A Mutual Influence-based Learning Algorithm

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Keywords: Mutual Influence, Q-Learning, Distributed W-Learning, Smart Cameras, Adaptive Control.

Abstract: Robust and optimized agent behavior can be achieved by allowing for learning mechanisms within the underlying adaptive control strategies. Therefore, a classic feedback loop concept is used that chooses the best action for an observed situation – and learns the success by analyzing the achieved performance. This typically reflects only the local scope of an agent and neglects the existence of other agents with impact on the reward calculation. However, there are significant mutual influences among agents population. For instance, the success of a Smart Camera's control strategy depends (in terms of person detection or 3D-reconstruction) largely on the current strategy performed by its spatially neighbors. In this paper, we compare two concepts to consider such influences within the adaptive control strategy: Distributed W-Learning and Q-Learning in combination with mutual influence detection. We demonstrate that the performance can be improved significantly, if taking detected influences into account.

1 INTRODUCTION

In order to cope with dynamic and potentially unknown conditions, the control of agent behavior is typically equipped with learning capabilities. This has been shown to result in more robust and self-optimizing behavior (Panait and Luke, 2005). In most cases, the learning concept relies on a local fitness measurement. This means that each agent can judge how good or bad its own performance is by measuring the state of its environment, and without taking global knowledge into account. The problem with this concept is that it assumes a direct effect of actions to performance and neglects significant other influences. The most important influence might come from other neighbored agents – measuring the current state of the environmental conditions might be a result of others' action.

Consider a Smart Camera (SC) Network (Valera and Velastin, 2005; Rinner et al., 2008) as example: Each SC can adapt its behavior in terms of pan, tilt, and zoom. The adaptive control mechanism has to cover different tasks, ranging from person detection to tracking throughout the network and to 3D-reconstruction of suspicious persons. Obviously, the current strategy of its neighbors in close spatial vicinity has significant influence on the success: (a) if it observes the same area, the person detection is less successful since one of both SCs does not report a novel detection event, and (b) if it does not share the same field of view, a 3D-reconstruction is not possible.

Within this paper, we discuss our approach to explicitly detect such mutual influences by identifying correlations between the neighbors' configuration and the own performance. This information is then included in the situation description of the learning mechanism which is responsible for deciding about the current configuration. The basic idea is here that as soon as influences are detected, the system should be able to learn how to take this information into account – without manually implementing a counter strategy.

The remainder of this paper is organized as follows: Section 2 describes the methodological basis by explaining our system model, the approach to detect mutual influences among distributed agents, and a brief introduction of the utilized learning algorithm. Afterwards, Section 3 evaluates the approach in comparison to the state-of-the-art, where influences are learned implicitly within the learning algorithm. This is done based on a simulation of a Smart Camera Network, where mutual influences within the control strategies can be observed. Section 4 gives an overview of the state-of-the-art. Finally, Section 5 summarizes the paper and gives an outlook to future work.

Rudolph, S., Tomforde, S. and Hähner, J.
A Mutual Influence-based Learning Algorithm.
DOI: 10.5220/0005697001810189
In *Proceedings of the 8th International Conference on Agents and Artificial Intelligence (ICAART 2016) - Volume 1*, pages 181-189
ISBN: 978-989-758-172-4

2 METHOD

In this section, we introduce the mutual influences detection and how it can be used to design more efficient learning algorithms. This is structured as follows. In Section 2.1, we give an introduction to the notion of mutual influence, and the applied detection method. Afterwards, Section 2.2 explains how the mutual influence information can be exploited in a learning algorithm.

2.1 Mutual Influence

As briefly scratched in the previous section, we want to utilize a mutual influence detection algorithm in order to improve the efficiency of learning algorithms. In order to define what is meant with this brief description of mutual influence, this section outlines our utilized system model which is inspired from standard machine learning notions. Despite the background in machine learning, the methodology is assumed to be applicable to all systems covering the basic system model. Afterwards, we continue this section with the presentation of the mutual influence detection algorithm. The method of the measurement of mutual influences has originally been proposed in (Rudolph et al., 2015a), therefore, we keep the description rather short in this work.

2.1.1 System Model

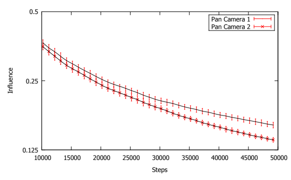
We start with a set of agents $\{A_1, \ldots, A_n\}$, where each agent can assume different configurations. Such a configuration typically consists of different parts. Consider a router as a simple example: The router can take varying configurations into account, such as the processed network protocol or parameter settings (i.e. for time-out intervals, buffer sizes, etc.). We define the whole configuration space of an agent A_i as cartesian product $C_i = c_{i1} \times \cdots \times c_{im}$, where c_{ij} are the parts of the configuration. A further assumption is that the particular configurations of individual agents are non-overlapping, meaning each agent has its own set of configurations, $c_{ij} \neq c_{kl}$ for all defined $i \neq k, j, l$. This does not mean that the configuration parts have to be completely disjoint in structure and values of the contained variables. For instance, two routers might have the possibility to configure the time-out interval, which would lead to the same set of possible configurations in these attributes, but on different devices. Such a relation is explicitly allowed within the model. Besides the configuration space, we need to consider a further element: the *local performance measurement*. In order to apply the proposed method, each agent has to estimate the success of its decisions at runtime – as a response to actions taken before. This is realized based on a feedback mechanism – with feedback possibly stemming from the environment of the agent (i.e. *direct* feedback) or from manual assignments (i.e. *indirect* feedback). This resembles the classic reinforcement model, where the existence of such a performance measurement (mostly called *reward*) is one of the basic assumptions, cf., e.g., (Wiering and van Otterlo, 2012).

2.1.2 Measurement

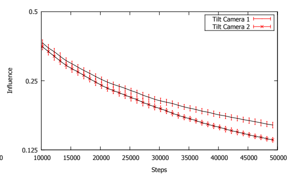
Given the described system model, we continue with the actual methodology for the measurement of mutual influences. The goal is to identify those parts of the configuration of the neighboring agents that have influence on the agent itself. Thereby, we focus on spatially neighbored agents (such as the cameras in the motivating example) – but the methodology is not restricted to this kind of neighborhood (i.e., "virtual neighborhoods" are also possible – for instance, routers in a data communication network). After the identification of influencing configuration parts, they can be addressed by a designer or by a self-adapting system itself.
In general, we are typically not interested in the question if an agent as a whole is influencing (some of) its neighbors, since the benefit of this information is negligible. In contrast, we want to detect specific configuration parameters whose optimal usage strategy is somehow influenced by the current settings of the neighbored agents. The basic idea of the algorithm is to make use of stochastic dependency measures that estimate associations and relations between the configuration parts of an agent and the performance of a second agent. These dependency measures are designed to find correlations between two random variables X and Y. As suggested in (Rudolph et al., 2015a), we use the *Maximal Information Coefficient* (MIC – (Reshef et al., 2011), see next subsection for details).
If using only dependency measures, the proposed method does not completely tackle the previously introduced notion of mutual influence. This method alone has some issues since the configuration of the agent itself is not taken into account. We explain this problem and present a solution to resolve this issue in Section 2.1.4.

2.1.3 Maximal Information Coefficient

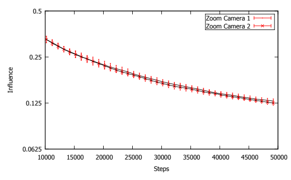
The *Maximal Information Coefficient* (MIC) is a measure of dependence between two real valued random variables. It has been introduced by Reshef et al. (2011) and is based on the *Mutual Information* that



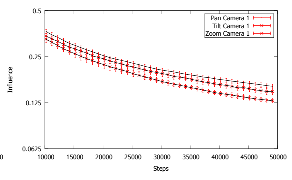
(a) The influence of the pan of Camera 1 and 2 on Camera 0.



(b) The influence of the tilt of Camera 1 and 2 on Camera 0.



(c) The influence of the zoom of Camera 1 and 2 on Camera 0.



(d) The influences of the pan, tilt and zoom of Camera 1 on Cam 0.

Figure 1: The results of the influence measurement based on 20 independent runs. The graphs show the Influence of the different configuration parts on Camera 0.

goes back to Shannon and Weaver (1949). Therefore, we start with a short introduction of the Mutual Information and then present the MIC in detail.
The mutual information is defined as:

$$I(X;Y) = \sum_{x \in X} \sum_{y \in Y} p(x,y) \log \left(\frac{p(x,y)}{p(x)p(y)} \right), \qquad (1)$$

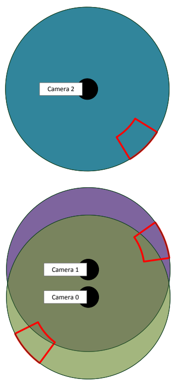
where $p(x,y)$ is the joint probability distribution of the discrete random variables X and Y variables. In addition, $p(x)$ and $p(y)$ are the corresponding marginal distributions. The measure quantifies how much information about X can be retrieved from the realization of Y and vice versa. The mutual information gives values ≥ 0 and only equals to zero if the two random variables are stochastically completely independent. An important advantage of this technique compared to other measures, such as, Pearson Correlation Coefficient (Pearson, 1895) or Kendall tau rank correlation coefficient (Olofsson, 2011), is the possibility to find non-linear dependencies. Often, the probability distributions $p(x)$, $p(y)$, and $p(x,y)$ are unknown and have to be estimated in order to calculate the mutual information. In the discrete case, this is mostly done with the straight forward method of counting the frequency of occurrence of the different events.
An adaption of the mutual information for continuous has been presented with the MIC. It picks up a possibility of avoiding the density estimation in the continuous case. That is the *binning* of samples, meaning the data is sorted into bins based on their similarity. Afterwards, the probability distributions are estimated for the bins. This again is an easy counting of frequency and the data is essentially discretized. The resulting distributions are used for the calculation of the discrete variant of the mutual information. The problem is that the manual choice of the bins is time consuming and can lead to deceptive results if not appropriate. Therefore, MIC has been equipped with a concept of always using the bins that lead to the maximal mutual information. Finding this bin configuration is computational heavy – which resulted in the utilization of a heuristic to tackle the problem. As a result, MIC is defined as:

$$MIC(X;Y) = \max_{n_x n_y < B} \frac{I(X;Y)}{\log(\min(n_x, n_y))}, \qquad (2)$$

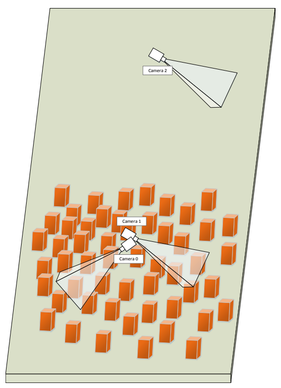
where n_x and n_y denote the number of bins for X and Y. The divisor $\log(\min(n_x,n_y))$ gives the maximal achievable mutual information given the number of bins and thus is used as normalizing factor. B typically denotes a function of the sample size N and limits the number of bins. This is necessary to avoid *trivial* partitioning, such as creating a single bin for each data point that most of the time create relatively high values for the mutual information. The initial paper introducing MIC proposes to use $B = N^{0.6}$ based on the described experiments.
In general, MIC shows some interesting properties. Similar to the mutual information, it is defined for values ≥ 0. In particular, it equals zero only if the random variables are completely independent. Furthermore, it is normalized and shows a good *equitability* in simulation results, i.e., that different types of association in the data can be compared.

2.1.4 Consideration of Own Configuration

As mentioned before, the use of dependency measures for the detection of influences is not straight forward in some cases. The issue appears if the own configuration of the agent A is essential for the determination of the influence of an agent B on A. This is if the configuration of B and the performance of A without taking into account the configuration of A lead to a distribution that does not indicate a dependency between them, but, there is an influence of B on A. This influence can then by revealed by using multiple estimators of the influence for the different configurations of A. The effect can be observed in already rather simple examples. One is given with example calculations of the mutual influence in (Rudolph et al., 2015a). For the measurement, it is sufficient to use two estimators and group the samples of all available configurations to the two estimators. But, sometimes the usage of more estimator can lead to a faster detection, as shown in (Rudolph et al., 2015b).



(a) A top view on the experimental setup with the pontenially observable areas of the cameras. The red areas show a possible configuration of the current field of view.



(b) A 3-dimensional illustration of the experimental setup. We see agray floor with orange blocks that represent targets. The targets are moving from left to right and vice versa. The observing cameras are depicted with their current field of view.

Figure 2: The experimental setup.

2.2 The Learning Algorithm

In this section, the reinforcement learning algorithm is presented. We chose the *Q-Learning* algorithm (Watkins and Dayan, 1992) as the basis of this work, since it is (i) well-known in the reinforcement learning domain and (ii) it has already been successfully applied in the Smart Camera domain, cf. (Rudolph et al., 2014). The algorithm has then been enhanced using the influence information of the system by adapting the state space of the learning algorithm in order to reflect the actual influences in the system. The remainder of the section gives an introduction to Q-Learning (see Section 2.2.1) and describes the details of the modification for application in the Smart Camera domain.

2.2.1 Q-Learning

The *Q-Learning* algorithm is a basic Reinforcement Learning technique that is well known and studied intensively. It has originally been proposed by Watkins and Dayan (1992). Like all RL techniques, Q-learning tries to solve the general RL Problem, i.e., to find an optimal policy for a given problem with respect to the long term reward $r \in \mathbb{R}$. The main idea is to find a Quality-function $Q : S \times A \to \mathbb{R}$ that approximates the reward for each state-action pair and takes into account the long term reward. To reach this goal, the value for each state-action-pair is initialized according to some of the various proposed methods, e.g., they are all set to a fixed value or they are set to a random value, and afterwards updated according to the rule

$$\begin{aligned} Q_{t+1}(s_t,a_t) = {} & Q_t(s_t,a_t) \\ & + \alpha\left(r_{t+1} + \gamma \max_a Q_t(s_{t+1},a) - Q_t(s_t,a_t)\right), \end{aligned} \tag{3}$$

where $Q_t(s,a)$ denotes the old Q-Value and $Q_{t+1}(s,a)$ the new one, each for a given state-action pair (s,a). Furthermore, r_{t+1} denotes the *reward* received in time step $t+1$ and therefore is the immediate reward for the action a_t taken in time step t. The discount factor $\gamma \in [0,1)$ determines the fraction of estimated future rewards that is taken into account in the present step. The learning rate $\alpha \in (0,1]$ determines how much the current experience, i.e. the current reward, is taken into account for approximating the Q-value.

2.2.2 Including Mutual Influence Information

After the presentation of the Q-learning algorithm, we depict how this information can be exploited to create a MI-based learning algorithm. Although we used Q-Learning as example for a learning algorithm, other techniques can be utilized as well.

The main idea is to include the parts of the configuration of a neighbor that have an influence on itself within its own state space. Considering two agents A_1 and A_2 with configuration space $C_1 = c_{1,1} \times c_{1,2}$ and $C_2 = c_{2,1} \times c_{2,2}$, where the influence measurement indicates that configuration part $c_{2,1}$ has a significant influence on agent A_1, we introduce this configuration part in the state space of it. The agent is then able to react to the actual configuration of its neighboring agent.

Looking into a more concrete example, we consider the Smart Camera domain that is also used for the experiments following later in Section 3. Following (Rudolph et al., 2014), a Q-learning algorithm can be designed by defining the situation and action parts: (a) the current pan, tilt and zoom configurations are used as situation (i.e., the state space), and (b) changes to these values (in terms of defined degree steps) serve as action space. More precisely, the states for each of the cameras can be of the form $[pan_i, tilt_i, zoom_i]$ and the actions could be the increase of pan, tilt or zoom, or the decease of pan, tilt or zoom, or no change to pan, tilt or zoom, i.e., of the form $[X_{i,pan}, X_{i,tilt}, X_{i,zoom}]$, where $X_{i,p}$ could be increase, decrease or no change. The actual configuration space of each camera would then also consist of the $[pan, tilt, zoom]$ configurations. But, the configuration space and state space are conceptually different and are not necessarily the same. Assuming that the pan of Camera 1 has a significant influence on Camera 0, we can apply the above described method of the enhancement of the state space of Camera 1. The new states could then have the form $[pan_1, tilt_1, zoom_1, pan_2]$. This enhancement of the state space will allow the camera to consider the configuration of its neighboring camera.

3 EVALUATION

In this section, we present the evaluation of the novel algorithm. First, we introduce the evaluation setting that is settled in the Smart Camera domain in Section 3.1. Afterwards, we show the results of the measurement of the influence in Section 3.2. Then a learning algorithm for the comparison of the performance of the algorithm is introduced in Section 3.3. At least, we show the results of the mutual influence-based algorithm and the comparison algorithm in Section 3.4.

3.1 Evaluation Setting

For the evaluation, we chose a Smart Camera application setting that requires a collaboration in order to reach an optimal result. Therefore, we define the goals: (i) detect new targets, and (ii) create 3D models of targets in an area (i.e., the goal is to provide a stereo reconstruction of suspicious persons). There is some research on techniques that allow to construct a 3D model from 2D pictures from different angles, see (Menze and Muhle, 2012; Menze et al., 2013) for an example.

The experimental setup is depicted in Figure 2. There (in particular in Figure 2a), we see a top down view on three cameras, marked as black dots. Around them, we see circles in different colors that show the potential observable areas of the cameras. We can see that a collaboration between Camera 0 and 1 is necessary for an optimal behavior of the cameras. Camera 2 is not involved with the other two cameras. Therefore, a collaboration is not helpful. In Figure 2b, we see a 3D model of the scene with example targets added, represented as orange boxes. In the scenario, the targets move from left to right and leave the scene or from right to left and leave the scene.

In the performance measure, we reflect the goals mentioned before. We rate the detection of a before unobserved target with a performance of 1 and the observation of multiple cameras with a performance of 2.5 while one or multiple cameras could observe multiple targets which are then added up. We chose the difference between the two possible observations in order to reflect that a 3D reconstruction of an target is much more valuable. Experiments with other weightings between the two goals have shown only minor effects on the mutual influence detection.

3.2 Measurement of Influence

Before the MI-based algorithm can be applied, it is necessary to gather the MI information for the scenario. The measurement of influence presented here is based on the results in in (Rudolph et al., 2015a). However, we present them here again in short since they are necessary for the understanding of the following results. Exemplary, we show the influence information for Camera 0. The values for the different parts of the configuration of Camera 1 and 2 are shown in Figure 1a, 1b and 1c. We see that the pan and tilt of Camera 1 are clearly more influencing than the counterparts of Camera 2. In Figure 1d, we can observe the comparison of the three parts of Camera 1. Here, the pan again has the highest measured influence, followed by the tilt. The influence of the zoom of Camera 1 is rather marginal, since the average is higher starting from $10,000$ steps.

3.3 Comparison Algorithm

As basis for a meaningful comparison, we chose the *Distributed W-Learning* algorithm (DWL) since it is a comparatively new reinforcement learning technique and is especially designed for multi agent systems. Furthermore, it has already been applied to a similar learning task in the Smart Camera domain (Rudolph et al., 2014). It has originally been proposed by Dusparic and Cahill (2010). It borrows the ideas of *Q-Learning* and *W-Learning* and extends them with a cooperative mechanism. Since Q-learning has been outlined in Section 2.2.1, we now introduce *W-Learning* (see Section 3.3.1) and on this basis, DWL is introduced (see Section 3.3.2).

3.3.1 W-Learning

An extension of Q-learning is W-learning. It was introduced by Humphrys (1995) and addresses the problem of a too large state space, i.e. there are too many states to handle in terms of memory, or the learning will be slowed down too much through the large number of states that have to be visited in order to learn the optimal policy and therefore makes the algorithm inapplicable. The proposed solution for this problem is to split the state space according to different goals. For every part there is a dedicated *Q*-Learner that approximates the value of the state-action pairs. For the update of the Q-values Equation 3 is used. In order to decide which W-Learner is allowed to execute its proposed action, for each W-Learner a separate W-value is introduced. It is updated using the equation

$$W_{i,t+1}(s_t) = (1-\alpha)W_{i,t}(s_t) + \alpha\left(Q_{i,t+1}(s_t,a_t) - r_{i,t+1} + \gamma \max_{a_i} Q_{i,t+1}(s_{t+1},a_i)\right), \quad (4)$$

where $W_{i,t}(s)$ denotes the former mentioned W-value for W-learner i at time t for state s. The parameters α and γ are as in the Q-learning update equation (i.e. Equation 3) the learning rate and the discount factor. Equally, $Q_t(s,a)$ is the Q-value at time t for the state-action pair (s,a). For the selection of the action to execute the W-learner with the highest W-value has to be found. The action that has the highest Q-value within this W-learner is selected and executed.

3.3.2 Distributed W-Learning

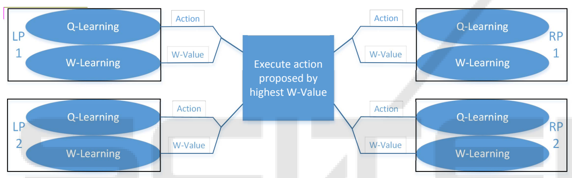


Figure 3: The Architecture of DWL.

In (Dusparic and Cahill, 2010), Distributed W-learning (DWL) is introduced. It is an adaption of the W-learning idea to distributed systems. Since they often create huge state spaces in most cases, a central optimization is not viable. Therefore, DWL introduces a W-learning process for each agent in the system and enhances it with *remote W-learner*. The architecture of the DWL decision process is depicted in Figure 3. The remote W-learner work similar to the former introduced W-learners, now denoted as local W-learner. The difference of the remote W-learner is that they use the state and reward of the neighbor agents to determine a proposed action. Through this mechanism, the neighbors can influence each others action and are assumed to find an optimal policy for the whole system. For some applications it might be useful to not value the opinion of the neighbors as high as the own. Therefore, to determine the local W-values, we use the same method as in W-learning, but, to determine the W-values of the remote policies a cooperation coefficient $0 \leq C \leq 0$ is introduced as a weight. Using a low C leads to a more *selfish* behavior. A high value for C lets the agent take its neighbors suggestions more into account. Other then stated in (Dusparic and Cahill, 2010), $C = 0$ does not lead to a fully non-cooperative behavior, since the W-values could be (and in practice sometimes are) negative. Just multiplying the remote W-values by C will not lead to the desired result. Therefore, in the case of a negative W-value, we divide by C.

3.4 Results

Here, we present the results of the different algorithms. We start with some information about the results that apply for all algorithms and then present the results for DWL in Sec 3.4.1. Then, we show the performance results of the MI-based algorithm in Section 3.4.2 and discuss the results in Section 3.4.3. Since Q-learning introduces two variables, the learning rate α and the discount factor γ, we would like to find an optimal parameter set for the task. However, due to computational reasons it is not possible to run full parameter studies including the collaboration factor c in DWL. Therefore, we run experiments with a single camera to find a parameter set for α and γ that allows an optimal learning behavior. We found that $\alpha = 0.3$ and $\gamma = 0.6$ fulfills this requirement and therefore used it for both algorithms, DWL and the MI-based algorithm.

For each setting, i.e., for DWL each parameter setting and for the MI-based algorithm each situation setting, we made 20 independent runs that last 500,000 steps and use the average for the graphs, typically enhanced with the standard deviation.

3.4.1 DWL

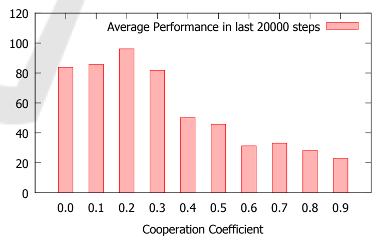


Figure 4: The results for DWL.

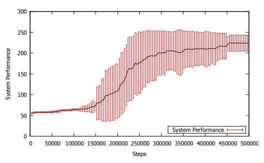
The results using the DWL algorithm are shown in Figure 4. Each bar shows the average performance of the last 20,000 steps. We see that a value of 0.2 for the Collaboration Coefficient C gives the maximum value of about 96 regarding the performance measure given in Section 3.1. For the minimum value of 0.0 for C DWL is equivalent to basic Q-learning and therefore has no collaboration mechanism any more. It gives a value of about 83. A collaboration factor of 0.1 and 0.3 also give a viable performance compared to the maximum value. Looking at a higher values, i.e. 0.4 and higher, we see that the collaboration does have a negative effect since it rather achieves the performance of non-collaborative behaviour, i.e. with C=0.

3.4.2 MI-based Algorithm

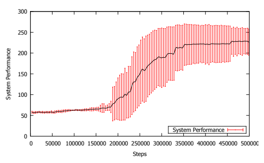
The results for the MI-based algorithm are presented in Figure 5. The data is enhanced with the standard deviation. In Figure 5a, we see the performance of the Q-Learning algorithm with the states of Camera 0 extended by the pan configuration of Camera 1. We can observe that a significantly higher performance as by DWL of approximately 225 is reached meaning that the introduced collaboration allows the system to find optimal strategies. Furthermore, the introduction of the pan is already sufficient to reach this goal. In Figure 5b and 5c, the graphs are similarly shaped to the one that only considers the pan. However, the differences are in the details. If more configuration parts are introduced in the states of Camera 1, we see that the performance rises slower in the beginning (between 150,000 and 300,000 steps). But later on (between 300,000 and 500,000) the *micro improvements* are learned faster if all configuration parts are included. In Figure 5d, we can observe the results for the inclusion of the tilt of Camera 1 in the states of Camera 0 without the consideration of pan. We see that a near optimal behavior is not found very often, but at least sometimes. The learning of a near optimal behavior explains the *jump* in the graph at around 230,000 steps and consequently a much higher standard deviation afterwards. However, most runs continue to process a strategy with a sub-optimal performance, resulting in an averaged reward of approximately 90. In Figure 5e, the runs with only the zoom of Camera 1 integrated in the states of Camera 0 are shown, respectively. The results again are far from optimal, but show that few runs can find a near optimal strategy. That again causes the *jump* at around 120000 steps.

3.4.3 Discussion

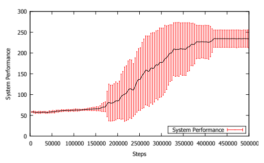
The presented results show that the MI-based approach clearly outperforms all other approaches. DWL can give better results than a non-collaborative algorithm for some parameter settings. However, it is far from an optimal behavior even after a learning phase of 500,000 steps. Concluding the results of the MI-based algorithm, we see that the mutual influence detection method has accurately identified the most influencing part of the configuration and therefore allows to learn optimal behavior. This can be seen since the runs with the pan included clearly outperform DWL and a non-collaborative learning. We have also seen that the inclusion of the less influencing parts (tilt and zoom) does improve the results, too. But this latter improvement is less strong compared to the usage of just pan, which has been identified as less effective by the MI detection method beforehand.



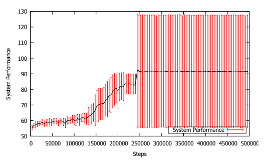
(a) The graphs show the system perfomance when the pan angle of Camera 1 is integrated in the state space of Camera 0.



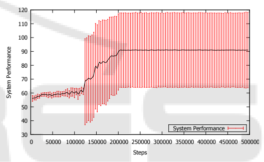
(b) The graphs show the system perfomance when the pan and tilt angle of Camera 1 is integrated in the state space of Camera 0.



(c) The graphs show the system perfomance when the pan and tilt angle, and the zoom of Camera 1 is integrated in the state space of Camera 0.



(d) The graphs show the system perfomance when only the tilt angle of Camera 1 is integrated in the state space of Camera 0.



(e) The graphs show the system perfomance when only the zoom of Camera 1 is integrated in the state space of Camera 0.

Figure 5: The results for the 3D-reconstruction scenario using the MI-based algorithm. The graphs show the system performance for the three configurations. Each graph is based on 20 runs with different random seeds. The line shows the average system performance and the error bars show the standard deviation.

4 RELATED WORK

In literature, several approach that try to formalize the mutual influences can be found. Most of these approaches focus on the influence through direct or indirect interactions. For instance, a model for interactions is proposed by Keil and Goldin (2003), but a method to detect the implicit interactions is not provided. Another approach is to use *stit* logic for model-

ing the interactions in multi agent systems (Broersen, 2010). The focus of this work is on the system specification and verification and therefore differs much from the focus of our work. In (Logie et al., 2008), a data mining approach for the detection of mutual influences in multi agent systems is proposed. Unfortunately, this is a position paper without concrete methods and results and no following works have been published, yet.
The presented method has similarities with the feature selection approach that originates in supervised learning and, recently, there are some promising attempts for the adaption to systems with performance measurement, i.e. the reinforcement learning domain, such as (Parr et al., 2008; Bishop and Miikkulainen, 2013; Hachiya and Sugiyama, 2010; Nguyen et al., 2013). All of these works have in common that they do not match the presented idea of a self-adapting and self-organizing system. In particular, they do not consider autonomic entities that interact and try to maximize the system utility based on what they can sense from their local environment and their local status. In contrast, they focus on the selection of features from given input sets for the particular learning algorithms. Within this work, we focus on the detection of the influence of the configurations of other system entities.
Furthermore, a variety of contributions can be found in literature with a focus on multi agent learning (Stone and Veloso, 2000). These works all belong to one of two categories: (i) *team learning* where a single learner is used for all the agents or (ii) *concurrent learner* where each agent has an own learner (Panait and Luke, 2005). In this work, we show how an optimal learning structure can be found in order to ensure an optimal learning behavior. We applied the technique to Q-Learning. However, other learning techniques, possibly especially designed for multi agent systems, can benefit from the mutual influence information as well.
There are several stochastic dependency measures that could be considered. The probably most prominent instance is the *Pearson Correlation Coefficient* (Pearson, 1895). In addition, a variety of further measures with a similar scope exist. In order to decrease the number of candidates to be applied for the detection task, we considered the following list of characteristics that define the requirements for this purpose: (i) The dependency measure should be able to find nonlinear dependencies between random variables. (ii) The dependency measure should only be zero if there is no dependency between the random variables. (iii) The dependency measure should be able to handle discrete and continuous random variables.

The MIC fulfills these criteria most appropriately. There are also other dependency measures that meet the criteria, such as, mutual information (Shannon and Weaver, 1949) or distance covariance (Szkely et al., 2007). But, some rather famous dependency measures are excluded by these criteria.

5 CONCLUSION

Based on the observation that an increasing part of technical systems is characterized by explicit and implicit dependencies among distributed entities, this paper presented a concept for optimizing the adaptation strategy of an internal control mechanism guiding the agent's behavior. The idea is to explicitly identify correlations between the particular configuration settings of a neighbored entity and the own performance measurement. We introduced a method to derive such correlation measures at runtime and integrate the corresponding information within the decision logic of the learning agent. To illustrate the possible impact, we chose Q-Learning as simple model-free reinforcement technique that is applied to learn a situation-action mapping online.

To demonstrate the improved performance, we compared the developed technique with D-Learning, which is a standard technique that combines Q-Learning-based online reinforcement learning approaches with similar learners for neighbor impact. In contrast to our concept, an integrated technique is performed. The evaluation showed that our approach that turns implicit in explicit dependency relations achieves a significant better performance and illustrated this within simulations of a Smart Camera scenario.

Future work mainly deals with more sophisticated solutions regarding the utilization of mutual influence information. On the one hand, this refers to other and more complex learning techniques – especially rule-based learning techniques that have to consider mutual influence estimations within their condition parts. On the other hand, more sophisticated approaches with respect to scalability issues are investigated. In this context, fast pre-estimators that identify reliably which entity is most probably having influence are developed.

REFERENCES

Bishop, J. and Miikkulainen, R. (2013). Evolutionary feature evaluation for online reinforcement learning.

In *Computational Intelligence in Games (CIG), 2013 IEEE Conference on*, pages 1–8.

Broersen, J. M. (2010). CTL.STIT: enhancing ATL to express important multi-agent system verification properties. In *9th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2010), Toronto, Canada, May 10-14, 2010, Volume 1-3*, pages 683–690.

Dusparic, I. and Cahill, V. (2010). Distributed w-learning: Multi-policy optimization in self-organizing systems. In *Proceedings of the 3rd IEEE International Conference on Self-Adaptive and Self-Organizing Systems (SASO)*. IEEE.

Hachiya, H. and Sugiyama, M. (2010). Feature selection for reinforcement learning: Evaluating implicit state-reward dependency via conditional mutual information. In Balczar, J. L., Bonchi, F., Gionis, A., and Sebag, M., editors, *ECML/PKDD (1)*, volume 6321 of *Lecture Notes in Computer Science*, pages 474–489. Springer.

Humphrys, M. (1995). W-learning: Competition among selfish q-learners. Technical report.

Keil, D. and Goldin, D. Q. (2003). Modeling indirect interaction in open computational systems. In *12th IEEE International Workshops on Enabling Technologies (WETICE 2003), Infrastructure for Collaborative Enterprises, 9-11 June 2003, Linz, Austria*, pages 371–376.

Logie, R., Hall, J. G., and Waugh, K. G. (2008). Towards mining for influence in a multi agent environment. In Abraham, A., editor, *IADIS European Conf. Data Mining*, pages 97–101. IADIS.

Menze, M., Klinger, T., Muhle, D., Metzler, J., and Heipke, C. (2013). A stereoscopic approach for the association of people tracks in video surveillance systems. *PFG Photogrammetrie, Fernerkundung, Geoinformation*, 2013(2):83–92.

Menze, M. and Muhle, D. (2012). Using Stereo Vision to Support the Automated Analysis of Surveillance Videos. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, pages 47–51.

Nguyen, T., Li, Z., Silander, T., and Leong, T. Y. (2013). Online feature selection for model-based reinforcement learning. In Dasgupta, S. and Mcallester, D., editors, *Proceedings of the 30th International Conference on Machine Learning (ICML-13)*, volume 28, pages 498–506. JMLR Workshop and Conference Proceedings.

Olofsson, P. (2011). *Probability, Statistics, and Stochastic Processes*. Wiley.

Panait, L. and Luke, S. (2005). Cooperative multi-agent learning: The state of the art. *Autonomous Agents and Multi-Agent Systems*, 11(3):387–434.

Parr, R., Li, L., Taylor, G., Painter-Wakefield, C., and Littman, M. L. (2008). An analysis of linear models, linear value-function approximation, and feature selection for reinforcement learning. In *Proceedings of the 25th International Conference on Machine Learning*, ICML '08, pages 752–759, New York, NY, USA. ACM.

Pearson, K. (1895). Notes on regression and inheritance in the case of two parents. *Proceedings of the Royal Society of London*, 58(1):240 – 242.

Reshef, D. N., Reshef, Y. A., Finucane, H. K., Grossman, S. R., McVean, G., Turnbaugh, P. J., Lander, E. S., Mitzenmacher, M., and Sabeti, P. C. (2011). Detecting novel associations in large data sets. *Science*, 334(6062):1518–1524.

Rinner, B., Winkler, T., Schriebl, W., Quaritsch, M., and Wolf, W. (2008). The evolution from single to pervasive smart cameras. In *Distributed Smart Cameras, 2008. ICDSC 2008. Second ACM/IEEE International Conference on*, pages 1–10.

Rudolph, S., Edenhofer, S., Tomforde, S., and Hähner, J. (2014). Reinforcement learning for coverage optimization through ptz camera alignment in highly dynamic environments. In *Proceedings of the International Conference on Distributed Smart Cameras*, ICDSC '14, pages 19:1–19:6, New York, NY, USA. ACM.

Rudolph, S., Tomforde, S., Sick, B., and Hähner, J. (2015a). A mutual influence detection algorithm for systems with local performance measurement. In *Proceedings of the 9th IEEE Conference on Self-Adaptive and Self-Organizing Systems (SASO)*. IEEE Press, to appear.

Rudolph, S., Tomforde, S., Sick, B., Heck, H., Wacker, A., and Hähner, J. (2015b). An online influence detection algorithm for organic computing systems. In *Proceedings of the 28th GI/ITG International Conference on Architecture of Computing Systems ARCS Workshops*.

Shannon, C. and Weaver, W. (1949). *The Mathematical Theory of Communication*. University of Illinois Press.

Stone, P. and Veloso, M. (2000). Multiagent systems: A survey from a machine learning perspective. *Autonomous Robots*, 8(3):345–383.

Szkely, G. J., Rizzo, M. L., and Bakirov, N. K. (2007). Measuring and testing dependence by correlation of distances. *Ann. Statist.*, 35(6):2769–2794.

Valera, M. and Velastin, S. (2005). Intelligent distributed surveillance systems: a review. *Vision, Image and Signal Processing, IEE Proceedings -*, 152(2):192–204.

Watkins, C. J. C. H. and Dayan, P. (1992). Technical note q-learning. *Machine Learning*, 8:279–292.

Wiering, M. and van Otterlo, M., editors (2012). *Reinforcement Learning: State-of-the-Art (Adaptation, Learning, and Optimization)*. Springer Verlag, Berlin / Heidelberg, Germany. ISBN-13: 978-3642276446.