A Co-adaptive Approach to XCS Classifier Systems

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Abstract: - We propose a co-adaptive approach to control coevolution-based eXtended Classifier System (XCS) parameters. By taking advantage of the on-line incremental learning capability of such systems, solutions can be produced that completely cover a target problem. The system combines the advantages of both adaptive and self-adaptive parameter-control approaches. Using a coevolution model means that two XCS can operate in parallel to simultaneously solve target and parameter-setting problems. Furthermore, the approach needs very little time to become efficient in terms of latent learning, since it only requires small amounts of information on performance metrics during early run-time stages. Test results indicate that our proposed system outperforms comparable models regardless of the target problem's stationary/non-stationary status.

Key-Words: - CA-XCS, co-adaptive, coevolution, Dyna, parameter adaptation, parameter setting problem

1 Introduction

Learning classifier systems (LCS) [2] were first introduced by John H. Holland (1975), who is also known as the father of genetic algorithms (GA). They use a combination of GA and reinforcement learning (RL) [8] to build adaptive rule-based systems that learn via on-line experiences [3, 11]. Depending on the architecture, LCS may be viewed as either an extended GA application or an RL algorithm. The GA component is responsible for comparing performance for the purpose of identifying better rules to replace unsuitable rules. The RL component is responsible for distributing credit among rules and resolving rule conflicts

Originally, LCS was not considered analyzable due to the complex nature of component interrelationships [3]. A renewed interest in LCS occurred after 1995, when Wilson proposed his eXtended Classifier System (XCS) [9] based on classifier prediction accuracy. A number of new models and applications have been presented since that time. Wilson retained most of Holland's original ideas and architecture, but also made several substantial changes that gave XCS at least four advantages [3, 9, 10]: a) easier analyzability; b) the ability to deal with complex problems (e.g., optimization issues) that had previously been considered unsolvable; c) the addition of a robust generalization mechanism capable of generating compact, complete, maximized, and accurate solutions [11]; and d) the capability to use various representations to specify classifiers [6, 7].

In the same manner as evolutionary computations (EC), the setting of parameters determines if XCS is capable of generating optimal or near-optimal solutions and its level of efficiency. All of the currently available approaches [1] to solving the parameter setting problem associated with LCSs have important drawbacks requiring improvement and modification. Our proposed co-adaptive approach, which is based on the coevolution concept and Dyna architecture [8], takes advantage of the incremental on-line learning capability of LCSs to produce solutions that completely cover a target problem.

The system simultaneously adapts parameters according to current learning performance and state. As shown in Figure 1, the framework consists of two LCSs. Main-XCS is responsible for solving the external target problem and meta-XCS is responsible for adapting internal parameters. We used the Dyna architecture to acquire the parameter control capability of meta-XCS in a short time period. Dyna uses an internal world model to save real experiences that are obtained during learning and uses them for an intensive latent learning process that shortens training time and speeds up the

construction of a complete set of solutions. In [5], Lanzi showed that a combination of Dyna and XCS (Dyna-XCS) was capable of greatly enhancing learning performance. For the present study we used Dyna-XCS to a) solve the slow-learning problem of the adaptive parameter control approach (which requires a long training period) and b) significantly enhance parameter control stability.

To solve the parameter control problem common to LCSs, we established a framework in which main-XCS and meta-XCS operate in parallel. Solutions co-evolve as the systems cooperatively adjust parameters to a given target problem. There are two advantages to using coevolution to solve the parameter setting problem: many benefits of the self-adaptive parameter control approach are maintained without expanding the target problem's original search space, and the premature convergence problem that often accompanies this approach is avoided.

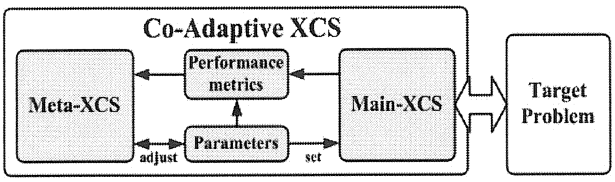

Figure 1. Co-adaptive XCS framework.

2 XCS Overview

In the same manner as traditional LCS, XCS is a problem-independent and adaptive machine learning model. As shown in Figure 2, XCS has four components: a finite classifier population, a performance component, a reinforcement component, and a rule discovery component. Stored classifiers control the system via a horizontal competition mechanism and perform tasks by means of vertical cooperation. The performance component governs interactions with the target problem. The input interface (detector) is used to transmit the current target problem state to the performance component and to determine dominant classifiers according to an exploration/exploitation criterion. Through the output interface (effector), any action advocated by dominant classifiers is executed and receives feedback. The reinforcement component (credit assignment component) uses an algorithm similar to Q-learning [8] to update the reinforcement parameters of classifiers that advocated the output action. Finally, the rule discovery component uses a GA to search for better or more general classifiers and to discard incorrect or more specific classifiers.

When running XCS, performance metrics are used to observe system performance and to express classifier populations. Kovacs [11] divided these performance metrics into two categories: performance measures and population state measures. Three well-known on-line metrics for measuring performance in research environments and real-world XCS applications are performance ρ, system error, and population size. Performance ρ and system error are used to measure XCS learning capability according to results from target problem interactions. As one would expect, the population size performance metric (defined as the number of macro-classifiers in a classifier population) belongs to the category of population state measures. It is used to measure XCS learning quality.

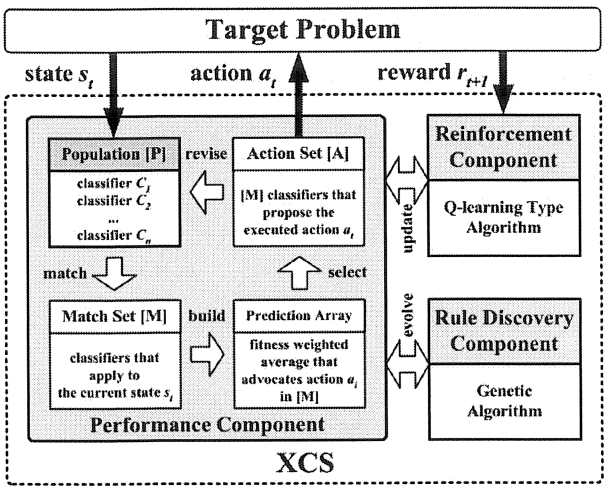

Figure 2. XCS architecture.

3 Co-Adaptive XCS (CA-XCS)

Our decision to use one XCS to adjust the parameters of other XCS system was based on its ability to deal with complex problems, especially its ability to represent various parameter control strategies [3, 6-7]. We used XCS to capture relationships and changing parameter patterns between parameter control strategies and to observe their effects on target problem. Its principal features include a) the combined advantages of adaptive and self-adaptive parameter control approaches that allow for the use of a coevolution model to simultaneously solve a target problem and parameter setting problem, and b) reduced time requirements for becoming efficient via a latent learning process that uses small pieces of information about performance metrics in the early stages of a run.

3.1 The Model

A schematic of the co-adaptive XCS (CA-XCS) architecture is shown in Figure 3. Its four principal components are main-XCS, meta-XCS, performance

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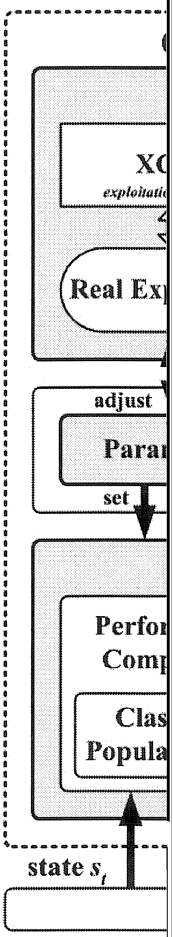

Figure 3. CA-

3.2 Meta-X

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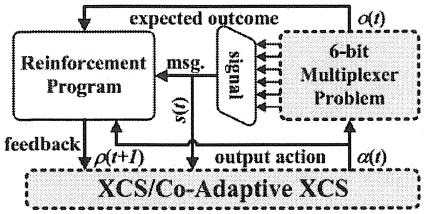
quality. During the early stages of a run, the mutation operator increases the level of novelty by moving classifiers within a search space. A higher mutation rate helps speed up the rule discovery component's ability to discover a set of appropriate classifiers from an extremely large search space. As an essential background operator during the later stages of a run, mutations increase the probability of finding a better solution. A lower mutation rate helps fine-tune existing classifiers without disturbing runs or decreasing learning performance as a set of optimal solutions is built. However, target problems have different characteristics. It is impossible to control the regularity and variety of situations that occur during the runtime, therefore it is difficult to predetermine the optimal mutation rate for a given target problem or to adjust the mutation rate during each stage of a run. Since the mutation operator is so important yet difficult to determine, in our experiments we a) allowed the main-XCS component in CA-XCS to learn a representative benchmark problems in the machine learning (ML) field, and b) arranged for the meta-XCS component in CA-XCS to adjust the mutation rate in the main-XCS component. This helped us achieve our goal of thoroughly understanding the relationships between the mutation rate and the benchmark problem.

4.1 6-bit Multiplexer Problems (6-MP)

Given the restrictions just described, we experimented with a co-adaptive parameter control approach in the form of the 6-bit multiplexer problem (6-MP)—a version of the well-known benchmark single-step problem for machine learning in general and LCSs in particular [9]. As shown in Figure 5, the input message signal transmitted to LCSs consists of a string of six binary digits in which the first (version A) or last (version B) two bits (called address bits) represent a binary index and the remaining bits represent data bits. The expected outcome is the value of the indexed data bit. For example, the expected outcome of "111110" in version A is 0, since the first two bits (11) represent index 3—the fourth bit following the address. The expected outcome of "010001" in version B is 1, since the second bit preceding the address is indexed.

6-MP is considered challenging because of its non-linear characteristic, yet it yields many useful generalizations that help in comparing learning performance in various models. During each cycle, the 6-MP produces signals by randomly setting all six bits. Expected outcomes are computed as single bits from the generated signals, which are transmitted as input messages to the LCS on request and returned as output actions that are compared with expected outcomes. A positive feedback score of 1,000 means that a reward was returned to the LCS for reinforcement; a feedback score of 0 means that a penalty was returned. During the run, the 6-MP continues to produce 6-bit messages with similar probabilities as the LCS tries to learn the correct mapping relations between signals and expected outcomes—thus developing an optimal solution.



$o_a(t) = f_{6\text{-}mp}(b_0,b_1,b_2,b_3,b_4,b_5) = \overline{b_0}\,\overline{b_1}\,b_2 + \overline{b_0}\,b_1\,b_3 + b_0\,\overline{b_1}\,b_4 + b_0\,b_1\,b_5$ *(version A)*

$o_b(t) = f_{6\text{-}mp}(b_0,b_1,b_2,b_3,b_4,b_5) = \overline{b_4}\,\overline{b_5}\,b_0 + \overline{b_4}\,b_5\,b_1 + b_4\,\overline{b_5}\,b_2 + b_4\,b_5\,b_3$ *(version B)*

Figure 5. The 6-bit Multiplexer Problem (6-MP)

With the exception of the mutation rate, the default parameter for our experiments was $N = 800$, $\beta = 0.2$, $\alpha = 0.1$, $\varepsilon_0 = 10$, $\nu = 5$, $\theta_{GA} = 25$, $\chi = 0.8$, $\theta_{del} = 20$, $\delta = 0.1$, $\theta_{sub} = 20$, $P_{\#} = 0.33$, $p_I = 10$, $\varepsilon_I = 0$, $F_I = 0.01$, $p_{explore} = 0.5$, *doGAsubsumption* = true, *doActionSetSubsumption* = true. All results discussed in this report represent an average of 30 runs. XCS performance metrics were recorded for each trial and computed as average moving window numbers in the last 50 trials.

4.2 Stationary Problem Experiment

In the first experiment we used the 6-MP to examine whether the meta-XCS component of CA-XCS could adjust the main-XCS component mutation rate. We used three original XCS (one each with fixed mutation rates of 0.01, 0.05, and 0.09) in the stationary problems to determine whether CA-XCS performance and learning quality was the best among all XCS version.

Performance metrics data from CA-XCS and three comparative XCS at fixed mutation rate of 0.01, 0.05, and 0.09 in the stationary 6-MP experiment are shown in Figure 6. When the XCS mutation rate = 0.09, the population metric was usually the worst and the performance ρ metric the best among the three XCS versions; furthermore, the system error metric decreased very quickly. When the XCS mutation rate = 0.01, performance ρ was the worst metric, the system error metric decreased very slowly, and the population size metric was the smallest among the three XCS versions; furthermore,

the number of classifiers was nearly half that of the XCS at the fixed mutation rate of 0.09.

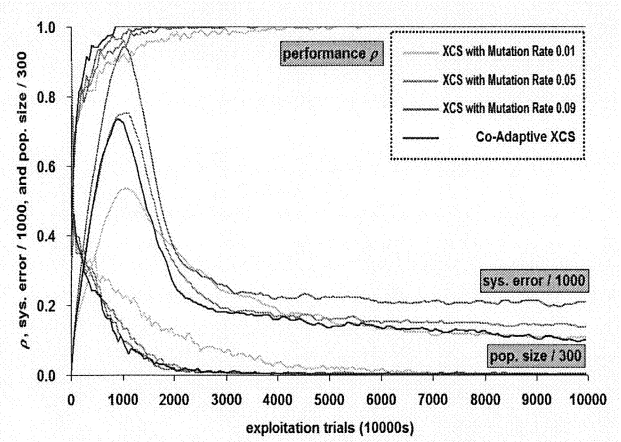


Figure 6. Data for CA-XCS performance ρ, system error, and population size performance metrics for the stationary 6-MP problem (version A) and other XCS versions with fixed mutation rates of 0.01, 0.05, and 0.09.

When the CA-XCS was applied to 6-MP learning, the performance and learning quality dilemmas were easily avoided. As shown in Figure 6, it took between 850 and 900 trials for CA-XCS to completely learn correct mapping relationships between the 6-MP input messages and expected outcomes. For the population size metric, the CA-XCS matched or outperformed the XCS at a fixed mutation rate of 0.01—that is, after 10,000 trials, approximately 21 classifiers were available for forming an optimal solution (Table 1).

Table 1. Classifier population [P] of CA-XCS in the stationary 6-MP problem (version A).

Condition	Action	Prediction	Prediction Error	Fitness
000###	1	0.0	0.0	0.8928974
#00#0#	1	0.0	0.0	0.0411975
#00#0#	0	1000.0	0.0	0.1067869
000###	0	1000.0	0.0	0.9535079
10##0#	0	1000.0	0.0	0.9527302
0#11##	0	0.0	0.0	0.1194703
10##1#	0	0.0	0.0	1.0
10##0#	1	0.0	0.0	0.9855281
01#1##	1	1000.0	0.0	0.9364153
001###	1	1000.0	0.0	1.0
11###0	0	1000.0	0.0	0.984052
001###	0	0.0	0.0	0.9173577
#1#1#1	1	1000.0	0.0	0.076873
01#0##	0	1000.0	0.0	0.9999906
10##1#	1	1000.0	0.0	0.999998
11###0	1	0.0	0.0	0.9992283
11###1	1	1000.0	0.0	0.9652512
01#0##	1	0.0	0.0	0.8710339
01#1##	0	0.0	0.0	0.9639262
0#00##	1	0.0	0.0	0.1633261
11###1	0	0.0	0.0	0.1633261
1####0	0	1000.0	0.0	0.0225657
#00###	0	1000.0	0.0	0.0144919

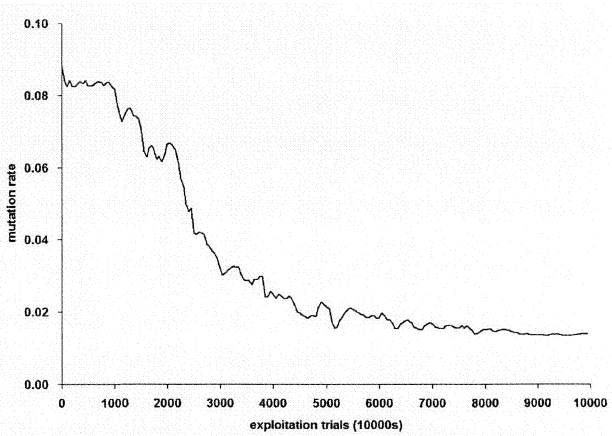


Figure 7. Variation in CA-XCS mutation rate adaptation process for the stationary 6-MP problem (version A).

Results from average mutation rate adaptation processes for CA-XCS in the stationary 6-MP (version A) are shown in Figure 7. The results support those from previous studies on EC mutation rates. During early run trials, the meta-XCS component tended to increase the mutation rate in the main-XCS component in order to produce classifiers capable of learning correct mapping relationships between 6-MP input messages and expected outcomes at maximum speed. In the later trials, it tended to decrease the mutation rate in order to fine-tune existing classifiers and to obtain an optimal solution.

As shown in Figure 7, a constant high-to-low oscillation was observed in the mutation rate of the main-XCS component. It appears as though the meta-XCS component of CA-XCS tested the influence of a lower mutation rate on the main-XCS component during early run trials and tested the influence of a higher mutation rate on the main-XCS component during later trials. Mutation rates were abandoned if they exerted negative impacts on performance and learning quality. In these cases, the meta-XCS component returned to the opposite end of the mutation rate range and rapidly mastered a link among the mutation rate, performance ρ metric, population size metric, and similar situations via a latent learning mechanism.

4.3 Non-Stationary Problem Experiment

Our second experiment was similar to the first except that the second made use of 6-MP versions A and B (Figs. 8 and 9). For this experiment we ran 20,000 trials—10,000 that were similar to the first experiment and 10,000 in which the input signal bit sequence was abruptly changed from version A to B. In the version B run, the two address lines were moved from the initial (b_0b_1) to final input signal bit

(b_4b_5) position. Whenever the bit sequence underwent a sudden change during the second 10,000 trials, the CA-XCS had to re-generalize the existing classifiers and rebuild an appropriate solution. The goal was to determine whether or not the CA-XCS could quickly reestablish a proper mutation rate following an abrupt change in the problem environment, recover the original learning performance and population size state, and still rebuild an optimal solution.

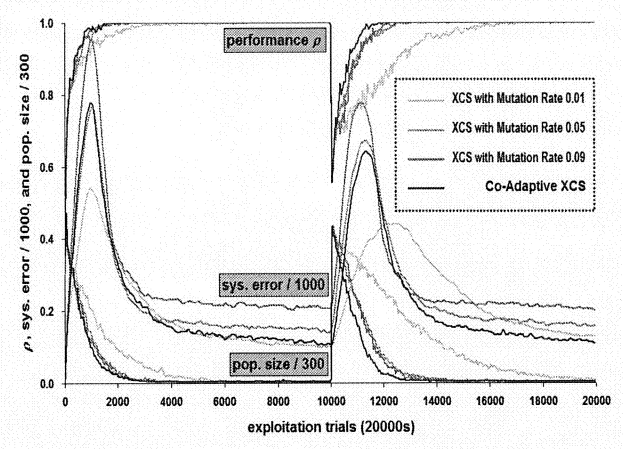


Figure 8. Performance ρ, system error, and population size performance metrics of CA-XCS and other XCS versions with fixed mutation rates of 0.01, 0.05, and 0.09 for the non-stationary 6-MP problem (versions A and B).

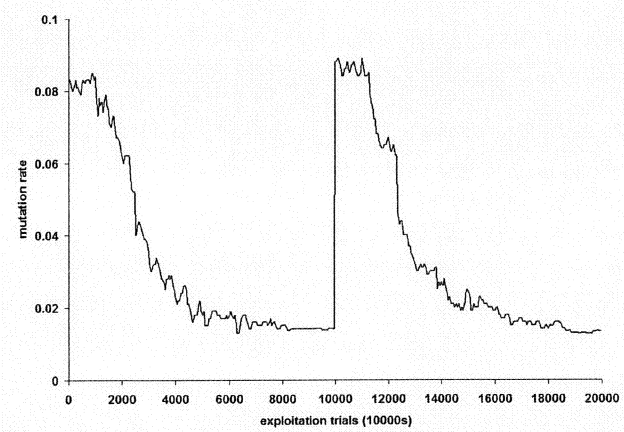


Figure 9. Mutation rate adaptation for the CA-XCS in the non-stationary 6-MP (versions A and B).

Details of CA-XCS performance are presented in Figure 8. Regardless of the performance metric, the system outperformed XCS at the fixed mutation rates of 0.01, 0.05, or 0.09. At a fixed mutation rate of 0.09, the performance ρ and system error metrics for the CA-XCS outperformed those from the XCS. At a fixed mutation rate of 0.01, the population size metric for the CA-XCS was similar to that from the XCS. An optimal solution aimed at the 6-MP version B was rebuilt after 20,000 trials.

As shown in Figure 9, the mutation rate curve has two peaks, the first just before 2,500 trials and the second between 10,000 and 12,400 trials. Each peak reflects the learning time required by the CA-XCS. According to these results, the CA-XCS is capable of handling non-stationary single-step problems at a high performance level.

5 Conclusions

Previous studies of ECs and LCSs describe the search for robust or optimal parameter sets for target problem solutions as a time-intensive trial-and-error task requiring large amounts of computation resources. Different parameter values are essential for inducing an optimal balance between exploration and exploitation at different run stages. In response to the common problem of setting parameters for practical applications, we extended the original LCS with a parameter control approach in order to enhance performance and learning stability.

Our proposal for a co-adaptive approach to LCS parameters is based on a coevolution process and a Dyna architecture. The approach takes advantage of the on-line learning capabilities of LCSs; solutions produced in this manner cover entire target problems. Results from our experiments show that the co-adaptive approach was successful in terms of setting parameters according to target problem properties. In both stationary and non-stationary problem experiments, the system outperformed the models it was tested against.

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