Attention Analysis in Flipped Classroom using 1D Multi-Point Local Ternary Patterns

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***Abstract*—Flipped Classroom is a mode of learning which is developed based on students' academic engagement inside and outside the classroom. In this learning pedagogy, students take lessons from pre-loaded lecture videos before coming to the classroom for doubt clearing, discussion, problem solving, etc. However, it is very difficult to ensure that students really pay attention while watching lecture videos.**

In this paper, we adopt a feature selection technique called 1D local binary pattern (1D-LBP) to analyze captured brain signals of the students. The proposed feature selection technique is termed as 1D Multi-Point Local Ternary Pattern (MP-LTP), which extracts unique statistical features from EEG signals. Subsequently, standard classification techniques are exploited to analyze the attention level of students. Experimental results show that the proposed method outperforms state-of-the-art classification techniques using LBP.

***Index Terms*—Electroencephalogram (EEG), Multi-Point Local Ternary Pattern (MP-LTP), Flipped Learning (FL), Discrete Wavelet Packet Transform (WPT)**

I. Introduction

Traditional classrooms as a learning pedagogy, have been ubiquitous and popular for a very long time. Students can interact with the teacher in real-time in a traditional classroom. However, due to time constraints, there is more focus on the instruction or lectures and less on practice and problem solving. Thus, students cannot be sufficiently trained in problem solving aptitude and critical thinking skills. Technology and AI have given rise to alternative learning techniques like Flipped Classroom [1], that can deal with such drawbacks. Flipped Classroom is a blend of traditional and online learning methods. In this mode, students can access pre-recorded lectures and reading material outside the classrooms as per their convenience [2]. Inside the class, the sole focus is on discussions, doubt clearing, critical thinking skills and real-life problem solving. However, it is difficult for the instructor to identify if the students are really paying attention while watching lectures outside the class. Monitoring the attention levels of students becomes important in this context.

In this study, we propose a method to record EEG signals, reduce the dimension using Discrete Wavelet Packet Transform (WPT) and encode them using 1D Multi-Point Local Ternary Pattern (MP-LTP) to obtain desired features. To validate the proposed feature engineering technique, standard classifier models and evaluation metrics are used.

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II. Data Set Description

Data collected from 44 participants (33 male and 11 female), aged between 17-20, are analyzed in this study. Each student has to watch five video lectures on C Programming Language. In order to obtain the ground truth, a pre-test and post-test on the video topic is conducted before and after a student watches a lecture. This will be used as ground truth. EEG data is collected as the students watch the video lectures.

III. Proposed Method

Each recorded EEG data is stored as a matrix of size (M X N), where M denotes the duration of video in seconds, and N denotes sampling rate (512 Hz). We trim out the first six and the last six seconds of recordings. Collected data is pre-processed using WPT to decompose the signals to get relevant features in time-frequency domain [3]. Four levels of decomposition are carried with $db4$ wavelet and finally, the approximation coefficients after fourth decomposition are used. These coefficients are converted into single dimension. To extract the features, we propose the MP-LTP method which is described below.

Let $L = \{l_1, l_2, \ldots, l_n\}$ be the single dimensional data obtained after applying WPT on a video. L is grouped into

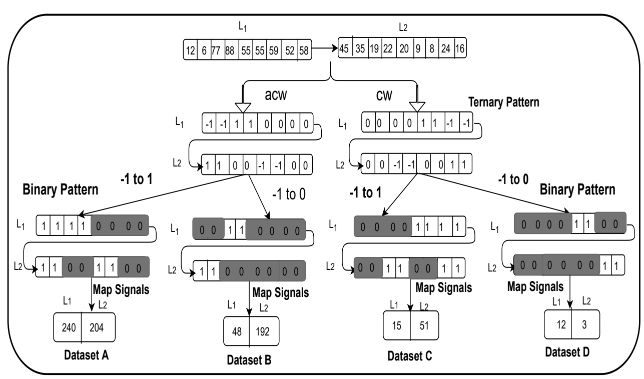

Fig. 1. Multi-Point Local Ternary Pattern Features (MP-LTP)

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a number of blocks in which each block contains nine consecutive values l_i. We assign a ternary bit to each value based on a threshold ϑ. The threshold ϑ is taken as half of the mean amplitude (α) of each record L.

In each block, the center element P_c (i.e 5^{th} element from left) is compared to the other non-central elements. If a non-central element's value is less than or equal to (P_c -ϑ), we assign -1. If it lies between (P_c-ϑ) and (P_c+ϑ), we assign it 0 and 1 for all other cases. Each string can be read from left to right (anti-clockwise) and from right to left (clockwise). This gives us two types of strings. We then convert these ternary strings into binary strings by replacing all -1s with 0 in one case and with 1 in another case. We finally convert the binary strings into decimal form, to create the feature dataset.

We thus obtain four different feature datasets A, B, C and D from the same video. A has Anti-Clockwise order and replacement of -1 with 1. B has same Anti-Clockwise order with -1 replaced with 0. C and D have Clockwise ordering, replacing -1 with 1 and -1 with 0, respectively. The MP-LTP process is shown in Fig 1.

As the primary idea comes from LBP, we also created datasets using LBP. We have two datasets ($Binary_{cw}$ and $Binary_{acw}$) after applying 1D Multi-point Local Binary Pattern (1D MP-LBP) in the same way as we did for MP-LTP.

To establish the effectiveness of our designed features, we establish a ground truth and split the feature datasets for training, validation and testing (70%, 10%, 20%). We train all four LTP datasets and the two binary datasets and perform validation. Based on minimum validation error, we select the best dataset for testing (each for LTP and LBP).

FEATURES VALIDATION AND TESTING: Attention level of a student can be obtained from pre-test (x) and post-test marks (y). We can to assign labels using equation (1). If x is greater than or equal to 80% of total marks, we assume that the student already has sufficient knowledge on the topic. Therefore the EEG data of that video is ignored. Here a is mean value of post-test marks of all students, b is the difference between mean values of post-test and pre-test marks and $ImpX$ ($ImpX = y - x$) is the improvement between the two tests.

$$A(x,y) = \begin{cases} \text{Discarded} & if\ (x >= 80\%) \\ \text{Inattentive} & if\ (y < a) \text{ And } (ImpX < b) \\ \text{Attentive} & Otherwise. \end{cases} \quad (1)$$

We use classifiers like Artificial Neural Network (ANN), K-Nearest Neighbors (KNN), Decision Trees (DT), Random Forests (RF) and Support Vector Machines (SVM) on the extracted feature sets and on state-of-the-art techniques (LBP [4], 1D-TP [5]) for comparison.

RESULTS AND ANALYSIS: We get the least validation error in Dataset A for MP-LTP and in $Binary_{acw}$ for LBP. From the results in Table I and Table II we can claim that 1D MP-LTP performs better than 1D MP-LBP technique and other state-of-the art method.

TABLE I
COMPARISON OF PERFORMANCE METRICS OF LBP METHODS

Technique	Model	Block Size	Precision	Recall	F1	Accuracy
LBP [4]	ANN	**Overlapping 7 segment**	66.66	96.55	78.86	65.90
	KNN		58.82	83.33	68.96	59.09
	DT		52.77	79.16	63.32	50.00
	RF		54.54	100.00	70.58	54.54
	SVM		54.54	100.00	70.58	54.54
1D MP-LBP	ANN	**Non Overlapping 9 segment**	68.18	100.00	81.08	68.18
	KNN		69.76	100.00	82.19	70.45
	DT		65.62	70.00	67.74	54.54
	RF		67.44	96.67	79.45	65.90
	SVM		68.18	100.00	81.08	68.18

TABLE II
COMPARISON OF PERFORMANCE METRICS OF 1D MP-LTP MODEL

Technique	Dataset	Model	Block Size	ϑ	Precision	Recall	F1	Accuracy
1D-TP [5]	$Dataset_1$	ANN	**Overlapping 9 segment**	0.05	65.90	100.00	79.45	65.90
		KNN			67.44	100.00	80.55	68.18
		DT			69.56	55.17	61.53	54.54
		RF			65.90	100.00	79.45	65.90
		SVM			65.90	100.00	79.45	65.90
	$Dataset_2$	ANN	**Overlapping 9 segment**	0.05	68.18	100.00	81.08	68.18
		KNN			69.76	100.00	82.19	70.45
		DT			68.75	73.33	70.97	59.09
		RF			68.18	100.00	81.08	68.18
		SVM			68.18	100.00	81.08	68.18
1D MP-LTP	Dataset A	ANN	**Non Overlapping 9 segment**	$\alpha/2$	75.00	100.00	85.71	75.00
		KNN			76.74	100.00	86.84	77.27
		DT			79.41	81.81	80.59	70.45
		RF			76.19	94.11	84.20	72.72
		SVM			75.00	100.00	85.71	75.00

IV. CONCLUSIONS AND FUTURE SCOPE

In this study, we propose a feature selection technique by analyzing attention levels in Flipped Classroom. Experimental results demonstrate that our 1D MP-LTP method outperforms any standard models. We can extend this in future, using LTP without converting to binary and with varying block sizes.

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