Urine and Copro Recognition with Generalized Entropy and Neural Networks

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Summary
We present the results for the study and classification of urine sediments and coproparasitoscopic specimens using neural networks. This method has the additional advantage of taking into account the internal geometry of certain structures and to classify them according to certain parameters such as fractal dimension and entropies. In this case we use Renyi and Tsallis entropies with order q. These results are introduced as information for a hierarchical neuronal network, and allows increasing the precision of the urine sediment and parasite microscopic determination..

Key words:
Neural Networks, Urianalysis, Fecal Material Analysis, Automated Microscopy, pattern recognition, generalized entropy.

1. Introduction

Even though microscopy is one of the most widely used procedures in the clinical laboratory, its precision still relies heavily on the performance of the human expert. Many procedures in the clinical laboratory depend on this technique that has not only to do with observation, but mainly depends on the interpretation of the information contained in visual images. [1,2]

Some of the procedures performed by microscopic visualization are of very common practice and have to do with tests that medical doctors prescribe very often and as a first approach for supporting a diagnostic. Urine sediment [3], fecal material [4], cytological examinations (pap smears), and bacteria screening, are only some of the most common examples of applications where no automation is available, and that today are time consuming procedures that rely heavily on the interpretation of the analyst.

Image processing and artificial neural networks [5,6], provide an opportunity for automating these procedures, helping this way, to standardize tests and making the results lack of the subjectivity associated to human interpretation of an image.

In this work we present two examples of automated microscopy, first we will present a system for urine sediment analysis where data available from a complementary analysis of the urine are used together with image processing and neural networks. The second example is a system for analyzing and finding parasites in fecal material, also by classifying images through a neural network. In both cases a previous clustering was performed using Renyi [7] and Tsallis [8] entropies, as well as the generalized fractal dimension.

In this work we analyze the importance of employing the fractal dimension as a parameter for urine and parasite classification when we implement a very simple neural network [9,10]. We obtained some interesting results for specific cases, but the efficiency is increased when compared with other methods

2. Urinary Sediments

The classification of urinary sediment [3, 10-12] is done in the different clinical laboratories generally using microscopy [2, 13, 14] and chemical analysis [8], which are complementary, and make possible a greater precision in the diagnosis. Until recently, microscopic determination was performed manually, which is a time consuming and tedious job, considering the number of fields that have to be examined per sample. Different methods, developed during the last decade, make automation possible and each of them has different particular advantages, but still only achieve around 90% efficiency [11]. Also, an important method is based on the flow cytometry system [12] (combining scattering and fluorescence), but this technology is not accessible for all institutions due to the cost and because a great number of samples is necessary for its implementation.

As a continuation of a previous work [16], our interest is the classification of the microscopic urine components through the study of their internal complex structure. This would be equivalent to analyzing the texture of the sediment contained in each sample, but by using fractal geometrical methods [7, 17, 18] that are not yet very common in this field of application. Parameters such as fractal dimension, lacunarity, and degree of self-similarity

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in different kinds of casts (hyaline cast, red blood cell cast, white blood cell cast, granular cast). With this, it is shown that the introduction of these new classification parameters improves the performance of the already existing methods. This kind of analysis is important since it allows the automation and classification of urine sediment since it uses a greater number of parameters than the ones considered by already existing methods. In order to increase the efficiency presented in Ref. [16], we will also introduce a "clusterization" using Renyi and Tsallis entropies as well as the generalized fractal dimension.

Basically, the urine contains elements in suspension, which for the observation at the microscope are obtained through sedimentation, by using centrifugation. The results encountered from these elements are important tools in the medical diagnostic because, normal and pathological concentrations of each element are very well established and studied. A general classification of sediments is: 1) epithelial cells (renal tubular, transitional, scamous); 2) crystals (triple phosphate, Uric Acid, Calcium Carbonate and oxalate); 3) red blood cells (non-glomerular, crenated and intact); 4) casts (hyaline, granular, red blood cell, white blood cell, waxy); 5) yeast and bacteria, 6) others. Fig. 1 shows some examples: a) eritrocytes, b) uric acid crystal, c) cast.

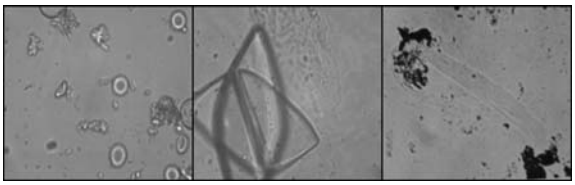

Fig. 1 – Some examples of urinary sediment: a) eritrocytes, b) uric acid crystal, c) cast

3. Coproparasitoscopy

Parasitology [19] has evolved much more slowly than other areas of clinical microbiology have, and therefore presents a notable lack of instrumentation, automation, and technological development.

For our knowledge, the only available commercial application that provides some automation has to do with sample preparation and not with the analytic part. Some studies have been made for identifying a single type of egg parasite (helminth) by using image processing and a neural network based on three morphological characteristics [20]. However there is still a lot to be done in this field, since what is found on the microscope are not only various different kinds of parasites, but they are also found in several development stages (eggs or wormlarvae). Fig. 2 shows some examples of parasites that can be found in fecal material.

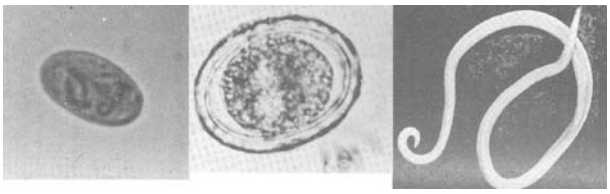

Figure 2 –. Examples of parasites (eggs and larvae) found in fecal material. a) *Giardia lamblia* egg, b) *Ascaris lumbricoides* egg, c) *Ascaris lumbricoides* adult worm

4. Complexity Parameters and Image Classification

We present here, a method for treating the problems associated with image processing, using complex geometry parameters. We will focus in fractal dimension and generalized entropy, but as can be seen in Fig. 3 several different parameters can be used as inputs for a neural network. These parameters are shown at the left side of the figure, however the parameters that are derived directly from the use of hardware can also be used, these are shown on the top of the figure and are: fringe projection, optical methods, scattering and fluorescence.

Since we are not using all the possible parameters, we only performed some tests with specific types of samples (sediments or parasites). We can expect, to obtain an increase in the precision and determination of the characteristics of urine and fecal material samples, as well as in the number of classified sediments and parasites once the rest of the parameters are considered. The present work is focused in increasing the precision in the tests performed in Ref. [16] with a simple perceptron net and the box-counting fractal dimension. In this work, we use generalized fractal dimension and entropies

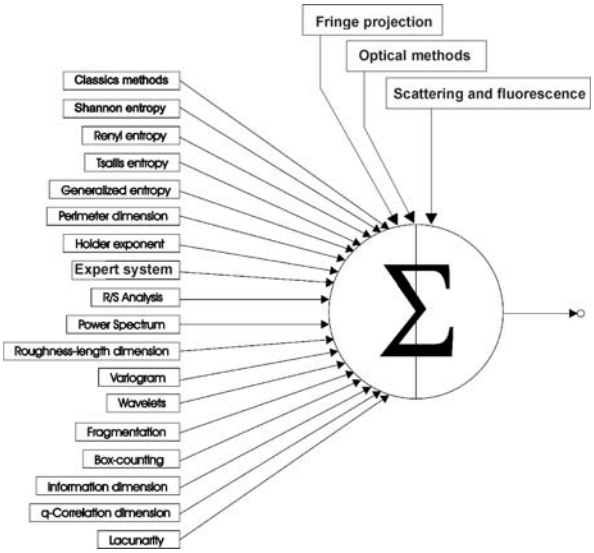

Figure 3 – Proposed method for the processing of images with complex geometry, using different parameters as inputs of the neural network

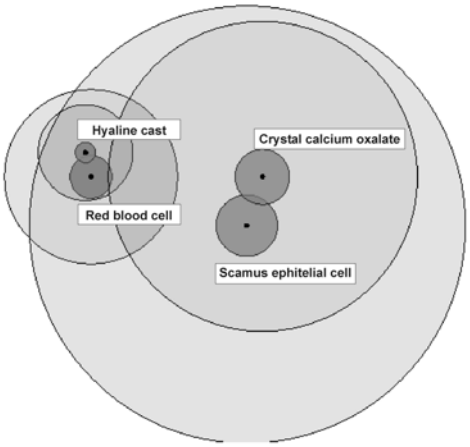

Fig. 4 – Clusters formed when using the generalized Renyi entropy (left), and Tsallis (right) in urinary sediment samples.

4.1 Generalized Entropy

We use here two different definitions of entropy that will be used as inputs for the neural network. They will be used, as we will see later on, for making a previous clusterization.

Renyi entropy:

$$S_q^R = \frac{1}{1-q}\log\left[\sum_{i=1}^{N} P_i^q\right]$$

Tsallis entropy:

$$S_q^T = \frac{1}{q-1}\left[1-\sum_{i=1}^{N} P_i^q\right]$$

For both cases Pi is a probability, which can be translated as the intensity (in pixels) of the image, q is the free parameter which identifies the order of the entropy.

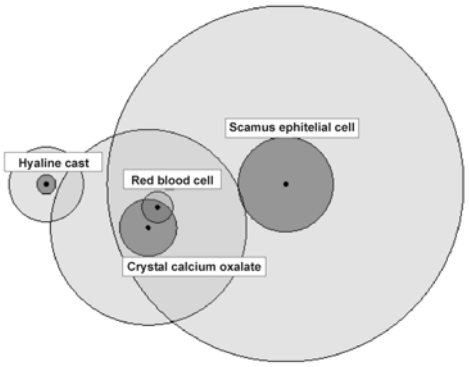

Fig. 5 – Clusters formed when using the generalized Renyi entropy (left), and Tsallis (right) in urinary sediment samples..

In Fig. 4, we can observe the results of calculating the total normalized entropy for the cases of Renyi and Tsallis in some types of urinary sediment. It can be seen, how several clusters are formed, according to the type of sediment, although they are superimposed in some degree, the introduction of other parameters changes the point of view, in the same way that it is different for each type of entropy. We must consider that in these results we are only considering the value q=5, but several other values for this parameter can be included.

4.2 Generalized Fractal Dimension

The generalized fractal dimension [21, 22] can be defined from the Renyi entropy in the form:

$$D_q = -\lim_{\varepsilon \to \infty} \frac{S_q^R(\varepsilon)}{\log(\varepsilon)}$$

and it can be demonstrated that D0 is the box-counting dimension, D1 is the information dimension and D2 the correlation dimension. In general, Dq (q>2) is the correlation dimension of order q.
As an example, in Fig. 4 we can see the application of the box-counting dimension to the case of leucocytes with a 400X magnification.

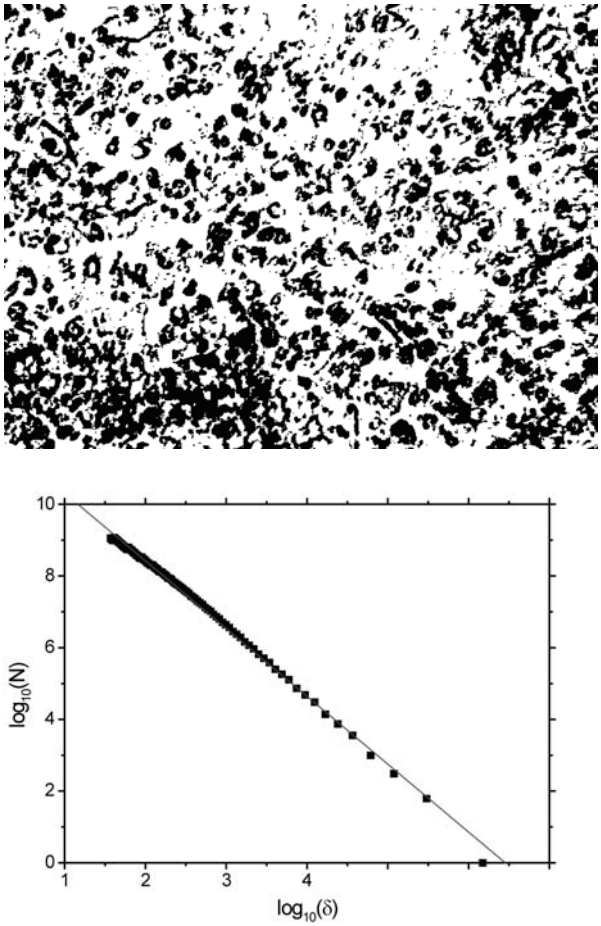

Fig. 6 – Leucocytes and their box-counting dimension

5. Results and Discussion

Combined with neural networks we use different methods for image processing, separating the color channels in the corresponding base RGB. With a simple neural network (perceptron multilayer and back propagation) we obtain very interesting results, for the classification of some sediments and parasites. We used an ANN with 4 layers, 150 neurons in the input layer, 100 neurons in the first hidden layer, 50 neurons in the second hidden layer, and only 5 neurons in the output layer. This network was trained with MatLab, using 1300 epocs and LogSig as transfer function for each layer. These parameters are the constituents of a very simple neural network for testing the possibilities of our method. This was useful for helping us know in deep, the structure of the problem. However, the best results were obtained with the tests performed when using the NeuroSolution software, where an ANN multilayer perceptron trained with static backpropagation was programmed. In Fig. 5 we show this neural network for the case of using as inputs 20 orders of entropy. This architecture was the one finally used when dealing with urinary sediment and in the determination of parasites. Four cases to be classified were considered.

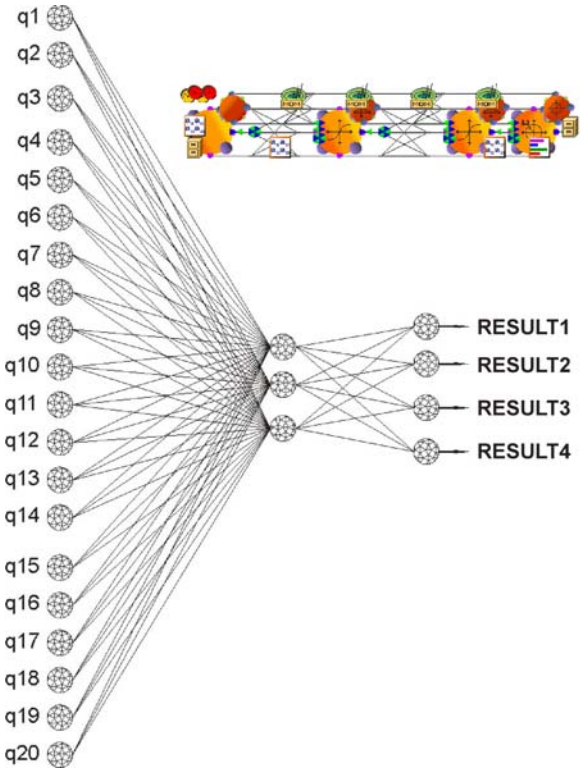

Fig. 7 – ANN with entropy as parameters, q=1,…,20, and the graphics as shown from NeuroSolution software.

Furthermore, the results obtained with the chemical method for urine analysis is taken into account by the neural network and both are integrated through the already developed software [23, 24] for the administration of clinical laboratories. All these considerations allow us to arrive to a precision of 99.2%, being able to improve the results given by other authors [25-27] (94%-95%) [9] when using neural networks. Still, more parameters need to be added as inputs for the neural network in order to increase efficiency (see Fig. 2), because if we consider that a clinical laboratory performs about 200 urine sediment determinations a day, this means that two of these determinations will have to be reviewed by the user. This number could increase if we consider that in the samples we can find not only urine sediments, but artifacts as well (hair, powder, pieces of glass, etc.). In the case of parasites, the precision is around 92.0%. This is because parasites have a more complex structure and might require a more complex ANN.

For their practical implementation and to obtain a product for commercialization in the market, some limitations exist, since the methods make reports and analysis to become very slow for a PC computer. Also, it is necessary that the elements being analyzed to have some texture or clusters in their structure. This means that we need to combine the results of the present paper with other traditional methods of classifications, as segmentation, morphology, edge detection, etc., to obtain better efficiency in the operation.

6. Conclusion

We show the possibility of implementing an ANN for static measurements in video-microscopy, using some complex geometry parameters. In this case the Tsallis and Renyi entropy were used, as well as the generalized fractal dimension. The precision shown in a previous work (Ref. [16]) increased to 99.2% for the case of urinary sediment. Also a high level of precision was obtained for the case of the determination of parasites in fecal material. For the case of the urinary sediment, the results of the biochemical analysis were taken into account, by the neural network, for the classification. However, we still have to consider the response of the system towards a real problem, and taking into consideration all the possibilities. For the case of the urinary sediment these possibilities are about 40, but for the case of parasites the number increases considerable, and therefore many other parameters of complex geometry would have to be considered in order to obtain results with higher precision.

Acknowledgments

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