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Morphological Classification of Sperm Heads Using Artificial Neural Networks

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Abstract

In male reproducible health and fertility and IVF (in-vitro fertilization), morphological analysis of sperm has been most important. But the traditional tools for semen analysis are subjective, imprecise, inaccurate, difficult to standardize, and reproduce mainly due to their manually oriented operations.

The purpose of morphological analysis of sperm is to microscopically type-classify sperm according to their morphological characteristics of heads. Until now, the strict criteria method has long been used in clinic to discriminate normal sperm from abnormal. This method cannot classify the diverse groups of abnormal sperm in detail and shows large variations in inter-operators and intra-operator.

In this paper, we have studied a new method of sperm morphological classification using artificial neural networks that are widely used in pattern recognition and image processing. With a multi-layer perceptron trained by the error back-propagation algorithm, profile features from digitized sperm images were classified into four classes that consisted of one normal group and three abnormal groups according to their morphological characteristics.

Keywords

Sperm morphological classification; Profile features; Artificial neural networks; Multi-layer perceptron

Introduction

The fertilizing capacity of human semen is above all estimated by the determination of sperm density, motility, and morphology. Although many new methods have been developed, allowing an objective determination of sperm density and motility, sperm morphology has still to be estimated in a subjective, irreproducible, ineffective way [3,7].

Most of traditional methods for sperm morphology analysis use strict criteria that have long been used in clinic to discriminate normal sperm from abnormal ones. It is difficult to classify the diverse groups of abnormal sperm in detail by this method and the evaluation can be subject to large variability between and within technician observations because of its too simplified and manually oriented operation. With a help of developed PC and image processing technology, we have studied a method overcoming the above limitations [1,4].

To classify sperm heads automatically according to their morphological characteristics, we applied artificial neural networks (ANN). The ANN was motivated by human neural systems that can learn and accumulate knowledge by the past experience and repeated training. They are heuristic systems that can produce optimal outputs to non-trained inputs by modifying their weights according to trained patterns repeatedly. For this reason, ANNs are used mainly in a field requiring classification of patterns to their nearest class, such as pattern recognition in image processing and speech analysis [12].

Materials and Methods

Images for Analyzing

Microscopic sperm images with magnification factor of 1000 were 8-bit A/D converted by the image-grabber [Raptor; Bit-Flow, Inc.] inside a PC [Intel Pentium-166]. One digitized gray image was 640 pixels wide and 480 long. Slices of semen specimens were stained using the Diff-Quik technique. After technicians reading through an analog CCD camera-monitor system, a VCR [NTSC] recorded microscopic images for analyzing by the automatic method studied.

Preprocessing for feature extraction

To take out features for ANN inputs, original digitized images were processed through basic image processing techniques. Firstly, applying edge operator to a raw image generated edge-intensity one. By projecting the edge image in x, y directions, high intensity parts in projections were marked in rectangles, which were perceived as sperm heads (Fig.1). Before extracting, the head parts with 80 pixels in width and length from an original image were oriented to their principal axis that was a longitudinal direction of sperm head (Fig.2)[5].

The gray-level histogram of selected parts as rectangles had bimodal characteristics due to the elliptic shape of sperm heads. This point rendered it easier to get a threshold for segmenting the image. The extracted images were segmented locally by applying the optimal threshold (Eq.2) based on Gaussian distributions and Bayes' decision rule [9], which determined a gray

level that minimized the error (Eq.1) of two segmented regions (Minimum Error Problem: MEP). The boundary points from segmented region were smoothed by the five points running average (Fig.3)[9].

$$e(T) = P_1 \int_{-\infty}^{T} f_1(x)dx + P_0 \int_{T}^{\infty} f_0(x)dx \text{ ------(1)}$$

$$\frac{de(T)}{dT} = 0$$

$$P_1 f_1(x) = P_0 f_0(x)$$

$$T^* = \frac{m_0 + m_1}{2} + \frac{\sigma^2}{m_0 - m_1} ln(\frac{P_1}{P_0}) \text{ -------(2)}$$

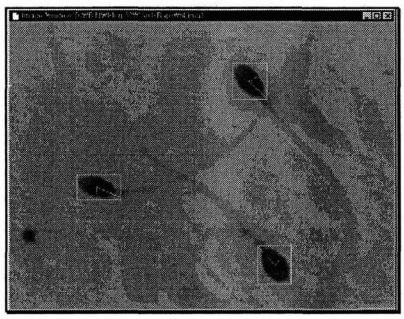

Figure 1 - Marked head parts by projection

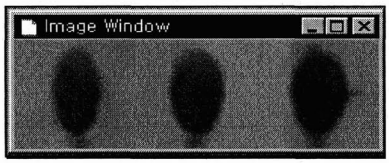

Figure 2 - Oriented and extracted sperm heads

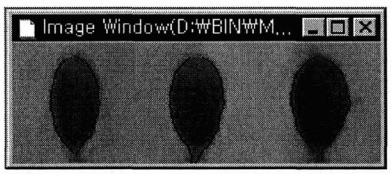

Figure 3 - Segmented and smoothed boundary of heads

Feature extraction

Sperm are largely classified into normal and abnormal groups according to their head morphology. The normal group has to have a balanced oval or elliptic shape head with 5~6(um) length (L), 2.5~3.5(um) width (W) and a proportional relationship, L/2≤W≤2L/3. The abnormal groups are subdivided into an elongated (tapering), a small, a megalo and an amorphous one according to its size, shape and the existence of defects. The amorphous group comprises the highest percentage of the abnormalities found in human sperm.

We can think of many kinds of features to represent morphological characteristics of sperm heads such as from simple parameters like Length, Width and Ratio of Width to Length to geometrical lengths of boundary points reaching their center of mass. In this study, we used profiles of x, y directions that are perpendicular to the y, x-axes of symmetry through a center of mass respectively (Fig.4)[4]. Typical profiles of four sperm classes are shown in Fig.5.

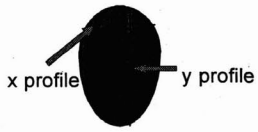

Figure 4 - Profiles of head in x, y directions

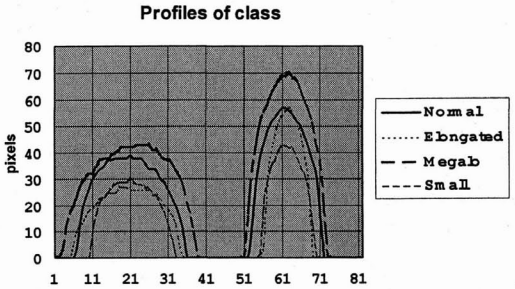

Figure 5 - Typical profiles of sperm class

Classification using neural networks

To classify sperm heads into their versatile category including more precise discrimination of normal sperm from abnormal and more specific categorization of abnormal groups, the ANN could provide solutions. We adapted a Multi-Layer Perceptron (MLP) appraised as efficient in classifying nonlinear patterns into their nearest, which consisted of an input layer, hidden layers and an output layer. For the supervised training of the MLP, the error back-propagation learning rule (EBP) is used, which renovates neuron to neuron weights by propagating errors to desired outputs inversely. The general structure of MLP by EBP rule is show in Fig.6. This is done by the generalized Delta rule, which is as follows (Eq. 3)[12].

$$\Delta_p W_{kj} = \eta \delta_{pk} O_{pk} \text{ ----------(3)}$$

$$\delta_{pk} = (T_{pk} - O_{pk}) \times O_{pk} \times (1 - O_{pk})$$

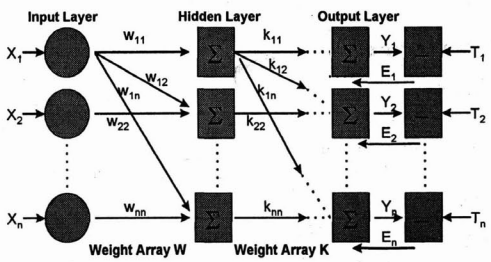

Figure 6 - General structure of MLP by EBP rule

We realized a 4-layer perceptron having two hidden layers. Inputs were 80 sampled profiles from both x and y directions.

Output layers were composed of 4 neurons representing a normal group and 3 abnormal groups, which are an elongated, a small and a megalo.

The images of semen specimens were obtained from 12 males visiting the andrology clinic of Seoul National University Hospital including patients and fertile persons. The number of sample images were restricted to 25~30 for each person. We made four training sets each of which were organized from 2 to 4 persons. Two technicians read all the sample images of the training sets. For the images of sperm two technician readings coincided, their features for training ANN were extracted and analyzed. The data distribution of sperm groups used for training is shown Table1.

Table 1 - Distribution of training data set

	Normal	Small	Megalo	Elong	Total
Group1	18	9	7	5	39
Group2	24	19	4	6	53
Group3	33	7	6	11	57
Group4	23	17	3	10	53
Total	98	52	20	32	202

Table 2 - Classification accuracy results according to training groups

	Group1	Group 2	Group3	Group4
G1	0.897	0.615	0.642	0.564
G2	0.792	0.868	0.811	0.868
G3	0.807	0.825	0.965	0.789
G4	0.811	0.811	0.868	0.943
Mean	0.822	0.792	0.837	0.807

Table 3 - Truly classified patterns of classes according to training groups

	Normal (98)	Small (52)	Megalo (20)	Elong (32)	Accuracy
Group1	87	46	13	20	0.822
Group2	94	36	5	25	0.792
Group3	96	43	7	23	0.837
Group4	88	48	3	24	0.807
Mean	91	43	7	23	

Results

The accuracy of classification according to groups used for training are shown in Table2 (Fig.7), where the first row represents training groups and the last row average accuracy rate. This accuracy rate is comparable to correlation value of manual reading between technicians in clinic. Table3 shows the distribution of truly classified sperm for all the patterns of each class used for analyzing.

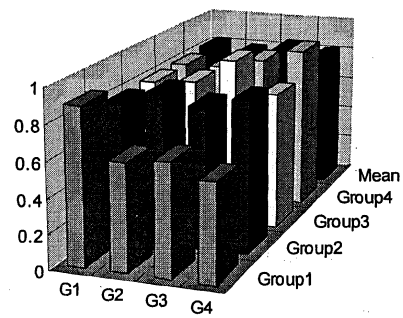

Figure 7 - Accuracy rate according to training groups

When we investigated the dependence of the classification accuracy on the MLP configuration of hidden layers, in the two-hidden-layer MLPs, combinations of 70 neurons in the first hidden layer and 60 in the second showed the best accuracy rate of classification. This seems to have something to do with the fact that input values of non-zero concentrate on the center of training profile patterns ranging from 60 to 70. In case of high learning rate, the MLP didn't reach a tolerance limit of error but oscillated within a constant amount of error. The oscillation in convergence of MLP occurred too when the phase of training patterns for each class were excessively various. This is due to the fact that similar patterns may have different desired outputs in the previous classification by the manual method.

The false classification rate of patterns was highest between Normal class and Small. It can be said that the relatively large number of training patterns for two groups caused this. However, the main cause of this is that the difference of image patterns between sperm belonging to two classes is small so, false classification may occur more frequently than other classes by technicians reading. The fact that the Normal class has more diverse characteristics such as elliptic or oval in its shape than others may be an another reason. The false classification between Megalo and Elong groups was caused, we think, by relatively small number of training patterns which failed to sufficiently train the MLP. Actually, the sperm belonging to Megalo and Elong appear rarely as a result of technician readings in clinic.

The goal of this study is to automatically classify sperm according to the characteristics of their head. As we look around in the above passage, for improving the performance of ANN, sufficient patterns of sperm images for training are essential. In addition to this, if more detailed classification were conducted for Normal class, we think our method for sperm morphology analysis by MLP can be used reliably.

Acknowledgments

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