Design of a Microelectronic Neurobridge Device for the Paralyzed Limbs and Motor Function Reconstruction

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ABSTRACT
To reconstruct the motor and sensory functions of human following brain nerve injury, we design a microelectronic neurobridge device as a replacement for the impaired brain nervous tissues. The sensory and motor functions are reconstructed for the paralyzed limbs. Models of this system are established along with the motor nerve signal detection device, signal acquisition device, microelectronic neurobridge testing machine, fast algorithm validation platform and action potential detection and recognition circuit. To solve the problem of low accuracy in detecting action potentials, we propose the core algorithm for the microelectronic neurobridge. This algorithm is based on constraints on amplitude thresholds and differential thresholds, and the time domain features are considered. The type feature vectors are obtained by K-means clustering with higher sensitivity and specificity. Real-time detection and processing of signals are achieved by using real-time fast algorithm. Human hand movement is detected by the double-channel microelectronic neurobridge device. Our findings provide a new solution to restore the motor functions of paralyzed patients.

Key Words: Paralysis, Brain Nerve Injury, Microelectronic Neurobridge, Action Potential Detection, Motor Function Reconstruction

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Introduction
Paralysis, defined as a complete or partial loss of tactile and motor functions of muscles due to brain nerve injury, has already become a global medical concern. Figure 1 shows the age distribution of paralyzed people released by an authority. The peak onset age of paralysis is 40 to 59 years old, accounting for about 48%. Those with paralysis and aged above 60 years old account for 32%. The average age of paralyzed people is 51 years old (Gao et al., 1997).

Paralysis is mainly caused by cerebral stroke (Rakusa et al., 2014). Brain nerve cells have limited regenerative ability, and the brain nerve injury will damage the environment for the generation of the nerve cells, leading to paralysis (Dobkin, 2000). Study has shown that neuroglial and myelin proteins are key factors inhibiting the regeneration of nerve cells at an early stage following brain nerve injury. Astroglia is the primary factor inhibiting the regeneration of nerve cells at a later stage following brain nerve injury (Hansson and Brismar, 2003). Paralysis is mainly caused by cerebral stroke (Rakusa et al., 2014).

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How to reconstruct the motor and sensory functions following brain nerve injury is among the major difficulties in paralysis research and treatment (Moskowitz, 1989). For the repair of the nervous system, advances in biomedicine, cardiac pacemaker and artificial retina are utilized, and some progress has been made in local motor and sensory reconstruction (Marqueste et al., 2004).

Microelectronic neurobridge is the new nerve signal and transmission technique developed in recent years (Björkman et al., 2005). Neurobridge device is based on microcomputer and receives and transmits the central nervous system signals in place of the impaired brain nerves. It is considered as a paralysis treatment system with a broad prospect (Almli and Stanley., 1992; Kemp et al., 2015).

We propose a microelectronic neurobridge device for motor and sensory reconstruction following brain nerve injury. This system can fulfil the functions that are once performed by the brain nerves. Our research sheds new light on the reconstruction of motor function for paralyzed patients.

**Microelectronic neurobridge device**

We propose a microelectronic neurobridge device for nerve signal reconstruction and transmission following brain nerve injury (Gale & Prigatano, 2010; Ewan and Martin, 2011). The general architecture of the neurobridge device is shown in Figure 2.

The nerve signal detection device is placed in the neuronal axon of motor cortex to detect action potentials. The signals are denoised, filtered and amplified before analog-to-digital conversion (ADC). Then the converted signals are input into the signal processor (Pruitt et al., 2016; Hokfelt et al., 1998; Banati et al., 2001). The core algorithm of the neurobridge device is the human action detection algorithm. The calculation results are feedback into the central controller. The system has a wireless receiver that enables offline computation. The results are converted into excitation waveforms via DAC. Finally, the excitation waveforms are converted into current output signals by functional electrical stimulation. These signals will stimulate the motor neuronal axons, inducing the generation of action potentials.
The signal detection device is responsible for denoising, amplifying and filtering of the raw signals, thus increasing the signal-to-noise ratio (SNR) and inhibiting low frequency drift. Raw signals contain several action potentials. It is necessary to identify the action potentials produced by the neurons through detection and separation algorithms so as to generate excitation pulses.

**Algorithms of the microelectronic neurobridge**

Action potential detection and classification are first analyzed. Data processing in microelectronic neurobridge mainly consists of two parts, training and bridging, as shown in Figure 4. Training can be done offline or online, while bridging must be done online. First the simulation data are input for the training. Attenuation factor is introduced to inhibit waveform mutation of the potential sequences:

\[
x’(n) = \begin{cases} 
  x(n), & 0 < n \leq 54 \\
  e^{-(n-54)^2/2}, & 54 \leq n \leq 64 \\
  0, & n = 65 
\end{cases}
\]

(1)

\[x(n)\text{ and } x'(n)\text{ are the data before and after adjustment, respectively. Before computation, estimation and elimination of environmental noises are performed first. Function } H(m, h) \text{ is defined as follows:}
\]

\[
H(m, h) = \begin{cases} 
  1, & R(x(n)) < R_{th}, n \in (m-h, m+h) \\
  0, & R(x(n)) \geq R_{th}, n \in (m-h, m+h) 
\end{cases}
\]

(2)

\[R(X) \text{ is the range of } x(n):
\]

\[R(x(n)) = \max(x(n)) - \min(x(n))
\]

(3)

\[R_{th} \text{ is the threshold for } R(X). \text{ Standard deviation for noise estimation is represented as}
\]

\[
\sigma_r(m, h) = \begin{cases} 
  \text{median} \left[|x(n)| \right], & n \in (m-h, m+h), H(m, h) = 1 \\
  0.6745, & n \in (m-h, m+h), H(m, h) = 0
\end{cases}
\]

(4)
Where \( m \) is the central coordinate, and \( h \) is the radius. Figure 5 shows the standard deviations for noise estimation by using the proposed method, conventional algorithm and future value algorithm. The noise signals used for the calculation obey a normal distribution. As the discharge frequency gradually increases, the error increases for each algorithm, and the increase amplitude is the greatest with the conventional algorithm. When the discharge frequency increases to 100Hz, the error with the conventional algorithm is 68%; that of the future value algorithm is 10.5%, while our proposed algorithm has an error of only about 2.6%.

Thus, the sensitivity \( S_n \) and specificity \( S_p \) of one algorithm in action potential detection are respectively given as follows:

\[
S_n = 1 - \frac{N_n}{N_t}, S_p = 1 - \frac{N_p}{N_d}
\]  

(6)

The larger the \( S_n \), the better the detection effect and the smaller the \( N_n \), the larger the \( S_p \), the lower the false detection rate.

Conventional amplitude threshold algorithm exhibits a higher sensitivity at the expense of \( S_p \). In other words, false detections are more frequent using the conventional amplitude threshold algorithm. We have made certain modifications on the basis of the conventional amplitude threshold algorithm, and the formula for the threshold algorithm is written below:

\[
\begin{align*}
\{ x(i) \geq Thr, x(i-1) < Thr \\
\{ x(i) - x(i-1) > \frac{a}{\sigma_n}
\end{align*}
\]

(7)

where \( Thr \) is the threshold; \( \sigma_n \) is the standard deviation of noise estimation; \( a \) is correlation coefficient.

Actual action potentials are detected using the proposed threshold algorithm, as shown in Table 1. The improved algorithm has a higher sensitivity, whose average is 99.39%. \( S_p \) increases dramatically, with an average of 96.28%, which verifies the validity and superiority of the proposed algorithm.

Sixteen datasets are used. Action potentials are detected using the conventional algorithm and the proposed algorithm, respectively, and the values of \( S_n \) and \( S_p \) using the two algorithms are shown in Fig. 6. Compared with conventional algorithm, our proposed algorithm has a great increase in sensitivity, while the specificity is generally maintained above 94%.

K-means clustering is applied to the action potentials detected above. Clustering can differentiate the action potentials produced by different neurons and extract the features for the same type of potentials. For the K-means clustering, the criterion function is expressed as follows:

\[
J_j = \sum_{i=1}^{n_j} \| x_{ij} - Z_j \|^2
\]

(8)
Figure 6. Comparison of two methods

Where $n_j$ is the sample size; $X_j$ is the feature vector of the sample; $Z_c$ is the cluster center. The set $J$ of all criterion functions is

$$ J = \sum_{j=1}^{n} J_j = \sum_{j=1}^{n} \frac{1}{X_j' - M_j} $$

(9)

Partial derivative is taken of formula (9):

$$ \frac{\partial}{\partial z_i} \sum_{j=1}^{n} \left[ X_j' - Z_c \right] = \frac{\partial}{\partial z_i} \sum_{j=1}^{n} \left[ X_j' - Z_c \right] = 0 $$

(10)

Let $x$ and $y$ be the feature vectors of the sample to be calculated. Using Euclidean distance $D(x, y)$ and Mahalanobis distance $D_M(x, y)$, the similarity measure of feature vector is calculated:

$$ D_O(x, y) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} $$

(11)

$$ D_M(x, y) = \sqrt{(x - y) \Sigma^{-1} (x - y)} $$

(12)

Table 2 shows the accuracy of action potential detection using K-means clustering, along with the calculated results of $D_O(x, y)$ and $D_M(x, y)$.

### Table 1. Improved detection results of amplitude threshold algorithm in action potentials

<table>
<thead>
<tr>
<th>Data set</th>
<th>Noise standard deviation</th>
<th>Total action potential</th>
<th>Undetected number</th>
<th>False drop number</th>
<th>Sensitivity %</th>
<th>Specificity %</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.05</td>
<td>3523(80)</td>
<td>0(188)</td>
<td>119</td>
<td>100</td>
<td>96.12</td>
</tr>
<tr>
<td></td>
<td>0.10</td>
<td>3530(771)</td>
<td>0(179)</td>
<td>180</td>
<td>99.81</td>
<td>95.27</td>
</tr>
<tr>
<td></td>
<td>0.15</td>
<td>3479(785)</td>
<td>0(217)</td>
<td>171</td>
<td>100</td>
<td>95.83</td>
</tr>
<tr>
<td></td>
<td>0.20</td>
<td>3486(783)</td>
<td>5(224)</td>
<td>202</td>
<td>100</td>
<td>93.96</td>
</tr>
<tr>
<td>2</td>
<td>0.05</td>
<td>3416(788)</td>
<td>0(209)</td>
<td>13</td>
<td>100</td>
<td>98.29</td>
</tr>
<tr>
<td></td>
<td>0.10</td>
<td>3517(819)</td>
<td>0(224)</td>
<td>68</td>
<td>99.38</td>
<td>98.35</td>
</tr>
<tr>
<td></td>
<td>0.15</td>
<td>3418(766)</td>
<td>1(230)</td>
<td>96</td>
<td>97.26</td>
<td>98.01</td>
</tr>
<tr>
<td></td>
<td>0.20</td>
<td>3533(814)</td>
<td>103(267)</td>
<td>89</td>
<td>100</td>
<td>97.42</td>
</tr>
<tr>
<td>3</td>
<td>0.05</td>
<td>3387(773)</td>
<td>0(234)</td>
<td>24</td>
<td>100</td>
<td>99.54</td>
</tr>
<tr>
<td></td>
<td>0.10</td>
<td>3465(817)</td>
<td>0(242)</td>
<td>80</td>
<td>100</td>
<td>96.94</td>
</tr>
<tr>
<td></td>
<td>0.15</td>
<td>3428(782)</td>
<td>18(267)</td>
<td>153</td>
<td>99.31</td>
<td>96.17</td>
</tr>
<tr>
<td></td>
<td>0.20</td>
<td>3428(782)</td>
<td>0(209)</td>
<td>13</td>
<td>100</td>
<td>98.29</td>
</tr>
</tbody>
</table>

### Table 2. Normality test of characteristic parameter selecting +K means clustering results

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Noise standard deviation</th>
<th>Action potential</th>
<th>European distance measure</th>
<th>Ma’s distance measure</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Total errors</td>
<td>Correct rate</td>
</tr>
<tr>
<td>1</td>
<td>0.05</td>
<td>3280(551)</td>
<td>0(15)</td>
<td>99.54%</td>
</tr>
<tr>
<td></td>
<td>0.10</td>
<td>3354(556)</td>
<td>0(17)</td>
<td>99.62%</td>
</tr>
<tr>
<td></td>
<td>0.15</td>
<td>3203(541)</td>
<td>0(27)</td>
<td>99.13%</td>
</tr>
<tr>
<td></td>
<td>0.20</td>
<td>2612(489)</td>
<td>4(68)</td>
<td>98.99%</td>
</tr>
<tr>
<td>2</td>
<td>0.05</td>
<td>3194(572)</td>
<td>0(3)</td>
<td>99.88%</td>
</tr>
<tr>
<td></td>
<td>0.10</td>
<td>3278(587)</td>
<td>45(4)</td>
<td>97.26%</td>
</tr>
<tr>
<td></td>
<td>0.15</td>
<td>3175(544)</td>
<td>17(23)</td>
<td>96.73%</td>
</tr>
<tr>
<td></td>
<td>0.20</td>
<td>2099(415)</td>
<td>81(28)</td>
<td>49.87%</td>
</tr>
<tr>
<td>3</td>
<td>0.05</td>
<td>3130(522)</td>
<td>0(0)</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>0.10</td>
<td>3234(579)</td>
<td>60(4)</td>
<td>97.17%</td>
</tr>
<tr>
<td></td>
<td>0.15</td>
<td>3185(564)</td>
<td>352(13)</td>
<td>88.26%</td>
</tr>
<tr>
<td></td>
<td>0.20</td>
<td>2456(457)</td>
<td>670(33)</td>
<td>66.35%</td>
</tr>
<tr>
<td>4</td>
<td>0.05</td>
<td>3206(589)</td>
<td>11(1)</td>
<td>98.45%</td>
</tr>
<tr>
<td></td>
<td>0.10</td>
<td>3276(520)</td>
<td>234(5)</td>
<td>90.74%</td>
</tr>
<tr>
<td></td>
<td>0.15</td>
<td>3050(577)</td>
<td>525(4)</td>
<td>84.73%</td>
</tr>
<tr>
<td></td>
<td>0.20</td>
<td>2332(388)</td>
<td>646(6)</td>
<td>68.84%</td>
</tr>
</tbody>
</table>
As seen from the table above, the effect of clustering based on $D_M(x, y)$ is better than based on $D_O(x, y)$. Since the number of dimensions in the features extracted using the probability density function is small, every feature vector has several wave peaks. Thus, under considerable environmental noises, the clustering effect is better based on $D_M(x, y)$.

**Reconstruction of motor function using microelectronic neurobridge for paralyzed patients**

Figure 7 shows the schematic for reconstructing the motor function for patients with cerebral palsy using microelectronic neurobridge. The nerve signals produced by the brain nerve system cannot be transmitted to the affected limbs, so the motor signals in the healthy limbs are detected using the microelectronic neurobridge device. These signals are converted into electrical stimulation signals through relevant algorithms, which are then applied to the affected limbs. In this way, the motor function is reconstructed.

Detection circuit for motor signals is expressed as:

$$G_{\text{max}} = 20 \log \left( \frac{3}{0.001} \right) = 69.54 \text{dB}$$

$$G_{\text{min}} = 20 \log \left( \frac{3}{\frac{1}{2} \cdot 2^{15} \cdot 10^{-6}} \right) = 63.32 \text{dB}$$

$$\text{Figure 7. Diagram of microelectronics muscle bridge based on stroke movement function reconstruction}$$

Figure 8 shows the flow chart of algorithms used in microelectronic neurobridge. OUT is the repository of excitation waveforms; ou is the explanation of the output status; Thr is the threshold for electromyographic signals; cnt is the counter; x is the value after the conversion of electromyography (EMG) signals; Len is the length of OUT. Following the flow chart in Fig. 8, the surface EMG signals and the excitation pulse signals are output and used for strength testing.

The subjects were males, physically healthy and aged 20-27 years old. The subjects sat straight on chairs, with the right arm on the armrest and the right wrist suspended. Different static loads were imposed on the right wrist, and the tests were performed for five times. After each test, the subjects took a rest for 5 min before the next test. Fig. 9 shows the curves of maximal volitional contraction (MVC) and stimulation frequency (SF) under different thresholds for electrical signals for two volunteers. Polynomial fitting was performed using the scattered values. The degree of linearity is expressed as follows:

$$L = \frac{\Delta SF_{\text{max}}}{SF_{\text{max}} - SF_{\text{min}}} \times 100\%$$

$$\text{Figure 8. Flow chart of algorithm hardware program}$$

The larger the L, the lower the degree of linearity. As seen from the figure, the larger the MVC, the larger the SF. Generally, MVS squared is linearly related to SF. Besides, when Thr=0.07, SF
under the same MVC is smaller than that when \( \text{Thr}=0.1 \). As analyzed above, the value of \( \text{Thr} \) should be properly adjusted for different positions of the human body, so as to improve the detection of motor signals.

\[
\begin{align*}
\text{Figure 9. Performance of single channel excitation pulse generating algorithm}
\end{align*}
\]

**Conclusion**

We establish a microelectronic neurobridge device to reconstruct the motor and sensory functions following brain nerve injury. This system can act as a substitute for the injured brain nerve cells. Our research offers a new solution for reconstructing the motor function for paralyzed patients.

Models of this system are established along with the motor nerve signal detection device, signal acquisition device, microelectronic neurobridge testing machine, fast algorithm validation platform and action potential detection and recognition circuit. To solve the problem of low accuracy in detecting action potentials, we propose the core algorithm for the microelectronic neurobridge. This algorithm is based on constraints on amplitude threshold and differential threshold and considers the time domain features. The type feature vectors are obtained by K-means clustering with higher sensitivity and specificity. Real-time detection and processing of signals are achieved by using the real-time fast algorithm. Human hand movement is detected by the double-channel microelectronic neurobridge.

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**References**


