Action Recognition Through Device Sensors

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Sensors: Our Future

- Heavily applicable in many areas
 - Security/Health
 - Education
 - Industry
- Integrated into everyday life
 - More and more integration into technology
 - Accelerometer
 - Gyroscope
 - Finger Print
 - Compass
 - etc...

Evolution of Sensor Use

- Increase in practicality (Miniaturization)
 - More readily available for the public
 - \circ Big business/government \rightarrow Everyone can use

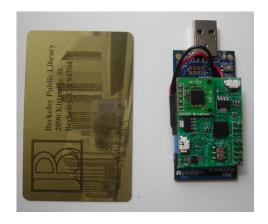


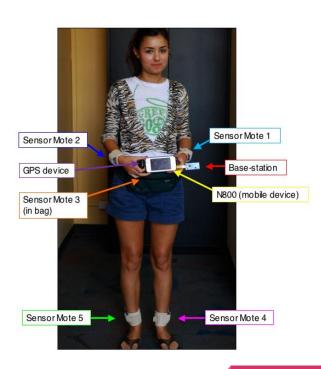




Previous Projects

- Main contributor: Allen Y. Yang
 - Data Collection Protocol for WARD (2009)





What is WARD?

- Public human action database
- Use of body sensors to send data through a network
- Logs movements of different subjects
 - o 20 human subjects (13M/7F)
 - o 2 weeks
 - 13 recognizable actions

Allen Y. Yang's Project Design

- Use of DexterNet
 - o 3 Layer architecture
 - BSL
 - PNL
 - GNL
- Pros
 - Removes necessity of other hardware monitors
 - Distributed Pattern Recognition
 - Reduces communication cost whilst preserving performance
- Exploits miniaturization of sensors

Our Project: Architecture

- Implementation of new hardware
 - \circ 2009 \rightarrow 2017
 - Smart Watch and Mobile Devices
 - Samsung S6 Edge
 - OS: Android
 - Samsung Gear S3 Wearable
 - OS: Tizen
 - Use sensor logs from mobile and wearable devices
 - Create data logs and apply them to WARD





Pros

- Large array of sensors
 - Mobile Device
 - Accelerometer, Gyroscope, Compass, Magnetometer
 - Watch
 - Accelerometer, Gyroscope, Compass, Magnetometer, 4-channel sound sensor
- Recognize new actions
 - One door closes, another door opens
 - Find new recognizable actions
 - Sound sensor: possibilities are endless

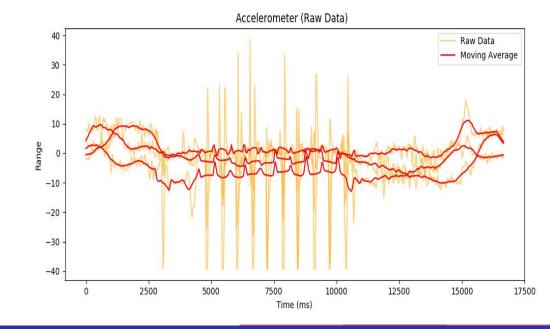
Challenges

- Versatility vs. Precision
 - Sacrificing multiple sensors for practicality
 - Harder to recognize human actions with 2 pieces of hardware
 - Certain actions cannot be differentiated
- Offline data logging
 - Data is saved to internal memory
 - No real-time functionality
- Tizen Android integration

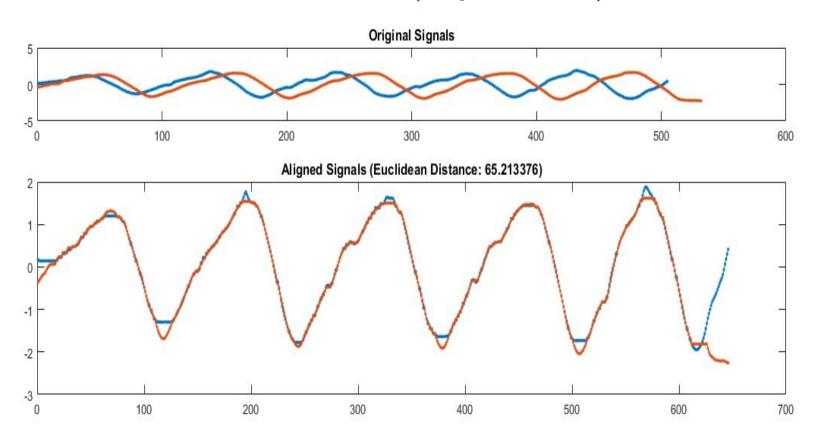


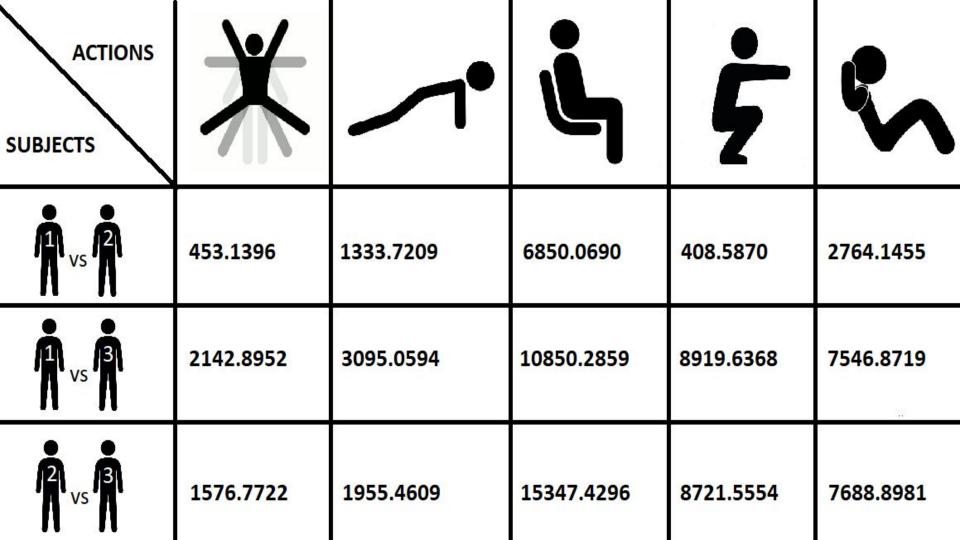
Data Logging

- Sensor Data saved onto mobile device
 - Tab separated values
 - 4 separate files
- Three sensor axis: X, Y, Z
 - Graphed on python/MATLAB
 - Moving Average Filter
- Compare action features
 - Dynamic Time Warping
 - Time-series algorithm



DTW: J vs. D (Squats 5x)





(A) Vector	JJ	PU	SS	SQ	SU
JNxD	448.2305	4247.0406	5325.2449	1894.4237	8969.9414
JNxN	1687.7892	3333.4114	16961.1449	8733.7938	15963.8875
JNxJ	38.9451	2848.6439	4652.6753	1610.5577	4029.9876
(G) Pitch	JJ	PU	SS	SQ	SU
JNxD	36.9305	101.1439	215.6683	321.4366	184.8711
JNxN	51.5676	73.0009	64.8086	61.7337	76.0791
JNxJ	12.6811	172.0071	217.9381	321.4366	179.4237
(G) Roll	JJ	PU	SS	SQ	SU
JNxD	48.2583	75.5987	218.336	66.8399	70.1634
JNxN	62.7086	63.7738	78.8307	73.0001	68.8761
JNxJ	10.8158	91.9781	135.5114	66.8399	93.9976
(G) Yaw	JJ	PU	SS	SQ	SU
JNxD	74.2453	113.7198	205.3022	87.5820	112.7518
JNxN	82.1154	74.2333	102.5962	95.7560	81.5021
JNxJ	35.7603	100.1559	97.4966	87.5820	92.4320
(M) Vector	JJ	PU	SS	SQ	SU
JNxD	5651.5856	34626.2761	43302.0076	11220.0451	65434.7465
JNxN	11290.5332	25854.8222	10724.1603	47154.8415	97068.5102
JNxJ	132.3367	21145.1436	33767.3311	11099.2611	27477.8490

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