Pain Recognition

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***Abstract* — Having a system that recognizes pain fast and accurately can be really useful in the medical field. Based on the fact that it is easier to collect in real time physiological data, I have been given the task to create a python script that reads in physiological data from two different CSV files in order to train random forests and use them to identify pain. After down-sampling and normalizing the data of the four biological signals on the files, Diastolic blood pressure, Systolic blood pressure, EDA and respiration, four different random forests, one for each biological signal, are trained and then used to predict testing data. The prediction is calculated using majority voting based on the prediction of the four random forests. In general, the use of majority voting had better results than the use of any of the four trained random forests. Nevertheless, using a random forest trained with handcrafted features works better than using raw data like I did in this report. A combination of video and imaging detection with this biological signal detection of pain will probably show better results.**

I Introduction

Accurate assessment of pain is very important in order to select the right treatment and in most cases, fast recognition of pain is valuable. That is why there is a lot of research about using technology to recognize pain. This topic is part of the emotion recognition problem. Letting technology recognize human emotions can be used to improve the user experience and, in the case of pain recognition, can be really valuable in the medical field.

There are different approaches to recognize pain. There is research on recognizing pain based on facial expressions on video. In “Pain Recognition Using Artificial Neural Network”, Monwar and Rezaei present an efficient video analysis technique to recognize pain from human faces. Their artificial neural network uses as input the detected faces, location and shape features (Monwar & Rezaei). Using neural networks and trained models is a common approach to this recognition problem. Although analyzing video is not the only technique used to identify pain.

There have been several improvements to this technique of recognizing emotion through video. In “Improving Pain Recognition Through Better Utilisation of Temporal Information”, Lucey et al. compare the task of recognizing pain from video to visual speech recognition. They propose compressing the spatial signal of the video instead of the temporal signal. They based their proposal in that “in visual speech recognition, it has been shown that incorporating the dynamic speech information into the features has significantly improved the recognition performance”. But one of the problems with this approach for pain recognition is the random duration and occurrence that certain emotions, like pain, can last (Lucey et al.).

Relying on human expressions of emotion is very tricky and can be unreliable because not everyone expresses emotions the same way nor the same amount of time. This is why there has been research on recognizing pain based on biological signals. In “Automatic Pain Recognition from Video and Biomedical Signals”, Werner, et al. propose an automatic pain recognition system combining information from video and biomedical signals, namely facial expression, head movement, skin response, electromyography and electrocardiogram. They concluded that “the combination of video and biomedical signals performed significantly better than the state-of-the-art approach” but only for high intensity pain and not for low pain intensities (Werner et al.). This differentiation is because of the different biological reactions that people can have to low intensity pain.

Furthermore, 3D images have also been used in the look-out for improvement of emotion recognition. In “Spontaneous and non-spontaneous 3D facial expression recognition using a statistical model with global and local constraints”, Fabiano and Canavan propose a new method for facial expression recognition using a statistical shape model with global and local constraints. They compare and analyze the proposed method on spontaneous 3D facial data and they show that the proposed method outperforms the current state of the art on two public databases.

All these methods rely on the amount of data that the neural networks and models are trained with. In “Automatic Recognition Methods Supporting Pain Assessment: A Survey”, P. Werner et al. review the literature that proposes and evaluates automatic pain recognition approaches, and discuss challenges and promising directions for advancing this field. They conclude that “Despite the significant progress, in order to impact clinical practice, more effort is needed in advancing knowledge and technology, in gathering the necessary data, and in improving and demonstrating the usefulness of recognition systems in real use cases” (P. Warnet et al.).

With the goal of understanding the process of some of these pain recognition techniques and based on the conclusion that physiological data is easier to collect in real-time, in order to identify and treat pain as soon as it occurs, I was tasked with the design of a Python script that analyzes biological signals in order to identify pain.

II Method

In this project, four random forests are trained with normalized and down-sampled data of each of the biological signals, Diastolic blood pressure, Systolic blood pressure, EDA and respiration, in order to use majority voting to determine the final prediction.

In the words of Leo Breiman, a random forest is a combination of tree predictors, such that “each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest” (L. Breiman). Decision tree algorithms are a sequence of if-else statements that are used to predict or classify a result based on the input data. Breiman proposed using a group of uncorrelated decision trees, a forest. This forest has to be first trained and then it can be used to classify data that the forest has not seen before. Random forest gives good results because it splits a random subset of features in each tree, so that the variance can be averaged across the trees.

For this project, two CSV files that contain recorded biological signals were given. Each CSV file had signals from 30 different people, for a total of 60 subjects. For each subject the Diastolic blood pressure, Systolic blood pressure, EDA and respiration were recorded in a controlled lab environment for two instances: when the subject was in pain and when they were not in pain. The columns of the CSV files are: Subject ID, Data Type (BP Dia_mmHg, LA Systolic BP_mmHg, EDA_microsiemens and Respiration Rate_BPM), Class (Pain and No Pain) and Data. Being Data of variable length, I had to down sample the information to 5000 frames and normalize it.

In order to down sample the data, I calculated the ratio, dividing the original total number of frames by 5000. Then I calculated the average of every group of data of length equal to the ratio, resulting in an output of 5000 values of the down sample data. After that, I took the maximum value of those 5000 and divided each value of the down sample data in order to normalize it between zero and one.

With this pre-processed data, from the first CSV file, four random forests were trained, one for every data type. Then, the validation process was performed with the down sampled and normalized data from the second CSV file. Every random forest analyzed their corresponding data type and depending on the majority of the classification results, the final result was decided. This means that if more than two random forests classified the data as pain, the final classification would be pain. And if more than two of the four random forests classified the data as no pain, the final class would be no pain. In the case that there was a tie, meaning that two random forests classified the data as pain and the other two classified as no pain, the final classification was selected randomly.

The validation was done using the final classifications after the voting process. In previous experiments I used only one random forest trained in all four data types. We want to see if we get better results with this score level fusion approach, using four different random forests and using majority voting for the final classification. The recall, accuracy score, precision score and confusion matrices are also calculated in order to compare the results to other experiments in this paper, but the final script only outputs the accuracy score.

III Experimental design and results

The script was run two times in order to compare the results of first using the data of the first CSV file as training and the second CSV as the validation data, this is the first scenario, and then swap them and use the data of the second CSV file as the training data and the CSV as the validation data, the second scenario. The results of the recall, accuracy, precision and confusion matrices are shown below.

Results of First Scenario	
Recall	0.67
Accuracy	0.68
Precision	0.69
Confusion Matrix	[21 9] [10 20]

Results of Second Scenario	
Recall	0.93
Accuracy	0.8
Precision	0.73
Confusion Matrix	[20 10] [2 28]

We can see that there is a big difference between the results of the tests scenarios. This is because of the data used to train the random forests. I also saved the results of the individual random forests on both scenarios to compare the result of the score fusion approach with individual random forests.

First Scenario Recall	
Diastolic BP	0.73
Systolic BP	0.63
EDA	0.6
Respiration	0.56

First Scenario Accuracy	
Diastolic BP	0.66
Systolic BP	0.73
EDA	0.51
Respiration	0.56

First Scenario Precision	
Diastolic BP	0.64
Systolic BP	0.79
EDA	0.51
Respiration	0.56

First Scenario Confusion Matrices	
Diastolic BP	[18 12] [8 22]
Systolic BP	[25 5] [11 19]
EDA	[13 17] [12 18]
Respiration	[17 13] [13 17]

We can see that the random forests trained with the Systolic blood pressure had better accuracy and precision than the fusion approach in the first scenario. This agrees with previous experiments I have conducted.

Second Scenario Recall	
Diastolic BP	0.83
Systolic BP	0.9
EDA	0.8
Respiration	0.63

Second Scenario Accuracy	
Diastolic BP	0.8
Systolic BP	0.75
EDA	0.61
Respiration	0.58

Second Scenario Precision	
Diastolic BP	0.78
Systolic BP	0.69
EDA	0.58
Respiration	0.57

Second Scenario Confusion Matrices	
Diastolic BP	[23 7] [5 25]
Systolic BP	[18 12] [3 27]
EDA	[13 17] [6 24]
Respiration	[16 14] [11 19]

In the second scenario, the random forest trained with the diastolic blood pressure had better accuracy and precision than the fusion approach. The fact that both diastolic and systolic blood pressure presented better results that the fusion approach in both scenarios is related to the response of the nervous system that prepares the body for stress conditions.

IV Discussion and conclusion

Comparing the results of this experiment with previous experiments where I trained a random forest using hand-crafted features based on the same biological signals, Diastolic blood pressure, Systolic blood pressure, EDA and respiration, the fusion approach is not better.

In previous experiments I did not use the raw data like in this experiment. Instead, I used the mean, variance, entropy, minimum value and maximum value of each data type per subject. And finally, the random forest was trained with the fusion of these features, showing better performance. The use of all four data types gave the highest accuracy of 0.9, with an average recall of 0.9, average precision of approximately 0.904 and an average confusion matrix of [[5.4, 0.6] ,[0.6, 5.4]].

Data fusion is a prevalent way to deal with imperfect raw data to capture reliable, valuable and accurate information. Feature fusion discriminates more than singular input features. Even in the previous experiment, the combination of the diastolic and systolic blood pressure, the EDA and respiration performed better than any of those features alone. That is because integrating multiple sources to produce an unified data about an entity helps the prediction models predict more accurately. It allows the model to consider relations between features and relations in their changes.

Based on the results of the experiments, I think analyzing physiological data is good for pain recognition. And it could be better with a combination of imaging analysis. But based on previous experiments I have done, the use of only images and video to recognize pain does not show better results than using biological signals. A combination of video detection and biological signals should be more accurate than any of the other two alone.

References

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