WISDM Smartphone and Smartwatch Activity and Biometrics Dataset

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Data Set:
WISDM Smartphone and Smartwatch Activity and Biometrics Data Set

Paper:
Smartphone and Smartwatch-Based Biometrics Using Activities of Daily Living

Introduction

Background and application area

Biometric identifiers:
Unique physical or behavioral characteristics of people.
Used to distinguish an Individual (identification or authentication).
Can’t be stolen, unlike password or ID card.

Physical biometric methods use physiological identifiers like fingerprints, face, iris and DNA.
Sometimes hard to use.

Behavioral biometric methods use behavioral identifiers like walking, handwaving, signature and voice.
Related to daily life and can be measured by common device.

Single identifier:
Gait: vision-based, floor-based, and wearable sensor-base
Soft touchscreen gestures like tap and drag
Soft keystroke gestures like duration and pressure
Sound properties
Gestures when people writing specific words or their signatures

More than one identifiers:
a few identifiers: walking, standing, jogging, sitting and running
Only smartphone as the measurement device

Problems considered

Importance of evaluating daily identifiers:
Find a base behavioral identifier which can be used individually to build a biometric system for identification or authentication.
Build a biometric system which uses normal daily behavioral identifiers to do identification or authentication.

E.g.
The daily behavioral data collected by smartphone can be used to secure the smartphone, or secure other devices like cars and house.

The paper we choose:
Analyzed 18 normal daily activities for behavioral biometric methods, and used the accelerometer and gyroscope sensors on smartphone and smartwatch to do identification and authentication.

Problems focused:
1. The value of smartphone, smartwatch and their combination for behavioral biometric methods.
2. The choose of accelerometer and gyroscope sensors on smartphone and smartwatch.
3. The performance of behavioral biometric methods for identification and authentication.
4. The performance of daily behavioral identifiers for biometric system.
5. The amount of training data.

Data Set and Paper

Data in detail

The ”WISDM Smartphone and Smartwatch Activity and Biometrics Data Set” is collected by Wireless Sensor Data Mining (WISDM) Lab in the Department of Computer and Information Science of Fordham University.

Table 1: Summary Information about Data Set [26]

Attribute	Value
Number of subjects	51
Number of activities	18
Minutes collected per activity	3
Sensor polling rate	20Hz
Smartphone used	Google Nexus 5/5x or Samsung Galaxy S5
Smartwatch used	LG G Watch
Number raw measurements	15,630,426

Table 2: Activities and Their Codes [26]

Activity	Code	Activity	Code	Activity	Code
Walking	A	Brushing Teeth	G	Kicking (Soccer Ball)	M
Jogging	B	Eating Soup	H	Playing Catch w/Tennis Ball	O
Stairs	C	Eating Chips	I	Dribbling (Basketball)	P
Sitting	D	Eating Pasta	J	Writing	Q
Standing	E	Drinking from Cup	K	Clapping	R
Typing	F	Eating Sandwich	L	Folding Clothes	S

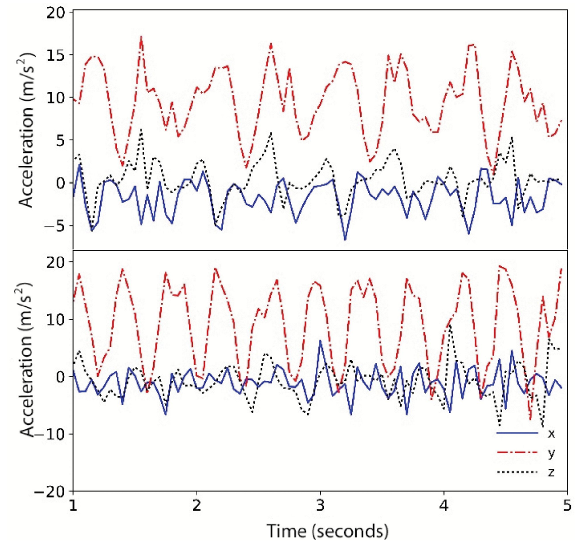
Raw sensor data format:

< *Subject ID, Activity Code, Timestamp, x, y, z* >

1608,A,111545844427476,4.319275,9.2408905,-0.7 7568054;

Table 3: Definition of Elements in Raw Data Measurements [26]

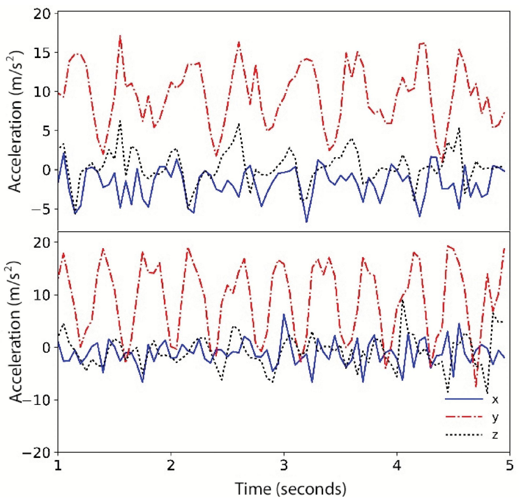
Field Name	Description
Subject ID	Integer. Uniquely identifies the subject. Range: 1600-1650.
Activity Code	Letter. Identifies a specific activity listed in Table 2. Range: A-S (no “N”)
Timestamp	Integer. Unix time
x/y/z	Real. Sensor value for x/y/z axis. May be positive or negative.



Data in detail

Time-series data

Labeled examples



Periodic:
Use 10 second data (200 items) to form a new example with 92 features and 1 label.

Labeled example data format:

Table 4: Definition of Elements in Arff Data [26]

Features	Description
ACTIVITY	The activity performed using one of the activity codes from Table 2
X{0-9}; Y{0-9}, Z{0-9}	The distribution of values over the x, y, and z axes
{X,Y,Z}AVG	Average sensor value over the window
{X,Y,Z}PEAK	Time in milliseconds between the peaks in the wave associated with most activities
{X,Y,Z}ABSOLDEV	Average absolute difference between each of the 200 readings and the mean of those values
{X,Y,Z}STANDDEV	Standard deviation of the 200 values
{X,Y,Z}VAR	Variance of the values
XMFCC{0-12}, YMFCC{0-12}, ZMFCC{0-12}	MFCCs represent short-term power spectrum of a wave
{XY, XZ, YZ}COS	The cosine distrances between sensor values for pairs of axes
{XY, XZ, YZ}COR	The correlation between sensor values for pairs of axes
RESULTANT	Average resultant value, computed by squaring each matching x, y, and z value, summing them, taking the square root, and then averaging these values over the 200 readings
Class	Subject ID

What was done in paper

Authentication:
The authentication task involves distinguishing an authorized subject from an imposter. Hence authentication is a classification problem involving two classes.

Training set:

Authorized subject	Other subject
90 seconds	270 seconds

Testing set:
The unauthorized subject data not overlap with that in training set.

Performance evaluation:
Equal Error Rate (EER)/Accuracy

Identification:
Each subject represents a different class—for the identification data set there are fifty-one classes.

Training set:
The training set must have data from all subjects.

Testing set:
Partitioned using 10-fold cross validation

Statistical tools used in paper

Classification Algorithm:
K-NN
K = 5
Uniform weights
Minkowski distance

Decision Tree

Random Forest
Maximum number of features considered is the square root of the number of features in the data
Number of decision trees in the forest is set to 10

Data set partition:
10-fold cross validation

Reproduce Result

Subject Authentication

Subject authentication is **a two-class task** which judges whether the activity data is from the person we select.

Three approaches to classification**: K Nearest Neighbor**, **Decision Tree** and **Random Forest**.

The paper shows results of the best algorithm (Random Forest) with 9 sensor combinations per activity and in average.

We reproduce results of all three algorithms.

Subject Authentication

Reproduced result using Random Forest

Activity Code	Accel Phone	Gyro Phone	Accel Watch	Gyro Watch	Phone	Watch	Accel	Gyro	All
A	86.1	89.2	87.5	75.0	82.5	84.9	87.5	84.6	86.0
B	92.8	83.1	84.4	79.2	89.7	82.8	91.8	82.9	87.9
C	97.8	83.1	88.9	85.3	90.6	83.1	88.8	80.4	85.2
D	77.5	85.8	86.1	83.1	85.6	84.7	89.2	77.9	85.2
E	86.7	84.2	88.6	82.2	88.9	80.0	92.2	82.5	87.7
F	91.7	84.2	89.7	82.8	91.3	84.2	80.0	80.0	85.0
G	96.4	78.9	90.3	77.5	90.1	84.3	86.9	77.5	87.7
H	90.3	88.3	87.2	80.3	88.8	82.8	87.1	80.0	87.3
I	90.8	86.7	84.7	82.8	88.9	82.8	89.3	80.0	86.9
G	85.8	84.7	83.6	83.1	87.2	86.4	85.3	79.2	86.3
K	96.1	83.1	81.7	80.8	84.0	85.8	86.9	80.0	89.4
L	99.2	84.2	85.0	75.0	91.9	83.1	92.5	79.6	86.5
M	91.1	86.9	89.2	83.3	87.8	86.5	87.9	79.2	87.1
O	91.1	86.4	86.9	80.6	84.4	83.6	86.7	77.9	86.3
P	96.7	86.9	87.2	82.5	91.8	83.2	86.0	80.0	84.0
Q	97.2	78.3	88.6	80.6	92.8	83.1	90.7	85.8	86.0
R	96.7	85.6	81.7	75.0	83.9	83.6	92.1	80.0	86.3
S	95.6	86.7	90.0	77.5	89.0	83.8	90.7	82.5	86.5

Subject Authentication

Reproduced result using K Nearest Neighbor

Activity Code	Accel Phone	Gyro Phone	Accel Watch	Gyro Watch	Phone	Watch	Accel	Gyro	All
A	80.8	80.0	80.8	71.9	80.0	74.7	82.2	76.1	81.3
B	84.4	77.8	81.1	74.2	83.6	79.0	88.8	75.3	81.0
C	91.1	79.4	79.7	76.9	81.5	79.6	86.4	75.0	80.4
D	82.8	83.9	83.1	76.1	79.6	74.4	85.4	75.1	81.8
E	82.5	79.7	84.2	78.3	85.0	73.5	89.0	76.9	78.5
F	86.4	74.7	79.2	70.8	81.0	77.5	81.0	76.8	78.5
G	93.1	70.6	82.2	72.5	79.6	78.2	81.8	75.8	78.8
H	77.2	76.1	83.3	71.4	81.1	76.4	84.0	77.1	82.5
I	81.4	75.8	78.9	67.5	81.1	77.6	82.2	73.8	80.5
G	81.4	82.8	78.1	74.7	82.2	78.6	82.1	74.2	80.8
K	93.1	76.7	75.6	76.9	72.9	74.2	80.8	77.2	80.8
L	93.1	78.3	78.9	75.3	85.0	78.1	86.8	77.6	82.5
M	90.3	76.1	85.6	77.2	84.6	76.4	84.7	76.1	80.0
O	83.9	79.4	80.6	75.0	80.8	74.6	80.8	77.9	78.6
P	95.3	78.3	79.7	72.8	82.9	78.1	86.9	73.1	79.0
Q	93.9	70.0	79.2	75.6	86.7	77.8	85.8	73.8	79.4
R	94.2	82.2	77.8	76.9	77.2	79.9	85.6	75.4	79.7
S	89.2	73.6	81.1	70.6	80.8	78.3	86.3	77.1	78.3

Subject Authentication

Reproduced result using Decision Tree

Activity Code	Accel Phone	Gyro Phone	Accel Watch	Gyro Watch	Phone	Watch	Accel	Gyro	All
A	82.8	75.0	80.3	75.0	81.9	75.0	78.1	75.0	77.6
B	85.3	81.7	78.9	75.0	79.2	73.5	79.9	76.8	77.8
C	90.6	72.8	75.0	75.0	86.0	75.0	82.5	80.0	77.6
D	78.1	78.1	82.8	75.0	75.8	75.0	79.2	75.0	76.7
E	81.9	76.1	81.1	75.0	85.1	75.0	80.8	75.0	78.3
F	87.2	79.2	77.5	75.0	81.4	75.0	81.4	75.0	73.8
G	96.1	78.6	80.0	75.0	81.1	75.0	79.2	76.5	77.4
H	83.1	75.0	78.6	75.0	85.4	75.0	82.5	75.0	79.0
I	87.8	78.3	75.8	75.0	81.9	78.3	80.6	75.0	78.2
G	84.4	79.7	69.7	75.0	82.4	75.0	82.2	75.6	76.8
K	96.7	71.7	78.6	75.0	81.8	75.3	76.9	76.0	77.3
L	83.3	80.8	76.1	75.0	81.1	75.0	78.1	75.0	77.6
M	85.3	76.7	77.8	75.0	81.1	75.0	80.0	75.0	76.7
O	89.7	77.5	75.0	75.0	78.2	75.0	82.9	75.0	78.8
P	91.4	84.4	79.4	75.0	81.8	75.0	78.8	75.0	76.7
Q	92.5	72.5	80.6	75.0	78.9	75.0	84.7	75.0	78.9
R	96.1	83.1	76.9	75.0	82.5	75.0	79.9	75.0	76.7
S	89.2	81.4	79.2	75.0	82.6	74.3	82.6	79.3	80.6

Subject Identification

Subject identification is **a multi-class task** which distinguishes subjects in each activity.

Three approaches to classification**: K Nearest Neighbor**, **Decision Tree** and **Random Forest**.

The paper shows the accuracy results of the best algorithm (Random Forest) with 9 sensor combinations per activity and in average.

We reproduce results of all three algorithms.

Subject Identification

Result from paper using Random Forest

Activity	Ac_p	Gy_p	Ac_w	Gy_w	Phone	Watch	Accel	Gyro	All
Walking	96.1	94.7	75.1	67.0	96.8	78.9	96.5	95.3	97.4
Jogging	94.7	92.5	75.0	74.3	96.0	82.1	95.7	95.2	98.0
Stairs	90.8	81.2	52.4	39.2	92.7	58.7	92.6	80.9	95.1
Sitting	90.1	56.3	70.4	30.1	91.5	69.3	93.1	55.9	92.0
Standing	85.8	47.1	64.1	27.0	86.8	61.2	90.5	46.6	89.9
Kicking	87.4	67.2	54.3	38.3	88.6	59.8	92.1	72.7	92.1
Dribbling	88.3	66.0	72.3	74.8	89.5	80.3	93.9	82.1	94.4
Catch	90.0	67.2	69.1	71.3	90.3	75.4	94.1	82.0	93.7
Typing	94.8	71.7	81.2	51.2	94.6	84.2	95.6	76.5	95.7
Writing	92.8	69.1	79.6	47.6	93.1	79.1	94.2	73.0	93.9
Clapping	94.8	72.8	83.4	73.9	93.8	85.3	96.6	86.1	96.7
Teeth	92.2	69.5	70.0	56.3	93.7	76.1	95.2	74.5	95.4
Folding	90.7	65.8	60.0	38.8	92.0	63.0	93.6	72.7	93.8
Pasta	94.1	56.9	67.2	38.1	94.0	71.6	96.6	61.1	96.3
Soup	94.3	56.5	74.1	50.4	95.8	76.6	96.3	66.9	96.6
Sandwich	92.9	62.8	61.9	37.6	92.6	62.1	95.9	68.5	95.2
Chips	93.3	56.8	62.6	38.7	93.2	62.4	96.0	66.3	94.9
Drinking	93.9	57.4	63.9	41.3	93.8	65.3	95.4	60.6	94.7
Avg	92.1	67.3	68.7	49.8	92.7	71.7	**94.7**	73.2	**94.8**

Subject Identification

Reproduced result using Random Forest

Activity	Ac_p	Gy_p	Ac_w	Gy_w	Phone	Watch	Accel	Gyro	All
Walking	98.5	96.1	86.3	73.1	98.9	88.6	98.8	98.9	98.8
Jogging	95.9	93.0	86.3	85.5	95.8	92.0	96.1	95.5	95.1
Stairs	93.9	83.1	71.6	49.7	94.6	78.3	95.3	94.9	94.5
Sitting	95.9	64.9	80.8	47.9	94.2	80.5	95.0	94.1	94.0
Standing	94.0	58.1	81.0	36.2	94.1	79.0	96.3	94.3	94.1
Kicking	98.3	77.5	89.3	59.3	97.3	92.2	98.2	97.7	97.6
Dribbling	96.9	77.3	81.9	63.1	95.9	81.9	96.7	96.2	96.2
Catch	96.9	64.6	86.8	64.8	96.7	90.0	97.8	96.6	96.4
Typing	97.6	65.1	80.6	47.7	96.7	84.4	97.7	96.8	96.2
Writing	97.2	64.5	84.1	50.9	97.3	87.5	98.1	97.1	97.3
Clapping	97.6	67.2	81.7	49.2	96.8	84.3	97.6	96.4	96.4
Teeth	97.1	67.0	78.9	41.6	97.3	80.1	98.0	97.0	97.0
Folding	92.2	68.3	64.1	43.7	92.9	72.1	93.8	93.9	93.7
Pasta	96.1	69.4	82.3	81.6	96.2	88.9	97.8	95.7	95.6
Soup	96.9	68.2	87.0	86.6	97.1	92.6	98.4	97.2	96.9
Sandwich	95.9	78.9	88.2	66.0	94.0	89.4	94.6	93.9	94.3
Chips	97.3	76.9	90.3	86.1	96.0	93.6	97.6	96.2	96.3
Drinking	94.0	68.8	70.7	49.8	94.3	80.3	96.0	93.4	93.9
Avg	**96.2**	72.7	81.8	60.1	95.9	85.3	**96.9**	95.9	95.8

Subject Identification

Reproduced result using K Nearest Neighbor

Activity	Ac_p	Gy_p	Ac_w	Gy_w	Phone	Watch	Accel	Gyro	All
Walking	88.6	51.3	49.1	29.7	94.2	59.1	89.5	59.1	93.6
Jogging	88.1	63.8	59.2	33.1	90.3	68.0	85.9	74.3	89.1
Stairs	72.7	25.6	30.2	21.2	77.5	37.9	70.2	45.3	78.6
Sitting	87.7	30.7	60.4	22.4	76.2	55.8	85.6	44.4	74.0
Standing	70.4	24.4	47.3	18.8	60.4	44.7	76.6	38.3	62.6
Kicking	87.1	28.0	59.6	18.5	84.4	62.1	91.0	46.6	83.6
Dribbling	81.9	24.5	51.4	24.3	79.3	58.8	85.4	46.4	82.2
Catch	86.3	20.4	50.4	22.0	73.9	57.8	88.5	41.0	72.7
Typing	82.9	24.5	52.8	16.7	75.8	52.8	89.5	42.1	78.3
Writing	84.8	17.9	51.9	13.7	72.4	48.9	89.1	32.2	73.0
Clapping	87.7	20.8	52.6	18.5	73.6	53.2	89.5	36.0	74.6
Teeth	85.8	24.1	49.8	12.0	75.7	45.9	88.3	39.3	77.5
Folding	73.2	20.1	26.7	14.4	72.9	32.2	68.8	37.0	72.8
Pasta	80.0	26.5	51.3	21.2	77.0	49.9	82.8	47.0	76.3
Soup	79.7	27.6	55.6	31.6	80.7	61.3	88.0	59.3	80.5
Sandwich	88.1	30.5	58.1	16.8	85.6	55.4	90.4	41.6	85.1
Chips	87.2	25.1	79.3	43.2	83.3	83.3	94.1	57.9	83.3
Drinking	80.3	24.6	42.2	13.8	78.0	40.2	80.6	39.3	78.3
Avg	**82.9**	28.4	51.5	21.8	78.4	53.7	**85.2**	45.9	78.7

Subject Identification

Reproduced result using Decision Tree

Activity	Ac_p	Gy_p	Ac_w	Gy_w	Phone	Watch	Accel	Gyro	All
Walking	92.9	87.3	66.6	53.9	91.9	69.3	89.9	86.0	91.7
Jogging	89.7	83.4	62.8	63.3	88.8	70.3	87.6	82.3	89.4
Stairs	84.8	60.3	44.8	30.6	85.5	46.1	83.2	61.1	85.1
Sitting	94.1	49.6	75.6	27.7	91.1	72.1	93.0	45.4	91.6
Standing	92.4	38.3	71.4	22.4	89.3	68.4	91.2	37.8	90.3
Kicking	96.8	58.3	79.3	38.3	94.8	82.6	94.3	60.5	94.6
Dribbling	95.7	58.9	62.0	48.9	92.0	60.8	92.7	65.7	93.4
Catch	95.6	46.4	72.2	43.4	93.2	73.0	95.4	51.8	93.7
Typing	96.4	43.1	59.8	26.8	94.5	61.2	92.6	47.3	94.0
Writing	93.3	42.2	67.0	29.6	94.3	66.9	93.5	44.5	94.0
Clapping	95.5	47.3	67.7	29.2	93.8	65.5	93.3	51.1	93.6
Teeth	95.9	48.1	57.3	24.1	93.4	55.7	94.3	44.6	93.6
Folding	82.2	43.4	43.8	25.0	80.2	47.1	83.9	46.9	81.1
Pasta	87.8	43.8	54.0	50.5	86.1	59.8	89.2	54.4	86.9
Soup	92.5	47.2	63.1	66.3	89.1	72.5	89.0	69.9	90.9
Sandwich	93.9	60.5	78.3	42.0	90.9	78.1	92.2	58.1	91.3
Chips	95.3	60.5	77.1	68.6	92.4	76.6	93.6	75.8	93.6
Drinking	89.2	45.9	44.4	23.3	85.8	50.3	86.3	49.7	85.0
Avg	**92.4**	53.6	63.7	39.7	90.4	65.4	**90.8**	57.4	**90.8**

Different Techniques

Subject Authentication

Using Support Vector Machine to identify subjects

Activity Code	Accel Phone	Gyro Phone	Accel Watch	Gyro Watch	Phone	Watch	Accel	Gyro	All
A	89.7	80.3	83.6	75.6	81.7	72.5	84.6	75.0	77.7
B	89.2	78.6	84.4	75.3	79.2	70.4	75.0	73.8	76.9
C	88.9	76.9	78.9	76.7	79.6	74.2	79.2	76.7	75.8
D	81.1	76.7	85.0	76.9	75.0	72.5	79.6	74.6	78.3
E	87.5	75.6	89.2	75.8	79.6	74.2	83.8	74.2	76.5
F	88.1	78.3	80.8	73.9	70.4	69.6	78.8	75.0	78.8
G	96.9	70.6	85.0	73.3	71.7	69.2	82.5	70.0	78.3
H	89.2	80.6	84.2	76.4	78.8	75.4	84.6	75.0	77.5
I	91.4	75.3	82.5	73.6	77.5	71.3	81.3	73.3	76.3
G	83.9	77.8	80.0	75.0	77.9	70.8	83.8	74.2	72.5
K	94.4	77.8	72.5	76.9	81.3	71.7	77.5	72.5	77.7
L	91.7	71.7	84.2	75.0	85.8	78.8	77.9	72.1	75.4
M	89.4	77.2	83.9	78.3	82.1	70.8	76.3	72.9	78.3
O	89.4	79.4	82.2	74.4	76.7	67.1	84.6	69.6	77.7
P	95.8	76.7	77.8	74.7	81.3	78.8	79.2	75.0	76.5
Q	96.7	65.6	84.4	75.0	82.5	69.2	85.0	75.0	77.5
R	91.9	71.1	83.1	75.0	79.6	72.5	78.3	70.8	80.2
S	90.8	75.3	81.9	70.0	76.3	72.5	77.5	75.0	76.7

Subject Identification

Using Support Vector Machine to identify subjects

Activity	Ac_p	Gy_p	Ac_w	Gy_w	Phone	Watch	Accel	Gyro	All
Walking	98.2	74.7	89.1	48.3	95.6	74.2	98.6	77.8	96.0
Jogging	96.3	77.9	89.6	60.0	92.8	82.8	96.6	83.0	93.0
Stairs	93.8	49.5	71.1	36.5	89.9	60.7	95.4	57.6	88.8
Sitting	94.9	39.7	70.1	25.9	88.5	68.1	92.5	47.9	89.0
Standing	89.4	34.4	68.2	23.2	85.8	63.8	89.4	46.4	85.8
Kicking	97.4	43.2	76.4	24.5	92.1	80.9	96.8	51.5	92.7
Dribbling	94.2	37.1	80.0	42.8	87.7	71.1	93.1	56.5	88.5
Catch	96.3	31.8	73.6	32.5	90.9	74.8	95.2	50.3	91.8
Typing	95.8	37.2	65.1	26.3	90.6	71.6	95.0	46.5	92.6
Writing	96.6	32.8	74.3	27.1	90.7	72.3	96.5	43.3	90.5
Clapping	96.2	34.8	70.6	22.4	91.1	70.2	95.6	43.5	91.7
Teeth	94.1	39.4	61.9	21.2	91.5	64.4	95.0	44.0	92.1
Folding	91.9	33.7	65.5	33.3	85.8	55.3	92.7	49.7	85.3
Pasta	95.3	36.9	84.0	53.4	88.5	68.9	98.1	57.5	89.3
Soup	96.3	38.3	89.2	64.5	87.6	78.6	98.3	70.3	88.9
Sandwich	93.8	44.2	81.3	23.7	90.4	74.0	92.9	49.7	90.9
Chips	95.9	37.9	90.7	56.9	93.3	85.3	97.1	66.1	93.1
Drinking	93.1	32.4	74.2	27.0	87.3	62.8	93.3	47.7	87.0
Avg	**95.0**	42.0	76.4	36.1	90.0	71.1	**95.1**	55.0	90.4

Discussion and Conclusion

Compare results of different techniques

K Nearest Neighbors

- **High interpretability**
- **Rather fast**
- **Relatively low accuracy**

Decision Tree

- **High interpretability**
- **Rather fast**
- **Unstable with small change in data**

Random Forest

- **More time-consuming to train**
- **Covariance reducing**
- **High accuracy**

Support Vector Machine

- **Not easy to interpret**
- **Not good performance in multi-class classification**

Method	Ac_p	Gy_p	Ac_w	Gy_w	Phone	Watch	Accel	Gyro	All
KNN	82.9	51.5	28.4	21.8	78.4	53.7	85.2	45.9	78.7
Tree	92.4	63.7	53.6	39.7	90.4	65.4	90.8	57.4	90.8
RF	96.2	81.8	72.7	60.1	95.9	85.3	96.9	95.9	95.8
SVM	95.0	42.0	76.4	36.1	90.0	71.1	95.1	55.0	90.4

Average accuracy among 18 activities with different method

Future work

Try different parameters of K-NN, Decision Tree, Random Forest, SVM.

Try other statistical learning techniques.

Try different feature extraction methods for time-series data.

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Thank you!

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