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Distributed computing methodology for training neural networks in an image-guided diagnostic application

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ABSTRACT

Distributed computing is a process through which a set of computers connected by a network is used collectively to solve a single problem. In this paper, we propose a distributed computing methodology for training neural networks for the detection of lesions in colonoscopy. Our approach is based on partitioning the training set across multiple processors using a parallel virtual machine. In this way, interconnected computers of varied architectures can be used for the distributed evaluation of the error function and gradient values, and, thus, training neural networks utilizing various learning methods. The proposed methodology has large granularity and low synchronization, and has been implemented and tested. Our results indicate that the parallel virtual machine implementation of the training algorithms developed leads to considerable speedup, especially when large network architectures and training sets are used.

1. Introduction

Distributed systems allow the deployment and utilization of heterogeneous, network-connected computing resources and offer the potential to analyze, share and manage medical imaging information in more flexible and intelligent ways, with a view to making evidence-based decisions, recognizing patterns and generating new hypotheses on-line [1]. The emergence of grid protocols in conjunction with distributed computing offers CPU and data handling capabilities to users and could provide decision support in clinical diagnosis [2]. Minimally invasive, image-guided diagnostic procedures and surgery are particularly benefited from advanced software and hardware infrastructures [3,4]. In this context, the integration of navigation systems with high tracking accuracy and manoeuvrability, real-time services, such as analysis of imaging data and classification, parallelization of computational methods, detection of similarities with data stored in collaborating sites, comparison of patient's images against the norm, information sharing and e-collaboration with other experts would definitely increase the efficiency of typical diagnostic procedures and surgeries [3–8].

Towards this direction, this paper investigates the use of a distributed computing methodology for an image-guided diagnostic scheme that employs Multi-layer Perceptrons (MLPs) for the detection of lesions in colonoscopy images and video sequences. To this end, we propose a way to partition the training set across multiple processors and we evaluate the speed performance of the distributed scheme with respect to a single processor implementation. The proposed distributed computing methodology utilizes the parallel virtual machine—PVM [9–11] software tools and libraries.

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2. Background

In medical practice, minimally invasive techniques, such as computed tomography, ultrasonography, confocal microscopy, computed radiography, magnetic resonance imaging or endoscopy are now permitting visualization of previously inaccessible regions of the body. Their objective is to increase expert's ability in identifying malignant regions and decrease the need for intervention while maintaining the ability for accurate diagnosis. Furthermore, it is possible to examine a larger area, study living tissue in vivo – possibly at a distance [12] – and, thus, minimize the shortcomings of biopsies, such as a limited number of tissue samples, a delay in diagnosis, infection, perforation and discomfort for the patient.

Colorectal cancer is the second leading cause of cancer-related deaths in the United States [13,14]. Screening is the current and most suitable prevention method for early detection and removal of colorectal polyps. If such polyps remain in the colon can possibly grow into malignant lesions. Colonoscopy is the most accurate screening technique for detecting polyps, also allowing biopsy of lesions and resection of most of the polyps [15]. Colonoscopic diagnosis is a particular challenging area, involving the extraction and interpretation of patterns from complex medical video sequences under variable perceptual conditions (resolution change, shadings, shadows, lighting condition variations, reflections, etc.), hypothesis generation and reasoning in relation to previous experiences of the medical experts [4,16–18]. When one considers that abnormalities are hard enough to diagnose, the problem is exaggerated greatly when the physicians do not know what they are looking for.

The use of intelligent approaches for the detection of lesions in colonoscopy has to meet a number of challenges [4,18]: the time varying nature of the process, changes in the perceptual direction of the physician, variations in the diffused light conditions. For example, though one can use bright lights, the effect in a tight organ is that light tends to diffuse which leads to some areas being clearly lit and others not so; thus potentially hiding abnormalities. Relating to diffused light and the restrictive nature of the organ, it is easily possible for shadows to appear, restricting further what is visible. Shadows can be caused by the endoscope itself, different sections and abnormalities themselves. Lastly, the limited manoeuvrability of the endoscope causes the views at which abnormalities are visible to be far from ideal; a bad view can easily exaggerate the noise present within the image and hide abnormalities.

In most of these cases, training examples or explicit knowledge are not able to capture all possible variations of the environment. Collaboration among experts, estimations of similarities with data held in remote sites, and fast analysis of imaging data can definitely increase the efficiency of the procedure.

3. Computational methods

Automatic detection of lesions in colonoscopy is subject to uncertainties due to inaccurate measurements and lack of precise modelling of lesion image characteristics (this is especially true for small size lesions) [19]. Given a colonoscopy image, the "true" features associated with the physical surface properties of the tissue are not exactly known to the system developer. Usually, one or more feature-extraction models [4,16,20] are used to provide values for each feature's parameters. The findings are then used to infer the correct interpretation.

In this work, we combine texture segmentation with neural networks for the automatic detection of lesions in colonoscopy images and video sequences. The following subsections describe the various computational methods and principles that we have considered in developing our approach.

3.1. *Texture classification*

Texture plays an important role in the characterization of regions in digital images. It carries information about the microstructure of the regions and the distribution of the grey levels. Texture is an inherent property of any image and of medical images in particular, given that the tissue itself carries a dominant textural appearance.

The classification of image regions within colonoscopy images can be treated as a texture classification problem by exploiting the textural characteristics of the corresponding regions for the discrimination between lesions and normal tissue samples. Automated classification and identification of colonic carcinoma using microscopy images have been proposed by ref. [21], but the use of clinical endoscopy video frames for the identification of colonic tumors has been considered only in limited instances [4,17,18,22,23]. Along this line of research, this paper makes use of texture information for the detection of malignant regions in colonoscopy images by employing some quantitative description of a texture.

Among a large variety of texture models, e.g. structural [24], statistical [25–27] and random process [28], this work uses statistical measurements based on second-order statistics [27]. These statistical descriptors have been estimated using the method of co-occurrence matrices applied to each region of an image. This method evaluates a series of matrices that describe the spatial variation of grey level values within a local area.

In our experiments, we have used the image data management facilities of CoLD [4] to compute four co-occurrence matrices for each sample area with a displacement of one pixel and angles of 0°, 45°, 90°, 135°. In this way, four features have been computed on each matrix to produce a 16-dimensional feature vector describing each tissue sample, namely the angular second moment, correlation, inverse difference moment and entropy, as defined by Haralick [27] (see ref. [4] for details).

3.2. *Training MLPs using back-propagation algorithms*

Let us consider an MLP whose l-th layer contains N_l neurons, $l = 1, \ldots, M$. Batch learning is realized by minimizing the error function E defined by:

$$E = \frac{1}{2} \sum_{p=1}^{P} \sum_{j=1}^{N_M} (y_{j,p}^{M} - t_{j,p})^2, \quad (1)$$