
BLACKE: Body Language Affect Classification by Keypoint Estimation

Undergrad-ient Descent Expedition:

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Abstract

Current state of the art development in affective classification of people on visual modalities usually focuses on facial expression recognition (FER) but it has some shortcomings in its real world usage. The present work tackles the affective classification problem in body language by using keypoint estimation as a pre-processing step as opposed to previously used convolutional methods. Naïve neural network classifiers are trained to test for the plausibility of the approach and the approach was found to be plausible. The present approach implies a significant dimensionality reduction in classifiers needed to solve this problem.

1 Introduction

Affective Computing is a rapidly growing interdisciplinary field that is concerned with interpretations and implications of human emotion in computation. It takes findings and motivations from computing science and psychology into account to piece together approaches to solve problems related to human affect. One of the most fundamental problems in Affective Computing is the classification of an individual's emotional state given some information about such individual on particular modalities such as text, auditory, behavioural, and visual.

For the visual modality, the present state of the art approach to addressing this problem is by applying Facial Expression Recognition (FER). The process involves training classifiers that first identifies faces and then taking the images of faces as a means to identify an individual's emotional state through another trained classifier [3]. The overall method is successful and current approaches with deep neural networks and such can achieve near perfect accuracy ratings on testing data.

While FER is a successful method, it is not applicable when the face of the individual is not seen or is covered by objects or body limbs. Observing facial information is often key and a dominant factor when it comes to deciding the current emotional state of a person. The absence of this information would imply a large increase in variability in evaluating the emotional state of a person, but in order to answer the question of "what is this person feeling", we have to look at tackling the problem with other available information.

1.1 Problem Statement

In the present work we want to address this shortcoming by identifying the emotional state of an individual in terms of only the body language that they are exhibiting (ie. their posture). There are still associations linked with understanding the emotional state of a person when just observing their body language. For example, hands covering face is usually associated with sadness or distress, and extended arms raised high up is usually associated with happiness or surprise. However, this is

inherently a difficult problem for humans, in particular with respect to some emotional states over others [4][2].

Previous work has been done on the topic using a neurologically inspired convolutional model that takes in visual data containing both body language and facial expressions [4].

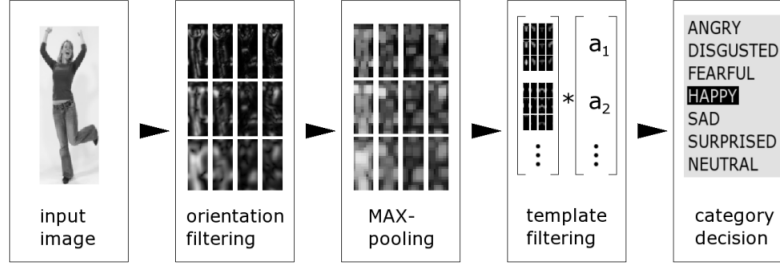


Figure 1: Model used in Schindler et al. 2008

As seen in Figure 1, the model takes in an input image and applies orientation filtering, pooling, and template filtering on the image before feeding the filtered data into a classifier to arrive at a category decision. It is noteworthy to see that the steps taken to filter and pre-process the image simulates corresponding to various areas of the human visual cortex, going from low level (ex. V1 area) information processing progressively to higher level information processing (ex. V4/IT area).

1.2 Proposed Work

While the convolutional filtering approach is plausible and able to perform just as well or better than human test subjects, the model is prone to accounting for extraneous information in its processing steps. The dataset that was used for their experimental work were custom constructed and standardized on neutral backgrounds so the introduction of non-neutral backgrounds (ie. in real life) may be a highly threatening confound.

The present work wishes to approach the same problem by using a different approach to pre-process the input data to a high level representation that primarily accounts for background noise as well as providing other features. Namely, using a representation of the pose of the body in the input image.

The underlying motivation in play here is as follows: Suppose one is visually observing a person, knowing about only the pose that the person is making preserves the relevant information regarding the person's emotional state (Figure 2).

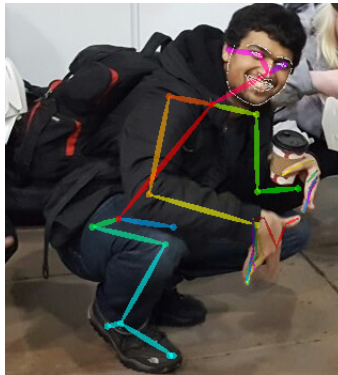


Figure 2: The extracted keypoints of the person's body and face contain the same amount of semantic information regarding the person's emotional state as the full image. Image courtesy of one of our authors Gurkaran Aujla

We hypothesize that using a presentation of body posture is a feasible alternative to convolutional pre-processing for classifying emotional states based on just body language. The confirmation of this

hypothesis would imply a significant dimensionality reduction to the input data needed for a classifier model, and that leads to more compact models and faster training times along with other implications.

1.3 Keypoint Estimation

To achieve the goal of representing a pose in a body, we look to applying keypoint estimation with OpenPose [1] [6] [8] created by the CMU Perceptual Computing Laboratory, which is open source and freely available for non-commercial use.

OpenPose is a system that allows for real-time keypoint estimation and detection of human bodies in images and videos. It is capable of finding estimated locations of several body keypoints in the body, hands, and face. It is capable of doing these simultaneously with multiple people as well.

OpenPose's basic algorithm finds each type of keypoint in all bodies simultaneously, and then finds the connection between these keypoints in a separate neural network. The program can take most image and video formats as inputs, and it will output a variety of formats depending on the configurations. For example, it can output an image with the keypoints overlaid on the people in the image (ex. Figure 2), it can also output JSON files for the keypoints. In the JSON file, it contains the (x, y) coordinates of every bone detected, as well as a confidence rating c for the position of each keypoint expressed as a percentage.

1.4 Viewpoint Invariance

As with all work done in computational vision, it is hard to know the exact shape, size and distance of an object in an image as it is only a projection of the original object. The problem of extracting this type of information is called the inverse projection problem, and it is a non-trivial problem.

The ability to account for the inverse projection problem and ultimately achieving viewpoint invariance in models has been a difficult task, especially when the only given information is just a two dimensional image most of the time. The present direction in accounting for this problem is by constructing 3D representations of the object seen in the image (for example refer to [5]). The present work faces many challenges related to this problem and they will be addressed separately in the coming sections.

2 Approach

In this section we describe various considerations and challenges toward setting up our models and the overall approach, and the steps taken to account for them.

2.1 Data

2.1.1 Dataset Composition

Constructing a dataset was a non-trivial task as it is difficult to find datasets that have faces, full body, and is labelled in a uniform manner. Previous work in this field involved manual construction of data from actors [4]. For the current work we are piecing together a dataset from various sources. However, since only the posture information will remain, the colorization, image dimensions, and actor identity are not preserved.

We used the BEAST dataset [2] from the Brain and Emotion Laboratory in Maastricht University which had labelled grayscale images of individuals with their face censored. Images in this dataset are categorized into four emotional categories: Happy, Sad, Angry, and Fearful. We also obtained another dataset from the same laboratory which had the same type of data but colored and larger to include in the dataset that we are piecing together [7].

Due to the fact that a dominant section of our dataset is standardized and has only four emotional categories, we restricted the amount of classes available in our dataset to be four as well.

From there onwards, the team found suitable images of people online by various means such as image search engines and news articles. The sampled images are then carefully hand-labelled. In order to generate more datapoints, we applied jittering techniques and reflections to transform the data that we already have to achieve a total of 1345 datapoints.

2.1.2 Pre-processing

To prepare any piece of data for the classifiers that we are going to train, the input image has to be fed through OpenPose first to extract a skeleton from the image. One particular advantage to using the Keypoint Estimation approach is that the input dimensions of the image and format do not matter; the output is invariant regardless of these factors. We chose to use the BODY_25 model which contains 25 body keypoints, as shown in Table 1.

Table 1: Body Keypoint numbers and corresponding body parts in BODY_25

0	1	2	3	4	5	6
Nose	Neck	R_Shoulder	R_Elbow	R_Wrist	L_Shoulder	L_Elbow
8	9	10	11	12	13	14
L_Wrist	MidHip	R_Hip	R_Knee	R_Ankle	L_Hip	L_Knee
15	16	17	18	19	20	21
L_Ankle	R_Eye	L_Eye	R_Ear	L_Ear	L_BigToe	L_SmallToe
22	23	24	25			
L_Heel	R_BigToe	R_SmallToe	R_Heel			

Each body keypoint that is extracted from the image comes with a 3-tuple of values (x, y, c) denoting the normalized coordinates (in percentages) of the keypoint and the confidence in the measurement in this point. The total comes to 75 numbers per body, which is significantly less data than an image.

2.2 Invariance

Depth perception is a major issue in the present work that has to be addressed. Objects that are closer appear larger than object that are farther away. Humans have a way to account for this issue by preconceived prior knowledge about the world as well as exploiting retinal disparity. However, judging from solely the keypoint information, it is hard to tell whether if someone is tall or if someone is close. The overall translation of the person will also have an impact on what the classifier receives, but the overall position of a person in an image have no bearing on the emotional state of the person.

We propose a transformation over the estimated keypoints that ultimately results in an invariant form that accounts for some of these issues.

2.2.1 Invariant Form Transformation

To begin, the immediate goal towards a fitting transformation should be that it is translation independent, where any arbitrary set of keypoints should be semantically equivalent to a translated version of those keypoints.

The secondary goal is to discard information regarding the length of the bones in the set of keypoint to account for depth perception.

The present approach takes advantage of the fact that the connections between the keypoints in a body exhibit a tree topology (ie. Each keypoint only has one parent keypoint). Therefore, partial information can be assigned to individual portions and the overall picture can be somewhat reconstructed from those pieces of information. For every keypoint and its parent, we construct a new set of values by the following formula:

$$(\theta_k, c_k) = \left(\arctan \left(\frac{y_k - y_{Pa(k)}}{x_k - x_{Pa(k)}} \right), \frac{c_k + c_{Pa(k)}}{2} \right)$$

Where k denotes a particular keypoint other than the "root" of the keypoint tree (the nose) and $Pa(k)$ denotes the parent keypoint of k . The resulting image of the transformation forms a new 2-tuple (θ, c) for all 24 of the non-root keypoints, which contains 48 numbers in total. Although it's not as significant, this transformation poses an even further dimensionality reduction than extracting keypoints.

2.3 Architecture

2.3.1 Models

Since we are starting with testing the hypothesis that using keypoint estimation is a feasible approach as opposed to convolutional filtering, we begin with naïve model architectures.

To begin with, we are going to work with three different feature sets: estimated keypoints, invariant form and a concatenation of the two. Each of these feature sets will correspond to a neural network that has the same structure except for the input layer.

The BLACKp network takes in the estimated keypoints, the BLACangle network takes in the invariant form of the keypoints. Lastly, since it is usually the case that more features leads to better models, we also introduce the BLACKpangle model that takes in the concatenation of the inputs to BLACKp and BLACangle. All three BLAC* networks have two fully-connected hidden layers of size 200 and then 128 neurons, the output is 4 neurons for the 4 emotional classes that we have in our dataset. All the activation functions being used in the models are Rectified Linear Units (ReLU) with bias terms enabled at every layer.

3 Experiments

3.1 Training

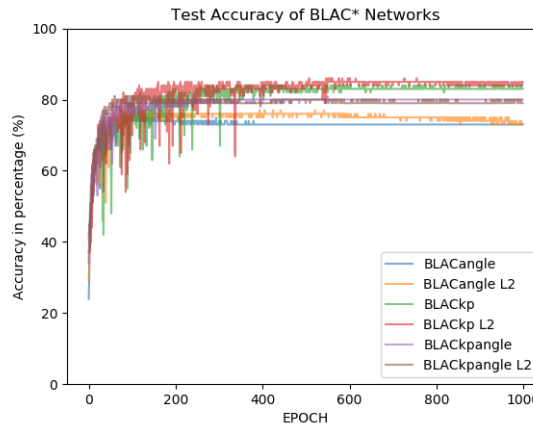
To begin, we have three main models BLACKp, BLACangle, and BLACKpangle. The criterion used is the cross entropy error function, and for every model we apply stochastic gradient descent (SGD) as the optimizer on batch sizes of 5 datapoints each. The learning rate for the SGD algorithm is inversely proportional to the current epoch (ie. $\eta = 1/\text{EPOCH}$) so it decays and we can prevent overstepping minimas in the error surface. For each model, we also try to train with L2-regularization appended to the cross entropy optimizer. In total, we have 6 models that we are training.

The models are trained with the pre-processed data on 1000 epochs for each model, with a 70-30 split between the training data and testing data.

The resulting test accuracy from training will be compared against each other and against works that have been previously done on the topic (ie. convolutional pre-processing method done in [7] [4]).

The training environment mainly consisted of a Intel Quad-Core i7-6700 with GPU acceleration enabled by a NVIDIA Geforce GTX 1050 Ti.

3.2 Results



4 Conclusion

5 Contributions

As with most group projects, each author of this paper contributed a considerable amount of work towards piecing together the project. Jack oversaw the project by organizing and delegating tasks for everyone as well as being the main composer of the paper and poster ¹. Jack and James formulated the theoretical groundwork in the project, Jack and Insoo then went forward with implementing the model and setting up the training environment.

A considerable proportion of the effort went into this project belonged to piecing together a dataset that we can work with. We had the blessing of the Brain and Emotion laboratory in Maastricht University to use their datasets as part of our dataset [2][7]. Aside from the BEAST dataset, Eric and James took the lead in finding images online to include to the dataset and manually hand-labelling them where necessary. After the dataset was complete, Gurkaran worked with OpenPose to extract keypoint information from the dataset as well as formulating and implementing the invariant forms for each datapoint. Insoo worked on taking the keypoint data and reorganizing it into a csv file that the models can take in. Eric and Karan worked on a live demo for the presentation.

We would also like to thank Professor Angelica Lim for consultations and guidance toward the design and theoretical groundwork for the project.

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¹The poster can be found here: <https://www.researchgate.net/project/BLACKIE>