# Curvelet-Based Texture Description to Classify Intact and Damaged Boar Spermatozoa

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**Abstract.** The assessment of boar sperm head images according to their acrosome status is a very important task in the veterinary field. Unfortunately it can only be performed manually, which is slow, non-objective and expensive. It is important to provide companies an automatic and reliable method to perform this task. In this paper a new method which uses texture descriptors based on the Curvelet Transform is proposed. Its performance has been compared with other texture descriptors based on the Wavelet transform, and also with moments based descriptors, as they seem to be successful for this problem. Texture descriptors performed better, and curvelet-based ones achieved the best hit rate (97%) and area under the ROC curve (0.99).

**Keywords:** Curvelet, classification, biomedical image, feature extraction.

## 1 Introduction

Semen quality assessment is a crucial task in artificial insemination processes both in medicine and in which the evaluation of the semen quality has great advantages. There is a whole market regarding farmers who regularly buy semen samples from companies which own production centres. Therefore, these companies must assure the quality of their products in order to guarantee that the semen will be optimal for fertilization.

There are many features involved on semen quality, such as concentration, motility, morphology and acrosomic integrity. Some of them can be quantified by using CASA (Computer Assisted Sperm Analisis) Systems. There are some works that use digital image processing to assess the morphology of human sperm, horse sperm [2], rat sperm or even characterise spermatozoa of several species [3].

Some veterinary experts hold that there is a direct relationship between sperm fertility and the state of their acrosome. The assessment of its state is usually carried out manually, by using stains. This manual process is not completely objective, it is time consuming and, in addition, it requires specialized equipment to be carried out. Therefore, the disposal of automatic methods to classify the

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spermatozoa by means of their acrosome state without using stains would be very interesting.

Texture analysis is a powerful tool in problems involving recognition or image retrieval [1], and thus it has been widely applied in the biomedical domain, to perform tasks of recognition of tissues and cells.

Second order statistical features derived from the Gray Level Cooccurrence Matrix (GLCM) have been widely used in texture analysis of tissues and cells since Haralick proposed them. There are some works focused on improving the descriptive power of co-occurrence matrices. For example, in [4] the impact of the dynamic range of the GLCM was assessed. Philips *et al.* analysed 3-D GLCM obtained from a set of CT images of the liver to get the directions which best characterised the textures, with the aim of considering only some directions, and thus reducing the number of computed features [5].

Methods based on signal processing are very useful in texture description, specially when they are combined with other methods. The Discrete Wavelet Transform (DWT) has proved to be very powerful in multi-resolution analysis of tissues and cells. Tsantis *et al.* applied the Wavelet transform to extract textural features towards malignancy risk evaluation of thyroid nodules in ultrasonography [6], achieving an area under the ROC curve of 0.96.

A few years ago some transforms have been developed as an alternative to Wavelets. Ridgelet transform yields detail coeffients along multiple radial directions on frequency domain, while Wavelet transform only extracts vertical, horizontal and diagonal details. The Curvelet transform [7] is an extension of the Ridgelet transform which allows to extract structural information along "wegdes" in the frequency domain, with multiple scales and orientations. Since Candès *et al.* had presented the Discrete Curvelet Transform (DCT) [8], it has been applied more and more to image analysis. Semler and Dettori presented a work comparing the Wavelet, Ridgelet and Curvelet transforms [9]. Results showed that the Curvelet-based descriptors outperform the Ridgelet and Wavelet-based ones.

The rest of the document is outlined as follows: The fundamentals about the Curvelet transform are explained in section 2. In section 3 the acquisition and segmentation of the images is explained, and their description is detailed in section 4. Finally, we show in section 5 the experimental results and the conclusions and future work lines will be explained in section 6.

## 2 Curvelet Transform

As we used digital images in this work, we need to use the discrete version of the Curvelet transform. This variant is linear and it takes cartesian matrices as an input. These matrices have the form $f\,[t_1, t_2]$, where $0 \leq t_1, t_2 < n$.

The implementation of the Discrete Curvelet Transform (DCT) has been carried out using the "wrapping" algorithm, described in [8]. This algorithm translates the curvelets at each scale and angle into a rectangular grid.

The rotations and coordinates defined for the continuous Curvelet transform cannot be applied as it is to Cartesian matrices. Therefore, it is necessary to replace those to their "Cartesian" equivalents.

## 3 Image Acquisition and Segmentation

Images have been acquired with a camera Basler Scout scA780-54fc linked to a computer to control its functions for storage purposes. On the other hand, the camera is connected to an epifluorescent microscope Nikon E-600, which allows us to observe the samples both under a fluorescent and positive phase contrast illumination. See Fig. 1.

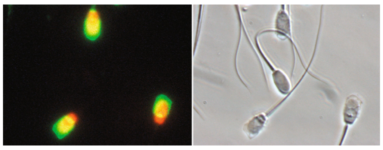

**Fig. 1.** Sample under fluorescent (left) and phase contrast (right) illumination

The images have been acquired with 100x magnification. In the first step, the sample is observed under fluorescent illumination. Once the spermatozoa are located and focused, the image is taken in real color. Afterwards, fluorescent illumination is turned off and the diaphragm of conventional light is opened to acquire another snapshot in positive phase contrast. Therefore two images have been acquired from each sample, which have a resolution of $780 \times 580$ pixels. It is necessary to point out that the description and classification is only carried out with the phase contrast images, but the fluorescence ones yield a ground truth, as only the heads with damaged acrosomes can be seen under fluorescent illumination (see Fig. 1). Therefore, the real color image is used to automatically label and crop each one of the spermatozoa in the gray level image, so we finally have just a spermatozoon per image (Fig. 2). The images have been obtained in CENTROTEC, a veterinarian research center interested in this problem.

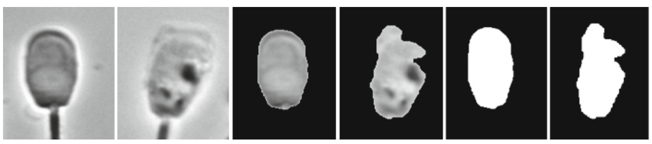

**Fig. 2.** From left to the right, original intact and damaged acrosome image, segmented and masked

Afterwards, the heads were segmented by means of the approach presented in [10], which automatically discards the bad segmented heads as well. Finally, the image set has 1851 images: 905 intact and 946 damaged acrosomes.

## 4 Characterization of the Acrosome Integrity

The goal of this work is to characterise and classify boar spermatozoa in terms of their acrosome integrity using multirresolution texture analysis. By looking at the aspect of the segmented heads (Fig. 2), it seems that a morphological approach could be successful to describe the images. In order to check whether this statement is right or not, Hu, Flusser, Legendre and Zernike moments have been assessed for this task. According to texture descriptors, second order statistics computed from both the original image and the Wavelet and Curvelet transforms, have been extracted. These descriptors have been called WCF and CCF by Arivazhagan *et al.* in [11] and [12], respectively. Table 1 shows a summary of the descriptors that have been assessed, along with the number of features that each one has.

**Table 1.** Descriptors used in the intact and damaged acrosomes classification experiment and their number of features

| **Descriptors** | WCF | CCF | Hu | Flusser | Legendre | Zernike |
|---|---|---|---|---|---|---|
| **Num. features** | 20 | 108 | 7 | 6 | 9 | 9 |

Classification results obtained by moments based descriptors will be compared with those achieved by texture descriptors as well.

### 4.1 Texture Descriptors Extracted from the Wavelet Transform

Information represented by spatial frequencies is often used for texture pattern recognition with satisfactory results because of its frequency domain localization capability. Therefore, Discrete Wavelet Transform (DWT) has been applied on the images with the goal of characterising their textures. Specifically, we have used the Haar family of Wavelets which, in spite of being the simplest, outperforms the Coiflet and Daubechies, as Dettori and Semler pointed out [9]. The DWT extracts the high-frequency components of a signal, so that they can be analysed separately. When the transform is applied on an image, four matrices of coefficients are obtained: approximations and horizontal, vertical and diagonal details. The first one holds almost all the energy of the image, while the other three hold the high frequency details.

We have extracted the Haralick features *Contrast*, *Correlation*, *Energy* and *Homogeneity* from the GLCMs of the original image and from the coefficients of the first sub-band (LL1, HL1, LH1 and HH1), as it was done in [11]. Finally, the texture is characterised by a vector of 20 features, which is called *WCF* (Wavelet Co-occurrence Features). The co-occurrence matrices were computed with distances 1, 2, 3 and 5 and the best results were achieved when $d = 1$. All features have been averaged over the orientations 0°, 45°, 90° and 135° to make them somehow invariant to rotation.

Image background pixels do not hold any practical information, so each head is cropped into its bounding box before describing it.

### 4.2 Texture Descriptor Extracted from the Curvelet Transform

The Discrete Curvelet Transform [8] has also been applied to describe the textures of the acrosomes, by means of the "wrapping" algorithm – which has already been used in [9] with successful results –. As it has been stated out in section 2, a Fourier transform is applied to the image yielding, for each scale and orientation, a product $U_j$, which is "wrapped" around the origin. Finally, the Curvelet coefficients are obtained by applying an inverse Fourier transform and they are represented in each scale and orientation by "wedges".

The descriptor based on the DCT is obtained by computing the co-occurrence matrices from the original image and each one of the matrices of Curvelet coefficients and averaging the *Contrast*, *Correlation*, *Energy* and *Homogeneity* over the GLCM orientations 0°, 45°, 90° and 135°, as it was done to extract the WCF descriptor. Once again, the best results have been achieved when the distance of the co-occurence matrix was $d = 1$.

This features have been extracted from the coefficients in several combinations of scales (3 and 4) and angles in the second scale (8, 12 and 16), resulting that the best classification results were achieved when combining 4 scales and 8 angles, which yielded 26 "wedges" per image. Therefore, CCF have 108 features, respectively.

### 4.3 Moments Based Descriptors

In order to assess whether the recognition of the acrosome integrity can be addressed by a shape-based approach, four different moments based descriptors have been extracted from the heads (Fig. 2).

The region of each head has been described by means of some moments based descriptors. In this work we are showing the results obtained by the Flusser and Suk affine moment invariants, Hu, Legendre and Zernike moments.

## 5 Experiments and Results

All images, characterised by means of their texture and their shape, have been classified with a Neural Network (NN) with a Multilayer Perceptron architecture. A list with all descriptors, along with the number of features that each one has, can be found in Table 1. The neural network has one hidden layer and a logistic sigmoid activation function for the hidden and output layers. Learning was carried out with a momentum and adaptive learning rate algorithm. Data were normalized with zero mean and standard deviation equal to one.

Several combinations of training cycles – 200, 300 and 400 – and neurons in the hidden layer – 2, 3 or 5 – have been assessed with all descriptors, in order to find the optimal network configuration. Classification has been carried out by stratified k-fold cross validation. In order to avoid possible random effects, this procedure has been repeated 10 times, and the results we are presenting are an average of these 10 runs.

**Table 2.** Accuracy (in %) in the NN classification of intact and damaged acrosomes

| Descriptor | Cycles | Neurons | Accuracy (%) | | |
|---|---|---|---|---|---|
| | | | Overall | Intact | Damaged |
| CCF | 200 | 5 | 97.00 | 97.29 | 96.73 |
| WCF | 400 | 3 | 96.43 | 96.30 | 96.56 |
| Hu | 400 | 5 | 82.76 | 85.39 | 80.24 |
| Flusser | 400 | 5 | 81.31 | 83.50 | 79.22 |
| Legendre | 400 | 5 | 71.74 | 76.93 | 66.76 |
| Zernike | 400 | 5 | 65.86 | 67.79 | 64.02 |

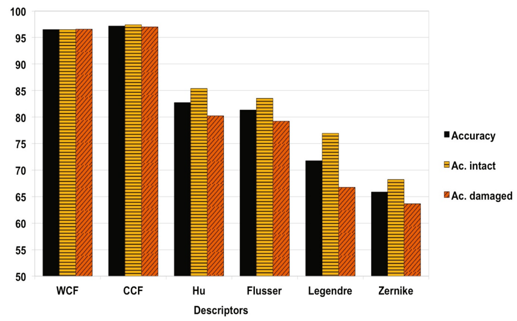


**Fig. 3.** Graph bar with the accuracy in the classification of intact and damaged acrosomes

Classification accuracy for each descriptor along with the configuration of the NN which have been achieved with are shown in Table 2.

First of all, regarding moments based descriptors, it is remarkable that none of them show better performance than any of the textural features. Hu moments outperform the others (with a hit rate of 82.76%), but they are still worse than the worst of the texture descriptors (WSF), whose accuracy is 87%. This proves that, contrary to what may be thought, moments based descriptors are not suitable for this problem, while texture analysis is much more accurate.

The best results have been achieved by CCF with accuracy of 97%, closely followed by WCF (96.43%). It is very remarkable that they achieve very balanced hit rates, which is very interesting for the veterinarian community, while the others do not (*i.e.* Legendre is the most imbalanced, with hit rates of 76.93% and 66.76% in the intact and damaged class, respectively). This can be more clearly seen in Fig. 3.

The cost of a wrong decision in this kind of problems is not equivalent. In fact, considering a spermatozoon to have an intact acrosome when it is actually damaged has a higher cost than on the contrary. Therefore, accuracy used as a single metric is not suitable to illustrate the performance of the classifier, and ROC (Receiver Operating Characteristics) analysis is a more powerful tool, as some voices from the machine learning community have been claiming [13]. Therefore, ROC curves of the descriptors and their AUC (Area Under the Curve) are shown in Fig. 4. Both of them confirm previous results, since the AUC of CCF is the highest, followed by WCF.

| Descriptor | AUC |
|---|---|
| WCF | 0.993 |
| CCF | 0.995 |
| Hu | 0.899 |
| Flusser | 0.888 |
| Legendre | 0.785 |
| Zernike | 0.716 |

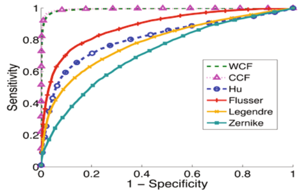


**Fig. 4.** ROC curves of the NN when classification of damaged and intact acrosomes, and his AUC

In order to find out whether these differences are statistically significant, a Wilcoxon signed-rank test between CCF (the descriptor which obtained the lowest AUC) and the others has been performed. The observations that have been taken as scores in the test are the Area Under the ROC Curves of each test fold at each iteration, so 100 scores per algorithm have been used. According to these tests, the differences between the AUCs of CCF and the others are statistically significant.

## 6 Conclusions

In this work we have assessed the performance of multi-resolution texture analysis in the frequency domain for recognising boar spermatozoa acrosome integrity. In particular, we have compared the performance of Curvelet-based descriptors with other well known features based on the Wavelet transform. Therefore, both transforms have been applied to the image, and then, first and second order statistics have been extracted from their coefficients to characterise the images. A glance at the segmented acrosomes would make the reader think that characterising them by means of their shape is a better approach. Therefore, some region descriptors based on moments have been calculated in order to check whether this assumption is right.

Classification has been carried out by means of a backpropagation Neural Network, using cross-validation. Results show on the one hand, that characterising the acrosomes by their shape is useless when trying to assess their integrity since the best hit rate (around 83%), achieved by Hu moments, is far from the worst of the texture descriptors assessed in this work (WSF), which achieved an accuracy of 87.26%. This is also noticeable if their AUC are compared (0.899 against 0.942). On the other hand, results also show that the best performance is obtained when using Curvelet transform, yielding a hit rate of 97%. It is also remarkable that the best texture descriptors – CCF and WCF – have also produced quite balanced hit rates, which is very appealing for the veterinary community.

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## References


1. Fan, J., Jiang, N., Wu, Y.: Automatic video-based analysis of animal behaviors. In: ICIP, pp. 1513–1516 (2010)
2. Hidalgo, M., Rodríguez, I., Dorado, J., Soler, C.: Morphometric classification of spanish throughbred stallion sperm heads. Animal Reproduction Science 103(3-4), 374–378 (2008)
3. Beletti, M.E., da Fontoura Costa, L., Viana, M.P.: A spectral framework for sperm shape characterization. Computers in Biology and Medicine 35(6), 463–473 (2005)
4. Mahmoud-Ghoneim, D., Alkaabi, M.K., de Certaines, J.D., Goettsche, F.-M.: The impact of image dynamic range on texture classification of brain white matter. BMC Medical Imaging 8, 18 (2008)
5. Philips, C., Li, D., Raicu, D., Furst, J.: Directional invariance of co-occurrence matrices within the liver. In: Proc. International Conference on Biocomputation, Bioinformatics, and Biomedical Technologies, BIOTECHNO 2008, June 29-July 5, pp. 29–34 (2008)
6. Tsantis, S., Dimitropoulos, N., Cavouras, D., Nikiforidis, G.: Morphological and wavelet features towards sonographic thyroid nodules evaluation. Comput Med. Imaging Graph 33(2), 91–99 (2009)
7. Candés, E.J., Donoho, D.L.: Curvelets, multiresolution representation and scaling laws. In: Proc. SPIE. Wavelet Applications in Signal and Image Processing VIII, vol. 4119, pp. 1–12 (2000)
8. Candés, E.J., Demanet, L., Donoho, D., Ying, L.: Fast discrete curvelet transforms. Multiscale Modelling & Simulation 5(3), 861–899 (2006)
9. Dettori, L., Semler, L.: A comparison of wavelet, ridgelet, and curvelet-based texture classification algorithms in computed tomography. Computers in Biology and Medicine 37(4), 486–498 (2007)
10. González-Castro, V., Alegre, E., Morala-Argüello, P., Suarez, S.A.: A combined and intelligent new segmentation method for boar semen based on thresholding and watershed transform. International Journal of Imaging 2(S09), 70–80 (2009)
11. Arivazhagan, S., Ganesan, L.: Texture classification using wavelet transform. Pattern Recognition Letters 24(9-10), 1513–1521 (2003)
12. Arivazhagan, S., Ganesan, L., Kumar, T.G.S.: Texture classification using curvelet statistical and co-occurrence features. In: Proc. 18th International Conference on Pattern Recognition, ICPR 2006, vol. 2, pp. 938–941 (2006)
13. Provost, F.J., Fawcett, T., Kohavi, R.: The case against accuracy estimation for comparing induction algorithms. In: Proceedings of the 15th International Conference on Machine Learning, pp. 445–453 (1998)