BITWISE SOURCE SEPARATION ON HASHED SPECTRA: AN EFFICIENT POSTERIOR ESTIMATION SCHEME USING PARTIAL RANK ORDER METRICS

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ABSTRACT
This paper proposes an efficient bitwise solution to the single-channel source separation task. Most dictionary-based source separation algorithms rely on iterative update rules during the run time, which becomes computationally costly as we employ an overcomplete dictionary and sparse encoding that tend to give better separation results. To avoid such cost we propose a bitwise scheme on hashed spectra that leads to an efficient posterior probability calculation. For each source, the algorithm uses a partial rank order metric to extract robust features to create a binarized dictionary of calculation. For each source, the algorithm uses a partial rank order metric to extract robust features to create a binarized dictionary of calculation. A simple voting-based dictionary search allows a fast and iteration-free estimation of mixing proportion at each entry of a signal spectrogram. We verify that the proposed BitWise Source Separation (BWSS) algorithm efficiently utilizes large, but hashed source-specific dictionaries, and produces sensible source separation results for the single-channel speech denoising task.

Index Terms— Speech Enhancement, Source Separation, WTA Hashing, Dictionary Learning

1. INTRODUCTION
The single-channel source separation problem has been widely studied as a latent variable model. The most common practice is to learn a source-specific dictionary from each source during training so that the source spectra can be reconstructed by a linear combination of the dictionary items. In this way a dictionary defines a discriminative subspace, where its corresponding source spectrum can reside. Using this kind of concept, the source separation procedure for a newly observed mixture spectrum performs another dictionary learning process, where the dictionaries are fixed from the ones the training part, while their activations are estimated using iterative algorithms. Nonnegative Matrix Factorization (NMF) [1, 2, 3] and Probabilistic Latent Semantic Indexing (PLSI) [4, 5, 6] are a popular choice for the modeling job. Meanwhile, a large overcomplete dictionary is another preferable option to preserve the manifold structure of the source spectra. It can be either learned by a manifold preserving quantization technique [7] or simply using the entire source spectra directly as in [8, 9].

As those approaches are based on an iterative algorithm to estimate the activation, a practical source separation system needs to be careful about the necessary resources. Iterative algorithms are not advantageous in two different senses. First, it is not a straightforward decision as to when to stop the iteration unless we have a dedicated predictor for this job [10]. Second, when it comes to the large overcomplete dictionaries, the accordingly enlarged activation matrix calls for even more computation.

Deep learning-based solutions tend to predict the separation results in an iteration-free manner by simply running a feedforward pass [11, 12, 13, 14, 15]. However, the deep neural networks also needs a lot of resources due to its enlarged structure, e.g. requiring millions of floating-point operations. Therefore, an efficient dictionary-based solution is still an option especially for a smaller separation problem with a lesser amount of training data.

To this end, a hashing-based speed-up was proposed in [9], which employs Winner Take All (WTA) hashing [16, 17] to expedite the reformulated EM updates. Because we seek a sparse activation of the dictionary items for a better manifold preservation, it first finds out the nearest neighbors of the current source estimation in the dictionaries based on the Hamming distance between the hashed spectra. Then, it refines the search results by doing a more exact search using cross entropy between the normalized spectra. In this way, the EM updates become faster as their operation can skip non-neighbors in the dictionary. However, this approach is not completely bitwise as it still involves the exact matching procedure. Also, it still relies on the EM iterations.

In this paper we propose a fully BitWise Source Separation (BWSS) scheme, where the dictionary search is done entirely among the hash codes. To this end, we propose to compare each of the partial rank orders for a randomly chosen Fourier coefficients of the mixture spectrum with the corresponding one from the source dictionaries, hoping that the partial rank orders of a source is preserved in the mixture. It is based on the W-disjoint orthogonality [18], which assumes that there exists a dominant source component in a time-frequency bin. It is convenient that WTA hashing approximately encodes this partial rank orders, so that the dictionary search job during the test time boils down to bitwise operations.

2. RELATED WORK

2.1. Dictionary-based Source Separation
Dictionary-based source separation methods commonly assume source-specific dictionaries, each of which contains a set of spectral templates that can linearly combine the test mixture. For example, for speech denoising we employ S and N that respectively contain $T_S$ and $T_N$ $F$-dimensional dictionary items. The dictionary can be either learned by latent variable models, such as NMF [6] or PLSI [19] or a large overcomplete dictionary, e.g. by using the magnitude spectra of the sources as they are as in [3, 2, 9].

Once we prepare the dictionaries, the separation job during the test time is to compute the posterior probability of the latent vari-
ables at the given time-frequency bin of the test spectrum $X_{f,t}$, namely $P(Z_{f,t} = z | X_{f,t}, S, N)$, where $Z_{f,t}$ indicates all the dictionary items from both sources, i.e. $z \in \{ 1, \cdots, T_S, T_S + 1, \cdots, T_S + T_N \}$. Note that the indices are conveniently grouped into the speech and noise parts. In the usual EM formulation, E-step computes the posterior probabilities as follows:

$$P(Z_{f,t} = z | X_{f,t}, W = |S, N|) = \frac{W_{f,t}^{m}H_{z \rightarrow f,t}}{WH},$$

where $W = |S, N|$ is the concatenated dictionaries and $H$ denotes their activation, which we estimated during the M-step. For example, if we adapt PLSI, the update rule for $H$ is

$$H = \frac{\sum_{f,t} P(Z_{f,t} = z | X_{f,t}, W)X_{f,t}}{\sum_{f,t} P(Z_{f,t} = z | X_{f,t}, W)X_{f,t}}. \quad (2)$$

After the convergence, we eventually consolidate the posterior probabilities to compute the new posterior probability over the two sources $P(Y_{f,t} = y| X_{f,t}, W)$, where $y$ indicates one of the two sources: $y = \{ 0, 1 \}$. For example,

$$P(Y_{f,t} = 0| X_{f,t}, W) = \sum_{z=1}^{T_S} P(Z_{f,t} = z | X_{f,t}, W),$$

$$P(Y_{f,t} = 1| X_{f,t}, W) = \sum_{z=T_S+1}^{T_S+T_N} P(Z_{f,t} = z | X_{f,t}, W), \quad (3)$$

which will work like a mask to recover the sources.

Although using larger dictionaries can lead to a better separation [8, 9, 2], the computational complexity of the EM-based update rules linearly grows as the size of the dictionaries $T_S$ and $T_N$ become larger. In [8], this issue was addressed by reformulating the estimation procedure of the activation matrix $H$ as a nearest neighborhood search problem by using WTA hashing, but it is still based on the EM-based iterative algorithm. This paper investigates an iteration-free dictionary-based method that finds the nearest neighbors in a bitwise manner using the partial rank order as hash codes.

2.2. Winner Take All (WTA) Hashing

WTA hashing [17] is a partial rank order based hashing algorithm which has been used to reduce a high dimension feature space to a low dimension feature space while partially preserving the topology of the data. Given a $F$ dimensional feature space, a data point $x = \{ x_1, \cdots, x_F \}$. WTA hashing proposes a set of $L$ permutations $\Theta$ of the dimensions where the $\ell^{th}$ permutation $\theta_{\ell} = \{ i_1^\ell, \cdots, i_K^\ell \}$. For a feature vector $x$, we index it with $\theta_{\ell}$ and extract the first $K$ features $\hat{x}_{\ell} = \{ x_{i_1^\ell}, \cdots, x_{i_K^\ell} \}$. $\hat{x}_{\ell}$ is a random subset of the $F$ features of $x$. Let

$$m_{\ell} = \arg \max \{ x_{i_m^\ell}, 1 \leq m \leq K \}. \quad (4)$$

Then $x_{m_{\ell}}$ is the winner of all $K$ feature values of $\hat{x}_{\ell}$. We repeat this procedure for $x$ for all the $L$ permutations in $\Theta$, then we have $L$ integers $\{ m_1, \cdots, m_L \}$ as the WTA hash code of $x$.

The meaning of $m_{\ell}$ is worth some discussion as it is closely related to our motivation of using it as a feature for computing similarity measure in later steps. Suppose two data points $x_1$ and $x_2$ have the same hash code for $\theta_{\ell}$. This implies that in the $\ell^{th}$ permutation, the same dimension wins over the other same $K - 1$ dimensions in $x_1$ and $x_2$. Adding any random noise to $x$ which does not perturb the rank order will not change the hash code for $x$, thus WTA hashing is a robust embedding method. When comparing each $\ell^{th}$ hash code of $x_1$ and $x_2$, we are estimating a binarized cosine similarity where 1 means two vectors have same dominant dimension and 0 means otherwise. The more matched permutation tests are, the more similar $x_1$ and $x_2$ are. WTA hashing has shown good performance in object detection [16] and source separation [2].

3. THE PROPOSED BITWISE SOURCE SEPARATION

3.1. Voting-based Likelihood Estimation: A Fast Dictionary Search in the Hash Code Space

We propose a nonparametric algorithm for estimating the posterior probability of a signal being one of two sources. To this end, we first calculate the likelihood of observing a time-frequency bin given one of the sources, but based on a simple vote-counting method by finding matches between hashed spectra. This algorithm works on two preprocessed dictionaries of clean speech and noise. For a new mixture spectra, the algorithm scans the two dictionaries to generate a mixture distribution of speech and noise, which can be then used to calculate the posterior probability of one of the sources given the time-frequency bin as in [7].

For example, suppose there are two sources which contribute to the observed mixture. We denote the magnitude spectrogram of the mixture signal by $X$, a $F \times T$ matrix where $F$ and $T$ being the number of frequencies and frames, respectively. We first use a partial rank order metric as described in [17] to generate $L$ integer embeddings of each column vector $X_{f,t}$, call each $X_{\theta_{\ell},t}, \ell \in \{ 1, \cdots, L \}$; the generation procedure is discussed in section 2.2. Let $\mathcal{X}$ denote the $L \times T$ embedding matrix of $X$. For the dictionaries we use the same procedure to generate their embedding matrices $S$ and $N$, respectively with dimension $L \times T_S$ and $L \times T_N$.

For each element $X_{\theta_{\ell},t}$, we search $S_{\ell,t}$ and $N_{\ell,t}$ to count the number of matches with each dictionary in the $\ell^{th}$ permutation sample, call it $S_{\ell,t}$ and $N_{\ell,t}$. Recall $X_{\theta_{\ell},t}$ is the index of the winning element in the $\ell^{th}$ permutation sample of $X_{\theta_{\ell},t}$. Combining $X_{\theta_{\ell},t}$ and $\theta_{\ell}$ we are able to track back to the corresponding original frequency bin $j = j_{X_{\theta_{\ell},t}}$, the true winner of $\theta_{\ell}$ for $X_{\theta_{\ell},t}$. Thus the total counts of matches with each dictionary that are possibly spread in $L$ slots of $S_{\ell,t}$ and $N_{\ell,t}$ are defined as follows, respectively:

$$\tilde{S}_{\ell,t} = \sum_{\ell} S_{\ell,t}, \quad \tilde{N}_{\ell,t} = \sum_{\ell} N_{\ell,t}. \quad (5)$$

The total counts $\tilde{S}_{\ell,t}$ and $\tilde{N}_{\ell,t}$ approximate the similarity of $X_{\theta_{\ell},t}$ to the two sources, respectively. Therefore, they also approximate the likelihood of observing $X_{\theta_{\ell},t}$ given one of the sources. In $\ell^{th}$ permutation sample that $X_{\theta_{\ell},t}$ has won, it is greater than the rest $K - 1$ frequencies in $X_{\theta_{\ell},t}_{\theta_{\ell,j_{X_{\theta_{\ell},t}},t}}$. Because we encode the rank order of only $K$ partial dimensions, the same relationship can be likely to be found in one of the source dictionaries more than in the other. Therefore, for $\theta_{\ell,j_{X_{\theta_{\ell},t},t}}$ to win in the same $\ell^{th}$ permutation sample, $S_{\ell,t}$ must be greater than the rest $K - 1$ frequencies in $\tilde{S}_{\ell,t}_{\theta_{\ell,j_{X_{\theta_{\ell},t},t}}}$, $\ell$. As we discussed earlier, this is a binarized cosine similarity.

3.2. Estimation of the Posterior Probability

Once we calculate the likelihoods in the form of the number of partial matches to the two dictionaries as in section 3.1, the rest of the job is to compute the posterior probabilities over the sources given the mixture spectrogram as in [1]. In the proposed BWSS system,
we escape from the EM iterations, but instead propose a bitwise method to estimate the posterior probabilities.

Let \( Y_{j,t} \) denote a Bernoulli random variable where 0 is clean speech and 1 is noise. Thus the likelihood of observing \( X_{j,t} \) is

\[
P(X_{j,t}) = \sum_{Y_{j,t} = \{0, 1\}} P(Y_{j,t})P(X_{j,t}|Y_{j,t}).
\]

We define a prior distribution on \( Y_{j,t} \) with a Bernoulli distribution with \( p = 0.5 \) to give a fair chance to both sources. Another assumption is that each frequency bin is independent of all the other bins in a different time frame, while it is dependent on the other frequency bins in the same time frame due to the rank ordering during hashing.

To adjust for the difference in the number of frames of the two dictionaries, we normalize the count of matches accordingly. Finally, the posterior probability for a given time-frequency bin is:

\[
P(Y_{j,t} = 0|X_{j,t}, S, N) = \frac{S_{j,t}}{S_{j,t} + N_{j,t} \cdot r},
\]

\[
P(Y_{j,t} = 1|X_{j,t}, S, N) = \frac{N_{j,t} \cdot r}{S_{j,t} + N_{j,t} \cdot r},
\]

where \( r = T_S/T_N \). Recall \( S_{j,t} \) and \( N_{j,t} \) are counts of matches with clean speech and noise dictionaries for a given frequency bin \( X_{j,t} \). For \( S_{j,t} \), it is the number of votes on the clean speech dictionary for \( X_{j,t} \) based on all the permutation samples that \( X_{j,t} \) has been involved in comparison and won; similarly \( N_{j,t} \) corresponds to the number of votes that \( X_{j,t} \) received from the noise dictionary. Thus, \( P(Y_{j,t} = 1|X, S, N) \) reflects the proportion of votes from clean speech dictionary for a frequency bin. Figure 1 shows an estimated mask using this posterior probability for source separation.

### 3.3. Computational Efficiency

The proposed source separation algorithm is fast and simple. It only requires a single pass per one of the two binarized source dictionaries for an integer of the mixture hash code, whose complexity is \( O(LK_TgT_N) \). Moreover, it can be implemented using cheap bitwise operations. The quality of the estimation depends on the quality of the dictionaries, while the speed depends on the size of the dictionaries and the length of the hash code \( L \) and the number of random samples \( K \). In our experiments, we found the BWSS algorithm performs well on reasonably sized dictionaries.

### 4. EXPERIMENTS

#### 4.1. The Data Set

Dialect 1 of TIMIT training set is used for constructing a clean speech dictionary. We divide the set into female and male group. For female training group, there are (14 speakers \( \times \) 10 utterances); for male training group, there are (24 speakers \( \times \) 10 utterances). For noise, we construct a noise dictionary with ten non-stationary noise types proposed in [19]. For testing, we use dialect 1 of TIMIT testing set. The female testing group has [4 speakers \( \times \) 10 utterances], and the male testing group has [7 speakers \( \times \) 10 utterances]. Each utterance is mixed up with 10 noise types. This gives us 400 and 700 noisy utterances for female and male cases, respectively. They are normalized to form a 0 dB Signal-to-Noise Ratio (SNR). Separation was done in a supervised way by assuming the noise type and the gender of the speaker are known, though we average over the gender due to the page limit.

Short-Time-Fourier-Transform (STFT) with a Hann window of 1024 samples and a hop size of 512 transforms the signals. To evaluate the final results, we used Signal-to-Distortion Ratio (SDR) as an overall source separation measurement along with Signal-to-Interference Ratio (SIR), and Signal-to-Artifact Ratio (SAR) [20], and Short-Time Objective Intelligibility (STOI) [21].

#### 4.2. Experiment Design

We first construct the hash code dictionaries during training as described in section 2.2, which yields 2 clean speech dictionaries (i.e. male and female) and 10 noise dictionaries. During source separation, a noisy utterance is processed using the clean speech dictionary of the same gender and a noise dictionary of the same noise type. Note that the two sources of the noisy speech are not seen
in the clean speech dictionary or noise dictionary. Hence our algorithm is a supervised learning approach.

### 4.3. Separation Results

#### 4.3.1. Variation in \( L \)

There are two parameters in the BWSS algorithm, \( L \) and \( K \). \( L \) is the number of permutation samples to be drawn from a time frame \( X \); \( K \) is the size of each permutation sample. More random samples mean the distribution of \( X \) is more exploited, and the better approximation to the posterior probability of each frequency bin \( X_{j,t} \). As \( L \) goes to \( \infty \), the sample posterior probability will converge to the true mixing distribution. However, large \( L \) will increase the dimension of source dictionaries \( S \) and \( N \), which will slow down the algorithm as discussed in Section 3.3.

Figure 2 shows the result of one randomly chosen female speaker on the noise type “birds”. \( F \) is the number of frequencies in the spectrogram. In our experiment we found the algorithm approximates stable posterior probability quickly as we increase \( L \). For \( L = 2F \) the result is already very close to \( L = 8F \).

#### 4.3.2. Variation in \( K \) and the noise types

In each permutation sample, a winner is selected from the \( K \) frequency bins. When \( K \) increases, the winner of each permutation sample will have a higher rank in overall frequencies. The effect of \( K \) is more evident and depends on noise type.

In general, a larger \( K \) tends to outperform smaller \( K \)’s, but not always. To investigate the relation between \( K \) and the noise types, we fix \( L = 8F \). As shown in Table 1 the improvement of SDR depends on both noise types and \( K \). The best improvement is achieved at \( K = 8 \) for noise 3, with 14.71 dB. Noise type 1, 6, 8, and 9 showcase more than 6 dB improvement when \( K \geq 16 \), while noise type 4 and 5 have similar improvement when \( K \geq 64 \). Noise type 2, 7, and 10 have less than 6 dB improvement in all \( K \). The improvement on SIR (Table 2) and SAR (Table 3) are more positive than on SDR. Noise type 2, 7, 10 remain to have less favorable performance than the rest. We only observe marginal improvement in STOI (Table 4); in some cases STOI even decreases. Although SDR and STOI does not always go well, this is very counterintuitive to us given more than 14 dB SDR improvement for noise type 3. We investigate this issue in future work.

#### 4.3.3. Non-uniform sampling of spectrum

Human speech is more concentrated in low to mid frequencies than high frequencies. Therefore, a weighted sampling scheme which favors low to mid range frequencies in generating each \( K \) permutation sample could give better source separation performance for the same \( L \). We use a Beta (1, 1.5) distribution instead of a uniform distribution on frequencies \( \{1, ..., F\} \) for this purpose. Holding other settings still, we observe moderate performance improvement \((\approx 0.5 \text{ dB})\) for small \( K \) \((\leq 16)\) but worse performance \((\approx -0.5 \text{ dB})\) for large \( K \) \((\geq 64)\). Non-uniform sampling could improve performance when we want to reduce computation cost.

### 5. CONCLUSION AND FUTURE WORK

We proposed a fully bitwise source separation algorithm. By reformulating the dictionary-based separation algorithm in the binary hash code domain, partial rank orders in particular, we could achieve a nonparametric and iteration-free posterior estimation process. Experiment shows convincing separation results for speech denoising tasks. Giving a temporal structure to the algorithm and its application to NMF basis vectors are potentially interesting future directions.
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