LOCAL PATTERN TRANSFORMATION TECHNIQUE FOR BRAIN SIGNAL EEG

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Abstract— Brain-ComputerInterface technology has increased considerable interest, in the automatic detection of states such as facial expression, voice, and physiological signals for developing and ensure the human-computer interaction with an effective way and better way. The brain stimulating signals are detected by the BCI (Brain-computer Interface) which based on the idea of emotional brain computer. BCI work can be in three steps first, collecting brain signal second step, interpreting the brain signal and third step, output command to connected machine according to the brain signal. the brain wave signals have specific unique electrical signals identified with a different individual and they are hard to imitate also. Electroencephalogram (EEG) catches the brain waves as electrical signals and utilized as a part of different applications including therapeutic services and human PC collaboration. In this proposed paper, we discuss local signal pattern transformation based feature extraction technique method for brain signal (EEG). In this paper, two functional feature extraction technique method namely One Dimensional Local Gradient Pattern (1D-LGP) and Local Neighboring Descriptive Pattern (LNDP) has been discussed for brain signal EEG for machine learning. The EEG raw dataset is provided by and is provided by Neurodynamics Laboratory, State University of New York Health Center Brooklyn, New York. The classification performance is evaluated is 10 fold classification technique in machine learning. 1D-LGP and LNDP both feature extraction technique with machine learning classifier achieved 88.90% and 90.93%, classification to EEG brain signal respectively. This study suggests LNDP could be an effective feature extraction technique for classification for EEG signal.

Keywords— Electroencephalogram (EEG) signals, One Dimensional Local Gradient Pattern (1D-LGP), Local Neighboring Descriptive Pattern (LNDP)

1. INTRODUCTION

The Brain comprises of around 90– 100 billion neurons. Electroencephalogram (EEG) catches the electrical exercises of these neurons by putting terminals on the scalp. This ability of EEG Signals makes it a vital device for application in different spaces of cerebrum inquire about. EEG signals are utilized in different applications, for example, finding of epilepsy and building biometric identification framework. Over the most recent couple of years, various structures have been proposed by scientists for EEG Signals classification. The two fundamental advances engaged with these systems are including extraction and classification. Feature extraction decreased the component of the info design by keeping the most vital property and establishes the function element vectors which are then given a contribution to a classifier to complete the classification. This pro-

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cedure is generally pursued while building a computerized signal classification framework.

EEG Signals of an individual are similarly as exceptional as fingerprints. The uniqueness of EEG signals are especially solid when an individual is presented to visual stimuli, and the Visual cortex zone of the brain on the rear of the head is the best spot to gauge Brain-waves, identified with the visual sense.

In this study, two viable feature extraction procedures technique called LNDP and 1D-LGP have been proposed for the classification of epileptic EEG signals. Both the strategies are computationally straightforward and heartless to the neighborhood and worldwide varieties. The harshness of LNDP and 1D-LGP conquer the restriction of 1D-LBP. These proposed technique procedure work in two stages. In the first stage, the neighborhood designs are changed and histogram development is finished. The Histogram represents the component vector of the relating EEG signal. Histogram classification is finished in the second stage. The histogram contains the auxiliary data of the EEG signal. The classification has been done with four distinctive AI classifiers. The classification execution is assessed with 10-crease cross approval thinking about the affectability, specificity, and precision.

2. RELATED WORK

In this examination, a successful methodology dependent on the one-dimensional nearby parallel example (1D-LBP) was proposed to separate quantitative highlights from EEG signals. Neighborhood paired examples (LBP) have been widely utilized for surface investigation of 2D pictures (1D-local binary pattern based feature extraction for the classification of epileptic EEG signals). Numerous variations of LBP have been connected to undertakings, for example, face location, face acknowledgment, outward appearance acknowledgment, sexual orientation acknowledgment, face verification, entryway acknowledgment, picture recovery, surface order, shape confinement, Also, object identification. Notwithstanding, they are touchy to neighborhood power varieties that regularly happen along with edge parts, for example, eyes, eyebrows, noses, mouths, hairs whiskers, or jaws because of inward factors and external factors. This sensitivity produces various examples of nearby force varieties and makes the preparation of face and human location by AdaBoost troublesome. To conquer this issue, we propose a novel face and human portrayal technique called LGP, which creates steady examples independent of nearby power varieties along edges (Local Transform Features and Hybridization for Accurate Face and Human Detection).

3. SYSTEM ARCHITECTURE

Fig. 1 Framework for EEG signal classification

Fig. 1 shows architecture for design and EEG signals are collected from the subjects using Non-invasive electrode system sensors which placed on the scalp to measure the electrical potential produced from the brain using EEG. In the extraction technique LNDP

block which converts the brain signal and interpreting them into a decimal form of values which generates LNDP CODE. The histogram will be formed using the LNDP code value and histogram function vector is given as input for the ANN classifier and ANN block will train the data and EEG signal of each subject will be classified.

4. METHODOLOGY AND MATERIALS

In this area, a concise discussion about the dataset, 1DLGP, LNDP Feature extraction methods and the classifiers utilized has been finished.

4.1. DATASET

This dataset consists of 20 individuals and is provided by Neurodynamics Laboratory, State University of New York Health Center Brooklyn, New York. There are 40 EEG Signals of every person. So the dataset contains a sum of 800 EEG Signals of 20 people. Here, the arrangement of Signals of an individual compares to a specific class. The EEG signals were recorded from 64 terminals framework and the inspecting recurrence was 256 Hz frequency for each second. Each subject was demonstrated a few pictures chose from the Snodgrass and Vanderwart picture set. The errand of every individual was to perceive these photos while shown on the CRT screen. To play out a reasonable test the separation between the screen and individual was set to one meter. Each image appeared for 3 sec. After an image has appeared, 1 sec EEG Signals was recorded. The time interim between two successive pictures appeared set for around. Dataset detail is shown in Table I.

Table I. Dataset

Number of subjects	Number of samples per subject	Number of features in each sample	Total number of samples
20	40	64*256	800

4.2. LOCAL NEIGHBORING DESCRIPTIVE PATTERN (LNDP) ALGORITHM

LNDP is a novel feature component extraction technique procedure dependent on nearby sample change which catches the area relationship and structures the auxiliary property of the example in Fig 2. It is performed by contrasting the estimation of the neighboring focuses on the example. The different strides of the LNDP include extraction strategy are as follows:

- ❖ Step 1: From the signal sample take neighboring point's values m .
- ❖ Step 2: For each signal select S_c , selecting $m/2$ from both forward and backward
- ❖ Step 3: Compute the difference of consecutive point. The difference is computed as: $d_i = p_i - p_{i+1}$, for $i = 0, \dots, m - 1$.
- ❖ Step 4: Compute LNDP Code S_c .

$$S_c^{LNDP} = \sum_{i=0}^{m-1} s(d_i)2^i$$

Where

$$S(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{otherwise} \end{cases}$$

$$LNDP_m(S_c) = \sum_{i=0}^{m-1} s(P_i - P_{i+1}) 2^i$$

Fig. 2 Computation of LNDP code for EEG signal S_c

4.3. ONE DIMENSIONAL LOCAL GRADIENT PATTERN (1D LGP) ALGORITHM

Like LBP, the LGP includes extraction procedure was proposed for face recognition for two dimensional (2D) face pictures. Despite the fact that the 1D-LBP include extraction procedure was proposed for signal preparing and effectively connected for epileptic EEG signal classification, the LGP based strategy is yet to be proposed for the equivalent. In this segment, 1D-LGP based feature component extraction procedure has been presented for epileptic EEG signal classification. The 1D-LGP technique saves the auxiliary property of an example. The different strides of the proposed 1D-LGP highlight extraction strategies are as per the following:

- ❖ Step 1: Set the number of neighboring point's m .
- ❖ Step 2: For each signal point S_c , select $m/2$ number of neighbor points in forwarding and backward directions.
- ❖ Step 3: Compute the gradient value of each neighboring point. The gradient value is computed as: $g_i = |P_i - S_c|$, for $i = 0 \dots m-1$.
- ❖ Step 4: Compute the mean gradient value. The mean gradient value is computed as follows:

$$g_{avg} = \frac{1}{m} \sum_{i=0}^{m-1} g_i$$

- ❖ Step 5: Compute the gradient code as: $g_{ci} = g_i - g_{avg}$, for $i = 0 \dots m-1$.
- ❖ Step 6: Finally 1D-LGP code of center point is calculated as

$$S_c^{1D-LGP} = \sum_{i=0}^{m-1} s(g_{ci}) 2^i$$

$$s(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{otherwise} \end{cases}$$

Fig. 3 Computation of 1D-LNDP code for EEG signal S_c

4.4. HISTOGRAM-BASED FEATURE VECTOR

As described in past areas, every change in transformation code represents to the local neighborhood design structure of a signal. The goal behind the histogram development of these change codes is that signal structure can be formed by the circulation of these codes in a helpful structure. The histogram graphically condenses the auxiliary dissemination in two-dimensional space, where the flat pivot contains the scope of change codes and the vertical hub contains the recurrence (number of events) of each code. Signals with comparable structures will have comparative graphical representations, though divergent Signals will have distinctive graphical represents. This graphical structure represents to the future element vector and utilized for classification. A small sample fragment of histogram highlights acquired with LNDP and 1D-LGP systems for various gatherings under this investigation. All the five gatherings have been utilized in this investigation. In the two systems, the first step is the calculation of change code for each signal point. When the code calculation for all the signal purposes of a signal is finished, these codes are produced as a histogram. This procedure is rehashed for every one of the signals. These histograms represent the component vectors of the relating EEG signals and in this way utilized for the classification utilizing diverse AI classifiers. The length of the component vector (l) relies upon the number of neighboring focuses (m) considered in assessing the change code and the relationship is given by the accompanying condition:

$$L=2^m$$

Various trials have been conducted and it is discovered that the best classification results are gotten when the quantity of neighboring focuses (m) is set to 8 and the length of the feature component vector is 256. The execution of LNDP procedure with the various number of neighboring focuses for some experiment cases.

5. EXPERIMENTAL RESULTS AND DISCUSSION

In this segment, the test results have appeared and the examination of results analysis has been done.

5.1. RESULTS

All the five subjects have been utilized in this investigation. In the two methods, the first step is the calculation of the change code for each brain signal point. When the transformation code calculation for all the signal purposes of a brain signal is finished,

these transformation codes are produced as a histogram. This procedure is rehased for every one of the Signals. These histograms represent to the future element vectors of the comparing EEG signals and in this way utilized for the classification utilizing distinctive AI classifiers.

Fig. 4 LNDP-Single Electrode System Histogram

Fig. 5 LNDP-64 Electrode System Histogram

5.2. DISCUSSION

As LNDP and 1D-LGP accomplished high classification feature exactness for various trial cases considered in this investigation. For the greater part of the test cases, the ANN classifier accomplished better classification precision. For case 90.93 % precision on both the test set and assessment set. Correspondingly, the 1D-LGP methods likewise accomplished high classification precision for various exploratory cases. For case, 1D-LGP accomplished 89 % classification exactness on the assessment set. Both the

strategies accomplished high classification exactness for other test cases too. On account of the arbitrariness, it is additionally discovered that for some trial cases the precision accomplished on the test set is better when contrasted with the assessment set. The all-out computational time for the preparation and classification of EEG signals is observed to be less for various classifiers. the comparison is shown in Fig 6.

Table II. Classification Percentage Accuracy of 1D-LGP & LNDP

Number of classes	Classifiers	Feature Extraction Technique	
		1D-LGP (Acc% + Std)	LNDP (Acc% + Std)
20	ANN	88.90 +-1.30	90.93 +- 1.19

Table III. Some techniques proposed in literature for biometric identification system

Year	Method	Subjects	Accuracy	Authors
2015	CNN	10	88.00	[3]
2016	WT+NN	5	95.00	[8]
2016	WT + ETA + LDA	30	83.00	[6]
2017	1DLGP + ANN	20	88.90	[1]
Proposed	LNDP+ANN	20	90.93	

It can be seen in Table III that the proposed model also achieves a high classification accuracy with 20 subjects.

Fig. 6 Result Comparison of Mean Accuracy (%)

6. CONCLUSION

In this paper, 1D-LGP and LNDP with ANN have been proposed for building an EEG based system. The effectiveness of the proposed framework has been tested with the

publicly available EEG dataset. The ANN classifier was used to carry out the classification process. The experimental results are compared with some of the existing techniques in the literature. From these experimental results, it could be interpreted that the proposed model is effective for developing an EEG based biometric identification system. In the future, the applicability of the proposed model can also be tested in different fields.

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