

#### Master's Thesis

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### Image registration dings mit machine learning

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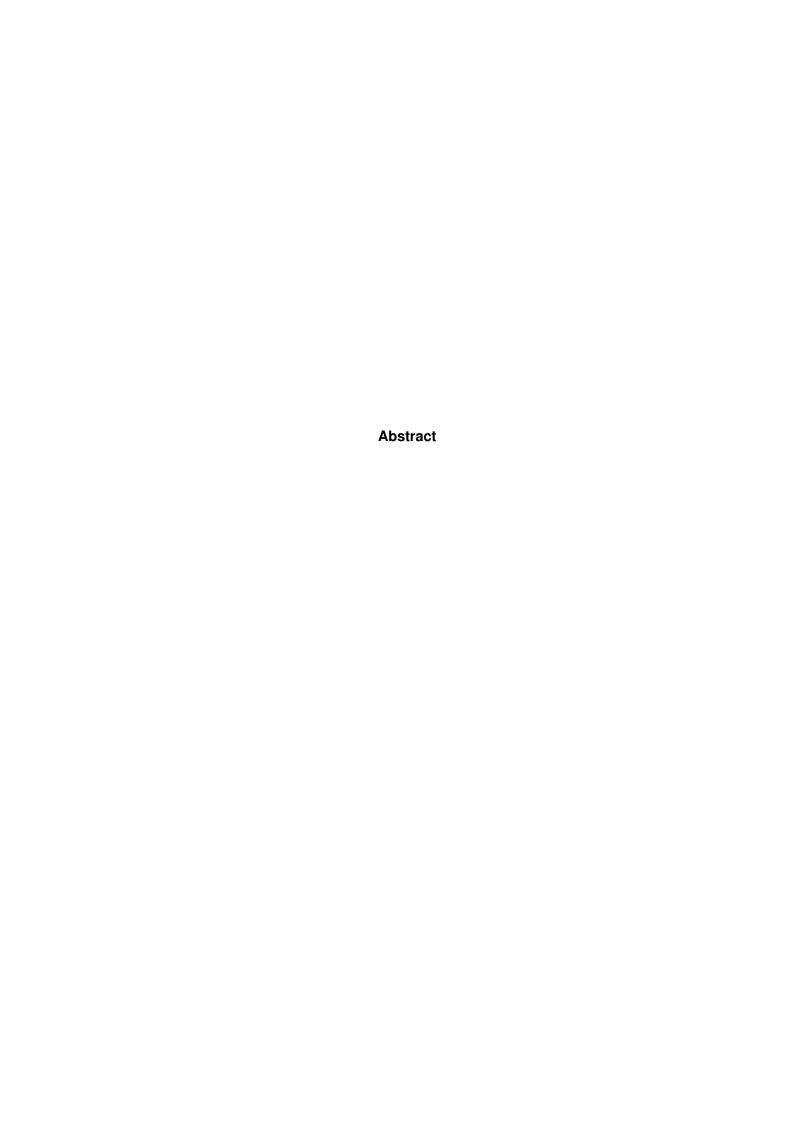
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Ich versichere an Eides statt, die vorliegende Arbeit selbstständig und nur unter Benutzung der angegebenen Quellen und Hilfsmittel angefertigt zu haben.
Hamburg, den ??.??.2010

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## 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  $s \in S$  and takes one of the possible available actions  $a \in \mathcal{A}(s)$ . The action

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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  $(S, \mathcal{A}, \mathcal{P}_{s,s'}^a, \mathcal{R}_{s,s'}^a, \gamma)$ 

- 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'
- $\gamma$ : Discount factor. $\gamma \in [0, 1]$  for computing the discounted expected return

# **S**Experimental Setup

## 4. Discussion

### Conclusion