FAINT OBJECT CLASSIFICATION USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT. Artificial Neural Network techniques are applied to the classification of faint objects, detected in digital astronomical images, and a Bayesian classifier (the neural network classifier, NNC hereafter) is proposed. This classifier can be implemented using a feedforward multilayered neural network trained by the back-propagation procedure (Werbos 1974).

1. Introduction

A large number of two-dimensional digital astronomical images is now available because of the advent of large CCDs or CCD mosaics and of the completion of digitized photographic surveys. One important goal of deep CCD surveys is to extract catalogs of the various types of astronomical objects that are present in the images. To accomplish this one has to: 1) detect the objects above the mean background; b) determine the position and extent of the objects; and c) classify them into appropriate morphological types. The last process, the classification of the detected objects, is a typical pattern recognition problem. The goal of pattern recognition usually is a discrimination or classification of a set of processes or events into one of a number of categories or classes. Figure 1 shows the flow-chart for a pattern recognition problem. It consists of two major steps: 1) an event is observed by some measurement device that produces an observation vector; and 2) the observation vector is fed into a pattern recognition system whose output is a classification into one of the final classes. The pattern recognition system can be separated into two subproblems. The first one, called feature extractor, consists of transforming the observation vector into the feature vector, whose components are called features and form the feature space. Afterwards, in a second step, this feature vector is passed into a classifier whose purpose is to make a decision about the pattern. The variety of approaches to solve the classifier problem can be divided into two main groups: 1) Non-Bayesian methods, in which the problem of pattern classification may be expressed in terms of the partition of the feature space; and 2) Bayesian methods, wherein the pattern recognition problem is formulated as a statistical decision problem using the Bayes' decision rule (Fu 1980).

In the astronomical context the measurement device is the telescope and specific software, observes and detects sources in the sky, giving an observation vector consisting of the CCD pixel intensities. The classical way (and the optimal) for performing the final classification is using an astronomer; however the astronomer has two disadvantages, slowness and subjectivity. The

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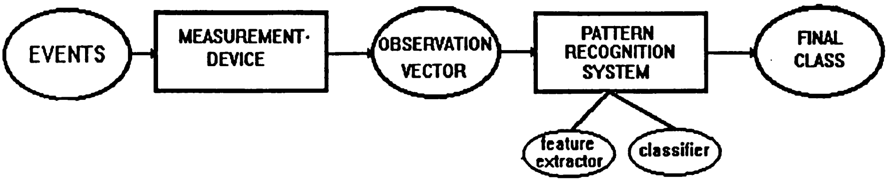

Figure 1. Flow-chart of the pattern recognition problem.

classifier proposed in this paper, the Neural Net Classifier (NNC), can be trained according to a subset, which is classified by an astronomer; if more than one investigator contributes to the initial classification, the NNC learns each decision pattern and produces a more uniform classification free of subjectivity. On the other hand, the computer-implemented NNC is faster than other methods, once the training process is accomplished. The Bayesian method chooses an object classification C_i which maximises $P(C_i \mid \mathbf{x})$, the probability that the object belongs to class C_i, given the observed distribution of pixel intensities $\mathbf{x}$. Since the NNC provides a Bayesian a posteriori probability $P(C_i \mid \mathbf{x})$ for each different input object (see Garrido & Gaitan 1991; Serra-Ricart et al. 1993b), it can be considered a Bayesian classifier.

Artificial neural network algorithms have been found to be useful in astronomy for unsupervised classification (Adorf & Meurs 1988; Serra-Ricart et al. 1993a), for scheduling observation time (Johnston & Adorf 1992), for adaptive optics (Angel et al. 1990), for interpolating multidimensional astronomical data (Serra-Ricart et al. 1993c), and to conduct morphological classification of galaxies (Storri-Lombardi et al. 1992).

2. The Method

A sample of simulated astronomical data was chosen in order to test the performance of the NNC. Simulations were made with the *artdata* package in the IRAF† (Image Reduction and Analysis Facility) environment (Tody 1986). The detection task was performed with the FOCAS package (Valdes 1982b). To apply the NNC for classifying astronomical objects, each input object should be characterized by an observed 2-D intensity distribution. It is well known that most of the object image information can be represented by using a sufficient number of a particular set of image moments (Yu & Mitra 1992), which has the desirable property of being invariable under image scaling (Hu 1962). Every input object was characterized by six quantities, the three normalized second moments of the intensity, and the three normalized second moments of the

† IRAF is distributed by the National Optical Astronomy Observatories, which is operated by the Association of Universities for Research in Astronomy, Inc. (AURA) under contract to the National Science Foundation.

detection area. These object moments were calculated by the task *evaluate* of the FOCAS package. The final adopted neural network architecture was 6 units in the input layer, one hidden layer with 13 units and 3 output units; such a neural network is described briefly as 6:13:3. The 6 input neurons are activated by the 6 moments defined previously. All the input moments were scaled between 0 and 1. Though the scaling can be done by the neural network during training, it would take a very long time to train the neural network using unscaled raw input values. Output neurons 1, 2 or 3 are activated by each input object class: noise (cosmic ray events), stars, or galaxies, respectively.

3. The NNC Performance

In Serra-Ricart et al. (1993b) a comparison of the classification results obtained from simulated data by the neural network classifier and by the well-established resolution classifier (RC, Valdes 1982a) is performed; a similar behaviour, up to the same faintness limit to which the resolution classifier works, is found in both classifiers. Even though the NNC offers a valid alternative to classical classifiers, the training process presents problems: a) a large and homogeneous training data set is needed, and the training set must contain a representative sample of patterns for each class; for this reason the NNC is inefficient when small data samples are treated. It should also be as free from misclassification as possible and span the full range of possibilities; b) it is a compute-intensive process.

4. Conclusions

In this paper we have presented an alternative method to classify faint objects from digital astronomical images using a layered feedforward neural network; and a Bayesian classifier, the NNC has been deduced. The NNC, which has learned from a training sample, can approximate non-linear decision surfaces and achieves similar classification results to those obtained using a Bayesian decision rule (Serra-Ricart et al. 1993b). However the NNC depends on the generalization power of neural networks and requires only a minimal a priori assumption (the NNC does not use an explicit galaxy model). The NNC is able to produce a final catalog of star/galaxy objects with a Bayesian probability class assigned to each different input object. The NNC offers a clear advantage over traditional methods in the classification of large samples of data. Such a fast automated procedure is the only practical way of classifying the enormous amounts of data obtained, for example, with CCD mosaics or digitized photographic plates (Odewahn et al. 1992). Whereas the RC needed approximately 30 minutes (on a SUN IPX workstation under the UNIX) to classify 10,000 detected objects, the NNC required, once the training process was done, about 30 seconds to make the same classification. Artificial neural networks lend themselves to implementation on massively parallel hardware. This is not only computationally interesting, but will also lead to the development of panoramic detectors with the hardware-implemented NNC attached to them, such that the system not only produces images, but also instantly classifies the detected objects.

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