Abstract

For machines to lipread, or understand speech from lip movement, they decode lip-motions (known as visemes) into the spoken sounds. We investigate the visual speech channel to further our understanding of visemes. This has applications beyond machine lipreading: speech therapists, animators, and psychologists can benefit from this work. We explain the influence of speaker individuality, and demonstrate how one can use visemes to boost lipreading.

1. Introduction

Machine lipreading (MLR) is speech recognition without audio input e.g. from a silent video. MLR research is of interest to computer vision engineers and speech researchers. Two current complimentary challenges in MLR are; to develop an end-to-end system or, to understand the visual speech signal to apply the knowledge to new domains such as speech therapy and animation. Our work addresses the latter challenge. Phonemes are the smallest sounds one can make [2], and a viseme is the visual equivalent [12]. Current knowledge of visemes is limited, there is no proven function, (often presented as a map) between visemes and phonemes. Our work here focuses on understanding visemes, in order to recognise the right phoneme.

1.1. Conventional lipreading machines

The conventional lipreading process has, at a high level, been adopted from audio recognition systems. This is: 1) track faces and extract features, 2) train a model and classify 3) filter output through a language network. Debates over the optimal tracking methods, features [13], and classifier method [25] remain but, pre-deep learning, the classic choices with accurate results were Active Appearance Model features [20] and Hidden Markov Model classifiers [23] (often built with the HTK toolkit [27] e.g. [19], [22], [24]).

1.2. Data

Available lipreading datasets are reviewed in [3] but the most accurate lipreading data to date are; BBC [14], TCD-TIMIT [16], Oulu [1], and RMAV [17]. We use RMAV.

2. The phoneme-to-viseme map play-off

We begin with a play-off to measure the effect of using different phoneme-to-viseme (P2V) maps from prior work. 120 P2Vs are tested with the conventional system on 12 talkers. The results are displayed in Figure 1 as a heatmap [8]. Consonant P2Vs are on the x-axis and vowel P2Vs on the y-axis. We see that a combination of Disney vowels [18] and Woodward consonants [26] perform best. This contrasts with [10] which concluded Lee’s visemes [19] achieved most accurate lipreading with isolated words which suggests that utterance duration affects visemes.

![Figure 1: Heatmap of lipreading P2V maps.](image)

Figure [2] is critical difference plots for the P2V maps. Critical difference is a measure of confidence intervals between different algorithms [15]. Overlapping bars join P2V maps which are not critically different. By comparing Figures [2a] and [2b] we see that consonant visemes vary less than the vowel sets. This observation is supported by lipreading practitioners (e.g. Nichie [21]), who advocate there are key shapes for articulator sounds (vowels) and gestures are formed by motion between the shapes, the motions are determined by consonants.

All P2V maps are fully tabulated in [4], [10].
3. Speaker independence

In [6] results show Speaker-Dependent (SD) visemes can improve lipreading accuracy. In Figure 3 this conclusion is reinforced with equivalent experiments on continuous speech talkers. Red plots show SD visemes, blue plots are Multi-speaker (MS) visemes, and orange are Speaker-Independent (SI) visemes. Speaker independence is the ability to lipread previously unseen talkers and is an obstacle for lipreading machines.

![Figure 3: Comparing multi-speaker, speaker-dependent P2V functions on six RMAV speakers.](image)

In [11] we learn there is a limitation on how useful all SI visemes within a set are towards recognition accuracy. A badly trained viseme is worse than no viseme. However with our SD visemes, (red plots in Figure 3) all visemes increase accuracy. So, whilst bad training data is more detrimental to classification than having less, with the right knowledge of visual gestures, our need for big data is reduced for accurate lipreading.

4. Boosting phonemes with visemes

We present an experiment in [9] which showed viseme sets with < 11 visemes are negatively affected by homophone confusions. The sets which are too large (> 35) do not differentiate sufficiently to for accurate lipreading. This means the range of optimum sizes is from 11 to 35 and varies by talker. Further to this, in [7] we designed a hierarchical training method which used viseme classifiers as initialisation models of phoneme classifiers, for all viseme set sizes. All talker mean results are in Figure 4 Phoneme HMMs initialised with visemes achieve higher accuracy.

![Figure 4: Boosting with network decoding and classifier units.](image)

We also tested the of the language network unit. In Figure 4 we show that a phoneme network is better than a word network. However, using a phoneme network means the final output is a phoneme string which requires further processing to understand but in [2] this effect is not significant.

5. Conclusions and the future

In our comparison of previous P2V mappings there is little difference between them but Disney’s outperforms others on continuous speech and Lee’s marginally outperforms others [10] on isolated words. This means that visemes vary, by speaker and, by utterance. We suggest that speaker individuality in visual speech is due to the variability with which different people use visual gestures whilst talking.

For speaker-dependent recognition there are choices when selecting a set of visemes containing fewer classes than the phoneme set, yet these sets outperform phoneme labelled classifiers. But phoneme classifiers are desirable as these are cross-speaker consistent so we ask is there a way of mapping similarities between SD visemes [5]? For not only can the right SD visemes out-perform phoneme classifiers, but when used to help train phoneme classifiers, they lipread significantly better [7] also.

Best results are achieved when the units match between classifiers and the language network, but not significantly so. So, for the purposes of decoding phonemes to the words spoken, the preferred network unit is words [7].

End-to-end systems perform well with big data and deep learning [14] but we are still to fully understand the visual speech signal. Understanding visual speech will mean we can improve adaptation between talkers in the future.
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