Automating time series feature engineering for activity recognition from synchronized inertial measurement units

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Outline

Human Activity Recognition (HAR)

HAR is an active research area within the field of *ubiquitous sensing*, which has applications in

- medicine (monitoring exercise routines),
- military (decision making in combat and training scenarios),
- sport (monitoring the potential for injuries and enhance athletes performance)

Óscar D. Lara and Miguel A. Labrador. "A Survey on Human Activity Recognition using Wearable Sensors". In: *IEEE Communications Surveys & Tutorials* 15.3 (2013), pp. 1192–1209

Amin Ahmadi et al. "Toward Automatic Activity Classification and Movement Assessment During a Sports Training Session". In: *IEEE Internet of Things Journal* 2.1 (2015), pp. 23–32

Challenges of HAR

- selection of the attributes to be measured,
- construction of a portable, unobtrusive, and inexpensive data acquisition system,
- design of feature extraction and inference methods,
- collection of data under realistic conditions,
- flexibility to support new users without the need of re-training the system,
- implementation in mobile devices meeting energy and processing requirements.

Ahmadi et al., "Toward Automatic Activity Classification and Movement Assessment During a Sports Training Session"

IMeasureU BlueThunder sensor

accelerometer range $\pm$ 16g

accelerometer resolution 16-bit

gyroscope range $\pm$ 2000 $^\circ/\mathrm{s}$

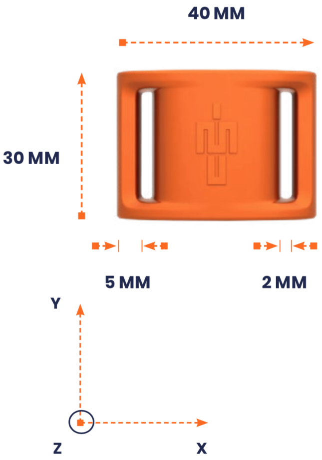
gyroscope resolution 16-bit

compass range $\pm$ 1200 μT

compass resolution 13-bit

data logging 500Hz

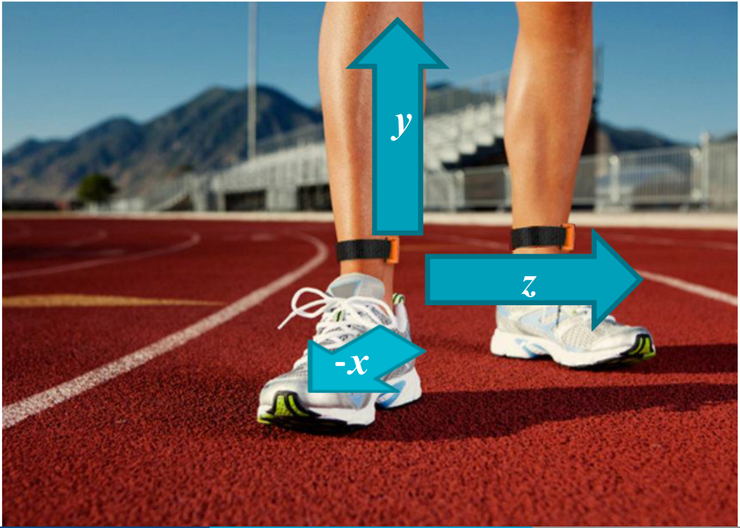
weight 12g



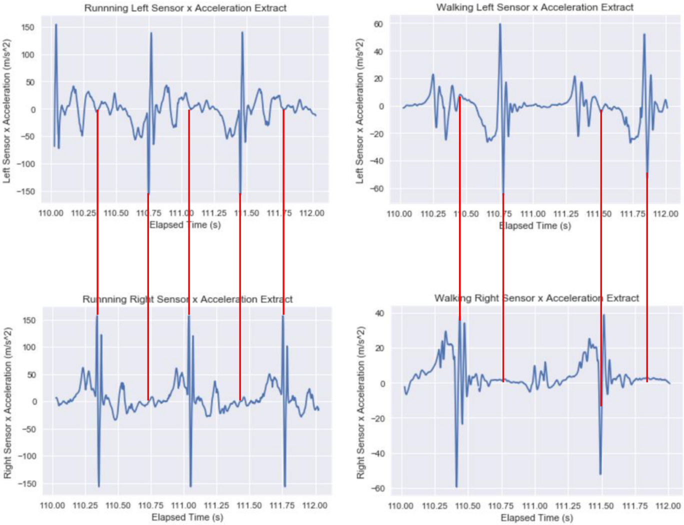
Andrew Wong and Rakesh Vallabh. *IMeasureU BlueThunder sensor*. Sensor Specification 1.5. Auckland: Vicon IMeasureU Limited, 2018

Synchronized sensors

Two sensors: 18 time series + 9 paired time series



Left-right and running-walking comparison



Feature Engineering

Feature transformation is about constructing new features from existing features; this is often achieved using mathematical mappings.

Feature generation is about generating new features that are often not the result of feature transformations (e.g. using domain-specific ways)

Feature selection is about selecting a small set of features from a very large pool of features (often included in feature analysis and evaluation).

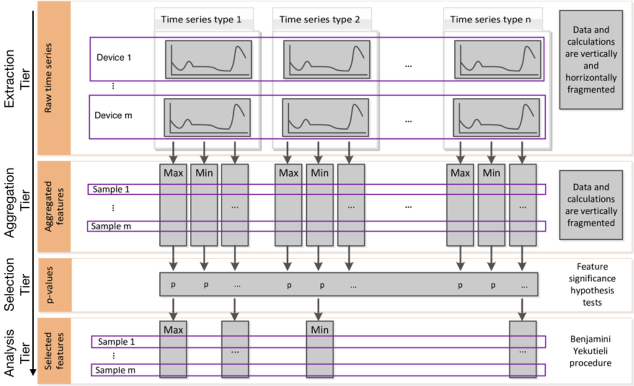
Feature analysis and evaluation is about concepts, methods, and measures for evaluating the usefulness of features and feature sets.

General automatic feature engineering methodology is about generic approaches for automatically generating a large number of features and selecting an effective subset of the generated features.

Feature engineering applications involve feature engineering but the focus is to solve some other data analytic tasks in specific contexts.

Guozhu Dong and Huan Liu, eds. *Feature engineering for machine learning and data analytics*. Boca Raton, FL: Taylor & Francis, 2018

General automatic feature engineering



Maximilian Christ, Andreas W. Kempa-Liehr, and Michael Feindt. *Distributed and parallel time series feature extraction for industrial big data applications*. Learning 1610.07717v1. Asian Conference on Machine Learning (ACML) Workshop on Learning on Big Data (WLBD). arXiv, 2016. URL: https://arxiv.org/abs/1610.07717v1

Feature selection (Hypothesis testing)

A feature X_ϕ is *relevant* or *meaningful* for the prediction of Y if and only if X_ϕ and Y are not statistically independent.
$\exists\ y_1, y_2$ with $f_Y(y_1) > 0, f_Y(y_2) > 0\ :\ f_{X|Y=y_1} \neq f_{X|Y=y_2}$

Null hypothesis

$$H_0^\phi = \{X_\phi \text{ is irrelevant for predicting } Y\},$$
$$H_1^\phi = \{X_\phi \text{ is relevant for predicting } Y\}.$$

Binary target

binary feature Fisher's exact test

non binary feature Kolmogorov-Smirnov test

FRESH algorithm

Feature extRaction on basis of Scalable Hypothesis testing (FRESH)

Data: Labelled samples comprising different time series
Result: Relevant time series features

```
for all predefined feature extraction algorithms do
    for all time series do
        for all samples do
            Apply feature extraction algorithm to time series
              sample and compute time series feature;
        end
        Test statistical significance of feature for predicting the
          label;
    end
end
Select significant features while preserving false discovery rate;
```

Feature extraction example

The Python package `tsfresh` also supports `sklearn`'s API.

```
from tsfresh import select_features, extract_features
from tsfresh.examples.robot_execution_failures import
↪  load_robot_execution_failures
from tsfresh.utilities.dataframe_functions import impute

df, y = load_robot_execution_failures()
X = extract_features(df, column_id="id",
↪  column_sort="time")
impute(X)
X_filtered = select_features(X, y)
```

Maximilian Christ et al. "Time Series FeatuRe Extraction on basis of Scalable Hypothesis tests (tsfresh – A Python package)". In: *Neurocomputing* 307 (2018), pp. 72–77. DOI: 10.1016/j.neucom.2018.03.067

Classification Running vs. Walking

- 560 seconds of mixed running and walking
- 280000 measurements for each of the 18 sensors (plus 9 paired measurements)
- 140 sections of 4s length (82 walking, 58 running)
- 16283 features in total
- 5212 statistically significant features (false discovery rate 50%)
- Random Forest achieves 100% accuracy under 10-fold cross-validation

Jonty Oram. “Classification of athletes’ motion from sensor data”. Research Report. The University of Auckland: Department of Engineering Science, 2017

Most important features

Naming scheme

kind name of the time series the feature is based on,

calculator name of the function, which has been used to extract the feature,

key-value pairs parameters configuring the respecitve feature calculator

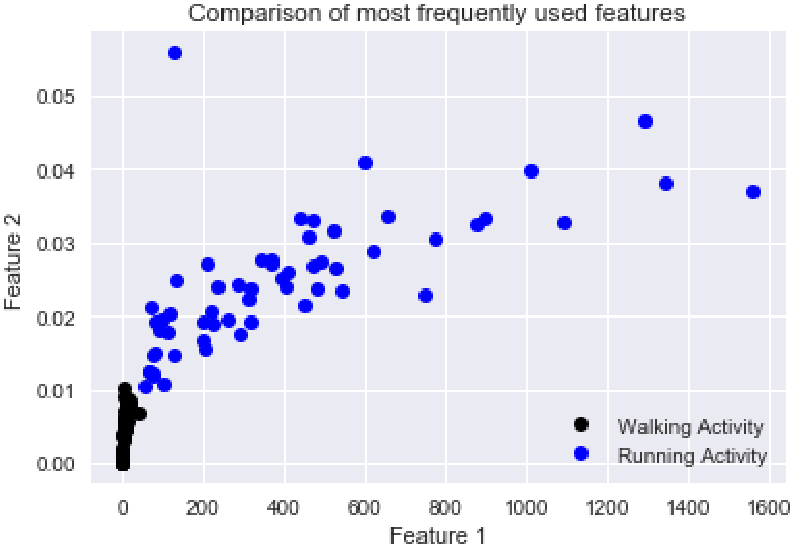
```
[kind]__[calculator]__[parameterA]_[valueA]__[parameterB]_[valueB]
```

Most important features

Ranked by mean feature importance of 100k random forests.

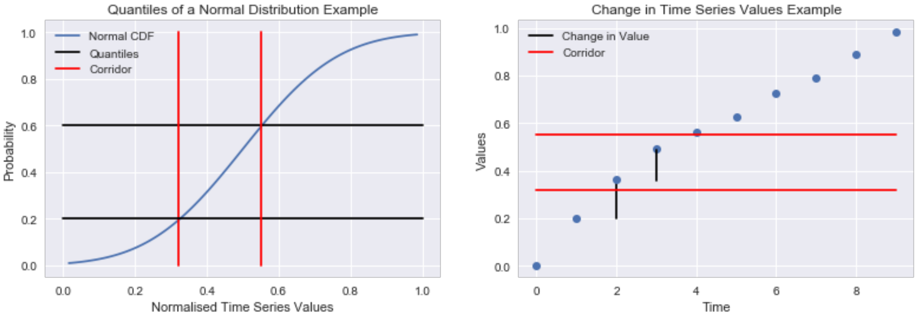
1. `gyro_z_l__change_quantiles__f_agg_"var"__isabs_False__qh_0.6__ql_0.4`
2. `accel_z_l__agg_linear_trend__f_agg_"min"__chunk_len_10__attr_"stderr"`
3. `gyro_y_diff__change_quantiles__f_agg_"var"__isabs_False__qh_1.0__ql_0.4`

Scatter plot of most important features



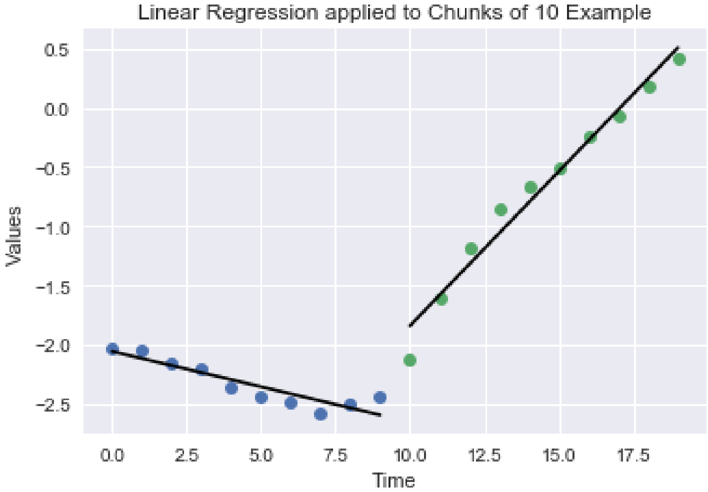
Change quantiles feature

```
gyro_z_l__change_quantiles__f_agg_"var"__isabs_False__qh_0.6__ql_0.4
```

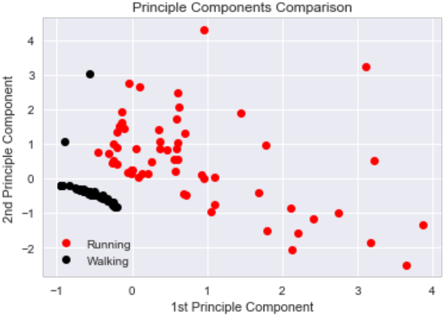


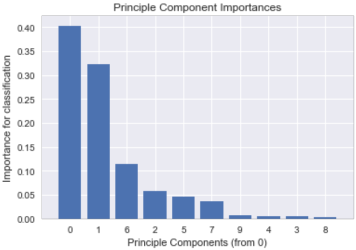
Agg linear trend feature

`accel_z_l__agg_linear_trend__f_agg_"min"__chunk_len_10__attr_"stderr"`

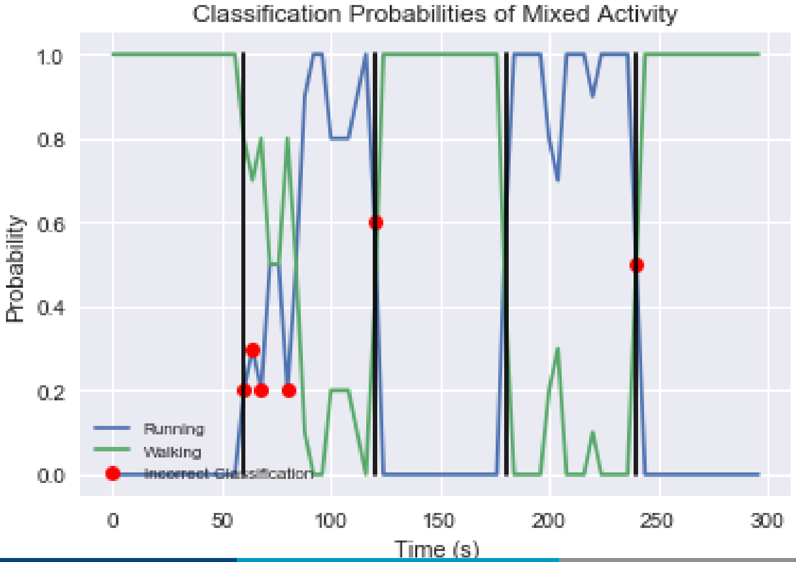


Principle components





Validation with separate run



References

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