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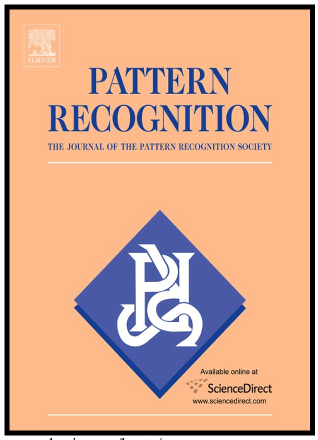

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Discriminative Sparse Flexible Manifold Embedding with Novel Graph for Robust Visual Representation and Label Propagation

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Abstract— We explore the problem of robust visual representation and enhanced label prediction. Technically, a *Discriminative Sparse Flexible Manifold Embedding* (SparseFME) method with novel graph is proposed. SparseFME enhances the representation and label prediction powers of FME by improving the reliability and robustness of distance metric, such as using the $l_{2,1}$-norm to measure the flexible regression residue encoding the mismatch between embedded features and the soft labels, and regularizing the $l_{2,1}$-norm on the soft labels directly to boost the discriminating power so that less unfavorable mixed signs that may result in negative effects on performance are included. Besides, our SparseFME replaces the noise-sensitive Frobenius norm used in FME by $l_{2,1}$-norm to encode the projection that maps data into soft labels, so the projection can be ensured to be sparse in rows so that discriminative soft labels can be learnt in the latent subspace. Thus, more accurate identification of hard labels can be obtained. To obtain high inter-class separation and high intra-class compactness of the predicted soft labels, and encode the neighborhood of each sample more accurately, we also propose a novel graph weight construction method by integrating class information and considering a certain kind of similarity/dissimilarity of samples so that the true neighborhoods can be discovered. The theoretical convergence analysis and connection to other models are also presented. State-of-art performances are delivered by our SparseFME compared with several related criteria.

Index Terms— Flexible manifold embedding, semi-supervised learning, $l_{2,1}$-norm regularization, novel graph construction, robust representation and recognition

1 Introduction

Label propagation (LP), as a powerful graph based semi-supervised learning (G-SSL) algorithm [1-12][25][37], has been arousing much attention in recent years due to its efficiency and effectiveness to image representation and classification. SSL algorithm can use both labeled and unlabeled data for learning, which is motivated by two facts. First, labeled data is usually hard and expensive to capture in the real world, while unlabeled ones are often readily available with low expense [1-2]. Second, using supervised prior of labeled data and pairwise relations to unlabeled data can effectively approximate the local geometry structures of all data [3-13][29-31][45][47][51].

Label propagation and its extensions [4-11][47] aim at propagating label information of labeled data to the unlabeled data based on the intrinsic relations between labeled and unlabeled data, and finally output the estimated