Using Force Sensors to Effectively Control a Below-Elbow Intelligent Prosthetic Device

Jeremy E. Blum, Byram Hills HS, Armonk, NY

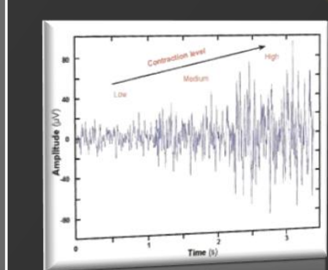
introduction

- US troops in Iraq required limb amputations at twice the rate of past wars (The Boston Globe, 2004)
- 795 amputations for soldiers in Iraq and Afghanistan since December 2001 (The Seattle Times, 2007)

Figure 1: Wounded Soldier (thememoryhole.org, 2004)

review of literature

Myoelectric Prosthetic Control



- Current applied state-of-the-art
- Residual muscle contractions control hand movements
- Uses myoelectric signals (MES) created by muscle contractions to control motor rotation (Muzumdar 2004)

Figure 2: Variation of Myoelectric Signal with Contraction Level (D.F. Lovely, 2004)

Problems with Myoelectric Control

- Inaccurately predicts muscle contraction one out of every 20 times (L. J. Hargrove et al., 2007)
- Surgical implantation necessary for accurate pattern recognition (Muzumdar, 2004)
- Signal processing necessary to remove electrical noise (L. P. J. Kenney et al., 1999)
- Each electrode can cost $2000 (P. Kyberd, 2007)

Force Sensors – A Better Solution?

- Piezoelectric devices (change in applied pressure results in change in output voltage)
- Can measure muscle contraction
- Never before used in multi-sensor, pattern recognition setup with the purpose of controlling a prosthesis (L.J. Kenney et al., 1999)

Advantages of Force Sensors

- Less Expensive ($20 each) (www.parallax.com)
- No Surgery Needed
- Potential to Eliminate or Reduce Need for Signal Processing

hypothesis

Muscle Contraction

Existing Method	Novel Method
Indirect Measurement	Direct Measurement
Implanted Myoelectrodes	Forearm Force Sensor
95% Accuracy	Accurate?

Below-Elbow Prosthetic Device

objectives

Objective 1
Build proof-of-concept prosthesis

Objective 2
Develop computer interface and acquire raw data

Objective 3
Write and implement input analysis program

methods and materials

1. Prosthetic Prototype

- Inputs: Force Sensor, Vibration Sensor
- Outputs: Vibration LED, Force Readout (0-6 Scale)
- Processor/Board
- Hand and Servo
- Chassis and Power Supply
- Programming (PBasic)

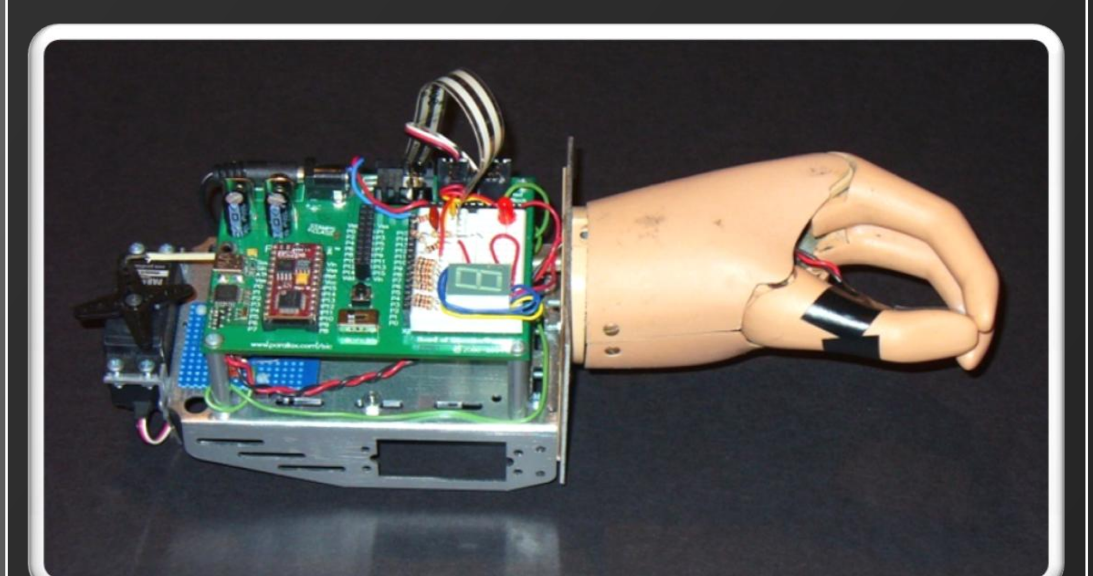


Figure 2: Prosthetic Prototype (Blum, 2007)

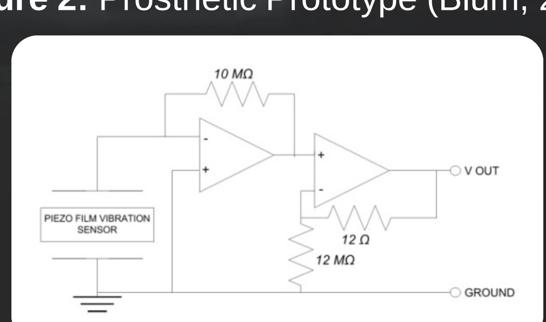
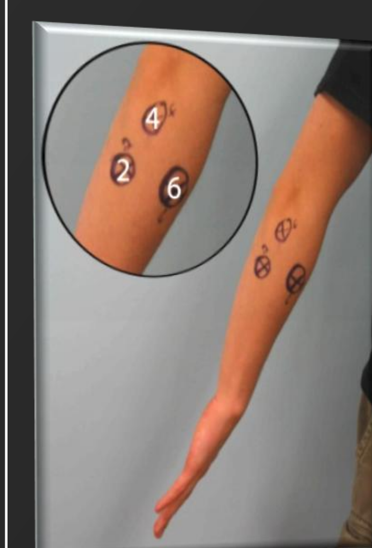


Figure 3: Vibration Sensor Circuit (Kyberd/Blum, 2007)

Figure 4: FlexiForce Sensor (tekscan.com, 2006)

2. Computer Interfaced Force Sensor Circuit

Forearm Muscles Used Shown in Green



- #2-Extensor Carpi Ulnaris (finger extension)
- #4-Supinator (wrist supination)
- #6-Extensor Carpi Radialis Brevis (wrist extension

Figure 5: Sensor Locations - Lateral Arm Aspect (Blum, 2007)

- #1-Pronator Teres (wrist pronation)
- #3-Flexor Digitorum Superficialis (finger flexion)
- #5-Flexor Carpi Ulnaris (wrist flexion)

Figure 6: Sensor Location - Medial Arm Aspect (Blum, 2007)

Figure 7: Internally mounted force sensors (Blum, 2007)

Figure 8: Cast fully equipped with sensors mounted (Blum, 2007)

Figure 9: Cast worn by Blum, Connected to DAQ (Blum, 2007)

Data Acquired for Each Muscle

Action Data
Contraction and relaxation cycle of target muscle

Resting Calibration Data
Relaxation of all muscles

Active Calibration Data
Contraction of target muscle

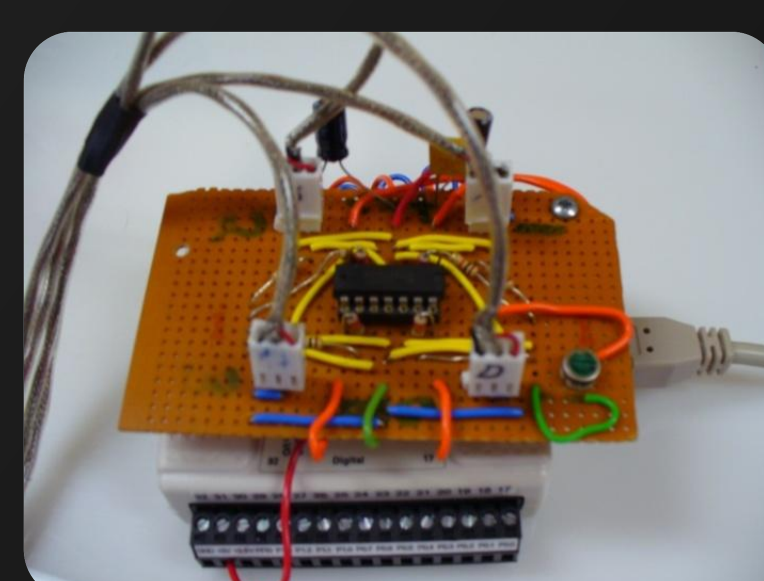


Figure 10: DAQ and amplification circuit board with four force sensors connected (Blum, 2007)

3. Computer Input Analysis Program

Linear Discriminant Analysis via SVEN Function
(Torunn Midtgaard, 2006)
$F(x) = Wx + w_0$

$F(x) > 0$ ACTIVATION
$F(x) \leq 0$ NO ACTIVATION
When calibration muscle matches activation muscle, F(x) *should* be > 0

1. Raw voltage signals from force sensors tested using an oscilloscope, MATLAB, and National Instruments LabView Software to ensure minimal interference
2. User enters sample rate and acquisition duration
3. Calibration data acquired for each of the six muscles; each muscle dataset saved as file
4. Resting data acquired once as comparison point; dataset saved as file
5. Activation data acquired for each of the six muscles; each muscle dataset saved as file
6. Saved data files imported for analysis
   a. Resting data imported and stored in memory; graph exported to image file
   b. Activation data imported and stored in memory; graph exported to image file
7. All six calibration data sets compared to the six action data sets, resulting in 36 outcomes. First, all six calibration data sets and resting data compared using SVEN Function. Results again compared via SVEN Function to activation data to determine if activation has occurred.
8. A SVEN graph, a smoothed SVEN graph, and a Digital On/Off graph are drawn and exported
9. Calibration graphs visually compared with their associated action data to determine if muscle differentiation occurred
10. The Digital On/Off signal can be used to activate a prosthesis

results and discussion

1. Prosthetic Prototype

- ✓ Hand opens and closes upon force input
- ✓ Force Approximation
- ✓ Hand can grip objects
- ✓ Slip circuit successfully arrests slip

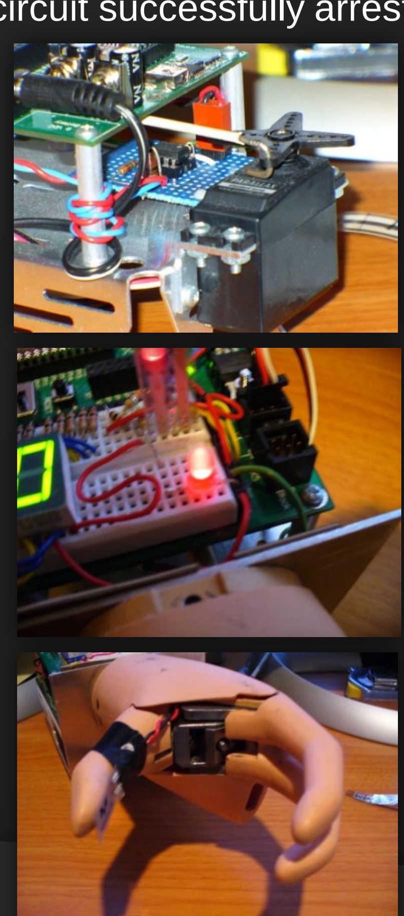


Figure 11 (a-c): (From top) Servo actuator and vibration amplification circuit board; LED # Force Readout (scale of 0-6) + Vibration Warning LED; hand with vibration sensor (Blum, 2007)

2. Computer Interfaced Force Sensor Circuit

The muscle being contracted should show the highest voltage to indicate proper differentiation (Channel color matches title color)

Finger Extension
(Extensor Carpi Ulnaris)

(a) Active Calibration Data for **Myoelectrodes** | (b) Active Calibration Data for **Force Sensors**

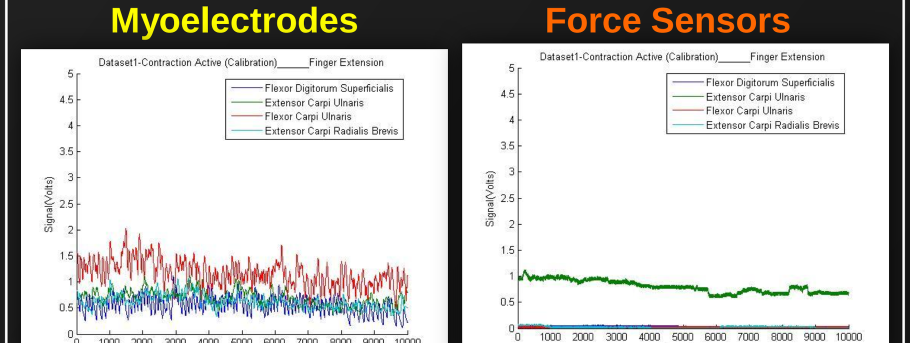


Figure 12(a & b): Comparison of Finger Extension Raw Calibration Data (Blum, 2007)

Wrist Extension
(Extensor Carpi Radialis Brevis)

(a) Active Calibration Data for **Myoelectrodes** | (b) Active Calibration Data for **Force Sensors**

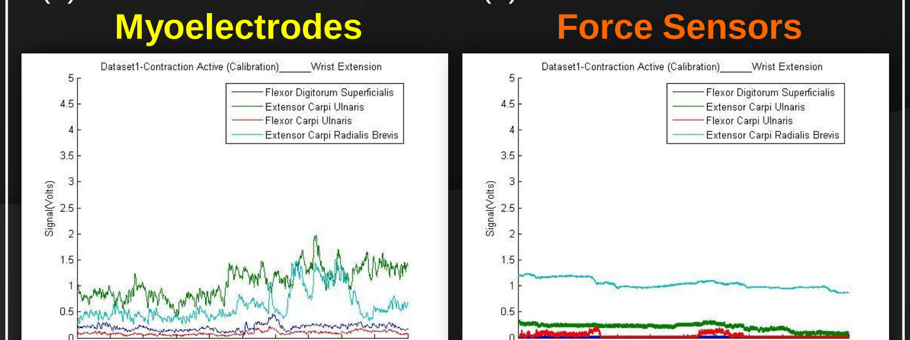


Figure 13 (a & b): Comparison of Wrist Extension Raw Calibration Data (Blum, 2007)

3. Computer Analysis Program

Since finger extension is the action being tested, only the finger extension SVEN graph should surpass zero (red line)

Finger Extension = Finger Extension
(Should exceed zero)

(a) SVEN Function for **Myoelectrodes** | (b) SVEN Function for **Force Sensors**

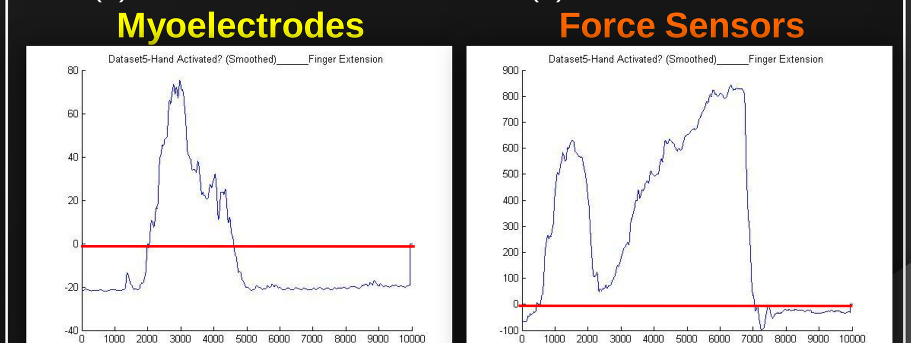


Figure 14 (a & b): Myoelectric and Force Sensor Finger Extension Smoothed SVEN Function (Blum, 2007)

Wrist Extension ≠ Finger Extension
(Should not exceed zero)

(a) SVEN Function for **Myoelectrodes** | (b) SVEN Function for **Force Sensors**

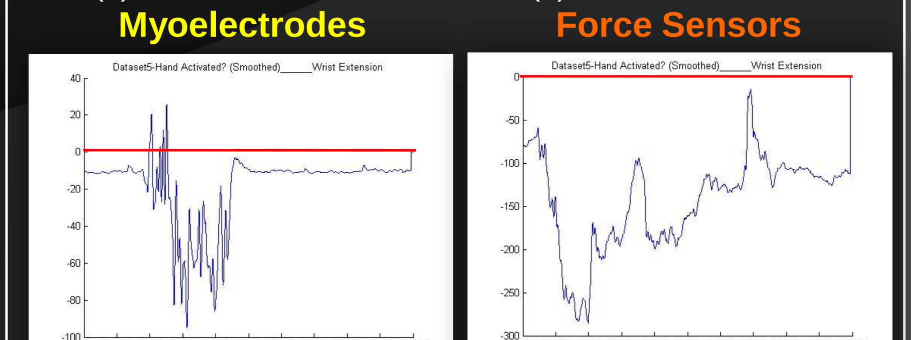


Figure 15 (a & b): Myoelectric and Force Sensor Finger Extension Smoothed SVEN Function (Blum, 2007)

conclusions

- No implantation → no risk of infection or sensor movement
- Pattern Recognition (SVEN function) mostly works without need for implantation
- Prosthesis can be easily removed
- Little interference + low cross-talk = high accuracy rates
- Sufficient voltage separation → eliminate post processing (voltage boundary can be measured using a comparator circuit with a fixed reference voltage)
- If post processing needed → SVEN algorithm needs perfecting
- Low cost

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