Electromyography (EMG) Applications for Rehabilitation and Prosthesis

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Outline

1. Introduction
2. EMG for paralyzed patients
3. EMG for amputees
4. Ending

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3. EMG for amputees
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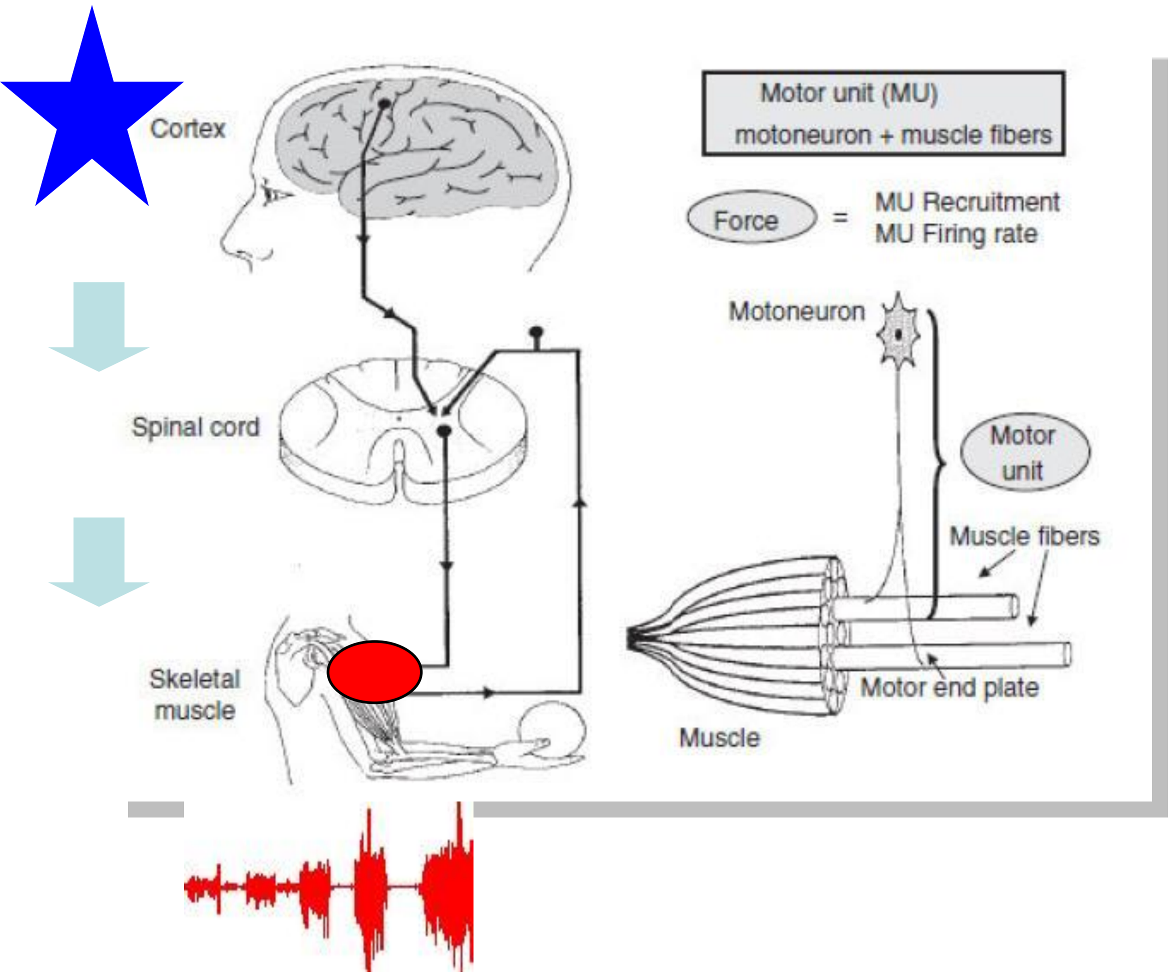
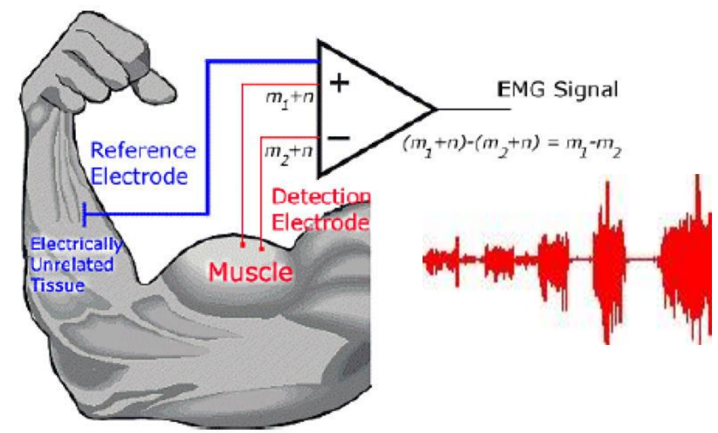
Background

Human Motor Control

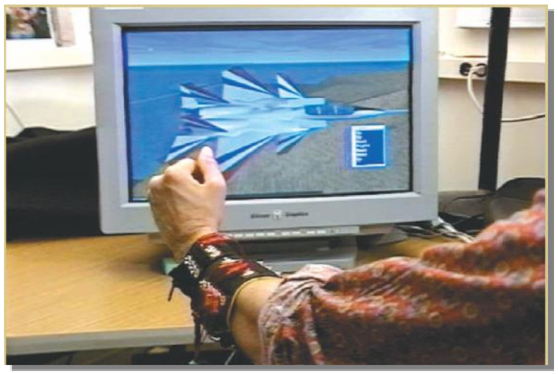


Electromyography (EMG)



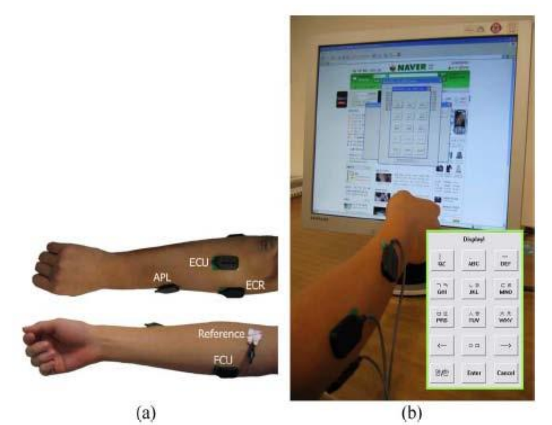
Background

EMG is a kind of Human-Machine Interface (HMI)



Aircraft Control

Entertainment



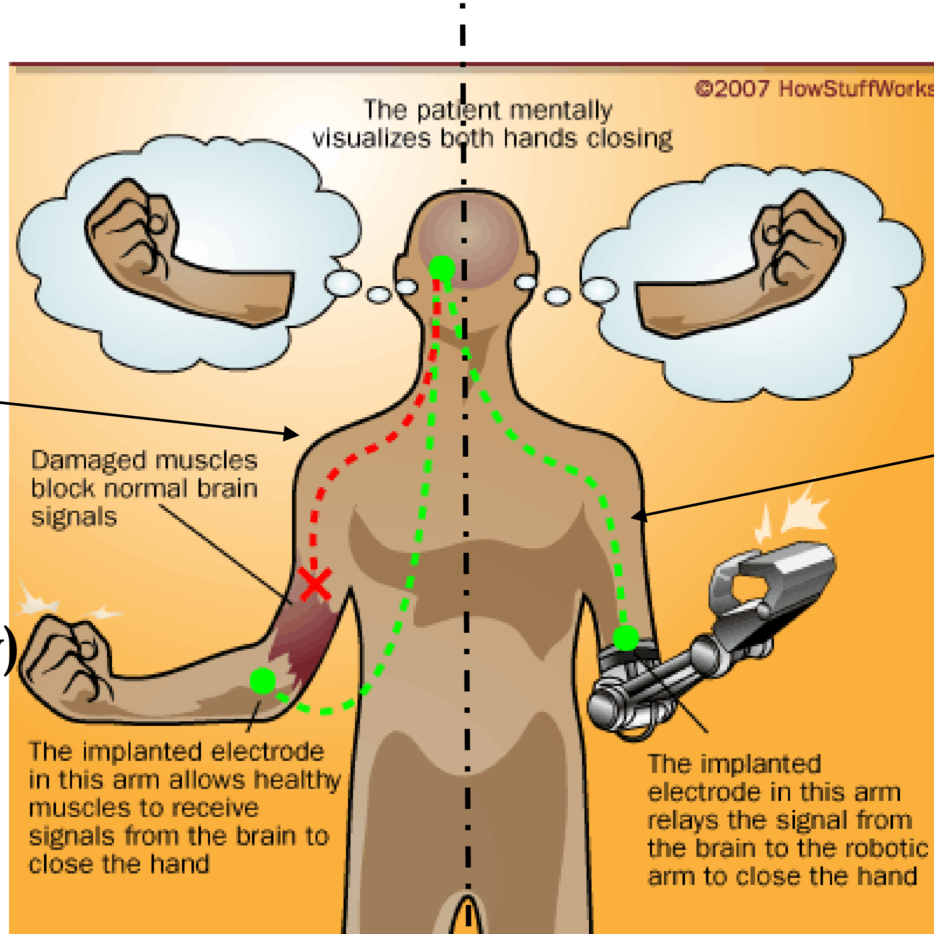
Computer Device Control

Exoskeleton Control

Our Targets

EMG

(Electromyography)



EMG

(Electromyography)

Rehabilitation for Paraplegics

Prosthesis for Amputees

Outline

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3. EMG for amputees
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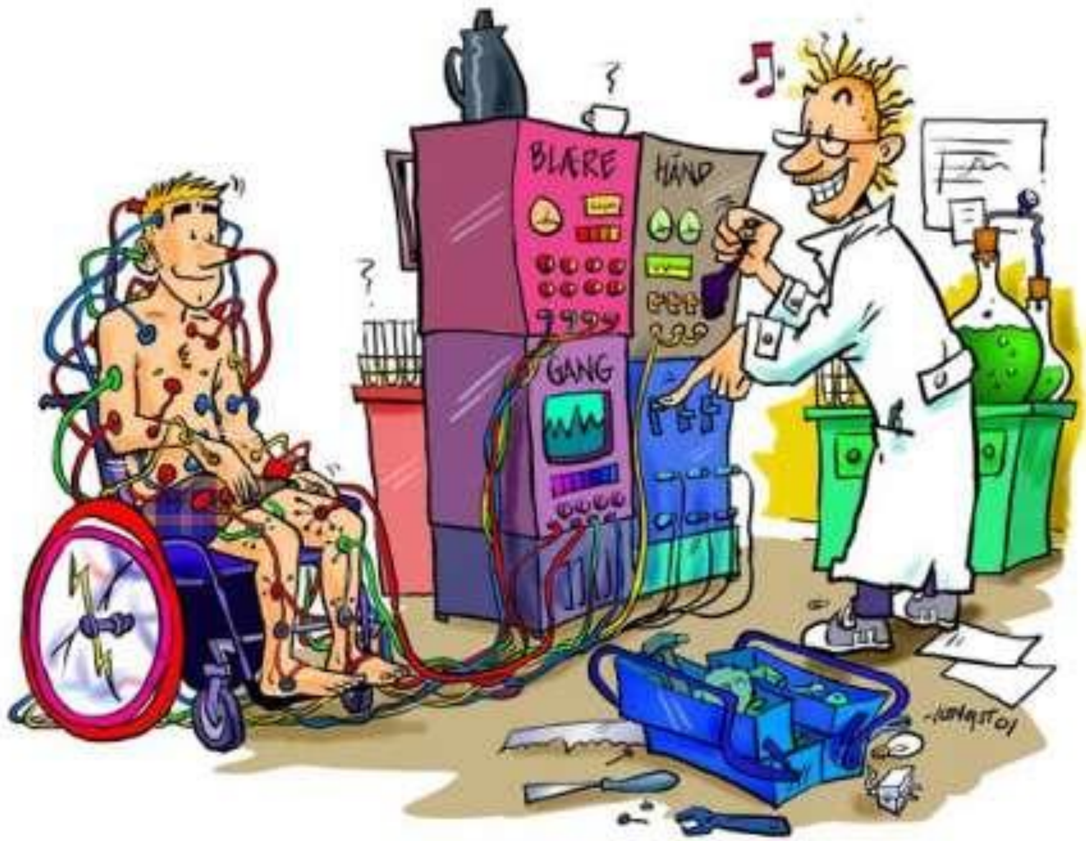
FES= Functional Electrical Stimulation

An important rehabilitation technique

Controlling electrical pulses of low level to stimulate the skeletal muscle in an attempt to restore the motor function and generate the desired motions for paralyzed patients.



Suitable Conditions for EMG+FES

1) The patient is **incompletely paralyzed**. He can weakly drive some muscles voluntarily, but the force is not enough to perform movement, or the movement is abnormal and awkward. Then the weak EMG that can be interpreted as a desire for a certain muscle contraction and it is recorded to stimulate the same muscle positively.

Suitable Conditions for EMG+FES

2) EMG from some **normal muscles** can be used to stimulate the paralyzed muscles (not symmetric ones) in the ipsilateral side of a limb. For example, the EMG of proximal muscles of upper limb is employed to stimulate the distal muscles to perform grasping via FES; the EMG from the wrist extensor muscles has been used to control the stimulation of the finger and thumb flexors in order to obtain a stronger tenodesis; the EMG of biceps is used to modulate the stimulation for triceps.

Suitable Conditions for EMG+FES

3) The patient is **hemiplegic**. The EMG information from one side of human limbs can be used to control the paralyzed symmetric muscles of the contralateral side via FES.

Case Study 1

Suitable Conditions for EMG+FES

4) Master slave control. The EMG information from healthy persons of master side, which remotely controlled the patients of slave side.

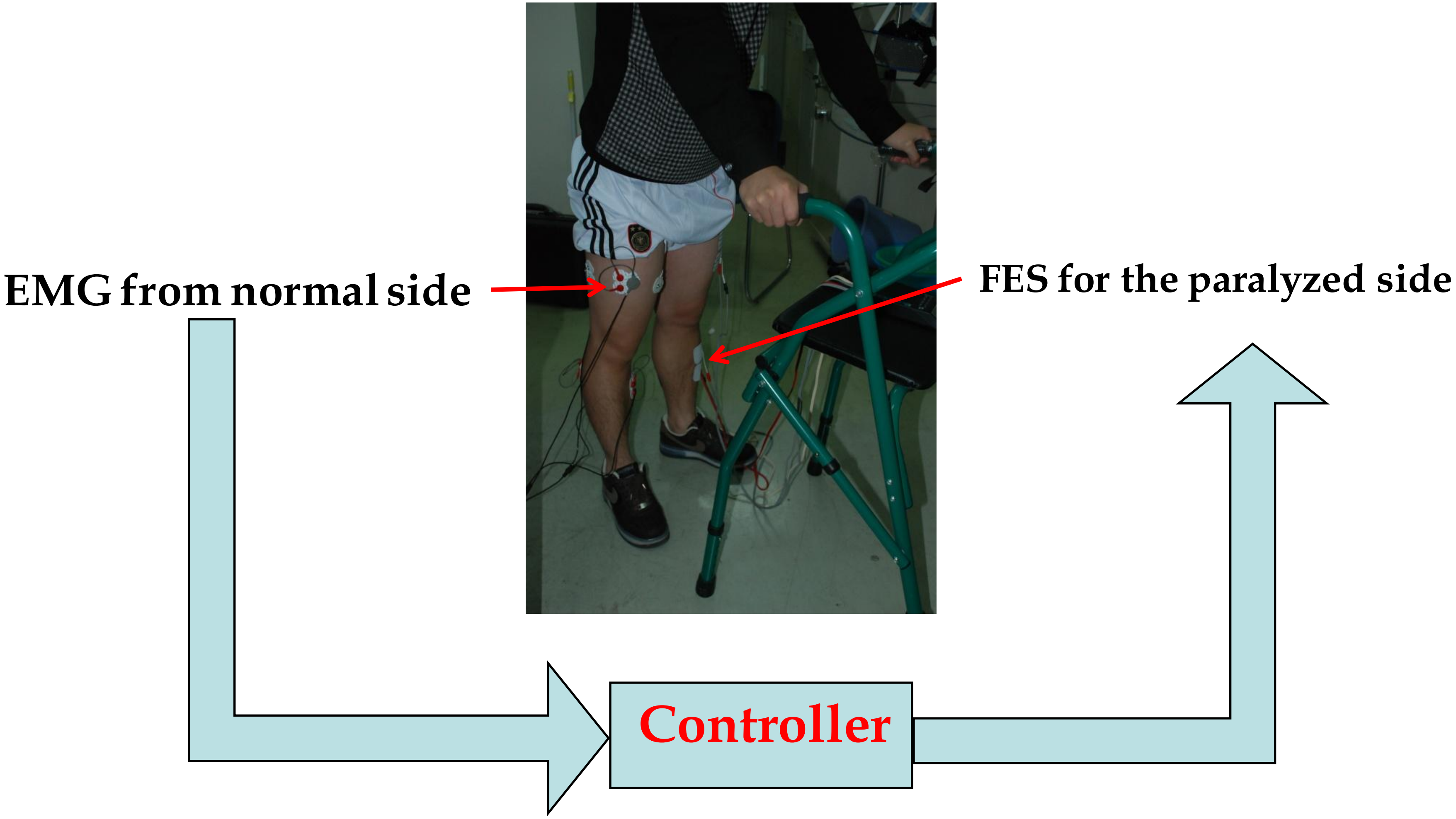
Case Study 2

Case Study 1

EMG in FES rehabilitation system for hemiplegic patients

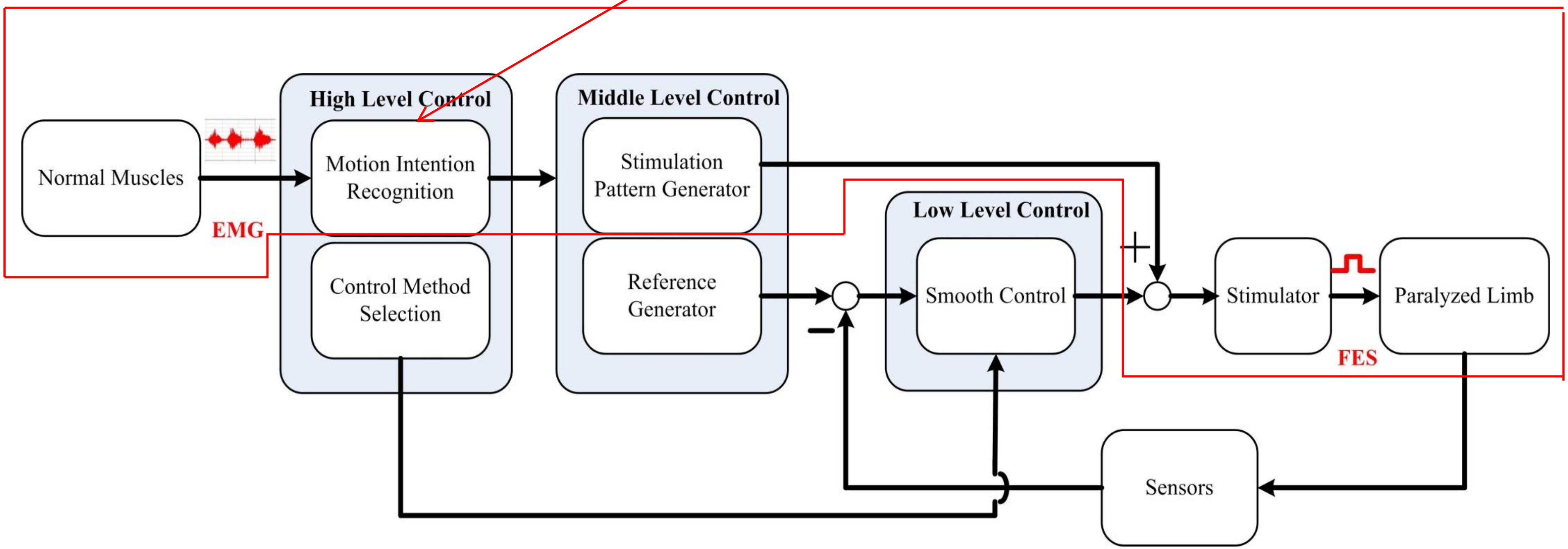
General Idea

Serve for Hemiplegic Patients!



Hierarchical FES Control System

Our focus: EMG based Recognition



The current work only realizes the feedforward components (circled by red lines).

EMG Measurement

Inside view

Outside view

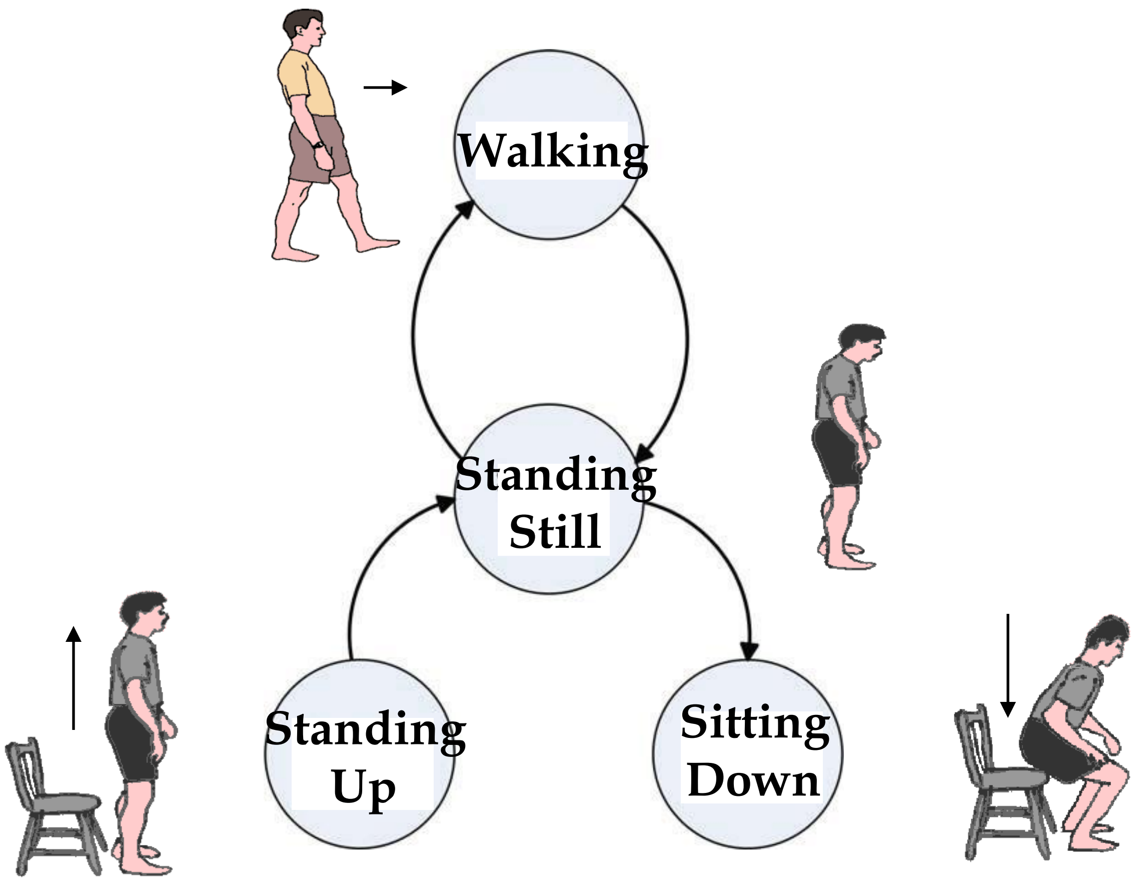
EMG Electrodes Location in Left Leg.

Six targeted muscles:

rectus femoris, vastus group, biceps femoris, Semimembranosus, gastrocnemius, soleus

Mega EMG System (ME6000)

States of Motion in Lower Limb

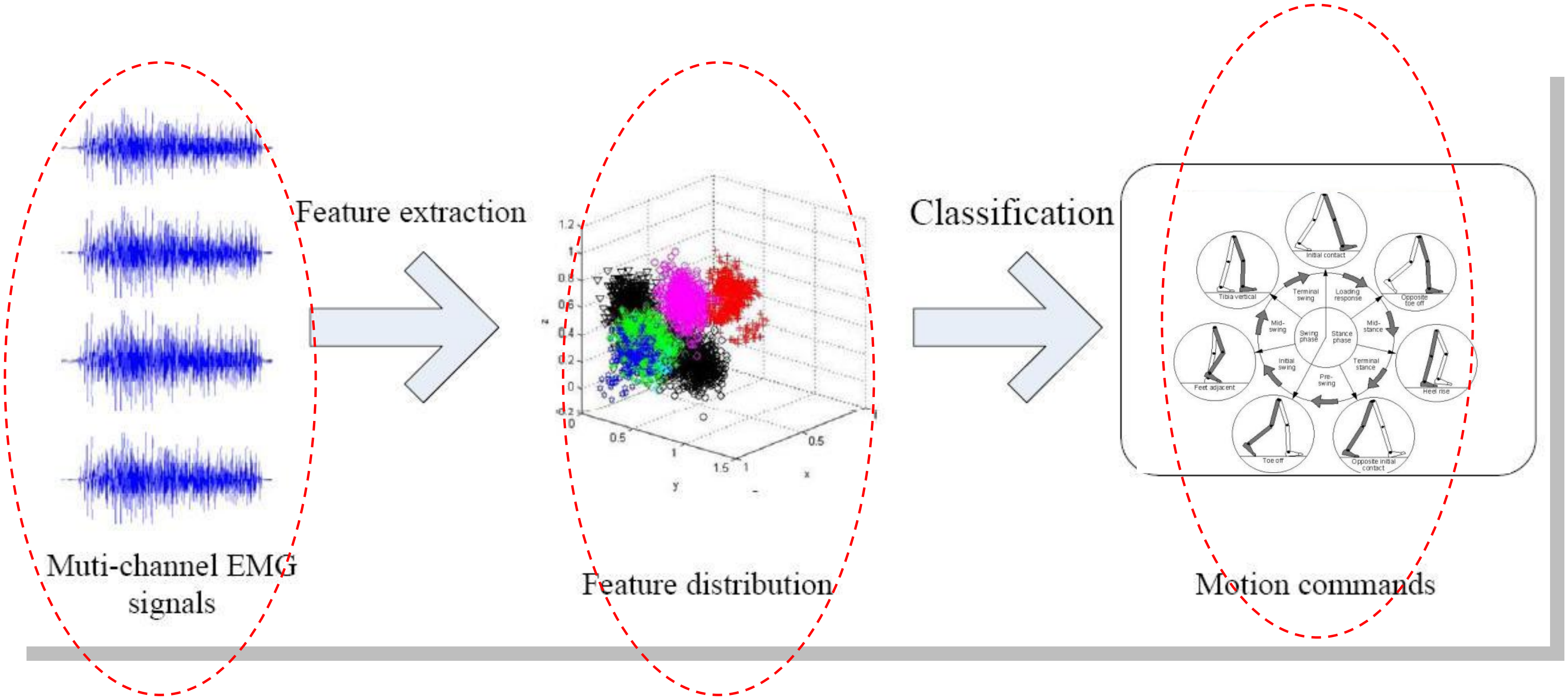


Four types of motions to be classified.

Protocol

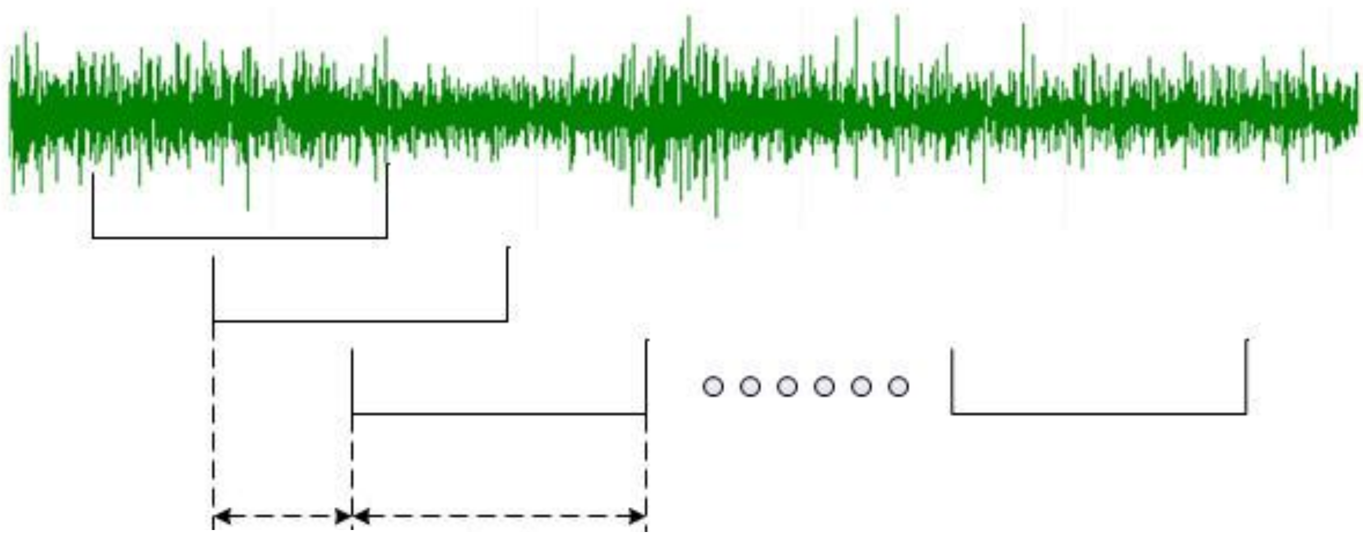
- Three healthy subjects took part in the EMG measurement.
- Six channels of EMG signals are acquired from six muscle groups on one leg.
- The subjects perform four types of movements: sitting down, standing up, stillness (standing quietly and keeping body balance), and walking in sequence.
- Every type of motion will be performed 60 times. The EMG signal acquired during the first 30 times will be used as training data, and that of the last 30 times as testing data.

EMG Processing



EMG Processing

EMG



Segmentation: Increment Analysis window

100 ms 200 ms

EMG Feature Extraction I

Time Domain Statistics (TDS) Features

Mean Absolute Value $\overline{X} = \frac{1}{N} \sum_{i=1}^{N} | x_i |$

Zero Crossing $x_i x_{i+1} \leq 0, and \mid x_i - x_{i+1} \mid \geq \varepsilon_z$

Slope Sign Changes $(x_{i+1} - x_i)(x_i - x_{i-1}) \geq \varepsilon_s$

Waveform Length $l = \sum_{i=1}^{N} | \Delta x_i |$

$$\Delta x_i = x_i - x_{i-1}$$

EMG Feature Extraction II

Fourier Cepstral (FC) Features

(1) Calculate the energy spectrum using the discrete Fourier transform

$$X[k] = \sum_{n=0}^{N-1} x[n] exp^{-j\frac{2\pi}{N}nk}, k = 0, 1, ..., N-1.$$

(2) Calculate FC coefficients from the nonlinear magnitude of the Fourier-spectrum transform directly using discrete cosine transform

$$FC_i = \sum_{k=0}^{N-1} Y_k cos(\frac{(k+1/2)(i-1)\pi}{N}), i = 0, 1, ..., N. \quad (7)$$

where $x(n)$ is the EMG data. $Y_k = f(|X[k]|)$ is a nonlinear transformation (e.g. logarithm of magnitude) of $|X[k]|$ that is the magnitude of Fourier coefficients, and N is the number of FC coefficients.

Classification

Classifiers:

Linear Discriminant Analysis (LDA)

Quadratic Discriminant Analysis (QDA)

$$p(\omega_i \mid y) = p(\omega_i)\frac{p(y \mid \omega_i)}{p(y)}$$

where $p(y \mid \omega_i)$ is the class-conditional probability density function (PDF)

$$p(y \mid \omega_i) = \frac{1}{(2\pi)^{\frac{P}{2}}|\Sigma_i|^{\frac{1}{2}}}\exp\{-\frac{1}{2}(y-\mu_i)^T\Sigma_i^{-1}(y-\mu_i)\}$$

Note: It is called LDA. When covariances Σ_i are assumed to be different, the decision boundaries are hyperquadric surfaces, and this is called QDA.

Fisher linear discriminant (FLD) is adopted to reduce the dimension before QDA classification in this work.

Results

Average Classification Accuracy of Three Subjects

Subjects	FC +LDA	FC(FLD) +QDA	AR +LDA	AR(FLD) +QDA	TDS +LDA	TDS(FLD) +QDA
ZJ	95.83	95.83	95.83	94.17	96.67	**97.50**
LZZ	**98.33**	97.50	92.50	90.00	96.67	95.83
YYC	97.50	**99.17**	94.17	94.17	92.50	90.83
Mean	97.22	**97.50**	94.17	92.78	95.20	94.72

Results

Average Classification Accuracy of Four Types of Movements

Subjects	FC +LDA	FC(FLD) +QDA	AR +LDA	AR(FLD) +QDA	TDS +LDA	TDS(FLD) +QDA
Walking	96.67	98.89	**100**	100	98.75	97.22
Standing up	95.56	**95.56**	87.78	86.67	92.04	91.94
Sitting down	**96.67**	95.56	88.89	84.44	90.01	89.72
Standing still	100	100	100	100	100	100
Mean	97.23	**97.50**	94.17	92.78	95.20	94.72

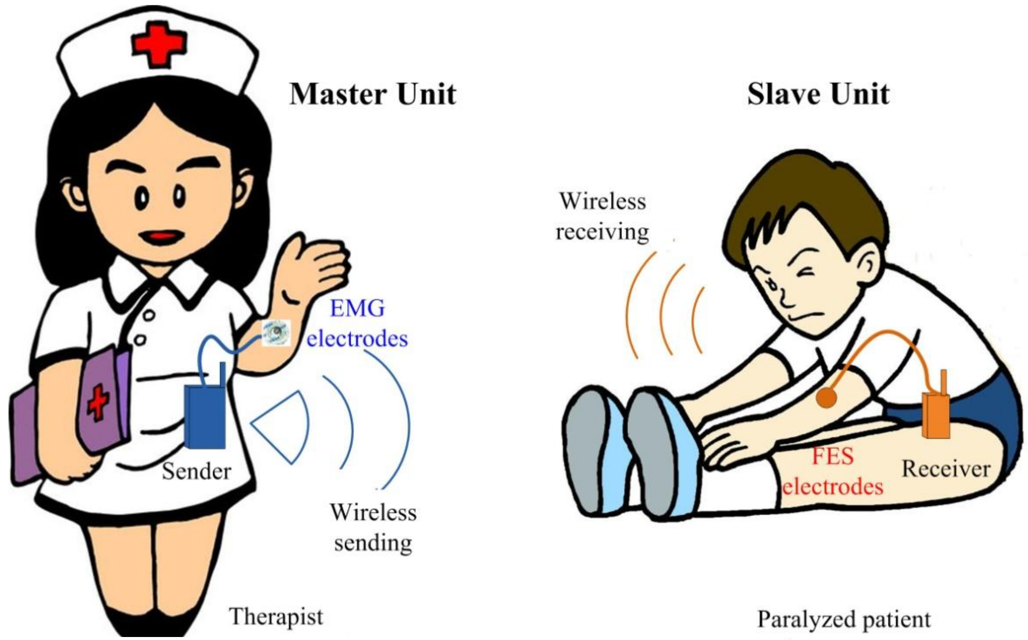
Demonstration

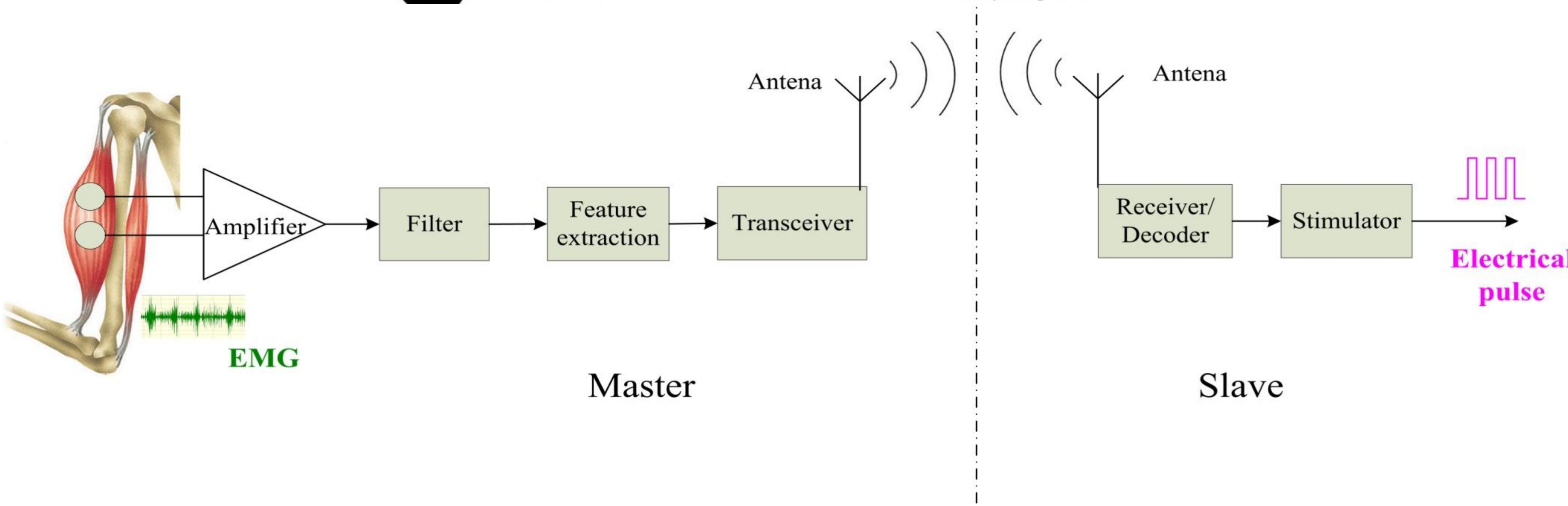
Offline EMG data Driven FES for Walking

Case Study 2

EMG in Master-Slave Gesture Learning System using FES

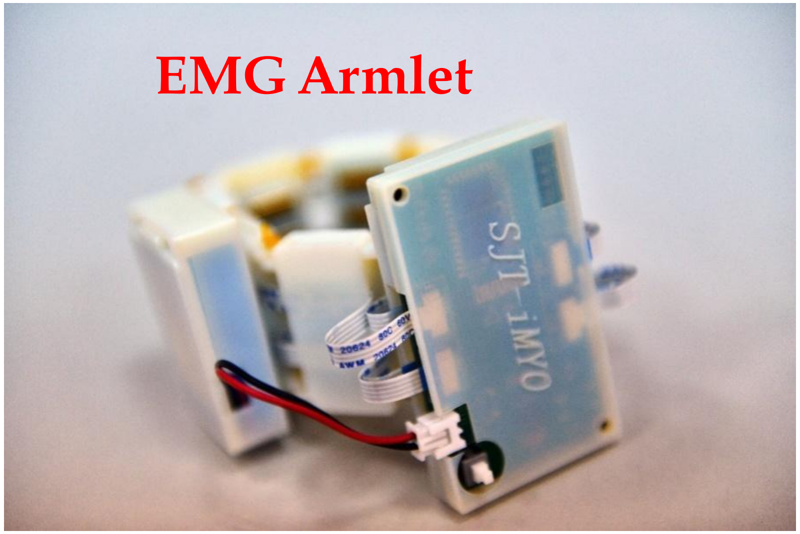
General Idea

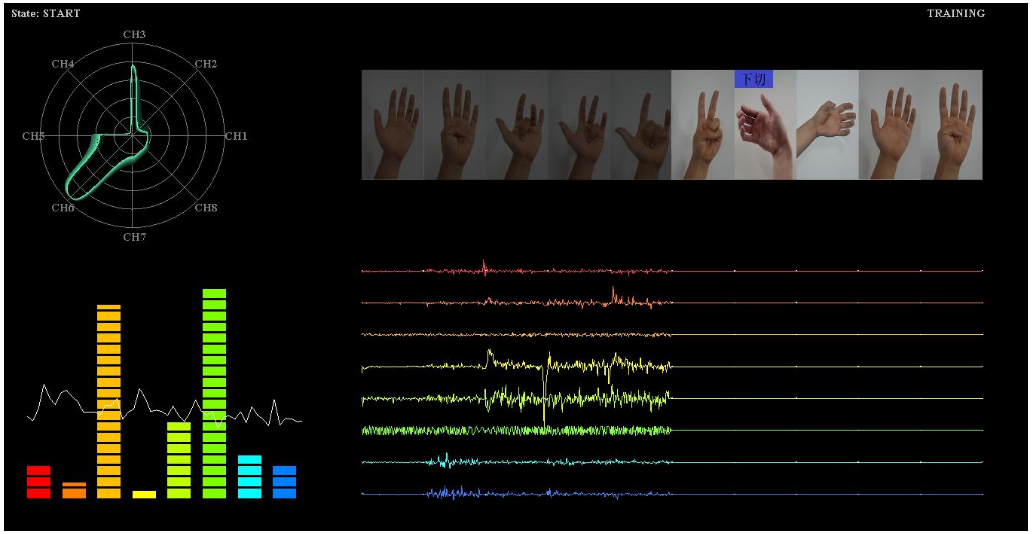




Master Side

EMG Signal Acquisition and Processing

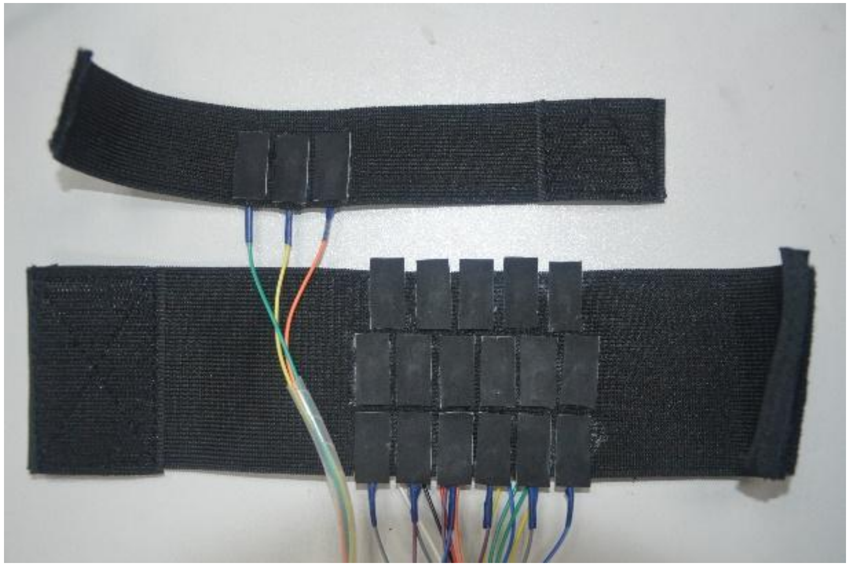


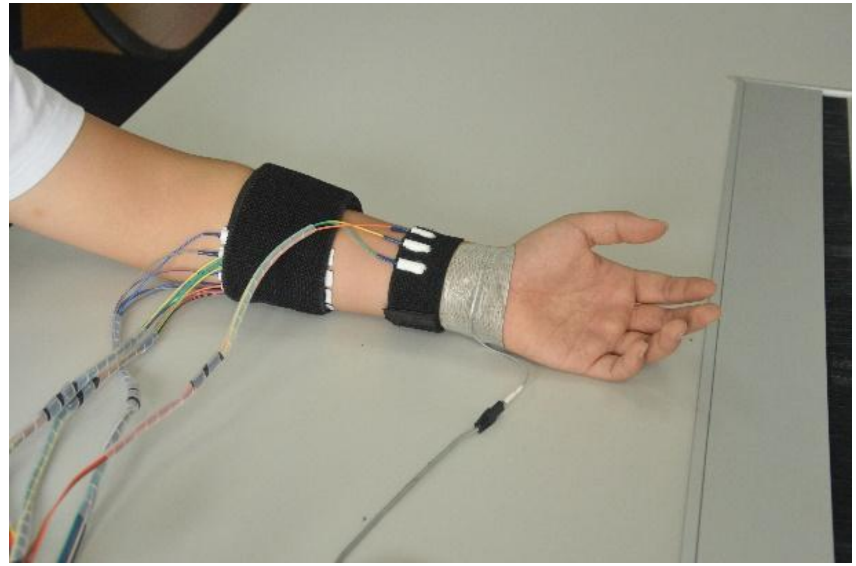


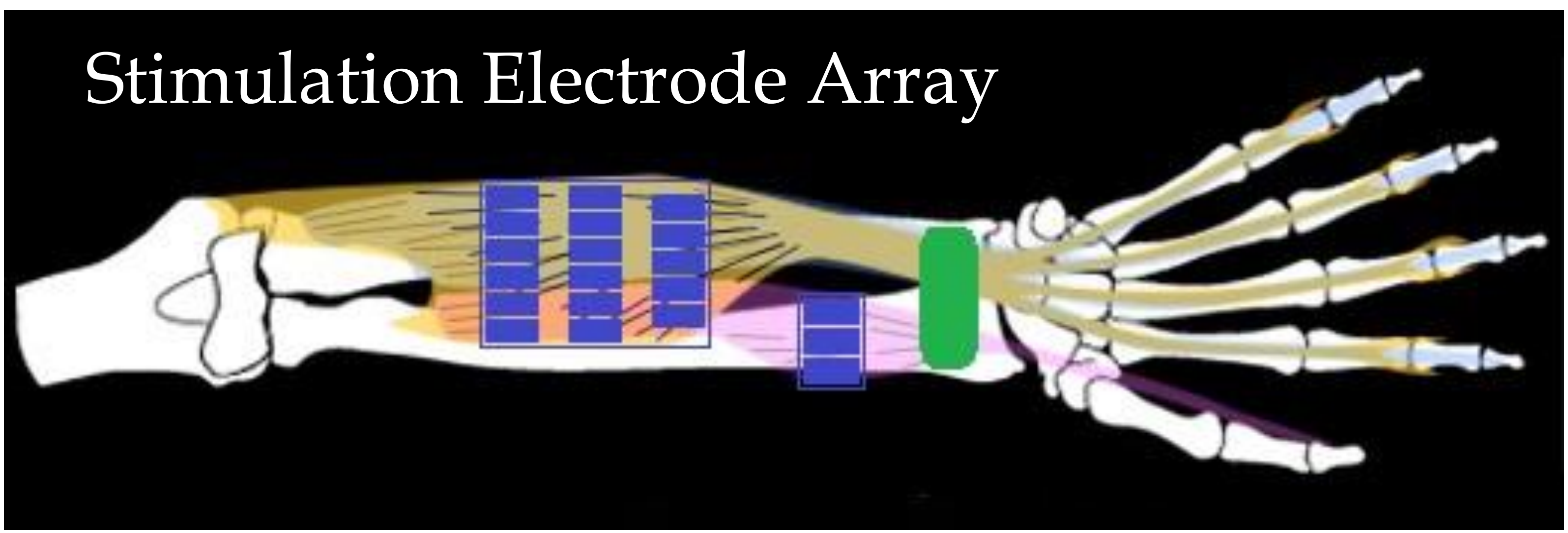
Features: Time Domain Statistics (TDS)
Classifier: Support Vector Machine

Slave Side

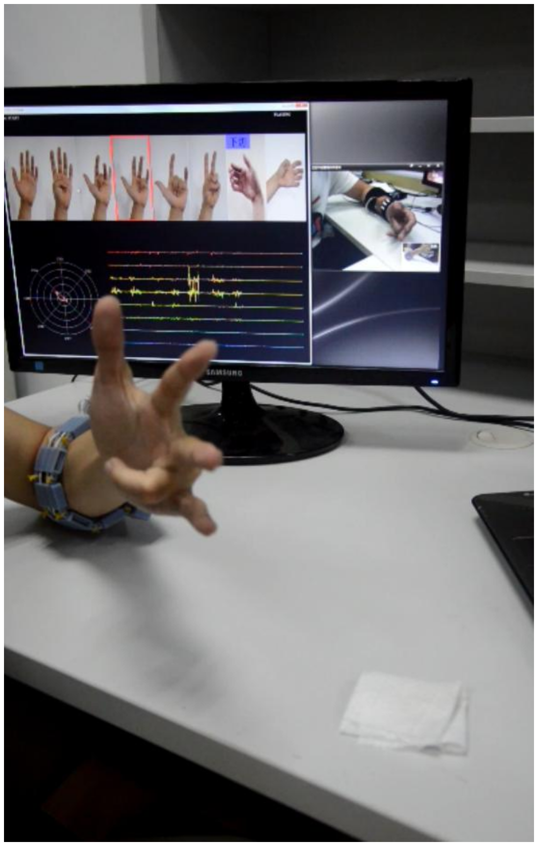
Functional Electrical Stimulation (FES)







Demonstration



Master Side

Wi-Fi

Slave Side

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EMG for Amputees

Case Study 3

Handwriting Recognition using EMG

Case Study 4

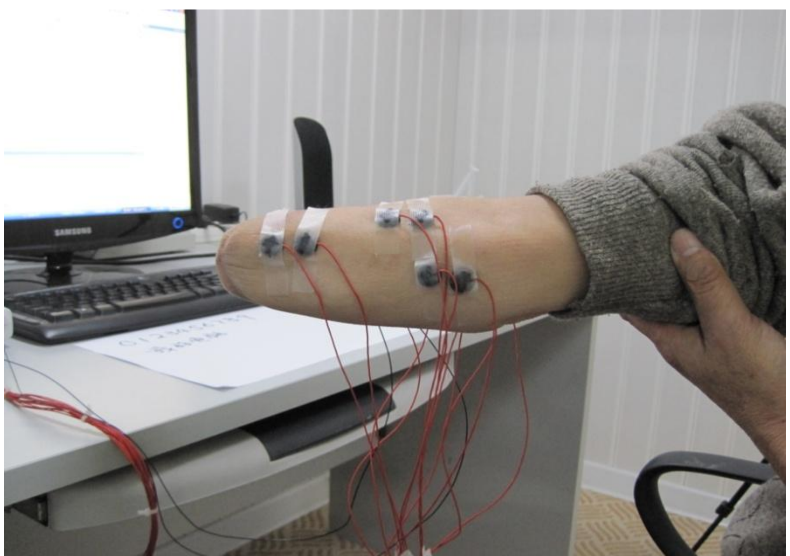
EMG Controlled Prosthetic Hand

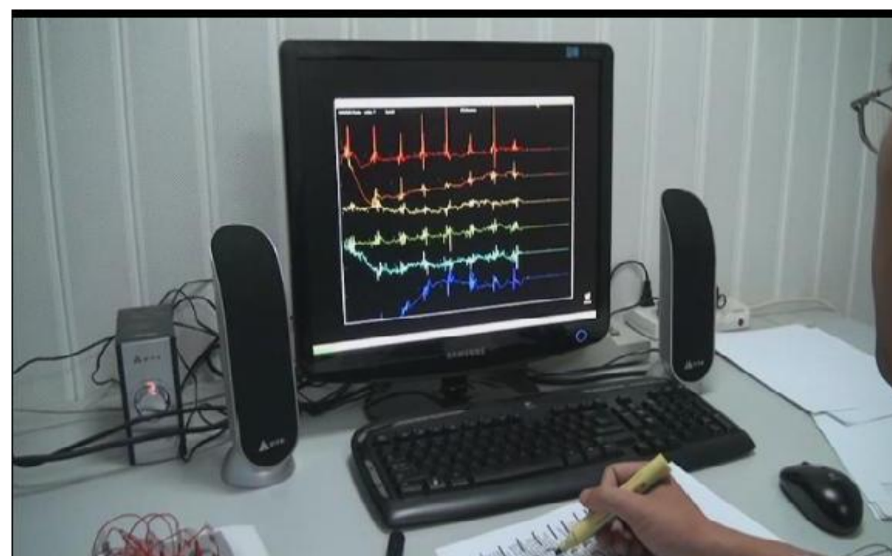
Case Study 3

Handwriting Recognition using EMG

Objective

- Allow a person (maybe disabled) to **communicate** or control the computer and mobile phones **without keyboard or other input devices**.
- Provide a natural, low-cost input way for **HMI (Human-Machine Interface) based on EMG**.



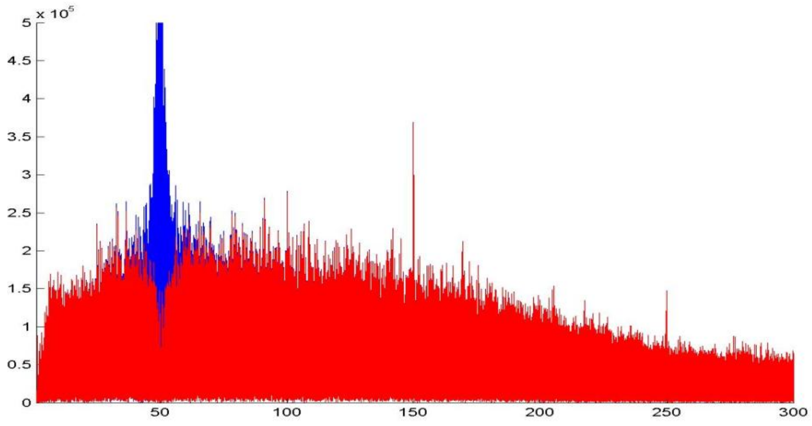


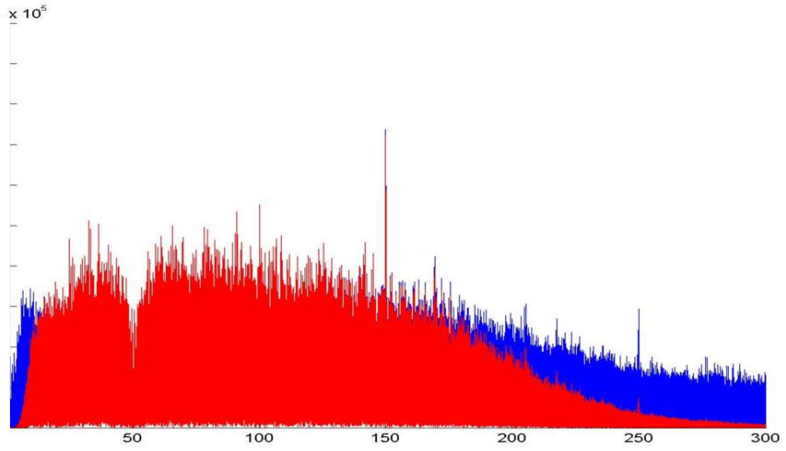
Method

1. Preprocessing
2. Onset and Offset Detecting
3. Template making
4. Template matching

Preprocessing

- Notch filter of 50Hz (power frequency), and bandpass filter for 10-200Hz

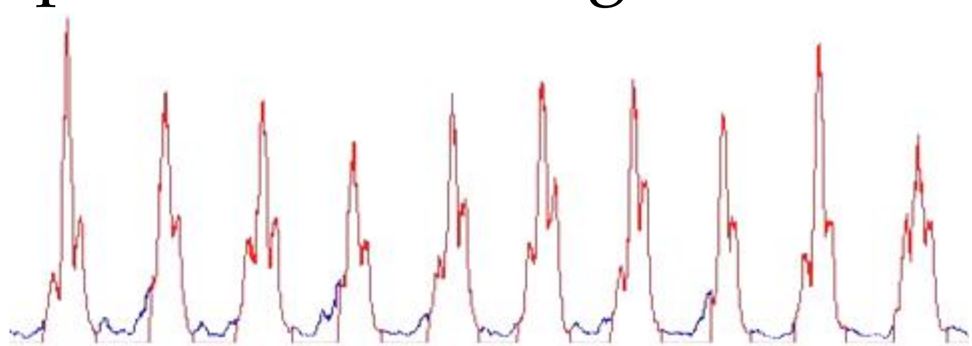


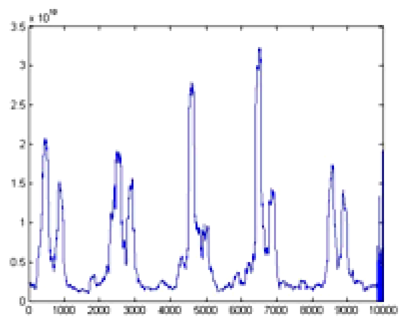


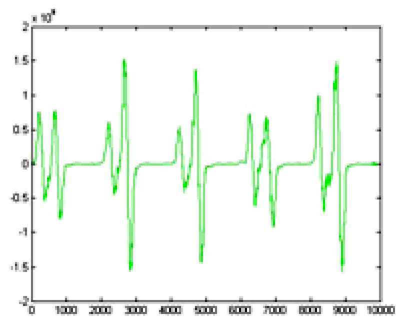
Blue (removed), Red (left)

Onset and Offset Detecting

- Detecting technique plays an important role for recognition.
- We set the threshold based on the energy and its slope of the EMG signal.



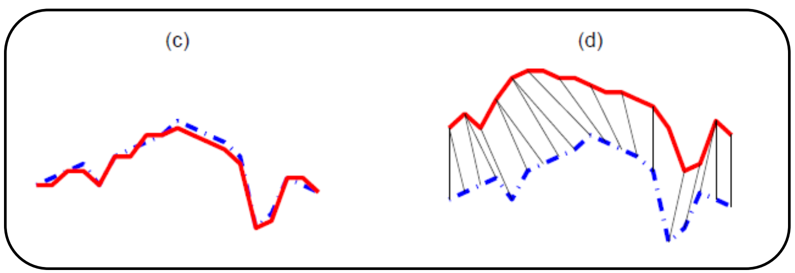




Template Making

Dynamic Time Warping (DTW) algorithm

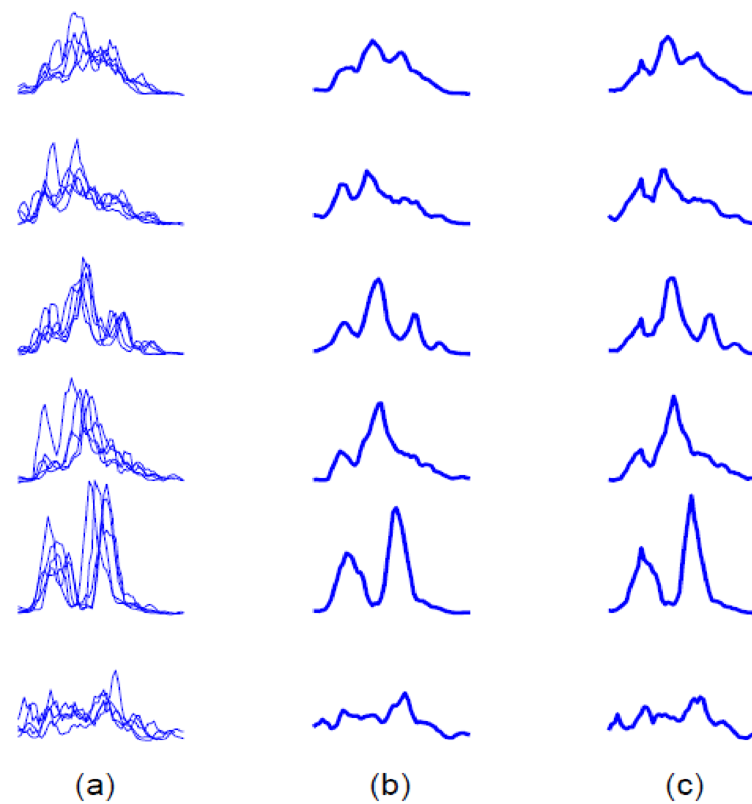
Conventional Processing



DTW

$$D_A(n,m) = D(n,m) + \min_{q \le m} D_A(n-1,q)$$

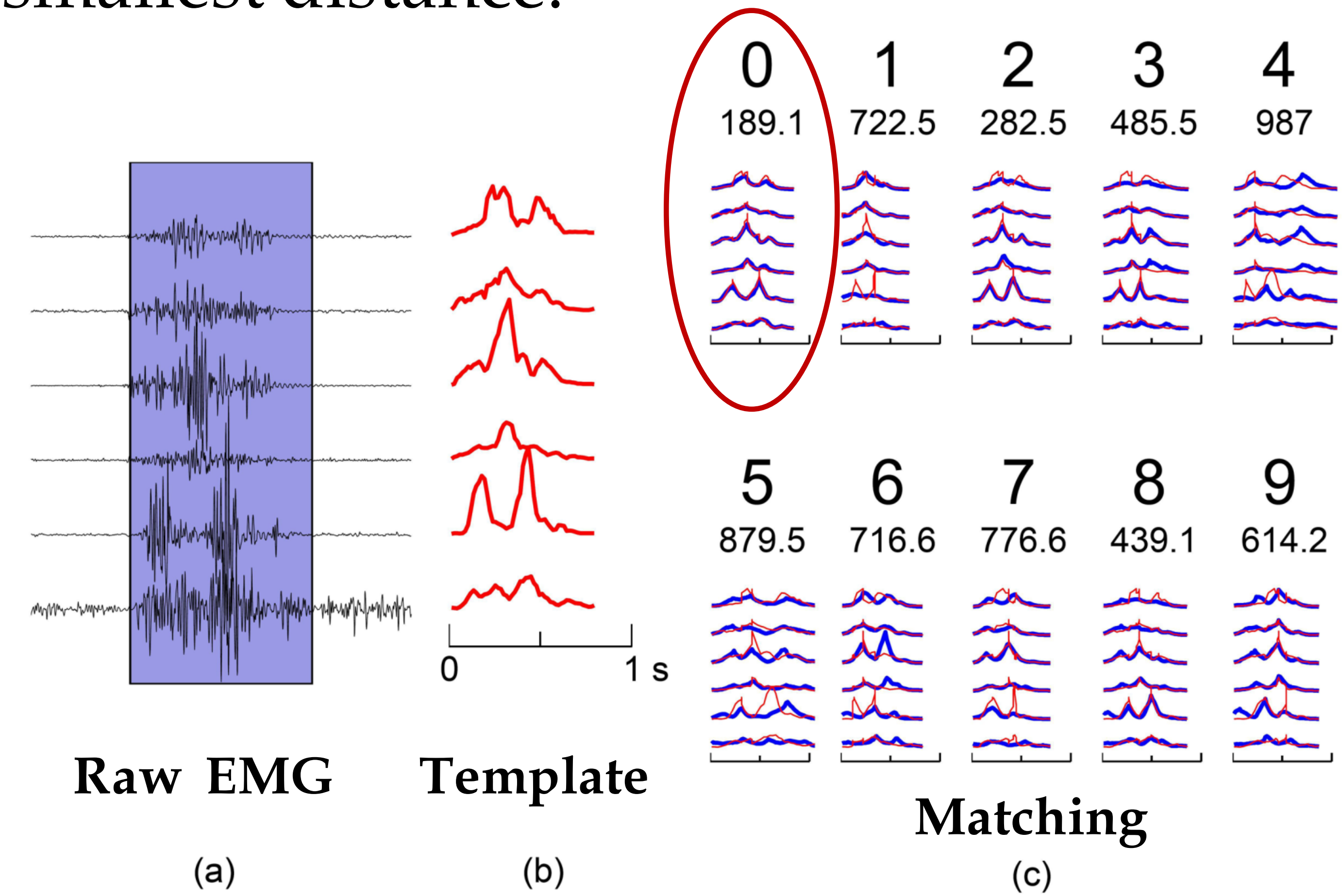
Minimize the cumulative distance between points m & n



Six-channel EMG | **Initial Template** | **Final Template**

Template Matching

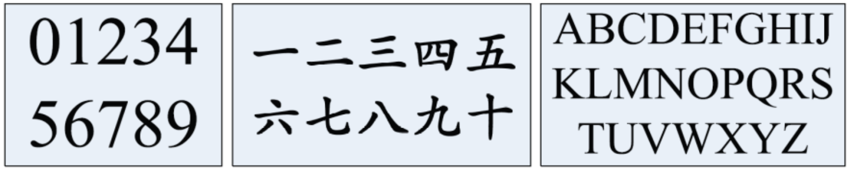
Compared with all the templates by DTW method, system recognize the character corresponding to the smallest distance.



Results

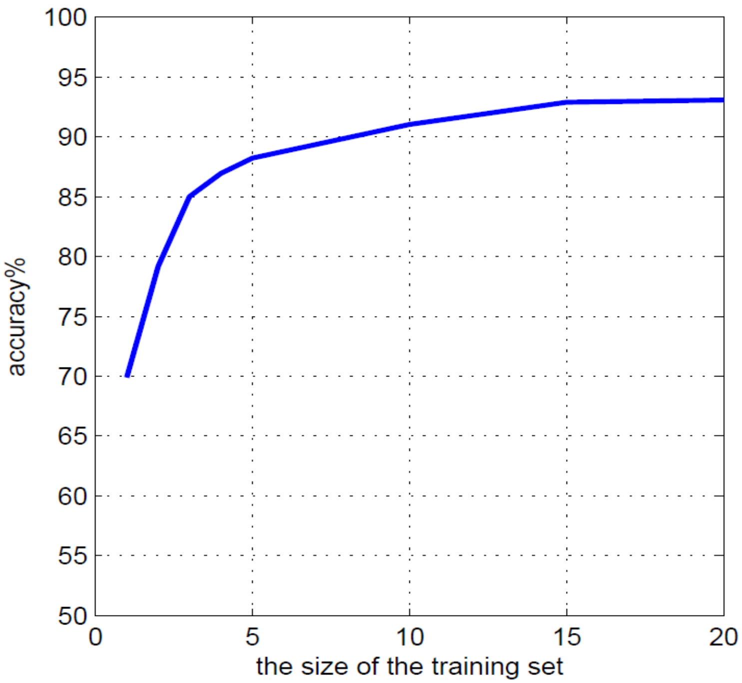
Performance on three character sets:

- digit characters from ‘0’ to ‘9’
- Chinese characters from ‘一’ (one) to ‘十’ (ten)
- capital letters from ‘A’ to ‘Z’



ACCURACY ON THREE CHARACTER SETS.

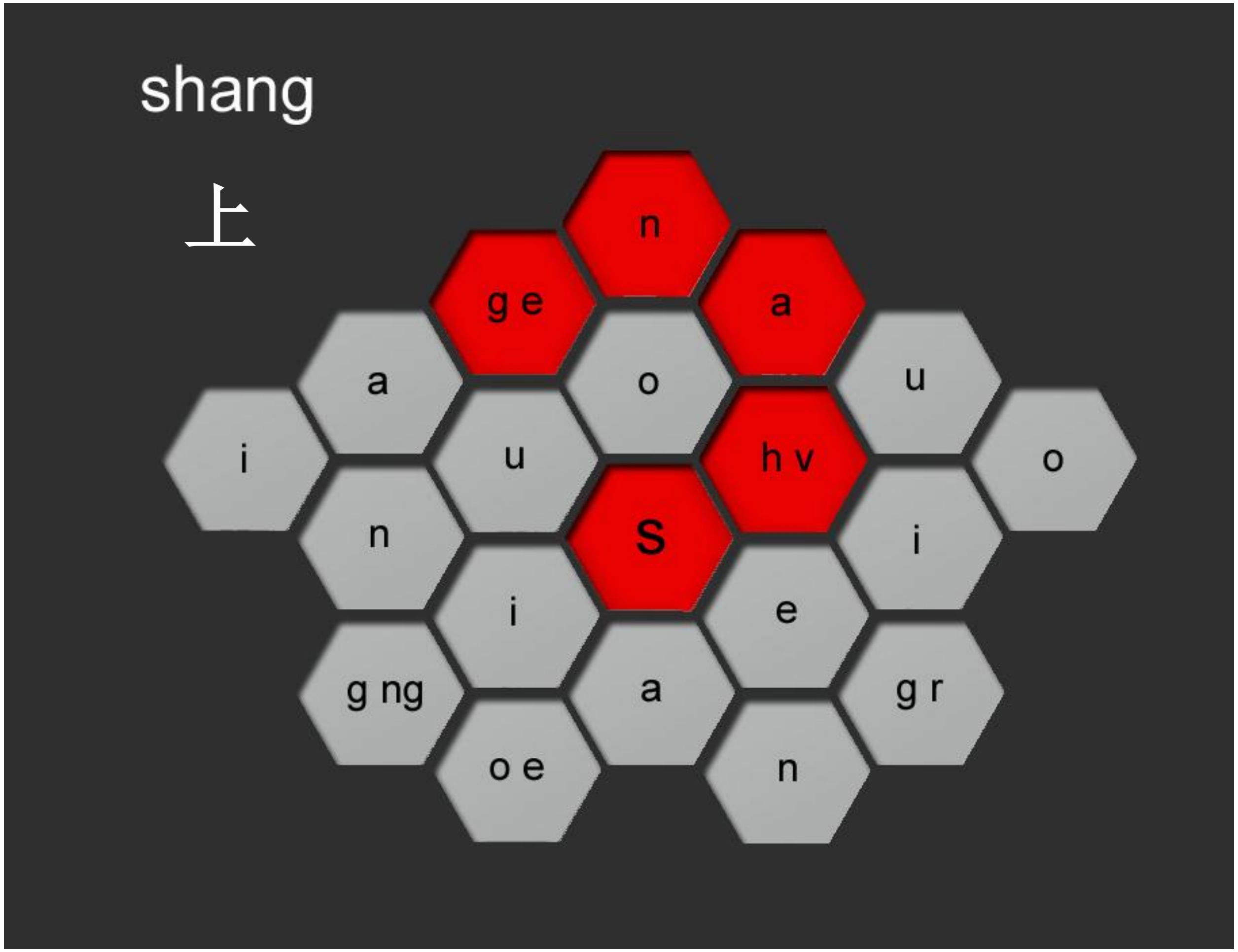
No.	character set	size	accuracy(%)
1	digits	10	98.25
2	Chinese	10	97.89
3	letters	26	84.29

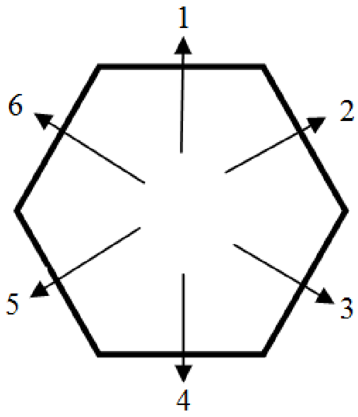


Combined with **AEVIOUS**

Online EMG collection → DTW → Human-Computer Interface

Visible HCI=AEVIOUS Input: Chinese character=>phonetic symbol (**Pin Yin**)



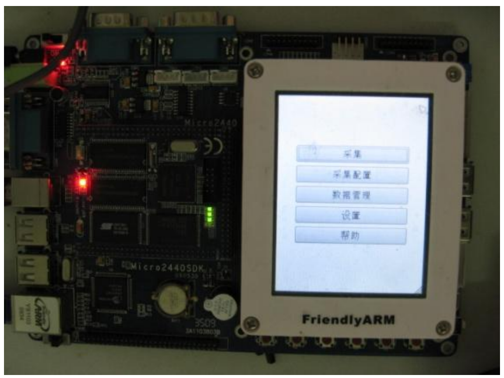


6 slide directions in a hexagon unit

Demonstration

Experiments on an amputee

Continuous Work

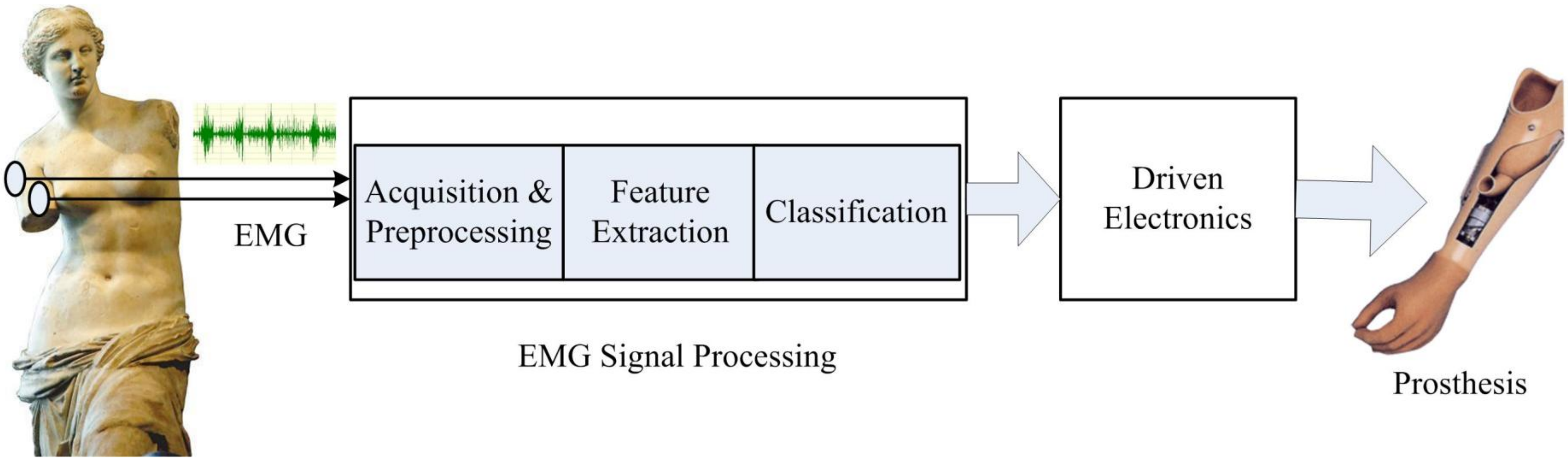


- improve EMG acquisition instrument
- apply on disabled with hand deficiency
- control mobile phone with Bluetooth

Case Study 4

EMG Controlled Prosthetic Hand

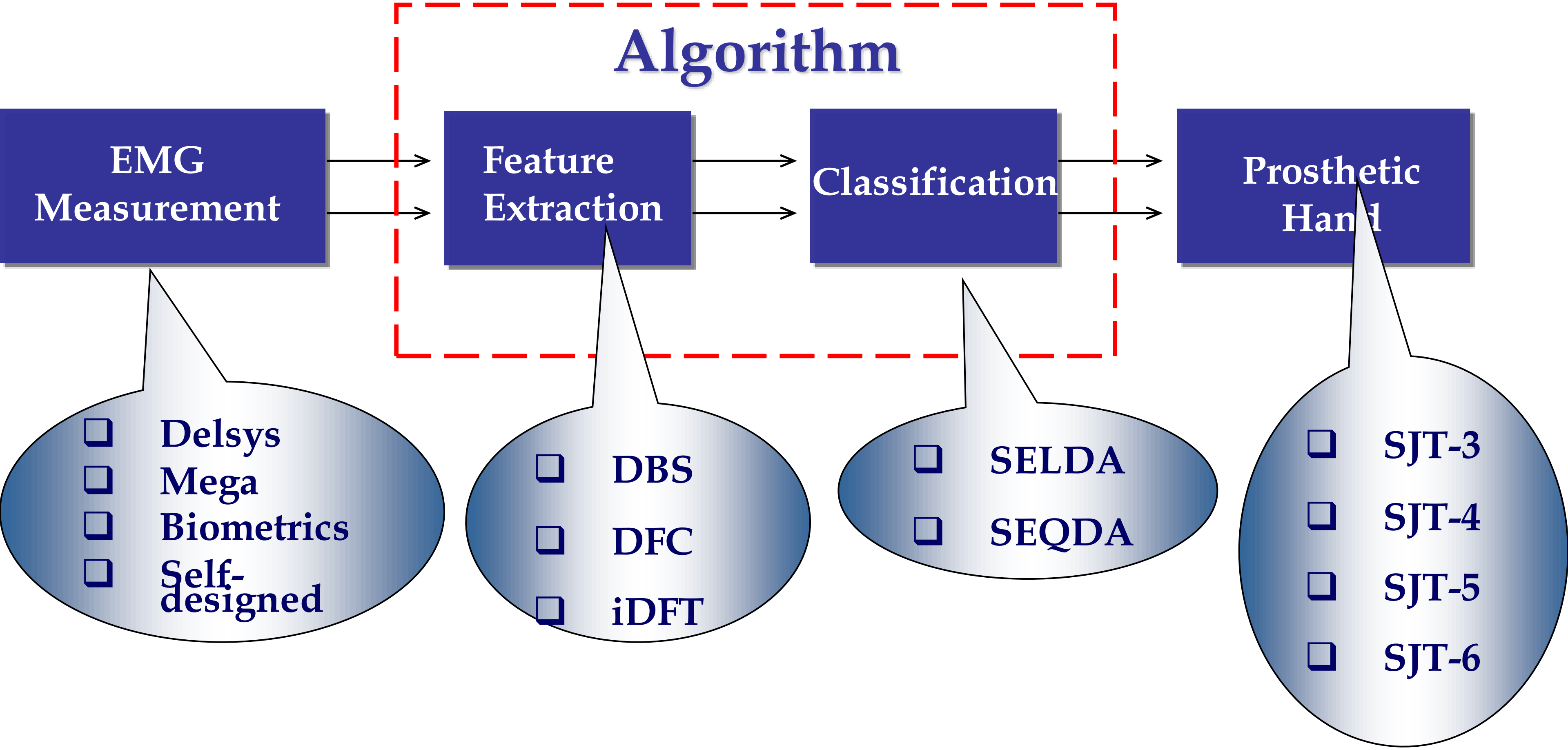
Basic Theory



Block diagram of EMG controlled prosthetic hand

Our Recent Work

EMG Signal Processing based on Pattern Recognition

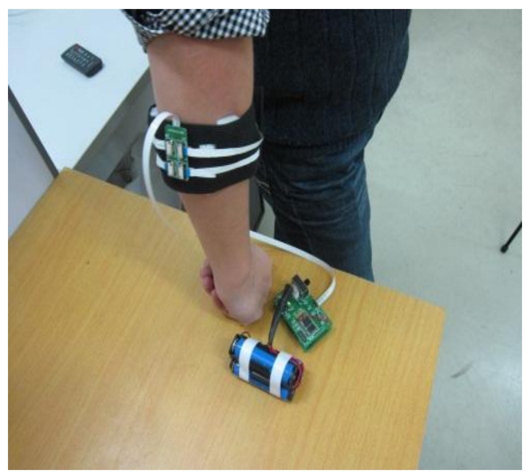


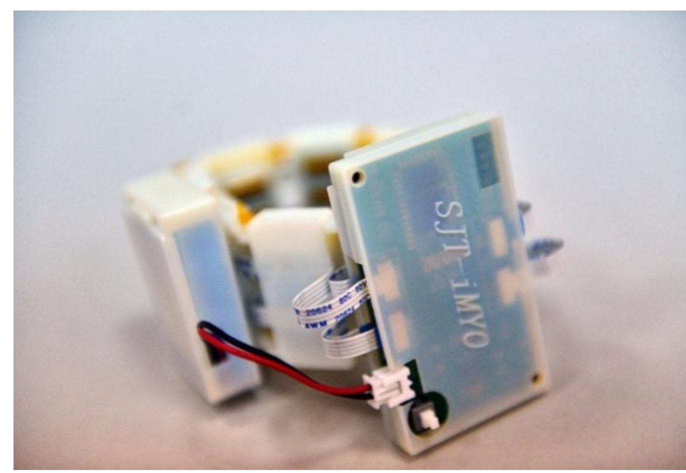
Our EMG Equipments

Delsys

Mega

Biometrics





Self-designed EMG armlet

Discriminant Bispectrum (DBS)

- *N*-th order cumulant function of a non-Gaussian stationary random signal *x(k):*

$$C_n^x(\tau_1, \tau_2, \ldots, \tau_{n-1}) = m_n^x(\tau_1, \tau_2, \ldots, \tau_{n-1}) - m_n^G(\tau_1, \tau_2, \ldots, \tau_{n-1})$$

- Bispectrum *B(w1,w2)* is defined as 2-dimensional Fourier transform of the 3rd order cumulant function:

$$B(\omega_1, \omega_2) = \sum_{\tau_2=-\infty}^{+\infty} \sum_{\tau_1=-\infty}^{+\infty} C_3^x(\tau_1, \tau_2,) \exp[-j(\omega_1 \tau_1 + \omega_2 \tau_2)]$$

- Direct estimation of bispectrum of *K* segments

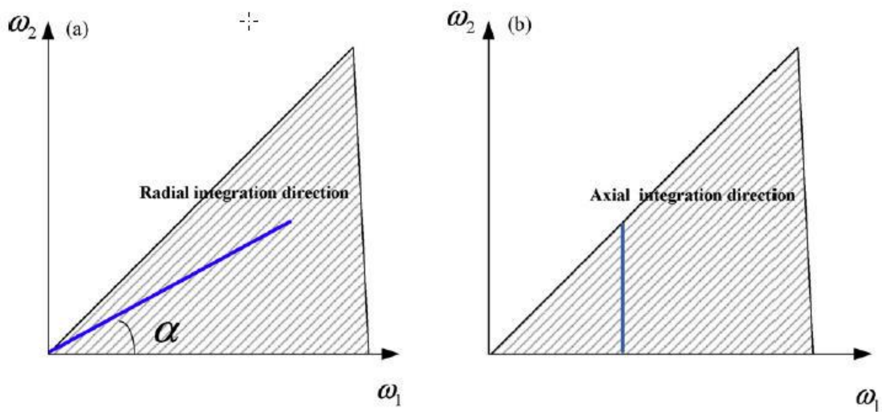
$$BS(\omega_1, \omega_2) = \frac{1}{K} \sum_{k=1}^{K} BS_k(\omega_1, \omega_2)$$

- Estimation of bispectrum in the *k*-th segment

$$BS_k(\omega_1, \omega_2) = \frac{1}{N^2} X(\omega_1) X(\omega_2) X^*(\omega_1 + \omega_2)$$

Bispectrum Integration

1-dimentional integration



+

2-D Bispectrum Matrix is transformed to 1-D integral feature

Fisher linear discriminant

$$J(W) = \frac{\det(W^T S_I W)}{\det(W^T S_N W)}$$

Dimension Reduction

[Chen XP, Zhu XY, **Zhang DG**, *Medical Engineering & Physics*, 2010]

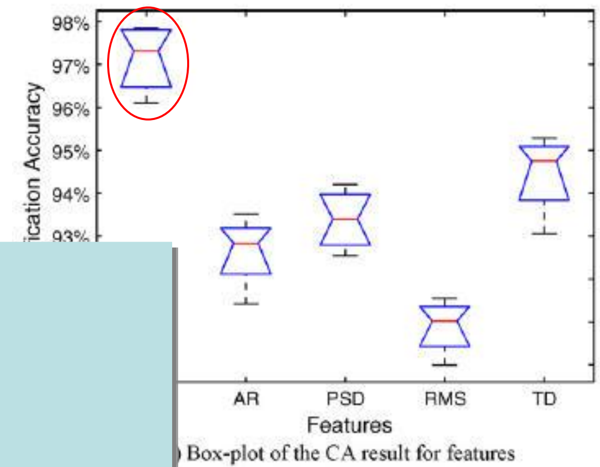
Results of DBS

Table 3
CA results (%) of different features and classifiers for each participant

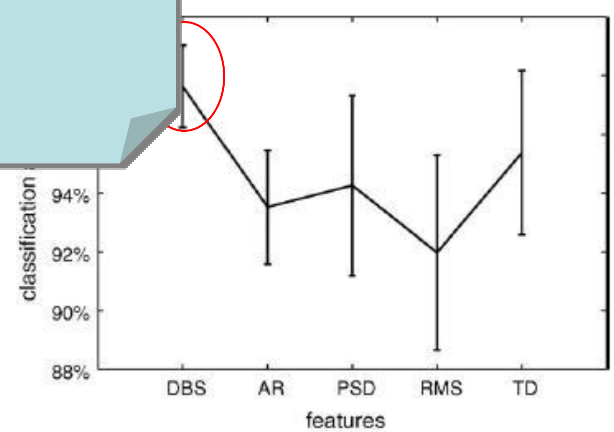
Participants (P)		DBS	AR	PSD	RMS	TD
P1	LLC	96.5	92.40	96.11	96.64	94.80
	GMM	97.5	94.80	96.41	93.79	96.21
	MLP	97.5	92.70	95.5	95.6	95.62
	SVM	97.4	94.30	96.33	94.00	96.79
P2	LLC	94.30				
	GMM	96.73				
	MLP	93.70				
	SVM	96.40				
P3	LLC	98.30				
	GMM	98.53				
	MLP	98.30				
	SVM	98.76				
P4	LLC	95				
	GMM	98.31				
	MLP	96.46				
	SVM	98.25				
P5	LLC	96.47				
	GMM	97.81				
	MLP	98.30				
	SVM	98.43				
P6	LLC	98.17	95.82	97.35	89.12	98.8
	GMM	99.31	96.57	98.59	92.73	99.1
	MLP	99.18	95.33	97.8	94.1	98.4
	SVM	99.41	97.16	97.8	94.1	99.2
P7	LLC	95.78	93.53	93.01	92.1	94.35
	GMM	98.92	95.16	93.46	93.8	96.31
	MLP	97.75	94.1	92.86	93.2	94.73
	SVM	98.63	95.32	93.7	94.5	96.24

Time Consuming:

- *DBS - 40ms*
- AR -28ms
- PSD - 38ms
- TDS - 2ms
- RMS - 0.5ms



) Box-plot of the CA result for features



(d) Mean/STD CA result for features

Fourier Cepstrum (FC)

- **Energy spectrum is achieved via discrete Fourier transform**

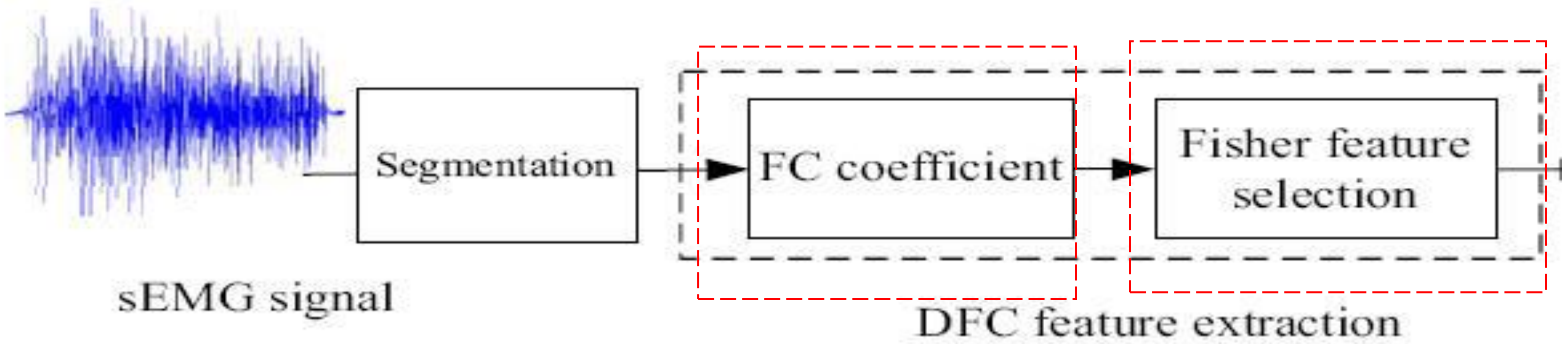
$$FC_i = \sum_{k=0}^{N-1} Y_k cos(\frac{(k+1/2)(i-1)\pi}{N}), i = 0, 1, ..., N.$$

- **FC coefficient**

$$X[k] = \sum_{n=0}^{N-1} x[n] exp^{-j\frac{2\pi}{N}nk}, k = 0, 1, ..., N-1.$$

is achieved from the nonlinear magnitude of Fourier-spectrum transform directly using discrete cosine transform (DCT).

Discriminant Fourier Cepstrum (DFC)



FC coefficients (FFT + DCT):

(1) Calculate the energy spectrum using the discrete Fourier transform

$$X[k] = \sum_{n=0}^{N-1} x[n] \exp^{-j\frac{2\pi}{N}nk}, \qquad k = 0, 1, \ldots, N-1. \tag{3}$$

(2) Calculate FC coefficients from the nonlinear magnitude of the Fourier-spectrum transform directly using DCT

$$FC_i = \sum_{k=0}^{N-1} Y_k \cos\left(\frac{(k+1/2)(i-1)\pi}{N}\right), \qquad i = 1, 2, \ldots, N, \tag{4}$$

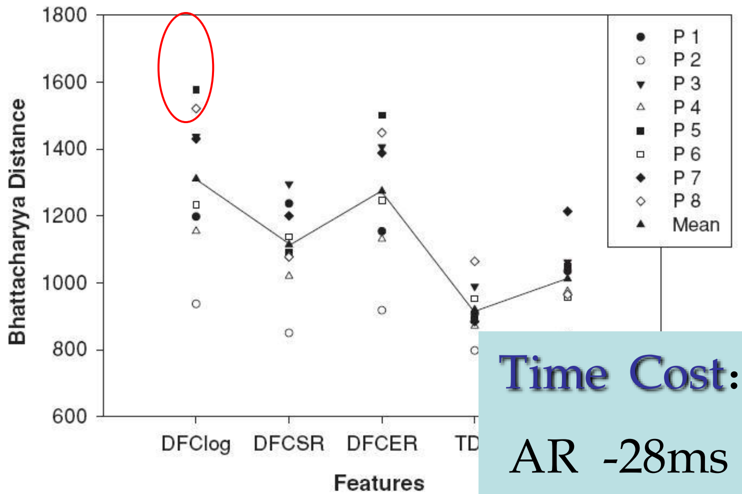
DFC feature

Fisher ratio feature selection:

$$J_{\text{fish}}(i) = \frac{S_B(i)}{S_W(i)}.$$

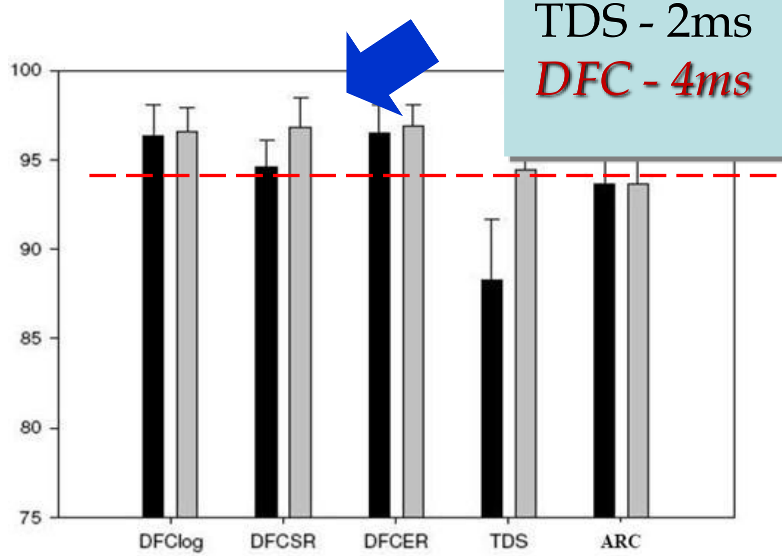
[Chen XP, Zhu XY, **Zhang DG**, *Physiological Measurement*, 2009]

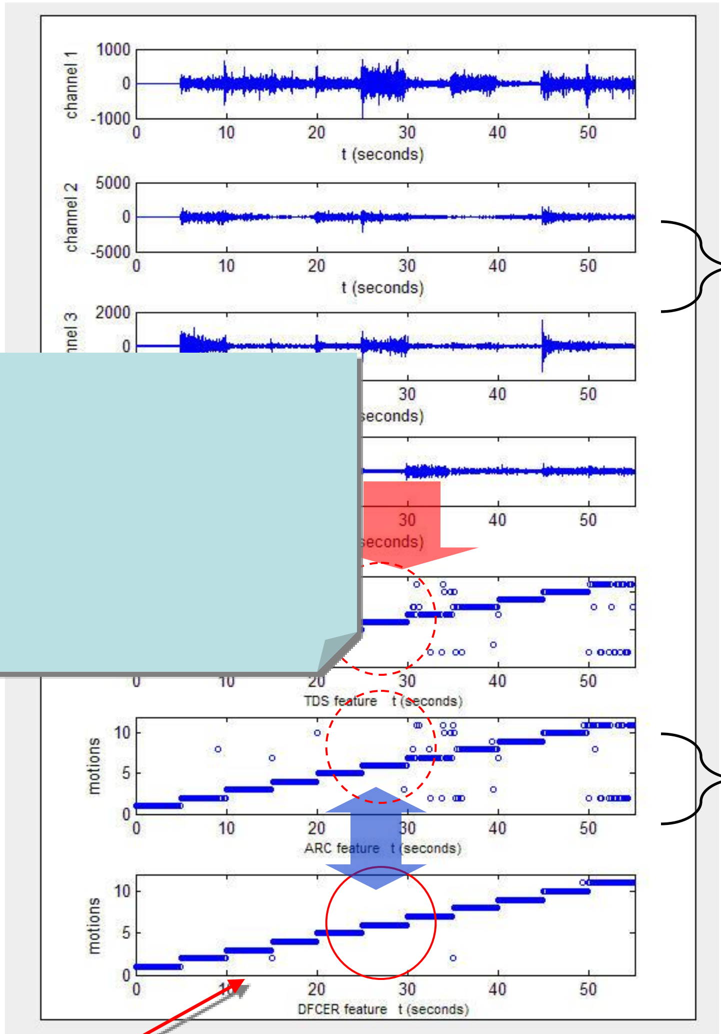
Results of DFC



Time Cost:

AR -28ms
TDS - 2ms
DFC - 4ms





Raw EMG

Command Output

Less mistakes

Expected Performance

1. At least 8 classes of motions can be recognized.
   Versatile functions

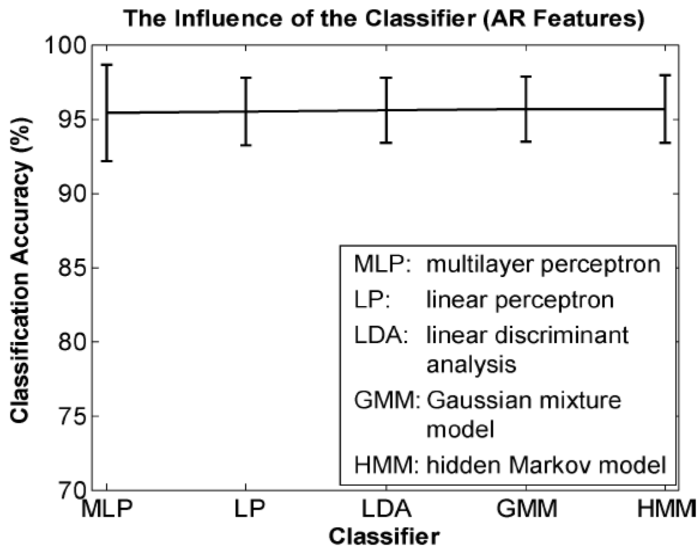
2. The recognition accuracy should be above 90%.
   Accurate control

3. The computation time of algorithms should less than 300ms.
   Fast response

Adaptive Classifier

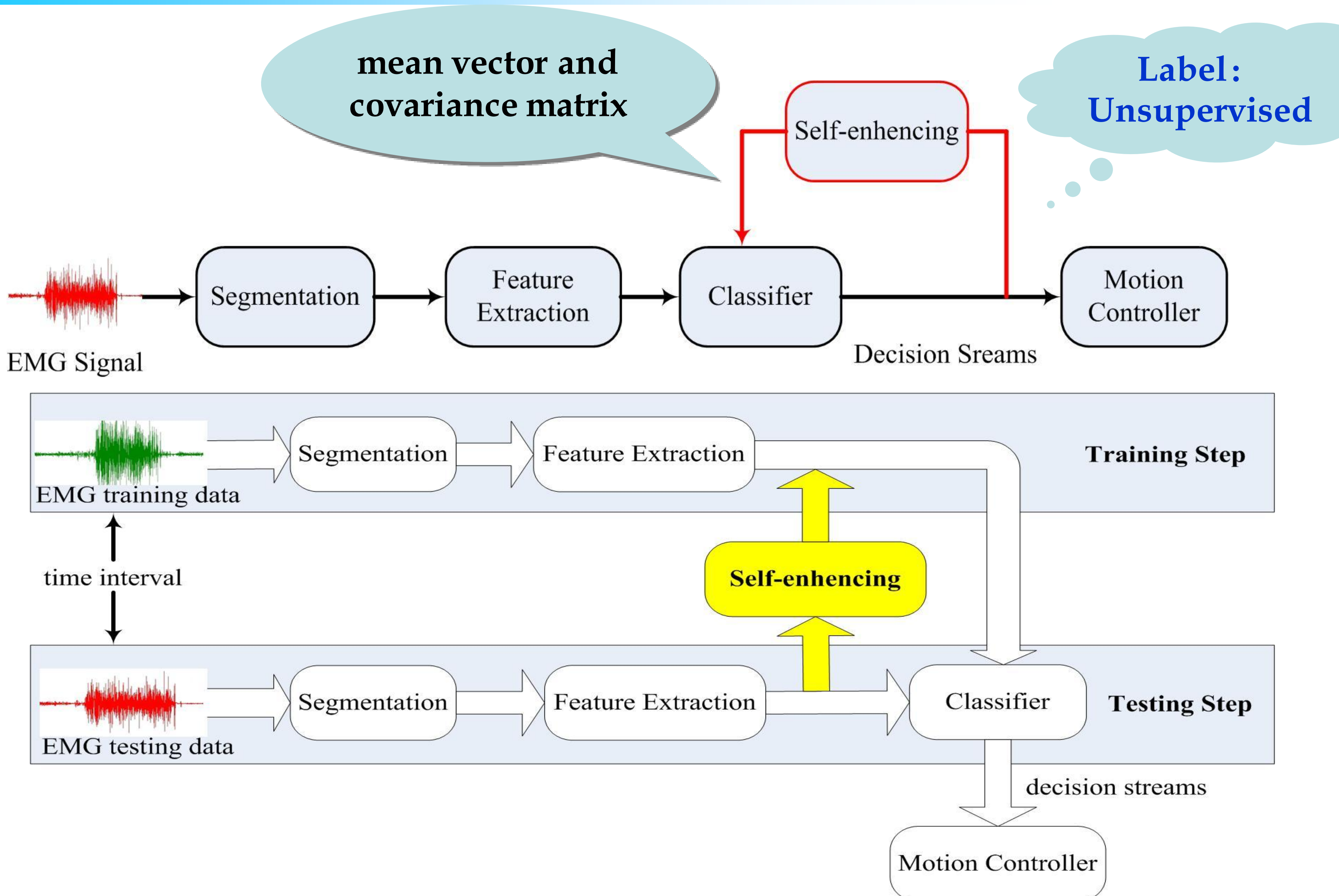
Self-enhancing adaptive classifier

- Increasing the training data set
- Information in testing data is used to update parameters of classifier.
- LDA and QDA is improved to self-enhancing classifiers.



[Chen XP, **Zhang DG***, Zhu XY, *J. NeuroEngineering & Rehabilitation*, 2013]

Adaptive Classifier



Conventional Classifiers

Linear Discriminant Analysis (LDA)

Quadratic Discriminant Analysis (QDA)

$$p(\omega_i \mid y) = p(\omega_i)\frac{p(y \mid \omega_i)}{p(y)}$$

where $p(y \mid \omega_i)$ is the class-conditional probability density function (PDF)

$$p(y \mid \omega_i) = \frac{1}{(2\pi)^{\frac{P}{2}}|\Sigma_i|^{\frac{1}{2}}}\exp\{-\frac{1}{2}(y-\mu_i)^T\Sigma_i^{-1}(y-\mu_i)\}$$

Note: It is called LDA. When covariances Σ_i are assumed to be different, the decision boundaries are hyperquadric surfaces, and this is called QDA.

Fisher linear discriminant (FLD) is adopted to reduce the dimension before QDA classification in this work.

Adaptive Classifier

The updated mean vector $\widetilde{\mu}_k$ for the kth class is

$$\widetilde{\mu}_k = \frac{nc_k * \mu_k + z}{nc_k + 1}$$

where ***z*** is the new EMG feature

the class covariance matrix $\widetilde{\Sigma}_k$ is updated by

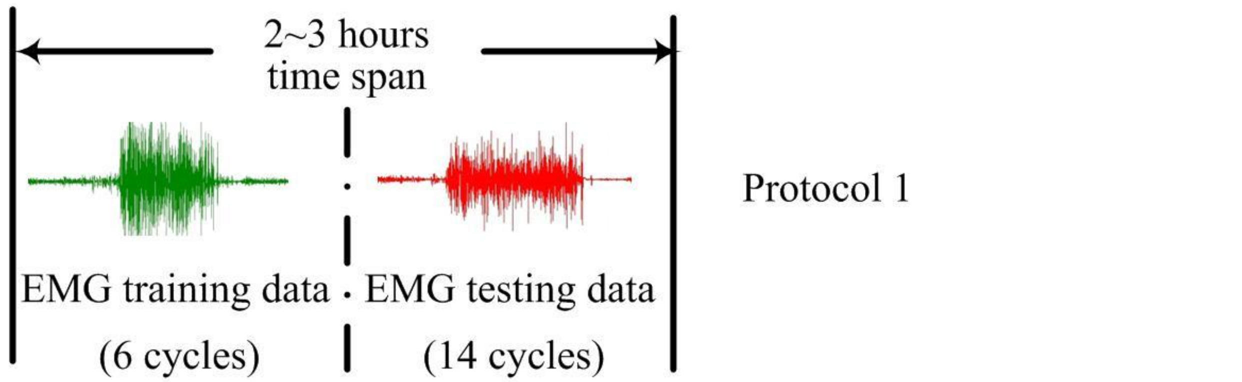
$$\begin{aligned}\widetilde{\Sigma}_k &= \frac{1}{nc_k+1}\widetilde{S}_k \\ &= \frac{1}{nc_k+1}S_k + \frac{1}{nc_k+1}C_k \\ &= \frac{nc_k}{nc_k+1}\Sigma_k + \frac{1}{nc_k+1}C_k\end{aligned}$$

Denote $S_k = \sum_{i=1}^{nc_k}(x_i - \mu_k)(x_i - \mu_k)^T$ $\quad C_k = \frac{n_k}{(nc_k+1)}(z - \mu_k)(z - \mu_k)^T,$

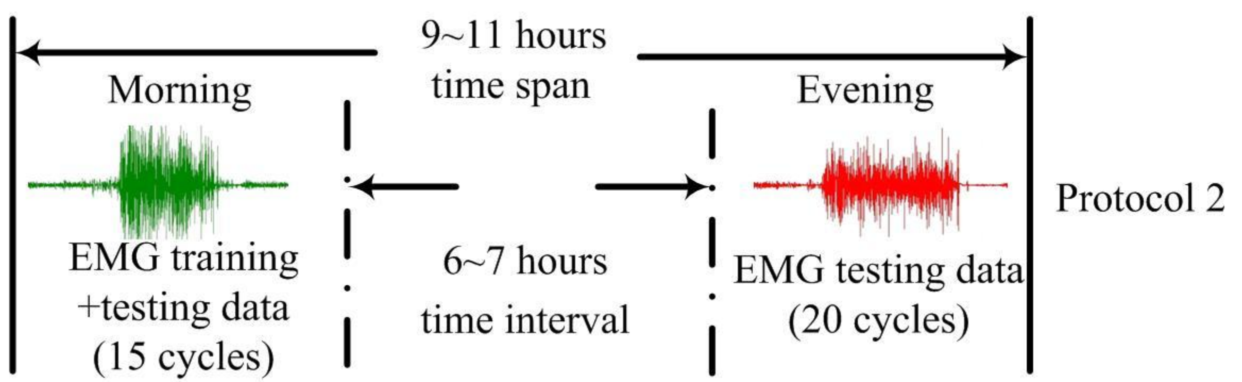
$\widetilde{S}_k = \sum_{i=1}^{nc_k+1}(x_i - \widetilde{\mu}_k)(x_i - \widetilde{\mu}_k)^T$ $\qquad \widetilde{S}_k = S_k + C_k$

Protocols

Conventional (short-term) Protocol

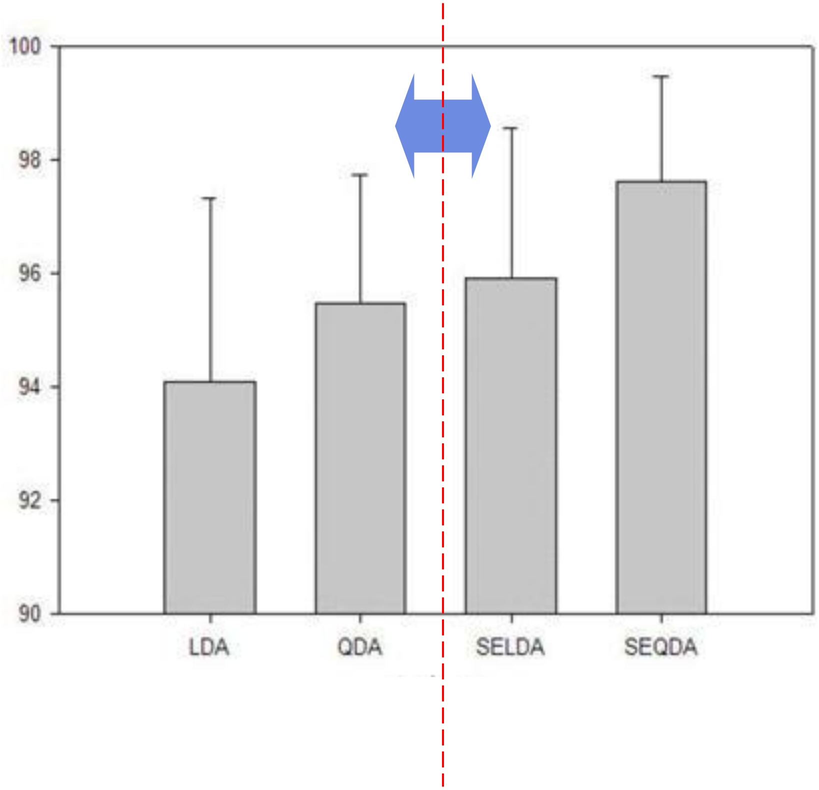


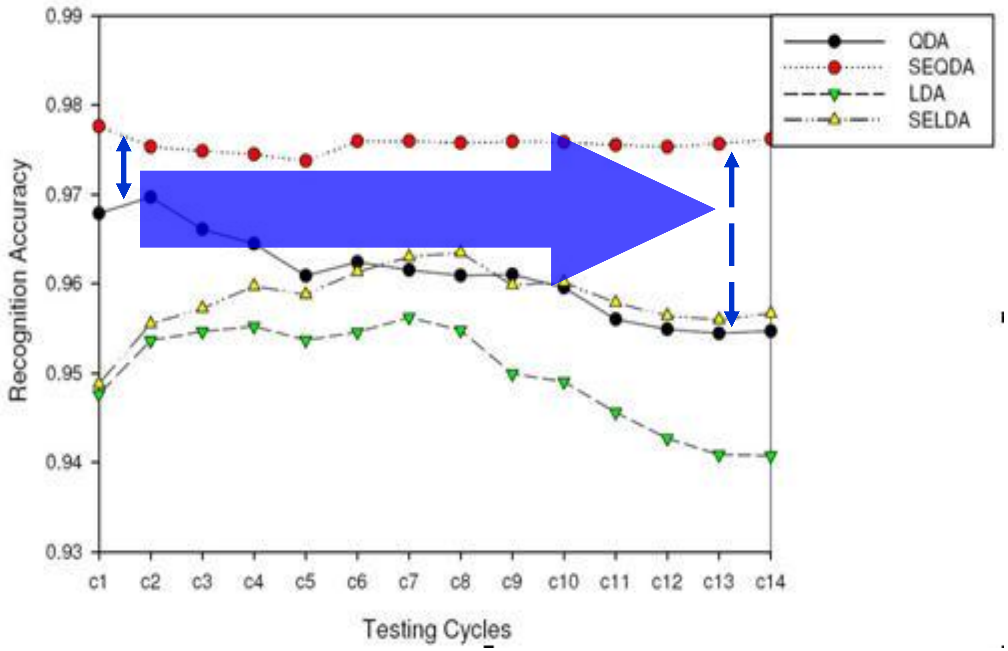
Long-term Protocol



Short-term Performance

Experiment results (unsupervised method)

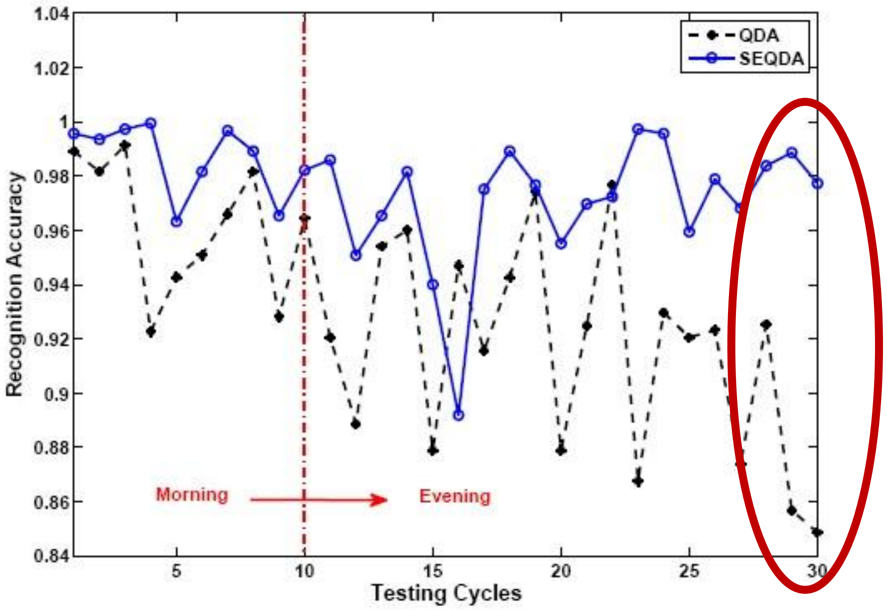


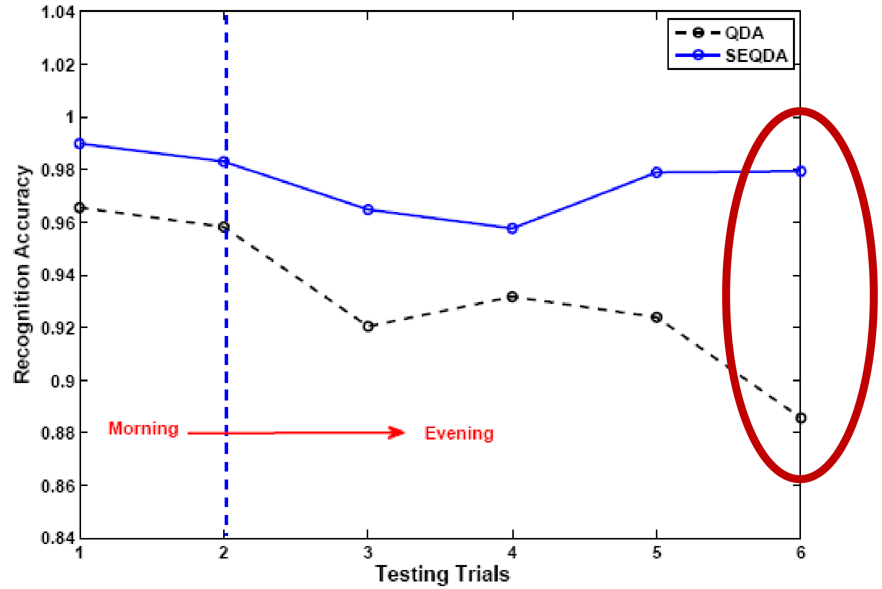


SEQDA（red） vs QDA（black）
SELDA（yellow） vs LDA（green）

Long-term Performance

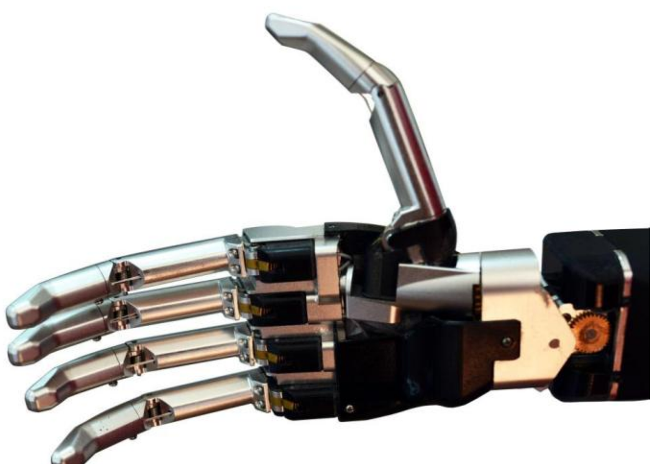
Experiment results (unsupervised method)





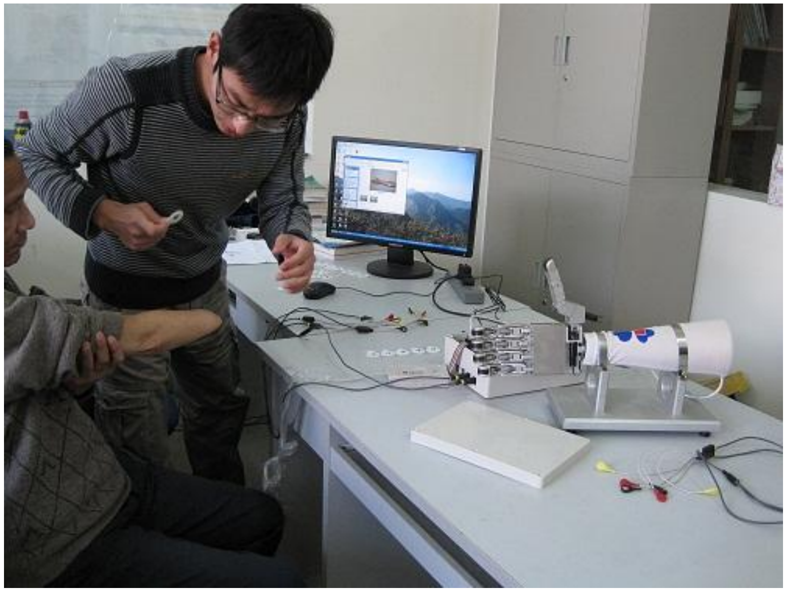
Prototypes of Prosthetic Hands

SJT-2~SJT-5 Hands



SJT-6 Hand

Experiment on Amputees



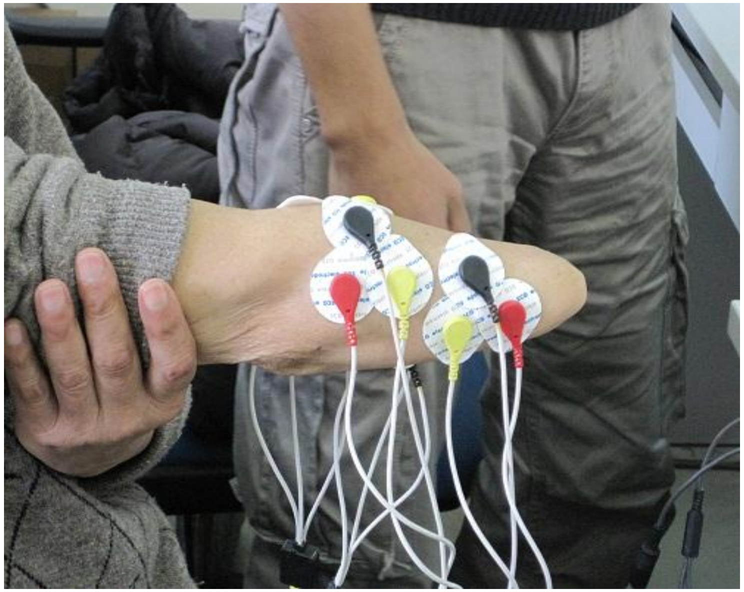
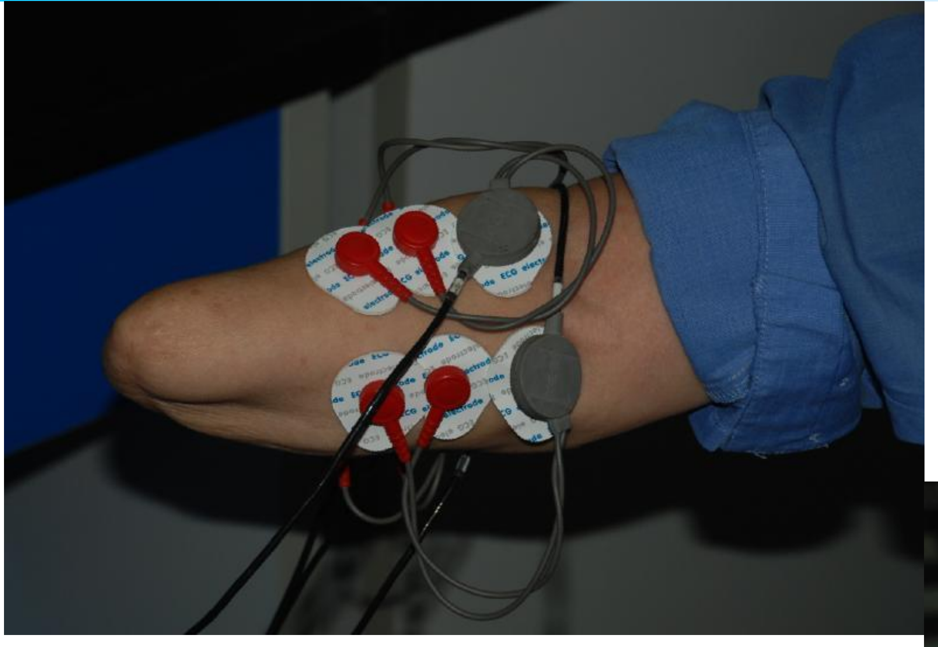


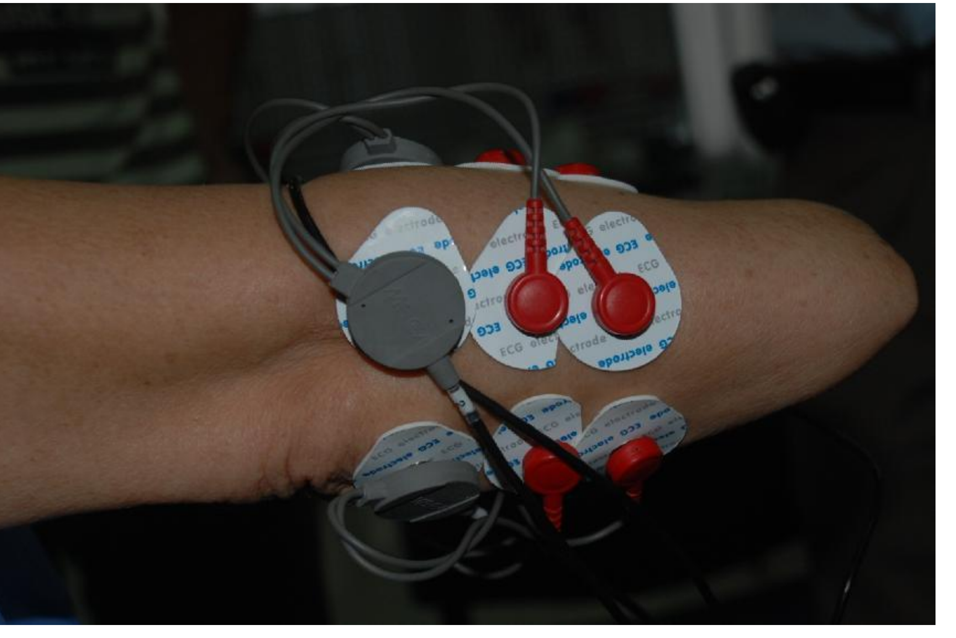
TABLE I
THE INFORMATION OF THE AMPUTEE SUBJECTS

Subject (gender, age)	Dominant Hand	Lower arm stump length (cm)	Cause of amputation	Time since amputation (years)	Prosthesis usage /type of prosthesis
Sub1 (M, 72)	Right hand	R. mid third (15)	Traumatic	34	Half day, myoelectric
Sub2 (F, 50)	Right hand	L. upper third (10)	Traumatic	25	Half day, myoelectric
Sub3 (F, 56)	Right hand	R. upper third (8)	Traumatic	31	All day, cosmetic
Sub4 (F, 57)	Right hand	L. mid third (17)	Traumatic	30	Half day, cosmetic
Sub5 (M, 60)	Right hand	L. mid third (16)	Traumatic	7	Half day, cosmetic
Sub6 (M, 36)	Right hand	R. mid third (16)	Traumatic	8	Half day, myoelectric

Placement of Electrodes



Anterior View



Posterior View

Demonstration

SJT-6 Prosthetic Hand Controlled by
SJT-iMYO EMG Armlet

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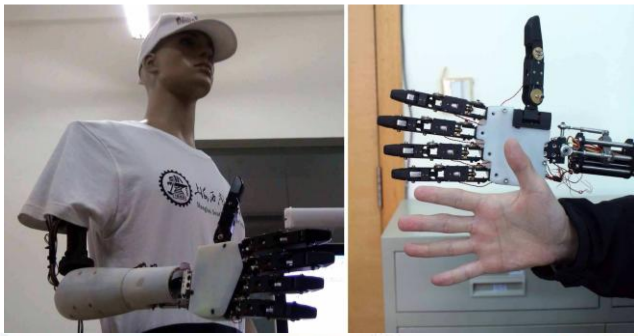
Biomechatronics & BioRobotics Lab



Welcome!

http://bbl.sjtu.edu.cn

The END

Thank you for your attention!

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