



Frame Perfect: Film Director Classification using Convolutional Neural Networks

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Introduction

Auteur theory, or the idea that the director of a film is its “author” and has a personal, recognizable artistic style, has been a significantly influential yet controversial paradigm within the film community since its inception in the 1950s.

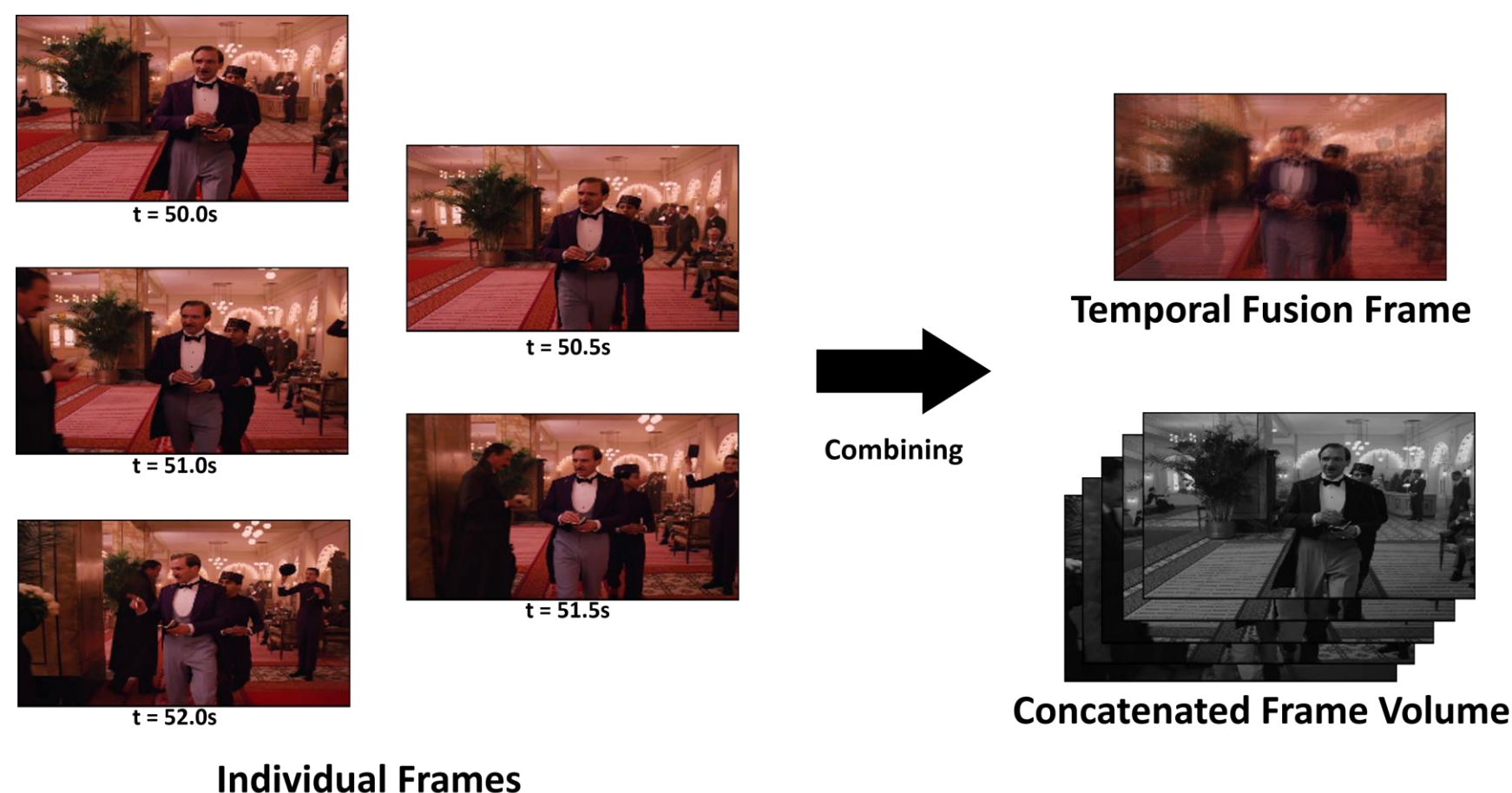
Goal: Can a CNN successfully recognize and classify the director from the visuals of a movie scene?

Data Processing

Raw data = Movie clips consisting of ~28,800 frames per director

Goal: Combine frames to incorporate temporal data

Methods: 1) Average frames in a Temporal Fusion Frame (TFF)
2) Stack frames to create a ‘volume’ of pixels
-Similar to Andrej Karpathy’s approach in [1]



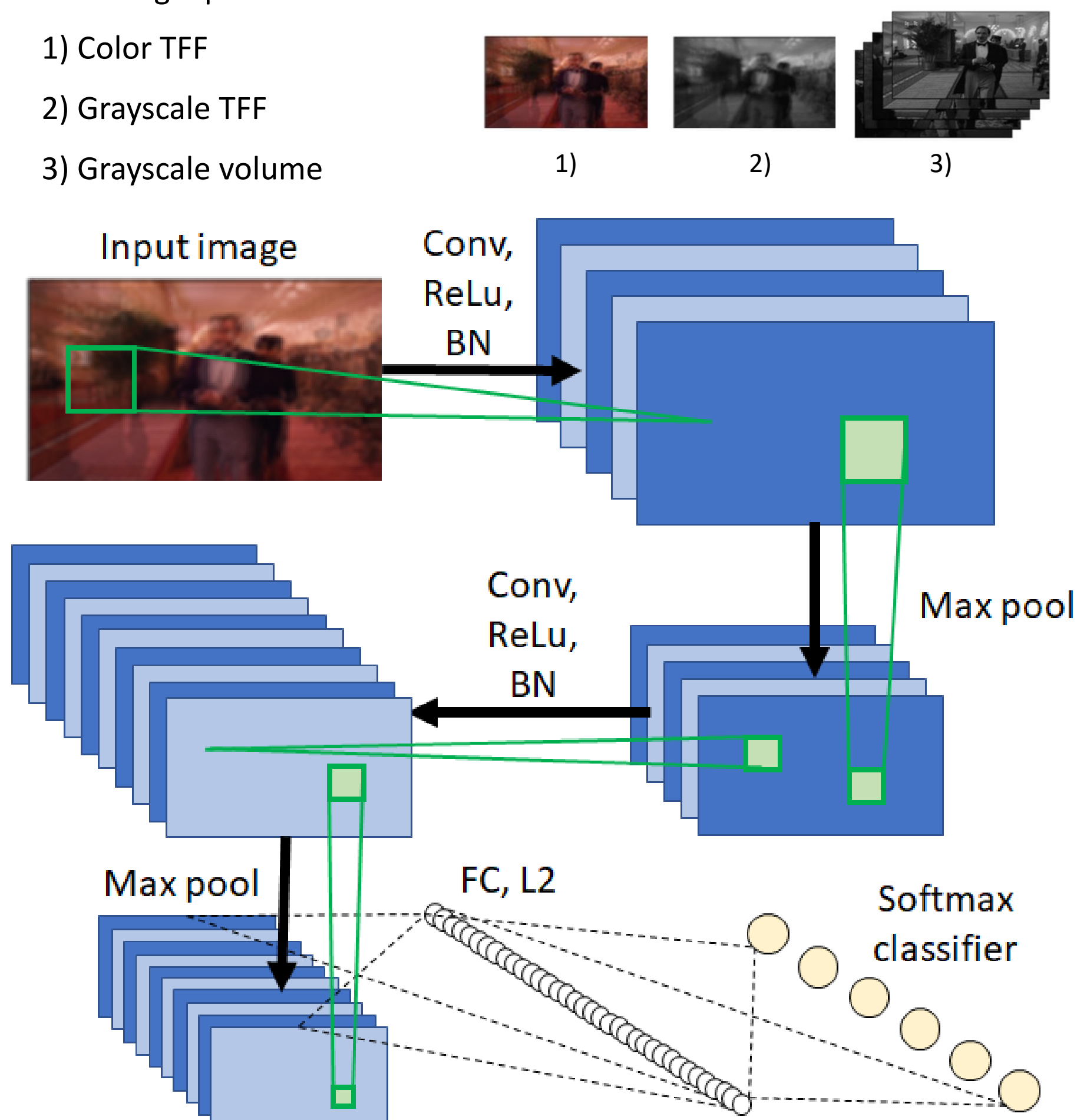
Combined 5 frames separated by 0.5s to create these ‘temporal frames’. The concatenated frame was converted to grayscale to meet memory constraints. The final number of temporal frames for each director is:

| | | |
|----------------------------------|--------------------------------------|---------------------------------|
| 1) Coen Brothers (495 frames) | 3) Quentin Tarantino (470 frames) | 5) Wes Anderson (451 frames) |
| 2) Michael Bay (471 frames) | 4) Stanley Kubrick (496 frames) | 6) Zack Snyder (465 frames) |

Predictor Architecture

Same architecture but differently tuned hyperparameters for each of the following inputs:

- 1) Color TFF
- 2) Grayscale TFF
- 3) Grayscale volume



$$Loss(p, y, w) = - \underbrace{\sum_{c=1}^{N_{dir}} y_{o,c} \log(p_{o,c})}_{\text{Cross Entropy Loss}} + \underbrace{\frac{\lambda}{2} \sum_{i=1}^L \|w_i\|^2}_{\text{L2-Regularization}}$$

Tried to help the model generalize by adding an L2 regularization term to the loss function, using Batch Normalization to shift and scale the data between layers [2], and by using Dropout with a rate of 20% to randomly remove neuron connections from the CNN [3].

Results

Baseline = SVC using a feature vector consisting of average color values

Oracle = Human labeling of test-set frames sent to the CNN

| Model | Training Set Accuracy | Test Set Accuracy |
|----------------|-----------------------|-------------------|
| Baseline (SVM) | 78.1% | 32.6% |
| Color TFF | 79.8% | 18.1% |
| Grayscale TFF | 41.7% | 22.5% |
| Frame Volume | 43.0% | 22.1% |
| Oracle (Human) | ~ | 86.1% |

| | | Predicted Director | | | | | | | | | | | | | | | | |
|-----------------|----------|--------------------|----|----|----|----|---------------|----|---|----|----|---|--------|----|----|----|----|----|
| Actual Director | Baseline | | | | | | Grayscale TFF | | | | | | Oracle | | | | | |
| | 6 | 14 | 11 | 0 | 0 | 10 | 33 | 2 | 1 | 13 | 0 | 0 | 48 | 0 | 0 | 1 | 0 | 0 |
| | 1 | 8 | 8 | 16 | 6 | 10 | 0 | 12 | 0 | 26 | 21 | 0 | 4 | 38 | 0 | 1 | 9 | 7 |
| | 8 | 0 | 25 | 6 | 8 | 5 | 0 | 14 | 7 | 1 | 41 | 0 | 0 | 0 | 60 | 0 | 0 | 3 |
| | 0 | 41 | 1 | 1 | 0 | 0 | 10 | 12 | 3 | 24 | 0 | 2 | 1 | 0 | 0 | 47 | 0 | 3 |
| | 0 | 0 | 6 | 2 | 48 | 0 | 43 | 0 | 2 | 20 | 0 | 2 | 0 | 0 | 0 | 1 | 66 | 0 |
| | 6 | 23 | 5 | 3 | 0 | 4 | 0 | 1 | 1 | 0 | 47 | 0 | 1 | 14 | 0 | 2 | 0 | 32 |

Discussion

TFF with large frame spacing were unclassifiable (16%). Slightly better with closer spacing

Predictors did not generalize well

- Temporal frames may not include enough information to differentiate
- Dataset size was limited due to memory constraints

Future work:

- Improve system to allow more data for each director
- Using transfer learning to fine tune a pre-existing image classifier

References

- [1] Andrej Karpathy et al. Large-scale video classification with convolutional neural networks. *2014 IEEE Conference on Computer Vision and Pattern Recognition*, pages 1725-1732, 2014
- [2] Sergey Ioffe and Christian Szegedy. Batch Normalization: Accelerating deep network training by reducing internal covariate shift. *ArXiv, abs/1502.03167*, 2015
- [3] Srivastava et al. Dropout: A Simple Way to Prevent Neural Networks from Overfitting. *2014 Journal of Machine Learning Research*, pages 1929-1958