Infeasibility Driven Evolutionary Algorithm with the Anticipation Mechanism for the Reaching Goal in Dynamic Constrained Inverse Kinematics

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ABSTRACT

A dynamic version of the Inverse Kinematics problem addresses the two main objectives: One objective is to find a configuration of joints such that a desired pose and orientation can be reached by a robotic arm. Another one is to preserve this state in a continuously changing environment. In this paper a reaching goal in dynamic constrained Inverse Kinematics is considered where either a target point to be reached or locations of obstacles or both can change in time. The Infeasibility Driven Evolutionary Algorithm is applied for an exploration of the set of possible joint angles configurations in every moment. Additionally, the anticipation mechanism based on Auto-Regressive Integrated Moving Average Model is used in order to speed up an adaptation process so that a population of candidate solutions can be directed in advance towards the most probable future global optima.

1. INTRODUCTION

A robotic arm in the 2-dimensional Inverse Kinematics (IK) [3] can be parametrized with a single starting point $(x_{start}, y_{start}) \in \mathbb{R}^2$ and $d > 0$ tuples $(l_i, \alpha_i^{min}, \alpha_i^{max})$ for $i = 1, \ldots, d$, where $l_i \in \mathbb{R}_+$ is the length of the i-th segment while $0 \leq \alpha_i^{min} < \alpha_i^{max} \leq 2\pi$ are, respectively, the minimum and maximum angles achievable by the i-th joint. Due to the rigidity of robotic arms it is assumed that once the above parameters are set, any configuration of an arm can be fully described with a vector of relative angles $\alpha = (\alpha_1, \alpha_2, \ldots, \alpha_d) \in \mathbb{R}^d$ where $\alpha_i \in [\alpha_i^{min}, \alpha_i^{max}]$ for $i = 1, \ldots, d$.

In this paper a reaching goal of such arm in the 2D environments with moving obstacles and/or a moving target point is considered. In the proposed approach the above goal is formulated as the Dynamic Constrained Optimization Problem (DCOP) set in the space of all the possible arm configurations with the restriction that only those ones that encode the arms which do not cross any obstacles at the moment can be treated as *feasible* whereas all the other ones are labeled *infeasible*.

The contribution of this paper is twofold. Firstly, an adaptation of the modified Infeasibility Driven Evolutionary Algorithm with the anticipation mechanism based on Auto-Regressive Integrated Moving Average Model (abbreviated mIDEA-ARIMA) [2] is proposed. As a result the process of maintaining the desired pose of a robotic arm is improved due to predictions of the most probable future landscapes that allow for acting prior to incoming changes. Secondly, an additional optimization criterion for minimizing the displacement between joint angles configurations obtained in the consecutive time steps is introduced. This modification assures a smooth motion of a robotic arm that otherwise would be expected to reconfigure itself in an instant in order to catch up with changing locations of global optima.

2. ALGORITHM

The strategy of maintaining a small fraction of good yet infeasible individuals in the population and minimizing their violation measure is the key aspect in Infeasibility Driven

Algorithm 1 Pseudo-code of mIDEA-ARIMA for IK

```
S_1 = RandomSamples()
P_1 = RandomPopulation()
Evaluate(P_1)
for t = 1 → N_gen do
  if the function F has changed then
    Re-evaluate(P_t)
    S_t = ReduceSamples(S_t ∪ P_t, M)
    Re-evaluate(S_t \ P_t)
    if t − 1 > N_train then
      P_t^exploit = ReducePopulation(P_t, size_exploit)
      P_t = P_t^exploit ∪ P_t^anticip
    end if
  end if
  P_{t+1} = IDEA_t(P_t, N_sub)
  if t > N_train then
    s_t^* = BestSample(S_t, F̃^(t+1))
    P_{t+1}^anticip = AnticipatingFraction(s_t^*, size_anticip)
  end if
  S_{t+1} = S_t
end for
```


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Evolutionary Algorithm (IDEA) [4] which plays a role of the basic search engine in the proposed approach.

A proactive variant of IDEA, named mIDEA-ARIMA, was introduced in [2]. It applies the anticipation mechanism based on Auto-Regressive Integrated Moving Average (ARIMA) [1] model in order to predict future values of a fitness function using past observations.

Algorithm 1 presents the pseudo-code of mIDEA-ARIMA for IK. In the initialization step it generates a random set of samples S_1 and a random population P_1 both of which have the size of $M > 0$ individuals. The main loop is run $N_{gen} > 0$ times. Anytime a change in the fitness function F is detected (e. g. by observing some samples in S_t), the population P_t is re-evaluated and joined to S_t. Then, the set S_t is reduced to the initial size of M individuals by removing the oldest samples. Eventually, the remaining $S_t \backslash P_t$ samples are also re-evaluated. In the initial $N_{train} > 0$ iterations the anticipation mechanism only collects the data and so it does not give any output. If $t - 1 > N_{train}$ (which means that the training period has ended in the previous step and so the anticipating fraction $P_t^{anticip}$ is now ready), the population P_t is reduced to the exploiting fraction $P_t^{exploit}$ consisting of $size_{exploit} \cdot M$ individuals ($0 < size_{exploit} < 1$). The population P_t then becomes the union of $P_t^{exploit}$ and $P_t^{anticip}$.

For each generation t the single step of IDEA is run. When it ends the ARIMA-based anticipation mechanism is invoked providing that $t > N_{train}$. As a result the new anticipating fraction $P_{t+1}^{anticip}$ is produced for the next generation and then the iteration completes.

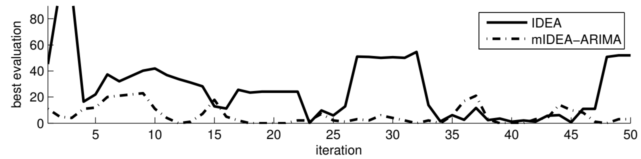
3. EXPERIMENTS

The experiments were performed on the three benchmarks being virtual arenas with the three types of moving obstacles and/or the target point. Each of the 9 experiments (3 arenas $\times$ 3 motion types: *sliding*, *swinging* and *zig-zag*) lasted for $N_{gen} = 100$ generations (one generation per time tick, $t = 1, 2, \ldots, 100$). For simplicity, all the angle ranges were set to $[0, 2\pi]$.

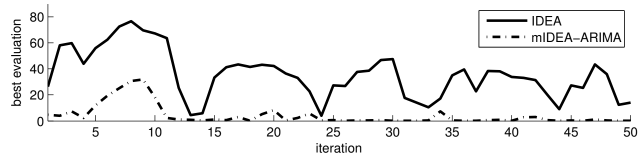
The objective function was the Euclidean distance between the end effector and the current location of the target point. Additionally, the following two minimization criteria were considered — *violation measure* (i. e. the Euclidean distance to the nearest feasible solution) and *displacement* (i. e. the Euclidean distance to the latest configuration of a given arm). Individuals with positive violation measures or displacements exceeding a predefined threshold $\eta_{max} \in \mathbb{R}_+$ were marked as *infeasible*.

The suggested mIDEA-ARIMA algorithm was run with the population of $M = 100$ individuals out of which 20% were infeasible ($size_{infeas} = 0.2$). The 10 variants of the anticipation fraction size ($size_{anticip} \in \{0.1, 0.2, \ldots, 1.0\}$) and the 5 variants of the robotic arm displacement threshold ($\eta_{max} \in \{1, 2, 3, 4, 5\}$) were considered. Each t-th step of the original IDEA_t was executed for $N_{sub} = 2$ generations. The training period of the ARIMA-based anticipation mechanism took $N_{train} = 10$ initial iterations of every run.

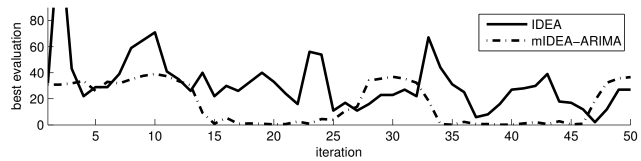
It turned out that mIDEA-ARIMA outperformed the original IDEA in all of the analyzed cases. The smallest difference between results obtained in these two approaches was observed in the presence of the sliding motion. The other two types of motion were evidently easier to deal with. The difference between results of IDEA and mIDEA-ARIMA was significantly greater than in the first case. Neither swinging motion nor the zig-zag one had any rapid shifts hence they were more likely to be predicted accurately.



(a) $\eta_{max} = 1$



(b) $\eta_{max} = 3$



(c) $\eta_{max} = 5$

Figure 1: Sample run of the initial 50 generations of IDEA and mIDEA-ARIMA in the arena with the swinging type of motion.

Figure 1 present the objective function values of best feasible individuals during sample runs of the initial 50 generations of IDEA and mIDEA-ARIMA in the arena with the swinging type of motion. It is visible that the highest performance of the proposed approach was achieved soon after the training period of the initial 10 generations had completed.

4. CONCLUSIONS & FUTURE WORK

In this paper the adaptation of mIDEA-ARIMA for the dynamic 2D constrained IK problem was proposed. Also, the additional optimization criterion for minimizing the displacement between joint angles configurations was introduced to assure the smoothness of a robotic arm motion.

The preliminary experiments demonstrated the superiority of the suggested proactive approach in comparison with the original IDEA in the examined IK problems. The future work should cover enlarging the anticipated time horizon from one step ahead to as many steps ahead as possible.

5. REFERENCES

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