TRANSFERRING FACE VERIFICATION NETS TO PAIN AND EXPRESSION REGRESSION

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ABSTRACT

Limited annotated data is available for the research of estimating facial expression intensities, which makes the training of deep networks for automated expression assessment very challenging. Fortunately, fine-tuning from a data-extensive pre-trained domain such as face verification can alleviate the problem. In this paper, we propose a transferred network that fine-tunes a state-of-the-art face verification network using expression-intensity labeled data with a regression layer. In this way, the expression regression task can benefit from the rich feature representations trained on a huge amount of data for face verification. The proposed transferred deep regressor is applied in estimating the intensity of facial action units (2017 EmotionNet Challenge) and in particular pain intensity estimation (UNBS-McMaster Shoulder-Pain dataset). It wins the second place in the challenge and achieves the state-of-the-art performance on Shoulder-Pain dataset. Particularly for Shoulder-Pain with the imbalance issue of different pain levels, a novel weighted evaluation metric is proposed.

Index Terms— CNN, regression, expression intensity

1. INTRODUCTION

Obtaining accurate patient-reported pain assessments is important to effectively manage pain. Hence, it is highly desired to develop an automated approach. Firstly, it simplifies the pain reporting process and reduce the strain on manual efforts. Secondly, it standardizes the feedback mechanism by ensuring a single automated metric that performs all assessments and thus reduces bias. Thirdly, it enables giving continuous-valued pain levels. There exist efforts to measure pain using the observational or behavioral effect caused by pain such as physiological data. Medasense© has developed medical devices for objective pain monitoring. Their basic premise is that pain may cause the vital signs such as blood pressure, pulse rate, respiration rate, SpO2 from EMG, ECG or EEG, alone or in combination to change and often to increase. However, it takes much more efforts to obtain physiological data than face images and videos from unobtrusive cameras.

Computer vision and supervised learning has come a long way in recent years, redefining the state-of-the-art using deep Convolutional Neural Networks (CNNs). However, the ability to train deep CNNs for automated pain assessment is limited by small datasets associated with labels of patient-reported pain levels, i.e., annotated datasets such as EmoPain [2], Shoulder-Pain [1], BioVid Heat Pain [3]. In particular we perform experiments on the Shoulder-Pain dataset which is designed for visual analysis only. The dataset contains 200 videos of 25 patients who repeatedly raise their arms (feeling pain) and then put them down (pain released). All frames per video are labeled with discrete-valued ground-truth pain levels, as illustrated in Fig. 1. Note that 91.35% of all images are labeled as pain level 0 which may induce trivial solutions.

Two pieces of recent works make progress in estimating pain intensity visually using the Shoulder-Pain dataset only: Ordinal Support Vector Regression (OSVR) [4] and Recurrent Convolutional Regression (RCR) [5]. Notably, RCR...
is trained end-to-end achieving sub-optimal performance. Please see reference therein for other existing works.

Although the limited labeled data prevents us from directly training a deep pain intensity regressor, we show that fine-tuning from a data-extensive pre-trained domain such as face verification can alleviate this problem. While our work is not the first attempt of this transferring idea, to our knowledge we are the first to apply it in pain intensity estimation.

To summarize, the main contributions of this work are:

- We address limited data with expression intensity labels by transferring face verification models to new tasks.
- We push the bound of the performance of the expression intensity estimation by a large margin.
- We propose to add center loss regularization to make the predicted values more close to discrete labels.
- A novel evaluation metric is proposed to fairly judge the performance on imbalanced dataset, such as the video-based Shoulder-Pain [1] where mostly painless expression occurs.

2. RELATED WORKS

For facial expression recognition in general, there is a trade-off between method simplicity and performance, i.e., image-based [6, 7] vs. video-based [8, 9, 10] methods. Furthermore, as videos are sequential signals, appearance-based methods including ours cannot model the dynamics given by a temporal model [11] or spatio-temporal models [12, 13, 14]. Linear models include sparse representation based method, ordinal regression [4, 15, 16] and boosting [17]. Similar tradeoff also lies in linear model vs. non-linear models. Among non-linear models, one approach is kernel-based methods [18] while another is deep learning [5, 10, 19, 20, 21]. By introducing more information, one approach is 3D models [22] while another is multi-modal models [23].

As regards transfer learning with deep networks, there exist recent works that regularize deep face recognition nets for expression classification - FaceNet2ExpNet [6]. During pre-training, they train convolutional layers of the expression net, regularized by the deep face recognition net. In the refining stage, they append fully-connected layers to the pre-trained convolutional layers and train the whole network jointly.

3. TRANSFERRED DEEP REGRESSOR

A face $f$ is visually generated by confounding factors the primary of which are the identity $i$, the facial expression $e$ and the head pose $p$. Normally, given a set of rich training examples $(f, l)$, deep face verification algorithms [24] seek a function $g : F \rightarrow I$ where $F$ is the input space spanned by all possible face appearances and $I$ is the output space formed by all possible identities. Now, given $g$ and limited training samples $(f, e)$, the problem that we are addressing is learning a function $h : F \rightarrow E$ where $E$ is the output space formed by all possible face expressions. A natural question is if we are able to transfer $g$ to $h$. In this section, we investigate how $g$ and $h$ can be related, since they are mappings from the same input space to different output space. Namely, given $g$, we design a network to learn $h$ by refining $g$ with a few additional training examples of $(f, e)$.

Our network is transferred from a state-of-the-art face feature learning and verification network [24] which is trained using the CASIA-WebFace dataset containing 0.5 million face images with identity labels. Now, we transfer the network to learn features for pain intensity regression with limited face images with pain labels. In detail, we remove all the fully-connected (FC) layers in the original network and then add two new FC layers. Since over-fitting is a severe problem when training with limited data, the number of neurons in our hidden FC layer is relatively smaller than those in the original network (50 vs 512), and Dropout [25] operation is applied before the two FC layers. We truncate the output of the second layer to be in the range of $[0, 5]$ by a scaled sigmoid activation $y = \frac{5}{1+e^{-x}}$ to fit the range of pain intensity level of the Shoulder Pain Dataset [1], which is also in range $[0, 5]$.

The architecture of the new added layers is shown in Fig. 2 details of which will be explained in the following sections.

3.1. Regression Loss

At the end of the network, we leverage both $\ell_1$ and $\ell_2$ norm distance to do the regression task.

$$\mathcal{L}_R = \| y - \tilde{y} \|^p_p$$  \hspace{1cm} (1)

where $I$ is the input image; $y \in \mathbb{R}^1$ is the output of the activated output of the last fully connected layer; $\tilde{y}$ is the ground truth label and $p$ denotes which norm should be used.

In practice, whether to choose $\ell_1$-norm or $\ell_2$-norm depends on the evaluation metrics, e.g. $\ell_2$-norm performs better on Mean Square Error (MSE) and $\ell_1$-norm performs better on Mean Absolute Error (MAE). However, we found that $\ell_1$-norm is a good choice for our experiment.

\[\text{Model available at} \ https://github.com/ydwen/caffe-face\]
When two kinds of classification loss functions, one is the Softmax, regressed values to be more 'discrete'. In this work, we try kinds classification signals on the loss function to make the falsely in the Shoulder-Pain dataset, it is natural to add some Since the pain intensity level is discretely labeled specifically, we can implement our regression loss in one layer.

\[ \ell_1 = |y - \hat{y}| \]

\[ \ell_2 = \sqrt{\sum x^2} \]

\[ \ell_i = \sum_{j=1}^{n} \left( W_i^T x + b_i \right) \]

\[ \|x - c_{\hat{y}}\|_p \]

**3.2. Regularizing by Reducing Inter-Class Variance**

Since the pain intensity level is discretely labeled specifically in the Shoulder-Pain dataset, it is natural to add some kinds classification signals on the loss function to make the regressed values to be more 'discrete'. In this work, we try two kinds of classification loss functions, one is the Softmax,

\[ L_S = -\log \frac{W_i^T x + b_i}{\sum_{i=1}^{n} W_i^T x + b_i}, \]

another is center loss \[ L_C = -\|x - c_{\hat{y}}\|_p \].

**4. EXPERIMENTS**

In this section, we present implementations and experiments. The project page² has been set up with programs and data.

**4.1. Dataset and Training Details**

We test our network on the UNBC-McMaster Shoulder-Pain dataset that is widely used for benchmarking intensity estimations of the pain expression in particular and facial action units in general. The dataset comes with four types of labels. The three annotated online during the video collection are the sensory scale (SEN), affective scale (AFF) and visual analog scale (VAS) ranging from 0 (no pain) to 15 (severe pain). Additionally, observers rated pain intensity (OP1) offline from recorded videos ranging from 0 (no pain) to 5 (severe pain). In the same way as previous works \[4, 5, 27\], we take the same online label and quantify the original pain level in the range of \([0, 15]\) to be in range \([0, 5]\).

The face verification network \[24\] is trained on CASIA-Webface dataset \[28\], which contains 494,414 training images from 10,575 identities. To be consistent with face verification, we perform the same pre-processing on the images of Shoulder-Pain dataset. To be specific, we leverage MTCNN model \[29\] to detect faces and facial landmarks. Then the faces are aligned according to the detected landmarks.

The learning rate is set to 0.0001 to avoid huge modification on the convolution layers. The network is trained over 5,000 iterations, which is reasonable for the networks to converge observed in a few cross validation folds. We set the weight of the regression loss to be 1 and the weights of Softmax loss and center loss to be 1 and 0.01 respectively.

**4.2. Pain Intensity Regression**

We run leave-one-out cross validation 25 times on the Shoulder-Pain dataset. Each time, the videos of one patient

²https://github.com/happynear/PainRegression
are reserved for testing. All the other videos are used to train the deep regression network. The performance is summarized in Table 1. It can be concluded from the table that our algorithm performs best or equally best on various evaluation metrics, especially the combination of smooth $\ell^1$ loss and $\ell^1$ center loss. Even though the MAE of using Softmax loss as regularization is also competitive, we find that it just learns to predict more zeros by observing the predicted curve.

### Table 1

| Methods                     | MAE↓  | MSE↓  | PCC↑  |
|-----------------------------|-------|-------|-------|
| smooth $\ell^1$             | 0.416 | 1.060 | 0.524 |
| $\ell^1$ + softmax          | 0.394 | 1.039 | 0.485 |
| $\ell^1$ + $\ell^1$ center loss | 0.389 | 0.820 | 0.603 |
| smooth $\ell^1$ + $\ell^1$ center loss | 0.456 | **0.804** | **0.651** |
| smooth $\ell^1$ + $\ell^2$ center loss | 0.435 | 0.816 | 0.625 |
| OSVR-L1 (CVPR16) [4]        | 1.025 | N/A   | 0.600 |
| OSVR-L2 (CVPR16) [4]        | 0.810 | N/A   | 0.601 |
| RCNN (CVPR16w) [5]          | N/A   | 1.54  | **0.65** |
| All Zeros (trival solution) | 0.438 | 1.353 | N/A   |

Table 1. Performance our regression network and related works on the Shoulder-Pain dataset for the estimation of pain level (i.e., pain expression intensity). MAE is short for mean absolute error deviated from the ground-truth labels over all frames per video. MSE is mean squared error which measures the curve fitting degree. PCC is Pearson correlation coefficient which measures the curve trend similarity (↑ indicates the larger, the better). The best is highlighted in bold.

### 4.3. Class Imbalance Problem

In Table 1, we provide the performance of predicting all zeros as a baseline. Interestingly, on the metrics MAE and MSE, zero prediction performs much better than several state-of-the-art algorithms. This is because the Shoulder-Pain dataset is highly imbalanced. 91.35% frames are labeled as pain level 0. Thus, for the regression algorithms, it is relatively safe to predict the pain level to be zero.

To fairly evaluate the performance, we propose the weighted version of evaluation metrics i.e. weighted MAE (wMAE) and MSE (wMSE) to address the dataset imbalance issue. For example, the wMAE is simply the mean of MAE on each pain level. In this way, the MAE is weighted by the population of each pain level.

We apply two techniques to sample the training data to make our training set more consistent with the new metrics. First, we eliminate the redundant frames on the sequences following [4]. If the intensity level remains the same for more than 5 consecutive frames, we choose the first one as representative frame. Second, during training, we uniformly sample images from the 6 classes to feed into the network. In this way, what the neural network ‘see’ is a total balanced dataset.

Using the new proposed metrics, the performance is summarized in Table 2. It can be drawn that the uniform class sampling strategy performs much better on the new evaluation metrics. Simply predicting all zeros no longer yields good performance. We have not compared with other works using the proposed new metrics because we find it challenging to obtain the predicted values of other works. However, we will provide the evaluation program in our project page and encourage future works to report their performance with the new evaluation metrics.

### Table 2

| Methods                             | wMAE↓ | wMSE↓ |
|-------------------------------------|-------|-------|
| smooth $\ell^1$                      | 1.596 | 4.396 |
| smooth $\ell^1$ + softmax            | 1.560 | 4.377 |
| $\ell^1$ + $\ell^1$ center loss      | 1.388 | 3.438 |
| smooth $\ell^1$ + $\ell^1$ center loss | 1.289 | 2.880 |
| smooth $\ell^1$ + $\ell^2$ center loss | 1.324 | 3.075 |
| $\ell^1$ + $\ell^1$ center loss + sampling | 1.039 | 1.999 |
| smooth $\ell^1$ + $\ell^1$ center loss + sampling | **0.991** | **1.720** |
| All Zeros (trival solution)          | 2.143 | 7.387 |

Table 2. Performance of our network when evaluated using the weighted MAE and weighted MSE. ‘sampling’ means the uniform class sampling technique is applied. Notably, $\ell^1$ center loss and sampling incrementally boost the performance.

### 4.4. Facial Action Unit Recognition in General

Replacing the regression layer with a Softmax layer, we apply our proposed method on the EmotionNet Challenge [4], a facial expression recognition in the wild challenge organized by the CBCSCL of Ohio State University. The competition has two tracks. The first one requires the detection of 11 action units (AUs), and the second one is an emotion recognition task. 26,117 and 2,477 labeled images are provided by the organizer for training the two tracks respectively. The predictions generated by our program are submitted to the organizer and they further evaluate our program’s output according to the metrics they previously defined. For the AU detection track, we got second place with averaged metrics of 0.7101, while the best is 0.7290. Our individual F-scores are all the top (F1 is 0.6405, F2 is 0.6354 and F.5 is 0.6380). For the emotion recognition task, we also got the second place. Our final score is 0.4799 while the top is 0.5968. It is noteworthy that the winning team comes from an industrial face verification company, who is capable of additional training data, and we only use the data provided by the organizer.

### 5. SUMMARY

Given the restriction of labeled data which prevents us to directly train a deep pain intensity regressor, fine-tuning from a data-extensive pre-trained domain such as identities can alleviate the problem. In this paper, we transfer a face verification network for pain intensity regression. The fine-tuned transferred network with a regression layer is tested on the UNBC-McMaster Shoulder-Pain dataset and achieves state-of-the-art performance on pain intensity estimation.

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3 For challenge details and results, please see [http://cbcsl.ece.ohio-state.edu/EmotionNetChallenge/](http://cbcsl.ece.ohio-state.edu/EmotionNetChallenge/)
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