Neurocomputing 74 (2011) 2603–2613

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Learning to collaborate in distributed environments by means of an awareness-based artificial neural network

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ARTICLE INFO

Available online 13 May 2011

Keywords:
Awareness
Collaboration
Distributed environment
Learning strategy
Artificial neural network

ABSTRACT

This paper is an extension of a previous work presented in International Work Conference on Artificial Neural Network 2009 (IWANN 2009). The paper contains more details and results of the strategy known as Collaborative Distributed Environment by means of an Awareness & Artificial Neural Network strategy (CAwANN). CAwANN is part of the structure of Awareness-based learning Model for distriButed collAborative enviRonment (AMBAR) which is an awareness-based learning model, developed for distributed environments, that allows nodes to accomplish an effective collaboration by means of a multi-agent architecture in which agents are aware of its surroundings by means of a parametrical and flexible use of this information. CAwANN is an ANN-based strategy used to include learning abilities into AMBAR aiming to improve the effectiveness and efficiency of collaboration process by learning three different processes: (1) to collaborate based on levels of awareness; (2) to select a potential candidate to negotiate on saturated conditions; and (3) to decide whether or not a node must change the information that describes its current conditions related with collaboration. Based on the definitions of efficiency and effectiveness presented in this paper and the results obtained from simulated conditions CAwANN has an average efficiency of 100% and an average effectiveness of 86%.

1. Introduction

Collaborative Distributed Environments (CDEs) are those in which multiple users in remote locations participate in shared activity aiming to achieve a common goal. Most of the distributed system work toward providing reliable, customized and quality of service guaranteed dynamic computing environments for end-users. The success of achieving this goal in proper time (efficiency) and/or to obtain the higher quality results (effectiveness) in these dynamic and distributed environments depends on implementing an appropriate collaboration model between nodes in the system. Moreover, this collaboration mechanism should include learning abilities necessary for the use of the previous experience acquired (with situations that occurred in the past) in order to improve new collaborations required.

The collaboration process described in this paper focuses on helping a node *N* in the distributed system to accomplish a task related with a set of resources. Then, for one cause or another: (1) some of these resources cannot be satisfied by the particular node *N*, and/or (2) even when the resources can be satisfied by the node, the help provided by the other nodes can improve the efficiency and/or the effectiveness of achieving the goal (the task in this case).

On the other hand, according to Computer Supported Co-operative Work (CSCW) awareness is a useful concept used to achieve cooperation and collaboration in distributed environments because it increases communication opportunities [19]. A collaborative process is leaded by five processes [14,16]: (1) co-presence, that gives the feeling that the user is in a shared environment with some other user at the same time; (2) awareness, a process where users recognize each other's activities on the premise of co-presence; (3) communication; (4) collaboration which together with communication permits users to collaborate with each other to accomplish the tasks and common goals; and (5) coordination which is needed to solve the conflicts impeding effective collaborations. In Computer Supported Collaborative Learning (CSCL), awareness plays an important role as it promotes collaboration opportunities naturally and efficiently [28], and it improves the effectiveness of collaborative learning.

In the same order of ideas, Spatial Model of Interaction (SMI) [1] is one of the awareness models proposed as a way to get any

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doi:10.1016/j.neucom.2011.04.002

knowledge of the immediately closer world in collaborative virtual environments. It is based primarily on the use of a variety of mechanisms that were defined for this model and to steer the interaction in a virtual environment. These are the concepts of medium, aura, focus, nimbus and awareness. The concept of awareness in this context, more explicitly awareness of interaction, is defined for quantifying the degree, nature and quality of the interaction between the elements of the environment.

By using a specific interpretation of the SMI-based awareness concept, Awareness-based learning Model for distriButed collAborative environment (AMBAR) [36] was proposed as a learning collaboration model for distributed environments. This concept was endowed with heuristic-based strategies aiming to take into account the information of awareness collaborations occurring in the environment for achieving the most appropriate future awareness situations. AMBAR's learning abilities are given by using one of the elements of this model called Collaborative Distributed Environment by means of an Awareness & Artificial Neural Network strategy (CAwANN). This element was also proposed in a previous work [32]. CAwANN is an ANN-based learning strategy that combines Neural-Gas (NGAS) [18], Radial Basis Function Network (RBFN) [12,15,39] and Multi-Layer Perceptron (MLP) [8] ANN-based models.

This paper is an extension of a previous work related with CAwANN and presents the details and results of this ANN-based learning-to-collaborate strategy. The remainder of the paper is organized as follows. Some related work is given in Section 2. Section 3 contains a brief technical background related with NGAS, RBFN, MLP and the simulated annealing method. Details of the AMBAR model are given in Section 4. Section 5 describes the CAwANN strategy that is the main subject of this paper. Details of the implementation and results of some experimental tests obtained by using CAwANN are given in Section 6. Finally, the last section includes the conclusions and outgoing future research related to this work.

2. Related work

Researchers in CSCW have already proposed awareness to: (1) give information on the surroundings of the target user [3]; (2) provide common or public space where users can gather and meet [4]; (3) simulate informal communicative opportunities in real world using computers [20]. These awareness-based models are implemented using multi-media technologies to bond physically distributed environments.

Regarding the context of awareness and recognizing the current context of a user or device, authors in [21] present an approach based on general and heuristic extensions to the growing neural gas algorithm classifier which allow its direct application for context recognition. The authors here used context awareness features for automatically classifying sensor data to recognize user or device context.

On the other hand, an approach for the optimization of the job scheduling in large distributed systems, based on a self-organizing neural network is presented in [27]. In this approach, the dynamic scheduling system should be seen as adaptive middle layer software aware of current available resources and making the scheduling decisions using the past experience. Another example of using neural network in a problem related with collaboration can be consulted in [2]. The authors then present an architecture aiming to address the problem in a collaborative learning activity to create groups among students. They used a neural network algorithm to obtain homogenous groups.

As far as we know, there is not any ANN-based strategy for learning cooperation on CDE by using the awareness information originated in this environment.

3. Technical backgrounds

NGAS is a Vector Quantization (VQ) [13,17,24–26] technique with soft competition between the units. VQ is the process of quantizing n-dimensional input vectors to a limited set of n-dimensional output vectors referred to as *code-vectors*. The set of possible *code-vectors* is called the *codebook*. The *codebook* is usually generated by clustering a given set of training vectors (called *training set*). Clustering can be described then, as the process of organizing the *codebook* into groups whose members share similar features in some way. The goal of clustering is to reduce large amounts of raw data by categorizing in smaller sets of similar items.

In each training step of NGAS, the squared Euclidean distances between a randomly selected input vector x_i from the training set and all *code-vectors* m_k are computed; the vector of these distances, expressed in (1) is d. Each center k is assigned a rank $r_k(d)=0, \ldots, N-1$, where a rank of 0 indicates the closest and a rank of $N-1$ the most distant center to x. The learning rule is expressed as it is indicated in (2)

$$d_{ik} = \|x_i - m_k\| = (x_i - m_k)^T * (x_i - m_k) \tag{1}$$

$$m_k = m_k + \varepsilon * h_\rho[r_k(d)] * (x - m_k) \tag{2}$$

$$h_\rho(r) = e^{(-r/\rho)} \tag{3}$$

In NGAS, a monotonically decreasing function of the ranking that adapts all the centers, with a factor exponentially decreasing with their rank is represented in (3). The width of this influence is determined by the neighborhood range ρ. The learning rule is also affected by a global learning rate ε. The values of ρ and ε decrease exponentially from an initial positive value ($\rho(0)$, $\varepsilon(0)$) to a smaller final positive value ($\rho(T)$, $\varepsilon(T)$) according to expressions (4) and (5), respectively, where t is the time step and T the total number of training steps, forcing more local changes with time

$$\rho(t) = \rho(0) * [\rho(T)/\rho(0)]^{(t/T)} \tag{4}$$

$$\varepsilon(t) = \varepsilon(0) * [\varepsilon(T)/\varepsilon(0)]^{(t/T)} \tag{5}$$

Radial basis functions were originally developed to discuss problems involving the adaptation of irregular topographic contours through a series of geographic data [15,39]. ANN's based on this technique (RBFNs) are among the best choices in models out there as an alternative to achieve excellent results in alignment of data caused either by stochastic or deterministic functions [11]. This model consists of three layers of processing units: the input layer, the output layer and a layer of hidden units. Information flows in one direction, from the input layer (elements sensors) to a layer of units that shows the system output. On the way, the information is processed in part by the intermediate (hidden) units. The learning process is a supervised-based strategy and provides a method to adjust the synaptic weights. Therefore, the network learns ($\vec{y}, \vec{s}$) correspondence, being $\vec{y}$ the input vector and $\vec{s}$ the associated output vector. The basis of this algorithm is the method of gradient descent that is used to minimize a function of quality. The most commonly used function is mean-squared error, whose expression can be seen in (6), where: O—output units; s—desired outputs; i—units index for output layer; and μ—learning patterns index. Expressions (7) and (8) are used to calculate the spread of hidden units and output units,