# Providing Effective Real-time Feedback in Simulation-based Surgical Training

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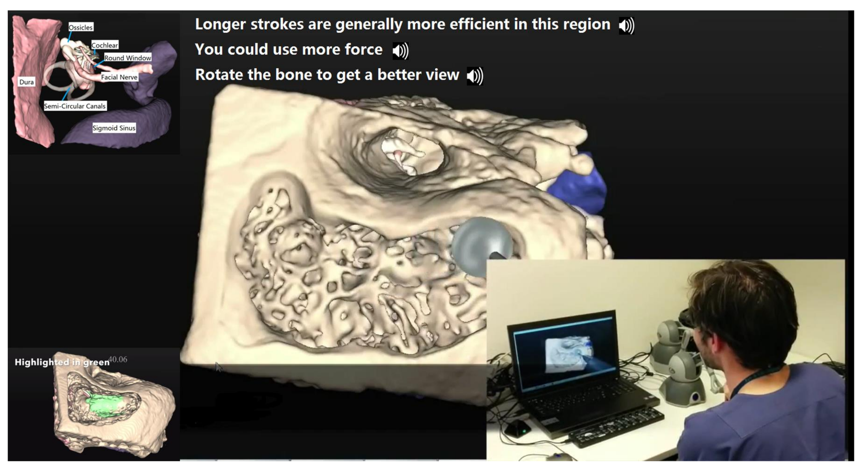
## Introduction

- Virtual Reality (VR) simulators are effective tools for surgical training.
- **Automated real-time performance feedback** is an essential part of VR based surgical training.

Challenges for feedback**:**

A. Effectiveness: should improve novice skill to expert skill
B. Simplicity: refers only one feature change: less distraction & cognitive load.
C. Efficiency: provided within 1s after novice skill is performed.



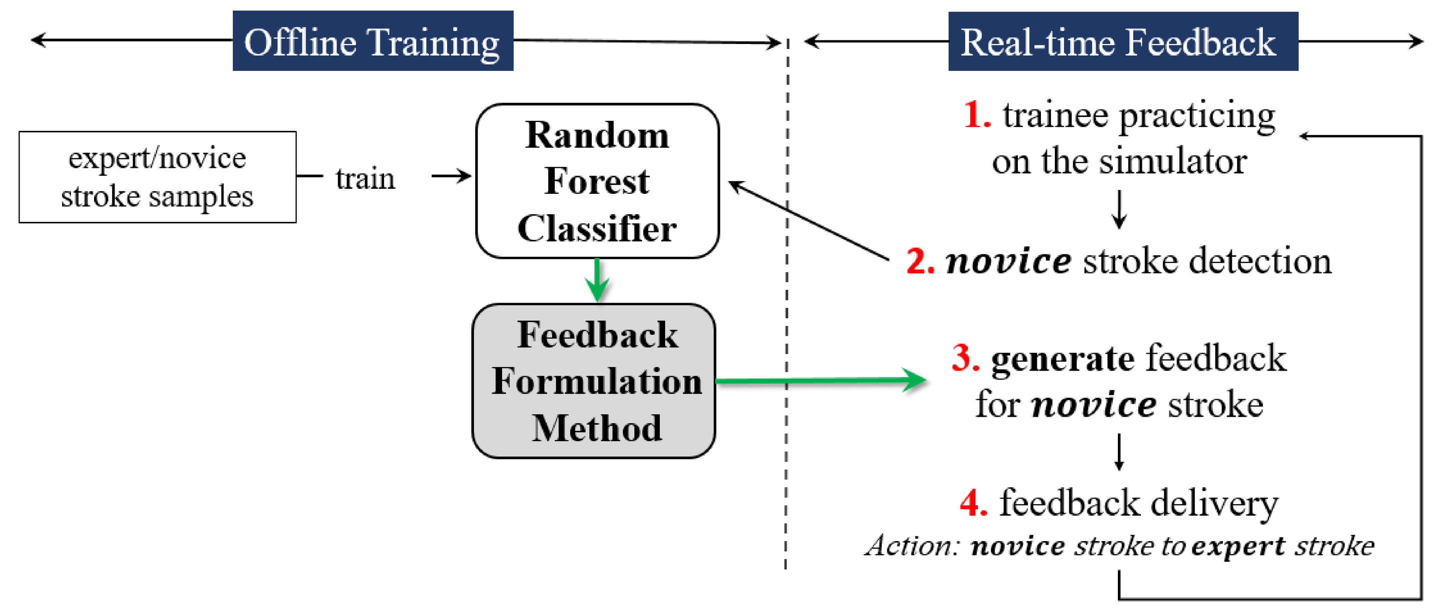

Our Virtual Reality Temporal Bone Surgery Simulator: 3D simulation with haptic drilling.

## Real-time Feedback Problem

- Surgical skill is defined by: drilling **stroke** (force, speed, duration, acceleration, straightness).
- Real-time feedback problem: find **optimal actions** to improve novice strokes detected in real-time during training:

*Problem:* Given a random forest classifier $F(x)$ and a novice instance $x$, the problem is to find the optimal action $A: x \to x_f$ that changes $x$ to an instance $x_f$ with at most one feature change such that $x_f$ has the highest probability of being in the expert class:

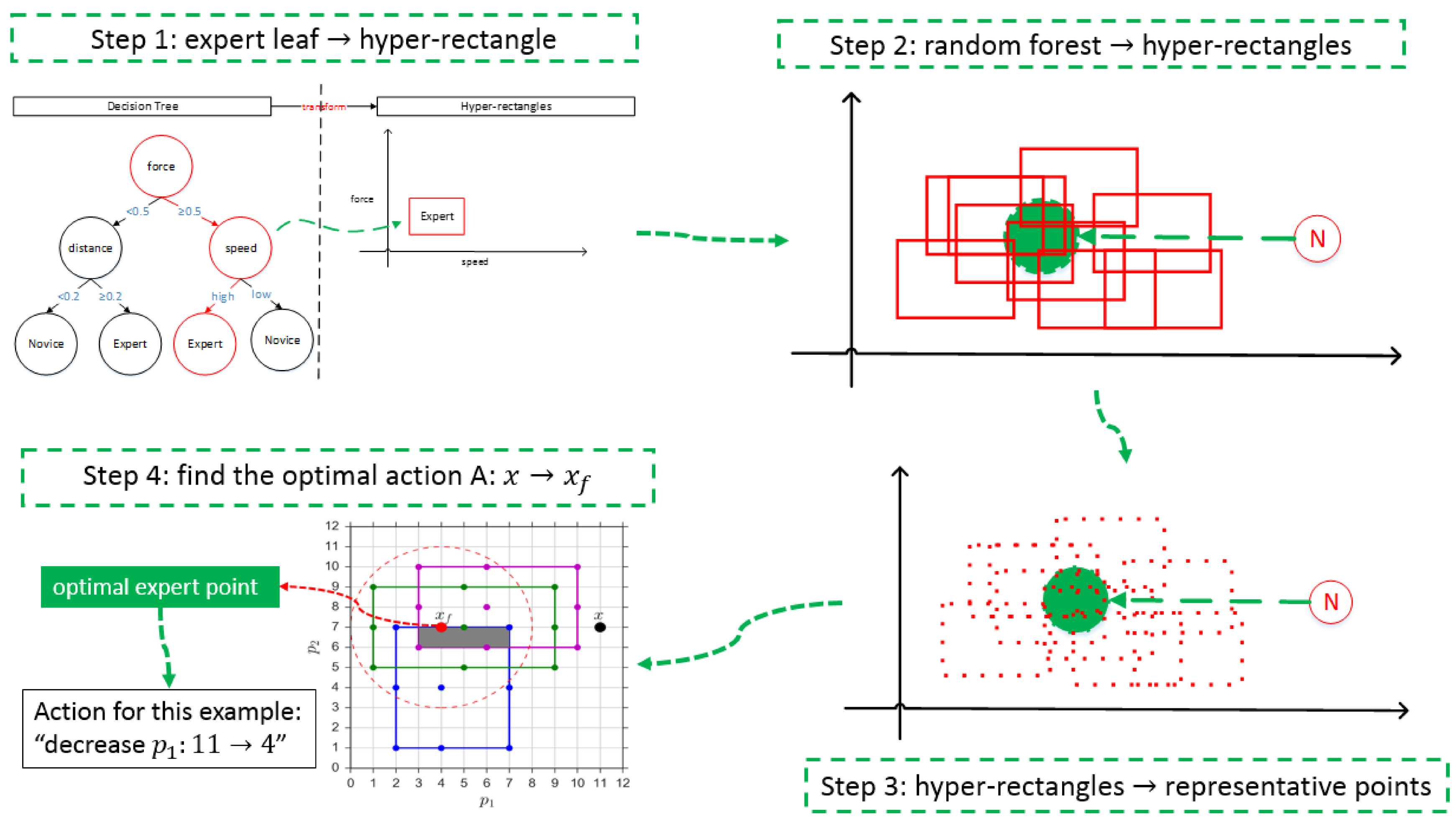
$$\underset{A: x \to x_f}{\operatorname{argmax}} F(x), \qquad \text{subject to } \|x - x_f\|_0 \leq 1$$




Real-time feedback formulation process

Feedback example, action $A: (force = \mathbf{0.2},\ speed = 0.3) \to (force = \mathbf{0.5},\ speed = 0.3)$ → feedback "**increase force to 0.5**".

## Random Forest based Feedback Formulation




Proposed method: **Discrete Approximation (DA)**

## Conclusions

- We discussed the problem of formulating feedback and proposed a novel method to formulate feedback using random forests.
- Random forests can be compressed to a few representative points using our discretization and approximation method.
- Our proposed method formulates highly effective feedback while remaining low time-cost, and it scales well to large random forests.

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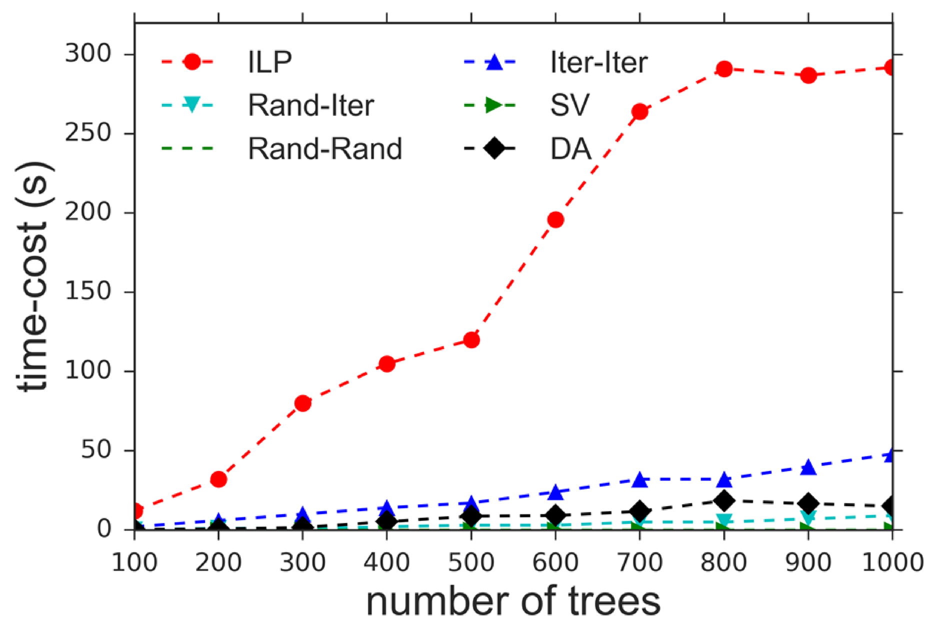
## Experiments

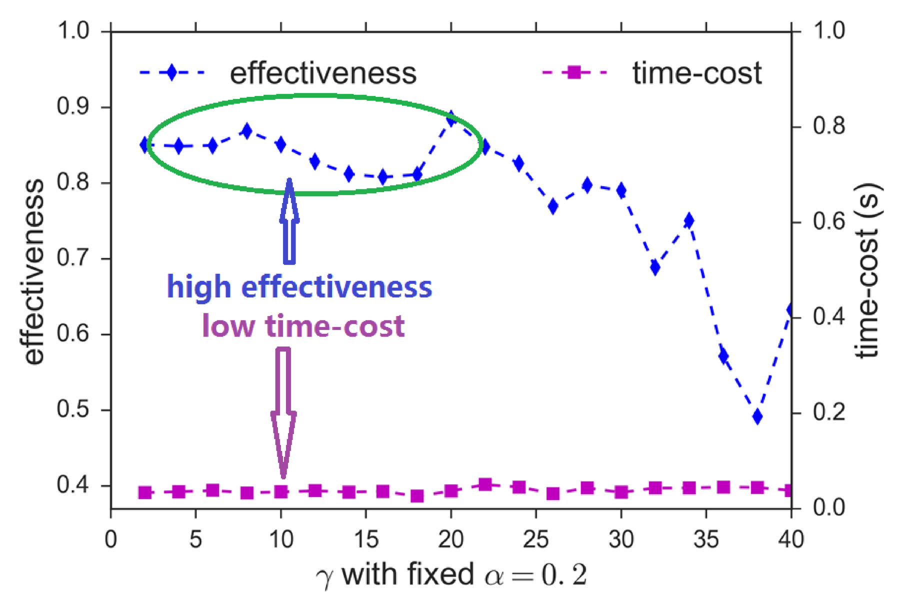
- Data: 28K expert strokes vs 32K novice strokes from 7 surgeons vs 12 students.
- **DA** vs 5 other methods: Performance and Scalability

| | Rand-Rand | Iter-Iter | Rand-Iter | ILP | SV | DA |
|---|---|---|---|---|---|---|
| success rate | 0.21±0.04 | **0.89±0.00** | 0.36±0.05 | **0.89±0.00** | 0.60±0.05 | **0.89±0.00** |
| effectiveness | 0.18±0.23 | **0.87±0.06** | 0.40±0.30 | **0.87±0.06** | 0.65±0.33 | 0.84±0.08 |
| time-cost (s) | **0.00±0.00** | 12.17±0.14 | 0.36±0.05 | 32.07±2.57 | 0.02±0.00 | 0.26±0.15 |

✓ **DA: high** success-rate & effectiveness while **low** time-cost




✓ **DA** scales well to large random forests




$\alpha$: how many points used for approximation
$\gamma$: search radius when search densest area for optimal expert point.

✓ **DA** balances time-cost and effectiveness with small $\alpha$ and $\gamma$.