

# Spectral Moment vs. Bark Cepstral Analysis of Children's Word-initial Voiceless Stops H. Timothy Bunnell, James Polikoff, and Jane McNicholas Speech Research Laboratory, Alfred I. duPont Hospital for Children, Nemours Children's Clinic, Wilmington, Delaware, USA (bunnell@asel.udel.edu)

# Procedure

Spectral moments analysis has been shown to be effective in deriving accussis features for classifying voccless stop release bursts [11], and is an analysis method that has commonly been cited in the dinical phonetics therature dealing with children's disourced speech. In this study, we compared the classification of stops //, //, and /// based on spectral moments with classification to based on an equal number of Bark Capstrum coefficients. Uterance-initial ///, // and //( 1338 samples in all yeare coefficients) therance-initial ///, // and //( 1338 samples in all yeare coefficients) therance-initial ///, // and //( 1338 samples in all yeare coefficients). an expan induced in the Constant Committee in the Constant of moment features at all four time intervals and vielded 78.0% correct discrimination. The best model of similar rank based on Bark cepstrum features vielded 86.6% correct segment discrimination

Spectral moments analysis, which describes speech spectrum shape in terms of its mean, variance, skewness, and kurtosis, has become a popular method of analysis for obstruent segments, especially in the literature on clinical phonetics [1-5]. Moments are attractive as spectral features because they are easy and unambiguous to calculate, have been shown to provide better segment discrimination than LPC coefficients for some segments [1], and have been shown to be useful in detecting subtle yet important differences in obstruents and fricatives produced by children and adults (e.g., [2-5]).

However, there are limitations to the range of phonetic segments for which spectral moments are believed to be appropriate [6], and, since the initial report of [1] we are not aware of any that have directly compared spectral moments to other equally tractable acoustic feature sets. In particular, there has been no direct comparison of spectral moments with the Mel or Bark cepstral feature sets that are commonly used as acoustic features for speech recognition [7].

The present study directly compared cepstral features and spectral moments features for the discrimination and classification of burst spectra from utterance-initial voiceless plosives /p/, /t/, and /k/. Additionally, we sought to approach this comparison using a much larger number of speakers and tokens than previous studies have reported, and to use statistical methods that would afford a better sense of the generality of our results [8]. Thus, for the present analyses, we report both immediate "discrimination" results, that is, how well models based on the acoustic feature sets discriminated cases within the full dataset on which they were trained, and also the results of 10-fold crossvalidation of the models in which results are reported for classification of unseen cases.

## Subjects

The subjects were a group of 208 children, whose ages ranged from six to eight years old. Each subject recorded a series of 100 individual English words in isolation for a corpus of children's speech that was recorded as part of an unrelated project in the Speech Research Laboratory.

## Stimul

Burst segments were extracted from word-initial voiceless stop consonants /p/ /t/ and /k/ and an attempt was made to balance phonemic context such that for each class of voiceless stop, the number and type of following phonemes occurred in roughly equal numbers. This resulted in a balanced set with 446 bursts to be analyzed for each stop. Each extracted burst was aligned so that the burst started at 20msec from the beginning of the waveform file (see Figure 1 for an example). Silence was padded to the end of the file to ensure that the total file was 100msec long.

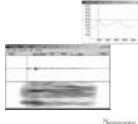
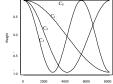


Figure 1. Release burst for word-initial [k] extracted from the word cultivate as spoken by a seven-year-old girl. The vertical line in the waveform spectrogram display indicates the location from which the spectral cross section (smaller panel) was computed using an LPC analysis with 20 msee window. 5

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Two acoustic analysis techniques were applied to the burst data. First, the moments program [9] was used to compute linear- and bark-frequency spectral moments in a sequence of four frames based on 20 msec windows beginning with a frame centered on the burst release and stepping through the subsequent friction and aspiration in 10 msec steps.



The second acoustic analysis duplicated the framing parameters of the moments analysis using a Bark cepstrum analysis program developed locally. In this analysis, six cepstral coefficients (DC and first five cosine terms - see

contribution to obstruent classification

and subsequent reports often omit use of the variance

component as not making a significant independent

Table 2. Percentage correct consonant classification from

85.0

86.6

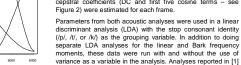


Figure 2. First four terms of Cepstrum indicating their relation to spectrum energy

Results are presented first for LDA discrimination. Table 1 shows the results for spectral moments data. All analyses used the RMS amplitude of the associated frame plus three or four spectral moments (i.e., a maximum of five parameters per frame). With just one exception, including the variance component in these analyses lead to better discrimination. With two exceptions, Bark-frequency moments data led to better stop discrimination than did linear-frequency moments.

Table 2 shows the results of corresponding LDA analyses using Bark cepstral coefficients. As with moments analyses, including additional analysis frames leads to improved discrimination. Overall, the six Bark cepstral coefficients provided significantly better discrimination of the stops than did the best spectral moments models (87.1 versus 78.0 percent correct). To demonstrate that this was not due simply to model rank, additional LDA analyses were run in which only the first five Bark cepstral coefficients were used. These analyses show that discrimination remains substantially better than the moments models of equal rank.

		Table 1. Percentage	ssificatio	n. Data	Table 2. Percentage correct consonant classification from							
		are averaged over ph	oneme	identity.			LDA analyses using Bark Cepstral coefficients. The first row					
			Burst	Burst+	Burst+	All	shows data broken o				es). The	
			Only	10	10+20		second row presents					
		Linear with Variance	63.8	74.4	75.9	76.1	classification overall					
		Bark with Variance	65.7	75.2	77.1	78.0	(dropping the 6 <sup>th</sup> coe					
		Linear w/o Variance	61.0	74.0	75.4	75.2		Burst	Burst+	Burst+	All	
		Bark w/o Variance	66.3	73.2	73.4	76.3		Only	10	10+20		
							Six parameter fit	p 77.6	89.0	89.7	90.6	
								t 63.9	82.2	83.2	85.0	
								k 67.7	83.0	85.0	85.9	
							Overall	69.7	84.8	86.0	87.1	
	4 -						Five parameter fit	69.5	83.9	85.7	86.6	
101	4 - 5 -	4 -2		2		P P P	Figure 3 shows the discrimination of the three stops by plotting their locations relative to the first and second linear discriminant functions for the best Barl cepstral model. The first linear discriminant primarith separates /k/ and /l/ bursts from /p/ bursts, while the second discriminant primarily separates /k/ from /l/.					
			LD1									

Figure 3. Position of each case on linear discriminant 1 (LD1) ersus linear discriminant 2 (LD2)

Results from 10-fold cross validation of the best LDA models are shown in Tables 3 and 4. As expected, classification of unseen cases is less accurate than discrimination within the training dataset. However, the overall better performance of the Bark Cepstral feature set remains evident in these analyses.

oments da	ta.			Predicted				
	I	Predicted		True	/k/	/p/	/t/	
True	/ <b>k</b> /	/ <b>p</b> /	/t/	/k/	376	· P' 9	6	
/ <b>k</b> /	310	51	85	,	27	400	1	
/ <b>p</b> /	36	365	45	/p/			-	
/t/	36	46	364	/t/	44	31	37	
ercentage	Correct = 7	7.65		Percentag	e Correct = 3	35.72		

As with previous analyses of stop release bursts (e.g., [1, 10]), we found that information in successive analysis frames distributed over the release burst contributes independently to accurate classification of stops. Unlike the initial reports of spectral moment analyses [1] which indicated that variance did not contribute to classification accuracy, we found generally better classification accuracy when all four moments were used. Our results also differed from the original report in finding that the Bark features lead to better overall performance than did linear frequency based moments. We attribute these differences to sampling error with the smaller dataset used by [1].

Perhaps the most important result of the present analyses, however, is the finding that Bark Cepstral features perform better than do spectral moments in overall classification accuracy. Given the substantial improvement in discrimination and classification performance observed here for the Bark-cepstral dataset (around 8 percent in the cross-validated analysis), we would discourage investigators from using spectral moments as acoustic features unless they wish to address specific hypotheses regarding features like the spectral mean energy or skewness. In particular, investigators interested in finding and characterizing general spectral differences, for example, to observe changes in the spectral characteristics of segments during speech training, may find that Bark-Cepstral features afford better ability to discriminate small changes than to spectral moments

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