Morse Code Recognition System with Adaptive Fuzzy Algorithm for the Disabled

Chung-Min Wu  Ching-Hsing Luo *  Shu-Wen Lin  Shih-Chung Chen  
Ming-Che Hsieh  Chun-Tang Chao  Cheng-Chi Tai

Department of Electrical Engineering, Cheng Kung University, Tainan, Taiwan, 720, ROC
1Department of Special Education National Tainan Teachers College, Tainan, Taiwan, 720, ROC
2Department of Electrical Engineering Southern Taiwan University of Technology, Tainan, Taiwan, 720, ROC
3Department of Information Education National Taitung Teachers College, Tainan, Taiwan, 720, ROC

Received 14 October 2002; Accepted 20 November 2002

Abstract

The Morse code is an efficient tool for the severe disabilities that is always used to represent various characters by a series of long-short sounds. To keep a fixed input speed that is difficult for the disabled people. In order to release the serious limitation of typing speed control, several algorithms were proposed to chase the typing pattern of a user, including adaptive unstable-speed prediction (AUSP), least mean square and matching (LMS&M), adaptive variable-ratio threshold prediction (AVRTP), and the back propagation neural network (BPN). It is successful to solve the problem of the irregular input speed, but the mathematic computation becomes more and more complex. In this study, we try to use fuzzy theory combining with the adaptive algorithm to recognize the Morse code, expecting to adapt all kinds of variation for users, and raising the recognition rate.

Keywords: Morse code, Disabilities, Fuzzy theory, Adaptive algorithm

Introduction

With the progress of information era, there are many assistive tools developed for the disabled to interact with their environment. The Morse code is an efficient tool for the severe disabilities that is always used to represent various characters by a series of long-short sounds. But a user must remember the miscellaneous Morse code and accept an exacting training on the stable typing speed with a fixed long-to-short ratio.

To keep a fixed input speed that is difficult for the disabled people. In order to release the serious limitation of typing speed control, several algorithms were proposed to chase the typing pattern of a user. After 1995, there are several algorithms proposed for unstable input speed by using adaptive and network signal processing techniques including adaptive unstable-speed prediction (AUSP)[1], least mean square and matching (LMS&M)[2], adaptive variable-ratio threshold prediction (AVRTP)[3, 4], the back propagation neural network (BPN)[5, 6]. The recognition rate of unstable typing pattern had significant improvement from AUSP algorithm (29.1%), LMS&M algorithm (81.6%) to AVRTP algorithm (94.0%)[4]. It’s successful to solve the problem of the irregular input speed, but the mathematic computation becomes more and more complex.

In this study, we try to use fuzzy theory combining with the adaptive algorithm [7-9] for the recognition of Morse code. The fuzzy process for its simple and fast-speed calculation is easily installed in the single-chip microprocessor as a real time recognition, and the adaptive algorithm can modify the parameters of membership functions for raising the recognition rate of Morse code. The recognition rate of the adaptive fuzzy algorithm is investigated in comparison to the previous ones.

Method

The fuzzy recognition method of Morse code is a single input single output system, and that has no standard rule to adjust the fuzzy membership functions for user’s condition, so the result of Morse code recognition is not fair. This study uses an adaptive algorithm trying to adjust the parameters of the membership function and lets the system trace the user’s typing pattern, expecting to adaptive all kinds of variation for user, and raising the recognition rate. The adaptive fuzzy recognition system structure is shown as the Figure 1.

The recognition procedure is described as follows:
1. To find the typing speed, the original input data $I_i$ is normalized by function $f_i$,
Figure 1. Adaptive fuzzy recognition system block diagram. 
- \( I_k \): Original Morse code input data.
- \( x_k \): Normalized Morse code input data.
- \( y_k \): Predictive output.
- \( e_k \): The difference between input \( x_k \) and output \( y_{k-1} \).
- \( e'_k \): The modified difference from \( e_k \) by a fuzzy algorithm.
- \( T_k \): Threshold to distinguish between long and short elements.

\[
\begin{align*}
I_k & \rightarrow f_T(I_k) \rightarrow x_k + e_k \rightarrow Fuzzy \ Recognition \rightarrow e'_k \rightarrow \text{Adaptive Algorithm} \rightarrow y_k \\
& \rightarrow y_{k-1} + Z^{-1}
\end{align*}
\]

Figure 2. The membership function of the conclusion. P1~P5: The variable range of defuzzifier. Five linguistic parameters fuzzy recognition system are: LN, negative large; SN, negative small; ZE, zero; SP, positive small; LP, positive large.

\[
f_T \begin{cases} 
    x_k = I_k, & \text{if } I_k < T_k \\
    x_k = \frac{1}{3}I_k, & \text{if } I_k \geq T_k
\end{cases}
\]  

Where \( T_k \) is the \( k \)th threshold to distinguish between long and short elements.

2. The prediction error \( e_k \), an input to the fuzzy algorithm, is created by the difference between \( x_k \) and \( y_{k-1} \),

\[
e_k = x_k - y_{k-1}
\]  

In the fuzzy algorithm, a linguistic fuzzy rule is utilized to calculate modified error \( e'_k \). Five linguistic parameters of fuzzy recognition system are: LN, negative large; SN, negative small; ZE, zero; SP, positive small; LP, positive large.

- Fuzzy rule 1: if \( e_k \) is LN then \( e'_k \) is LN (highest speed)
- Fuzzy rule 2: if \( e_k \) is SN then \( e'_k \) is SN (high speed)
- Fuzzy rule 3: if \( e_k \) is ZE then \( e'_k \) is ZE (normal speed)
- Fuzzy rule 4: if \( e_k \) is SP then \( e'_k \) is SP (slow speed)
- Fuzzy rule 5: if \( e_k \) is LP then \( e'_k \) is LP (lowest speed)

3. Based on the values of \( e'_k \) and \( y_{k-1} \), the predictive output \( y_k \) and threshold \( T_k \) are updated by

\[
y_k = y_{k-1} + e'_k
\]  

\[
T_k = 2y_{k-1}
\]  

4. The adaptive algorithm to adjust the parameters \( P_j \) of membership function for the fuzzy recognition system with defuzzifier (Figure 2) is presented next to minimize the cost function \( C_f \).

\[
C_f = 0.5e_k^2 + 0.5(x_k - y_{k-1})^2
\]  

\[
P_j = P_{j-1} - \epsilon \frac{\partial C_f}{\partial P_j}
\]

where \( \epsilon \) is the step size and is usually a small positive number.

By repeating steps 1~4, the system can automatically adjust the threshold value \( T_k \) in response to the typing speed variation. \( T_k \) is 2 times of \( y_{k-1} \) because 2 is the middle value between 3 and 1 (i.e., the long-to-short ratio is equal to 3:1).

**Results and Discussion**

This section proceeds the recognition analysis for two algorithms: adaptive fuzzy and AVRTP algorithm [4]. There are twelve human-typed data sets: six data sets typed by wireless experts and the other data sets typed by a teenager with cerebral palsy. Tables 1 and 2 show their characteristics including mean, coefficient of variation (CV) and average ratio of long to short. \( L_m \) is the mean value of long elements (dash or long-silence), and \( S_m \) is the mean value of short elements (dot or short-silence).

\[
\text{Mean value: } \sum_{i=1}^{k} \frac{I_i}{k}, \quad I_i \text{ is the input data}
\]  

\[
\text{Coefficient of variation (CV): } \frac{\text{std}}{\text{mean}} \times 100\%.
\]  

\( \text{std} \) is standard deviation.
Table 1 The data analysis for experts

<table>
<thead>
<tr>
<th>No.</th>
<th>Lm (ms)</th>
<th>CV %</th>
<th>Sm (ms)</th>
<th>CV %</th>
<th>Lm/Sm</th>
<th>Lm (ms)</th>
<th>CV %</th>
<th>Sm (ms)</th>
<th>CV %</th>
<th>Lm/Sm</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>249</td>
<td>12</td>
<td>63</td>
<td>13</td>
<td>4.0</td>
<td>429</td>
<td>27</td>
<td>129</td>
<td>12</td>
<td>3.3</td>
</tr>
<tr>
<td>2</td>
<td>263</td>
<td>12</td>
<td>99</td>
<td>16</td>
<td>2.7</td>
<td>273</td>
<td>29</td>
<td>115</td>
<td>18</td>
<td>2.4</td>
</tr>
<tr>
<td>3</td>
<td>304</td>
<td>15</td>
<td>57</td>
<td>19</td>
<td>5.3</td>
<td>586</td>
<td>24</td>
<td>124</td>
<td>29</td>
<td>4.7</td>
</tr>
<tr>
<td>4</td>
<td>318</td>
<td>14</td>
<td>61</td>
<td>18</td>
<td>5.2</td>
<td>765</td>
<td>28</td>
<td>130</td>
<td>22</td>
<td>5.9</td>
</tr>
<tr>
<td>5</td>
<td>365</td>
<td>10</td>
<td>102</td>
<td>15</td>
<td>3.6</td>
<td>532</td>
<td>15</td>
<td>177</td>
<td>15</td>
<td>3.0</td>
</tr>
<tr>
<td>6</td>
<td>197</td>
<td>17</td>
<td>60</td>
<td>22</td>
<td>3.3</td>
<td>363</td>
<td>23</td>
<td>87</td>
<td>25</td>
<td>4.2</td>
</tr>
</tbody>
</table>

Table 2 The data analysis for a teenager with cerebral palsy

<table>
<thead>
<tr>
<th>No.</th>
<th>Lm (ms)</th>
<th>CV %</th>
<th>Sm (ms)</th>
<th>CV %</th>
<th>Lm/Sm</th>
<th>Lm (ms)</th>
<th>CV %</th>
<th>Sm (ms)</th>
<th>CV %</th>
<th>Lm/Sm</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>619</td>
<td>22</td>
<td>163</td>
<td>53</td>
<td>3.8</td>
<td>2724</td>
<td>37</td>
<td>418</td>
<td>38</td>
<td>6.5</td>
</tr>
<tr>
<td>2</td>
<td>677</td>
<td>27</td>
<td>110</td>
<td>66</td>
<td>6.2</td>
<td>2561</td>
<td>39</td>
<td>479</td>
<td>40</td>
<td>5.3</td>
</tr>
<tr>
<td>3</td>
<td>812</td>
<td>24</td>
<td>79</td>
<td>66</td>
<td>10.3</td>
<td>1794</td>
<td>38</td>
<td>463</td>
<td>28</td>
<td>3.9</td>
</tr>
<tr>
<td>4</td>
<td>634</td>
<td>21</td>
<td>73</td>
<td>42</td>
<td>8.7</td>
<td>1717</td>
<td>35</td>
<td>540</td>
<td>21</td>
<td>3.2</td>
</tr>
<tr>
<td>5</td>
<td>755</td>
<td>28</td>
<td>125</td>
<td>49</td>
<td>6.0</td>
<td>1443</td>
<td>48</td>
<td>376</td>
<td>20</td>
<td>3.8</td>
</tr>
<tr>
<td>6</td>
<td>969</td>
<td>26</td>
<td>139</td>
<td>49</td>
<td>7.0</td>
<td>1495</td>
<td>34</td>
<td>332</td>
<td>32</td>
<td>4.5</td>
</tr>
</tbody>
</table>

Figure 3. The recognition rates of expert data by two algorithms
As shown in these tables, the mean value and the coefficient of variation for the disabled are much larger than those for the expert. The average ratio of long to short shows that it is very difficult for the disabled person to follow 3:1 rule when inputting Morse code. The long-to-short ratio variation for a disabled person is so large that it is difficult to be recognized. Figures 3 and 4 are the recognition results for expert and the disabled person by two algorithms. Apparently, The adaptive fuzzy algorithm has better average recognition rate than the other. In Figure 3, the average recognition rates of expert data are very high for both two algorithms (98.78% of AVRTP, 99.34% of adaptive fuzzy). When the long-to-short ratio is smaller than 3, as indicate data at #2, AVRTP recognition method receives worse recognition than adaptive fuzzy recognition method due to the adaptive fuzzy algorithm is able to adapt the variations of long-to-short ratio, because it can adjust the parameters of membership function to minimize the cost function. In Figure 4, it demonstrates the significant recognition improvement by fuzzy algorithms. Their average recognition rates are 92.97% for AVRTP, and 98.37% for adaptive fuzzy. Here also proves that adaptive fuzzy algorithm has the best adaptation to recognize the unstable patterns typed by the disabled person.

**Conclusion**

In this study, the unstable Morse code sequences are recognized by adaptive fuzzy recognition method. The results demonstrate the significant improvement in the recognition rate of the unstable Morse code sequences by adaptive fuzzy algorithm. Especially, the adaptive fuzzy algorithm is able to adjust the parameters of membership function and adapt the variations of long-to-short ratio. Not only the recognition rate increases in comparison to the previous ones, but also the calculation is simple and fast. In the future, adaptive fuzzy algorithm invented here will be installed in portable assistive tools and modified further to be challenged by the diverse degree of disabilities.

**Acknowledgment**

This research was supported by the National Science Council, Taiwan, Republic of China, under contract NSC91-2614-E-006-001 and NSC91-2614-E-006-003.

**Reference**


適應性模糊演算法應用於身心障礙人士的摩斯碼辨識系統

吳崇民 羅錦興 林淑玟 陳世中 謝明哲 趙春棠 戴政祺

成功大學電機工程研究所
台南師範學院特殊教育學系
南台技術大學電機工程學系
台東師範學院資訊教育學系

收件日期 2002年10月14日；接受日期 2002年11月20日

摘 要

摩斯碼對重度身心障礙者來說是一種有效率的溝通工具，使用者利用長短音的序列組合便可表示出各種字元。但要身心障礙者保持固定的輸入速度是非常困難的。為了消除摩斯碼在輸入速度上的嚴格限制，有許多演算法被用來以追蹤使用者的打字速度，包括適應性不穩定速度預測演算法(AUSP)、最小均方根及相配演算法(LMS&M)、適應性可變率閥值預測演算法(AVRT)及倒傳遞類神經網路(BPN)等演算法。這些演算法雖然成功地解決了使用者不穩定輸入速度的問題，但在數學運算上，也相對的變得更加複雜。本研究試著以模糊理論配合適應性演算法來辨識摩斯碼，期望能滿足使用者各種不穩定的輸入速度，以提高摩斯碼辨識率。

關鍵詞：摩斯碼、身心障礙、模糊理論、適應性演算法

* 通訊作者：羅錦興
電話：886-6275-7575 ext.62375；傳真：+886-6276-1758
電子郵件信箱：chluo@ee.ncku.edu.tw