Distributed Prediction of Carbon Dioxide Exchange Using CBR-BDI Agents

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Abstract. This paper presents a model constructed for the evaluation of the interaction of the atmosphere and the ocean. The work here presented focuses in the development of an agent based architecture that has been constructed for the evaluation of the interaction, between the atmosphere and the ocean waters, of several parameters. Such evaluation needs to be made continuously in a dynamic environment and therefore requires the use of autonomous models that evolve with the time. The proposed architecture incorporates CBR-agents whose aim is to monitor the evolution of the interaction of parameters and facilitate the creation of an explanation model. The system has been tested and this paper presents the results obtained.

Keywords: CBR-BDI, Air-Sea, Monitoring, Evaluation.

1. Introduction

Agents and multiagent systems are adequate for developing applications in dynamic, flexible environments. Agents can be characterized through their capacities in areas such as autonomy, communication, learning, goal orientation, mobility, persistence, etc. Autonomy, learning and reasoning are especially important aspects for an agent. These capabilities can be modelled in different ways and with different tools [1]. One of the possibilities is the use of Case Based Reasoning (CBR) systems. This paper presents a CBR based deliberative agent that incorporates neural networks to implement the retrieve, reuse, revise and retain stages of the CBR system. The CBR-BDI agent [2] is the core of a distributed system which mission is to monitor the interaction between the ocean surface and the atmosphere. Initially the system has been used to evaluate and predict de quantity of CO_2 exchanged in the North Atlantic Ocean. The aim of this work is to obtain an architecture that makes it possible to construct dynamic systems capable of growing in dimension and adapting its knowledge to environmental changes. Several architectures have been proposed for building deliberative agents, most of them based on the BDI model. In the BDI model the internal structure of an agent and therefore its ability to choose a course of action is based on mental attitudes. The advantage of using mental attitudes in the design and realization of agents and multi-agent systems is the natural (human-like) modelling and the high abstraction level. The BDI (Beliefs, Desires, Intentions) model uses Beliefs as information attitudes, Desires as motivational attitudes and Intentions as deliberative attitudes for each agent. The method proposed in [3, 4] facilitates the CBR systems incorporation as a reasoning engine in BDI agents, which makes it possible for an agent to have at its disposal a learning, adaptation and a greater degree of autonomy than a pure BDI architecture [4]. BDI agents can be implemented by using different tools. One very interesting tool is Jadex [5], a BDI reasoning engine that can be used on top of different middleware infrastructures such as JADE [6]. Jadex agents deal with the concepts of beliefs, goals and plans. Beliefs, goals and plans are objects that can be created and handled within the agent at execution time. Jadex has the advantage of allowing programmers to include their own deliberative mechanisms. In this case this mechanism will be a CBR system. Moreover the system will benefit from all the communication advantages that JADE provides.

In the next section we review the relationships that can be established between CBR and BDI concepts. Section three describes the environmental problem that motivates most of this research. Section four describes the CBR-BDI agent based system developed. Finally the conclusions and some preliminary results are presented.

2. CBR-BDI Agents

The purpose of case-based reasoning (CBR) is to solve new problems by adapting solutions that have been used to solve similar problems in the past. The deliberative agents, proposed in the framework of this investigation, use this concept to gain autonomy and improve their problem-solving capabilities. A CBR-BDI agent is composed of a reasoning cycle that consists of four sequential phases: retrieve, reuse, revise and retain. Each of these activities can be automated, which implies that the whole reasoning process can be automated to a certain extent [4]. Accordingly, agents implemented using CBR systems could reason autonomously and therefore adapt themselves to environmental changes. The CBR system is completely integrated into the agents' architecture. The CBR-BDI agents incorporate a "formalism" which is easy to implement, in which the reasoning process is based on the concept of intention. Intentions can be seen as cases, which have to be retrieved, reused, revised and retained. This makes the model unique in its conception and reasoning capacities. The structure of the CBR system has been designed around the concept of a case. A straight relationship between CBR systems and BDI agents can also be established if the problems are defined in the form of states and actions.

The relationship between CBR systems and BDI agents can be established by implementing cases as beliefs, intentions and desires which lead to the resolution of the problem. As described in [7], in a CBR-BDI agent, each state is considered as a belief; the objective to be reached may also be a belief. The intentions are plans of actions that the agent has to carry out in order to achieve its objectives [3], so an intention is an ordered set of actions; each change from state to state is made after carrying out an action (the agent remembers the action carried out in the past, when it was in a specified state, and the subsequent result). A desire will be any of the final states reached in the past (if the agent has to deal with a situation, which is similar to a past one, it will try to achieve a similar result to the previously obtained one).

Case: <Problem, Solution, Result>	**BDI agent**
Problem: initial_state	Belief: state
Solution: sequence of <action, [intermediate_state]>	Desire: set of <final_state>
Result: final_state	Intention: sequence of <action>

3. Air Sea Interaction Problem

In recent years a great interest has emerged in climactic behaviour and the impact that mankind has had on the climate. One of the most worrying factors is the quantity of CO_2 present in the atmosphere. Until only a few years ago, the photosynthesis and breathing processes in plants were considered as the regulatory system that controls the presence of CO_2 in the atmosphere. However, the role played by the ocean in the regulation of carbon volume is very significant and so far remains indefinite [8]. Current technology offers the possibility of obtaining data and estimates that were beyond expectations only a few years ago.

The goal of this project is to construct a model that calculates the global air-sea flux of CO_2 exchanged between the atmosphere and the surface waters of the ocean, as well as the global budgets of CO_2 for the whole oceanographic basin. In order to create a new model for the CO_2 exchange between the atmosphere and the oceanic surface a number of important parameters must be taken into consideration: sea surface temperature, air temperature, sea surface salinity, atmospheric and hydrostatic pressures, the presence of nutrients and the wind speed vector (module and direction) [9]. These parameters can be obtained from oceanographic ships as well as from satellite images. Satellite information is vital for the construction of oceanographic models, and in this case, in order to produce estimates of air-sea fluxes of CO_2 with much higher spatial and temporal resolution, using artificial intelligence models than can be achieved realistically by direct in situ sampling of upper ocean CO_2. In order to handle all the potentially useful data to create daily models in reasonable time and at a reasonable cost, it is necessary to use automated distributed systems capable of incorporating new knowledge. Our proposal is presented in the following section.

4. CBR-BDI Modelling Agent

This agent will have two principal functions. The first is to generate models which are capable of predicting the atmospheric/oceanic interaction in a particular area of the ocean in advance. The second is to permit the use of such models. the reasoning cycle of a CBR system is included among the activities, composed of stages of retrieval, reuse, revise and retain. Also, an additional stage is used that introduces expert's knowledge. This reasoning cycle must correspond to the sequential execution of some of the agent roles. The Modelling agent carries out roles to generate models such as Jacobean Sensitivity Matrix (JSM), Pondered Weigh Technique (PWT), Revision Simulated Equation (RSE), and other roles that allow it to operate with the models calculated, like Forecast Exchange Rate, Evaluate Model or Consult model. The roles used to carry out the stages of the CBR cycle are now described.

Jacobean Sensitivity Matrix (JSM): This role is in charge of carrying out the retrieval stage. In order to do this it needs to use a method that guarantees the recuperation of cases whose characteristics are similar to the current problem. The Jacobean Sensitivity Matrix (JSM) is used in this case for data clustering and retrieval [10]. The Jacobean Sensitivity Matrix method is a novel approach for feature selection. It can be used to visualize and extract information from complex, and highly dynamic data. The model is based in the principal component analysis and is used to identify which input variables have more influence in the output of the neural network used to perform the principal component analysis. The neural network identifies the beliefs stored by the agent that can be more useful to solve a given problem. The mathematical model is now outlined.

If JSM is a matrix NxM where N is the number of input of the neural network and M is the number of output of the neural network. And if the element S_{ki} in the matrix represents the sensitivity (influence) of the output k over the input I, then (1).

$$S_{ki} = \frac{\partial y_k}{\partial x_i} = \frac{\partial f_k(net_k)}{\partial x_i} = \frac{\partial f_k(net_k)}{\partial net_k}\frac{\partial net_k}{\partial y_j}\frac{\partial y_j}{\partial net_j}\frac{\partial net_j}{\partial x_i} = \frac{\partial f_k(net_k)}{\partial net_k}\left(\sum_{j=1}^{H} w_{kj}\frac{\partial f_j(net_j)}{\partial net_j}w_{ji}\right) \quad \textbf{(1)}$$

Where w_{ij} is the weight of the connection between the input neuron i and the hidden neuron j. w_{kj} is the weight of the connection between the hidden neuron j and the output neuron k. y_k is the output obtained for neuron k of the output layer. Then $y_k = f_k\ (net_k)$. y_j is the output obtained for neuron j of the hidden layer. Then $y_j = f_j\ (net_j)$. x_i is the input for neuron i and f_h is the activation function in neuron h. Then

$$net_j = \sum_{i=1}^{N} w_{ji}\, x_i \ + \theta_j \quad \textbf{(2)}$$

$$net_k = \sum_{j=1}^{H} w_{kj}\, y_j \ + \theta_k \quad \textbf{(3)}$$

Where H is the number of neurons in the hidden layer, θ_j is the value of threshold of neuron j of the hidden layer and θ_k is the value of threshold of neuron k of the output layer.

Pondered Weigh Technique (PWT): The reuse is carried out using the cases selected during the retrieval stage. The cases are pondered [11] and the bigger weight is given to the one that more resembles the current problem in the following way:

$$p^* = \frac{1}{\sum_{r=1}^{Z} e^{-|a-r|}} \sum_{r=1}^{Z} e^{-|a-r|} p^r \quad \textbf{(4)}$$

Where $p*$ is the solution prediction, Z is the number of retained cases from the base of beliefs, a is the measure of minimum similarity between the retained cases from the base of beliefs and the current case, p^r is the retained prediction r-th from the base of beliefs and r is the measure of similarity between the retained cases r-th from the base of beliefs and the current case.

Revision Simulated Equation (RSE): During the revision stage an equation (F) is used to validate the proposed solution p^*.

$$F = kso(pCO_2SW - pCO_2AIR) \tag{5}$$

Where F is the flux of CO_2, k is the gas transfer velocity (6), so is the solubility verifying (7) and pCO_2 is the partial pressure of CO_2 (8).

$$k = (-5{,}204Lat + 0{,}729Long + 2562{,}765)/3600 \tag{6}$$

$$so = e^{\left(\frac{93{,}4517}{100tk} - 60{,}2409 + 23{,}3585\log(100tk) + s(0{,}023517 - 0{,}023656 \bullet 100tk + 0{,}0047036 \bullet 1002tk)\right)} \tag{7}$$

$$pCO_2 = A + BLong + CLat + DSST + EYear \tag{8}$$

As can be seen in (6), k depends on *Lat* (Latitude), Long (Longitude). As can be seen in (7) *so* depends on tk = 273,15 + t. where t is the temperature and s is the salinity. Finally, in (8) it is possible to observe that pCO_2 depends on the *SST*. *SST* is the temperature of the marine surface or air as it corresponds to pCO_2SW or pCO_2AIR. The coefficients of the equation (8) depend on the month, as shown it Table 1.

Table 1. Months\Coefficients values

Months\Coefficients	A	B	C	D	E
Feb	-2488	-0,42	4,98	-12,23	1,38
May	-7642	-0,9	-1,74	-20,77	4,14
Jun	-4873	-0,85	1,3	-15,64	2,66
Jul	-7013	-0,025	3,66	-7,07	3,64
Aug	-3160	-0,69	0,84	-11,31	1,8
Sep	-1297	0,43	-4,19	-17,06	1,05
Oct	83	-0,81	4,81	-10,92	0,076
Nov	747	0,2	-0,73	-17,3	-0,062
Dec	-4306	0,38	-0,22	-17,13	2,45

During the revision, the agent compares the obtained F value with predicted one and if the prediction differs in less than 10% the case is stored on the base of beliefs. As has been shown the CBR-BDI agents use a CBR system, at a low level of implementation, which is the reason for using cases. One case for the CBR consists of a problem (initial situation and a number of goals) and the plans to resolve it. For oceanic/atmospheric interaction, we define the problem in terms of the attributes shown in Table 2:

Table 2 shows the description of a case: DATE, LAT, LONG, SST, S, WS, WD, Fluo_calibrated, SW pCO_2 and Air pCO_2. Flux of CO_2 is the value to be identified.

As mentioned in the section 2 there is a correspondence between cases and BDI agents. To use a deliberative BDI model that utilises a CBR mechanism, it is necessary to transform the case representation by the CBR system into a BDI formalisms. The BDI model deals with:

- Beliefs, representing the state of the problem, with certain knowledge about the surroundings and the agent itself. In the problem presented the attributes DATE, LAT, LONG, SST, S, WS, WD, Fluo_calibrated, $SWpCO_2$ and $AirpCO_2$ will be used as belief. A beliefs base will be used in which each belief is a ProblemDescription type containing all the attributes mentioned in Table 2.
- Desires, that represent those final states to which the agent wishes to arrive or reach. In this case, it deals with three goals:
    - Predict the flux of CO_2 exchanged between the sea surface and the atmosphere, using a window of two or three weeks.
    - Calculate the best parameters to use in order to improve the prediction for different window sizes.
    - Calculate the most suitable prediction window in relation to a maximum % error allowed.

  An agent stores all the goals in a similar way to the beliefs.
- Intention, that represents the sequence of actions that should be followed in order to reach the final state or goal. This new attribute is introduced into the case description. The sequence of actions to be carried out is generally formed by the stages of the reasoning cycle and the different algorithms executed in each one of those stages. In general an agent will have available various pre-defined plans or intentions that could be called up and modified at the execution time. The selection of plans is made through the agent CBR-BDI, JSM, PSW and RSE mechanisms.

The tools offered by the Jadex tool [5] have been used for the storing and use of beliefs, desires and intentions or plans. In this way, we have been able to construct a deliberative BDI agent capable of reasoning through the use of a CBR mechanism. The agent manages cases and carries out CBR cycles.

5. Results and Conclusions

The system described above was tested in the North Atlantic Ocean during 2005. Although the system is not fully operational and the aim of the project is to construct a research prototype and not a commercial tool, the initial results have been very successful from the technical and scientific point of view. The construction of the distributed system has been relatively simple using previously developed CBR-BDI libraries [2, 7, 12]. The formalism defined in [4] facilitates the straight mapping between the agent definition and the CBR construction.

The fundamental concept when working with a CBR system is the concept of case, and it is necessary to establish a case definition. A case in the air-sea exchange problem, managed by the Modelling agent, is composed of the attributes described in Table 2. Cases can be viewed, modified and deleted manually or automatically by the agent (during its revision stage). The agent plans (intentions) can be generated using different strategies since the agent integrates different algorithms.

Table 2. Case Attributes.

Case Field	Measurement
DATE	Date (dd/mm/yyyy)
LAT	Latitude (decimal degrees)
LONG	Longitude (decimal degrees)
SST	Temperature (ºC)
S	Salinity (unitless)
WS	Wind strength (m/s)
WD	Wind direction (unitless)
Fluo_calibrated	fluorescence calibrated with chlorophyll
SW pCO_2	surface partial pressure of CO_2 (micro Atmospheres)
Air pCO_2	air partial pressure of CO_2 (micro Atmospheres)
Flux of CO_2	CO_2 exchange flux (Moles/m^2)

The system has been tested during the last three months of 2005 and the results have been very accurate. Table 3 presents the results obtained with the Multiagent systems and with mathematical Models [13] used by oceanographers to identify the amount of CO_2 exchanged. The numerical values represent the million of Tonnes of carbon dioxide that have been absorbed (negative values) or generated (positive value) by the ocean during each of the three months.

Table 3. Million of tones of $C0_2$ exchanged in the North Atlanthic.

	Oct. 04	Nov. 04	Dec. 04	Jan. 05	Feb. 05
Multiagent System	-19	21	33	29	29
Manual models	-20	25	40	37	32

The values proposed by the CBR-BDI agent are relatively similar to the ones obtained by the standard technique. While the CBR-BDI Modelling Agent generates results on a daily basis without any human intervention, the Casix manual modelling techniques require the work of one researcher processing data during at least four working days. Although the system proposed requires further improvements and more work the initial results are very promising. Compared to the previously CBR-BDI models developed based on Hebbian Learning (CoHel) [14, 15] or variational calculus techniques (VCBP) [4, 7], the results obtained with the reasoning engine presented in this paper are very similar to those obtained applying hebbian learning and give a quicker response than VCBP engines. This work present the development of new algorithms to improve the CBR engine incorporated in the BDI agent. These algorithms are included in each of the stages of the CBR reasoning cycle.

The framework generated facilitates the incorporation of new agents using different modelling techniques and learning strategies so that further experiments will allow us in the future to compare these initial results with the ones obtained by other techniques. It also facilitates the application of the architecture presented in this paper, specially the CBR-BDI agents, to any other dynamics environments, such as tourism, robotic, recommender systems, ambient intelligence, etc.

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References

1. Wooldridge, M. and Jennings, N. R. (1995) Agent Theories, Architectures, and Languages: a Survey. In: Wooldridge and Jennings, editors, Intelligent Agents, Springer-Verlag, pp. 1-22.
2. Corchado J. M. and Laza R. (2003). Constructing Deliberative Agents with Case-based Reasoning Technology, International Journal of Intelligent Systems. Vol 18, No. 12, December. pp.: 1227-1241
3. Bratman, M.E. (1987). Intentions, Plans and Practical Reason. Harvard University Press, Cambridge, M.A.
4. Glez-Bedia M., Corchado J. M., Corchado E. S. and Fyfe C. (2002) Analytical Model for Constructing Deliberative Agents, Engineering Intelligent Systems, Vol 3: pp. 173-185.
5. Pokahr, A., Braubach, L. and Lamersdorf W. (2003) Jadex: Implementing a BDI-Infrastructure for JADE Agents, in: EXP - In Search of Innovation (Special Issue on JADE), Vol 3, Nr. 3, Telecom Italia Lab, Turin, Italy, September 2003, pp. 76-85.
6. Bellifime, F. Poggi, A. and Rimasa, G. (2001) JADE: a FIPA2000 compliant agent development environement. Proceedings of the 5th international conference on autonomous agents (ACM).
7. Corchado J. M., Pavón J., Corchado E. and Castillo L. F. (2005) Development of CBR-BDI Agents: A Tourist Guide Application. 7th European Conference on Case-based Reasoning 2004. LNAl 3155, Springer Verlag. pp. 547-559.
8. Santamaría J. and Nieto J. (2000) Los agujeros del cambio climático. World Watch no. 12. pp 62-65.
9. Takahashi T., Olafsson J., Goddard J. G., Chipman D. W. and Sutherland S. C. (1993) Seasonal Variation of CO2 and nutrients in the High-latitude surface oceans: a comparative study. Global biochemical Cycles. Vol. 7, no. 4. pp 843-878.
10. Montaño J.J, Palmer A. (2002): Artificial Neural Networks, opening the black box. Metodología de las Ciencias del Comportamiento 4(1) 77-93.
11. De Paz, Y. D. R. (2005) Mixture Weibull distribution using artificial neural networks with censurated data PHD thesis, chapter 3.
12. Corchado J. M. and Lees B. (2001). A Hybrid Case-based Model for Forecasting. Applied Artificial Intelligence. Vol 15, no. 2, pp.105-127.
13. Lefevre N., Aiken J., Rutllant J., Daneri G., Lavender S. and Smyth T. (2002) Observations of pCO2 in the coastal upwelling off Chile: Sapatial and temporal extrapolation using satellite data. Journal of Geophysical research. Vol. 107, no. 0
14. Corchado J.M., Aiken J., Corchado E., Lefevre N. and Smyth T. (2004) Quantifying the Ocean's CO2 Budget with a CoHeL-IBR System. ECCBR 2004: 533-546
15. Bajo J. and Corchado J. M. (2005) Evaluation and monitoring of the air-sea interaction using a CBR-Agents approach Proccedings of the 6th Internacional Conference on Case-based Reasoning, ICCBR'05, LNAI pp. 50-62. Springer Verlag.