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Improving the Recognition of Handwritten Characters using Neural Network through Multiresolution Technique and Euclidean Distance Metric

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ABSTRACT
Good recognition accuracy can be achieved through a combination of multiple classifiers rather than a single classifier. The present paper deals with the handwritten English character recognition using multiresolution technique with Discrete Wavelet Transform (DWT) and Euclidean Distance Metric (EDM). Recognition accuracy is improved by learning rule through the Artificial Neural Network (ANN) along with Euclidean distances in case of misclassification. Handwritten characters are classified into 26 pattern classes based on appropriate property i.e. shape. Features of the handwritten character images are extracted by DWT used with appropriate level of multi resolution technique and then each pattern class is characterized by a mean vector. Distances from unknown input pattern vector to all the mean vectors are computed by EDM. Minimum distance determines the class membership of input pattern vector.EDM provides a good recognition accuracy of 90.77%. In case of misclassification, the learning rule through ANN improves the recognition accuracy to 95.38% by comparing the generated recognition scores and then product of recognition scores with Euclidean distances further improves the recognition accuracy to 98.46%. Weight matrix of the misclassified class is computed using the learning rule of ANN, then the misclassified input pattern vector is fused with the computed weight matrix to generate the recognition score. Maximum score corresponds to the recognized input character.

General Terms
Discrete wavelet transform, Euclidean distance metric.

Keywords
Learning rule, Feature extraction, Handwritten character recognition, Bounding box.

1. INTRODUCTION
The shape variation of handwritten characters causes the misclassification, therefore multiresolution of handwritten characters is important for the correct recognition. Using multiresolution [1,2] we can reduce the size of characters without losing the basic characteristics of characters, therefore more accuracy and better recognition rate can be achieved using multiresolution. The extensive applications of Handwritten Character Recognition (HCR)in recognizing the characters in bank checks and car plates etc. have caused the development of various new HCR systems such as Optical Character Recognition (OCR) system. There are so many techniques of pattern recognition such as template matching, neural networks, syntactical analysis, wavelet theory, hidden Markov models, Bayesian theory and minimum distance classifiers etc. These techniques have been explored to develop robust HCR systems for different languages such as English (Numeral) [3-5], Farsi [6], Chinese (Kanji) [7,8], Hangul (Korean) scripts [9], Arabic script [10] and also for some Indian languages like Devnagari [11], Bengali [12], Telugu [13-15] and Gujarati [16]. HCR is an area of pattern recognition process that has been the subject of considerable research interest during the last few decades. Machine simulation of human functions has been a very challenging research field since the advent of digital computers [17]. The ultimate objective of any HCR system is to simulate the human reading capabilities so that the computer can read, understand, edit and do similar activities as human do with the text. Mostly, English language is used all over the world for the communication purpose, also in many Indian offices such as railways, passport, income tax, sales tax, defense and public sector undertakings such as bank, insurance, court, economic centers, and educational institutions etc. A lot of works of handwritten English character recognition [3-5,17] have been published but still optimal training time and high recognition accuracy of handwritten English character recognition is an open problem. Therefore, it is of great importance to develop automatic HCR system for English language. In this paper, efforts have been made to develop automatic HCR system for English language with high recognition accuracy and minimum classification time. HCR is a challenging problem in pattern recognition area. The difficulty is mainly caused by the large variations of individual writing style. To get high recognition accuracy and minimum classification time for HCR, we have appliedmulti resolution technique using DWT[1,2] and EDM[18,19]. Recognition accuracy is improved by learning rule used by the ANN [20,21]and further its product with Euclidean distances in case of misclassification. Experimental results show that the proposed method used in this paper for handwritten English character recognition is giving a very high recognition accuracy and minimum classification time. In what follows we briefly describe the different techniques used in our paper.

2. HISTORY OF RELATED WORKS

The researchers in the field of pattern recognition are referred to survey papers and text books for good exposure of the HCR system. In the earlier works, the automatic recognition of characters can be classified into two categories- recognition of the machine-printed characters and the recognition of handwritten characters [17]. Machine-printed character recognition systems generally used template matching in which an image is compared to a library of images. Handwritten characters used low-level image processing techniques on the binary image to extract feature vectors, which are then fed to statistical classifiers [17]. Now, writing has been the most natural mode of collecting, storing, and transmitting information in this world, it is used for communication among humans and also for communication of humans and computer systems [17]. The origins of character recognition can be found in 1870 when Carey invented the retina scanner, which is an image transmission system using a mosaic of photocells, and later in 1890 when Nipkow invented the sequential scanner which was a major breakthrough both for modern television and reading machines [22-25]. One of the earliest attempts in character recognition was that of the Russian scientist Tyuring in 1900 where he described a method to develop an aid for the visually handicapped [17,22]. Fourier d'Albe's Otophone in 1912 and Thomas' tactile "relief" device in 1926 were the next attempts in character recognition. In the middle of the 1940s, the first character recognizers were developed with the development of digital computers [17,26]. The commercial character recognizers appeared in the 1950s, when electronic tablets capturing the x–y coordinate data of pen-tip movement was first introduced. This innovation motivated the researchers to work on the on-line handwritten character recognition problem [17,27]. The commercial character recognition systems can be divided into four generations on the basis of versatility, robustness and efficiency. The first generation systems include the characteristics of constrained letter shapes which the character recognition systems read. Such machines were available in the beginning of the 1960s. IBM 1418 was the first widely commercialized character recognition system of this generation, which was designed to read a special IBM font, 407 [28,29]. The second generation is characterized by the recognition capabilities of a set of regular machine-printed characters as well as hand-printed characters. IBM 1287 was the first and famous character recognition system (restricted to numerals only) in this generation, which was exhibited at the 1965 New York world fair. Such machines appeared in the middle of 1960s to early 1970s [28,29]. This machine combined analog and digital technology in terms of hardware configuration. The first automatic letter-sorting machine for postal code numbers of Toshiba was also developed during this period. The methods were based on the structural analysis approach [29]. The third generation can be characterized by the character recognition of characters having poor print quality and hand-printed characters for a large data set of characters. Such machines were available during the decade 1975 to 1985 [28-31]. The fourth generation can be characterized by the character recognition of complex documents including text, graphics, table and mathematical symbols, unconstrained handwritten characters, color document, low-quality noisy documents like photocopy and fax etc. [29]. Structural approaches in addition to the statistical methods [32,33] and shape recognition techniques were used during 1980 to 1990. These techniques suffered from the lack of powerful computer system and data acquisition devices. The character recognition systems really progressed during the period after 1990. New development tools and methodologies were used, which are empowered by the continuously growing information technologies. Image processing and pattern recognition techniques were used in the early 1990s [17]. Nowadays, more powerful computers and more accurate electronic equipments such as scanners, cameras, and electronic tablets are available. The methodologies such as neural networks (NNs), hidden Markov models (HMMs), support vector machines (SVMs), fuzzy set reasoning, minimum distance classifiers and natural language processing are used for the classification. In character recognition literature that has appeared so far, each recognizer is solely dedicated to a specific alphabet. So far we have seen systems that can recognize English (Latin), Japanese, Chinese, Cyrillic (Russian), Arabic, Indian and Greek characters [22]. Wunsch and Laine [34] used wavelet descriptors for multiresolution to recognized the hand printed characters in 1995. Wunsch and Laine described a character recognition system that relies upon wavelet descriptors to simultaneously analyze character shape at multiple levels of resolution. Shostakovich and Thrasher [35] described two algorithms at the core of the new Kodak Image link ™ OCR numeric and alphanumeric handprint modules in 1996. Lee et al. [36] proposed two stages of character recognition system: a feature extraction stage for extracting multiresolution features with wavelet transform and a classification stage for classifying unconstrained handwritten numerals with a simple multilayer cluster neural network in 1996. In 1997, Morns and Dlay [37] used Fourier descriptors and a new form of dynamic semi-supervised neural network called the Dynamic Supervised Forward-Propagation Network (DSFPN), although based upon the unsupervised Counter propagation Network (CPN), trains using a supervised algorithm. Liu et al. [38] proposed a neural network architecture and multi resolution locally expanded high order neural network (MRLHONN) to solve the problem of handwritten numeral recognition in 1997. Jun et al. [39] used multiresolution hierarchy through wavelet transform for the recognition of handwritten Chinese characters in 1997. Chen et al. [3] developed a handwritten numeral recognition descriptor using multi wavelets and neural networks based on contour of the numeral in 2003. Pujari et al. [40] developed an intelligent character recognizer for Telugu scripts using wavelet multi-resolution analysis for the purpose extracting features and associative memory model to accomplish the recognition tasks. Chen et al. [41] proposed an invariant pattern recognition descriptor by using the radon transform, the dual-tree complex wavelet transform and the Fourier transform in 2009. Desai [16] proposed an optical character recognition (OCR) system for handwritten Gujarati numbers using multi layered feed forward neural network in 2010.

3. THE PROPOSED HCR SYSTEM

A complete flowchart of handwritten English character recognition system is given in the following figure [22,29,42].

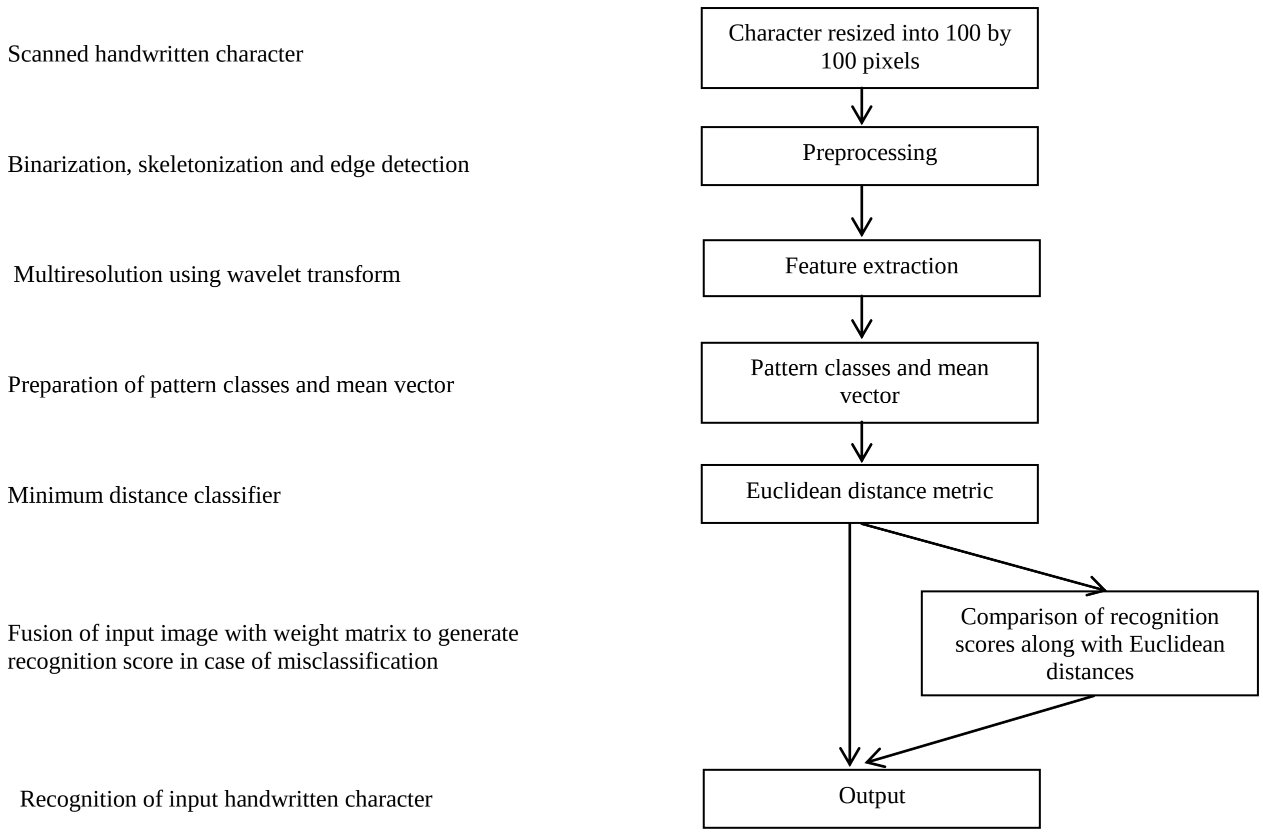


Figure 1: A flowchart of handwritten character recognition system

4. FEATURE EXTRACTION USING WAVELET BASED MULTIRESOLUTION

4.1 Data collection

First of all, the data of English characters is collected in the written form on blank papers by people of different age groups. These characters are written by different blue/black ball point pen. The collected samples of handwritten characters are scanned by scanner into JPEG format on 600 dpi [43]. Then all the characters are separated and resized into 100 by 100 pixel images. The example of the samples of handwritten characters is given below.

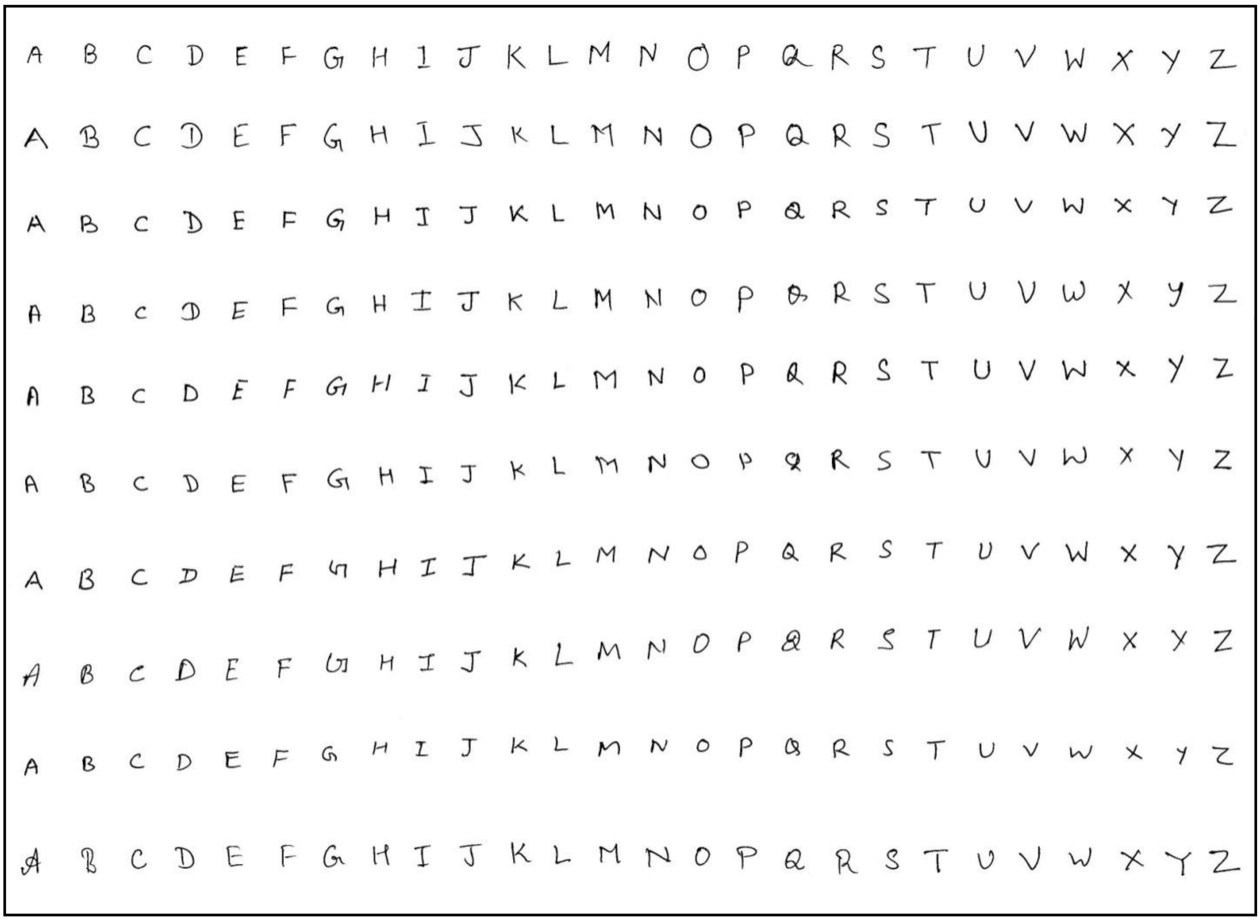


Figure 2: Sample of characters written by different persons

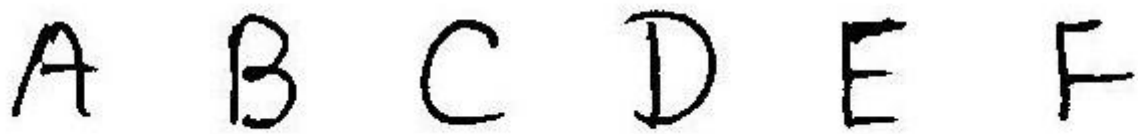


Figure 3: Some original handwritten character images separated from the sample

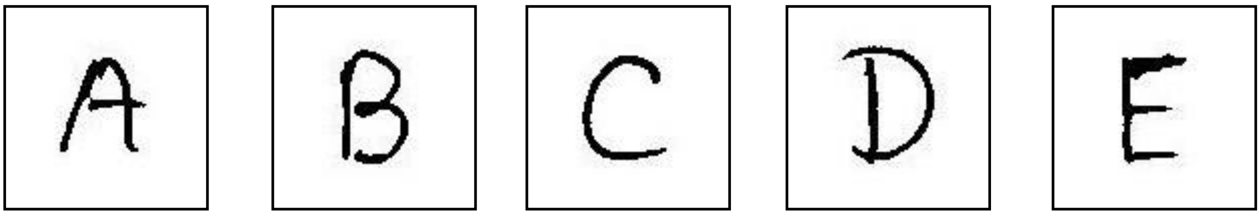


Figure 4: Some handwritten characters resized into 100 by 100 pixel images

4.2 Preprocessing

The separated RGB character images of 100 by 100 pixel resolution are converted into grayscale images and then the grayscale images is again converted into binary images using appropriate gray scale thresh holding. Now, binary image is thinned using skeletonization infinite times. Edges of these thinned images are detected using appropriate thresh holding and then further dilated using appropriate structure element [1,44,45]. These steps are known as preprocessing. The preprocessing steps are given in the following figure.

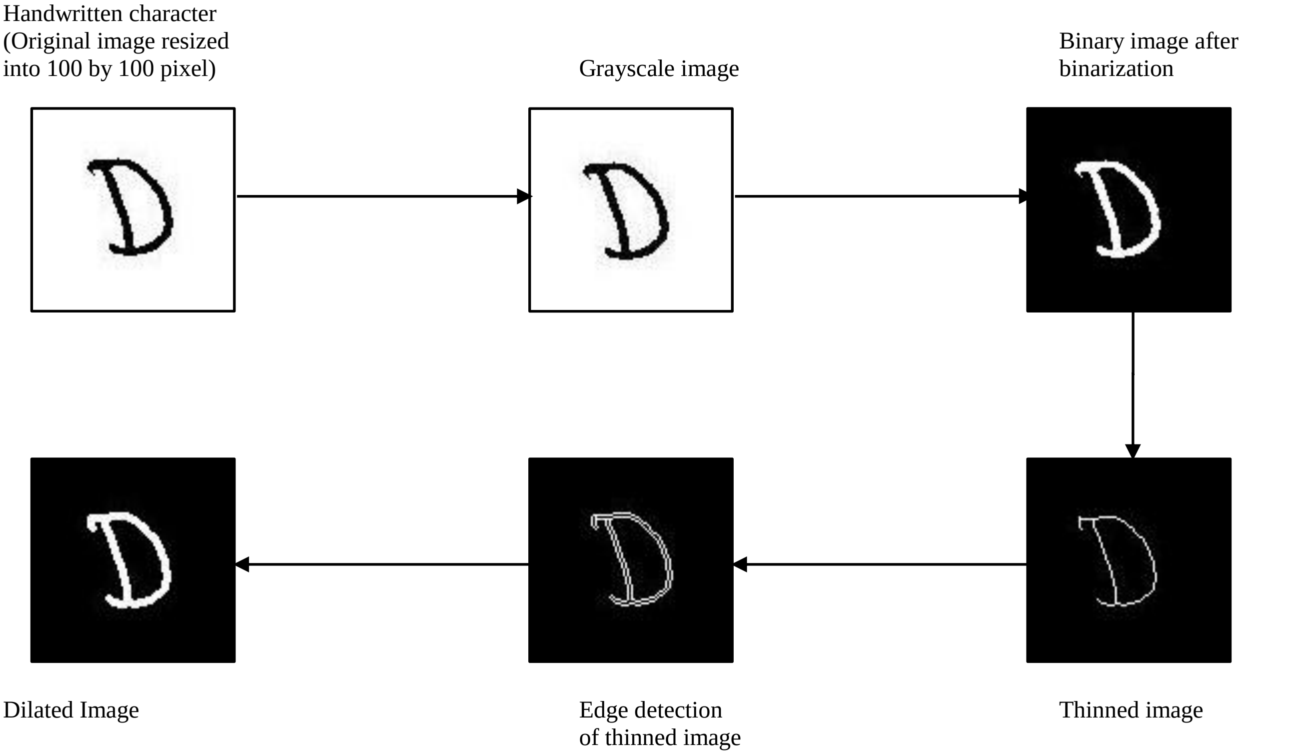


Figure 5: Results of preprocessing steps applying on a handwritten character

4.3 Discrete wavelet transform

Representation of images in various degrees of resolution is known as multi resolution process. In multiresolution process, images are subdivided successively into smaller regions [34,46]. Wavelets are used as the foundation of multiresolution process. In 1987, wavelets are first shown to be the foundation of a powerful new approach to signal processing and analysis called multiresolution theory [2]. Multiresolution theory is concerned with the representation and analysis of images having more than one resolution. We use this technique in HCR. Multiresolution technique is applied on the preprocessed images and this is achieved by applying DWT [46,47]. Here, pattern vectors are generated that are used for training purpose for both EDM and ANN. DWT has given good results in different image processing applications [3,7,36,47,48]. It has excellent spatial localization and good frequency localization properties that makes it an efficient tool for image analysis. There are different multiresolution techniques such as image pyramids, subband coding and DWT. We have used DWT in this paper. DWT maps a function of a continuous variable into a sequence of coefficients. If the function being expanded is a sequence of numbers, like samples of a continuous function *f(x, y)*, the resulting coefficients are called the DWT of *f(x, y)* [1,2]. DWT of an image *f(x, y)* of size $M \times N$ is defined as

$$W_{\varphi}(j_0,m,n)=\frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\varphi_{j_0,m,n}(x,y) \qquad (4.3.1)$$

$$W_{\psi}^{i}(j,m,n)=\frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\psi_{j,m,n}^{i}(x,y), \quad i=\{H,V,D\} \qquad (4.3.2)$$

for $j \geq j_0$ and

$$f(x,y)=\frac{1}{\sqrt{MN}}\sum_{m}\sum_{n}W_{\varphi}(j_0,m,n)\varphi_{j_0,m,n}(x,y) + \frac{1}{\sqrt{MN}}\sum_{i=H,V,D}\sum_{j=j_0}^{\infty}\sum_{m}\sum_{n}W_{\psi}^{i}(j,m,n)\psi_{j,m,n}^{i}(x,y) \qquad (4.3.3)$$

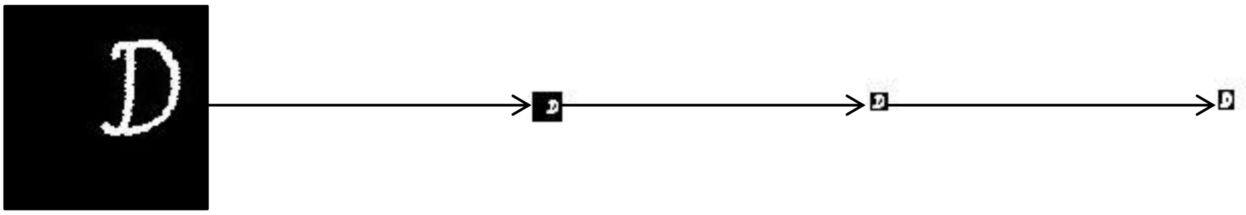
where, j_0 is an arbitrary starting scale and

$$\varphi_{j,m,n}(x,y) = 2^{j/2}\,\varphi(2^j x - m, 2^j y - n)$$
(4.3.4)

and

$$\psi^i_{j,m,n}(x,y) = 2^{j/2}\,\psi^i(2^j x - m, 2^j y - n),$$
i = {H, V, D}(4.3.5)

where index i identifies the directional wavelets that assumes the values H,V and D. Wavelets measure functional variations such as intensity or gray-level variations for images along different directions. Directional wavelets are ψ^H, ψ^V and ψ^D. ψ^H measures variations along columns (like horizontal edges), ψ^V measures variations along rows (like vertical edges) and ψ^D measures variations along diagonals [1,2].Eqs. (4.3.4) and (4.3.5) define the scaled and translated basis functions. $f(x, y)$, $\varphi_{j,m,n}(x,y)$ and $\psi^i_{j,m,n}(x,y)$ are functions of the discrete variables x = 0, 1, 2, 3, …, M-1 and y = 0, 1, 2, 3, ..., N-1. The coefficients defined in Eqs. (4.3.1) and (4.3.2) are usually called approximation and detail coefficients, respectively. $W_\varphi(j_0, m, n)$ Coefficients define an approximation of $f(x, y)$ at scale j_0. $W^i_\psi(j,m,n)$ coefficients add horizontal, vertical and diagonal details for scales $j \geq j_0$. We normally let $j_0 = 0$ and select $N = M = 2^j$ so that $j = 0, 1, 2, 3, \ldots, J - 1$ and m, n = 0, 1, 2, 3, …, 2^j - 1 [1,2]. Eq. (4.3.3) shows that $f(x, y)$ is obtained via the inverse DWT for given W_φ and W^i_ψ of Eqs. (4.3.1) and (4.3.2).DWT can be implemented using digital-filters and down-samplers [1,2]. We have used MATLAB for programming [44]. DWT is applied three times on each dilated character image generated in the second part, and finally the reduced character image is captured into a bounding box and then, resized into 10 by 8 pixels image. The effect of multi resolution on the dilated character obtained in second part is given in the following fig. 6.



Dilated image | Character image after multi resolution | Character image captured into bounding box | Resized into 10 by 8

Figure 6: Character image after applying multiresolution and captured into bounding box

5. CLASSIFICATION AND IMPROVING RECOGNITION ACCURACY

5.1 Classification using EDM

In this part, EDM is used to classify the unknown input pattern vectors. Pattern vectors generated in the third part are grouped into 26 classes based on their similar properties. Each class contains pattern vectors and mean vector of each class is computed i.e. each class is characterized by its mean vector. We prepare such a matrix whose rows are these mean vectors. Distance from input pattern vector to each mean vector is computed and minimum distance shows the class of input pattern vector to which it belongs [17, 22, 29, 49, 50].

The EDM is significantly simplified under the following assumptions [20,21]:

- The classes are equiprobable.
- The data in all classes follow Gaussian distributions.
- The covariance matrix is the same for all classes.
- The covariance matrix is diagonal and all elements across the diagonal are equal.

Given an unknown pattern vector x, assign it to class w_i if

$$\|x - m_i\| \equiv \sqrt{(x-m_i)^T (x-m_i)} \leq \|x - m_j\|, \quad \forall i \neq j \tag{5.1.1}$$

EDM is often used, even if we know that previously stated assumptions are not valid, because of its simplicity. It assigns a pattern to the class whose mean is closed to it with respect to the Euclidean norm [44].

Suppose, p_i shows the pattern vector, w_j shows the pattern class, m_j shows the mean vector of j^{th} class and x_i shows the component of pattern vector. Mean vector is used as the representative of the class of vectors :

$$m_j = \frac{1}{N_j}\sum_{p_i \in w_j} p_i \quad , \; j = 1, 2, 3, \ldots\ldots\ldots\ldots\ldots, W \text{ and}$$

$$i = 1, 2, 3, \ldots\ldots\ldots\ldots\ldots, N_j \quad (5.1.2)$$

Where, N_j is the number of pattern vectors in the class w_j and W is the number of pattern classes. Euclidean distance classifier is defined as:

$$D_j(x) = \left\| x - m_j \right\| \equiv \sqrt{(x-m_j)^T (x-m_j)}$$

$$, \; j = 1, 2, 3, \ldots\ldots\ldots\ldots\ldots, W \quad (5.1.3)$$

Where, x is the input pattern vector and $D_j(x)$ is the distance from x to mean vector of the j^{th} class. Input pattern vector x will belong to class w_j if $D_j(x)$ is the smallest distance. The Euclidean distancesfrom the unknown input characters of a test sample of handwritten characters to the mean vector of each class are given in the following Tab. 1 and Tab. 2.

Table 1: Computed Euclidean distances from the unknown input characters 'A' to 'M' of a test sample of handwritten characters.

	Unknown input characters 'A' to 'M'												
Characters with respect to which Euclidean distances are computed	A	B	C	D	E	F	G	H	I	J	K	L	M
A	**7.334**	12.226	14.663	14.720	11.244	13.388	10.019	12.403	14.909	14.043	12.901	15.468	10.863
B	10.274	**9.942**	13.929	11.935	9.038	13.424	9.414	12.776	13.407	11.356	13.515	13.438	11.632
C	12.862	13.981	**9.226**	14.246	10.863	14.084	12.542	15.737	13.046	12.918	15.104	11.429	12.673
D	11.047	15.419	13.491	**8.348**	10.914	14.192	12.557	16.481	10.061	11.870	16.353	14.411	10.551
E	12.022	12.251	13.182	14.354	**6.818**	9.752	10.030	12.480	13.007	12.260	14.006	11.415	11.825
F	10.488	13.133	14.901	16.502	9.659	**8.716**	11.627	12.158	15.507	14.352	13.360	12.858	10.980
G	10.339	13.850	14.073	13.545	11.373	14.902	**6.412**	13.611	13.486	12.709	14.986	12.861	11.627
H	9.625	14.532	14.791	18.332	13.453	13.681	13.047	15.209	19.218	14.850	15.157	14.071	12.129
I	14.162	16.110	13.553	9.693	11.226	14.713	12.437	15.294	**5.233**	11.935	16.735	15.467	13.376
J	14.599	15.657	14.662	12.126	12.235	12.863	12.819	14.573	8.502	**10.922**	16.953	16.281	13.168
K	11.488	14.378	13.626	16.576	11.688	13.766	11.419	**12.084**	15.286	16.161	**10.385**	12.518	11.216
L	15.910	14.829	13.654	18.253	12.221	15.263	13.017	15.512	16.442	15.173	15.439	**6.523**	15.154
M	11.134	16.610	13.012	16.180	14.876	13.924	13.616	15.721	16.933	16.587	14.781	15.127	**8.352**
N	10.622	15.576	13.734	17.168	13.560	15.088	11.414	14.704	17.671	16.384	13.461	12.966	11.580
O	11.211	12.695	11.075	12.404	11.825	14.719	11.967	15.735	13.979	11.426	15.709	12.503	10.854
P	10.057	14.523	14.321	15.914	10.102	9.569	12.855	14.101	15.586	14.531	15.445	14.447	11.276
Q	10.811	13.790	13.526	12.265	9.948	14.176	7.660	13.091	11.559	12.463	14.999	13.793	11.445
R	11.302	13.675	14.709	15.200	10.178	12.369	9.340	12.489	13.914	14.420	12.964	13.110	10.957
S	10.729	14.603	11.961	11.088	10.246	14.181	11.164	15.062	10.663	12.241	14.227	15.086	12.579
T	14.421	17.284	15.585	12.968	13.389	13.298	13.902	15.350	9.069	12.911	17.211	16.516	12.814
U	14.060	15.352	12.251	16.388	13.419	16.473	13.732	17.211	17.185	12.925	17.668	10.864	13.916
V	13.923	16.828	14.015	15.999	13.479	16.290	13.228	16.298	15.809	14.651	18.272	11.957	15.247
W	14.219	17.416	14.079	17.284	14.158	17.299	12.253	16.104	17.186	16.074	16.934	13.271	14.322
X	10.909	16.010	14.515	14.791	12.287	14.148	12.383	13.617	13.105	15.095	12.800	15.177	11.759
Y	13.007	17.305	15.079	14.045	14.365	14.719	13.768	15.514	12.811	13.211	16.827	15.753	12.803
Z	12.785	14.555	13.301	11.726	10.819	13.614	12.409	14.880	8.873	11.391	15.752	13.919	11.904

Table 2: Computed Euclidean distances from the unknown input characters 'N' to 'Z' of a test sample of handwritten characters.

Characters with respect to which Euclidean distances are computed	Unknown input characters 'N' to 'Z'												
	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
A	13.555	16.687	10.494	12.492	10.160	13.108	14.101	16.158	14.464	13.674	11.843	15.983	16.129
B	13.812	13.485	11.183	12.077	10.187	12.529	14.696	14.058	14.667	13.097	13.250	16.213	14.974
C	15.999	14.257	13.406	9.599	10.116	10.963	12.663	14.234	14.658	12.598	15.575	16.388	15.505
D	15.686	12.727	12.735	13.219	11.472	10.050	10.291	14.453	11.832	12.241	13.348	14.399	14.466
E	14.630	13.148	9.023	11.210	8.958	12.669	12.156	13.683	13.768	11.864	13.735	17.328	12.677
F	14.517	14.995	8.086	13.167	10.139	14.697	12.430	15.102	14.189	13.811	14.350	17.336	14.869
G	13.124	13.333	11.257	10.065	10.906	12.553	13.643	12.428	11.214	10.720	13.285	15.405	15.948
H	10.517	15.767	11.093	15.749	13.463	15.003	15.541	12.521	14.079	12.700	15.185	15.880	16.947
I	17.992	16.126	14.111	11.784	10.025	8.265	9.865	16.514	12.411	13.709	11.433	14.834	13.555
J	18.747	15.066	12.790	12.248	11.714	11.603	10.575	15.999	14.255	14.918	12.179	15.246	12.246
K	11.693	17.909	11.696	13.594	8.833	12.708	12.715	15.245	13.201	12.133	12.269	17.871	16.787
L	15.747	15.556	15.202	12.202	12.739	14.470	14.585	12.569	13.967	10.878	16.594	17.844	16.152
M	11.176	16.271	10.624	14.590	12.835	14.450	13.306	14.167	14.049	14.478	13.710	15.904	16.754
N	**8.758**	15.879	11.826	14.793	12.131	13.303	14.407	11.928	11.684	10.486	14.954	15.974	18.195
O	14.844	**10.670**	12.464	11.446	12.205	12.098	13.787	11.223	13.609	11.909	15.744	13.481	16.195
P	14.947	15.152	**5.967**	14.033	10.616	14.050	12.001	15.594	13.675	13.900	15.132	17.101	14.564
Q	13.796	14.374	10.721	**8.843**	9.341	12.015	13.734	14.368	12.403	12.116	12.901	15.868	15.577
R	12.964	15.617	9.187	11.401	**7.853**	13.011	13.141	15.600	13.742	13.248	13.007	17.645	15.509
S	13.612	15.087	13.111	13.165	8.841	**6.652**	11.574	15.035	12.742	12.730	12.354	15.537	14.889
T	18.443	16.891	12.941	13.525	11.568	11.382	9.326	17.142	12.548	15.433	12.268	14.136	14.290
U	13.442	12.109	13.785	14.355	14.523	13.094	14.789	**7.111**	11.933	8.538	17.095	13.730	16.348
V	14.478	16.301	13.631	14.205	12.845	12.301	13.533	11.703	**7.795**	7.562	16.757	13.740	17.069
W	12.973	16.710	13.368	14.212	13.499	13.985	15.053	12.435	12.614	**6.992**	16.055	16.826	17.203
X	12.818	18.536	12.440	14.302	10.272	11.612	11.512	16.244	12.660	13.027	**9.335**	16.623	15.389
Y	15.256	16.904	13.460	14.696	13.048	11.595	11.576	14.191	10.200	13.624	12.154	**11.662**	15.650
Z	17.522	15.561	12.918	11.203	10.290	10.713	**9.245**	15.659	13.648	13.125	10.275	15.425	**11.801**

In the above tables, the minimum Euclidean distances are shown as bold. As we can see that all the characters except the characters 'H' and 'T' are recognized successfully. For example, suppose that the unknown input character is 'A' then we can see from Tab. 1 that minimum Euclidean distance corresponds to the character 'A', hence the EDM correctly recognize the input character as 'A'. Different character images are tested with this proposed HCR system and we find that the system has a high recognition accuracy. But there are some mismatches by the EDM, these are for the characters 'H' and 'T'. The character 'H' is wrongly recognized as 'K' and the character 'T' is wrongly as 'Z'. To improve the recognition accuracy further, the mismatched characters are compared by using recognition scores along with Euclidean distances [27-29]. The method used for this purpose is described in the next part.

5.2 Improving recognition accuracy using ANN

Neural networks are the simplified models of the biological neuron system. Neural networks are parallel distributed processing systems that are made up of highly interconnected computing elements called neurons. Neurons have the ability to learn and thereby acquire knowledge and make it available for use. The technology, which has been developed as simplified imitation of computation by neurons of human brain, has been termed Artificial Neural Systems (ANS) technology or ANN or simply neural networks [18]. This has been used as an inductive tool in the character recognition process. In this part, the learning rule used by the ANN is described with examples.To store the information about the handwritten characters, character pattern vectors of the same class are introduced to the ANN one by one. With the help of these character patterns the ANN generates weight matrixfor all the classes [51-53]. Each weight matrix is of size 10 × 8 pixels. We denote the weight matrix for the k^{th} character by WM_k. For the learning process, each pixel of the weight matrix WM_k is initialized with zero. When a character pattern is introduced to the ANN, the values of the weight matrix will be changed by the ANN by using the following rule [45].

- If the value of the $(i, j)^{th}$ pixel of the character pattern is 1 then add +1 to $WM_k(i, j)$.
- If the value of the $(i, j)^{th}$ pixel of the character pattern is 0 then add -1 to $WM_k(i, j)$.

The above rules are repeated for different pattern vectors of the same class and the weight matrix for all the classes so formed are stored in the neural network to improve the recognition accuracy. The weight matrix formed after introducing 15 pattern vectors of the handwritten characters 'H' and 'T' is given below:

$$\begin{pmatrix} 13 & 13 & 13 & 15 & 15 & 15 & 11 & 3 \\ 15 & 15 & 15 & 15 & 15 & 15 & 13 & 5 \\ 15 & 15 & 15 & 15 & 15 & 15 & 15 & 5 \\ 15 & 15 & 15 & 15 & 15 & 15 & 15 & 5 \\ 15 & 15 & 15 & 15 & 15 & 15 & 15 & 5 \\ 15 & 15 & 15 & 15 & 15 & 15 & 15 & 5 \\ 15 & 15 & 15 & 15 & 15 & 15 & 15 & 5 \\ 15 & 15 & 15 & 13 & 15 & 15 & 15 & 5 \\ 11 & 11 & 13 & 11 & 11 & 9 & 7 & 3 \\ 3 & 3 & 3 & 3 & 3 & 3 & 1 & -3 \end{pmatrix} \qquad \begin{pmatrix} 11 & 13 & 13 & 15 & 15 & 15 & 15 & 13 \\ 15 & 15 & 15 & 15 & 15 & 15 & 15 & 13 \\ 15 & 15 & 15 & 15 & 15 & 15 & 15 & 13 \\ 15 & 15 & 15 & 15 & 15 & 15 & 15 & 13 \\ 9 & 15 & 15 & 15 & 15 & 15 & 15 & 5 \\ -5 & 13 & 15 & 15 & 15 & 13 & 11 & -13 \\ -7 & 13 & 15 & 15 & 15 & 13 & 9 & -15 \\ -9 & 13 & 15 & 15 & 13 & 13 & 7 & -15 \\ -9 & 11 & 15 & 15 & 13 & 13 & 7 & -15 \\ -11 & 7 & 11 & 11 & 9 & 9 & 1 & -15 \end{pmatrix}$$

$$WM_{'H'} \qquad\qquad WM_{'T'}$$

Figure 7: Weight matrix for the handwritten character 'H' and 'T'.

Here, the method used by the ANN to recognize the misclassified characters is described [16,54,55]. The weights of different character patterns $WM_k{}^{'s}$ generated in this part are used for the recognition of the misclassified characters. Suppose the misclassified character is denoted by *TV*. Now,it is fused with the weight matrices WM_k of different characters to generate the recognition scores. We denote the recognition score for the k^{th} weight matrix with respect to the misclassified character by RS_k^{tv}.The recognition score for the test image is generated by using the following equation:

$$RS_k^{tv} = \frac{\sum_{i=1}^{10}\sum_{j=1}^{8} TV(i, j) * WM_k(i, j)}{\varphi(WM_k)} \qquad (5.2.1)$$

where $\varphi(WM_k)$ is the sum of all the positive values of WM_k.The maximum value of the RS_k^{tv} corresponds to the recognized character. After testing with large amount of samples of handwritten characters, we observe that the mismatches occur among the similar type of characters. Now, recognition scores of the misclassified characters with respect to the weight matrices for different characters 'A' to 'Z' are generated using the Eq. (5.2.1). These scores are used to improve the recognition accuracy in case of misclassification. The recognition scores of the misclassified characters are given in the following Tab. 3.

Table 3: Generated recognition score of the misclassified characters.

Characters with respect to which recognition scores are generated	Misclassified characters									
	H	T	B	D	J	E	I	K	S	X
A	1.1875	0.7941	1.4715	1.3444	0.8731	1.4534	1.1764	1.0853	1.3835	1.3644
B	1.1824	0.8042	**1.4461**	1.3687	0.8793	**1.4410**	1.1633	1.0786	**1.3775**	1.3638
C	0.9639	0.6623	1.1955	1.1238	0.7247	1.1881	0.9514	0.9066	1.1253	1.1131
D	1.0445	0.7148	1.2710	**1.1747**	0.7918	1.2791	**1.0340**	0.9704	1.2135	1.2009
E	1.1915	0.8137	**1.3939**	1.2958	0.9003	**1.4214**	1.1749	1.0594	1.3740	1.3630
F	1.1574	0.8728	1.3063	1.2125	0.9229	1.3469	1.1587	0.9971	1.2950	1.3168
G	1.0500	0.7141	1.2921	1.2010	0.7899	1.2883	1.0388	0.9845	1.2300	1.2065
H	**1.1328**	0.7647	1.3867	1.2683	0.8518	1.3845	1.1145	1.0602	1.3118	1.3029
I	1.0301	0.7037	1.2717	1.1947	0.7687	1.2629	**1.0176**	0.9414	1.2108	1.1939
J	1.1777	0.8148	1.2934	1.2285	**0.8986**	1.3725	1.1660	1.0344	1.3432	1.3432
K	**1.1080**	0.7578	1.3683	1.2824	0.8325	1.3579	1.0929	**1.0230**	1.2954	**1.2799**
L	1.1984	0.5782	1.6058	1.4359	0.5244	1.3633	0.9435	0.9596	1.0863	1.1989
M	0.9916	0.6772	1.2293	1.1492	0.7498	1.2197	0.9799	0.9366	1.1631	1.1414
N	0.9990	0.6873	1.2209	1.1464	0.7558	1.2232	0.9874	0.9341	1.1636	1.1498
O	1.0868	0.7455	1.3302	**1.2590**	0.8170	1.3297	1.0715	0.9991	1.2697	1.2502
P	1.2325	0.8941	1.2685	1.1472	0.9823	1.3679	1.1901	0.9981	1.3374	1.3751
Q	1.0527	0.7204	1.3061	1.2214	0.7971	1.2956	1.0397	0.9904	1.2317	1.2127
R	1.1481	0.7765	1.4171	1.3001	0.8591	1.4030	1.1333	1.0440	1.3376	1.3218
S	1.1081	0.7550	1.3490	1.2580	0.8312	1.3499	1.0953	1.0096	**1.2858**	1.2802
T	1.1559	**0.8105**	1.3548	1.2844	**0.8871**	1.3807	1.1435	1.0546	1.3182	1.3359
U	1.0237	0.7035	1.2679	1.1945	0.7742	1.2596	1.0109	0.9612	1.1955	1.1818
V	1.0263	0.7073	1.2640	1.1926	0.7749	1.2603	1.0129	0.9571	1.1971	1.1828
W	0.9773	0.6698	1.2095	1.1244	0.7406	1.2032	0.9679	0.9241	1.1424	1.1232
X	1.0394	0.7121	1.2830	1.1937	0.7884	1.2778	1.0287	**0.9783**	1.2155	**1.1912**
Y	1.1431	0.7813	1.3813	1.3205	0.8563	1.3994	1.1128	1.0586	1.3186	1.3101
Z	0.9956	**0.6850**	1.2347	1.1634	0.7549	1.2251	0.9828	0.9326	1.1626	1.1494

In the above tables, the recognition scores of the misclassified characters are shown as bold. These misclassified characters are from different test samples of handwritten characters. Tables of Euclidean distances for all the samples are not shown here except for a single test sample shown in the Tab.1 and Tab. 2. For example, suppose that the unknown input character is ‘T’ then we can see from Tab. 3 that recognition score with respect to the character ‘T’ is greater than with respect to the character ‘Z’ while in Tab. 1 minimum Euclidean distance wrongly corresponds to the character ‘Z’. Hence the ANN correctly recognizes the input character as ‘T’. We can see from Tab. 3 that the misclassified characters ‘H’, ‘T’, ‘B’, ‘J’ and ‘K’ are recognized correctly only by comparing the recognition scores generated by the learning rule of ANN. Other misclassified characters are correctly recognized by comparing the recognition scores along with the Euclidean distances [56,57]. Different character images are tested with this proposed HCR system and we find that the system has a high recognition accuracy. But there are some mismatches by the ANN, these are for the characters ‘S’ and ‘X’ of a test sample. The character ‘S’ is wrongly recognized as ‘B’ and the character ‘X’ is wrongly as ‘K’.

Euclidean distances from the misclassified character image TV to its class and the class of misclassification are measured by using the equation:

$$D(TV, MV) = \sqrt{\sum (TV(i,j) - MV(i,j))^2}$$

(5.2.2)

where, MV is the mean vector of the said class.

Suppose the Euclidean distances from the above said classes are $d1$ and $d2$ respectively. Recognition scores of the input vector corresponds to the above said classes are $s1$ and $s2$ respectively. Then, we use the following condition to improve the recognition accuracy:

if
$d1 \le d2$, then the input character is recognized otherwise misclassified.
else if
$d1 \times s1 \ge d2 \times s2$, then the character is recognized otherwise misclassified.
End

6. EXPERIMENTAL RESULTS

150 samples (3900 characters) were collected from 150 persons of different age groups, 26 from each. First, 100 samples (2600 characters) were used to train the proposed HCR system and next 50 samples (1300 characters) were used to test the proposed HCR system. An analysis of experimental results has been performed and shown in the table given below.

Table 4: The Result showing the average recognition accuracy. Here, it is 98.46%.

Test Data Set (A – Z)	Level of Multiresolution	Methods	Average Recognition Accuracy (%)
10 by 8 Pixels	3	Euclidean distance metric	90.77
		Learning rule of neural network	95.38
		Neural network along with Euclidean distance metric	**98.46**

Here, we compare our results using the new approach with those of other authors. The method used by Chen et al.[3] gets recognition rate of 92.20% for handwritten numerals. The method of Romero et al.[47] gets 90.20% recognition accuracy over the test data for handwritten numerals. The method used by Pal and Singh [55] gets recognition accuracy of 94% for handwritten English characters. The method of Mowlaei et al. [46] gets recognition rates of 92.33% and 91.81% for 8 classes of handwritten Farsi characters and numerals respectively. Also the method in [46] yields are cognition rate of 97.24% for handwritten postal addresses.

7. CONCLUSION

From the above Tab. 4, we observe that the recognition accuracy increases to 95.38% from 90.77% when we apply learning rule of neural network and it further increases to 98.46% when we incorporate Euclidean distances to the recognition scoresas a new approach.Work is going on, we are trying to further improve the recognition accuracy in terms of data samples and recognition process time using some other methods and techniques so as to get the consistency in recognition accuracy. In this paper, we introduced a new approach which is a combined effect of the Euclidean distance metric and artificial neural network. We used this new technique only for the unrecognized characters and get a very good recognition performance.

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