Prototype for a virtual keyboard based on IMUs and machine learning

Paul Bienkowski & Carolin Konietzny

TAMS, Fachbereich Informatik, Universität Hamburg

2017-05-16

- welcome the audience
- introduce ourselves
- explain this is our bachelor's thesis defense

Contents

- 1, 2 Paul
- 3, 4 Caro
- Demo & Conclusion together

Introduction

Motivation

Traditional Keyboards

Pros

- easy to learn
- precise
- universal
- cheap

- present pros and cons
- it's still the most common choice
- phones get smaller → deviceless
- **voice**: inaccurate, only nat. language, environment dependent
- **handwriting**: slow, touch screen, surface, inaccurate
- **visual methods**: very slow, good for handicapped users

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Alternatives

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

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Vision

1. record finger movements and input while typing

- simple to generate learning data
- complex movement we don't fully predict: (example with B key)
- **BUT FIRST!** let's see who did this already

Vision

1. record finger movements and input while typing
2. use machine learning for input prediction

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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

- simple to generate learning data
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Related Work

Sensor Gloves

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

→ overview at [1]

- flex sensor gloves started 1987

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

- **gest**
- raised ~200k USD on kickstarter in Oct 2015
- out of business within half a year, no funding
- **senseboard**
- weird project, no information available, no images
- same idea as we did
- **hi5vrglove**
- intended for VR gaming
- very new
- no typing software
- same hardware specs
- **gest at least advertised with keyboard functionality**

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

- flex sensors
  - only 1 dimensional
  - not suited for horizontal movement
  - only relative data
- Visual system
  - hard to extract characteristic data
  - often inaccurate
  - no freedom gain
- IMUs
  - small, cheap, robust
  - easy to use and understand
  - provide good accuracy high dimensional data
  - capture characteristic movement (ie. yaw AND pitch)
- **6 IMUS, 5 fingers, 1 for reference at back of hand**

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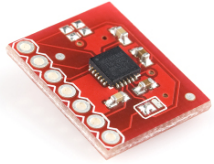
IMUs



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

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Sensors

Inertial Measurement Units (IMUs)

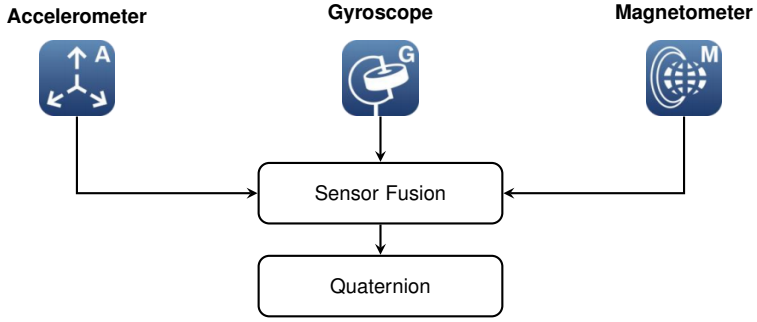
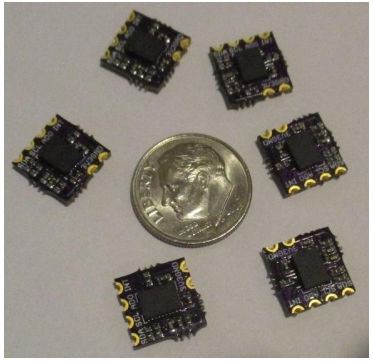


Figure 5: Sensor Fusion Overview

Sensors

Wearable BNO055 Nano Board



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

Figure 6: Wearable BNO055 Nano Board

- we had to choose between MPU-9150 and BNO-055
- both seemed fit
- BNO easier to use
- very small board available
- but more expensive

Sensors

Wearable BNO055 Nano Board

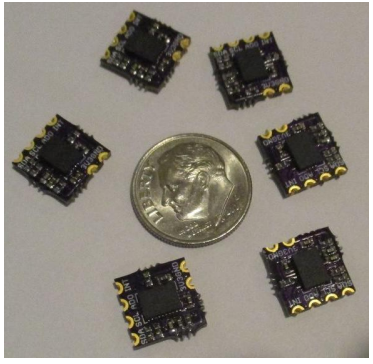


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Figure 6: Wearable BNO055 Nano Board

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

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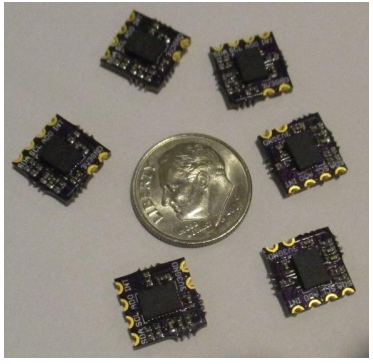

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however...

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

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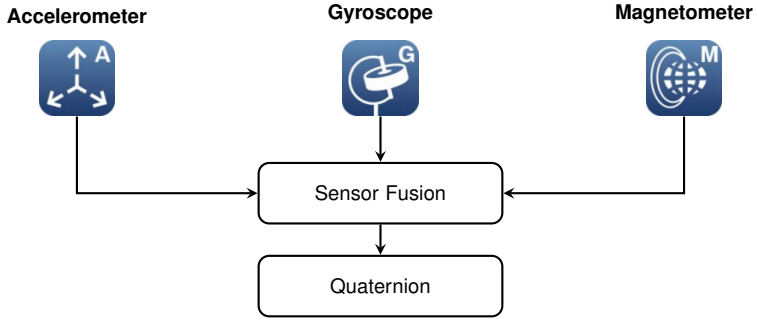

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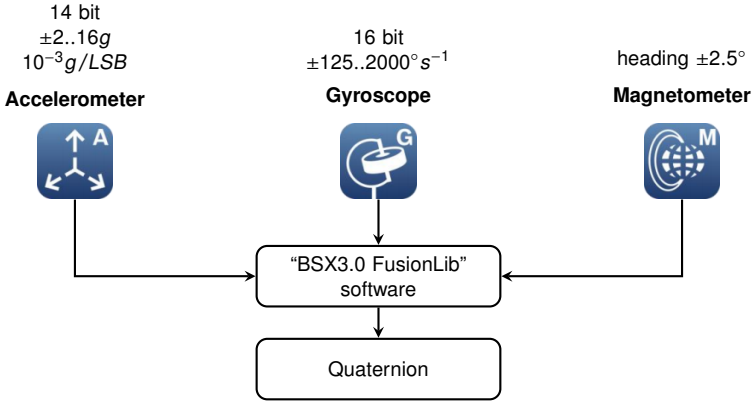

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Microprocessor

Adafruit Feather M0 WiFi

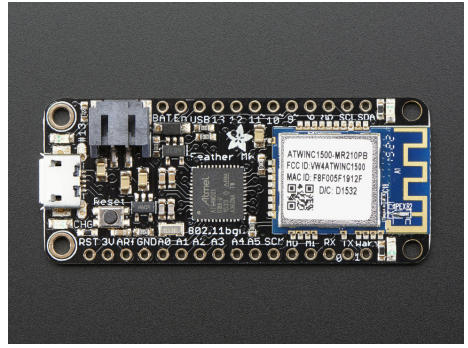

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Figure 7: Adafruit Feather M0 WiFi - ATSAMD21 + ATWINC1500 product image

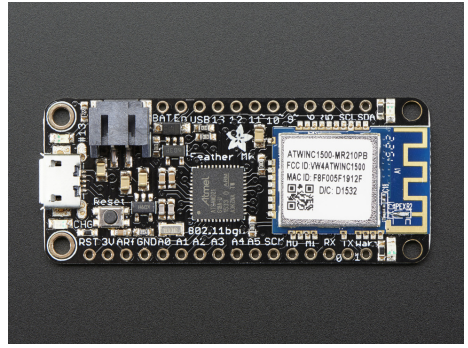
- we chose this microprocessor
- alternative was Teensy 3.2, but that had some disadvantages
- small & light → required for hand-attached device
- WiFi → no cable that impedes movement
- enough SERCOMs
- LiPo charger is useful

- we need EEPROM for WiFi credentials → so we attached one ourselves
- more expensive than Teensy

Microprocessor

Adafruit Feather M0 WiFi

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



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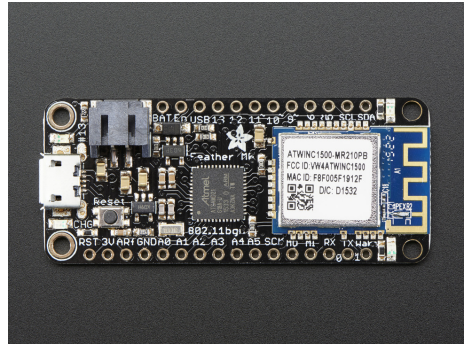

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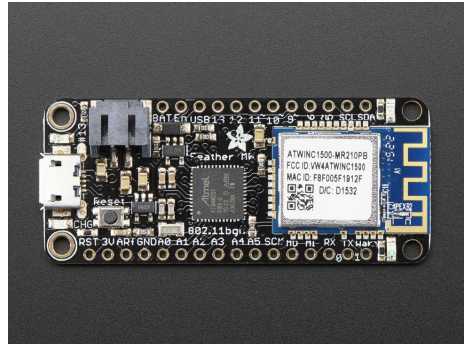

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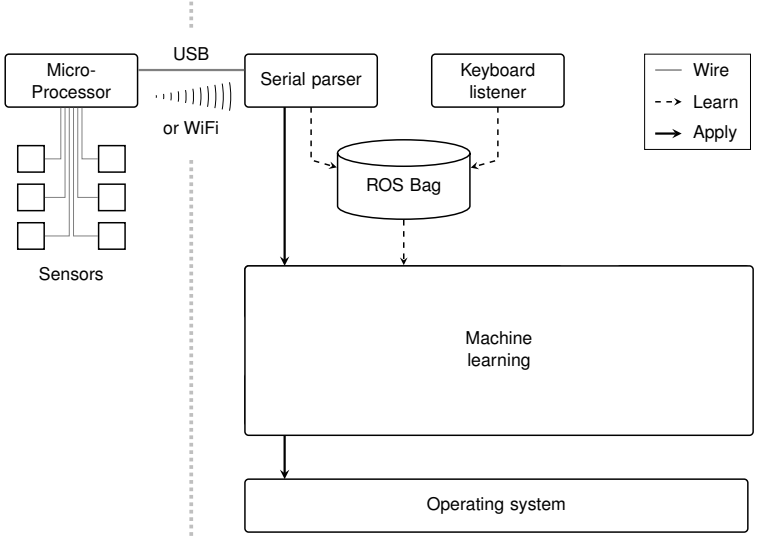

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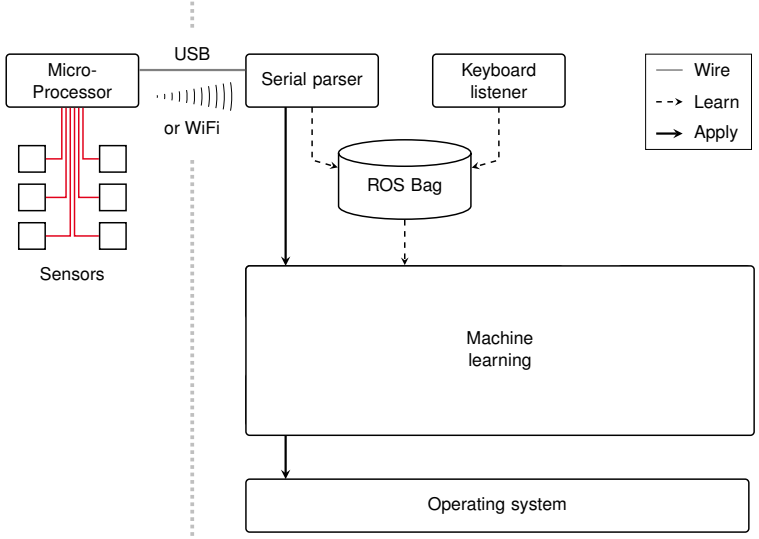

I2C Bus

Requirements

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

- these are the available pins for the different SERCOMs on the Feather M0
- we need pads 0 und 1 for I2C (fixed)
- pins 2, 4, 7, 8 are required for WiFi
- so we picked the red marked

I2C Bus

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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*

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I2C Bus

Arduino Setup

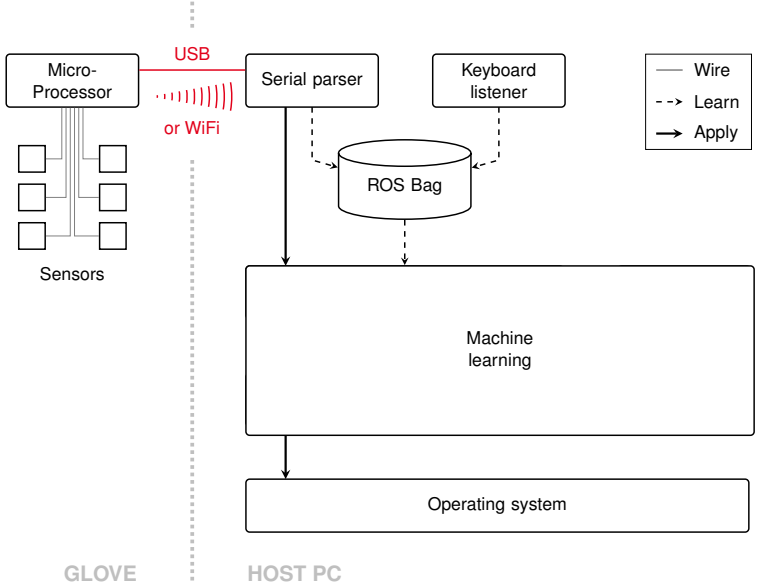
```
#include <Wire.h>
#include <wiring_private.h>

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

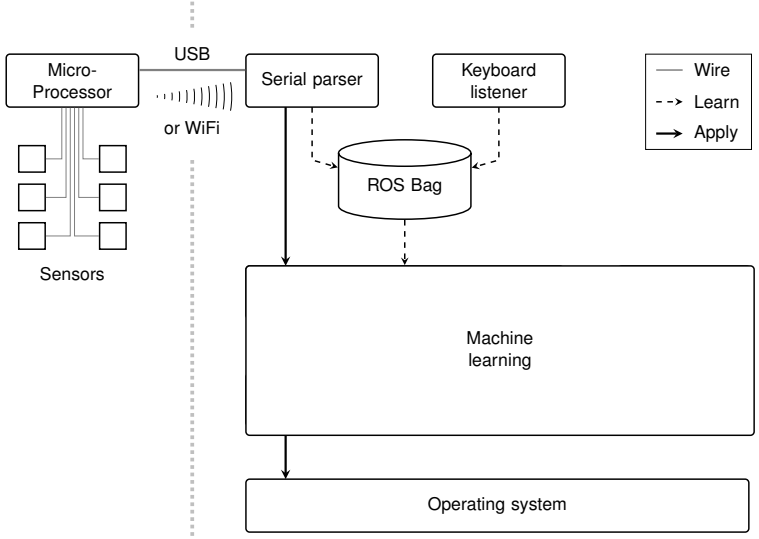
System design

Other Considerations

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

Machine Learning

Machine Learning



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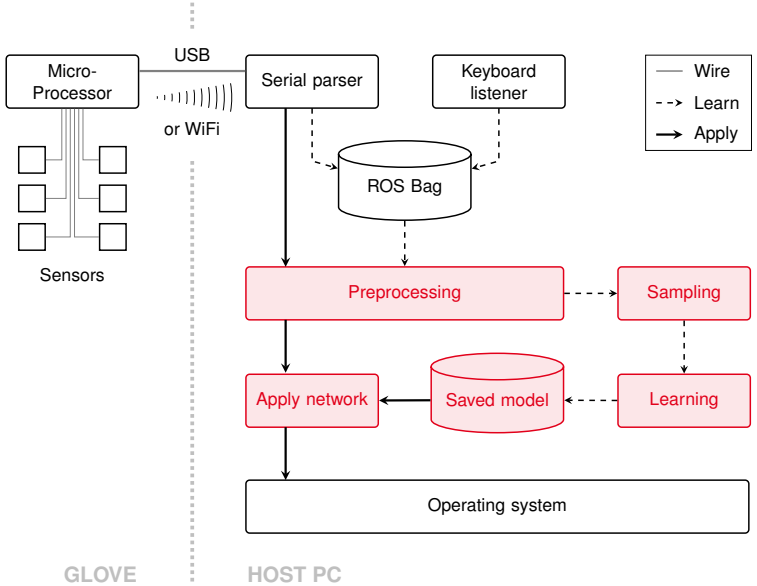


Introduction

Supervised and Unsupervised learning

	Supervised	Unsupervised
Learning Data	• input X • target values Y	• input X
What is learned	mapping function $Y \approx f(X)$	model of data structure
Examples	• classification • regression	• clustering • association

- warum machine learning (und nicht vorgegebene gesten erkennen)
- supervised unsupervised
- vorteile/ nachteile
- warum supervised

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]

- **ARE** general-purpose
- easiliy generate data
- not important how (we dont know movement of fingers)
- tradeoff: complex calculation <-> data needed to learn
- bridge: NN we were interested in

Recurrent Neural Networks

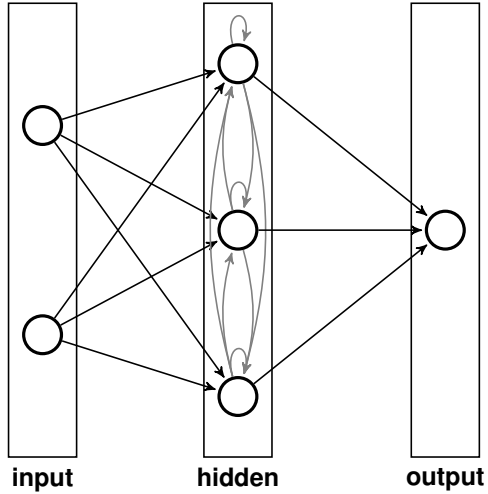


Figure 8: Simplified Recurrent Network

- sequences of data, not necessarily same length
- dependencies between data
- ie handwriting, language recognition, driverless cars, accident prediction
- forecast
- Aufbau
- Vanishing Gradient Problem

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)

- fast!
- Problems with RNN!
- oversampling, undersampling
- penalize choosing neg class wrongly
- for theoratical math problems
- SOLUTION: not RNN
- **Look at actual data**

Problems

Imbalanced Data

Problem

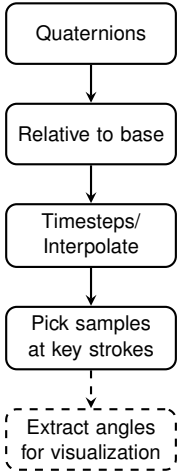
Only 2% of our samples are keystrokes (positive class)

Possible solutions [2]

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

- fast!
- Problems with RNN!
- oversampling, undersampling
- penalize choosing neg class wrongly
- for theoratical math problems
- SOLUTION: not RNN
- **Look at actual data**

Preprocessing and Sampling

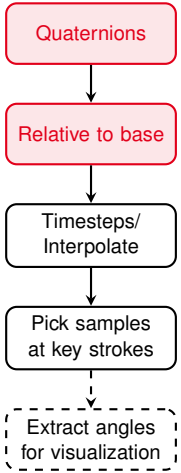


1. Quat:
   - absolute orientation (heading north)
   - goal: independent of direction
   - solution: use relative quaternions (handbase)
   - hand relative to moving average
   -

$$q_{rel} = q_{abs} \cdot inv(q_{abs,parent})$$

2. interpolate
   - fixed timesteps
   - need all imu data
3. sampling
   - time 0 : keystroke
   - 8 timesteps before + after
   - visualization: many keystrokes, angles **yaw, pitch**
   - acceleration (linear acceleration)
   - gyroscope (angular velocity (rotate speed))
   - (spherical) linear interpolation → see next slide

Preprocessing and Sampling



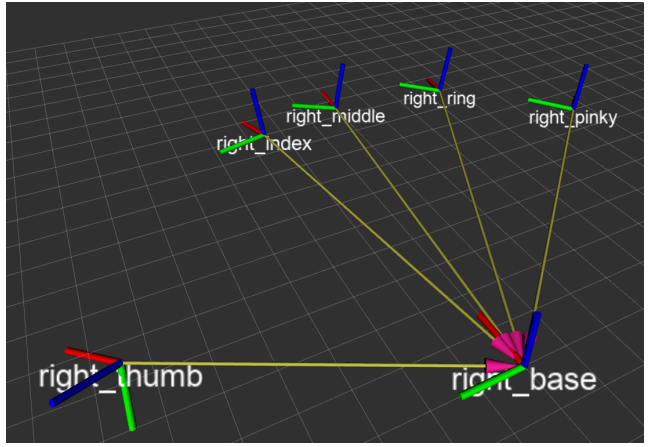
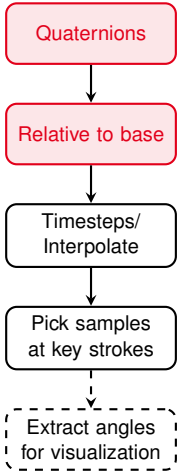


Figure 9: Visualization of relative quaternion rotations, idle pose

1. Quat:
   - absolute orientation (heading north)
   - goal: independent of direction
   - solution: use relative quaternions (handbase)
   - hand relative to moving average
   -
   $$q_{rel} = q_{abs} \cdot inv(q_{abs,parent})$$
2. interpolate
   - fixed timesteps
   - need all imu data
3. sampling
   - time 0 : keystroke
   - 8 timesteps before + after
   - visualization: many keystrokes, angles **yaw, pitch**
   - acceleration (linear acceleration)
   - gyroscope (angular velocity (rotate speed))
   - (spherical) linear interpolation → see next slide

Preprocessing and Sampling



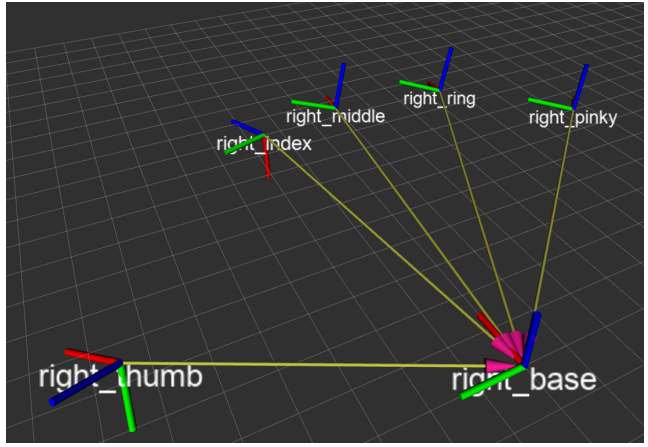
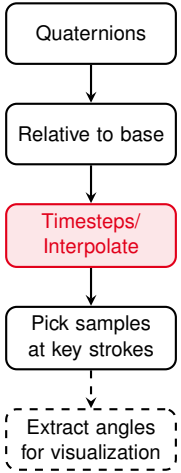


Figure 10: Visualization of relative quaternion rotations, index finger bent

1. Quat:
   - absolute orientation (heading north)
   - goal: independent of direction
   - solution: use relative quaternions (handbase)
   - hand relative to moving average
   -
   $$q_{rel} = q_{abs} \cdot inv(q_{abs,parent})$$
2. interpolate
   - fixed timesteps
   - need all imu data
3. sampling
   - time 0 : keystroke
   - 8 timesteps before + after
   - visualization: many keystrokes, angles **yaw, pitch**
   - acceleration (linear acceleration)
   - gyroscope (angular velocity (rotate speed))
   - (spherical) linear interpolation → see next slide

Preprocessing and Sampling



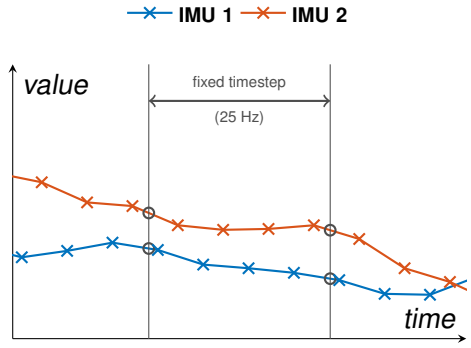
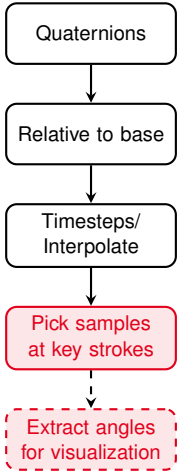


Figure 11: Interpolation of the IMU data (simplified)

1. Quat:
   - absolute orientation (heading north)
   - goal: independent of direction
   - solution: use relative quaternions (handbase)
   - hand relative to moving average
   -
   $$q_{rel} = q_{abs} \cdot inv(q_{abs,parent})$$
2. interpolate
   - fixed timesteps
   - need all imu data
3. sampling
   - time 0 : keystroke
   - 8 timesteps before + after
   - visualization: many keystrokes, angles **yaw, pitch**
   - acceleration (linear acceleration)
   - gyroscope (angular velocity (rotate speed))
   - (spherical) linear interpolation → see next slide

Preprocessing and Sampling



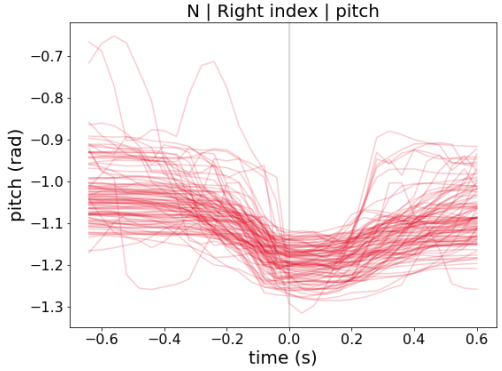


Figure 12: Multiple repetitions of the N key stroke, overlayed at the moment of pressing the key (center line); value plotted is extracted relative pitch angle of right index finger.

1. Quat:
   - absolute orientation (heading north)
   - goal: independent of direction
   - solution: use relative quaternions (handbase)
   - hand relative to moving average
   -
   $$q_{rel} = q_{abs} \cdot inv(q_{abs,parent})$$
2. interpolate
   - fixed timesteps
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   - time 0 : keystroke
   - 8 timesteps before + after
   - visualization: many keystrokes, angles **yaw, pitch**
   - acceleration (linear acceleration)
   - gyroscope (angular velocity (rotate speed))
   - (spherical) linear interpolation → see next slide

Preprocessing and Sampling

Real Preprocessed Data

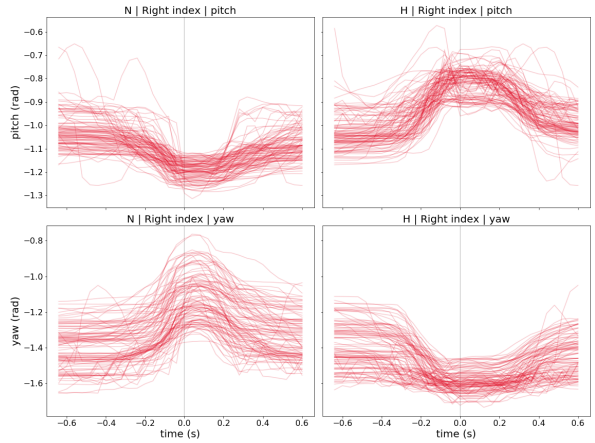


Figure 14: Multiple repetitions of N (*left*) and H (*right*) key strokes, overlayed at the moment of pressing the key (center line); value plotted is extracted relative pitch (*top*)/yaw (*bottom*) angles of right index finger.

- we tried to visualize what we got
- 1 finger, left: N, right: H
- Quaternion: yaw, pitch
  - quat is enough, acc and gyro data can be used additionally → requires more training
  - finger cant roll relative to hand → no roll necessary (only hand)
- actual moment of keystroke!
- hill, valley!
- visibly different –> detectible!!

Convolutional Neural Networks

Convolution and Pooling

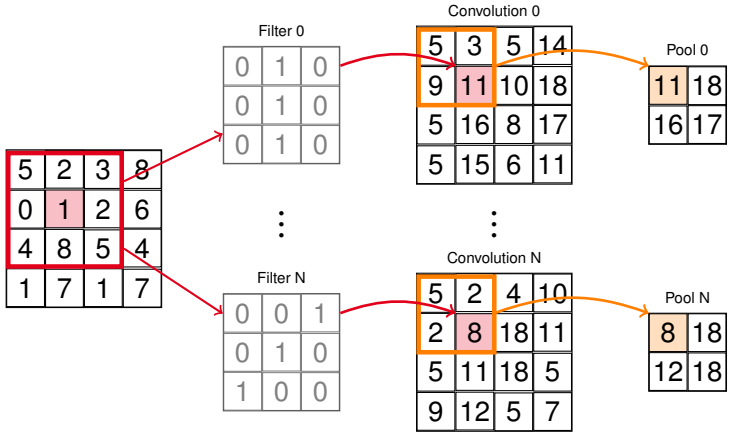
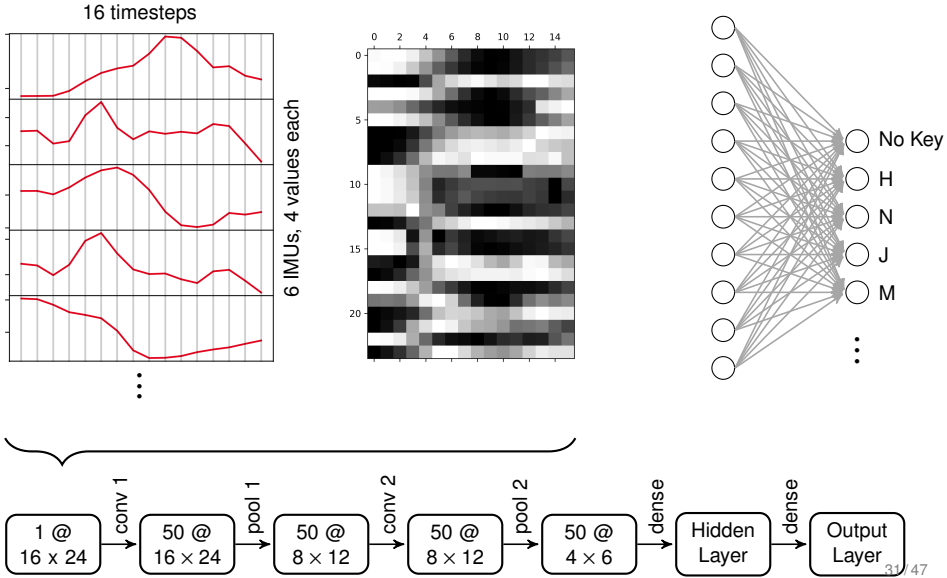


Figure 15: Feature Extraction with CNN

- convolute (element wise multiplication)
- pool (max)
- filters (50)
- 3 x 3 x 50
- convolute, pool..
- fully connected layer as classifier

Convolutional Neural Networks

Our Implementation



- each key has same amount of samples
- one sample = one keystroke
- filter randomly initialized
- filter are learned!
- matrix with numbers instead of color scheme
- 2 x convolute and pooling
- MSE: $(1/n) * \sum_{n=0}^{N}(pred - act)^2$

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

- Theano is a scientific mathematical library
  - large scale calculations
  - often numpy arrays
- Lasagne is a ML-Framework based on Theano
  - focused on Neural Networks

Phase 1 – Slow Single Finger

Overview

1 finger, 2 keys

- index finger moving between N, H
- pauses
- mostly detect pressed N
- always ignore H

Phase 1 – Slow Single Finger

Overview

1 finger, 2 keys

Goals:

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

- index finger moving between N, H
- pauses
- mostly detect pressed N
- always ignore H

Phase 1 – Slow Single Finger

Accuracy and Cost Function

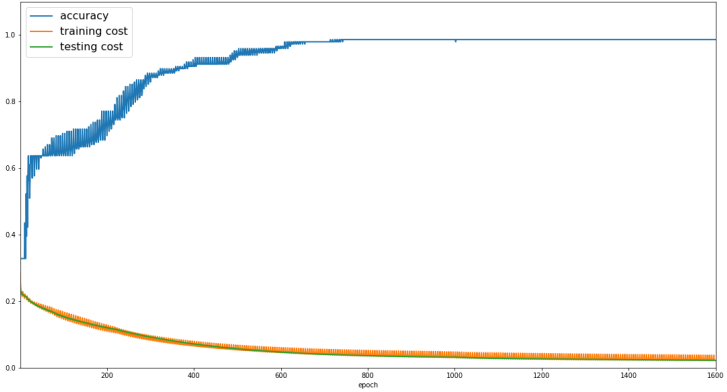


Figure 17: Test results in the first 1600 epochs of learning phase 2

- 1600 epochs
- accuracy: amount of correctly classified samples
- 1 epoch: 1 batch
- 1 batch: 100 samples
- 1 sample: 1keystroke or nokey: 16 timesteps

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

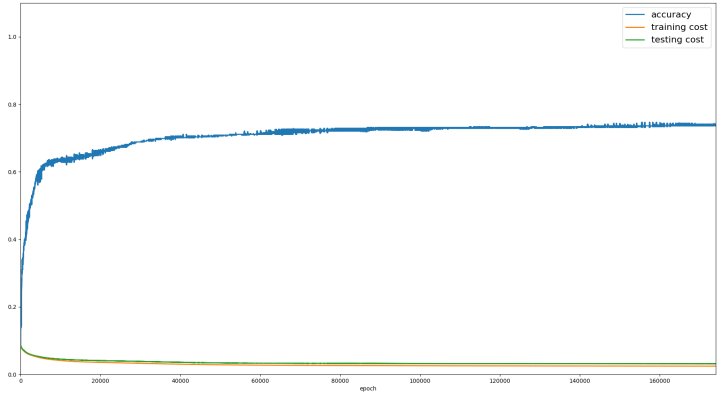


Figure 18: Test results in the first 160000 epochs of learning phase 2

- over 160000 epochs → much more epochs necesarry
- accuracy only near 70%

Phase 2 – Slow Multiple Fingers

Evaluation of Predictions

Actual \ Predicted	no key	U	I	G	H	J	B	N	M	SPC
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]

- left : actual, right: predicted
- wrong classificated:
  - no key as j
  - h as j
  - space as j
- apple keyboard doesnt need much finger movement to press key
- → mechanical keyboard??!
- additional stuff:
  - recall precision needs to be balenced (–> imbalanced data!!)
  - recall: RECALL :D avoid FN!
  - precision: avoid FP
  - accuracy: TP / ALL
  - recall: TP/ TP + FN how many relevant items (TP + FN) are selected
  - precision: TP/ TP + FP how many selected items are relevant

Phase 3 – Fast Typing

Overview

5 fingers, 27 keys

- future (we did not do this yet)
- next step: online learning
- modification of movements

Phase 3 – Fast Typing

Overview

5 fingers, 27 keys

Goals:

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

- future (we did not do this yet)
- next step: online learning
- modification of movements

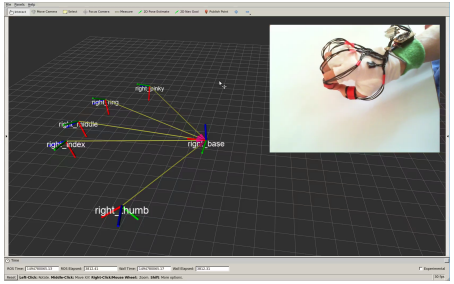
Demo

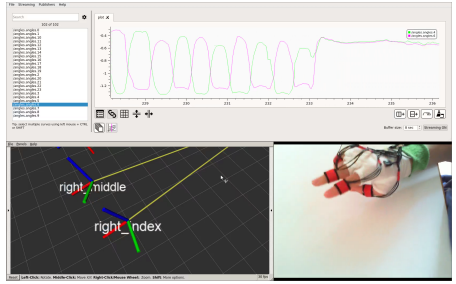
Demo

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.

- fscore, recall, precision
- delay
  - keystroke in middle
  - 8 timesteps before and after
- learn on more data (accel, gyro..)
  - learn more about hand position not only orientation

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

- fscore, recall, precision
- delay
  - keystroke in middle
  - 8 timesteps before and after
- learn on more data (accel, gyro..)
  - learn more about hand position not only orientation

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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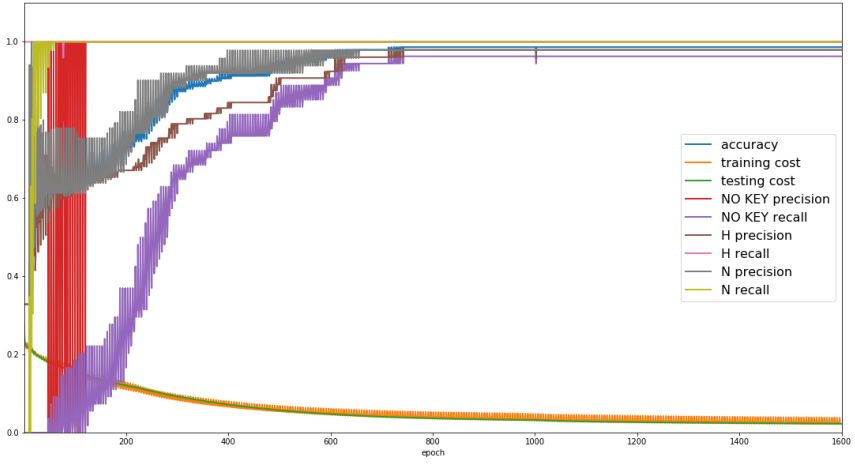

Figure 20: Performance metrics of phase 1, including per key precision and recall