# Development of Classification Algorithm for Estimating Physical Task Demands Using Inertial Sensors

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## Introduction

- Prolonged awkward postures and high force exertions during manual work are known risk factors for musculoskeletal disorders [1].
- Successful work design and injury prevention programs rely on quantifying cumulative exposures to ergonomic risk factors under naturalistic work conditions.
- Wearable inertial sensors show strong potential for field-based ergonomics assessments; however, algorithms to classify physical tasks and demands are necessary.

**The study objective is to:**

1. Compare various classification techniques with data obtained from inertial sensors,
2. Develop an algorithm to classify physical task demands.

## Data Collection

**Participants:**
15 right-handed males (age: 24.21 ± 3.98 years, height: 176.52 ± 47 cm)

**Experimental Procedure**
• Task: Participants exerted a horizontal isometric push and pull force on a height adjustable handle instrumented with a 6 dof load cell

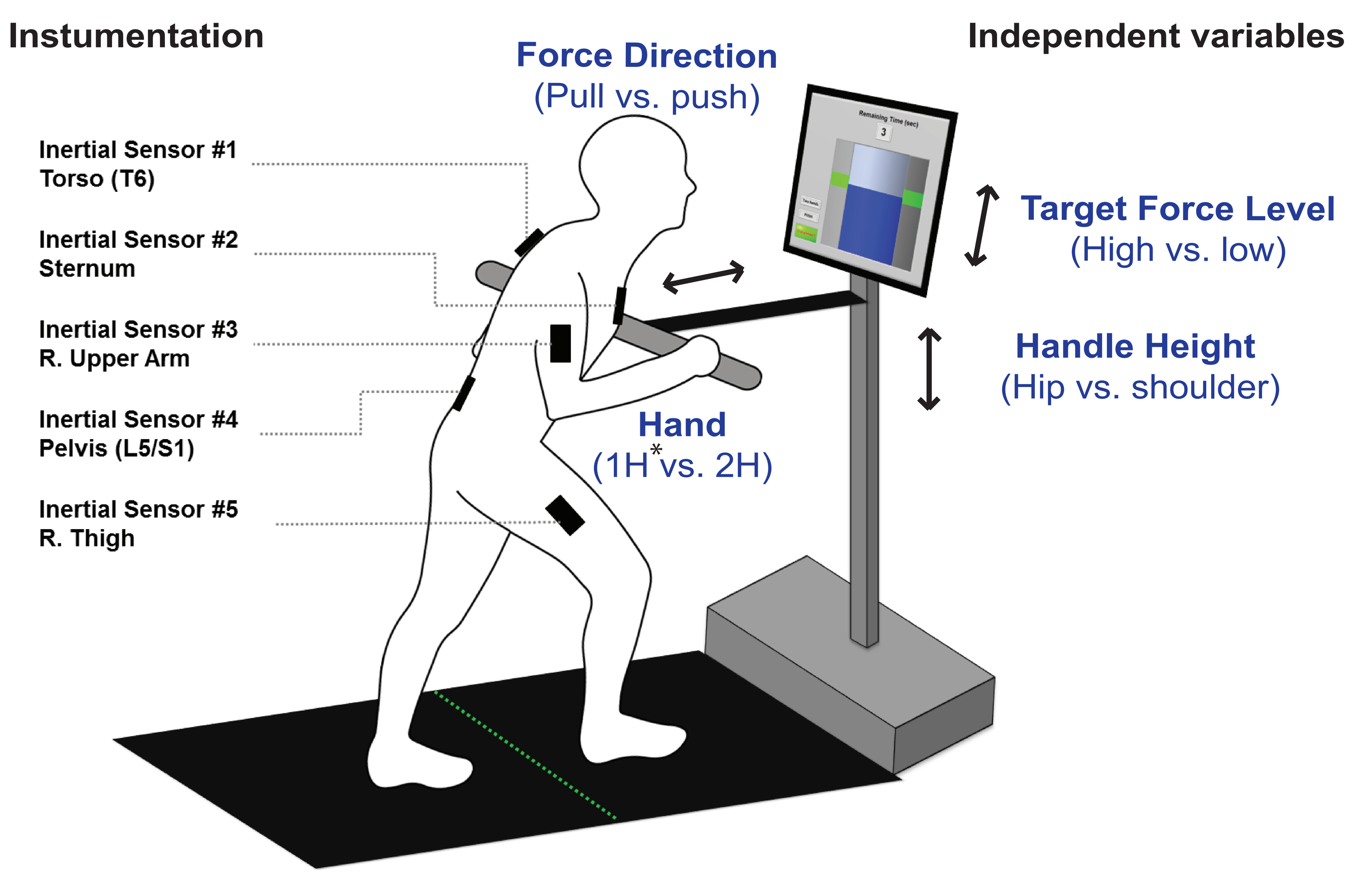



**Fig. 1.** Experiment setup showing anatomical reference location for the inertial sensors (YEI Inc., #1~5, on the left) and indepentent variables (on the right). Target force level was set as a % of maximum push exertion force (MVE) at hip height using the test metrics shown below.

| Handle Height | Target Force | Force Direction and Magnitude % MVE | |
|---|---|---|---|
| | | Push | Pull |
| Shoulder | Low | 19.2 | 15.9 |
| | High | 57.7 | 47.6 |
| Hip | Low | 25.0 | 20.6 |
| | High | 75.0 | 61.9 |

Shoulder = 0.77 x Hip

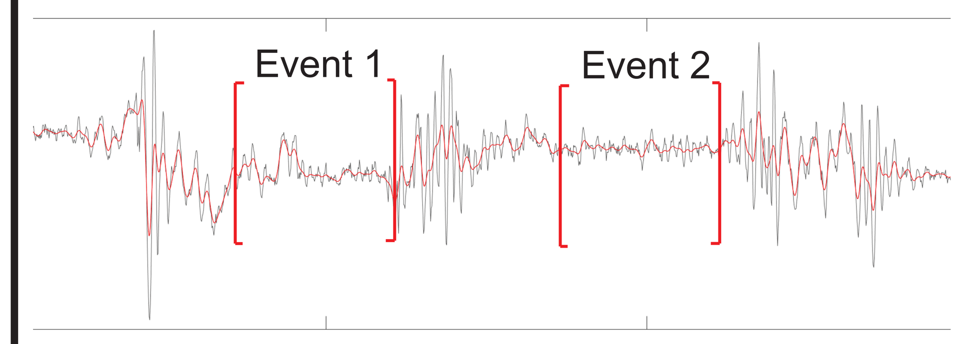
PULL = 0.83 x PUSH

* Target force for 1H = 0.73 x 2H [2]

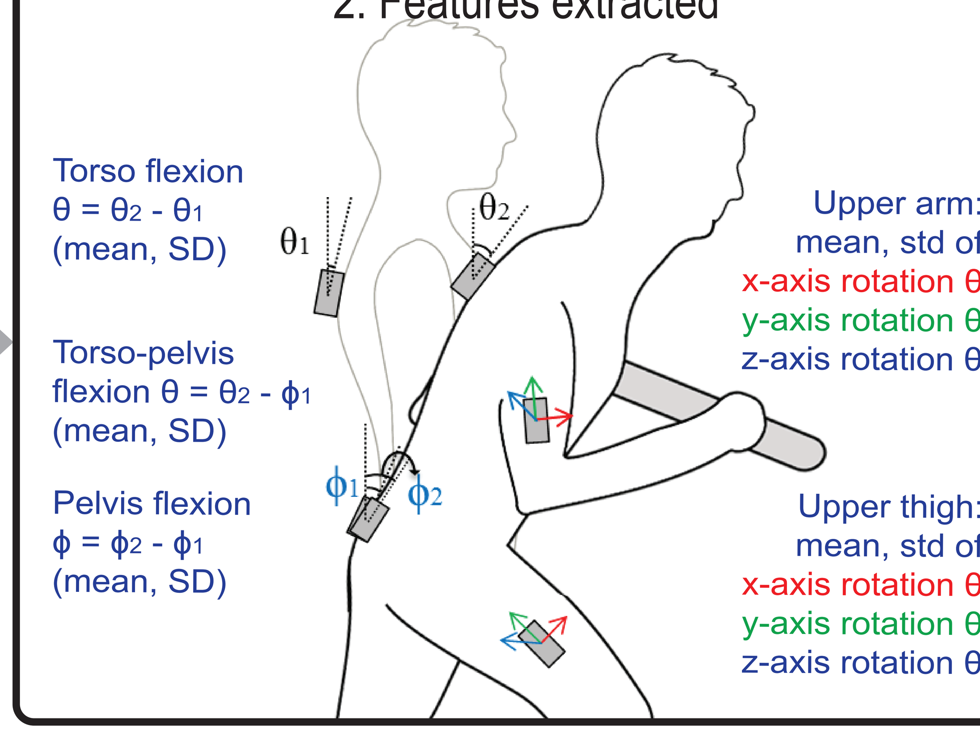
## Data Analysis and Results

### 1. Preprocessing & Segmenting

- Sampling frequency: 100 Hz
- Filtering: second-order low-pass zero-lag Butterworth filter (6 Hz cut-off frequency)
- Event segmentation: 3s of isometric exertion within target force range

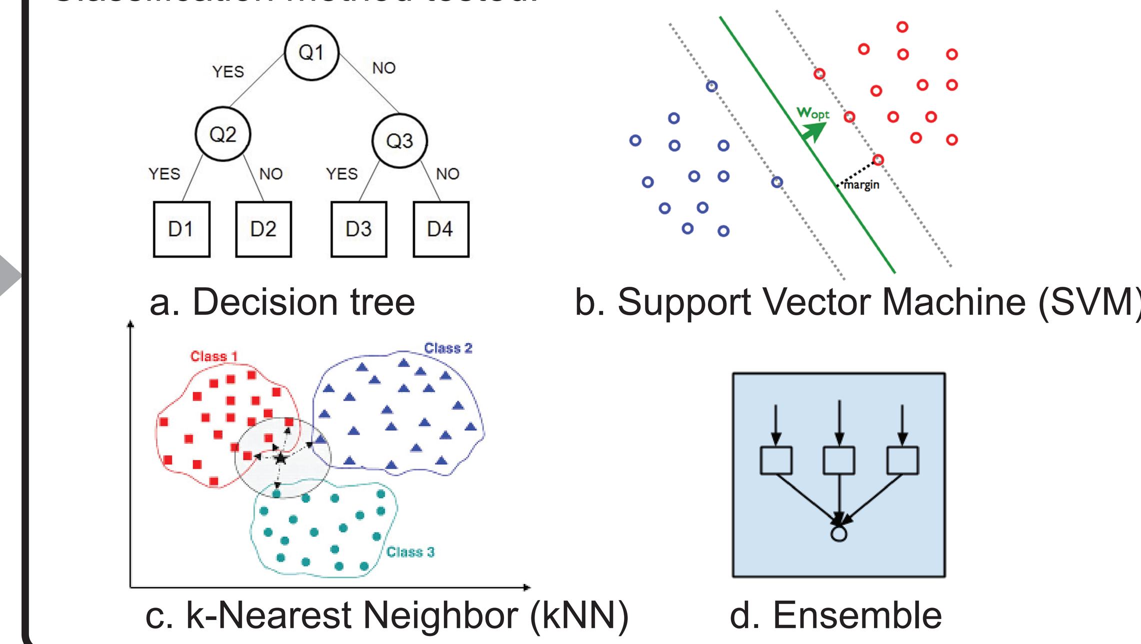



### 2. Features extracted




### 3. Classification

Classification method tested:




### 4. Classification Performance

Comparison of classification performance at Level 1

| Method | Accuracy (%) |
|---|---|
| a. Decision tree | |
| Simple decision tree | 87.8 |
| Complex decision tree | 88.7 |
| b. SVM | |
| Linear SVM | 86.8 |
| Quadratic SVM | 87.1 |
| Fine Gaussian SVM | 66.9 |
| c. kNN | |
| Fine kNN | 82.6 |
| d. Ensemble | |
| Boosted tree | 93.6 |
| Bagged tree | 98.8 |

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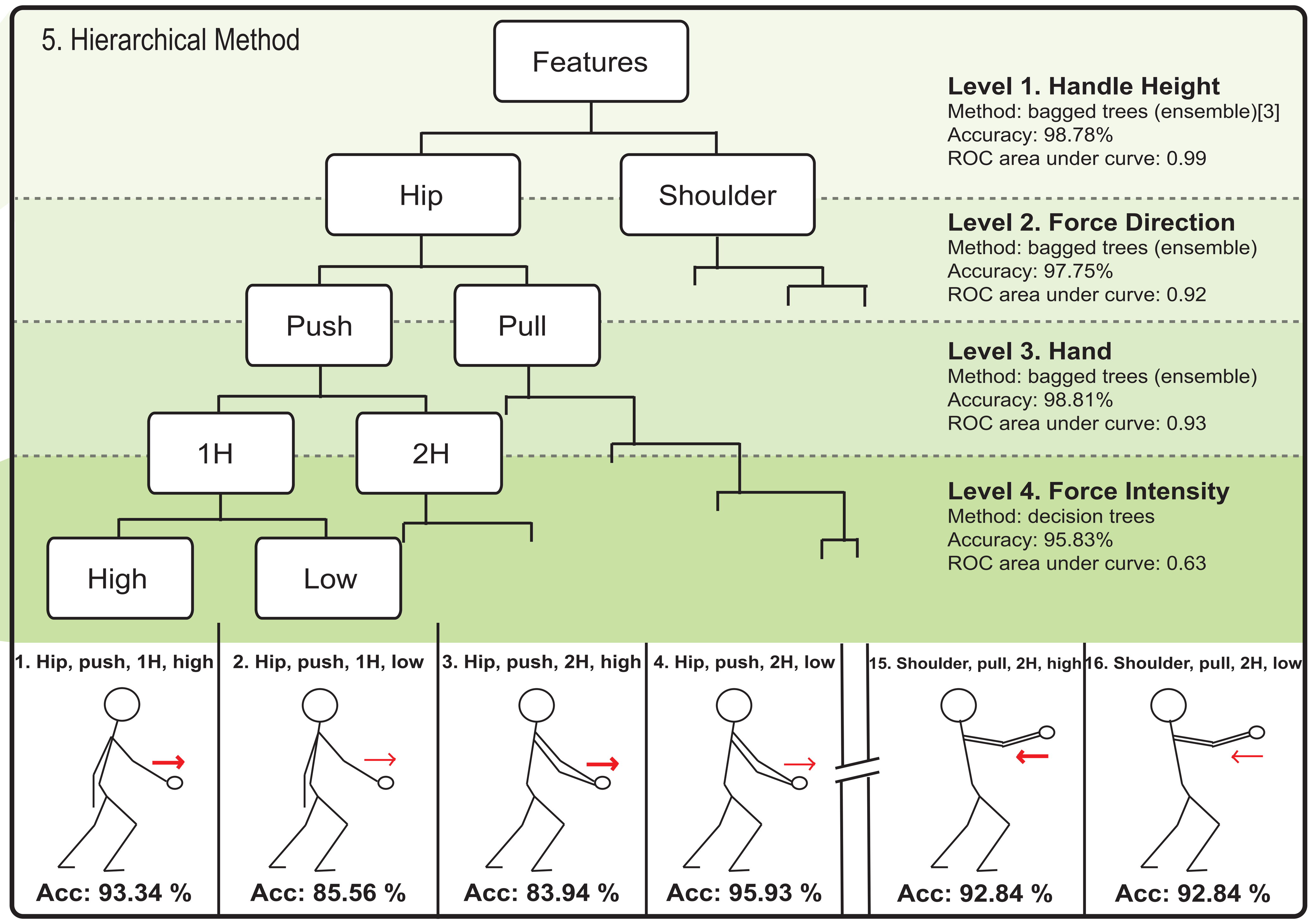
Comparison of classification performance at Level 4

| Method | Accuracy (%) |
|---|---|
| a. Decision tree | |
| Simple decision tree | 95.8 |
| Complex decision tree | 80.9 |
| b. SVM | |
| Linear SVM | 75.8 |
| Quadratic SVM | 77.5 |
| Fine Gaussian SVM | 60.2 |
| c. kNN | |
| Fine kNN | 67.9 |
| d. Ensemble | |
| Boosted tree | 74.5 |
| Bagged tree | 74.3 |

### 5. Hierarchical Method




## Finding & Next Steps

- Overall classification accuracy for all 16 classes was 91.40 %, which was higher than 39.9% when the hierarchical method was not used.
- Order of variables in hierarchical structure affects the quality of classification accuracy. In this analysis, type of variables chosen for each level was selected in advance by a prior knowledge on the data [4]. Bagged trees and decision trees outperformed compared to other classification methods.
- Work is on-going to identify tasks such as lifting, walking, and carrying, and task intensities of each task type.
- Test on the performance of the algorithm in the field involving manual work

## Acknowledgements

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## References

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[3] Chau, T. (2001). A review of analytical techniques for gait data. Part 1: fuzzy, statistical and fractal methods. Gait & posture, 13(1), 49-66.
[4] Sol I. Lim, Andrea Case, Clive D'Souza. (2016). Comparing Postural Responses to Push and Pull Task Demands using Optical Motion vs. Inertial Measurement. 9th International Scientific Conference on the Prevention Work-Related Musculoskeletal Disorders (Accepted).