Literature review

Human daily activity recognition by fusing accelerometer and multi-lead ECG data

link:
https://www.researchgate.net/publication/261210398_Human_daily_activity_recognition_by_fusing_accelerometer_and_lead_ECG_data

General info

Acceloremeter data with ECG records can be used simultaneously to achieve better accuracy.

Using GMM gives good results, but requires a lot of adaptation for particular activity type

single-lead ECG could be insuffiecient for use for people with cardiac abnormalities

RVM gives better results, then SVM and is more suitable for real-time systems

Data → divide into small fixed windows → extract features → LDA (for reducing dimensionality) → multiclass RVM classification (one-vs-all) → results from each lead and accelerometer are fused using decision tree (linear opinion pool)

Preprocessing

50 % overlap for sliding window has been shown, as effective for activity recognition

Since the length of each heartbeat is different due to inherent heart rate variability, it is necessary to perform the preprocessing steps that involve detection of R-Peak and alignment of ECG beats, time-warping of ECG beats, correction ford bias, and amplitude scaling for normalizing each heartbeat waveform to the same time duration and amplitude range

Feature extraction

Acceleration data

The time-domain features: mean, median, zero-cross rate, mean of minima, averaged derivatives, cross-correlation, signal magnitude are as well as mean low and mean rectified high pass filtered signals

The frequency-domain features: energy, the magnitude of the first six components of FFT analysis as well as the energy of 0.2Hz window around the main frequency over total energy

ECG data

The conventional features: the mean and variance of the instantaneous heart-rate

Other: the PCA error vector, the Hermite polynomial expansion coefficients, and the standard deviation of multiple normalized beats

Results

Classes: lying (LY), sitting (SI), standing (ST), walking (W), walking-upstairs (WU), walking-downstairs (WD), running (R).

With 2 leads achieve 93 %, 2 leads + accelerometer achieve 97 % accuracy. Maximum 99.57 % with all leads and accelerometer.

Activity Recognition Using Wearable Physiological Measurements: Selection of Features from a Comprehensive Literature Study

link: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6960825/

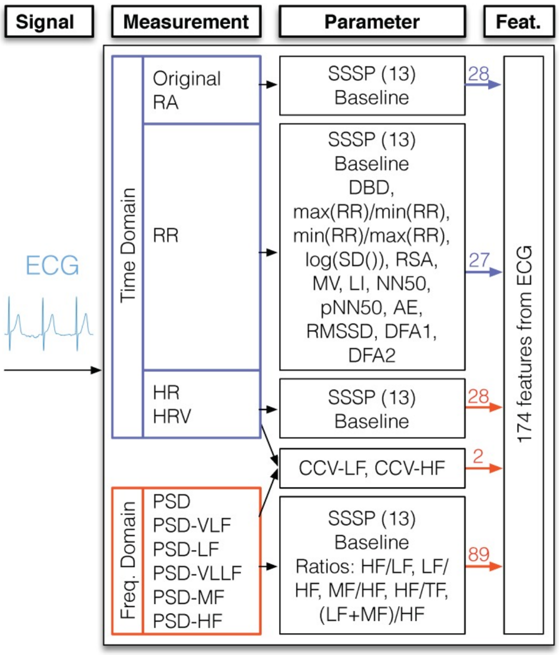
Feature extraction

The most frequently used features: frequency bands, power ratios, HRV, SDNN, Number of NNs in 50 ms (NN50), pNN50

Standard Set of Statistical Parameters (SSSP), and they include: mean, median, standard deviation, 25% trimmed mean, skewness, kurtosis, maximum, minimum, percentile 25%, percentile 75%, geometric mean, harmonic mean and mean absolute deviation.

Baseline:

$$y_i = z_i \cdot \beta + y_{i-1} \cdot (1 - \beta)$$



Classification

Several classifiers are used to compare perfomance: LSLC, SVM, feed-forward NN, kNN, Random Forest,

Genetic algorithm was used for feature selection

Window selection

There are some features that require a minimum window length to be calculated, such as, HRV triangular index, which takes at least 20 min to be calculated, Standard Deviation of NN intervals (SDNN) index, calculated as mean standard deviations of all NN intervals for all 5 min segments of the entire recording, and for all derivatives (Standard Deviation of Successive Differences (SDSD), Standard Deviation of sequential 5-min RR interval (SDANN)). Choosed to use only < 60 s to handle dataset.

For ECG later 60s was the best choice

Results

Random Forest, SVM and NN shows best results (error < 27 %)

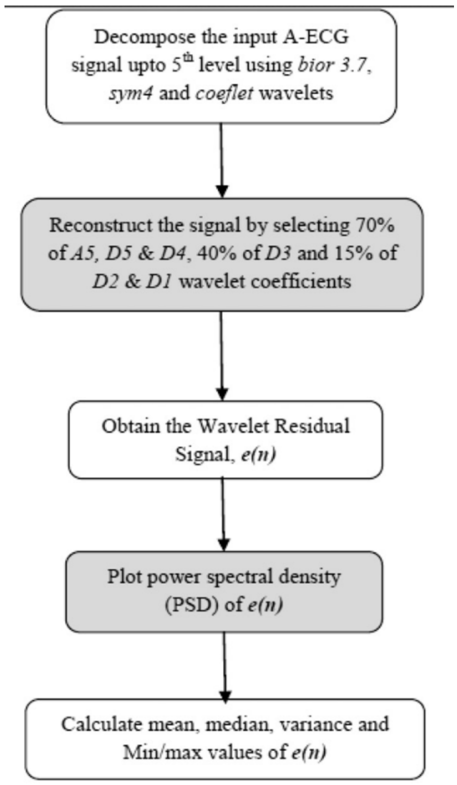
SVM and Random Forest need less features

Physical activities recognition from ambulatory ECG signals using neuro-fuzzy classifiers and support vector machines

link: https://www.tandfonline.com/doi/abs/10.3109/03091902.2014.998372?scroll=top&needAccess=true&journalCode=ijmt20

Feature extraction

Use of wavelet transforms for time-frequency domain feature extraction



Gabor transform has been applied for extracting the distinct, time-frequency features of motion artifacts signals.

Classification

Neuro-fuzzy classifier (nearly the same, as conventional Neural Network, but contains 'fuzzy perceptron' — weights are modeled as fuzzy sets) and SVM (with liner, poly, rbf kernel) are compared. And SVM with poly, rbf have the best accuracy

Human activity recognition adapted to the type of movement

link: https://sci-hub.do/https://www.sciencedirect.com/science/article/abs/pii/S0045790620306789

General info

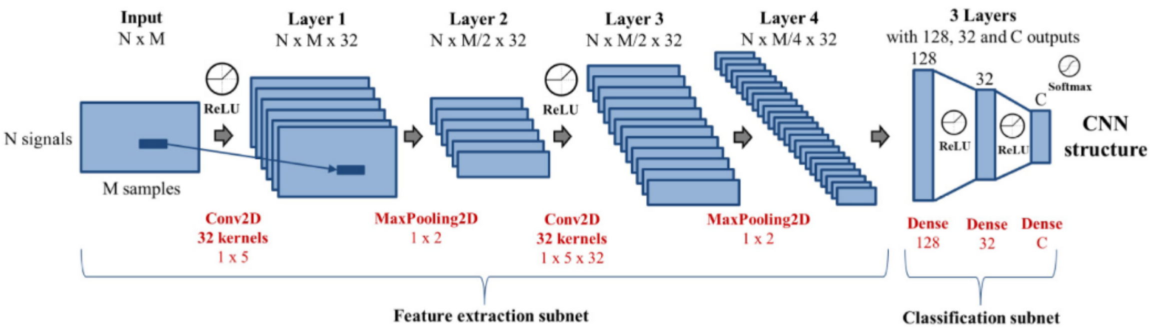
Highlights the fact, that previous papers does not investigate difference between motions, that are classified.

Preprocessing

Using Hamming function with 0.25 s shift.

Classification

CNN is used with matices NxM, where N = 3*n (n is amount of sensors), M = size of window.



Alternatively, to extract the temporal model inside each window first two fully-connected layers were substituted by LSTM.

Cross-validation should be used, as amount of data is not big

Results

Raw signal usage outperforms frequency specter with longer window in repetitive tasks.

Raw signal usage gives better results, then frequency specter with a shorter window in non-repetitive tasks.

Frequency specter gives better results when classifying posters with longer window size.

Multimodal Physical Activity Recognition by Fusing Temporal and Cepstral Information

link: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4326092/

General info

Use of cepstral domain of ECG signal, as its feature calculation uses short fixed length processing windows and thus does not need the preprocessing steps of heartbeat segmentation and normalization.

Feature extraction

Accelerometer features:

Conventional Temporal Accelerometer Features

mean absolute deviation	zero crossing rate	energy
$(20, 40, 60, 80)^{th}$ percentile	spectral entropy	kurtosis
cross correlation	mean crossing rate	median
mean of maxima	mean of minima	mean
standard deviation	root mean squre	skewness

For the **ECG** sensor, the mean and variance of the instantaneous heart-rate constitute the conventional features. The other three features sets are comprised of features that describe the discriminative activity information for the ECG signals. These features result from more complex processing of the ECG signal: 1) PCA error vector 2) the Hermite polynomial expansion coefficients, and 3) the standard deviation of multiple normalized beats

signal is modeled as:

$r_{ij}(t) = \theta_i(t) + \chi_{ij}(t) + \eta_{ij}(t)$

where $\theta i(t)$ is the cardiac activity mean (CAM) which is the normal heart signal, $\chi ij(t)$ is an additive motion artifact noise (MAN) due to ith class of activities, and $\eta ij(t)$ is the sensor noise present in the ECG signal.

1) PCA is used for extracting MAN

2) Hermite Polynomial Expansion is used to model CAM component, and the resulting coefficients serve as another feature set for classification.

3) the sum of standard deviations for all the normalized bins (D bins) in the window is also employed as a feature, as we see that higher intensity states (walking) have a larger standard deviation than lower-intensity ones (lying).

Cepstral features:

Using cepstral features to model the frequency information of the native signal allows us to separate inherent convolutive effects by simple linear filtering.

The ECG base-line wanders and high-frequency noises can result in drastic frame-to-frame phase changes. Furthermore, the properties of the “excitation” source of the sensor signal (e.g., ECG heart rate and accelerometer speed) also vary from frame to frame, which makes the phase not very meaningful. Because of this, the complex cepstrum is rarely adopted for real-life signals. Thus, in this activity recognition application, we use only the real cepstrum which is based on spectral magnitude information from the sensor signals.

The filter energies are more robust to noise and spectral estimation errors and thus have been extensively used as the golden feature set

Cepstral features with Cepstral mean subtraction and cepstral variance normalization are more robust against the session variability.

Classification

Classification from the time domain is done by SVM and from the cepstral domain by GMM. After that results after fused.

ECG and accelerometer cepstral features are not concatenated and fused at the feature level due to the compatibility issues arising from different time shift and window length configurations and different sampling frequencies. However, the cepstral features from each axis of the accelerometer are concatenated to construct a long cepstral feature vector in each frame.

For fusing different scores loglikehood of estimators is estimated by linear regression

Results

By the use of cepstral domain mean accuracy is increased by 5 % from 89 to 94.

the performances in setting 2 are noticeably lower than in setting 1 because of the mismatch between training and testing data due to the session variability. The ECG systems can drop their performance by up to 30% while the accelerometer systems are relatively more robust with only a 15% decrease.