Non-negative Kernel Sparse Coding frameworks for Efficient Analysis of Motion Data

Babak Hosseini
Cluster of Excellence in Cognitive Interactive Technology (CITEC)
Bielefeld University, Bielefeld, Germany

bhosseini@techfak.uni-bielefeld.de

Abstract

Recently, sparse coding methods have been widely in the area of attention due to their notable benefits to data driven applications such as classification, clustering and information retrieval [1, 2, 3]. A typical sparse coding model tries to approximate input signals y as $y = Dx$ using the learned dictionary D and a sparse vector x. It provides a sparse model for the data which can capture the important (primitive) characteristics of the dataset. Also, constructing the sparse coding framework in a non-negative way can lead to more understandable models of the data [4, 5]. Therefore, an interesting area of application is to use sparse coding for motion datasets such as human activity to achieve a sparse meaningful model for it.

A typical challenge for human motion data is their non-vectorial and high-dimensional representation, however as a solution using alignment techniques such as DTW [6, 7] let us transfer the data to the kernel space by calculating their pairwise similarities. Although there are various kernel based sparse coding frameworks which use kernel representation of the dataset [2, 8, 9]; there are two important aspects to consider while modeling the motion data:
1-How meaningful the learned model is regarding the original data.
2-How to efficiently deal with different dimensions of the data.
For researchers in the area of Human Activity Analysis it is important to obtain models which can still be interpretable regarding its components, so that they can apply their higher level analysis afterwards. For example a model for walking examples is desirable to present meaningful characteristics of walking motion.

To that aim we have designed a specific sparse coding framework which uses the kernel representation of the motion data in order to produce a non-negative representation of the dataset [10]. We demonstrate that in that framework different human activities can be modeled using motion primitives constructed from similar types of motions.

Our other framework is a feature based sparse coding designed to take into account the dimension aspect of the motions using multi-manifold

representation [11]. It finds an efficient model through various combinations of available dimensions in the human motion such as assigning importance weights to different joints of the body. This representation is able to provide more interpretable model of human activity regarding its internal components of the motion, and also can achieve better classification on retrieval performance. Moreover, we can demonstrate that having such a model can make it possible partially recognize unseen categories of activities.

References

[1] Z. Jiang, Z. Lin, and L. S. Davis, "Label consistent k-svd: Learning a discriminative dictionary for recognition," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 35, no. 11, pp. 2651–2664, 2013.

[2] V. M. Patel and R. Vidal, "Kernel sparse subspace clustering," in *Image Processing (ICIP), 2014 IEEE International Conference on.* IEEE, 2014, pp. 2849–2853.

[3] B.-C. Chen, Y.-H. Kuo, Y.-Y. Chen, K.-Y. Chu, and W. Hsu, "Semi-supervised face image retrieval using sparse coding with identity constraint," in *Proceedings of the 19th ACM international conference on Multimedia.* ACM, 2011, pp. 1369–1372.

[4] R. He, W.-S. Zheng, B.-G. Hu, and X.-W. Kong, "Nonnegative sparse coding for discriminative semi-supervised learning," in *Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on.* IEEE, 2011, pp. 2849–2856.

[5] L. Zhuang, H. Gao, Z. Lin, Y. Ma, X. Zhang, and N. Yu, "Non-negative low rank and sparse graph for semi-supervised learning," in *CVPR 2012.* IEEE, 2012, pp. 2328–2335.

[6] B. Hosseini and B. Hammer, "Efficient metric learning for the analysis of motion data," in *IEEE International Conference on Data Science and Advanced Analytics (DSAA), 2015.*, Oct 2015, pp. 1–10.

[7] J. Blackburn and E. Ribeiro, "Human motion recognition using isomap and dynamic time warping," *Human motion–understanding, modeling, capture and animation*, pp. 285–298, 2007.

[8] H. V. Nguyen, V. M. Patel, N. M. Nasrabadi, and R. Chellappa, "Design of non-linear kernel dictionaries for object recognition," *IEEE Transactions on Image Processing*, vol. 22, no. 12, pp. 5123–5135, 2013.

[9] Z. Chen, W. Zuo, Q. Hu, and L. Lin, "Kernel sparse representation for time series classification," *Information Sciences*, vol. 292, pp. 15–26, 2015.

[10] B. Hosseini, F. Hülsmann, M. Botsch, and B. Hammer, "Non-negative kernel sparse coding for the analysis of motion data," in *International Conference on Artificial Neural Networks.* Springer, 2016, pp. 506–514.

[11] B. Hosseini and B. Hammer, "Non-negative multi-kernel sparse coding frameworks for analysis of motion data," *Submitted Article*, 2017.