

Deep Recurrent Multi-instance Learning with Spatio-temporal Features for Engagement Intensity Prediction

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Contributions

- We developed a deep multi-instance learning framework that accepts multiple input features, and evaluated how different modality performs using our framework.
- Furthermore, to take full advantage of all available data, we make new data split for model ensemble.
- Experimental results demonstrate the effectiveness of our method, and we eventually win the challenge with MSE of 0.0626.

Introduction of Our Approaches

Multiple Instance Learning Framework

- We formulate the problem as a multi-instance regression. A video sequence v is divided as k segments such as $v = [s_1, s_2, s_3, \dots, s_k]$, and each video clip is regarded as an instance. We extract M different modality features $F_k = [f_k^1, f_k^2, f_k^3, \dots, f_k^m]$ from a segment and feed them into our framework.

Multi-modal Features

- LBP-TOP features are extracted for each video clip, which is used as fine-grained facial feature in our approach.
- We use the C3D network pretrained in Sports-1M dataset, and crop the subject body using OpenPose. Then C3D features are extracted by body images in a segment.
- We capture the gaze and head movement features using OpenFace while body posture characteristics via OpenPose

Dataset Split and Model Ensemble

- We generate new data splits by utilizing all validation data for training. We make the training class balanced as much as possible.

Our Pipeline

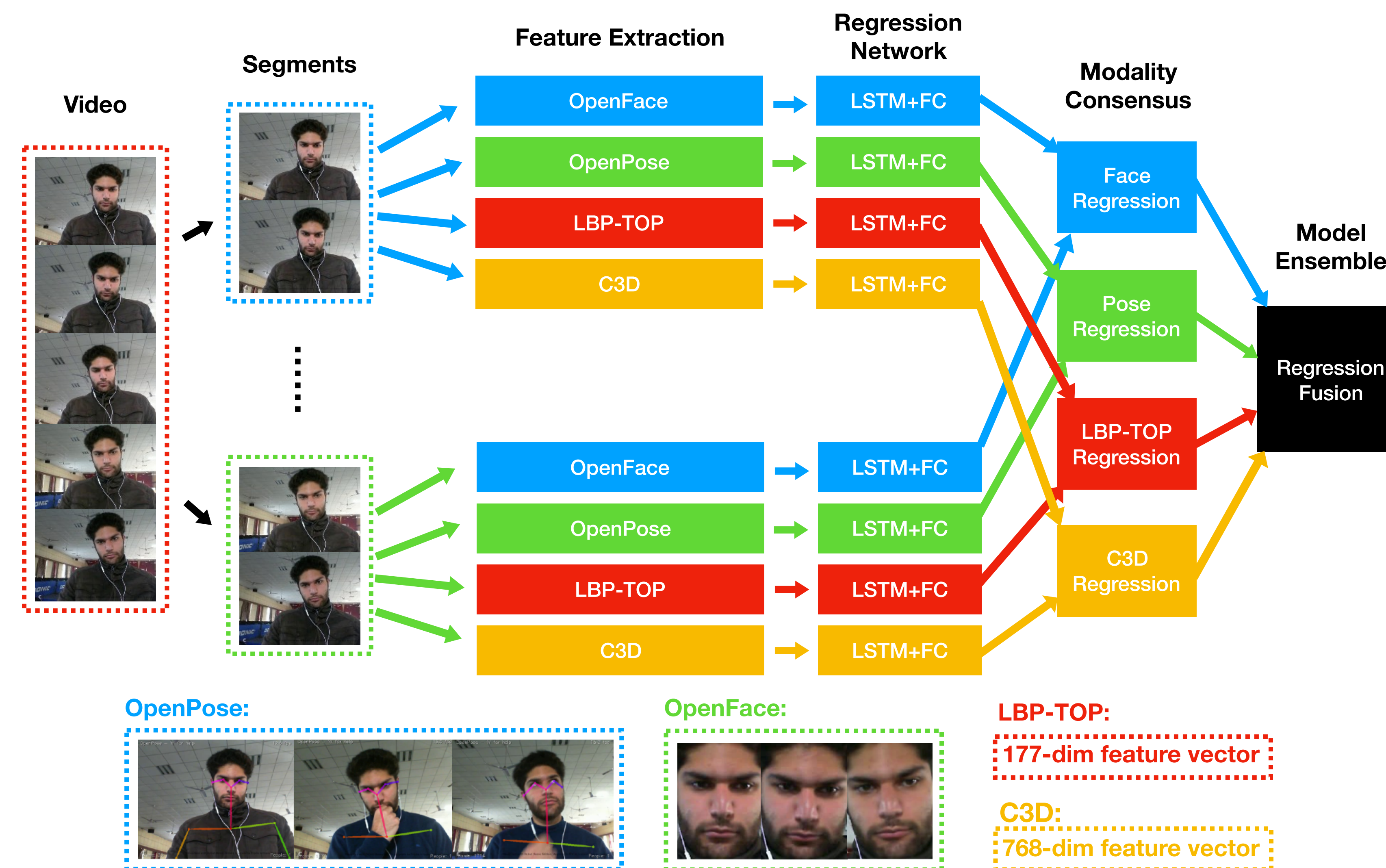


Figure 1: The system pipeline of our approach.

Our Submissions

- ① OpenPose features only in new split.
- ② OpenPose features using all data.
- ③ OpenFace and OpenPose features in new split.
- ④ OpenFace and OpenPose features in official split.
- ⑤ (3) + LBP-TOP + C3D
- ⑥ (3) + (4)
- ⑦ OpenFace in new split + LBP + C3D

Table 3: MSE Results of all models of submissions.

Runs	Validation ($\times 10^{-4}$)		Test ($\times 10^{-4}$)				
	Overall		NE	BE	E	SE	Overall
1	853		2180	917	540	4407	1040
2	123		3854	1169	753	2210	1353
3	364		2505	473	154	1628	626
4	734		3185	1076	508	1477	1072
5	541		2781	541	198	1443	698
6	782		2987	725	174	988	745
7	431		2275	589	257	2676	730

Conclusions

- We presented our approach in this paper for the engagement intensity prediction in the Emotion Recognition in the Wild Challenge 2018.
- We developed a deep multi-instance learning framework that accepts multiple input features, and evaluated how different modality performs using our framework.
- Statistical feature, local descriptor and deep representation are employed and they compensate for each other. Furthermore, to take full advantage of all available data, we make new data split for model ensemble.

MSE Results on Validation set of official split

Table 1: MSE Results on Validation set of **official split**

Method	MSE	Normalized MSE
2 LSTM + OpenFace	0.0847	0.0821
1 LSTM + OpenFace	0.0853	0.0830
1 LSTM + OpenPose	0.0717	0.0739
2 LSTM + OpenPose	0.0734	0.0732
1 LSTM + LBP-TOP	0.0909	-
1 LSTM + C3D	0.0865	-

- In the Table 1, the model using facial features gets MSE of 0.085 around and the one using 2 LSTM layers generates a little better result. As for the model using posture features, it outperforms the face-based one by 0.01 generally, which is a powerful proof that our OpenPose features can contribute more to the engagement intensity prediction.

Table 2: MSE Results on Validation set of **new split**

Method	MSE	Normalized MSE
2 LSTM + OpenFace	0.0398	0.0410
2 LSTM + OpenPose	0.0853	0.0830
1 LSTM + OpenPose	0.0671	0.0717

- In Table 2, it is amazing that our new split reduces the MSE. Our face-based approach on new split achieves 0.0398 MSE and pose-based one attains best MSE of 0.0671. Our adjustment of quantitative balance leads to better convergence, and moreover, the supplement of official validation data enhances the generalization of our approach, which blossoms a lot in the ensemble with the models optimized by official data.



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