NON-NEGATIVE MATRIX FACTORIZATION ON THE ENVELOPE MATRIX IN COCHLEAR IMPLANT

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ABSTRACT

Cochlear implants (CIs) require efficient speech processing to maximize information transfer to the brain, especially in noise. Since speech information in CI is coded in the waveform envelope which is non-negative and is highly correlated to firing of auditory neurons, a novel CI processing strategy is proposed in which sparse constraint non-negative matrix factorization (NMF) is applied to the envelope matrix of 22 frequency channels in order to improve the CI performance in noisy environments. The proposed strategy is evaluated by subjective speech reception threshold (SRT) experiments and subjective quality rating tests at three SNRs. Compared to the default commercially available CI processing strategy, the advanced combination encoder (ACE), the NMF algorithm significantly enhanced speech intelligibility and improved speech quality in the 0 dB and 5 dB for normal hearing subjects with vocoded speech, but not in the 10 dB.

Index Terms— Cochlear implants, non-negative matrix factorization, speech enhancement, vocoder.

1. INTRODUCTION

Non-negative matrix factorization (NMF) [1],[2] has recently attracted interest at the intersection of many scientific and engineering disciplines, such as image processing, speech processing and pattern classification [3, 4, 5, 6, 7, 8, 9]. NMF is useful for transforming high dimensional data sets into a lower dimensional space [5]. Moreover, instead of developing holistic re-presentations, NMF usually conducts parts-based decomposition and reconstruction using non-negativity constraints [1].

Cochlear implants (CIs) are electrical devices that help to restore hearing for the profoundly deaf. The main principle of CIs is to stimulate the auditory nerve via electrodes surgically inserted into the inner ear. With the development of new speech processors and algorithms, CI users benefit more and more from CIs [10], however, the average speech perception performance of CI users decreased dramatically in the presence of background noise. One potential reason is the limited number of channels in CIs. Most CI strategies only use the envelope information to generate the electrical pulse and drive the CI electrical stimuli. Motivated by the non-negativity of the envelopes in CI channels and different NMF algorithms that have been developed to extract the desired signal from the noisy observations, this paper tries to explore whether a basic NMF can be used to improve the performance of CI users in noisy environments.

Basically, given an input non-negative matrix, NMF is a method to factorize it into two non-negative matrices. Depending on the application, the estimated non-negative factors may have different interpretations. In speech processing, the input matrix is usually the magnitude or the power spectrogram of the observed signal, where the spectra are stored column-wise in it. In our application, the input is a matrix that consists of the envelopes of CI channels, named *envelopegram* here. Considering the computation complexity of NMF and an envisaged real-time implementation in the future, a basic NMF method with a sparse constraint [11] is applied.

After a brief introduction about sparse constraint NMF in Section 2, Section 3 presents an example to show the applicability of the NMF on the *envelopegram* and the potential to be used in CI strategies. The sparse NMF speech processing strategy is adapted to CI in section 4. Finally, to further evaluate the proposed strategies, the results of subjective speech reception threshold (SRT) and quality experiments in different signal-to-noise ratios (SNRs) at two sparsity levels are presented in Section 5.

2. SPARSE CONSTRAINT NMF

Given a non-negative matrix $\mathbf{Z}$, NMF is a method to factorize $\mathbf{Z}$ into the NMF basis matrix $\mathbf{W}$ and component matrix $\mathbf{H}$ so that $\mathbf{Z} \approx \mathbf{WH}$. To do the factorization, a cost function $D(\mathbf{Z}||\mathbf{WH})$ is usually defined and minimized. There are several possibilities for defining the cost function and various procedures for performing the consequence minimization [12, 13, 14]. In this paper an EUC-NMF, where the square Euclidean distance $D_{Euc}(\mathbf{Z}||\mathbf{WH}) = \frac{1}{2}\left\|\mathbf{Z} - \mathbf{WH}\right\|_2^2$ is used as the cost function, which is equivalent to Maximum Likelihood (ML) estimation of $\mathbf{W}$ and $\mathbf{H}$ in additive i.i.d. Gaussian noise. Since the basic NMF allows a large degree of freedom, different types of regularizations have been used in the literature to derive meaningful factorizations for a specific application. In this paper, the EUC-NMF will be combined with a L_1 - regularized least square sparseness penalty function through a least absolute shrinkage and selection operator (LASSO) framework.

In our application, $\mathbf{Z}$ is the envelope of CI-channels in multiple frequency bands. NMF is applied to factorize the envelope matrix into two matrices consisting of NMF basis vectors $\mathbf{W}$ and the NMF components $\mathbf{H}$ that represents the activity of each basis vector over time. As standard NMF usually provides sparseness of its components to certain degree, an additional sparseness constraint is applied to explicitly control the sparsity of the NMF component matrix $\mathbf{H}$. In this paper, the L_1 norm of $\mathbf{H}$ is used as the sparsity measure and

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the optimization algorithm proposed by Hoyer [11], [15] is applied to obtain non-negative matrices $\mathbf{W}$ and $\mathbf{H}$. In future it might be preferable to optimize the sparseness for each individual CI user.

2.1. Problem Formulation

Let $\mathbf{Z}$ denote an $N \times M$ envelope matrix of one analysis block where N and M indicate the number of channels and the number of frames, respectively. Given the non-negative envelope matrix $\mathbf{Z}$, we aim to obtain the basis matrix $\mathbf{W}$ and component matrix $\mathbf{H}$ such that

$$D(\mathbf{Z}||\mathbf{WH}) = \frac{1}{2}\left\|\mathbf{Z} - \mathbf{WH}\right\|_2^2 + \lambda g(\mathbf{H}) \tag{1}$$

is minimized, under the constraints $\forall_{i,j,k} : w_{ik} \geq 0, h_{kj} \geq 0$, $\lambda \geq 0$, where $g(\mathbf{H}) = \sum_{k=1}^{K}\sum_{j=1}^{M} h_{kj}$.

The parameter λ in equation (1) control the sparsity level which handles the compromise between the NMF approximation and the sparsity.

2.2. Algorithm Description

As proposed by Hoyer [11], [15], an iterative algorithm is implemented to minimize the cost function in (1), in which the basis matrix $\mathbf{W}$ and the component matrix $\mathbf{H}$ are updated by gradient descent and multiplicative update rules respectively. The whole algorithm can be described as follows:

1. Initialize basis matrix $\mathbf{W}$ and component matrix $\mathbf{H}$ with random positive matrices $\mathbf{W}^0$ and $\mathbf{H}^0$, and rescale each column of $\mathbf{W}^0$ to unit norm.

2. Iterate until convergence:

a. $\mathbf{W} \leftarrow \max(\mathbf{W} - \mu(\mathbf{WH} - \mathbf{Z})\mathbf{H}^T, 0)$

b. Rescale each column of $\mathbf{W}$ to unit norm, i.e., $\mathbf{w}_k = \mathbf{w}_k \Big/ \sqrt{\sum_{i=1}^{N} \mathbf{w}_{ik}^2}$

c. $\mathbf{H} \leftarrow \mathbf{H}(\mathbf{W}^T\mathbf{Z})/(\mathbf{W}^T\mathbf{WH} + \lambda)$

The variable $\mu = 1$ is the step size.

3. NMF ON THE ENVELOPE DOMAIN

To show the applicability of NMF in the envelope domain, in this section, we set $\lambda = 0$. Four single words (BIN, PIN, DIN, TIN) from 20 sets vocabulary of 80 words [16] were used. This material was used in a variant of the four-alternative auditory feature test (FAAF) [17]. Figure 1 shows the waveforms of four clean words in one set (BIN, PIN, DIN, TIN).

3.1. CI Envelope Extraction

The envelope extraction procedure is similar to the standard advanced combination encoder (ACE) strategy [18]. First, a pre-emphasis filter attenuates low frequencies and amplifies high frequencies, to compensate for the -6 dB/octave natural slope in the long term speech spectrum; Second, short time fourier transfer (STFT) is applied to the input speech signal to obtain the spectrogram; Then the 22 - channel *envelopegram* is extracted by summing the power at frequency bins within each band. Figure 2 shows the corresponding envelopes of 22 channels, the *envelopegram*. The STFT frame length is 128 samples with 75% overlap at sampling rate $fs = 16$ KHz. The x-axis is the time frame bins, $T \approx L/(0.25 * 128)$ is the total short-time frame number for each individual word, where L is the length of the corresponding word in

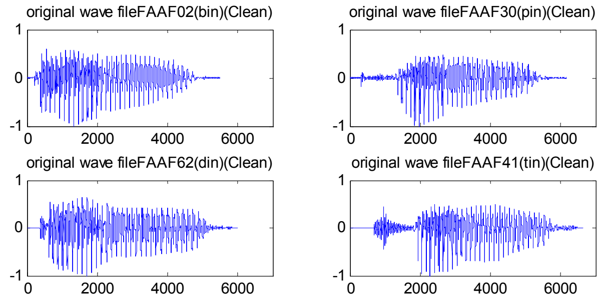


Fig. 1. Waveforms of 4 example sounds (BIN, PIN, DIN, TIN) in the time domain.

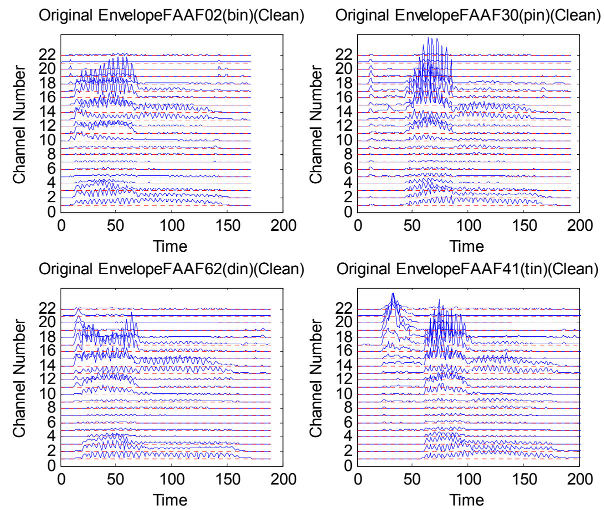


Fig. 2. *Envelopegram* of the corresponding CI envelopes from the 4 sounds shown in Fig. 1.

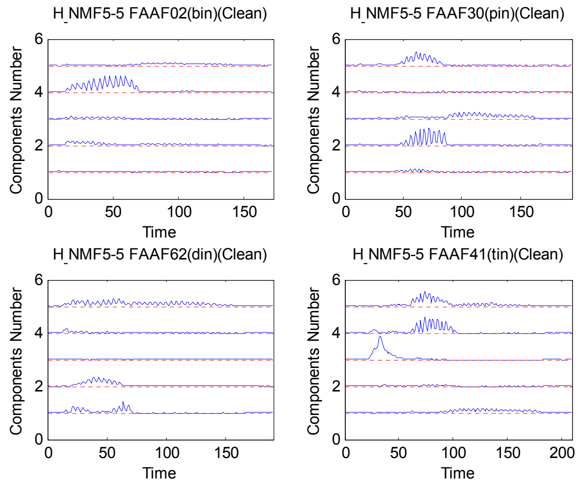
samples. Since the envelopes are non-negative, NMF should work properly for the *envelopegram*.

3.2. NMF Analysis on the Envelopegram

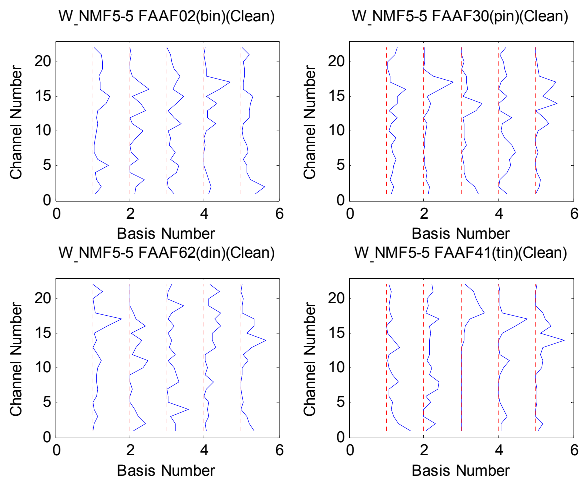
For the purpose of demonstration, NMF was applied to the whole *envelopegram* with dimension of 22*T for each word individually and the decomposition dimension was set to $K = 5$. Figure 3 (a) shows the component matrix, which determines the activity of different basis vectors over time. Figure 3 (b) shows the basis vectors for different words. Note that although the basis vectors are different for each word, the component matrices reflect similar patterns along time dimension for all the words, but not necessarily in the same order of basis number. In the following subsection, the effect of the number of the components in the reconstruction of the *envelopegram* will be further investigated.

3.3. Reconstructed Envelope

In this study the *envelopegram* is factorized by the NMF into the basis and component matrices where some components correspond to the speech source and others correspond to the noise source. The application of sparse NMF can be interpreted by assuming that the



(a) Component matrices (H)



(b) Basis matrices (W)

Fig. 3. The component matrices (a) and the basis matrices (b) of the example words 'bin', 'pin', 'din' and 'tin'.

smaller NMF components correspond either to the noise basis vectors, or they do not contribute significantly to the intelligibility of speech. By normalizing each basis vector to unit norm and by applying sparseness constraint to the factorization, the small NMF components will be removed and hence a more sparse signal will be obtained while effectively reducing redundancy and hence performing noise reduction.

Figure 4 shows the reconstruction of the envelopes with different components for the word "DIN". This analysis illustrates that: 1) the representation in the NMF domain is more sparse than in the time domain, indicating that NMF can reconstruct speech with reduced information by choosing only few components. In this example, components 1 and 4 alone can reconstruct most of the envelope information (see Fig. 4 top left panel). This reflects that speech has a high degree of redundancy and only few components are necessary to reconstruct an intelligible speech signal [19], [20]. In this paper, the sparsity and the amount of information in the reconstructed signal is controlled by λ. 2) The inherent correlation in the speech signal is conserved in the component matrix after applying NMF. As illustrated in the top-left panel of Fig. 4 and in the Fig. 3 (a), the NMF components (the activity of basis vectors) tend to be continuous over time; in other words, if a basis vector is active (meaning that its corresponding coefficient is relatively large in the component matrix) at a specific time-frame, it will often remain active for several time-frames. This might be used as additional factor for improving iteration speed and speech reconstruction in future.

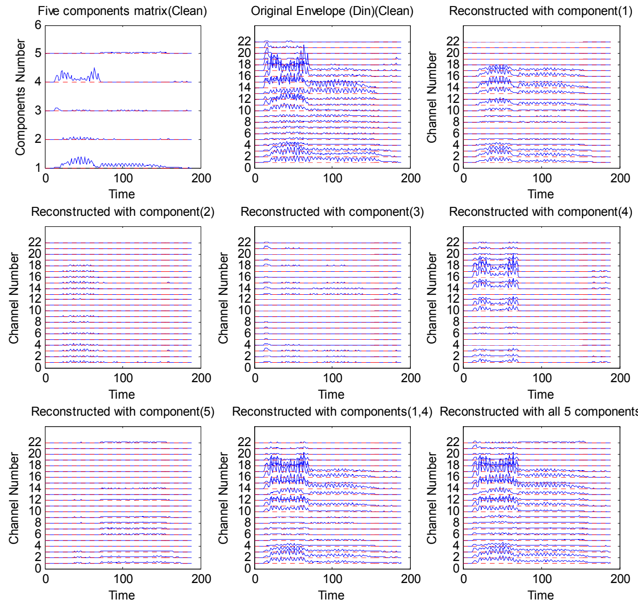


Fig. 4. An example of the reconstruction with different components.

4. SPARSE NMF STRATEGY FOR CIS

Our former researches have shown that some statistic based speech processing algorithms can improve the speech intelligibility for CI users by reducing the redundancy of noisy speech [21], [22], [23]. The proposed algorithm can therefore possibly enhance the speech intelligibility by increasing the sparseness of the reconstructed signal. In order to adapt this algorithms to CI implementation, this part will introduce the sparse NMF strategy for CIs aimed to further improve the performance of CI users in noisy environments.

Considering the real-time implementation for CI products in the future, the sparse NMF algorithm is applied to the *envelopegram* with a block by block batch processing, by buffering a certain number of continuous frames in each channel. Suppose $z(t)$ is the measured noisy speech signal, $z_{i,j}$ is the envelope-time bin in the i^{th} channel of the j^{th} frame, which is calculated according to the ACE strategy [18]. $\mathbf{Z}$ is an $N \times M$ *envelopegram*, where each column is the $N = 22$ channel envelope bin, $M = 10$ is the number of frames used in each analysis block, which is the same as the one used in [22] in order to provide the same input signal in each analysis block and short enough to allow real-time implementation. The processed envelopes are reconstructed from the modified sparse NMF components. At last, appropriate channels are selected for stimulation in a real CI or to obtain a vocoder simulation that can be tested in experiments with normal hearing (NH) listeners. The vocoded signals are produced by summating noise modulated corresponding envelopes after channel selection [24].

In this paper, the buffer length is set to $M = 10$; therefore, the systematic delay caused by buffering (considering a frame length of

8 ms, and 75 % overlap) is around 20 ms. The total delay imposed by the algorithm is equal to the sum of the buffering time and process time for each block. The sparsity constraint parameter λ in equation (1) is decided by a two-step sparsity level selection procedure described in [25]. The algorithm has been implemented and will be tested on the same real-time CI research platform as in [26] which was provided by $Cochlear^{TM}$ in the future.

5. SUBJECTIVE EXPERIMENTS

As stated in [25], the optimized λ for better SRT probably lies between 0.08 and 0.13. Aimed to compare the sparse NMF strategies within this λ range to the ACE strategy, both the intelligibility and quality experiments were carried out with noise vocoded speech and NH participants in this section. All experiments were performed in a sound-isolated room with the sounds presented bi-aurally through a Sennheiser HDA 200 headphone with a Creek OBH-21SE headphone amplifier. Bamford-Kowal-Bench (BKB) sentences [27] were used in all the subjective experiments. BKB sentence lists are standard British speech materials with 21 lists. Each list contains 50 keywords in 16 sentences. Babble noise was added to the speech material at different long-term signal-to-noise ratio (SNR). All participants were native English speakers with no previous experience of BKB sentence lists. All experiments were approved by the Human Experimentation Safety and Ethics Committee, Institute of Sound and Vibration Research, University of Southampton, UK.

5.1. SRT Experiment

Ten NH (6 males, 4 females, and aged 18-26) were recruited. The SRT experiment was used to test the speech perception ability [28]. The SNR required for 70.7% correct recognition in each condition was found with a two-up one-down adaptive procedure. A sentence was classified to be correctly identified when at least two keywords were correctly repeated [16]. The SNR level varied adaptively with a 1 dB step size. The ACE strategy and three NMF strategies with different sparsity conditions (λ = 0.08 ('NMF008'), 0.10 ('NMF010') and 0.13 ('NMF013')) were tested.

On average, there was a 0.74 dB improvement for NMF010 and a 0.92 dB improvement for NMF013 compared to the ACE strategy. A one-way repeated-measures ANOVA with LSD post-hoc test shows that the differences between the strategies are significant [F(3, 27) = 7.13, $p < 0.05$]. The following comparisons are significantly different: NMF010 < ACE ($p = 0.037$), NMF013 < ACE ($p = 0.012$), NMF010 < NMF008 ($p = 0.003$) and NMF013 < NMF008 ($p = 0.006$).

5.2. Subjective Quality Experiments

To further evaluate the sparse NMF strategies with selected sparsity constraint parameters λ = 0.1 and 0.13 chosen in [25], subjective quality experiments in different SNRs were performed to compare the performance of the NMF010 and NMF013 sparse strategies with the ACE strategy. The aim of this experiment was to give an indication whether the sparse NMF strategy can improve the quality of the noisy speech and which sparsity level was preferred. Five NH subjects were recruited (all male, aged between 20 to 26 years) in this experiment. Three conditions were tested in Babble noise at three different SNRs (0, 5 and 10 dB). Four speech conditions were also compared, involving a) ACE processed vocoded clean speech ('ACE clean'), b) ACE processed vocoded noisy speech ('ACE noisy'), c) and d) sparse NMF processed noisy speech with λ = 0.1 and 0.13 respectively ('NMF010', 'NMF013'). Each speech group consisted of the same seven individual BKB sentences with the corresponding SNR and the named processing strategies, which were vocoded and concatenated into one long presentation as testing speech.

A multi-comparison preference rating test was introduced to evaluate the quality of the speech, in which the global speech quality is evaluated for each session, i.e., each SNR (0, 5 and 10 dB). Participants were asked to rate the presentations by giving a score between 0 and 100 according to their perceived general quality (higher = better). The participants were allowed to repeat the speech stimuli as often as they wanted and they could give identical scores when unable to rate differently.

The experiment shows that all subjects rate the ACE clean speech highest quality. More interestingly, all subjects prefer NMF processed speech to the corresponding ACE noisy speech in conditions 0 and 5 dB, and three out of five prefer at 10 dB SNR. A one-way repeated-measure ANOVA with Fisher's LSD posthoc test shows that the effect of different strategies on the quality performance are significant [F(3, 12) = 38.3, $p < 0.001$]. Both sparse NMF010 and NMF013 significantly improved the quality of vocoded speech compare to the noisy ACE strategy for 0 and 5 dB ($p < 0.05$), but there is no statistically significant improvement for 10 dB. There is no significant difference between NMF010 and NMF013 for 0 and 10 dB, while NMF010 significantly ($p < 0.05$) outperforms NMF013 at 5 dB.

These results indicate that the sparse NMF speech processing strategy is able to improve both speech intelligibility and quality for vocoded speech. Further evaluation in CI users is necessary in the future, especially when there are more disagreement in the literature on whether the vocoder simulation can be used to predict the quality performance of CI users or not.

Table 1. The Paired-compared win/loss number

Strategy	ACE	NMF008	NMF010
NMF008	1:9		
NMF010	8:2	9:1	
NMF013	9:1	8:1, 1:1	5:5

6. CONCLUSIONS

A sparse constraint NMF is applied to the envelopes of CI-channels in order to improve the performance of CIs in noisy environment, in which the *envelopegram* is sparsified in the NMF domain, and only a few basis vectors are active for each time-frame. This algorithm is extended to CI implementation with a block by block batch processing technique for real-time implementation. Subjective listening experiments demonstrated that the proposed sparse NMF strategy can outperform the existing ACE strategy when using appropriate sparsity, especially at low SNRs. This is evident for both speech intelligibility and quality, at least as far as can be gauged from NH listeners and noise vocoder CI simulation. Speech intelligibility in the sparse NMF strategy benefits from noise reduction more than ACE, because only the key parts of the signal are chosen for reconstruction. However, at high SNRs, speech quality becomes more important and distortion caused by over sparsification may increase listening effort. The sparse NMF strategy shows promise for achieving better speech perception for CI users, especially the intelligibility. Further experiments with CI users and the evaluation of our real-time implementation are necessary.

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