Dynamic Time Warp Distances as Feedback for EEG Feature Density

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***Abstract*—This work presents a feature detection method built around a dynamic time-warping (DTW) -based confusion matrix. It can be used to discern potential features with minimal data manipulation and minimal prior knowledge. This technique provides a robust distance measurement between sample electroencephalogram (EEG) signals that form the basis of a confusion matrix indexed against events carried out as part of shared data from the PhysioNet Imagined Motion database. DTW matches signals by reconstructing the common time axis to match the amplitudes of signals as closely as possible. The resulting confusion matrices present visual patterns, or motifs, useful for distinguishing artifacts and potential features of interest in each motion trial. The results suggest this technique could be used as a tool to find areas of interest within EEG recordings and then to map them to similar occurrences.**

***Index Terms*— EEG, Dynamic Time Warping, Feature Development, Outlier Detection, Confusion Matrix**

I. Introduction

Electroencephalogram signals measure scalp biopotentials and are used as proxies for assessing brain activity. In general, EEG signal research strives to develop algorithms that quantify similarities between various signals and to achieve subject and context independent feature extraction [4] [7]. Numerous feature extraction and feature separation methods have been proposed, but have yielded only modest performance [1]. The lack of a definitive feature classification scheme across varied brain activity suggests there is space to develop an approach applicable to open ended feature searching. We hypothesize that raw data can be harnessed with minimal manipulation to cultivate an effective classifier independent of the specific brain activity.

The most common EEG processing tools focus on seizure detection via frequency analysis [6] [9], movement initiation via spatial filtering [2], and stimulus recognition/response via event-related potentials [3]. Techniques targeted at each of these problems have been demonstrated with adequate performance, but tend to translate poorly for solving other EEG signal processing problems. This suggests that either different EEG features are relevant to solving different problems, or the underlying mechanisms driving variability in EEG signaling remain unknown [5].

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The distinct approaches to finding features and anomalies in EEG records stem from *a priori* knowledge about the subject and the search target. Anomalies complicate analysis because their presence impacts multiple channels or persists for long durations. Anomalies obscure the target features or even present as the target features of interest depending on how they occur as data artifacts [10], brain computer interface (BCI) illiteracy [11], or non-standard techniques [12]. In many cases, anomalies cannot be avoided given the environment or nature of the subject and can lead to additional manipulation of the data prior to feature detection.

The tool proposed uses raw data to match samples through the time warped distance between signals. By reviewing data from subjects performing cyclical tasks, similar cyclical patterns should emerge in a DTW distance confusion matrix. Patterns within a given sample and across task orientated sets of samples should appear naturally when viewed as a DTW based confusion matrix. Anomalies would present as non-cyclical horizontal or vertical lines, making it clear where data of poor quality is located in the recording resulting in quick visual verification of the recorded signals.

II. Methods

A. Data Sets

The PhysioNet EEG Motor Movement/Imagery Dataset contains recordings of 109 subjects at 160Hz from 64 electrodes placed in the standard 10-20 configuration. Each recording captures a single trial, with 14 unique trials per subject, each containing 30 tasks [8]. Half the trials require physical movement and half require imagined movement. The tasks are divided into contrasting actions: opening/closing fists (event T1) versus feet (event T2), opening/closing the left (T1) versus the right (T2) fist, and a rest state (T0).

Figure 1 shows a trial sequence broken down into task order for the specific case of Trial 4. Each task's duration is 4

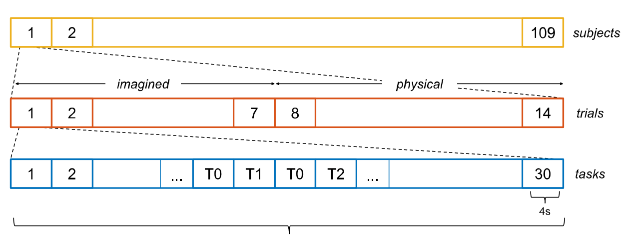

Figure1: Graphical representation of data. Each trial contains 30 tasks which can be either event T1 (fists/left), T2 (feet/right), or T0 (rest)

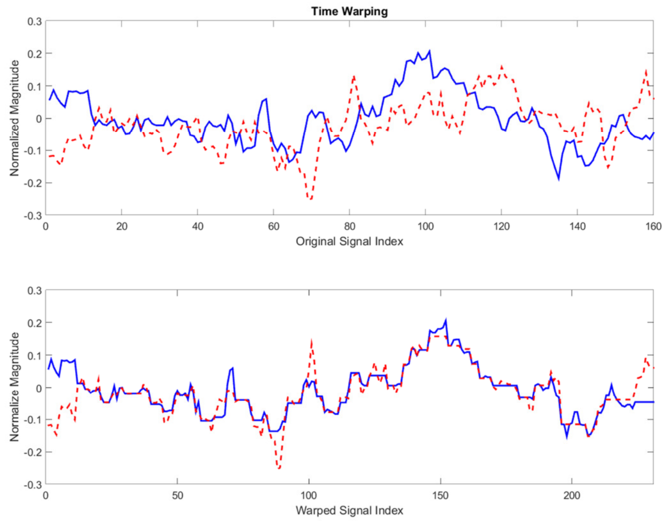

Figure 2: Time warping of original signal's windows, top, to produce distance between each window's warped version, bottom.

seconds. There were two additional recordings per subject, resting eyes open (REO) state and resting eyes closed (REC) state, which serve as calibration files and were not used in this work.

B. *Data Processing*

Each 120 second trial was segmented into 1-second (160 samples) windows, with 75% overlap between successive windows. Each window was normalized prior to calculating the DTW distance between all other windows for that channel in the given trial. DTW rebuilds two signals by searching for the most overlapping path given their duration and amplitude. Warped signals often appear to lengthen in time as points are resampled when the time distance penalty is less than the magnitude distance penalty; this is seen in Figure 2. How far the function searches in time for a suitable point is controlled by the DTW window parameter. The size of the DTW window is set to the window size of 160 samples to ensure an exhaustive search.

C. *Confusion Matrix*

The resultant DTW distance matrix is organized by event and window index. The events are ordered starting with rest events (T0), followed by T1 events and then T2 events. Within the event groupings, the individual windows are order by their sampling order. This produces a confusion matrix that retains

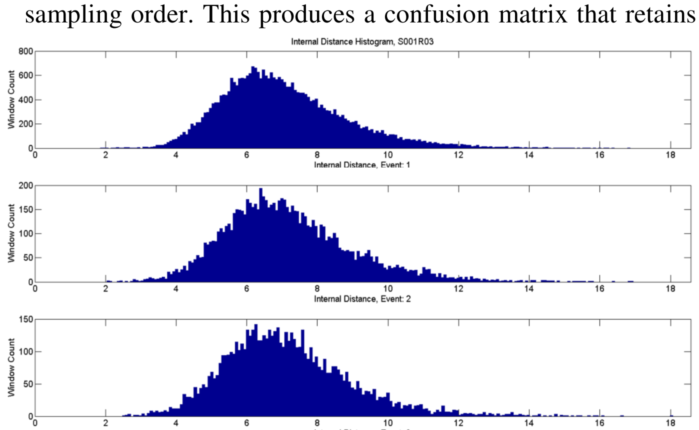

Figure 3: Histogram data, 200 bins, of internal event window distance comparisons

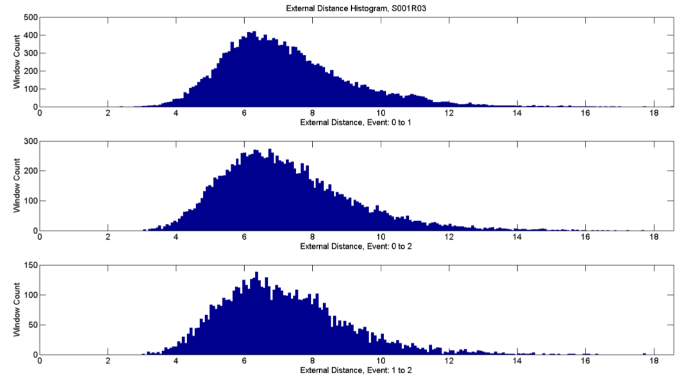

Figure 4: Histogram data, 200 bins, of external event window distance comparisons

time series representation within the event groupings.

This organizational structure positions matched windows along the positive diagonal axis of the matrix. For clarity, these values are set to null so they appear as white space when displayed. The color map for the matrix was developed to mute the majority of the most commonly seen distances and highlight outliers from the distance calculations. Figure 3 shows one instance of the resultant histograms when comparing event groups against each other.

The distributions show a substantial portion of distances fall between 6 and 8 with a tail reaching to 18. Due to this the interval 6 to 8 is deemphasized by making it gray while outlier values, below 6 and above 10, are more vibrant contrasting colors. When performing the same measurement on external event measurements, similar distributions are found in Figure 4. This enables one color map to suffice for analysis as both relationships cover a closed distance.

III. Results

A confusion matrix was generated for each trial of subject S001, Figure 5 shows the results for trial 6. In Figure 5 there is an artifact that occurs in the 3rd T1 event and continues into the 6th T0 event; this is evident by the extreme distances recorded from the warping, visualized as pink and red responses and the strong blue responses along the diagonal. This artifact is the strongest characteristic of the confusion matrix, but it does not prevent the rest of the matrix from

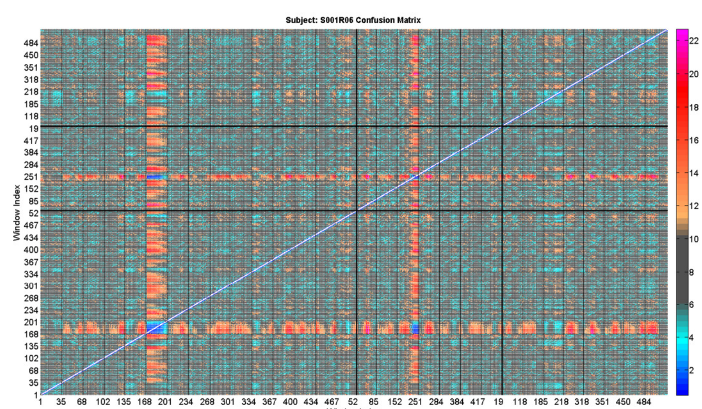

Figure 5: Detection of an artifact in the recording from windows 152 to 180. The black lines grouping the events with the lower left box being T0 compared to T0, middle left T0 to T1, and upper left T0 to T2.

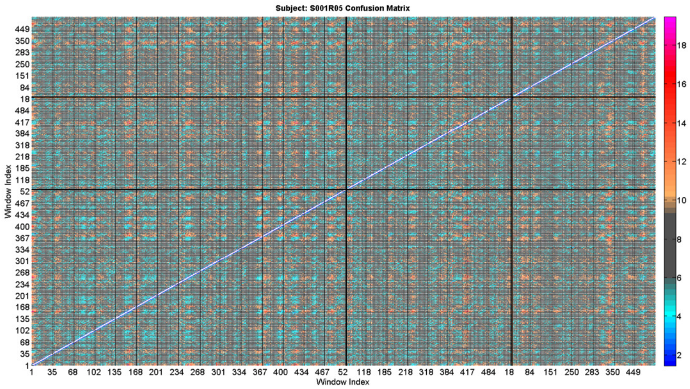

Figure 6: Resultant confusion matrix of motion trial requiring opening/closing of fists and feet

being evaluated.

The 3rd T2 event, starting at window 185, presents as an artifact diverging from the color pattern of the other T2 events; it reports low distance to the previously identified artifact making it something different from its group and the previous artifact.

Given the tight histogram distributions shown in Figures 3 & 4, other samples that strongly match to these two artifacts are not going to be areas of response to the targeted test stimulus. The three boxes along the diagonal present with similar color patterns across the samples in the given event window. The off-diagonal boxes represent distances between different events. These show unique color patterns when taken as a group in that comparing T0 to T2 more consistently shows orange distances while T0 to T1 patterns are firmly light blue in the absence of the artifact.

Trial 6, in Figure 5, represents imagined motion of opening and closing both fists or feet and trial 5, in Figure 6, of the same subject shows the results of actual opening/closing of the fists or feet. No major artifacts are present which is evidenced by the uniform color distribution and that the color bar has a substantial decreased ranged, maximum of 19 instead of 22.5.

The on-diagonal boxes present with similar patterns and color schemes although a few sections, like the 5th and 7th T2 events, appear as outliers in their group. Comparing T0 to T1 and T2 to T1 via the horizontal axis shows a strong presence of larger distances in the T0 to T1 off-diagonal box. Overall matches between T0 produce larger distances as noted by the stronger presence of orange.

Horizontal and vertical striations can be seen throughout Figure 6. These stripes shift from blue/green to gray to orange depending on the event, most noticeable looking vertically at the T1 events. The T0 to T1 orange distances are replaced with green distances in the T1 to T1 box and then with mostly gray in the T1 to T2 box on top. These distinctions would make it possible to separate the three states without prior knowledge.

Trial 3 of subject S001, shown in Figure 7, involves opening/closing the left or right fist. It is enlarged to draw attention to the diagonal patterns within each event. These are most noticeable in the T1 on-diagonal comparison window where bands of orange and green distances are parallel to the white null line. Consistency along the diagonal is representative of the distance changing in time; if the relationship between events is similar the color should be static. This leads to a ‘candy cane’ pattern which can be seen developing in many of the columns.

With the increased size, the minimal distance of the

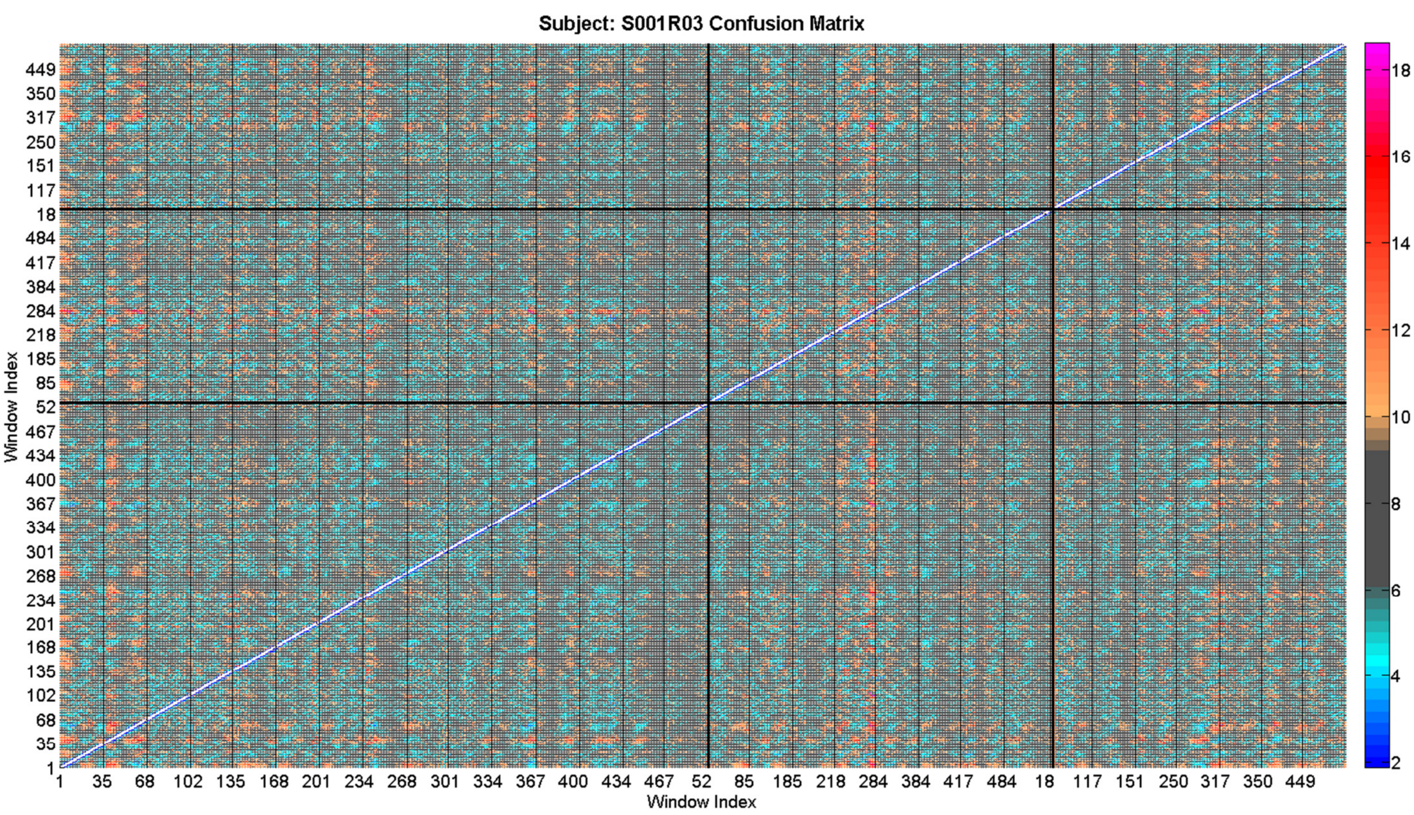

Figure 7: Resultant confusion matrix of motion trial requiring opening/closing of left first and right fist

following and preceding windows can be seen as the deep blue diagonal lines on either side of the white identity null diagonal. In areas where this blue is obscured, the 4th T1 event it is possible that an anomaly occurred during that time. This anomaly presents differently from those captured in Figure 5 as the increase in distance is neither as pronounced nor is the color pattern as erratic.

IV. CONCLUSION

Applying only normalization and DTW to the raw data, a robust confusion matrix is generated that highlights artifacts and potential features of interest in one algorithm. The color codes are important for discerning artifacts from potential features while visual motifs of colors are indicative of subject specific events. The result is as a simpler visual representation than the raw waveforms that highlight regions of interest without prior knowledge from the interpreter.

The ideal confusion matrix pattern would be diagonal rays parallel to the distance identity null, a candy stripe motif, as seen in Figure 8. Such sequences signify a static waveform pattern between two events. The color of these stripes would lead to classification where smaller distances increase the likelihood of a feature match and larger distances represent divergent features. Taking the entire column's pattern into account an 'ideal' event can be found that best exemplifies the relationships between a given event and the three (T0, T1, T2) events.

Sequences that break the candy stripe motif are suggestive of artifacts, noticeable in Figure 5 and 6. Variations in the color scheme of the motif are not guaranteed to be artifacts, but should be treated as anomalies. They could be a failure of the subject to comply with the test protocol or be indicative of an overall shift in the state of the subject.

Given the cyclic nature of the trials and that the subjects are following prompts the event boundaries show an increase in outlier distances. The strongest outliers, labeled with red and pink, are commonly found on the transitional lines between tasks. The edges of window indexes 168, 350, 367, and 417 in Figure 7 have a strong red presence near the transition across all tasks. When plotted versus time this makes it feasible to distinguish the transitions, but not to the point they are separable from artifacts.

The color map chosen may not be universal, but could be adjusted based upon the histogram of the subject's data. Updating the colors and the range of values they cover should not detract from the motif nor artifact detection. In fact the color maps and histograms could even be used to discern the overall quality of the recording. The presence of artifacts could be seen through the smoothness of the distribution and range of distance values found in the histogram.

Ideally, each event column should be striped with the shortest distances centered on the identity diagonal and larger distances appearing as you get away from the diagonal. This pattern forms a wave orthogonal to the diagonal axis repeating every event when the sample index of the event matches. This is what causes the main null diagonal, where each event is

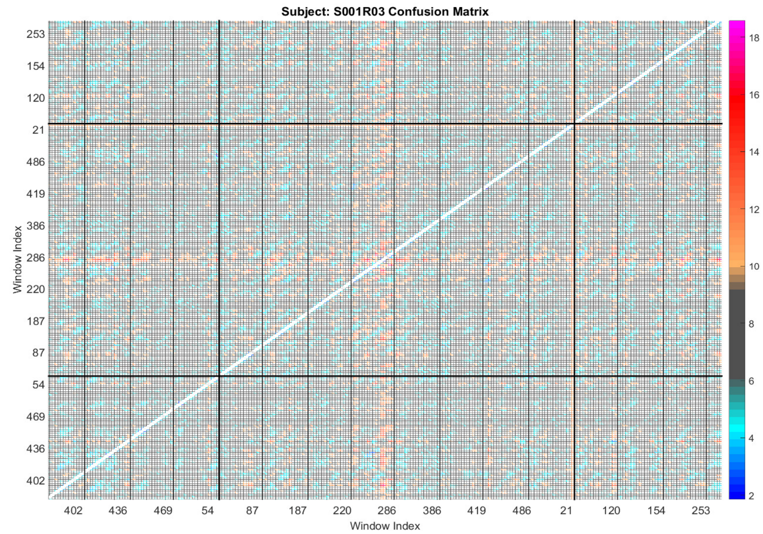

Figure 8: Zoomed view of T1 to T1 comparison showing diagonal blue and orange stripes parallel to the identity diagonal.

matched to itself. At window 284's artifact in Figure 8, this is best seen in the on-diagonal T1-T1 box. This occurrence is rare in the studied data, but adjusting the color map may improve the distinction.

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