Vitality assessment of boar sperm using N Concentric Squares resized and Local binary pattern in gray scale images.

Oscar García-Olalla, María Teresa García-Ordás, Diego García-Ordás, Laura Fernández-Robles, Enrique Alegre
Universidad de León, {ogaro,mgaro,l.fernandez,enrique.alegre}@unileon.es, diego.ordas@gmail.com

Abstract

In this work, we propose a new texture descriptor made by combination of Local binary pattern (LBP) and N-concentric squares resized (NCSR) in order to classify boar spermatozoa as dead or alive using gray scale images. Several configurations have been carried out using Support Vector Machine classifier and the best result (78.67% of hit rate) was obtained when evaluating NCSR of 50 features and LBP with 16 neighbours. This result outperforms all the previous works concerning this field and it is very encouraging to the veterinarian community for automatizing this process.

Keywords: texture classification, Local binary pattern, Biomedical image, sperm vitality

1 Introduction

Sperm assessment is a key factor for the porcine industry. Nowadays, lots of companies in the world are trying to obtain as better as possible pork flesh and, at the same time, at the lower price available. The main reason is the huge demand of alimentary products obtained from porcine meat. The way to do it is by selecting the semen used in artificial insemination i.e. to assess the semen of the donor boars, picking the best specimens up and using only the best ones.

For several years, the CASA (Computer-Assisted Semen Analysis) systems have been used for assessing the sperm quality. These systems analyze the concentration, mobility and some simple geometric measures of the spermatozoa's head to characterize abnormal head shapes, obtaining an assessment of the studied sample based on that values. However, there are three valuable criteria used by veterinary experts that CASA systems are not yet able to automatically analyze, as are the number and presence of proximal and distal droplets, the integrity of the acrosomal membrane and the vitality of the sample based on the presence of dead or alive spermatozoa.

A great number of works have addressed some of the problems related to the semen analysis using digital image processing. Most of them uses CASA systems for evaluating the sperm motility [4] or for studying the relationship among sperm cell motility patterns, morphology and boar fertility [5, 12]. Other research groups have developed methods to characterize the spermatozoa shape by using spectral approaches [3, 10], or they have been looking for subpopulations [11] using shape descriptors over the head of the spermatozoa.

Nowadays, the evaluation of the acrosome vitality of the spermatozoon heads is carried out manually, using stains because there are not any computer assisted tools for that process. This manual assessment has several drawbacks such as its high cost in terms of time, its lack of objectivity, or the requirement of specialized veterinarian staff and equipments. Hence, it would be very interesting to get an automatic classification of the acrosomes as dead or alive.

Texture analysis and classification have been used in the literature applied to a wide range of fields with high performance [8] but there are few computer vision works which deal with boar sperm analysis. Furthermore, computer-based systems designed for semen analysis tasks should reliably segment the heads of the spermatozoa [6], extract the patterns which characterize them and finally classify those patterns in order to estimate how many dead spermatozoa are present in the sample.

In this way, few works have studied the evaluation of the vitality of a sample classifying the spermatozoa heads as dead or alive. In one of them, [1, 2], Alegre et al obtained a 76.80% of hit rate, testing with images with 100× magnification.

The rest of the paper is organized as follows: Section 2 describes the adquisition methodology and the descriptors used. Results achieved with the different descriptors are presented in section 4. Finally, section 5 shows our conclusions.

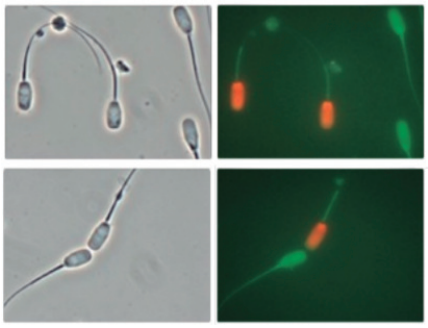

Figure 1: Figures show images in positive phase contrast (left) and images with fluorescent stains (right) respectively. Alive spermatozoa are coloured in red and dead ones are coloured in green.

2 Methods

2.1 Image acquisition and preprocessing

The set of images used has been captured in CENTROTEC, an Artificial Insemination Centre that is a University of Leon spin-off. The sperm was obtained from boars of three different races: Piyorker, Large White and Landrace. 450 pairs of images have been obtained using a Nikon Eclipse microscope and a Baster A312f camera of progressive scan. Each of these pairs contains an image in positive phase contrast and a fluorescent image obtained using two different stains: propidium iodide (PI) that dyes dead spermatozoa as red and dichlorofluorescein (DCF) for turning green the alive spermatozoa, see fig. 1. More information about the sample preparation can been found in [9]. We have captured the phase contrast images for developing and testing the texture descriptors evaluated on the proposed method. The fluorescent images were used to obtain the ground truth in order to label all the heads in the data set.

After we have labelled all the images, each head is registered automatically in order to assure scale and rotation invariance. First of all, the heads are rotated to its vertical position. This is performed by relating an sperm head with an ellipse and correcting the orientation of the major axis to achieve verticality. Then, the image is right and left cropped leaving head's pixels untouched. Afterwards, the coordinates of the tail are detected. Evaluating if the tail is placed in the bottom half or in the top half of the image will let us know if the spermatozoon has its head up or down respectively. In the second case, the image is flipped, leading to equal orientations. Then, the image is up and down cropped leaving head's pixels intact.

2.2 Local Binary Pattern

Local Binary Pattern (LBP) [7] is a gray-scale texture descriptor that extracts the local spatial structure of an image. Given a pixel, a pattern code is computed by comparing this pixel with the value of its neighbours:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p \ , \ s(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases} \tag{1}$$

where g_c is the value of the central pixel, g_p is the value of its neighbour p, P are the number of neighbours and R is the radius of the neighbourhood.

After LBP is obtained for each pixel, a histogram is built in order to describe the whole image using $P + 2$ bins, yielding the feature vector of the image. The pattern extraction process for one pixel is shown in Figure 2.

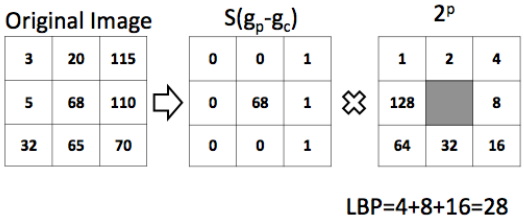

Figure 2: Local Binary Pattern process over one pixel in gray scale level.

2.3 NCSR

The N Concentric Squares Resized (NCSR) descriptor [2] gathers the grey levels along N equidistant squares that are concentric to the bounding box of the interest image as we can see in fig. 3.

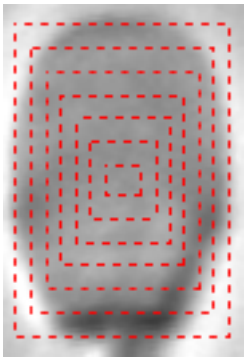

Figure 3: Spermatozoon image is divided in N squares. In this case, N=7.

The value assigned to N sets the number of squares obtained. As N increases, the squares will get

Table 1: Results obtained in [2]

	NCSR	Haral13	PS10N	PS20N	PS10	FlussGrey	Zern	HuGrey	HuBW	FlussBW
NNError	23.20%	24.07%	24.93%	25.14	25.24%	28.63%	30.55%	32.44%	39.50%	40.47%

closer. All the N squares are concatenated making up one vector whose longitude depends on the size of the image and the number of squares extracted. As we have been working with registered images, all the images are vertical and have the same size. The first part of the vector is the horizontal segment closer to the left upper corner of the image, the second part is the vertical segment of the outer boundary that is closer to the right side of the image, the third part is the horizontal segment at the bottom and the last part of the outer square is the vertical segment closer to the left side of the image. The four segments are concatenated constituting the vector that comes from the outer square. Later, the same process is followed with the rest of the inner squares concatenating all the resulting vectors into one. The grey levels gathered along this vector are the maximum value in the 3×3 neighbourhood of each position. The distances between squares are given by the equations 2 and 3.

$$NpbHs = \frac{\frac{nRows}{2}}{N+1}, N = 1, 2, 3, \ldots \quad (2)$$

$$NpbVs = \frac{\frac{nCols}{2}}{N+1}, N = 1, 2, 3, \ldots \quad (3)$$

where NpbHs and NpbVs are the number of pixels between Horizontal and Vertical segments, respectively; and nRows, nCols are the number of rows and columns of the image.

In the end, a Fourier transform based interpolation is carried out resizing the length of the descriptor. In our case, we have proved with feature vectors of dimension 25, 50, 75 and 100.

3 Results

Alegre et al in [2] achieved a hit rate of 76.80% using neural networks and NCSR with 100 elements in the feature vector. In their work, some classical descriptors have been evaluated obtaining worse hit rate than their proposed descriptor. In table 1 we can see these results.

We have used Support Vector Machine (SVM) without kernel and "Least Squares" learning algorithm slightly outperforming the accuracy of NCSR with 100 elements (76.84%). For that reason, all the results in this paper were obtained using SVM classification.

First, results using different elements in the feature vector of NCSR were calculated (view fig. 5), demonstrating that the best resizing was the carried out with 100 elements.

The proposed descriptor is composed of the NCSR feature vector and the LBP histogram with 8 and 16 neighbours. Using the best size of NCSR with the LBP the hit rate decrease. The reason of that is the unbalanced weight of the two descriptors due to the size of their feature vectors (Fig 4). In order to solve this problem and taking into account that the hit rate variance between different sizes of the NCSR vector was too slow (Fig. 5), we proved LBP with all of the NCSR descriptors used in figure 5.

Figure 4: Distribution of the features in the proposed descriptor using NCSR with 100 elements and LBP histogram with 8 neighbours. As we can see, using this configuration the LBP influence is poor.

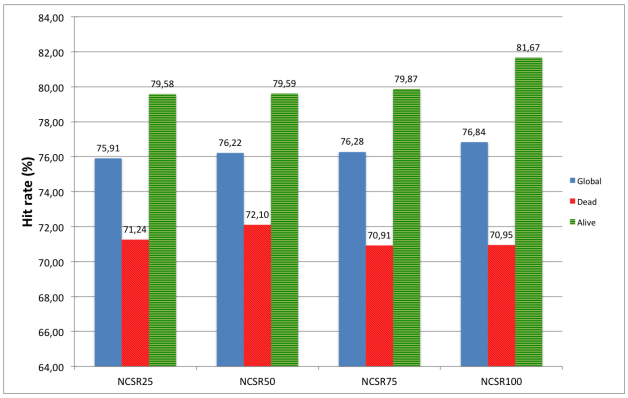

Figure 5: Results using 25, 50, 75 and 100 elements in the feature vector.

In Fig. 6 we can see the performance of the NCSR+LBP method for different sizes and neighbours. The best result is obtained combining NCSR resized to 50 elements, with LBP with 16 neighbours, yielding a descriptor of 68 features. It is important to note that two of the worst results were achieved with the NCSR of size 100 due to the low influence of LBP in these descriptors. However, the worst result is obtained with NCSR25 and LBP8. The reason of this low performance is the lack of information in the resize process and the low number of neighbours used in

the LBP method.

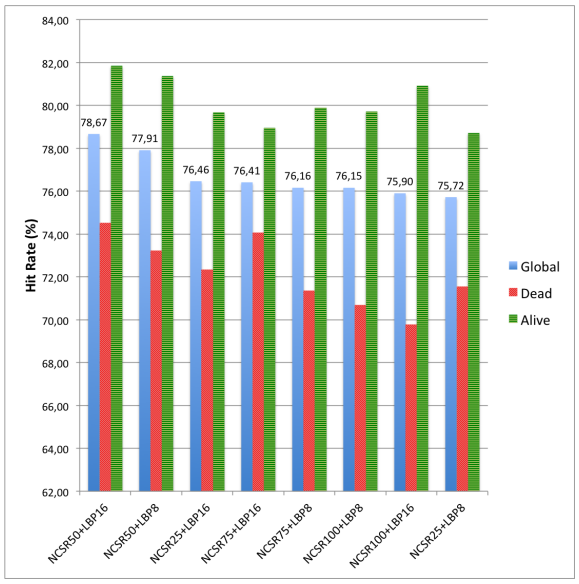

Figure 6: Results of the sperm classification in dead or alive using SVM and different configurations of LBP and NCSR. The best results were achieved using NCSR with 50 features and LBP with 16 neighbours.

A comparison of the proposed method and the original NCSR descriptor proposed in [2] can be shown in fig.7. As we said before, the best performance was achieved by evaluating NCSR50 with LBP16. The graphic shows clearly how the method improve their results when the size of the NCSR vector is 50 and we combine it with LBP. However, results become worse when the number of elements in NCSR is 100.

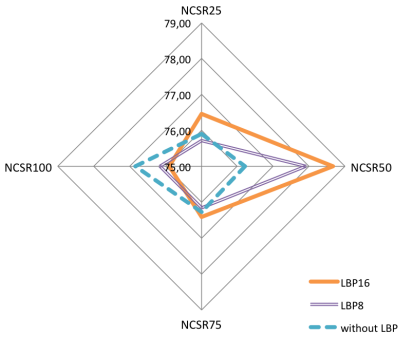

Figure 7: Comparison between the NCSR method and the proposed merge with LBP.

4 Conclusions

A new description method has been proposed in order to distinguish automatically boar sperm in dead or alive. This method consists of merging local binary pattern and N-Concentric Squares Resized feature vectors into one to better characterization of the sperm cell. We have tried several configurations of the experiment using different values to obtain the Fourier transform based interpolation in NCSR algorithm and two neighbourhood sizes (8 and 16) in local binary pattern. The best result was 78.67% of hit rate and it was obtained using NCSR with a feature vector of 50 elements concatenated with LBP and 16 neighbours outperforming the results achieved by the original method proposed in [2].

Acknowledgements

This work has been supported by grants DPI2009-08424, PR2009-0280 and via the pre doctoral FPU fellowship program from the Spanish Government.

The authors would like to thank CENTROTEC for providing us the semen samples and for their collaboration in the acquisition of the images.

Bibliography

[1] Enrique Alegre, Oscar Garcia-Olalla, Victor Gonzalez-Castro, and Swapna Joshi. Boar spermatozoa classification using longitudinal and transversal profiles (ltp) descriptor in digital images. In *International Workshop on Combinatorial Image Analysis*, 2011.

[2] Enrique Alegre, M.T. Garcia-Ordas, Victor Gonzalez-Castro, and S. Karthikeyan. Vitality assessment of boar sperm using ncsr texture descriptor in digital images. In *Iberian Conference on Pattern Recognition and Image Analysis proceedings*, 2011.

[3] M. Beletti, L. Costa, and M.Viana. A spectral framework for sperm shape characterization. *Computers in Biology and Medicine*, 35:463–473, 2005.

[4] A. Contri, C. Valorz, M. Faustini, L. Wegher, and A.Caluccio. Effect of semen preparation on casa motility results in cryopreserved bull spermatozoa. *Theriogenology*, 74:424–443, 2010.

[5] B.A. Didion. Computer-assisted semen analysis and its utility for profiling boar semen samples. *Theriogenology*, 70:1374–1376, 2008.

[6] V. Gonzalez-Castro, E. Alegre, P. Morala-Arguello, and S.A. Suarez. A combined and intelligent new segmentation method for boar semen based on thresholding and watershed transform. *International Journal of Imaging*, 2:70–80, 2009.

[7] R.L. Kashyap and A. Khotanzed. A model-based method for rotation invariant texture classification. *IEEE Transactions on PAMI*, 8:472–481, 1986.

[8] P. Perner, H.Perner, and B. Muller. Texture classification based on the boolean model and its application to hep-2 cells. *Proc. 16th International Conference on Pattern Recognition*, 2:406–409, 2002.

[9] L. Sanchez, N. Petkov, and Enrique Alegre. Statistical approach to boar semen evaluation using intracellular intensity distribution of head images. *Cellular and Molecular Biology*, 52:38–43, 2006.

[10] L. Severa, L. Machal, L. Svabova, and O. Mamica. Evaluation of shape variability of stallion sperm heads by means of image analysis and fourier descriptors. *Animal reproduction science*, 119:50–55, 2010.

[11] L. Thurston, P.Watson, A.Mileham, and W.Holt. Morphologically distinct sperm subpopulations defined by fourier shape descriptors in fresh ejaculates correlate with variation in boar semen quality following cryopreservation. *Journal of Andrology*, 22:382–394, 2001.

[12] J. Verstegen, M. Iguer-Quada, and K.Onclin. Computer assiisted semen analyzers in andrology research and veterinry practice. *Theriogenology*, 57:149–179, 2002.