Physiological signal (Bio-signals)

Method, Application, Proposal
Bio-Signals

1. Electrical signals
   - ECG, EMG, EEG etc

2. Non-electrical signals
   - Breathing, pH, movement etc
General Procedure of bio-signal recognition system

1. Sensing
2. Preprocessing
3. Feature Extraction
4. Classification
5. Application
Preprocessing

• Purpose: Eliminate common noises such as inherent equipment noise
• However, signals may be hindered by moving artifacts
• Filters are required!
Case Study

• Removing high f noise in ECG signal for disease diagnosis
• Implementation

1. Extract a single cycle of ECG
2. Set cut-off frequency, sampling frequency. $F_s > 2f_c$
3. Define the filter function and apply to signal
4. Calculate the SNR value
   $$SNR (dB) = 10 \log (signal \ power)/(noise \ power)$$
5. View the ECG waveform

Reference: COMPARISON OF VARIOUS FILTERING TECHNIQUES USED FOR REMOVING HIGH FREQUENCY NOISE IN ECG SIGNAL, Priya Krishnamurthy1, N.Swethaanjali2, M.Arthi Bala Lakshmi3, 2015
Result

Original ECG Signal with High Frequency Noise

Using Butterworth Filter

Using Chebyshev Filter

<table>
<thead>
<tr>
<th>FILTER TYPE</th>
<th>ORDER</th>
<th>AVERAGE SIGNAL POWER (dB)</th>
<th>NOISE POWER (dB)</th>
<th>SNR (DB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chebyshev</td>
<td>7</td>
<td>-22.3961</td>
<td>-54.9677</td>
<td>32.6144</td>
</tr>
<tr>
<td>Butterworth</td>
<td>12</td>
<td>-22.3961</td>
<td>-49.7623</td>
<td>27.3233</td>
</tr>
<tr>
<td>Hamming</td>
<td>10</td>
<td>-22.3773</td>
<td>-75.544</td>
<td>53.1697</td>
</tr>
<tr>
<td>Hanning</td>
<td>10</td>
<td>-22.3773</td>
<td>-75.4026</td>
<td>53.024</td>
</tr>
<tr>
<td>Bartlett</td>
<td>10</td>
<td>-22.3773</td>
<td>-75.5158</td>
<td>53.1373</td>
</tr>
<tr>
<td>Kaiser</td>
<td>10</td>
<td>-22.3773</td>
<td>-76.2669</td>
<td>53.8885</td>
</tr>
</tbody>
</table>
Cognitive State
- Emotion Recognition
- Music

Digital Age
- Gaming
- Digital Hand

Healthcare
- Disease detection
- Rehabilitation
- Brain and Body computer interface
Emotion Recognition

- Six emotions
- Extract characteristic parameters from EMG, RV, SKT, SKC, BVP, HR
- Classification by SVM
- 85% in general recognition

Gaming: Baseball

- Eye movement feature of 9 directions
- EEG, EOG signal processing algorithms

Fig. 5. Experimental environment

Gaming Controlling via Brain-Computer Interface Using Multiple Physiological Signals, 2014
Digital Hand
Pattern recognition of number gestures based on a wireless surface EMG system

• Xun Chen, Jane Wang
• Biomedical Signal Processing and Control
Fig. 3. Illustration of the sEMG electrode pair placement: CH1, over extensor pollicis brevis muscle; Ch2, over extensor digitorum muscle; CH3, over flexor digitorum profundus muscle; and CH4, over flexor digitorum superficialis muscle.
ACTIVE SEGMENT → MOTION DETECTION → FEATURE SET EXTRACTION → CLASSIFICATION ALGORITHM

\[ \nu = (\nu_1, \nu_2, \ldots, \nu_n) \]

\[ \nu \in \text{Class J}, \quad J \in \{1, 2, \ldots, 10\} \]
Fig. 5. An example of 4-channel sEMG signals and the corresponding motion detection results of Chinese number gestures.
Features

- Hudgins’ time domain features.
- Autocorrelation and cross-correlation coefficients
- Spectral power magnitudes
Classifications

- k-Nearest neighbor
- Linear discriminant analysis
- Quadratic discriminant analysis
- Support vector machine
Feature Combining

• Combine the three feature with multi kernel leaning improves results further to 97.93 percent in offline case
Fig. 7. Comparisons of the overall recognition accuracies when employing different feature sets and different classifiers.
On-line experiment
Summary

• Machine learning technique is relatively easy to perform quite well
• The training and testing subjects need to be the same (or else there is a domain adaptation problem)
• The performance between different testing subjects are large, some recognition rate for some numbers for some subjects are lower than 80 percent.
• Mentioned in the paper, the reasonable electrode placement helps a lot to achieve a great performance
EMG-based Hand Gesture Recognition for Realtime Biosignal Interfacing Jonghwa

Kim, Stephan Mastnik, Elisabeth André
Lehrstuhl für Multimedia Konzepte und ihre Anwendungen Eichleitnerstr. 30, D-86159 Augsburg, Germany
Keywords

- Biosignal Analysis
- Electromyogram
- Human-Computer Interaction (HCI)
- Gesture Recognition
- Neural Interfacing
- Remote Control car
Gesture Selection

• The hand should be situated in a posture called the home position.

• Test over 20 different gestures.

• Select 4 gestures: Press, Left, Right, Circling
System Structure
Signal Acquisition

- NeXus-10™ with Myoscan-Pro™ EMG sensor
- EMG signals of up to 1600 µV in an active range of 20 to 500Hz
- Each pair of electrodes is used to examine mainly one single muscle.
Preprocessing & Pattern Extraction

• A simple detrending function:

• An incoming preprocessed value was marked as the beginning of a pattern if a certain defined threshold value was reached.

• The detection of a pattern ending in the system were achieved by observing the root mean square (RMS) of the last 16 incoming values.
Feature Extraction & Calibration

- maximum, minimum, mean value, variance, signal length and root mean square, fundamental frequency (FFT), Fourier variance, positions of the maximum and the minimum, zero-cross, number of occurrences

- For Calibration, We recorded 10 or 20 samples of each gesture per user.
Classification

- kNN
- Bayes
- Combination 1
- Combination 2
- 40 test sets
- Each subject, we recorded 20 training samples and 20 test samples.
### Result

#### Table 1. Average classification rates of all test sets

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Average classification rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Combination 1</td>
<td>94.38%</td>
</tr>
<tr>
<td>Combination 2</td>
<td>93.94%</td>
</tr>
<tr>
<td>KNN</td>
<td>93.84%</td>
</tr>
<tr>
<td>Bayes</td>
<td>91.84%</td>
</tr>
</tbody>
</table>

#### Table 2. Average classification rates for each gesture

<table>
<thead>
<tr>
<th>Classifier</th>
<th>G 1</th>
<th>G 2</th>
<th>G 3</th>
<th>G 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Combination 1</td>
<td>96.88%</td>
<td>92.63%</td>
<td>92.75%</td>
<td>95.25%</td>
</tr>
<tr>
<td>Combination 2</td>
<td>96.75%</td>
<td>91.75%</td>
<td>91.88%</td>
<td>95.38%</td>
</tr>
<tr>
<td>KNN</td>
<td>96.75%</td>
<td>91.63%</td>
<td>91.75%</td>
<td>95.25%</td>
</tr>
<tr>
<td>Bayes</td>
<td>93.38%</td>
<td>90%</td>
<td>87.88%</td>
<td>96.13%</td>
</tr>
</tbody>
</table>

#### Table 3. Comparison of phase 1 and phase 2

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Phase 1</th>
<th>Phase 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Combination 1</td>
<td>95.25%</td>
<td>95.63%</td>
</tr>
<tr>
<td>Combination 2</td>
<td>95.13%</td>
<td>94.88%</td>
</tr>
<tr>
<td>KNN</td>
<td>95.13%</td>
<td>94.63%</td>
</tr>
<tr>
<td>Bayes</td>
<td>92%</td>
<td>93.75%</td>
</tr>
</tbody>
</table>

#### Table 4. Comparison of male versus female subjects

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Males</th>
<th>Females</th>
</tr>
</thead>
<tbody>
<tr>
<td>Combination 1</td>
<td>94.20%</td>
<td>93.67%</td>
</tr>
<tr>
<td>Combination 2</td>
<td>93.84%</td>
<td>93.28%</td>
</tr>
<tr>
<td>KNN</td>
<td>93.84%</td>
<td>93.20%</td>
</tr>
<tr>
<td>Bayes</td>
<td>91.07%</td>
<td>88.56%</td>
</tr>
</tbody>
</table>
### Table 5. Comparison of subjects taller than the average height versus smaller subjects

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Taller</th>
<th>Smaller</th>
</tr>
</thead>
<tbody>
<tr>
<td>Combination 1</td>
<td>95.73%</td>
<td>92.71%</td>
</tr>
<tr>
<td>Combination 2</td>
<td>95.42%</td>
<td>92.29%</td>
</tr>
<tr>
<td>KNN</td>
<td>95.42%</td>
<td>92.22%</td>
</tr>
<tr>
<td>Bayes</td>
<td>93.02%</td>
<td>90.21%</td>
</tr>
</tbody>
</table>

### Table 6. Comparison of subjects which are heavier than the average weight versus lighter subjects

<table>
<thead>
<tr>
<th>Classifier</th>
<th>More Heavy</th>
<th>Lighter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Combination 1</td>
<td>92.73%</td>
<td>94.51%</td>
</tr>
<tr>
<td>Combination 2</td>
<td>92.39%</td>
<td>94.03%</td>
</tr>
<tr>
<td>KNN</td>
<td>92.39%</td>
<td>93.96%</td>
</tr>
<tr>
<td>Bayes</td>
<td>89.32%</td>
<td>92.08%</td>
</tr>
</tbody>
</table>

### Table 7. User independent gesture classification rates

<table>
<thead>
<tr>
<th>Classifier</th>
<th>G1</th>
<th>G2</th>
<th>G3</th>
<th>G4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Combination 1</td>
<td>98%</td>
<td>87%</td>
<td>93.34%</td>
<td>94.34%</td>
</tr>
</tbody>
</table>

Result
Our Project

• Quad-copter
• Gesture Recognition
• Electromyogram
• Biosignal Analysis
• Computer Vision
• Machine Learning
Reference

• http://scholarbank.nus.edu.sg/bitstream/handle/10635/19070/ZhaoWEI.pdf?sequence=1