Deep Weakly Supervised Domain Adaptation for Pain Localization in Videos

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November 19 2020

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Presentation Overview

1. Introduction

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2. Background on Weakly-Supervised Methods for Domain Adaptation

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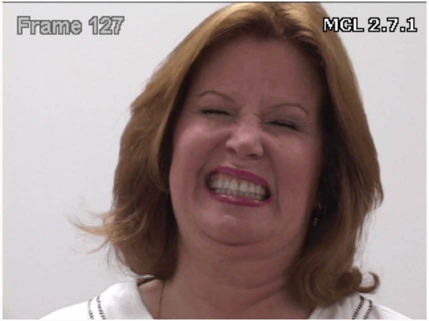
1. Introduction

Pain Detection in Health Care

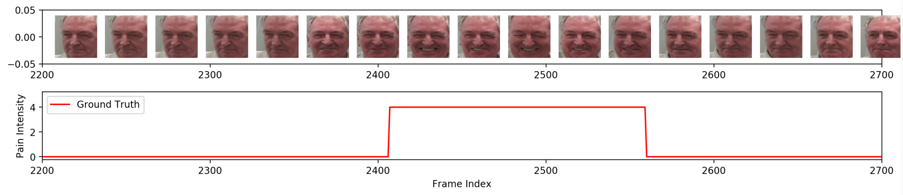
- Pain is a primary symptom of any malfunctioning in our body.
- Need for uninterrupted and contact-free monitoring of patients.
- Facial expressions convey significant information for pain detection.



Images taken from UNBC-McMaster pain dataset [Lucey et al., 2011]

Challenges in Pain Intensity Estimation

- Labeling of pain intensity levels in video frames is very expensive.



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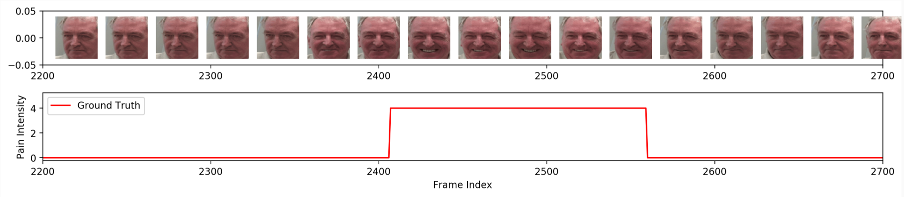


- Level ambiguity due to subtle differences across intensities (pain and non-pain frames at left and right respectively)

Images taken from UNBC-McMaster pain dataset [Lucey et al., 2011]

Challenges in Pain Intensity Estimation

- High inter-subject variability (subject identity bias)

Images taken from Recola [Ringeval et al., 2013] and UNBC-McMaster [Lucey et al., 2011]

Challenges in Pain Intensity Estimation

- High inter-subject variability (subject identity bias)

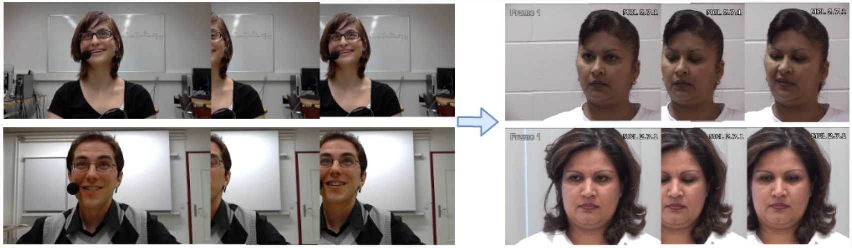
- Domain shift affected by several factors such as pose, occlusion and out-of plane head movements

Images taken from Recola [Ringeval et al., 2013] and UNBC-McMaster [Lucey et al., 2011]

2. Background on Weakly-Supervised Methods for Domain Adaptation

Why Domain Adaptation?

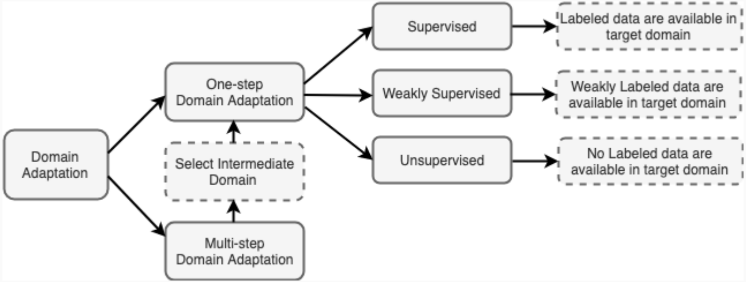
- Deep learning models are data hungry methods that requires millions of labeled examples.
- Models do not generalize well to new domains i.e., fail to cope with domain differences.

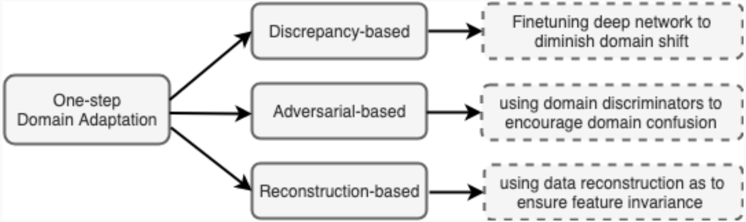


Source Dataset (Recola)   Target Dataset (UNBC-McMaster)

Images taken from Recola [Ringeval et al., 2013] and UNBC-McMaster [Lucey et al., 2011]

Domain Adaptation Approaches





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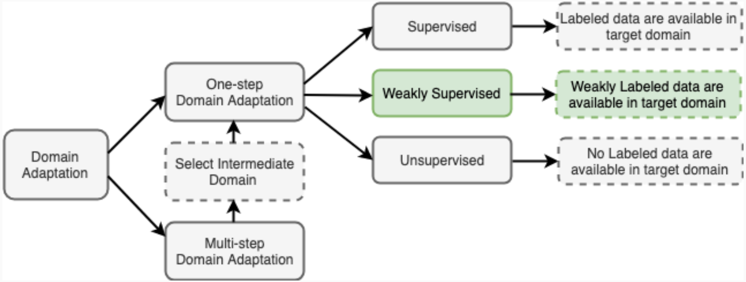
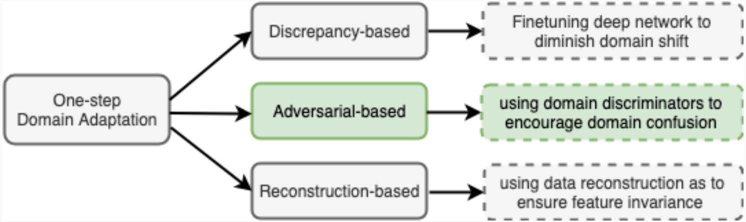
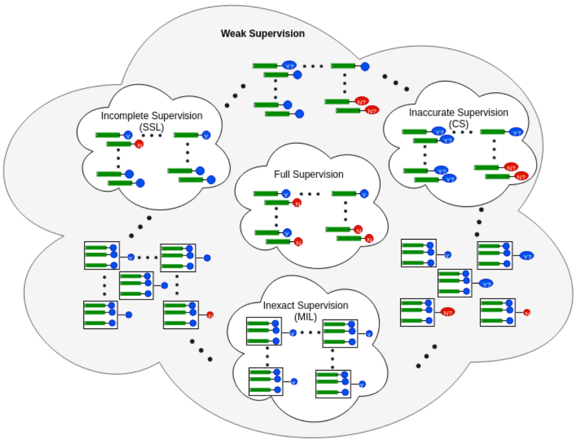




Weakly Supervised Learning (WSL)



Bars denote feature vectors; red/blue marks labels; “?” implies label may be inaccurate. Intermediate subgraphs depict some situations with mixed types of weak supervision. [Zhou, 2018]

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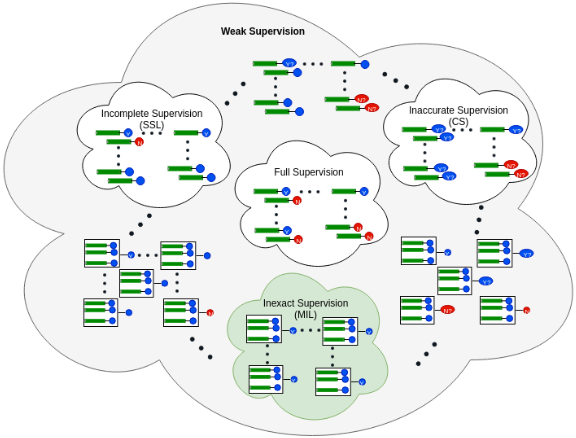

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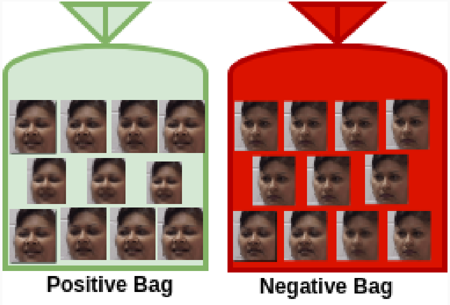
Multiple Instance Learning (MIL) for Facial Expressions

- Bag denotes video sequence with multiple frames (instances).
- Positive Bag corresponds to video sequence with atleast one expression frame.
- Negative Bag corresponds to video sequence with only neutral frames.



MIL Approaches for Pain Estimation

- [Sikka et al., 2014] extracted spatiotemporal features (SIFT) and proposed pain localization and classification using MIL assuming video sequence as bag and subsequence as instance.

  $\longrightarrow$ Does not provide pain intensity levels for individual frames.

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- [Ruiz et al., 2018] proposed multi-instance dynamic ordinal random fields by modeling the relation between ordinal levels and given observation (frames) using normal distribution.

  $\longrightarrow$ Does not efficiently capture the spatiotemporal relationships.

Limitations of SOA Approaches

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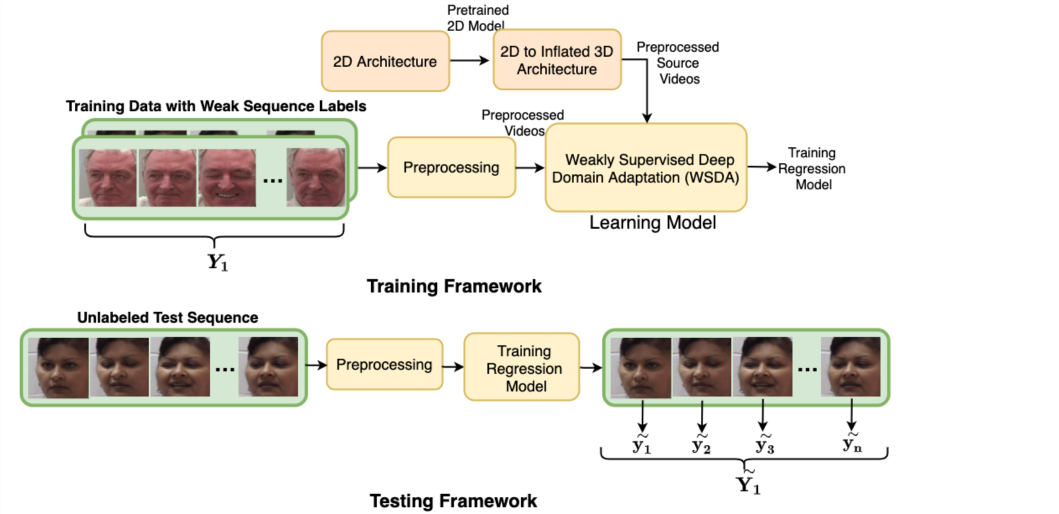
- Regression of pain expressions is an under-researched problem.
- The potential of deep learning models is not explored with MIL due to lack of representative data.
- The temporal dynamics of pain expressions is not effectively captured in the existing approaches.

3. Proposed Approach

Overall Framework



Weakly Supervised Deep Domain Adaptation (WSDA)

- The training mechanism has four major modules : feature extractor, source loss, target loss and domain loss.
- 3D CNN is used for capturing spatiotemporal features and adversarial domain adaptation is deployed to optimize the domain loss.
- Source and target losses are computed using full source labels and weak target labels respectively.

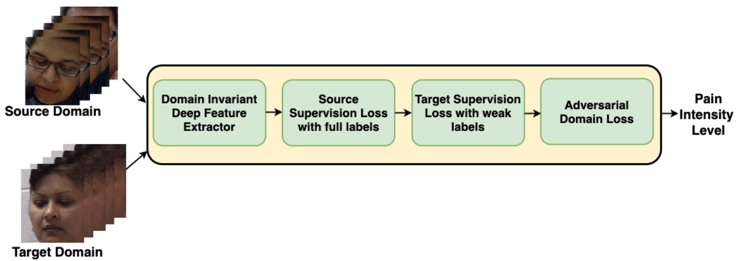
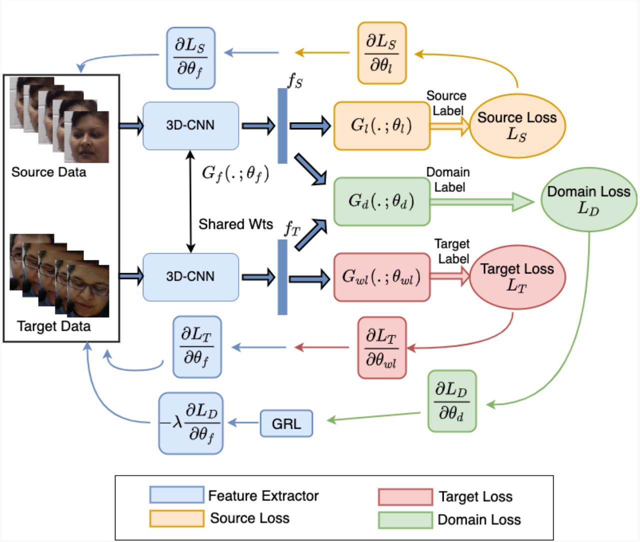


Figure: Block Diagram of the proposed approach

Weakly Supervised Deep Domain Adaptation (WSDA)



Weakly Supervised Deep Domain Adaptation (WSDA)

Source Loss

$$L_S = \frac{1}{N_s} \sum_{\substack{i=1 \\ d_i=0}}^{N_s} \sum_{j=1}^{n_i} ((G_l(G_f(x_i^j)) - y_i^j))^2$$

x_i^j : j$^{\text{th}}$ frame of i$^{\text{th}}$ sequence in source domain
y_i^j : label of j$^{\text{th}}$ frame of i$^{\text{th}}$ sequence
N_S: # of sequences in source domain

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Target Loss

$$L_T = \frac{1}{N_T} \sum_{\substack{i=1 \\ d_i=1}}^{N_T} \sum_{j=1}^{n_i} ((G_l(G_f(X_i)) - Y_i))^2$$

X_i : $\mathrm{i^{th}}$ sequence of target domain

Y_i : Weak label of $\mathrm{i^{th}}$ sequence

N_T: # of sequences in target domain

Weakly Supervised Deep Domain Adaptation (WSDA)

Domain Loss

$$L_d = \frac{1}{N_s+N_T} \sum_{\substack{i=1 \\ d_i=0,1}}^{N_s+N_T} \sum_{j=1}^{n_i} [-d_i^j \log \left(G_d(G_f(x_i^j)) \right)$$

$$- (1\text{-}d_i^j) \log \left(1 - G_d(G_f(x_i^j))\right)]$$

x_i : j^{th} of i^{th} sequence of source or target domain

d_i: domain label of i^{th} sequence

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x_i : jth of ith sequence of source or target domain

d_i: domain label of ith sequence

Overall Loss

$$L = L_S + L_T - \lambda L_d$$

λ : trade-off parameter between domain loss and prediction loss

4. Results and Discussion

Results with Baseline Training Models

Training Scenario	PCC ↑	MAE ↓
Supervised (source data only)	0.295	1.630
Supervised (target data only)	0.447	0.804
Supervised (source $\cup$ target)	0.612	0.543
Unsupervised DA	0.413	0.874
WSDA (ours)	0.676	0.774
Supervised DA	0.812	0.454

Table: PCC and MAE performance of I3D model trained under different scenarios.

Results with Varying Sequence Lengths

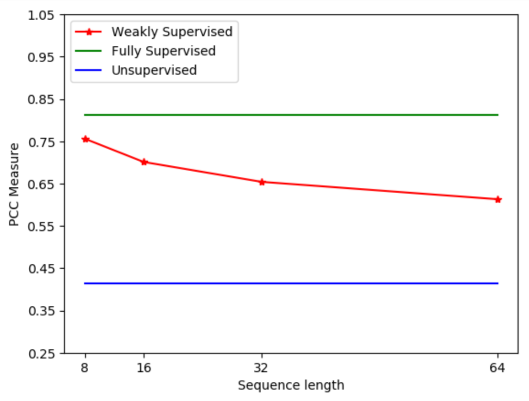

Figure: PCC accuracy of I3D model trained with deep WSDA levels with decreasing level of weak supervision on target videos.

Visualizations of Pain Localization on two subjects

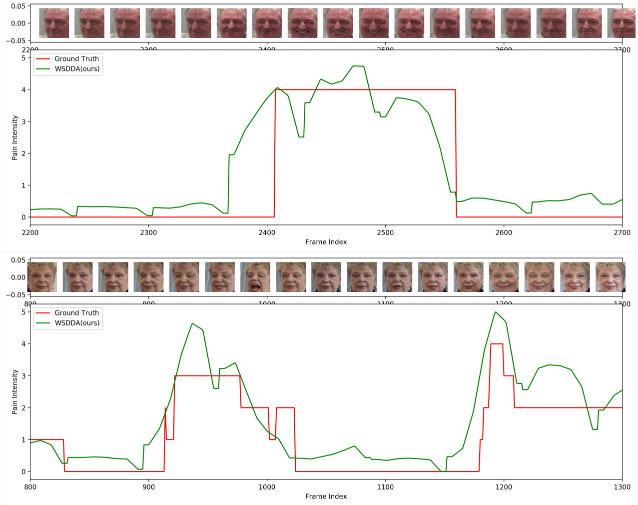

Figure: Visualization of pain localization on two different subjects. From top to bottom: scenario where ground truth (GT) shows no pain, but our deep WSDA approach correctly localizes pain. Scenario with multiple peaks of expressions

Comparison with state-of-the-art approaches

Method	Frame-level			Sequence-level		
	PCC ↑	MAE ↓	ICC ↑	PCC ↑	MAE ↓	ICC ↑
Weakly-Supervised						
MIR [Hsu et al., 2014]	0.350	0.840	0.240	0.63	0.940	0.630
MILBOOST [Sikka et al., 2014]	0.280	1.770	0.110	0.380	1.700	0.380
MI-DORF [Ruiz et al., 2018]	0.400	0.190	0.460	0.670	0.800	0.660
Deep WSDA (ours)	**0.630**	**0.714**	**0.567**	**0.828**	**0.647**	**0.762**
Semi-Supervised						
BORMIR [Zhang et al., 2018]	0.605	0.821	0.531	-	-	-
Fully Supervised						
LSTM [Rodriguez et al., 2018]	0.780	0.500	-	-	-	-
SCN [Tavakolian and Hadid, 2019]	0.920	0.320 (MSE)	0.750	-	-	-

Table: PCC, MAE and ICC performance of proposed and state-of-art methods.

5. Conclusion

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- We propose a deep WSDA model that can significantly improve the performance of the system.
- Domain Adaptation is explored for pain intensity estimation with weak labels.
- Deep models are exploited for efficient feature extraction of the pain expressions.
- An extensive set of experiments are conducted with various baselines using various combinations of source and target domains.

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