

# Estimating speech from lip dynamics

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## Abstract

The goal of this project is to develop a limited lip reading algorithm for a subset of the English language. We consider a scenario in which no audio information is available. The raw video is processed and the position of the lips in each frame is extracted. We then prepare the lip data for processing and classify the lips into visemes and phonemes. Hidden Markov Models are used to predict the words the speaker is saying based on the sequences of classified phonemes and visemes. The GRID audiovisual sentence corpus [10][11] database is used for our study.

## 1 Introduction and Overview

The capacity of machines to learn and understand this world grows daily. Many of their feats surpass human limits. Every day, they reveal incredible abilities that were thought impossible before. One such example is [1] where audio could be retrieved from a video by analyzing minute vibrations of objects in it ranging from a glass of water to a bag of chips. We have a much more humble goal of extracting the spoken words from the visuals in a video.

This is an attempt to use classification algorithms and Hidden Markov Models to perform visual speech recognition. Videos from the GRID Audiovisual Sentence Corpus database [10][11] are used in the project. The GRID database contains a set of 1000 videos of a single speaker. Each video is approximately 3 seconds in length, and contains a man speaking a collection of words chosen to encompass each sound possible in spoken English. The database includes transcripts of each video, with the locations of each word in the video by frame numbers.

This report details the extraction of lip contours from each video, the identification of phonemes being spoken using classification methods, and prediction of speech using Hidden Markov Models (HMM). The lip contours for each video frame are extracted using active contour masks, dynamic mode decomposition, edge detection and color classification. Then we use classification algorithms like naive Bayes and k-nearest neighbors to map the contours to phonemes/visemes. Finally we use hidden Markov models to analyze sequences of classified phonemes/visemes to predict what words they are.

## 2 Theoretical Background

### 2.1 Feature Extraction

Lip reading is a complicated task and there are no "go-to" algorithms for detecting and tracking the position of an individual's lips. We can use Matlab's built in active contour and edge detection to hope to do background/foreground separation on the video. We can also use DMD to do background/foreground separation. The assumption is the speaker's face is stationary enough that it is possible to detect the lips as the foreground. In practice, this is not the case. We can also classify the pixel colors of the video frames and segment the lips based on the idea that the speaker's lip color is different from their skin color. For color classification, we can project the pixel color into the LAB color space to achieve better classification results. In either of these different strategies we also need to isolate the general mouth region of the speaker so that we will not also detect eyes, nose, etc.

## 2.2 Phonemes and Visemes

Phonemes are the smallest identifiable sound unit in the sound system of a language.<sup>[6]</sup> According to Zhong, et al, phonemes are “basic sound segments that carry linguistic distinction.”<sup>[7]</sup> In theory, visemes are the analogous basic units in the visual domain. However, there is no agreement on a common definition for visemes in practice<sup>[8]</sup>. In audio speech recognition, phonemes are detected and used to reconstruct speech. In visual speech recognition, only visemes can be detected. Phonemes form the basis for a spoken language, and hence automated lipreading typically employs a mapping from phonemes to visemes. Many such mappings can be found in the literature, but all suffer from the issue of there being more phonemes than visemes, resulting in a many-to-one map.<sup>[8]</sup> For instance, this project uses 37 phonemes and 11 visemes. See Table (1) for the phoneme to viseme map used in this project.

Table 1: Phoneme to Viseme Map from Lee and York, 2000, via [8].

Viseme Number	Viseme Label	Associated Phonemes
1	P	b p m
2	T	d t s z th dh
3	K	g k n l y hh
4	CH	jh ch
5	F	f v
6	W	r w
7	IY	iy ih
8	EH	eh ey ae
9	AA	aa aw ay ah
10	A0	ao oy ow
11	UH	uh uw

## 2.3 Hidden Markov Models

A Markov model involves the transition of a particular state to other states based on transition probabilities. A future state is only dependent on the current state and not the states before it. Now, consider that at every state, there would be real world observations. These observations are controlled by the emission probabilities at each state.

For example, if we were to represent the ever changing weather, the states would be sunny, rainy or snowing and the observations would be summer clothes, rain boots or snow shoes. We can see that the emission probabilities for each observation is different depending on the state. To be more clear, the emission probabilities depend on the states.

We look at Hidden Markov Models (HMM). We decide that this is a relevant model because the words spoken are those defined by language and thus occur in specific patterns and not randomly. For example, given the first letter of word 'k', the probability that the next letter is a vowel is much higher than it being a consonant. A machine learning algorithm without this would be as inefficient as the initial Enigma machine in the movie "The Imitation Game". HMMs are very popular in the fields of speech [2] and gesture recognition [4] [5].

Although HMMs have fascinating problems related to evaluation and decoding, our interests are in learning. We have a sequence of observations and our aim is to estimate the transition and observation matrices that created that. The Baum-Welch algorithm [3] gives us that and we train a transition and observation matrix for each word by using sequences corresponding to different instances of that word. In our weather example, we could take the sequences of weather in a few cities and train an HMM to find which city produces a test sequence of weather. A month of sunshine is unlikely to be Seattle but California would be a better guess.

So, given the features from the videos, we find the states. The states are the units of words, here chosen to be phonemes.

## 3 Implementation and Development

### 3.1 Feature extraction

#### 3.1.1 Obtaining the initial mask

The first step is to determine the general location of the mouth in each frame. Matlab has a built in facial recognition package “Cascade Vision Detector” which uses the Viola-Jones algorithm to detect the facial features of people. We use the Cascade Mouth detector to determine the location of the face in each frame of each movie. This algorithm is not perfect however and we often detect the eyes or chin of the subject in question. We filter out these false detections by looking at the position of the mouth. The speaker is in generally the same location in each movie so we know if a detected mouth position is too low or too high we can throw that region out. We refer to this detected mouth region as the *initial mask*. We need a good initial mask in order to properly filter our results. Without knowing the general mouth region our algorithms will act on the whole face, but we consider only the lips for our project. Therefore, really our objective is to separate the lips from the mouth region.

#### 3.1.2 Active contour

Next we convert the image to grayscale. On the grayscale image we can apply Matlab’s built in active contour and edge detection, as well as the DMD algorithm we develop in homework 4. We can experiment with the different segmentation types for Matlab’s active contour and edge detection. For active contour, Chan-Vese gives poor results with irregular edges. Edge method for active contour gives smoother regions but irregular shapes. Active contour takes many iterations to properly converge and gives poor results. From the figures of active contour, we see the inconsistent lip region detected. Because we are trying to determine the changes in lip shape over time, active contour is not suitable because the results it produces vary too much. Additionally, because it is extremely slow, active contour is not ideal for our purposes. We need to process a large number of videos so a fast algorithm is preferable. If active contour was more computationally efficient it might be possible to use a large number of iterations for each frame in order to obtain a consistent result.

#### 3.1.3 Canny edge detection

Matlab’s built in edge detection has many different methods which produce different results. We consider using Canny, Prewitt and Sobel edge detection. Canny typically finds the “strong” edges whereas Sobel and Prewitt tend to pick out more detail in the image. We are really only interested in the lips, and ideally want only 1 contour, so we decide to use Canny edge detection. We want to detect the outside and inside edge of the lips, but all methods typically detect the inside edge of the lip. When using Matlab’s “edge”, it is important to consider the threshold. Too low a threshold value will produce other features of the face and possibly noise. Too high a threshold and we will not pick out the entire lip. Therefore we decide to start at a high threshold value, and if we do not find a large enough edge, we lower the threshold and do the detection again. Typically we only need to lower the threshold once or twice. We set a minimum number of detected pixels in the edge to decide whether or not to automatically lower the threshold. Although this may seem expensive, in practice we only need to lower the threshold for certain frames, and so most of the time we only need to do the algorithm once. Additionally, edge is much faster than active contour, so this method is still much faster than active contour, and gives more consistent results in well. Overall the Canny edge detection finds a good edge for the lips but it oftentimes only picks out part of the mouth or sometimes picks out other features around the mouth as well, like the chin or space between the nose and mouth.

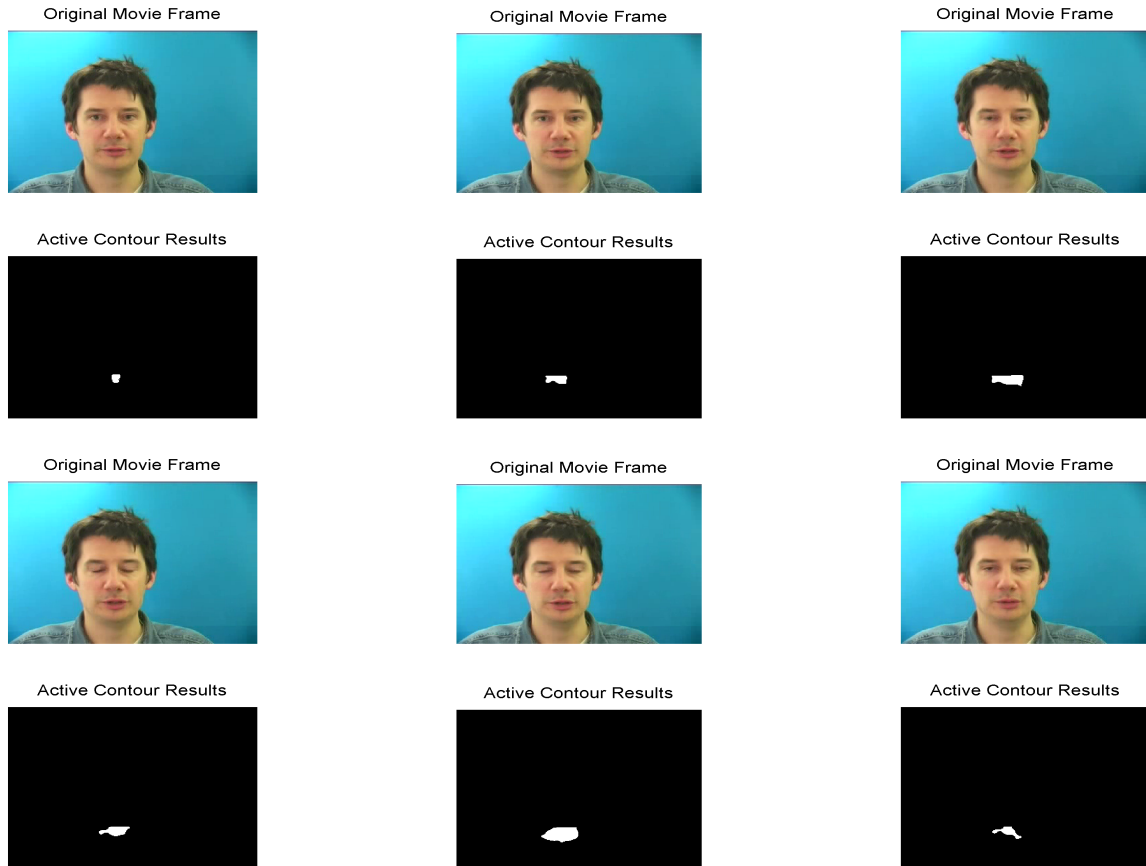


Figure 1: Active Contour Results for selected frames. Active contour provides an inconsistent lip profile because it never properly converges.

### 3.1.4 Dynamic mode decomposition

Next we use the DMD algorithm we developed in homework 4 to try foreground/background separation. We find that the face moves too much, and there is too much variation in the speaker's skin around the mouth to properly use DMD. We detect many points that are not on the lip. While DMD is good at separating the man's face from the background, it cannot accurately separate the lips from mouth region. It might be possible to alter the brightness and contrast of the separated image using DMD to obtain a better result, but it would still be too inconsistent to obtain good results for the rest of the project.

### 3.1.5 Color classification

Thus far, all of the methods discussed have acted on grayscale frames of the color movie. We now consider a technique for acting on the color frames. If we assume that the lips of the speaker have a distinct color from the rest of the speaker's mouth region (i.e. the skin, teeth, inside of the mouth) then we can determine the lip region by classifying the colors of the mouth region. It is possible to do this using the RGB values of each pixel. We instead represent each pixel with it's LAB color space values. The point of LAB colors is that they match how human vision perceives colors. The L stands for lighting and AB are values corresponding to color. By classifying each pixel into one of up to 4 clusters based on it's AB values with a k-means algorithm, we can separate the lips from the rest of the mouth region. The number of clusters created varies per frame because in some frames, the teeth and inner



Figure 2: Canny Edge Detection results for selected frames. Although it captures the profile of the lips, it does not always capture the entire contour. It also does not show the inside of the lips.

mouth can be grouped in their own clusters. Other frames, the speaker has their mouth closed so only 2 clusters are needed. We can differentiate between the clusters by looking at the calculated centroid positions of each cluster. It is determined experimentally that the lip region has the highest A color value, and it usually has the lowest B color value as well. Color classification is fairly fast and accurate. It gives the thickness as well as the shape of the lips. It's only downside is that it often classifies the left and right sides of the lips into a different cluster. Color classification typically picks out an ellipse in the middle of the lips as opposed to the whole lip region. Overall, color classification is determined to give the most accurate results, and edge detection is a close second. In hindsight, it would have made much more sense to use a classification algorithm, like knn-search, instead of k-means. Although we choose the wrong algorithm to use our results are still acceptable.

In general the best results come from either more computationally expensive or mathematically sophisticated techniques. For example, training a neural net to classify the lip region of each frame would probably be the most effective technique overall, but would be very computationally costly and require manually determining the lip region for training. Many papers in the literature consider fitting a vector to fit the lip region and then track the lips by moving points of the vector and measuring the change of shape. They then can compute the most likely shape by comparing it to known positions of the lip. This method relies more heavily on analysis but also requires manual training as well. In general, lip tracking is a classification problem where the goal is to classify the pixels that belong to the lip of the speaker.

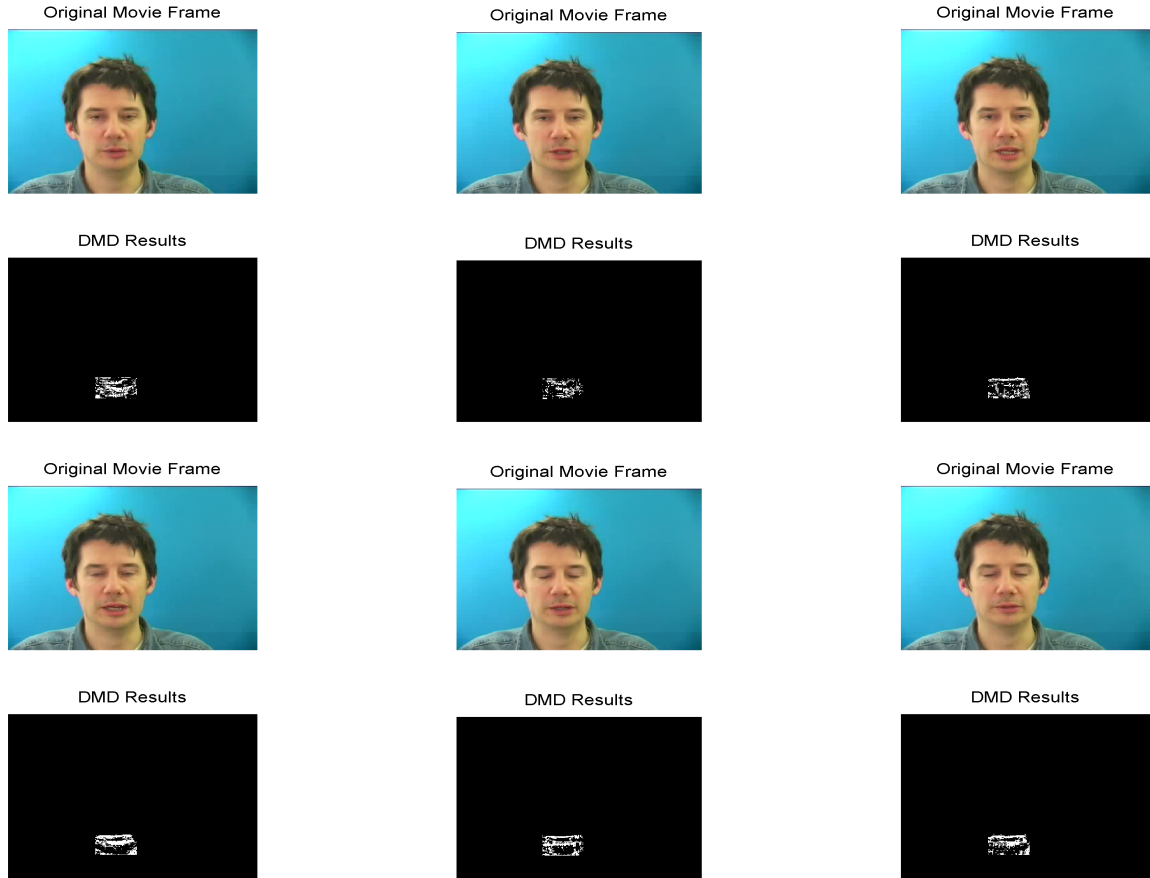


Figure 3: DMD results for selected frames. DMD is not ideal in this situation because the background (the man's face) is not completely stationary.

### 3.2 Extracting Phonemes

Using the nltk library in Python, we convert every word to its constitutive arpabet phonetics. It gives the following output for the words - f', 'see', 'sea', 'compute', 'comput', 'cat'. Only 'comput' fails because it isn't a real word

```
['EH1', 'F']
['S', 'IY1']
['S', 'IY1']
['K', 'AH0', 'M', 'P', 'Y', 'UW1', 'T']
'comput'
['K', 'AE1', 'T']
```

From the words spoken in our videos, we get a set of 36 unique phonemes. The code for this is shown in using B.1. From the transcripts, we extract all the data into a csv file using B.2

### 3.3 Extracting Subtitles and Assigning Phonemes

The Corpus Grid II database contains a *.txt* file for each video containing the words spoken and corresponding frames for each word. These were downloaded and extracted into Matlab using the *textscan* function in Matlab. The words were deconstructed into their phonemes, and phonemes were assigned

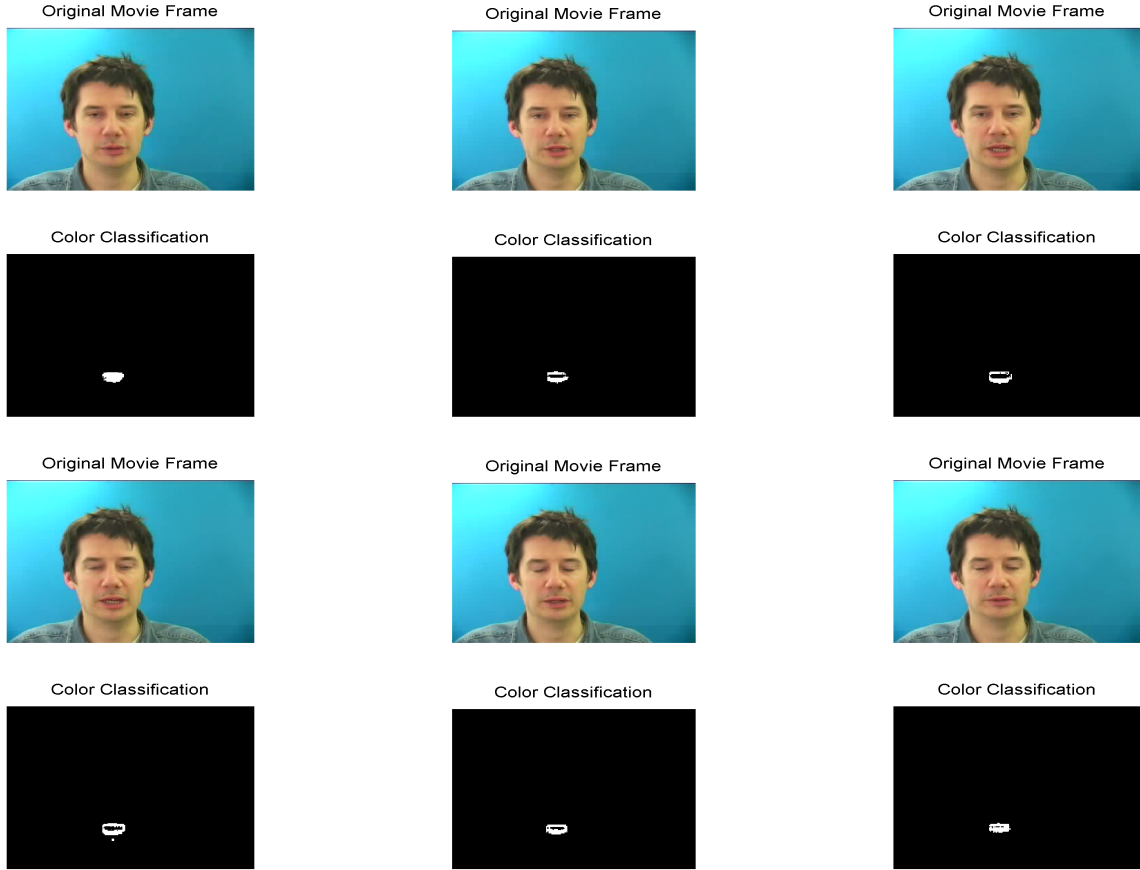


Figure 4: Color Classification for selected frames. Arguably the best overall method for capturing the movement of the lips.

to each frame to create the training set. The assignment of a phoneme label to each frame was done by assigning each phoneme from a word to an equivalent number of the video frames corresponding to the phonemes in each word.

### 3.4 Phoneme and Viseme Classification

The data matrix was created by reshaping each frame in each video in to a single column. When each column was reshaped, its saved phoneme was checked, and the corresponding viseme index was saved to create the labels for a classification algorithm. The columns for each video frame were then concatenated in order to form the data matrix. The singular value decomposition was computed of the matrix of video frames. Classification was performed on first 30 columns of the  $V$  matrix using both a Naive Bayes and a k-nearest neighbors algorithm. Classification was done with a random 75% of the data used for training and the remaining 25% of the data for cross validation.

### 3.5 Word Classification using HMMs

Once a phoneme classifier has been created, we apply it onto the whole dataset of 1000 videos to obtain 1000 phoneme sequences of length 74. If we use phonemes, we will get sequences of numbers which are between 1 and 37. If we use visemes, we get sequences with numbers between 1 and 11.

Our objective is to map sequence of phonemes/visemes to words. This is where we utilize the

capability of Hidden Markov Models to incorporate the temporal dynamics of the phoneme changes and thus "remember". So, even if our phoneme classification is erroneous, the patterns generated by the classifier can be mapped onto words resulting in higher accuracy.

We have the 1000 sequences. From the video dataset, A.7 extracts sequences corresponding to each word (using regular expressions). This leaves us with a list of sequences for each word. For each word, the list is divided up into training and test sets. We train an HMM for each word. This means that each word has a unique transition matrix and observation matrix associated with it. All the training is done in A.5. The functions used for training the HMM are from Kevin Murphy's HMM toolbox [9].

Then, when we have an unknown sequence, we run it through the HMMs of all the words and find the "loglikelihood" that it might be that word. When we find the HMM for which it has the highest "loglikelihood", it means that the sequence is most likely to be the word associated with that HMM. The results are estimated using A.6.

## 4 Computational Results

### 4.1 Phoneme and Viseme Classification

For phoneme identification, the classification using a k-nearest neighbors algorithm only 11.6103% accuracy on average on the cross validation over 176 trials. For viseme identification, the k-nearest neighbors method had 19.7355% accuracy over 30 trials. More trials were not performed due to the Matlab *knnsearch* function being computationally intensive.

The naive bayes classification algorithm applied to identification of phonemes had an average accuracy of 3.49% over 1000 trials. For viseme classification, the naive bayes algorithm had an average accuracy of 9.1357% over 1000 trials.

### 4.2 Word Classification using HMMs

The identification of the right word definitely depends on the words it is compared against. For this purpose, the results are presented in 2 and 3 show the word to be detected, the other words and its accuracy.

Using the phoneme classification, the results seem to be good in general. Although the accuracy does go down with more words, it is still very good and definitely better than random guessing in most cases.

We notice that the best identified words by the viseme classification might not be the same as those by the phoneme classification. The word "bin" is an example which is easily identified by the phoneme classification but not so well when the states are visemes. In contrast, the word "blue" is better identified now. On exploring the viseme assignment, the viseme 11 was quite over-assigned which might have played a role. The results are still very good for the viseme classification.

Although there were a few more words and many more permutations to try out, we restricted ourselves to these selected ones under the time constraints.



Table 2: Classifying words after classifying frames into phonemes

Word Classification using 37 phonemes		
Word	Set	Accuracy
bin	bin , blue	87.5 %
blue	bin, blue	36 %
blue	red, blue	76 %
four	four, white	60 %
bin	bin , white	62.5 %
five	blue , five	60 %
red	red , eight	72 %
bin	bin , blue, green	75 %
green	green, white, five	44 %
five	five, blue, four, white	50 %
green	green, white, five, red	28 %
bin	bin , blue, green , red	75 %
bin	bin , blue, red, white	56.2 %
blue	bin , blue, red, white	28 %
five	four , five, red, white	45 %
bin	bin , blue, green , red, eight	75 %
bin	bin , blue, green , red, white	50 %
four	four , five, green , red, white	30 %
five	four , five, green , red, white	40 %

Table 3: Classifying words after classifying frames into visemes

Word Classification using 11 Visemes		
Word	Set	Accuracy
bin	bin , blue	50 %
blue	bin, blue	68 %
blue	red, blue	92 %
four	four, white	75 %
bin	bin , white	68.8 %
five	blue , five	65 %
red	red , eight	65 %
bin	bin , blue, green	25 %
four	bin , four, green	35 %
red	red , white, green	35 %
green	green, white, five	32 %
green	green, white, blue	36 %
five	five, blue, four, white	50 %
green	green, white, five, red	32 %
bin	bin , blue, green , red	12.5 %
bin	bin , blue, red, white	12.5%
blue	bin , blue, red, white	68 %
five	four , five, red, white	50 %
bin	bin , blue, green , red, eight	12.5 %
bin	bin , blue, green , red, white	12.5 %
four	four , five, green , red, white	30 %
five	four , five, green , red, white	25 %

## 5 Summary and Conclusions

Finding bottlenecks during our attempt enables others to devise ways to evade them next time. There are a number of things we could improve upon.

- The best way to improve the results in this project is to improve the lip detection. The videos used in this project were of low quality, making the accurate detection of lip contours difficult. The database used has higher quality versions of the videos. However high quality videos are  $\approx 2.4$  GB each, for a total of 2.4 Terabytes of data for the whole data set. This is an unrealistic amount of data for the hardware available for this project.
- Another short coming of this project is the assignment of an equal number of video frames to each phoneme from the given frame locations of each word. This is a poor way to determine which phoneme is being spoken in each video frame. If we had a dataset in which we had frames corresponding to each phoneme, the accuracy would easily increase.
- In the phoneme classification, we used only naive bayes and k-nearest neighbours. Even though, knn gave us high accuracy, it was computationally expensive and we did not have sufficient time to classify the whole dataset. Results could have further been improved with a more sophisticated classification algorithm, for instance a classification tree or neural network.
- Apart from Hidden Markov Models, Recurrent Neural Networks are widely popular for activities that involve sequential events and memory. TensorFlow has a great RNN package in Python which is worth exploring.
- Kevin Murphy's HMM toolbox is widely popular as the best HMM toolbox in Matlab. However, it cannot handle sequences of different length during training. We worked around this problem by using stop states and chopping the sequence off. But that is far from a perfect fix. Searching for better toolboxes or making our own scripts to do the E-M step of the algorithm is a better idea.
- We used 37 phonemes in our classification. That is a tall order for any classifier. By using 11 visemes, we tried to cut this down. This can be better improved choosing the sets to group together. Unsupervised learning could be a good option to experiment on to find good clusters.
- HMMs are trained using an initial guess of the transition and observation matrices. If we could figure out a way to get a good initial guess especially in the context of phonemes/visemes in speech, there would be a huge improvement.
- Lastly, 1000 videos would correspond to around 200 instances for the average word. This is not a particularly large sample size. So, using more videos will lead to better results.

Given an unknown video sequence where only the words in our dictionary are spoken, we have a technique to identify the words spoken to a good level of accuracy. We also have a good exposure to top tier methods for image processing, classification and hidden markov models as well as their limitations. The project was also a good example of collaborative research and use modern day tools like Git for version control and to speed up progress. All the code, the report and some very useful .mat files can be found on our GitHub repository [12].

## References

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- [10] <http://spandh.dcs.shef.ac.uk/gridcorpus/>
- [11] <http://www.ee.surrey.ac.uk/Projects/LiLiR/datasets.html>
- [12] [https://github.com/Dirivian/dynamic\\_lips](https://github.com/Dirivian/dynamic_lips)

## A MATLAB Code

### A.1 Contours.m

```
1 obj=VideoReader('vid1.mpg');
2 vidFrames = read(obj);
3 numFrames = get(obj,'numberOfFrames');
4 [mov]= getmovout(vidFrames,numFrames-1);
5 X=frame2im(mov(50));
6 A=rgb2gray(X);
7 mask = zeros(size(A));
8 mask(400:450,320:400) = 1;
9 bw = activecontour(A,mask,300);
10 figure, imshow(bw), title('Active Contour mask');
11 [~, threshold] = edge(A, 'sobel');
12 fudgeFactor = .5;
13 BWs = edge(A,'sobel', threshold * fudgeFactor);
14 figure, imshow(BWs), title('binary gradient mask');
```

### A.2 Assign Labels

```
1 function [ labels ] = assignlabels2(cropvid,frameLocs,words)
2 %UNTITLED10 Summary of this function goes here
3 % Detailed explanation goes here
4 %Inputs:
5 %cropped videos (struct)
6 %frameLocs
7 % words
8 %
9 %
10 % Outputs:
11 % labels: cell array of cells containing the phoneme at each frame
12 %
13 %Begin Function
14
15 numVids = length(cropvid);
16
17 labels = cell(numVids,1);
18
19 for k = numVids:-1:1
20     v = cropvid{k};
21     fL = floor(frameLocs{k}/1000);
22     lab = cell(size(v,3),1);
23     for j = 1:length(fL)-1
24         %Break this word into phonemes
25         ph = assignphoneme(words{k}(j));
26         %Get number of phonemes in this word
27         numPh = length(ph);
28         %get frame indices for this word to be distributed accross
29         x1 = fL(j);
30         x2 = fL(j+1);
31         %number of frames per phoneme
32         nf = round((x2-x1)/numPh);
33         xprev = x1;
34         if xprev == 0
35             xprev = 1; %make sure 0 index isnt called
36         end
37         for i = 1:numPh-1
38             xnext = xprev + nf; %overwrite next
39             for ii = xprev:xnext-1
40                 lab{ii} = ph{i};
41             end
42             xprev = xnext; %overwrite prev
```

```

43         end
44         for ii = xprev:size(v,3)
45             lab{ii} = ph{end};
46         end
47     end
48     labels{k} = lab; %store in output
49     clear lab %clear temp variable
50 end
51 end

```

### A.3 SVD and Classify

```

1
2 % Required functions:
3
4 % lipcrop
5 % assignlabels
6 % assignphoneme
7
8 %Required variables to already be in workspace:
9 %
10 % frameLocs
11 % words
12 %Begin Script:
13
14 clearvars -except lipread frameLocs words
15 %% Crop, Assign Labels, create individual data matrices
16
17 %Crop videos based on contour mask
18 cropVid = lipcrop(lipread);
19
20 %Assign labels to each frame
21 labels = assignlabels2(cropVid, frameLocs, words);
22
23 %Sort and create data arrays
24 [X, tags, vinds] = hmmdata(cropVid, labels);
25 numPix = size(X,1);
26 numVids = size(X,2);
27
28 %% SVD
29
30 [U,S,V] = svd(X, 'econ');
31
32 %% Create Classification Matrices
33
34 for k = 1:1000
35     q = randperm(numVids);
36     qind = round(numVids*0.75);
37     q1 = q(1:qind);
38     q2 = q(qind+1:end);
39
40     trainData = V(q1,1:30);
41     testData = V(q2,1:30);
42     trainTags = tags(q1)';
43     testTags = tags(q2)';
44
45     hmmNBdata = V(:,1:30);
46
47     nb = NaiveBayes.fit(trainData, trainTags);
48     pre = nb.predict(testData);
49
50     acc(k) = 100*sum(pre==testTags)/length(pre);
51 end
52

```

```

53 %compute accuracy
54
55 %disp(['Accuracy was ' num2str(acc) '%'])
56
57 knnind = knnsearch(trainData, testData);
58 acc2 = 100*sum(knnind==testTags)/length(knnind);
59 % disp(['Accuracy was ' num2str(acc2) '%'])

```

## A.4 Creation of Data Matrix and Classification Labels

```

1 function [X, tags, vinds] = hmmdata(cropVid, labels)
2 %UNTITLED Summary of this function goes here
3 % Detailed explanation goes here
4
5 kmax = size(cropVid{1}(:, :, :), 3);
6 numPix = size(cropVid{1}(:, :, :), 1)*size(cropVid{1}(:, :, :), 2);
7 numVids = kmax*length(cropVid);
8
9 %Initialize Data Matrix
10 counter = 1;
11 vinds = cell(length(cropVid), 1);
12 X = zeros(numPix, 36749);
13 for j = length(cropVid):-1:1
14     thisLab = labels{j};
15     thisVid = cropVid{j}(:, :, :);
16     numv = 1;
17     for k = 1:size(thisVid, 3)
18         %Get DM index of this phoneme
19         phonemeInd = checkviseme(thisLab(k));
20
21         %If SIL, store in SIL array
22         if phonemeInd <= 0
23             continue
24         end
25         %this phoneme is a regular phoneme:
26
27         %Increment to store in right place
28
29         %Get Frame to store
30         thisFrame = thisVid(:, :, k);
31
32         %Reshape frame
33         xframe = reshape(thisFrame, numPix, 1);
34
35         %Store frame in corresponding DM
36         X(:, counter) = xframe;
37         tags(counter) = phonemeInd;
38         vinds{j}(numv) = counter;
39         counter = counter + 1;
40         numv = numv + 1;
41     end
42 end
43 end

```

## A.5 makethehmm2.m

```

1 O = 36;
2 Q = 37;
3
4 prior1 = normalise(rand(Q, 1));
5 transmat1 = mk_stochastic(rand(Q, Q));
6 obsmat1 = mk_stochastic(rand(Q, O));

```

```

7 binmat = binmatrix(1:200,1:7);
8 binmat(binmat==0)=4;
9 [LL, priorbin, transmatbin, obsmatbin] = dhmm_em(binmat, prior1, transmat1, obsmat1, '
    max_iter', 500);
10 bluemat = bluematrix(1:200,1:7);
11 bluemat(bluemat==0)=4;
12 [LL, priorblue, transmatblue, obsmatblue] = dhmm_em(bluemat, prior1, transmat1, obsmat1
    , 'max_iter', 500);
13 whitemat = whitematrix(1:200,1:6);
14 whitemat(whitemat==0)=4;
15 [LL, priorwhite, transmatwhite, obsmatwhite] = dhmm_em(whitemat, prior1, transmat1,
    obsmat1, 'max_iter', 500);
16 greenmat = greenmatrix(1:200,1:6);
17 greenmat(greenmat==0)=4;
18 [LL, priorgreen, transmatgreen, obsmatgreen] = dhmm_em(greenmat, prior1, transmat1,
    obsmat1, 'max_iter', 500);
19 redmat = redmatrix(1:200,1:6);
20 redmat(redmat==0)=4;
21 [LL, priorred, transmatred, obsmatred] = dhmm_em(redmat, prior1, transmat1, obsmat1, '
    max_iter', 500);
22 eightmat = eightmatrix(1:80,1:6);
23 eightmat(eightmat==0)=4;
24 [LL, prioreight, transmateight, obsmateight] = dhmm_em(eightmat, prior1, transmat1,
    obsmat1, 'max_iter', 500);
25 fourmat = fourmatrix(1:80,1:7);
26 fourmat(fourmat==0)=4;
27 [LL, priorfour, transmatfour, obsmatfour] = dhmm_em(fourmat, prior1, transmat1, obsmat1
    , 'max_iter', 500);
28 fivemat = fivematrix(1:80,1:8);
29 fivemat(fivemat==0)=4;
30 [LL, priorfive, transmatfive, obsmatfive] = dhmm_em(fivemat, prior1, transmat1, obsmat1
    , 'max_iter', 500);
31
32 setmat = setmatrix(1:200,1:8);
33 setmat(setmat==0)=4;
34 [LL, priorset, transmatset, obsmatset] = dhmm_em(setmat, prior1, transmat1, obsmat1, '
    max_iter', 500);
35
36 laymat = laymatrix(1:200,1:11);
37 laymat(laymat==0)=4;
38 [LL, priorlay, transmatlay, obsmatlay] = dhmm_em(laymat, prior1, transmat1, obsmat1, '
    max_iter', 500);
39
40 placemat = placematrix(1:200,1:7);
41 placemat(placemat==0)=4;
42 [LL, priorplace, transmatplace, obsmatplace] = dhmm_em(placemat, prior1, transmat1,
    obsmat1, 'max_iter', 500);

```

## A.6 resultshmm.m

```

1 clear resultg31 resultg32 resultg4 resultbl21 resultbl22 resultbl4 resultr3 resultr2
    resultb21 resultb22 resultb3 resultb41 resultb42 resultb51 resultb52 resultfour2
    resultfour3 resultfour5 resultfive2 resultfive41 resultfive42 resultfive5;
2 resg31 =0;
3 resg32 =0;
4 resg4 =0;
5 resbl21 =0;
6 resbl22 =0;
7 resbl4 =0;
8 resr3 =0;
9 resr2 =0;
10 resb21 =0;
11 resb22=0;
12 resb3 =0;

```

```

13 resb41 =0;
14 resb42 =0;
15 resb51 =0;
16 resb52 =0;
17 resfour2 =0;
18 resfour3 =0;
19 resfour5 =0;
20 resfive2 =0;
21 resfive41 =0;
22 resfive42 =0;
23 resfive5 =0;
24 dimend =225;
25 for i = 201:225
26
27 k = greenmatrix(i,1:6);
28 k(k==0)=4;
29 loglikbin = dhmm.logprob(k, priorbin, transmatbin, obsmatbin);
30 loglikblue = dhmm.logprob(k, priorblue, transmatblue, obsmatblue);
31 loglikgreen = dhmm.logprob(k, priorgreen, transmatgreen, obsmatgreen);
32 loglikred = dhmm.logprob(k, priorred, transmatred, obsmatred);
33 loglikwhite = dhmm.logprob(k, priorwhite, transmatwhite, obsmatwhite);
34 loglikeight = dhmm.logprob(k, prioreight, transmateight, obsmateight);
35 loglikfour = dhmm.logprob(k, priorfour, transmatfour, obsmatfour);
36 loglikfive = dhmm.logprob(k, priorfive, transmatfive, obsmatfive);
37 lllkg31 = [ loglikwhite ; loglikgreen; loglikfive ];
38 lllkg32 = [ loglikwhite ; loglikgreen; loglikblue ];
39 lllkg4 = [ loglikwhite ; loglikgreen; loglikfive ; loglikred ];
40 if loglikgreen ==max(lllkg31)
41 resultg31(i-200)=1;
42 resg31 = resg31+1;
43 else
44 resultg31(i-200)=0;
45 end
46 if loglikgreen ==max(lllkg32)
47 resultg32(i-200)=1;
48 resg32 = resg32+1;
49 else
50 resultg32(i-200)=0;
51 end
52 if loglikgreen ==max(lllkg4)
53 resultg4(i-200)=1;
54 resg4 = resg4+1;
55 else
56 resultg4(i-200)=0;
57 end
58
59 k = bluematix(i,1:7);
60 k(k==0)=4;
61 loglikbin = dhmm.logprob(k, priorbin, transmatbin, obsmatbin);
62 loglikblue = dhmm.logprob(k, priorblue, transmatblue, obsmatblue);
63 loglikgreen = dhmm.logprob(k, priorgreen, transmatgreen, obsmatgreen);
64 loglikred = dhmm.logprob(k, priorred, transmatred, obsmatred);
65 loglikwhite = dhmm.logprob(k, priorwhite, transmatwhite, obsmatwhite);
66 loglikeight = dhmm.logprob(k, prioreight, transmateight, obsmateight);
67 loglikfour = dhmm.logprob(k, priorfour, transmatfour, obsmatfour);
68 loglikfive = dhmm.logprob(k, priorfive, transmatfive, obsmatfive);
69 lllkbl21 = [ loglikbin ; loglikblue; ];
70 lllkbl22 = [ loglikred ; loglikblue; ];
71 lllkbl4 = [ loglikwhite ; loglikred;loglikbin ; loglikblue; ];
72
73 if loglikblue ==max(lllkbl21)
74 resultbl21(i-200)=1;
75 resbl21 = resbl21+1;
76 else
77 resultbl21(i-200)=0;
78 end

```



```

79 if loglikblue ==max(l1lkb122)
80 resultb122(i-200)=1;
81 resb122 = resb122+1;
82 else
83 resultb122(i-200)=0;
84 end
85 if loglikblue ==max(l1lkb14)
86 resultb14(i-200)=1;
87 resb14 = resb14+1;
88 else
89 resultb14(i-200)=0;
90 end
91
92 k = redmatrix(i,1:6);
93 k(k==0)=4;
94 loglikbin = dhmm.logprob(k, priorbin, transmatbin, obsmatbin);
95 loglikblue = dhmm.logprob(k, priorblue, transmatblue, obsmatblue);
96 loglikgreen = dhmm.logprob(k, priorgreen, transmatgreen, obsmatgreen);
97 loglikred = dhmm.logprob(k, priorred, transmatred, obsmatred);
98 loglikwhite = dhmm.logprob(k, priorwhite, transmatwhite, obsmatwhite);
99 loglikeight = dhmm.logprob(k, prioreight, transmateight, obsmateight);
100 loglikfour = dhmm.logprob(k, priorfour, transmatfour, obsmatfour);
101 loglikfive = dhmm.logprob(k, priorfive, transmatfive, obsmatfive);
102 l1lkr2 = [ loglikred ; loglikeight ];
103 l1lkr3 = [ loglikwhite ; loglikgreen ; loglikred ];
104 if loglikred==max(l1lkr2)
105 resultr2(i-200)=1;
106 resr2 = resr2+1;
107 else
108 resultr2(i-200)=0;
109 end
110 if loglikred==max(l1lkr3)
111 resultr3(i-200)=1;
112 resr3 = resr3+1;
113 else
114 resultr3(i-200)=0;
115 end
116 end
117
118 for i = 201:216
119
120 k = binmatrix(i,1:6);
121 k(k==0)=4;
122 loglikbin = dhmm.logprob(k, priorbin, transmatbin, obsmatbin);
123 loglikblue = dhmm.logprob(k, priorblue, transmatblue, obsmatblue);
124 loglikgreen = dhmm.logprob(k, priorgreen, transmatgreen, obsmatgreen);
125 loglikred = dhmm.logprob(k, priorred, transmatred, obsmatred);
126 loglikwhite = dhmm.logprob(k, priorwhite, transmatwhite, obsmatwhite);
127 loglikeight = dhmm.logprob(k, prioreight, transmateight, obsmateight);
128 loglikfour = dhmm.logprob(k, priorfour, transmatfour, obsmatfour);
129 loglikfive = dhmm.logprob(k, priorfive, transmatfive, obsmatfive);
130 l1lkb21 = [ loglikbin ; loglikblue; ];
131 l1lkb22 = [ loglikbin ; loglikwhite; ];
132 l1lkb3 = [ loglikbin ; loglikblue; loglikgreen; ];
133 l1lkb41 = [ loglikbin ; loglikgreen; loglikblue ; loglikred ];
134 l1lkb42 = [ loglikbin ; loglikwhite; loglikblue ; loglikred ];
135 l1lkb51 = [ loglikbin ; loglikgreen; loglikblue ; loglikred ; loglikeight ];
136 l1lkb52 = [ loglikbin ; loglikgreen; loglikblue ; loglikred ; loglikeight ];
137 if loglikbin ==max(l1lkb21)
138 resultb21(i-200)=1;
139 resb21 = resb21+1;
140 else
141 resultb21(i-200)=0;
142 end
143 if loglikbin ==max(l1lkb22)
144 resultb22(i-200)=1;

```

```

145 resb22 = resb22+1;
146 else
147 resultb22(i-200)=0;
148 end
149 if loglikbin ==max(lllkb3)
150 resultb3(i-200)=1;
151 resb3 = resb3+1;
152 else
153 resultb3(i-200)=0;
154 end
155 if loglikbin ==max(lllkb41)
156 resultb41(i-200)=1;
157 resb41 = resb41+1;
158 else
159 resultb41(i-200)=0;
160 end
161 if loglikbin ==max(lllkb42)
162 resultb42(i-200)=1;
163 resb42 = resb42+1;
164 else
165 resultb42(i-200)=0;
166 end
167 if loglikbin ==max(lllkb51)
168 resultb51(i-200)=1;
169 resb51 = resb51+1;
170 else
171 resultb51(i-200)=0;
172 end
173 if loglikbin ==max(lllkb52)
174 resultb52(i-200)=1;
175 resb52 = resb52+1;
176 else
177 resultb52(i-200)=0;
178 end
179 end
180
181 for i = 81:100
182
183 k = fourmatrix(i,1:7);
184 k(k==0)=4;
185 loglikbin = dhmm.logprob(k, priorbin, transmatbin, obsmatbin);
186 loglikblue = dhmm.logprob(k, priorblue, transmatblue, obsmatblue);
187 loglikgreen = dhmm.logprob(k, priorgreen, transmatgreen, obsmatgreen);
188 loglikred = dhmm.logprob(k, priorred, transmatred, obsmatred);
189 loglikwhite = dhmm.logprob(k, priorwhite, transmatwhite, obsmatwhite);
190 loglikeight = dhmm.logprob(k, prioreight, transmateight, obsmateight);
191 loglikfour = dhmm.logprob(k, priorfour, transmatfour, obsmatfour);
192 loglikfive = dhmm.logprob(k, priorfive, transmatfive, obsmatfive);
193 lllkfour2 = [ loglikfour ; loglikwhite; ];
194 lllkfour3 = [ loglikbin ; loglikfour; loglikgreen; ];
195 lllkfour5 = [ loglikfive; loglikfour; loglikgreen; loglikred; loglikwhite; ];
196 if loglikfour ==max(lllkfour2)
197 resultfour2(i-80)=1;
198 resbfour2 = resfour2+1;
199 else
200 resultfour2(i-80)=0;
201 end
202 if loglikfour ==max(lllkfour3)
203 resultfour3(i-80)=1;
204 resbfour3 = resfour3+1;
205 else
206 resultfour3(i-80)=0;
207 end
208 if loglikfour ==max(lllkfour5)
209 resultfour5(i-80)=1;
210 resfour5 = resfour5+1;

```

```

211 else
212 resultfour5(i-80)=0;
213 end
214
215
216 k = fivematrix(i,1:8);
217 k(k==0)=4;
218 loglikbin = dhmm.logprob(k, priorbin, transmatbin, obsmatbin);
219 loglikblue = dhmm.logprob(k, priorblue, transmatblue, obsmatblue);
220 loglikgreen = dhmm.logprob(k, priorgreen, transmatgreen, obsmatgreen);
221 loglikred = dhmm.logprob(k, priorred, transmatred, obsmatred);
222 loglikwhite = dhmm.logprob(k, priorwhite, transmatwhite, obsmatwhite);
223 loglikeight = dhmm.logprob(k, prioreight, transmateight, obsmateight);
224 loglikfour = dhmm.logprob(k, priorfour, transmatfour, obsmatfour);
225 loglikfive = dhmm.logprob(k, priorfive, transmatfive, obsmatfive);
226 lllkfive2 = [ loglikfour; loglikwhite; ];
227 lllkfive41 = [ loglikblue; loglikfour; loglikfive; loglikwhite; ];
228 lllkfive42 = [ loglikred; loglikfour; loglikfive; loglikwhite; ];
229 lllkfive5 = [loglikfive; loglikfour; loglikgreen; loglikred; loglikwhite; ];
230 if loglikfive ==max(lllkfive2)
231 resultfive2(i-80)=1;
232 resbfive2 = resfive2+1;
233 else
234 resultfive2(i-80)=0;
235 end
236 if loglikfive ==max(lllkfive41)
237 resultfive41(i-80)=1;
238 resbfive41 = resfive41+1;
239 else
240 resultfive41(i-80)=0;
241 end
242 if loglikfive ==max(lllkfive42)
243 resultfive42(i-80)=1;
244 resbfive42 = resfive42+1;
245 else
246 resultfive42(i-80)=0;
247 end
248 if loglikfour ==max(lllkfive5)
249 resultfive5(i-80)=1;
250 resfive5 = resfive5+1;
251 else
252 resultfive5(i-80)=0;
253 end
254 end

```

## A.7 binsorter.m

```

1 binind =0;
2 blueind =0;
3 whiteind =0;
4 greenind =0;
5 redind =0;
6 layind =0;
7 placeind =0;
8 setind =0 ;
9 zeroind =0;
10 oneind =0;
11 twoind =0;
12 eightind=0;
13 fourind=0;
14 fiveind=0;
15 sevenind=0;
16 againind=0;
17 pleaseind=0;

```

```

18 soonind=0;
19 expr = '[blps][bgrw][abwi][abcdefghijklmnopqrstuvwxyz][0123456789][asnp].align';
20 expr1= '[b][bgrw][abwi][abcdefghijklmnopqrstuvwxyz][0123456789][asnp].align'; %bin
21 expr2= '[blps]b[abwi][abcdefghijklmnopqrstuvwxyz][0123456789][asnp].align'; %blue
22 expr3= '[blps]w[abwi][abcdefghijklmnopqrstuvwxyz][0123456789][asnp].align'; %white
23 expr4= '[blps]g[abwi][abcdefghijklmnopqrstuvwxyz][0123456789][asnp].align'; %green
24 expr5= '[blps]r[abwi][abcdefghijklmnopqrstuvwxyz][0123456789][asnp].align'; %red
25 expr6= '[l][bgrw][abwi][abcdefghijklmnopqrstuvwxyz][0123456789][asnp].align'; %lay
26 expr7= '[p][bgrw][abwi][abcdefghijklmnopqrstuvwxyz][0123456789][asnp].align'; %place
27 expr8= '[s][bgrw][abwi][abcdefghijklmnopqrstuvwxyz][0123456789][asnp].align'; %set
28 expr9 = '[blps][bgrw][abwi][abcdefghijklmnopqrstuvwxyz]0[asnp].align'; % zero
29 expr10 = '[blps][bgrw][abwi][abcdefghijklmnopqrstuvwxyz]1[asnp].align'; % one
30 expr11 = '[blps][bgrw][abwi][abcdefghijklmnopqrstuvwxyz]2[asnp].align'; % two
31 expr12 = '[blps][bgrw][abwi][abcdefghijklmnopqrstuvwxyz]8[asnp].align'; % eight
32 expr13 = '[blps][bgrw][abwi][abcdefghijklmnopqrstuvwxyz]4[asnp].align'; % four
33 expr14 = '[blps][bgrw][abwi][abcdefghijklmnopqrstuvwxyz]5[asnp].align'; % five
34 expr15 = '[blps][bgrw][abwi][abcdefghijklmnopqrstuvwxyz]7[asnp].align'; % seven
35 expr16 = '[blps][bgrw][abwi][abcdefghijklmnopqrstuvwxyz][0123456789]a.align'; % again
36 expr17 = '[blps][bgrw][abwi][abcdefghijklmnopqrstuvwxyz][0123456789]p.align'; % please
37 expr18 = '[blps][bgrw][abwi][abcdefghijklmnopqrstuvwxyz][0123456789]s.align'; % soon
38 for i = 1:1000
39 j=w(i,1);
40 video = predvis(i); % check this
41 vid = video{1};
42
43 framvec= frameLocs(i);
44 framevec=framvec{1};
45
46 %for bin
47 s=regexp(j,expr1);
48 if isempty(s{1})
49 else
50 binind = binind +1;
51 a = floor(framevec(2)/1000);
52 b = floor(framevec(3)/1000);
53 c = b-a +1 ;
54 binmatrix(binind, 1:c) = vid(1:c);
55 end
56 %for blue
57 s=regexp(j,expr2);
58 if isempty(s{1})
59 else
60 blueind = blueind +1;
61 start = floor(framevec(2)/1000);
62 a = floor(framevec(3)/1000);
63 b = floor(framevec(4)/1000);
64 c1 = a-start +1 ;
65 c2 = b-start +1 ;
66 bluematrix(blueind, 1:c2-c1+1) = vid(c1:c2);
67 end;
68
69 %for white
70 s=regexp(j,expr3);
71 if isempty(s{1})
72 else
73 whiteind = whiteind +1;
74 start = floor(framevec(2)/1000);
75 a = floor(framevec(3)/1000);
76 b = floor(framevec(4)/1000);
77 c1 = a-start +1 ;
78 c2 = b-start +1 ;
79 whitematrix(whiteind, 1:c2-c1+1) = vid(c1:c2);
80 end;
81
82 %for green
83 s=regexp(j,expr4);

```

```

84 if isempty(s{1})
85 else
86 greenind = greenind +1;
87 start = floor(framevec(2)/1000);
88 a = floor(framevec(3)/1000);
89 b = floor(framevec(4)/1000);
90 c1 = a-start +1 ;
91 c2 = b-start +1 ;
92 greenmatrix(greenind , 1:c2-c1+1) = vid(c1:c2);
93 end;
94
95 %for red
96 s=regexp(j,expr5);
97 if isempty(s{1})
98 else
99 redind = redind +1;
100 start = floor(framevec(2)/1000);
101 a = floor(framevec(3)/1000);
102 b = floor(framevec(4)/1000);
103 c1 = a-start +1 ;
104 c2 = b-start +1 ;
105 redmatrix(redind , 1:c2-c1+1) = vid(c1:c2);
106 end;
107
108 %for lay
109 s=regexp(j,expr6);
110 if isempty(s{1})
111 else
112 layind = layind +1;
113 start = floor(framevec(2)/1000);
114 a = floor(framevec(2)/1000);
115 b = floor(framevec(3)/1000);
116 c1 = a-start +1 ;
117 c2 = b-start +1 ;
118 laymatrix(layind , 1:c2-c1+1) = vid(c1:c2);
119 end;
120
121 %for place
122 s=regexp(j,expr7);
123 if isempty(s{1})
124 else
125 placeind = placeind +1;
126 start = floor(framevec(2)/1000);
127 a = floor(framevec(2)/1000);
128 b = floor(framevec(3)/1000);
129 c1 = a-start +1 ;
130 c2 = b-start +1 ;
131 placematrix(placeind , 1:c2-c1+1) = vid(c1:c2);
132 end;
133
134 %for set
135 s=regexp(j,expr8);
136 if isempty(s{1})
137 else
138 setind = setind +1;
139 start = floor(framevec(2)/1000);
140 a = floor(framevec(2)/1000);
141 b = floor(framevec(3)/1000);
142 c1 = a-start +1 ;
143 c2 = b-start +1 ;
144 setmatrix(setind , 1:c2-c1+1) = vid(c1:c2);
145 end;
146
147 %for zero
148 s=regexp(j,expr9);
149 if isempty(s{1})

```

```

150 else
151 zeroind = zeroind +1;
152 start = floor(framevec(2)/1000);
153 a = floor(framevec(6)/1000);
154 b = floor(framevec(7)/1000);
155 c1 = a-start +1 ;
156 c2 = b-start +1 ;
157 zeromatrix(zeroind , 1:c2-c1+1) = vid(c1:c2);
158 end;
159
160 %for one
161 s=regexp(j,expr10);
162 if isempty(s{1})
163 else
164 oneind = oneind +1;
165 start = floor(framevec(2)/1000);
166 a = floor(framevec(6)/1000);
167 b = floor(framevec(7)/1000);
168 c1 = a-start +1 ;
169 c2 = b-start +1 ;
170 onematrix(oneind , 1:c2-c1+1) = vid(c1:c2);
171 end;
172
173 %for two
174 s=regexp(j,expr11);
175 if isempty(s{1})
176 else
177 twoind = twoind +1;
178 start = floor(framevec(2)/1000);
179 a = floor(framevec(6)/1000);
180 b = floor(framevec(7)/1000);
181 c1 = a-start +1 ;
182 c2 = b-start +1 ;
183 twomatrix(twoind , 1:c2-c1+1) = vid(c1:c2);
184 end;
185
186 %for eight
187 s=regexp(j,expr12);
188 if isempty(s{1})
189 else
190 eightind = eightind +1;
191 start = floor(framevec(2)/1000);
192 a = floor(framevec(6)/1000);
193 b = floor(framevec(7)/1000);
194 c1 = a-start +1 ;
195 c2 = b-start +1 ;
196 eightmatrix(eightind , 1:c2-c1+1) = vid(c1:c2);
197 end;
198
199 %for four
200 s=regexp(j,expr13);
201 if isempty(s{1})
202 else
203 fourind = fourind +1;
204 start = floor(framevec(2)/1000);
205 a = floor(framevec(6)/1000);
206 b = floor(framevec(7)/1000);
207 c1 = a-start +1 ;
208 c2 = b-start +1 ;
209 fourmatrix(fourind , 1:c2-c1+1) = vid(c1:c2);
210 end;
211
212 %for five
213 s=regexp(j,expr14);
214 if isempty(s{1})
215 else

```

```

216 fiveind = fiveind +1;
217 start = floor(framevec(2)/1000);
218 a = floor(framevec(6)/1000);
219 b = floor(framevec(7)/1000);
220 c1 = a-start +1 ;
221 c2 = b-start +1 ;
222 fivematrix(fiveind , 1:c2-c1+1) = vid(c1:c2);
223 end;
224
225 %for seven
226 s=regexp(j,expr15);
227 if isempty(s{1})
228 else
229 sevenind = sevenind +1;
230 start = floor(framevec(2)/1000);
231 a = floor(framevec(6)/1000);
232 b = floor(framevec(7)/1000);
233 c1 = a-start +1 ;
234 c2 = b-start +1 ;
235 sevenmatrix(sevenind , 1:c2-c1+1) = vid(c1:c2);
236 end;

```

## B Python Code

### B.1 Phonemes.py

```

import nltk

arpabet = nltk.corpus.cmudict.dict()
k=[j for j in 'abcdefghijklmnopqrstuvwxyz']
t= ['again', 'soon', 'now', 'please','bin', 'lay', 'place','set', 'blue', \
    'green','red','white', 'at','by', 'with', 'in', 'zero','one', 'two',\
    'three','four','five','six','seven','eight','nine'];
g = k+t
ph=[]
for word in g:
    wl=arpabet[word]
    myString = ' '.join(str(r) for v in wl for r in v)
    print( word+' :'+ myString)
    for w in wl:
        ph = ph +w
uniqueph = set(ph)

```

### B.2 Transcripts.py

```

import csv
import os
os.chdir("align")
beach = os.listdir()
with open("tes.csv", "w") as f:
    for sand in beach[:-1]:
        text_file = open(sand, "r")
        lines = text_file.read().split(',')
        k = lines[0]
        g = k.split()
        writer = csv.writer(f)
        writer.writerow(g)

```