HR-NMF MODELING FOR EXTERNAL NOISE REMOVAL OF NON-STATIONARY SIGNALS

[PAPER ID: ICITER-C114]

ASHWINI V.NANDURKAR
G.H.Raisoni College of Engineering And Management,Sant Gadge Baba Amravati University Amaravti India Email: nandurkarashwini@gmail.com

SHRIKANT J. HONADE
Assistant professor, G.H.Raisoni College of Engineering And Management,
Sant Gadge Baba Amravati University Amaravti India Email:shrikant.honade@raisoni.net

NITIN N. MANDAOGADE
Head of department, G.H.Raisoni College of Engineering And Management,
SantGadge Baba Amravati University Amaravti India Email:nitin.mandaogade@raisoni.net

ABSTRACT:

This paper implements formulations and algorithms of non-negative matrix factorization (NMF) for multichannel extensions. Herewe proposed multiple frequency model for the removal of background noise in the audio signals also we tried to analyze response of non-stationary signals. The performance of the proposed model is compared with the existing multiple frequency models using available datasets like babble, car, factory and train. Finally several real data are analyzed using both with MFCC HR- NMF and Without MFCC HR- NMF model. We use the usual traditional (LSEs) to compute parameters of the model during the execution and obtain the theoretical comparative good results also.

INTRODUCTION:

In the past twenty decadesnumber of researchers are trying to tackle the problem several stationary signals.Researchers are trying to implement a differentmodels toanalyze this problem. Several models like Moving Average (MA), Autoregressive (AR) or Autoregressive Moving Average (ARMA) are being used extensively for analyzing stationary signals. Analyzing non-stationary signals is the most challenging task.

Two methods was proposed for implementationof NMF bases modeling according to compute the better results.Single channelseparation is performed by the multichannel extensions of NMF with the ARMA mechanism. Finally several real data are analyzed using the both with MFCC HR- NMF and Without MFCC HR-NMF model.Experimental results show that 1) good SNR Ratio, and 2) Removal of noise from the external sources with microphones were evaluated successfully. The advantage of this system model is that it is simple for a user to perform and typically easy to implement.

OBJECTIVES:

Estimation of a clean speech signal from a noisy recording is a typical signal estimation task. But due to the non-stationary of the speech and most of the practical noise signals, and also due to the importance of the problem, significant amount of research has been devoted to this challenging task.

- Implementation of HR-NMF model.
- Implementation of ARMA model.

PROPOSED SYSTEM:

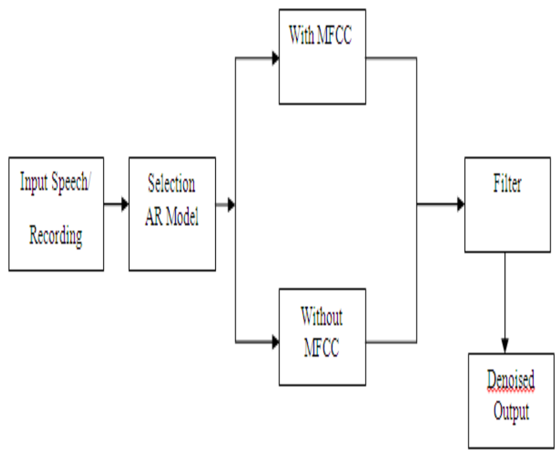

Fig. No.1. Proposed System Model

Our proposed method works allows end-users to listen the noise free sound, as shown in Fig. 1. The proposed noise reduction system uses MFCCs to obtain the filtered output.

EXPERIMENTAL SETUP:

We examined the proposed model for NMFwith real time dataset and existing database of speech.Setsof audio database were generated.Convolution is done on the speech or wav file to compute the impulse responses. Execution of model and parameterestimation donein a real roomwhich contain a external.The impulse responses were measured bytraditional way of maximum length. We made major twosets of database. One is Real time and second is existing data in the format. This datasets then further categorized and evaluate with the MFCC and Without MFCC for the performance. Listed in Table I, which can be found with the existing records in the format tested with additive white Gaussian noise for MFCC. Comparison is shown with SNR response,MSE, PSNR and time. And Table II, which can be found without MFCC for the existing records in the format tested with additive white Gaussian noise.Comparisonis shown with SNR response,MSE, PSNR and time. The algorithms were coded withMatlab and run on awindows processor.

As like Table I and Table II evaluation of real time signals are shown in table III and Table IV.At the end graph shows the comparative analysis of all test of both signals.

EXPERIMENTAL RESULTS:

Following figures shows the different output result waveforms and the respective performance

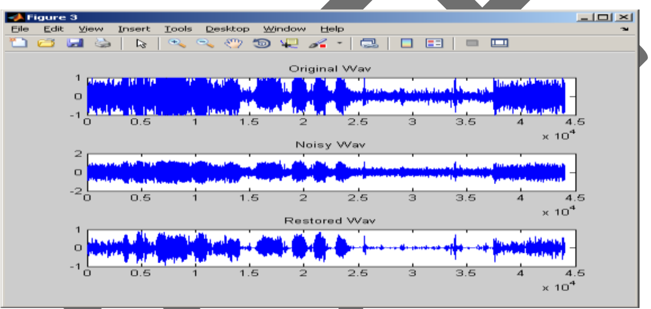

Fig. No.2.Output Signals from Noisy Input

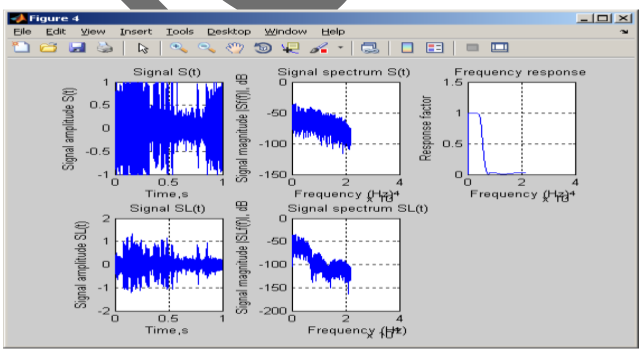

Fig.No.3. Output SignalsPerformance of Noisy Input

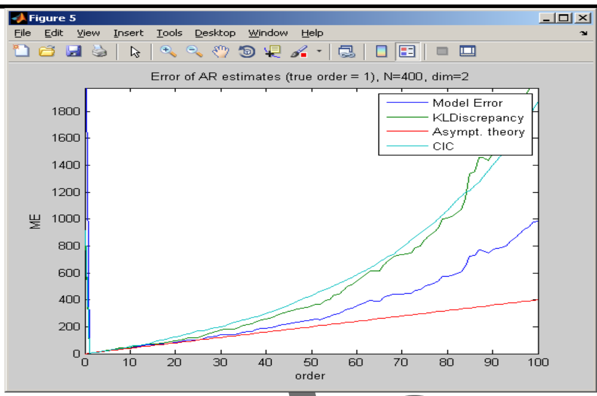

Fig.No.4.Output Signals AR estimation

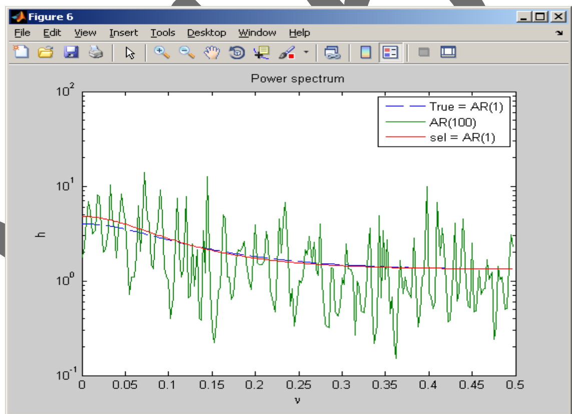

Fig.No. 5. Output Signals power spectrum

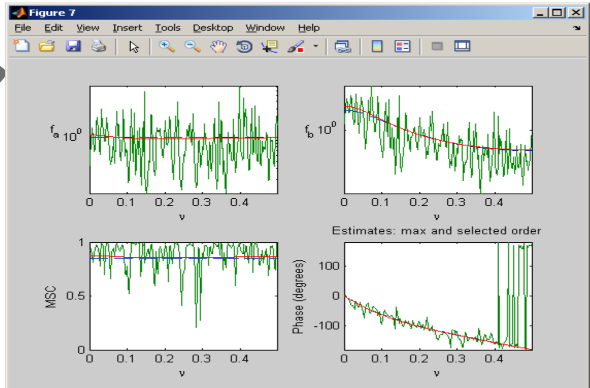

Fig. No.6.MSE Response of Output Signal

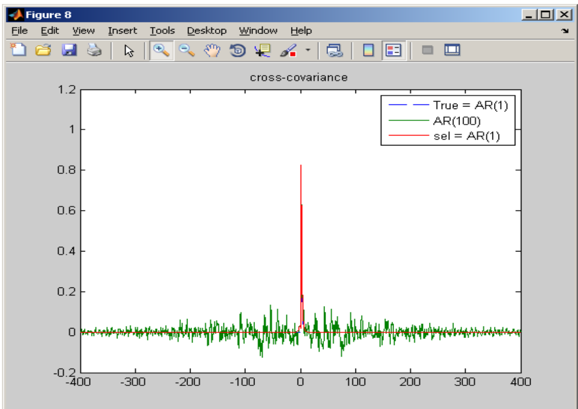

Fig.No. 7: Output Signal Cross-covarience

Table 1:Results with MFCC HRNMF for Existing File

SIZE(Kb)	PSNR(db)	SNR(db)	MSE	TIME(sec)
59.3	51.48	7.76	0.001	0.76
50.3	46.36	1.54	0.003	0.58
62.7	44.57	1.76	0.005	0.73
66.4	42.29	4.23	0.003	0.72
46.8	41.52	5.05	0.007	0.56
47	46.26	4.93	0.002	0.63
45	45.08	7.18	0.005	0.46

Table 2:Results without MFCC HRNMF for Existing File

SIZE (Kb)	PSNR (db)	SNR(db)	MSE	TIME(sec)
59.3	55.4	7.85	0.002	0.48
50.3	48.76	9.58	0.004	0.45
62.7	44.59	3.13	0.005	0.45
66.4	47.96	7.63	0.007	0.35
46.8	42.45	11.1	0.008	0.37
47	50.68	6.15	0.004	0.4
45	45.54	8.99	0.005	0.36

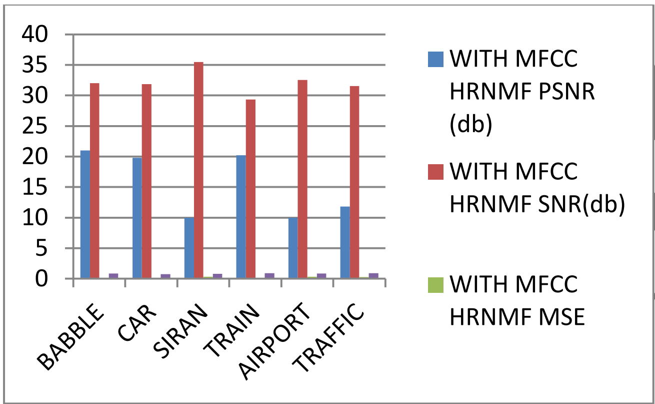

Fig.No.6. Graph with MFCC HRNMF for Existing file

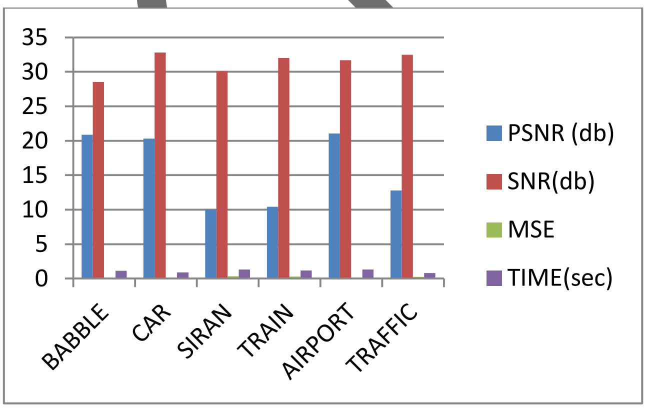

Fig.No.9. Graph without MFCC HRNMF for Existing file

Table 3: Comparative analysis between existing methods and proposed method

Existing methods							Proposed method
Signal to noise ratio in (db)							
Noise type	LMS	NLMS	RLS	NMF	NMF -PSC	LMS-PSC	HRNMF
Airport	5.4	6.34	8.3	6.4	10.5	11.8	35
Babble	5.2	6	6.2	4.5	6.7	10.8	26.53
Train	7.3	7.4	7	8	12	14.5	27.09
Car	_	_	_	_	_	_	27.02
Factory	_	_	_	_	_	_	24.81
White	3.74	4.2	7.2	4.7	6	11	8.36

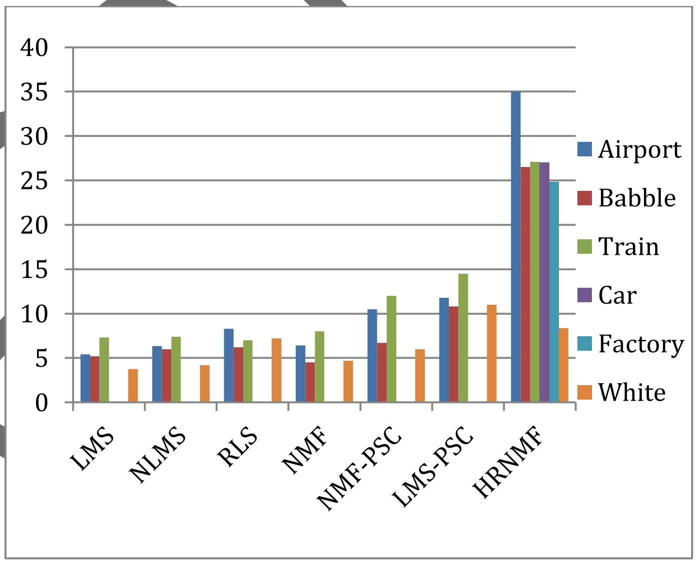

Fig.No.9. Comparative analysis between existing methods and proposed method

APPLICATIONS:

This model is able to t resolve the computationalcomplexity. Gives the improved SNR and restore the file accurately. Due to this feature it can be applicable not only practice purpose but also in real word applications. Some of them are mention bellow. Applications of Noise Suppression in the general sense, noise suppression has applications in virtually all fields of communications.

Applications in telephony, audio voice recording, and electronic voice communication.

There are various applications of speech enhancement mobile communication located in a noisy environment, communications over internet, such as Skype or Google Talk.

CONCLUSION:

This dissertation investigated the application of NMF for the background noise removal. We derived and evaluated speech enhancement algorithms In different noise conditions from the results shown it can be interpreted that HRNMF model performs better as compared to other algorithms when used for noise reduction. It can also be concluded that MFCC HR-NMF with phase spectrum compensation performs better than simple HR-NMF. Therefore it is seen that the model improves the performance of the conventional methods and results in better restored noisy signal.

REFERENCES:

i. Hiroshi Sawada and et.al *"Multichannel Extensions of Non-negative Matrix Factorization with Complex-valued Data",* IEEE Workshop on Applications of Signal Processing to Audio and Acoustics (WASPAA 2011)

ii. H. Sawada, H. Kameoka, S. Araki, and N. Ueda, *"New formulations and efficient algorithms for multichannel NMF"*,in Proc. WASPAA 2011, Oct. 2011, pp. 153–156.

iii. R. EsfandiarZavarehei, SaeedVaseghi, and Qin Yan*"Noisy speech enhancement using harmonic-nois model and codebook-based post-processing,"* MAY 2007 VOL. 15, NO. 4, pp. 1194-1203.

iv. Zhoaozhang Jin and DeLiang Wang,*"A Supervised learning approach to monaural segregation of reverberant speech,"* May 2009 VOL.17.NO.4, pp. 625-638.

v. N.Bertin,R.Badeau and E. Vincent*"Enforcingharmonicity and smoothness in Bayesian non-negative matrix factorization applied to polyphonic music transcription,"*Mar. 2010, vol. 18, no. 3, pp.538–549.

vi. Paul H. Peeling, A. TaylanCemgil and Simon J. Godsill, *"Generative Spectrogram Factorization Models for Polyphonic Piano Transcription"* March 2010, VOL18 NO.3, pp519-527.

vii. Michael Stark, Michael Wohlmayr and Franz Pernkopf, *"Source–Filter-Based Single-Channel Speech Separation Using Pitch Information,"* February 2011, VOL19, NO. 2, pp. 242-255

viii. RomainHennequin, Roland Badeau, and Bertrand David, *"NMF with Time–Frequency Activations to Model Non stationary Audio Events,"* May 2011, VOL. 19, NO. 4, pp. 744-753.

ix. Bin Gao, W. L. Woo and S. S. Dlay, *"Adaptive Sparsity Non-Negative Matrix Factorization for Single-Channel Source Separation,"* September 2011, VOL.5, NO.5, pp. 989-1001.

x. Jonathan Le Roux and Emmanuel Vincent, "*Consistent Wiener Filtering for Audio Source Separation",* MARCH 2013, VOL. 20, NO. 3, pp. 217-220.

xi. JoonasNikunen and Tuomas Virtanen, *"Direction of arrival based spatial covariance model for blind sound source separation,"* MARCH 2014 VOL. 22, NO. 3, pp. 727-739.

xii. Roland Badeau, Senior and Mark D. Plumbley, *"Multichannel High-Resolution NMF for Modeling Convolutive Mixtures of Non-Stationary Signals in the Time-Frequency Domain,"* November 2014, VOL. 22, NO. 11, pp. 1670-1680.

xiii. T. Virtanen, *"Monaural sound source separation by nonnegative matrix factorization with temporal continuity and sparseness criteria,"* IEEE Trans. Audio, Speech, Lang. Process., vol. 15, no. 3, pp. 1066–1074,Mar. 2007.

xiv. Liutkus, R. Badeau, and G. Richard, *"Informed source separation using latent components,"* in Proc. 9th International Conference on Latent Variable Analysis and Signal Separation (LVA/ICA), Saint Malo,France, Sep. 2010, pp. 498–505.

xv. G. Hu and D. L. Wang, *"Monaural speech segregation based on pitch tracking and amplitude modulation,"* IEEE Trans. Neural Netw., vol.15, no. 5, pp. 1135–1150, Sep. 2004.

xvi. G. Hu and D. L. Wang, *"An auditory scene analysis approach to monaural speech segregation,"* in Topics in Acoustic Echo and Noise Control, E. Hansler and G. Schmidt, Eds. New York: Springer, 2006, pp. 485–515.

xvii. K. W. Wilson, B. Raj, and P. Smaragdis, *"Regularized non-negative matrix factorization with temporal dependencies for speech denoising,"* in Proc. Int. Conf. Spoken Language Process. (Interspeech), 2008, pp.411–414.

xviii. M. N. Schmidt and J. Larsen, *"Reduction of non-stationary noise using a non-negative latent variable decomposition,"* in IEEE Workshop on Machine Learning for Signal Process. (MLSP), oct. 2008, pp. 486–491.

xix. G. J. Mysore and P. Smaragdis*, "A non-negative approach to semi supervised separation of speech from noise with the use of temporal dynamics,"* in Proc. IEEE Int. Conf. Acoustics, Speech, and Signal Process. (ICASSP), May 2011, pp. 17–20.

xx. P. Smaragdis, B. Raj, and M. V. Shashanka, *"A probabilistic latent variable model for acoustic modeling,"* in Advances in Models for Acoustic Process. Workshop, NIPS. MIT Press, 2006.

xxi. N. Mohammadiha, T. Gerkmann, and A. Leijon, *"A new approachfor speech enhancement based on a constrained nonnegative matrix factorization,"* in IEEE Int. Symp. on Intelligent Signal Process And Communication Systems (ISPACS), Dec. 2011, pp. 1–5.

xxii. N. Mohammadiha, P. Smaragdis, and A. Leijon, *"Prediction based filtering and smoothing to exploit temporal dependencies in NMF,"*in Proc. IEEE Int. Conf. Acoustics, Speech, and Signal Process.(ICASSP), may 2013, pp. 873–877.

xxiii. B. Raj, R. Singh, and T. Virtanen, *"Phoneme-dependent NMF for speech enhancement in monaural mixtures,"* in Proc. Int. Conf. Spoken Language Process. (Interspeech), 2011, pp. 1217–1220.

xxiv. H. Radfar, R. M. Dansereau, and A. Sayadiyan, *"A maximum likelihood estimation of vocal-tract-related filter characteristics for single channel speech separation,"* J. Audio, Speech, Music Process, vol. 1, pp. 15, 2007.

xxv. Jingdong Chen, Jacob Benesty, Yiteng (Arden) Huang,and Simon Doclo, *"New Insights Into the Noise Reduction Wiener Filter"* IEEE Transactions on audio speech and language processing, vol. 14, no. 4,pp.1218-1233, JULY 2006.

xxvi. Er. MannuSingla Mr. Harpal Singh, *" Paper on Frequency based audio Noise Reduction using Butter Worth, Chebyshev& Elliptical Filters"* , vol. 3, Issue 10, pp.5989-5995 IJRITCC October 2015,

xxvii. KomalSingla, Er. Sikander Singh, *"Audio Noise Reduction Using Different Filters"* International Journal for Technological Research in Engineering, vol. 1, Issue 11, pp.1373-1375,July-2014.

xxviii. R. R. Porle, N. S. Ruslan, N. M. Ghani, N. A. Arif, S. R. Ismail, N. Parimon, M. Mamat,*" A Survey of Filter Design for Audio Noise Reduction"* Journal of Advanced Review on Scientific Research, ISSN , Vol. 12, No.1. Pp. 26-44, 2015.

xxix. Rajeev Aggarwal, Sanjay Rathore,Jai Karan Singh,MukeshTiwari,Vijay Kumar Gupta,Dr. AnubhutiKhare,*"Noise Reduction of Speech Signal using Wavelet Transform with Modified Universal Threshold"* International Journal of Computer Applications ,Vol.20,No.5,pp. 14-19, April 2011.

xxx. S. Kırbız and B. Gunsel, *"Perceptually Weighted Non-negative Matrix Factorization for Blind Single-Channel Music Source Separation."* 21st International Conference on Pattern Recognition, pp. 226-229, November 2012.

xxxi. Juan S. Calderon Piedras, Alvaro. D. Orjuela-Canon, David A. SanabriaQuiroga, *" Blind Source Separation from Single Channel Audio Recording Using ICA Algorithms"*

xxxii. Ta-Hsin Li and Jerry D. Gibson *"Time-Correlation Analysis of Nonstationary signals with Application to Speech Processing"* IEEE. Time-Freq. Time-Scale Analysis,pp. 449-452, 1996.

xxxiii. Bin Gao, W. L.Woo, and S. S. Dlay, *"Unsupervised Single-Channel Separation of Nonstationary Signals Using GammatoneFilterbank and Itakura–Saito Nonnegative Matrix Two-Dimensional Factorizations"* IEEE TRANSACTIONS ON CIRCUITS AND SYSTEM, pp.662-675,VOL. 60, NO. 3, MARCH 2013.

xxxiv. BIN.GAO, W.L. WOO and S.S. DLAY, *"Single Channel Audio Source Separation"*, Issue 4, Vol 4,pp.173-182, April 2008.

xxxv. Cedric Fevotte and Jerome Idier, *"Algorithms for nonnegative matrix factorization with the β-divergence",* pp. 1-24 March 7, 2011.