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3D-Discrete Wavelet and Multiwavelet Transform Based on Recognition System Design ofLatin Handwritten Text Features Extraction

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Abstract:*Handwriting recognition is a wayto knowthe letters or words are present in handwritten text. This technique is very important to communication between man and machine and can help in handwritten documentsprocessing automatically. It is a part of the Optical Character Recognition (OCR), thatdeal with machine-print only.The proposed system is a character-based recognition and it is a writer independent system. The recognition responsibility of the proposed system is for 52 character classes [uppercases (A-Z) and the lowercases (a-z)]. The suggested system includes the essential stages needed for most of the pattern recognition systems. These stages are the preprocessing stage, the features extraction stage, the pattern matching and classification stage and the postprocessing stage. The proposed methods employ threeDimensional Discrete Multiwavelet transform Critically Sampledand also three Dimensional Discrete Wavelet transform (3D-DMWTCS, DWT)using multiresolution image decomposition techniques working together with multiple classification methods as a powerful classifier. The classification stage is designed by using a minimum distance classifier depending on Euclidean Distance which has a high speed performance. The system design also includes a modest postprocessing stage that makes a consistency between the recognized characters within the same word in relation to their upper and lower cases. Theoverallclassification accuracy of proposed systemscan be obtained are 95.76 percent with 3D-DMWTCS and 94.05percent with 3D-DWT based on the Rimes database.*

Key word: *3D-DMWTCS, 3D-DWT, dpi, HWR, RR, OCR, ED, MDC.*

I. Basic Concepts ofthe Handwriting Recognition

Handwriting(HW) is one of the most important methods of communication used by civilized peoples. It is used for both personal (e.g. letters, notes, addresses on envelopes, etc.) and business communications (e.g. bank cheques, business forms, etc.). The writing is a physical process where the brain sends an order through the nervous system to the arm, hand and fingers, where together they manipulate the writing tool. Therefore, a person's handwriting is as unique as human fingerprints and facial features. However, it varies depending upon many factors (age, education, temper, left or right handed writer, etc.).With the emergence of computer, it became possible that the machines can also reduce the amount of mental work required for many tasks. One of these tasks is the recognition of human handwriting. Of course, significant progress in the way of handwriting recognition computer has been, but the computer will not be able to read human handwriting as well as a human being. Even so, it does not hurt to try to develop technology that can approach the ability to recognize of humans. Since the handwriting is very important that allow people communicate each other, it is important to found an easy way tointeractive with thecomputer [1, 2]. Handwriting recognition (HWR) system can be "on-line" or "off-line". It is "online" when pressed by the pen on the personal data assistants' electronic (PDA) devices screen where they are pressed account pen and indicate immediately on screen. It is "off-line" when it is useda previously written text, such as any image scanned by a scanner. The on-line problem is usually easier than the off-line problem since more information is available. So far, most of the off-line handwriting recognition systems are applied to reading letters, postal addresses and then automatic sorting of postal mail, processing forms like bank cheques or discrimination of the different scripts for individual writers (Handwriting identification) [3].

II. Model for off-lineHandwriting Recognition

Handwriting Recognition HWR is interpretation of data which describes handwritten objects to generate a description of that interpretation in a desired format. Or in other words it is a determination what characters or words are existent in the image of text have handwritten words or characters. The significant benefit of HWR system was in communication between man and machine and convertsthe handwritten documents image to understand from the machine. And use a wide range of techniques to perform off-line handwriting recognition. To transform this image to understandable information by computers requires solving a number of difficult problems. Firstly, preprocessing steps are achieved on the image to reduce some undesirable variability that only contributes to complicate the recognition process. Operations like binarization, noise removal, skew, slant and slope corrections, thinning, smoothing, normalization, etc. are carried out at this stage. The second step is the segmentation of the word in a series of basic units such as characters or semi characters recognition. However, segmentation may not be present in all systems. Recognition approaches can be either “Holistic” or segmentation-based. “Holistic” means that words or sentence are processed as a whole without segmentation into characters or strokes [6, 7]. In segmentation-based approaches, whole or partial characters are recognized individually after they have been extracted from the text image. The final step is to extract discriminated features from the input pattern to either build up a feature vector or to generate graphs, string of codes or sequence of symbols. However, the characteristics of the features depend on the processing steps; say whether segmentation of words into characters was carried out or not. The pattern recognition model to handwriting recognition consists of pattern training, that is, one or more patterns corresponding to handwritten words or characters of the same known class are used to create a pattern representative of the features of that class. The recognition includes a comparison of the test pattern with each class reference pattern and measuring a similarity score (e.g. distance, probability) between the test pattern and each reference pattern [8, 9]. The pattern similarity scores are used to decide which reference pattern best matches the unknown pattern. The postprocessing or verification may also be included in some systems. Therefore, it is necessary to consolidate the recognition process as a source of knowledge such as modelsof language [10]. “There are limited vocabularies” is one of the most important aspects of systems that rely on large vocabulary because it contributes to improve the accuracy as well as to reduce computation. In the case of systems that deal with large vocabularies, other additional modules may be included such as pruning or lexicon reduction mechanisms [11, 12]. If we desire a system to distinguish objects of different types, it must be first decided which characteristics of the objects should be measured to produce descriptive parameters called (features) of the object, and the resulting parameters values comprise the feature vector for each object. Proper selection of the features is important, since only these will be used to identify the objects.Good features have four characteristics [13, 14]; Discrimination, Reliability, Independence and Small Numbers. The complexity of a pattern recognition system increases rapidly with dimensionality of the system. More importantly, the number of objects required to train the classifier and to measure its performance increases exponentially with the number of features. And it is necessary to avoid the redundancy.The important step to achieving good recognition performance isthe features extraction step. For off-line HWR systems the feature extraction methodology is based on one or more of Global features and Geometrical and topological features. The geometrical and topological (structural) features describe the geometry and topology characteristic of a character. Some examples of extracted features are strokes and bays (kerning) in various directions, dots, end points, intersections of line segments (junctions), loops, curves (turnings), etc. as shown in Figure (1). Each of these features can be encoded by a single number. The topologicaland geometrical features implicate a high tolerance to distortion and style variations. Due to complexity of extracting the geometrical and topological features and the great variations in local properties of HW characters, it is rather difficult to generate feature masks. But once they are implemented, they can process characters at high speed independently, asshown in [15] are examples of using the geometrical features.

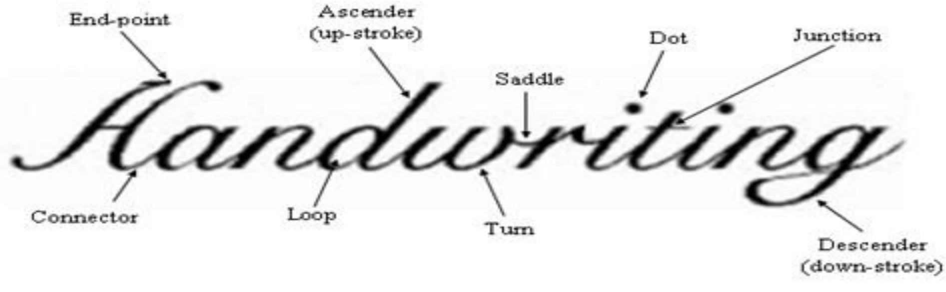


Figure 1 Geometrical and topological features

Statistical featuresare derived from the statistical distribution of pixels of a character. They are computed over images or regions of imagesas numerical measures [16, 17]. They include(the aspect ratio of the character, histograms of chain code directions, Fourier descriptors, moments, characteristic loci, crossing and distances, pixel densities). The statistical features take some dynamic information and topological into account and consequently can tolerate minor distortions and style variations [18, 19].

III. Feature Extraction Using 3D-Wavelet and Multiwavelet Transformsand Classification

Discrete Multiwavelet transform given a good indication in applications of signal processing. Recent work on Multiwavelet have been studies the basic theory, methods of constructing new multifilters and the denoising and compression applications in of video and image [12, 17, 20, 21, 22]. The algorithms for computing three dimensional discrete Multiwavelet transform Critically Sampled (3D-DMWTCS) have been described in this section in a simple and easy way to verify procedure using matrix multiplication and addition. To compute 3D-DMWTCS one must know how compute 1, 2D- discrete Multiwavelet transforms Critically Sampled. In 3D- discrete Multiwavelet transformation Critically Sampled algorithm is defined in 3D, so the transformation procedure will done successively in x-, y- and z-directions.

For a 2D-DMWTCS, the procedure was applied to each vector in x-direction first, and then to each vector in y-direction. Similarly, in 3D- discrete Multiwavelet transformation Critically Sampled the procedure is defined in 3D and the transformation algorithm is applied successively in x-, y- and z-direction.

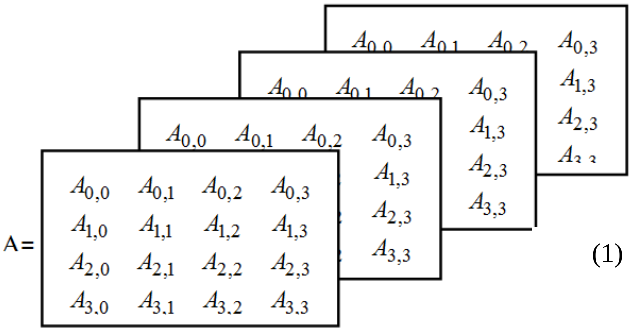
1. Computation Method of 3D-DWT

The Discrete Wavelet transformation was given good indication in applications of digitalsignal processing. Recent work on wavelet have been studies the basic theory, methods of constructing new multifilters and the denoising and compression applications in of video and image [17, 18, 19, 22].The computation methods of 1, 2 and 3D of DWT are shown in [17,20,22,23,24].

2. Computation Method of 3D-DMWTCS

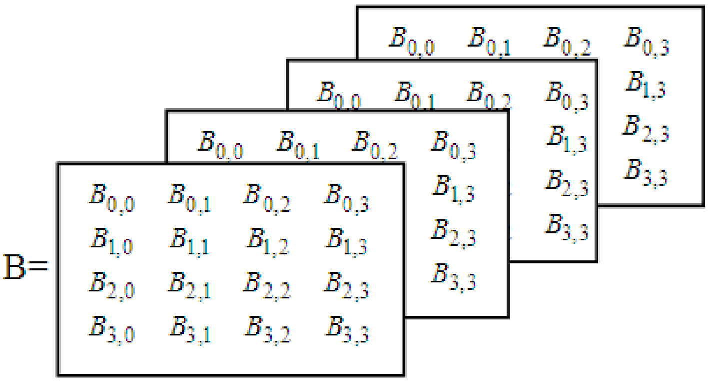
Let's take a general 3D signal, for example any $N \times N \times M$ matrix. The computation 3D-DMWTCS need the following procedure:

1. construct 3D-matrix $A$to represent the 3D input signal,



(1)

2. Using 2D DMWTCS algorithm to each NxN input matrix, which result in a B matrix ($N \times N \times M$).



(2)

3. Using 1D-DMWTCS algorithm shown in [22,23] tocompute 1D-DMWTCS to each element of $N \times N$ matrix in all M matrices in z-direction, which can summarized as follows:

a. For each i,j element in the 1st matrix construct a vector of $M \times 1$ for each element in z-direction output matrices from 2D-DMWTCS in step 2, this operation is done as below:

$$V(i,j) = \begin{bmatrix} B_{i,j,0} & B_{i,j,1} & B_{i,j,2} & B_{i,j,3} \end{bmatrix}^T_{1 \times M} \qquad (3)$$

Where $i, j = 0,1,2,\cdots,N$

b. Applying 1D-DMWTCS algorithm to each the construct vector $V(i,j)$.

4. Repeat step 3 for all construct vector i, j.

Finally, a$N \times N \times M$ of 3D-DMWTCS matrix results from the $N \times N \times M$ original matrix using 3D-DMWTCS.

The main features of 3D-DMWTCS type are the ability to provide localized frequency information about characterimage. Such information is particularly beneficial for classification. Fora single charactercontaining binary image, there are many preprocessing procedures performed previous to feature extraction. The most important thing is to make our system independent of each character concerning its shape, position (location in the word) and size. In relation to its shape normalization, this can be achieved by slant and skew corrections steps. Concerning stroke width normalization, this is done by (thinning) approach and successive steps of stroke thickening. These steps leave each stroke with approximately the same width. Related to character position normalization, it is achieved by first character segmentation and then found the bounding rectangle of each character. This way will remove any differences caused by the location of character inside each image. The next stage of this rectangle bounding will be change the scaled of character to a (32×32) pixel image (A^{j+1}), in order to scale (size) normalization and take multi-copy. The wavelet decomposition is applied at one level of resolution, yielding four subband images {Approximations (A^j), Horizontal details (D_H^j), Vertical details (D_V^j) and Diagonal details (D_D^j)} each containing 16 × 16 pixels. Therefore, the feature vector is formed by these subband images with $(1\times d)$ dimensions, where $d= 4 \times 16 \times 16$. Figure 2 illustrates the 1-level of 3D-(DMWTCS or DWT) step. For each subband image, the values of the (wavelet or Multiwavelet) coefficients are normalized to the range [0, 1]. Figure 3 shows the 3D-(DMWTCS or DWT) coefficients for all subbands [19]. The main information is concentrated at the approximation subband and the other are distributed in the other subband images. Other experiments were done to find out which subband contains more important characteristics (important features for recognition).These experiments used the same test data set and the same data base. The results show the features relevance to the recognition process. The features that are extracted from the approximation subband contribute by about 53% of the importance in the recognition task, while the features extracted from the all other subbands contribute with about 47% of the significance in the recognition process. But this conclusion does not mean that the correct recognition is about 53 % by using the approximation only.

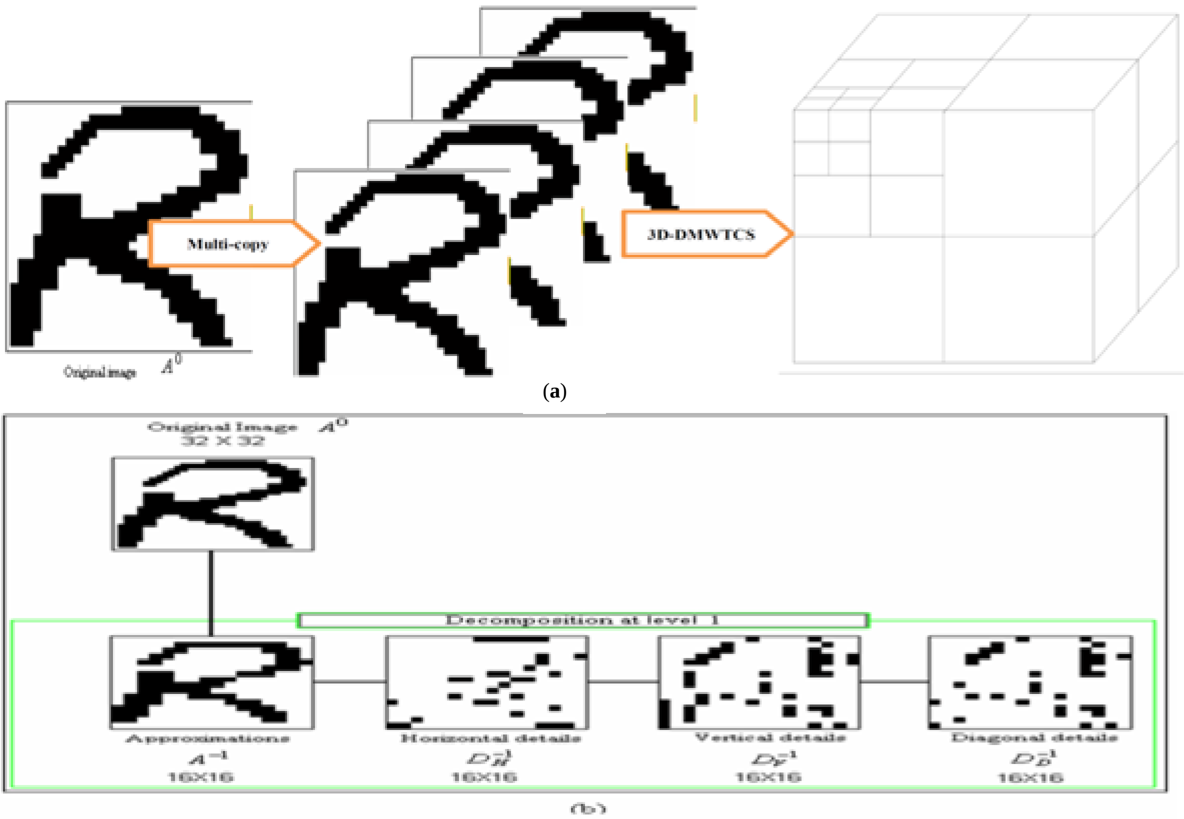


Figure (2) decomposition of 3D-DMWTCS on character image: a-square view mode b- Tree view mode

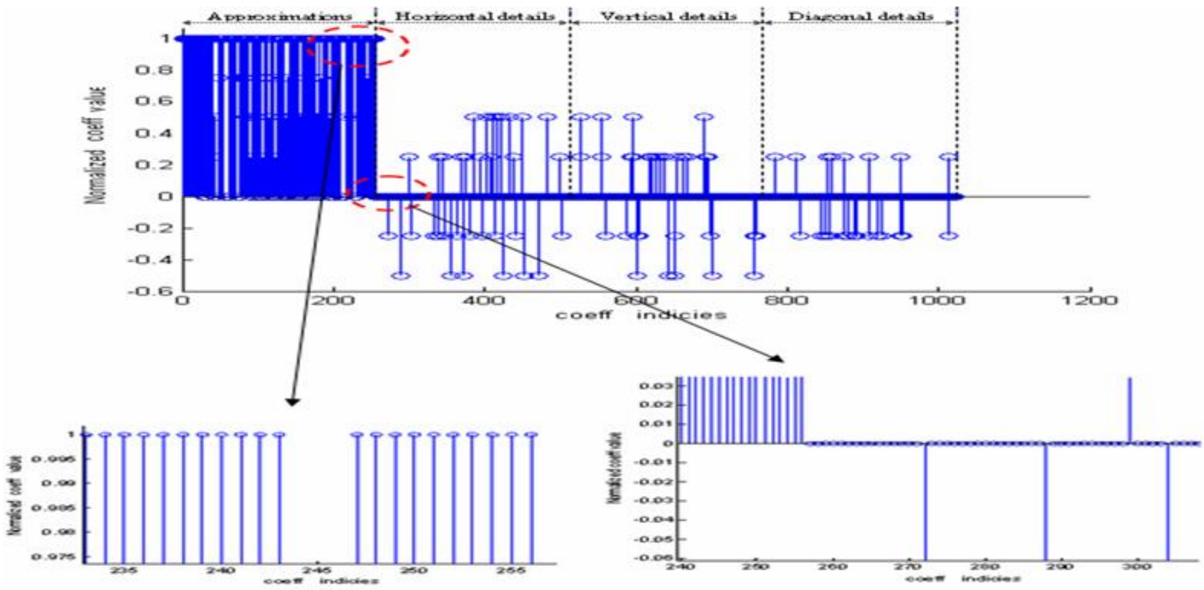


Figure (3) 3D-DMWTCS normalized coefficients

IV. Training and testing phases of the recognition task

The goal of the training phase is to extract and prepare the best parameter values (features) of the character models. The training phase is deals with handwritten characters (some timeis called letters) to known and defined letters classes. Each input letter image is adequately preprocessed and its relevant features are then extracted from the preprocessed image forming a feature vector (f_{dx1}), where d is the features number. For each character class, the feature vectors is generated which are also known as the class reference feature vectors. These vectors have the goal of representing its corresponding character classes. This class reference feature vectors are produced by the using of 3D-(DMWTCS or DWT). As a result, the system has reference feature vectors which are forming the feature matrix F as stated in equation (4). F contains $M\times 52$ feature vectors f where M is the number of training samples and (52) is the number of letter classes (upper lower cases of Latin alphabet). For example: $f_{1,1}$ and $f_{2,1}$are the feature vectors of the letter (A) of the first and second training samples and so on while $f_{1,2}$ and $f_{2,2}$ are the feature vectors of the letter (B) of the first and second training samples and so on. Each column in **F** represents the features of one class for M training samples. The size of the feature matrix depends on the feature vector dimension and the number of the available training samples M.

$$F = \begin{bmatrix} f_{1,1} & f_{1,2} & \cdots & \cdots & f_{1,52} \\ f_{2,1} & f_{2,2} & \cdots & \cdots & f_{2,52} \\ . & . & . & . & . \\ . & . & . & . & . \\ f_{M,1} & f_{M,2} & \cdots & \cdots & f_{M,52} \end{bmatrix} \ldots (4)$$

An extendedtraining phase, i.e., more samples of handwritten letters with various styles would improve the system performance. The training data set have to be with various styles rather than to be of large quantity. The testing phase of the classification, an image from an unknown class is initially preprocessed and then having its feature vector extracted using the same techniques in the training phase. From this initially extracted feature vector, for each distinct letter class, a new and different feature vector is then produced. Next, the classifier is used to define the input handwritten character to the class that best enlarges the input image.

1. The Minimum Distance Classifier (MDC)

The implemented minimum distance classification based on calculating and comparing the Euclidean Distances (*ED*). The Euclidean Distances are between the feature vector of the unknown input character (to be classified) and the reference feature vectors as shown in equation (5) [19].

$$ED_n = \| f_i - f_{m,n} \| = \sqrt{\sum_{m=1}^{M} \left| f_i - f_{m,n} \right|^2} \qquad n=1, 2 \ldots 52 (5)$$

Where $\| f_i - f_{m,n} \|$ denotes the Euclidean Distance between the vectors f_i and $f_{m,n}$.

$f_i$is the feature vector of the unknown input character pattern, the subscript (i) is denotes to the word "input". $f_{m,n}$is the m^{th} feature vector of the n^{th} character class that belongs to the feature matrix **F**.

$$CED_n = \sum_{m=1}^{M} ED_{m,n} \quad n=1, 2\ldots 52\ldots \quad (6)$$

$$CED=[CED_1 \; CED_2 \; \ldots\ldots CED_{52}] \qquad \ldots(7)$$

Where CEDn is the Class Euclidean Distance of the nth character class for M training samples and CED is the Class Euclidean Distance vector.The smallest CEDwill be the chosen class in CED. In other words; it is the smallest distance between the vector of input feature and the vector of most representatives (nearest) of the reference feature vectors. Figures 4and5 show some examples of how minimum distance classifier work to classify the HW letters T&z whichappear at the left bottom corner of each plot. The x-axes of the plots represent the 52 characters classes of upper and lower cases. The y-axes are the EDs between the input features vector and the reference features vectors as shown in equation (7).

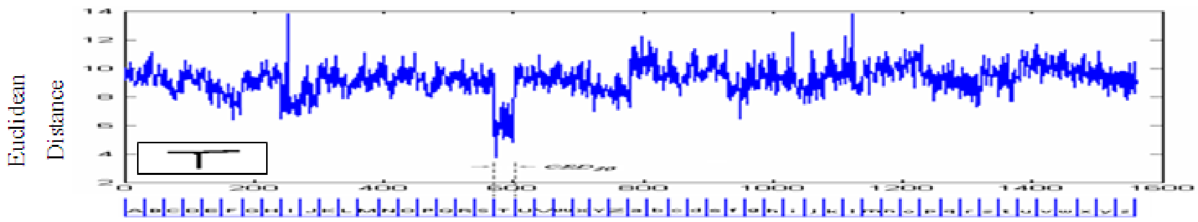


Figure (4) Letter "T" classification

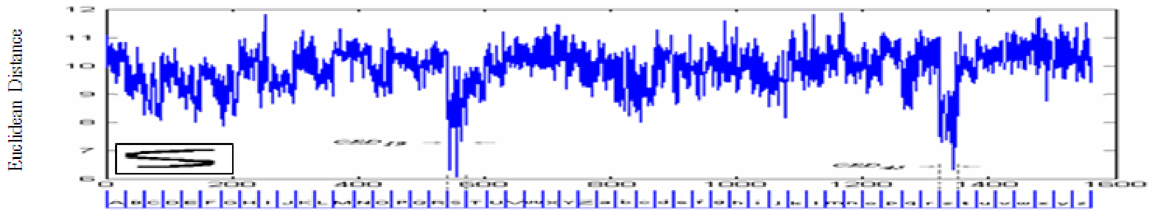


Figure (5) Letter "S" classification

Concerning Figure 4, the $CED_{20}$is the smallest among all CEDs. The CED_{20} is the sum of M Euclidean Distances of the 20^{th} class that belongs to the letter " T ", therefore, the input letter will be classified as T and so on for the other inputs.Figure(5) shows the letter "s-lowercase" classification. It is clear there are two smallest CEDs(CED_{19} and CED_{45}). The letter "s-lowercase" will be classified as "S-uppercase" since $CED_{19}<CED_{45}$. The recognition between letters with approximately having similar patterns of their upper and lower cases is still an open problem till this point of the proposed recognition system. Such letters are "s" and "S", "w" and "W", "z" and "Z" "c" and "C" etc. The unique difference between their upper and lower patterns is the size. The size difference is lost by the size normalization step at the preprocessing stage which may waste this feature between upper and lower cases of the letters above. This problem will be discussed and partially treated at the postprocessing stage.The false classification may come from calculating the smallest ED which may give an assurance to a wrong class as shown in figure (6). Figure (7) shows the avoiding of the false classification for the HW letter "Y" as letter V. It is clear that there is some similarity between the HW "Y" with the letter V which is the reason for this very small ED.

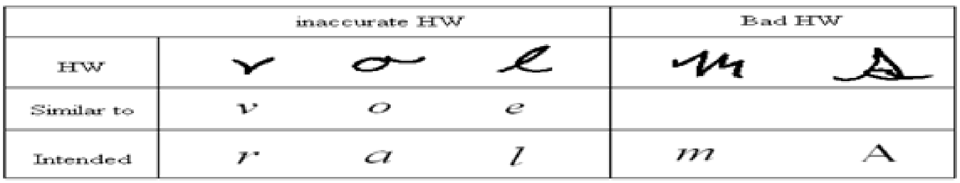


Figure (6) Inaccurate and bad HW

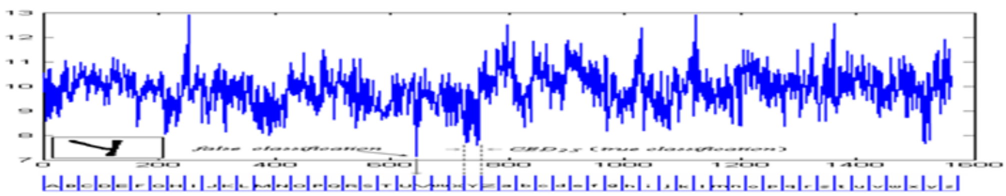


Figure (7) True and false classification

Sometimes the false classification could not be avoided due to the great similarity between the input HW letter and the unintended character class as shown in Figure (8). The input HW letter is “ r ”, but it is classified as “ v ” due to the great similarity between them. The solution of this problem is beyond the scope of this work (out of the proposed system ability). The Recognition process will be character by character and the designed program preserves the recognized characters to their words.

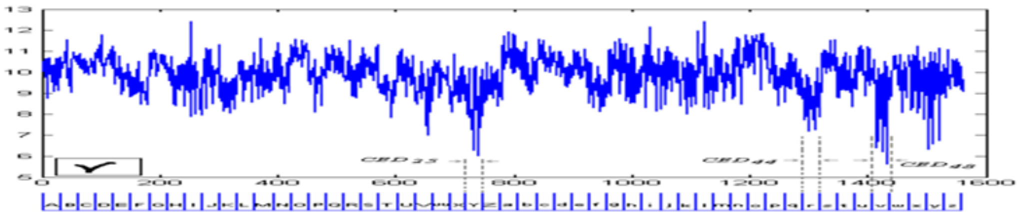


Figure (8) false classification due to not good HW

2. Postprocessing

The postprocessing step includes all processes that may be made to enhance the recognition and make the decision by different ways such as the prior contextual knowledge, integration of grammatical and syntactic knowledge, spelling, punctuation mark … etc. It focuses on solving the problem of the bad recognition between the characters between their upper and lower cases. The principle of its processing depends upon the comparison between the recognized characters within the same word. The normal word may contain all letters with their lowercases as “university” or may have only the first one with its uppercase especially if this word at the beginning of the sentence as “University of Babylon” or it represents a name as or “Babylon”. It is not proper that the word is written in lowercase letters except one or more letters at its middle or last in uppercase as in “*uniVersitY*”. Sometimes, the terms may be written with all letters in uppercases as in "Handwriting Recognition". This case can be easily discovered by the inspection of the recognized letters with the same word and the adjacent ones.

3. Data Base Collection and Document Image Acquisition

The proposed handwriting recognition system is with two phases; the first is the training phase that uses training handwritten samples while the second is the testing and recognition phase that needs test samples. The collected database for training must include different handwritten styles related to the scope of the proposed system. The data base was collected locally from various right hand and left hand writers with different ages, educations, temper etc. Characters were written by writers using specific forms on plain, white paper sheets with black ink pen to give clear strokes with sharp edges. Each filled form contains 52 Latin characters including the upper (A-Z), lower (a-z) cases and (0-9) numerical digits as shown in Figure 9. The collected data base depends upon the variety not on the quantity. The selection of the training samples must avoid as possible the redundant HW styles.The proposed handwriting recognition system processes data that were captured from a flatbed scanner. They were scanned at 150-dots-per-inch resolution, in 256 levels of gray to produce one file per writer. The next task is to segment each form into its component characters. The pixel histogram calculations based segmentation algorithm takes a simple approach, looking for the gaps between lines and characters. Figure (10) shows the segmentation results.

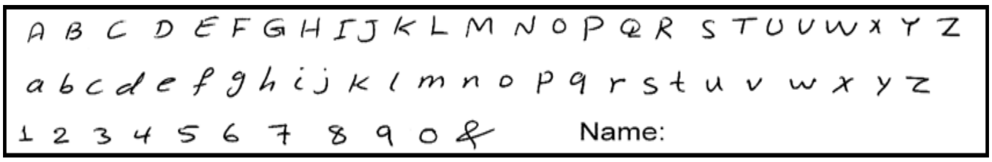


Figure (9) HW data collection form

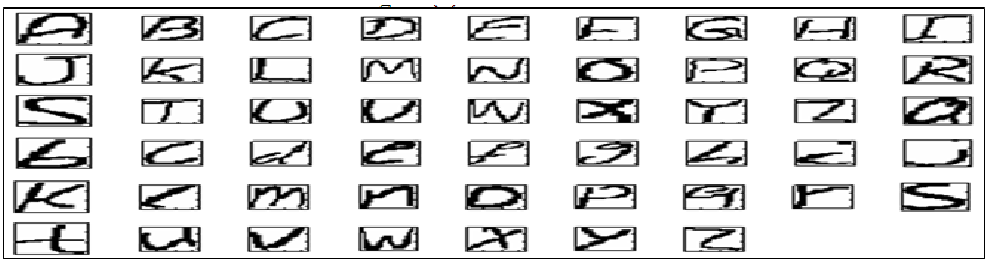


Figure (10) HW characters after the segmentation process from the form.

Each segmented character will pass through some steps (preprocessing steps) to be under the effects of same steps that the test samples will pass. These steps are binarization, thinning, thickening the strokes in order to smooth them and make all strokes approximately with the same thickness and characters resizing (size normalization) to be (32×32) pixels. These steps will make processing independent of strokes thickness and characters sizes. Figure (11) shows some of the characters of the training data set classified as their classes processed by the above steps.The attention during the data base collection was upon the quality not on quantity of the collected HW samples. The selection of the training samples process was avoiding the redundancy of characters samples. The redundancy is useless or unavailing. A large number of training HW samples may include bad HW writing styles and may make a negativity recognition process. Figure (12) shows the steps of the proposed HWRS. Figure (13) shows the block diagram of a complete proposed Handwriting Recognition System.

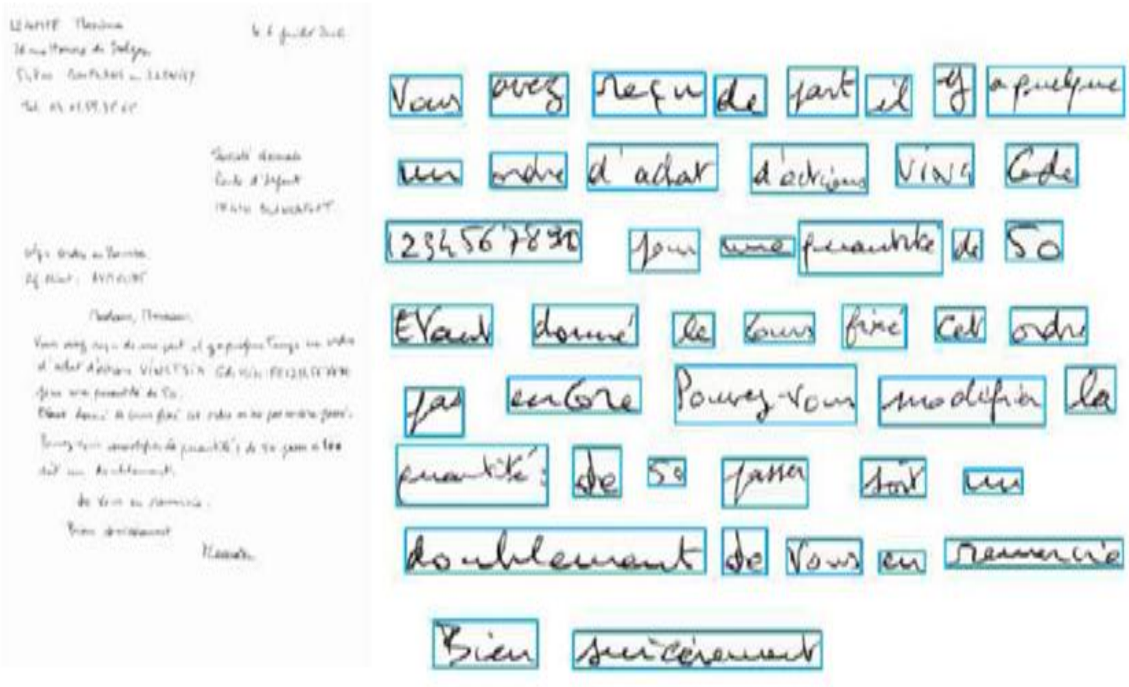


Figure (11) some mail letters handwritten of the Rimes of the training database and extractedwords data set classified as their classes and processed by the normalization steps.

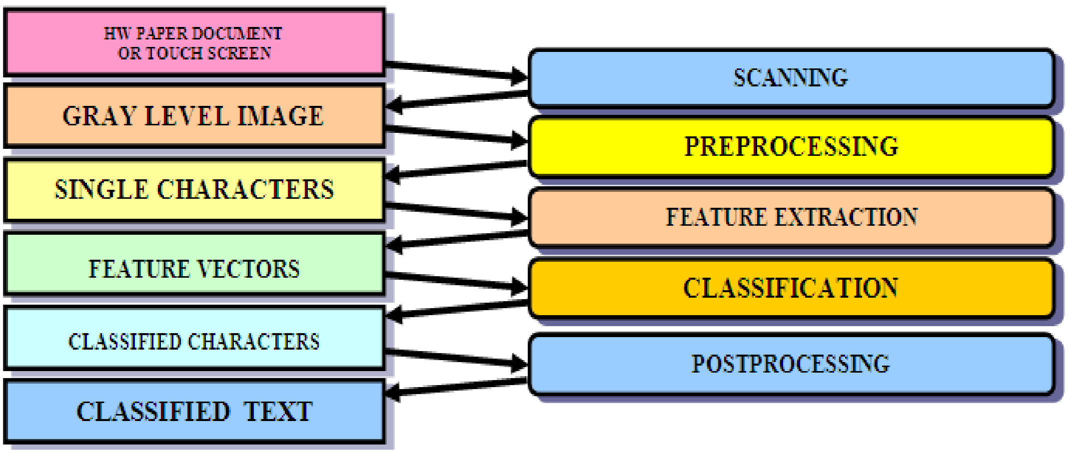


Figure (12) Steps of the proposed HWRS

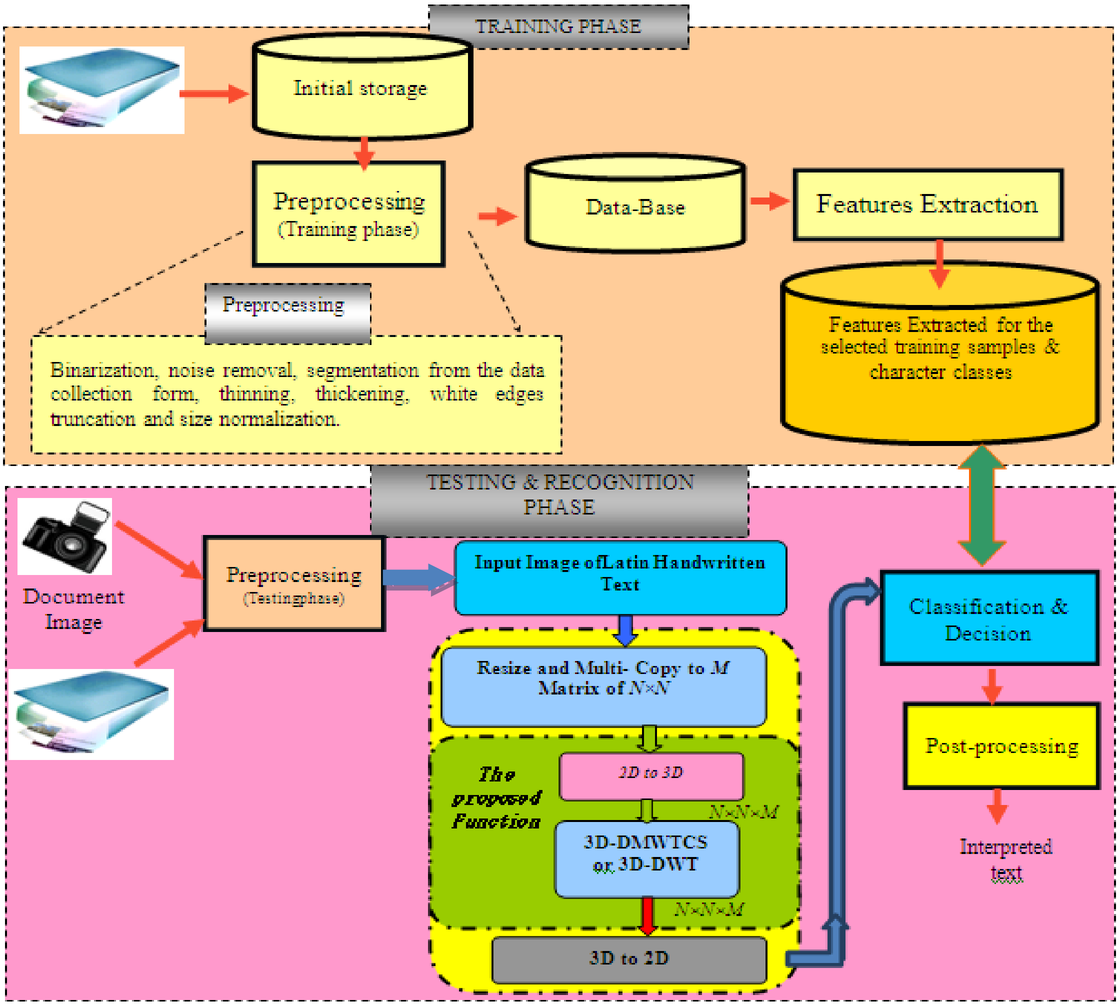


Figure (13) Block diagrams of the proposed HWRS

Figure (14) shows the raw handwritten texts written by different writers that under test in column (a) and the same texts after the recognition in column (b) by the proposed Handwriting Recognition System before the postprocessing step.

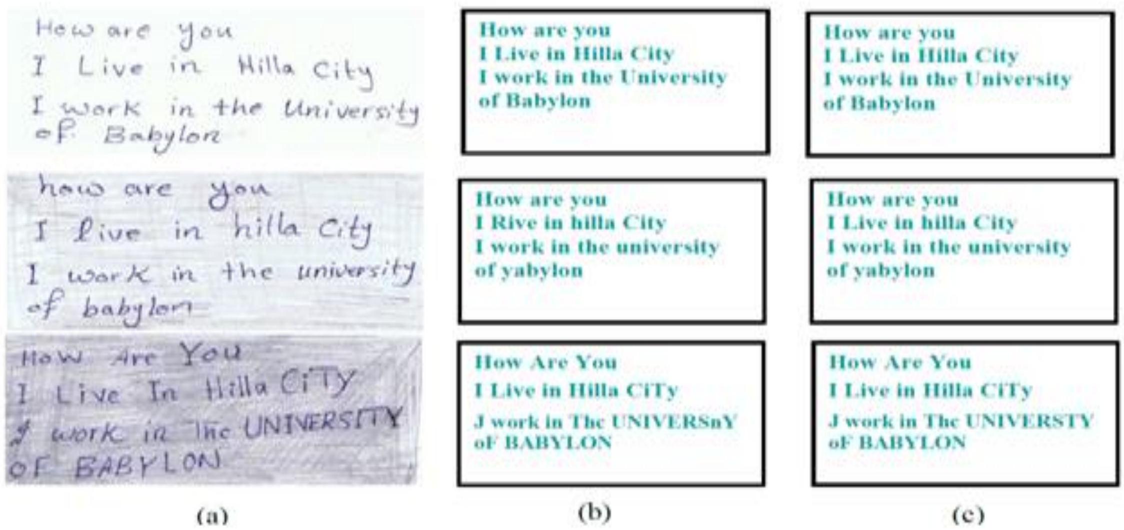


Figure (14) HW Recognition examples (a) Raw Handwritten text. (b) The recognized text Using 3D-DWT
(c)The recognized text Using 3D-DMWTCS

V. Performance Evaluation of the Proposed HWRS

The performance evaluations of the proposed systems done by depend on the Rimes database [25], [26]. This database was collected in 2006, andcontains about 12,500 documents of handwritten images collected from 1,300 volunteers. This database providesdata relative to advanced mailrooms and Panel of documents provides considerable volatility and makes the database one of the challenges. The Rimes database enabled the researchers to handle the recognition of the logo, and retrieval of documents structure,character and word recognition. Since 2007,this databasehas been evaluated several times [19], which enable participants tocompare their results. The database contained of 59,203 wordimages,and classified intothree subsets: training subset consists from 44,197 images, validationsubsetconsists of 7,542images, and testingsubset consists of7,464. In this work, the use of pre-segmented images of a particular word by the database to perform an isolated word recognition. Theproposed handwriting recognition systems are designed to be off-line character-based recognition system. Therefore; the system performance evaluation will be concerned with character recognition. This section focuses on the evaluation of the recognition task, accuracy rate, and the recognition time as well as the proposed integrated recognition system. The following evaluation experiments were made using a Laptop Toshiba of 2.2 GHz,4 dual cores, 8Gbyte internal memory RAM and the system has 2Mbyte cache memory. The proposed system was built and tested using Matlab2014a. The histograms and tables of this evaluation were achieved by using the locally collected HW samples.

1. Recognition Rate Evaluation

In order to evaluate the proposed systems, two types of experiments were performed. In the first one the system was trained with the Rimes database. The Recognition Rate (RR %) was examinedby letters of the Latin alphabetic characters. The uppercase (A-Z) and the lowercase (a-z) were been separately evaluated as shown in Figures 15 and 16. It is clear that the characters having simple patterns like C, O can be recognized more accurately (high RR) than characters with more complexity (having multiple strokes and junctions) like R, K, q etc. By comparing the results shown in Figures 15 and 16, the RR of the uppercase characters is higher than of their lowercases. The reason behind this result is that the uppercase letters are always more obvious than the lowercases since the first have more right-angled straight strokes than the curved ones.

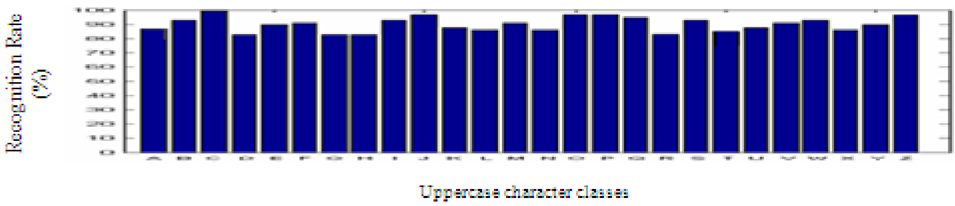


Figure 15 The Recognition Rate (%) inspected by letters of the Rimes database for uppercase letters.

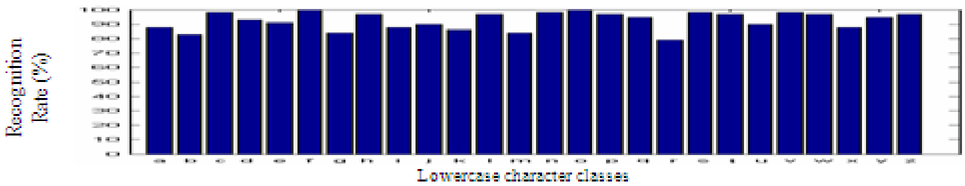


Figure 16 The Recognition Rate (%) inspected by letters of the Rimes database for lowercase letters.

The second experiment was the Recognition Rate (%) inspection for 100 testing samples for both upper and lower characters cases. Two of the test handwritten samples were the same as used for the training and they showed a RR of 100% (circled ones). Other test samples were written by the same persons who contributed in the training samples and these samples showed very high RR. The other test samples were new HW samples. The weak or bad HW test samples gave the worst results as shown in Figure 17.Table 1 summarizes the results of the two inspection experiments for 2&3D-Wavelet and 2&3D- Multiwavelet [17].

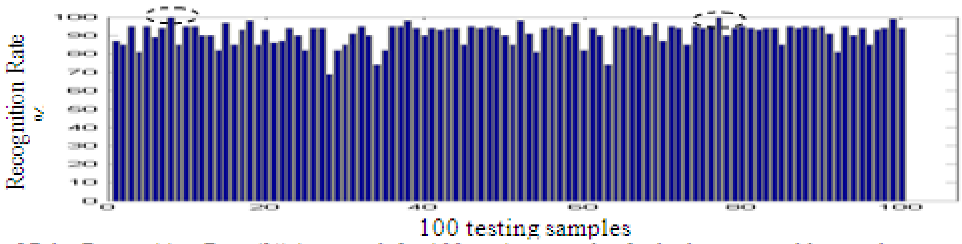


Figure 17 the Recognition Rate (%) inspected for 100 testing samples for both upper and lower characters cases.

Table 1 Recognition Rate (%) of the proposed systems.

Characters Classes	2D-DWT RR%	2D-DMWTCS RR%	3D-DWT RR%	3D-DMWTCS RR%
Uppercase (26 classes) inspected by letters	**92.61**	**94.38**	**95. 36**	**97.24**
Lowercase (26 classes) inspected by letters	**89.88**	**91.63**	**92.75**	**94.27**
Upper/lower (52 classes) inspected by writers	**91.1**	**93.005**	**94.05**	**95.76**

2. Recognition Time Computations

The main challengesare speed up the recognition process and increase recognition accuracy.Althoughthese two aspectscontradictory. It is easier to speed up recognition processwithoutlose some accuracy. But it is much more difficult to increase the speed of the recognition process andkeep or upgradethe accuracy. The recognition time of the proposed handwriting recognition system depends on many factors, The features and the specifications of the processing system like microprocessor speed and the available processing memory; size of the HW document to be recognized (number of sentences, words and characters); The scanning resolution (dpi); The degree of the HW document noise; The degree of the lines skew; degree of the characters slant; HW style (discrete or mixed styles), which effecton characters segmentation step; type and the decomposition level of the 3D-DMWT; number of the training data samples (size of the data-base); It is worth mentioning that the designed system uses some Matlab functions and subroutines that may slow down the processing speed.The goal is the minimization of the recognition time as possible. The recognition time that will be computed is per one character since the proposed HWRS is a character-based recognition. The HW document that is under test was a moderate noisy document and consists of six sentences (lines) with different skews namely L1, L2 … L6. These lines contain about 28 individual words (wo) with about 131 characters with different slants. The HW doc was scanned by flat scanner at 256 gray scales with 150-dpi resolution. The 3D-DMWTCS was by using Daubechies family at level 1 of decomposition that extracts 1024 features per character.Concerning the skew estimation and correction step, it is clear that the time required for long sentences is more than that for shorter ones. For the word segmentation, the time required to segment a line into individual words depends upon the number of the words and the characters which form it (line size). The time needed for the slant estimation and correction also depends upon the word size and its slant degree. As regard the thinning and thickening step, many experiments were made to compute the time required for this process and find the average time per character.There is interference between the segmentation and the recognition steps of the proposed system. Once the character is segmented, it will be delivered to the recognition step that includes the features extraction and the classification steps. Therefore; the needed time will be counted for these steps together.

VI. General Discussion

The proposed off-line recognition systemsare complete modular (writer-independent) for the handwritten text. Theproposedsystems deal with discrete and mixed HW styles in the upper and lower cases of Latin script lettersand it is based on character recognition. The proposed systemsusing(3D- DWT and DMWTCS)-based as a features extractor. The classifier was trained bythe Rimes database during the training phase. Patterns matching and classification is during the recognition phase. However, the presented algorithm significantly improves the word and character segmentation and then recognition enhancementusing (3D- DWT and DMWTCS). With the application of the proposed approach one avoids any effect on the characters connectivity in the word and makes a negligible change in their aspect ratios and on shape nature. Some troubles may occur when a text line includes different skews to the words but rarely the writer himself writes with hills and dips. The presented algorithmsin every case improve the word and character segmentation significantlyand then recognition enhancement. With the application of the proposed approach one avoids any effect on the characters connectivity in the word and makes a negligible change in their aspect ratios and on shape nature. The proposed method includes a successive approximation to the non-skewed version of the word directly. This direct approximation can decrease the processing time of the skew angle estimation.When a word itself includes characters with different slants but rarely the writer himself writes a word with different characters orientations, the using of the proposed approaches one can avoids any effect on the characters connectivity in the word and makes a negligible change in their aspect ratios and on its shape nature.

VII. Conclusions

The work developed in this paper aims to design an online system of high recognition accuracy of Latin handwritten types using (3D- DWT and DMWTCS).Wavelet and Multiwavelet representation has the advantage that the variations in the character shapes caused by the writing styles of different persons will cause only minor changes in the wavelet representation. The main information and features are concentrated at the approximation subband and the others are distributed in the other subband images. The recognition process depends on the features included in the approximation subband by about 53%. Using (3D- DWT and DMWTCS) for features extraction makes the recognition system need only a small training set to achieve high recognition accuracy. Regarding to the training samples (Data-Base), the collected data base depends upon the variety not on the quantity for the proposed HWRS based on (3D- DWT and DMWTCS). The selection of the training samples must avoid the redundant HW styles as possible. The relation between the number of the training samples and the Recognition Rate (RR) is not in direct proportional. The random increase in the training samples will not of necessity increase the RR; it may confuse the recognition process. Low resolution scanning (less than 100 dpi) will give erosion characters patterns. The high resolution scanning (more than 200 dpi) will increase the pixel size and improve the recognition but increase the time of the processing steps. The suitable resolution was 150 dpi. The capturing color mode has an effect on the recognition. The experiments show that the scanning with 256 gray scales is better than black/white or color mode. The proposed HWRS based on (3D- DWT and DMWTCS) system achieve an overall classification accuracy of 95.76 percent with 3D-DMWTCS and 94.05 percent with 3D-DWT using the Rimes database. These results have a gain of 2.75dB and 4.66dB for 3D-DMWTCS compare with (2D- DMWTCS andDWT) respectively.

References

[1]. Alhajj R. and Ashraf E., Sept. "Multiagents to Separating Handwritten Connected Digits" IEEE transactions on systems, man, and cybernetics—part a: systems and humans, Volume 35, Issue 5,2005.

[2]. A.-L. Bianne, C. Kermorvant, and L. Likforman-Sulem, "Context- Dependent HMM Modeling Using Tree-Based Clustering for the Recognition of Handwritten Words," Proc. SPIE DocumentRecognition and Retrieval, 2010..

[3]. Assabie Y. and Bigun J" Writer-independent offline recognition of handwritten Ethiopic characters", In: Proc. 11th ICFHR, August 19-21, Montreal, 2008.

[4]. Ballesteros J., Travieso C.M., Alonso J.B. and Ferrer M.A, " Slant estimation of handwritten characters by means of Zernike moments", IEE electronics letters vol.41 no.20, 29th September,2005

[5]. Bruce K., 2009 "Multiwavelets for Quantitative Pattern Matching" Proceedings of the 42nd Hawaii International Conference on System Sciences, pp 1- 10.

[6]. Cheng-Lin L., Jaeger S. and Nakagawa M. "Online recognition of Chinese characters: the state-of-the-art", IEEE transactions on pattern analysis and machine intelligence, vol. 26, no. 2, February 2004.

[7]. Gao X., Fen X., and Bodong L., "Construction of Arbitrary Dimensional Biorthogonal Multiwavelet Using Lifting Scheme" IEEE Transactions On Image Processing, VOL. 18, NO. 5, MAY, pp 942-955,2009.

[8]. Lorigo L., and Govindaraju V."Offline Arabic Handwriting Recognition: A Survey", IEEE transactions on pattern analysis and machine intelligence, vol. 28, no. 5, 2006.

[9]. Morita M., Sabourin R., BortolozziF.andChing Y. "Segmentation and recognition of handwritten dates: an HMM-MLP hybrid approach", International Journal on Document Analysis and Recognition IJDAR vol.6, pages: 248-262, 2004.

[10]. Oliveira L. and Sabourin R. "support vector machines for handwritten numerical string recognition", 9th international workshop on frontiers in handwriting recognition, October 26-29, Kokubunji, Tokyo, Japan, pages: 39-44, 2004.

[11]. Rodolfo P., Gabriela S., Tsang I. and George D "Text Line Segmentation Based on Morphology and Histogram Projection" 10th International Conference on Document Analysis and Recognition, pp 651-655., 2009.

[12]. Suriya K. , Kitti A., Thanatchai K. "Recognition of power quality events by using Multiwavelet-based neural networks" Elsevier Ltd., Electrical Power and Energy Systems Vol 30 ,pp 254–260, 2008.

[13]. K. Ubul, A. Adler and M. Yasin, "Multi-Stage Based Feature Extraction Methods forUyghur Handwriting Based Writer Identification," In Genetic Algorithms in Applications, InTech , 2012.

[14]. Shanker A., Tajagopalan A. "Off-line signature verification using DTW", Pattern Recognition Lett. 28, pp1407–1414, 2007.

[15]. Xue H. and V. Govindaraju, "Hidden Markov Models combining discrete symbols and continuous attributes in handwriting recognition", IEEE transactions on pattern analysis and machine intelligence, vol. 28, no. 3, March 2006.

[16]. Yousri K., Thierry P., AbdelMajid B., "A Multi-Lingual Recognition System for Arabic and Latin Handwriting" 10th International Conference on Document Analysis and Recognition, pp 1196-1200, 2009.

[17]. Matheel E., Rabab F., "Novel Video Denoising Using 3-D Transformation Techniques," International Journal of Engineering and Advanced Technology (IJEAT), Volume-2, Issue-5, June 2013.

[18]. R. Cruz, G. Cavalcanti, and T. Ren, "An ensemble classifier for offline cursive character recognition using multiple feature extraction techniques," in The 2010 International Joint Conference on Neural Networks (IJCNN),pp. 1 –8, July 2010.

[19]. M. A. Abuzaraida, A. M. Zeki and A. M. Zeki, "Segmentation Techniques for Online Arabic Handwriting Recognition: Asurvey," in 3rd International Conference on Information and Communication Technology for the Moslem World, Jakarta,Indonesia, , pp. D37-D40,2010.

[20]. R. Smith, "History of the Tesseract OCR engine: what worked and whatdidn't ," in DRR XX, San Francisco, USA, Feb. 2013.

[21]. KN. Sriraam and R. Shyamsunder. "3-D Medical Image Compression Using 3-DWavelet Coders", Digital Signal Processing, 21(1):100–109, January 2011.

[22]. Ibrayim, M., and Askar H., "Design and implementation of prototype system for online handwritten Uyghur character recognition," Wuhan University Journal of Natural Sciences,vol. 17 no. 2, pp. 131-136, April 2012.

[23]. Dreuw, P., Rybach, D., Heigold, G., and Ney, H., Guide to OCR for Arabic Scripts Chp. Part II: RWTH OCR: A Large Vocabulary Optical Character Recognition System for Arabic Scripts, Springer, London, UK, pp. 215-254,July, 2012.

[24]. M. A. Abuzaraida, A. M. Zeki and A. M. Zeki, "Feature Extraction Techniques of Online Handwriting Arabic Text Recognition," In Proceeding of the 5th International Conference on Information and Communication Technology for the Muslim World (ICT4M), pp. 1-7. 2013,

[25]. http://rimes.it sudparis.eu/, 2010.

[26]. E. Augustin, M. Carre, E. Grosicki, J.-M. Brodin, E. Geoffrois, and F. Preteux, "Rimes Evaluation Campaign for Handwritten Mail Processing," Proc. Int'l Workshop Frontiers in Handwriting Recognition, pp. 231-235, 2006.