From physical agents to recommender agents

Josep Lluís de la Rosa, Esteve del Acebo, Beatriz López, Miquel Montaner
Universitat de Girona
Av. Lluís Santaló s/n
17071 Girona, Spain
peplluis@eia.udg.es,acebo@ima.udg.es,{blopez,mmontane}@eia,.udg,es

Abstract

In this paper, we argue in favour of the interchange of research results between physical agents and recommender systems. Certain properties, such as introspection and physical foundations of physical agents, are mapped into agents that model and make recommendations to users from the subjective, content-based point of view of products and services. How this real-to-virtual mapping of properties and behaviours can be performed is the main goal of our work, from which we expect to obtain a general concept of recommender agents which improves the state of the art in terms of performance and maintainability. Furthermore, new features of the recommender agents could be also mapped to the physical agents discipline. Some of the features explained are installed in two personalization company products: Proto-agent and Habitat-Pro.

1. Introduction

Researchers think that physical agents and recommender agents belong to two different research lines and, so far, research on both kinds of agents has been performed separately. However, we have found analogies between the two.

A physical agent is an entity whose actions and co-operation with other agents are limited and conditioned by its physical body, typically a robot [Asada97]. A recommender agent is an entity whose actions and co-operation with other agents are limited and conditioned by the combination of: the modelling of preferences of particular users, building content models and the modelling of social patterns [Maes94]. Since physical agents commit to better actions according to introspected capabilities from the physical body ([de la Rosa99], [Oller00]), in the same way recommender agents would commit to better transactions according to introspected tastes of human beings. Thus, we think that most of the results obtained in the physical world, like automatic control-oriented concepts, such as excitation, dynamics and stability of the physical bodies ,can be imported to the recommender field.

How this real-to-virtual mapping of properties and behaviours can be performed is the main goal of our work. We expect to obtain a general concept of recommender agents that is an improvement on current understanding, in terms of performance and maintainability. Furthermore, new features of the recommender agents could also be mapped to the discipline of physical agents.

This paper is organised as follows: First, we outline the properties of physical agents and recommender agents in sections 2 and 3 respectively. Then, we explain the analogies between both kinds of agents in section 4. Section 5 is devoted to experimental results and finally, in section 6 we offer several conclusions.

2. Physical agent properties

Robotics research has been focused for years on the development of modular systems composed by perception, reasoning and actuator components. More recently, GOFAIR (Good Old Fashioned Artificial Intelligence and Robotics, [Mackworth93]) has moved towards new approaches in order to obtain an operational cognitive integration. Most of these approaches are preceded by Brooks research [Brooks91] which claimed that AI techniques did not work either in real time systems or in dynamic environments, and that the key issues in robot development are situation and embodiment.

On the one hand, situation means that robots are in the world. They do not deal with abstract situations but with the "here and now" of the environment that has a direct influence on the system behaviour. On the other hand, embodiment underlines the fact that robots have body, they directly receive world inputs, their actions are part of the world's dynamics and have immediate effects on robot sensors. Sensing and acting are highly interconnected; they cannot be separated [Asada97].

Research on physical agents is framed within this new line of Robotics. From situation and embodiment follow several properties of physical agents, among which we want to distinguish introspection, subjectivity and perception of the co-operative world.

First, introspection is perception of the agent's own physical body. Physical inputs and outputs from the environment (dynamics of the physical body) are mapped in the knowledge base of each agent in what we call physical knowledge. Such knowledge is represented by a further declarative control level and a further declarative supervision level [Müller96] and is declared by means of capacities. According to the capacities gathered though introspection, the physical agent is able to make compromises in the co-operative world. [1]

Second, subjectivity in the perception of the physical world: the actions of the physical agent are conditioned by its capacities. For example, 10 m might be a long distance for a low-speed physical agent, but the same distance could be a quite short one for a high-speed robot. Moreover, 10 m could be a long distance even for a high-speed robot if its battery is low.

And third, perception of the co-operative world: each physical agent has capacities and it is able to sense the capacities of the other agents that live in its environment; biased, of course, by its own capacities. For example, agent A has a low precision capacity and for this agent, B and C could be two co-operative agents with a higher precision in relation to its own. Perception of the co-operative world is, therefore, also subjective and so has been used in developing multi-agent physical systems that co-operate in solving tasks. Perhaps the first results have been obtained in games, like in the Robocup tournaments (see, for example, [Oller00]), and then these results have been passed on to other domains, such as teamwork, rescue, and military operations, among others.

With regard to introspection, it is clear that physical agents are complex physical systems, and they are not easy to understand for use in a computational way, based on capacities. Being physical systems, however, we can take advantage of automatic control theory to build dynamic models by using identification methods: temporal, frequential and stochastic identification.

So, we propose to extend the identification methods from control theory to physical agents theory, and therefore extend the *excitation* concept. Figure 1 shows how to identify a dynamic system from an input/output point of view, according to the current thinking ([Eykhoff74], [Ljung94], [Schoukens91], [Walter97]).

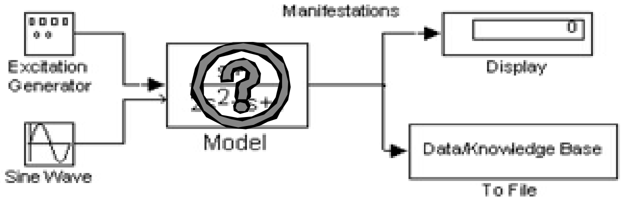

Figure 1. Identification through excitation.

[1] It is important to note that the term capacity is related to the dynamics of the physical body. Other static features, such as for example, being holonomic or not, is knowledge that can be programmed a priori.

There is a theory based on stochastic systems identification that measures random input data and the consequent output of the system [Schoukens91] [Walter97]. These techniques can get towards an approximation of the model. The drawback is that if the input data is poor, that is, if the system is not persistently excited, then there is no chance of any sort of correct identification of the system. In other words, the models are poor ([Ljung94] and [Walter97]).

So, for any model, the excitation of the system is crucial. The more excited a system is, the more modes are excited and tend to manifest (output); otherwise, there may be several hidden modes that are not known. The models contain a state, that is, the system responds differently depending on the inner state, and this state depends on the history of previous inputs (convolution). The response of impulsion input is called homogeneous response, and other, more complex inputs are the heterogeneous response (see Figure 2).

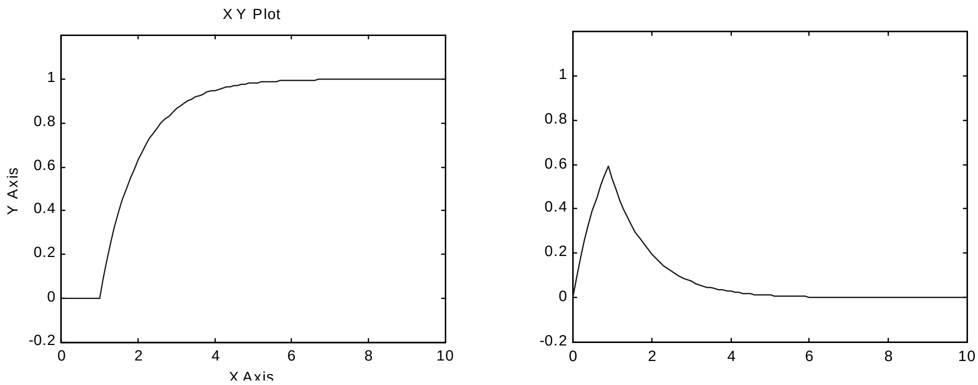

Figure 2: Heterogeneous (excited/forced) response (left);
Homogeneous (non-excited/unforced) response (right)

What if a system is highly complex? For instance, in those cases where there are many inputs and outputs. With control theory, the proposed solution is to identify every input-output pair and to obtain several models. Thus, the interactions among excitation and manifestations can be studied one by one.

Transferring these concepts to physical agents, a physical agent is a type of highly complicated system that we need to understand. So,

1. One way to understand the complexity of physical agents is to study several inputs/outputs.
2. The physical agents have to be persistently excited, that is, by several types and a lot of excitation.
3. The physical agents have strong states that make them respond in several ways to the same inputs: for example saturation, minimum phase, delays, temporal dynamical constants, relay behaviour (contradictions-“it takes longer going from New York to Barcelona than from Barcelona to New York”), etc.

One possible way of building physical agents is by taking advantage of these concepts borrowed from Systems Engineering theory and applying them when modelling such agents.

3. Recommender agents

The introduction of Internet, World Wide Web, communications networks, and widespread computation and storage capabilities, has resulted in a global information society with a growing number of users around the world. Information, the precious raw material of the digital age, has never been so easy to obtain, process and disseminate through the Internet. Yet, with the avalanche of information at our doors, there is a rapidly increasing difficulty of finding what we want, when we need it, and in a way that better satisfies our requirements. It is often necessary to make choices without sufficient personal experience of the alternatives.

Recently, in the Artificial Intelligence community, there has been a great deal of work on how AI can help to solve the information overload problem and some research has been focused on what is called recommender systems. The main task of a recommender system is to locate documents, information sources and people related to the interests and preferences of a single person or a group of people [Sangüesa00]. This involves then, the construction of user models and the ability to anticipate and predict the user's preferences.

Intelligent agents have a set of characteristics that make them a natural choice as a basis for the construction of recommender systems. In Figure 3 we show our model of personalization and recommendation. Several users interact with a habitat (an e-commerce portal, for example) through a set of agents that represent them. Agents have a twofold mission. On the one hand, they interact among each other, and with the users they represent. On the other hand, they filter the information that arrives to the users from the habitat and the other agents.

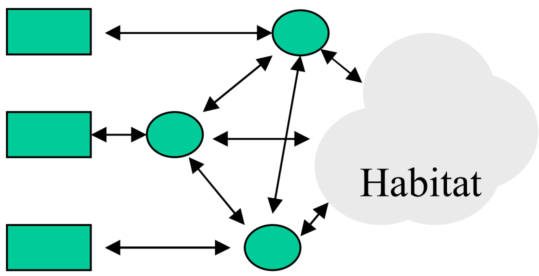

Figure 3. Our model of personalization and recommendation using agents. Circles represent agents and squares represent users.

Agents are individuals, in the sense that each agent represents or "belongs" to a single user. Agents have knowledge about the tastes and aims of the users they represent, and are capable of learning from their interactions with the users and the environment.

In addressing the task of assisting users with recommendations, three information filtering methods are currently proposed [Montaner01]: demographic filtering, content-based filtering and collaborative filtering. Demographic filtering methods use descriptions of the people in order to learn a relationship between a single item and the type of people that like that object. Content-based filtering methods use descriptions of the content of the items to learn a relationship between a single user and the description of the items. Collaborative filtering methods use the feedback of a set of people on a set of items to make recommendations, but ignore the content of the items or the descriptions of the people. Every method has some advantages and drawbacks (see [Muntaner01]). A well-known problem of content-based filtering, for example, is the fact that items dissimilar to ones offered previously to a user are never suggested for advice. Then, in recent years, researchers claim that hybrid systems offer better performance. So, content-based filtering methods can be complemented by collaborative filtering methods that provide new items for similar users.

In collaborative filtering systems, agents with similar profiles exchange recommendations. However, when a similar agent gives unsuccessful advice, there is no way to ignore it. Over and over again this agent causes a decline in the other agent's performance. Marsh proposes the concept of trust to make our agents less vulnerable to others [Marsh94]. Trust is fundamental for any kind of action in an uncertain world; in particular it is crucial for any form of collaboration with other autonomous agents. Applying the concept of trust in the collaborative world, we can solve the problem that arises when a similar agent gives frustrated recommendations by decreasing the trust in this agent and ignoring its advice in the future. Trust is formed and updated over time through direct interactions or through information provided by other members of the society they have had experience of. Each event that can influence the degree of trust is interpreted by the agent to be either a negative or a positive experience. If the event is interpreted as a negative experience the agent will lose his trust to some degree and if it is interpreted as positive, the agent will gain trust to some degree. The degree to which the sense of trust changes, depends on the trust model used by the agent. This implies that the trusting agent performs a form of continual verification and validation of the subject of trust over time [Montaner02].

4. Properties mapping

We have identified several properties inherent in physical agents and some others developed for recommender agents. Table 1 shows a summary of them.

From Physical Agents		To Recommender Agents
Introspection (perception of its own physical body)		
Subjectivity (perception of the physical world)		
Subjectivity (perception of the co-operative world)		Trust
Identification of systems (excitation)		

Table 1. Initial list of physical agent and recommender agent properties.

What we want to do is complete the table. First by shifting properties of physical agents to the recommendation field and then by returning to the physical agents research field with new insights from recommender agents.

We can shift properties from physical agents to recommender agents with the following in mind:

- An important point is to ensure that the agent is able to *commit* to both individual and co-operative actions with a set of other agents, within a highly changing environment [Oller99]

- Human perception performs as a selective filter whose goal is to avoid the person becoming inoperative due to information saturation. From this viewpoint, perception is a defence mechanism. But it also means that perception makes the information subjective: the person receives the things that make sense to him or her.

- We can regard customers, and people in general, as behaving like dynamic systems when selecting e-services and products from web sites. This gives us a hint of how to deal with them, so that they can be stimulated to show interest in products and services of companies and in the same way, so that they can be satisfied. Features like saturation or steady states, or random excitation are key-features imported from the automatic control domain, which have great potential for improving knowledge on every customer.

So, it is clear that:

- Recommender systems should be aware of their capacities for representing user interest, induced from the user profile. That is, being aware to what extent the agent is covering a given taste of the user and then being able to advise (i.e., commit) accordingly.

- User profiles of recommender agents, being models of the user, are subjective from the perception point of view. Thus, recommender agents should be aware of such subjectivity and exploit it accordingly.
- Excitation is a way to enrich user models when, by means of any machine learning method, we have obtained a probably stable but poor model of the user.

Now we can fill in the gaps and we get table 2.

From Physical Agents		**To Recommender Agents**
Introspection (perception of its own physical body)	→	Recommendation based on capacities.
Subjectivity (perception of the physical world)	→	Subjectivity/Affinity
Subjectivity (perception of the co-operative world)	←	Trust
Identification of systems (excitation)	→	Excitation

Table 2. Properties mapping and shift of insights.

Vice versa, that is, shifting insights from the recommender agent field to the physical agent field, we believe that research performed on trust can be used by physical systems to model social relations.

5. Experimental results

Our experiments have been carried out in two stages. First we developed Proto-agent, an agent-based recommender system based on case-based reasoning. With Proto-agent we prove to some degree the shift of the identification property of physical agents to excitation in recommender systems. Currently, we are finishing Habitat-Pro™[(1)] to test introspection and subjectivity/affinity. First, we will give our results on Proto-agent and then we will outline what our approaches are to introspection and subjectivity in Habitat-Pro.

5.1 Proto-Agent: results on excitation

In order to test excitation, we built an environment where every proto-agent represents a person. Each agent emulates the decisions of the person in a certain field, for example, e-commerce. A proto-agent is a bare agent that contains only one good single input and single output model of a specific aspect of human behaviour on the Internet. That is, the model of human behaviour in contracting or getting goods and services. It does not yet incorporate the proactivity that a basic agent should present.

The proto-agent is case-based. Cases represent excitation, from the viewpoint of Systems Engineering, that is, input and outputs regarding human behaviour. So, our starting point for modelling the proto-agent behaviour involves the following excitations:

1. The transaction history of the person in a certain area: this is the excitation feature for the state of the model.
2. The contextual information by means of click stream and contextual offers response: this is the excitation feature for the present state of the model.
3. The response to limited offers from a company: again by click stream, it shows another aspect of the present state of the model, but this is a response of the person to the excitation feature of the company.

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(1) Habitat-Pro™ is the Trade Mark of Agents Inspired Technologies, a spin-off company of the University of Girona.

4. The response to suggestions (offers) from other persons: again by click stream, shows still another aspect of the present state of the model, that is response of the person to the excitation feature of the community of users.

Let us start with a consistent customer. As depicted in the plot in Figure 4, we can see how the knowledge of the person stabilizes and becomes saturated at a maximum degree of performance. To reach the performance level 1 means the user is known completely. However, it is unrealistic to assume that a person is consistent and invariable over time, or that we can achieve perfect knowledge of his/her hidden modes.

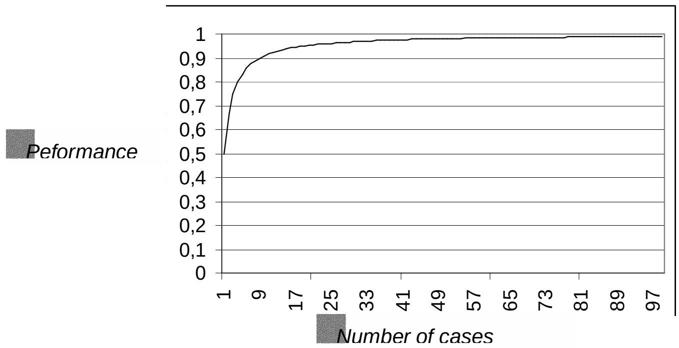

Figure 4. Stabilisation and performance saturation for a consistent customer.

A more typical case is the following regular customer, whose plot is shown in Figure 5. The same 1st order envelope of the consistent customer appears but with much more noise and oscillation over the saturation state. The user again stabilizes and the performance does not increase any more.

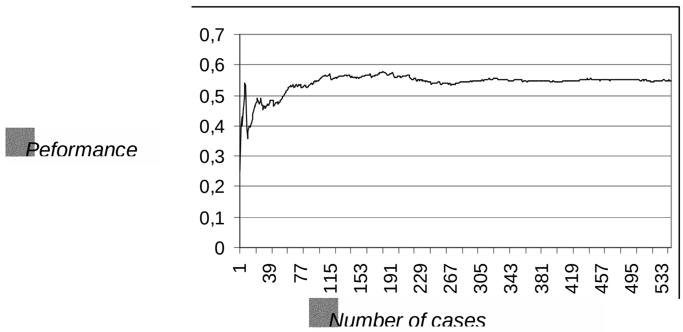

Figure 5. Stabilisation and performance saturation for a regular customer.

However, an interesting result of case-based reasoning (CBR) is that the stabilization of the performance indicates the correct number of cases required to achieve a settled performance, which in this case is 115 cases to achieve a 50% steady state response.

In order to maintain persistent excitation, we extended the CBR cycle (see Figure 6). This way, the new cases proposed to the user could be obtained from random proposal or by collaborative filtering or from other sorts of excitation which stimulate the user. If the user confirms the solution then this case is introduced into the case base.

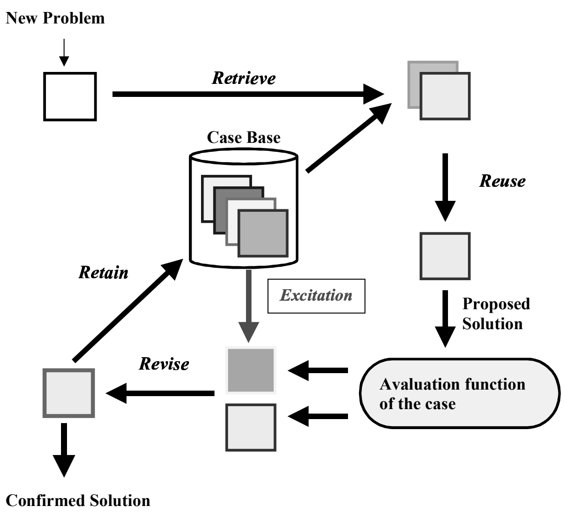

Figure 6. New CBR cycle resulting from incorporating persistent excitation.

The results of the excitation experiment can be seen in Figure 7. The plots show that performance stabilises at 78%, an improvement of approximately 50%. All the experiments performed in our laboratory follow this pattern of between 30-60% improvement, which shows that including the excitation method from physical agents theory to the recommender agents is quite profitable, and a very promising field in which to do further research i.

Figure 7. Results of the new CBR cycle.

5.2 HABITAT-PRO™: introspection and subjectivity

The heart of Habitat-Pro™ is a Java application server together with a Java Virtual Machine (JVM). Agents "live" as servlets inside the JVM. The application server administrates the JVM, creating and destroying on request, agents and other servlets and support objects. Additionally, there is a database that stores, among other data, the user and product profiles used by the agents. (See the architecture of the system in Figure 8).

SYSTEM ARCHITECTURE

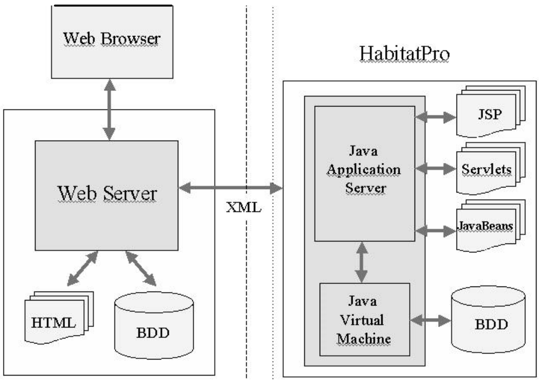

Figure 8: HabitatPro™'s architecture. To the left, the external system (for example, an e-commerce site). To the right, the structure of the agent based personalization system Habitat-Pro.l

Introspection in Habitat-Pro

Personalization in Habitat-Pro is based on a somewhat fuzzyfied version of the well-known concept of Attribute-Value pair. We identify the concept of attribute with the one of property or characteristic of a product (for example colour or price). The values that the attributes can take (for example greenish or cheap) are, in general, subjective. The meaning of a value can vary depending on the person or agent that uses, defines or assigns it. It is necessary, then, to use sophisticated techniques to use and manipulate them.

User and product modelling in Habitat-Pro™ is carried out by defining two new concepts from the attribute-value pair concept:

- Image of a product: the set of attribute-value pairs that characterize the product.
- Image of a user: the set of attribute-value-weight triplets, codifying the preferences of the user and the strength of those preferences.

Preferences of the user are dynamic and are updated accordingly, though interaction with the physical world.

Perception of the physical world/Model adjustment in Habitat-Pro

Learning from experience and from perception of the physical, "outer", world is an essential characteristic of agency. In Habitat-Pro, the knowledge incorporated and used by the agents is basically concerned with the preferences and tastes of the users. Learning, therefore, consists of a progressive refinement of the image of the users.

Each time a customer buys a product, the image of the customer is refined in order to adjust it to this fact. We maintain, for each attribute and user, not only some kind of mean value, but also a weighting that essentially reflects the degree of dispersion of the values for the attribute in the set of products purchased by the client. In this way, attributes for which the customer usually acquires products with similar values have high weightings, while attributes with more dispersed values have lower ones.

The magnitudes of the updates of the customer images vary depending on different parameters such as:

- The interest shown by the customer: a customer can show a slight interest (asking for more information about it, for example) or a strong interest (buying it).
- The kind of product involved: we are more confident when adjusting the image of the customer who is purchasing an expensive or very specific item than we are when adjusting the image of a customer who is buying a pizza, for example.
- The reliability of the image of the customer: meaning essentially, the number of interactions between the customer and Habitat-pro.
- The time between image updates: people change their tastes over time. Adjustments in the images of customers are larger when the images are "old".

Perception of the cooperative world/Trust in Habitat-Pro

Habitat-Pro addresses matters of trust in a very straightforward way. It is possible to assign confidence or trust values to the recommendations that agents make, by associating two quantities to each agent (or, more precisely, to the image of the user represented by the agent):

- The reliability of the agent: which basically measures the number of times that the customer has purchased or shown some interest in some product and, thus, the number of times that his image has been updated.
- The quality of the agent: which measures the specificity of the tastes of the customers. It's clear that it's easier to make good recommendations to a customer with a sharp image (with high weightings for the attributes) than for a customer with a soft one (with low weightings, corresponding to a user with a more random shopping pattern).

6. Conclusions

In this paper we have analysed several properties of physical agents that can enrich research into recommender systems. This is the case with introspection of physical capacities, and subjectivity from interaction with the physical world. Furthermore, identification theories from Systems Engineering can be used to represent the minimal set of inputs and outputs required by an agent in order to obtain a good model. Inversely, recommender systems can provide insights regarding interaction in the co-operative world, through trust formalisms.

We have presented the first prototypes developed to test our theories and we have shown some initial results. We think that this collaboration between the two lines of research, physical agents and recommender systems, creates a synergy from which each discipline can make bigger advances. We will continue in this line, looking for further opportunities for new knowledge transference between the two research lines.

References

[Asada97] Asada M., Kuniyoshi Y., et al. The RoboCup Physical Agent Challenge, *First RoboCup Workshop in the XV IJCAI-97 International Joint Conference on Artificial Intelligence*, pp.51-56, 1997.

[Brooks91] Brooks, R.A. "New Approaches to Robotics". Science, Vol. 253, September 1991m pp. 1227-1232, 1991.

[de la Rosa99] de la Rosa J.Ll., Garcia R., Innocenti B., Muñoz I., Figueras A., Ramon J.A., Montaner M., "Rational Dynamical Physical Agents", 3rd Robocup Workshop, Vol. on RoboCup-99: Robot Soccer World Cup III, Lecture Notes in AI Nº1395, Eds. Springer-Verlag, Estockholm (Sweden). July 31-August 6, 1999.

[Eykhoff74] Eykhoff P, Systems Identification, *John Wiley & Sons*, 1974.

[Mackworth93] Mackworth, A.K. "On Seeing Robots". In: Basu, A. And Li, X. (eds), Computer Vision: Systems, Theory and Applications. Singapore: World Scientific Press, 1:13, 1993.

[Maes94] Maes, P., "Agents that reduce work and information overload" Communications of the ACM vol. 37 no. 7, pp 30-40, July 1994.

[March94] March S. P. "Formalising trust as a computational concept". PhD Thesis, Department of Computing Science and Mathematics, University of Stirling, 1994.

[Montaner01] Montaner, M., "A Taxonomy of Personalized Agents on the Internet". Technical Report TR-UDG-2001-05-1. Departament d'Electrònica, Informàtica i Automàtica. Universitat de Girona. May, 2001.

[Montaner02] Montaner, M., López B., de la Rosa, J.L. "Developing trust in Recommender Agents". *Submitted to AAMAS 2002.*

[Müller96] Müller, J.P. . "The Design of Intelligent Agents. A Layered Approach". Lecture Notes in Artificial Intelligence, Vol. 1177. Ed. Springer-Verlag. 1996.

[Ljung94] Ljung L. and Glad T., Modeling of Dynamic Systems, *Prentice Hall International Inc., 1994*.

[Oller00] Oller A., de la Rosa J.Ll., García R, Ramon JA, Figueras A. "Micro-Robots playing soccer games: a real implementation based on a multi-agent decision-making structure", Int. Journal of Intelligent Automation and Soft Computing. Special Issue on Soccer Robotics: MIROSOT '97, Vol. 6, No. 1, January 2000.

[Oller99] Oller A, de la Rosa J.Ll., and del Acebo E., "DPA2: Architecture for Co-operative Dynamical Physical Agents", MAMAAW '99, Valencia June 1999.

[Sangüesa00] Sangüesa R., Cortés U., Faltings, B. W9 Workshop on Recommender Agents. Agents 2001.

[Schoukens91] Schoukens J. and Pintelon R., Identification of Linear Systems; A Practical Guideline to Accurate Modeling, *Pergamon Press,* 1991.

[Walter97] Walter E and Pronzato L., Identification of Parametric Models from Experimental Data, *Springer Verlag*, 1997.