SVM APPROACH TO CLASSIFY BOAR ACROSOME INTEGRITY OF A MULTI-FEATURES SURF DESCRIPTION

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Abstract

In order to overcome the classification of invariant local features descriptors with Support Vector Machine, an approach which successfully deals with having more than one descriptor per image is presented. Interest points in images of boar spermatozoa heads are detected and described using SURF in order to classify their acrosome as intact or damaged. This approach is based on the classification of heads, taking into account that a head usually contains more distinctive points of their own class than doubtful points which could be misclassified, and it is compared with the classification of simple interest points. Experiments show that it obtains a satisfactory performance reaching a hit rate of 90.91% which indicates that this approach could be an alternative for classifying invariant local features descriptors.

Key words: SURF, Support Vector Machine, invariant local features, image classification, image recognition.

1 INTRODUCTION

Better semen quality leads to higher fertilization potential of a sperm sample for artificial insemination, both in medicine and veterinarian fields. Regarding the last one, many industries are involved with buying and selling semen samples which makes the assessment of its quality a crucial task for their business in order to assure an optimal product. Specifically, porcine industry aims at obtaining better individuals for human consumption.

Many features related with semen quality are nowadays measure with CASA (Computer Assisted Sperm Analysis) Systems such as sperm concentration and mobility characteristics [2]. Nevertheless, the vitality of the sample based on the presence of dead or alive spermatozoa and the integrity of the acrosome membrane cannot be quantified automatically with these systems. Manual processes are not completely objective, they are time consuming and, moreover, require specialized equipment to be carried out.

Invariant local features approaches are a more and more powerful tool involving object recognition and classification tasks since segmentation is no longer needed. There has been an impressive body of work on extending local features to be invariant to full affine transformations, starting with Scale Invariant Feature Transform (SIFT) method proposed by Lowe in 1999 [6] [7] which extracted highly distinctive features searching over all scales and image locations. Later on in 2006, Bay et al. proposed SURF (Speeded-Up Robust Features) which approximates or even outperforms previously proposed schemes with respect to repeatability, distinctiveness, and robustness, and yet can be computed and compared much faster mostly thanks to the use of integral images for image convolutions [1]. In 2009, Chandrasekhar et al. [3] presented Compressed Histogram of Gradients (CHoG). They represented gradient histograms as tree structures, which can be efficiently compressed, and they showed how to efficiently compute distances between descriptors in their compressed representation eliminating the need for decoding. In 2010, Ã·zuysaletal et al. [8] presented a fast keypoint recognition method using random Ferns, avoiding the computationally expensive patch preprocessing to handle perspective distortion by using hundreds of simple binary features and models class posterior probabilities.

In this paper, we propose a new approach that can be applied when methods based on invariant local features (ILF) are used to estimate the integrity of the acrosome membrane. In those cases, a number of features vectors, corresponding with interest points, are used to describe each object. In our case, each spermatozoon head is describe with SURF and we propose a classification method that is different from the classical kNN used with ILF descriptors.

The rest of the paper is organised as follows: In section 2 the acquisition and preprocessing of the images is explained. Description and classification of the images is detailed in section 3. Finally, we show in section 4 the experimental results. Conclusions will be explained in section 5.

2 IMAGE ACQUISITION AND PREPROCESSING

A camera Basler Scout scA780-54fc linked to a computer had been used to acquire images. This camera was also connected to an epifluorescent microscope Nikon E-600, which allowed us to observe the samples both under a fluorescent and positive phase contrast 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 780×580 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. Hence, the real color image is used to automatically label and crop each spermatozoa in the gray level image, so we finally have just a spermatozoon per image. Consequently, most of the spermatozoa come from different takings, which means that illumination is not completely constant, leading to a robust method to illumination changes. Information about the sample preparation can be found in [9]. The images have been obtained in CENTROTEC, a veterinarian research center interested in this problem.

Afterwards, heads are registered automatically in order to assure scale and rotation invariance. More information about the registration can be found in [4]. Bad registered images are manually discarded. Finally, the image set has 1717 images: 856 intact and 861 damaged acrosomes. Figure 1 shows 4 intact and damaged registered spermatozoa heads.

3 IMAGE DESCRIPTION AND CLASSIFICATION

We have chosen to use SURF to detect and describe local interest points of our data set and then classify them by means of SVM approach.

3.1 SURF DETECTOR AND DESCRIPTOR

SURF approach for interest point detection uses a very basic Hessian-matrix approximation ($\mathsf{H}(x,\sigma)$) defined in equation 1 that relies on box

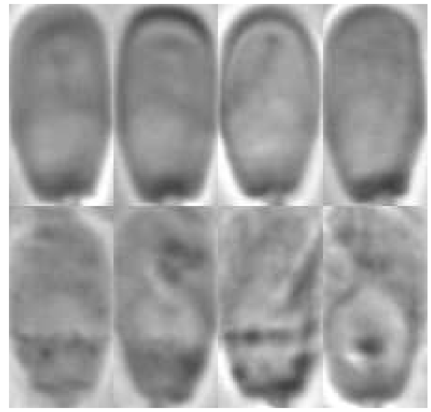

Figure 1: Four intact heads (top row) and four damaged heads (bottom row) from our registered dataset.

filters as approximations of the Gaussian second order derivatives. This lends itself to the use of integral images which reduces the computation time drastically. Interest points are found at different scales (see Figure 2).

$$\mathsf{H}(x,\sigma) = \begin{bmatrix} D_{xx}(x,\sigma) & D_{xy}(x,\sigma) \\ D_{xy}(x,\sigma) & D_{yy}(x,\sigma) \end{bmatrix} \qquad (1)$$

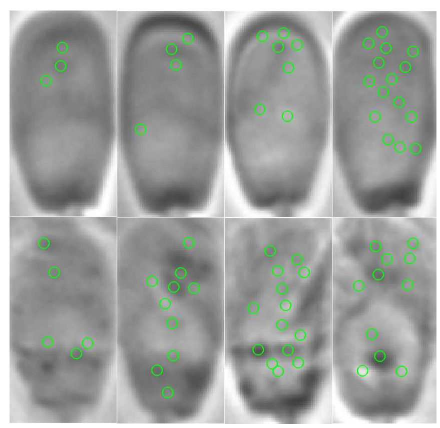

Figure 2: SURF interest points found in heads of Figure 1.

For the extraction of the descriptor, the first step consists of constructing a square region centred around the interest point and oriented along the reproducible orientation assigned. The region is split up regularly into smaller 4×4 square sub-regions and for each sub-region, Haar wavelet responses are computed. Then, the wavelet responses d_x and d_y in horizontal and vertical directions respectively are summed up over each sub-region and form a first set of entries in the feature vector. In order to bring in information about the polarity of the intensity changes, the sum of the absolute values of the responses, $|d_x|$ and $|d_y|$ is also extracted. Hence, each sub-region has a four-dimensional descriptor vector V for its underlying intensity structure:

$$V = (\sum d_x, \sum d_y, \sum |d_x|, \sum |d_y|) \qquad (2)$$

Concatenating this for all 4×4 sub-regions, this results in a descriptor vector of length 64 (Figure 3).

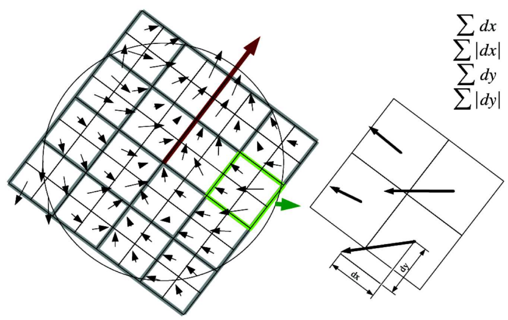

Figure 3: Oriented quadratic grid with 4×4 square sub-regions laid over the interest point (left). For each square, the wavelet responses are computed. The 2×2 sub-divisions of each square correspond to the actual fields of the descriptor. These are the sums d_x, $|d_x|$, d_y, and $|d_y|$, computed relatively to the orientation of the grid (right).

3.2 SUPPORT VECTOR MACHINE CLASSIFICATION

The fact that several interest points are found in each image means that we have to deal with several descriptors depending on the number of interest points per image. Therefore, many well-known classifying algorithms which work with one vector per image cannot be directly applied in this situation.

Invariant local features works usually trust in Nearest Neighbours algorithms in order to classify interest points descriptors [6] [7]. For instance, an approach would lie in comparing each test image with every training image and set the test image class as the most repeated class over the k most alike training comparisons. Nevertheless, no algorithms are known that can identify the exact nearest neighbours of points in high dimensional spaces that are any more efficient than exhaustive search. In order to overcome the disadvantages that the traditional k-nearest neighbour classification technique presents, such as slow speed and low efficiency [5], we have chosen to adapt SVM for several features vectors per image.

Hence, we concatenated all interest points descriptors in a matrix. As it is shown in Figure 4, we ended up with a 17122×64 matrix, where each row represents an interest point descriptor, being sorted into images, whereas each column represents a SURF feature. Additionally, we defined a label vector in which each point belonging to an intact head is labelled as intact and vice versa.

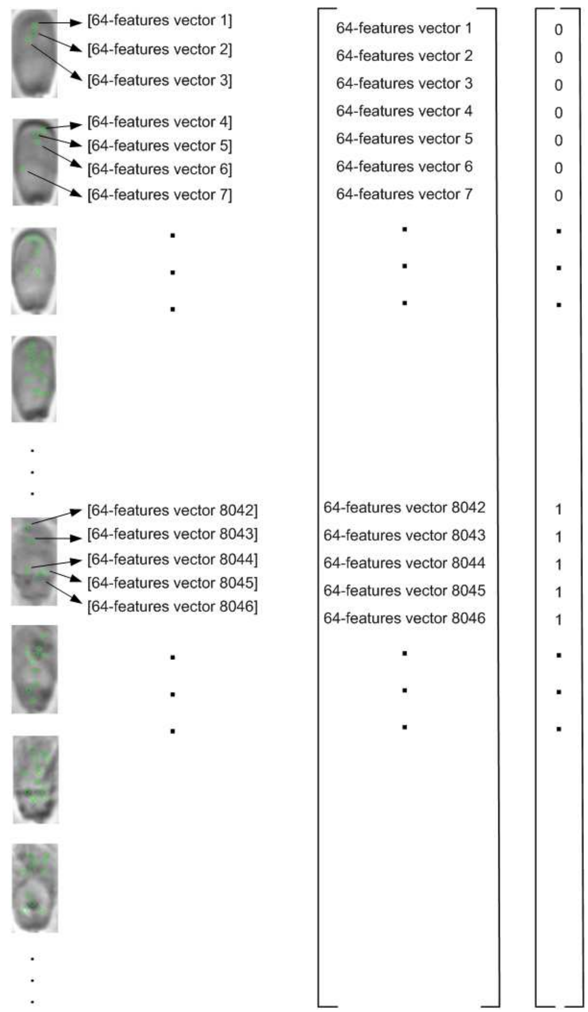

Figure 4: Each point detected in a head is described by a 64 feature vector using SURF (left). All points descriptors are orderly stored in rows into a matrix (middle). For each point, the label associated to its head class is written in a vector of classes (right).

3.2.1 SVM applied to interest points

Spermatozoa heads with damaged acrosome heads show regions such as black dots that could be easily located as corners (see Figure 1). This hypothesis means that damaged class visually present potential keypoints different from possible keypoints in the intact class. Our first idea was to consider each individual point as intact or damaged depending on their head class. This means that a point belonging to an intact head is treated as an intact point and hence a point belonging to a damaged head is treated as a damaged point. With this purpose, we implemented a lineal Least Squares SVM training for individual points. k-fold validation was carried out with k=10 over all points (see Figure 5 left) and then error measures were averaged. Therefore, results will show the percentage of correctly matched points.

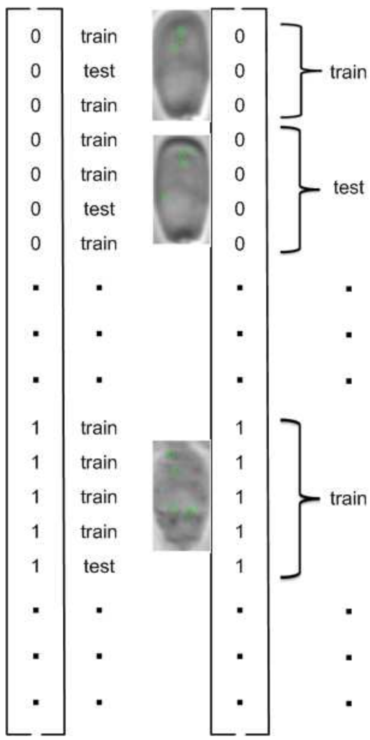

Figure 5: k-folds applied to points (left). k-folds applied to heads (right).

3.2.2 SVM applied to heads

In Figure 1, it is noticeable that there are points distinctive enough which can be undoubtedly seen either as intact or as damaged points whereas there are some others found in both classes that could be mistaken. Nevertheless, it seems that an intact image contains more distinctive intact points than doubtful points and the analogous happens with damaged images.

Following this reasoning, we decided to implement again a lineal Least Squares SVM training for individual points but this time the k-fold validation (k=10) was accomplish over the heads rather than the points (see Figure 5 right). Consequently, points of 90% of the total amount of heads, no matter how many points were described in each one, were selected to train our classifier. Besides, results were computed as well or bad classified heads, being a well classified head the one that has a greater number of points well matched than the amount of mismatched points.

4 RESULTS AND DISCUSSION

Figure 6 shows the hit rates obtained with the two approaches proposed. Hit rates of each class -intact and damaged acrosomes- are also plotted. Taking heads into account achieves an overall hit rate of 90.91% compared with just a 72.57% obtained considering interest points, which means an improvement of 25.27% when classifying heads.

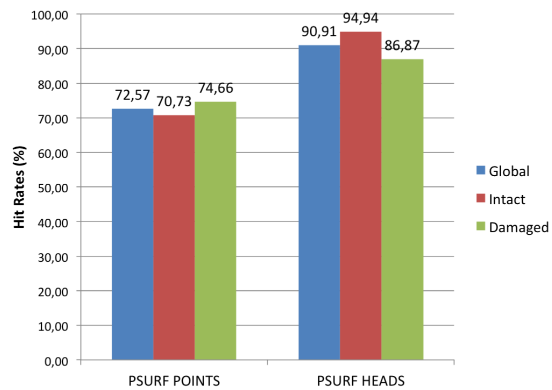

Figure 6: Global, intact and damaged hit rates using SURF and SVM applied to interest points (PSURF POINTS) and to heads (PSURF HEADS).

It is also noticeable that when classifying points, damaged heads were better classified than intact ones, whereas when heads are considered, the opposite situation is yielded. An explanatory reason is that while damaged points are in general more distinctive than intact points, damaged heads contains areas where it is clear that acrosome is damaged together with some areas where it is not appreciable and hence they could be considered as intact and lead to misclassifications.

5 CONCLUSIONS

In this work we have proposed an approach to overcome the classification of SURF descriptors, which produces several descriptors per image, with traditional SVM classifiers reducing computing time over kNN algorithms. This work is developed with the purpose of recognising boar spermatozoa acrosome as intact or damaged.

Two methods were implemented. Firstly, we considered individual points as intact or damaged after the class of their belonging head and classified them, reaching a hit rate of 72.57%. Secondly, we classified heads instead of points, considering a head as well classified if it had a bigger number of points well classified than misclassified. This yielded a hit rate of 90.91%.

The best result achieved (90.91%) makes this approach an effective substitute for classifying invariant local features descriptors. Furthermore, this approach can be widespread to different invariant local features descriptors (SIFT, Histogram of Oriented Gradient, etcetera) and to other conventional classifying algorithms (Neural Networks and others).

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