On the Evaluation of Inversion Mapping Performance in the Acoustic Domain

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\section*{Abstract}

The two measures typically used to assess the performance of an inversion mapping method, where the aim is to estimate what articulator movements gave rise to a given acoustic signal, are root mean squared (RMS) error and correlation. In this paper, we investigate whether “task-based” evaluation using an articulatory-controllable HMM-based speech synthesis system can give useful additional information to complement these measures. To assess the usefulness of this evaluation approach, we use articulator trajectories estimated by a range of different inversion mapping methods as input to the synthesiser, and measure their performance in the acoustic domain in terms of RMS error of the generated acoustic parameters and with a listening test involving 30 participants. We then compare these results with the standard RMS error and correlation measures calculated in the articulatory domain. Interestingly, in the acoustic evaluation we observe one method performs with no statistically significant difference from measured articulatory data, and cases where statistically significant differences between methods exist which are not reflected in the results of the two standard measures. From our results, we conclude such task-based evaluation can indeed provide interesting extra information, and gives a useful way to compare inversion methods.

\textbf{Index Terms}: Inversion mapping, evaluation, HMM synthesis

\section{1. Introduction}

Humans produce speech by moving articulators, such as the lips and tongue, to manipulate airspaces in the vocal tract, which dynamically filters and “shapes” sound energy arising from vibrating vocal folds or turbulent air movement. Manipulating articulators to produce an audible acoustic speech signal may be termed an articulatory-to-acoustic mapping. The reverse operation, taking an acoustic signal and estimating what sequence of generated acoustic parameters and with a listening test involving 30 participants. We then compare these results with the standard RMS error and correlation measures calculated between each estimated articulatory trajectory and the natural, recorded one. RMS error gives an indication of the overall distance between two trajectories, while correlation indicates synchrony and similarity of shape. While these are undoubtedly useful measures, they are not necessarily ideal. First, though they can compare systems and identify the best so far, they cannot tell us when we have reached the best performance possible, or how close that optimal inversion is. It does not seem reasonable to reduce RMS error to zero and to obtain perfect correlation. In purely practical terms, articulography technology is imperfect, so there is unavoidably some degree of error intrinsic in the data. Moreover, significant evidence suggests multiple articulator configurations may have the same acoustic effect, so inverting this would be a one-to-many, or ill-posed, mapping and there may always be some “residual” error. The position of some articulators, for example, may be categorised critical to the production of a given phone, while others might have little or no impact on the acoustic signal [27, 20]. In addition, we cannot assume RMS error and correlation alone provide a complete and perfect performance measure. In which case, solely optimising these may not ultimately lead to optimal inversion.

With these uncertainties in mind, this paper proposes an alternative “task-based” evaluation. Several tasks could serve this purpose, for example comparing word error rates in articulation-based ASR. But, in view of the supposed many-to-one nature of the articulatory-to-acoustic mapping, it seems most compelling to evaluate inversion performance in the acoustic domain using some kind of articulatory-to-acoustic mapping. We propose to use a recently developed articulatory-controlled statistical parametric synthesis system for this purpose. We find little work has previously been done on evaluating and comparing arbitrary inversion methods in the acoustic domain. Granted, articulatory synthesiser “mimics” inherently optimise articulatory control parameters according to an acoustic error criterion, and acoustic error rates are often reported. But this has not been for arbitrary inversion methods; in fact, they are generally restricted to using the given articulatory synthesis model. Meanwhile, [29] used GMM-based resynthesis [15] to compare inverted artic-
ulatory parameters with natural ones. But their focus was to evaluate the feasibility of their approach to accent modification using articulation from inversion, rather than to evaluate inversion mapping performance per se. In summary, we are not aware of any previous work that has investigated whether synthesis task-based evaluation can provide additional insight into inversion performance. So, to investigate this, we evaluate four inversion methods, and broadly address two questions. First, does an acoustic evaluation provide additional information beyond RMS error and correlation scores? Second, does task-based evaluation provide any indication of how close an inversion mapping is to optimal inversion?

2. Synthesiser with articulatory control

Our experiments here use a variant of the HMM-based statistical parametric approach to speech synthesis [30] that was specifically developed to incorporate articulatory control [28]. Due to limited space, we only give a very brief overview of this Feature-space-switched Multiple Regression HMM (FSS-MRHMM) synthesiser, but full details may be found in [28]. In standard HMM-based synthesis, context-dependent states with distributions over segment durations, \( f_0 \) and spectral features are first trained on a speech corpus. To synthesise speech, textual context features are extracted from input text which, together with state duration distributions, identify the appropriate HMM state sequence. The distributions over the spectral parameters in this state sequence may then be processed with the Maximum Output Probability Parameter Generation (MOPPG) algorithm [31] to give synthesis parameter trajectories which are sent to a vocoder (with \( f_0 \) and other source parameters) to algorithm [31] to give synthesis parameter trajectories which are sent to a vocoder (with \( f_0 \) and other source parameters) to produce audible speech.

The FSS-MRHMM differs from the standard approach in several ways, the most significant of which is illustrated in Fig. 1. Instead of associating distributions over acoustic features with each state, the (spectral) distributions in the FSS-MRHMM are dependent on external input articulatory parameters. This dependency is modelled as the weighted sum of a set of linear mappings, which in turn is mediated by a separate “control” GMM which is fitted to the articulatory training data as an additional training step. Specifically, the distribution over acoustic features \( x_t \) given the exogenous articulatory features \( y_t \) for state \( q_t = j \) at frame \( t \) is modelled as

\[
b_j(x_t|y_t) = \sum_{k=1}^{M} \gamma_k(t) N(\mu_k + \mu_j, \Sigma_k),
\]

where feature vectors \( x_t \in \mathbb{R}^{D_x} \) and \( y_t \in \mathbb{R}^{D_y} \) consist of static parameters and their velocity and acceleration derivatives, with static acoustic feature dimensionality \( D_x \) and articulatory dimensionality \( D_y \); \( N(\mu, \Sigma) \) denotes a Gaussian distribution with mean vector \( \mu \) and covariance matrix \( \Sigma \); \( \gamma_k(t) = [y_t^T, 1]^T \in \mathbb{R}^{D_x+1} \) is simply an expanded articulatory feature vector; \( k \) is the component index for the separate control GMM containing \( M \) mixture components; \( \gamma_k(t) = P(m_k = k|y_t) \) is the probability for mixture component \( m_k = k \) given the articulatory features \( y_t \) at time \( t \); and \( A_k \in \mathbb{R}^{D_x \times D_y+1} \) is the trained linear transform matrix associated with mixture component \( k \). Hence, the acoustic distributions are made to depend on both the input articulatory feature sequence and the textual context features that govern the selection of the “residual” acoustic mean vector \( \mu_j \) and covariance matrix \( \Sigma_j \) for each state. In order to reduce the potential for conflict and ensure a high degree of dependency upon the input articulatory features, we can mod-
acoustic frames were used.

3.2. Codebook mapping

Codebooks have been used in numerous studies, of which [16] is a well-known early example. The codebook consists of a large database of acoustic-articulatory vector pairs, either from recordings of human articulatory movements (e.g. [17]), or from sampling the parameter space of an articulatory synthesis model (e.g. [18]). To perform inversion, the database is searched to find the best vector pairs to match an input acoustic vector sequence. A variety of criteria have been tested to define what “best” means. At the simplest, Euclidean distance might be used to find the nearest acoustic vector, though there are numerous more elaborate variants of the codebook approach (e.g. [33]). The method we used is most similar to [34]. For each input vector, we find the nearest 5000 candidate acoustic vectors, using a KD-tree for efficient search. We then use Viterbi search to find the path through this sequence of candidate vector pairs that minimises the sum of a target and join cost. The target cost is the Euclidean distance between the input acoustic vector and the candidate’s acoustic vector. The join cost measures the suitability of the candidate’s articulatory vector for extending the paths constructed so far. Unlike [34], we use Euclidean distance between the candidate and the articulatory frame that immediately follows the path’s articulatory vector in the original database. This means articulatory frames that are contiguous in the database automatically get a join cost of zero, while using the same articulatory frame at subsequent time steps in the Viterbi search does not automatically get a zero join cost. Also unlike [34], we just weighted the target and join costs equally, rather than optimising this with a validation set, since it is more important for our purposes here to have a wider range of inversion performance. Finally, no context window was used.

3.3. Multilayer perceptron (MLP)

The MLP is a type of ANN that is well known as a non-linear regression method and needs little introduction here. The MLP has been used for inversion in many studies (e.g. [20, 21]). Here, we used a separate MLP for each articulator channel (i.e. each coordinate of each articulator point). Each MLP had a single hidden layer containing 100 units with a tanh activation function, and was trained using the scaled conjugate gradients (SCG) optimisation algorithm, using a validation set to decide when to stop training. A context window of 10 frames was used.

3.4. Trajectory mixture density network (TMDN)

In principle, the inversion function may feature one-to-many mappings, and the TMDN is a type of ANN that is able to take this into account by modelling full distributions over static and derived dynamic articulatory features and then using the MOPPG algorithm to generate smooth output trajectories [23]. Here, we used a TMDN with 100 units in a single hidden layer, each with a tanh activation function. We used one TMDN for each articulator channel separately, with output density functions containing 1, 2 or 4 Gaussian mixture components, and using the SCG algorithm and a validation set for training. As with the MLP, a context window of 10 frames was used.

4. Experiment

4.1. Articulatory-acoustic data

We used the electromagnetic articulography (EMA) and audio data (session 1) from the mngu0 corpus [26] for the experiments, with sensor coils attached midsagittally to the upper and lower lips, the lower incisor and the tongue tip, body and dorsum. The male British English subject was recorded reading 1263 prompts using a Carstens AG500 articulograph [35]. This records sensor coil positions in 3D Cartesian space and two angles of rotation at 200Hz sample rate. The prompts were selected from newspaper text using a Multisyn [36] text-selection tool to ensure phonetic diversity.

STRAIGHT analysis [37] was used to convert the audio data to frequency-warped line spectral frequencies (LSF) of order 40, plus gain, at a frame rate to match the EMA. We used the movements of the EMA coils in the midsagittal plane only, giving a total articulatory frame size of 12 (x- and y-coordinates for 6 coils). Three subsets of the data were created: a training set of 1137 prompts without an index number ending in ‘0’, a validation set with 63 prompts with an odd integer preceding the final 0; and a test set with the remaining 63 prompts. Since some methods (e.g. the ANNs) are sensitive to data scaling, all EMA and LSF features vectors were z-score normalised. The data was used unnormalised to train the FSS-MRHMM synthesis system. Finally, to construct the acoustic context windows, the given number of alternate acoustic frames was selected, centred on the articulatory frame. So, for example, for a ten-frame context window, the time difference between the two end frames would be 90msec and the total acoustic vector size would be 410 (5msec frame shift, 41 parameters each frame).

4.2. Inversion mapping – standard measures

The inversion methods in Section 3 were trained and evaluated using the standard articulatory RMS error and correlation measures. In addition, for each inversion system we evaluated the effect of lowpass filtering using a second order Butterworth filter with 10Hz cutoff. All these results are presented in Fig. 3. The codebook gave the lowest performance, then the linear mappings, with increasing context window sizes generally improving results moderately. In all cases apart from TMDN (for which the MOPPG already provides smoothing), lowpass filtering improved results. Finally, the MLP and TMDN turned out to give similar performance in fact. This does not match previous results [23]. This may be because [23] used MOCHA, whereas here we have used mngu0. There is evidence to suggest inconsistency in the articulator positions between different sections of the MOCHA corpus [38], which is not apparent in mngu0. It is possible, therefore, that multiple Gaussian components in the TMDN gave better performance in [23] by mitigating the effects of data inconsistency, rather than by giving any benefit for the inversion mapping per se. Further investigation will be required to confirm or discount this conjecture. Overall, though, we observe a reasonable spread of performance according to these two standard measures, as desired. Finally, since we have lower
\section{5. Conclusions}

We have investigated the use of an articulatory-controlled HMM-based synthesiser to evaluate inversion mapping performance. There is little prior work in this direction, and our aim was simply to demonstrate whether i) such acoustic evaluation can provide useful information beyond the commonly used RMS error and correlation measures, and ii) whether such task-based evaluation can provide any indication of how close an inversion mapping is to the optimum performance possible. From our results, we conclude that this indeed can provide useful extra information for the purpose of comparing inversion methods. In terms of our second question, we have indeed found one inversion system performed with no statistically significant difference from the use of natural EMA trajectories. At this stage, however, we cannot conclude this system has reached optimal inversion performance, but merely that it has reached sufficient performance for the given articulatory synthesis task.

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7. References


