Spatial Histogram Equalization of Complex-valued Acoustic Spectra in Modulation Domain for Noise-Robust Speech Recognition

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Abstract—This paper proposes to enhance the complex-valued acoustic spectrograms of speech signals via the technique of histogram equalization (HEQ) to produce noise-robust features for recognition. The presented method extends our previous work in the task of spectrogram enhancement and has two significant aspects. First, we process the real and imaginary parts of acoustic spectrograms separately, and therefore both of the corresponding magnitude and phase components can be enhanced implicitly. Second, we apply FIR filters to the intra-frame acoustic spectra to acquire the respective local structural statistics, which are subsequently employed to perform various types of HEQ on the acoustic spectrograms for robustifying the resulting speech features. All experiments were carried out on the Aurora-2 database and task. The performance of the presented methods was thoroughly tested and verified by comparisons with other well-known robustness methods, which reveals the capability of our methods in promoting the noise robustness of speech features.

I. INTRODUCTION

Environmental sources of disturbance, such as ambient noise, interferences caused by recording devices and transmission channels, often give rise to a severe mismatch between the acoustic conditions for training and testing speech data. Such a mismatch will no doubt cause significant degradation in the performance of an automatic speech recognition (ASR) system. In order to deal with the environmental mismatch problem, numerous methods have been proposed in literature to improve ASR robustness over the past few decades, which can be broadly split into the following three categories: enhancement, normalization and adaptation \[6, 7, 16\], while these techniques can be conducted either in the speech feature domain or in the acoustic model domain.

Among the various types of speech feature representations, Mel-frequency cepstral coefficients (MFCCs) \[11\] have been proven to be one of the most effective features for speech and speaker recognition tasks. MFCCs are derived on top of the linguistic information cues that are part and parcel for speech recognition. In addition, a rich family of methods that explicitly employ filtering on the temporal sequence of logarithmic critical-band spectra or MFCCs have been developed. Representative methods include, but are not limited to, RASTA \[4\], CMVN plus ARMA filtering (MVA) \[2\] and temporal structure normalization (TSN) \[15\]. These temporal filtering approaches in general emphasize the relatively low varying components (except for the DC part) of the feature temporal sequence, which encapsulate ample linguistic information cues that are part and parcel for speech recognition. Yet another stream of thought focuses on directly modifying the (cepstral) modulation spectrum, which is specifically referred to as the Fourier transform of the temporal sequence of MFCCs. Methods developed along this stream of research include, among others, spectral histogram equalization (SHE) \[9\] and modulation spectrum replacement/filtering (MSR/MSF) \[8\].

In the aforementioned temporal processing techniques, the intra-frame features are often assumed mutually uncorrelated implicitly, and thereby they can be processed in a separate manner. However, in \[14\] the authors claimed that the uncorrelatedness assumption is not necessarily true, revealing that in the method of CHN, even though each cepstral channel is processed by histogram equalization (HEQ) in isolation, a significant histogram mismatch still exists among the training
and testing cepstral features for the low-pass filtered (LPF) and high-pass filtered (HPF) portions of the intra-frame cepstra. To ameliorate this problem, the method of spatial-HEQ presented in [14] manages to perform HEQ on the LPF and HPF portions to eliminate such a mismatch for the CHN-preprocessed cepstra.

We recently present a promising HEQ-based feature extraction algorithm, termed as MAS-HEQ, [5] to reduce the noise effect on the acoustic spectral features in the modulation domain for robust speech recognition. In MAS-HEQ, the real and imaginary components of the complex-valued acoustic spectrogram associated with an utterance are individually converted to the modulation domain via discrete Fourier transform (DFT), and the magnitude part of the resulting modulation spectra are processed with HEQ accordingly.

Building on these observations, this paper proposes a novel noise-robust feature extraction scheme that extends the stream of HEQ research in two significant aspects. First, referring to the idea of MAS-HEQ, the real and imaginary acoustic spectra are separately processed, and thus both of the corresponding magnitude and the phase components can be enhanced implicitly. Second, a series of FIR filters are designed and then applied to the intra-frame acoustic spectra to produce sub-band components (as what spatial-HEQ does to intra-frame cepstra). In this way, some or all sub-band acoustic spectra are in turn processed with HEQ in the modulation domain.

The rest of this paper is organized as follows. Section II provides essential background on HEQ and briefly describes how it can be employed for robust ASR. Section III elucidates the notion and various instantiations of the proposed methods. The experimental settings and a series of ASR experiments are presented in Section IV. Finally, Section V concludes this paper and suggests avenues for future work.

II. HISTOGRAM EQUALIZATION

Histogram equalization (HEQ) is a simple and effective feature normalization technique for robust speech recognition. Most of the HEQ-based methods have been developed under the assumptions that the transformed speech feature distributions of the noisy (or testing) data should be closely identical to that of the reference (or training) data and each feature vector dimension can be normalized independently of each other. Under the above two assumptions, the aim of HEQ is to find a transformation that can convert the distribution of each feature vector component of the input (or testing) speech into a predefined target distribution which corresponds to that of the training (or reference) speech. In the HEQ algorithm, the mapping procedure can be represented by

\[ x_{n} = F_{X}^{-1}(F_{X}(x_{n})), 0 \leq n \leq N - 1 \]  

where \( \{x_{0}, x_{1}, ..., x_{N-1}\} \) is viewed as the sample set of a random variable \( X \) with a cumulative distribution function (CDF) \( F_{X}(\cdot) \), and the CDF of another random variable \( Y \) with the obtained new data series \( \{y_{0}, y_{1}, ..., y_{N-1}\} \) as samples can be close to a predefined target CDF \( F_{Y}(\cdot) \) as long as the total number of data, \( N \), is sufficiently large.

III. PROPOSED METHODS

A. Spatial Sub-band Spectral Histogram Normalization in Modulation Domain

This sub-section provides the procedures of the proposed method in constructing new speech features that are expected to be more noise-robust than MFCCs. In the preprocessing stage, any utterance \( x[l] \) in the training and testing sets is shaped by a high-pass pre-emphasis filter, and framing as well as windowing operations are performed in turn. Then, each windowed frame signal is transformed to the acoustic frequency domain via short-time Fourier transform (STFT), and the resulting complex-valued acoustic spectrum is denoted by

\[ X[n,k] = X_{r}[n,k] + jX_{i}[n,k], \]

\[ 0 \leq n \leq N - 1, 0 \leq k \leq K - 1, \]

(2)

where \( X_{r}[n,k] \) and \( X_{i}[n,k] \) denote the acoustic real and imaginary spectra, respectively, and \( n \) and \( k \) respectively refer to the indices of frame and discrete frequency, and \( N \) and \( K \) are respectively the total number of frames and acoustic frequency bins. Next, the acoustic real and imaginary spectra, with respect to a fixed frequency bin \( k \), are processed via the following steps.

Step 1: Acquire the slow- and fast-varying contexts of the acoustic real and imaginary spectra within any specific frame \( n \) via simple two-point FIR filters. Note that we just show the example of the real spectrum hereafter, and the imaginary spectrum is processed in the same way. Therefore, we have:

\[ \text{LPF: } X_{r}^{LP}[n,k] = \frac{1}{2}(X_{r}[n,k] + X_{r}[n,k - 1]), \]

(3)

\[ \text{HPF: } X_{r}^{HP}[n,k] = \frac{1}{2}(X_{r}[n,k] - X_{r}[n,k - 1]), \]

(4)

where \( X_{r}^{LP}[n,k] \) and \( X_{r}^{HP}[n,k] \) are the low-pass and high-pass filtered (denoted by LPF and HPF) sub-bands of spatial contexts for the (intra-frame) real spectrum for frame \( n \).

Step 2: Compute the (inter-frame) modulation spectrum separately for each real and imaginary sub-band spectra obtained in Step 1 with respect to any specific frequency bin \( k \) by discrete Fourier transform (DFT):

\[ \chi_{r}^{band}[k,m] = \sum_{n=0}^{N-1} X_{r}^{band}[n,k] e^{-j\frac{2\pi nk}{N}}, \]

\[ 0 \leq m \leq N - 1, \]

(5)

where \( m \) refers to the index of the discrete modulation frequency, and the superscript, "\( \text{band} \)" can be either of "lp" and "hp", corresponding to low-pass and high-pass filtered parts, respectively. The resulting LPF and HPF modulation spectra can be expressed in polar form as

\[ \chi_{r}^{band}[k,m] = A_{r}^{band}[k,m] e^{j\theta_{r}^{band}[k,m]}, \]

(6)

where \( A_{r}^{band}[k,m] \) and \( \theta_{r}^{band}[k,m] \) represent the magnitude and phase components of \( \chi_{r}^{band}[k,m] \), respectively.

Step 3: Apply HEQ to update the magnitude components of the modulation spectra obtained in Step 2, while keeping the phase components unchanged. The resulting new magnitude
cepstral coefficients (MFCCs) as the ultimate speech features associated with each frame in Eq. (9) to Mel-frequency filters can be employed to perform the sub-band division: performance in speech recognition. For example, when the process can be flexibly set to investigate the corresponding difference filters is applied to obtain two intra-frame (spatial) B.

It hereafter. we will use the short-hand notation “SBMAS-HEQ” to denote is to implement MAS-HEQ [5] in a spatial sequence to produce MFCC. 

logarithmic operation, and discrete cosine transform (DCT) in Eq. (9) is passed through a Mel-frequency filter bank, so as to assure that the sum of three filter outputs is identical to the original full-band intra-frame spectrum.

Magnitude component with the original phase component, we obtain the new (enhanced) sub-band modulation spectrum: 

\[ X_{\text{LP}}[k, m] = \mathcal{F}_{\text{LP}}^{-1}(\mathcal{F}_{\text{LP}}(X[k, m])) \]

real and imaginary spectra. Then, as the reverse of Step 1, we add these LPF and HPF sub-bands together to form the new acoustic real and imaginary spectra, respectively denoted by \( \hat{X}_r[n, k] \) and \( \hat{X}_i[n, k] \), and accordingly the final complex-valued acoustic spectrum can be obtained by 

\[ \hat{X}[n, k] = \hat{X}_r[n, k] + j\hat{X}_i[n, k]. \]  

At the final stage, we convert the acoustic spectrum \( \hat{X}[n, k] \) associated with each frame in Eq. (9) to Mel-frequency cepstral coefficients (MFCCs) as the ultimate speech features for speech recognition. That is, the magnitude of \( \hat{X}[n, k] \) in Eq. (9) is passed through a Mel-frequency filter bank, logarithmic operation, and discrete cosine transform (DCT) in sequence to produce MFCC.

B. More Spatial Sub-bands Arrangement

In the preceding sub-section, a set of two-point average and difference filters is applied to obtain two intra-frame (spatial) sub-band (LPF and HPF) components. However, the number of intra-frame sub-bands during the proposed equalization process can be flexibly set to investigate the corresponding performance in speech recognition. For example, when the number of sub-bands is assigned to 3, a set of three-point filters can be employed to filter the sub-band division:

LPF: \( X_{\text{LP}}[n, k] = \frac{1}{3}X_r[n, k] + X_r[n, k - 1] + X_r[n, k - 2] \), (10)  

BP:F: \( X_{\text{BP}}[n, k] = \frac{2}{3}X_r[n, k] - 2X_r[n, k - 2] \), (11)  

HPF: \( X_{\text{HP}}[n, k] = \frac{1}{3}(X_r[n, k] - X_r[n, k - 1] + X_r[n, k - 2]). \) (12)  

For these three filters, LPF is simply a three-point moving average filter, HPF is derived by multiplying the impulse response of LPF with \( e^{\text{i}\pi k} = (-1)^k \), and BPF is constructed so as to assure that the sum of three filter outputs is identical to the original full-band intra-frame spectrum.

Step 4: Take the inverse DFT of the new sub-band real and imaginary modulation spectra from Step 3 as the reverse of Step 2 to construct the new LPF and HPF acoustic real and imaginary spectra. Then, as the reverse of Step 1, we add these LPF and HPF sub-bands together to form the new acoustic real and imaginary spectra, respectively denoted by \( \hat{X}_r[n, k] \) and \( \hat{X}_i[n, k] \), and accordingly the final complex-valued acoustic spectrum can be obtained by 

\[ \hat{X}[n, k] = \hat{X}_r[n, k] + j\hat{X}_i[n, k]. \]  

As for the baseline experiment, each utterance of the training and testing sets were converted to a series of 39-dim MFCC feature vectors (c0, c1-c12 plus their delta and delta-delta). The frame length and shift were set to 25 ms and 10 ms, respectively. In particular, each of the robustness algorithms to be evaluated was to produce the 13 static cepstra (c0, c1-c12) only, and then the 26 dynamic cepstra were computed accordingly.

More specifically, the acoustic model for each digit was a left-to-right continuous density HMM with 16 states, and each state has a 20-mixture diagonal GMM. The training and recognition processes were conducted via the HTK recognition toolkit [13], which followed the setup originally defined for the ETSI evaluations.

B. Experimental Results

For the purpose of comparison, the performance of SBMAS-HEQ and some well-known feature robustness methods are firstly evaluated in terms of speech recognition accuracy, and the corresponding results are listed in the upper part of Table I. In particular, we additionally perform CMS on the cepstral features derived from the presented various instantiations of SBMAS-HEQ. Note that the CMS procedure has been also inherently embedded in all of the other methods shown in Table I, except for MFCC baseline and AFE.

Consulting the upper part of Table I we notice several particularities. First, it comes as no doubt that every method can give rise to significant improvements in recognition accuracy for all the three test sets as compared to the MFCC baseline. Second, HEQ outperforms the linear compensation methods, CMS and CMVN, probably because it can normalize all orders of the moments of the speech features. Next, CGN constrains the dynamic range of CMS features to eliminate the outlier data and MVA adopts a fixed ARMA filter to enhance the low time-varying components of CMVN features, both of which can achieve performance competitive to or better than HEQ. TSN employs a data-driven temporal filter and thus produces better results than MVA. Finally, our recently proposed MAS-HEQ behaves better results than SHE. In comparison, SHE performs DFT on the cepstra while MAS-HEQ performs DFT on the acoustic spectra. Therefore, the recognition results reflect that when considering the effectiveness of processing speech features in the modulation

IV. EXPERIMENTS AND RESULTS

A. Experimental Setup

The speech recognition experiments were conducted under various noise conditions with the Aurora-2 connect digit database and clean-condition training task [3]. The Aurora-2 database is a subset of the TI-DIGITS, and the task consists of the acoustic model training with clean noise-free utterances and the recognition of the noise-corrupted utterances at different signal-to-noise ratios (SNRs), in which Test Sets A and B are artificially contaminated with eight different types of real world noises (e.g., the subway noise, street noise, etc.) in a wide range of SNRs (-5 dB, 0 dB, 5 dB, 10 dB, 15 dB, 20 dB and Clean) and Test Set C contains both additive noise and channel distortion.

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HPF: \( X_{\text{HP}}[n, k] = \frac{1}{3}(X_r[n, k] - X_r[n, k - 1] + X_r[n, k - 2]). \) (12)  

For these three filters, LPF is simply a three-point moving average filter, HPF is derived by multiplying the impulse response of LPF with \( e^{\text{i}\pi k} = (-1)^k \), and BPF is constructed so as to assure that the sum of three filter outputs is identical to the original full-band intra-frame spectrum.
domain via HEQ, the acoustic spectra seem to be a better choice than the cepstra.

Table I

<table>
<thead>
<tr>
<th>Methods</th>
<th>Set A</th>
<th>Set B</th>
<th>Set C</th>
<th>Avg</th>
<th>RR</th>
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<tbody>
<tr>
<td>MFCC</td>
<td>54.87</td>
<td>48.87</td>
<td>63.95</td>
<td>54.29</td>
<td>-</td>
</tr>
<tr>
<td>CMS</td>
<td>66.81</td>
<td>71.79</td>
<td>67.64</td>
<td>68.97</td>
<td>32.12</td>
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<tr>
<td>CMVN</td>
<td>75.93</td>
<td>76.76</td>
<td>76.82</td>
<td>76.44</td>
<td>48.46</td>
</tr>
<tr>
<td>HEQ</td>
<td>80.03</td>
<td>82.05</td>
<td>80.10</td>
<td>80.85</td>
<td>58.11</td>
</tr>
<tr>
<td>CGN</td>
<td>80.08</td>
<td>81.48</td>
<td>80.20</td>
<td>80.66</td>
<td>57.69</td>
</tr>
<tr>
<td>MVA</td>
<td>80.89</td>
<td>82.00</td>
<td>81.49</td>
<td>81.45</td>
<td>59.42</td>
</tr>
<tr>
<td>TSN</td>
<td>83.26</td>
<td>84.50</td>
<td>82.83</td>
<td>83.67</td>
<td>64.27</td>
</tr>
<tr>
<td>SHE</td>
<td>83.37</td>
<td>85.08</td>
<td>83.47</td>
<td>84.08</td>
<td>65.17</td>
</tr>
<tr>
<td>AFE</td>
<td>87.68</td>
<td>87.10</td>
<td>86.27</td>
<td>87.17</td>
<td>71.93</td>
</tr>
<tr>
<td>MAS-HEQ</td>
<td>86.49</td>
<td>88.13</td>
<td>84.98</td>
<td>86.84</td>
<td>71.21</td>
</tr>
</tbody>
</table>

The lower parts of Table I provide the results of the variants of the proposed SBMAS-HEQ method, which are labeled with bracketed numbers ((1), (2), \ldots) and identified with different superscripts and/or subscripts. The subscripts, (2) and (3), correspond to the number of sub-bands being 2 and 3, respectively, and the superscript indicates which sub-band(s) would be processed by MAS-HEQ. For example, the term SBMAS – HEQ\textsuperscript{hp} (labeled by (3)) signifies the SBMAS-HEQ method in which each intra-frame spectrum is divided into 3 sub-bands, and all sub-bands are MAS-HEQ processed.

From the lower parts of Table I, we find the following:

1. Both SBMAS – HEQ\textsuperscript{hp} (labeled by (2)) and SBMAS – HEQ\textsuperscript{hp} (labeled by (3)) produce better outcomes than MAS-HEQ in most cases, which implies that further normalizing the spatial contexts of acoustic spectra is beneficial. However, SBMAS – HEQ\textsuperscript{hp} (labeled by (2)) and SBMAS – HEQ\textsuperscript{hp} (labeled by (2)) apparently require higher computation complexity than MAS-HEQ since they have to process all of the sub-band complex-valued spectra individually.

2. As for the 2-sub-band case, SBMAS – HEQ\textsuperscript{hp} (labeled by (2)) and SBMAS – HEQ\textsuperscript{hp} (labeled by (3)) consistently outperform SBMAS – HEQ\textsuperscript{hp} (labeled by (2)), they achieve very close results. Thus, SBMAS – HEQ\textsuperscript{hp} (labeled by (2)) probably suffers from the problem of over normalization, and simply normalizing either the LPF or HPF as in SBMAS – HEQ\textsuperscript{hp} (labeled by (2)) and SBMAS – HEQ\textsuperscript{hp} (labeled by (2)) can not only reduce the computation cost, but also provide better performance.

3. When the original acoustic spectra is split into 3 sub-bands, and only one sub-band is selected for HEQ compensation, we find that compensating either of HPF (SBMAS – HEQ\textsuperscript{hp} (labeled by (3))) and BPF (SBMAS – HEQ\textsuperscript{hp} (labeled by (3))) is better than compensating LPF (SBMAS – HEQ\textsuperscript{hp} (labeled by (3))), and both SBMAS – HEQ\textsuperscript{hp} (labeled by (3)) and SBMAS – HEQ\textsuperscript{hp} (labeled by (3)) can provide relative error reduction rates of over 73.50% as compared with the baseline MFCC system, superior to all the other methods listed in Table I. As a result, among the various SBMAS – HEQ instantiations, we can achieve nearly optimal performance via simply applying spatial spectral division and compensating a single sub-band.

4. Furthermore, compensating more than one sub-band in the 3-sub-band case does not necessarily produce better results relative to single-band compensation, which is probably a sign of over normalization. For example, SBMAS – HEQ\textsuperscript{hp} (labeled by (3)) (73.07%) behaves slightly worse than SBMAS – HEQ\textsuperscript{hp} (labeled by (3)) (73.70%) and SBMAS – HEQ\textsuperscript{hp} (labeled by (3)) (73.68%) in relative error rate reduction.

To go a step further, Table II lists the recognition accuracy rates of MFCC baseline, MAS-HEQ and various SBMAS-HEQ instantiations for each individual SNR case but averaged over ten noise types. By looking at Table II, we have some findings as follows:

1. Compared with the MFCC baseline, the various forms of SBMAS-HEQ provide significantly better recognition accuracy rates in noise-corrupted cases, but most of them behave slightly worse than MFCC in the clean noise-free case, which indicates that there is still room for improvement in SBMAS-HEQ.

2. As for the methods that deal with the entire spatial band, SBMAS – HEQ\textsuperscript{hp} (labeled by (3)) performs the best, followed by SBMAS – HEQ\textsuperscript{hp} (labeled by (2)) and then MAS-HEQ, at the cases of median and low SNRs (SNR \textless 15 dB). These results indicate that the arrangement of more sub-bands leads to better performance at worse noise situations.

3. Relative to processing the entire spatial band (e.g., SBMAS – HEQ\textsuperscript{hp} (labeled by (3)) which normalizes all of the three sub-bands). Simply normalizing parts of the sub-bands (e.g., SBMAS – HEQ\textsuperscript{hp} (labeled by (3)), SBMAS – HEQ\textsuperscript{hp} (labeled by (3)) and SBMAS – HEQ\textsuperscript{hp} (labeled by (3))) produces superior accuracy rates in the cases of Clean and SNRs greater than 5 dB. Therefore, the computation complexity of SBMAS-HEQ can be lowered by reducing the number of processing sub-bands without the cost of performance degradation while the noise level is moderate.

As a final point, we examine the proposed methods by the capability of reducing the modulation spectrum distortion caused by noise. Figs. 1(a) to 1(d) depict the averaged PSD...
curves of the first MFCC feature c1 for the 1001 utterances in the Test Set B of the Aurora-2 database for three SNR levels, clean, 10 dB and 0 dB (with airport noise) before and after the Test Set B of the Aurora-2 database for three SNR levels, respectively. First, for the unprocessed case, as shown in Fig. 1(a), the environmental noise results in a significant PSD mismatch over the entire frequency range [0 50 Hz]. Second, from Figs. 1(b) to 1(d), we see that the PSD mismatch caused by the environmental noise can be considerably suppressed after performing MAS-HEQ and two forms of SBMAS-HEQ especially for the SBMAS – HEQ\textsubscript{alt}\textsubscript{(3)}-processed PSDs as shown in Fig. 1(d), which mismatch at high frequencies is significantly reduced.). This again reveals that the proposed normalization methods can provide a more noise-robust feature representation.

V. CONCLUSIONS

In this paper, we have proposed a novel feature extraction framework for joint equalization of real and imaginary acoustic spectra in producing noise-robust speech features for recognition. The local contextual information of acoustic spectra is taken into consideration via filtering the intra-frame spectrum into sub-band components, followed by individual HEQ processing in modulation domain. The experimental results demonstrate the effectiveness and viability of the presented framework in reducing the effect of noise in speech recognition. As to future work, we envisage several directions, including exploring the integration of our methods with more other robustness methods and further confirming our observations on larger-scale ASR experiments.

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