Master's Thesis

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Image registration dings mit machine learning

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Hamburg, den ??.??.2010

Contents

Abstract

1

Introduction

2 Theory

2.1 Parametric image registration

2.1.1 Landmark-based registration

2.1.2 Principal axes-based registration

2.1.3 Optimal linear registration

Intensity-based registration

Correlation-based registration

Mutual information-based registration

2.2 Non-parametric image registration

2.2.1 Elastic registration

2.2.2 Fluid registration

2.2.3 Diffusion registration

2.2.4 Curvature registration

2.3 Reinforcement learning

In Reinforcement Learning, an agent is supposed to learn a specific behavior by trial-anderror. The agent interacts with its environment to collect experiences. Figure 2.6 illustrates the basic concept behind Reinforcement Learning. At each time step t = 1, 2, 3, ... the agent is in a certain state $s \in \mathcal{S}$ and takes one of the possible available actions $a \in \mathcal{A}(s)$. The action changes the environment and the agent ends up in a new state st+1. Furthermore, it receives a reward Rt+1 from the environment that serves as a feedback about how good it was to take action at in state st

2.3.1 Markov Decision Process

The Markov Assumption assumes an independence of past and future states, meaning that the state and the behavior of the environment at time step t are not influenced by the past agent-environment interactions $a_1, ..., a_{t-1}$ If the RL-task can fulfill the Markov Assumption, it can be formulated as five-tuple Markov Decision Process $(\mathcal{S}, \mathcal{A}, \mathcal{P}^a_{s,s'}, \mathcal{R}^a_{s,s'}, \gamma)$

- $\mathcal{S}$: set of states
- $\mathcal{A}$: set of actions. $\mathcal{A}(s)$ is the best action in state s.
- $\mathcal{P}^a_{s,s'}$: Transition probabilities. It is the probability of the transition from s to s' when taking action a in state s at time step t.
- $\mathcal{R}^a_{s,s'}$: Reward probabilities. It defines the immediate reward the agent receives after the transition from s to s'
- γ: Discount factor.$\gamma \in [0, 1]$ for computing the discounted expected return

3
Experimental Setup

4
Discussion

5
Conclusion