Master’s Project: Implementation of a Human Feedback Based Locomotion (FBL) and its Control by means of a Biologically inspired Feedforward Component

Florin Dzeladini

February 8, 2013
Introduction

Context

Human locomotion modeling
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Previous work

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→ implemented in 2011 by Steve Berger at Biorob during its master thesis and called here FBL.

In its original form the FBL model is not controllable
## Introduction

### Context
Human locomotion modeling

### Previous work

→ implemented in 2011 by Steve Berger at Biorob during its master thesis and called here FBL.

In its original form the FBL model is not controllable

### Initial goal of the project
Add a feedforward component to the FBL model in order to make it controllable
Plan

1. I: Reproduction of the Geyer Model (FBL)
   - Model
   - Optimization
   - Results

2. II: FBL sensory signal analysis
   - Feedback loops reorganization
   - Feedback loops signal analysis
   - minimal FBL

3. III: FBL extensions
   - CPG component
   - Locomotion control and adaptation

4. Conclusion & Future work
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4 Conclusion & Future work
Goal

- Obtaining a stable walking gait comparable to human walking
- Assess the similarity of this gait with a human gait
Geyer Model

General Characteristics

Lower limb model of a human (only 2D)
Foot modeled as simple solid line
Ligament modeled by joint soft limit
Joint driven by Hill-based muscle model
Muscle activity generated by simple feedback rules acting during different cycle phases
Four different types of feedback

Figure inspired from [Geyer and Herr, 2010]
Geyer Model

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Feedback type

- Muscle length feedback (2)
- Muscle force feedback (1)
- Joint overextension prevention feedback (2)
- Ground feedback (1)
- Stability feedback (3)

( ) : the number of parameters associated to the feedback and tuned during the optimization process.
I: Reproduction of the Geyer Model (FBL) Model

Feedbacks organization

Figure inspired from [Geyer and Herr, 2010]
Feedbacks organization

Different feedback rules generated depending on which state is the limb.

- Contacts of both limbs?
- Weight bearing transfer *
- Stance reflexes
  - Yes
  - Contact?
    - Yes
    - Stance reflexes
    - No
    - Swing reflexes

- Contact sensors (toe & hill)
- Swing reflexes
  - Yes
  - Contact?
    - Yes
    - Stance reflexes
    - No
    - Swing reflexes

Figure inspired from [Geyer and Herr, 2010]
Different feedback rules generated depending on which state is the limb
Ground sensors used to detect limb state (stance, swing, stance end)

Figure inspired from [Geyer and Herr, 2010]
Objectives of the first part

- Obtaining a stable walking gait comparable to human walking
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- Obtaining a stable walking gait comparable to human walking
- Assess the similarity of this gait with a human gait
Optimization

Parameters: All parameters associated to the feedback rules (28 in total)

Objective function includes:
- Energy consumption of the muscle (model from [Bhargava et al., 2004])
- Similarity with human (joint angle correlation with human data [Winter, 2009])
- Stability factor (SNR of step length)
- Desired gait characteristics (speed, step length)

Algorithm: Particle Swarm Optimization (PSO):
- Simple PSO
- Stage PSO
- Parameters: All parameters associated to the feedback rules (28 in total)
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- simple PSO
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The assessment of the similarity with human is made for:

- Joint angles
- Joint torques
- Ground reaction forces

The similarity is tested on the results of different optimization with increasing criterion:

- Exp 1: Energy consumption
- Exp 2: Energy consumption + SNR step length
- Exp 3: Energy consumption + SNR step length + Joint similarity
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- Joint angles
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I: Reproduction of the Geyer Model (FBL) Results

Similarity with human: Joint angles

- Increase in number of criterion used → Increase in correlation.
- Visually confirmed.
- Increase in number of criterion used → Increase in correlation.
- Visually confirmed.
Similarity with human: Movies

Experiment 1  Experiment 2  Experiment 3

Asymmetry
The highest correlation of joint angles show a small left right asymmetry.

Possible reason: Overspecialization, stick to local minima

→ add an extra criterion accounting for left right asymmetry minimization
Similarity with human: Joint torques

- Hip
- Knee
- Ankle

---

Increase in number of criterions

→ Knee torque correlation decreases during stance

The lack of heel and toe could possibly explains this decrease
Similarity with human: Joint torques

Increase in number of criterions → Knee torque correlation decreases during stance
I: Reproduction of the Geyer Model (FBL)  Results

Similarity with human: Joint torques

Increase in number of criterions → Knee torque correlation decreases during stance

The lack of heel and toe could possibly explains this decrease
Limitation

The obtained gait has a very little resistance to perturbations.

Experiment 3 on wavy ground
Increasing robustness: environments

Random push

- Force of the push increases push after push.
- Randomness:
  - Force application & Force angle
  - Push duration & Inter push duration

\[
F_i = \frac{i}{N} f, \quad f \sim N(\mu_f, \sigma_f^2).
\]

\[
h_i \sim U(-\frac{1}{2} h_{\text{trunk}}, \frac{1}{2} h_{\text{trunk}}).
\]

\[
\alpha_i \sim N(0, \sigma_{\alpha}^2).
\]

\[
d_{i}^{\text{mpert}} \sim F(d_1 = 50, d_2 = 50).
\]

\[
\frac{1}{5} d_{i}^{\text{mpert}} \sim \Gamma(k = 1.5, \theta = 2.0)
\]
Increasing robustness: environments

**Wavy ground environment**
- Slope of the waves increases waves after waves.
- Randomness:
  - First wave position
  - Distance between waves
  - Waves length

\[ \alpha_i = \frac{i}{N} \alpha_{\max}. \]

Probability distribution function
\[ l_i \sim \mathcal{N}(\mu_l, \sigma_l^2). \]
\[ s_i \sim \mathcal{N}(\mu_s, \sigma_s^2). \]
\[ d \sim \mathcal{N}(\mu_d, \sigma_d^2). \]
Increasing robustness - Experiments

A new optimization is designed:

- Each trial in the optimization is run 5 times and the worst score is kept
- The different optimized criterion are:
A new optimization is designed:

- Each trial in the optimization is run 5 times and the worst score is kept.
- The different optimized criterion are:
  - Trunk angle
  - Joint similarity
  - Cost of transport
Increasing robustness - Experiments

A new optimization is designed:

- Each trial in the optimization is run 5 times and the worst score is kept
- The different optimized criterion are:
  - Trunk angle
  - Joint similarity
  - Cost of transport

Two new optimizations are run

- one on the wavy ground
- one on the random push environment.
Increasing robustness - Results

Experiments

- exp flat ground: optimization on flat ground
- exp random push: optimization with random pushes
- exp wavy ground: optimization on wavy ground

A Joint angles correlation

B Pushing resistance

C Mean slope change resistance
Experiments evaluated on Random Push environment

- Exp Flat Ground (exp 3 in the report)
- Exp Random Push (exp 6a in the report)
- Exp Wavy Ground (exp 7a in the report)
Increasing robustness - Results

Experiment evaluated on Wavy Ground environment

Exp Flat Ground (exp 3 in the report)

Exp Random Push (exp 6a in the report)

Exp Wavy Ground (exp 7a in the report)
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4 Conclusion & Future work
II: FBL sensory signal analysis

Question addressed

- What are the sensory signals that generate the more variable periodic pattern?
- What are the sensory signals that are the most important?
Model reorganization

The direct sensors to muscle mapping is split into:
- Sensors (SEN)
- Sensory Interneurons (INsen)
- Motoneurons (MN)

Questions:
- How similar are INsen signals between solutions of different experiments?
- How similar are INsen signals between cycles within a specific solution?
The direct sensors to muscle mapping is split into:

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Questions:
- How similar are INsen signals between solutions of different experiments?
- How similar are INsen signals between cycles within a specific solution?
INsen signal comparison: exp flat ground and exp wavy ground

Observation

- High correlation of INsen of muscle sensors
- Lower correlation of INsen of stability/ground sensors
- Lowest correlation for INsen of muscle sensors related to TA and VAS muscles
Questions:

- What are the more similar INsen signals?
- What are the INsen signals that show the more stable periodic pattern?
Questions:
- What are the more similar INsen signals?
- What are the INsen signals that show the more stable periodic pattern?

The analysis of the similarity is made using three different measurements:
- The stability factor $s$
- The variability of the first momentum
- The variability of the second momentum

details in the report
INsen signal comparison within one experiment

INSEN variability

INSEN 1st momentum variability

INSEN 2nd momentum variability

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**Observations**

- Low variability of INsen of muscle sensors
- Highest variability for the INsen of VAS muscle sensors
- High variability for the INsen of stability/ground sensors
II: FBL sensory signal analysis  

INsen signal comparison within one experiment

IN$_{SEN}$ variability

IN$_{SEN}$ 1st momentum variability

IN$_{SEN}$ 2nd moment variability

* GLU<GLU MFF SW  * HAM<HAM MFF SW  * HF<HF MFF SW  * GAS<GAS MFF ST  * TA>TAMS ST  * SOL>SOL MFF ST  * VAS>VAS MFF ST  * TA>TAMS CY  * GLU<GLU GIF ST  * TRUNK>GROUND ipsi  * TRUNK>GROUND contra  * GROUND ipsi  → VAS GCF ST  → and

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FBL and FBL$_{\text{min}}$ comparison (base: solution of exp7a)
III: FBL extensions

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4. **Conclusion & Future work**
Goal

- Add a Central Pattern Generator component to the model
  → introduction of a control variable: the frequency of the CPG
Biological basis

CPG are neural networks that have the ability to generate oscillatory signal.

Some biological CPGs are found in the reticular formation

- Breathing CPGs
Biological basis

CPG are neural networks that have the ability to generate oscillatory signal.

Some biological CPGs are found in the reticular formation

- Breathing CPGs
- Swallowing CPGs
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Assumption I: locomotion CPGs exists and are located in the reticular formation

Action mainly on proximal muscles
Biological basis

CPG are neural networks that have the ability to generate oscillatory signal.

Some biological CPGs are found in the reticular formation
- Breathing CPGs
- Swallowing CPGs

Assumption I: locomotion CPGs exists and are located in the reticular formation
Action mainly on proximal muscles

Assumption II: CPGs component is hidden in the FBL model
CPGs signal mimics some INsen signal
Model: oscillator

Oscillator: Arbitrary Wave Oscillator (AWO)

Property: can have an arbitrary shape given by a bounded continuous function $g(t)$

Equation:

\[
\dot{\theta} = \omega \quad \dot{x} = \gamma \left( g(\theta) - x \right) + dg \quad \theta \cdot \dot{\theta} + K
\]

where:
- $\theta$: oscillator phase
- $K$: perturbation term (set to 0)
- $\gamma$: speed of convergence (set to 100)
- $g(t)$: shape of the oscillator
- $x(t)$: output of the oscillator
Model: oscillator

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Property: can have an arbitrary shape given by a bounded continuous function $g(t)$

Equation:

\[
\begin{align*}
\dot{\theta} & = \omega \\
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\end{align*}
\]

where:

- $\theta$ oscillator phase
- $K$ perturbation term (set to 0)
- $\gamma$ speed of convergence (set to 100)
- $g(t)$ shape of the oscillator

$x(t)$ is the output of the oscillator
Model: frequency control

Goal: keep the CPG synchronized with the motion.
Note: The zero phase of the CPGs corresponds to the moment swing/stance transition.

The phase of the CPGs is controlled in two ways

- If CPGs frequency < Locomotion frequency: the phase is restarted.
  ⇔ If the limb touches the ground and the phase of the oscillator is not equals to 0

Equations:

\[ \beta = \omega \cdot \frac{1}{1 - p} \]  
\[ \Gamma = \ln \left( \frac{1}{1 - p} \right) + \frac{p}{1 - p} \]  

Where, \( p \) is the percentage of the period of the oscillator after which the slowing down mechanism enters in action.
Model: frequency control

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The phase of the CPGs is controlled in two ways

- If CPGs frequency $<\text{Locomotion frequency}$: the phase is restarted.
  $\Leftrightarrow$ If the limb touches the ground and the phase of the oscillator is not equals to 0
- If CPGs frequency $>\text{Locomotion frequency}$: a slowing down mechanism enters in action

Equation:

$\beta = \omega \cdot \frac{1}{1 - p}$ (1)

$\Gamma = \ln \left(1 - p\right) + \frac{p}{1 - p}$ (2)

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- If CPGs frequency $> \text{Locomotion frequency}$: a slowing down mechanism enters in action
  $\rightarrow$ ensures that oscillators will not start a new period before the cycle has ended.
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\Gamma = \ln(1-p) + \frac{p}{1-p} \quad (2)
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Where, $p$ is the percentage of the period of the oscillator after which the slowing down mechanism enters in action.
Models description

III: FBL extensions  CPG component

A

\( \text{IN}_{\text{SEN}} \)

- GFS \( \rightarrow \) GCF
- JAS \( \rightarrow \) GIF
- MLS \( \rightarrow \) MLF
- MFS \( \rightarrow \) MFF

\( \text{IN}_{\text{BAS}} \)

f(t)

\( t \)

\( \text{IN}_{\text{CPG}} \)

f(t)

\( t \)

B

\( \text{IN} \rightarrow \text{MN} \rightarrow \text{MTU} \)

- FBL
- \( \text{FBL}_{\text{min}} \)
- 3FBL

C

FBL

- \( \text{IN}_{\text{SEN}} \)
- \( \text{IN}_{\text{BAS}} \)
- \( \text{IN}_{\text{CPG}} \)

\( \text{FBL}_{\text{min}} \)

- \( \text{IN}_{\text{SEN}} \)
- \( \text{IN}_{\text{BAS}} \)
- \( \text{IN}_{\text{CPG}} \)

3FBL

- \( \text{IN}_{\text{SEN}} \)
- \( \text{IN}_{\text{BAS}} \)
- \( \text{IN}_{\text{CPG}} \)
## Models description

<table>
<thead>
<tr>
<th>FBL</th>
<th>$FBL_{min}$</th>
<th>3FBL</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>GCF</strong></td>
<td>X</td>
<td></td>
</tr>
<tr>
<td><strong>GIF</strong></td>
<td>X X X</td>
<td></td>
</tr>
<tr>
<td><strong>MLF</strong></td>
<td>X</td>
<td></td>
</tr>
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<td>X X X X X</td>
<td></td>
</tr>
<tr>
<td><strong>IN_SEN</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>IN_BAS</strong></td>
<td>X X X</td>
<td>X X</td>
</tr>
<tr>
<td><strong>IN_CPG</strong></td>
<td></td>
<td>X X</td>
</tr>
</tbody>
</table>

| **GCF** | X |     |
| **GIF** | X X X |     |
| **MLF** | X |     |
| **MFF** | X X X X X |     |
| **IN\_SEN** |     |     |
| **IN\_BAS** | X X X | X X |
| **IN\_CPG** |     | X X |

| **GCF** | X |     |
| **GIF** | X X X |     |
| **MLF** | X |     |
| **MFF** | X X X X X |     |
| **IN\_SEN** |     |     |
| **IN\_BAS** | X X X | X X |
| **IN\_CPG** |     | X X |

Models comparison

Joint angles correlation

Pushing resistance

Mean slope change resistance

Models:  
- FBL
- 3FBL
- FBL−
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4. Conclusion & Future work
Goal

- Add constant signal modeling simple actions of primitive upper brain structures on the spinal cord
  → introduction of two control variable kind: amplitude and offset of the INs
Biological basis

Movement regulation and stabilization involves:

- Reticular formation
- Vestibular nuclei

Both structures project to the spinal cord.
Biological basis

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Movement regulation and stabilization involves:

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- Vestibular nuclei
Movement regulation and stabilization involves:
- Reticular formation
- Vestibular nuclei

Both structures project to the spinal cord.
Control variable

The control is made at 3 different level:
- Internal frequency of the CPGs
- Amplitude of IN
- Offset of IN

Introduced control vector

\[
C_{FBL}^{trl} = \{ A_{IN_{SEN}}, O_{IN_{SEN}}, A_{IN_{CPG}}, O_{IN_{CPG}}, A_{IN_{BAS}}, O_{IN_{BAS}} \}
\]
\[
C_{FBL_{min}}^{trl} = \{ A_{IN_{SEN}}, O_{IN_{SEN}}, A_{IN_{BAS}}, O_{IN_{BAS}} \}
\]
\[
C_{3FBL}^{trl} = \{ A_{IN_{SEN}}, O_{IN_{SEN}}, A_{IN_{CPG}}, O_{IN_{CPG}}, A_{IN_{BAS}}, O_{IN_{BAS}}, \omega \}
\]
Example: online adaptation to increasing slope

A

B

slope %

no online control  online control

Models

FBL  FBL-  3FBL

0  5  10  15  20  25  30

22 m 160 m
Example: 3FBL online control of speed

Variation of \((\omega, A_{INCPG})\) → speed changes between 0.9 to 1.4 [m/s]
The possibility to vary parameters of the gait online opens the way to systematic search study of the effect of the variation of the control variable on gait characteristics.
3FBL Systematic search \((\omega, O_{\text{INBAS}})\)
### 3FBL Systematic search

<table>
<thead>
<tr>
<th>Id</th>
<th>Name</th>
<th>Range</th>
<th>Std.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$O_{INBAS}$</td>
<td>$[-0.01;0.01]$</td>
<td>0.0</td>
</tr>
<tr>
<td>2</td>
<td>$O_{INCPG}$</td>
<td>$[-0.01;0.01]$</td>
<td>0.0</td>
</tr>
<tr>
<td>3</td>
<td>$A_{INBAS}$</td>
<td>$[0.7;1.6]$</td>
<td>1.0</td>
</tr>
<tr>
<td>4</td>
<td>$A_{INCPG}$</td>
<td>$[0.7;1.6]$</td>
<td>1.0</td>
</tr>
<tr>
<td>0</td>
<td>$\omega$</td>
<td>$[0.65;1.8]$</td>
<td>0.85</td>
</tr>
</tbody>
</table>

### Observations

- Great variation of double stance duration
- Change in speed possible without losing in stability
- Change in speed possible without changing the gait frequency
Conclusion

Q: Is a change in regime (switch from walking to running) possible by simply varying the control variable? Not with the FBL model.

→ Adapt the FBL model with the changes made by J.Wang on the rule for entering in stance end phases.
Plan

1 I: Reproduction of the Geyer Model (FBL)
   ■ Model
   ■ Optimization
   ■ Results

2 II: FBL sensory signal analysis
   ■ Feedback loops reorganization
   ■ Feedback loops signal analysis
   ■ minimal FBL

3 III: FBL extensions
   ■ CPG component
   ■ Locomotion control and adaptation

4 Conclusion & Future work
FBL model gives good results in similarity with human gaits. 

→ Knee torque correlation could be increased by:

- adding a toe
- adding a structure to absorb the shock at ground contact

Make the model a 3D model.

FBL model robustness can be increased by optimizing the controller on a perturbed environment.

30% of the reflexes of the FBL model can be replaced by constant signal without losing in quality of the gait.
Online speed adaptation possible by varying the frequency of CPGs (replacing feedback acting on hip muscle).

Simple control rules acting on interneurons opens the way to an online adaptability of the model to environment changes.

→ Modeling some regulatory structures like the cerebellum by adding an artificial neural network that:
  - takes environment information as input
  - generates values of the control vector as output
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References I


