The Effect of Nonlinear Wavelet Transform Based De-noising in Sperm Abnormality Classification

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Abstract— **Morphological sperm analysis is one of the crucial steps in the male-based infertility diagnosis. Currently, analyses are mostly performed by visual assessment technique because of its easy implementation, quick response and cheapness properties. However, the expertise level of the observer has great importance in the visual assessment technique. Results can be different and misleading according to the observer analysis capability. Therefore, human factor should be eliminated and the analysis should be performed by an objective computerized system. In this study, we used descriptor-based features in the classification of the normal, abnormal and non-sperm patches. Additionally, we investigated the effects of two de-noising techniques in the classification performance due to the presence of noises in the patches. Results indicate that the de-noising processes have great importance in the classification performance. Moreover, a wavelet based adaptive de-noising approach dramatically increased the performance to 86% with support vector machine polynomial kernel classifier.**

Keywords— Sperm Morphological Analysis, Adaptive De-noising, Speed Up Robust Features, Support Vector Machine

I. Introduction

Infertility is one of the most common problems in the world. Today, 15% of the world population is dealing with the infertility problem and 30-50% of the cases are related to men based infertility which refers to the male factor [1]. Semen analysis is the first step in the male factor diagnosis in the infertility because of its easy implementation, fast applicability and quick result. Analysis is performed by computerized or manual techniques. Computerized techniques named as computer assisted sperm analysis (CASA) are expensive because of being a complete system including microscopy, imaging environment and software. However, CASA is more effective and trustful when compared with manual technique [2]. On the other hand, manually observation named as visual assessment technique is easier to apply and cheaper [3]. Therefore, many laboratories are currently performing the tests by visual assessment technique. However, the human factor in the visual assessment diagnosis results in inconsistent outputs due to the expertise and experience differences of the observers. This named as the observer variability problem in the analysis [4]. In order to increase sperm analysis performance, human factor should be eliminated and computerized solutions should be utilized with minimum cost. In this respect, different studies have been performed to design automatic morphological sperm analysis systems in the literature.

Chang et al. investigated the sperm head characteristic by their two-stage framework approach [5]. They segmented the acrosome and nucleus inside the headpiece of spermatozoon to research the abnormaility in details. In the first stage of their framework, they extract the sperm parts automatically as the region of interest (ROI) parts from the stained images by k-means clustering technique. Then, they performed another clustering in the second phase to form sub-segments as acrosome and nucleus. In this step, they used histogram statistical analysis with clustering idea. In another study, Chang et al. obtained the images by using the optical microscope camera [6]. They aimed to introduce a gold standard procedure for the morphologic analysis to the literature. After obtaining the stained images of sperm specimen, they manually cropped and rotated each sperm patches. Then, they used three different shape-based descriptors as Hu moments, Zernike moments and Fourier, for feature extraction of cropped patches. Support Vector Machine (SVM), K Nearest Neighbor (KNN), Naïve Bayes (NB) and Decision Tree (DT) are utilized for the classification process. Due to the low resolution of the camera in the study and the 5-class abnormality level, their classification accuracy performance was measured around 58%. In another abnormality classification study, Shaker et al. manually cropped the sperm patches from the stained images and rotated each sperm patch to one specific direction similar to Chang et al. standard [7]. Then, they used a dictionary-learning schema to classify the 4 abnormalities in the SVM model. They also tested their technique on the Chang et al. dataset [6]. They reported that they achieved 92.2% accuracy for their datasets (HuSHem) and also increased the accuracy performance to 62% for Chang et al. dataset (SCIAN-Morpho).

Similar to Chang et al. and Saker et al., we published a new sperm morphological dataset obtained by a different image acquisition approach. In our previous studies, we investigated clustering and wavelet based classification for morphological sperm analysis using stained images after they are preprocessed for de-noising. In [8], we evaluated *k*-means and fuzzy c-means techniques on the segmentation of sperm cells in the stained images. We also evaluate the effect of Modified Overlap Group Sparsing (MOGS) technique as preprocessing technique on the clustering performance. We used MOGS for enhancing the sperm and minimize the effect of other particles to segmentation performance. Then, we classified the extracted ROI by using the blob analysis as normal sperm, non-sperm and abnormal sperm. In another study, we used wavelet-based features with different level decomposition settings in the classification of each patches as sperm, non-sperm, abnormal sperm [9]. We compared SVM and DT classifier success rates which were trained by different level wavelet features. The accuracy was measured as 82% with SVM based classifier using level 7 dual tree discrete wavelet transform (DTDWT) wavelet features.

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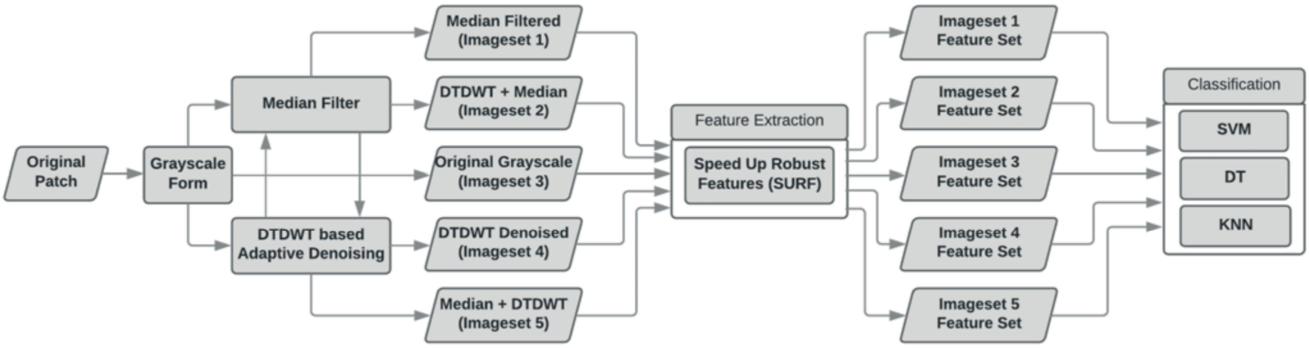

Figure 1. The Flow Diagram of Methodology

In this study, we utilize a descriptor-based feature extraction technique, Speed Up Robust Features (SURF), in the classification of our data. We also evaluate the impact of two de-noising techniques on the classification performances: DTDWT based adaptive de-noising and conventional median filters.

The organization of the paper is as follows; the data set and methods used in the study is given in Section II. The SVM, DT and KNN based classification results with different kernels and preprocessing scenarios is given in Section III. In the last part, the results is interpreted and the future methods that can be used in subsequent studies is discussed.

II. Material and Methods

In this study, we investigate the effect of two de-noising preprocessing techniques in the classification of image patches. We form different image sets by performing individual application of median filter and DTDWT based adaptive de-noising methods. Additionally, the cascade application of these two preprocessing steps are also tested to validate their fused affect. Then, we utilize the one of the descriptor based feature extraction techniques, SURF, to extract the features of each image set to use in the classification, individually. Kernel, rule and distance based conventional machine learning techniques as SVM, DT and KNN are employed in the classification step. The performances is measured as the accuracy rate for each image set and classifier. The flow diagram of the methodology is given in Fig. 1.

A. Data Acquisition and Dataset Information

Images are obtained by a smartphone that is mounted over the ocular part of the microscopy with a designed tool. This data acquisition approach has been introduced and tested on motile sperm detection problem in [10]. Images are acquired after the staining process of semen specimen. Experts performed staining process with a modified hematoxylin/eosin assay according to the morphological analysis procedure defined by WHO [1]. Staining process provides better visualization of spermatozoa and other particles. However, the excessive use of the substance in the staining process may create non-sperm spots in the image. These spots mislead experts in the analysis. Additionally, they affect the abnormal sperm counting due to the high similarities to the abnormal spermatozoa. In this study, we investigate the classification of particles in the stained images. In this respect, we manually cropped the normal, abnormal and non-sperm particles from the obtained ocular images and created dataset. Totally 536 particles including 179 normal, 109 abnormal and 248 non-sperm have been cropped. The data acquisition and dataset creation process is illustrated in Fig. 2. The total numbers of the each class in the created dataset is presented in Table 1.

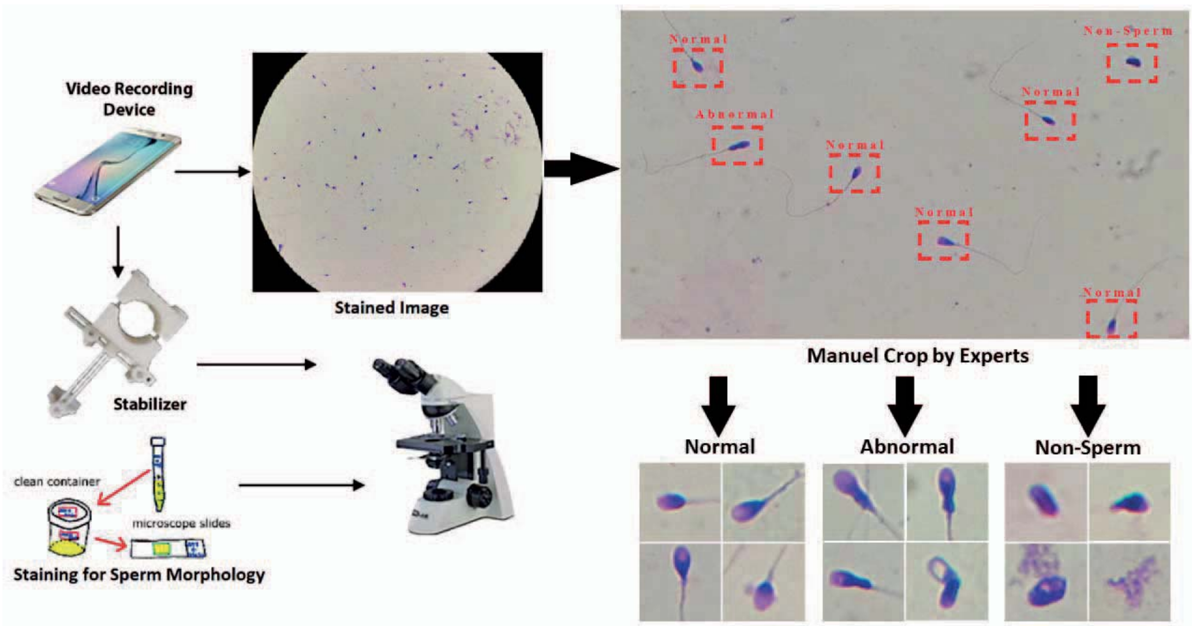

Figure 2. Data Acquisition Approach

TABLE I. NUMBER OF CROPPED PATHCES

Normal Sperm	179
Abnormal Sperm	109
Non-Sperm	248
Total	536

B. Preprocessing Techniques

Classical median filtering and adaptive wavelet transform based de-noising preprocess steps are applied to the data set in order to increase the classification performance of SURF based model. Median filtering is applied as a nonlinear method to remove impulsive noise while preserving edge information. Various window sizes such as 3×3, 5×5, 9×9, 15×15 and 45×45 are applied during the median filtering analysis part for validation. Additionally, as an alternative nonlinear de-noising method, the performance of the local adaptive wavelet transform based preprocess is tested. In this approach, the image is decomposed with the DTDWT, which is used in order to take advantage its near shift-invariance and directional selectivity, resulting into real and imaginary wavelet coefficients. Later, a bivariate shrinkage function is applied to the magnitude of the complex coefficients since the real and imaginary parts are not shift invariant individually but the magnitudes are. In this approach, the noise estimated by using a robust median estimator which is applied to a small segment of the image resulting in local noise estimation [11]. The effects of applied preprocessing techniques on example images of each class can be seen in Fig. 3.

C. Feature Extraction

Scale-Invariant Feature Transform, SIFT is a successful feature detection algorithm proposed by Lowe [12]. The SURF-algorithm [13] is based on the same principles and steps, but uses a different scheme and is faster to give better results.

Integral images refer to the sum of all the pixels in the rectangular block between itself and the starting point. The area of this rectangular block can be calculated faster than normal image [14]. The sum of all the pixels in the integral image for all x and y points can be performed by using Equation (1).

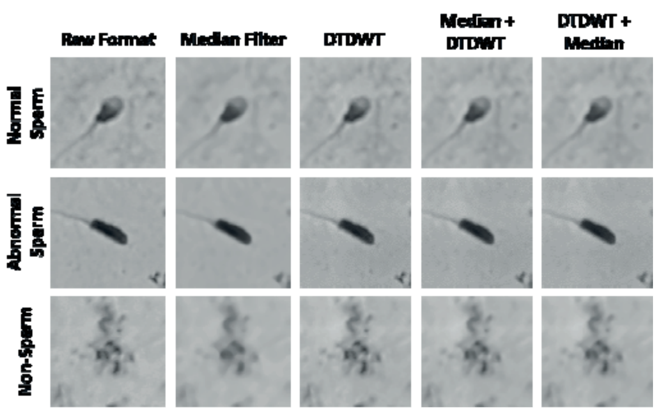

Figure 3. The preprocessing effects on cropped patches

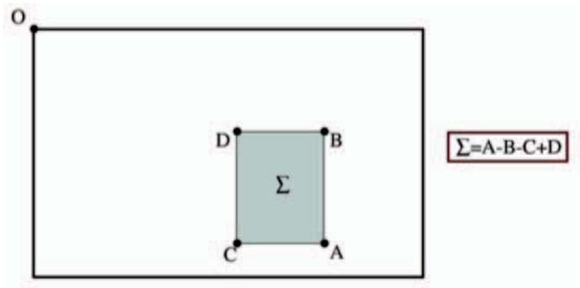

Figure 4. Calculation sum of a rectangular area in the integral image

$$I(x,y) = \sum_{i=1}^{i \le x} \sum_{j=1}^{j \le y} I(i,j) \tag{1}$$

where x and y represent the pixels to be calculated and the limit point. Summing process is performed over all *(i, j)* pairs starting at *(0, 0)* up to the indicated *(x, y)* points. The integral image is calculated by changing x and y for the whole image.

This process is applied to each point as shown in Fig. 4. Each point contains its own density information. The density of the rectangle taken from any part of the images is calculated in four steps. The sum of the values of two corner points is subtracted from the corner with the greatest value. Afterwards, the corner with the smallest value is added to the result. This allows field intensity calculations to be performed independently of the size.

The SURF method uses the Hessian matrix as a detector. The locations where the determinant of this matrix is maximum are used as image regions. This determinant is used to find the maximum and minimum points in the images with second-order derivative. In addition, the scale and position are also found using the determinants of the Hessian matrix [14]. Then, The SURF descriptor identifies the interest points in the image according to the calculated this Hessian Matrix. Totally 128 features are extracted for each interest points. An illustration of SURF based interest points and extracted feature matrix is given in Fig. 5.

D. Classification

We employed several conventional machine-learning techniques to compare the performance of the classification results. SVM classifiers with linear, Gaussian (RBF), polynomial and quadratic kernels are utilized as an example of kernel base classifier. Additionally, DT and KNN is performed as rule and distance based classifiers respectively. Results were discussed by comparing the accuracies of each classifier models over different formed image sets.

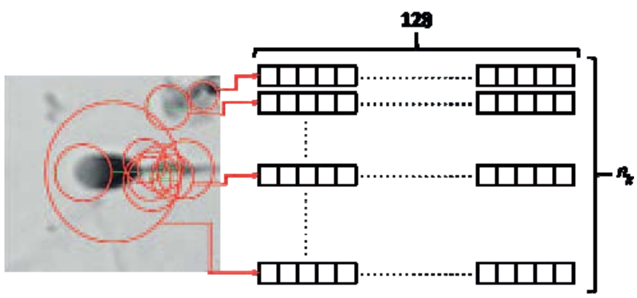

Figure 5. SURF based feature extraction

III. Test Results

In this study, we organized testing and training part of the each image sets and performed the tests by using K Fold cross validation idea. We selected K as 5 which refers to 429 images for training step for each utilized classifier model and 107 images for testing the classifier performance. In the classification models, different kernels have been tested for SVM. Penalty Parameter (c) is set to 1.

According to the obtained results presented in Table 2, highest accuracy (85.42%) is obtained by using SVM polynomial model over the DTDWT based adaptive de-noised image set. In this approach the noise type is accepted as a white Gaussian Noise and this assumption performs better when compared with the median filtering in which the noise accepted as impulsive.

Median filter is also an efficient de-noising technique for KNN and polynomial SVM model but ineffective for other models. The size of the median filter is the main parameter for the classification performance where 15×15 and 45×45 sizes cause information lost in the image. Therefore, the performance were measured less in those preprocessing parameters. 5×5 size is observed as the most effective size for our dataset according to the results. Therefore, we only select this size as the median filter size in the cascade application of two preprocessing steps.

In the cascade application of median filter and adaptive de-noising preprocessing steps, results indicate that the accuracy is most increased for RBF SVM model. However, the most accurate classification was achieved by single adaptive de-nosing technique.

IV. Conclusion

In this study, a DTDWT based adaptive de-noising preprocessing step and one of the conventional preprocessing step as median filter were compared in terms of sperm classification performance. Sperm morphological analysis system is proposed and the obtained results are compared with each other.

The results show that both preprocessing techniques increased the classification performance of SVM and KNN classifier. Higher accuracies are achieved with the adaptive de-noised images when compared with the classical median filter de-nosing process. In the adaptive de-noising method, the image is decomposed with the DTDWT, which has shift invariance and direction selectivity property, and a robust local threshold is estimated by using wavelet coefficients. In this approach, the noise is estimated by using a local window whose size can be controlled and this results in a better representation of noise and higher de-noising performance.

In future, in order to increase the classification performance, additional spatial domain based features such as Features from Accelerated Segment Test (FAST), Binary Robust Invariant Scalable Keypoints (BRISK), or KAZE can be extracted for to be combined in ensemble learning idea. Addition to these handcraft techniques, a deep learning technique to automatize the detection without any preprocessing step can also be tested.

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TABLE II. Classification Results

		Original	Adaptive Denoising	Median Filter					Median (5x5) + Adaptive D.	Adaptive D. + Median (5x5)
				3x3	5x5	9x9	15x15	45x45		
SVM	Quad	83.39	**84.99**	83.17	83.53	82.53	81.11	61.78	83.71	83.57
	Poly	82.77	**<u>85.42</u>**	83.79	84.34	83.79	80.97	61.22	84.17	83.55
	RBF	82.12	81.86	81.91	82.09	81.94	78.18	65.54	82.29	**83.95**
	Lin	79.02	79.37	79.02	**81.26**	80.18	80.04	64.24	79.63	81.03
DT		**76.84**	75.40	75.22	73.60	71.53	69.28	60.41	72.84	76.11
KNN		80.59	81.51	82.16	**82.75**	80.45	74.16	61.85	81.92	81.06