1

A Drawing-Aid System using Supervised Learning

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1. Introduction

In an educational front, learning support for handicapped students is important. For these students, several types of support systems and devices have been studied (Fujioka et al., 2006; Uesugi et al., 2005; Ezaki et al., 2005a, 2005b; Kiyota et al., 2005; Burke et al., 2005; Ito, 2004; Nawate et al., 2004, 2005). Among others, for the student suffering from paralysis of a body, drawing on a computer is widely used as occupational therapy. The drawing on a computer usually employs the control devices such as a track ball, a mouse controller, and so on. However, some handicapped students have difficulty in operating these control devices. For this reason, the development of drawing-aid systems has been receiving much attention (Ezaki et al., 2005a, 2005b; Kiyota et al., 2005; Burke et al., 2005; Ito, 2004; Nawate et al., 2004, 2005). In the development of drawing-aid systems, two types of approaches have been studied: a hardware approach and a software approach. In the hardware approach (Ezaki et al., 2005a, 2005b; Kiyota et al., 2005; Burke et al., 2005; Ito, 2004), exclusive control devices must be developed depending on the conditions of handicapped students. Therefore we focused on a software approach (Ito, 2004; Nawate et al., 2004, 2005). In the software approach, the involuntary motion of the hand in device operations is compensated for to draw clear and smooth figures. The influence of the involuntary contraction of muscles caused by the body paralysis can be separated into hand trembling and sudden action.
In previous studies of the software approach, several types of compensation methods have been proposed (Ito, 2004; Nawate et al., 2004, 2005; Morimoto & Nawate, 2005; Igarashi et al., 1997; Yu, 2003; Fujioka et al., 2005) to draw clear and smooth figures in real time. Among others, a moving average method (Nawate et al., 2004) is one of the simplest of methods that do not include the difficulty such as figure recognition or realization of natural shapes. The simple algorithm of this method enables drawing-aid in real time. However, this method has difficulty in tracing the tracks of a cursor, because the cursor points in the track are averaged without distinguishing sudden actions from hand trembling. For this reason, a compulsory elimination method (Nawate et al., 2004) is incorporated with the moving average method. In the compulsory elimination method, the points with large differences in angle are eliminated by calculating a movement direction of the track. The judgement of this elimination is determined by a threshold parameter. However, to eliminate the influence of sudden actions, it has difficulty in determining the threshold parameter. Since the degree of sudden action and hand trembling depends on the conditions of handicapped students, the

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threshold parameter must be determined by preliminary experiments. Therefore, this method is very troublesome.

In this paper, a drawing-aid system to support handicapped students with nerve paralysis is proposed. The proposed system compensates for the influence of involuntary motions of the hand in mouse operations. Different from the conventional method such as a moving average method, the proposed method alleviates the influence of involuntary motions of the hand by using weight functions. Depending on the conditions of handicapped students, the shape of the weight function is determined automatically by using supervised learning based on a fuzzy scheme. Therefore, the proposed method can alleviate the influence of sudden movement of the hand without preliminary experiments, unlike conventional methods, which have difficulty in reducing it. The validity of the proposed algorithm is confirmed by computer simulations.

2. Conventional method

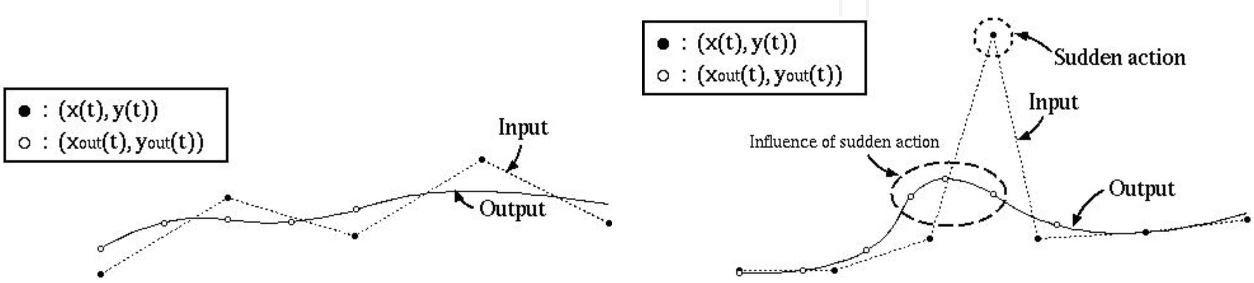
2.1 Moving average method

The compensation using the moving average method is based on the following equations:

$$x_{out}(t) = \sum_{t=I-N}^{I} \frac{x(t)}{N} \quad \text{and} \quad y_{out}(t) = \sum_{t=I-N}^{I} \frac{y(t)}{N}, \tag{1}$$

where $x(t)$ and $y(t)$ are t-th coordinates of mouse points in a track, $x_{out}(t)$ and $y_{out}(t)$ are coordinate values after compensation, I is the present time, and N is the number of averaged points. Figure 1 shows the smoothing of involuntary motions by Eq.(1). In Fig.1, the broken line shows a straight line affected by involuntary motions caused by body paralysis, and the solid line is a smoothed track obtained by the conventional method. As Eq.(1) and Fig.1 (a) show, small trembling of the track can be smoothed off by averaging the coordinate values of cursor points. In this method, however, the parameter N must be increased to alleviate the influence of sudden action in the track of a cursor. As Fig.2 shows, when the parameter N is small, the influence of sudden actions strongly remains in the smoothed track. The increase of parameter N causes the difficulty in realizing accurate tracing of the track. Furthermore, another problem occurs in drawing sharp corners when the parameter N is large. In proportion to the increase of the parameter N, the sharp corner becomes a smooth curve due to averaging points.

To reduce the influence of sudden action, the following method is incorporated in the moving average method.



(a) (b)

Fig. 1. Smoothing of influence of involuntary motions by using moving average method.
(a) Hand trembling. (b) Sudden action.

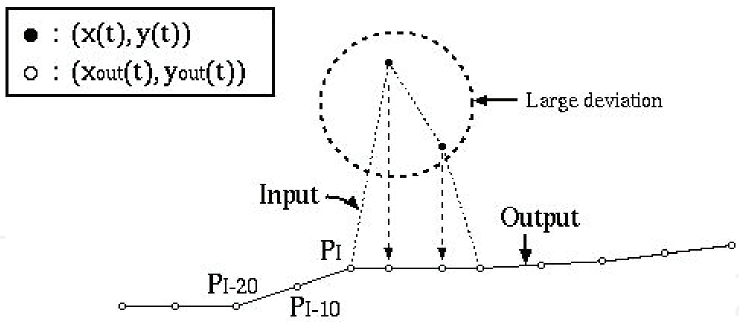


Fig. 2. Elimination of sudden action by using compulsory elimination method.

2.2 Compulsory elimination method

The compulsory elimination method proposed in (Nawate et al., 2004) is as follows. First, for the present point P_I, a moving direction of a track is calculated by averaging the points from P_{I-20} to P_{I-10}. According to the moving direction, the points with large difference in angle are eliminated as shown in Fig.2. The judgement of this elimination is determined by a threshold parameter. Therefore, this method has difficulty in determining the threshold parameter, because the degree of sudden action and hand trembling depends on the individual conditions of handicapped students. The adverse effect of sudden action is caused when the threshold value is larger than the value of the calculated angle. Depending on the degree of handicap of a student, the threshold parameter must be determined by preliminary experiments. Therefore, this method is very troublesome.

3. Proposed method

3.1 Main concept

Compensation using the proposed method is based on the following equations:

$$x_{out}(t) = \frac{\sum_{t=I-N}^{I} W_x(D_x(t))x(t)}{\sum_{t=I-N}^{I} W_x(D_x(t))} \quad \text{and} \quad y_{out}(t) = \frac{\sum_{t=I-N}^{I} W_y(D_y(t))y(t)}{\sum_{t=I-N}^{I} W_y(D_y(t))}, \tag{2}$$
$$(\, W_x(D_x(t)) \in [0, \ 1] \quad \text{and} \quad W_y(D_y(t)) \in [0, \ 1]\,)$$

where $W_x(D_x(t))$ and $W_y(D_y(t))$ denote the weight functions for the input coordinates $x(t)$ and $y(t)$, respectively. The weight functions $W_x(D_x(t))$ and $W_y(D_y(t))$ in Eq.(2) are given by

$$W_x(D_x(t)) = \frac{1}{1+\exp\{\alpha(D_x(t)-TH)\}}$$
$$\text{and} \quad W_y(D_y(t)) = \frac{1}{1+\exp\{\alpha(D_y(t)-TH)\}}, \tag{3}$$

where

$$D_x(t) = \min\{|x(t)-x(t-1)|, |x(t+1)-x(t)|\}$$
$$\text{and} \quad D_y(t) = \min\{|y(t)-y(t-1)|, |y(t+1)-y(t)|\}, \tag{4}$$

In Eqs.(3) and (4), α is a damping factor, *TH* denotes a threshold parameter, and *min* denotes a minimum operation. As Eq.(2) shows, different from the conventional method, the proposed method can alleviate the influence of involuntary motions continuously. Figure 3 shows an example of the weight function. When a sudden action arises, the value of $D_x(t)$ (or $D_y(t)$) becomes large as shown in Eq.(4). Therefore, the weight $W_x(D_x(t))$ (or $W_y(D_y(t))$) becomes small when the sudden action arises. As Eqs.(2) and (3) show, the influence of a sudden action can be alleviated according to the decrease of $W_x(D_x(t))$ (or $W_y(D_y(t))$). However, the optimal shape of the weight functions depends on the condition of the handicapped student. Thus the shape of the weight function is determined by using supervised learning based on a fuzzy scheme.
The learning algorithm will be described in the following subsection.

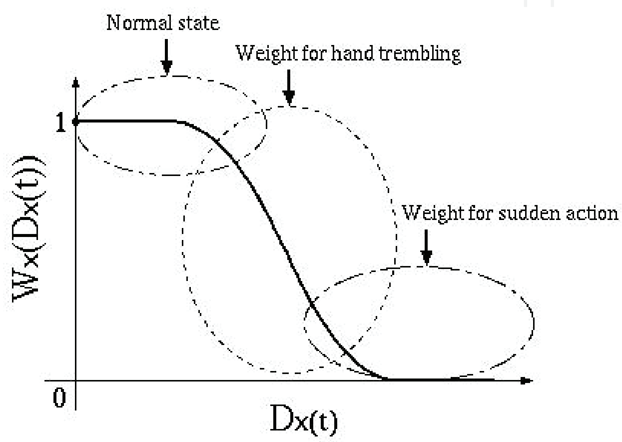


Fig. 3. Weight function.

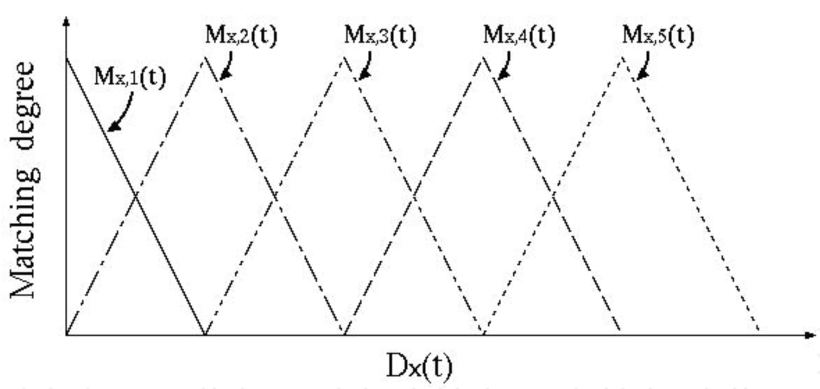


Fig. 4. Examples of triangular membership functions.

3.2 Determination of weight function

Weight functions are approximated as piecewise-linear functions. For inputs $D_x(t)$ and $D_y(t)$, matching degrees $M_{x,n}(t)$ and $M_{y,n}(t)$ are determined by the following equations:

$$M_{x,n}(t) = \mu_{x,n}\left(D_x(t)\right) \quad \text{and} \quad M_{y,n}(t) = \mu_{y,n}\left(D_y(t)\right), \tag{5}$$

respectively, where the parameter n $(=1, 2, \ldots ,k)$ denotes the fuzzy label (Zadeh, 1965)for inputs $D_x(t)$ and $D_y(t)$, and $\mu_{x,n}(D_x(t))$ and $\mu_{y,n}(D_y(t))$ are triangular membership functions (Zadeh, 1968). Figure 4 shows an example of the triangular membership function when n=5.
The output fuzzy sets

$$\frac{M_{x,1}(t)}{S_{x,1}(t)}+\cdots+\frac{M_{x,k}(t)}{S_{x,k}(t)} \quad \text{and} \quad \frac{M_{y,1}(t)}{S_{y,1}(t)}+\cdots+\frac{M_{y,k}(t)}{S_{y,k}(t)},$$

are defuzzified by the centre-of-gravity method (Zadeh, 1973), where $S_{x,n}(t)$ and $S_{y,n}(t)$ are singleton's elements [17-18], / is Zadeh's separator, and + is a union operation. The defuzzified outputs $W_x(D_x(t))$ and $W_y(D_y(t))$ corresponding to the weight functions are given by

$$W_x\left(D_x(t)\right)=\frac{\sum_{n=1}^{k} S_{x,n}(t)M_{x,n}(t)}{\sum_{n=1}^{k} M_{x,n}(t)} \quad \text{and} \quad W_y\left(D_y(t)\right)=\frac{\sum_{n=1}^{k} S_{y,n}(t)M_{y,n}(t)}{\sum_{n=1}^{k} M_{y,n}(t)}, \tag{6}$$

respectively. To simplify the above-mentioned operations, the membership functions are chosen such that the summation of the matching degrees becomes 1. Thus, Eq.(6) can be rewritten as

$$W_x\left(D_x(t)\right)=\sum_{n=1}^{k} S_{x,n}(t)M_{x,n}(t) \quad \text{and} \quad W_y\left(D_y(t)\right)=\sum_{n=1}^{k} S_{y,n}(t)M_{y,n}(t). \tag{7}$$

As Eqs.(6) and (7) show, the weight functions are approximated as piecewise-linear functions. Figure 5 shows an example of the piecewise-linear function. In Fig.5, $B_{x,n}$ and $B_{y,n}$ denote sample inputs which correspond to the coordinate values of the horizontal axis of boundary points. The shape of the piecewise-linear functions depends on $S_{x,n}(t)$ and $S_{y,n}(t)$.

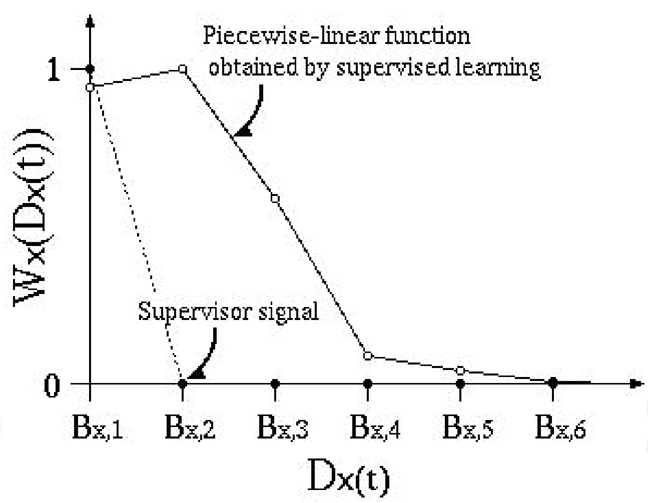


Fig. 5. Weight function obtained by supervised learning.

The singleton's elements $S_{x,n}(t)$ and $S_{y,n}(t)$ are determined by supervised learning. The learning dynamics for $S_{x,n}(t)$ and $S_{y,n}(t)$ are given by

$$\begin{aligned}
S_{x,n}(t+1) &= \begin{cases} S_{x,n}(t)+\eta_1 M_{x,n}(t) & (if \quad M_{x,n}(t)\neq 0), \\ S_{x,n}(t)+\eta_2\left\{H_{x,n}-S_{x,n}(t)\right\} & (if \quad M_{x,n}(t)=0), \end{cases} \\
S_{y,n}(t+1) &= \begin{cases} S_{y,n}(t)+\eta_1 M_{y,n}(t) & (if \quad M_{y,n}(t)\neq 0), \\ S_{y,n}(t)+\eta_2\left\{H_{y,n}-S_{y,n}(t)\right\} & (if \quad M_{y,n}(t)=0), \end{cases}
\end{aligned} \tag{8}$$

where $S_{x,n}(t)$ and $S_{y,n}(t)$ satisfy

$$S_{x,n}(t) = \begin{cases} 1 & (if \quad S_{x,n}(t) > 0), \\ 0 & (if \quad S_{x,n}(t) < 0), \end{cases} \quad \text{and} \quad S_{y,n}(t) = \begin{cases} 1 & (if \quad S_{y,n}(t) > 0), \\ 0 & (if \quad S_{y,n}(t) < 0), \end{cases} \tag{9}$$

respectively. In Eq.(8), η_1 (<1) and η_2 (<1) denote learning parameters, and $H_{x,n}$ and $H_{y,n}$ are supervisor signals. The initial values of $S_{x,n}(t)$ and $S_{y,n}(t)$ are set to $S_{x,n}(0)$=0.5 and $S_{y,n}(0)$=0.5, respectively, because the optimal shape of the weight function changes according to the condition of the handicapped student.

When all the matching degrees $M_{x,n}(t)$'s and $M_{y,n}(t)$'s satisfy $M_{x,n}(t)\neq 0$ and $M_{y,n}(t)\neq 0$, respectively, Eq.(8) can be rewritten as

$$S_{x,n}(t+1) = S_{x,n}(t) + \eta_1 M_{x,n}(t) \quad \text{and} \quad S_{y,n}(t+1) = S_{y,n}(t) + \eta_1 M_{y,n}(t) \ . \tag{10}$$

To save space, let us consider only the behaviour of $S_{x,n}(t)$. Since $S_{x,n}(t)$ is expressed by

$$\begin{gathered} S_{x,n}(1) = S_{x,n}(0) + \eta_1 M_{x,n}(0) \\ S_{x,n}(2) = S_{x,n}(1) + \eta_1 M_{x,n}(1) \\ \cdots \\ S_{x,n}(I-1) = S_{x,n}(I-2) + \eta_1 M_{x,n}(I-2) \\ S_{x,n}(I) = S_{x,n}(I-1) + \eta_1 M_{x,n}(I-1) \ , \end{gathered}$$

the following equation can be obtained:

$$S_{x,n}(I) = S_{x,n}(0) + \eta_1 \sum_{t=0}^{I-1} M_{x,n}(t) \ . \tag{11}$$

As Eqs.(9) and (11) show, the singleton's elements $S_{x,n}(t)$ and $S_{y,n}(t)$ become $S_{x,n}(t)$=1 and $S_{y,n}(t)$=1, respectively, when $I\rightarrow\infty$. Hence, $S_{x,n}(t)$ (or $S_{y,n}(t)$) becomes large when $D_x(t)$'s (or $D_y(t)$'s) are close values.

On the other hand, when all the matching degrees $M_{x,n}(t)$'s and $M_{y,n}(t)$'s satisfy $M_{x,n}(t)$=0 and $M_{y,n}(t)$=0, respectively, Eq.(8) is rewritten as

$$\begin{aligned} & S_{x,n}(t+1) = S_{x,n}(t) + \eta_2 \{H_{x,n} - S_{x,n}(t)\} \\ \text{and} \ & S_{y,n}(t+1) = S_{y,n}(t) + \eta_2 \{H_{y,n} - S_{y,n}(t)\}. \end{aligned} \tag{12}$$

From Eq.(12), the learning dynamics can be expressed by

$$\begin{aligned} & S_{x,n}(t+1) - H_{x,n} = (1-\eta_2)\{S_{x,n}(t) - H_{x,n}\} \\ \text{and} \ & S_{y,n}(t+1) - H_{y,n} = (1-\eta_2)\{S_{y,n}(t) - H_{y,n}\}. \end{aligned} \tag{12}$$

Since $S_{x,n}(t)$ of Eq.(13) is expressed by

$$\begin{gathered} S_{x,n}(1) - H_{x,n} = (1-\eta_2)\{S_{x,n}(0) - H_{x,n}\} \\ S_{x,n}(2) - H_{x,n} = (1-\eta_2)\{S_{x,n}(1) - H_{x,n}\} \end{gathered}$$

$$\cdots$$

$$S_{x,n}(I-1)-H_{x,n}=(1-\eta_2)\{S_{x,n}(I-2)-H_{x,n}\}$$

$$S_{x,n}(I)-H_{x,n}=(1-\eta_2)\{S_{x,n}(I-1)-H_{x,n}\},$$

the following equation can be obtained:

$$S_{x,n}(I)-H_{x,n}=(1-\eta_2)^I\{S_{x,n}(0)-H_{x,n}\}. \tag{14}$$

As Eq.(14) shows, the singleton's elements $S_{x,n}(t)$ and $S_{y,n}(t)$ become $S_{x,n}(t)=H_{x,n}$ and $S_{y,n}(t)=H_{y,n}$, respectively, when the conditions obtain that $0<\eta_2<1$ and $I\to\infty$. Hence, $S_{x,n}(t)$ and $S_{y,n}(t)$ approach $H_{x,n}$ and $H_{y,n}$, respectively, when $D_x(t)$'s (or $D_y(t)$'s) are not close values. From Eqs.(11) and (14), the singleton's elements satisfy the following conditions:

$$S_{x,n}(t)\in\lfloor H_{x,n},\ 1\rfloor \quad \text{and} \quad S_{y,n}(t)\in\lfloor H_{y,n},\ 1\rfloor. \tag{15}$$

For the sample inputs $B_{x,n}$ and $B_{y,n}$ which correspond to the boundary points of piecewise-linear functions, the supervisor signals $H_{x,n}$ and $H_{y,n}$ are chosen as

$$H_{x,n}(t)=\begin{cases}1 & (if \quad n=1),\\ 0 & (if \quad n\neq 1),\end{cases} \quad \text{and} \quad H_{y,n}(t)=\begin{cases}1 & (if \quad n=1),\\ 0 & (if \quad n\neq 1),\end{cases} \tag{16}$$

respectively (see Fig.5). The weight functions which satisfy $S_{x,n}(t)=H_{x,n}$ and $S_{y,n}(t)=H_{y,n}$ are the worst case.

4. Numerical simulation

To confirm the validity of the proposed algorithm, numerical simulations were performed by assuming a screen with 8,000×8,000 pixels.

Figure 6 (a) shows the simulation result of the moving average method incorporated with the compulsory elimination method. The simulation of Fig.6 (a) was performed under the conditions where the number of the averaged points N=20 and the threshold value is 5

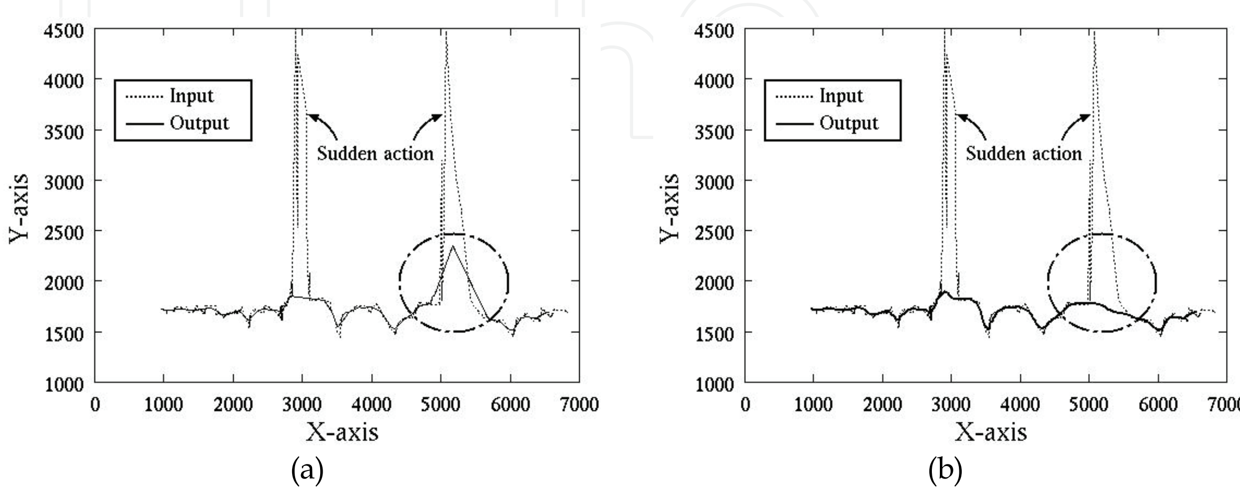


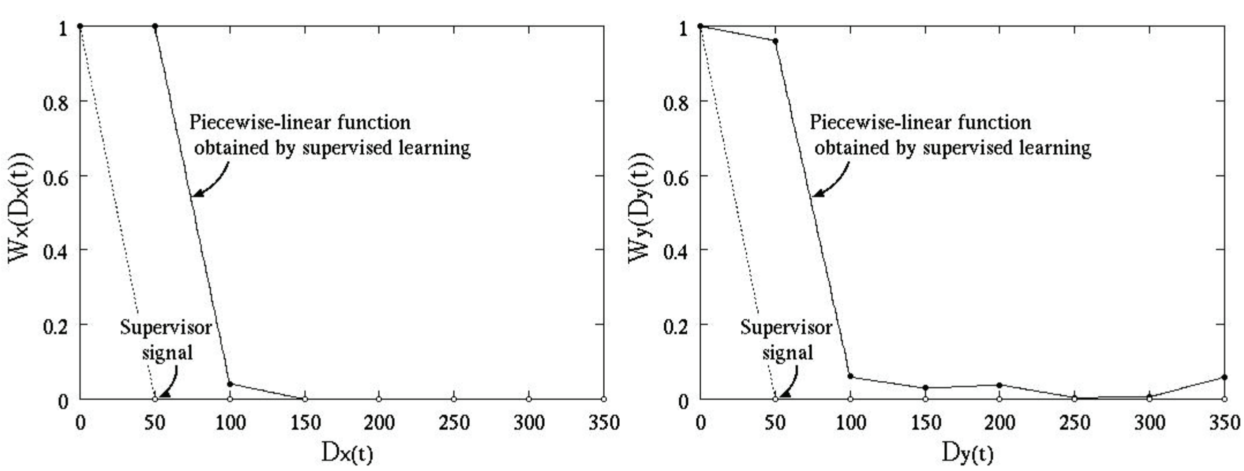
Fig. 6. Simulation results. (a) Conventional method. (b) Proposed method.

pixels (Nawate et al., 2004). As Fig.6 shows, preliminary experiments are necessary for the conventional method in order to determine the threshold value.
Figure 6 (b) shows the simulation result of the proposed method. The simulation shown in Fig.6 (b) was performed under conditions where the number of averaged points N=20, the number of singleton's elements k=8, and the learning parameter η_1=0.1 and η_2=0.01. The number of boundary points in the weight function depends on the parameter k. In proportion to the increase of k, the flexibility of the weight function is improved. However, the flexibility of the function has the relation of a trade-off with computational complexity. In the meaning of an approximation of the sigmoid function of Fig.3, parameter k must be larger than 4.
The membership functions $\mu_{x,n}(D_x(t))$ and $\mu_{y,n}(D_y(t))$ used in the simulation shown in Fig.6 (b) are

$$\mu_{x,n}(D_x(t)) = \begin{cases} 1-|D_x(t)-50(n-1)|/50 & (if \quad 1 > |D_x(t)-50(n-1)|/50) \\ 0 & (if \quad 1 \leq |D_x(t)-50(n-1)|/50) \end{cases}$$

$$\text{and} \quad \mu_{y,n}(D_y(t)) = \begin{cases} 1-|D_y(t)-50(n-1)|/50 & (if \quad 1 > |D_y(t)-50(n-1)|/50) \\ 0 & (if \quad 1 \leq |D_y(t)-50(n-1)|/50) \end{cases}, \quad (n = 1,\ldots,8), \tag{17}$$

respectively. As Fig.6 (b) shows, the proposed method can alleviate the influence of sudden actions effectively. For the input image of Fig.6 (b), the weight functions shown in Fig.7 were obtained by supervised learning. Figure 8 shows the behaviour of singleton's elements. As Fig.8 shows, to adjust the shape of the weight functions, the values of the singleton's elements change dynamically. In Figs.7 and 8, the values of $S_{x,3}(t)$ - $S_{x,8}(t)$ and $S_{y,3}(t)$ - $S_{y,8}(t)$ are very small. This result means that the influence of involuntary action is alleviated when $D_x(t)$>100 or $D_y(t)$>100. Of course, depending on the condition of handicapped students, the values of $S_{x,n}(t)$ and $S_{y,n}(t)$ are adjusted automatically by supervised learning. As Fig.8 shows, the rough shape of the weight function is almost determined within t=100.



(a) (b)

Fig. 7. Weight functions obtained by supervised learning. (a) $W_x(D_x(t))$. (b) $W_y(D_y(t))$.

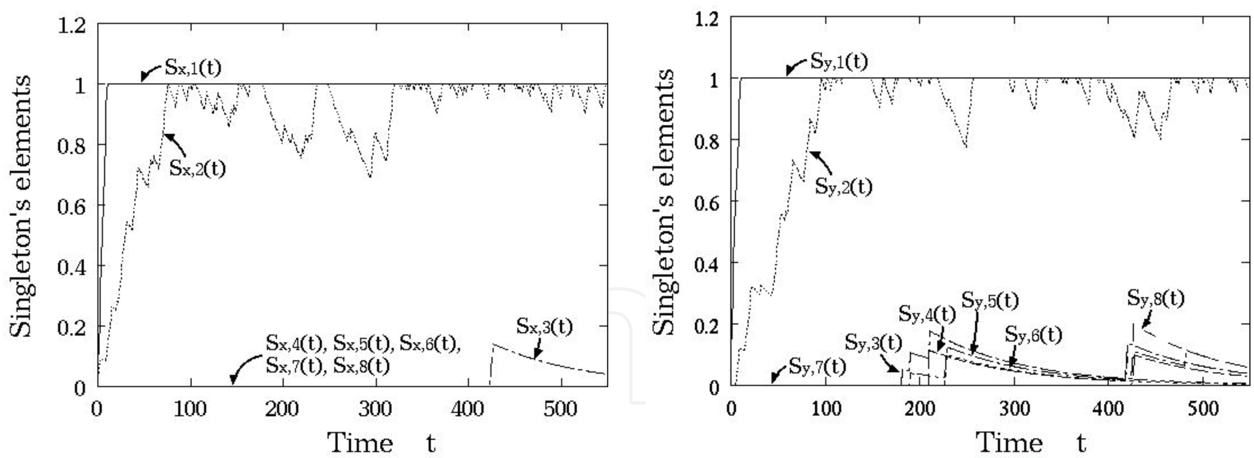


Fig. 8. Learning processes of singleton's elements. (a) $S_{x,n}(t)$. (b) $S_{y,n}(t)$.

5. Conclusion

A drawing-aid system to support handicapped students with nerve paralysis has been proposed in this paper. By using the weight functions which are determined by supervised learning, the proposed method continuously alleviates the influence of involuntary motions of the hand.

The characteristics of the proposed algorithm were analyzed theoretically. Furthermore, numerical simulations showed that the proposed method can alleviate the influence of hand trembling and sudden action without preliminary experiments.

Hardware implementation of the proposed algorithm is left to a future study.

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