Multimodal Learning: Examples in Gesture and Audio-Visual Speech Recognition

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Abstract

1 Introduction

2 Related Work

3 Presentation of Basic Network Architectures

4 Datasets and Preprocessing

Many datasets were explored during my internship. The three main datasets being used are given in details below. Two of them are for gesture recognition: Creative Senz3D [14, 15] and ASL Finger Spelling [26], and one is for AVSR: Avletters [13].

4.1 Creative Senz3D

The dataset contains gestures perfomed by 4 different people, each performing 11 different static gestures repeated 30 times each. For each sample, color, depth and confidence frames are available. I only used the color and depth frames of this dataset. The original size of each image is 480×640 and they're resized to 299×299 pixels before being fed to the network. No other preprocessing are done. For both color and depth images I use the three color channels (even though a priori only one channel is needed for depth maps).

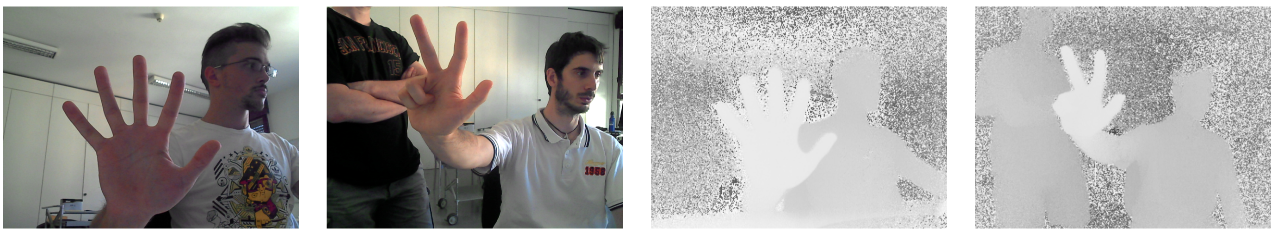

Figure 1: Example images in the Creative Senz3D dataset.
Left Two) Color images.
Right Two) Corresponding depth images.
All of the images are of size 480×640 and contain the the entire upper body of the subject.

4.2 ASL Finger Spelling

The dataset is composed of more than 60000 images in each modality (RGB and depth images are given). Five subjects are asked to perform the 24 static signs in the American Sign Language (ASL) alphabet (excluding j and z which involve motion) a certain number of times, captured with similar lighting and background.

Images of this dataset are of variable sizes. The data preprocessing includes resizing each image to 83×83 pixels, and adjusting contrast of depth maps. Only very late in my internship I added the Z-normalization (normalize to zero mean and unit of variance) as a preprocessing step and the only result that was largely changed is presented in 6.2.

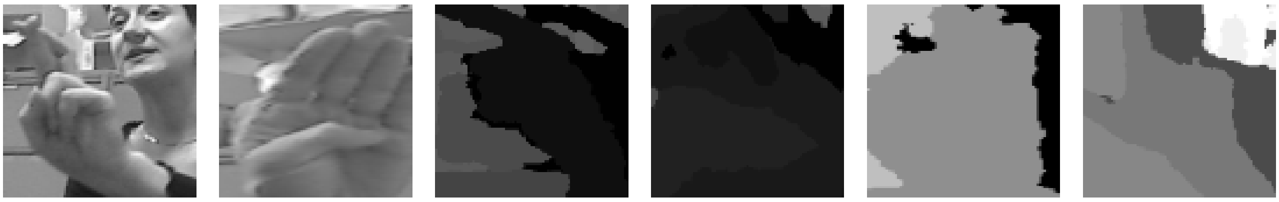

Figure 2: Example images in the ASL Finger Spelling dataset (after preprocessing).
Left Two) Grayscale intensity images.
Middle Two) Depth maps after adjusting contrast.
Right Two) Depth maps after Z-normalization.
Images of this dataset have variable sizes, and they're all resized to 83×83 before being fed to the network. Generally only the hand region is contained in image.

4.3 AVletters

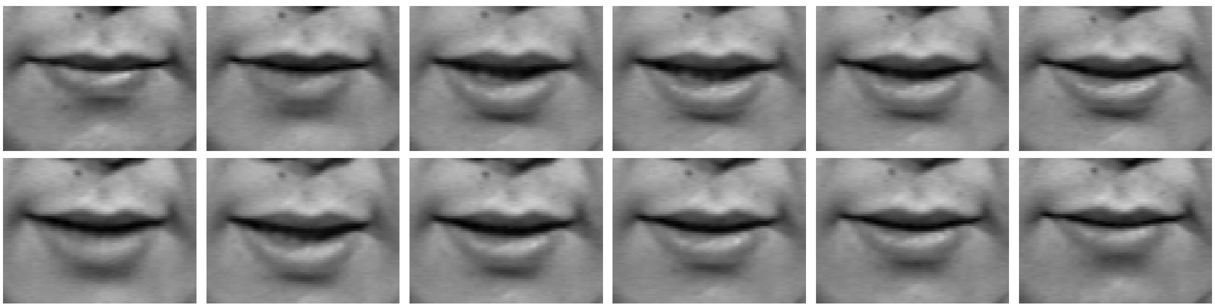

Figure 3: Example visual input for the AVletters dataset (left to right, top to bottom). Pre-extracted lip regions of 60×80 pixels are provided. Each image sequence is resampled to be of length twelve in order to give an input of fixed size to the network.

5 Experimental Setup

6 Experiences and Results: Unimodal Cases

6.1 Classification

With every new dataset, I began with training a classifier on it in a totoally supervised manner. This gave me an insight into its data quality, the preprocessing effectiveness and ensured that further experiments could be conducted. CNN is then one of the most suitable architecture for this purpose.

6.1.1 Creative Senz3d

No satisfying results were acquired. It may be due to to a lack of data quantity, variety, and the fact that the head is also contained in the image increases significantly the classification difficulty.

Subject Dependent. In a subject dependant setting, images are separated randomly into training set (3/4) and validation set (1/4). Therefore, during the validation phase, the classifier doesn't need to deal with data from an individual that it has never seen before. In this case, for RGB images, all of the classifiers are able to have a classification accuracy that is closed to 100%. This holds true even for a perceptron. On the other hand, for depth images, the classification accuracy is between 60% and 70% using a perceptron and near 90% for other CNN architectures that were tested.

Subject Independant. On the contrary, the classifier faces individuals never seen before during validation in a subject independant setting. In my case, the training set consists of images coming from the first three individuals while the validation set contains images of the final subject. With the various architectures (including single-layer perceptron and CNNs varying from three to ten hidden layers) that I implemented, none of them is able to generalize the learned model to the new individual. The pre-trained InceptionV4 architecture achieves a prediction accuracy of 30% for color images and 20% for depth images (better than chance).

6.1.2 ASL Finger Spelling

The large number of data contained in this dataset and the relatively simple image content (single hand instead of the entire upper body) makes the classification task much easier. By using the CNN architecture shown in Figure 4, we can achieve a classification accuracy of respectively 80% and 70% for intensity and depth images (Table 1) in an subject-independant setting (four subjects for training and one subject for validation). We may not need that many layers in the CNN architecture, but further tests were not carried out since it's not the essential point of my internship.

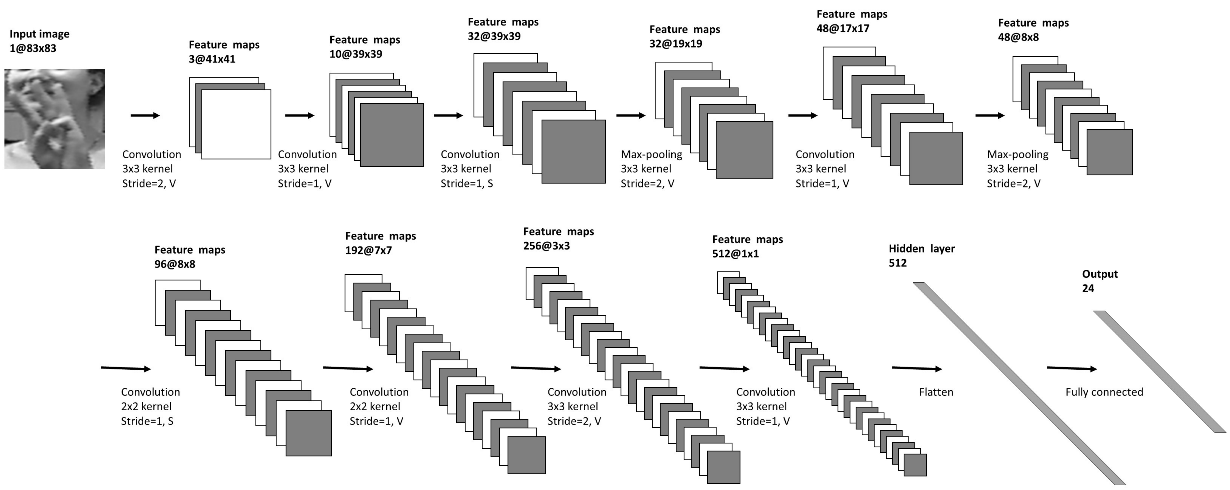

Figure 4: **CNN architecture used for the Finger Spelling dataset.**
The input of the nework is a one-channel image of size 83×83. It contains ten hidden layers. S stands for 'SAME' padding and V stands for 'VALID' padding (see text).

6.1.3 AVletters

One can refer to Figure 9 for the main CNN architectures that are used in this dataset. Notice that 3d CNNs are employed to deal with video inputs. Considering the small number of available data, a speaker-dependant setting was used, but it didn't save me from the problem of overfitting. The classification accuracy is of 100% for training data but only of 60% or 55% for validation data depending on the input modality (audio then video).

Curiously, for audio data, I get exactly the same classification performance regardless of the used architecture (perceptron or CNNs) or the fact that if deltas and delta-deltas are also given in input. This is not the case when I test with another audio dataset (not mentioned in the Datasets and Preprocessing section beacause it wasn't used for main experiences). For video input, the use of data augmentation techniques only decrease the learning speed for the training part but doesn't improve the performace for validation.

6.2 Convolutional auto-encoder

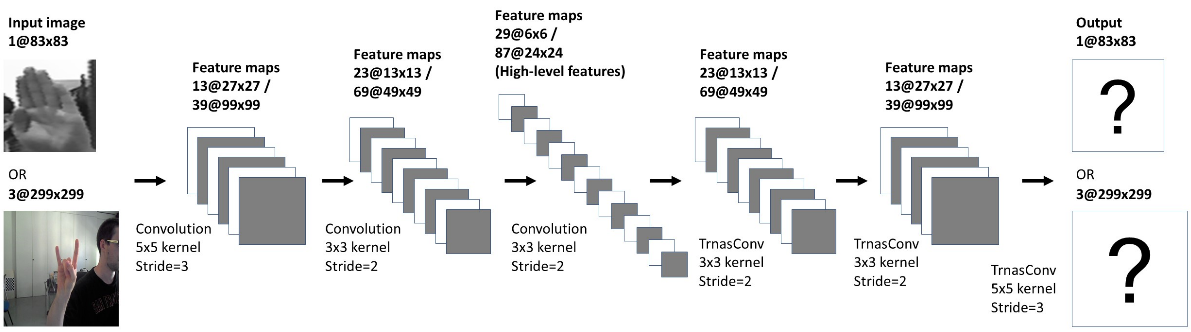

Figure 5: Convolutional auto-encoder architecture with three convolutional layers and three tranposed convolutional layer.
Activation values of the middle layer are taken as high-level features of the input image. Inputs of the network can be of different sizes. We only use valid paddings here.

Figure 6: Image restoration using convolutional auto-encoder.
Left) Clean Image.
Middle) Noisy image [input].
Right) Restored image [output].

7 Experiences and Results: Multimodal Cases

7.1 Learning shared representation

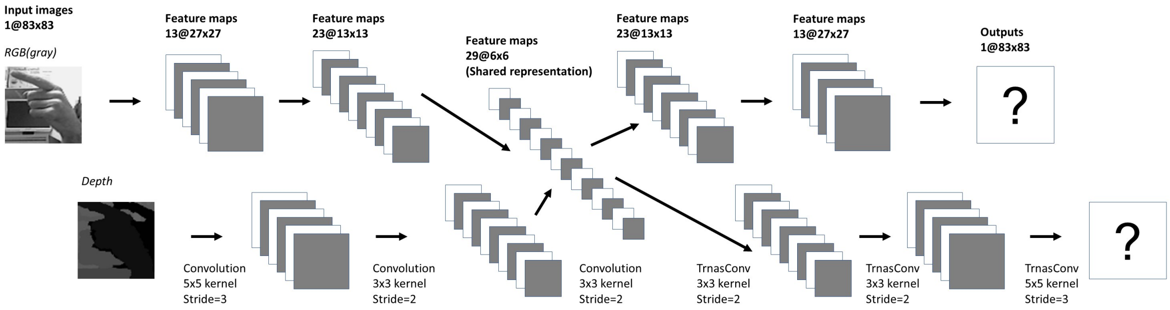

Figure 7: The bimodal convolutional auto-encoder model that is used to learn shared multimodal representation.
We simply take the CAE architecture that is introduced earlier (Figure 5) for each modaliy but force them to have a shared middle layer by adding the corresponding activation values. We then try to reconstruct the two images separately through two disjoint paths.

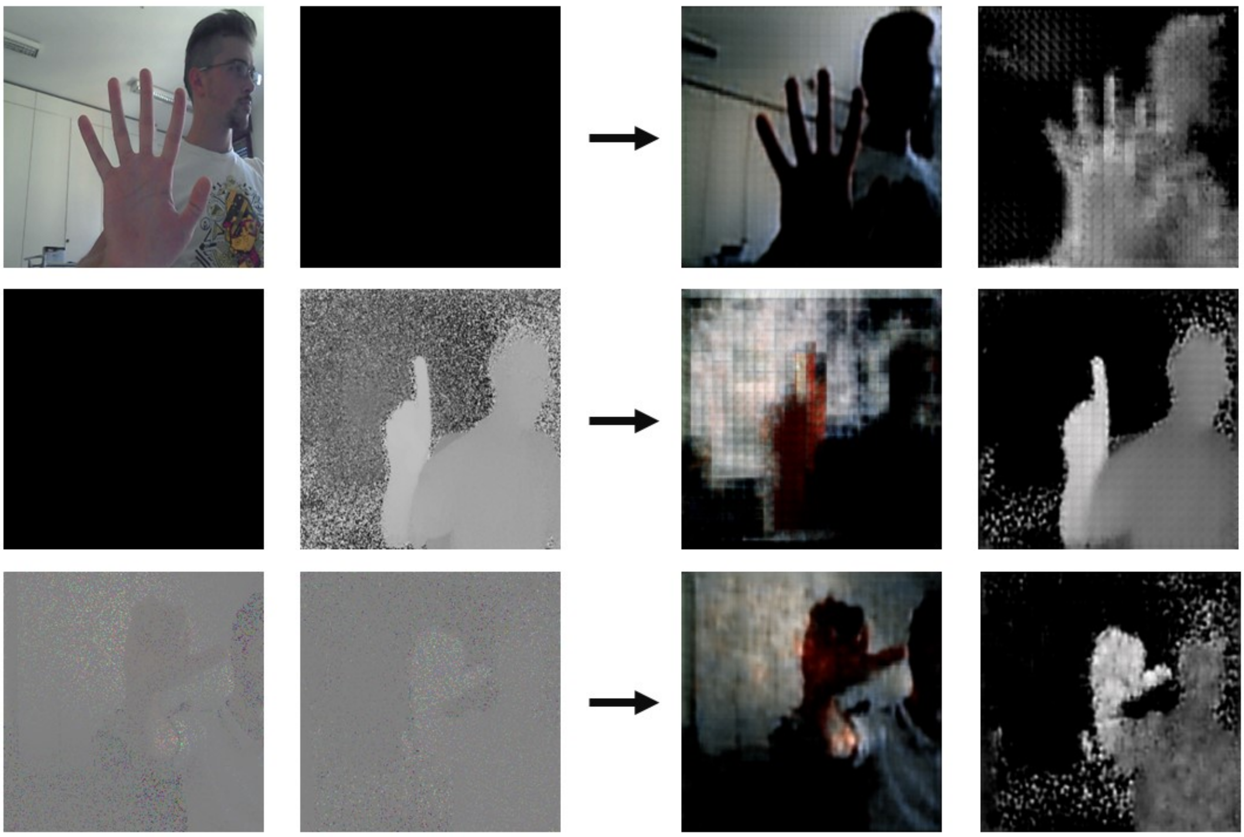

Figure 8: Restore color and depth images from incomplete input information.
Top) Only the color image is given.
Middle) Only the depth image is given.
Botttom) Both modalities are given but with little information (10% of pixels).

7.2 Transfer learning

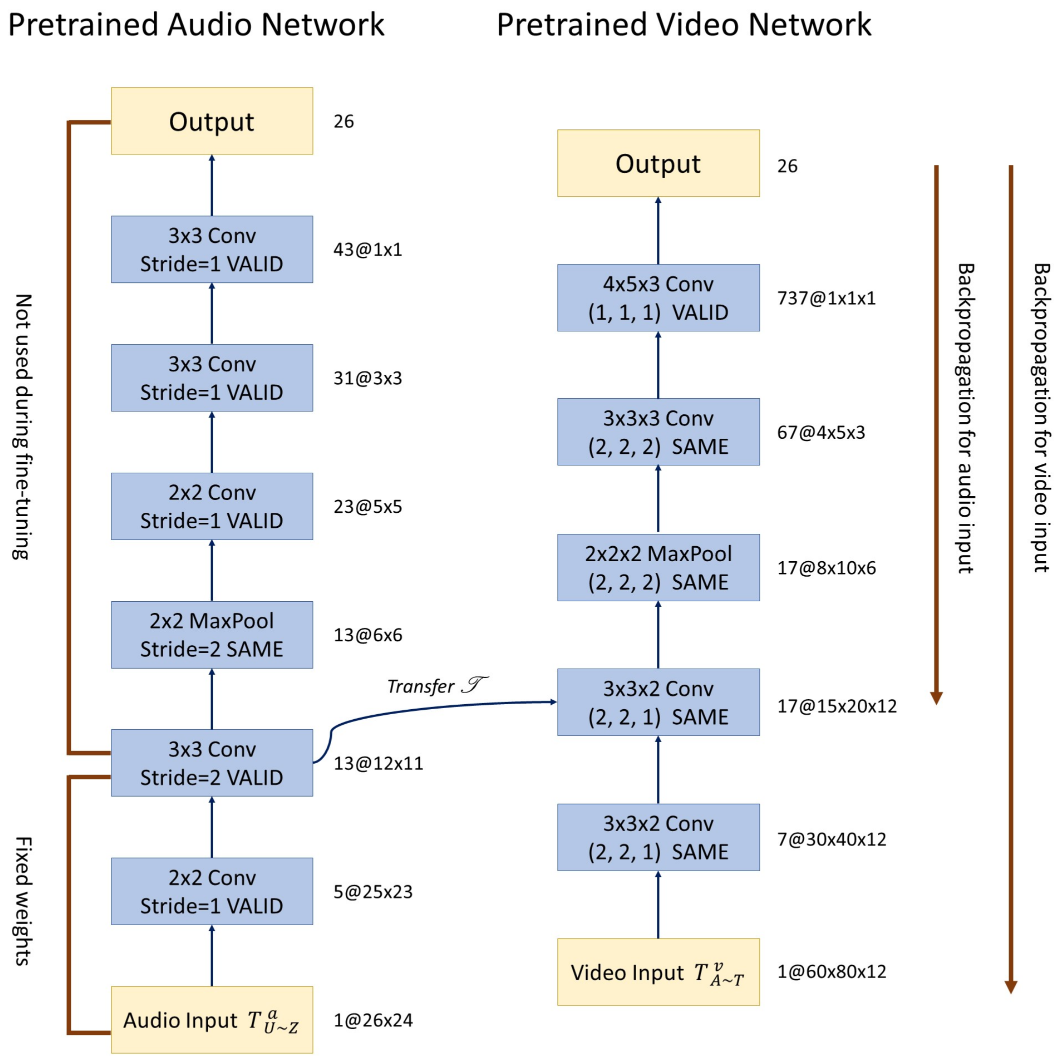

Figure 9: Illustration of the transfer learning approach applied in audio and lip-reading speech recognition tasks.
We first learn two separated model for audio and visual inputs (in my cases two CNNs) and try to fine-tune the video network with transferred audio data.

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