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Dynamic Time Warping: A Single Dry Electrode EEG Study in a Self-paced Learning Task

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***Abstract*—This study investigates dynamic time warping (DTW) as a possible analysis method for EEG-based affective computing in a self-paced learning task in which inter- and intra-personal differences are large. In one experiment, participants (*N*=200) carried out an implicit category learning task where their frontal EEG signals were collected throughout the experiment. Using DTW, we measured the dissimilarity distances of EEG signals between participants and examined the extent to which a k-Nearest Neighbors algorithm could predict self-rated feelings of a participant from signals taken from other participants (between-participants prediction). Results showed that DTW provides potentially useful characteristics for EEG data analysis in a heterogeneous setting. In particular, theory-based segmentation of time-series data were particularly useful for DTW analysis while smoothing and standardization were detrimental when applied in a self-paced learning task.**

***Keywords*—DTW; Self-paced learning; Neurosky MindWave**

I. Introduction

When Calvo and D'Mello [1] reviewed the state of the art in affective computing research in 2010, emotion analysis employing electroencephalography (EEG) was relegated to the background: "Regrettably the cost, time resolution, and complexity of setting up experimental protocols that resemble real-world activities are still problematic issues that hinder the development of practical applications that utilize these techniques" (p. 26) [1].

Notable advances have been made in EEG-based analysis since Calvo and D'Mello's review primarily due to pioneering work by [2-8]; however, the same problems still plague EEG-based emotion analysis. Unlike face-based or voice-based methods, collecting EEG signals in a natural setting is far more complicated. Because many useful EEG features are time-locked, stimulus presentation and response collection need to be tightly controlled. A typical experiment consists of a brief presentation of emotional stimuli (e.g., affective images taken from the IAPS [9]) where participants' EEG signals are collected in an event-locked brief time-window [3]. Because almost all EEG-based studies employ a within-subjects design, one can come up with viable EEG features, but these features are barely useful for emotion recognition beyond the same person in the same task [10].

What analysis procedure can be applied in a self-paced learning environment (e.g., intelligent tutoring systems) where individual users interact with computers freely for a long period (e.g., more than 10 minutes)? In an attempt to investigate this questions, we employed dynamic time warping [11] as a possible analysis method and examined its applicability in a self-paced naturalistic learning environment where EEG signals were collected continuously throughout the experiment by a single dry electrode mobile device (Neurosky Mindwave Mobile).

II. Related Work

A. EEG-based affective computing

Complex human behavior, such as perception, object recognition, motor coordination, attention, and emotion expression and experience, results from synchronous coordination between excitatory and inhibitory neurons in cortical and subcortical areas of the brain [12]. For example, to reach and grab an object by a hand, excitatory signals sent from the primary motor cortex are modulated by inhibitory signals from the basal ganglia to control thousands of muscle fibers [13]. Likewise, in experiencing and expressing affects and motivation, signals processed in the limbic system are modulated by signals sent from the prefrontal cortex [14-16], generating a variety of oscillatory interactions [12, 17].

These excitatory and inhibitory neural interactions license complex nonlinear human behavior, giving rise to oscillatory electrical signals on the scalp. As such, affective states, such as temperament, personality and cognitive dissonance, are known to be associated with EEG signals that are captured in frontal lobe regions [18, 19].

Despite its compelling physiological basis, EEG-based affective computing has not fully materialized due to the following limitations: its data acquisition cost is prohibitively high as compared to other affective computing methods using facial expressions, voice, gaits, and cursor motion; EEG-based studies require strict experimental settings where the presentation of stimuli should be well marked and time-locked.

Due to these limitations, existing EEG studies in affective computing are mostly conducted with a small number of subjects (Ns < 20) in a restricted setting where emotionally salient stimuli such as pictures, film or music clips, are shown for a brief duration (5~16 seconds) in a predefined temporal schedule [3, 20, 21]. Prominent EEG features are extracted offline in a short temporal window, and are processed for classification of self-reported affective experience, such as like or dislike of musical excerpts, or positive or negative valence related to facial expressions attached to a particular event [20, 21]. However, it is unclear how useful these methods are in a natural setting when users interact with computers without much constraint. Indeed, experiments congruent to a real-world situation, such as self-paced interactions with computers, are rare. A notable exception is the study by Kothe et al. [4] where participants engaged in self-paced emotion imagination with eyes closed (see also [6-8] for other exceptions).

The problem is that it is unclear what EEG features are useful in a self-paced setting and how to extract these features in this setting. To make EEG-based affective computing viable, a method that can handle heterogeneity of task environments (e.g., participants are engaged in an actual learning task) should be scrutinized. Here, we investigate the possibility of applying dynamic time warping.

B. *Dynamic Time Warping*

Dynamic time warping (DTW) is a class of algorithms that allow comparing two sets of ill-aligned time series data (e.g., different lengths) by stretching or compressing them locally (Fig. 1). DTW algorithms were developed in the 1970s in the field of speech recognition where the heterogeneity of input data (e.g., words said as “oh, no” vs. “Ooooh, NOO!”) was commonplace [11]. DTW has been successfully employed for large scale information retrieval [22], ERP, and EEG analyses and applications [23, 24], though, to our knowledge, no investigation has been made in the context of EEG-based affective computing. In our analysis, we adopted the dtw package for the R statistical software developed by [25]. The basic algorithm described below is based on [11, 25, 26].

Basic algorithm. Assume that the goal is to measure the distance between two time series, X = (x_1,…., x_N) and Y = (y_1,…., y_M) of lengths N and M with a dissimilarity function f:

$$d(i, j) = f(x_i , y_j) \geqslant 0 \quad (1)$$

The gist of the DTW algorithm is to measure the dissimilarity distance of two sequential data sets by applying warping functions □(k), where k = 1… T. Given □, the algorithm computes the distance between warped time series X and Y:

$$d_\emptyset(X,Y) = \sum_{k=1}^{T} d(\emptyset_x(k), \emptyset_y(k))\, m_\emptyset(k)/M_\emptyset \quad (2)$$

where $m_\emptyset(k)$ and $M_\emptyset$ are coefficient and constant for normalization. To ensure meaningful warping, several constraints, such as monotonicity, is applied to preserve time ordering. The main thrust of DTW is to find the optimal warping □ that minimizes the distance between X and Y:

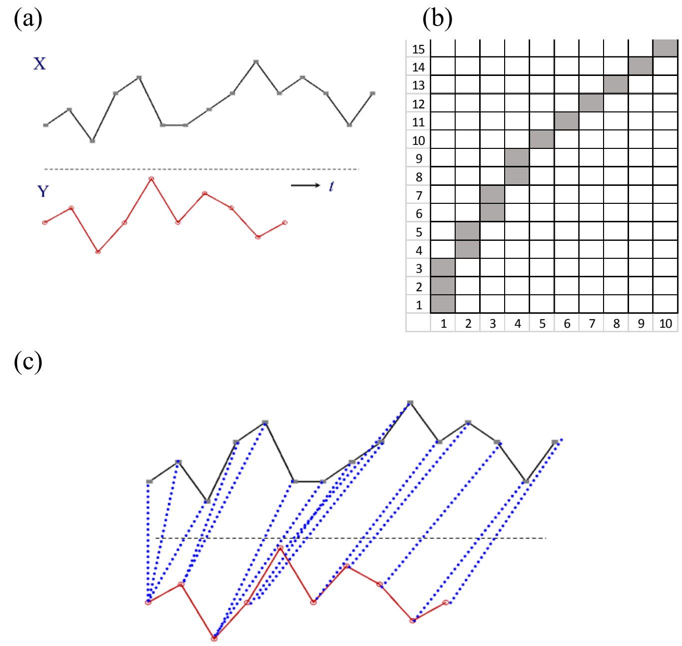
$$D(X,Y) = \min_\emptyset d_\emptyset(X,Y) \quad (3)$$

In other words, given every possible pairing of individual elements of X and Y, DTW is to find the optimal path sequence $p=(p_1,\ldots, p_L)$ with $p_\ell = (n_\ell , m_\ell)$ that satisfies the following conditions:

(i) Boundary condition (the first and the last pairs should be the first and the last elements of X and Y): p_1 = (1, 1), p_L = (N, M)

(ii) Monotonicity condition (no backward path): $n_1 \leqslant n_2 \cdots \leqslant n_L$ and $\leqslant m_1 \leqslant m_2 \cdots \leqslant m_L$.

(iii) Step size condition (no skipping): $p_\ell+1$ - p_l ∈ {(1, 0), (0, 1), (1, 1)} for l ∈ [1: L − 1].



pairs = (X, Y) =(1, 1), (1, 2), (1, 3), (2, 4), (2, 5), (3, 6), (3, 7), (4, 8), (4, 9), (5, 10), (6, 11), (7, 12), (8, 13), (9, 14), (10, 15)

Fig. 1. An illustration of a DTW algorithm. (a) two time series data with different lengths are applied to DTW. The algorithm finds the optimal path (pairing) that yields the smallest dissimilarity between the data. (b) and (c) are matrix and graphical representations of the path (b) and pairing (c).

Fig. 1 illustrates the DTW algorithm. Given two time series data with different lengths and shapes (X = (x_1,…, x_{15}), Y = (y_1,…, y_{10})), DTW applies a dynamic programming method and finds an optimal path (aligning X and Y) that satisfies the time-preserving conditions (i.e., boundary, monotonicity, and step size) and minimize the distance between X and Y, where the distance can be measured by city block or Euclidean, among others.

This brief investigation suggests that DTW provides potentially useful characteristics for EEG data analysis in a highly heterogeneous setting where inter-personal and intra-personal differences (i.e., differences among multiple participants and differences within a task in a single person) are rampant. For example, given a task that involves complex learning (e.g., students are expected to learn physics or algebra using an advanced intelligent tutoring system), both inter- and

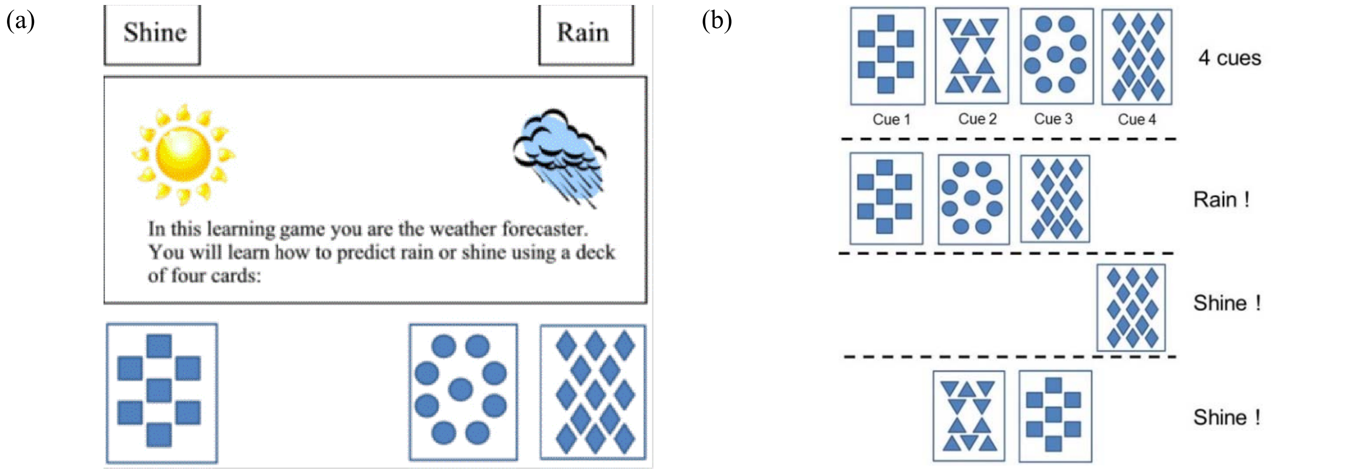


Fig. 2. An illustration of the category learning task. (a) The participant received arbitrary card combination one at a time and learned to classify each card as "shine" or "rain" by trial and error. After each trial, the computer gave feedback.

intra-individual differences are large. Some students may respond fast while other students are slow (inter-personal difference). The same student may respond fast to solve a particular problem but slow in another problem (intra-personal difference). Their task engagement levels may vary widely between- and within-students. Because DTW allows comparisons of heterogeneous time series data, it has the potential to overcome these problems. In one experiment, we tested this idea.

III. Experiment

We employed a neuropsychological implicit learning task developed by Knowlton and Squire [27] where participants (*N*=200) were instructed to learn two arbitrary categories ("shine" and "rain") that are depicted by combinations of cards (Fig. 2). Prior to the experiment, no information about card combinations and their outcomes ("shine" or "rain") was given; thus participants had to learn the "concepts" of "shine" or "rain" by trial and error. Participants received feedback (e.g., "Yes. It's shine") right after each response. The card combinations were set so that individual cards were probabilistically associated with either category (thus, memorizing explicit rules that divide two categories was not helpful). Thus, "implicit" learning was required in this task.

Throughout the category learning task (a total of 150 trials lasting about 13 minutes), we collected participants' EEG signals at the left frontal scalp (targeting at the Fp1 location) using Neurosky MindWave Mobile (see the Apparatus section for the device specification). Shortly after the category learning task, participants rated their feelings with the Positive and Negative Affective State Expanded (PANAS-X) [28] and indicated their attitudes toward learning with VandeWalle's goal orientation questionnaire [29].

PANAS-X measure 11 specific affects on a 1-5 Likert scale (e.g., fear, self-assurance, attentiveness) along with two broader affects (positive or negative affects). Internal consistency reliabilities (Cronbach's alpha) measured with a cumulative total of more than 8,000 subjects were .80 or higher (the medians of Cronbach's alpha coefficients). The median test-retest reliabilities obtained from two broad affects and 11 specific affects measured in a 2-month retest interval with 399 subjects was .59 [28, 30]. Brown et al. [31] recruited 350 outpatients with different types of anxiety disorders; the study shows that the degree of positive and negative affects assessed by the PANAS are related to various types of anxiety disorders such as mood disorders; generalized anxiety disorder panic disorder; obsessive-compulsive disorder; social phobia, suggesting that this measurement schedule is applicable to assess the degree of mood.

VandeWalle's goal orientation questionnaire, which was given after PANAS-X, assessed attitude toward learning (i.e., goal orientation). We adopted this questionnaire to conduct "theory-based" EEG analysis (see the Result section). Goal orientation is related to self-regulation strategies (cognitive process for goal setting, effort and planning). The questionnaire rates individuals with three types of goal orientation: "learning-centered goal" (LG), "performance-centered goal (PG), and "avoid performance goal" (APG). In the learning-centered goal orientation (LG), the learner views challenging situations as an opportunity to learn. In the performance-centered goal (PG), the learner is more inclined to display their competence (e.g., showing off how competent they are); in the avoid-performance goal, the learner fears revealing his / her incompetence.

To predict self-rated feelings of participants, EEG signals collected from individual participants were supplied to DTW, which measured dissimilarity distances of every pair of EEG signals obtained from all participants. A k-Nearest Neighbor (k-NN) algorithm (k = 4) was applied to predict participants' self-reported emotions (i.e., positive affect, negative affect, attentiveness, and fear). We focused on these emotions because of their significance in a learning system (e.g., intelligent tutoring system) [32]. We employed Spearman's rank correlation to assess prediction performance of our method (Fig. 3).

A. *Method*

1) Participants Participants were undergraduate students participating for course credit. Among 212 participants who were recruited for this experiment, 200 participants completed the entire experiment (female = 159; male = 45).

2) Procedure All participants conducted the category learning task first and then finished two questionnaires—PANAS-X and the goal orientation questionnaire. In the category learning task, participants received 14 combinations of cards one at a time (150 trials in total) and learned to predict whether each combination belonged to "shine" or "rain" categories on the basis of feedback that was provided after each response (Fig. 2). Each card was probabilistically linked to the outcome of "shine" approximately 75, 57, 43, 25 % of the time.

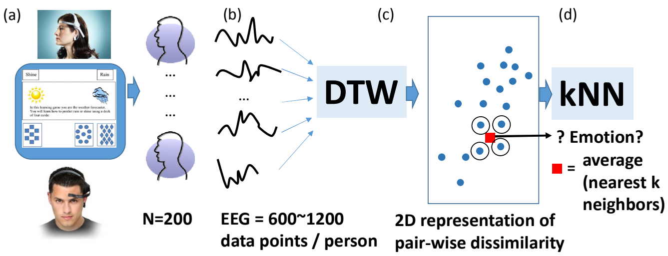


Fig. 3. An illustration of the experiment. (a) During the category learning task, participants' EEG signals were collected. Dissimilarity distances of every pair of EEG signals were measured by DTW—(b) and (c). To predict the emotion rating of a participant (red square), emotion ratings of k-nearest neighbors (participants) were averaged—(d).

To start a trial, the participant first pressed the Next button, the cursor was then placed automatically at the center of the button, and the stimulus picture (card combination) was presented on the monitor (Fig. 2). To indicate a selection, participants pressed a target button (either the left or right button shown at the top left / right corner of the screen). The stimulus disappeared soon after and feedback was presented (e.g., "Yes. It's shine"). This cycle was repeated 150 times. The task was self-paced.

3) Apparatus and Materials

The category learning task was administered by a customized Visual Basic.Net program. The program collected participants' response, response times, and EEG signal simultaneously. For EEG data acquisition, we employed Neurosky MindWave Mobile (http://neurosky.com/). This device has been used in other neuropsychological studies and has been shown to be reliable and comparable to research-grade medical EEG devices. For example, Johnstone et al. [33] compared Neurosky MindWave Mobile to another research-grade system (Nuamps, Neuroscan, Compumedics, Melbourne Australia) and reported that power spectra obtained from the two systems were highly correlated in eye-closed and eye-opened resting conditions. Hemington and Reynolds [34] also applied the system to test children with Fetal Alcohol Spectrum Disorder (FASD) and found different frontal EEG activities in children with FASD and normal controls.

The single dry electrode was placed at a left-forehead location (targeted at Fp1) with the reference electrode placed on the left earlobe. The EEG signal was recorded at a sampling rate of 512 Hz and was processed internally by Neurosky's proprietary program ThinkGear^{TM}. The single dry sensor placed at the left forehead and reference electrode assessed potential differences (voltages), which were amplified 8000x to enhance the EEG signals. The signals were passed by low and high pass filters to preserve signals in the 1-50Hz range. After correcting for possible aliasing, these signals were sampled at 512Hz. The EEG signal was then sent to the computer by BlueTooth (Kinivo BTD-400 Bluetooth USB Adapter). Each second, Neurosky's proprietary algorithm ThinkGear^{TM} applied standard FFT on the filtered signal and produced commonly recognized eight EEG powers: delta (0.5 -2.75Hz), theta (3.5 – 6.75 Hz), low-alpha (7.5 – 9.25Hz), high-alpha (10 – 11.75Hz), low-beta (13 – 16.75Hz), high-beta (18 – 29.75Hz), low-gamma (31 – 39Hz), and mid gamma (41 – 49.75Hz) together with proprietary eSense^{TM} *attention* and *meditation* meters, which were computed with a wide spectrum of brain waves in both time and frequency domains. The attention meter, which measures attentiveness of the user, is said to have more emphasis on the beta wave, and the meditation meter, which measures the calmness and levels of self-control, has more emphasis on the alpha wave. The meter value is reported on a relative scale of 1-100.

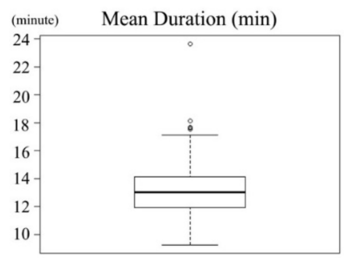


Fig. 4. Mean durations for the category learning task (minutes)

B. Results

This section begins with summaries of basic behavioral data—durations for the category learning task, mean response times for individual trials, and task accuracy—followed by results from the EEG analysis.

Basic behavioral results. On average, participants spent approximately 13 minutes to complete the category learning task (M = 13.2 minutes; SD = 1.83). Because the task was self-paced, there was a wide range of individual differences in completing the task. Some participants spent nearly 20 minutes or more while others finished the task in less than 10 minutes (Fig 4).

Response times for individual trials also varied widely. On average, participants responded to each trial in 2.2 seconds (SD = 0.62). However response times became shorter as the learning task progressed. In the first 30 trials, participants responded in 2.7 seconds (SD = 0.81); in the last 30 trials (trials 121-150), the average response time dropped to 1.7 seconds (SD = 0.52) (Fig. 5a). In the same vein, categorization accuracy was subject to trials. Accuracy improved as trials progressed (Fig. 5b). This preliminary analysis suggests that

(a) (b)

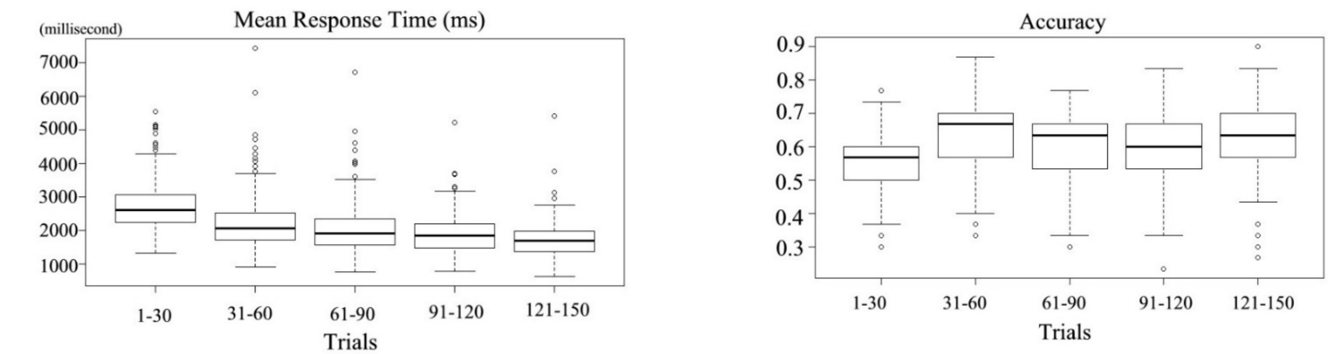


Fig. 5. Boxplots for (a) response times and (b) accuracy shown relative to five blocks of learning trials. Mean and standard deviations of response times decreased as the learning trial progressed. Mean accuracy also followed trials.

response patterns (response times and accuracy) varied widely both within and between participants.

C. EEG analysis

In our EEG analysis, we first examined the impact of DTW with powers of 8 spectral bands and two meters, *attention* and *meditation*, which were collected throughout the category learning task every second (1 Hz) (600 to 1300 data points per participant in each spectral band). For all band signals, we calculated relative band powers following the procedure adopted by Johnstone et al. [33]; we summed the powers of all eight bands and then divided the power for each band by the total, which was expressed as a percentage. For the DTW algorithm, we employed the default values specified in the R package dtw (Euclidean distance and no windowing) [25]. In k-NN, we fixed k = 4 in all our analyses following the recommendation by Enas and Choi ($k=(N)^{2/8}$) [35]. No parameter tuning was employed in our data analysis. Below we begin with a basic analysis and then examine the impact of standardizing, smoothing, and segmenting. We also discuss "theory-based" knowledge-driven analysis.

TABLE 1 BASIC RESULTS

Band	Hz	Positive Affect	Negative Affect	Attentive	Fear
Delta power	0.5 -2.75Hz	-	-	-	-
Theta power	3.5-6.75Hz	-	-	0.15*	-
Low Alpha power	7.5-9.25Hz	-	-	-	-
High Alpha power	10-11.75Hz	-	-	-	-
Low Beta power	13-16.75Hz	-	-	-	-
High Beta power	18-29.75Hz	-	0.14 *		
Low Gamma power	31-39.75Hz	-	-	-	-
Mid Gamma power	41-49.75Hz	-	-	-	-
Attention meter	~ Beta	0.14*	-	0.22 ***	-
Meditation meter	~ Alpha	-	0.13#	-	0.21***

Note. Spearman's correlation coefficients for predicted and observed emotion ratings. p****< 0.001; 0.001 ≤ p*** < 0.005; 0.005 ≤ p** < 0.01; 0.01 ≤ p* < 0.05; 0.05 ≤ $p^{\#}$ < 0.1. The correlations whose p values are above 0.1 are indicated by "-".

Basic analysis. As Table 1 shows, DTW using the attention and meditation meters demonstrated superior performance. Given the attention meter, we found small but highly significant correlations between predicted and observed emotion ratings for attentiveness and positive affect to some extent. The meditation meter, which corresponds to calmness and mental control, also predicted emotion ratings of fear, which is related to task anxiety of learners. In addition, we found that theta and high beta powers had significant predictive performance. Because the attention and meditation meters were most useful, we focus on these two measures in the subsequent analyses.

Standardizing lengths of time series data. In this analysis, we standardized all time series data into 100 or 200 data points and applied DTW for standardized data sets. For example, given two time series data with 1000 and 600 data points, respectively, we normalized them into 200 points by dividing each data set into 200 equally spaced bins and calculating the mean in each bin. In this manner, all EEG signals obtained from individual participants were reduced to an equal length (either 100 or 200 data points). This analysis however weakened DTW's prediction performance (Table 2). Apparently, standardizing the length of data points was detrimental.

TABLE 2 STANDARDIZING

	data points	Positive Affect	Negative Affect	Attentive	Fear
Attention meter	100	0.16*	-	-	-
	200	-	-	-	-
Meditation meter	100	-	-	-	-
	200	-	-	-	0.13#

Smoothing data points. EEG data are prone to noise. To capture overall trends of time series signals, smoothing by moving averages is a common practice for time series data preprocessing. Here, we employed a window size of 10, 20, or 30 and examined the impact of smoothing. This measure however completely eliminated the prediction performance of DTW. All correlations disappeared after smoothing.

Segmentation. The lack of significant performance in our DTW analysis through standardizing and smoothing suggests that the advantage of DTW analysis most likely stemmed from DTW's ability to tune in local trends of EEG signals. To test this idea, we employed theory-based data segmentations. As Fig. 5 shows, learning occurred earlier in the task. In this regard, some segment of learning trials could be more informative than other parts for DTW-based EEG assessment. Following this logic, we divided individual time series data into three segments according to the sequence of the learning trials—early, middle and late segments. In the early segment, we selected the first 40% of the data points in each participant. In the middle segment, we selected the middle 40% of the data points. In the last 40% segment, we selected the last 40% of the data points (there were about 10% overlaps). For each segment, we applied DTW separately. As Table 3 shows, this procedure helped emotion prediction. In particular, the meditation meter collected earlier in the task turned out to be particularly useful.

TABLE 3 SEGMENTING

	learning trials	Positive Affect	Negative Affect	Attentive	Fear
Attention meter	early	-	-	0.14*	-
	middle	0.14#	-	-	-
	late	-	-	-	-
Meditation meter	early	-	0.23****	-	0.20***
	middle	-	-	-	0.14*
	late	-	-	-	

TABLE 4 GOAL ORIENTATION

	goal		Positive Affect	Negative Affect	Attentive	Fear
Attention meter	LG	high	-	-	0.18#	-
		low	-	-	-	-
	PG	high	-	-	-	-
		low	-	-	0.22*	-
	APG	high	-	-	-	-
		low	0.24*	-	0.22*	-
Meditation meter	LG	high	-	-	-	-
		low	-	0.19#	-	-
	PG	high	-	-	-	-
		low	-	-	-	-
	APG	high	-	-	-	-
		low	-	-	-	-

Participants' goal orientation. Another important theory-based parameter is personal differences. Individual learners have different attitudes toward learning. Some learners focus on mastering the task (learning goal—LG), while others are more concerned with task performance (performance goal—PG) or avoid revealing one's performance (avoid performance goal—APG). These different learning attitudes of individual learners are known to influence their learning experience profoundly [36]. Here, using VandaWelle's goal orientation questionnaire, we divided participants into high / low categories of goal orientations (high/low LG, PG, APG) and applied DTW separately. This theory-driven approach improved prediction performance of DTW (Table 4).

IV. Discussion

A. Summary and Implications

Examining feelings of computer users using EEG signals in a heterogeneous learning environment is difficult due to various limitations inherent in EEG-based analysis. In this study, we investigated the possibility of applying DTW, which has been successfully implemented in speech recognition, information retrieval, and motion detection. Results from the experiment provide both promising and cautionary messages. On the positive side, the study suggests that DTW is useful for EEG-based affective computing in a naturalistic setting. On the other hand, results also highlight the difficulty of applying DTW. We offer the following caveats.

a) Straightforward measures of spectral powers had little use for DTW analysis.

As in other EEG-based emotion analysis (see [3]), careful feature extraction appears critical. We used proprietary emotion meters, attention and meditation. We do not know exactly how these meters are calculated. Nonetheless, identifying important EEG features from raw data appears critical to improve DTW performance. The distributions of individual frequencies inside particular bands (e.g., [4]) may provide a fruitful avenue.

b) Smoothing and standardizing hampered DTW performance

To our surprise, smoothing with rolling windows did not improve DTW's prediction performance. Smoothing is useful to clarify an overall trend of time series data. Our finding that smoothing eliminated correlations suggest that DTW was effective in capturing some local characteristics of EEG signals. It appears that some feature extraction method, such as identifying local motif of time series data [37], can be particularly useful for DTW application of EEG-based affective computing.

c) Theory-based segmentation was helpful.

Segmenting learning trials and learners into some meaningful units seem to improve DTW's prediction performance. Dividing the participants in terms of their attitudes also improved the performance. Some background knowledge about the task at hand and the characteristics of the person who is actually engaging in the task are likely to enhance the resolution of DTW prediction.

d) Future directions

Comparisons with other methods using advanced DTW such as Canonical Time Warping [38, 39] should be performed in the context that adopt different EEG features applied in different settings [40].

B. Conclusion

This study shows possible avenues and hurdles for DTW-based EEG analysis for affective computing in a self-paced learning task. The study suggests that identifying local features that can enhance prediction performance is critical. For this, both theory-based and data-driven approaches should be incorporated. On the theory-based side, it is important to know more about the attitude and personality of the learners as well as specific constraints of the task at hand. On the data-driven side, identifying local features, such as local motifs of time series data, are likely to improve DTW-based affective computing.

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