

# One-handed Keystroke Biometric Identification Competition

John V. Monaco<sup>1</sup>, Gonzalo Perez<sup>1</sup>, Charles C. Tappert<sup>1</sup>, Patrick Bours<sup>2</sup>, Soumik Mondal<sup>2</sup>,  
Sudalai Rajkumar<sup>3</sup>, Aythami Morales<sup>4</sup>, Julian Fierrez<sup>4</sup>, Javier Ortega-Garcia<sup>4</sup>

1. Pace University, 2. Gjøvik University College, 3. Tiger Analytics, 4. Universidad Autónoma de Madrid



## INTRODUCTION

Is it possible for a keystroke biometric system to give accurate results when typing behavior is severely impaired?

This competition aimed to answer that question. Participants built classifiers using a labeled keystroke biometric dataset with normal typing behavior only. They then attempted to identify the subjects in an unlabeled dataset that contained some samples that were typed with only one hand. This scenario simulates a severe user handicap.

Baseline results indicate a severe degradation in performance for one-handed keystroke samples. Participants had to construct novel classifiers capable of identifying normal and handicapped samples in this competition that ranked the identification accuracy under several different typing conditions.

The winning group was awarded a Futronic FS88 Fingerprint Scanner.

## DATA

Three online exams were administered to 64 undergraduate students. Keystrokes were collected using a plugin for Moodle that captures key press and release timestamps on the client and sends this information back to the server.

To simulate a typing impairment, students were instructed to

- Type normally with both hands on the first exam.
- Type with left hand only on the second exam.
- Type with right hand only on the third exam.

Samples were created by taking 500-keystroke segments separated by at least 50 keystrokes apart. The labeled dataset consisted of one normally-typed sample per student. The unlabeled dataset contained 471 samples from all three typing conditions. Not all of the students in the labeled dataset also appeared in the unlabeled dataset. All samples were provided in millisecond precision and normalized to begin at time 0 to avoid linking the samples by the time the test was taken.

Competition participants were allowed to make up to one submission per day, using a plugin for Moodle developed by the authors. Results were automatically scored and remain publicly available:

<http://biometric-competitions.com/mod/competition/leaderboard.php?id=7>

## COMPETITION RESULTS

Rank	Team	Both	Left	Right
1	Gjøvik University College	$82.8 \pm 2.7$	$30.5 \pm 4.0$	$40.2 \pm 4.2$
2	Sudalai Rajkumar S	$82.8 \pm 2.6$	$27.5 \pm 3.9$	$32.1 \pm 4.0$
3	Universidad Autónoma de Madrid	$69.5 \pm 3.2$	$16.8 \pm 3.3$	$20.4 \pm 3.4$
[Baseline]		$61.1 \pm 3.4$	$6.2 \pm 2.1$	$9.5 \pm 2.5$

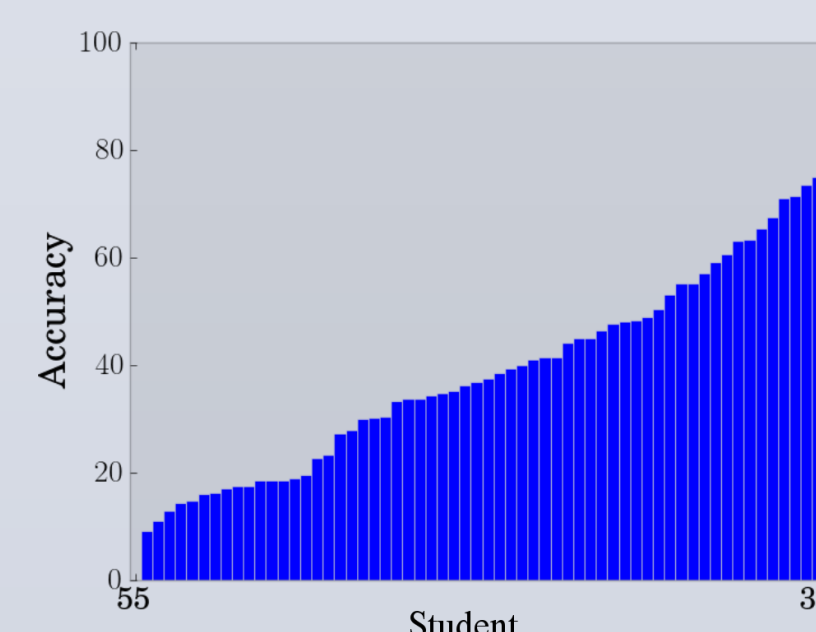
Accuracy for handedness vs. typing condition

		Condition			
		Both	Left	Right	Avg.
Handedness	Ambidextrous	38.9	14.3	1.5	21.2
	Left	41.3	14.6	10.6	25.0
	Right	55.1	17.8	24.4	35.9
	Avg.	53.7	18.3	23.7	35.2

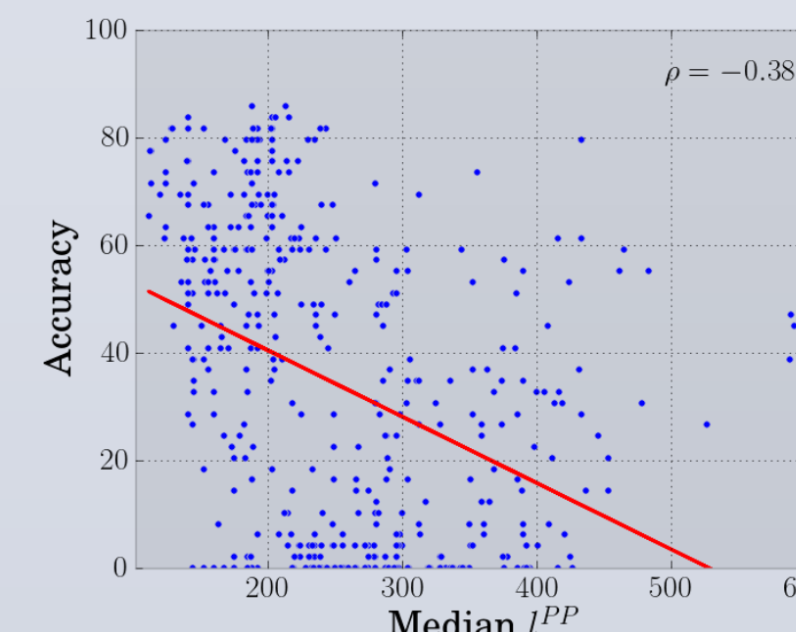
Accuracy for each typing style

Typing style	No. Samples	Accuracy
Hunt-and-peck	91	$43.2 \pm 0.74$
Hunt-and-peck hybrid	144	$33.5 \pm 0.56$
Touchtype	162	$30.5 \pm 0.52$

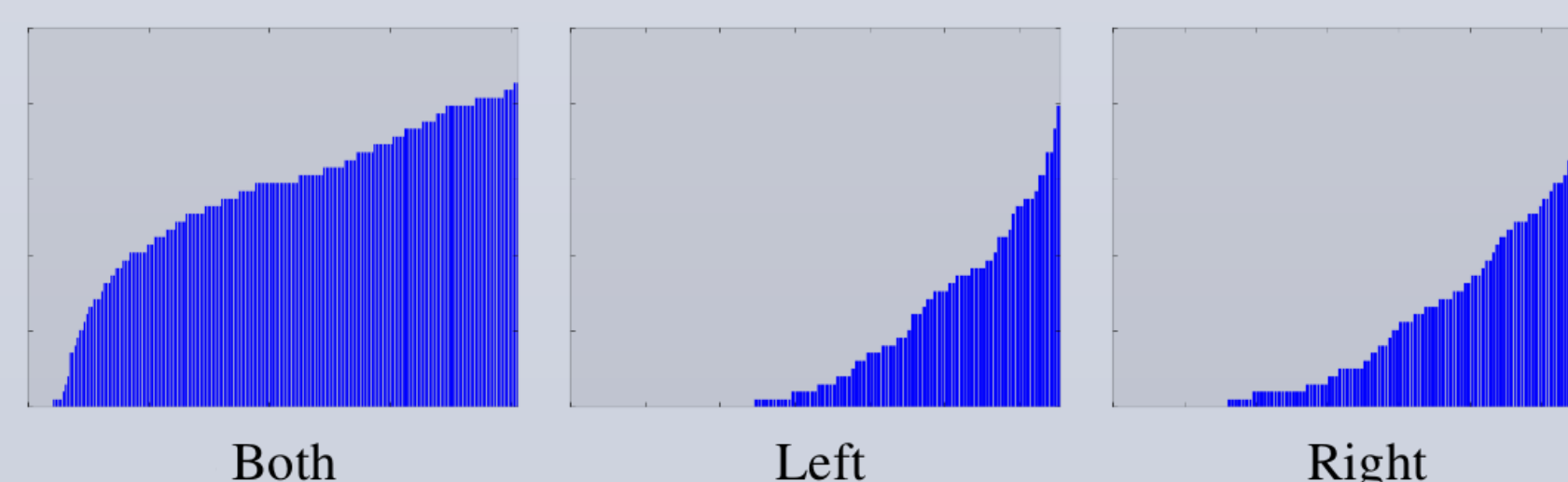
Accuracy distribution per student



Accuracy vs. typing speed



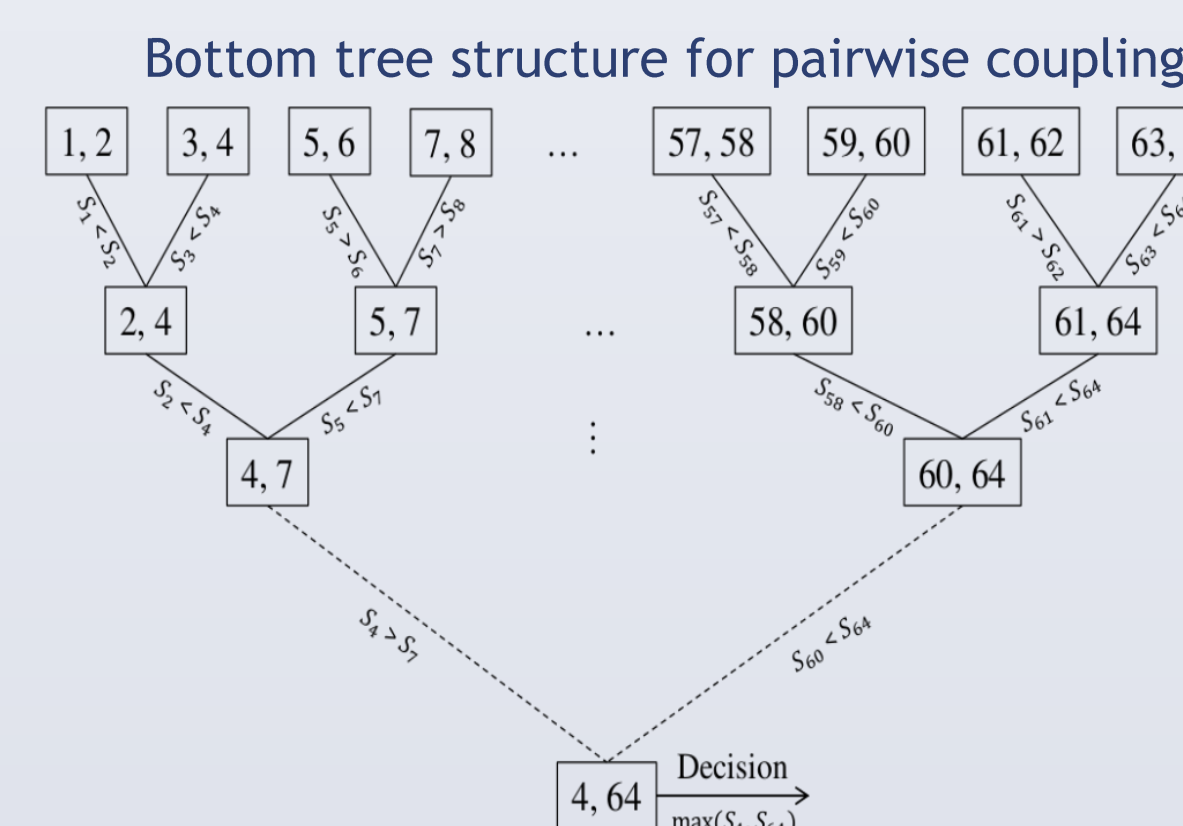
Accuracy distribution per sample for each typing condition



## WINNING STRATEGIES

### First place

- Duration features only
- Multi-classifier pairwise coupling with 2 regression models and a prediction model
  - Artificial Neural Network (ANN)
  - Counter-Propagation Artificial Neural Network (CPANN)
  - Support Vector Machine (SVM)
  - Weighted fusion of classifier scores
- Features corresponding to the typing condition
  - Left-side keyboard features for left-hand typing
  - Right-side keyboard features for right-hand typing



### Second place

- Duration, press-press latency, and release-press latency features
  - Grouped features based on keyboard layout (left vs. right, top vs. bottom)
- Random Forest classifier
- Features corresponding to typing condition, similar as above.

### Third place

- Duration, release-press latency, and trigraph features
  - trigraph features: press to release of alternate keystrokes
- Fusion of normalized distance between feature vectors and Least Squares Support Vector Machine (LS-SVM)
  - Meta-parameters of the LS-SVM determined on an independent dataset
  - Weighted fusion of classifier scores based on individual classifier performance

## ACKNOWLEDGEMENTS

The authors would like to acknowledge the support from the National Science Foundation under Grant No. 1241585. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation or the US government.