A Complex Matrix Factorization Approach to Joint Modeling of Magnitude and Phase for Source Separation

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Abstract—Conventional NMF methods for source separation factorize the matrix of spectral magnitudes. Spectral phase is not included in the decomposition process of these methods. However, phase of the speech mixture is generally used in reconstructing the target speech signal. This results in undesired traces of interfering sources in the target signal. In this paper the spectral phase is incorporated in the decomposition process itself. Additionally, the complex matrix factorization problem is reduced to an NMF problem using simple transformations. This results in effective separation of speech mixtures since both magnitude and phase are utilized jointly in the separation process. Improvement in source separation results are demonstrated using objective quality evaluations on the GRID corpus. As a side result, we have also investigated the intelligibility improvement aspect of target speaker in the presence of interfering speaker.

Index Terms - Non Negative Matrix Factorization, Complex Matrix Factorization, Source Separation, Phase Reconstruction

1. INTRODUCTION

Monaural speaker separation is challenging in the presence of a competing speaker, due to all the information mixed up in a single channel. This results in degradation of intelligibility of the target speaker speech in the presence of an interfering speaker. This is mainly because the interfering speaker has more or less similar characteristics to target speaker. Hence, the interfering speaker information could be considered as babble noise for target speaker. There have been significant breakthroughs to tackle this problem in the yesteryear. Though, when compared to humans’ innate ability to separate mixed speech intuitively, the separation algorithms have a long way to go. This serves as a motivation to develop such source separation systems, which can achieve performance comparable to humans.

In literature, many source separation algorithms have been developed. Computational auditory scene analysis (CASA) [1], hidden Markov models (HMM) [2], sinusoidal modeling [3] and non-negative matrix factorization (NMF) [3]. NMF [4], [5] has been widely used for source separation. In NMF, power spectrograms have been analyzed to reveal underlying latent components of audio signals. Other methods include modifying conventional NMF by applying sparseness constraints and achieving temporal continuity of sources [6].

A novel method to factorize complex matrices is proposed in this paper. This method converts the complex matrix factorization problem to a non-negative matrix factorization (NMF) problem by using simple transformations. Conventional NMF factorizes the magnitude of the input complex matrix, hence disregarding phase. Additionally, phase of the mixed signal is generally used for individual signal reconstruction which brings undesired traces of interfering sources in the target signal. In the proposed method, phase is taken into account while decomposition itself and thus is called complex matrix factorization (CMF). CMF has been attempted before in [7]–[10]. Some of these methods assume a probabilistic approach while estimating the error where as our method involves a deterministic approach to solve the problem at hand.

NMF has been used for various applications other than source separation. A denoising method using NMF has been explained in [11]. In [12] NMF has been applied to polyphonic music transcription. Speech Enhancement has also been performed using an NMF framework in [13]–[15]. Multi-channel source separation using factorization of complex data has been discussed in [16]. We will, instead, look into application of the proposed CMF in supervised single-channel separation domain. Our proposed method converts the complex matrix to a non-negative matrix while maintaining the integrity of the problem. Hence, for all methods based on an NMF framework, CMF could be a desired alternative.

Objective evaluations on separated individual speech signals are used for illustrating the significance of the proposed method when compared to other single channel source separation methods in literature. GRID corpus database has been used in the performance evaluation. As a side result, we have also investigated the intelligibility improvement of target speaker information in the presence of interfering speaker. To evaluate the intelligibility improvement, the Speech Intelligibility Index (SII) [17]–[19] and fractional Articulation Index (fAI) [20] are used in this work.

Terminologies used throughout the paper are as follows. $|A|$ and $\phi_A$ gives the magnitude and phase respectively of a complex matrix $A$. $\|\|$ represents the Frobenius norm in all cases.

The remainder of this paper is organized as follows.
Section II describes problem formulation for source separation in an echoic environment. In Section III, Matrix Factorization is explained along with the Complex Matrix Factorization (CMF) formulation. An algorithm is also proposed to incorporate the new theory into application. Section IV deals with Performance Evaluation of phase reconstruction and speech separation. Finally, in Section V the discussion is concluded with future prospects of the proposed theory.

II. PROBLEM FORMULATION

Let us consider a mixed speech signal \( z(n) \) consisting of two speakers \( z_1(n) \) and \( z_2(n) \). The objective of speaker separation is to obtain the estimates of \( z_1(n) \) and \( z_2(n) \) where \( n \) are the time samples. Speech signals have huge amount of variation in time-domain, hence signals are transformed to frequency-domain for further analysis. Let \( Z(k,m), Z_1(k,m) \) and \( Z_2(k,m) \) represent the STFT of \( z(n), z_1(n) \) and \( z_2(n) \) respectively. Here, \( k \) represents frequency bin index and \( m \) corresponds to the frame index in STFT. Since STFT is linear, we can write

\[
Z(k,\omega) = Z_1(k,\omega) + Z_2(k,\omega) \quad (1)
\]

\[
|Z(k,\omega)| e^{j\phi_2(k,\omega)} = |Z_1(k,\omega)| e^{j\phi_1(k,\omega)} + |Z_2(k,\omega)| e^{j\phi_2(k,\omega)} \quad (2)
\]

Standard separation methods involve constructing trained bases [21] for both the speakers in question. With the constructed bases, corresponding weights are calculated for a mixture giving way to estimation of separated speech signals.

We use speech \( z_i(n) \) of the \( i \)th speaker from the training set of clean speech to generate a bases vector set \( X_{\text{train}} \). This bases vector set can be used to estimate weights \( H_i \), corresponding to each speaker. Both, generating a bases vector set and estimation of weights require CMF. Hence the problem reduces to finding an accurate technique to estimate complex bases \( X_{\text{train}} \) and corresponding weights \( H_i \) such that \( Z_i \approx X_{\text{train}} H_i \).

III. CMF APPROACH TO JOINT MODELING OF MAGNITUDE AND PHASE

Non negative matrix factorization is a widely accepted method for single-channel source separation. Decomposition of the speech into basis vectors and corresponding weights has been shown to work well for signal-channel mixtures. In general, Non-Negative Matrix Factorization (NMF) has been used to factorize the magnitudes in the given matrix. Phase, is either taken to be equal to the input signal or is reconstructed via various methods.

Given a Non-Negative Matrix \( Z \), we factorize it to non-negative factors \( X \) and \( H \) such that

\[
Z \approx XH \quad (3)
\]

This problem does not have a closed-form solution. Classically, numerical solutions have been computed by constructing an appropriate optimization problem. We have fast converging iterative algorithms which ensure reduction in distance between \( Z \) and \( XH \) after successive updates.

The proposed Complex Matrix Factorization has been formulated for Euclidean Distance metric, hence Euclidean Distance is minimized in the classic NMF domain

\[
\min \| Z - XH \|^2 \quad \text{with respect to } X \text{ and } H \quad (4)
\]

\( Z, X \) and \( H \) are Non-Negative Matrices

Iterative Updates in [5], that ensure convergence of \( X \) and \( H \), are given as follows

\[
X_{mn} \leftarrow X_{mn} \frac{(ZH^T)_{mn}}{(XH^T)_{mn}} \quad (5)
\]

\[
H_{np} \leftarrow H_{np} \frac{(X^T Z)_{np}}{(X^T X)_{np}}
\]

It has been proved in literature that every update will decrease the distance between \( Z \) and \( XH \). Stability of the updates have also been discussed in [22].

In Section III-A, we start with a new method of Complex Matrix Factorization (CMF) which is used to reconstruct phase and magnitude jointly, within the NMF framework. Discussion related to the need of phase reconstruction is covered in Section III-B. Reconstruction of individual speech signals is talked about in III-C. In Section III-D, an algorithm has been proposed which incorporates all the modifications.

A. The proposed complex matrix factorization approach

Consider \( Z \) to be a complex matrix. Let the bases vectors be denoted by a matrix \( X \) and the corresponding weights by \( H \). Here \( X \) is complex and \( H \) real. Also, let \( \hat{Z} = XH \). To reduce CMF to NMF, we perform separation in \( Z, \hat{Z}, X \) and \( H \) (also shown in Figure 1) via a simple transformation given as follows

\[
\hat{Z} = \hat{Z}_{+r} - \hat{Z}_{-r} + j \left( \hat{Z}_{+i} - \hat{Z}_{-i} \right) \quad (6)
\]

where,

\[
\hat{Z}_{+r} = \max \left( 0, \text{real} \left( \hat{Z} \right) \right) \quad \hat{Z}_{-r} = -\min \left( 0, \text{real} \left( \hat{Z} \right) \right)
\]

\[
\hat{Z}_{+i} = \max \left( 0, \text{imag} \left( \hat{Z} \right) \right) \quad \hat{Z}_{-i} = -\min \left( 0, \text{imag} \left( \hat{Z} \right) \right)
\]

Fig. 1. Illustrating CMF for joint modeling of phase and magnitude
where max, min, real and imag are element-wise functions, taking maxima, taking minima, real part and imaginary part of each element.

\( Z \) is also separated as described in Equation 7, whereas \( X \) and \( H \) are to be separated as follows

\[
X = X_{+r} - X_{-r} + j (X_{+i} - X_{-i})
\]  

(8)

\[
H = H_{+} - H_{-}
\]  

(9)

where \( X_{+r}, X_{-r}, X_{+i}, X_{-i}, H_{+} \) and \( H_{-} \) are non-negative matrices.

Simplifying and comparing LHS and RHS of \( \tilde{Z} = XH \) we get

\[
\begin{align*}
\hat{Z}_1 &= \hat{Z}_{+r} = X_{+r}H_{+} + X_{-r}H_{-} \\
\hat{Z}_2 &= \hat{Z}_{-r} = X_{+r}H_{-} + X_{-r}H_{+} \\
\hat{Z}_3 &= \hat{Z}_{+i} = X_{+i}H_{+} + X_{-i}H_{-} \\
\hat{Z}_4 &= \hat{Z}_{-i} = X_{+i}H_{-} + X_{-i}H_{+}
\end{align*}
\]  

(10)

Lastly, for convenience sake let

\[
\begin{align*}
\hat{Z}_1 &= \hat{Z}_{+r} \\
\hat{Z}_2 &= \hat{Z}_{-r} \\
\hat{Z}_3 &= \hat{Z}_{+i} \\
\hat{Z}_4 &= \hat{Z}_{-i}
\end{align*}
\]  

(11)

With all the equations in place, let us move to the transformation of CMF to NMF. Apply triangle inequality to Equation 4 to get

\[
\min_{\hat{X}, \hat{H}} \| \tilde{Z} - \hat{X} \hat{H} \|_2^2 \leq \min_{\hat{X}_i H_i} \sum_{k=1}^{4} \| Z_k - \tilde{Z}_k \|_2^2
\]  

(12)

As \( Z_k \)'s and \( \tilde{Z}_k \)'s are independent of each other we get

\[
\min_{\hat{X}_i H_i} \| \tilde{Z} - \hat{X} \hat{H} \|_2^2 \leq \sum_{k=1}^{4} \min_{\hat{X}_i H_i} \| Z_k - \tilde{Z}_k \|_2^2
\]  

(13)

The problem now reduces to \( \min_{\hat{X}_i H_i} \| Z_k - \tilde{Z}_k \|_2^2 \) for all \( k \in \{1, 2, 3, 4\} \). RHS value of Equation 13 gives an upper bound to the solution of the optimization problem in Equation 4. Hence convergence of RHS of Equation 13 guarantees convergence of the cost function in Equation 4.

Now, we have 4 optimization problems to be solved simultaneously with same variables having dependencies on different cost functions. Solving them sequentially would lead to a bias towards the first optimization problem. To avoid divergent solutions, we combine the sub-matrices to get a single matrix. This is shown as follows

\[
\begin{pmatrix}
\hat{Z}_{+r} & \hat{Z}_{-r} \\
\hat{Z}_{+i} & \hat{Z}_{-i}
\end{pmatrix}
= 
\begin{pmatrix}
X_{+r} & X_{-r} \\
X_{+i} & X_{-i}
\end{pmatrix}
\begin{pmatrix}
H_{+} & H_{-} \\
H_{+} & H_{-}
\end{pmatrix}
\]  

(14)

or,

\[
\begin{pmatrix}
\hat{Z}_1 & \hat{Z}_2 \\
\hat{Z}_3 & \hat{Z}_4
\end{pmatrix}
= 
\begin{pmatrix}
X_1 & X_2 \\
X_3 & X_4
\end{pmatrix}
\begin{pmatrix}
H_1 & H_2 \\
H_3 & H_4
\end{pmatrix}
\]  

(15)

\[
\hat{Z}_c = X_c H_c
\]  

(16)

As \( H_1 = H_4 \) and \( H_2 = H_3 \), we perform an update after every NMF iteration which takes care of the aforementioned constraints.

\[
H_1, H_4 \leftarrow \frac{H_1 + H_4}{2} \\
H_2, H_3 \leftarrow \frac{H_2 + H_3}{2}
\]  

(17)

The CMF problem is now reduced to an NMF problem of the form

\[
\min \| Z_c - X_c H_c \|_2^2 \text{ with respect to } X_c \text{ and } H_c
\]  

(18)

\( X_c \) and \( H_c \) are Non-Negative Matrices.

This can be solved by various methods in literature, of which one of them is referred to in Equation 5.

B. Significance of phase spectrum in reconstruction of individual signals

In general, phase of the individual source signals is not used in estimating the separated signals. The original phase of the mixture is taken as it is for the reconstructed separated signal in the conventional methods [23]. However, phase plays an important role in the reconstruction of individual source signals. This can be noted in [24], where the estimated signal's SNR increases by up to 1.8 dB. In this work, phase is taken into account in the decomposition process itself. This leads to a robust speech reconstruction method with improved perceptual quality.

C. Reconstruction of individual speech signals

For the \( i \)th speaker, trained bases \( X_{\text{train}(i)} \) are obtained by applying CMF on

\[
\tilde{Z}_i \approx X_{\text{train}(i)} \hat{H}_i
\]  

(19)

Given a mixed speech signal \( Z \) of speaker \( i \) and \( j \) in STFT domain, and \( X_{\text{train}(i)} \)'s as known and fixed quantities, we solve for \( H_i \) and \( H_j \) by applying CMF on

\[
\tilde{Z} \approx \begin{pmatrix} X_{\text{train}(i)} & X_{\text{train}(j)} \end{pmatrix} \begin{pmatrix} H_i \\ H_j \end{pmatrix}
\]  

(20)

Separated speech signals \( Z_i^{\text{estm}} \) and \( Z_j^{\text{estm}} \) are estimated by

\[
Z_i^{\text{estm}} \leftarrow X_{\text{train}(i)} H(i) \\
Z_j^{\text{estm}} \leftarrow X_{\text{train}(j)} H(j)
\]  

(21)

D. Algorithm to compute bases and weights using the proposed CMF method

The algorithmic steps to compute the bases \( X \) and corresponding weights \( H \) are listed in Algorithm 1.

1. **Initialization:** Random non-negative values are assigned to \( X_{+r}, X_{-r}, X_{+i}, X_{-i}, H_{+} \) and \( H_{-} \).
2. **Rearrange these sub-matrices to form \( X_c \) and \( H_c \) as shown in Equation 15 and 16.
3. \( Z_c^{(ij)} \leftarrow X_c^{(ij)} \frac{X_{c} H_{c}^T}{(X_{c} H_{c})^T (X_{c} H_{c})} \)
4. \( H_c^{(jk)} \leftarrow X_c^{(jk)} \frac{H_c^T}{(X_{c} H_{c})^T (X_{c} H_{c})} \)
5. \( H_1, H_4 \leftarrow \frac{H_1 + H_4}{2} \) and \( H_3, H_2 \leftarrow \frac{H_3 + H_2}{2} \).
6. **Repeat:** Step 2 through 5 for a number of iterations to minimize the distance between \( Z \) and \( Z_c \).
7. **Termination:** \( X \leftarrow X_1 - X_2 + j (X_3 - X_4) \) and \( H \leftarrow H_+ - H_- \) to reconstruct the actual factors along with the correct phases.
IV. PERFORMANCE EVALUATION

Section IV-A describes the database used for performance evaluation of the algorithm. Spectrographic Analysis and Phase reconstruction are discussed in Section IV-B and IV-C respectively. The best results in Tables are presented in bold throughout this paper.

A. Database

Grid-Corpus Database [25] is used for testing purposes in this work. This database consists of 1000 clean speech signals for each of the 34 speakers listed. Audio-Intelligibility tests indicated that speech material is understandable without the video, hence the database is used to test and compare various algorithms.

Mixtures of speech signals are generated with target to interference ratio equal to 1. The experiments are performed in a supervised manner. We use 200 speech signals of first 10 speakers for training and use 100 speech signals of the same speakers for testing. The proposed algorithm is compared with other methods in literature using the testing set.

B. Spectrographic Analysis

Training data from Grid-Corpus [25] was used to estimate bases vectors for each speaker. The proposed algorithm in Section III-D was applied to estimate the separated signals from a given mixture of speech signals which are a part of the Testing data. A sample of reconstructed Spectrograms by the proposed CMF and CMF in [9] are depicted in Figure 2.

C. Phase Reconstruction Accuracy

Simulations were performed by factorizing STFT of some speech signals. This was done to test the convergence of Algorithm-III-D for complex signals. Figure 3 gives a pictorial representation of phase of a column vector of STFT of input (Z) versus estimated phase of the respective column vector of STFT of output (\(\hat{Z}\)).

As mentioned in Section III-B, the importance of the phase spectrum in the reconstruction is highlighted for the proposed method. It can also be seen that the reconstructed phase has similar shape as that of original phase. In particular, the reconstructed phase matches significantly with the original phase spectrum for lower FFT points. This results in the improvement in the intelligibility scores (see Section IV E) for proposed method in comparison other methods used herein.

D. Objective evaluation of reconstructed speech signals

Reconstruction was performed for 500 mixtures generated from Grid-Cropus. Non-negative matrix factorization (NMF), Non-negative tensor factorization (NTF) [26], Complex-matrix factorization in [9] (CMFbrian) and the proposed Complex-matrix factorization have been used on the same testing data to extract individual speech signals from a given mixture. Objective evaluation values PESQ, target to interference ratio loss (TIRLoss) and excitation spectra correlation (TIRESC) have been calculated for all factorization methods and are listed in Table I. TIRLoss and TIRLESC are values similar to SNRLoss and SNRLESC defined in [27] with the signal being replaced by the target-speaker and noise by interference.

PESQ [28] gives an overall speech quality evaluation on a scale of 1 (bad) to 5 (good). TIRLoss gives a quantitative value to loss due to interference on a scale of 0 (good) to (bad). TIRESC \((= [\text{TIRLoss}][1 - r^2])\) is also a value between 0 (good) to 1 (bad), where \(r\) is the correlation coefficient between the clean speech and reconstructed speech of the target speaker.
The mean scores ($\mu$) obtained, imply that CMF performs much better than NTF and NMF. It performs equally well when compared to CMFbrian. The standard deviation ($\sigma$) of PESQ and TIRloss values of reconstructed speech by CMF is lower than CMFbrian which indicates that the performance of CMF remains more consistent than CMFbrian.

E. Intelligibility Improvement Evaluation

In this work, we have evaluated the intelligibility improvement of a target speaker obtained by proposed method CMF using SII and fAI. To model an average amount of information that is audible and usable for listeners, the SII is being used to model the same mathematically. SII in general provides a monotonic relationship between the speech understanding and intelligibility scores, which lies in between 0 (not intelligible at all) and 1 (highly intelligible).

On the other hand, the fAI is an another widely used method for computing intelligibility of target signal in the presence of masker signal. This measure accounts for non-linear distortions introduced by source separation algorithms. It gives values between 0 (low intelligibility) to 1 (high intelligibility) of a target signal information.

As mentioned in Section IV-A that Target-to-Interference (TIR) ratio equal to 1 (i.e 0 dB) is used in evaluation. However in addition to TIR equal to dB, we have also used -10 dB and -5 dB TIR’s in evaluation of intelligibility improvement.

| Methods     | PESQ $\mu$ | PESQ $\sigma$ | TIRloss $\mu$ | TIRloss $\sigma$ | TIRloss ESC $\mu$ | TIRloss ESC $\sigma$ | SII $\mu$ | SII $\sigma$ | fAI $\mu$ | fAI $\sigma$ |
|-------------|------------|---------------|---------------|------------------|-------------------|---------------------|-----------|------------|----------|------------|
| NMF         | 0.81       | 0.56          | 2.03          | 0.50             | 2.31              | 0.55                | 0.38       | 0.40       | 0.12     | 0.05       |
| CMFbrian    | 0.96       | 0.02          | 0.96          | 0.01             | 0.89              | 0.05                | 0.89       | 0.01       | 0.12     | 0.05       |
| CMF         | 0.74       | 0.14          | 0.50          | 0.1              | 0.12              | 0.05                | 0.69       | 0.72       | 0.81     | 0.56       |

In Table II, we have presented mean scores for SII and fAI obtained on complete GRID corpus database at various TIRs. In general, higher the SII and fAI scores, better is the method for improving the intelligibility of separated speakers. As it is evident that with an increase in TIR, the scores are increasing for all methods. The baseline NMF and NTF methods have more or less similar SII and fAI scores at different TIRs.

The proposed method CMF has been able to improve the SII scores from 4 % to 7 % in comparison to CMFbrian, when TIR increases from -10 dB to -5 dB respectively. On the other hand for fAI, the improvement for CMF increases from 7 % 10 % compared to CMFbrian for the same increase in TIRs. As TIR further increases to 0 dB, the SII and fAI scores for both CMF and CMFbrian are similar. Additionally, the proposed CMF method outperforms the NTF and NMF baseline methods significantly at all TIRs.

V. Conclusion

A new method of complex matrix factorization (CMF), which jointly utilizes both the spectral magnitude and phase is proposed in this work for single channel source separation. In this work the phase spectrum is incorporated into the decomposition stage, along with magnitude, making it a complex factorization method. Additional contributions of this work include converting the complex matrix factorization method into a standard NMF method using simple transformations.

Its superiority is demonstrated with respect to other methods, using magnitude only reconstruction, motivating the need for incorporating phase into the decomposition process. Although this method has been applied to single-channel source separation, the proposed algorithm and can be applied to any generalized NMF method with applications in speech enhancement, music transcription and multi channel source separation. In addition, the proposed method also finds its application in speech intelligibility improvement when interfering source is considered to be a noise source. The Speech Intelligibility Index (SII) and fractional Articulation Index (fAI) scores confirm the utility of the proposed method for task of speech intelligibility improvement.

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