In this paper, we present a sparsity-aware deep network for automatic 4D facial expression recognition (FER). Given 4D data, we first propose a novel augmentation method to combat the data limitation problem for deep learning. This is achieved by projecting the input data into RGB and depth map images and then iteratively performing channel concatenation. Encoded in the given 3D landmarks, we also introduce TOP-landmarks over multi-views, an effective way to capture the facial muscle movements from three orthogonal planes. Importantly, we then present a sparsity-aware network to compute the sparse representations of convolutional features over multi-views for a significant and computationally convenient deep learning. For training, the TOP-landmarks and sparse representations are used to train a long short-term memory (LSTM) network. The refined predictions are achieved when the learned features collaborate over multi-views. Extensive experimental results achieved on the BU-4DFE dataset show the significance of our method over the state-of-the-art methods by reaching a promising accuracy of 99.69% for 4D FER.

Index Terms— Affect, augmentation, deep learning, 4D facial expression recognition, landmarks

1. INTRODUCTION

Facial expressions (FEs) are one of the most important, powerful and natural signals to convey and understand human emotions. Many works have been reported in this regard to automate facial expression analysis due to its tremendous applications in medical diagnosis, social robots, self-driving cars, educational well-being and several other human-computer interaction methods. This paved the way for the rise of many facial expression recognition (FER) systems [1] using the recently-trending computer vision technologies like deep learning. Dating back to 1970s, the pioneer study done by Ekman and Friesen [2] gave birth to affective computing by presenting the six universal human facial expressions which are happiness, anger, sadness, fear, disgust and surprise.

To recognize such expressions, many machine learning methods have been proposed in the literature which commonly use static or dynamic 2D images. However, such methods face challenging problems of sensitivity towards pose variations, lighting conditions and occlusions. With the advent of high-speed and high-resolution 3D data acquisition equipment, the research direction is recently steered towards FER systems based on static and dynamic 3D face models. Being more robust towards aforementioned problems, and providing additional geometry information [3], the dynamic 3D data (also known as 4D) conveniently stores the facial deformations when a facial expression is triggered. Importantly, the release of large-size facial expression datasets containing 3D/4D face scans (e.g., the BU-4DFE dataset [4]) has allowed 4D FER by fetching facial deformation patterns both spatially as well as temporally.

1.1. Related Work

To learn from the underlying 3D facial geometry, a number of methods are reported [5], which only rely on the static 3D data, i.e., apex frames. On the other hand, 4D data provides complimentary spatio-temporal patterns allowing deep models to significantly understand and predict the facial expressions. For instance, Sun et al. [6] and Yin et al. [4] proposed a method based on Hidden Markov Models (HMM) to learn the facial muscle patterns over time. In another attempt, using random forest, Ben Amor et al. [7] presented a deformation vector field mainly based on Riemannian analysis to benefit from local facial patterns. Likewise, Sandbach et al. [8] proposed free-form deformation as representations of 3D frames and then used HMM and GentleBoost for classification. Moreover, the authors in [9] used support vector machine (SVM) and represented geometrical coordinates and its normal as feature vectors, and as dynamic local binary patterns (LBP) in another work [10]. Similarly, to extract features from polar angles and curvatures, a spatio-temporal LBP-based feature was proposed in [11].

By using the scattering operator [12] on 4D face scans, Yao et al. [13] applied multiple kernel learning (MKL) to pro-
duce effective feature representations. Similarly, the authors in [14] proposed statistical shape model with local and global constraints to recognize FEs. They claimed that local shape index and global face shape can be combined to build a required FER system. For automatic 4D FER via dynamic geometrical image network, an interesting model was proposed by Li et al. [15]. They generated geometrical images after the differential quantities were estimated where the final emotion prediction was a function of score-level fusion from different geometrical images. Another recent method exploits the sparse coding-based representation of LBP difference [16]. The authors first extracted appearance and geometric features via mesh-local binary pattern difference (mesh-LBPD), and then applied sparse coding to recognize FEs.

1.2. Motivation

Despite many attempts to automate 4D FER, we believe there exist many loopholes that need attention. For example, the data available to train a deep network for 4D FER is very limited. This calls for efficient data augmentation techniques to satisfy the data-hungry nature for deep learning. Moreover, despite the fact that the multi-views of 4D faces jointly capture facial deformations, and that landmarks also encode specific movement patterns, their role is often ignored. Importantly, the need of appropriate facial feature representations is vital in the success of a 4D FER system.

1.3. Contributions

In the light of above discussion, our contributions in this work are 3-fold as follows:

- We present ∞-augmentation which is a simple yet efficient method to combat 3D/4D data limitation problem.
- We introduce TOP-landmarks over multi-views to extract landmark cues from three orthogonal planes.
- Inspired from compressed sensing theory, we compute sparse representations from extracted deep features to not only provide simplified descriptors, but to also reduce computational complexity during deep learning.

The rest of the paper is organized as follows: our proposed 4D FER method is explained in Section 2. In Section 3, we present and discuss our extensive experimental results to validate the efficiency of the proposed method. Finally, Section 4 concludes the paper.

2. OUR PROPOSED METHOD

In this section, we explain our proposed method for automatic 4D FER. First, we augment our data to extend the dataset size for better deep learning. Second, we extract the facial patterns encoded in landmarks on three orthogonal planes to aid our expression recognition system. We then extract deep features which are then collaboratively learned with landmarks for an accurate expression recognition. To leverage the correlations between ∞-augmentation, TOP-landmarks and our sparse representations, the proposed sparsity-aware deep learning is explained as follows.

2.1. ∞-Augmentation

To overcome the limitation of unavailability of large-scale 3D/4D dataset (e.g., only 606 videos in the BU-4DFE [4] dataset), we propose a novel augmentation method. With our simple yet efficient method, the 3D/4D data can be theoretically augmented infinite times, hence the name, ∞-augmentation. From the given 3D point-clouds, we first compute projected 2D images as RGB texture and depth map images. Inspired by the RGB color model, we then propose to concatenate the R/G/B channels and luminance information of the input projected images as various channels of our output augmented image. By varying the order in which the inputs are concatenated, and by including an obtained output image as input for next rounds, we iteratively achieve ∞-augmentation. In Fig. 1 we show twenty-five (25) random augmented samples generated using our method with single input sample for each of the six expressions. The different colors correspond to appearance of the augmented samples.

2.2. TOP-Landmarks

Inspired by LBP-TOP [17], we propose TOP-landmarks to extract effective landmark cues from three orthogonal planes and then use it during deep learning over multi-views (left, front and right). For each of the multi-views, we project all the given 3D landmarks over XY, XZ and YZ planes as shown

Please visit [https://youtu.be/pnzwjYGLkbo] for a detailed illustration of our proposed ∞-augmentation method.

Fig. 1: Samples from the proposed ∞-augmentation method.
in Fig. 3. The projected points are then normalized to ensure correspondence across different frames. As shown, we then compute the Euclidean distance for each point to store the position of each landmark point from origin. Finally, we concatenate the three distance vectors from each plane to compute the resultant TOP-landmarks.

2.3. Sparsity-Aware Deep Learning

For a significant performance improvement, we propose our deep network to be sparsity-aware as shown in Fig. 2. As shown in this figure, once we project the 4D data as RGB texture and depth maps over multi-views, we then augment the data for increasing the training data. Note that instead of using frontal view only, we resort to multi-views and then have a score-level fusion to incorporate the facial muscle movements from the side-views as well. For computational convenience, we use GoogLeNet [18] to extract deep features from the augmented data. Given an input deep feature vector and pre-determined dictionary, the sparse signal are then computed conveniently in a single step as shown in Fig. 2. This is not only useful for accurate FER due to efficient sparse representations, but is also computationally convenient by resizing features to 30 samples only. Note that our pre-determined dictionary contains wavelet basis which are suitable for the deep features as also validated by the results in the next section.

Finally, we create a long short-term memory (LSTM) network with a sequence input layer, Bi-LSTM layer with 2000 hidden units, 50% dropout layer followed by FC, Softmax and classification layer. Consequently, we use the extracted sequences of TOP-landmark and sparse features, all over multi-views to train the LSTM network first, and then collaboratively recognize expressions.

3. EXPERIMENTAL RESULTS

3.1. Dataset and Experimental Settings

To validate the efficiency of our proposed method, we use the BU-4DFE [4] dataset. This dataset contains video clips of 58 females and 43 males (total 101 subjects) having all six human facial expressions. Each clip has a frame rate of 25 frames per second (fps) lasting approximately 3 to 4 seconds. For experimental settings, we use a 10-fold subject-independent cross-validation (10-CV). Instead of using key-frames [13] or employing sliding windows [8], we use entire 3D sequences. For extracting deep features, we use the pre-trained GoogLeNet [18]. However, we also show our results on other pre-trained models. All of our experiments are carried out on a GP100GL GPU (Tesla P100-PCIE), and the training time takes approximately 3 days. Additionally, 25 random augmented samples are used for all the experiments.

3.2. Role of Multi-Views

To highlight the importance of multi-views, we show the confusion matrix of our experiments in Fig. 4. Despite stronger similarities between angry, disgust and fear expressions, the results indicate that our method accurately predicts the expressions validating its effectiveness. Also, as shown in Fig. 4, the results are better when all the views are taken into

Fig. 2: Overview of the proposed sparsity-aware deep learning for 4D FER.

Fig. 3: Calculation of TOP-landmarks.
account. Importantly, a higher accuracy is achieved when both TOP-landmarks and sparse representations are utilized.

### 3.3. Comparison with the State-of-the-Art Methods

In Table 1, we compare the accuracy of our method with several state-of-the-art methods on the BU-4DFE dataset. As illustrated, our method outperforms the existing methods in terms of correct expression recognition. This is mainly due to the extensively collaborative scheme of our method for an accurate expression recognition where the prediction scores are refined from its collaborators. Importantly, we show the effect of using dense vs. sparse representations and also how the TOP-landmarks assist in achieving significant results. As shown, the sparse representations not only intuitively reduce the computational burden but also lead to a more accurate system by less over-fitting and more generalization, hence, raising the accuracy from 93.70% to 98.78%. By using TOP-landmarks, our method further reaches a promising accuracy of 99.69%.

### 3.4. Comparison with Other Pre-Trained Models

Finally in Table 2, we compare the results achieved by extracting deep features from other pre-trained models to validate the effectiveness of our method. Specifically, we use AlexNet, VGG16, VGG19, Inception-v3, ResNet18, ResNet50 and ResNet101. The table gives an overall impression that TOP-landmarks significantly improve the recognition accuracy. It also shows a similar trend, as seen in Table 1, that sparse features lead to a better system performance. The superior performance of GoogLeNet is due to several very small convolutions in order to drastically reduce the number of parameters.

### 4. CONCLUSIONS

We proposed sparsity-aware deep learning to automate 4D FER. We first combated the problem of data limitation for deep learning by introducing ∞-augmentation. This method uses the projected RGB and depth map images, and then proceed to concatenate them in channels over an iterative

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**Table 1:** Accuracy (%) comparison with the state-of-the-art methods on the BU-4DFE dataset.

| Method            | Experimental Settings | Acc.  |
|-------------------|----------------------|-------|
| Sandbach et al. [8] | 6-CV, Sliding window | 64.60 |
| Fang et al. [10]   | 10-CV, Full sequence | 75.82 |
| Xue et al. [19]    | 10-CV, Full sequence | 78.80 |
| Sun et al. [6]     | 10-CV, -             | 83.70 |
| Zhen et al. [13]   | 10-CV, Full sequence | 87.06 |
| Yao et al. [13]    | 10-CV, Key-frame     | 87.61 |
| Fang et al. [9]    | 10-CV, -             | 91.00 |
| Li et al. [15]     | 10-CV, Full sequence | 92.22 |
| Ben Amor et al. [7] | 10-CV, Full sequence | 93.21 |
| Zhen et al. [20]   | 10-CV, Full sequence | 94.18 |
| Bejaoui et al. [16] | 10-CV, Full sequence | 94.20 |
| Zhen et al. [20]   | 10-CV, Key-frame     | 95.13 |

**Table 2:** Accuracy (%) comparison on the BU-4DFE dataset by using other pre-trained deep models.

| Model           | Dense  | Dense+TOP-L | Sparse+TOP-L |
|-----------------|--------|-------------|--------------|
| Inception-v3    | 80.01  | 89.35       | 82.91        |
| AlexNet         | 67.18  | 82.98       | 88.55        |
| VGG16           | 71.45  | 85.12       | 89.97        |
| ResNet18        | 76.34  | 87.36       | 91.60        |
| ResNet101       | 76.65  | 87.71       | 91.70        |
| ResNet50        | 83.74  | 91.06       | 93.93        |
| VGG19           | 84.54  | 91.66       | 94.33        |
| GoogLeNet       | 93.70  | 98.78       | 99.69        |
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