ICA vs NMF vs PCA for BSS: Independent Component Analysis (ICA) versus Non-negative Matrix Factorization (NMF) versus Principal Component Analysis (PCA) for Blind Signal Separation (BSS) of both audio and images

Marcos Cantu
Boston University
Boston, MA 02215
cantu@bu.edu

Michael Clifford
Boston University
Boston, MA 02215
jcliff@bu.edu

Andrew Novicki
Boston University
Boston, MA 02215
novicki@bu.edu

Austin Welch
Boston University
Boston, MA 02215
austinmw@bu.edu

Abstract

We intend to implement, compare and contrast several approaches to Blind Signal Separation (BSS). While we will be learning Principal Component Analysis (PCA) in EC503 later this semester, we'd like to learn about, and develop MATLAB code for, both Independent Component Analysis (ICA) and Non-negative Matrix Factorization (NMF) approaches to BSS of both audio signals and images. Ours is a team of four; two team members (Marcos Cantu and Michael Clifford) are primarily interested in audio and time-series analysis whereas the other two team members (Austin Welch and Andrew Novicki) are primarily interested in image processing. Hence, the division of labor will follow accordingly with two sub-teams working on audio and image processing, respectively. We will test the ICA, NMF and PCA algorithms, and variants thereof, on both simple and more challenging datasets of both audio signals and images (a total of four datasets). While the scope of our project may change in the coming weeks as we become more familiar with the ICA, NMF and PCA algorithms, our starting intent is to compare and contrast the respective strengths and weaknesses of these three distinct approaches to the BSS problem.

1. Introduction

Our course project will consist of a comparison between three approaches to the *Blind Signal Separation* (BSS) problem for both audio signals and images. While the algorithm we will be learning in class, *Principal Component Analysis* (PCA) [23, 28] will be included in the comparison, it is not expected to perform as well (Fig. 1) as the other two algorithms: *Independent Component Analysis* (ICA) and *Non-negative Matrix Factorization* (NMF).

While the ICA and NMF algorithms are presented here within the context of the field of *Machine Learning* [5, 13, 31], both algorithms first gained traction within the field of *computational neuroscience* [19, 25]. This presents a unique opportunity to explore a topic in machine learning that relates to auditory and visual sensory processing, as well as *Digital Signal Processing* (DSP) [33, 42] of both 1-D signals and images. One of the challenges will be testing the ICA and NMF algorithms on both types of signals.

2. Literature Review

Blind Signal Separation (BSS) [11, 27, 7] defines a broad class of signal processing problems where there are multiple signal sources and multiple sensors (signal receivers) and the signal sources are mixed together in some unknown (blind) fashion. The goal of BSS is to estimate the mixing process so that it can be inverted to generate the original separate signals. *Independent Component Analysis* (ICA) [24, 2, 4, 20, 18, 26, 29, 21] was first put forth as an approach to solving the BSS problem in 1984 [16]. Although ICA for BSS was first discussed in the context of neural circuits and synapses [16, 22, 19], it was more rigorously put forth by Comon in 1994 [10] and gained popularity in both the neural networks and computational neuroscience fields in 1995 when Bell and Sejnowski [3], developed an improved ICA algorithm. In a 1999 *Nature* paper by Seung and Lee [25], *Non-negative Matrix Factorization* (NMF) [9, 30, 12, 25, 41, 39] emerged as an alternative to ICA. Since their emergence in the 1990s, the ICA and NMF algorithms have been applied to numerous problems in machine learning and signal processing. For the project summarized here, we will assess the effectiveness of the NMF and ICA (and PCA) algorithms for solving the BSS problem for both mixtures of audio signals and mixtures of images.

3. Problem Formulation and Solution Approaches

The BSS problem consists of finding a solution to the following linear equation describing a mixing process:

$$x = A \cdot s \qquad \leftrightarrow \qquad s = A^{-1} \cdot x$$

Where x is a vector defined as the output of multiplying the original signal vector s with an unknown mixing matrix A. Can we find an estimate for A^{-1}, effectively reverse the mixing process, and isolate the original signal vector s? This problem is complicated further by the fact that the original signal vector, s, is also unknown.

The ICA approach to BSS posits that each signal $s_i(t)$ is independent of of every other signal $s_j(t)$ in the mixture. Hence, the algorithm relies on a measure of independence. In the *FastICA* [17] algorithm, this is effected through maximizing the kurtosis. The PCA algorithm is ill-suited for recovering the original sources (Fig. 1) because it finds orthogonal directions of maximum variance whereas the ICA algorithm finds maximum independence. The NMF algorithm decomposes a data matrix Y as a product of two matrices A and X having only non-negative elements [8]. One difficulty in using NMF for BSS is that the algorithm has a non-convex solution space with many local minima [30, 1].

4. Implementation (Datasets + MATLAB code)

4.1. PCA, ICA and NMF for Audio

Datasets and Evaluation for Audio.
We intend to use datasets from the *2015 Signal Separation Evaluation Campaign* (SISEC) [32] and/or the *Blind Audio Source Separation evaluation database* (BASS-dB) [15]. Performance of the algorithms will be evaluated using the *BSS Eval* toolbox [38, 14].

PCA audio implementation in MATLAB
The project guidelines suggested that we explore at least one algorithm that is part of the syllabus. For our BSS topic, this will be Principal Component Analysis (PCA), which we anticipate will not perform as well (Fig. 1) as the ICA and NMF algorithms.

ICA audio implementation in MATLAB
For ICA approaches to BSS of audio signals, we intend to implement and test both Bell and Sejnowski's ICA algorithm [3] and Hyvarinen's *FastICA* [17] algorithm.

NMF audio implementation in MATLAB
We intend to implement and test both Smaragdis' *Non-Negative Matrix Factor Deconvolution* (NMFD) [36] and and Schmidt and Mørup's *Non-Negative Matrix Factor 2-D Deconvolution* (NMF2D) [35].

4.2. PCA, ICA and NMF for Images

Datasets and Evaluation for Images.
We will use the COREL Image Database [40, 37]. Images are labeled into categories in the database, and the mixed images (Fig. 2) will be generated by combining images from different categories. Performance of the algorithms will be evaluated using the *BSS Eval* toolbox [38, 14].

PCA images implementation in MATLAB
As in the audio implementation (Fig. 1), it is expected that the PCA algorithm will underperform in the BSS task for images. It is not expected to be useful or successful for solving the BSS problem but will be used for comparison.

ICA images implementation in MATLAB
For ICA approaches to BSS of image signals, the implementations of Bell and Sejnowski's ICA algorithm [3] and Hyvarinen's *FastICA* [17] algorithm developed in Section 4.1 (audio) will be adapted for use with 2-D signals.

NMF images implementation in MATLAB
We will implement and test NMF algorithms described by both Lee and Seung [25, 26] and Cichocki, Zdunek and Amari [8, 43, 7, 9]. Lee and Seung's algorithm describes actual non-negative matrix factorization whereas Cichocki, Zdunek and Amari describe using the approach for BSS.

5. Experimental Results

We plan to have preliminary results to share in our course project *Progress Report*, which is due Friday, April 14th.

6. *Fall Back Plan* and Conclusion

Fall Back Plan We will try to implement the PCA, ICA and NMF algorithms in MATLAB ourselves from looking at the original equations and pseudocode. If our code isn't functional, our "*Fall Back Plan*" is to use already extant code from the toolboxes provided by the original authors.

Conclusion While the scope and specifics of our project may change as we become more familiar with the ICA, NMF and PCA algorithms, our starting intent is to compare and contrast the respective strengths and weaknesses of these three distinct approaches to the BSS problem.

7. Description of Individual Effort

We will have two sub-teams implementing the BSS algorithms for use with audio signals and images, respectively. Subteam 1 (Marcos Cantu and Michael Clifford) will work primarily on Section 4.1 (PCA, ICA and NMF for Audio) while Subteam 2 (Andrew Novicki and Austin Welch) will focus on Section 4.2 (PCA, ICA and NMF for Images).

Figures

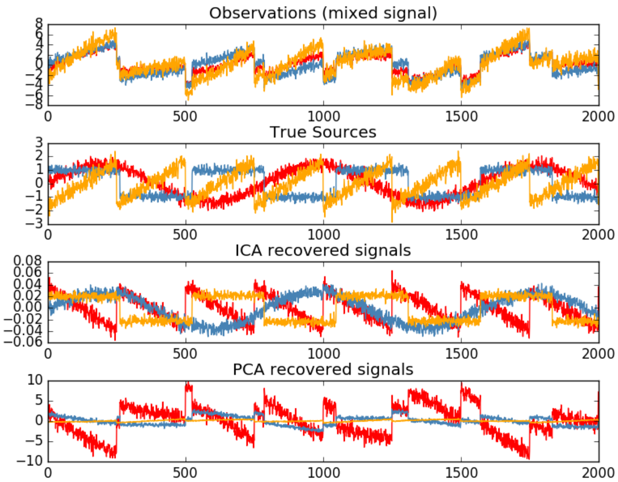

Fig. 1. PCA is not expected to perform as well as ICA. This figure is from an online tutorial [34] on using *fastICA* in Python to estimate the three true sources (sinusoidal, square and saw tooth signals, respectively) from the mixtures. Note that, unlike the ICA algorithm, the PCA algorithm cannot recover the waveforms of the true sources.

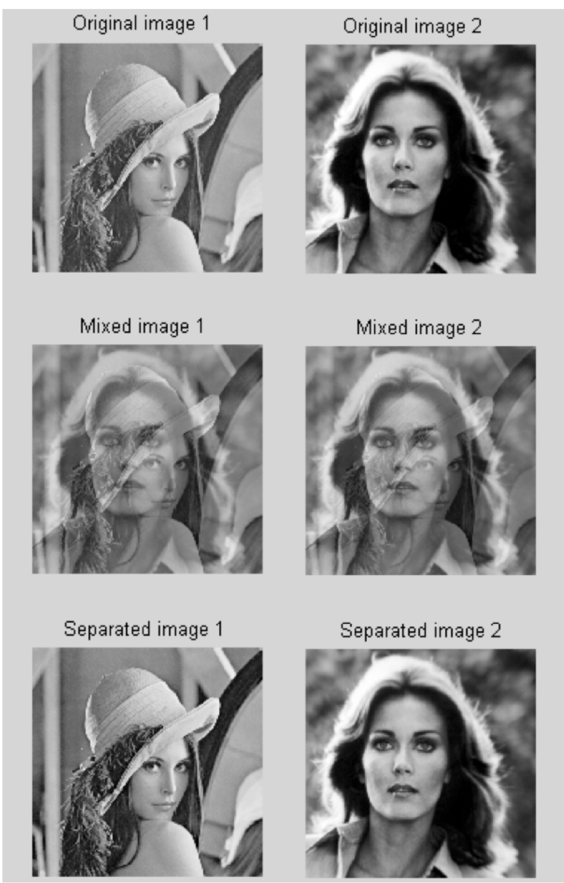

Fig. 2. An example of *within-category* image mixtures, and their separations, is shown above (adapted from [6]).

References

[1] Algorithms and applications for approximate nonnegative matrix factorization. *Computational Statistics and Data Analysis*, 52(1):155 – 173, 2007.

[2] T. Adali, C. Jutten, J. Marcos, T. Romano, and A. K. Barros, editors. *Independent Component Analysis and Signal Separation*. Springer, 2009.

[3] A. J. Bell and T. J. Sejnowski. An information-maximization approach to blind separation and blind deconvolution. *Neural Computation*, 7(6):1129–1159, 1995.

[4] E. Bingham, S. Kaski, J. Laaksonen, and J. Lampinen, editors. *Advances in Independent Component Analysis and Learning Machines*. Elsevier, 2015.

[5] C. Bishop. *Pattern Recognition and Machine Learning*. Springer, 2006.

[6] N. Chen and P. D. Leon. Blind image separation through kurtosis maximization. In *Conference Record of Thirty-Fifth Asilomar Conference on Signals, Systems and Computers (Cat.No.01CH37256)*, volume 1, pages 318–322 vol.1, Nov 2001.

[7] A. Cichocki and S.-i. Amari. *Adaptive Blind Signal and Image Processing*. Wiley, 2002.

[8] A. Cichocki, R. Zdunek, and S. Amari. New algorithms for non-negative matrix factorization in applications to blind source separation. In *2006 IEEE International Conference on Acoustics Speech and Signal Processing Proceedings*, volume 5, pages V–V, May 2006.

[9] A. Cichocki, R. Zdunek, A. H. Phan, and S.-I. Amari. *Nonnegative Matrix and Tensor Factorization*. Wiley, 2009.

[10] P. Comon. Independent component analysis, a new concept? *Signal Process.*, 36(3):287–314, Apr. 1994.

[11] P. Comon and C. Jutten. *Handbook of Blind Source Separation*. Academic Press, 2010.

[12] A. M. Darsono, T. C. Chuan, M. S. Saat, and A. A. Md Isa. A study of blind source separation using nonnegative matrix factorization. *ARPN Journal of Engineering and Applied Sciences*, 11(18):10702–10708, 2016.

[13] R. O. Duda, P. E. Hart, and D. G. Stork. *Pattern Classification*. Springer, 2000.

[14] C. Févotte, R. Gribonval, and E. Vincent. Bss_eval toolbox user guide–revision 2.0. 2005.

[15] V. Gribonval. Bass-db: the blind audio source separation evaluation database.

[16] J. Herault and B. Ans. Circuits neuronaux a synapses modifiables: decodage de messages composites par apprentissage non supervise. *Comptes.-Rendus de lAcademie des Sciences*, 299(III-13):525528, 1984.

[17] A. Hyvarinen. Fast and robust fixed-point algorithms for independent component analysis. *IEEE Transactions on Neural Networks*, 10(3):626–634, 1999.

[18] A. Hyvärinen. Independent component analysis: recent advances. *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, 371(1984), 2012.

[19] A. Hyvärinen and Y. Kano. *Independent Component Analysis for Non-Normal Factor Analysis*, pages 649–656. Springer Japan, Tokyo, 2003.

[20] A. Hyvärinen and E. Oja. Independent component analysis: Algorithms and applications. *Neural Netw.*, 13(4-5):411–430, May 2000.

[21] A. Hyvärinen and E. Oja. *Independent component analysis: algorithms and applications*. John Wiley & Sons, 2000.

[22] C. Jutten and Herault. Blind separation of sources, part i: An adaptive algorithm based on neuromimetic architecture. *Signal Processing*, 24:1–10, 1991.

[23] J. Karhunen, P. Pajunen, and E. Oja. The nonlinear PCA criterion in blind source separation: Relations with other approaches. *Neurocomputing*, 22(13):5 – 20, 1998.

[24] I. Koch. *Analysis of Multivariate and High-Dimensional Data*. Cambridge University Press, 2014.

[25] D. D. Lee and H. S. Seung. Learning the parts of objects by nonnegative matrix factorization. *Nature*, 401:788–791, 1999.

[26] D. D. Lee and H. S. Seung. Algorithms for non-negative matrix factorization. In *In NIPS*, pages 556–562. MIT Press, 2000.

[27] A. Liutkus, R. Badeau, and G. Richard. Gaussian processes for underdetermined source separation. *IEEE Transactions on Signal Processing*, 59(7):3155–3167, July 2011.

[28] L. Ma and H. Li. *An Algorithm Based on Nonlinear PCA and Regulation for Blind Source Separation of Convolutive Mixtures*, pages 1–9. Springer Berlin Heidelberg, Berlin, Heidelberg, 2007.

[29] R. Martin-Clemente and S. Hornillo-Mellado. Image processing using ica: a new perspective. In *MELECON 2006 - 2006 IEEE Mediterranean Electrotechnical Conference*, pages 502–505, May 2006.

[30] A. Mirzal. NMF versus ICA for blind source separation. *Advances in Data Analysis and Classification*, 11(1):25–48, 2017.

[31] K. P. Murphy, editor. *Machine Learning: A Probabilistic Perspective*. MIT Press, 2012.

[32] N. Ono, Z. Rafii, D. Kitamura, N. Ito, and A. Liutkus. The 2015 signal separation evaluation campaign. In *Proceedings of the 12th International Conference on Latent Variable Analysis and Signal Separation - Volume 9237*, LVA/ICA 2015, pages 387–395, New York, NY, USA, 2015. Springer-Verlag New York, Inc.

[33] A. V. Oppenheim and R. W. Schafer. *Discrete-Time Signal Processing*. Prentice Hall Press, Upper Saddle River, NJ, USA, 3rd edition, 2009.

[34] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.

[35] M. N. Schmidt and M. Mørup. *Nonnegative Matrix Factor 2-D Deconvolution for Blind Single Channel Source Separation*, pages 700–707. Springer Berlin Heidelberg, Berlin, Heidelberg, 2006.

[36] P. Smaragdis. *Non-negative Matrix Factor Deconvolution; Extraction of Multiple Sound Sources from Monophonic Inputs*, pages 494–499. Springer Berlin Heidelberg, Berlin, Heidelberg, 2004.

[37] D. Tao. The corel database for content based image retrieval. url= https://sites.google.com/site/dctresearch/home/content-based-image-retrieval. 2009.

[38] E. Vincent, R. Gribonval, and C. Fevotte. Performance measurement in blind audio source separation. *IEEE Transactions on Audio, Speech, and Language Processing*, 14(4):1462–1469, July 2006.

[39] D. Wang, R. Vipperla, N. Evans, and T. F. Zheng. Online non-negative convolutive pattern learning for speech signals. *IEEE Transactions on Signal Processing*, 61(1):44–56, Jan 2013.

[40] J. Z. Wang, J. Li, and G. Wiederhold. Simplicity: Semantics-sensitive integrated matching for picture libraries. *IEEE Trans. Pattern Anal. Mach. Intell.*, 23(9):947–963, Sept. 2001.

[41] Y. X. Wang and Y. J. Zhang. Nonnegative matrix factorization: A comprehensive review. *IEEE Transactions on Knowledge and Data Engineering*, 25(6):1336–1353, June 2013.

[42] J. W. Woods. *Multidimensional signal, image, and video processing and coding*. Elsevier/Academic Press, Burlington, MA, 2006.

[43] R. Zdunek and A. Cichocki. *Blind Image Separation Using Nonnegative Matrix Factorization with Gibbs Smoothing*, pages 519–528. Springer Berlin Heidelberg, Berlin, Heidelberg, 2008.