Classification of images using semi-supervised learning and structural similarity measure

H. Cecotti and B. Gardiner

Intelligent Systems Research Centre, Ulster University, Londonderry, UK

Abstract

In this paper, we evaluate the performance of graph-based semi supervised learning (SSL) for the classification of images, by using the structural similarity index measure (SSIM) to build the adjacency matrix of the graph. Performance evaluation was carried out with the TID2013 database. The results support the conclusion that SSIM can be efficiently used with graph-based SSL to retrieve images that are similar.

Keywords: Image processing, Semi-supervised learning, Structural Similarity Measure.

1 Introduction

Image quality assessment (IQA) has become an important issue in applications dealing with large number of images. IQA aims to use computational models to measure the image quality consistently with subjective evaluations. The most efficient IQA methods take into account the human visual system (HVS) and image features based on the luminance, the contrast, and the frequency content. The most famous IQA is the structural similarity (SSIM) index. This technique is motivated by the need to capture the loss of structure in the image. The main assumption in SSIM is that HVS is highly adapted to extract the structural information from the visual scene. Such a distance can be exploited in classifiers that are based on the estimation of distances. Most of the semi-supervised learning approaches rely on the cluster assumption, which assumes that examples associated to the same cluster, or the same group of clusters, will share the same label. The techniques rely also on the manifold assumption. It considers that examples that are close to each other will have the same label. The label prediction of an example x will depend on both the labelled and unlabelled examples that are very close to x. Depending on the data, these two assumptions can be difficult to satisfy. The goal of this paper is to combine graph-based semi-supervised learning and the SSIM index in order to build the graph that is used for label propagation. A key issue is to determine the ideal size of the neighbourhood and to what extent different image deformations may provide a bridge across images of the same class.

2 Methods

The SSIM index is based on the computation of three terms (the luminance, the contrast, and the structural term) [Wang et al., 2004]. For the graph-based SSL method, we have considered label propagation. This method requires only the size of the neighbourhood (k) to create the adjacency matrix. A graph $g = (V, E)$ is defined by the nodes $V = \{1, \dots, n\}$, which represent all the n examples of a training database $X = \{x_1, \dots, x_n\}$, and edges E, which represent the similarities between examples. The similarities are typically represented by a weight matrix $W \in \mathbb{R}^{n \times n}$. A cell $W(i, j)$ corresponds to the similarity between the example x_i and x_j, i.e., the edge (i, j) in E. If x_i and x_j are close to each other (they belong to the same neighbourhood), then $W(i, j)$ has a non-zero value. In this study, $W(i, j)$ is estimated with SSIM. For the evaluation of the method, we have also considered the mean square error (MSE) as a distance between two images. Furthermore, $W(i, j)$

 ISBN 978-0-9934207-1-9

is set to 1 if an image belongs to the k^{th} closest neighbours, otherwise it is set to 0. In a multiclass problem, the label propagation algorithm is used for each class (one vs. all), and then the results are combined to determine the class of each example [Bengio et al., 2006]. We have used the TID2013 database (available at http://ponomarenko.info/tid2013.htm). TID2013 contains 25 colour images, and each image is deformed into 120 images. We consider here all the deformed images (3000). For the evaluation, we consider one image per class, i.e. one of the 120 deformed image for each image template.

3 Results

The matrices representing the distances between each image using SSIM and MSE are depicted in Fig. 1. For SSIM, each value is between 0 and 1. Values close to 1 represent a high similarity. For MSE, values (in the order of x10^4) close to 0 represent a high similarity between two images. The evolution of the accuracy in relation to the size of the neighbourhood (k) for the creation of the adjacency matrix highlight the importance of this parameter. With a large neighbourhood, all the deformed examples of an image are clustered together and the labels can be easily propagated. With $k = 110$, all the labels are perfectly propagated, i.e., with 25 labelled images, it is possible to label the remaining 2975 images with a perfect accuracy. However, when k is small (e.g. 20), the performance is significantly lower as there is no bridge allowing the labels to be propagated from one type of deformations to another.

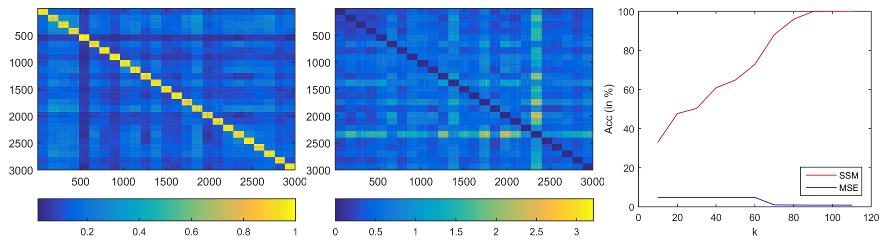

Figure 1: Matrices representing the distances between each image (**left**: SSIM **middle**: MSE). Accuracy (in %) in relation to the size of the neighbourhood (k) in the graph-based SSL method (**right**).

4 Conclusion

IQA techniques such as SSIM do not require any training for estimating the difference between images, therefore suitable for large databases that can contain sets of images that are very similar, and where it is not required to cluster images based on high level features (e.g. semantic content). In this study, we have considered the TID2013 database and evaluated to what extent graph based semi-supervised learning could be used to retrieve the label of all the deformed images based only on a randomly selected image of each class. Further work will include the analysis of other distances and the evaluation of the type of deformations that can be managed.

References

[Bengio et al., 2006] Bengio, Y., Dellalleau, O., and Roux, N. L. (2006). Label propagation and quadratic criterion. In O. Chapelle, B. S. and Zien, A., editors, *Semi-supervised learning*, pages 35–58. MIT Press.

[Wang et al., 2004] Wang, Z., Bovik, A. C., Sheikh, H. R., and Simoncelli, E. P. (2004). Image quality assessment: From error measurement to structural similarity. *IEEE trans. Image Processing*, 13(1).

 ISBN 978-0-9934207-1-9