Gait Event Detection Using an LSTM Network

10-701 Project Presentation

Pablo Iturralde
Yin Zhong
Jakob Bauer

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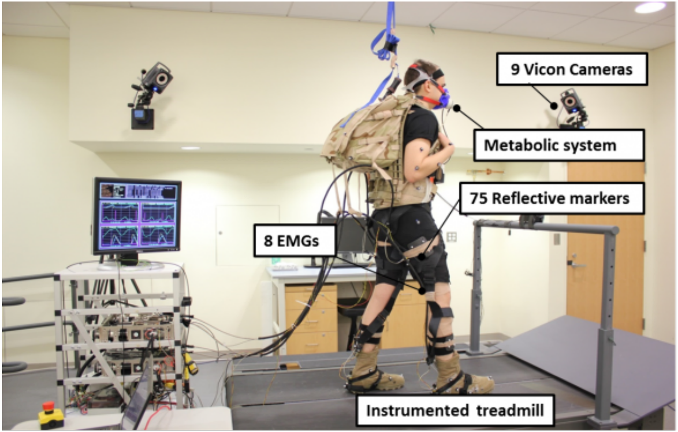
Introduction



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$\} \times \{$Heel Strike, Toe Off$\}$ (4*N bools)
- **Dataset:**
  - 8 subjects $\times$ 3 trials $\times$ 10 000 samples @ 100 Hz
  - Ground truth from force plates on treadmills

Our Approach

- Objectives:
  - Empirical feature-engineering should be minimal
  - Number of manually-picked parameters (window size, threshold, filter cutoff, etc.) should be minimal
  - Dependence of one gait cycle on those preceding it should be exploited
- Proposed solution: LSTM-based RNN
  - Recognition of periodic patterns even in presence of input noise
  - Robust and precise learning of rhythmic timing

Network architecture

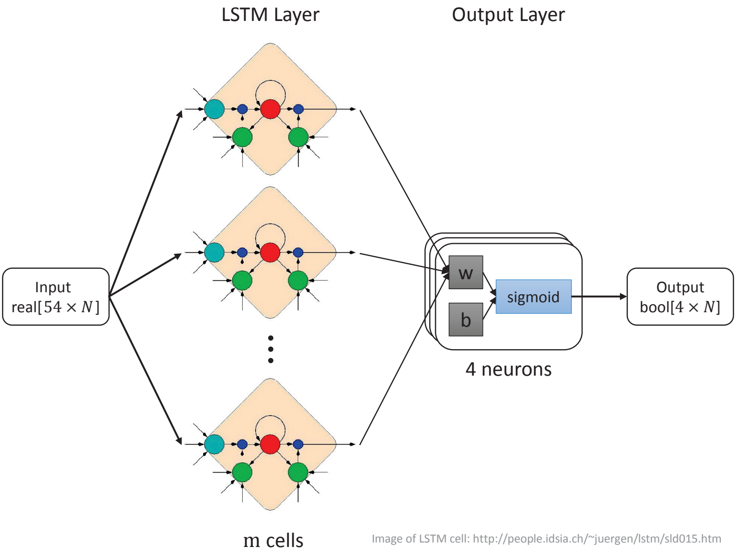


Image of LSTM cell: http://people.idsia.ch/~juergen/lstm/sld015.htm

Implementation

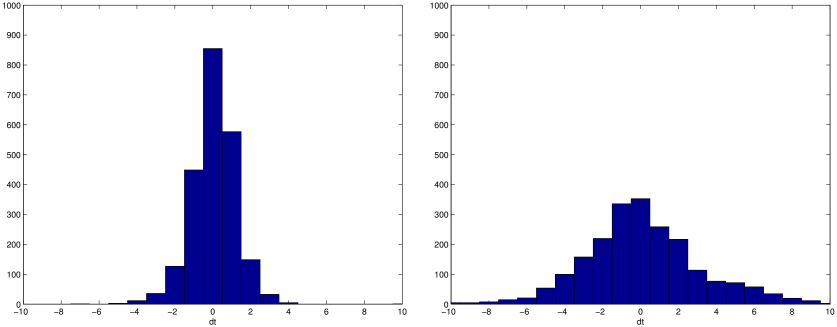
- Torch/Lua on AWS EC2 GPU instance (g2.2xlarge)
- Start with LSTM code example by de Freitas
    - Adapt to our problem setup
    - Problem: Does not converge out of the box
    - Tweaks: Learning rate, mini-batch, regularization, etc.
- Further work:
    - Train on GPU (currently only runs on CPU cores)
    - Explore other network architectures
    - Improve time invariance

Results

	deviation		mistake	
	mean	std	mean	std
Foot velocity	4.84	3.74	2260.2	560.4
Feed-forward NN	0.85	1.48	211.1	204.5
LSTM	2.35	3.87	306.6	360.5

Table 1: Comparison of results for $N = 30$, $T = 2.5\,\mathrm{s}$.

Results



(a) Feed-forward NN

(b) LSTM

Figure 1: Absolute deviations, $N = 30$, $T = 2.5\,\mathrm{s}$.

Q&A

Thank you for your attention!

Human Gait Cycle

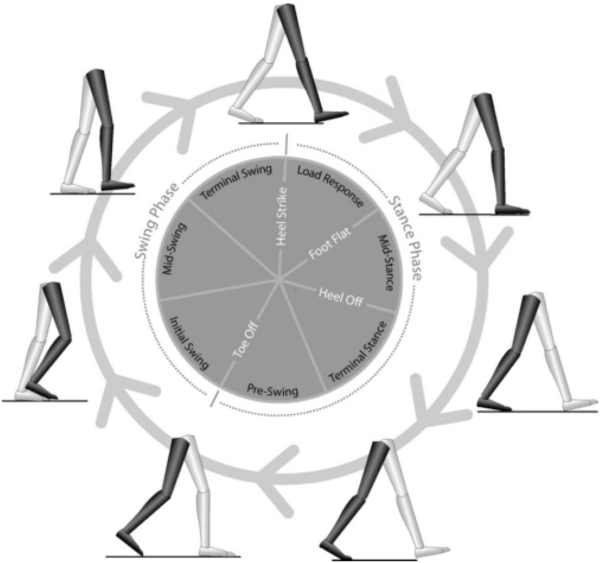


Figure 2: Gait events [Rueterbories et al., 2010]