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

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<th>t</th>
<th>target</th>
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<th>y</th>
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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
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.

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

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

\[
(0.3, 0.4, 0.1, 0.05, 0.05, 0.1)
\]

standSit, sit, walk, run, jump, lying

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

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

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th>PAMAP</th>
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<th>USCHAD</th>
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Review

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