

Survey on Supervised Classification using Self Organising Maps

Nupur Choudhury¹, Rupesh Mandal²

*Department of Computer Science and Engineering, Sikkim Manipal Institute of Technology
Sikkim, India*

Abstract— Image classification is an important topic in digital image processing, and it could be solved by pattern recognition methods. This paper is a survey based on Self Organising Maps used as a supervised algorithm for image classification. It is observed that SOM can be used as a supervised method, and can have better advantages: better predictions, easier to interpret and better stability.

Keywords— SOM, SOM-KS, hit map, saliency map, colour space, entropy index.

I. INTRODUCTION

Image classification refers to the task of extracting information classes from a multiband raster image. The resulting raster from image classification can be used to create thematic maps. Depending on the interaction between the analyst and the computer during classification, there are two types of classification: supervised and unsupervised. Image Classification: Assumptions Similar features have similar spectral responses. The spectral response of a certain feature is unique when compared to other features of interest. By measuring the spectral reply of a recognized characteristic, we can use this information to discover all occurrences (instances) of that aspect.

A. Supervised Image Classification Page Layout

- Idea: Using samples with known identities (i.e., assigned pixels to information classes), the algorithm classifies pixels with unknown identities.
- Classification Procedure: The procedure starts by the user selecting and naming areas on the image, which correspond to the classes of interest. These classes correspond to information classes. Then, the image classification algorithm will find all similar areas which are algorithm dependent.

B. Unsupervised Image Classification

- Concept: The image is automatically segmented into spectral classes based on natural groupings found in the existing data.
- Classification procedure: The user inputs some classification parameters. The algorithm proceeds by finding pixels with similar spectral properties. After the classification, the user names each class (i.e., the user relates the spectral classes to the relevant information classes). In several cases, classification will be assumed by means of a computer, with the employ of mathematical

classification techniques. Classification will be prepared according to the following methods as shown:

Step 1: Definition of Classification Classes: Depending on the objective and the characteristics of the image data, the classification classes should be clearly defined.

Step 2: Selection of Features: Features to discriminate between the classes should be established using multispectral and/or multi-temporal characteristics, textures etc.

Step 3: Sampling of Training Data: Training data should be sampled consecutively to find out suitable decision rules. Classification technique such Classification techniques such as supervised or unsupervised learning will then be decided on the basis of the training data sets.

Step 4: Estimation of Universal Statistics: Various classification techniques will be compared with the training data, so that an appropriate decision rule is selected for subsequent classification.

Step 5: Classification: Depending up on the decision rule, all pixels are classified in a particular class. There are two methods of pixel by pixel classification and per-field classification, with respect to segmented regions.

Step 6: Verification of Results: The classified results should be checked and verified for their accuracy and reliability.

C. Supervised & Unsupervised Classification

- Supervised image classification procedure: Select training data, Classify the image, Accuracy assessment.
- Unsupervised image classification procedure: Classify the image, Identify clusters, Accuracy assessment.

II. LITERATURE SURVEY

A. Types of image segmentation techniques:

Researchers have investigated natural image segmentation for many years. Segmentation methods are mainly classified as follows: feature-space-based techniques, image-domain-based techniques, and edge-based techniques. Clustering, histogram thresholding, and so forth are feature-space segmentation techniques; split-and-merge, region growing, edge-based and neural-network-based methods are image-domain segmentation techniques. Some researchers categorized the segmentation methods based on two basic properties of the pixels in relation to their local neighbourhood: discontinuity and similarity. Corresponding methods based on discontinuity property of the pixels are called boundary-based methods, while those based on similarity property are called region-based methods.

B. Feature-space-based:

The feature-space based method is composed of two steps, feature extraction and clustering. Feature extraction is the process to find some characteristics of each pixel or of the region around each pixel, for example, pixel value, pixel colour component, windowed average pixel value, windowed variance, Law's filter feature, Tamura feature, and Gabor wavelet feature, etc. After we get some symbolic properties around each pixel, clustering process is executed to separate the image into several "meaningful" parts based on these properties. There are also many kinds of clustering algorithms, for example, Gaussian mixture model, mean shift, and the one of our project, "normalized cut".

C. Image Domain Based:

Image-domain based method goes through the image and finds the boundary between segments by some rules. The main consideration to separate two pixels into different segments is the pixel value difference, so this kind of methods couldn't deal with textures very well. Split and merge, region growing, and watershed are the most popular methods in this class.

D. Edge Based:

The third class is edge-based image segmentation method, which consists of edge detection and edge linking. There are another few methods are also reported towards the image segmentation. Those are 1. Clustering methods 2. Compression-based methods 3. Histogram-based methods. 4. Region-growing methods. 5. Partial differential equation-based methods. 6. Graph partitioning methods. The clustering methods using the K-means algorithm is an iterative technique that is used to partition an image into K clusters. Compression based methods postulate that the optimal segmentation is the one that minimizes, over all possible segmentations, the coding length of the data. The connection between these two concepts is that segmentation tries to find patterns in an image and any regularity in the image can be used to compress it. The method describes each segment by its texture and boundary shape. Histogram-based methods are very efficient when compared to other image segmentation methods because they typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the clusters in the image. Colour or intensity can be used as the measure. A refinement of this technique is to recursively apply the histogram-seeking method to clusters in the image in order to divide them into smaller clusters. This is repeated with smaller and smaller clusters until no more clusters are formed.

In fact, with the crossover of different disciplines, it is impossible to "segment" each segmentation technique clearly and each segmentation method can be classified into different categories by its different features. For example, neural-network method is, in fact, a kind of learning/training progress which touches every aspect of the segmentation, and it makes use of features or domain

information of an image too. Methods involving multiple disciplines usually get better results. In recent years, methods like JSEG, mean shift, normalized cuts, and so forth have achieved certain success and are often used as benchmarks for natural image segmentation. Mean shift detects modes of the probability density of colours occurring jointly in image and colour domains and shows a good performance on segmenting the images with strong variations of density. Researchers like Shi and Malik[R2] treated the segmentation as a graph partitioning problem. A weighted undirected graph is constructed by taking the pixels as the nodes of graph. The graph is partitioned by optimizing the criterion of normalized cut based on the computation of Eigen values. JSEG makes a multi scale analysis in the image domain of a clustering map obtained from quantization in colour domain. Consisting of two independent stages of colour quantization and spatial segmentation, it is an unsupervised segmentation especially being robust when applied to scenes where texture predominates.

III. BACKGROUND

A. Clustering and Image Segmentation

Clustering methods provide us with a different view of the image segmentation. However, directly clustering methods like k-means and their variants are not acceptable considering the computational cost and a priori cluster number k needed. SOM with properties such as the input space approximation, topological ordering, and density matching, allied with the simplicity of the model and the ease of implementation of the learning algorithm, makes itself a promising clustering tool. SOM is also helpful for visualization, cluster extraction, and data mining, and it has been proved to be successful for high dimensional data, where traditional methods may often fail or be insufficient. Rarely simple SOM is implemented directly on image segmentation. Some researchers modified and expanded the typical SOM, while others combined SOM with other methods. Researchers presented a new SOM with a variable topology for image segmentation. The proposed fast convergent network is capable of colour segmenting images satisfactorily with a self-adaptive topology where SOM-based clustering method was applied to the spectral data of remotely sensed image.

B. Saliency Map and Image Segmentation.

In most cases, the aim of image segmentation is object recognition, image retrieval, or scene understanding, and so forth, which serves as a necessary and the first step of high-level, object-based applications. Therefore, correct segmentation of salient objects in the image is more important than segmenting other minor parts correctly. It is an interesting topic covered by many researchers. Object recognition in an image follows top-down or bottom-up method. The first method needs priori knowledge of the top level, with face detector, human body. As a basic step in image processing, image segmentation and object extraction are also facilitated by saliency map. On one hand, some authors defined their own saliency map for their research. The saliency map being guidance to the image

processing and object detection many researches are expanded, and a lot of achievements gained. Applications like image retrieval, image retargeting, image content analysis, image fusion, and image quality assessment were all more or less based on the saliency map.

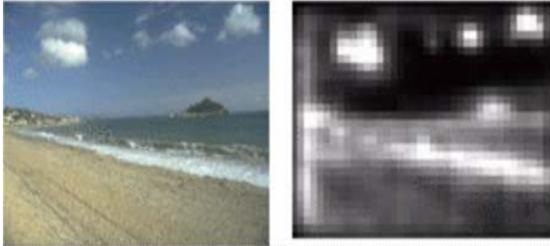


Fig1: Visual scene on the left and the corresponding saliency map on the right. [R1]

C. Self-Organizing Map

SOM, first put forward by Kohonen, is a kind of widely used unsupervised artificial neural network. The map is a group of node units represented by prototype vectors lying in a 2-dimension space usually though occasionally nodes are set in one or multi-dimensional space. These units are connected to adjacent units by a neighbourhood function. Prototype vectors are initialized with random or linear methods and “folded” in the 2-dimension space. Then, they are trained iteratively by randomly selected input samples sequentially or in batches and updated according to the neighbour function. After the training, prototype vectors become stable and “unfolded” themselves in the 2-dimension-space map. The typical features of SOM are topology visualization of the input patterns and representation of a large number of input patterns with a small number of nodes. The most important attribute of SOM is that the input patterns which are similar in the input space are also nearby with each other topologically in the output space, the nodes map.

D. k-Means and Image Evaluation

After the large quantities of pixel data are projected to a 2-dimension space to become a member in a group of nodes in a simple and fast way, a typical k-means method is adopted to cluster the prototype vectors. Clustering the SOM prototype vectors instead of directly clustering the data is a computationally effective approach. As a kind of unsupervised learning method, clustering is divided to be hierarchical or partitional. The formal one can be agglomerative (bottom-up) or divisive (top-down). The latter one, partitional clustering, decides all clusters at once. Being a typical partitional clustering method, k-means method assigns each point to the cluster with the nearest center. The main steps of a standard k-means algorithm include the following. (1) Set the number of cluster as k and randomly generate k clusters and determine the cluster centers, or directly generate k random points as cluster centers. (2) Assign each point to the nearest cluster center, usually calculated with Euclidean distance. (3) Re-calculate the new cluster centers. (4) Repeat steps (2) and (3) until convergence criterion is met. The main advantages of k-means algorithm are its simplicity. Its disadvantages are

heavy computation if the amount of data is large. It may not yield the same result with each run, since the resulting clusters depend on the initial random assignments. To overcome its disadvantages, the k-means is run for at least ten times to avoid instability caused by random assignments. Because the number of prototype vectors is very small, the computation cost is not a problem.

IV. METHODOLOGY

In present in this paper a SOM-based k-means method (SOM-K) and a further saliency map-enhanced SOM-K method (SOM-KS). In SOM-K, pixel features of intensity and L^*u^*v colour space are trained with SOM and followed by a k-means method to cluster the prototype vectors, which are filtered with hits map. A variant of the method, SOM-KS, adds a modified saliency map to improve the segmentation performance. Both SOM-K and SOM-KS segment the image with the guidance of an entropy evaluation index. Compared to SOM-K, SOM-KS makes a more precise segmentation in most cases by segmenting an image into a smaller number of regions. At the same time, the salient object of an image stands out, while other minor parts are restrained. The computational load of the proposed methods of SOM-K and SOM-KS are compared to J-image-based segmentation (JSEG) and k-means and are found to be better.

A. *The main contributions of the method are the following.*

- SOM-K, a new unsupervised natural image segmentation method based on SOM and k-means. Intensity and L^* , u^* , and v^* values of a colour image are taken as features to be trained by a SOM network. The output prototype vectors are filtered by the hit map at first and clustered by the k-means method. A best image segmentation result can be obtained according to the entropy-based segmentation evaluation method. The method is proved to be robust to natural colour image segmentation through experiments.
- A modified saliency map which uses intensity, orientation, and colour components R , G , B , and Y and adopt the contrast-based image attention model. After that, all saliency maps are resized to the original size and combined together to be a saliency map.
- SOM-KS, an unsupervised natural colour segmentation method guided by image saliency map. Unlike other saliency map-based segmentation methods the modified saliency map information is directly combined with intensity and $L^*u^*v^*$ to segment a natural colour image through SOM and k-means in an automatic manner. This method enhances the attractive objects in the image and restrains the less salient parts, which can reduce the processing workload for further processing.

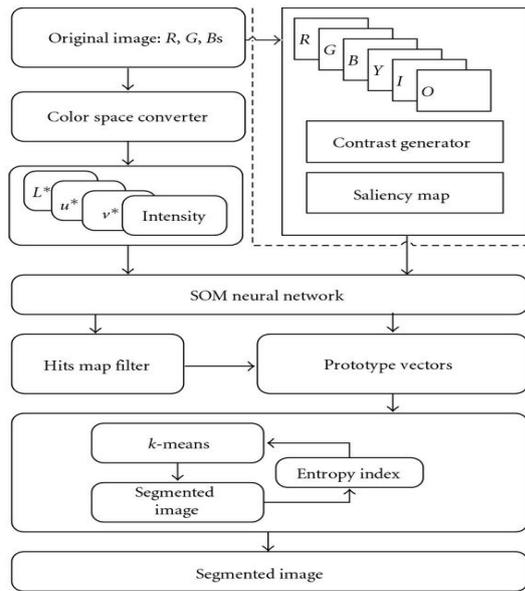


Fig 2: Flowchart of SOM-KS method. [R3]

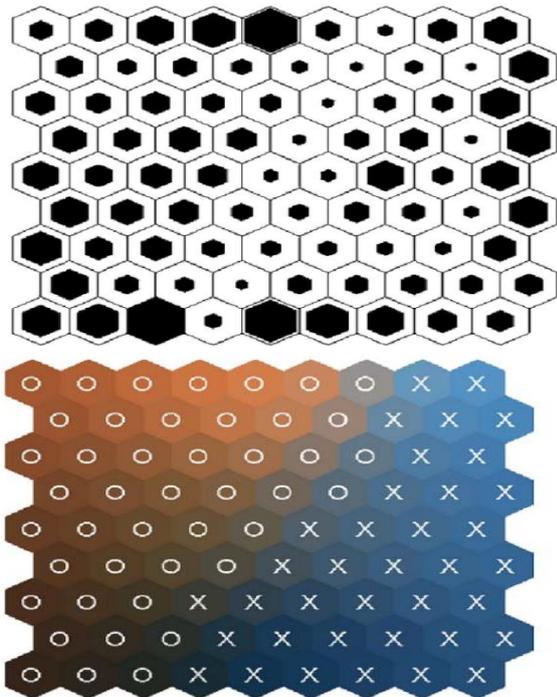


Fig 3: Hit Map Process [R3]

Clustered SOM nodes (a) and hit map (b) of an image. Colour features G , and B of the image are processed with the proposed SOM-K method. Pixels are clustered (or quantized) into 81 prototype vectors (nodes), whose colours (RGB in prototype vectors) are shown in (a). The image consists of mainly two colours with different tones, brown and blue in (a). Each prototype vector is a representative of a group of pixels. Total 81 representatives are further clustered with k-means into 2 clusters marked with \times and \circ . The right figure (b) shows the hits map of the SOM. The larger the black area in each node, the more it is hit by input patterns. The hits map is used as a filter to delete the prototype vectors. Those prototype vectors with zero hits

are deleted, because they do not represent any input patterns. Some segmentation results and their comparisons.

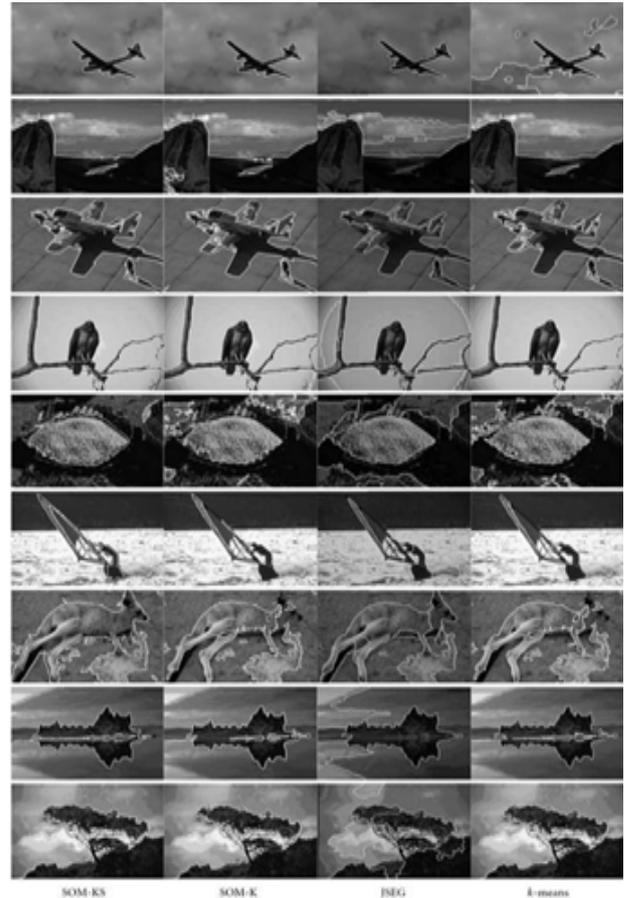


Fig 4: Segmentation results between various segmentation techniques, R[3]

B. Entropy Index comparison and Computational complexity:

No matter for good or for unacceptable segmentation, comparisons among them are subjective. Though index itself is not comparable to human selection, it is a kind of objective measure after all. For entropy index, a small value means a better segmentation. SOM-K, SOM-KS, and k-means have similar entropy index values, and in many cases, they are superimposed with each other. This also agrees with their segmentation results. Apparently, for most images, the SOM-K, SOM-KS, and k-means show good and stable performances with low values than JSEG does.

K-means or SOM-based methods have linear computational complexities. Compared to SOM-K, SOM-KS needs more than double times to finish segmentation. Apparently, the excess time comes from the saliency map. That is, a cost for a precise segmentation. It deserves a good result with time cost. In summary, we can see that compared with k-means, SOM-K has similar segmentation performance and saves more time than k-means does. SOM-KS further enhances the segmentation performance with moderate increase in computational time and still being low than k-means. SOM-K uses similar time with JSEG, but with substantial segmentation improvement.

V. CONCLUSION

The SOM-K(S) method can deal with most of the natural colour image in the test dataset. But the involved k-means method leads to unexpected results. This comes from the random initialization of k-means. The Self-Organizing Map (SOM) provides an orderly mapping of an input high dimensional space in much lower dimensional spaces, so it can play the role of dimension reduction and feature extraction that is used for segmentation. Furthermore, because it can provide partial invariance to translation, rotation, scale, and deformation in the image sample, combined with other neural networks methods, more and more segmentation techniques using SOM will be studied in the future.

REFERENCES

- [1] Tutorial on "Saliency map" [Available online: http://nl.wikipedia.org/wiki/Saliency_map , dte: 17/03/2014].
- [2] Shi and Malik, Segmentation_ white, Normalized Cuts and Image Segmentation , Proc. CVPR 1997.
- [3] Dongxiang Chi, "Self-Organizing Map-Based Color Image Segmentation with k-Means Clustering and Saliency Map," ISRN Signal Processing, vol. 2011, Article ID 393891, 18 pages, 2011. doi:10.5402/2011/393891
- [4] Tuevo Kohonen, Erkki Oja., Olli Simula, Ari Visa, Jari Kangas, Enginnering appliactions of the self organising map, Proceedings of IEEE, VOL.84, NO.10, October 1996
- [5] Lital Badash and Rostislav Pinski, Digital Image processing , Chapter 10 Image segmentation, Oct. 2010
- [6] Saleh Aly, Atsushi Shimada, Naoyuki Tsuruta, Rin-ichiro Taniguchi, "Robust Face Recognition Using Multiple Self-Organized Gabor Features and Local Similarity Matching", ICPR, 2010, 2010 20th International Conference on Pattern Recognition (ICPR 2010), 2010 20th International Conference on Pattern Recognition (ICPR 2010) 2010, pp. 2909-2912, doi:10.1109/ICPR.2010.713T.
- [7] Kohonen, Self-Organizing Maps, Springer, Berlin, 1997.
- [8] T. Serre, L. Wolf, S. Bileschi, M. Riesenhuber, T. Poggio, Robust object recognition with cortex-like mechanisms, IEEE Trans. Pattern Analysis and Machine Intelligence, (2007), 411-426.
- [9] T. Sim, S. Baker, M. Bsat, The CMU pose, illumination, and expression database, IEEE Trans. PAMI, (2003) 1615-1618.
- [10] Qiu Chen, Koji Kotani, Feifei Lee and Tadahiro Ohmi, Tohoku University, Japan, Face Recognition Using Self-Organizing Maps. ISBN 978-953-307-074-2, April, 2010
- [11] Longin Jan Latecki, Image Segmentation, CIS 601 Fall 2004.