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Colour image segmentation using the self-organizing map and adaptive resonance theory

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Abstract

We propose a new competitive-learning neural network model for colour image segmentation. The model, which is based on the adaptive resonance theory (ART) of Carpenter and Grossberg and on the self-organizing map (SOM) of Kohonen, overcomes the limitations of (i) the stability–plasticity trade-offs in neural architectures that employ ART; and (ii) the lack of on-line learning property in the SOM. In order to explore the generation of a growing feature map using ART and to motivate the main contribution, we first present a preliminary experimental model, SOMART, based on Fuzzy ART. Then we propose the new model, SmART, that utilizes a novel lateral control of plasticity to resolve the stability–plasticity problem. SmART has been experimentally found to perform well in *RGB* colour space, and is believed to be more coherent than Fuzzy ART.

Keywords: Adaptive resonance theory; Colour image segmentation; Neural networks; Lateral control; Network plasticity; Network stability; Self-organizing map

1. Introduction

The problem considered in this paper is the segmentation of colour images for which many methods have been proposed in the literature. Amongst the non-classical methods, the application of artificial neural networks (ANN) is prominent. In recent years, motivated by the remarkable characteristics of the human visual system (HVS), researchers have applied ANNs to various problems in pattern recognition [1]. ANNs have several advantages over many conventional computational algorithms, among which the most important are (i) massive parallelism, (ii) better adaptability to different data sets, (iii) fault-tolerance to missing, confusing and noisy data, and (iv) optimal (or 'near optimal') performance.

Networks for three types of classification have been employed: supervised, unsupervised and a combination of the two. In the segmentation of colour images, unsupervised learning is preferred to supervised learning because the latter requires a set of training samples, which may not always be available. Furthermore, adaptive neural-network computing methods are more effective and efficient than traditional ones. Since the focus of this paper is on the application of competitive-learning neural networks to the problem of colour image segmentation, we review the relevant results in some detail below.

In unsupervised, self-organizing neural networks, the two dominant models are the self-organizing map (SOM) [2,3] and adaptive resonance theory (ART) [4,5], both of which are based on competitive learning.

SOM, which was originally introduced for the visual display of one-and two-dimensional data sets, has the same functional ideas as many other clustering algorithms. The SOM neural network is a topology-preserving map in which adjacent vectors in (^{n} are mapped to adjacent (or identical) cells in the array, and adjacent cells in the array have similar position vectors in (^{n}. The purpose of the self-organization process, as described by Kohonen [2,3], is to find values for the position vectors such that the resultant mapping is topology- and distribution-preserving[1].

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[1] By a distribution-preserving mapping we mean, that for a random vector with the probability density function, $p(X)$, each cell has the same probability of being the target of the mapping. Stated otherwise this means that the relative density of position vectors in (^{n} approximates the probability density of $p(X)$.

Dekker [6] presented the use of SOM network for quantization of colour graphics images. By adjusting a quality factor, the network is shown experimentally to produce images of much greater quality with longer running times, or slightly better quality with shorter running times than existing methods. In a refined version of the SOM, the output can be used for a controlled training of the next layer network in the manner of Lampinen and Oja [7], who proposed a multi-layer self-organizing map, HSOM, as an unsupervised clustering method. Analogous to multi-layer feed-forward networks, the HSOM (i) forms arbitrarily complex clusters, (ii) provides a natural measure for the distance of a point from a cluster by giving appropriate weights to all the points belonging to the cluster, and (iii) produces clusters that match the desired classes better than the direct SOM or the classical *k*-means or ISODATA algorithms.

Traven [8] has investigated the application of a competitive learning algorithm to statistical pattern classification using both local spectral and contextual features, but it is a supervised learning procedure in which the image must first be manually segmented. Ghosal and Mehrotra [9] describe a Kohonen self-organizing feature map for segmenting range images using local information provided by the orthogonal Zernike moments. However, the application of their algorithm is limited to planar and 1-D quadratic surface patches of gray level images. Papamarkos et al. [10] applied a tree clustering procedure to achieve colour reduction. In each node of the tree, a principal component analyzer and a Kohonen self-organized feature map (SOFM) neural network define the colour classes for each node. A limitation of this method is that the maximum number of final colours has to be specified *a priori*. Uchiyama and Arbib [11] employ competitive learning as a tool for colour image segmentation. After demonstrating the equivalence of vector quantization and cluster-based techniques, they apply their algorithm to gray scale and colour images. The final results appear to be essentially no different from those obtained by clustering.

A hierarchical two-stage SOM network is employed in [12] as a pattern classifier to enhance the results of conventional single-stage SOM without *a priori* information on the appropriate number of clusters to be used in the segmented image. However, the map size for both stages needs to be heuristically determined, and it is found to be difficult to achieve optimally sized maps.

The ART architecture is also a self-organizing network that allows the system to switch between a *learning* or *plastic* state (in which the network parameters may be modified) and a *stable* or *fixed* state for operation. Fig. 1 presents the general structure of the families of ART models.

The ART-based network involves three groups of neurons: an input or comparison stage, an output or recognition stage, and a mechanism to control the degree of similarity of patterns placed on the same cluster (a reset mechanism). Each neuron in the input stage is connected to all the neurons in the output stage using feedforward weights; conversely, each neuron in the output stage is connected to all the neurons in the input stage using feedback weights. Control signals C1 and C2 along with a reset signal R facilitate comparison of the inputs with a 'vigilance pattern' in order to determine whether a new class pattern should be created for any given input pattern.

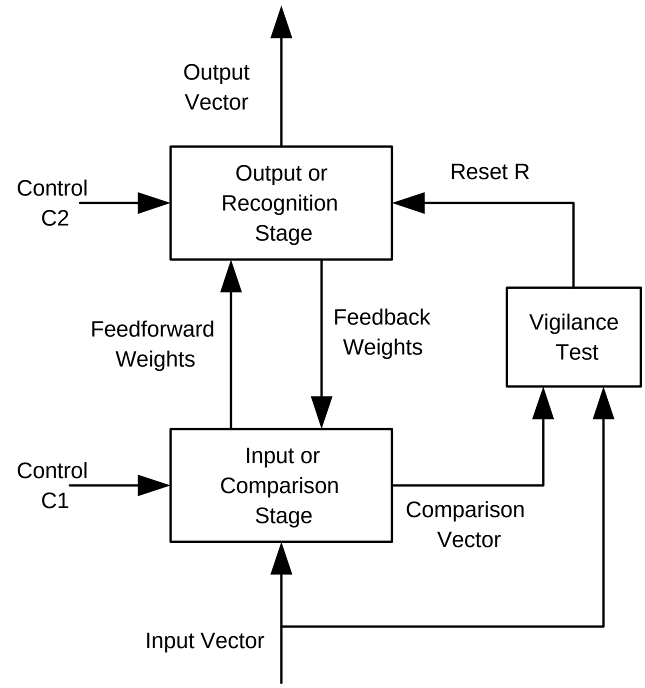

Fig. 1. General architecture of the ART.

There are many versions of the ART model [4,5], among which we cite ART1, ART2 [13], and Fuzzy ART [14]. The first can stably learn to categorize binary input patterns presented in an arbitrary order. The second, ART2, discovers input data clusters of either analog or binary patterns (presented in an arbitrary order) without considering their actual size. It has the ability to produce hierarchical clustering that is insensitive to non-uniform variations in the input data distribution [15]. The third model, Fuzzy ART, incorporates computations from fuzzy set theory into ART1. For a detailed operation of the ART-based networks, the reader may refer to [15,16]. It should be noted here that ART does not need any pre-specified number of clusters.

ART networks are designed to be both stable and plastic, i.e. they learn a new pattern equally well at any stage of learning. The core issue in the application of ART networks, for instance, to colour image segmentation is the stability–plasticity dilemma which can be described as follows. It is desirable that the closer the network is to its converged state, the more strongly it should resist the erasing of the information learned earlier. On the other hand, if the network is far from its converged state or when there are previously unseen inputs, it should be more sensitive to the learning of any new input pattern, although this learning