Deep Domain Adaptation for Ordinal Regression of Pain Intensity Estimation Using Weakly-Labelled Videos

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Abstract

Predicting the level of facial expression intensities based on videos allow capturing a representation of affect, which has many potential applications such as pain localisation, depression detection, etc. However, state-of-the-art DL(DL) models to predict these levels are typically formulated regression problems, and do not leverage the data distribution, nor the ordinal relationship between levels. This translates to a limited robustness to noisy and uncertain labels. Moreover, annotating expression intensity levels for video frames is a costly undertaking, involving considerable labor by domain experts, and the labels are vulnerable to subjective bias due to ambiguity among adjacent intensity levels. This paper introduces a DL model for weakly-supervised domain adaptation with ordinal regression (WSDA-OR), where videos in target domain have coarse labels representing of ordinal intensity levels that are provided on a periodic basis. In particular, the proposed model learn discriminant and domain-invariant representations by integrating multiple instance learning with deep adversarial domain adaptation, where an Inflated 3D CNN (I3D) is trained using fully supervised source domain videos, and weakly supervised target domain videos. The trained model is finally used to estimate the ordinal intensity levels of individual frames in the target operational domain. The proposed approach has been validated for pain intensity estimation on using RECOLA dataset as labeled source domain, and UNBC-McMaster dataset as weakly-labeled target domain. Experimental results shows significant improvement over the state-of-the-art models and achieves higher level of localization accuracy.

1. Introduction

Facial behavior Analysis has been a growing area of interest in computer vision and affective computing, and has great potential for many applications in health care, human computer interaction, sociable robots, autonomous-driving, etc. It was shown that only one-third of human communication is conveyed through verbal components and two-third of communication is communicated through non-verbal components [8]. Among non-verbal components, facial behavior plays a major role in conveying the mental state and emotions of a person, which can be reflected by the movements of facial muscles. Since all humans have the same facial structure and muscles, various types of facial expressions can be differentiated by the modulation of the facial muscles. Key challenges that deteriorates the recognition performance state-of-the-art systems in real-world FER applications are linked to the subjective variations of facial expressions, operational capture conditions (illumination, pose, resolution, etc.), and lack of representative training videos with labels.

Facial Expression Recognition (FER) can be formulated as classification or regression problem. Although classification of facial expressions have been widely explored in the literature, regression of facial expressions remains largely unexplored despite its practical importance. Regression can be further considered as continuous regression (real values) or ordinal regression (discrete levels) of expression intensities. Ordinal regression of recognizing discrete levels has immense potential for various applications such as age estimation, expression level estimation, etc, where the various classes or levels exhibit a natural order among them. Due to the ease of obtaining annotations of discrete expression levels, and its relevance in practical applications, this paper will focus on facial expression intensity estimation as ordinal regression problem.

Inspired by the performance of DL models, some authors explored their feasibility for estimating facial expression intensity levels [33], [23]. However, facial expressions are sparse in nature as they occur infrequently in videos, resulting in highly imbalanced classes. This poses a major
challenge for DL models. The limited amount of relevant labelled data and the highly imbalanced classes (intensity levels) remains a bottleneck to develop a robust DL models. Another challenging aspect is the complexity of annotating the expression levels – a time-consuming process requiring domain experts. Moreover, the obtained labels are vulnerable to label ambiguity due to the subtle difference of expression levels between consecutive frames. This results in a subjective bias caused by the domain experts. In practical scenarios, videos are often coarsely labeled, which underscore the need to formulate the problem of expression intensity level estimation in the context of weakly-supervised learning.

In-spite of the challenges, most of the existing work on expression intensity level recognition has leverage state-of-the-art DL models for supervised learning. However, we have focused on weakly supervised learning framework still exploring the feasibility of leveraging the potential of DL models. Due to the availability of limited annotations in many practical applications, weakly supervised learning is gaining attention as it has immense potential in improving the bottle-neck of labeling mechanism, which will result in efficient learning from the data.

Depending on the mode of availability of labels (annotations), weakly supervised learning can be classified to three categories: Incomplete Supervision, Inexact Supervision and Inaccurate Supervision. Incomplete Supervision refers to the scenario, where annotations are provided only for a subset of the data-set. In case of Inexact Supervision, annotations are provided for the entire data-set but at coarse level instead of accurate annotations. Inaccurate Supervision deals with data with noisy annotations though annotations are provided for the entire data-set. In the context of facial expression intensity estimation, it is often feasible to obtain labels of expression intensities on period basis for video sequences or entire video, which falls in the category of inexact supervision. Multiple Instance Learning (MIL) has been widely used in the context of inexact or coarse annotations in many recognition applications such as object recognition, text categorization, context based image retrieval, etc. However, most of the existing approaches relevant to MIL for expression intensity estimation are based on traditional approaches [20, 26, 14].

Another challenging problem is the variability of data capture scenarios, which will result in differences in data distributions of the test data from the training data. In most of the real world applications, there is considerable shift or divergence between the data distributions of development and operational environments, resulting in the deterioration of performance of the developed models in operational capture conditions. Domain Adaptation (DA) techniques have been widely used to deal with the problem of difference in capture conditions. Therefore, we have explored domain adaptation based approaches pertinent to DL models to adapt the models trained in development environment to the operational environment by domain invariant representations. Though domain adaptation has been well explored for classification, it is still at rudimentary level for ordinal classification.

In this paper, we have primarily addressed the problem of exploring DL models with limited discrete annotations relevant to facial expressions using deep domain adaptation for localization of expression intensity levels using only sequence level labels. We propose a generic framework of Weakly Supervised Deep domain Adaptation with Ordinal Regression (WSDA-OR) using labels of source domain and weak sequence level labels of target domain in addition to adversarial based domain loss to estimate the intensity levels of individual frames of weakly labeled target domain. Specifically, we have addressed the problem of pain intensity estimation as ordinal regression problem using domain adaptation with 3D CNN models (I3D), especially focusing on multiple instance learning in order to deal with coarsely labeled data from videos. Deep domain adaptation is deployed in an adversarial fashion, where inflated 3D-CNN (I3D) model is trained using weak supervision loss along with domain loss and source supervision for accurate estimation of pain intensities in the target operational domain.

2. Related Work

2.1. DL Models for Expression Intensity Level Estimation

Most of the DL based approaches for expression intensity estimation have been proposed in the framework of supervised learning due to the requirement of sufficient data for data-hungry deep models. Sabri et al. [17] investigated the ability of siamese and triplet networks for expression intensity estimation in videos. They have used sequential image pairs capturing the temporal dynamics of the sequence similar to Ren et al. [11] and showed that the internal representations of triplet networks are efficiently capturing accurate localization of discriminative features, improving the generalization capability of the network. In all these approaches, basic CNN models are used with 3 convolutional layers and 1 fully connected layer due to the minimal amount of available data.

Xiang et al. [22] proposed temporal convolutional networks, where 1-D convolution is performed over the frame based feature vectors along the temporal dimension. They are able to detect the pain levels for both frames and videos. Egede et al. [3] used handcrafted features based on shape and appearance combined with deep-learned features to estimate pain intensities using relevance vector regressor (RVR) and showed that their approach performs well even in small sample settings. Jing et al. [34] combined CNN
and RNN and proposed a unified framework RCNN for estimating the pain intensities. The input images are cropped, warped and converted to frame vectors, which are then fed to the RCNN network to incorporate the temporal dynamics. However, fixed kernel depths fails to capture the varying range of temporal dynamics of facial expressions. In order to address this problem, Tavakolian et al. [23] proposed a 3D deep architecture for capturing the spatio-temporal information of the pain expressions by deploying 3D convolutional kernels of varying temporal depths. Rodrigue et al. [13] used VGG Face pre-trained CNN network [9] for capturing the facial features and further fed to the LSTM network to exploit the temporal relation between the frames. They further showed that the performance of the pain recognition system can be enhanced by relying on the entire face images instead of only facial features. All these approaches assume the availability of frame level annotations which is not feasible in real-time applications.

2.2. Deep Domain Adaptation

Domain Adaptation has been widely used for many applications related to facial analysis such as face recognition, facial expression recognition, smile detection, etc. The performance of recognition system significantly degrades when there is a domain shift in the test images which can be due to variations in pose, illumination, resolution and capture conditions. Wang et al. [25] provided a survey of the deep domain adaptation (DA) approaches, with applications in visual recognition. Unsupervised DA has been widely used for many applications related to facial analysis such as face recognition, facial expression recognition, smile detection, etc. Enver et al. [18] proposed a regression framework for personalized facial expression recognition, where classifiers are generated for the individuals of the source data rather than a generic model for the entire source data. Wang et al. [28] proposed unsupervised domain adaptation approach for small target data-set using Generative Adversarial Network (GAN), where GAN generated samples are used to fine-tune the model pretrained on the source dataset. Zhu et al. [26] explored unsupervised domain adaptation approach in the feature space, where the mismatch between the feature distributions of the source and target domains are minimized still retaining the discriminative information among the face images related to facial expressions. Contrary to the existing DA approaches for facial expression analysis, we have explored domain adaptation in the context of adapting source data with full labels to target data with coarse labels.

2.3. Multiple Instance Learning

Inspired by the framework of multiple instance learning, several approaches have been proposed for analysis of facial expressions, where detection of facial expressions provides semantic information over a short sequence of images. Adria et al. [16] proposed a novel approach for categorization of facial behaviors, where the conventional MIL is extended to multi concept MIL, where multiple expressions on the same video sequence are analyzed and high level semantic labels are detected for videos. Jianfei et al. [29] proposed an engagement level prediction of a subject while watching an educational video in diverse conditions and different environments using multi-modal approach, where they have used body and face dynamics using C3D and LSTM models. Sikka et al. [20] developed automatic pain recognition system for pain localization in the framework of MIL, where video segments are represented as bags of multiple subsequences and MILBOOST [24] is used for instance-level pain detection Chen et al. [2] proposed a novel two stage approach for pain detection in a sequential manner: one at the individual frame level and the other at sequence level. They deployed a novel strategy to encode AU combinations using individual AU scores and multiple instance learning (MIL) is used in combination with multiple clustered instance learning (MCIL) to learn pain from video sequences.

Ruiz et al. [15] proposed multi-instance dynamic ordinal random fields (MI-DORF) based on multiple instance learning for modeling temporal sequences of ordinal instances, where bags are defined as temporal sequences labeled as ordinal variables. The instance labels are considered as latent ordinal variables, which are obtained by incorporating high order cardinality potential relating bag and instance labels in the energy function. Yong et al. [32] designed a deep convolutional neural network based on weakly supervised learning for intensity estimation of Action Units(AUs) of facial expressions with limited annotations of AUs, where only the annotations of peak and valley frames of the AUs are considered. Despite the advancement of MIL for various applications in computer vision, not much work has explored the estimation of expression intensity level in using state-of-the-art DL architectures.

Unlike the above mentioned approaches, our approach focus on estimating expression intensity level estimation using DL models in conjunction with MIL framework for localization of expression intensity levels. One of the closely related works to our proposed approach is Praveen et al. [10], where deep domain adaptation is explored for pain localization in videos in the context of multiple instance learning. They have also considered source domain as fully labeled and explored adversarial deep domain adaptation to adapt to the weakly labeled videos in target domain. However, they have formulated the pain intensity estimation as continuous regression problem, whereas we have focused on the problem of ordinal classification due to the ease of obtaining annotations and its relevance in practical scenarios. Moreover, we have associated the weak supervision of la-
labels by aggregating all the frames pertinent to maximum intensity level whereas [10] uses only single frame of the sequence corresponding to the maximum intensity level.

The major contributions of the paper includes the following aspects. First, we provide a generic framework of deep domain adaptation of ordinal regression for target data with weak sequence level labels using the supervised data in source domain. Second, we have shown that considering multiple frames pertaining to maximum intensity levels provides rich information unlike the conventional MIL approaches for intensity level estimation, which relies only on the single frame with maximum intensity level. Finally, we have evaluated our approach for various scenarios of weakly supervised videos and showed the robustness of the approach for pain intensity estimation.

3. Problem Formulation

Let \( D = \{(X_1, Y_1), (X_2, Y_2), \ldots, (X_N, Y_N)\} \) represents the data-set of facial expressions of videos from source and target domains. \( X_i \) denotes a video sequence of the training data with a certain number of frames. In case of source domain, \( Y_i \) denotes a structured label vector with frame level annotations of the corresponding video sequence \( X_i \), whereas for target domain, \( Y_i \) represents an ordinal intensity value i.e., sequence level ordinal intensity value of the corresponding video sequence, which is given by

\[
Y_i = \begin{cases} 
    \{y_{i1}, y_{i2}, \ldots, y_{in}\} & \text{if } X_i \in \text{source domain} \\
    y_i & \text{if } X_i \in \text{target domain}
\end{cases}
\]  

where \( n_i \) denotes the number of frames in the corresponding sequence \( X_i \). \( N \) represents the number of training sequences. Specifically, \( X_i = \{x_{i1}, x_{i2}, \ldots, x_{in}\} \) represents the temporal sequence of \( n_i \) observations (frames) and \( x_{it} \) denotes \( t^{th} \) frame in \( i^{th} \) sequence, where \( t \in \{1, 2, \ldots, n_i\} \).

The objective of the problem is to estimate a generic ordinal regression model \( F : X \rightarrow H \) from the training data \( D \) in order to predict the expression intensity level of frames of unseen test sequences, where \( X \) denotes the video sequences of training data and \( H \) represents the hidden label space of frame-level annotations of the target domain. The estimated intensity levels of the individual frames of the sequences in the target domain is predicted as structured output \( H_i \in H \), where \( H_i = \{h_{i1}, h_{i2}, \ldots, h_{in}\} \) and each frame \( x_{it} \) of the sequence is assigned a latent ordinal value \( h_{it} \).

In the conventional setting of Multiple Instance regression [3], the relationship between the coarse label \( Y_i \) and latent ordinal states \( H_i \) is modeled by assigning the maximum value of \( H_i \) to the bag label \( Y_i \) as:

\[
Y_i = \max_{H_i}(H_i) \quad \forall (X_i, Y_i) \in D \tag{2}
\]

If the label \( Y_i \) is 0, then all the frames in the sequence \( X_i \) will be assigned 0 i.e., neutral frame. In case of weak supervision, the target labels are assumed to be sequence level labels, whereas for unsupervision, the target data is assumed to have no labels.

4. Proposed Approach

Inspired by the performance of DL models, domain adaptation has been explored in conjunction with deep feature learning, termed as deep domain adaptation and found to outperform shallow methods. Most of the existing approaches pertinent to domain adaptation in the setting of weakly supervised learning deals with semi-supervised learning, where accurate labels are provided for partial data. However, we have explored domain adaptation in the context of multiple instance learning for ordinal regression, where coarse high level labels are provided instead of partial accurate labels. In the proposed framework, the deep features are learned by jointly optimizing the domain invariance, which minimizes the discrepancy between source and target domains and label predictor (using labels of source domain) still exploiting the weakly annotated target data. We have explored adversarial learning based domain adaptation as it was shown to yield superior performance in the framework of DL models for videos [6].

Let \( S \) represents the source data-set, which is fully labeled videos and \( T \) denotes the target data-set, which is weakly labeled videos. The deep network architecture consists of three major building blocks : feature mapping, label predictor and domain classifier. Let \( G_f \) represents the feature mapping function, where the parameters of this mapping are denoted by \( \theta_f \). Similarly, the feature vectors of source domain and target domain are mapped to the corresponding labels using \( G_l \) and \( G_{wl} \), whose parameters are denoted by \( \theta_l \) and \( \theta_{wl} \) respectively. Finally, the mapping of feature vector to the domain label is obtained by \( G_d \) with parameters \( \theta_d \).

4.1. Label Smoothing

Due to the ordinal nature of pain intensity levels, we have formulated the problem of pain intensity estimation as ordinal regression, which attempts to solve classification problem still retaining the ordinal relationship among the labels. Label Smoothing [22] is widely used to improve the generalization capability by replacing the hard labels with soft labels. In the proposed framework, Label smoothing is used for the ordinal target labels in order to counterfeit the problem of limited data and explore the association of the data sample with all the labels by minimizing the high confidence predictions of the corresponding labels, thereby allowing the contribution of the rest of the labels. The soft
labels of the ordinal target labels are given by

\[ q_i = \begin{cases} 
1 - \varepsilon, & k = y_i \\
\varepsilon / (K - 1), & k \neq y_i 
\end{cases} \quad (3) \]

where \( \varepsilon \in [0, 1] \) represents the label smoothing parameter, \( k \in \{1, 2, ..., K\} \) and \( K \) denotes the number of ordinal intensity levels.

4.2. Multiple Frame Aggregation for MIL pooling

Compared to the single frame based approach [10], association of weak labels over aggregate of multiple frames have significantly improved the performance of our approach as shown in Table 1. For the sake of ordinal regression, the number of output units of the weak supervision layer \( G_{wl} \) (last fully connected soft-max layer) of the I3D network is equal to the number of intensity levels to be predicted. The aggregate of frames predicted as maximum intensity levels within the sequence is obtained as

\[ P(x_i) = \frac{1}{N_{ti}} \sum_{j \in \text{max}(1...n_i)} (G_{wl}(G_f(x^j_i))) \quad (4) \]

where \( P(x_i) \) denotes the average of the output responses (logits) predicted as maximum intensity levels and \( N_{ti} \) represents the number of frames of the corresponding sequence predicted as maximum intensity level.

4.3. Overview of the Proposed Approach

In the deep neural network, the feature mapping layers share same weights between the source and target domains to ensure common feature space between source and target domains. It has been shown that the label prediction accuracy on the target domain will be same as that of the source domain by ensuring the similarity of distributions between source and target domains [19]. Next, adversarial mechanism is deployed between the domain discriminator \( G_d \), which maximizes the discrimination between source and target domains and feature extractor \( G_f \), which is learned by minimizing the domain discrepancy between source and target domains. During training, label prediction loss is minimized on the source domain by optimizing the parameters of \( G_f \) and \( G_l \) in order to learn the feature mapping given the labels, while simultaneously ensuring the features to be domain-invariant. This is achieved by maximizing the loss of the domain classifier to minimize the discrepancy between the source and target domains while the parameters of \( G_d \) are learned by minimizing the loss of domain classifier to discriminate source and target domains. The label prediction loss \( (L_S) \) for the source domain is defined by

\[ L_S = \frac{1}{N_s} \sum_{i=1}^{N_s} \sum_{j=0}^{d_i} \text{MSE}(G_l(G_f(x^j_i)), y^j_i) \quad (5) \]

where \( d_i = 0 \) represents the source domain, \( N_s \) denotes the number of video sequences in the source domain and \( n_i \) denotes the number of sub-sequences in the corresponding video sequence. In addition to source labels, the weak labels of target domain is also used in the feature learning mechanism where the parameters of \( G_{wl} \) are optimized by mapping the weak labels of the target data to the corresponding labels. Contrary to MIL based approaches for expression intensity estimation, which relies on the specific single frame with maximum intensity level [10], we have explored multiple frames with maximum predicted intensity levels to associate with the weak sequence level label, thereby improving the training mechanism due to the deployment of more number of frames with maximum intensity level. Compared to the single frame based approach [10], association of weak labels over aggregate of multiple frames have significantly
improved the performance of our approach as shown in Table [1]. For the sake of ordinal regression, the number of output units of the weak supervision layer \( G_w \) (last fully connected soft-max layer) of the I3D network is equal to the number of intensity levels to be predicted. The aggregate of frames predicted as maximum intensity levels within the sequence is obtained as

\[
P(x_i) = \frac{1}{N_t} \sum_{j \in \text{max}(1,..,N_t)} (G_w(G_f(x_j^i)))
\]

where \( P(x_i) \) denotes the average of the output responses (logits) predicted as maximum intensity levels and \( N_t \), represents the number of frames of the corresponding sequence predicted as maximum intensity level. The prediction loss associated with the weak supervision of the target domain is estimated as cross entropy (CE) loss between the soft version of target labels [22] and predicted response \( P(x_i) \) which is given by

\[
L_T = \frac{1}{N_T} \sum_{i=1}^{N_T} CE(P(x_i), y_i)
\]

where \( y_i \) denotes the ordinal level of the video sequence in the target domain and \( N_T \) represents the number of video sequence in the target domain.

In order to counterfeit the problem of limited data and highly imbalanced classes, we have used label smoothing [22] for the ordinal target labels in our proposed framework. Since domain classification is a typical binary classification problem, we have used logistic regression in order to diminish the domain differences between source and target domains, where the logistic loss function is given by

\[
L_d = \frac{1}{N_s + N_T} \sum_{i=1}^{N_s+N_T} \sum_{d_i=1}^{n_i} \sum_{j=1}^{n_j} \text{logistic}(G_d(G_f(x_j^i)), d_j^i)
\]

where \( d_j^i \) denotes the domain label of the \( j^{th} \) frame of the \( i^{th} \) video sequence.

The overall loss of the deep network architecture is given by

\[
L = L_S + L_T - \lambda L_d
\]

where \( \lambda \) is the trade-off parameter between the objectives of label prediction loss and domain prediction loss and the parameters of \( \theta_i, \theta_wl, \theta_f \) and \( \theta_d \) are jointly optimized using Stochastic Gradient Descent (SGD) as shown below:

\[
\theta_f \leftarrow \theta_f - \alpha (\frac{\partial L_S}{\partial \theta_f} + \frac{\partial L_T}{\partial \theta_f} - \lambda \frac{\partial L_d}{\partial \theta_f})
\]

\[
\theta_i \leftarrow \theta_i - \alpha \frac{\partial L_S}{\partial \theta_i}
\]

\[
\theta_wl \leftarrow \theta_wl - \alpha \frac{\partial L_T}{\partial \theta_wl}
\]

\[
\theta_d \leftarrow \theta_d - \alpha \frac{\partial L_D}{\partial \theta_d}
\]

where \( \alpha \) is the learning rate of the optimizer. At the end of the training, the parameters of \( \theta_i, \theta_wl, \theta_f \) and \( \theta_d \) are expected to give a saddle point for the overall loss function as given by:

\[
\hat{\theta}_f, \hat{\theta}_i, \hat{\theta}_wl = \arg \min_{\theta_f, \theta_i, \theta_wl} L(\theta_f, \theta_i, \theta_wl, \theta_d)
\]

\[
\hat{\theta}_d = \arg \max_{\theta_d} L(\hat{\theta}_f, \hat{\theta}_i, \hat{\theta}_wl, \theta_d)
\]

At the saddle point, the feature mapping parameters \( \theta_f \) minimize the label prediction loss to ensure discriminative features and maximizes the domain classification loss to constrain the features to be domain-invariant. In order to back-propagate through the negative term in our loss function, a special gradient reversal layer (GRL) is deployed in our SGD optimization framework, which is elaborated in detail in [4]. The value of lambda is modified over successive epochs, such that the supervised prediction loss dominates at the early epochs of training. Further details on training mechanism can be found in [4].

5. Results and Discussions

5.1. Experimental Setup:

The proposed approach has been evaluated on UNBC-McMaster data-set [7], which is widely used for pain intensity level estimation in the context of multiple instance learning. The data-set contains 200 videos of facial expressions captured from 25 individuals, performing a series of active range of motion tests resulting in 47,398 frames of size 320x240. Each video sequence is annotated using PSPI score at frame-level on a range of 16 discrete pain intensity levels (0-15). Due to the sparse nature of pain expressions and high level imbalance among various intensity levels, we followed the widely adapted quantization strategy i.e., the pain levels are quantized to 5 ordinal levels as: 0(0), 1(1), 2(2), 3(3), 4-5(4), 6-15(5). In our experiments, we followed the same experimental protocol as that of [10] in order to have a fair comparison with state-of-the-art results, where Leave-One-Subject-Out (LOSO) cross-validation strategy is deployed i.e., 15 subjects have been used for training, 9 subjects for validation and 1 for testing in each cycle.

Due to the availability of labels for every frame, RECOLA [12] data-set is used as source domain, where each video sequence is obtained for a duration of 5 minutes and annotated with an intensity value between -1 to +1 for every 40 msec (same as frame rate of 25fps) i.e., all the
frames are annotated. The video sequences of UNBC (target) and RECOLA (source) data-sets are converted to sub-sequences of 64 frames with a stride of 8 to generate more samples for the learning framework, resulting in 10496 sub-sequences for RECOLA and 2890 sub-sequences for UNBC data-set. In order to incorporate the setting of weakly supervised learning in target domain (weakly labeled videos), only coarse labels of the sub-sequences of UNBC data-set are considered i.e., the maximum intensity level within a sub-sequence is assigned as coarse annotation to formulate the problem of multiple instance learning for ordinal regression.

The faces are detected, normalized and cropped using MTCNN [30] and resized to 224 x 224. In our experiments, I3D architecture is used, where Inception-v1 architecture is used as base model, which is inflated from 2D pre-trained model on ImageNet to 3D CNN for videos of facial expressions. We have used Stochastic Gradient Descent (SGD) as our optimization technique for training the model with a momentum of 0.9, weight decay of 1e5. The initial learning rate is set to 0.001 and annealed according to a schedule pre-determined on the cross validation set for every 5 epochs after 20 epochs. Due to the difference between the number of samples (sub-sequences) between source and target domain, batch size of 4 is used for source domain and 2 for target domain. Due to the huge imbalance among various intensity levels of the samples (sub-sequences) of the target domain, weighted random sampling is deployed for loading the data to counteract the problem of level imbalance. An early stopping strategy is used for model selection to avoid over-fitting. The performance of the proposed approach is measured in terms of Pearson Correlation Coefficient (PCC), Intra class correlation (ICC(3,1)) and Mean-Average-Error (MAE).

5.2. Results with Baseline Training Models:

In order to analyze the impact of domain adaptation and availability of annotations of source and target domains, the performance of the proposed approach has been evaluated by conducting a series of experiments with various baseline models, where I3D training models are generated by varying the data ranging from using only source data with full labels to the entire data-set of source and target domains with full labels as shown in Table 1. For the sake of reducing computational complexity, we have conducted the series of experiments by considering subject 16 of target data as test data and rest of the subjects for training and validation. In all these experiments, the performance of the training model has been validated on the test data of the target domain.

Initially, we have considered only the source domain with full labels without target domain and generated the training model. Due to the domain differences between train data (source) and test data (target), the generated training model exhibits poor performance. Next, we consider only the target data with full labels without source data and generate the training model, which shows significant improvement in performance as both train data and test data comes from the same domain (target). Subsequently, we use both source data and target data with full labels without domain adaptation for generating the training model and found that the performance was further improved as training data spans wide range of variation in source and target domains.

Now we conduct another series of experiments with domain adaptation, where the training data is obtained from source data with full labels and target data with varying levels of supervision. By considering the full labels of source domain, labels of target domain are gradually reduced by decreasing the frequency of annotations i.e., labels are provided for longer duration of sequences. Specifically, we have conducted experiments for sequence lengths of 8,16,32 and 64. As we gradually reduce the amount of labels of the target domain, we can observe that the performance of our approach gradually drops, which is depicted in Fig 2. However, our approach still performs at par with full supervision as there is only minimal decline, which is attributed to the domain adaptation as we are leveraging source data to adapt to target domain using adversarial domain adaptation. We have further evaluated the two extremes of supervision i.e., no supervision and full supervision. Therefore, I3D model in conjunction with domain adaptation was found to achieve superior results even with minimal supervision of target data.

| Training Scenario | Method | Frame-level | Sequence-level |
|-------------------|--------|-------------|---------------|
| Supervised (source data only) | MIR [5] | 0.350 | 0.840 | 0.240 | 0.940 |
| Supervised (target data only) | MILBOOST [20] | 0.280 | 1.770 | 0.110 | 0.380 |
| Supervised (source ∪ target) | MIR [5] | 0.350 | 0.840 | 0.240 | 0.940 |
| Unsupervised DA | WSDA-OR (ours) | 0.649 | 0.452 | 0.566 | 0.698 |
| Proposed (WSDA-OR with single frame) | WSDA [10] | 0.630 | 0.714 | 0.567 | 0.606 |
| Proposed (WSDA-OR with multiple frames) | Semi-Supervised | 0.605 | 0.821 | 0.531 | - |
| Supervised DA | Fully Supervised | 0.605 | 0.821 | 0.531 | - |

| Method | PCC↑ | MAE↓ |
|--------|------|------|
| MIR [5] | 0.350 | 0.840 |
| MILBOOST [20] | 0.280 | 1.770 |
| MIR [5] | 0.350 | 0.840 |
| WSDA-OR (ours) | 0.649 | 0.452 |
| WSDA [10] | 0.630 | 0.714 |
| BORMIR [13] | 0.605 | 0.821 |
| LSTM [13] | 0.780 | 0.500 |
| SCNet [21] | 0.920 | 0.320 (MSE) |

Table 1. PCC, ICC and MAE performance of I3D model trained under different scenarios.

Table 2. PCC, ICC and MAE performance of proposed and state-of-art methods
5.3. Comparison with State-of-Art Methods:

In most of the existing state-of-the-art approaches for weakly supervised learning, traditional machine learning approaches have been explored due to the problem of limited data with limited annotations. However, we have used DL-based I3D model along with source data to compensate the problem of limited data using domain adaptation. Our work is closely related to that of Praveen et al [10] and thereby compare our work with [10], which is deployed as continuous regression problem for pain intensity estimation.

We have also provided visualization of some of our results for pain localization i.e., frame-level prediction for two subjects as shown in Figure 5.3. Due to the ordinal nature of the labels, the proposed approach, which is formulated as ordinal classification accurately localizes pain even though it was not provided in ground truth.

Another approach relevant to our work is MI-DORF [14], which uses graph based models to capture the temporal relationship of the frames and ordinal relationship of labels. We have further compared our approach with that of [20], which was proposed for classification of pain events at sequence level. Unlike the existing classification approaches based on multiple instance learning, which estimates sequence level labels, we have estimated the ordinal intensity level of the individual frames using weak supervision of sequence level labels in target domain. Compared to the classification based approaches [26], [20], regression based approaches [14] are found to show superior performance due to the fact that intensity level estimation is closely related to the problem of regression. However, failing to exploit the discrete nature of labels shows poor performance in accurately tracking the pain intensity levels as that of the ground truth. Therefore, we have exploited both the ordinal nature and discrete nature of the labels in our formulation, which significantly improves the performance of the approach and effectively tracks the pain intensity levels as reflected in the performance evaluation metrics as shown in Table 2.

Some of the widely used evaluation metrics for the problem of ordinal classification are Person Correlation Coefficient (PCC), Intraclass Correlation (ICC(3,1)) and Mean Absolute Error (MAE). PCC measures the inter correlation between the targets and predictions, which efficiently conveys the correlation or similarity between the two signals (predictions and targets). The proposed approach shows superior performance in terms of PCC compared to ICC and MAE, thereby effectively tracks the pain intensity levels of the individual frames as shown in Figure 5.3. ICC(3,1) is widely used to measure the degree of correlation and agreement between the measurements, whereas MAE is widely used for predictive regression tasks. Since ICC is more reliable than PCC for sequence-level estimation as it efficiently captures the intraclass correlation, the proposed exhibits higher performance of ICC for sequence-level estimation compared to frame-level estimation.

We have further compared the performance of the approach to that of state-of-the-art fully supervised as well as partially annotated scenarios. In the context of weak annotations, [33] is proposed for estimation of facial action unit intensity estimation, however it requires the location of peak and valley frames for training. On the contrary, our approach does not require any prior information pertinent to peak and valley frames still performing at par with that of [33].

6. Conclusions

In this work, we have proposed a generic framework of deep domain adaptation for ordinal regression of facial expression intensity estimation. Contrary to the existing approaches for expression intensity estimation, which explored deep learning models for regression, we have shown that exploiting ordinal nature of the labels significantly improves the performance of the system to accurately track the pain intensity levels. Contrary to the existing approaches [10] for MIR, we have deployed multiple frames by associating the weak sequence label with the average of all the frames pertinent to maximum intensity level instead of a single frame. We have conducted extensive set of experiments with various baseline models using various combinations of source and target data-set and shown that the performance of our proposed approach significantly outperforms over the state-of-the-art approaches.
Figure 3. Visualization of pain localization on two different subjects. From top to bottom: scenario where ground truth (GT) shows no pain, but our deep WSDA approach correctly localizes pain. Scenario with multiple peaks of expressions.

References

[1] Stuart Andrews, Ioannis Tsotschantaridis, and Thomas Hofmann. Support vector machines for multiple-instance learning. In S. Becker, S. Thrun, and K. Obermayer, editors, Advances in Neural Information Processing Systems 15, pages 577–584. MIT Press, 2003.

[2] Zhanli Chen, Rashid Ansari, and Diana J. Wilkie. Learning pain from action unit combinations: A weakly supervised approach via multiple instance learning. CoRR, abs/1712.01496, 2017.

[3] Joy Egede, Michel F. Valstar, and Brais Martínez. Fusing deep learned and hand-crafted features of appearance, shape, and dynamics for automatic pain estimation. CoRR, abs/1701.04540, 2017.

[4] Yaroslav Ganin and Victor Lempitsky. Unsupervised domain adaptation by backpropagation. In Proceedings of the 32Nd International Conference on International Conference on Machine Learning - Volume 37, ICML’15, pages 1180–1189. JMLR.org, 2015.

[5] K. Hsu, Y. Lin, and Y. Chuang. Augmented multiple instance regression for inferring object contours in bounding boxes. IEEE Transactions on Image Processing, 23(4):1722–1736, April 2014.

[6] Arshad Jamal, Vinay P. Namboodiri, Dipti Deodhare, and K. S. Venkatesh. Deep domain adaptation in action space. In BMVC, 2018.

[7] P. Lucey, J. F. Cohn, K. M. Prkachin, P. E. Solomon, and I. Matthews. Painful data: The unbc-mcmaster shoulder pain expression archive database. In Face and Gesture 2011, pages 57–64, March 2011.

[8] Albert Mehrabian. Communication Without Words, pages 193–200. 09 2017.

[9] O. M. Parkhi, A. Vedaldi, and A. Zisserman. Deep face recognition. In British Machine Vision Conference, 2015.

[10] R. Gnana Praveen, E. Granger, and P. Cardinal. Deep weakly supervised domain adaptation for pain localization in videos. In 2020 15th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2020) (FG), pages 883–890, Los Alamitos, CA, USA, may 2020. IEEE Computer Society.

[11] Y. Ren, J. Hu, and W. Deng. Facial expression intensity estimation based on cnn features and rankboost. In 2017 4th IAPR Asian Conference on Pattern Recognition (ACPR), pages 488–493, Nov 2017.

[12] F. Ringeval, A. Sonderegger, J. Sauer, and D. Lalanne. Introducing the recola multimodal corpus of remote collaborative and affective interactions. In 2013 10th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG), pages 1–8, April 2013.

[13] P. Rodriguez, G. Cucurull, J. Gonzalez, J. M. Gonfaus, K. Nasrollahi, T. B. Moeslund, and F. X. Roca. Deep pain: Exploiting long short-term memory networks for facial expression classification. IEEE Transactions on Cybernetics, pages 1–11, 2018.

[14] A. Ruiz, O. Rudovic, X. Binefa, and M. Pantic. Multi-instance dynamic ordinal random fields for weakly super-
vised facial behavior analysis. *IEEE Transactions on Image Processing*, 27(8):3969–3982, Aug 2018.

[15] Adria Ruiz, Ognjen Rudovic, Xavier Binefa, and Maja Pantic. Multi-instance dynamic ordinal random fields for weakly-supervised facial behavior analysis. *CoRR*, abs/1803.00907, 2018.

[16] Adria Ruiz, Joost Van de Weijer, and Xavier Binefa. Regularized multi-concept mil for weakly-supervised facial behavior categorization. In *Proceedings of the British Machine Vision Conference*. BMVA Press, 2014.

[17] Motaz Sabri and Takio Kurita. Facial expression intensity estimation using siamese and triplet networks. *Neurocomputing*, 313:143 – 154, 2018.

[18] Enver Sangineto, Gloria Zen, Elisa Ricci, and Nicu Sebe. We are not all equal: Personalizing models for random expression analysis with transductive parameter transfer. In *Proceedings of the 22Nd ACM International Conference on Multimedia*, MM ’14, pages 357–366, New York, NY, USA, 2014. ACM.

[19] Hidetoshi Shimodaira. Improving predictive inference under covariate shift by weighting the log-likelihood function. *Journal of Statistical Planning and Inference*, 90(2):227 – 244, 2000.

[20] Karan Sikka, Abhinav Dhall, and Marian Stewart Bartlett. Classification and weakly supervised pain localization using multiple segment representation. *Image and Vision Computing*, 32(10):659 – 670, 2014. Best of Automatic Face and Gesture Recognition 2013.

[21] Miao Sun, Tony X. Han, Ming-Chang Liu, and Ahmad Khodayari-Rostamabad. Multiple instance learning convolutional neural networks for object recognition. *CoRR*, abs/1610.03155, 2016.

[22] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna. Rethinking the inception architecture for computer vision. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2818–2826, June 2016.

[23] Mohammad Tavakolian and Abdenour Hadid. Deep spatiotemporal representation of the face for automatic pain intensity estimation. *CoRR*, abs/1806.06793, 2018.

[24] Paul Viola, John Platt, and Cha Zhang. Multiple instance boosting for object detection. In *Advances in Neural Information Processing Systems 18*, pages 1417–1426, January 2007.

[25] Mei Wang and Weihong Deng. Deep visual domain adaptation: A survey. *Neurocomputing*, 312:135 – 153, 2018.

[26] C. Wu, S. Wang, and Q. Ji. Multi-instance hidden markov model for facial expression recognition. In *2015 11th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG)*, volume 1, pages 1–6, 2015.

[27] Gregory D Hager Trac D Tran Xiang Xiang, Ye Tian. Assessing pain levels from videos using temporal convolutional networks. In *IEEE Winter Conference on Applications of Computer Vision (WACV) 2018 workshops*, 2018.

[28] Xiangjun Wang Xiaojing Wang and Yubo Ni. Unsupervised domain adaptation for facial expression recognition using generative adversarial networks. In *Computational Intelligence and Neuroscience*, 2018.