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Articulatory features for speech-driven head motion synthesis

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Abstract

This study investigates the use of articulatory features for speech-driven head motion synthesis as opposed to prosody features such as F0 and energy that have been mainly used in the literature. In the proposed approach, multi-stream HMMs are trained jointly on the synchronous streams of speech and head motion data. Articulatory features can be regarded as an intermediate parameterisation of speech that are expected to have a close link with head movement. Measured head and articulatory movements acquired by EMA were synchronously recorded with speech. Measured articulatory data was compared to those predicted from speech using an HMM-based inversion mapping system trained in a semi-supervised fashion. Canonical correlation analysis (CCA) on a data set of free speech of 12 people shows that the articulatory features are more correlated with head rotation than prosodic and/or cepstral speech features. It is also shown that the synthesised head motion using articulatory features gave higher correlations with the original head motion than when only prosodic features are used.

Index Terms: head motion synthesis, articulatory features, canonical correlation analysis, acoustic-to-articulatory mapping

1. Introduction

Speech sound may be complemented with visual information (e.g. movements of the mouth; lips, jaw and tongue, and also eyebrows, eyelids, and head movements). Such complementary information increases speech intelligibility. Munhall et al. [1] found that the display of head motion improves speech perception. Research on speech-driven talking faces began with work on synthesis of lip and mouth motions that are synchronised with speech, i.e. lip sync. [2]. In contrast to the lip sync on which a significant number of studies has been done, automatic synthesis of head motion from speech has not been studied that extensively, especially in terms of the use of machine learning techniques.

Grad et al. [3] showed a link between the prosody expressed by the voice and that given by the head. Yehia et al. [4] proposed a frame-wise mapping based on a linear-regression model to estimate head rotation angles (Euler angles) from F0. They found that the linear model had to be separately trained on each utterance sample otherwise the correlation between F0 and head motion almost disappeared. A GMM-based simple frame-wise mapping has also been employed for a talking head [5], longer temporal information was used in [6] and [7]. In the former, HMMs were employed to map F0 and energy to a frame-wise VQ code of head rotation angles, whereas in the latter a discrete HMM was used to decode a sequence of animation cluster codes from the pitch and intensity features at every input syllable. Sargin et al. [8] developed a fully HMM-based approach for mapping the trajectory of F0 and intensity to the one of head rotation angles, in which parallel HMMs were used to cluster trajectory-ries of speech and head motion separately. Hofer et al. [9, 10] proposed the use of human-understandable head-motion units (e.g. nodding and shaking) as the model unit of HMMs. In their approach HMMs are trained with the combined streams of audio speech features (MFCC, F0, and energy) and head rotation angles. Despite the very low frame-wise correlations they found between the speech and head motion features, it was shown that head motion units were correctly recognised with an accuracy of approximately 70% on a free-speech data set, and reasonably natural head motions were synthesised.

Apart from linguistic features available from text, it is clear that the literature has focused on the speech features that are derived directly from acoustic signals. The present study, on the other hand, investigates the use of articulatory features for head motion prediction for the first time. The rationale for considering articulatory features is that there is some evidence that articulatory movements, e.g. opening the jaws, contribute to the movement of the head [11]. Articulatory features have been used successfully for automatic speech recognition [12] and emotional speech synthesis [13], but not yet for head motion synthesis.

The challenge of using articulatory features for head motion synthesis is that the training data of the target speaker normally do not come with articulatory data such as electromagnetic articulography (EMA), meaning supervised training of the model that maps speech features to articulatory features is not possible. To tackle this problem, semi-supervised learning using speaker adaptation is employed in this study.

It should be noted that, compared with the previous studies, which employed head-motion data of only one or two speakers, the present study employs the data of 12 people in order to improve the reliability of experiments in terms of speaker variety.

2. Speech driven head motion synthesis

The outline of the proposed approach is depicted in Figure 1.

2.1. Articulatory features prediction

To predict the articulatory features from speech, we used HMM-based acoustic-to-articulatory inverse mapping. In [14, 15], the author develop a multi-speaker inverse mapping system based on supervised adaptation, where each HMM of acoustic stream was adapted to the new speaker’s voice using the maximum likelihood linear regression (MLLR) technique and a small amount on labelled audio data.

In the present study, we consider a more realistic scenario where no labelled speech data are available for the target speaker. To address the problem, we developed a semi-supervised adaptation technique, where we train initial models on the labelled data of a different speaker, and we adapt the models to the target speaker in an unsupervised manner.

The minuio corpus [16] was employed to train the ini-
2.2. Speech driven head motion synthesis

Similar to the articulatory prediction form speech, we estimate the head motion from the predicted articulation. In training stage, streams of head motion and articulatory feature vectors are used to train multi-stream HMMs, whose model units are determined by the HMM-based clustering technique described in Section 3.3.1. For each stream, the emission probability density function of each state is modelled by a multivariate Gaussian distribution with a diagonal covariance matrix.

In the mapping stage, i.e. head motion synthesis stage, the sequence of head motion feature vectors (i.e. rotations of the head) $\hat{Z}$ is estimated from the intermediate articulatory feature vectors $Y$ predicted from speech feature vectors $X$ (as shown in Eq. 1). The mapping form acoustic speech to head motion is performed as such

$$\hat{Z} = \arg\max_{Z,Y} \left\{ p(\hat{Z}|\lambda^{y,x}, Q^{y,x}) P\left(\lambda^{y,x}, Q^{y,x}|Y\right) \right\}$$

where $\lambda^{y,x}$ and $Q^{y,x}$ are the parameters set of the articulatory-head motion HMM, $Q^{y,x}$ is the head-motion cluster HMM state sequence decoded from the predicted articulatory features $Y$, and $\lambda^{y,x}$ is the parameters set of the acoustic-articulatory HMM and $Q^{y,x}$ is the phone-size HMM state sequence decoded from acoustic speech. $\hat{Z}$ is obtained by maximizing all conditional probabilities. After predicting the articulatory features $Y$, we decode the head-motion cluster HMM state sequence by maximizing $\left\{ p(\hat{Z}|\lambda^{y,x}, Q^{y,x}) \right\}$ using the Viterbi algorithm. Second, we synthesise the head motion by estimating $\hat{Z} = \arg\max_{Z} \left\{ p(\hat{Z}|\lambda^{y,x}, Q^{y,x}) \right\}$, using the MLPG algorithm [18].

3. Experiments

3.1. Data sets

In the present study, we used 12 speakers (denoted by $A00$ to $A11$) and 12 speakers (denoted by $B00$ to $B11$) of the Edinburgh Speech Production Facility (ESPF) corpus [19]. This corpus contains speech movements over time synchronously recorded with audio and electropalatography. The signal was sampled at 100 Hz and their first derivatives were extracted.

3.1.1. Articulatory data

The electropalatography data have been recorded by means of an Electromagnetic Articulograph (EMA) that tracks motion of flesh points of the articulators thanks to small electromagnetic receiver coils glued on the organs. Six coils are used: a jaw coil is attached to the lower incisors, whereas three coils are attached to the tongue tip, the tongue middle, and the tongue back; a coil is attached to the upper lip coil and another one to the lower lip coil in the midsagittal plane. The data was down-sampled to 100 Hz and their first derivatives was added.

3.1.2. Head motion data

Head motion is represented by the head correction of the articulatory data. Extra four coils attached to the upper incisor, to the nose and to the left and right ears served as references to extract the head correction. Head translations and rotations were calculated in order to remove the contribution of head movement.

Figure 1: Overview of the speech driven head motion synthesis system.
from the articulatory data. In this study, head motion are represented by head rotations ($\theta_x$, $\theta_y$, $\theta_z$) about the z, y and x axes, respectively. The data was down-sampled to 100 Hz and their first derivatives were added.

### 3.1.3. Acoustic features extraction

Audio-speech signal was recorded, synchronously with EMA data, at a sampling frequency of 22,050 Hz and down-sampled to 16 kHz. Pitch denotes the combined features of the fundamental frequency (F0) that was extracted via an autocorrelation and cepstrum based method, log-energy, loudness contours, voicing probability, and voice quality. All these features (i.e. Pitch) were extracted with openSMILE [20], and then smoothed with a moving average filter with a window length of 10 frames. The first 12 MFCCs and 12 LPCs were extracted using SPTK\(^1\). Two other LPC representation was tested: Log Area Ratios (LAR) represented by 12 LPC reflection coefficients extracted using HTK\(^2\) and Line Spectral Pairs (LSP) coefficients calculated from the 12 LPC. Pitch, MFCCs, LPC, LAR and LSP were computed from the audio signal over 25 ms windows at a frame rate of 10 ms to match the frame rate of the articulatory and head motion data. Their first time derivatives (i.e. delta parameters) were also added.

### 3.2. Head motion and speech correlation

Canonical correlation analysis (CCA) is employed in the present study to measure the linear relationship between two streams of vectors. The original CCA between two column vectors of random variables, $X \in \mathbb{R}^d$ and $Y \in \mathbb{R}^d$ is defined as the maximisation problem of the correlation between the linear combinations $A^TX$ and $B^TY$, with respect to the set of canonical coefficients $A \in \mathbb{R}^p$ and $B \in \mathbb{R}^q$. It is possible to find $d$ sets of canonical coefficients, where $d = \min(p, q)$.

We define global CCA as the average of $d$ canonical correlations over the whole data streams such that

$$r_G = \frac{1}{d} \sum_{i=1}^d \max_{A,B} \text{corr} \left( A^{(i)T}X_{[1:T]}, B^{(i)T}Y_{[1:T]} \right)$$  \hspace{1cm} (3)

The resulting matrices $U^{(i)}_{[1:T]} = A^{(i)T}X_{[1:T]}$ and $V^{(i)}_{[1:T]} = B^{(i)T}Y_{[1:T]}$ are the $i^{th}$ canonical variables that maximise the Pearson’s correlation corr(). In practice, it is important to use a sufficiently large set of samples to avoid the trap of spurious correlations.

Since the correlations between the speech and head motion streams are believed to change over time, it is more useful for us to define a local CCA for a time window of $n$ frames that starts at $t^{th}$ frame such that

$$r_L = \frac{1}{d} \sum_{i=1}^d \text{corr} \left( A^{(i)T}X_{[t:t+n-1]}, B^{(i)T}Y_{[t:t+n-1]} \right)$$  \hspace{1cm} (4)

where $A^{[i]}$, $B^{[i]}$ are the canonical coefficients obtained in the global CCA.

Average local CCA over time can be defined as

$$r_{L} = F^{-1} \left( \frac{n}{T} \sum_{t=1}^{T-n+1} F(r_t) \right)$$  \hspace{1cm} (5)

where $F(r)$ is the Fisher transformation defined as $\frac{1}{2} \ln \left( \frac{1+r}{1-r} \right)$, which is employed to make the values additive, and $F^{-1}(\cdot)$ is its inverse function. Note that if $n = T$ then $r_L = r_G$.

Figure 2 presents the global CCA, $r_G$, between speech and head motion features. Figure 3 presents the average local CCA, $r_L$, between speech and head motion features.

### 3.3. Speech driven head motion synthesis

#### 3.3.1. Clustering of head motion data

Data annotation is an essential step in the HMM training process. However, manual annotation is often time-consuming and expensive. In our experiments, the training data of head motions was automatically labelled using an HMM-based clustering technique.

We used GMM clustering to initialise the HMMs. Over the whole data of each speaker, GMM with $K$ distributions was trained using the EM algorithm. Then, the data was decoded using the trained GMM into $K$ clusters. Each cluster was used to

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\(^1\)http://sp-tk.sourceforge.net

\(^2\)http://htk.eng.cam.ac.uk
initialise an HMM. The HMMs parameters were re-estimated using the EM algorithm and then new cluster labels were decoded using the Viterbi algorithm. This process was repeated until convergence was reached.

In order to find the optimal number of clusters and the optimal HMM topology that match best with the task of head motion synthesis, we varied the number of clusters, $K$. To define the best HMM configuration, we synthesise the head motion trajectories from the recognised sequence of clusters and the trained HMMs. Then, we evaluate it by a comparison with the original head motion trajectories. Preliminary experiment shows that the optimal number of clusters varies between 11 and 15, although it varies across the speakers.

A similar experiment was done for the number of states per HMM to confirm that there is no clear strategy for deciding the optimal number of states when clustering is concerned. Thus the number was fixed to 5 for the following experiments.

3.3.2. Evaluation of head motion synthesis

We used 15 clusters to train speaker-dependent multi-stream HMMs. 5-state left-to-right no-skip context-independent HMMs were used to model speech and head motion streams. A 3-fold cross validation procedure was used to evaluate the performance of the predicted head motion. Figure 5 presents the average local CCA $r_L$ between original and estimated head motion from different speech features, for all speakers. By looking to the results over all speakers, head motion estimated form both measured and predicted articulatory features are more correlated with original head motion than those predicted for form both measured and predicted articulatory features are more correlated with original head motion than those predicted for form both measured and predicted articulatory features are more correlated with original head motion than those predicted for form both measured and predicted articulatory features are more correlated with original head motion than those predicted for form both measured and predicted articulatory features are more correlated with original head motion than those predicted for.

Figure 4: Distribution of local CCA, $r_L$, between speech and head motion features over all speakers.

Figure 5: Head motion synthesis from speech: average local CCA, $r_L$, between original and estimated head motion. Minimum, mean and maximum values over the speakers for each input speech features are shown as well.

Figure 6: Head motion synthesis from speech: mean over all speakers of the average local CCA, $r_L$, between input speech features and estimated head motion.

4. Conclusion and perspectives

This paper presents the effectiveness of articulatory features for head motion synthesis from speech. In real-world head motion synthesis scenarios, it is not practical to assume the availability of articulatory measurements from a user. To address this challenge, HMM-based acoustic-to-articulatory mapping techniques have been proposed to predict articulatory features from an acoustic signal. This study confirmed that the articulatory features estimated from speech were more effective than prosodic and cepstral features for speech-driven head motion synthesis. Since those features are expected to be complementary, it would be interesting to investigate more sophisticated manners of feature integration. Further studies will include an extension to speaker-independent models with speaker adaptation and subjective evaluation of synthesised animation.

Another motivation of using HMM-based acoustic-to-articulatory mapping is to use the predicted articulatory features for lip sync. The lip motion may be modelled using two features, that is, the mouth opening (i.e. determined by the distance between y-coordinates of the coils attached to the upper and lower lip) and the mouth pucker (i.e. determined using x-coordinates of the coils attached to the upper and lower lip).

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6. References


