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Incremental clustering of sonar images using self-organizing maps combined with fuzzy adaptive resonance theory

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ABSTRACT

In this paper we introduce a new unsupervised segmentation algorithm for textured sonar images. A Dynamic Self-Organizing Maps (DSOM) algorithm capable of incremental learning has been developed to automatically cluster the input data into relevant classes of seabed. DSOM algorithm is an extension of classical Self-Organizing Maps (SOM) algorithm combined with Adaptive Resonance Theory (ART) technique. The proposed approach is based on growing map size during learning processes. Starting with a minimal number of neurons, the map size increases dynamically and the growth is controlled by the vigilance threshold of the ART network. To assess the consistency of the proposed approach, the DSOM algorithm is first tested on simulated data sets and then applied on real sidescan sonar images. The results obtained using the proposed approach demonstrate its capability to successfully cluster sonar images into their relevant seabed classes, very close to those resulting from human expert interpretation.

1. Introduction

Image segmentation is an important step in the image analysis chain. It addresses the problem of dividing an images into homogeneous groups of pixels based on a similarity measure. In terms of a priori knowledge, two families of image segmentation algorithms can be distinguished: the supervised and the unsupervised approaches. The supervised algorithms rely on training phase, which is based on a precise and comprehensive a priori knowledge of the type or label of the training data. The widely used supervised algorithms are based on Maximum a Posteriori (MAP) or Maximum Likelihood (ML) technique (Duda et al., 2001).

Seafloor classification is the segregation of sonar images of seabed into separate physical entities or classes. It is very useful and active area of research in the field of seabed mapping, marine geophysics, geological survey, exploring underwater natural resources, marine habitat and underwater acoustics. Similar to the segmentation of ordinary natural images, the segmentation of sonar images with supervised algorithms requires ground truth data. In practice such ground truth is difficult to acquire (underwater video, dredge or core data sampling) and therefore labeling the seabed types often reduces to a few discrete locations. The supervised approach gives satisfactory results only when a comprehensive training set is available. If the training set lacks a particular kind of seabed, it will be unknown to the classifier and the classification will be reduced to the closest known sediment class. As it is not always feasible to have seabed ground truth classes and to know the entire seabed types before the training phase, an unsupervised algorithm capable to determine clusters according to statistical similarity and independently to the expert interpretation is suitable for sonar images. Recent progress in underwater robotics has been aimed at developing autonomous underwater vehicles (AUVs), which allow automatic data collection and interpretation with on board processing techniques and unsupervised algorithms for classification (Wynn et al., 2014). Hence, the unsupervised algorithms can be implemented in real time on these AUVs to fully automate the seabed classification of unknown areas.

The unsupervised approaches exploit the resemblance between statistics features estimated from images, with no a-priori knowledge about data labeling or number of classes. In this case, clustering algorithms are used to gather pixels or regions in similar groups. Approaches to unsupervised learning include: clustering algorithms (e.g., ISODATA, K-means, mixture models and hierarchical clustering) (Hastie et al., 2009; Acharyya, 2008), blind signal separation generally used for dimensionality reduction and features extraction (e.g., Principle Component Analysis (PCA), Independent Component Analysis (ICA)) (Acharyya, 2008) and neural network models using

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unsupervised learning. Among these models, Self-Organizing Maps (SOM) developed by (Kohonen, 1982) and Adaptive Resonance Theory (ART) developed by (Carpenter and Grossberg, 1988) have been chosen as they have successfully solved many different kinds of problems in various research fields (for example (Kohonen et al., 1996; Carpenter et al., 1998; Kim et al., 2001)).

In this work, a new approach for unsupervised segmentation of sidescan sonar images is proposed. Our approach is based on the mixture of two neural network algorithms: the SOM and ART algorithms. The SOM algorithm is a powerful tool for clustering and data mining. It has been used for mapping high-dimensional data into generally one, two or three dimensional feature map (Kohonen, 2013). One of the important characteristic of SOM algorithm is its ability to preserve the topology of input space using neighborhood function. It means that input data which is similar in term of features distance will be close after projection by SOM algorithm. This topological preservation of data allows best visualization and identification of data clusters. The SOM algorithm is classically presented as two-dimensional (2D) grid of neural nodes. A group of close nodes on the grid is a cluster and represent a certain class of the given data. However, classical SOM algorithm has some limitations $i.\ e.$ the size of the grid and the number of nodes have to be predetermined, whereas the proposed method dynamically increase the size of the neural map that incrementally characterize the detection of new classes systematically. The problem of determining the size of the grid in SOM depends on the size of the data and the structures of the clusters. In this regard, many approaches exist to determine the size of the grid, for example: Sammon's projections or empirical methods (Sammon, 1969), which are based on the cardinality of the input data (e.g. $5\sqrt{N}$, where N is the number of observations), another approach given in (Vesanto and Alhoniemi, 2000) is used to create a large grid with additional stages of clustering. But in practice, many experiments and simulation need to be conducted to define the appropriate size of the map. In the case of unknown structure of the data, an incremental or dynamic structure of the grid is suitable.

The remainder of this paper is organized as follows. Section 2 introduces the related works for dynamic neural network. Section 3 reviews the SOM and Fuzzy ART algorithms and then describes the proposed DSOM algorithm for incremental clusters detection. Experimental results are shown in Section 4 and finally conclusion is given in Section 5.

2. Related works

Artificial Neural Networks (ANNs) are computational models (inspired by the functioning of cerebral cortex) which are capable of extracting meaning, detecting trends and patterns in complex data of heterogeneous nature (Hansen and Salamon, 1990). The SOM is one of the well known algorithm of ANN models and it is widely used in numerous applications for visualizing (visualization of high dimensional data into low dimensional views), clustering problems without the knowledge of class memberships and image classification. Several works used SOM algorithm on various fields of research. For example, (Kinnunen et al., 2012) uses the SOM algorithm for unsupervised objects discovery. In remote sensing, for hyperspectral imagery, (Liu et al., 2010) proposed an approach based on SOM and fuzzy membership for decomposition of mixed pixels. Several authors have successfully applied different approaches of ANN to the problem of seafloor classification (Muller et al., 1997; Stewart et al., 1994; Bourgeois and Walker, 1919; Maillard et al., 1992; Vink et al., 2000). Similarly, the use of fuzzy ART algorithm for the segmentation of acoustic image is implemented by (Vink et al., 2000). To overcome the limitation of the fixed size grid of the classical SOM algorithm, several dynamic neural network models have been proposed.

The Neural Gas Algorithm (NGA) developed by (Martinetz et al., 1993) is an unsupervised neural network, which successively add units (or nodes) to an initial small network by evaluating local statistical measures gathered during previous adaptation steps.

Another algorithm called Growing Cell Structures (GCS) developed by (Fritzke, 1994) is based on the basic approach of NGA with fixed topology dimensionality (2-D or 3-D). In (Alahakoon et al., 2000), the authors proposed a Dynamic Self-organizing Maps with controlled growth (GSOM) for knowledge discovery. The advantage of GSOM is the control of the size of the grid using spread factor. The spread factor in this case is independent of data dimensionality and can be used as threshold to create different maps with different dimensionality.

3. Dynamic Self-Organizing Maps (DSOM)

The proposed algorithm is based on the combination of two neural network models : SOM and Fuzzy ART algorithm. Before presenting details of the proposed DSOM algorithm, a brief overview of the SOM algorithm and Fuzzy ART theory are given.

3.1. Self-Organizing Maps (SOM)

The SOM algorithm converts a complex non linear high dimensional input data into low dimension representation using geometric relationships of the input space (Kohonen, 1998).

A typical SOM network consists of two layers neural architecture i.e. input neural layer and output neural layer as given in Fig. 1. Each p dimensional input vector $\mathbf{x}_k = (x_{k,1}, x_{k,2}, \ldots, x_{k,p})^T$, in the input layer $\mathbf{X}$ is fully connected to all neurons in the output layer $\mathbf{Y} = \{y_j: j = 1, 2, \ldots, m^2\}$, where m is the order of the neural map in the output layer, which allows the self-organization.

The directed link between the input layer $\mathbf{X}$ to the output layer $\mathbf{Y}$ is given by synaptic weight vector $\mathbf{w}_j = (w_{j,1}, w_{j,2}, \ldots, w_{j,p})^T$ (where $j \in \{1, 2, \ldots, m^2\}$ is the index of j^{th} node of the output neuron) from input layer $\mathbf{X}$ to output layer neuron y_j. These weights (which can be any real number) are updated iteratively by the learning algorithm based on the neighborhood.

The learning principle of the SOM algorithm is to pick an input vector $\mathbf{x}_k$ and find the corresponding, so called winner node y_{j^*} (j^* is the index of the winning neuron), by finding the index of the nearest weight vector with $j^* = \mathrm{argmin}_j \|\mathbf{w}_j - \mathbf{x}_k\|$.

Afterwords, the winner node y_{j^*} is promoted by adjusting its corresponding weights $\mathbf{w}_{j^*}$ towards the nearest input vector $\mathbf{x}_k$. In order to ensure that vectors close in distance and topology in the input space are associated with nearby neurons on the map, not only $\mathbf{w}_{j^*}$ gets adjusted but also the weights of all nodes in the neighborhood of y_{j^*} are also adjusted. The weight vector adjustment is done by the following equation:

$$\mathbf{w}_j(t+1) = \mathbf{w}_j(t) + \alpha(t).\ V(j, j^*, t).\ [\mathbf{x}_k - \mathbf{w}_j(t)] \tag{1}$$

Where t represents the time-step and $\alpha(t)$ is learning rate, it is a decreasing function given by:

$$\alpha(t) = \alpha_0(1 - t/T) \tag{2}$$

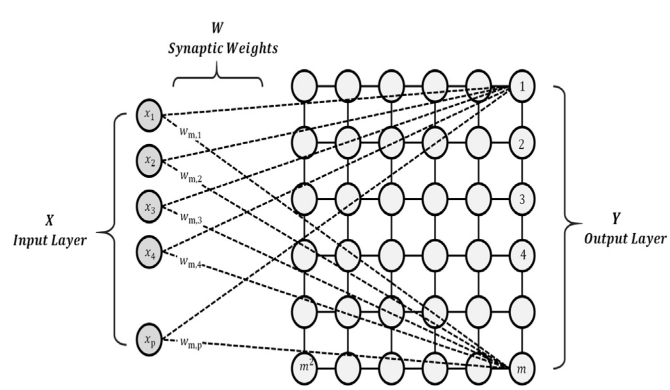

Fig. 1. Schematic SOM network.