

# LPC for Formant Analysis of Concurrent Vowels

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**Abstract**— This report focuses on understanding the effects of noise on the formant representations of both single and concurrent vowels. The dataset used for this purpose included values of single and concurrent vowels at two fundamental frequencies, 100 Hz and 126 Hz respectively. With the help of Linear Predictive Coding (LPC), the formant frequencies were first found for these vowels. Following this, using various speech signals [6], Speech Spectrum Shaped Noise was generated. After this, the noise was added to the vowels for 3 different SNR values. The formant frequencies were then again estimated for these corrupted signals having different SNR levels. An analysis has been carried out to investigate the effects of the different SNR levels on the formants. Further, an attempt has been made to understand which vowels (both single and concurrent) are more susceptible to noise.

**Keywords**—LPC, Formants, Concurrent Vowels, Speech Spectrum Shaped Noise, SNR.

## I. INTRODUCTION

The general character of the speech signal varies at the phoneme rate, which is on the order of 10 phonemes per second, while the detailed time variations of the speech waveform are at a much higher rate. That is, the changes in vocal tract configuration occur relatively slowly compared to the detailed time variation of the speech signal. The sounds created in the vocal tract are shaped in the frequency domain by the frequency response of the vocal tract. The resonance frequencies resulting from a particular configuration of the articulators are instrumental in forming the sound corresponding to a given phoneme. These resonance frequencies are called the formant frequencies of the sound. On analyzing the frequency spectrum of a speech signal, various peaks can be observed. The formant frequencies correspond to local maxima in the spectrum. To identify these formants, linear predictive coding proves extremely useful. On carrying out LPC analysis for a speech signal, a prediction polynomial  $A(z)$  in  $z^{-1}$  is obtained. In the pole-zero plot of  $A(z)$ , the zeros lying close to or on the unit circle correspond to the formant frequencies of the speech signal. Figure 1 shows the frequency spectrum of a speech signal along with the LPC spectrum of the signal. The peaks in the LPC spectrum correspond to the formant frequencies.

The report has been divided into IV sections. Section II presents the methodology used with brief explanations of the theory behind the report. Section III presents the results and discussion on the observations made. The final Section IV contains the conclusions, limitations and future scope of the project.

## II. METHODOLOGY

A dataset of single and concurrent vowels [6] was used. The generation and analysis was done in three stages – finding the formant frequencies with the help of LPC; generation of Speech Spectrum Shaped Noise; addition of Speech Spectrum Shaped Noise at different SNR values to the formant representation of the signals; analyzing the effects that the different SNR levels of noise have on the formant representation of both single and concurrent vowels.

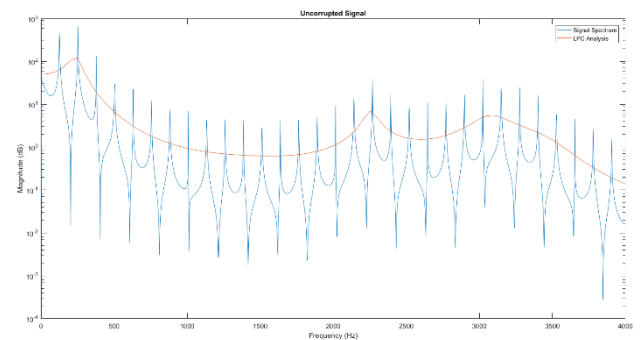


Fig. 1: LPC analysis of a speech signal (in dB)

### 1. LINEAR PREDICTIVE CODING [1]

For LPC analysis, the sampled speech signal is modeled as the output of a linear, slowly time-varying system excited by either quasi-periodic impulses (during voiced speech), or random noise (during unvoiced speech). Over short time intervals, the linear system is described by an all-pole function of the form:

$$H(z) = \frac{S(z)}{E(z)} = \frac{G}{1 - \sum_{k=1}^p a_k z^{-k}}$$

The major advantage of this model is that the gain parameter,  $G$ , and the filter coefficients  $a_k$  can be estimated in a very straightforward and computationally efficient manner by the method of linear predictive analysis. The speech samples  $s[n]$  are related to the excitation  $e[n]$  by the difference equation:

$$s[n] = \sum_{k=1}^p a_k s[n-k] + Ge[n]$$

A linear predictor with prediction coefficients,  $a_k$ , is defined as a system whose output is

$$\tilde{s}[n] = \sum_{k=1}^p \alpha_k s[n-k]$$

The prediction error is defined as

$$d[n] = s[n] - \tilde{s}[n] = s[n] - \sum_{k=1}^p \alpha_k s[n-k]$$

Hence, the prediction error sequence is the output of an FIR linear system whose system function is

$$A(z) = 1 - \sum_{k=1}^p \alpha_k z^{-k} = \frac{D(z)}{S(z)}$$

If the speech signal obeys the model mentioned above exactly, and if  $\alpha_k = a_k$ , then  $d[n] = Ge[n]$ . Thus, the prediction error filter,  $A(z)$ , will be an inverse filter for the system,  $H(z)$ , i.e.,

$$H(z) = \frac{G}{A(z)}$$

The set of predictor coefficients  $\{\alpha_k\}$  are to be found from the speech signal directly to obtain a useful estimate of the time-varying vocal tract system. This must be done to minimize the mean-squared prediction error over a short segment of the signal. The short-time average prediction error is defined as

$$E_{\hat{n}} = \langle d_{\hat{n}}^2[m] \rangle = \left\langle \left( s_{\hat{n}}[m] - \sum_{k=1}^p \alpha_k s_{\hat{n}}[m-k] \right)^2 \right\rangle$$

Where  $s_{\hat{n}}[m]$  is a segment of speech that has been selected in a neighborhood of the analysis time, i.e.

$$s_{\hat{n}}[m] = s[m + \hat{n}] \quad -M_1 \leq m \leq M_2$$

The notation  $\langle \rangle$  denotes averaging over a finite number of samples. The values of  $\alpha_k$  that minimize  $E_{\hat{n}}$  can be found by setting  $\partial E_{\hat{n}} / \partial \alpha_i$ , for  $i = 1, 2, \dots, p$ , thereby obtaining the equation

$$\sum_{k=1}^p \alpha_k \langle s_{\hat{n}}[m-i] s_{\hat{n}}[m-k] \rangle = \langle s_{\hat{n}}[m-i] s_{\hat{n}}[m] \rangle$$

Where  $i = 1, 2, \dots, p$ .

Defining,

$$\varphi_{\hat{n}}[i, k] = \langle s_{\hat{n}}[m-i] s_{\hat{n}}[m-k] \rangle$$

Then the minimization condition can be written as

$$\sum_{k=1}^p \alpha_k \varphi_{\hat{n}}[i, k] = \varphi_{\hat{n}}[i, 0] \quad 1 \leq i \leq p$$

In matrix form, the above equation can be written as

$$\Phi \alpha = \psi$$

The above matrix equation can be solved to find the vector  $\alpha = \{\alpha_k\}$ .

The minimum mean-squared prediction error can be shown to be

$$E_{\hat{n}} = \varphi_{\hat{n}}[0, 0] - \sum_{k=1}^p \alpha_k \varphi_{\hat{n}}[0, k]$$

#### A. Computing the Predictor Coefficients using Autocorrelation Method

There are two methods of linear predictive analysis – the Covariance method and Autocorrelation Method. The authors have used the Autocorrelation method for this project.

In the autocorrelation method, the analysis segment  $s_{\hat{n}}[m]$  is defined as

$$s_{\hat{n}}[m] = \begin{cases} s[n+m]w[m] & -M_1 \leq m \leq M_2 \\ 0 & \text{otherwise} \end{cases}$$

where the analysis window  $w[m]$  is used to taper the edges of the segment to zero. The window is defined such that analysis segment is zero outside the range  $-M_1 \leq m \leq M_2$ . Hence,  $d_{\hat{n}}[m]$  is non-zero only in the range  $-M_1 \leq m \leq M_2$ .

Therefore,

$$E_{\hat{n}} = \sum_{m=-M_1}^{M_2+p} (d_{\hat{n}}^2[m]) = \sum_{m=-\infty}^{\infty} (d_{\hat{n}}^2[m])$$

Using this,

$$\varphi_{\hat{n}}[i, k] = \sum_{m=-\infty}^{\infty} s_{\hat{n}}[m] s_{\hat{n}}[m + |i - k|] = \phi_{\hat{n}}[|i - k|]$$

Thus, the resulting set of equations for the optimum predictor coefficients is therefore:

$$\sum_{k=1}^p \alpha_k \phi_{\hat{n}}[|i - k|] = \phi_{\hat{n}}[i] \quad 1 \leq i \leq p$$

Some of the properties implied by the mathematical structure of the equations yielded by the autocorrelation method are

1. The mean-squared error is greater than 0. With this method, it is theoretically impossible for the error to be exactly zero because there will always be atleast one sample at the beginning and one at the end of the prediction error sequence that will be nonzero.
2. The matrix  $\Phi$  is a symmetric positive-definitive Toeplitz matrix.
3. The roots of the prediction error filter  $A(z)$  are guaranteed to lie within the unit circle of the  $z$ -plane so that the vocal tract model filter is guaranteed to be stable.
4. The equations can be solved efficiently by using the Levinson-Durbin algorithm.

#### B. The Levinson-Durbin Recursion

The matrix equation  $\Phi \alpha = \psi$  can be written as

$$\begin{bmatrix} \phi[0] & \phi[1] & \dots & \phi[p-1] \\ \phi[1] & \phi[0] & \dots & \phi[p-2] \\ \dots & \dots & \dots & \dots \\ \phi[p-1] & \phi[p-2] & \dots & \phi[0] \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \dots \\ \alpha_p \end{bmatrix} = \begin{bmatrix} \phi[1] \\ \phi[2] \\ \dots \\ \phi[p] \end{bmatrix}$$

The vector  $\psi$  has almost the same values as the matrix  $\Phi$ . Due to this special structure, it is possible to design a recursive algorithm for inverting the matrix  $\Phi$ .

The prediction error system function satisfies

$$A^{(i)}(z) = A^{(i-1)}(z) - k_i z^{-i} A^{(i-1)}(z^{-1})$$

### C. Roots of the Prediction Error System Function

The system function of the prediction error filter is a polynomial in  $z^{-1}$  and can be expressed in terms of its zeros as

$$A(z) = 1 - \sum_{k=1}^p \alpha_k z^{-k} = \prod_{K=1}^p (1 - z_k z^{-1})$$

The zeros of  $A(z)$  are the poles of  $H(z)$ . Figure 2 shows an example of the roots (marked with  $\times$ ) of a 12<sup>th</sup> order predictor. Note that eight (four complex conjugate pairs) of the roots are close to the unit circle. These are the poles of  $H(z)$  that model the formant resonances. The remaining four roots lie well within the unit circle, which means that they only provide for the overall spectral shaping.

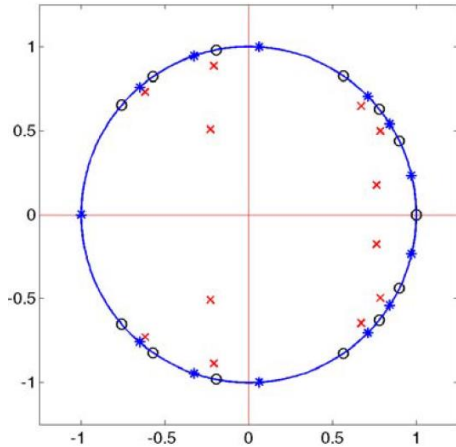


Fig. 2: Poles of  $H(z)$  (zeros of  $A(z)$ ) marked with  $\times$  and LSP roots marked with  $*$  and  $o$

## 2. SPEECH SPECTRUM SHAPED NOISE

For our analysis, it was required to generate speech spectrum shaped noise. For this purpose, an input of 30 different speech samples was taken. [5] These speech samples were randomized and added together to generate the speech spectrum shaped noise. [3] (Fig. 4)

The sampling frequency of this noise is 10000 Hz; same as the sampling frequency of the audio files of the single and concurrent vowels, which were down sampled from 100000 Hz to 10000 Hz. This noise was then added to the vowels for 3 different SNR values i.e. 5 dB, 15 dB and 30 dB. Following this, LPC analysis was carried out on these corrupted signals to observe the effects of different noise levels on the formants.

The following figure (Fig. 3) shows the results before and after addition of Speech Spectrum Shaped Noise.

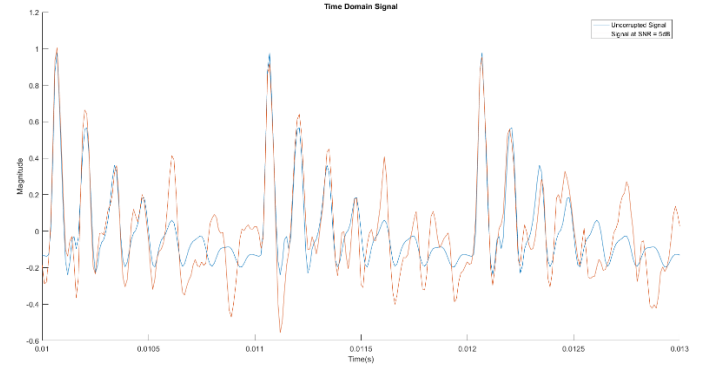


Fig. 3: Time domain representation of 'ae' at a fundamental frequency of 100 Hz before and after corruption with Speech Spectrum Shaped Noise at an SNR of 5 dB

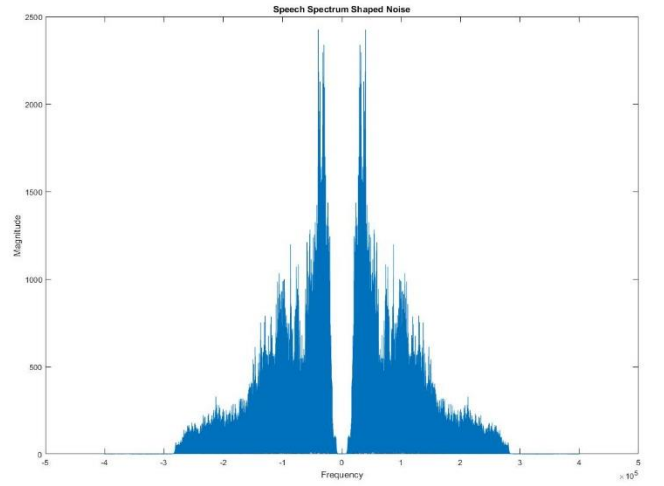


Fig. 4: Speech Spectrum Shaped Noise

## 3. ANALYSIS OF NOISE EFFECTS ON SINGLE VOWELS

Each of the single vowels considered for the analysis were with two different fundamental frequencies i.e. 100 Hz and 126 Hz. The vowels analyzed were AE, AH, EE, ER and OO. The analysis was carried out for two filters orders; 15 and 31. The frequencies highlighted in green are the formant frequencies. They were identified based on the following two criteria:

- Bandwidth of the peak should be less than 100 Hz.
- If two formants are close (around 150 Hz), the one with the greater magnitude was chosen.

An explanation for the use of the aforementioned methods for thresholding has been provided in the discussion section of this report.

AH 100	Root of Predictor Polynomial (Hz)	0	0	758.308	1051.41	1578.56	2954.03	3368.4	3991.47	5
	Bandwidth (Hz)	75.8437	309.633	26.5389	30.0061	506.862	48.4127	76.6419	837.536	255
	Magnitude (dB)	0.94098	0.90818	0.72513	0.963	0.9672	0.90909	0.67767	0.52891	0.34
AE 100	Root of Predictor Polynomial (Hz)	0	0	756.431	1449.36	1545.87	2449.03	3364.26	3859.19	5
	Bandwidth (Hz)	80.8557	252.971	25.5179	31.5901	397.143	40.9124	77.0077	569.525	251
	Magnitude (dB)	0.90776	0.72922	0.94989	0.48886	0.96108	0.96844	0.6071	0.90339	0.72
EE 100	Root of Predictor Polynomial (Hz)	85.6042	225.804	1501.08	2254.89	3049.57	3347.97	4769.57	5000	
	Bandwidth (Hz)	165.949	31.2696	303.13	29.0996	46.9049	72.3504	361.609	899.187	
	Magnitude (dB)	0.96147	0.81177	0.96409	0.68323	0.94276	0.91309	0.63482	0.32305	
ER 100	Root of Predictor Polynomial (Hz)	0	0	446.567	1152.19	1204.09	2673.06	3463.62	4242.92	5
	Bandwidth (Hz)	68.8219	377.822	29.6242	63.4871	27.4865	151.097	154.718	160.378	161
	Magnitude (dB)	0.81598	0.81747	0.82331	0.82706	0.96605	0.92332	0.96346	0.91715	0.62
OO 100	Root of Predictor Polynomial (Hz)	0	0	235.564	835.961	2116.01	2823.3	3501.72	4260.19	5
	Bandwidth (Hz)	70.7196	847.478	23.9209	41.4528	166.232	260.245	240.988	233.808	233
	Magnitude (dB)	0.7454	0.74542	0.73872	0.72106	0.81148	0.94924	0.97039	0.91497	0.34
AH 126	Root of Predictor Polynomial (Hz)	135.174	757.026	1044.53	1671.38	2942.82	3362.06	3561.11	5000	
	Bandwidth (Hz)	121.394	15.2535	25.2213	306.126	55.0286	93.692	377.119	197.283	
	Magnitude (dB)	0.78043	0.88893	0.93319	0.62257	0.68066	0.9688	0.98101	0.85852	
AE 126	Root of Predictor Polynomial (Hz)	159.271	756.848	1440.5	1562.49	2443.27	3362.5	3469.99	5000	
	Bandwidth (Hz)	107.322	14.3035	39.33	234.592	36.6378	172.744	130.202	550.763	
	Magnitude (dB)	0.955	0.84907	0.80487	0.50052	0.95178	0.74468	0.98219	0.87383	
EE 126	Root of Predictor Polynomial (Hz)	173.111	239.095	1422.71	2253.98	3071.74	3160.55	3469.99	5000	
	Bandwidth (Hz)	136.305	18.4433	275.578	20.7085	60.7803	190.307	105.047	386.436	
	Magnitude (dB)	0.97431	0.61532	0.87634	0.92647	0.7873	0.7073	0.97709	0.84258	
ER 126	Root of Predictor Polynomial (Hz)	197.482	481.693	1129.9	1274.9	2399.85	3300.43	4214.4	5000	
	Bandwidth (Hz)	91.8932	35.2765	19.4647	34.2533	191.097	161.07	173.443	231.532	
	Magnitude (dB)	0.74755	0.80416	0.81676	0.78652	0.95787	0.97584	0.95664	0.89094	
OO 126	Root of Predictor Polynomial (Hz)	79.1043	240.469	863.053	1588.14	2249.58	3380.51	4262.31	5000	
	Bandwidth (Hz)	170.003	17.0434	26.685	401.621	45.5967	117.349	134.134	168.247	
	Magnitude (dB)	0.80943	0.84488	0.86289	0.94431	0.60369	0.96702	0.97881	0.80765	

Fig. 5: Formants for uncorrupted signals with LPC filter order 15

AH 100	Root of Predictor Polynomial (Hz)	0	0	757.323	1048.32	1781.46	2957.96	3376.44	3900.26	5000
	Bandwidth (Hz)	84.8736	241.807	25.248	28.6257	402.797	50.4446	76.1317	884.976	251.49
	Magnitude (dB)	0.93858	0.90876	0.72904	0.96467	0.96877	0.89884	0.73796	0.6028	0.32887
AE 100	Root of Predictor Polynomial (Hz)	0	0	756.403	1448.53	1543.16	2449.93	3363.63	3749.33	5000
	Bandwidth (Hz)	82.5844	244.804	25.4656	31.7132	391.919	41.4174	77.7146	537.344	239.725
	Magnitude (dB)	0.90696	0.7399	0.94928	0.50903	0.96093	0.96851	0.6111	0.90142	0.73519
EE 100	Root of Predictor Polynomial (Hz)	0	0	227.908	1427.3	2257.36	3044.99	3342.67	4347.06	5000
	Bandwidth (Hz)	123.641	241.656	29.6872	195.324	28.8165	47.1547	70.2028	534.454	271.203
	Magnitude (dB)	0.96444	0.78235	0.96338	0.8561	0.7381	0.94247	0.91556	0.7112	0.51088
ER 100	Root of Predictor Polynomial (Hz)	0	0	438.73	1132.78	1194.95	2601.43	3295.33	4208.44	5000
	Bandwidth (Hz)	56.4659	849.992	27.6367	101.297	20.6698	175.357	186.288	181.19	183.705
	Magnitude (dB)	0.79386	0.79637	0.79129	0.80223	0.9315	0.96587	0.97436	0.88048	0.34365
OO 100	Root of Predictor Polynomial (Hz)	0	0	235.939	824.427	1736.7	2444.57	3141.66	3992.12	4672.54
	Bandwidth (Hz)	62.2813	22.0891	48.7092	180.788	210.738	198.046	246.318	274.716	0
	Magnitude (dB)	0.94063	0.97262	0.92472	0.79677	0.76734	0.77968	0.73379	0.70807	0
AH 126	Root of Predictor Polynomial (Hz)	136.6	756.797	1044.27	1746.15	2944.16	3364.53	3632.81	5000	0
	Bandwidth (Hz)	122.411	15.6834	26.2955	277.483	56.8629	91.3027	444.592	205.922	0
	Magnitude (dB)	0.9675	0.98048	0.85742	0.70561	0.93104	0.8916	0.772	0.57196	0
AE 126	Root of Predictor Polynomial (Hz)	153.482	757.073	1441.35	1585.6	2446.74	3338.3	3531.6	5000	0
	Bandwidth (Hz)	112.938	14.845	37.4844	255.079	37.6808	125.57	162.016	906.905	0
	Magnitude (dB)	0.81579	0.85402	0.95375	0.95399	0.98152	0.86769	0.72576	0.31993	0
EE 126	Root of Predictor Polynomial (Hz)	48.4169	240.494	1374.42	2254.3	3070.66	3166.36	3465.32	5000	0
	Bandwidth (Hz)	165.731	16.5158	169.964	21.9549	60.379	192.532	105.457	310.436	0
	Magnitude (dB)	0.97279	0.67699	0.87588	0.92693	0.7851	0.80768	0.97946	0.81199	0
ER 126	Root of Predictor Polynomial (Hz)	115.353	460.345	1145.34	1269.77	2466.41	3139.2	4297.3	5000	0
	Bandwidth (Hz)	145.008	37.1928	22.8144	57.1553	132.04	93.6879	198.639	346.214	0
	Magnitude (dB)	0.88893	0.7791	0.64722	0.84711	0.9307	0.97174	0.95434	0.83342	0
OO 126	Root of Predictor Polynomial (Hz)	0	0	243.158	845.324	1696.48	2474.22	3153.65	4483.94	5000
	Bandwidth (Hz)	72.9993	1628.69	12.8574	43.6856	148.006	140.973	102.415	191.827	811.828
	Magnitude (dB)	0.7858	0.87924	0.83765	0.83028	0.94658	0.98397	0.91235	0.36053	0.12916

Fig. 6: Formants for corrupted signals (SNR=30 dB) with LPC filter order 15

Fig. 7 and Fig. 8 show the above analysis for one of the single vowels – AE, at a fundamental frequency of 100 Hz, for an LPC order of 15, with and without noise at 15 dB SNR, respectively.

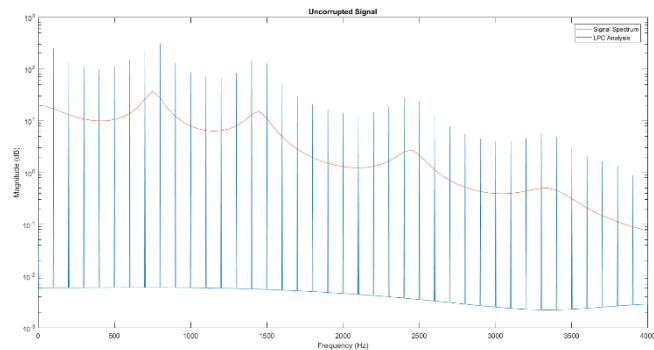


Fig. 7: Analysis of uncorrupted 'ee', for a fundamental frequency of 100 Hz with LPC filter order 15

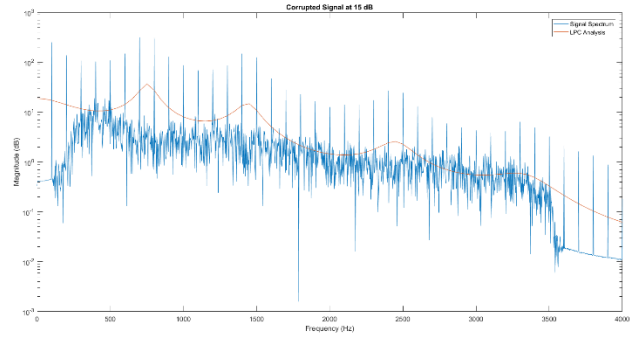


Fig. 8: Analysis of 'ee' corrupted with Speech Shaped Spectrum Noise at an SNR of 15 dB, for a fundamental frequency of 100 Hz with LPC filter order 15

#### 4. ANALYSIS OF NOISE EFFECTS ON CONCURRENT VOWELS

The concurrent vowels analyzed were AH-AE, EE-AH, EE-OO at fundamental frequencies of 100 Hz (both) and 100 Hz + 126 Hz respectively. The analysis was carried out for filter order of 31 only. The formant frequencies were identified based on the following two criteria:

- Bandwidth of the peak should be less than 50 Hz.
- If two formants are close (around 150 Hz), the one with the greater magnitude was chosen.

An explanation for the use of the aforementioned methods for thresholding and the results of using the same have been comprehensively discussed in the following section.

### III. RESULTS AND DISCUSSION

#### A. Single Vowels

The analysis of single vowels showed that order 15 LPC filter was more suitable as compared to order 31. [4] The higher order LPC filter returned intermediate local maxima which could be falsely interpreted as formant frequencies. The roots of the prediction polynomial were estimated. However, to truly interpret a certain root as the formant frequency, two methods were used, namely thresholding based on bandwidth and magnitude. The formants are sharp peaks in the frequency spectrum. Hence the ones with a lower bandwidth and hence higher sharpness were used to determine the formants. After the bandwidth thresholding, magnitude thresholding was performed, wherein if two peaks occurred close to each other, (in a range of  $\approx 150$  Hz), the one with the higher magnitude was chosen as the Formant frequency.

Uncorrupted	F0	F1	F2	F3
"ah" 100Hz	758.3	1051.4	2954.0	3368.4
"ah" 126Hz	757.0	1044.5	2942.8	3362.1
"ae" 100Hz	756.4	1449.4	2449.0	3364.3
"ae" 126Hz	756.8	1440.5	2443.3	-
"ee" 100Hz	225.8	2254.9	3049.6	3348.0
"ee" 126Hz	239.1	2254.0	3071.7	-
"er" 100Hz	446.6	1204.1	2673.1	-
"er" 126Hz	481.7	1274.9	-	-
"oo" 100Hz	235.6	836.0	-	-
"oo" 126Hz	240.5	863.1	2249.6	-

**Table 1: Results for Uncorrupted Signals at LPC order of 15**

SNR 30 dB	F0	F1	F2	F3
"ah" 100Hz	757.3	1048.3	2958.0	3376.4
"ah" 126Hz	756.8	1044.3	2944.2	3364.5
"ae" 100Hz	756.4	1448.5	2449.9	3363.6
"ae" 126Hz	757.1	1441.3	2446.7	-
"ee" 100Hz	227.9	2257.4	3045.0	3342.7
"ee" 126Hz	240.5	2254.3	3070.7	-
"er" 100Hz	438.7	1194.9	-	-
"er" 126Hz	460.3	1269.8	3139.2	-
"oo" 100Hz	235.9	824.4	-	-
"oo" 126Hz	243.2	845.1	-	-

**Table 2: Results for SNR value of 30 dB at LPC order of 15**

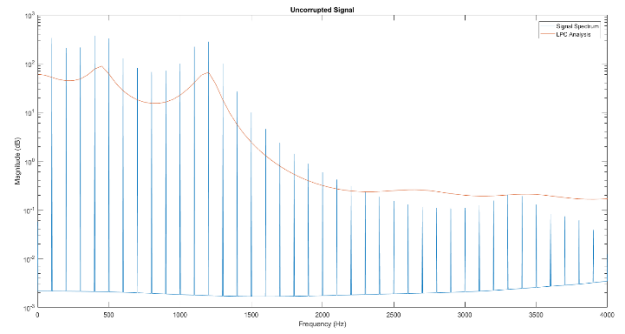
SNR 15 dB	F0	F1	F2	F3
"ah" 100Hz	751.9	1041.1	3421.8	-
"ah" 126Hz	755.5	1047.4	3284.4	-
"ae" 100Hz	755.4	1443.7	2455.3	3345.7
"ae" 126Hz	759.2	1442.7	2480.7	3238.9
"ee" 100Hz	217.9	2269.3	3062.2	3376.9
"ee" 126Hz	233.2	2275.6	3068.9	3411.8
"er" 100Hz	442.1	1176.0	3228.7	-
"er" 126Hz	432.7	1167.7	2705.7	3236.3
"oo" 100Hz	198.3	-	3183.3	-
"oo" 126Hz	231.9	2729.5	3251.4	-

**Table 3: Results for SNR value of 15 dB at LPC order of 15**

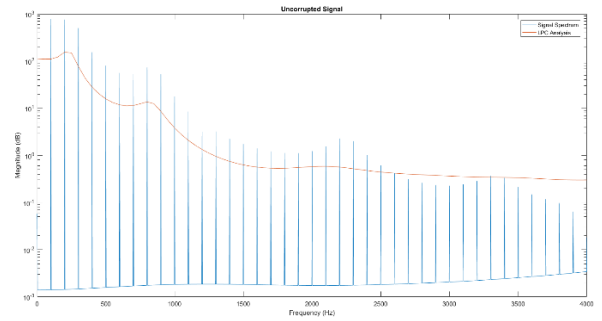
SNR 5 dB	F0	F1	F2	F3
"ah" 100Hz	784.0	-	3350.1	-
"ah" 126Hz	808.4	-	3259.0	-
"ae" 100Hz	755.0	1427.1	2567.5	3216.2
"ae" 126Hz	299.4	756.1	1435.6	3307.5
"ee" 100Hz	-	-	3065.7	3378.8
"ee" 126Hz	256.2	-	3287.8	-
"er" 100Hz	450.5	1172.9	1726.6	2864.9
"er" 126Hz	435.6	1149.8	2731.1	3251.0
"oo" 100Hz	233.4	2779.3	3276.7	-
"oo" 126Hz	259.3	2723.3	3248.6	-

**Table 4: Results for SNR value of 5 dB at LPC order of 15**

The results show that the formant frequencies of a certain vowel with different fundamental frequencies (F0) have approximately the same Formant frequencies, as expected. Vowels like 'ae' and 'er' have stronger and more prominent formant peaks as compared to 'oo'. (Figs. 7, 10 and 11) From the tables, it's clear that certain vowels are more susceptible to noise as compared to the others.

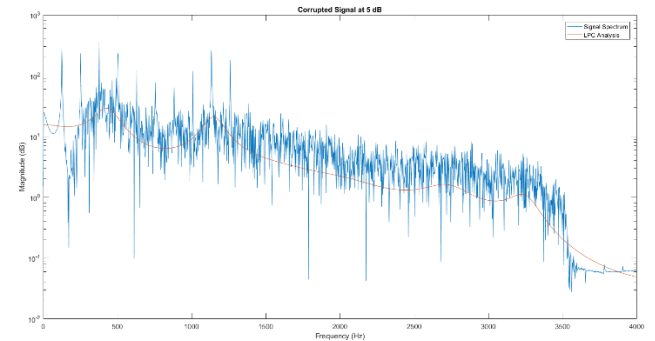


**Fig. 10: Frequency Spectrum of uncorrupted 'er' at a fundamental frequency of 100 Hz with LPC filter order 15 (More prominent formant peaks are seen)**



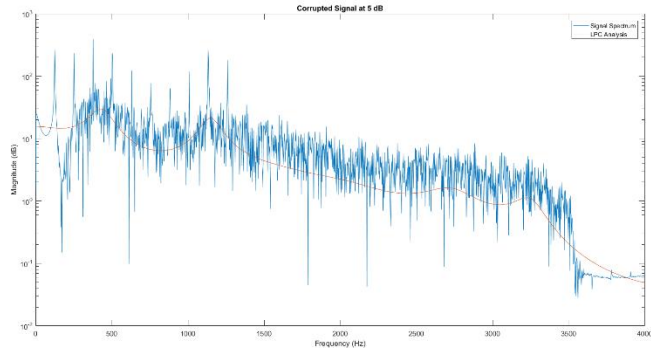
**Fig. 11: Frequency Spectrum of uncorrupted 'oo' at a fundamental frequency of 100 Hz with LPC filter order 15 (Less prominent formant peaks are seen)**

However, vowels with lesser fundamental frequency (100 Hz) are more immune to noise. 'er' and 'ae' be recognized at an SNR of 5dB (Figs. 12 and 13), unlike all the other samples. However, 'oo' couldn't be recognized at an SNR of 15dB (Fig. 14). To identify single vowels, it is sufficient to test their formant frequencies F1 and F2 and the difference between the two [7].

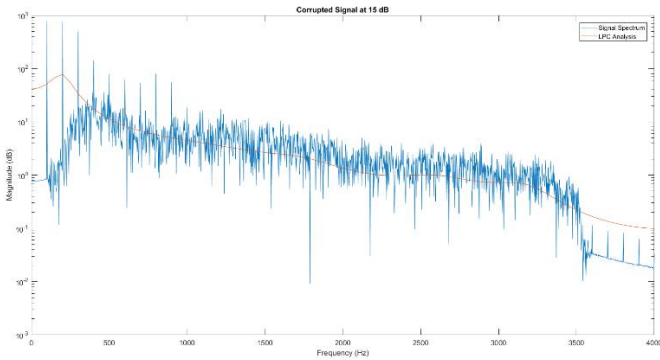


**Fig. 12: Frequency Spectrum of 'er' corrupted with noise of 5dB at a fundamental frequency of 100 Hz with LPC filter order 15 (More immune to noise)**





**Fig. 13: Frequency Spectrum of 'er' corrupted with noise of 5dB at a fundamental frequency of 126 Hz with LPC filter order 15 (Less immune to noise)**



**Fig. 14: Frequency Spectrum of 'oo' corrupted with noise of 15dB at a fundamental frequency of 100 Hz with LPC filter order 15 (Less immune to noise)**

### B. Concurrent Vowels

A similar analysis was done for Concurrent Vowels. However, it was observed that the filter order had to be increased from 15 as used for Single vowels. The filter order had to be chosen in such a way so that it estimates the formant frequencies which correspond to the formant frequencies of the constituting vowels. Hence, LPC of order 31 was sufficient for the above case.

The bandwidth thresholding was performed for a bandwidth for <50Hz and magnitude thresholding was done for a range of 150 Hz.

Uncorrupted	F'1	F'2	F'3	F'4	F'5	F'6
"ah" 100 Hz						
"ae" 100 Hz	765.3	982.7	1446.8	2475.9	2998.6	3356.6
"ee" 100 Hz						
"ah" 100 Hz	169.2	728.8	888.7	1072.0	2332.1	2974.6
"ee" 100 Hz						
"oo" 100 Hz	141.6	296.9	850.9	2259.0	3072.4	
"ah" 100 Hz						
"ae" 126 Hz	760.5	1016.1	1501.9	2482.3	2984.0	3381.0
"ee" 100 Hz						
"ah" 126 Hz	174.0	753.4	996.7	2276.6	2967.6	3135.3
"ee" 100 Hz						
"oo" 126 Hz	273.3	876.8	2296.2	2996.1	3145.9	3366.8

**Table 5: Results for uncorrupted signals at LPC order of 31**

SNR 30dB	F'1	F'2	F'3	F'4	F'5	F'6
"ah" 100 Hz						
"ae" 100 Hz	762.8	983.9	1449.1	2478.6	3001.2	-
"ee" 100 Hz						
"ah" 100 Hz	175.4	738.5	1081.7	2250.1	3007.7	3392.6
"ee" 100 Hz						
"oo" 100 Hz	285.3	824.5	2269.2	3368.7	-	-
"ah" 100 Hz						
"ae" 126 Hz	760.0	1017.1	1502.3	2488.0	2968.0	3392.6
"ee" 100 Hz						
"ah" 126 Hz	162.8	751.9	1001.5	2265.9	3006.2	3395.2
"ee" 100 Hz						
"oo" 126 Hz	272.4	872.1	2280.2	3013.6	3381.6	3924.5

**Table 6: Results for SNR value of 30 dB at LPC order of 31**

SNR 15dB	F'1	F'2	F'3	F'4	F'5	F'6
"ah" 100 Hz						
"ae" 100 Hz	755.5	984.4	1449.9	-	-	-
"ee" 100 Hz						
"ah" 100 Hz	155.6	751.6	1007.5	2261.3	3389.7	-
"ee" 100 Hz						
"oo" 100 Hz	153.8	758.1	1017.1	1491.3	3380.4	-
"ah" 100 Hz						
"ae" 126 Hz	146.2	301.1	2262.9	-	-	-
"ee" 100 Hz						
"ah" 126 Hz	161.4	748.9	1060.1	2267.0	-	-
"ee" 100 Hz						
"oo" 126 Hz	158.0	273.4	2264.7	3028.0	-	-

**Table 7: Results for SNR value of 15 dB at LPC order of 31**

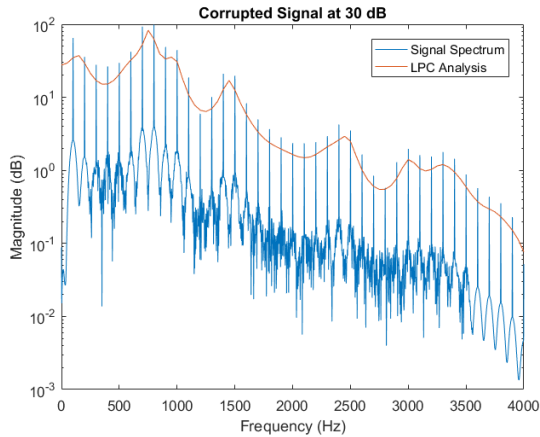
SNR 5dB	F'1	F'2	F'3	F'4	F'5	F'6
"ah" 100 Hz						
"ae" 100 Hz	444.0	752.5	992.1	-	-	-
"ee" 100 Hz						
"ah" 100 Hz	156.0	411.4	750.4	1010.7	3376.1	-
"ee" 100 Hz						
"oo" 100 Hz	448.0	756.7	1028.4	3373.2	-	-
"ah" 100 Hz						
"ae" 126 Hz	163.8	3362.2	-	-	-	-
"ee" 100 Hz						
"ah" 126 Hz	422.9	761.7	1032.0	-	-	-
"ee" 100 Hz						
"oo" 126 Hz	199.5	3359.7	-	-	-	-

**Table 8: Results for SNR value of 30 dB at LPC order of 31**

The results obtained show that formant frequencies obtained for concurrent vowels do not necessarily correspond to the formant frequencies of the constituting vowels. This can be attributed to the following reasons:

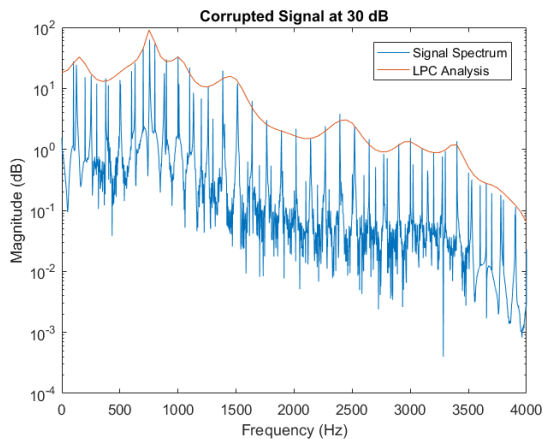
- The formant frequencies of the two vowels are same or very close to each other ( $\approx 50$  Hz). The case of 'ah' (100 Hz) and 'ae' (100 Hz) can be considered here. Their F1 frequencies are 758 Hz and 756 Hz, which shows up as F'1 (765.3 Hz) in the formant representation of their concurrent vowel. (Fig. 15)

- b. In the case of vowels with same fundamental frequencies, the harmonics, situated at integral multiples of the fundamental frequencies, superimpose to give maxima, which does not necessarily correspond to any formant frequency of any of the constituting vowel. Eg. F<sub>3</sub> of 'ee'(100 Hz) and 'ah'(100 Hz).



**Fig. 15: Frequency Spectrum of 'ah-ae' corrupted with noise of 30 dB at a fundamental frequency of 100 Hz (both) with LPC filter order 31 (F<sub>1</sub> frequencies are very close to each other which shows up at F<sub>1</sub>)**

The concurrent vowels are much more prone to noise as can be seen from the attached figure. Also the vowels with different fundamental frequencies (F<sub>0</sub>) are less prone to noise as compared to the ones with same fundamental frequency [8]. (Figs. 15 and 16).



**Fig. 16: Frequency Spectrum of 'ah-ae' corrupted with noise of 30 dB at a fundamental frequency of 100 Hz (ah) and 126 Hz (ae) with LPC filter order 31 (Less prone to noise)**

#### IV. CONCLUSION AND SCOPE FOR FURTHER RESEARCH

From the analyses above it the authors conclude that LPC analysis isn't very efficient in identifying the formants in case of concurrent vowels. However, the analysis works well enough

for single vowels. Another method to identify concurrent vowels is with the help of a neural cancellation filters which are capable of segregating weak targets from competing harmonic backgrounds. [9]

Secondly, the authors conclude that for identifying the formants, bandwidth thresholding (100 Hz for single vowels and 50 Hz for concurrent vowels) is necessary. This however is ineffective for higher formants (F<sub>3</sub>, F<sub>4</sub> etc.) because their bandwidth is larger than that of F<sub>1</sub> and F<sub>2</sub>. To account for this problem, dynamic thresholding can be used.

The autocorrelation method was used for finding out the predictor polynomial coefficients. These coefficients can be calculated using the Covariance method.

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## APPENDIX:

### A. Code for plotting the Graphs:

```
close all;
clear all;

%SSN Generation
%*****
[noise
Fs]=audioread('SpeechSpectrumShapedNoise.wav');
noise=noise(4000:7999);
%*****
[x11 Fs]=audioread('ah_ae_0.wav');
[x21 Fs]=audioread('ah_ae_4.wav');
[x31 Fs]=audioread('ee_ah_0.wav');
[x41 Fs]=audioread('ee_ah_4.wav');
[x51 Fs]=audioread('ee_oo_0.wav');
[x12 Fs]=audioread('ee_oo_4.wav');
audio=[x11, x21, x31, x41, x51, x12];

for j=1:6
    a=audio(:,j);
    x=decimate(a,10);
    audio_uncorrupted(:,j)=x;
    SNR=5;
    rms_noise=rms(x)*10^(-0.05*SNR);
    noise=(rms_noise/rms(noise)).*noise;
    x_corrupted=x+noise;
    audio_corrupted(:,j)=x_corrupted;
end

Fs=Fs*0.1;
figure;
hold on;
t=1/Fs:1/Fs:length(x)/Fs;
plot(t,x);
plot(t,x_corrupted);
xlabel('Time(s)');
xlim([0.1 0.13]);
ylabel('Magnitude');
title('Time Domain Signal');
legend('Uncorrupted Signal','Signal at SNR =
5dB')

f=linspace(0,Fs,length(x));
for j=1:6;
    y=fft(audio_uncorrupted(:,j));
    figure;
    semilogy(f,(abs(y)));
    xlabel('Frequency (Hz)');
    ylabel('Magnitude (dB)');
    hold;
    a=lpc(audio_uncorrupted(:,j),31);
    b=1;
    [h,w]=freqz(b,a,100);
    w=w*Fs/(2*pi); % w is assigned as formant
frequency
    semilogy(w,(abs(h)));
    xlim([0 4000]);
    legend('Signal Spectrum','LPC Analysis')
    title('Uncorrupted Signal');
end

for j=1:6;
    y=fft(audio_corrupted(:,j));
    figure;
    semilogy(f,(abs(y)));
    xlabel('Frequency (Hz)');
    ylabel('Magnitude (dB)');
    hold;
    a=lpc(audio_corrupted(:,j),31);
    b=1;
    [h,w]=freqz(b,a,100);
    w=w*Fs/(2*pi); % w is assigned as formant
frequency
    semilogy(w,(abs(h)));
```

```
xlim([0 4000]);
legend('Signal Spectrum','LPC Analysis')
title('Corrupted Signal at 5 dB');
end
```

### B. Code for Generating the Roots of LPC Prediction Polynomial

```
close all;
clear all;

%SSN Generation
%*****

[noise
Fs]=audioread('SpeechSpectrumShapedNoise.wav');
noise=noise(4000:7999);
%*****
[x11 fs]=audioread('ah_100.wav');
[x21 fs]=audioread('ae_100.wav');
[x31 fs]=audioread('ee_100.wav');
[x41 fs]=audioread('er_100.wav');
[x51 fs]=audioread('oo_100.wav');
[x12 fs]=audioread('ah_126.wav');
[x22 fs]=audioread('ae_126.wav');
[x32 fs]=audioread('ee_126.wav');
[x42 fs]=audioread('er_126.wav');
[x52 fs]=audioread('oo_126.wav');
disp(fs);
audio=[x11, x21, x31, x41, x51, x12, x22, x32, x42,
x52];
audio_corrupted=zeros(4000,10);
audio_uncorrupted=zeros(4000,10);
for j=1:10
    a=audio(:,j);
    x=decimate(a,10);
    audio_uncorrupted(:,j)=x;
    SNR=5;
    rms_noise=rms(x)*10^(-0.05*SNR);
    noise=(rms_noise/rms(noise)).*noise;
    x_corrupted=x+noise;
    audio_corrupted(:,j)=x_corrupted;
end

f=linspace(0,Fs,length(x));
OUTPUT_lpc=zeros(18,9);
for j=1:10;
    disp(j);
    a=lpc(audio_uncorrupted(:,j),15);
    b=1;
    [h,w]=freqz(b,a,100);
    w=w*Fs/(2*pi); % w is assigned as formant
frequency
    rts=roots(a);
    rts = rts(imag(rts)>=0);
    angz = atan2(imag(rts),real(rts));
    [frqs,indices] = sort(angz.*(Fs/(2*pi)));
    bw = -1/2*(Fs/(2*pi))*log(abs(rts(indices)));
    nn = 1;
    OUTPUT_lpc((j-1)*3+1,1:length(frqs))=frqs;
    OUTPUT_lpc((j-1)*3+2,1:length(bw))=bw;
    OUTPUT_lpc((j-1)*3+3,1:length(rts))=abs(rts);
end
```



