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A neural-network-based approach to detecting rectangular objects

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Abstract

Many man-made objects are composed of a number of some simple geometric shapes such as lines, circles, rectangles, etc. Therefore, the detection of rectangular objects is an important issue to some practical applications such as the detection of buildings and vehicles in aerial imagery, the detection of license plates in car images, etc. Several methods have been proposed for solving the problem of the detection of rectangular objects. While some approaches are based on the detecting lines, some approaches are based on the Hough transform. Each approach has its own advantages and disadvantages (e.g., computational load). In this paper, we propose a class of neural networks with a special type of neural junctions for the detection of rectangular objects. The proposed neural networks can be trained in either an unsupervised mode or a batch mode. In contrast to some popular clustering algorithms such as the fuzzy *c*-means algorithm and the fuzzy *c*-rectangular shells algorithm, our approach is not based on minimizing an objective function but based on the idea of competitive learning. Based on the idea of competitive learning, the computational load can be decreased. Several data sets were tested to illustrate the effectiveness of our proposed approach.

Keywords: Neural networks; Cluster analysis; Detection of rectangles; Clustering algorithm

1. Introduction

Cluster analysis is one of the basic tools for exploring the underlying structure of a given data set. It has been playing an important role in solving many problems such as biology, medicine, society, psychology, pattern recognition, and image processing. The primary objective of cluster analysis is to partition a given data set of multidimensional vectors (patterns) into the so-called homogeneous clusters such that patterns within a cluster are more similar to each other than patterns belonging to different clusters. Cluster seeking is very experiment-oriented in the sense that no cluster algorithm can deal with all situations. Some extensive and good overview of clustering algorithms can be found in the literature [5,18,19]. There are two major difficulties encountered in clustering data: (1) the presence of large variability in cluster geometric shapes and (2) the number of clusters not always being known *a priori*. The problem of estimating the number of clusters is not examined in this paper.

While it is easy to consider the idea of a data cluster on a rather informal basis, it is very difficult to give a formal and universal definition of a cluster. In order to mathematically identify clusters in data, it is usually necessary to first define a measure of distance that will establish a rule for assigning patterns to the domain of a particular cluster center. As it is to be expected, the distance measure is very problem dependent. Different distance measures result in different types of clusters (e.g., compact hyper-spheres, compact hyper-ellipsoids, lines, shells, etc.). Recently, several clustering algorithms with different distance measures have been developed for clustering data sets with different geometric shapes [4,7–9,11,13,16,26,31,32]. These algorithms are used to detect compact clusters [4,11,13,16,32], straight lines [7,13,32], or shells [8,9,26,31]. More recently, a kind of "point symmetry distance" was proposed [29,30] to group data into a set of clusters of different geometrical structures. In addition, some clustering algorithms have

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also been proposed on the particular purpose and application [1,2,12,14,15,23,35].

The detection of rectangular objects is of much interest in some practical applications such as the detection of buildings and vehicles in aerial imagery [20–22,24,25,27,28,33,36], particles with rectangular shapes [37–39], man-made rectangular objects [34], license plates [3,22], etc. Fig. 1 illustrates some examples. While some approaches are based on the detection of lines some approaches are based on the Hough transform. Each approach has its own advantages and disadvantages (e.g., computational load). Although linear clustering algorithms, in principle, are capable of finding rectangles (since a rectangle consists of four edges), they need another complementary algorithm to help them to decide which four detected lines should be combined together to form a rectangle. In addition, line algorithms detect lines instead of edges. Therefore, simple linear clustering algorithms are not sufficient for detecting rectangles. Understandably, the detection of rectangles needs further treatments. The fuzzy c-rectangular shells (FCRS) algorithm was developed especially for the purpose of detecting rectangular shells [17]. In the FCRS algorithm the contour of a rectangle is assembled by four lines, each described by a normal equation, $(\underline{x}-\underline{p})^{\mathrm{T}}\underline{n}=0$, in which $\underline{p}\in\Re^2$ is a point of the considered line and $\underline{n}\in\Re^2$ is the normal vector of the line. Then the fuzzy c-rectangular shell distance measure is defined as

$$d^2(\underline{x},\underline{v},r_0,r_1)=(\min\{(\underline{x}-\underline{v})^{\mathrm{T}}\underline{n}_s+r_{s \bmod 2}\,|\,s\in\{0,1,2,3\}\})^2, \tag{1}$$

where $\underline{v}\in\Re^2$ is the center of the considered rectangle and the unit normal vectors $\underline{n}_s$ are numbered in the counter-clockwise manner from 0 to 3, and r_s denotes the half edge length. Minimize the objective function

$$\sum_{j=1}^{N}\sum_{i=1}^{C}\mu_{i,j}^{m}d^2(\underline{x}_j,\underline{v}_i,r_{i0},r_{i1}), \tag{2}$$

where m is a weighting exponent (called fuzziness index) usually set to 2.0, $\mu_{i,j}\in[0,1]$ is the grade of membership of data point $\underline{x}_j$ to the ith cluster, N is the number of data points, and C is the number of clusters. The goal of the FCRS algorithm is to partition the N data vectors into C rectangular shells represented by $\underline{v}_i$, r_{i0}, and r_{i1} for $1\leqslant i\leqslant C$. Detailed descriptions about how to compute, in an iterative procedure, the solution for minimizing the objective function in Eq. (2) can be found in [17,18]. Although the FCRS algorithm is capable of detecting rectangular shells, it is computationally expensive and sometimes very sensitive to the initialization [17,18].

In this paper, we propose to train a single-layer neural network composed of neurons with rectangular neural-type junctions to cluster data into rectangular shells. The training procedure can be performed in either an unsupervised mode or a batch mode. By adopting the learning algorithm in either one mode we can avoid the need of solving a system of non-linear equations consisting of the partial derivatives. The organization of the paper is set up accordingly. First, we introduce the neurons using rectangular neural-type junctions in Section 2. In Section 3, the training algorithms for the networks are described. Simulation results of data sets are provided in Section 4. Section 5 concludes this paper.

2. Neurons with rectangular neural-type junctions

The most frequently encountered neural-type junctions in neural network applications today are junctions that consist of a linearly summing device followed by an activation function of the sigmoid type. It is true that linearity is sometimes enough for the purpose of learning; however, it is possible to model neural junctions in other ways to endow the networks with a variety of useful properties. In fact, the production of postsynaptic potential (PSP) in biological neurons is, most likely, a non-linear process. Linear junctions are by no means the only choice to represent the real process happening among neurons. This motivated us to build a new model of neurons that make good use of this non-linearity [10,31,32]. In this paper, we consider a new type of neural junctions to endow neurons with such type of junctions with the ability of detecting rectangular shells.

In mathematical terms, we describe a neuron j with rectangular-type junctions by writing the following equations:

$$y_k=\sum_{i=1}^{n}w_{jki}x_i \quad \text{for } 1\leqslant k\leqslant n \tag{3}$$

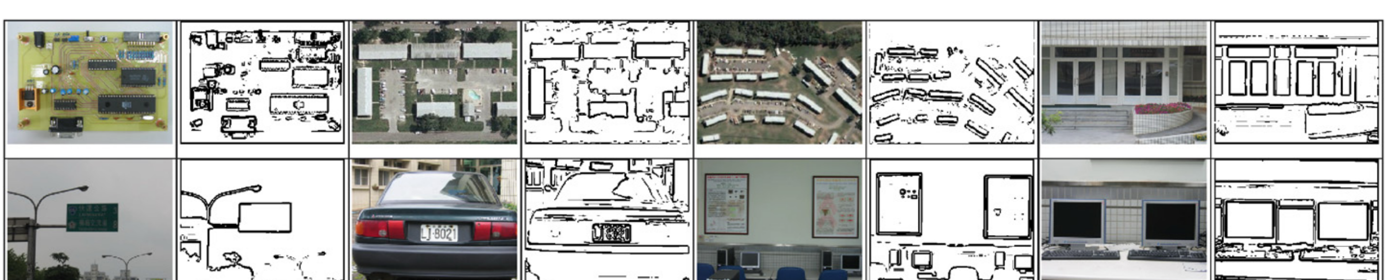

Fig. 1. Examples of rectangular objects.