Kernel Learning for Extrinsic Classification of Manifold Features

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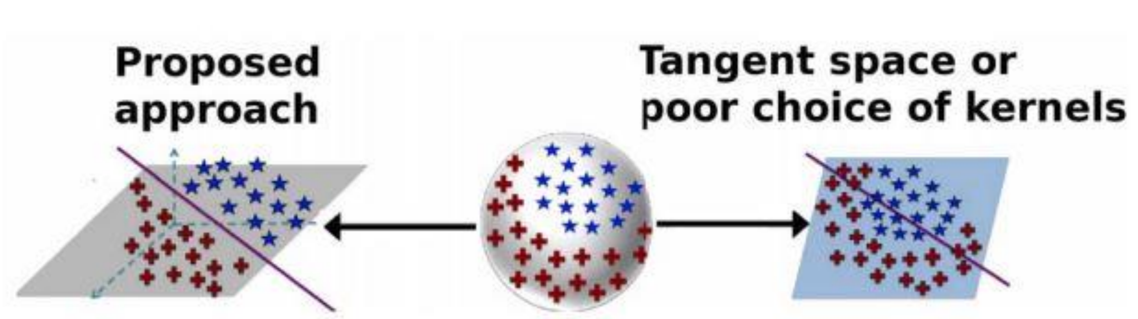
Introduction

Often in computer vision applications, features lie on Riemannian manifolds. Learning algorithms such as discriminant analysis, partial least squares, support vector machines, etc. cannot be applied directly to these features as they are non-Euclidean. We then map the manifolds to Euclidean spaces using kernels. Bad choice of kernels give poor results.

In this paper, author addresses the issue of kernel-learning. The problem has been formulated as a convex optimization problem and solving it using multiple kernel learning approach.



Previous Work

- **Nearest Neighbour** : Nearest-neighbor classifier based on some appropriately defined distance or similarity measure
- **Bayesian Framework** : Use the Bayesian framework by defining probability density functions (pdfs) on manifolds
- **Euclidean Mapping** : Discriminative approaches like LDA, PLS, SVM, Boosting, etc., can be extended to manifolds by mapping the manifolds to Euclidean spaces.

Experiment

To learn a good kernel-classifier combination for features that lie on Riemannian manifolds, the following two criteria should be satisfied :

(i) **Risk functional** associated with the classifier in the mapped space should be **minimized** for good classification performance
(ii) The mapping should **preserve** the underlying **manifold structure**.

The problem is hence represented as an optimization problem $\min_{\mathcal{W},\mathcal{K}} \quad \lambda\,\Gamma_s(\mathcal{K}) + \Gamma_c(\mathcal{W},\mathcal{K})$

where $\Gamma_s(\mathcal{K})$ corresponds to manifold structure and $\Gamma_c(\mathcal{W},\mathcal{K})$ to classifier costs.

Due to the superior generalization properties, author has used **SVM** as the **classifier**. To preserve the manifold structure, distances have been constrained in the mapped space to be close to the manifold distances.

On combining both the classifier and the structure costs, the solution to **kernel-learning** becomes solving a **semi-definite programming** problem.

In an SDP, both training and test data need to be present while learning the kernel matrix. Also solving SDP's are computationally expensive.

Hence, instead of using standard solvers such as SeDuMi, we use **MKL approach** in which we parameterize the kernel as a linear combination of fixed base kernels.

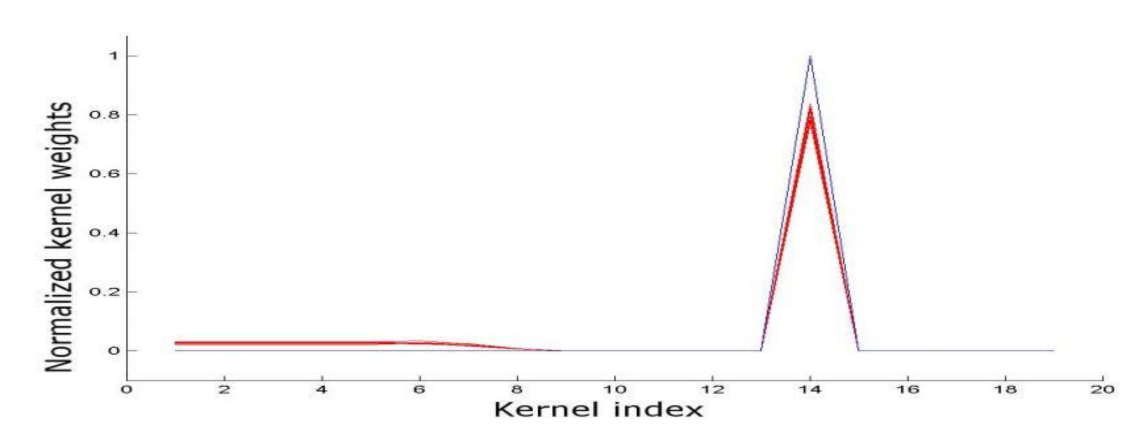
The, thus obtained optimization problem can be efficiently solved using **reduced gradient descent** or any other constrained-convex-optimization-problem solver.

Experiments were performed on **Computer Vision** applications using the following features :

1. **Linear subspaces** - Grassmann Manifolds : e.g. Mercer kernel, Projection kernel, etc.
2. **Covariance features** : e.g. kernel based on log-Euclidean space

The proposed approach was tested on three applications:

- **Face recognition - YouTube celebrities** : This dataset has 1910 video clips of 47 subjects collected from the YouTube
- **Object recognition - ETH80** : This dataset for object recognition task has images of 8 object categories with each category including 10 different object instances. Each object instance has 41 images captured under different views, which form an image set
- **Human activity recognition - INRIA IXMAS** : This dataset consists of 10 actors performing 11 different actions, each action executed 3 times at varying rates while freely changing the orientation



Normalized kernel weights for the S-MKL(blue) and the proposed method(red) on the INRIA IXMAS dataset

Results

dataset	NN	S-MKL [17]	SM-P [21]	SM-NP [21]	Proposed approach
INRIA IXMAS	80.0	**90.0**	82.4	87.87	**90.0**

Recognition rates for human activity recognition on the INRIA IXMAS dataset using dynamical models

dataset	NN	S-MKL [17]	GDA [8]	Proj + PLS [24]	Proposed approach
YouTube	62.8	64.3	65.7	67.7	**70.8**
ETH80	93.2	93.7	92.8	95.3	**96.0**

Recognition rates for image set-based face and object recognition tasks using linear subspaces

dataset	NN	S-MKL [17]	CDL-LDA [24]	CDL-PLS [24]	Proposed approach
YouTube	40.7	69.7	67.5	70.1	**73.2**
ETH80	92.7	93.7	94.5	96.5	**98.2**

Recognition rates for image set-based face and object recognition tasks using covariance features

Conclusion

In the paper, the author introduced a general framework for developing extrinsic classifiers for features that lie on Riemannian manifolds using the kernel learning approach.

The research can be extended to other classifiers other than SVM. The paper uses kernel manifold-structure as a regularizer. Other regularizers can be used which can make better use of underlying manifold structure.