Temporal Neural System Applied to Arabic Online Characters Recognition

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Abstract: *This work presents survey, implementation and test for a neural network: Time Delay Neural Network (TDNN), applied to on-line handwritten recognition characters. In this work, we present a recognizer conception for on-line Arabic handwriting. On-line handwriting recognition of Arabic script is a complex problem, since it is naturally both cursive and unconstrained. This system permits to interpret a script represented by the pen trajectory. This technique is used notably in the electronic tablets. We will construct a data base with several scripters. Afterwards, and before attacking the recognition phase, there is a constructional samples phase of Arabic characters acquired from an electronic tablet to digitize Noun Database. Obtained scores shows an effectiveness of the proposed approach based on convolutional neural networks.*

Keywords: *Isolated handwritten characters recognition, on-line recognition, convolution neural network, TDNN.*

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1. Introduction

Cursive writings acknowledgment remains dependably an open issue in both printed or transcribed styles. This is because of the challenges in which analysts and designers have gone up against, for example, the fluctuation of the shape, the style, and the inclination of the content. The Arabic manually written content is normally cursive, hard to process, and introduces wide inconstancy.

The development of new gadgets of seizure, like coupled pens for numeric papers, grants to produce on-line archives in an extremely effective manner. Real records can be produced because of these gadgets; they can comprise on note archives, course reports, tests duplicates, drafting, and so on. It extends the application fields of the on-line composing seizure which is bound regularly to little size terminals (PDA, Smartphone) where just the acknowledgment of the characters is legitimized.

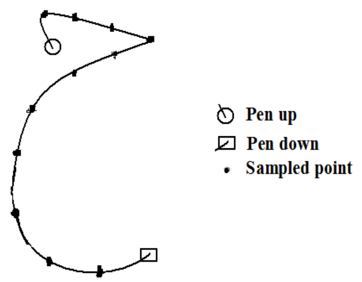


Figure 1. On-line writing, (numeric ink).

On-line reports speak to another wellspring of data in regular dialect in which few acknowledgment-based applications exist. On account of on-line transcribed record, it is about the tested direction of the accessible composition instrument under the state of (x(t); y(t)) focuses succession in the space, flawless in time. Along these lines, it is conceivable to remember a character stroke by stroke as outlined in Figure 1.

The utilization of measurable methodologies allowed an immense advancement in the penmanship acknowledgment area. Among the methodologies that have been put to commitment, the association based methodologies (neural systems) that have a solid separating power and an ability to build outskirts of choices in enormous measurement spaces, and then again the displaying dependent on the Shrouded Markovs Models (HMMs) [1] utilizes a parametric way to deal with model the perceptions successions created by stochastic procedures (written by hand contents for instance), that are progressively evident when it is about word acknowledgment. The HMMs have a huge ability to display the perceptions conveyance for each shape class to perceive.

For the confined characters, it is the worldwide shape that is taken in thought the neural systems are considerably more adjusted, they present the preferred standpoint to be good with the constant methodologies and also the 2D pictorial nature of the content [5].

Thinking about the idea of the manually written flag and our desire to process it (on line) where time is an indistinguishable information of the information flag, we bowed on the most adjusted neural systems for this sort of uses which utilize the associations with deferrals Time-Delay Neural Networks (TDNN) presented by Alexander Waibel and Geoffrey Hinton.

They previously uncovered their superior exhibitions in the acknowledgment of separated letters

[8, 13] they should have the capacity to add to the acknowledgment of words likewise [7], or even sentences [6].

It is the topic of the works made in the setting of this article. Various works have quite recently been driven on the neural frameworks for the affirmation of the deciphered arrangement yet remain generally lacking in reason of the inconveniences fundamentally bound to the multifaceted idea of the physically composed banner and the detachment of on-line data bases.

It is the protest of the works created in the setting of this paper. Numerous works have just been driven on the neural systems for the acknowledgment of the written by hand composing yet remain commonly inadequate in reason of the challenges basically bound to the multifaceted nature of the manually written flag and the inaccessibility of on-line information bases [10].

2. On-Line Handwriting Signal

The user composes normally with a stiletto on a slate or a screen. The acknowledgment programming translates the composed characters or words to change them into numerical characters.

Three properties describe the on-line acknowledgment:

1. The composition arrange idea (strokes transient succession)
2. The following elements (speed, increasing speed, pen raise).
3. Following skeleton (no stroke thickness).

The primary business manually written acknowledgment programming's have been coordinated in electronic coordinators gave a stiletto allowing characters or words and sentences seizure and here and there gave of console. Outside of this essential market of little close to home partners, different applications have been produced from realistic tablet and recently of computerized pens.

In the therapeutic condition, for the seizure and capacity of data by the bed of the patients, for the restorative medicine seizure.

In the instruction world, to help the instructor in his undertaking of preparing of the composition that can just oversee a solitary youngster at any given moment amid his motion of composing creation. As much in the school as the therapeutic condition, to recognize rapidly the distinctive reasons identified with the clairvoyant and engine unrests (Parkinson, sclerosis.) and to class disappointments (dyslexia).

Furthermore, in the gatherings universe, with the likelihood of holding notes, explanations, and preservations of all composed or oral hints of the distinctive mediating gatherings of the gathering.

The main research axes on on-line recognition can be summarized like follows:

- Words, sentences or texts recognition while using contextual knowledge (specific to the document, linguistics, etc.,).
- Automatic adaptation to a writer's writing from a generic recognition system.
- The presentation of the recognition results, the pen interface ergonomics, document edition.
- The education tools that help in the writing training, the detection of unrests related to the writing.
- The writer's authentication, the signatures recognition.

3. On Line Handwriting General Recognition Process

Automatic handwriting recognition has been a well-established research area for thirty years. This domain is divided into two categories:

1. Online writing recognition acquired by a digital tablet that restores the order of the plot in addition to other information such as the speed and pen pressure.
2. Off-line writing recognition acquired by a scanner or camera where, therefore, only an image of the handwritten data is provided to the recognition system.

Historically, offline recognition systems have been the most investigated because of their proven potential in large-scale commercial applications such as automatic mail sorting and automatic reading of bank check amounts. However, the explosion of PDAs, Tablet-PCs and Smartphones on the global market and the economic interest that has accompanied it has boosted the research and development of efficient online recognition systems.

The maturity of the systems already developed, the recognition of characters and words in the case of online writing under unconstrained conditions is far from being solved, especially for the Arabic language for which research does not exist has grown over the last five years.

Despite records paper that is digitalized as pictures, the on-line reports (explicitly the characters and motions) are supplied as electronic ink. The on-line records can be seized while utilizing a few kinds of peripherals as showed in Figure 2.

Figure 2. Online data entry devices.

These distinctive peripherals make that recorded electronic ink can be of various natures and characteristics. The handy areas are tremendous, from composing writings to charts seizure and even to shapes recharging or reports release signals.

Be that as it may, the primary trouble met in the acknowledgment of the manually written composing is the fluctuation of the composition styles. Without a doubt, the state of the transcribed characters shifts a great deal from an author to another and notwithstanding for a given essayist as indicated by the setting of the character (the situation in the word, the neighboring letters).

This inconstancy is a wellspring of ambiguousness between characters since one following can have distinctive significances as indicated by the specific situation or to the essayist. These properties make that the acknowledgment of the manually written composing is a handy space for exceptionally rich shape acknowledgment in troubles and in difficulties.

In this work, we focus just on separated character acknowledgment (letters). Without a doubt, this tricky is the premise of numerous perplexing frameworks allowing words, sentences and messages acknowledgment.

A little enhancement of the characters acknowledgment productivity can allow to diminish the intricacy of the accompanying advances.

The contrast between the two spaces of the on-line and out-line manually written composition, handled independently, live in the idea of the preparing information (fleeting or spatial) and of the data that one can separate in an objective of acknowledgment.

We are intrigued here in the acknowledgment in the on-line space, this one knows an enthusiasm with the approach of the data society in which we enter with specifically the need of versatility and access to data without suspending. The acknowledgment charts are all inclusive normal and decrease themselves in two ideas:

- *The Preprocessing*: they concern the acquirement and the normalization of data and serve to suppress the noises led by the context at the time of the acquirement (sampling frequency of the graphic tablet, quality of digitalization of the scanner, extraction of the text in a document) and those generated by the human.
- *Features extraction*: in this section, we present a preview of the methods of feature extraction used in character recognition. Actually, in addition to the taxonomy presented in Figure 3, the character recognition domain can be described by the data collection method, feature extraction methods, classification or data representation format methods.

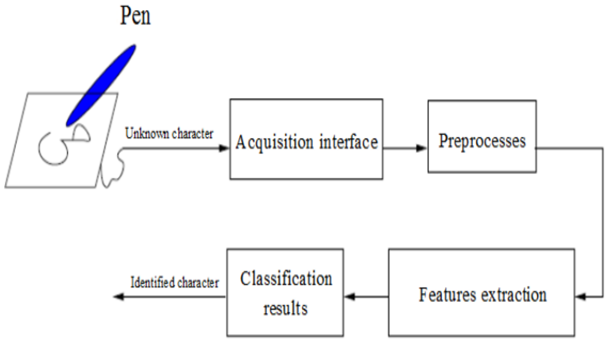


Figure 3. General handwriting recognition system.

The proposed recognition system can be represented schematically according to Figure 3. It includes a preprocess step permitting to normalize the size of character and to sample the tracing in a stationary number of equidistant points. The second step consists in the feature extraction from the previously gotten tracing, this description constitutes the input of the neural network (TDNN in our case, we will give more details in the following section). This one is going to provide on the output layer, after the attainment of training, the class of the character presented to the entry [9].

4. Time Delay Neural Networks

Time Delay Neural Networks (TDNN) are convolutional networks out of their topology, they include a sliding window corresponding to a restricted vision field of the aggregate signal. They have been used initially in speech recognition [4], but they have been used successfully as well in the isolated character recognition like the numbers or words. Our choice of this type of neural network is dictated by the fact that this network can correspond to our constraints: sturdiness toward the translation and also a big generalization capacity [2, 3].

TDNN differ of the classic Multi-Layers Perceptron (MLP) by the fact that it takes a certain notion of time. Instead of taking all the input layer neurons at the same time, it accomplishes a temporal sweep. The TDNN input layer takes a specter window and sweeps the imprint. The TDNN permits also to recognize the signal less strictly than with the classic MLP [15] (in other words, it can hold small shifting).

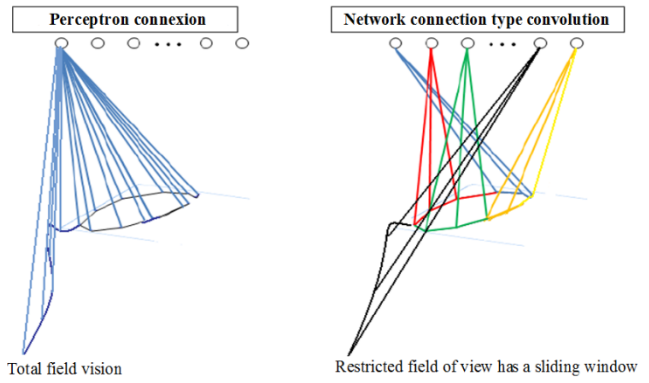


Figure 4. Connections' illustrations in MLP and TDNN.

4.1. Structure

TDNNs are established like PMCs from an information layer, shrouded layers and a yield layer, however they vary by the between layer joins association. TDNNs present a few limitations that allow them to have a specific reentrancy degree by fleeting movement and bending.

These utilization three thoughts:

- *Shared Weights*: the shared weights allow to decrease the quantity of parameters of the neural system and initiate an imperative speculation limit. The weights are shared by the fleeting heading, for a trademark information, the window related to this information will have similar weights as indicated by the transient bearing. This limitation involves an ability to remove the distinctions with the breadth movement of the flag. This idea of shared weights is the conduct assumed of the human cerebrum where a few neurons compute a similar capacity on various information sources.
- *Worldly Window*: the idea of worldly window suggests that each neuron of the layer L+1 is just associated with one subset of the L layer (we don't have an aggregate availability). The measure of this window is the equivalent between every two given layers. This worldly window allows that each neuron has just a nearby vision of the flag; it tends to be seen like a unit of identification of a neighborhood normal for the flag.
- *Deferral*: in expansion to the two past limitations, we present postponements between two progressive windows for a given layer. On top of that, each layer has two directions a temporal direction and a characteristic direction.

4.2. Functioning

The objective of TDNN isn't to take in the flag fundamentally yet to extricate its highlights. The main layer gets the flag, and afterward one or a few shrouded layers change the flag into varieties of highlights. A neuron distinguishes a neighborhood normal for the bend variety. The field of vision of the neuron is confined to a restricted worldly window. With the imperative of the mutual weights, a similar neuron is copied toward the path time (the equivalent copied grid of weight) to recognize the nearness or the nonappearance of a similar trademark in better places along the flag. While utilizing a few neurons to each transient position, the neuron arrange does the location of various highlights: the yield of the distinctive neurons deliver another trademark vector for the predominant layer.

The worldly segment of the flag is continuously wiped out with the movement of its change in trademark by the predominant layers, to repay this misfortune, the quantity of neurons in the trademark bearing has been expanded.

4.3. Training

To prepare the TDNN, we utilize the exemplary calculation of back-spread of the inclination however in its stochastic form (the weights are refreshed to each precedent). The math stages are equivalent to portrayed before.

4.4. Implementation

Having been required so as to influence a specific number of tests to decide the most adjusted topology to our application that we wanted, with respect to the multi-layers perceptron, to create not a specific neural system but rather a neuronal test system enabling us to display it. We pursued a similar idea for the MLP, however we experienced a few challenges for the back-engendering of the blunder, subtler than MLP.

For the usage, we utilized a stage of 0.01, introduced the inclinations and the weights between -0.1 and 0.1.

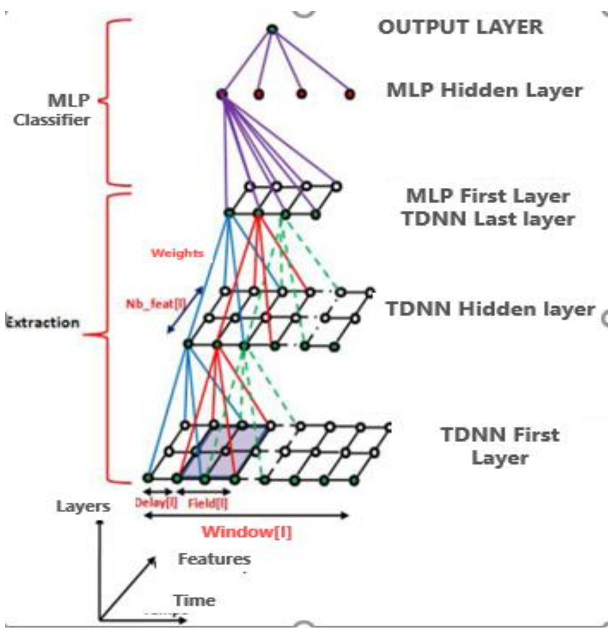


Figure 5. Connections' illustrations in MLP and TDNN.

4.5. Implementing TDNN on Scripting

Most of the architectures for the character recognition include two principle parts (as described in figure 5. The first, corresponding to the low layers, implements the successive convolutions permitting to transform the features progressively in a much more meaning size toward the problem TDNN. The second corresponds in a classic MLP, it receives in the input the outputs set of the TDNN part.

Some remarks are essential, such as:

- A neuron of a layer of a perception is connected to all neurons of the previous layer but for a convolutional neural network, a neuron is connected to a subset of neurons of the previous layer.
- Every neuron can be seen as a detection unit of a local characteristic.

The two stated blocks are completely configurable; they are described by the variables presented in Figure 5.

The Extraction part is characterized by:

- The number of layers, *nb_layer,*
- The number of neurons of every layer according to the temporal direction, *window_T,*
- The number of neurons of every layer according to the characteristic direction, *nb_feat,*
- The size of the temporal window seen by every layer (except the input layer), the number of neurons of the L layer seen by a neuron of the layer *L+1*, *field_T,*
- The temporal delay (number of neurons) between every window, delay.
- A neuron is identified by its L layer, its characteristic f, and the emplacement temporal t. For every neuron are defined:

1. An output, or activation of the neuron, *x[L][f][t]*
2. A weights matrix of the outputs, *w[L][f][f[L -1]] [t]*
3. A weight vector of the slants, *w_biais[L][f]*
4. The weighted sum of the inputs, *v[L][f][t]*
5. The term of error for the back-propagation of the gradient, *y[L][f][t]*
6. The gradient, *delta[L][f][f[L-1]] [t]*.

And the Classifier part is characterized by:

- The number of layers, *NN_nb_layer,*
- The number of neurons of every layer *NN_nb_neuron*layer.

A neuron of the classifier is identified by its layer L, and its location t.

For every neuron of the classifier are defined:

- An output, or activation of the neuron, *x[L][t]*
- a matrix of the weights of the inputs, *w[L][t][t[L -1]]*
- the weighted sum of the inputs, *v[L][t]*
- the term of error for the back-propagation of the gradient, *y[L][t]*
- The gradient, *delta[L][t][t[L -1]]*.

The first layer of the network acquires the features of the signal. One or several hidden layers of the neural network (extraction phase) transform a sequence of characteristic vectors in another sequence of characteristic vectors of superior order. A neuron detects a local topological characteristic of the trajectory of the stiletto. The field of vision of the neuron is restricted to a limited temporal window. With the constraint of the shared weights, the same neuron is duplicated in the time direction (the same duplicated weights matrix) to detect the presence or the absence of the same characteristic in different places along the trajectory of the signal. While using several neurons (nb_feat) on every temporal position, the neurons network does the detection of different features: the outputs of the different neurons produce a new characteristic vector for the superior layer.

The operations accomplished by a layer of the TDNN are of type convolution. Every k neuron of the layer L +1 has a core of w size (number of neurons of the temporal window of the *L* layer) * *f* (number of features of the *L* layer).

The temporal component of the representation of the signal is eliminated progressively in sampling the convolution to every layer. To compensate this loss of information, the number of features is multiplied. We have an architecture of type bipyramidal. This bipyramidal network converts temporal information progressively into information of type feature.

Finally, the first layer of the classifier part (entirely connected MLP) corresponds to the last layer of the extraction part.

5. Pre-processing Phase

The depicted already engineering has for objective to order and to perceive the Arabic disconnected characters originating from our information base NOUN-DATABSE in its first form 1.0 containing the 28 letters of the Arabic letter set, built with on line obtaining and the assistance of a WACOM BAMBOO adaptation 5.08-6.

In this preliminary form, we restricted various 20 essayists, each author grabbed the letters in order multiple times, for an aggregate of 2800 characters.

Furthermore, of the data bound to the character himself (extractions of the diverse highlights), we will record some data on the authors chose to add to the development of the premise. The data entirety up on the main name, the last name and the date of the seizure, the appended character and its event (Figure 6).

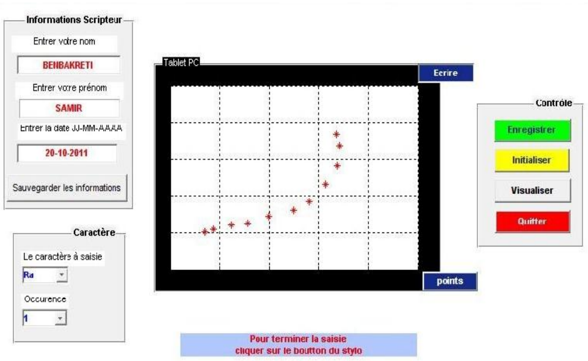


Figure 6. On-line acquirement of the character "Ra".

The system describes previously will be implemented to classify the isolated characters coming from our basis noun database.

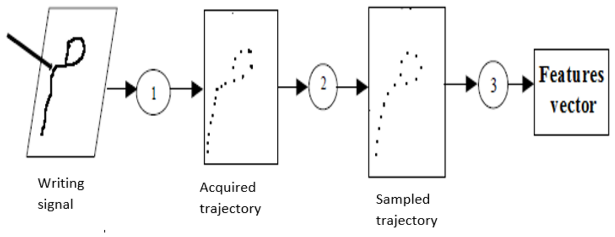
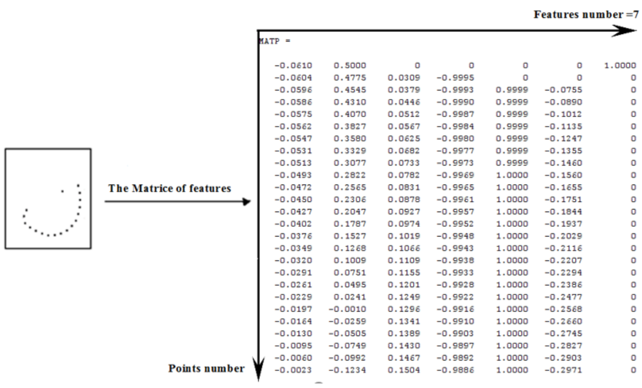


Figure 7. Representation of the on-line extraction process.

From this information, we test these focuses spatially to get equidistant indicates thus turned out to be freed from the fluctuation of the speed of the following (Figure 7). Hence, we should understand a standardization of the purposes of each character to what all characters have a similar number of focuses. At that point to a bridge, the features extraction for each point in the character licenses to build a network of 7*17 cells, the highlights are: the directions in x and y, the cosines of the heading (cos. what's more, sin.), the cosines of the bend (cos. furthermore, sin.) and the position pen up \ pen down of the stiletto.

When the procedure of extraction of the highlights is done, the grid of trademark whose measure results from the item between the quantity of highlight and the quantity of focuses speaking to each character (stationary number gotten in a trial way) will be spread in the TDNN to do the grouping and to perceive the character (Figure 8).



MATP =

-0.0610	0.5000	0	0	0	0	1.0000
-0.0604	0.4775	0.0309	-0.9995	0	0	0
-0.0596	0.4545	0.0379	-0.9993	0.9999	-0.0755	0
-0.0586	0.4310	0.0446	-0.9990	0.9999	-0.0890	0
-0.0575	0.4070	0.0512	-0.9987	0.9999	-0.1012	0
-0.0562	0.3827	0.0567	-0.9984	0.9999	-0.1135	0
-0.0547	0.3580	0.0625	-0.9980	0.9999	-0.1247	0
-0.0531	0.3329	0.0682	-0.9977	0.9999	-0.1355	0
-0.0513	0.3077	0.0733	-0.9973	0.9999	-0.1460	0
-0.0493	0.2822	0.0782	-0.9969	1.0000	-0.1560	0
-0.0472	0.2565	0.0831	-0.9965	1.0000	-0.1655	0
-0.0450	0.2306	0.0878	-0.9961	1.0000	-0.1751	0
-0.0427	0.2047	0.0927	-0.9957	1.0000	-0.1844	0
-0.0402	0.1787	0.0974	-0.9952	1.0000	-0.1937	0
-0.0376	0.1527	0.1019	-0.9948	1.0000	-0.2029	0
-0.0349	0.1268	0.1066	-0.9943	1.0000	-0.2116	0
-0.0320	0.1009	0.1109	-0.9938	1.0000	-0.2207	0
-0.0291	0.0751	0.1155	-0.9933	1.0000	-0.2294	0
-0.0261	0.0495	0.1201	-0.9928	1.0000	-0.2386	0
-0.0229	0.0241	0.1249	-0.9922	1.0000	-0.2477	0
-0.0197	-0.0010	0.1296	-0.9916	1.0000	-0.2568	0
-0.0164	-0.0259	0.1341	-0.9910	1.0000	-0.2660	0
-0.0130	-0.0505	0.1389	-0.9903	1.0000	-0.2745	0
-0.0095	-0.0749	0.1430	-0.9897	1.0000	-0.2827	0
-0.0060	-0.0992	0.1467	-0.9892	1.0000	-0.2903	0
-0.0023	-0.1234	0.1504	-0.9886	1.0000	-0.2971	0

Figure 8. The extraction features.

The training, i.e., the determination of the weights is the important points in the conception of a neuronal system; these calculations use the data set of the temporal set to search the best weights so that the neural network reproduces the behavior of the system. Ideally, these must permit to converge quickly to the global minimum of the cost function.

The TDNN is a sequence of two networks, the first is a dynamic network and the second is a static network (as shown previously). For the training of these two sub-networks, we can apply the method of training as the method of back-propagation of the gradient with the constraint of shared weights. However, the used version is the version said of the "stochastic gradient" that permits to converge more quickly than the true gradient, or the methods of second order as the algorithm of Lavenberg-Marquardt, the algorithm Newton, Quasi-Newton, Gauss-Newton. We tested first order methods which are the back-propagation of the gradient (for reasons of calculation and memory space) as well as the "resistant" back-propagation of the gradient: Rprops and two second order methods, the method of Lavenberg-Marquardt (LM) and that of the conjugated gradient (SCG).

The primary property of the TDNN is the ability to distinguish the neighborhood includes paying little respect to their situation in time. The TDNN is a dynamic feed-forward system, where data engenders itself from the contribution to the yield without in reverse return and the elements is situated in the layer of contribution, as deferral. The TDNN emerges of a system of great neurons, similar to the MLP by the way that it considers a specific feeling of time. In other words that to the place to take in the meantime in record all neurons of the information layer, it takes a window of the apparition at that point completes a worldly scope.

What enables the system to take in thought the nearby highlights of the transient arrangement of precipitations. The utilization of shared weights licenses to diminish the quantity of parameters of the neural system while driving a progressively vital speculation limit.

The TDNN's tried design of premise is a system of 3 layers, the principal layer is the info layer of the system, the second is the shrouded layer of the extraction part and the main layer of the grouping part (the capacity of enactment being a sigmoid), the latter is the yield layer (the capacity of actuation being a straight capacity). We give next an engineering precedent.

6. Experiences and Results

In our work, we ceased the preparation when the mistake (EQM or MSE) winds up negligible (10e-3), or the quantity of emphasis achieves 100. At that point the system is esteemed from the information that are distinctive of those utilized amid the preparation. This last portion of information is called test set.

The progression of the inclination and the progression of preparing are the deciding components in the speed of intermingling of the neural system. The season of learning increments rapidly with the unpredictability of the system, it is important to locate an ideal advance. More the progression is little, more the quantity of cycles of the preparation premise will be essential. In any case, more the progression is enormous, more the fundamental number of cycles will be less yet the system dangers to wander. We would say, we settled the progression of preparing to 0,01 and the most extreme number of cycles to 100.

The outcomes are referenced in the accompanying experiences:

6.1. Experience 1

In a first time and in order to test our model, we are going to launch the training only for 3 characters (alef, ba, ta) with the mentioned previously requisite architecture.

The performance matrix (Per) that regroups the characters badly classified and those well classified of every character, give us a preview on the general rate of the characters badly classified (C).

Table 1. Performance matrices of the first three characters.

performance Matrix (Per)	Negative False	Positive False	Positive True
Alef	0.0216	0.0078	0.9784
Ba	0.0078	0.0059	0.9922
Ta	0.0059	0.0216	0.9941

The general rate of characters badly classified, C=0.0118 is equivalent to 1.18% and 98.82% of rate of training of the three characters.

The Confusion Matrix (CM) regrouping the number of well classified samples in the diagonal is the following:

CM= [499] [0] [11]
[4] [506] [0]
[0] [3] [507]

6.2. Experience 2

The same previous architecture is renewed, but while varying the functions of training.

In this section, we have shown the influence of the method of the back-propagation of error gradient under several versions on the model and with the consideration of the time convergence.

It is very difficult to know what algorithm of training of a network “feedforward” will be the fastest for a problem. It depends on a lot of factors, including:

- The complexity of the problem.
- The number of vectors (or points) of data on the set training.
- The number of weights and slants in the network.
- The goal of the network used for the recognition of shapes (discriminative analysis) or the approximation of functions.

It is necessary to perform a training to determine the weights allowing in the output of the neural network to be as near as possible to the fixed objective.

This training takes place thanks to the minimization of a function, named cost function, calculated from the examples of the basis of training and the output of the neural network; this function determines the objective to reach.

We tested two algorithms of the first order: the back- propagation of the Descendant Gradient (GD) and the “resistant” back-propagation of the gradient (PR) and two second order algorithms: the Levenberg-Marquart algorithm (LM) and the algorithm of the Conjugated Gradient (SCG).

The following table sums up the different results.

Table 2. Results of the variations of the training function.

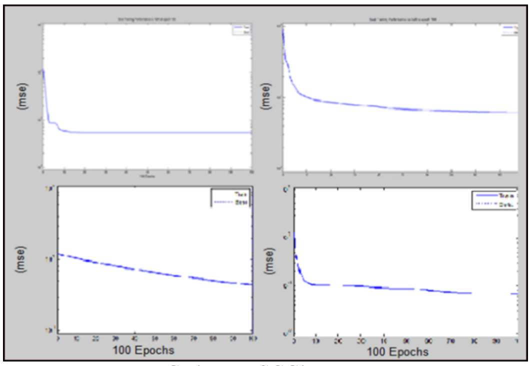
(3 characters)	LM	RP	GD	SCG
MSE	6.33.10e-4	2.510e-2	0.29	1.10e-3
C	0.0006%	1.18 %	42.48%	0.003%
Time	12m.03s	6m.47s	6m.43s	14m12s

6.3. Discussion

The LM algorithm got the lowest EQM as well as a very low rate of characters badly classified (C) neighboring 0%, it is more efficient than the other algorithms, with the detriment of its execution time which is more elevated. However, we cannot carry a definitive judgment on this algorithm unless its capacity of generalization is confirmed.

Therefore, we are going to increase the number of classes (of characters) to 7, here are the results:

LM’s error RP’s error



GD’s errorSCG’s error

Figure 9. Comparison between the MSE of different functions of training.

After 100 iterations, the graphs of the MSE show us clearly that the algorithm of Lavenberg-Marquart converges more quickly and reaches the minimum after only some iterations (about 15 iterations) but is not the case of the other algorithms that converges slowly, especially the algorithm ofdescendant gradient GD whose error remains very big (the approximation is coarse of data).

Table 3. Variation results of in the training function after increasing the number of characters to 7.

(7 characters)	LM(2)	RP	GD	SCG(2)
MSE	53.10e-3	61.10e-3	0.43	67.10e-3
C	35%	33 %	%81	38%
Time	3h22m11s	48m13s	53m	1h25m04s

When the size of the network increases, the performances of the LM algorithm weakened relatively, outside of the these enormous requirements of storage and time execution has more than 3 hours, the algorithm doesn't possess an interesting generalization capacity when it is about solving a problem of shape recognition, even though the MSE is always as bass as the one of the other algorithms, the rate of samples badly classified (C=35%) increased appreciably by previous experience.

The "PR" algorithm presents the best results concerning the rate (C) and the requirements of the memory for this algorithm are relatively small in comparison to the other algorithms, translate by the result in a small-time execution (Time=48 minutes).

Even though the second order algorithms are relatively more effective, we notice that a TDNN network is capable to do a good precision recognition by a simple training of the first order (PR).

The use of these training algorithms reappears of the virtual storage problems in the Matlab environment programming, what didn't allow us to increase again the numbers classes (of characters) to 28. On the other hand, we estimate that Matlab represents an excellent programming tool in the laboratory in the case of the matrix calculates (as in our case).

6.4. Experience 3:WindowSize T Influence

This experience is about the influence of the size of the temporal window on the results of the model. We recall that all previous experiences have been made with a temporal window of 4 neurons. This size will be increased until the obtaining of the best possible results:

Here is a summary table of the results gotten:

Table 4. Window size variation Results.

(3 characters)	T=4	T=5	T=6	T=7
MSE	25. 10e-3	8. 10e-3	20. 10e-3	22. 10e-3
C	1.18 %	1.05 %	0.85 %	1.11 %
Time	6m47s	7m06s	7m37s	8m39s

The results show that the MSE decreases while the width of the applied temporal window in the input of the TDNN is increasing. The lowest error corresponds to the window of 5 neurons. It means that we head toward better rates when we increase the width; however, when we pass the width of size 6, we find that the EQM increases. The same report is made with regard to the rate (C), except that it is better for T=6.

Consequently, the most suitable size resides between 5 and 6 neurons concerning c (cm and per) and of error rate (MSE) as the shows the Figure 10.

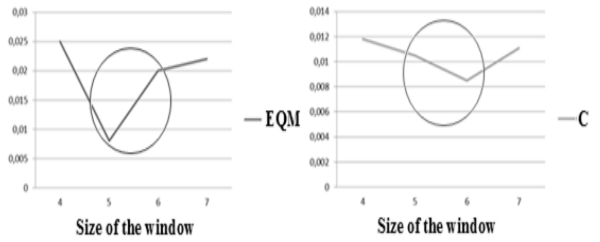


Figure 10. Variation of (C) and (MSE or EQM) according to the size of the temporal window.

To decide between 5 and 6, we increased the number of classes (7 characters), the results are mentioned in the Table 5.

Table 5. Variation of the size after increasing the number of classes.

(7 characters)	T=5	T=6
MSE	61. 10e-3	66. 10e-3
C	33 %	37.51 %
Time	52m49s	1h01m43s

This table shows that the best results have been gotten with a size of 5 neurons and fix the optimal size of the temporal window applied to the input of the TDNN to five.

We note therefore, that by dimensionality of the size of the window, one influences the capacity of memorization of the TDNN. More one increases the size of the window, more the number of free parameters increases and more one increases the capacity of memorization. However, a very important memorization capacity can harm the power of generalization of the network and can dive again the results in the mediocrity.

6.5. Experience 4: General Training

The resistant back-propagation algorithm (Rprop) requires like all others algorithms seen previously the enormous needs of memory, the size of the input matrix that propagates in the architecture of the TDNN, which, as well, does not facilitate the task. These reasons pushed us to divide the general training in four parts. The division takes in consideration the ability to compare one character to another that resembles to it like (jim, ha, kha).

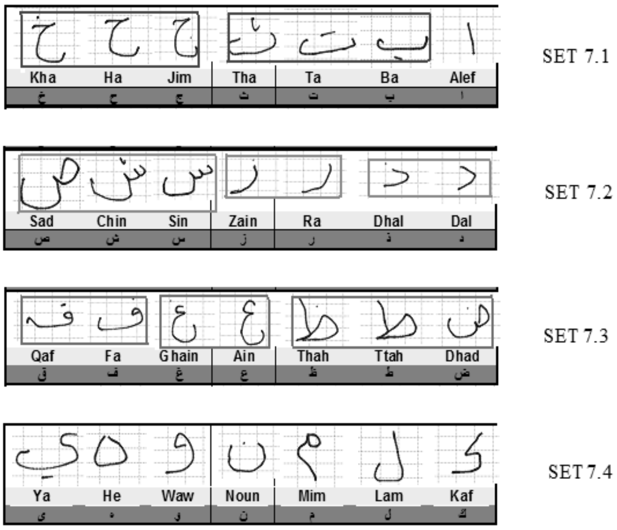


Figure 11. Four sets training illustration.

The results are summarized in the following table.

Table 6. The C, MSE rates and the execution time for every Set.

Architecture (7 characters)	SET 7.1	SET 7.2	SET 7.3	SET 7.4
MSE	61. 10e-3	63. 10e-3	72. 10e-3	64. 10e-3
C	33 %	30 %	37.2 %	28 %
Time	49m07s	49m21s	48m21s	52m48s

6.6. Generalization Phase

The experience made already, enabled us to characterize the perfect engineering of our TDNN arrange. The imperatives of memory, because of the utilized material in one side, and on the opposite side to the uniqueness of the calculations of preparing subsequent to expanding the quantity of classes (of characters), didn't enable us to make the preparation of the 28 characters to a similar time, from where the division forced of the four sets regrouping every seven characters. All things considered, the division has been accomplished in an approach to have the capacity to contrast the character test with the other neighboring classes that look like it, (precedent: Ra and Zin). These imperatives resonated on the period of speculation and test.

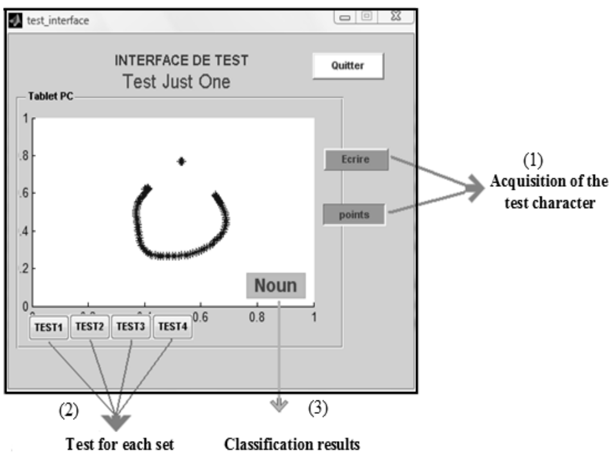


Figure 12. Test of on line character "Noun".

For a superior comprehension, we explained a realistic interface, enabling the framework to regroup the means: of securing, of highlight extraction grid and particularly the arrangement, as appeared in the accompanying (Figure 12).

Let's recall that the goal of this work, is to make an acquirement, an extraction and recognition of Arabic characters in a dynamic way or rather to say, an on-line way and this is beyond the quality of the recognition rate of the questionable characters especially when it is about neighboring characters.

Figure 13 shows the generalization rates of all the characters.

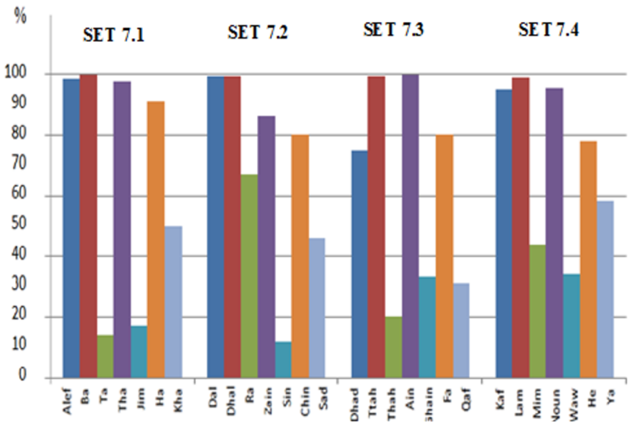


Figure 13. The generalization rates of the four SETs.

The recognition rates gotten in this figure shift, beginning by 14,31% for the character Ta and can achieve the greatest recognition rate of 99,61% for the Lam character.

To upgrade the outcomes, we contrasted our work with the one understood by Tlemsani and Benyettou [11, 12] that utilized the dynamic Bayesians network systems (DBN) to imagine the arrangement of characters recognizer. How about we take note of that similar information base NOUN-DATABASE has been utilized by the creator.

We notice that the recognition rates for the groups 7.1 and 7.3 are relatively similar, while those of the other groups 7.2 and 7.4 are differed, with a special mention for the group 2 containing the letters (Dal, Dhal, Ra, Zain, Sin, Chin, Sad) that reached the 70%.

The advantage of our application founded on the TDNN model, is that it permits a faster on-line execution −goal of the works− than that of the model proposed in the DBN, nevertheless, this last possesses have the capacity to load all the 28 characters to the same time.

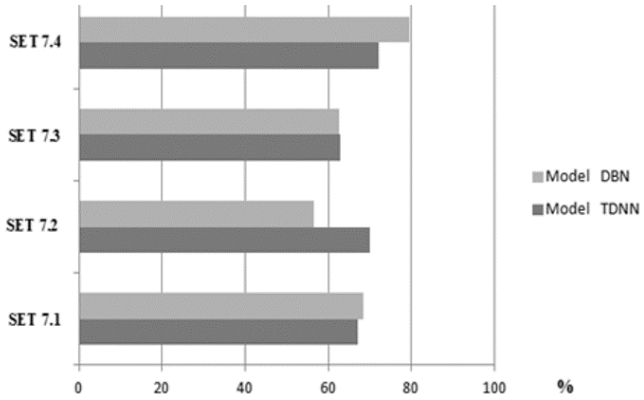


Figure 14. Comparison between TDNN models and DBN using recognition rate.

7. Conclusions

Automatic handwriting recognition of has been a well-established area of research for thirty years. This domain is divided into two categories: Recognition of online writing acquired by a digital tablet that restores the order of the plot in addition to other information such as the speed and pressure of the pen, and recognition of the off-line writing acquired by a scanner or camera where, therefore, only an image of the handwritten data is provided to the recognition system. Historically, offline recognition systems have been the most investigated because of their proven potential in large-scale commercial applications such as automatic mail sorting and automatic reading of bank check amounts. However, the explosion of PDAs, Tablet-PCs and Smartphones on the global market and the economic interest that has accompanied it has boosted the research and development of efficient online recognition systems.

Despite the maturity of the systems already developed, the recognition of characters and words in the case of online writing under unconstrained conditions is far from being solved, especially for the Arabic language for which research does not exist. has grown in size over the last five years.

The methodology being proposed in this paper builds up an answer dependent on TDNN neural systems for on-line acknowledgment of progressively obtained disconnected transcribed characters, and to dissect all imperatives that weigh on this system. The neurons systems speak to another strategy of information handling.

Solidly, they result in calculations putting in play the ideas related to the idea of the human cerebrum for the preparation thought. How about we take note of that the TDNN is a dynamic feed-forward system, this trademark is situated in the information layer as postponement. The TDNN separated itself of a great neural system as the MLP, by the way that it considers a specific feeling of time; at the end of the day, rather than considering every one of the neurons in the information layers in the meantime, it takes a range window at that point completes a transient breadth.

In the objective to achieve an on-line acknowledgment of the secluded Arabic characters, we developed our information base, which speaks to a critical help for all conceivable future works in the area. After the achievement of the fragile advance that is the highlights extraction, we completed a progression of investigation on our TDNN show.

This system was prepared with first request calculations (relative Gradient and safe back-propagation and others of second request (Lavenberg-Marquardt) in the objective to characterize the perfect features of our system. The gotten scores demonstrate that TDNN being connected to the detached Arabic character acknowledgment bargains sensible outcomes, we gauge that we can consummate the model by the methods for half and half techniques, the present inclinations make a beeline for neuro-Markovian frameworks.

As future work, the section toward the second step while handling the words and the sentences particularly speak to a fascinating test with a guaranteed improvement of our new information base of on-line Arabic composition [14]. The objective of this paper is to contribute in a horrendous improvement (negligible on the Arabic composition) that the area of acknowledgment of the non-compelled composing manually written have ever knew. We expect to coordinate this part additionally in more broadened topics and increasingly complex like the acknowledgment of words while utilizing the logical and lexical requirements.

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