Prototype for a virtual keyboard based on IMUs and machine learning

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Introduction

Motivation

Traditional Keyboards

Pros

- easy to learn
- precise
- universal
- cheap

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- not adjustable to task → „shortcuts”

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Alternatives

- voice recognition
- handwriting recognition
- visual methods (eye tracking)

https://en.wikipedia.org/wiki/File:Blackberry-Q10-transparent.png

Vision

1. record finger movements and input while typing

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Vision

1. record finger movements and input while typing
2. use machine learning for input prediction
3. remove keyboard
4. type everywhere

Related Work

Sensor Gloves

- gesture detection [5] [19] [8]
- sign language detection [8] [13]
- music generation [14]
- medical applications [3]

→ overview at [1]

Related Work

Alternative Keyboard Inputs

- buttons on glove [12]
- braille gloves [4]
- "The Learning Keyboard" [7] → Kinect

Figure 1: The Keyglove - a wearable, wireless, open-source input device

https://vimeo.com/23269969

Related Work

Commercial Products

- *Gest* [9] ($ 199, 988 on Kickstarter)
- *Project Virtual Keyboard* [16]
- *Hi5 VR Glove* [10] → VR Gaming

`https://gest.co/`

Figure 2: Gest general purpose interaction wearable

`http://hi5vrglove.com/`

Figure 3: Noitom Hi5 VR Glove

Related Work

In Research

no research project combines

sensor + keyboard data → machine learning

Project Goal

Of course we won’t build a fully working keyboard in 2 bachelor theses.

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Goal

Design a system for recording characteristic hand movements of typing and the corresponding input.

Define an approach for utilizing machine learning to map the recorded data back to the keyboard input.

Evaluate the quality of such mapping and discuss whether this principle could be turned into a working keyboard alternative.

System design

Desired System Properties

- utilizes machine learning
- detects characteristic values
  - fast (goal 100Hz)
  - accurate
  - independent of pose
- non-obstructive
  - flexible
  - wireless
  - light
- software suitable for fast prototyping
- cheap

Sensors

Possible Choices

Flex sensors

https://www.flickr.com/photos/indiamos/3060497602

Figure 4: Possible types of sensors; *left* resistive flex sensors

Sensors

Possible Choices

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Visual system

https://de.wikipedia.org/wiki/Kinect#/media/File:Xbox-360-Kinect-Standalone.png

Figure 4: Possible types of sensors; *left* resistive flex sensors, *center* Kinect for Xbox 360

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IMUs

https://://organicmonkeymotion.wordpress.com/category/propeller/

Figure 4: Possible types of sensors; *left* resistive flex sensors, *center* Kinect for Xbox 360, *right* InvenSense MPU-9150 IMU

Sensors

Inertial Measurement Units (IMUs)

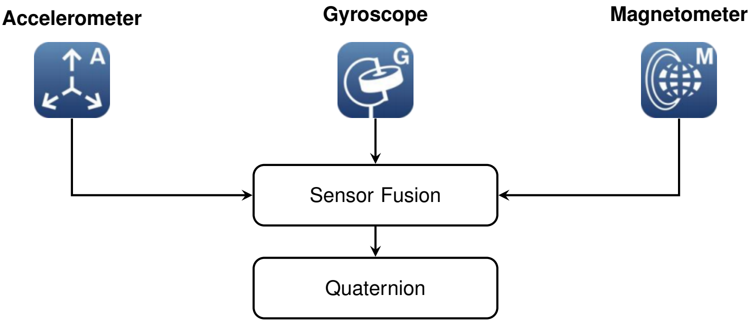
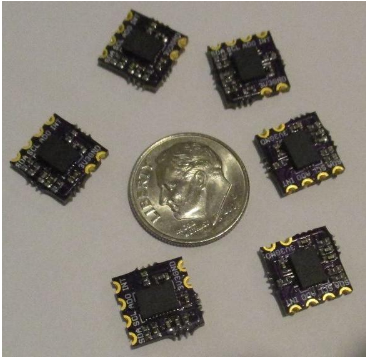


Figure 5: Sensor Fusion Overview

Sensors

Wearable BNO055 Nano Board



https://www.tindie.com/products/onehorse/wearable-bno055-nano-board/

Figure 6: Wearable BNO055 Nano Board

Sensors

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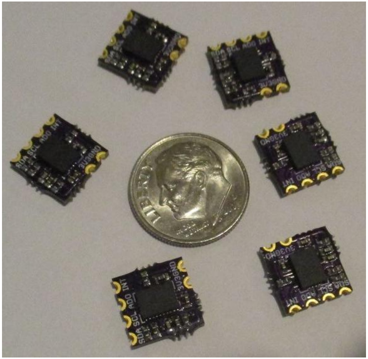

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- 32 bit System-in-Package
- tiny (10 mm × 10 mm)
- easy to use
- good performance (~100 Hz)

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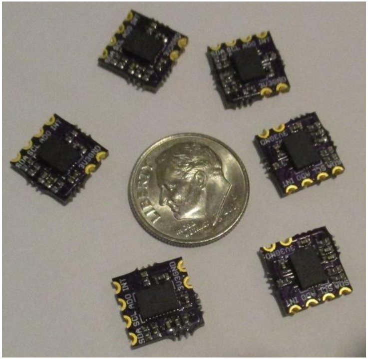

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Figure 6: Wearable BNO055 Nano Board

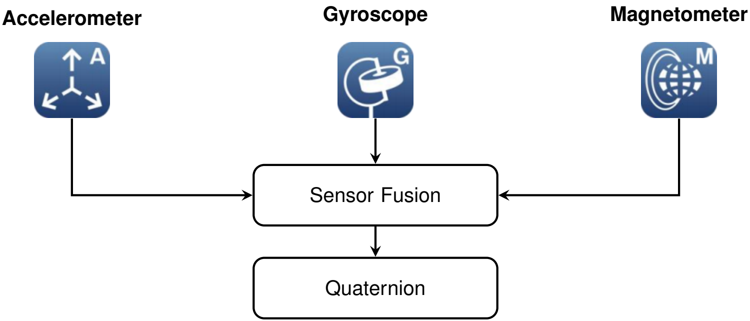
- 32 bit System-in-Package
- tiny (10 mm × 10 mm)
- easy to use
- good performance (~100 Hz)

however...

- ca. 24 € each
- ships from USA
- gyro clipping problems

Sensors

Inertial Measurement Units (IMUs)



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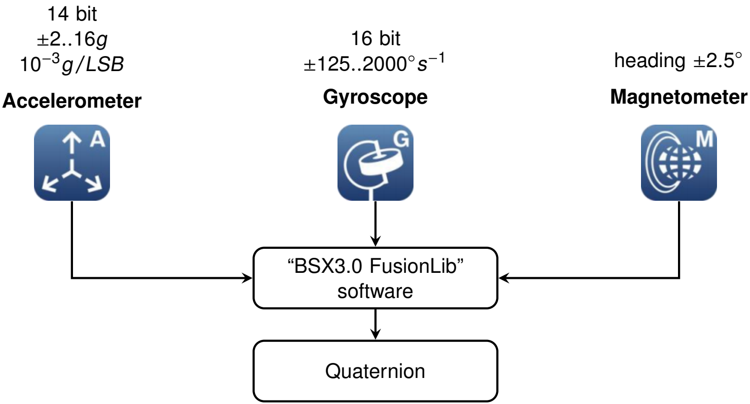

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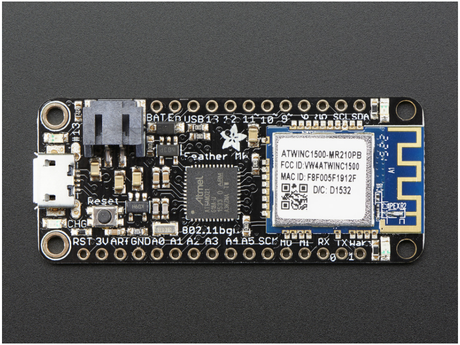
Microprocessor

Adafruit Feather M0 WiFi



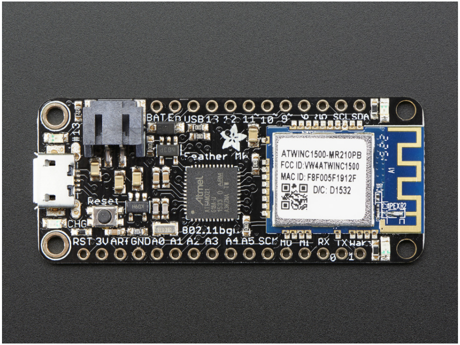
https://www.adafruit.com/product/3010

Figure 7: Adafruit Feather M0 WiFi - ATSAMD21 + ATWINC1500 product image

Microprocessor

Adafruit Feather M0 WiFi

- very small and lightweight (6.1g)
- on-board WiFi
- 6 SERCOMs (SPI/I2C/UART)



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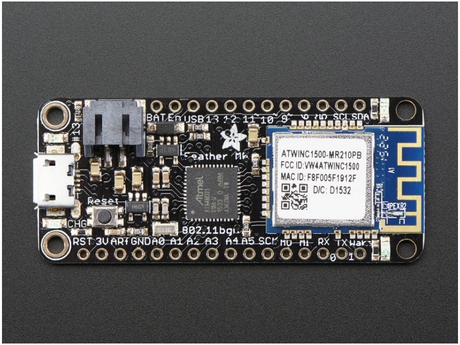
- 256KB FLASH, 32KB SRAM
- LiPo charger



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- on-board WiFi
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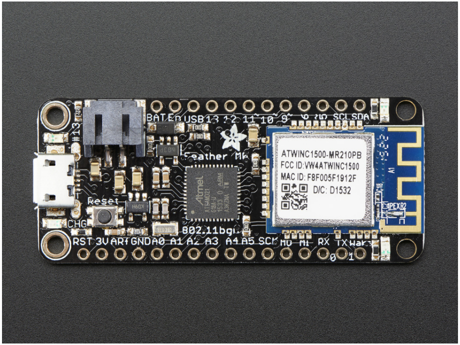
- Arduino® compatible
- 256KB FLASH, 32KB SRAM
- LiPo charger

however...

- no EEPROM
- ca. 40 € each



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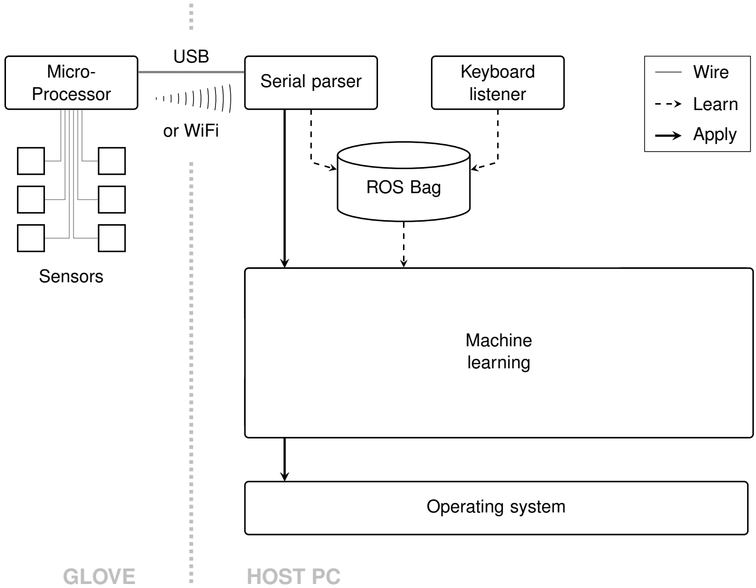
Architecture



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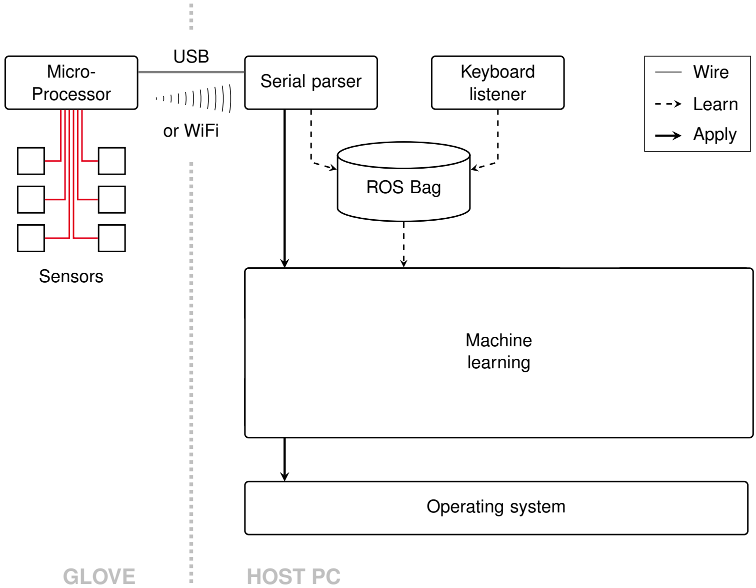

I2C Bus

Requirements

$$\frac{6 \text{ IMUs}}{2 \ \frac{\text{addresses}}{\text{IMU}}} = 3 \text{ buses}$$

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	Primary pads				Alternative pads				
SERCOM	0	1	2	3	0	1	2	3	Used by
0	4	3	1	0	A3	A4	8	9	Serial1
1	11	13	10	12					
2	22		2	5	4	3	1	0	
3	20	21	6*	7*	11	13	10	12	Default I2C
4	22		23*	24*	A1	A2	2	5	SPI
5	A5*		6	7	20	21			Debug Port

* need to be configured as *SERCOM alt*

Table 1: Available SERCOM pin pads on Adafruit Feather M0 WiFi

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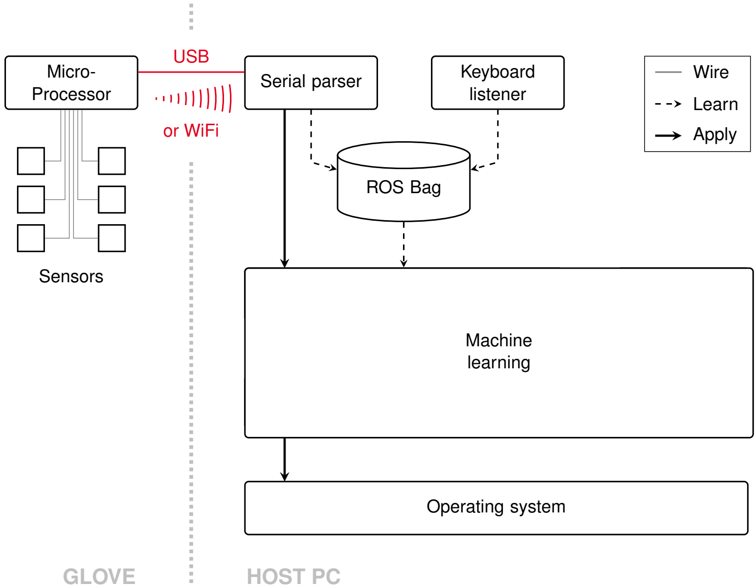
Table 1: Available SERCOM pin pads on Adafruit Feather M0 WiFi

I2C Bus

Arduino Setup

```
#include <Wire.h>
#include <wiring_private.h>

TwoWire wire0(&sercom0, A3, A4);
TwoWire wire1(&sercom3, 11, 13);
TwoWire wire2(&sercom5, 20, 21);

void setup() {
    wire0.begin(); wire0.setClock(400000L);
    wire1.begin(); wire1.setClock(400000L);
    wire2.begin(); wire2.setClock(400000L);
    delay(100);

    pinPeripheral(A3, PIO_SERCOM_ALT); // SERCOM0.0 (alt)
    pinPeripheral(A4, PIO_SERCOM_ALT); // SERCOM0.1 (alt)
    pinPeripheral(11, PIO_SERCOM_ALT); // SERCOM3.0 (alt)
    pinPeripheral(13, PIO_SERCOM_ALT); // SERCOM3.1 (alt)
    pinPeripheral(20, PIO_SERCOM_ALT); // SERCOM5.0 (alt)
    pinPeripheral(21, PIO_SERCOM_ALT); // SERCOM5.1 (alt)
}
```

Glove ↔ PC connection



Glove ↔ PC Connection

WiFi

```
// Setup
WiFi.setPins(8, 7, 4, 2);
WiFi.begin();

// Scan for networks (optional)
uint8_t ssidCount = WiFi.scanNetworks();
for (uint8_t i = 0; i < ssidCount; i++) {
    printf("- %s\n", WiFi.SSID(i));
}

// Connect to WPA2 network
uint8_t status = WiFi.begin(MY_SSID, MY_PASSPHRASE);
while (status != WL_CONNECTED) {
    delay(500);
    status = WiFi.status();
}

// Send data via UDP
WiFiUDP wifiUdp;
wifiUdp.begin(8080);
wifiUdp.beginPacket(TARGET_IP, TARGET_PORT);
wifiUdp.write(buffer, length);
wifiUdp.endPacket();
```

Capabilities

- WEP & WPA2
- Scan networks
- UDP, TCP, SSL
- HTTP Client
- HTTP Server

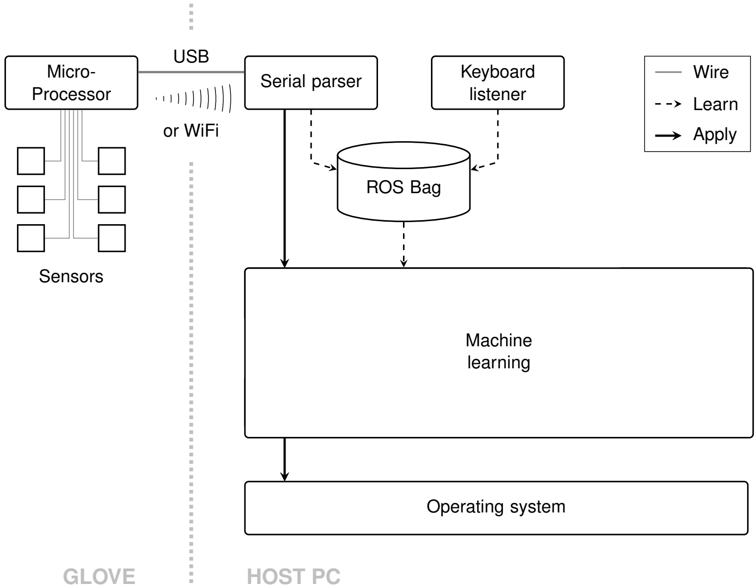
System design

Other Considerations

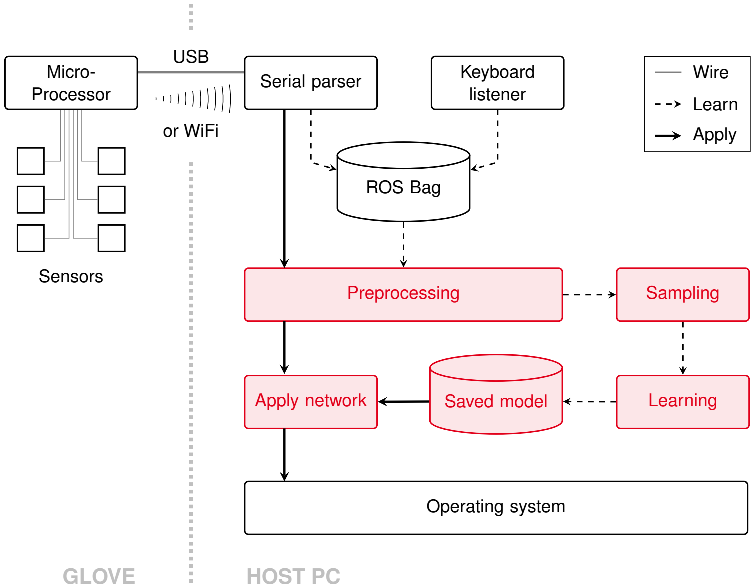
- serial protocol for data transmission
- attachment to the hand
- use ROS for recording & data analysis

Machine Learning

Machine Learning



Machine Learning



Neural Networks

Strengths and Weaknesses [18]

Pros

- general-purpose
- many variations
- fast to apply once learned
- able to detect complex relationships

Cons

- requires large dataset
- blackbox[1], difficult to "understand"
- slow to learn
- can overfit

[1] there are some rule-extraction algorithms [17]

Recurrent Neural Networks

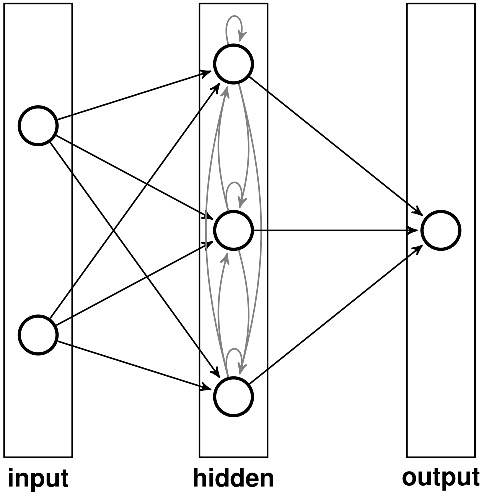


Figure 8: Simplified Recurrent Network

Problems

Vanishing Gradient Problem (Hochreiter [11])

Problem

Deep networks require a lot of training

Problems

Vanishing Gradient Problem (Hochreiter [11])

Problem

Deep networks require a lot of training

- during backpropagation, error is lost with each layer
- first layers receive slowest updates
- unrolled RNNs are very deep

Problems

Imbalanced Data

Problem

Only 2% of our samples are keystrokes (positive class)

Problems

Imbalanced Data

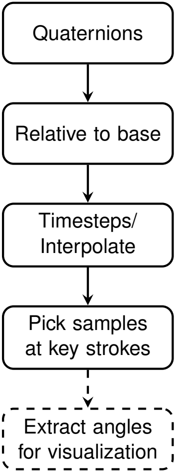
Problem

Only 2% of our samples are keystrokes (positive class)

Possible solutions [2]

- gather lots of data and train a lot
- resampling
- penalize
- generate synthetic data

Preprocessing and Sampling



Preprocessing and Sampling

Quaternions

↓

Relative to base

↓

Timesteps/ Interpolate

↓

Pick samples at key strokes

⇣

Extract angles for visualization

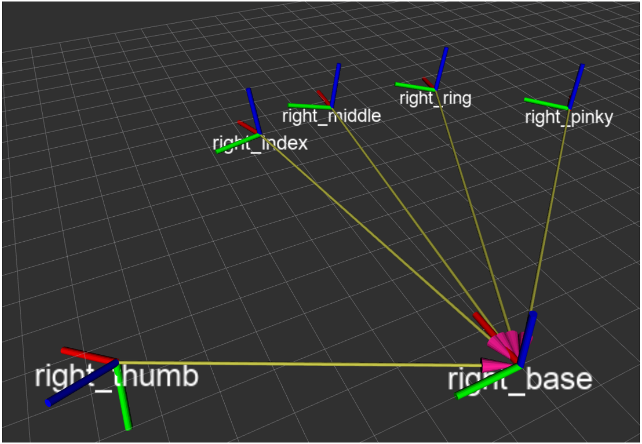
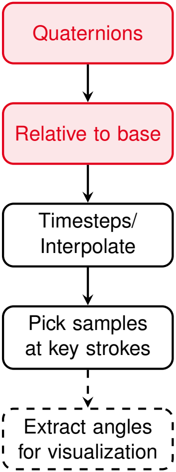


Figure 9: Visualization of relative quaternion rotations, idle pose

Preprocessing and Sampling



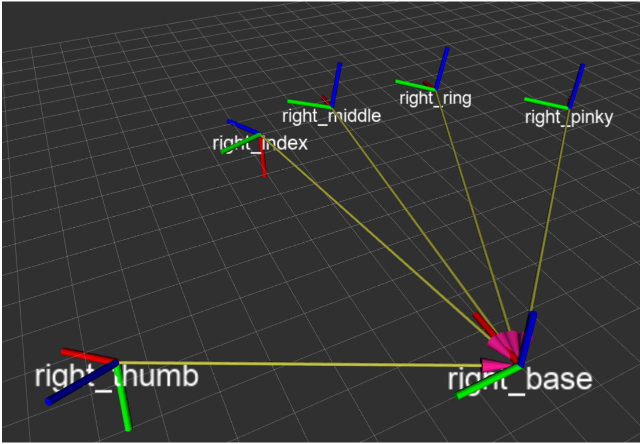
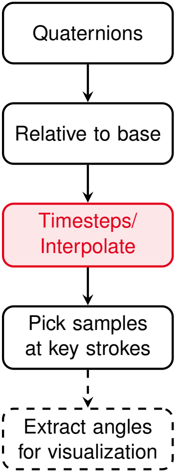


Figure 10: Visualization of relative quaternion rotations, index finger bent

Preprocessing and Sampling



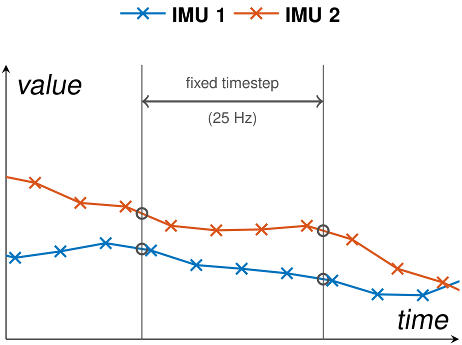
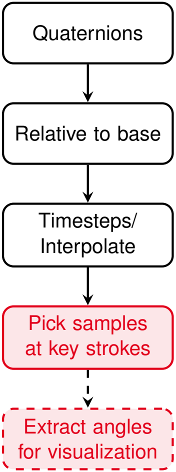


Figure 11: Interpolation of the IMU data (simplified)

Preprocessing and Sampling



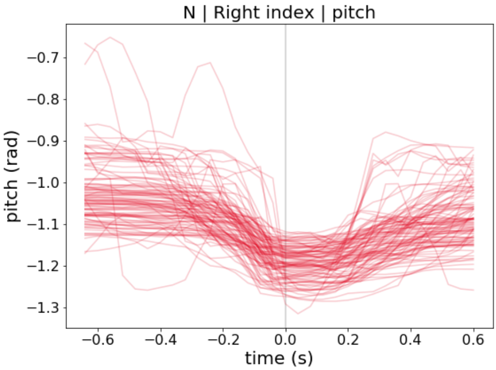


Figure 12: Multiple repetitions of the N key stroke, overlayed at the moment of pressing the key (center line); value plotted is extracted relative pitch angle of right index finger.

Preprocessing and Sampling

Real Preprocessed Data

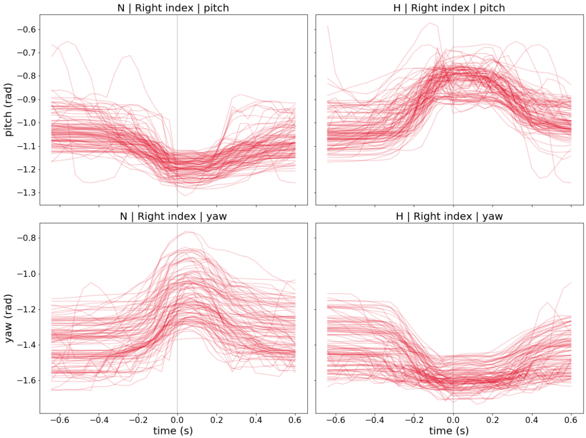


Figure 14: Multiple repetitions of N (*left*) and H (*right*) key strokes, overlayed at the moment of pressing the key (center line); value plotted is extracted relative pitch (*top*)/yaw (*bottom*) angles of right index finger.

Convolutional Neural Networks

Convolution and Pooling

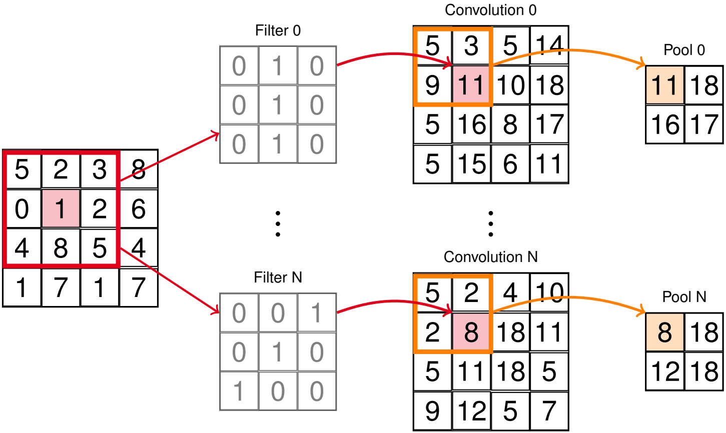
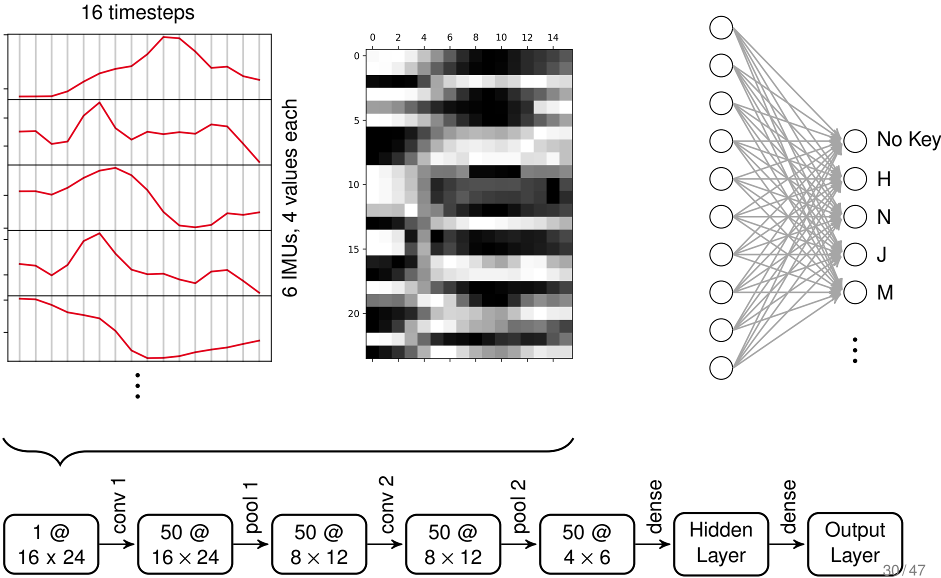


Figure 15: Feature Extraction with CNN

Convolutional Neural Networks

Our Implementation



Experiments

Phase 0 – Pipeline Setup

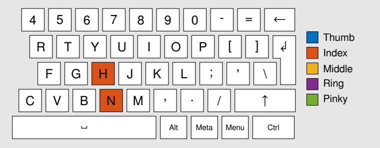
```
imu_ids: [0, 1, 2, 3, 4, 5]
key_codes: [21, 22, 23, 34, ...]
sequence_length: 16

epochs: 0 //infinite
learning_rate: 0.002
batch_size: 100
sampling_rate: 25

network_type: cnn2d
cost_function: mse

convolution_n_filters: 50
convolution_filter_size: [3, 3]
convolution_n_pairs: 2
convolution_arr_dense: [10]
```

Figure 16: Example of a configuration file (truncated)

- easily adjustable
- repeatable experiments

Phase 1 – Slow Single Finger

Overview



1 finger, 2 keys

Phase 1 – Slow Single Finger

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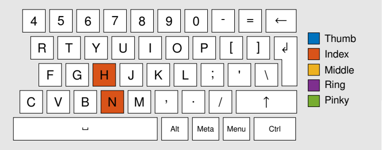


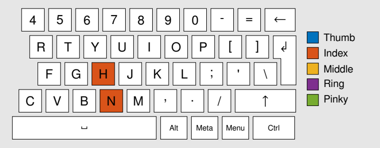
1 finger, 2 keys

Goals:

- detect keystrokes, ignore idle pose
- distinguish between close keys
- evaluate the configuration of the CNN

Phase 1 – Slow Single Finger

Accuracy and Cost Function



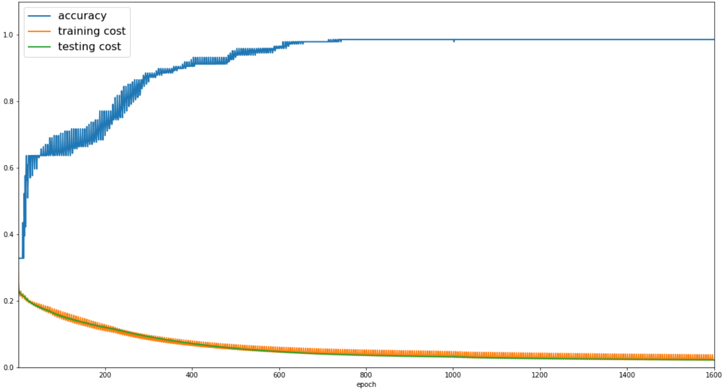
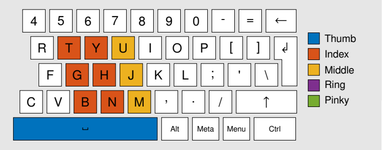


Figure 17: Test results in the first 1600 epochs of learning phase 2

Phase 2 – Slow Multiple Finger

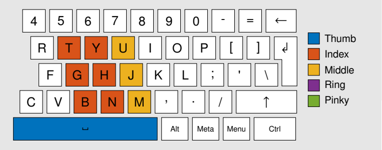
Overview



3 fingers, 10 keys

Phase 2 – Slow Multiple Finger

Overview



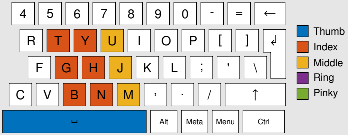
3 fingers, 10 keys

Goals:

- distinguish between fingers
- handle hand movement

Phase 2 – Slow Multiple Fingers

Accuracy and Cost Function



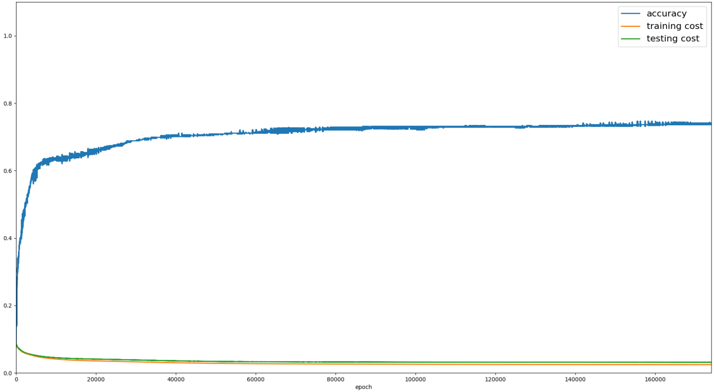
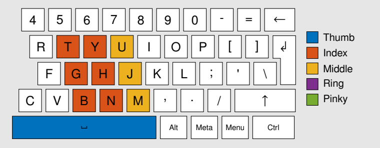


Figure 18: Test results in the first 160000 epochs of learning phase 2

Phase 2 – Slow Multiple Fingers

Evaluation of Predictions

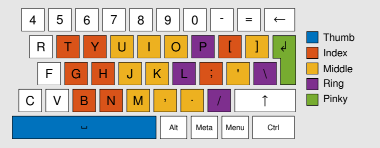


		Predicted									
		no key	U	I	G	H	J	B	N	M	SPC
Actual	no key	0	13	5	9	5	121	2	6	3	0
	U	0	175	0	0	0	0	0	0	0	0
	I	0	1	167	0	0	0	0	0	0	0
	G	0	0	0	181	0	0	0	0	0	0
	H	0	1	5	0	1	169	0	0	0	0
	J	0	0	1	0	1	215	0	3	0	0
	B	0	0	0	0	0	0	167	0	0	0
	N	0	0	0	0	0	0	0	180	0	0
	M	0	0	0	0	0	0	0	0	190	0
	SPC	0	0	0	0	4	178	1	0	0	0

Figure 19: Confusion matrix[15]. From this we calculate the accuracy and per key recall & precision [6]

Phase 3 – Fast Typing

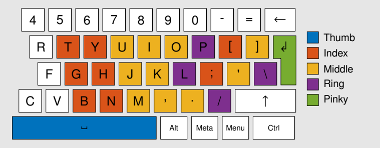
Overview



5 fingers, 27 keys

Phase 3 – Fast Typing

Overview



5 fingers, 27 keys

Goals:

- recognizing every righthand key stroke
- achieve high accuracy
- learn a robust model
- fluent typing

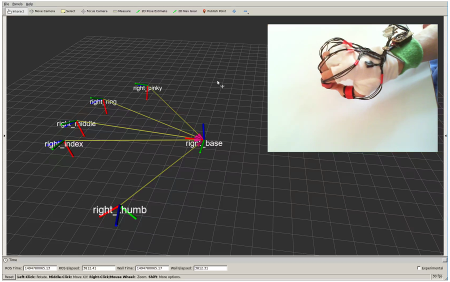
Demo

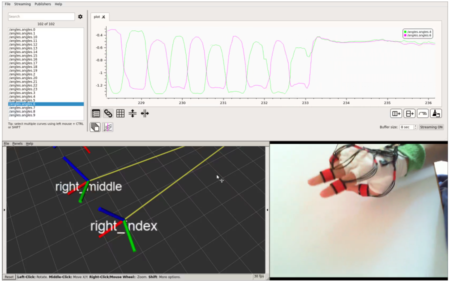
Demo

The Glove

Demo

Backup Videos





Conclusion

Results System Design

Goal (Reminder)

Design a system for recording characteristic hand movements of typing and the corresponding input.

Results System Design

Goal (Reminder)

Design a system for recording characteristic hand movements of typing and the corresponding input.

Successes

- the architecture proved suitable
- the glove is non-obstructive
- performance is good enough for a prototype

Improvements

- gyro clipping
- single robust glove
- generalization to different hand types

Results Machine Learning

Goal (Reminder)

Define an approach for utilizing machine learning to map the recorded data back to the keyboard input.

Results Machine Learning

Goal (Reminder)

Define an approach for utilizing machine learning to map the recorded data back to the keyboard input.

Successes

- slow typing can be distinguished
- preprocessing helps the learning progress
- CNNs can distinguish between different keys

Improvements

- better accuracy
- reduce delay
- detect holding a key
- detect different modes →(non-)writing position

Outlook

Goal (Reminder)

Evaluate the quality of such mapping and discuss whether this principle could be turned into a working keyboard alternative.

Outlook

Goal (Reminder)

Evaluate the quality of such mapping and discuss whether this principle could be turned into a working keyboard alternative.

- reduce delay, remove lookaheads
- increase prediction quality
- two hands
- generalize glove & model
- implement online learning
- better hand pose reconstruction for more use cases

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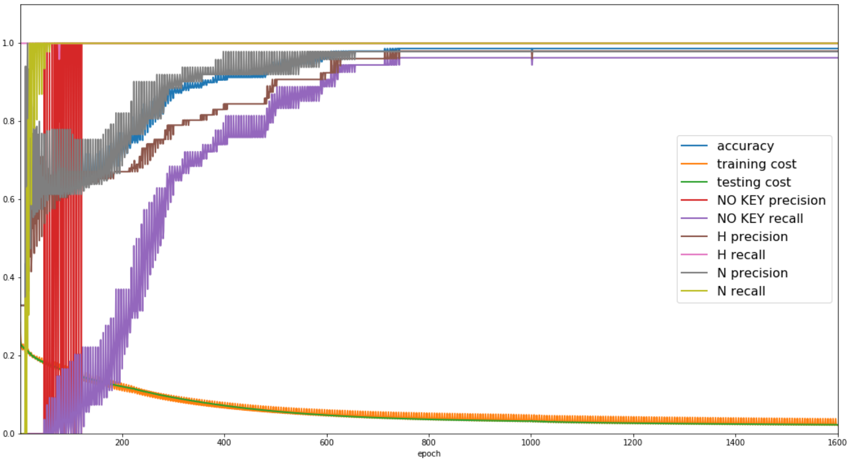

Figure 20: Performance metrics of phase 1, including per key precision and recall