

## Training Set of Data Bin for Small Black Pixels Neighborhood Recognition of Each Boundary

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### ABSTRACT

*We first describe how to “fuzzify” the estimated binary columns to create a [0,1]-valued column. We refer to this [0,1] -valued column as the soft segmentation column of the noisy spectrogram column. Similarly to the collection of soft segmentation columns as the soft segmentation image, or simply as the soft segmentation. The band-dependent posterior probability that the hard segmentation column value of pixel is 1, given that bin and the binary values in the neighborhood configuration of the pixel are equal. Symbolically, each pixel of the soft segmentation column is set to the soft segmentation column value of the pixel in a row was set to zero.*

### KEYWORDS:

#### 1. INTRODUCTION

Spectrograms are more likely to have arisen from signal segments containing noise only (rather than speech and noise). For this reason, we initially define the bin delimiters in each bin. In other words, the band-dependent bin delimiters are set sequentially; the next band-dependent bin delimiter was set to the lowest gray scale value with corresponding noisy grayscale values in that range appear in the training set [1-5]. The denominator, 256, was chosen arbitrarily to be the maximum allowable number of bins. For some noisy grayscale

value, corresponding ones in binary images become more probable than zeros. This means that for some noisy grayscale value, it is more likely that speech was present than not. The last bin is defined to contain strictly less than zeros [4-5]. Sampled the prior distribution using the Metropolis Algorithm. We then estimated the percent of black pixels in each band and compared it to the percent of black pixels in the training set. Several other neighborhoods were considered for the binary prior. We found that with our banding we could accurately estimate cliques and separator distributions

containing more than five pixels from the given training set. By that we mean that for cliques containing more than five pixels, we found that there existed at least one binary clique configuration that appeared less than thirty times in the training set. Furthermore, not all collections of cliques formed neighborhoods for which Graphical Model theory could be used. These constraints were the reason for the chosen small neighborhood. For each band, the bin delimiters and the number of bins used were stored, which were not the same for the different bands and SNR values. The reason for such binning is to ensure that for each bin  $q$ , the counts in  $\text{hist0}[q, b]$  and  $\text{hist1}[q, b]$  are at least  $b \text{ count } 1 [b] / 256c$ . That way, small bin counts that lead to poor estimation of the noise information probability are avoided. Several other binning methods were tested, including uniform linear binning and uniform log binning [5]. Both the uniform linear and uniform log binning contained bins whose histogram counts were smaller, less than 30, that is the reason that we used the much more complex binning described above. It is known that the probability of an image appearing in the Metropolis sequence is as likely as the probability of the image in the distribution.

## 2. MATERIALS AND METHODS

We take the estimated binary column and the noisy grayscale spectrogram column to estimate the clean grayscale spectrogram column that corresponds to the unknown clean speech signal. The meaning of such a column is that it locally estimates the

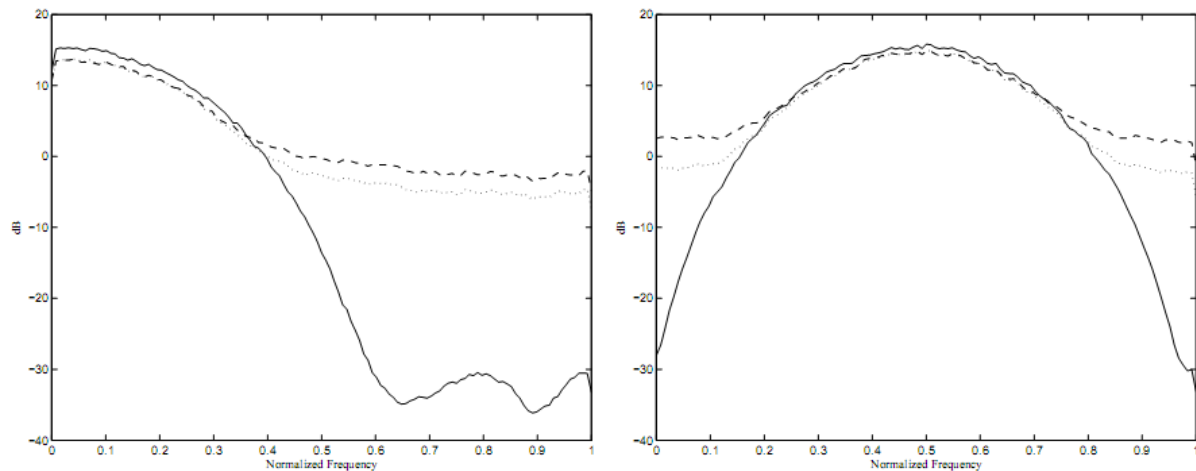
conditional probability that a time-frequency location in the spectrogram contains clean speech. In the implementation, the posterior column values are set using one look-up table value from the float table. Notice that these images are indeed smoother than the hard segmentations. The paper consisted of two parts. First, we estimated the clean speech signals from the estimated clean spectrograms with several values of  $K$  for one word. We then looked at the spectrograms of the estimated clean speech signals. Ideally, these two spectrograms (the estimated clean speech spectrogram and the spectrogram of the estimated clean speech) should be the same. We found that the spectrogram of the estimated clean speech signal with  $K=20$  iterations looked closest to the estimated clean spectrogram. Next, we chose a column for which the estimated clean spectrogram and the spectrogram of the estimated clean speech signal visually differed. Notice that the areas that were set to white in the hard segmentations, did not necessarily remain white in the soft segmentation. That way area in which the hard segmentation may have made the “wrong” decision, the noisy speech signal is not completely eliminated. Furthermore, areas which contained high values in the noisy spectrograms, were preserved with a lower value. This makes sense and is a desired behavior.

## 3. RESULT AND DISCUSSION

Fourier Transform finite-length, real-valued, discrete time sequence into an image. Henceforth, by sequence, we mean a finite-

length, real-valued discrete time sequence. To be precise, each operator  $\mathcal{S}$  in the family is determined by three positive integer parameters ( $L$ - the length of the sequence,  $I$ - the number of rows in the DATA BIN, and  $s$ - the time skip step) and a window function  $W$ . The window function  $w$  is a sequence of

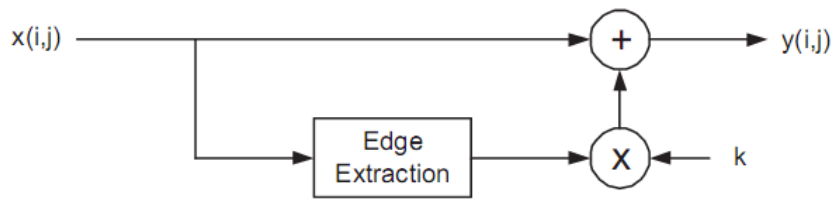
$2I-2$  real numbers. The domain is the set of sequences  $x$  of  $L$  real numbers,  $x[0], x[1], \dots, x[L-1]$ . The range of  $\mathcal{S}$  is the set of  $I \times J$ -dimensional complex-valued images, where for  $i < I$  and  $j < J$ . Figure 1 illustrates data bit percentage for signals.



**Fig.1.** Data bit percentage for signals.

Spectrograms contain a wide range of real values. We therefore performed some post-processing of the spectrograms to get images that are useful. First a new image was created that contains the spectrogram values in decibels (dB). The decibel values were calculated from the spectrogram values. We chose the value 100 since it is a commonly used value. Next we set the value of the maximum amplitude to be the largest dB value in the new image. Dynamic range is the range of viewable dB values and was set to 50 dB since that is the commonly used value. Therefore, the minimum amplitude is defined as  $minimum\ amplitude = maximum\ amplitude - dynamic\ range$ . Figure 2: Edge extraction block diagram for fast recognition

of boundary. In the new image, all dB values below the minimum amplitude were set to the minimum amplitude. Finally the modified dB values were converted into a 0-255 integer scale by Henceforth, such a post-processed image of the spectrogram is referred to as the spectrogram image; these are the images used for display in this text. Since the two images are scaled independently, they are visually hard to differentiate. To test the accuracy of our spectrogram software we visually compared the spectrogram images produced by our software to those produced with the same parameters using [2].



**Fig.2.**Edge extraction block diagram for fast recognition of boundary

#### 4. CONCLUSION

The “fuzzification” described here was more specific to the problem at hand and seemed to provide results that were better than expected with the simple “fuzzification” techniques. Next, we estimated the clean grayscale column that represents the unknown clean speech segment by multiplying the noisy grayscale spectrogram column by the soft segmentation column, pixel by pixel. This can be considered as using the soft segmentation column to mask the noisy grayscale spectrogram column. Since the soft segmentation column is a  $[0,1]$ -valued column, the effect of the multiplication of the soft segmentation column by the noisy spectrogram column is that the spectrogram values are dampened.

#### REFERENCE

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