An Effective Image Feature Classification using an improved SOM

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Abstract. Image feature classification is a challenging problem in many computer vision applications, specifically, in the fields of remote sensing, image analysis and pattern recognition. In this paper, a novel Self-Organizing Map, termed improved SOM (iSOM), is proposed with the aim of effectively classifying Mammographic images based on their texture feature representation. The main contribution of the iSOM is to introduce a new node structure for the map representation and adopting a learning technique based on Kohonen SOM accordingly. The main idea is to control, in an unsupervised fashion, the weight updating procedure depending on the class reliability of the node, during the weight update time. Experiments held on a real Mammographic images. Results showed high accuracy compared to classical SOM and other state-of-art classifiers.

Keywords: image feature classification; self organizing maps; texture features; topology preservation; neural networks.

1 Introduction

Image feature classification [1,2] presents a challenge in many computer vision applications. It plays a significant role in the fields of remote sensing, image analysis and pattern recognition. Recently, content-based image classification and retrieval received increasing attention through numerous applications [3] in the field of education, entertainment, military and biomedicine. With the enormous growth of computational power, image retrieval/classification have become more demanding in the area of computer vision. However, the success of solving such problems lies in the issues of object-based image understanding, proper representation of image contents and suitable learning algorithms.

The Self-Organizing Map (SOM) [4,5] (also called Kohonen network) is an artificial unsupervised network characterized by the fact that its neighbouring neurons develop adaptively into specific detectors of different vector patterns. The neurons become specifically tuned to various classes of patterns through a competitive, unsupervised and self organizing learning. The spatial location of a neuron in the network (given by its coordinates) corresponds to a particular input vector pattern. Similar input vectors correspond to the same neuron or to neighbour neurons. One important characteristics of SOM is that it can simultaneously perform the feature extraction and it performs the classification as well [6].
In the medical field, SOM has been used extensively in an efficient and effective way. In [7] a classification methods based on multilayer perceptrons and Kohonen self-organizing map classifiers for image data to identify Alzheimer’s disease. Starting from the idea to consider the SOM as a cell characterizing a specific class only, Victor presents in [8] a new neural classification model called Concurrent Self-Organizing Maps (CSOM), representing a winner-takes-all collection of small SOM networks. Each SOM of the system is trained individually to provide best results for one class only. The CSOM model proved to have better performances than SOM, both for the recognition rate and also for reduction of the training time. In [3] Tommy proposes a new image classification approach through a tree-structured feature set. In this approach, the image content is organized in a two-level tree, where the root node at the top level represents the whole image and the child nodes at the bottom level represent the homogeneous regions of the image. The tree-structured representation combines both the global and the local features through the root and the child nodes. The tree-structured feature data are then processed by a two-level self-organizing map (SOM), which consists of an unsupervised SOM for processing image regions and a supervising concurrent SOM (CSOM) classifier for the overall classification of images. DAR-REN et al. [9] applies the self-organizing maps (SOMs) to classify the benign and malignant sonographic breast lesions.

The classical SOM and most of its variations rely on a fully unsupervised learning procedure. This is because of the node structure of the map does not provide any possibility of utilizing the class label while training the SOM resulting in unstable behaviour when classifying pattern, especially in the real data with the presence of the noise and artifacts. Moreover, for the classification purpose, mapping can result in divided clusters because it requires that nearby points behave similarly. Motivated by the issues above, a simple but effective improvement in the classical SOM is proposed in this paper aiming to integrate and take advantage of the probability of a particular node to be a winner by a voting criteria.

The paper is organized as follows. Section 2 provides a brief discussion on the advantages of using SOM for the classification over the traditional classification models. In Section 3 an effective texture representation method is briefly discussed. Section 4 provides a discussion on the proposed model and its implementation. Then, an experimental study and conclusions with some possible future directions are provided in Sections 5 and 6 receptively.

2 SOM-based Classifier

The SOM neural network is one of the most popular unsupervised neural network models, which simultaneously performs a topology-preserving projection from the data space onto a regular two-dimensional grid [4]. There are some reasons to use a SOM as a classifier: (i) Weights representing the solution are found by iterative training, (ii) SOM has a simple structure for physical implementation and interpretation, (iii) SOM can easily map large and complex distributions
An Effective Image Feature Classification using an improved SOM

and (iv) generalization property of the SOM produces appropriate results for the input vectors that are not present in the training set \[10\].

A basic SOM network is composed of an input layer, an output layer, and network connection layer. The input layer contains neurons for each element in the input vector. The output layer consists of neurons that are located on a regular, usually two-dimensional grid and are fully connected with those at the input layer. The network connection layer is formed by vectors, which are composed of weights in the input and output layer.

The neurons in the map are connected to adjacent ones by a neighbourhood relation dictating the topological structure of the neurons. Each neuron \(i\) in the map is represented by an \(n\)-dimensional weight or reference vector \(w_i = [w_1, \ldots, w_n]^T\), where \(n\) is equal to the number of neurons in the input layer.

When an input vector \(x \in \mathbb{R}^n\) is presented to the network, the neurons in the map compete with each other to be the winner (or the best-matching unit, BMU) \(b\), which is the closest to the input vector in terms of some kind of dissimilarity measure such as Euclidean distance as follows,

\[
||x - w_b|| = \min\{||x - w_i||\}
\] (1)

During training session, weights of neurons are topologically arranged in the map within a certain geometric distance and are moved toward the input \(x\) using the self-organization learning rule as represented in formula below :

\[
w_i(t + 1) = w_i(t) + \eta h_{bi}(t)[x(t) - w_i(t)]
\] (2)

where \(t = 0, 1, 2, 3, \ldots\) is the time lag, \(\eta\) is a small positive learning rate and \(h_{bi}(t)\) is the neighborhood kernel around the BMU \(b\) at time \(t\). In general, \(h_{bi}(t)\) can be defined as

\[
h_{ci}(t) = h(||r_c - r_i||, t)
\] (3)

where \(r_c, r_i \in \mathbb{R}^2\) are the location vectors of neurons \(c\) and \(i\), respectively, and when \(||r_c - r_i||\) increases, \(h_{ci}\) decreases to zero gradually. This leads to local relaxation or smoothing effects on the weight vectors of neurons in the neighbourhood of the BMU. Therefore, similar input vectors are grouped into a single neuron or neighbouring ones in the map when learning is accomplished.

SOM has been used as classifier by projecting the data vectors belong to higher dimensional input space \(n\) into \(m\) many code-book vectors of size \(n\) organized in a two dimensional lattice structure. SOM provides two fundamental issues: the first is the clustering of data and the second is the relationship between the clusters. The clustering is an unsupervised learning while the relationship between clusters can be seen in the planar surface by checking the distances between the code-book vectors. Although it is difficult to deduce exact relationship between those, since the code-book vector size is much greater than the planar surface size of 2, this gives us an insight about the classification regions. What is proposed here is totally different from what was proposed in the previous works, a novel training algorithm for SOM as well as a new node structure to meet the proposed training is introduced. Another point is to apply the algorithm in a set of already selected features.
3 Mammographic Image representation

In this section, a short discussion of an image texture feature extraction method is provide for effective Mammographic image representation.

The Grey Level Co-occurrence matrix (GLCM) provides a full texture description of an image in a statistical fashion. Simply, the GLCM technique computes first the probability of co-occurrence between two grey levels \( i \) and \( j \) given a relative orientation and distance for all possible co-occurring grey level pairs in an image window. Then, a set of selected statistics are applied to the entire matrix to calculate the texture features. In this work, the four most commonly and practically used features (e.g., Dissimilarity, uniformity, entropy and contrast) [11,12,13] have been selected for the model evaluation. The following four statistics will be used exclusively in this work:

1. Dissimilarity = \( \sum_{i,j=1}^{G} C_{ij} |i - j| \).
2. Uniformity = \( \sum_{i,j=1}^{G} C_{ij}^2 \).
3. Entropy = \( -\sum_{i,j=1}^{G} C_{ij} \log C_{ij} \).
4. Contrast = \( \sum_{i,j=1}^{G} C_{ij} (i - j)^2 \).

Where, \( C_{ij} \) represents co-occurring probabilities stored inside GLCM. \( G \) represents number of grey level available.

For a more accurate feature extraction and a further investigation of the localization property of the represented features, the process of extracting textural information from Mammographic image depends on first identifying the object of interest as a reprocessing step. As a consequence, However, it is required to segment the images first as a pre-processing step before the feature extraction process. As a consequence, a bloc wise partitioning method [14] is used in this work, which can be described as follows (see Figure 1):

1. If the image contains inhomogeneity regions then a set of \( SN \) seeds are automatically selected and their associated regions are growing in a similar way to [15,16]. Otherwise, divide the entire image into \( SN \) non-overlapping sub-images \( SI = \{ I_1, I_2, \ldots, I_{SN} \} \).
2. Split each of these \( SN \) sub-images into other \( M \) blocks \( I_j = \{ B_1, B_2, \ldots, B_M \} \), \( j = 1, 2, \ldots, SN \).
3. For each bloc \( B_i \), \( i = 1, 2, \ldots, M \), construct a bloc representing set of texture feature vectors.
4. Use the \( k \)-means algorithm to cluster the feature vectors into several classes for each sub-image \( I \) independently.
5. For each cluster in \( I_i \), \( i = 1, 2, \ldots, SN \), construct a sub-image representing set of texture feature vectors \( F_k = \{ f_1, f_2, \ldots, f_X \} \), \( k = 1, 2, \ldots, L \); where \( L \) is the number of classes each of which contains \( X \) texture features.
6. Build the final set of texture features representing the overall image in the form of a single transaction of the final dataset (set of images) \( T_i = \{ t_1, t_2, \ldots, t_c \} \), where \( c \) is the number of images, \( t_i \) is a vector of the size \( (SN \times L \times X) \), \( i = 1, 2, \ldots, c \).
7. For each \( T_i = \{ t_1, t_2, \ldots, t_c \} \) add the class label of its image.
An Effective Image Feature Classification using an improved SOM

texture feature vectors

Fig. 1. The architecture of bloc wise feature extraction method with $SN = 6$, $M = 6$ and $L = 3$ for simplification.

4 iSOM Classifier

As mentioned in previous sections, SOM is designed to be unsupervised learning technique. We here enhance the SOM network to be used for supervised learning (classification) by introducing a new node structure and an enhanced learning utilizing the class label in the weight update step.

First, every node is represented with the set of connection weights $w = \{w_0, w_1, \ldots, w_n\}$ where $n$ is the number of attributes, and a set of winning class counters ($WCC^m$) $c^m = \{c_1, c_2, \ldots, c_m\}$ where $m$ is the number of classes, this representation provides the possibility of utilizing the class label provided in the training set while training the SOM. We can simply say the vector $WCC$ is introduced to the node structure to provide a voting criteria, so such nodes with maximum $WCC_i$ are pulled during the weight update process. Shifting such nodes towards the BMU which is definitely of the same class increases the means of relationship between such nodes. At the same time leaving nodes from other class dims the relationship between such nodes and their un-similar neighbours.

In every iteration after computing the distance between the input vector and SOM elements using 1, the winning node is activated, this step is typically as proposed in classical Kohonen SOM, even though several distance function can be used, the main idea is to measure the similarity between objects independently from the data.

The next step after identifying the BMU is to increase the $WCC_i$ by one for the $i^{th}$ class accordingly. This increment gives more confidence that this node is targeted by an example of class $i$, this confidence indicates a similarity between both the input example and the winning node.

At the final stage what we call a constrained weight update is performed, the problem with traditional SOM is that all the neighbours are blindly attracted or pulled towards the winning node, the term constrained means selecting some node which are fitted to the criteria that is clear here, those nodes which are mostly targeted by examples from the same class are suppose to belong to the same cluster, and those nodes not mostly targeted by examples from other classes should come closer to this cluster, so they are left.
We can simply express this as, when a winning node is activated, and before performing the weight update, a vote is conducted, the only set of nodes in the neighbourhood with maximum class counter that is equal to the current instance class label will be considered as neighbour nodes. For an instance $E_j$ belongs to class $C_i$, $X^T = \text{Max}||WCC||$, where Max is a function that returns the set of nodes with maximum $WCC_i$, finally the weight update given in 2 will be performed over $X$, at the same the $WCC_i$ will be increased by one.

Figure 2 illustrate the learning process of SOM based on the proposed node structure. Every node is represented with the set of connection weights, and a set of winning class counters such that with maximum WCC (black nodes) are pulled during the weight update process. Shifting such nodes towards the BMU which is definitely of the same class increases the means of relationship between such nodes. At the same time leaving nodes (grey nodes) from other class dims the relationship between such nodes and their un-similar neighbours.

the rest of the algorithm will go according to the classical SOM explained the previous section, including the weight decrease given in 3 for relaxation.

Selecting nodes which are supposed to be related to the winning node and update their weights towards the winning node and leaving those nodes that are most probably belong to different class, could enhance training in terms of time as well as generated model quality.

Implementation

1. Randomly set the initial values for all the connection weights.
2. For every node in the grid set the class counters to zero.
3. If training set is not empty, select an instance from the training set and go to next step else go to step 7.
4. Compute the distance between the selected instance and every node in the network and select the winning node accordingly.
5. For every node in the neighbourhood
   - Select nodes where the maximum class counter is the same as the winning node.
   - Update weights for the selected nodes in previous step.
An Effective Image Feature Classification using an improved SOM

- Increase the corresponding class counter of the node.

6. Go to step 3.
7. If no of epochs > LIMIT then exit, Else go to step 2.

Table 1. The classification rate in terms of Precision, Recall and F-score by the iSOM and SOM models.

| SOM map size | iSOM model | SOM model |
|--------------|------------|-----------|
|              | Precision  | Recall    | F-score  | Precision | Recall | F-score |
| 10 × 10      | 94.73      | 76.92     | 84.9     | 79.12     | 79.74  |
| 15 × 15      | 94.33      | 88.76     | 91.46    | 79.59     | 84.86  |
| 20 × 20      | 97.87      | 85.26     | 91.13    | 98.18     | 93.1   | 95.57   |
| 25 × 25      | 100        | 90.84     | 95.2     | 75.96     | 83.25  |

5 Experimental Results

To demonstrate quantitatively the accuracy of the iSOM model in the classification, we have used the Precision, Recall, and F-score metrics. Such that 10-fold cross validation process is used. They are defined as follows:

\[
\text{Precision} = \frac{TP}{TP + FP}, \quad (4)
\]

\[
\text{Recall} = \frac{TP}{TP + FN}, \quad (5)
\]

\[
F\text{-score} = \frac{2PR}{P + R}, \quad (6)
\]

where \(TP\), \(FP\), and \(FN\) represent, resp., the numbers of true positive (abnormal), false positive, and false negative (normal) foreground pixels. We also have compared the accuracy with SOM model and other classifiers. In this experiment 142 images from the mini-MIAS database of mammograms data set [17] are selected randomly for model testing and evaluation. The sample is distributed between classes as follows: Normal class \((n=60)\), and abnormal class \((n=82)\).

Table 1 illustrates comparison between classical SOM and enhanced SOM classifier to classify images based on image feature set extracted using textural extraction method based on our Bloc-wise \(ROI\) selection method described in section 3 with \(SN = 6\), \(M = 8\) and \(L = 3\).

Comparison between the classical SOM and iSOM shows better performance in terms of precision, recall as well as the f-score with different map sizes. We can also say that the time consumed in training both the networks differs and again the enhanced SOM wins, as the number of update operations performed...
by the enhanced SOM is much less compared to the classical SOM due to the proposed constrained weight update. One more point could be concluded from the experiment indicates the enhanced SOM could reach the best accuracy in less time as we mentioned, as well as with less memory consumed if you simply look to the map size.

The proposed iSOM couldn’t only show high accuracy when compared to the classical SOM but comparing with other famous classifiers in the field like Bayesian, Radial bases function network and others using weak experimenter, see Table 2.

| Classifier    | Precision | Recall  | F-score |
|---------------|-----------|---------|---------|
| RBF           | 58.76%    | 93.33%  | 68.31%  |
| Simple Logistic| 76%       | 76.08%  | 76.05%  |
| Bagging       | 87.56%    | 75.49%  | 78.87%  |
| J48           | 93.10%    | 92.85%  | 92.95%  |
| NaiveBayes    | 58.97%    | 78.12%  | 67.60%  |

6 Conclusion and Future Work

In this paper, four texture features derived from the co-occurrence matrix was used. For this, a textural extraction method based on accurate ROI selection for obtaining efficient image representation has been utilized.

The main characteristic of the SOM-based classifier is the conservation of the topology: after learning, close observations are associated to the same class or to close classes according to the definition of the neighbourhood in the SOM network. This feature allows considering the resulting classification as a good starting point for further developments. The paper presents a novel classifier inspired by the classical SOM, termed improved SOM (iSOM), by introducing a new node structure and adopting the underlying self organizing learning procedure such that for the same number of neurons, iSOM has better recognition performances than SOM. Experimental results confirm the good performance of the iSOM when compared to other state-of-art classifiers.

As a future development, There are several research directions such as: 1) consider several and more effective image-based features (e.g., global information and other kind of local information), more samples for the evaluation and more prototype-based algorithms for the comparison; 2) develop iSOM to be working on a parallel fashion by applying more than 2 iSOMs in a concurrent fashion and cope with the multi-class classification problems; 3) besides the use of more than 2 iSOMs, we mention the possibility of extending the proposed model such that the underlying neurons are incrementally added/removed and trained to overcome the limitation of manually adapting the topology of the network.
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