Dual Tree Complex Wavelet Transform Based Sperm Abnormality Classification

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Abstract—In the proposed study, Dual Tree Complex Wavelet Transform (DTCWT) based statistical features that are derived from normal sperm, abnormal sperm and non-sperm patches are fed to Support Vector Machine classifier with the aim of three class discrimination. The obtained results are compared with the classical dyadic discrete wavelet transform and the superiority of the proposed method has been shown in terms of accuracy and F-measure metrics. The results show that higher accuracy and F-measure scores have been obtained with the proposed approach due to the shift invariance and better direction selectivity property of the DTCWT.

Keywords—Discrete Wavelet Transform; Dual Tree Complex Wavelet Transform; Support Vector Machines; Sperm Abnormality Classification

I. INTRODUCTION

Today, infertility is one of the most common disease over the population. World Health Organization (WHO) reported that the almost 15-20% of all couples have difficulties to get pregnancy [1]. WHO publishes the reference values in the reports to use as a guide in the examination of the human sperm and updates the parameters according to the current status. The quality of sperm is rapidly decreasing according to the reports. The reference rate was 80% in the first edition of the handbook published in 1980 [2] while it was updated to 4% in the 2010 version [3]. In this respect, male infertility analysis, which named as spermiogram, is a crucial and important task in the infertility diagnosis.

Spermiogram analysis includes several steps. In the first step, experts observe the semen specimen in terms of the physical aspects such as viscosity, pH, color and smell. Then, the sample is investigated for the sperm morphology, concentration, and motility analysis. Morphology analysis consists of the size and shape evaluation of head, mid-piece and tail parts of each sperm. Different standards are defined for the morphological assessment in literature. According to the one of the well-known standard, Kruger, the normal morphology sperm ratio should be between 4% and 14% of the sperm concentration [4]. The sample having the ratio over 14% is described as "perfect". The normal morphological sperm ratio below 4% is defined as abnormal and has a high effect on infertility.

Two evaluation techniques as visual and computerized assessments are currently used in the morphological analysis. In the visual assessment technique, sample was stained before the analysis. Then, sample is manually investigated under the microscope by an expert. This technique is cheap and practical way which is currently used in many laboratories. However, the results of the visual analysis strongly depend on the experiences and expertness. This problem is called as the observer variability problem [5], in which the obtained results may differ depending on the observer. In another technique, Computer Aided Sperm Analysis (CASA), analysis is performed on computer based systems. This technique is more reliable, consistent, and objective, when compared to the visual analysis. It isolates the human factor [6]. On the other hand, CASA systems are more expensive compared to the visual assessment technique. Additionally, the algorithms employed in CASA systems need to be improved in many aspects especially for the morphological analysis [7, 8]. Therefore, CASA systems are less preferred in laboratories and new low cost automatic approaches for analyzing the sperm morphology is a necessity.

The first step of the sperm concentration analysis is the sperm detection in the CASA systems. Olalla et al. used the Otsu thresholding and wavelet transform in the sperm detection step in their study [9]. Then, they classified the detected sperm into normal and abnormal by using Support Vector Machines. They focused on only acrosome defects in terms of binary classification, therefore, system resulted in high accuracy. Alegre et al. performed the preliminary segmentation with the same approach and formed the classifier model by extracting Haralick and the counter features from the detected sperm [10, 11]. They also used the same model to detect acrosome-based abnormalities as in [9].

Instead of classifying the only acrosome based abnormality, Khachane et al. proposed a fuzzy rule-based classification technique for more detailed sperm classification [12]. Sperm were examined, by using segmentation, into detailed sub-segments as head, mid-piece and tail. They used the spatial features such as major and minor axes, regional area and circumference length information of segmented sperm pieces in the classification. Authors have defined fuzzy logical expressions [12]. In the detection of the only sperm head region, Chang et al. applied a more sophisticated two-step feature extraction and classifier design for the detection of not only acrosome but also the sperm core [13]. They performed the combinational version of clustering idea and histogram analysis. *K*-means clustering was applied in the histogram analysis. In addition, they used different color spaces for clustering.

In the proposed study, the classical dyadic discrete wavelet transform (DWT) and the dual tree complex wavelet transform (DTCWT) is applied to the dataset with the aim of capturing the

sperm morphology. DTCWT and DWT based statistical features are obtained by using the wavelet coefficients which are extracted from the images. Then, the SVM models with different kernels are employed as the learner in the classification step.

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

II. MATERIALS AND METHODS

A. Data Acquisition Step and Dataset Information

Ocular images of the microscope is obtained by a smartphone based data acquisition technique which is graphically illustrated in Figure 1. The details of this approach was introduced in [14].
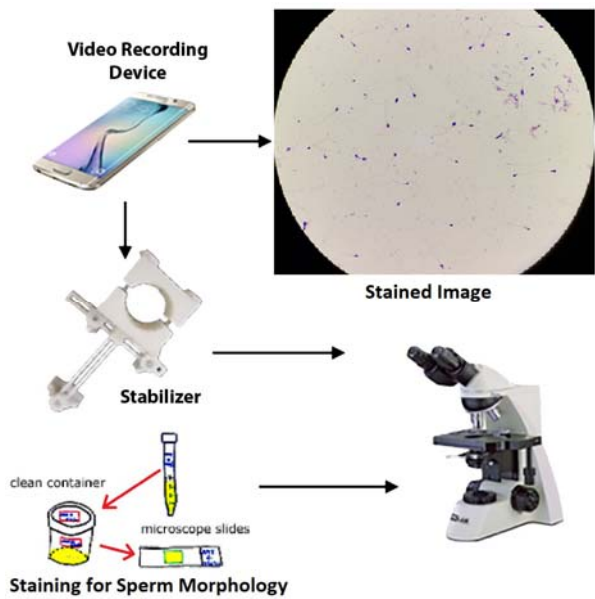

Fig. 1. Data Acquisition Approach

To be used in classification procedure, 536 patches have been manually cropped from the microscopic ocular images of 13 subjects by an expert. Each patch was labelled as normal sperm, abnormal sperm and non-sperm. The created data set information is given in Table 1.

TABLE I.	SPERM NUMBER
Normal Sperm	179
Abnormal Sperm	109
Non-Sperm	248
Total	536

Patch images were obtained after staining process of semen sample. Staining process provides the better morphological examination of each sperm. A small part of the stained image of entire ocular image is given in Figure 2 with the manual cropped patches which will be used in the feature extraction and the classification step.
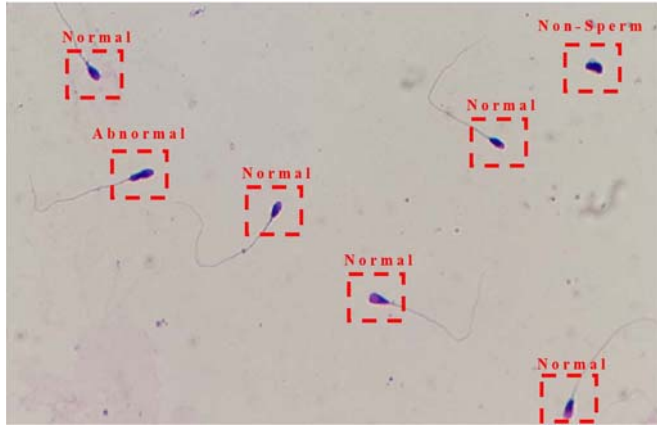

Fig. 2. An example of stained image and the cropped pathces

Scientifically, a normal sperm is about 5-6 micrometers long, 2.5-3.5 micrometers wide, and is characterized by an oval head in a single long tail. In case of abnormality, various shapes can be observed. Additionally, the images includes different clusters than normal/abnormal sperms because of the staining process which is labelled as non-sperm in this study. An example of normal/abnormal sperm and clusters occurred by the stain and other factors is presented in Figure 3.
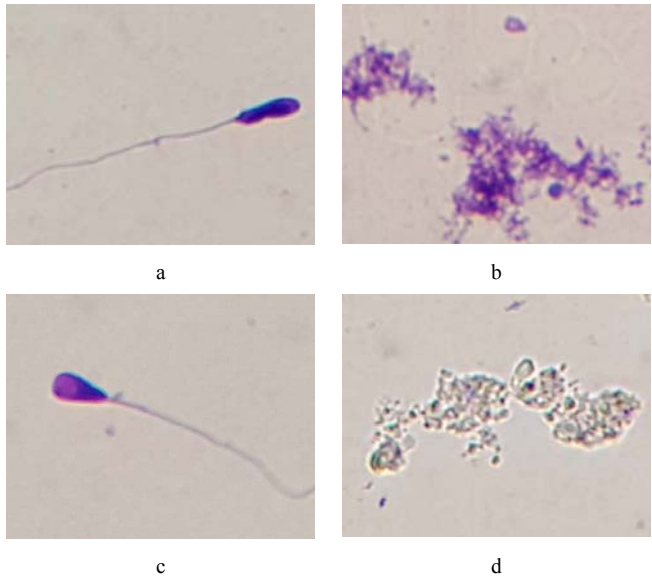

Fig. 3. Example patches: a) Abnormal Sperm, b) Cluster occurred by the staining process, c) Normal Sperm, d) Optical microscope effects

B. Feature Extraction

Classical DWT and DTCWT were applied to 536 patches for feature extraction. Subsequent to coefficient extraction steps; statistical features as mean, standard deviation and the entropy of the raw sub-band coefficients are extracted for each patch. Later, each resultant statistical features combined and given to the classifier as a single row vector for the discrimination of normal sperm, abnormal sperm and stained particles.

Wavelet Transform (WT) is an effective signal processing tool for analyzing nonstationary signals due to its adaptive

frequency resolution property. The continuous WT provides a time-scale (TS) representation of signals, which have good frequency resolution at low frequencies and good time resolution at high frequencies, by scaling and shifting the mother wavelet ($\psi(t)$). Function as formulated in (1)

$$CWT(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \psi\left(\frac{t-b}{a}\right) dt \quad a,b \in R, \ a \neq 0 \quad (1)$$

where a is the scale, b is the translation parameter and $f(t)$ is the input signal. In practical applications, to discretize the WT and make it appropriate for computer analysis, a fast algorithm called as discrete WT (DWT) is employed. However, classical dyadic DWT suffers from being shift variance property, i.e., small shifts in the image causes dramatic changes in the energy distribution of decomposition sub-bands. This unpredictable energy change degrades the classification performance of the learning models when the raw DWT coefficients and/or their statistics are utilized as features. Dual tree complex wavelet transform (DTCWT), which is nearly shift invariant, was proposed as a modified version of classical DWT with 2^N redundancy where N is the signal dimension. In the DTCWT [15], two set of real wavelets, which have 90° phase difference, are employed and the algorithm is implemented by using two real DWTs consist of the low and high pass filter pairs that satisfy nearly complexity property. When the DTCWT is applied to images, at the end of decomposition stage, six directionally selective sub-bands having ±15°, ±45° and ±75° for each scale are obtained, while only vertical and horizontal direction information can be achieved in ordinary DWT.

C. Classification

Support Vector Machine (SVM) is employed as the main classifier with different kernel and cost parameters in the classification step of extracted features from the patches. SVM is one of the prominent classification algorithm which can be used in large-scale data sets and provides more efficient results than statistical and neural classifiers. In SVM, higher classification accuracies can be achieved by even small size train sets with the help of well-fitted cost function in kernel space [16].

SVM uses the core idea of kernel based learning, which aims to separate data in high dimensional feature space by mapping data points with a kernel function. SVM creates a decision surface between the samples of different classes by finding the optimal hyperplane that is closest to the deciding training samples (support vectors). That way an optimal classification can be achieved for linearly separable classes. In case of linearly inseparable situations, different kernel versions of SVM are defined. The main purpose of kernel approach in SVM is to transform the data to a higher dimensional space ($\Theta : R\,n \to R$, $> n$) where binary classification can be achieved linearly again. Kernel functions are mainly used to define cost function, and the response of the cost function defines the weight and bias values in the learning model. In order to define well-fitted settings of SVM on the sperm abnormality classification problem, RBF, Polynomial, and Linear kernels and their different parameters are tested.

D. Performance Metrics

In the proposed study, the results are compared in terms of "Accuracy" and "F-Measure" metrics. Accuracy rate refers the number of correctly classified samples within all samples. F-Measure score gives more detailed analysis on the model classification success. In the calculation of F-Measure score, not only the correct classification, but also the rate of the incorrect predictions as precision and recall are considered in the performance analysis.

III. TEST RESULTS

Train and test set are split by using 5-fold cross validation. SVM model was trained with four part which equals to 429 images and tested on the rest of the images (107). This technique was repeatedly performed five times and the final classification performance was measured by averaging the results obtained from each fold. In the classification model, different kernels have been tested. Two sigma and degree parameters for radial basis and polynomial kernels have been performed in the tests. Penalty Parameter (c) is set to 1. As seen in Table 2, highest accuracy (82.33%) and F-measure scores (79.22%) are obtained with DTCWT based statistical features when the decomposition level

TABLE II.   CLASSIFICATION RESULTS

| Level | Wavelet Type | Polynomial Kernel | | | | Radial Basis Kernel | | | | Linear Kernel | |
| | | d=3 | | d=2 | | σ = 0.1 | | σ = 1 | | | |
		Acc (%)	F1 (%)	Acc (%)	F1 (%)	Acc (%)	F1 (%)	Acc (%)	F1 (%)	Acc (%)	F1 (%)
9	DTCWT	80.42	77.36	80.79	77.52	78.92	75.18	79.42	76.68	80.79	76.83
	DWT	75.19	71.13	75.00	70.78	77.62	73.61	78.12	74.81	80.04	76.92
8	DTCWT	81.53	78.17	80.60	77.35	80.60	77.40	82.04	78.69	80.97	77.53
	DWT	75.75	71.49	75.38	71.07	78.18	73.82	79.13	75.12	80.04	76.10
7	DTCWT	80.22	76.29	80.78	76.83	81.53	77.92	**82.33**	**79.22**	81.90	78.16
	DWT	76.30	71.68	75.93	71.51	77.61	72.65	78.15	74.15	79.29	75.03
5	DTCWT	79.66	75.55	80.78	76.52	79.48	75.95	80.24	78.91	81.90	78.40
	DWT	74.24	69.41	74.25	69.08	77.98	73.13	78.99	75.38	80.78	77.16
3	DTCWT	70.72	64.86	72.02	66.84	73.14	65.67	74.31	68.17	72.76	65.75
	DWT	69.03	64.59	72.01	65.04	72.57	65.28	73.07	66.08	72.39	65.70

is chosen as 7 and RBF kernel (σ = 1) is employed. This shows that optimum frequency resolution is achieved with 7 level analysis and higher number of decomposition levels than 7 give redundant information for sperm classification problem.

In Figure 4, the accuracies obtained with the DTCWT and the DWT is compared for various decomposition levels and it is seen that for all the levels DTCWT has higher accuracies. Additionally, in Figure 5, for the optimum level number (for 7), the performances of SVM kernels are given. As it is seen, for all the kernels, DTCWT shows better performance than the classical DWT.
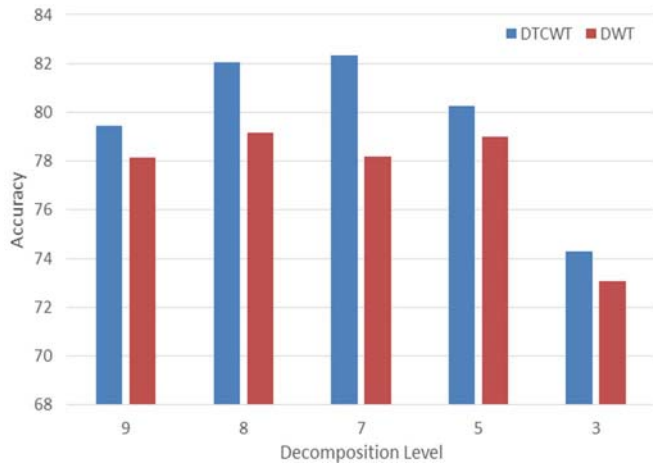

Fig. 4.The classification results of RBF Kernel (σ = 1) based SVM in different decomposition levels
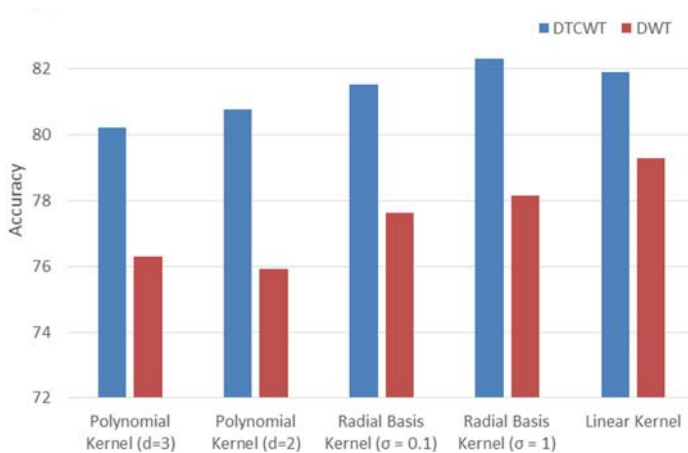

Fig. 5.All classification results in level 7 decomposition level

IV. CONCLUSSION

In this study, a DTCWT based sperm morphological analysis system is proposed and the obtained results are compared with the classical DWT based features. In order to validate superiority of the proposed algorithm, various wavelet decomposition levels and the classification scenarios are tested. The results show that higher accuracies and F1 scores are achieved with the proposed system when compared with the classical DWT based approaches due to the shift invariance and better direction selectivity property of the DTCWT. In future, in order to increase the classification performance, additional features based on

spatial domain analysis such as Speeded-Up Robust Features (SURF) and Features from Accelerated Segment Test (FAST) can be extracted for to be combined with wavelet features in ensemble learning. Addition to these handcraft techniques (SURF and FAST) approach, a deep learning technique to automatize the detection without any preprocessing step can be tested.

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