Optimizations and Fitting Procedures for the Liljencrants-Fant model for Statistical Parametric Speech Synthesis

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1. Introduction

Every parametric speech synthesizer requires a good excitation model to produce speech that sounds natural. In this paper, we describe efforts toward building one such model using the Liljencrants-Fant (LF) model. We used the Iterative Adaptive Inverse Filtering technique to derive an initial estimate of the glottal flow derivative (GFD). Candidate pitch periods in the estimated GFD were then located and LF model parameters estimated using a gradient descent optimization algorithm. Residual energy in the GFD, after subtracting the fitted LF signal, was then modeled by a 4-term LPC model plus energy term to extend the excitation model and account for source information not captured by the LF model. The ClusterGen speech synthesizer was then trained to predict these excitation parameters from text so that the excitation model could be used for speech synthesis. ClusterGen excitation predictions were further used to reinitialize the excitation fitting process and iteratively improve the fit by including modeled voicing and segmental influences on the LF parameters. The results of all of these methods have been confirmed both using listening tests and objective metrics.

Index Terms: Speech synthesis, Liljencrants-Fant model, statistical parametric synthesis

2. Related Work

A variety of methods have been proposed and tested for estimating excitation source parameters both as a means of accurately measuring voice quality[4, 5, 6], to provide an improved source parameterization for speech synthesis[7, 8, 9, 10, 11, 12], and as a means of improving the ability to convey emotion and expressiveness in synthesis[13, 14]. In most cases, the LF model has been chosen to represent the voiced source parameters, although several alternatives have also been explored (e.g., [15, 10, 16]). The process of estimating LF parameters typically begins by inverse filtering the acoustic speech signal either manually (e.g., [8]) or automatically (e.g., [11, 12, 9]) to remove the contribution of vocal tract resonances from the signal. Thereafter, estimates of the LF parameters can be derived either directly from measures of isolated pitch epochs [11, 12], or by using search strategies that attempt to locate the best parameters by minimizing an error measure either in the time domain [4], the spectral domain [9] or a combination of the two [8].

The current approach shares features with many of these related studies, but takes a novel approach to combining voiced, mixed, and voiceless excitation by employing the LF model for a voiced source along with a low order LPC fit to information in the differentiated glottal flow that is not captured by the LF model. This approach blends smoothly from voiced to voiceless regions by allowing the LPC fit to dominate the signal in regions where the LF model parameters are difficult or impossible to estimate.

3. Liljencrants-Fant model

The Liljencrants-Fant model[17] (LF model) was developed in the 1980’s as a mathematical way of describing the glottal flow derivative. The reason for this being that derivative of the glottal flow was easier to model as compared to the glottal flow itself.

The model itself consists of the following equation:

\[
e(t) = \begin{cases} \frac{E_0 e^{\alpha t} \sin(\omega_g t)}{-E_0} \left[ e^{-\varepsilon (T_c-T_e)} - e^{(T_e-T_c)} \right] & t < T_e \\ 0 & T_e < t < T_c \end{cases}
\] (1)

Figure 1 depicts a plot of the LF model for typical values of the parameters. The parameters \( T_e, T_c, T_a, T_e \) are explained in the figure. The parameters \( E_0, \alpha \) and \( \varepsilon \) can be determined from the positive peak. The glottal frequency \( \omega_g \) can be determined from the fundamental period \( T_0 \).

4. Iterative Adaptive Inverse Filtering

The spectra of the vocal tract and the glottal source are deeply intertwined with each other. Since the LF model was designed
specifically to model the glottal source derivative, we need to separate the spectrum of the glottal source from that of the vocal tract.

The Iterative Adaptive Inverse Filtering method as first described in [18] does this by iteratively making estimates of the glottal source spectrum and vocal tract spectrum and alternatively inverse filtering with one to get better estimates of the other. The final estimate of the glottal source spectrum is then far better than could otherwise have been obtained with simpler inverse filtering methods. The specific technique we use is more or less identical to the setup described comprehensively in Raitio et. al[2] but in the interests of keeping the paper as self-contained as possible, we provide a block diagram that describes the process in Figure 2.

The result of Iterative Adaptive Inverse Filtering is a set of LPC coefficients (which we convert to LSPs) that provide an estimate of the vocal tract spectrum and the glottal source function (the outputs of the two shaded blocks in Figure 2).

While it could be argued that the IAIF procedure might not produce a glottal source spectrum that is perfectly separated from vocal tract effects, we were more interested in getting a glottal source estimate that could be modeled well for speech synthesis. For that purpose, we believe that this method is sufficient.

5. Fitting LF Model parameters

Automatic extraction of LF model parameters from running speech has been approached in a variety of ways and with varying degrees of success [11]. We tried a variety of time- and frequency-domain methods for fitting LF parameters to the IAIF residual. The one reported here is the best performing for this particular task. While we found that spectral fitting worked well in some cases, it had a tendency to be quite unstable and would fail to find a proper fit in other cases. In contrast to this, one time-domain method was found to produce consistent and reasonable estimates for the LF Model parameters.

Our analysis windows were 70 msec wide and stepped in 5 msec increments through the IAIF-estimated source waveform while fitting LF model parameters. The LF parameters obtained for the single pitch pulse that spanned the center of each analysis window were output as the parameters for each 5-msec frame. Thus, the time-domain fitting, which is inherently pitch-synchronous, was used to obtain parameter estimates for a uniform frame rate. Fitting the LF model was a two-stage process in which we first located a probable instance of maximum glottal closure rate ($T_e$ in the LF model), and then optimized parameters for a pitch pulse around that closure event. We did this by generating a model LF pitch pulse with $T_0$ set to something close to the speaker’s maximum pitch period and default shape parameters. This pitch pulse was then convolved with the windowed signal. The magnitudes, locations and spacing of peaks in the convolved signal were used to estimate voicing, pitch period locations, and $F_0$ within the window. If a pitch period was located in a region that spanned the center of the window, that period was then passed to a second stage optimization where the $T_p$, $T_e$, $T_a$, and amplitude parameters were iteratively adjusted to reduce an RMS error metric until no further improvement was found.

The second stage optimization was quite simple. The pitch period duration $T_0$ was held constant and the three temporal parameters, $T_p$, $T_e$, and $T_a$ (quantized to the sampling interval for the digital waveform) were adjusted by one sample forward or backward on each iteration. Similarly, the amplitude term was adjusted by 1dB on each iteration. A new pitch pulse was generated and the RMS error term was reevaluated following the adjustment of each parameter. If the adjustment of a parameter resulted in a reduction in the error term, the new parameter value was kept, otherwise the adjustment was discarded and the direction of change for that parameter on the next iteration was reversed. Iteration was stopped when no parameter...
adjustments in any direction led to further reduction in the RMS error.

This process, while very inefficient, seemed to be quite robust when supplied with reasonable starting estimates of $T_0$ and $T_e$, despite moderately strong F1-second harmonic influence on the source waveform.

We must remember that the LF model is only an approximation of the shapes in the glottal flow derivative. The glottal flow derivative contains a lot of high frequency content that the LF model fails to capture. Without these high frequency components, the synthesized speech tends to sound hollow and muffled. To model these components, we subtract the fitted LF model from the glottal derivative. A low order LPC (we used a 4th order LPC) is then fit to the remaining components that are not captured by the LF model.

Modeling it this way also has the advantage that we do not need to make a voicing decision. We had originally tried making a voicing decision and then using either the LF model or white noise depending on whether the particular phone was voiced. This approach worked really well when the voicing decisions were perfect. However, it is extremely difficult to get accurate voicing information. Whenever the voicing decision was incorrect, it either made the synthesized speech sound exceedingly jarring or sound hoarse like a smoker’s voice. There is also a lot of uncertainty about what best to do in regions where the speech transitions from a voiced to unvoiced region or vice versa. These problems can be mitigated by modeling the residual of the LF model.

![Figure 3: Fitting to the residual: the raw glottal flow derivative is in black, the estimated LF model is in blue and the residual error is in red](image)

5.1. Results

To test the quality of our models, we conducted listening tests on Amazon’s Mechanical Turk using the Testvox framework[19] where listeners were asked to choose between two systems. The first system was a synthesizer that used Line Spectral Pairs and the above described (LF) models for the residual. The second system was a baseline system that used an identical vocal tract model but a mixed excitation (ME) residual[20]. Listeners were asked to pick the system which they thought sounded more natural. 19 listeners were asked to choose between 10 utterances generated by each system resulting in 190 tests between the two systems. In 116 of those tests, listeners judged our system to be more natural. In 4 of the tests, listeners did not have a preference.

A Generalized Estimating Equation (GEE) model was used with listeners repeated over sentences to test the hypothesis that the model intercept is zero, in other words, that the odds of a listener selecting the LF version were equal to the odds of the listener selecting the ME version as more natural sounding. The model coefficient for the intercept was 0.595 with a standard error of 0.2525, a Wald Chi-Square of 4.002 with 1 degree of freedom and a p-value of 0.045. We can thus reject the hypothesis of equal odds and conclude that listeners preferred to LF model versions of the sentences.

6. Improving the Fit

The LF model fitting process described in a previous section is essentially a form of gradient descent and so is highly dependent on starting from a good initial position. Statistical Parametric Synthesis[21] provides us with an elegant way of getting good initial estimates. We start by fitting the LF model to frames of speech at 5 msec intervals, as described earlier, with a window large enough to contain at least two or three glottal pulses. We then use these parameters along with the the vocal tract model to build a synthetic voice in the ClusterGen framework. ClusterGen involves building a set of Classification And Regression Trees (CARTs)[22] that learn a mapping between the phones (with context) and the feature vectors, LSPs and LF parameters in this case.

One of the most unique parts of our approach is this: we use these CARTs to predict the LF parameter values of our entire database. The LF fitting process then uses these predicted parameters as seed values. These are used to create the model shape that is convolved with the frame to detect the glottal pulse and also as one of the multiple possible initializations in the gradient descent. By iteratively using CARTs to initialize the LF fitting and feeding the result of fitting process back into the CART training, we are able to get a very good final estimate of the true LF parameters. This final estimate is better than the first estimate for two reasons. Firstly, the prediction processing using the CARTs has a smoothing effect on the parameter estimates which helps to remove outliers. Secondly, the use of multiple appropriate initializations greatly improves the chances of the gradient descent process finding the optimum parameter values.

![Figure 4: Iterative estimation of LF parameters](image)

The ClusterGen system models the fundamental frequency $F_0$ independent of the other parameters. Since the LF parameters, $T_0$, $T_e$, $T_p$, $T_s$ implicitly model the $F_0$, using these parameters directly in the ClusterGen system results in a mismatch between ClusterGen’s smooth $F_0$ contour predictions and the implicit $F_0$ in the LF parameters. This causes the synthesized speech to sound shaky as if the speaker were about to cry. We
can avoid this problem by representing the LF parameters as \( F_0 \)-independent dimensionless parameters: Open Quotient (OQ), Speed Quotient (SQ) and Return Quotient (RQ)[23].

\[
OQ = \frac{T_s + T_p}{T_0} \quad (2)
\]

\[
SQ = \frac{T_s}{T_p - T_0} \quad (3)
\]

\[
RQ = \frac{T_s}{T_0} \quad (4)
\]

Using a \( F_0 \)-independent representation also lets us use models like the Statistical Phrase Accent Model[24] to impose specific intonations to the speech.

6.1. Results

We iterated the fitting process several times with initializations provided by ClusterGen which were fed back to the synthesizer. Listening tests that test the naturalness of the synthesized speech were inconclusive and the difference in quality between iterations was subtle. Even speech researchers who listened to the synthesized speech from the first and last iterations acknowledged that the speech sounded different but had difficulty in making a decision on which one sounded more natural. Empirical evidence suggests that this difficulty arose from the LPC model that is used to model the remainder of the LF fitting process.

We were interested in two objective metrics. The first one was the prediction error. This is the error that we get as a result of limitations of the CARTs that ClusterGen uses. The reasoning was to try to push the fitting process into a space that ClusterGen could model well. The second metric was the RMSE and Correlation of the fitting process itself. These were computed for every pitch period where the LF model was being fit. While a low value for the second metric means the fitting process is going well, a low score for the first metric need not necessarily indicate that the fitting process works well. For example, if a bug in the code caused the parameters of every single pitch period in the database to be identical, then the ClusterGen predictions would be perfect all the time. However, we must not assume that optimizing the fitting metric alone is sufficient. The fitting process is worthless to us unless we can predict the values from the text. Therefore, our modeling technique must be able to do well under both metrics. Table 1 shows us that both the metrics indicate that our models get better as the iterations progress. Even in the case where the fitting RMSE starts to increase a little, the correlation still keeps improving.

Table 1: \textit{RMSE and Correlation of Fitting}

<table>
<thead>
<tr>
<th>Iteration number</th>
<th>LF Fitting Prediction</th>
<th>RMSE</th>
<th>Corr</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>406.89 0.482</td>
<td>4.840</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>405.94 0.479</td>
<td>6.909</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>395.17 0.518</td>
<td>5.611</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>391.57 0.534</td>
<td>5.061</td>
<td></td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>389.98 0.543</td>
<td>4.836</td>
<td></td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>389.65 0.547</td>
<td>4.722</td>
<td></td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>390.06 0.550</td>
<td>4.661</td>
<td></td>
<td></td>
</tr>
<tr>
<td>30</td>
<td>390.56 0.551</td>
<td>4.636</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

7. Optimizing the Synthesizer itself

While we use CMU’s ClusterGen Statistical Parametric Speech Synthesizer [25] to model the LF parameters, there is nothing specific to ClusterGen that could not be done in any other parametric synthesizer such as HTS [26]. The only reason we used ClusterGen is because we are more familiar with our own system.

As our parameterization of speech in this model is with LSPs and LF parameters and the original phonetic and HMM state labeling is carried out with MFCCs (through EHMMS [27]), we know that the labels will not be optimized for this alternative parameterization. We therefore make use of our move\textit{Label} algorithm [28] which moves phoneme and HMM state boundaries based on how well the parameters at either side of the boundary can be predicted. This technique typically produces models better than the equivalent of doubling the data.

This technique has been used to optimize MCEP-based models but the LSP and LF have more varied magnitudes thus causes unimportant weighting of the importance of each parameter. Thus we convert all the parameters to \textit{Z}-scores (number of standard deviations from the mean), even though not all parameters are actually Gaussian. This allows a more equal optimization of the parameters. We measure LSP distortion as root mean squared difference between predicted LSPs and a held out set (in the un-\textit{Z}-scored domain). We multiplied this by 1000 to give us a cosmetically nice number. For LF distortion, we again use root mean squared difference between prediction and held out data (non-\textit{Z}-scored domain) but no scaling was necessary. We did 20 iterations each.

Table 2: \textit{Move Label} metrics

<table>
<thead>
<tr>
<th>Optimization</th>
<th>Pass</th>
<th>LSPD</th>
<th>LFD</th>
<th>Duration</th>
<th>RMSE</th>
<th>Corr</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>7.472</td>
<td>4.829</td>
<td>0.907</td>
<td>0.425</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LF</td>
<td>7.245</td>
<td>5.015</td>
<td>0.957</td>
<td>0.305</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LSP+LF</td>
<td>7.961</td>
<td>3.702</td>
<td>0.961</td>
<td>0.310</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LSP+LF+Dur</td>
<td>7.379</td>
<td>4.657</td>
<td>0.946</td>
<td>0.313</td>
<td>0.878</td>
<td>0.479</td>
</tr>
</tbody>
</table>

Standard Deviation for the baseline system was 0.385 for LSPD and 0.589 for LFD. All other SDs are of similar magnitude.

The LSP+LF, which gave the lowest LFD, produced speech which we informally identified as being more smooth than the baseline, but the durations (in text to speech) were different enough to be less desirable. When we added the duration optimization constraint to our move\textit{Label} optimization it converges quicker, but the spectral quality of the signal is not perceptibly different from the baseline (though the durations are better).

8. Conclusions

This work shows a novel method to derive LF parameters from appropriately extracted residuals. Addressing excitation modeling is currently one of the more important issues in statistical parametric synthesis that should offer the brightness and naturalness that high quality (and costly-to-develop) unit selection synthesizers offer. Also more importantly this will allow us to address issues in modeling different speech styles efficiently. This work also continues our direction in investigating non-standard parameterizations of speech and complementing our Statistical Phrase Accent Model for \( F_0 \) [24] where the trajectory over accents is parameterized, and articulatory feature use in statistical parametric synthesis [29].
9. References


