries in which cervical cancer screening programs have been established.

The approach to detection generally used to capture digital images of visually normal cells from patients of known diagnosis (cancerous / pre-cancerous condition or normal). A variety of features such as nuclear area, optical density, shape and texture features are then calculated from the images, and linear discriminant analysis is used to classify individual cells as either "normal" or "abnormal". An individual is then given a diagnosis on the basis of the proportion of abnormal cells detected on her Pap smear slide (Fig. 1).

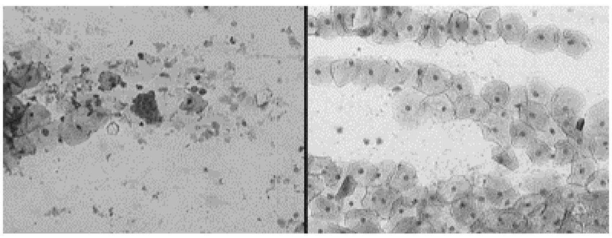

Fig.1. A sample of Pap smear images.

We discussed three methods of recognition biomedical images. The general scheme of automated diagnosis from digital images showed on (Fig. 2) [7].

The first method is statistical wavelet analysis. It is based on the using technique of wavelet analysis. The attention of researchers gradually turned from frequency based analysis to scale-based analysis when it started to become clear that an approach measuring average fluctuations at different scales might prove less sensitive to noise. In this case we use statistical features of multispectral information. Pattern classifiers like neural networks viewed as technique that take as input large sets of labeled data and find a nonlinear decision surface that separates the in-class ("normal" cells) patterns from the out-of-class ("abnormal" cells) patterns [8,9].

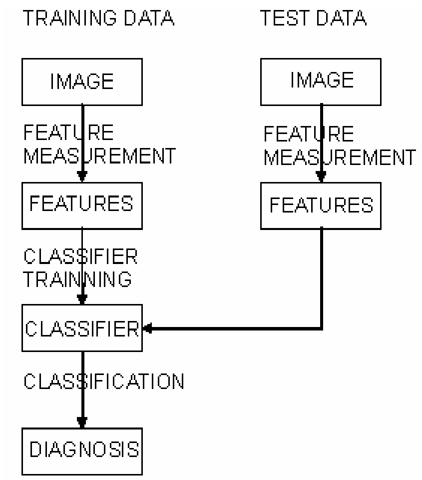

Fig.2. Automated diagnosis from digital images

The second system is "Brute force" approach. It is finds a certain class of objects in static images of completely unconstrained, cluttered scenes without making any assumptions on the scene structure or the number of objects in the scene. In the context of our pattern classification problem, we are interested in presenting the system with a set of example patterns of both classes from a set of training data and have it automatically learn the characteristics that describe each class and differentiate one class from the other. The positive examples are labeled as +1 and the negative as -1. The goal, and measure of success, is the degree of performance that the trained system achieves on a set of examples that were not present in the training set, or test set. What we are determining when using the test set to evaluate the performance is how well the system is able to generalize to data it has never seen.

The third method combine two above approaches - statistical and "brute force".

We construct wavelet transform from full image, like statistical method and from patterns of fixed size of the image, like "Brute force" method. So we get statistical features of multispectral information.

After that we used neural net to classification biomedical images, after extracting of feature vectors [10].

Wavelet theory presents a synthesis of these different approaches [11-12]. The example of wavelet transform showed on (Fig.3).

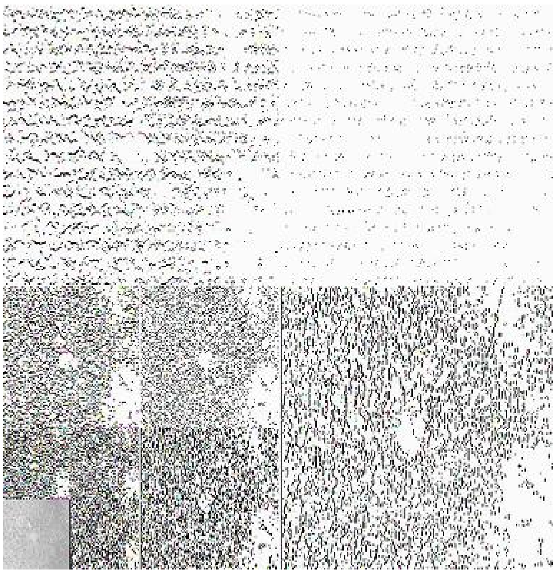

Fig. 3. Example of wavelet transform.

Our main motivation for using wavelets is that they capture visually plausible features of the shape and interior structure of objects that are invariant to certain transformations[13-14]. The result is a compact representation where dissimilar example images from the same object class map to similar feature vectors. A representation that encodes local, oriented, intensity differences (like Haar wavelets) would yield similar feature vectors where the features corresponding to uniform regions are zero and those corresponding to boundaries are non-zero.

After that, we are compare methods with each other.

II. STATISTICAL WAVELET ANALYSIS

One of the key issues in the development of an object detection system is the representation of the object class. Our challenge is to develop a representation that achieves high inter-class variability with low intra-class variability.

We construct wavelet transform based image recognition algorithm from discrete wavelet transform in orthonormal wavelet Haar based (Fig.4.). The representation that we use is a dictionary of Haar wavelets in which there is a large set of features that respond to local intensity differences at several orientations.

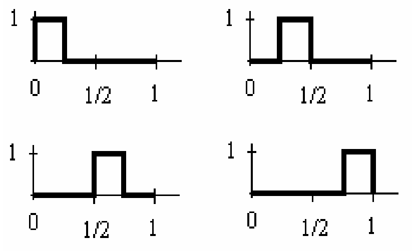

Fig. 4. Haar wavelet basis

The first step of recognition algorithm is to obtain 2-dimension decomposition of the original image over N octaves from 0 to J -N +1 by recursively filtering N time with highpass filter g(t) and lowpass filter h(t) applied alternately in the x and y directions, giving on each octave images HHj, BHj, HBj and BBj from BBj - 1. Each image BBj at octave j is the input original image approximation with 4 degree j resolution. From j-1 level of resolution to j discrete wavelet transform algorithm for image decomposition are describe as [5,8] where j is level of resolution, k, l are the coordinates of images HHj, BHj, HBj and BBj.

$$BB_j(k,l) = \frac{1}{2}\sum_{n=0}^{2^j-1}\sum_{m=0}^{2^j-1} h^{'}(2k-n)h^{'}(2l-m)BB_j-1(n,m)$$

$$HB_j(k,l) = \frac{1}{2}\sum_{n=0}^{2^j-1}\sum_{m=0}^{2^j-1} g^{'}(2k-n)h^{'}(2l-m)BB_j-1(n,m)$$

$$BH_j(k,l) = \frac{1}{2}\sum_{n=0}^{2^j-1}\sum_{m=0}^{2^j-1} h^{'}(2k-n)g^{'}(2l-m)BB_j-1(n,m)$$

$$HH_j(k,l) = \frac{1}{2}\sum_{n=0}^{2^j-1}\sum_{m=0}^{2^j-1} g^{'}(2k-n)g^{'}(2l-m)BB_j-1(n,m)$$

m, n=0.. 2^j -1,

k, l=0.. 2^{j-1} -1,

j=0..J,

L= 2^j -1,

$h^{'}$(n)=h(L-n-1),

$g^{'}$(n)=g(L-n-1),

N, m are the coordinates of image BBj-1, g(t), h(t) are the impulse response quadrature mirror filters.

The filter impulse responses g(t) and h(t) are derived from Haar scaling function and Haar wavelet accordingly[15]:

$$Fh(t) = \begin{cases} 1, & 0 \le t < 1/2 \\ -1, & 1/2 \le t < 1 \\ 0, & t < 0, \ t \ge 1 \end{cases},$$

$$Dh(t) = \begin{cases} 1, & 0 \le t < 1 \\ 0, & t < 0, \; t \ge 1 \end{cases},$$

$$\text{Mean}= M = \frac{1}{n*m}\sum_{i=1}^{n}\sum_{j=1}^{m} x_{ij} \; ,$$

$$\text{standard deviation} = D = \left(\frac{1}{n*m}\sum_{i=1}^{n}\sum_{j=1}^{m} (x_{ij} - M)^2 \right)^{\frac{1}{2}},$$

median absolute deviation =

$$MedAD = median\left(\sum_{i=1}^{n}\sum_{j=1}^{m} \left| x_{i,j} - M \right| \right)$$

$$\text{mean absolute deviation} = MeanAD = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} \left| x_{ij} - M \right|}{n*m}.$$

III. "BRUTE FORCE" APPROACH

We presented a "Brute force" system. The core of "Brute force" system extracting a feature vectors from the patterns of a fixed size of image [16].

For a given pattern, the wavelet transform computes the responses of the wavelet filters over the image. Each of the three oriented wavelets - vertical, horizontal, and diagonal - are computed at several different scales allowing the system to represent coarse scale features all the way down to fine scale features. In our object detection systems, we use 2 consecutive scales of wavelets. The resulting high dimensional feature vectors are used as training data for our classification engine.

The system learns using patterns of a fixed size, but in general images we do not know what size objects we will be looking for, how many of these objects will be in the scene, and where they will be located. To detect objects at all sizes and locations, we implement a brute force search in the image looking at all locations and sizes of patterns. We assume that the orientations that we are interested in must be expressed in the training data.

From the example images of cells shown in (Fig. 1), it is clear that a pixel-based representation is plagued by a high degree of variability. A learning-based approach would have a difficult time finding a consistent definition of a person using this type of representation. We describe a new representation where the features are derived as the responses of filters that detect oriented intensity differences between local adjacent regions. This is accomplished within the framework of Haar wavelets and the particular transform we use results in dictionary of these Haar features.

The Haar wavelets representation encodes local, oriented, intensity differences would yield similar feature vectors where the features corresponding to uniform regions are zero and those corresponding to boundaries are non-zero. In fact, since, in our representation, we encode only the magnitude of the intensity difference, the feature vectors for this simple two example case would be identical. The raw value of a coefficient may not necessarily be indicative of a boundary; a weak coefficient in a relatively dark image may still indicate the presence of an intensity difference that is significant for the purposes of classification. To reduce these effects on the features used for classification, we normalize a coefficient's value against the other coefficients in the same area. For the normalization step, we compute the average of each wavelet's class (vertical; horizontal; diagonal×2; 4) over the current pattern and divide the wavelet response at each spatial location by its corresponding class average.

We calculate the averages separately for each class since the power distribution between the different classes may vary. For a given pattern p the class averages are:

$$avg_{o,c} = \frac{1}{n}\sum_{i \in p} w_{o,s}(i)$$

where o denotes a fixed orientation, s denotes a fixed scale, i indexes into the wavelets in the pattern p, and *w, o, s* denote the n individual wavelet coefficients at orientation o and scale s. The normalization for all wavelets within the pattern p is then:

$$w^*_{o,s} = \frac{w_{o,s}(i)}{avg_{o,s}}$$

Three classes of feature magnitudes will emerge: ensemble average values much larger than one, which indicate strong intensity difference features that are consistent along all the examples; values that are much less than one, which indicate consistent uniform regions; and values that are close to one, which are associated with inconsistent features, or random patterns.

We compute the wavelet transform for a given pattern in each of the three colour channels and then, for a wavelet at a specific location and orientation, we use the one that is largest in magnitude amongst the three channels. Once we have generated the feature vectors for an object class and have done the same for a set of images not in our object class, we use a learning algorithm that learns to differentiate between the two classes. The particular learning engine we use is a neural network.

IV. COMBINE STATISTICAL AND "BRUTE FORCE"APPROACHES

The third method combine two above approaches - statistical and "brute force".

The statistical wavelet method and "Brute force" method gets good rate of recognition. But using both methods of extracting of feature vectors allows the third system to use the most rate of recognition.

So, combining methods we can calculate the features of discrete wavelet transformation from full image, like statistical wavelet method and from patterns of a fixed size of image, like "Brute force" method. After extracting of feature vectors, we using neural net to classification biomedical images (Fig.5.) [17-19].

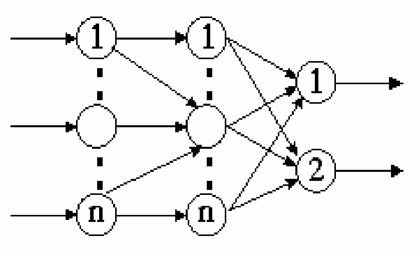

Fig. 5. Architecture of the neural network

The selected design approach for the neural network topology used a feed-forward network with a single hidden layer. The training method selected was backpropagation using a variable learning rate. These choices were selected because of their simplicity, robustness, and minimal memory requirements. (Second derivative methods turned out to require too much memory.) An adaptive learning rate approach was selected to compensate for the slow training times associated with backpropagation networks.

The input layer of this network is a set of n units, which accept the elements of an n-dimensional input feature vector. The input units are fully connected to the hidden layer with r hidden units. The goal of the hidden layer is to cluster the data and reduce its dimensionality. The output layer supplies the response of neural network to the activation pattern applied to the input layer.

The core detection system is one that learns from examples. We present it with a set of training data that are images of the object class we would like to detect and a set of data that are examples of patterns not in the object class, and the system derives an implicit model from this data (Fig.6.).

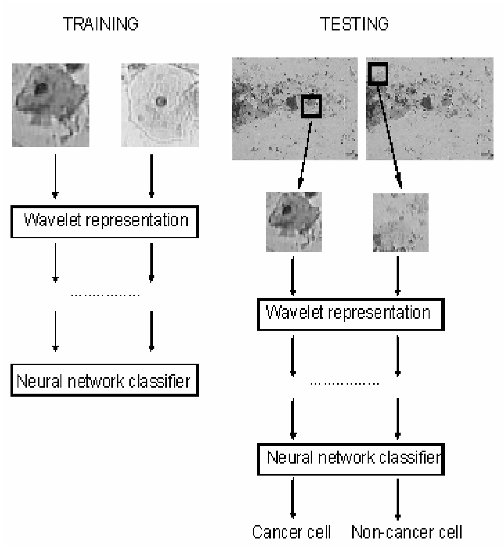

Fig. 6. The training and testing phases of our system.

V. CONCLUSION

This thesis has presented a general trainable framework for object detection in static images that is successfully applied "abnormal" cell detection in static images.

This thesis has presented some promising first steps in augmenting the core static detection system with different modules. These techniques and others should be investigated further and extended.

One of the big leaps we have taken in this thesis is our choice of representation, Haar wavelets. While we have shown that this wavelet representation achieves excellent results when compared to other representations.

While we have not pushed this system to be the "best" detection system in a particular domain, though this certainly may be possible, we have shown its applicability to a wide range of object classes. We feel that in practical uses of this system, the proper architecture should combine a focus of attention module with our static detection system. We have presented preliminary results here as well.

Our system [20] was trained on 50 images with known diagnosis, 25 images with cancerous cells and 25 images with normal cells. System was tested on 35 "abnormal" images and 50 "normal" images. Result showed in Table I and (Fig. 7).

TABLE I

COMPARISON OF CLASSIFICATION ACCURACY USING DIFFERENT TYPES OF FEATURES

Number of Images	Statistical wavelet approach	"Brute force" approach	Combined method
5	44%	49%	52%
10	47%	54%	59%
15	49%	58%	65%
20	51%	65%	72%
25	54%	70%	76%
30	57%	73%	80%
35	59%	75%	81%
40	65%	78%	83%
45	70%	79%	86%
50	78%	81%	88%

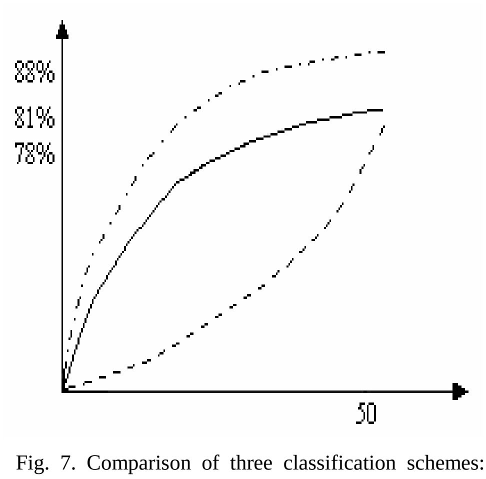

Fig. 7. Comparison of three classification schemes: a)statistical wavelet (dashed line) b) "Brute force" (solid line) c) combined method (above)

Also, for all three methods good recognition rates of 78%, 81% and 88% are obtained. The result shows high potential for using wavelet features to provide complementary cues.

REFERENCES

[1] R.A. Smith, V. Cokkinides, and H.J. Eyre, "American Cancer Society Guidelines for the Early Detection of Cancer, 2005", *CA Cancer J Clin*, 2005, v.55, pp. 31–44.

[2] M. Follen and R. Richards-Kortum, "Emerging Technologies and Cervical Cancer", *Journal of the National Cancer Institute*, Vol. 92, No. 5, 363-365, March 1, 2000.

[3] C.J. McDonald, "Cancer Statistics, 1999", *CA-Cancer Journal for Clinicians*, 49 (1999).

[4] G.F. Sawaya and Grimes DA, "New technologies in cervical cytology screening: a word of caution", Obstet Gynecol, 1999;94:307-10.

[5] B.M. Schroeder, "ACS updates guideline for the early detection of cervical neoplasia and cancer", *American Family Physician*, (2003),67(9): 2011–2016.

[6] G.F. Sawaya, et al., "Current approaches to cervical-cancer screening", *New England Journal of Medicine*, (2001),344(21): 1603–1607.

[7] D. L. G. Hill, P.G. Batchelor, M. Holden, and D. J. Hawkes, "Medical image registration", *Physics in Medicine and Biology*, 2001, v.46, pp.1-45.

[8] A.V. Katsuk, "Application of wavelet in image analysis", *8th International Symposium on science and technology*, 2004, pp. 140-142.

[9] M.C. Ploting, "Scheming with Wavelets", *Mathematics Magazine*, v. 69, n5, 1996, pp. 323-343.

[10] A.N. Bondarenko and A.V. Katsuk, "Computer analysis of biomedical images", unpublished.

[11] S.A. Karkanis, D.K. Iakovidis, D.E. Maroulis, D.A. Karras and M. Tzivras "Computer-Aided Tumor Detection in Endoscopic Video Using Color Wavelet Features", *IEEE transaction on information technology in biomedicine*, v.7, n3, September 2003, pp. 141-152.

[12] I, Daubechies, "Ten Lectures on Wavelets", *CBMS-NSF Regional Conference Series in Applied Mathematics*, SIAM: Philadelphia, (1992).

[13] D. B.Percival and Walden A. T. "Wavelet Methods for Time Series Analysis", *Cambridge University Press*, (2000).

[14] P.L. Dragotti and M. Vetterli, "Wavelet footprints: theory, algorithms, and applications", *IEEE Transactions on Signal Processing*, vol. 51, pp.1-18, May 2003.

[15] N.G. Khartishvili, I.M. Chkheidze, D. Ronsen and F.I. Indzhia "Piramidalnoe kodirovanie izobrazhenii", *Radio i sviaz*, 1996, p. 192.

[16] A.N. Bondarenko and A.V. Katsuk, "Metod priamogo poiska v veivlet-analize meditsinskih izobrazhenii", *Nauka, Tekhnika, Innovatsii, Vserossiiskaya Nauchnaya konferentsia*, NSTU, in press. (Rus)

[17] G. Giacinto, F. Roli and G. Fumera, "Unsupervised Learning of Neural Network Ensembles for Image Classification", *IEEE Int. Joint Conf. On Neural Network,* 2000, v.3, pp. 155-159.

[18] C. Bishop, "Neural networks for pattern recognition", *Clarendon Press, Oxford Press, NewYork, 2 edition*, 1995.

[19] L.V. Fausett, "Fundamentals of neural networks: architectures, algorithms, and applications", *Saddle Brook, NJ: Prentice-Hall*; 1994.

[20] A.V. Katsuk, "Analis meditsinskih izobrazenii v zadache raney diagnostiki raka", unpublished.