A Comprehensive Study of Activity Recognition Using Accelerometers

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Activity Recognition Using Accelerometers

• Overview
  • Activity recognition
  • Traditional ML approach
  • Neural Networks
  • Conditional Random Fields
Activity recognition
Activity recognition

• Attempting to discern the actual activities that are occurring in a specific moment

• Accelerometers
  • Tri-axial accelerometers provide a low-power and high fidelity measurement of force along the x, y and z directions

• There is significant potential for accurately predicting activities of daily living with accelerometers
The nature of an accelerometer
The nature of an accelerometer
Sample data view

- Sampling rate of 20Hz
- Time window of 1s

| t         | target   | x     | y     | z     |
|-----------|----------|-------|-------|-------|
| 46.012    | a_walk   | 1.082 | -0.088| 0.024 |
| 46.06186  | a_walk   | 1.072 | -0.126| 0.078 |
| 46.1119   | a_walk   | 1.186 | -0.144| 0.13  |
| 46.16195  | a_walk   | 1.044 | -0.218| 0.174 |
| 46.212    | a_walk   | 0.976 | -0.144| 0.162 |
| 46.26186  | a_walk   | 0.94  | -0.068| 0.112 |
| 46.3119   | a_walk   | 0.914 | -0.168| 0.12  |
| 46.36195  | a_walk   | 0.908 | -0.19 | 0.142 |
| 46.412    | a_walk   | 0.998 | -0.288| 0.118 |
| 46.46186  | a_walk   | 0.97  | -0.228| 0.088 |
| 46.5119   | a_walk   | 0.904 | -0.354| 0.148 |
| 46.56195  | a_walk   | 0.864 | -0.488| 0.14  |
| 46.612    | a_walk   | 0.918 | -0.706| 0.056 |
| 46.66286  | a_walk   | 0.944 | -0.706| 0.032 |
| 46.7129   | a_walk   | 1.152 | -0.864| -0.008|
| 46.76295  | a_walk   | 0.966 | -0.736| -0.154|
| 46.813    | a_walk   | 1.058 | -0.754| -0.194|
| 46.86286  | a_walk   | 0.944 | -0.74 | -0.234|
| 46.9129   | a_walk   | 0.818 | -0.968| -0.16 |
| 46.96295  | a_walk   | 0.678 | -1.05 | -0.25 |
| 47.013    | a_walk   | 0.578 | -1.064| -0.096|
In this study

• Sampling rate 30Hz
• Time window of 3s
What activities are we interested in?

• ADL activities (Activities of Daily Living)
• Walking
• Sitting
• Running
• Jumping
• Lying
• Stair descending
• Stair ascending
• ...
Data-Sets Used in This Work

• HAR
  • 6 labeled activities: walking, walking up stairs, walking down stairs, sitting, standing and lying down

• USCHAD
  • 12 labeled activities: walking forward, walking left, walking right, walking upstairs, walking downstairs, running forward, jumping, sitting, standing, sleeping, elevator up, elevator down
Data-Sets Used in This Work

• PAMAP2
  • 18 labeled activities: lying, sitting, standing, walking, running, cycling, Nordic walking, watching TV, computer work, car driving, ascending stairs, descending stairs, vacuum cleaning, ironing, folding laundry, house cleaning, playing soccer, rope jumping
Location of accelerometers on the human body

- The wrist of the dominant arm
- Hip(belt)
- Ankle
- Trouser pocket
Traditional ML approach
Features Used in This Study

• Time-domain features
  • mean, standard deviation, correlation, acceleration ..

• Frequency domain features
  • gathered after FFT transformation is applied: entropy, energy, coherence, etc
Features Used in This Study

• Hand-Crafted Features
  • “statistical”
    • Statistical measures from time domain and frequency domain
    • Sparse regularization for eliminating least informative features

• Empirical Cumulative Distribution Function (ECDF) features
  • Features are computed from the empirical cumulative distribution of all axes
Classification Models Used in the ML approach

• Random Forest
  • RF-CRF

• Logistic Regression
  • LR-CRF
Neural networks using MLP, CNN, LSTM and CRF
Classification Models Used in This Work

• Unstructured models (“independently and identically distributed”)
  • Multi-layer Perceptron
  • CNN
  • LSTM

• Structured models (conditional random fields)
  • MLP-CRF
  • CNN-CRF
  • LSTM-CRF
Multi-Layer perceptron

- Hidden layer with 100 units
- ReLu + Softmax
- Optimization is done with maximum likelihood
- $f(X) = \sigma_2 (\sigma_1 (Xw_1 + b_1) w_2 + b_2)$
Convolutional Neural Networks

- Input data
- Convolution
- Dropout
- Normalization

- No pooling was used
Convolutional Neural Networks

- 5-fold parameter selection
  - Dropout rate: \{0.1, 0.2, 0.5\}
  - Training epochs: \{8, 16, 32, 64, 128, 256\}
  - minimize categorical cross entropy
Recurrent Neural Networks

• Squashing function (tanh)
• During backpropagation suffers from the Vanishing gradient
• Shrinks as it backpropagates through time

![Diagram of RNN](image)

\[
\begin{align*}
A & \rightarrow h_t \\
A & \rightarrow h_t \\
\vdots & \quad \vdots
\end{align*}
\]
Recurrent Neural Networks
Long short term memory
Long short term memory

- **Architecture:**
  - LSTM layer with 64 units and dropout (selected in cross validation)
  - LSTM layer with 32 units and dropout (selected in cross validation)
  - Flattening layer
  - Fully connected with 16 units; ReLU activations and dropout
  - Output layer with softmax

- Trained with the Adam optimiser and parameters are tuned to minimize categorical cross entropy.
Conditional Random Fields (CRFs)

• Model the sequential nature of the data with CRF
• Uses SGD for training (in this case)
• Estimating the probability of a sequence by using the Viterbi algorithm:

\[ P_{\text{CRF}}(y_m | x_m) = \frac{1}{Z_{\text{CRF}}} \prod_{n=1}^{N_m} \exp\{\lambda^T f(y_{m,n-1}, y_{m,n}, x_m, n)\} \]
Conditional Random Fields (CRFs)

• For training the goal is maximizing the conditional log likelihood

$$\sum_{(\bar{x}_i, \bar{y}_i) \in (X, Y)} \log \frac{\exp \sum_{z=1}^{d} w_z F_z(\bar{x}_i, \bar{y}_i)}{\sum_{\bar{y}'} \exp \sum_{z=1}^{d} w_z F_z(\bar{x}_i, \bar{y}')}. $$

• General feature function(s):

$$F_z(\bar{x}_i, \bar{y}_i) = \sum_{j} f_z(x_{ij}, y_{ij-1}, y_{ij})$$
Conditional Random Fields (CRFs)

The idea: One cannot simply transition from ‘sitting’ to ‘running’ without an intermediate activity

\[
F_z^{(5)}(\vec{x}_i, \vec{y}_i) = \sum_j f_z^{(5)}(g_z(x_{ij}), y_{ij})
\]

\[
F_z^{(6)}(\vec{x}_i, \vec{y}_i) = \sum_j f_z^{(6)}(g_z(x_{ij}), y_{ij-1}, y_{ij})
\]
Conditional Random Fields (CRFs)

\[
\begin{align*}
(0.3, 0.4, 0.1, 0.05, 0.05, 0.1) \\
\text{standSit, sit, walk, run, jump, lying}
\end{align*}
\]

\[
F_z^{(6)}(\bar{x}_i, \bar{y}_i) = \sum_j f_z^{(6)}(g_z(x_{ij}), y_{ij-1}, y_{ij})
\]

\[
f(x_{ij}, y_{i,j-1}, y_{i,j}) = \begin{cases} 
1, & (y_{i,j-1} == "standSit") \text{ and } (y_{i,j} == "sit") \text{ and } (x_{i,j} > 0.5) \\
0, & \text{otherwise}
\end{cases}
\]
Results

| HAR         |       |       | PAMAP       |       |       | USCHAD      |       |       |
|-------------|-------|-------|-------------|-------|-------|-------------|-------|-------|
| Model       | iid  | CRF  | Model       | iid  | CRF  | Model       | iid  | CRF  |
| stat-LR     | 0.937| 0.950| stat-LR     | 0.850| 0.910| stat-LR     | 0.864| 0.899|
| ecdf-LR     | 0.940| 0.964| ecdf-LR     | 0.690| 0.791| ecdf-LR     | 0.778| 0.839|
| CNN         | 0.940| 0.950| CNN         | 0.731| 0.740| CNN         | 0.771| 0.776|
| LSTM        | 0.917| 0.966| LSTM        | 0.816| 0.842| LSTM        | 0.831| 0.899|
Review

• Activity recognition
• Traditional ML approach
• Neural Network approach
Thank you for your attention!