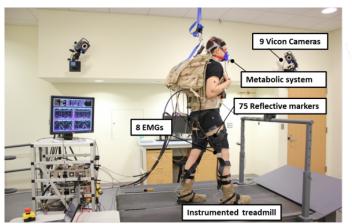
Sequence Labeling for Gait Analysis using LSTM 10-701 Project Presentation

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Introduction



from http://biodesign.seas.harvard.edu/soft-exosuits

Goal: Accurately detect gait events (heel strike, toe off) in video-based motion capture data of human walking gait

Introduction

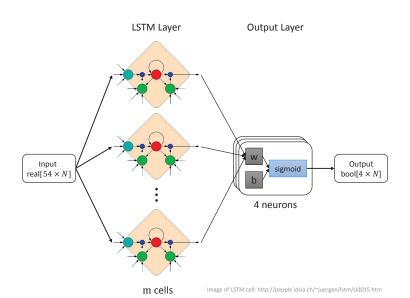
- ▶ **Problem:** Sequence labeling
 - ▶ Input: 3D locus of 18 motion capture markers (54*N reals)
 - ▶ Output: {Left, Right} × {Heel Strike, Toe Off} (4*N bools)
- Dataset:
 - ▶ 8 subjects × 3 trials × 10 000 samples @ 100 Hz
 - Ground truth from force plates on treadmills

Our Approach

Objectives:

- Gross mis-predictions should be avoided even with the presence of input noise
- 2. Number of manually-picked parameters (window size, threshold, filter cutoff, etc.) should be minimal
- Algorithm that generalizes to healthy and pathological subjects, treadmill and over-ground walking
- Proposed solution: LSTM-based RNN
 - Shown to work with timeseries data in sequence labeling and prediction tasks
 - Can possibly learn and exploit temporal correlations of data

Network architecture



Implementation

- ► Torch/Lua on 1 AWS EC2 GPU instance (g2.2xlarge)
- Start with LSTM code example by de Freitas
 - Adapted to our problem setup
 - Parameter tweaking to achieve convergence
 - Improved results through adaptive gradients, mini-batch, regularization.
- ▶ N-fold cross-validation to evaluate performance
- Further work:
 - Explore alternative network configurations
 - Assess time/space invariance
 - Generalize to stroke subjects and over-ground trials

Results

	deviation	deviation (frames)	
	mean	std	
Foot velocity	4.84	3.74	
Feed-forward NN	0.85	1.48	
LSTM	2.35	3.87	

Table 1: Comparison of results for N = 30, T = 25 s.

Results

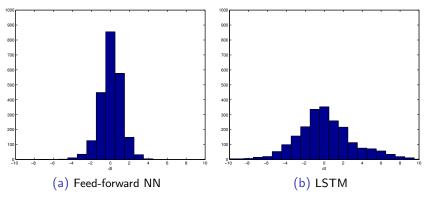


Figure 1: Absolute deviations, N = 30, T = 25 s.

Thank you for your attention!

Human Gait Cycle

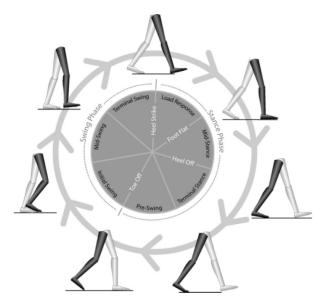


Figure 2: Gait events [Rueterbories etal., 2010] Figure 2: Gait events