Identifying Emotional Feature Coupling using Dynamic Time Warping

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ABSTRACT

The purpose of this project is to identify correlated features with similar dynamic sequencing using dynamic time warping (dtw), to discover unique social signal in datasets for different emotional categories. One main problem is the dtw score between two timed data under the same emotional category is dominated by their difference in length and fluctuation speed, rather than similarity in feature geometry, defeating the purpose of social signal recognition. Our approach to the problem was to instead, searched for feature alignments of each single data and compared results amongst different affective groups. This method identifies the most outstanding feature in a data and using to extract other features with high proximity in time series alignment for a representative signal of the emotional category. This eliminates the issue of errors from time mismatch between possibly similar data and it is visually comprehensive.

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1 INTRODUCTION

Our work is motivated by the possibility of further data classification and providing statistic values using dynamic time warping (dtw) on time series data recognition to discover dynamic signals of emotional representations. Our goal is discovering how time series features sharing the same pattern, couple differently based on the emotional group they belong to. There are already works for facial emotional expression classification on dynamic data [2], we are using facial feature as data as well, however our work differentiates in it identifies features with similar motion pattern based on single data rather data to data comparison, by successfully identifying feature motion coupling difference between each group, allows the extension of expression recognition beyond facial representation to bodily motion signals. Another difference between our work and existing work is the algorithm uses normalized data rather than raw data which could identify inconspicuous features with more motion similarities as oppose to features that are less similar but closer in values. One difficulty with dynamic feature coupling between data is the differences in dynamic data time length being a separating factor. Two data containing the same dynamic patterns can have a large dtw score merely due one containing extra sequence of motion due to time length difference. Our approach to the problem was to identify motion coupling between features in the same data using dtw, a single data at a time and compare the results. Finding a suitable method for clustering the resulting sets of coupled feature data from each emotional group was also difficult, as the data provides many possibilities for means of clustering. In our work, we choose to highlight the most common recurring sets of feature data within each group for general comparison.

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2 APPROACH

The dataset is composed of 200 to 400 csv files for each of the four selected emotions (happiness, sadness, anger, disgust) containing facial action units(AU) intensity data, extracted from GifGif [3] using OpenFace [1] notebook. We extracted the set of features having similar dynamic pattern with top scoring feature (coupling set) in the data of each emotional group and returned the top coupling set for result.

2.1 Pre-processing

Data are annotated with video number for distinguishing purposes. Features that not Au-intensity are dropped, and low confidence, zero success rows frames are removed. Multi-face data are processed to contain only the most commonly occurring face id. Data after processing containing more than less than 5 frames are dropped. Since we are using normalized data from dtw matrix calculation, data variance will be magnified during normalization. Therefore, we want to exclude insignificant, low variance features in the original data to not disturb coupling accuracy.

2.2 Dtw feature coupling

Algorithm for dtw feature coupling involves calculating dtw cost matrix, extracting the highest scoring feature (identifying feature) from original data, finding the coupling set- features with most similar dynamic patterns as the identifying feature, based on the dtw cost matrix using computed threshold value. Cost matrix is computed by calculating the accelerated dtw scores from pipy library for each row and column, where row and column contains the normalized time sequence values each all features in the data.

2.3 Data analysis

Two ways of data analysis were performed on the extracted grouping of coupling set. One method was displaying the highest recurring coupling sets of data from the same emotional group to show possible social signals, variations in coupling sets between each emotional group. Another method of analysis is using AU Relationship Graph - where the probability of one AU feature couple to another AU feature in each emotional group is graphed to provide a visual understanding of general coupling set data.

3 EXPERIMENT AND RESULTS

The evaluation for sections of the project are based on results using data analysis in the previous section, through manually by analyzing the visual, and numerical data representations of each progress results of the work.

3.1 Coupling Set Evaluation

The selection for the coupling sets was evaluated by comparing the plot for original data, data excluding insignificant feature, and data containing only features in the coupling, and examining the Gif associated with the data. This section of the project is overall successful, as comparison, we also plot the coupling set using direct Euclidean alignment instead of accelerated dtw, which in most cases showed the same results, but in some cases one presented a better feature coupling than the other. For example, from the comparison between fig.1 and fig.2 we can see the coupling set of features follow a similar time series pattern.

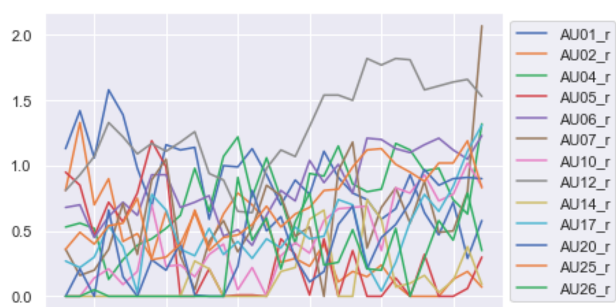

Figure 1: after low significance data are removed (sadness video 50)

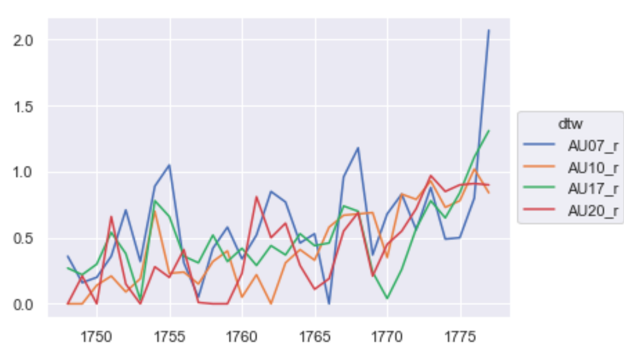

Figure 2: features in a coupling set using dtw(sadness video 50)

3.2 Grouping Coupling Set Evaluation

The clustering group signifies top features with dynamic motions similar to the most representative feature of the data. Grouping of coupling set show a distinctive result for lower-face data in the happiness group, coupling set AU12 and AU25 in lower-face datasets representing the occurred in approximately 1/4 of the dataset. This represents the motion of laughing which could account as a social signal. However, the grouping results of other dataset gave less significant meanings. There were no other outstanding coupling sets in grouping number. This method of clustering coupling set is not able to provide further statistical significance.

3.3 AU Relation Graph Evaluation

AU Relation Graph visually displays the probability of one AU feature coupling with another in the emotional group. AU relation graph denotes the similarity and difference between AU coupling or each emotional group. For example, fig2,3,4,5 shows AU1 (Inner brow raiser) has the highest likelihood of coupling with AU4 (brow lower) in anger, AU6 (cheek raiser) and on AU1 (no coupling) in happiness, AU2 (outer brow raiser), AU5 (Upper lid raise) and AU7 (lid tighten) in disgust, and AU2 (Outer brow raiser) and AU5 (Upper lid raiser) in sadness. An example of similarity in general trend is the AU2 has the highest likelihood of being clustered with AU1 for all data (raising inner and outer eye brows). Overall, the graph is successful in showing data trend and which features generally couple together in each emotional group. AU relation graph can be used as a general trend, however, it cannot be solely used for classification given a single coupling set.

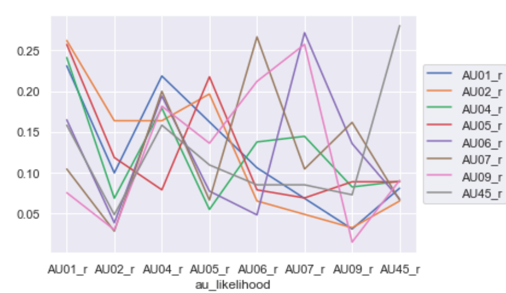

Figure 3: upper-AU relationship graph (anger)

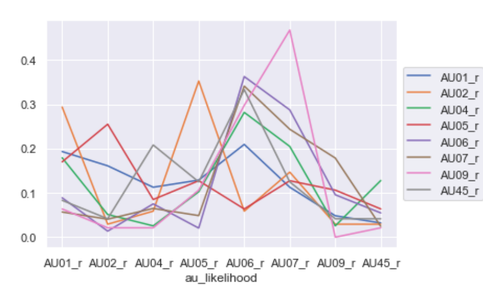

Figure 4: upper-AU relationship graph (happiness)

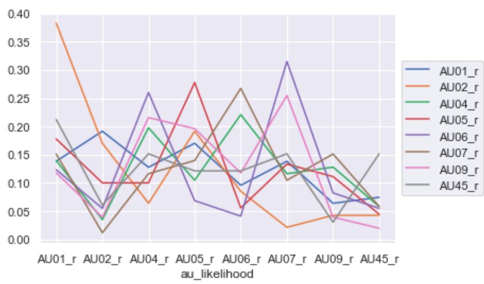

Figure 5: upper-AU relationship graph (disgust)

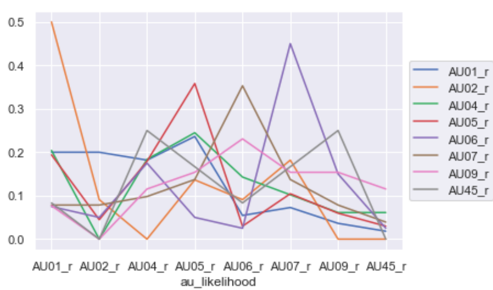

Figure 6: upper-AU relationship graph (sadness)

4 DISCUSSION

The aim of this project was to use dtw to obtain a coupling of features, and using the set of coupling features to harvest significant statistic results that can be used to identify new social signals. Identifications of unique grouping for social signals is unsuccessful in this project with the approach we have taken. The feature coupling was overall successful, however the analysis of the data could not present the distinctive results we anticipated. One thing that can be changed in this project is instead of finding the coupling sets for the highest valued AU, returning of coupling sets for all AU in a list may be more useful. For example, AU relation graph may be biased due to the having a specific representative feature the coupling set. Another improvement can be to truncate the data to fit a single pattern sequence rather than using the entire data that may contain multiple sequences in expression. Our attempt in doing so was to split the data into frames by local minimal value of a single feature. However, most frame are too short (3-4) timestamps to be useful. For future development, other feature data could be incorporated to create coupling set, for a more indepth of analysis.

5 CONCLUSION

The nature of this project is finding methods to use dtw to perform coupling of independent features, and using the results to find social signals. Overall feature coupling was successful, however, we are unable to use such data to identify separating social signal unique to each emotional groups. The process and results in this project can be improved and use as reference for future developments.

6 APPENDIX

section 3.1: Collection Process: answered in body. section 3.2: Composition: There are no bias in the data, as the data contains GIF's for all ages, gender and races. There are no confidential Data as it is extracted and analyzed from open source code. section 3.3: Collection Process: answered in body. section 3.4: Pre-processing: answered in body. section 3.5: Uses: The dataset has not yet been used for tasks. Dataset could possibly be used to support classification of other projects, or data analysis. There are no tasks for which the dataset should not be used section 3.6: Distribution. The data collected from the project would be open source possibly distributed on Github. The dataset will not be distributed under copyright licensing. There are no third parties imposed IP-based or other restrictions on the data associated with the instances. section 3.7: Maintenance. The will not be maintenance of the dataset produced by the project. Older version will continue to be supported and maintained. Others can perform any extend/augment/build on/contribute to the dataset by modifying the code to generate them.

7 CITATIONS AND BIBLIOGRAPHIES

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