Cooperative Neighborhood Learning: Application to Robotic Inverse Model

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Keywords: Multiagent Learning, Distributed Problem Solving, Learning by Endogenous Feedback, Inverse Kinematics Learning.

Abstract: In this paper we present a generic multiagent learning system based on context learning applied in robotics. By applying learning with multiagent systems in robotics, we propose an endogenous self-learning strategy to improve learning performances. Inspired by constructivism, this learning mechanism encapsulates models in agents. To enhance the learning performance despite the weak amount of data, local and internal negotiation, also called cooperation, is introduced. Agents collaborate by generating artificial learning situations to improve their model. A second contribution is a new exploitation of the learnt models that allows less training. We consider highly redundant robotic arms to learn their Inverse Kinematic Model. A multiagent system learns a collective of models for a robotic arm. The exploitation of the models allows to control the end position of the robotic arm in a 2D/3D space. We show how the addition of artificial learning situations increases the performances of the learnt model and decreases the required labeled learning data. Experimentations are conducted on simulated arms with up to 30 joints in a 2D task space.

1 INTRODUCTION

One of the challenges of robotic interactive systems is to learn without having any intrinsic knowledge of the tasks they will have to solve. To do so, they need internal curiosity mechanisms to avoid biases, maximize genericity and provide adaptation to their environment (Oudeyer et al., 2014). Such a system is also called an agnostic system (Kearns et al., 1994). To design it, it is essential to generate knowledge through processes and actions that are purely internal to an interactive system. We call this type of process: "learning by endogenous feedback".

The constructivist approach has shown to be attractive for robotics where a child learner, using assimilation and accommodation (Piaget, 1976), can be replaced by a robot learner which is confronted to its physical real world (many parameters, many interconnections, feedback loops, non-linearity, threshold effects, dynamics...). Considering this physical world as a complex system allows to generalize the conceptualization of learning and thus to make it generic. Control in this context requires a complex artificial controller able to differentiate and face all kinds of situations (Ashby, 1956). A relevant approach for this problem is context-based adaptive multiagent systems. Inspired from contructivism, it is able to deal with complex systems. This self-adaptive approach allows communication between fragments of learnt models to enhance their performances. Our goal is to learn from small amount of examples as additional examples are internally generated. This paper focuses on self-enrichment of knowledge fragments through learning by multiagent systems. Another of our concern is the scalability of the proposed learning architecture that is applied to the inverse control of robotic arms.

In the paper, we begin by giving a quick overview of the work around inverse models in robotics and computer graphics. We follow with the presentation of the studies that led to Context Learning. We then detail our contribution which is Endogenous Context Learning coupled with a new exploitation of the learnt models. We evaluate the learning across metrics of control performance and data.

2 BACKGROUND

In this section, we provide a brief outline of inverse models in robotics and computer graphics. We introduce Context Learning inspired by Constructivist

Dato, B., Gleizes, M. and Migeon, F.
Cooperative Neighborhood Learning: Application to Robotic Inverse Model.
DOI: 10.5220/0010303203680375
In *Proceedings of the 13th International Conference on Agents and Artificial Intelligence (ICAART 2021) - Volume 1*, pages 368-375
ISBN: 978-989-758-484-8

Learning and present the state of various works carried out in this theme.

2.1 Inverse Models

Robotic applications usually rely on task space controllers. The model allowing to control a robot in its task space is called the Inverse Kinematic Model (*IKM*). It can be calculated with analytical approaches for rigid bodied robots of low DOF (Degrees Of Freedom). These approaches perform poorly on complex systems with lot of DOF or soft robots as they are difficult to model (Thuruthel et al., 2016). Common methods for solving *IKM* of a redundant manipulator systems are numerical solutions: pseudo-inverse methods (Bayle et al., 2003) and Jacobian transpose methods (Hootsmans and Dubowsky, 1991). They allow better scalability for higher DOF but they still rely on the availability of accurate robot parameters which can be difficult to obtain. Recent motion caption techniques allow to generate pre-learnt postures and use data-driven approaches for Inverse Kinematics problems (Ho et al., 2013; Holden et al., 2016). Hybrid methods combine previous techniques and attempt to reduce the complexity of the problem by decomposing it in several components (Unzueta et al., 2008). Data-driven techniques are the most exploited approaches in the last decades in the domain of computer graphics (Aristidou et al., 2018). We also found geometric approaches that provide direct solutions using geometrical heuristics (Jamali et al., 2011). From the point a view of developmental robotics, Baranes and Oudeyer (Baranes and Oudeyer, 2013) tackled the Inverse Kinematics problem by using intrinsically motivated goal exploration while learning the limits of reachability.

Future robots will possess soft joints and high numbers of DOF making them difficult or yet impossible to model. Thus, learning the *IKM* for complex robots is an inevitable way. The implemented architecture for learning the *IKM* presented is this paper can be considered as a data-driven approach.

2.2 Constructivism and MultiAgent Systems

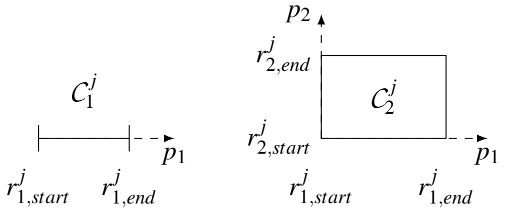
Context Learning is inspired by Constructivist Learning, which is a theory from Piaget's work on child development (Piaget, 1976). According to this theory, knowledge is a construction based on the observation of a subject's environment and the impact of its actions. The basic unit of knowledge in this theory is the *schema*. It aggregates several perceptions and, in most cases, several actions (Guerin, 2011). Proposed by Drescher (Drescher, 1991) then formalized by Holmes (Holmes et al., 2005), it has been reused by combining it with Self-Organizing Maps (SOM) (Chaput, 2004; Provost et al., 2006) and model-based learning (Perotto, 2013).

The Multiagent Systems approach (Ferber, 1999), and in particular the AMAS (Adaptive Multiagent Systems) approach (Georgé et al., 2011), gives a system adaptive properties to deal with unexpected situations, which is appropriate for learning systems (Mazac et al., 2014; Guériau et al., 2016). An AMAS is a complex artificial system composed of fine-grained agents promoting the emergence of expected global properties. It allows to cope with the complexity of the world (non-linearity, dynamics, distributed information, noisy data and unpredictability) as defined by Ashby (Ashby, 1956). Numerous experiments have shown such properties in areas such as the control of biological processes, the optimal control of motors or robotics learning (Boes et al., 2015).

2.3 Context Learning

The contribution in this paper is based on the AMOEBA system (Agnostic MOdEl Builder by self-Adaptation) (Nigon et al., 2016). It relies on Context Learning and implements supervised online agnostic learning capable of generalizing with continuous training data. This section presents the formalism of Context Learning and the functioning of the AMOEBA system.

Context Learning is a problem of exploring a search space with n dimensions and estimating a local model based on any machine learning technique (neural networks, linear regression, SVMs, nearest neighbor, k-means...). An instance of the learning system learns an output called the prediction vector $\mathcal{O}'_m \in \mathbb{R}^m$ according to a hidden function $\mathcal{F}(\mathcal{P}_n) = \mathcal{F}(p_1,\ldots,p_i,\ldots,p_n) = \mathcal{O}_m$ with $\mathcal{O}_m \in \mathbb{R}^m$ the desired predictions or the oracle values. $\mathcal{P}_n$ is the vector of inputs called the ***perceptions*** and $\mathcal{P}_n = [p_1,\ldots,p_n] \in \mathbb{R}^n$. The *perceptions* can be the state of robot (sensors, position, speed ...) or a situation of an environment (temperature, luminosity, noise...). The vector $\mathcal{L}_{n,m} = [\mathcal{P}_n, \mathcal{O}_m]$, composed of *perceptions* associated with desired predictions, defines a ***learning situation***, which is similar to a *schema* in Piaget's theory. A learnt model is represented by a *Context Agent* $\mathcal{C}_n^j$ with j the j^{th} pavement in dimension n which represents a part of the *schema*. A *Context Agent* is an intelligent autonomous agent that locally represents a part of the global function $\mathcal{F}$ with a local function $f_n^j(p_1,\ldots,p_i,\ldots,p_n) = o_m^j$ with $o_m^j \in \mathbb{R}^m$. It is a parallelotope of dimension n associated with a machine learning model. The parallelotope is defined by validity ranges $\mathcal{R}_n^j = [r_1^j, \ldots, r_i^j, \ldots, r_n^j]$ with $r_i^j = [r_{i,start}^j, r_{i,end}^j]$ which represents a validity interval on a perception p_i (Fig. 1). All *Context Agents* use the same set of inputs $\mathcal{P}_n$.



(a) Dimension 1 (b) Dimension 2

Figure 1: Parallelotopes Validity Ranges in dimension 1 and 2.

The *Context Agents* have a confidence $c^j \in \mathbb{Z}$ to evaluate themselves in relation to others. A *Context Agent* is therefore defined by its validity ranges, its model and its confidence $C_n^j = \{\mathcal{R}_n^j, f_n^j, c^j\}$. In this study, each *Context Agent* has a local linear regression model f_n^j. In this case, the prediction vectors and the oracle predictions are a real values O_1' and O_1. A *learning situation* is then $\mathcal{L}_{n,1} = [\mathcal{P}_n, O_1]$.

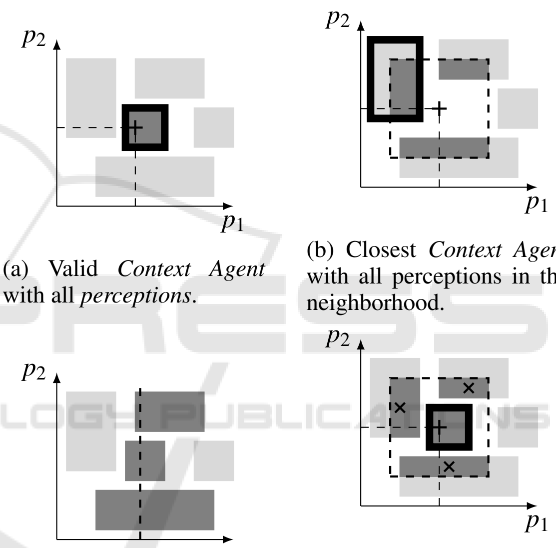
2.4 Exogenous Learning Rules

Learning with *Context Agents* in AMOEBA (Nigon et al., 2016) is based on several simple rules. Each execution cycle is either a learning cycle or an exploitation cycle. For learning cycles, the input is a *learning situation* $\mathcal{L}_{n,1}$ and for exploitation cycles, the input is an *exploitation situation* that is only *perceptions* $\mathcal{P}_n$.

Learning Cycles. During learning cycles, if the *perceptions* $\mathcal{P}_n$ belong to the validity ranges of an existing *Context Agent*, it is a *Valid Context Agent* (Fig. 2a). It proposes a prediction with its model. If there are several *Valid Context Agents*, the prediction of the one with the best confidence is retained. It is called the *Best Context Agent* for the current execution cycle. If it gives a good prediction, it increments its confidence. If the prediction is bad all *Valid Context Agents* reorganize themselves by following adaptive behaviors. To know if the prediction of a *Context Agent* is good or bad, an error margin and an inaccuracy margin are used. They are given by the user of the learning mechanism. A prediction is good if the error with the oracle's prediction O_1 is less than the inaccuracy margin.

Exploitation Cycles. During the exploitation, if they are several *Valid Context Agents*, the one with the higher confidence is the *Best Context Agent*. It provides the prediction output O_1'. If there aren't any *Valid Context Agents*, the closest *Context Agent* to the *perceptions* is designated as the *Best Context Agent*.

Shortcomings. The presented rules suffer from a lack of local interactions between the *Context Agents*. This approach proposes a distributed learning method that is adaptive with respect to the oracle values but not between the knowledge fragments. Another issue is the scalability of the local added interactions. AMOEBA does not possess any mechanism allowing *Context Agents* to communicate locally without activating all the *Context Agent* of the system.



(a) Valid *Context Agent* with all *perceptions*.

(b) Closest *Context Agent* with all perceptions in the neighborhood.

(c) Valid *Context Agents* on exploitation with only the perception p_1.

(d) Cooperative neighborhood learning situations; the *endogenous learning situations* are represented with diagonal crosses.

Figure 2: *Context Agents* Mechanisms; *Best Context Agent*, valid *Context Agents* and neighborhood areas are filled darker; *Best Context Agents* are boxed; the neighborhood is represented by a dotted box.

3 ENDOGENOUS CONTEXT LEARNING

Endogenous Context Learning is an enhancement of Context Learning using internal information to self-generate new *learning situations*. In the next sections, we differentiate *exogenous learning situations* and *endogenous learning situations* which are respectively provided by an external entity and self-

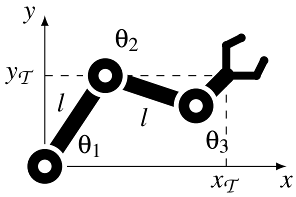


Figure 3: 3 joints robotic arm with segments of equal length l in a 2D task space.

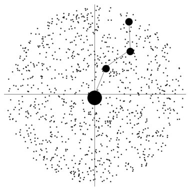


Figure 4: Exploration with a 3 joints robotic arm simulation after 1000 training situations.

generated by the learning mechanism. This mechanism is based on a collaboration inside the neighborhood of the *Context Agents*. The presented process is operational regardless of the number of dimensions.

3.1 Neighborhood

A *Context Agent* is considered as a neighbor of the *perceptions* if its validity ranges intersect a neighborhood area surrounding the current *perceptions*. The size of this area results from the *precision_range*, a parameter chosen by the user of the learning mechanism. For a perception p_i, there is a default radius creation for a *Context Agent* $r_i^{creation} = (p_i^{max} - p_i^{min}).precision\_range$. p_i^{max} and p_i^{min} are the maximum and minimum experienced values by the learning mechanism on the perception p_i. From this, it results an approximation error distance $d_i^{aed} = 0.25.r_i^{creation}$. The neighborhood area radius is $r_i^{\mathcal{N}} = k^{\mathcal{N}}.r_i^{creation}$.

3.2 Endogenous Learning Rules

To take advantage of the neighborhood in the learning process, it is necessary to modify the rules of AMOEBA. The inaccuracy margin is removed so there is only an error margin chosen by the user of the learning mechanism to define its accuracy expectations.

Bad Prediction Situation. The distance to the *learning situation* is greater than the error margin. The *Context Agent* is not valid for this *learning situation*. Its prediction is not accurate enough given expected precision. It moves one of its ranges to exclude the current *perception* and it decreases its confidence. It always chooses the range that least affects the volume of its validity ranges. If the distance to the *learning situation* is less than the error margin, the agent's confidence increases and it updates its model with the current *learning situation*. There is only one margin to define whether a *Context Agent* is good or bad. The agents' models are regularly updated to be robust to noise.

Uselessness Situation. A *Context Agent* is useless if one of its *validity ranges* has a critical size below d_i^{aed}.

Unproductive Situation. The mechanism of extending the closest good *Context Agent* remains the same. The closest good *Context Agent* extends one of its ranges towards the new situation. The novelty appears at the creation of a new *Context Agent* if needed. If there are neighbors, they are used to initialize the properties of the new agent. If there are no neighbors, the created agent uses initialization values based on the perception limits of the search space and on the parameters chosen by the system user.

3.3 Cooperative Neighborhood Learning

In order to enhance the learning process, each *Best Context Agent* communicates with its neighbors to ask them for *endogenous learning situations* $\mathcal{L}_n^{endo} = [\mathcal{P}_n^{endo}, O_1^{endo}]$. This has for objective to locally smooth the models between them. As for the perception neighborhood radiuses, the prediction neighborhood radius is defined as it follows $r_{O_1}^{\mathcal{N}} = k^{\mathcal{N}}.(O_1^{max} - O_1^{min}).precision\_range$. The *perceptions* $\mathcal{P}_n^{endo}$ of the *endogenous learning situation* are chosen randomly in the intersection of the neighborhood and the neighbor's validity ranges (fig. 2d). The prediction O_1^{endo} is asked to the model of the neighbor. Only neighbors that have a close last prediction share an *endogenous learning situation*. If the difference between the endogenous prediction and the last *Best Context Agent* prediction $|O_1^{endo} - o_{1,last}^{Best\ Context\ Agent}|$ is lesser than $r_{O_1}^{\mathcal{N}}$, the *endogenous learning situations* is retained. The set of all retained *endogenous learning situations* is used to update the *Best Context Agent* model with a weight w^{endo}. To satisfy this weight, artificial *Learning Situations* are generated. They are distributed on the current model according to a normal law centered in the validity ranges center and with a standard deviation of $((r_{i,end}^j - r_{i,start}^j)/10)^{\frac{1}{2}}$. This distribution ensures that the center of the model, is slightly altered. The *endogenous learning situations* are then used to estimate new regression parameters using Miller's regression (Miller, 1992).

3.4 Context Exploitation

The addition of the neighborhood is useful to optimize the exploitation, specially when there aren't any valid *Context Agents*. In this case, the *Best Context Agent* is the closest *Context Agent* to the *perceptions* among the *Context Agents* neighbors (Fig. 2b). If they are no neighbors, it is the closest *Context Agent* among all the *Context Agents*. The neighborhood speeds up the exploitation when there are neighbors and a lot of *Context Agents* in the whole system.

In the case that all the *perceptions* are not provided for the exploitation, we propose a new way of exploiting the models. The given subset of *perceptions* is used to define the set of valid *Context Agents*. The *Best Context Agent* is then chosen using the distance to the sub-*perceptions*. The unspecified *perceptions* are set by default to the center of the validity ranges of the *Best Context Agent*. Fig. 2c shows an exploitation with the sub-*perception* p_1 only.

4 INVERSE KINEMATICS LEARNING CASE STUDY

For our experimentations, we repeat one of the experimental setups of Baranes and Oudeyer (Baranes and Oudeyer, 2013) which is the learning of the inverse kinematics with a redundant arm. We consider a robotic arm with segments of equal length and n joints in a 2D plane: $(\theta_1, \theta_i, \ldots, \theta_n)$ (Fig. 3 shows an example for 3 joints). To control it, one must use its Forward Kinematic Model FKM and its Inverse Kinematic Model *IKM* which are both non linear models dependent on the characteristics of the arm. The Forward Kinematic Model is used to calculate the position of the robot tool in a task space from the angles of each joint: $FKM(\theta_1, \theta_i, \ldots, \theta_n) = (x_{\mathcal{T}}, y_{\mathcal{T}})$ for a task space of two dimensions. The analytical Inverse Kinematic Model gives all the possible angle vectors for a desired tool position: $IKM(x_{\mathcal{T}}, y_{\mathcal{T}}) = (\theta_1, \theta_i, \ldots, \theta_n), (\theta_1, \theta_i, \ldots, \theta_n)', \ldots$

We propose here to learn the *IKM* using the *FKM* as a supervisor and to exploit the learning without using all the *Perceptions*. This approach is independent of the joints number of the considered robots.

Training. The training is made from several random joints configurations $(\theta_1^{rdn}, \theta_i^{rdn}, \ldots, \theta_n^{rdn})$. The corresponding position of the end of the robot arm is given by the Forward Kinematic Model : $FKM(\theta_1^{rdn}, \theta_i^{rdn}, \ldots, \theta_n^{rdn}) = (x_{\mathcal{T}}^{rdn}, y_{\mathcal{T}}^{rdn})$. The *perceptions* for the learning mechanism are the position of the end of the robot $(x_{\mathcal{T}}^{rdn}, y_{\mathcal{T}}^{rdn})$ and all the corresponding angles except the last one $(\theta_1^{rdn}, \theta_i^{rdn}, \ldots, \theta_{n-1}^{rdn})$. The *perceptions* vector is $(x_{\mathcal{T}}^{rdn}, y_{\mathcal{T}}^{rdn}, \theta_1^{rdn}, \theta_i^{rdn}, \ldots, \theta_{n-1}^{rdn})$. The last angle θ_n^{rdn} is the prediction of the local models. The global function that is learnt by the mechanism is $\mathcal{F}_{\theta_n}(x_{\mathcal{T}}^{rdn}, y_{\mathcal{T}}^{rdn}, \theta_1^{rdn}, \theta_i^{rdn}, \ldots, \theta_{n-1}^{rdn}) = \theta_n^{rdn}$. We define the training *learning situations* as *exogenous learning situations* given by the joints configuration of the robot and its *FKM*: $\mathcal{L}_n^{exo} = [(x_{\mathcal{T}}^{rdn}, y_{\mathcal{T}}^{rdn}, \theta_1^{rdn}, \theta_i^{rdn}, \ldots, \theta_{n-1}^{rdn}), \theta_n^{rdn}]$.

Exploration. The generation of the random angles for the joints is done following a normal distribution. Considering that an outstretched arm is defined by all the angles being set to 0 rad, the distribution of each angle is centered around this value except for θ_1 which has an homogeneous random distribution between 0 and 2π. The dispersion is set empirically for 3, 10 and 30 joints with the objective of having homogeneous situations in the task space (Fig. 4 shows an example of exploration with 3 joints after 1000 *exogenous learning situations*). The obtained dispersion depending on the number of joints is : $2.5593n^{-0.479}$.

Exploitation. As we are learning the *IKM*, the goal here is to get a set of angles to position the end of the robotic arm in a point $\mathcal{P}_{xy}^{goal} = (x_{\mathcal{T}}^{goal}, y_{\mathcal{T}}^{goal})$ (fig. 3). All $\mathcal{P}_{xy}^{goal}$ are randomly generated in the reachable zone of the task space. It is an exploitation without all the *perceptions* and the sub-*perceptions* are $x_{\mathcal{T}}^{goal}$ and $y_{\mathcal{T}}^{goal}$. The learning mechanism is given $(x_{\mathcal{T}}^{goal}, y_{\mathcal{T}}^{goal})$ and it provides a joints configuration $(\theta_1^{explo}, \theta_i^{explo}, \ldots, \theta_n^{explo})$.

5 EXPERIMENTATIONS

In this section, we present our results achieved with the addition of *endogenous leaning situations* in the learning of robotic arms inverse models. A learning cycle corresponds to a configuration for the robotic arm. The learning mechanism receives an *exogenous learning situation* at each learning cycle. The inverse models to be learnt are non linear models of high dimensions (up to 30). We chose to stop at 30 to match the numbers of degrees of freedom on a usual humanoid robot. We are aware that on a humanoid all linkages are not serial. The goal here is to test our approach with the same degrees of freedom order of magnitude.

5.1 Metrics

Goal Error. To appraise the score of the learnt *IKM*, we evaluate the proposals of the learning mechanism. We calculate the end position error of the robot in the task space $\mathcal{E}_\mathcal{T}$. This error is the distance between the randomly asked positions $\mathcal{P}^{goal}_{xy}$ in the reachable task space and the position resulting from the exploitation of the learning $\mathcal{P}^{explo}_{xy}$. This error is normalized by the diameter of the reachable space $\mathcal{D}_{reachable}$ which is a disk in this case: $\mathcal{E}_\mathcal{T} = ||\overrightarrow{\mathcal{P}^{goal}_{xy}\mathcal{P}^{explo}_{xy}}||/\mathcal{D}_{reachable}$. The prediction metric is calculated over exploitation cycles where the mechanism is asked to make angles predictions to get the goal position.

Endogenous Data. To evaluate the impact of the cooperative neighborhood mechanism on the goal performances, we are interested in the number of generated *endogenous learning situations* $\mathcal{L}^{endo}_n$.

5.2 Results

The presented results are averaged over 15 learning experiences. Each learning experience is stopped after 1000 training cycles. The goal errors are averaged over 200 exploitation cycles. The stretched length for each tested arms is the same (50 units in our simulation). Each arm segment is the same size. For each arm size scenario, the size of the reachable space is the same. The error margin is set to 1. The weight w^{endo} of *endogenous learning situations* is 0.1. The code is implemented in java with the framework AMAK (Perles et al., 2018) and it is executed on a machine[1] with Ubuntu 18.04.3 LTS.

Arm Dimensions. Figure 5 shows that without cooperative neighborhood learning the best performance is obtained for 2 joints and with a *precision_range* of 1%. The *precision_range* of 1% also gives lower mean error for the arms of 2, 3 and 6 joints than the *precision_range* of 3%. For arms with more joints the gap is less visible. We can also see that the mean error and its dispersion increase up to 10 joints. Then, they decrease as the number of joints gets bigger.

Neighborhood Sizes. Figure 6 shows that the size of the neighborhood has an impact on the mean error for the arms of 2, 3 and 6 joints. With a *precision_range* of 3% the error decreases and reaches a minimum value with a delay in the neighborhood size for the different arms. It then increases for 2 and 3 joints for high neighborhood sizes. For 10, 20 and 30 joints (Fig. 7), the error only decreases for 10 joints. The other cases are not impacted by the variation of neighborhood.

Endogenous Data. Figures 8 and 9 represent the same experimentation than 6 and 7 but focusing on the variation of the error according to the *endogenous learning situations*. Fig. 8, for 6 joints and a *precision_range* of 3%, the more *endogenous learning situations* there are, the lower the error is. For 2 and 3 joints, we find the same behavior than Fig. 6, there is an optimal situation beyond which the error increases. For 10 joints with a *precision_range* of 3% (Fig. 9), more *endogenous learning situations* reduce the error. But for 20 and 30 joints, the *endogenous learning situations* don't reduce the goal error, they even slightly increase it.

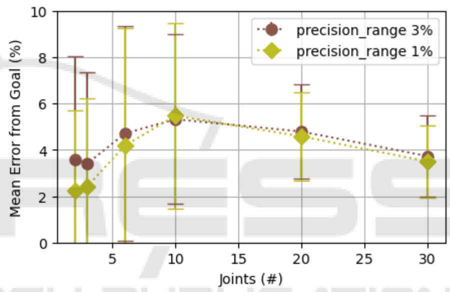


Figure 5: Mean errors from goal depending on robotic arm sizes (2, 3, 6, 10, 20 and 30 joints) without cooperative neighborhood learning. Learning cycles = 1000; exploitation cycles = 200; averaged overs 15 learning experiences.

5.3 Discussion

We have seen that the lowest error is obtained for the lowest arm dimensions. The error increases up to 10 joints and it decreases for higher arm dimensions. At low dimensions, the good performance is due to the low redundancy of the problem making the exploration less extensive. The decreasing of the error at high dimensions is caused by the exploitation of the *Context Agents* with *sub-perceptions*. If the requested goal $\mathcal{P}^{goal}_{xy}$ during the exploitation is in a less explored area, it is the closest model that is used for the last angle prediction. The smaller the size of the last arm segment, the smaller the distance error on the goal. Which is the case for the higher dimensions. The rest of the angles are fixed using the validity ranges of the *Best Context Agent*.

Figures 6, 7, 8 and 9 showed that the expansion of the neighborhood can lead to better or worse per-

[1] Intel(R) Core(TM) i7-4790 CPU @ 3.60GHz $\times$ 8, RAM 31.4 GB.

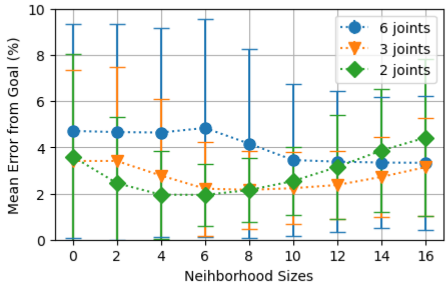


Figure 6: Mean errors from goal depending on mean neighborhood sizes over robotic arms of 2,3 and 6 joints. Learning cycles = 1000; exploitation cycles = 200; averaged overs 15 learning experiences. *precision_range* = 3%.

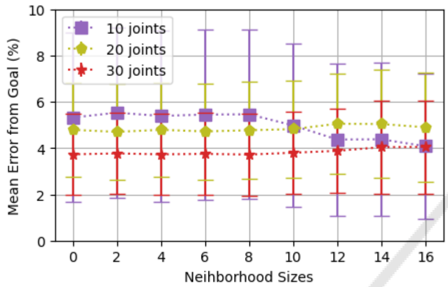


Figure 7: Mean errors from goal depending on mean neighborhood sizes over robotic arms of 10,20 and 30 joints. Learning cycles = 1000; exploitation cycles = 200; averaged overs 15 learning experiences. *precision_range* = 3%.

formances by generating more *endogenous learning situation*. The point of best performance is different for each arm sizes which shows that the neighborhood behaves differently with higher dimensions. Past this point, the error increases because the *endogenous learning situations* are too far from the *Context Agent* to bring a coherent smoothing. At high dimensions, *endogenous learning situations* are harder to generate because of the large exploration space. This is why, for the same neighborhood sizes, there are more *endogenous learning situations* at low dimensions. Moreover, beyond 10 joints, the performances are not affected by the *endogenous learning situation*.

5.3.1 Related Work

The magnitude of the mean goal reaching errors of the Self-Adaptive Goal Generation RIAC algorithm (SAGG-RIAC) (Baranes and Oudeyer, 2013) is close to our results. The difference is that SAGG-RIAC uses around 10^4 micro actions for each goal to obtain comparable goal errors. Our approach instantaneously gives a set of angles to reach any goal after one training of 1000 *learning situations*.

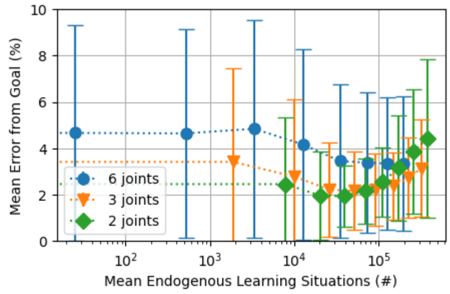


Figure 8: Mean errors from goal depending on mean *endogenous learning situations* over robotic arms of 2, 3 and 6 joints. Learning cycles = 1000; exploitation cycles = 200; averaged overs 15 learning experiences. *precision_range* = 3%.

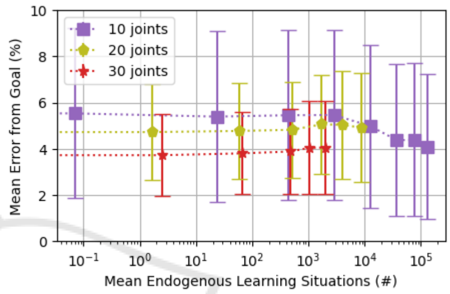


Figure 9: Mean errors from goal depending on mean *endogenous learning situations* over robotic arms of 10, 20 and 30 joints. Learning cycles = 1000; exploitation cycles = 200; averaged overs 15 learning experiences; *precision_range* = 3%.

6 CONCLUSION AND PERSPECTIVES

In this paper, we have proposed an extension of a Context-based learning multi-agent system which has already proven to be suitable to complex systems and that is directly inspired by Constructivism. This is a generic approach because it does not rely on the underlying application. This work was applied on the learning of the Inverse Kinematic Models of robotic arms with different numbers of joints. Self-observation of self-adaptive multiagent systems allowed us to add collaboration between fragments of learning which are the *Context Agents*. Based on the internal detection of close *Context Agents* models, we proposed the generation of *endogenous learning situations* that led to better performances on Inverse Kinematic Model learning. This work has shown that the generation of *endogenous learning situations* makes it possible to reduce *exogenous learning situations* as the performance improvement with endogenous cooperative learning attests.

The proposed approach needs to be refined in order to select the right size of neighborhood according to the dimension of the exploring space to maximize performance. The scalability was not discussed here but the generation of *endogenous learning situations* at high dimensions needs also to be optimized to access to more neighbors with reasonable execution times. Another promising lead is to decompose the learning into several local instances of the learning mechanism, one for each joint. This would reduce the high-dimensional problem into several low-dimensional problems where the cooperative neighborhood learning is more effective. It will also ensure that the performances are independent of the number of dimensions, and that the execution time is linearly dependent on the dimensions.

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