Morse Code Recognition System with Adaptive Fuzzy Algorithm for the Disabled

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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_k is normalized by function f_T,

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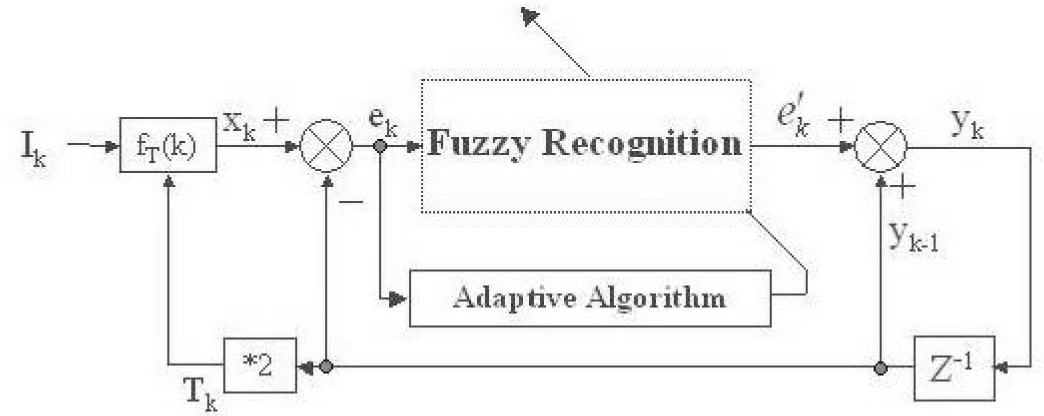

Figure 1. Adaptive fuzzy recognition system block diagram. I_k: Original Morse code input data. x_k: Normalized Morse code input data. y_k: Predictive output. e_k : The difference between input x_k and output y_{k-1}. e'_k : The modified difference from e_k by a fuzzy algorithm. T_k: Threshold to distinguish between long and short elements.

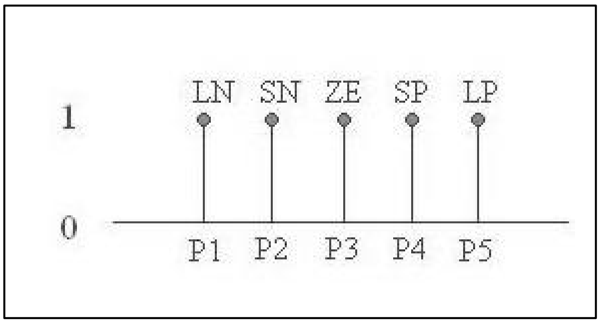

Figure 2. The membership function of the conclusion. P1~P5: The variable range of defuzzifier. Five linguistic parameters fuzzy recognition system are: LN, negative large; SN, negative small; ZE, zero; SP, positive small; LP, positive large.

$$f_T \begin{cases} x_k = I_k, & \text{if } I_k < T_k \\ x_k = \frac{1}{3} I_k, & \text{if } I_k \geq T_k \end{cases} \quad (1)$$

Where T_k is the kth 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},

$$e_k = x_k - y_{k-1} \quad (2)$$

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

$$y_k = y_{k-1} + e'_k \quad (3)$$

$$T_k = 2\, y_{k-1} \quad (4)$$

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).

$$C_f = 0.5 e_k^2 = 0.5(x_k - y_{k-1})^2 \quad (5)$$

$$P_j = P_{j-1} - e_s \frac{\partial C_f}{\partial P_{j-1}} \quad (6)$$

where ε_s 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. Lm is the mean value of long elements (dash or long-silence), and Sm is the mean value of short elements (dot or short-silence).

Mean value: $\frac{\sum_{i=1}^{k} I_i}{k}$, I_i is the input data (7)

Coefficient of variation (CV): $\frac{std}{mean} * 100\%$,

std is standard deviation. (8)

Table 1 The data analysis for experts

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

Table 2 The data analysis for a teenager with cerebral palsy

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

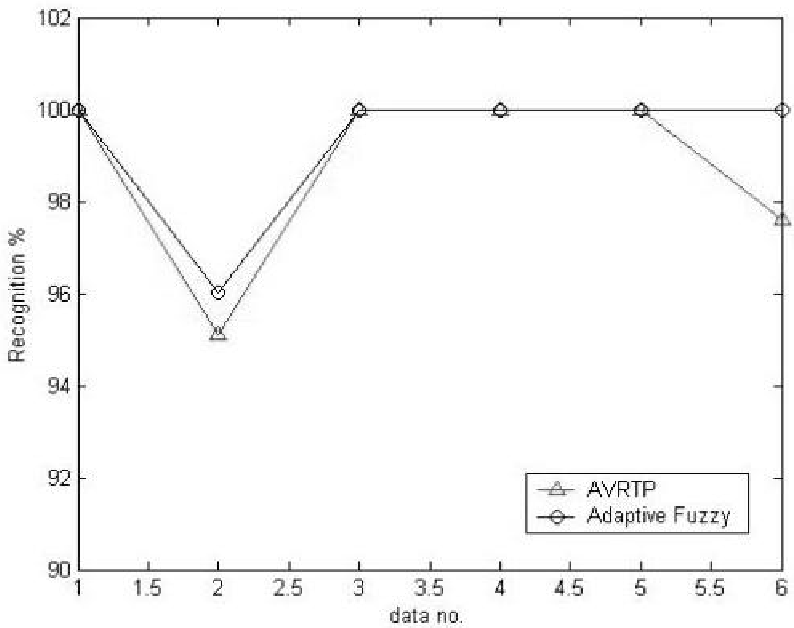

Figure 3. The recognition rates of expert data by two algorithms

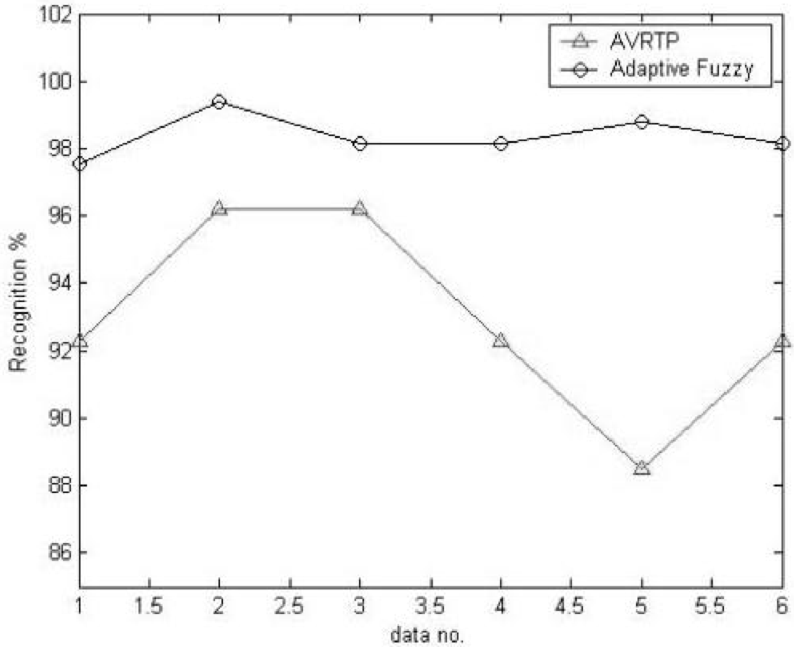

Figure 4. The recognition rates of the disabled person by two algorithms

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.

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Reference

[1] C. H. Luo, and C.H. Shih, "Adaptive Morse-coded single-switch communication system for the disabled", *International Journal of Bio-Medical Computing*, 41: 99-106, 1996.

[2] C. H. Shih, and C. H. Luo, "A Morse-code recognition system with LMS and matching algorithms for persons with disabilities", *International Journal of Medical Informatics*, 44: 193-202, 1997.

[3] C. H. Luo and M. C. Hsieh, "Morse Code Typing Training of a Teenager with Cerebral Palsy using Microcomputer Technology", *Augmentative and Alternative Communication*, 15: 1-6, 1999.

[4] M. C. Hsieh, C. H. Luo, and C. W. Mao, "Unstable Morse code recognition with adaptive variable-ratio threshold prediction for physically disabled persons", *IEEE Trans. Rehab. Eng.*, 8(3): 405-413, 2000.

[5] D. T. Fuh, and C. H. Luo, "Unstable Morse code recognition system with back propagation neural network for person with disabilities", *J. Med. Eng. & Tech.*, 25(3): 118-123, 2001.

[6] D. T. Fuh, and C. H. Luo, "Unstable Morse code recognition system with Expert-Gating Neural network", *Biomedical Engineering Applications Basis and Communications*, 2002 (accepted).

[7] C. W. Tao and J. Taur, "Design Fuzzy Controllers with adaptive rule insertion", *IEEE Trans. on systems*, MAN, and Cyberneetics-part B: Cyberneetics, 29(3): 389-397, june 1999

[8] C. H. Yang and C. H. Luo, "An Adaptive Algorithm for Morse Code Recognition", *International Journal of The Computer, The Internet and Management*, 7(1): 1-8, 1999.

[9] C. H. Yang, C. H. Luo, Y. L. Jeang, and G. J. Jon, "A novel approach to adaptive Morse code recognition for disabled persons", *Mathematics and Computers in Simulation* 54:23–32, 2000.