Collaborative Agents for Drilling Optimisation Tasks Using an Unsupervised Connectionist Model

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Abstract. The purpose of this study is the optimization of drilling tasks in the construction of big auto-carrier storage warehouses. This is carried out by applying different Artificial Intelligence (AI) techniques: a cooperative unsupervised connectionist model (focused on the detection of some optimal drilling conditions) and software agents. These agents can collaborate to save drilling time and waste by interchanging information about the conditions of drill bits and the kind of material to be drilled.

1 Introduction

One of the biggest demands on present industrial field is the storage of goods in suitable places. For this reason it is necessary to build up big warehouses for auto-carrier storage. Up to now, the drilling of slabs made of reinforced concrete, which is necessary to place shelves on the mentioned warehouses, has been made manually by workers. This is a disadvantage due to the possible human errors which may produce a big economical loss. In order to automate this drilling task, it was decided to design a robot-based approach, where robots are equipped with mechanical tools to perform these tasks.

To control these robots, a multiagent system, which consists on various collaborative agents [1], is proposed. The application of the agent paradigm involves saving a lot of time and money.

2 System Structure

In this system, different robots must be capable of setting up the position of the bits and their diameters, to suck in, to filter and to recirculate the water for drilling, to test the tool conditions during automatic changing when it is required. In this way, it is easier to achieve a better assembly quality, decreasing the drilling execution time and achieving a less tool wear. All these factors imply an increment of the drilling instruments duration and the elimination of corrections. They have sensors to detect the type of material to be drilled depending on the exchange of information about the conditions of the drill bits and the material to be drilled. This is done in order to use the more adapted drill bit for each type of material drilled at that moment and according to the conditions.

The system works by means of contract net [2]. There are two types of agents: A tester agent (contracting agent) and several drilling agents (contracter agents). The tester agent supply to the drilling agents the holes and type of material to drill, and these will respond with their position and the drill bit conditions. Then, the tester agent choose the most adapted one between all the supplies the most adapted

Also, if any drilling agent has some problems, it will indicate them to the tester agent. Then the last one will ask to another drilling agent to perform the task assigned to the drilling agent under problems.

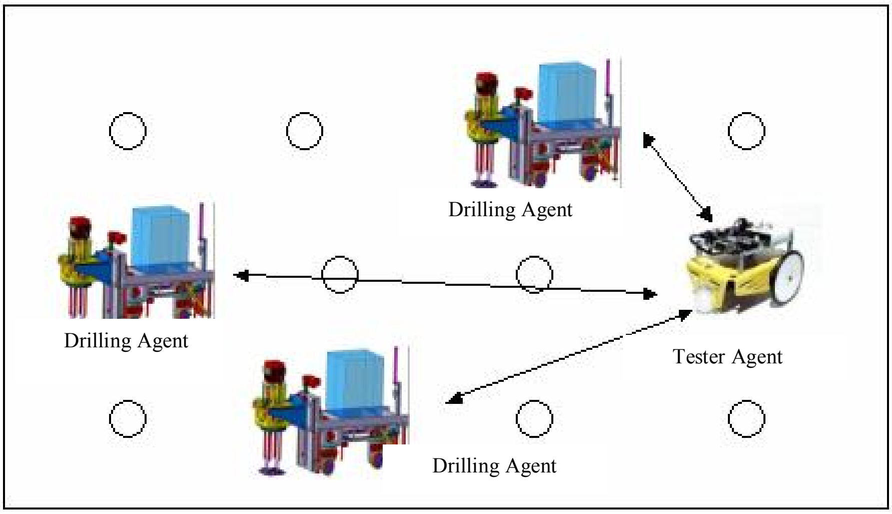

Fig. 1. System Structure

The Fig.1 shows the system structure, where there are one tester agent and several drilling agents.

3 Agents Structure

Both, drilling agent and tester one have the same structure. It is a hybrid architecture inspired on Interrap [3]. This model is divided into three vertical layers as is showed in Fig.2:

- Behavior layer.
- Planning layer.
- Cooperation layer.

At the lower level, a reactive behavior is used while at the higher ones, a deliberative behavior is followed.

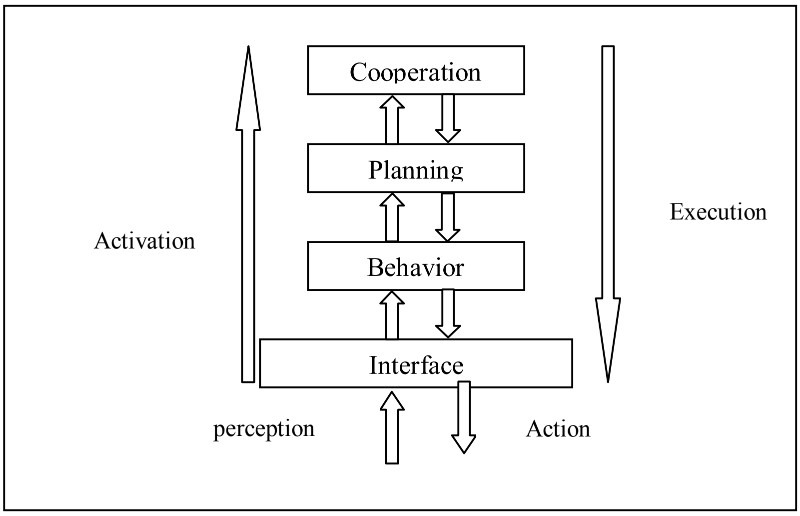

Fig. 2. Vertical layers architecture

3.1 Tester Agent Structure

The tester agent layers are:
- Behavior layer: the type of material to be drilled is detected by different sensors.
- Planning layer: the goal is the optimization of the route followed to make the measurements
- Cooperation layer: with the information relative to each hole a negotiation process begins to decide what agent makes the drilled task.

3.2 Drilling Agent Structure

The drilling agent layers are:
- Behavior layer: it is responsible for carrying out the drilling process, controlling the conditions of drill bit waste and changing the drill bit if necessary.
- Planning layer: it decides the drilled order based on the negotiation and the optimal conditions are taken into account, depending on the type of material that may be found. For this purpose, an unsupervised connectionist architecture based on Cooperative Maximum Likelihood Hebbian learning (CMLHL) [4, 5, 6] is used. Lateral connections, obtained from the Rectified Gaussian Distribution [10] were added to the Maximum Likelihood Hebbian Learning (MLHL) method by Corchado *et al.* [7, 8, 9] which enforced a greater sparsity in the weight vectors.

These lateral connections were initially introduced to the basic MLHL network for the identification of different filters from video images [7, 8].

– Cooperation layer: the drilling agent negotiates with the tester agent.

4 Unsupervised Neural Model

In this section we present the model on which the parameters optimization for each agent is based.

Exploratory Projection Pursuit (EPP) [11, 12] is a statistical method focused on identifying structure in complex high dimensional data. It projects the data onto a low dimensional subspace in which the search for structure is done by eye. However not all projections will reveal the data's structure equally well. There is an index that measures how “interesting” a given projection is, and then represents the data in terms of projections that maximize that index. To identify “interesting” features in data, it is necessary to look for those directions onto which the data-projections are as far from the Gaussian as possible. Corchado *et al.* [7, 8, 9] presented a neural version of EPP in which the learning rule is given by:

$$\Delta W \propto -\frac{\partial J}{\partial W} = -\frac{\partial J}{\partial \mathbf{e}}\frac{\partial \mathbf{e}}{\partial W} \approx y(p\,|\,\mathbf{e}\,|^{\text{p-1}}\ \text{sign(e)})^{\text{T}} \ . \tag{1}$$

where T denotes the transpose of a vector. It is expected that for leptokurtotic residuals values of p<2 would be appropriate, while for platykurtotic residuals values of p>2 would be appropriate.

Therefore the network operation is:

– Feedforward:

$$y_i = \sum_{j=1}^{N} W_{ij} x_j, \forall i \tag{2}$$

– Lateral Activation Passing

$$y_i(t+1) = [y_i(t) + \tau(b - Ay)]^+ \ . \tag{3}$$

– Feedback:

$$e_j = x_j - \sum_{i=1}^{M} W_{ij} y_i, \forall j \ . \tag{4}$$

– Weight change:

$$\Delta W_{ij} = \eta . y_i . sign(e_j) | \, e_j \, |^{p-1} \tag{5}$$

Where τ represents the strength of the lateral connections, η is the learning rate, b is the bias parameter, p is a parameter related to the energy function and A is a symmetric matrix used to modify the response to the data.

This method has been linked to the standard statistical method of EPP [4, 6, 8, 9, 10]. The final model used in this research is called Cooperative Maximum Likelihood Hebbian Learning [4, 5] and it is and extension of MLHL model.

5 Data Set Description

The study has been performed using different data sets [14] obtained from concrete test tubes and concrete test tubes with steel bars drilling, having 158 samples.

We have studied several variables and their response in a discrete range of values. These values are: Applied strength (N), range: 65, 80.5, 96, 111.5. Refrigerating volume water of the tool (l/min), which avoids its overheating and evacuates the waste, range: 2, 3, 4, 5. The speed of turn (r.p.m), range: 1000, 2000, 3000, 4000. And the drilling time (s): 158 different times.

6 Results

The model presented above has been used to identify the optimal drilling conditions under the following three situations: In the first one the bit faces only a concrete slab. In the second one, the bit faces mainly the concrete slab and a small portion of a steal bar. And finally, the bit faces mainly a steal bar and the concrete slab.

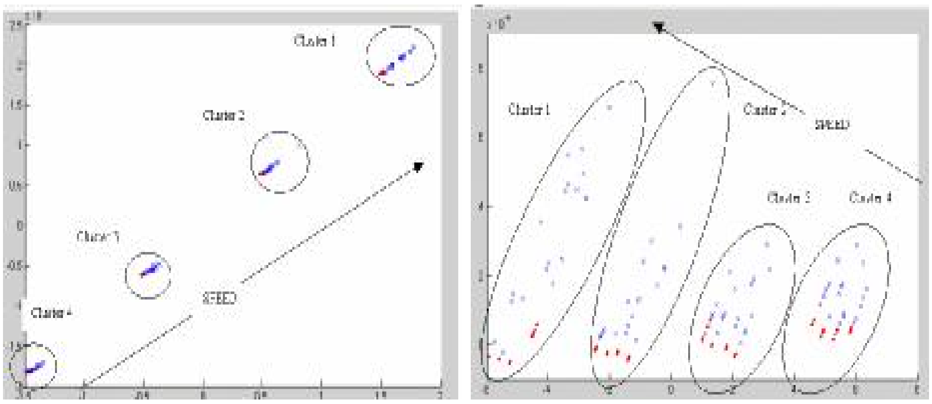

Fig. 3. Principal Component Analysis, PCA (left figure) and Cooperative Maximum Likelihood Hebbian Learning (right figure). CMLHL method identifies a projection which spreads the data out more than PCA**.**

As it is shown in Fig. 3, the model classified four groups in a very clear way mainly in an axis attending to the speed. Some kind of internal structure can be seen. For a better understanding, we have studied this structure provided by CMLHL.

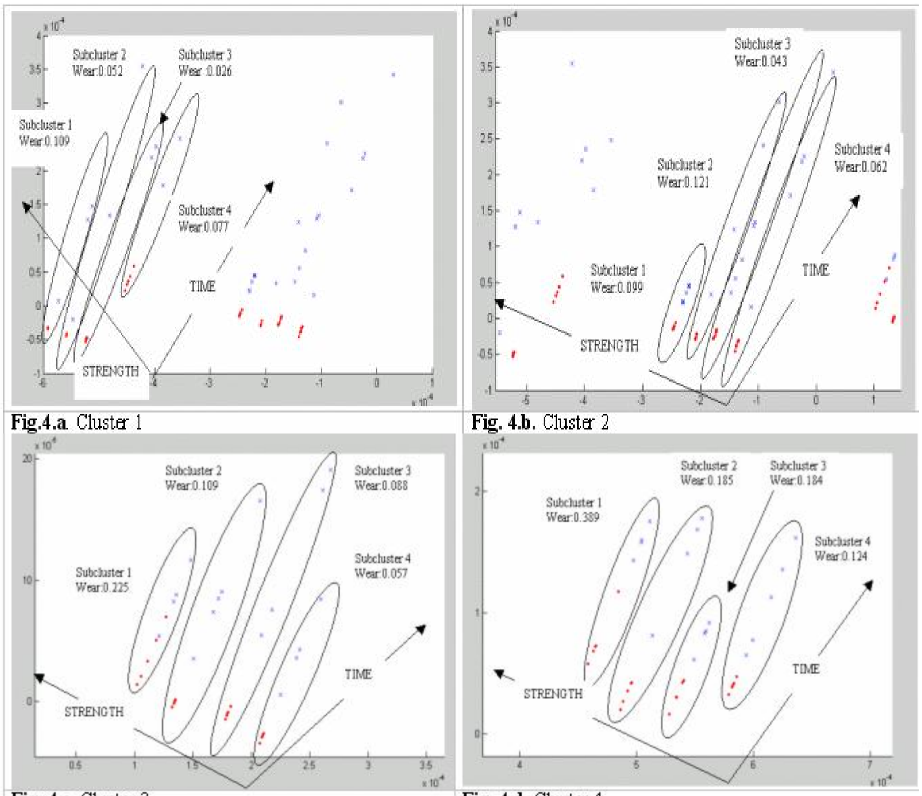

Fig.4.a Cluster 1 **Fig. 4.b.** Cluster 2
Fig. 4.c. Cluster 3 **Fig. 4.d.** Cluster 4
Fig. 4. Wear Conditions and Structure of each of the four cluster

On this second classification, where we are studying the different four subclusters, the applied strength and time have been the decisive parameters. We have noticed that the ordinate axe (Figure 4.a, 4.b, 4.c and 4.d) is related to the strength and that the coordinate axe (Figure 4.a, 4.b, 4.c and 4.d) is related to the applied time.

The distance between the measures in the subclusters is related to the drilling time. This is why the measures of the drilling of concrete test tubes with steel bars take more time than concrete test tubes ones.

Once the results have been analyzed, we can state that the lower wear of the diamond bits take place in each cluster for subcluster 3 and 4. This means that for the same speed, the best results are related to a medium or shorter strength and shorter time. The best conditions are related to subcluster 3 of cluster 1 (parameters: strength 80.5 N; 4000 r.p.m; time between 300 and 700 seconds and a medium volume) as we can see in Figure 4.a. Of course, these results are related to the range of values used on the test, but in other hand quite common ones for this drilling task.

It is important to remark that the best conditions are not the ones related with the biggest values of strength. We have noticed that the use of a small refrigerating volume may produce an extreme warming of the bit and so for a bad elimination of the waste. In the opposite case, the use of an excessive amount of it may produce the breaking of the labs in a wrong way.

7 Conclusions

In this paper we have reviewed CMLHL and showed how capable is for the identification of the optimal drilling conditions, minimizing costs derived from time employed as well as waste, and consequently, from the total cost.

The proposed system has a high scalability level, to increase or decrease the number of robots (drilling agents) without having any problem. If any drilling agent has some problems it will indicate them to the tester agent. Then the last one will ask to another drilling agent to perform the task assigned to the drilling agent under problems.

Acknowledgments

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