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Hand Written Numeral Digit Recognition Network- Supporting Identification and Segmentation

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Abstract: The research articulates the significance of multiple classifiers utilized in order to obtain higher accuracy, while work- ing on pattern recognition for Hand Written Numeral. Research constitutes of applications for back propagation networks for successful hand written recognition of digits, working on the principal of minimal data pre-processing via optimised network architectures. Concerned is raised on Devanagari numerals recognition in order for specific experimentation via multiple classifiers increasing the efficiency and reliability of the results.

Index Terms: Pattern recognition, numeral recognition, classier combination, non constrained recognition, artificial in-telligence, multiple classifiers combination, knowledge modelling.

I. Introduction

The handwritten recognition techniques have now been studied for decades. But there exists few loopholes while analysing lower level information or degraded quality numerals. e.g. issues faced while dealing with postal codes, numerals of few Indian scripts. Prior work executed on simple digits depicts that the network architecture has strong influence over the network's ability of generalization. But the architecture design lacks prerequisite knowledge pertaining to the problem which creates gaps in the analysis. schemes applied for classification of numerals, majorly observes differences in classification strategies schemes of feature extraction. Inclusion of few formulas have led to incomplete reasoning and ignorant beliefs e.g. D-S Formula for data analysis in recogni0tion use make use of probability.

In the articulation, we identify the best existing classication method for digit determination. Exploit maximum information on variation style, features and similarities of numerals. Our objective is to propose a neural network based architecture that supports information integration in order to gain reliable and efficient numeral recognition. Advantageous overview of existing approaches will also be highlighted.

A. Hand written recognition for digits

Handwritten digit recognition is relative computer vision task. Wherein the inputs are of either white or black pixels, with well separated digits from their background, and specific output output categories.

B. Preprocessing Technique

Performing steps of binarization, acquisition, and preliminary segmentation. Segmentation where in each numeral digit is separated from its neighbour digit. Invoking of a back- propagation network is at a particular size, which is required for normalization of character sizes. Transformation applied to attain the aspect ratio of the numeral, and is done after removing exteriors marks from image of a digit. Transforming linearly the resultant gray level instead of binary. Therefore scaled between -1 to 1 range.

II. Literature Review

1) Existing Work And Methodology:

A. Extraction Of features

In the existing work each numeral digit is assumed to be unconstrained, isolated and discriminated against their backgrounds. Figure 1 displays the sample of numeral dig- its. Scanning on pre-processed performs removal of noise from digits . Median based filtering approach is followed by. Invari- ant digits are represented via similarity transformation over each numeral applying component analysis principal. This resultant normalised image of digits. Obtained numeral images then thinned down for descriptive feature extraction using

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through SPTA algorithm (For binary patterns). Pre-processing thus results into following classifying features:

- 1. Moment features with prole curves.(e.g. Left, Right)
- 2. Features of Density.
- 3. Descriptive features and their components

Fig. 1. Numerals[0-9] image

- 1) Classification of Numerals: Design of neural network supports classification here. Representation of numeral digits as feature vectors elevates satisfactory outcomes of various classiers which are then connected via connectionist plans. The neural based network architecture comprises of:
 - (1) Maps self-organized at their lowest layer.
 - (2) Single layer structure laid on the nets from the maps.
 - (3) Segment features through Multi Layer Perception (MLP) classier.
 - (4) Combination of nets to integrate.

3-layered MLP implemented for feature segmentation. Trained net through algorithm of back propagation. Similar dimensions of the input vectors and no. of identified segment types in the training set. Take an input numeral pattern which is unknown, extraction of density features, their prole and segment features. The combination layer companioning the style categories of outcomes adjacent various numerals and gives input to the meta-pi network for integration. Ultimate classication is adopted via a winner take all strategy where, the units of global outcomes provides optimum activation for identifying numeral digits.[1]

- 2) Network: Remainder recognition is completely gained via multi layered network. All adaptive network connections in the network are adaptive, with heavy constraints, trained hrough back-propagation. Network takes 16 x 16 normalized image to obtain a composed result. Well connected network with humongous discriminating powers with many parameters for correct generalization. Connection schemes with restrictions should be devised with prior knowledge on shape recog- nition combined to local features.. The network can achieve this by limiting the connections in the initial few layers itself. Adding to it, if a detector for feature is utilized on any one part of the image, it can be utilized onother parts as well. Due to some salient features from a distorting character might be slightly dislocated from their position as typical characteristic. In reciprocation scanning of input image with single neuron with receptive local field, storing the states of this neuron in in adjacent locations forms a feature map .Prcocesses can be parallelly performed with implementation of the feature map, as a plane of neurons. Feature map units are compelled to operate same function on diverse parts of an image. Quirky side effect of the technique (weight sharing), is free parameters reduction in large numbers. Also, a shift invariance to an extent is occurs in the system. Input shifts will shift the outcomes on the feature map, leaving it unchanged otherwise. Therefore it is vital to have numerous feature maps, that extract varied feature from a single image.[2]
- 3) Behaviour Knowledge Space Method: Analysis of the reasons why almost every recognition method require inde- pendent assumption revealing classifier equality, derivation of information useful in combination level over perplexing a single classifier matrix. Both the situations should be pre- assumed to decided if classifiers are equal. In order to forfeit assumption, derive information from knowledge space, that concurrently records the decisions from all the classifiers on each and every sample learned. As the knowledge space records behaviour of entire set of classifiers, approach is called Behavior Knowledge Space for derivation of final decisions.[3]

III. Statistical Analysis of Numeral Digit Profile Value

A. Statistical Measures

This dataset consists of features of hand written numerals ($^{\circ}0^{\circ}-^{\circ}9^{\circ}$) which are the profile correlation for hand written numeral digits. Actually size of the active input parts is 16 x 16, while the actual input is taken for

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2 x 3 plane to abstrain from problems overlapping boundary. Figure 2 depicts the statistical analysis.

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Fig. 2. Profile Corelation Values Of Numeral Data

We have used hand written numeral recognition data set from UCI Machine Learning Repository. It comprises of 649 profile features from which our analysis is on a sample of 9 such features and its correlation values. Using a probabilistic neural network to generate efficient and required results.

As per Table I meta pi net when receives as an input the digit numeral's image with reduced resolution .i.e 2 X 3 .Density features extracted giving a balancing average of 311.7778888, mediatizing value 236 with no repetetive values in sample learned. Skewing factor at 0.144757 gives a positive curve for density features. Therefore, density value skewed at a grid grater than 0.3 then the adjacent component in the vector Table.....

| Table | I Result Table | | | | | |
|-----------|----------------|--|--|--|--|--|
| Measure | Result Value | | | | | |
| Mean | 311.7777778 | | | | | |
| Median | 236 | | | | | |
| Mode | No Mode | | | | | |
| Skewness | 0.144757934 | | | | | |
| Std | 298.43206 | | | | | |
| Deviation | | | | | | |
| Variance | 89061.69444 | | | | | |

feature is 1,else is 0.From the quantification thus it can be said that the Feature Vector has 0 corresponding components.

IV. **Results and Analysis**

Prototype model for successful recognition is implemented. Experimentation was done sampling on 9 specific values. Examples of analysis on data used as shown in Figure 1. Descriptive features are identified with various segment types.. Enhanced capability of the net in identifies the clear results. Categorization results are implemented for factual decision. Individualistic numeral digits are categorised into maximum 2 categories style. Inspite of unimodular outcomes discussed here, abilities for different modules are versioned. Rejection capability of other average numerals is found and classification schemes are portrayed.

Proposed Idea for Zip Code Digit Recognition While Database That Trains and V. **Tests**

The network is a parent/super set of one used in the working.Lay emphasis on methods of solution relying massively on automatic learning and lesser on hand designed preprocessing. Digits written in different zipp codes, with sizes varying with styles of writing. Supplementation of printed digits from 35 different fonts can be done. The fonts printed in the test set can be other than fonts printed in the training set.

VI. Conclusion

The ultimate network connection, their weights collected from back propagation are effectively implementable on any digital signal processing hard ware.Ranging from camera- classified image, for larger than ten digits/sec. Novel features from meta pi network into the work identifies and integrates specic

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information style into the recognition schemes. The de-rived architecture is successfully applicable for every numeral digit recognition problem. Results of experimentation depict the high potential of the outcomes from research conducted.

References

- [1] Bajaj, R., Dey, L., Chaudhury, S. (2002). Devnagari numeral recognition by combining decision of multiple connectionist classifiers. Sad- hana, Springer (2002).
- [2] LeCun, Yann, et al. "Handwritten digit recognition with a back- propagation network." Advances in neural information processing sys- tems. 1990.
- [3] A Method of Combining Multiple Experts for the Recognition of Un-constrained Handwritten Numerals ,Y. S. Huang and C. Y. Suen, IEEE Transactions on Pattern Analysis , 1995.