Deep Spatio-Temporal Video Based Analysis for Shoulder Pain Intensity Measurement

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Motivation

- Pain assessment and management are important across a wide range of disorders and treatment interventions[1].
- The standard clinical assessment of pain is limited primarily to the subjective reports (e.g., Visual Analog Scale (VAS)).
- While convenient and useful, subjective reports have several limitations (e.g., inconsistent metrics, reactivity to suggestion).
- ***We propose an automatic and objective pain intensity measurement using spatio-temporal changes in facial expression.***

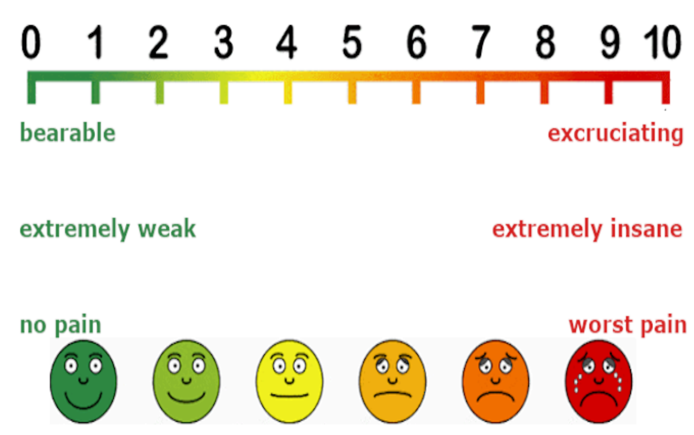
Dataset

UNBC McMaster Pain Archive[2]

- 25 Participants with shoulder pain
- 200 video sequences

For each video sequence:

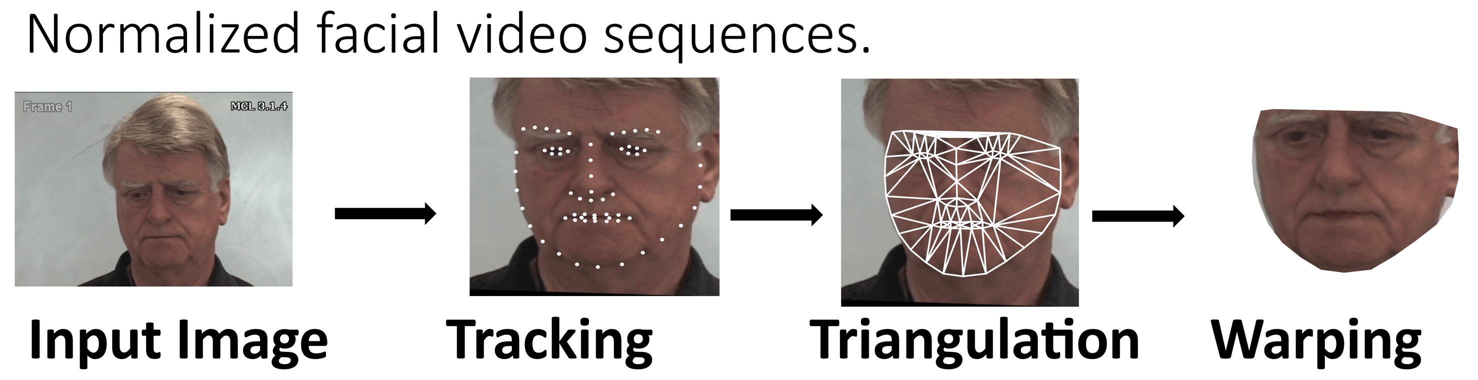
- Three self-reported pain scores
  - ✓ Affective Scale (AFF)
  - ✓ Sensory Scale (SEN)
  - ✓ Visual Analogue Scale (VAS)



- Offline Observer Pain Intensity Rating (OPI)

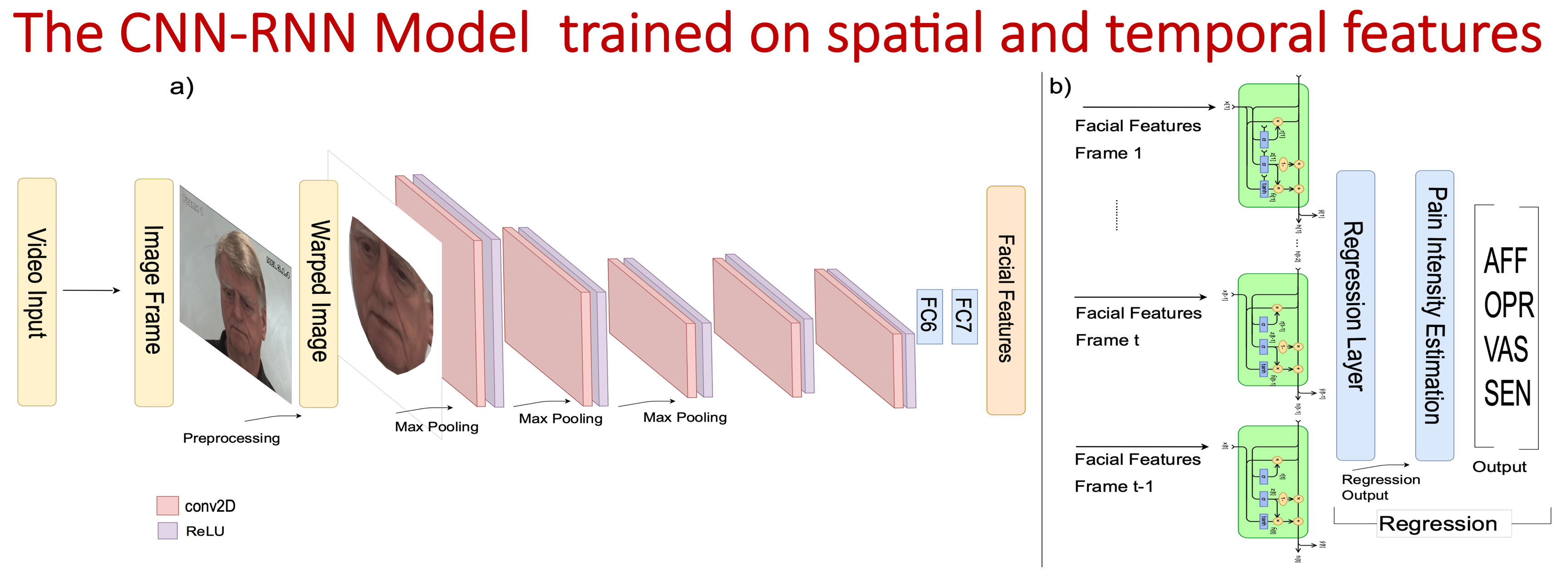
Face Registration And Warping

- 66 facial points tracked using Active Appearance Model[2].
- Face registration and warping using Delaney triangulation.
- Normalized facial video sequences.



End-to-End Spatio-Temporal Deep Model

The CNN-RNN Model trained on spatial and temporal features



CNN: AlexNet[3] trained to learn frame-by-frame spatial feature (4096D per frame).
RNN: 2-layer GRU[4] trained to learn per-video temporal dynamics of facial features.

Loss Function:

MSE   Inter-variance Loss.   L2 Regularisation

$$\frac{\alpha}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2+(1-\alpha)Var(\hat{Y})+\lambda\sum_{p=1}^{P}(\beta_p)$$

Inter-variance loss penalizes the difference between self-reported and observer's reported pain scores.

Experimental Setup

Stratified distribution of data

- Dataset is split into five independent folds
- Well distributed pain intensities per fold.
- Ensures model training is not biased due to skewed training distribution.

Fold #	AFF	VAS	OPR	SEN
Fold 1	97.47	97.6	93.86	97.95
Fold 2	98.93	99.42	99.45	98.41
Fold 3	97.89	98.28	98.33	97.86
Fold 4	98.39	98.28	99.25	97.96
Fold 5	93.92	96.79	98.37	96.23

[a]Mean square similarity with the entire Pain Archive

Data distribution across 5 folds: Mean Square similarity to the entire dataset

Two level 5 fold Cross Validation

```
params = [num layers, dropouts, learning_rate, λ]
for outer_fold (5) do
    min_val_loss = infinity; test_data = data[outer_fold];
    train_val_data = data - test_data;
    for inner_folds do
        val_data = data[inner_fold];
        train_data = train_val_data - val_data;
        net.init(params[inner_fold]);
        net.fit(train_data);
        val_loss = net.history['valid_loss'];
        if val_loss < min_val_loss then
            net.save_params(params[inner_fold]);
            min_val_loss = val_loss;
            min_param_idx = params[inner_fold];
        end
        test_net = net.init(params[min_param_idx]);
        test_net.fit(train_val_dataset);
        test_loss = evaluate(test_net,test_data);
    end
end
```

Algorithm 1. Nested two level cross validation

Experimental Results

- Mean Absolute Error (MAE) in pain intensity measurement: VAS [0-10], OPI [0-5]

			Random Distribution		Stratified Distribution	
Method	Setting	Pain Scale	MAE (VAS)	MAE (OPI)	MAE (VAS)	MAE (OPI)
Our Model	One Label	VAS	2.98	-	2.57	-
	One Label	OPI	-	1.46	-	1.33
	Two Labels	VAS,OPI			2.25	1.72
	Four Labels	VAS,OPI,AFF,SEN	3.09		2.54	1.39
DeepFaceLift Liu et al	3rd Neural Net Layer	VAS, OPI	2.34	-	-	-
		VAS	2.24	-	-	-
	Neural Net Layer	VAS, OPI	2.41	-	-	-
		VAS	2.22	-	-	-

- Our Model: spatio-temporal modelling of temporal changes (OPI and VAS).
- DeepFaceLift[5]: summary statistics as proxy of temporal changes (VAS only).

Conclusions

- Automatic, objective, and reliable measurement of pain intensity from facial expression is feasible.
- The proposed loss function exploits the consistency between different pain intensity measures.
- Stratifying data on average improved VAS and OPI results by 13.6% and 8.9%, respectively .
- OPI offers a more objective assessment of pain intensity.

References

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