온라인 서명자동인식을 위한 개선된 DTW

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요 약

Dynamic Programming Matching(DPM)은 순차적으로 구성된 문제를 수학적으로 최적화 시키는 기술로서 패턴인식 분야에서 다년간 중요한 역할을 해왔다. 서명인식을 위한 대부분의 실제적 적용에서는 Sakoe and Chiba [9]의 실제구현 버전이 기반이 되어 왔는데, 일반적으로 *slope constraint p* = 0의 방법이 적용되어 왔다. 이 논문에서는 이 경우에는 전진탐색에 의한 휴리스틱한 방법을 적용한 MDPM이 상당한 처리시간의 단축 뿐만 아니라 약간의 인식능력 향상을 가질 수 있음을 보여준다.

The Modified DTW Method for on-line Automatic Signature Verification

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ABSTRACT

Dynamic Programming Matching (DPM) is a mathematical optimization technique for sequentially structured problems, which has, over the years, played a major role in providing primary algorithms in pattern recognition fields. Most practical applications of this method in signature verification have been based on the practical implementational version proposed by Sakoe and Chiba [9], and is usually applied as a case of *slope constraint p* = 0. We found, in this case, a modified version of DPM by applying a heuristic (forward seeking) implementation is more efficient, offering significantly reduced processing complexity as well as slightly improved verification performance.

키워드 : Dynamin Time Warping(DTW), 서명 인증(Signature Verification), 패턴인식(Pattern Recognition)

1. Introduction

Signature verification techniques are generally categorized into two groups depending on the type of features used for the classification process : functional approaches and parametric approaches.

In the first group, the trajectory of the signature is considered as a mathematical time function, $F(t)$. The functions for both reference signature and test signature are compared for verification by evaluating the similarity (or dissimilarity) between them.

The main issue for this approach is how to evaluate the similarity between them.

Obviously, the straightforward method for this evaluation will be *linear correlation*. However, this is not valid for signature verification as the two samples generally have different signal lengths and non-linear distortion with respect to the time parameter, even if they are produced under the same environment and by the same writer. Random variations exist, which can create portions of signals, deletions, additions and gaps due to pauses or hesitations of the writer [8].

Dynamic Programming Matching (DPM) is a mathematical optimization technique for sequentially structured problems, which has, over the years, played a major role in providing primary algorithms for automatic signature verification [1, 5, 9, 11]. In the pattern recognition field, it has been particularly used to eliminate the timing differences between two differently originating pattern signals. Hence it is called as the *Dynamic Time* Warping (DTW) method owing to its non-linear time-normalization function.

The DTW method matches two corresponding functions on the time axis dynamically through compressing or expanding one axis so that the maximum fit is attained with the other. Most practical applications of this method in signature verification [7, 10, 12, 14] have been based on the practical implementational version proposed by Sakoe and Chiba [9], which is an analytical optimization method unlike other's rather heuristic approaches[1].

For practical use in signature verification, it is usually

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applied as a case of *slope constraint* $p=0$ as, apart from the fact that this provides the simplest and the fastest implementation owing to the least constraint (see (Figure 2)), the slope constraint on the warping function has been noted to be merely time-consuming.

The problem in the DPM application to signature verification was that many writers have an unstable pattern of signature writing, which confuses the DTW mechanism. A different approach from the opposite perspective to investigate the DTW function is performed by applying a heuristic (forward seeking) implementation of DTW under the assumption that the applied patterns satisfy the preconditions for the DTW function, i.e., the patterns have only a monotonic and continuous shift on the time axis. Thus a modified version of DPM in this context is developed.

To verify the proposed method, experiments are applied under the same conditions and using the same data base to standardize and simplify the test for both conventional and proposed DTW methods.

The results have proved the proposed method to be efficient, offering significantly reduced processing complexity as well as slightly improved verification

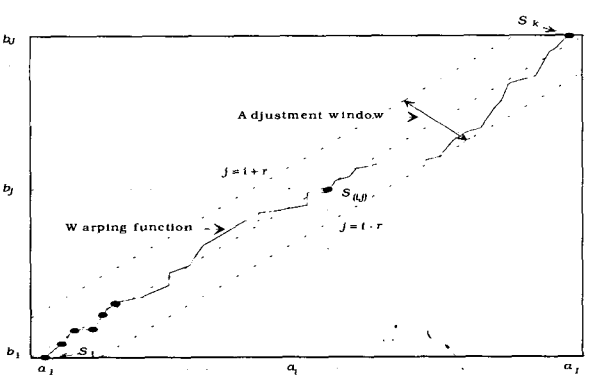
2. DPM for Signature Verification

2.1 DPM Basics [5, 9, 14]

Consider two different signals as sequences of feature vectors :

$$\begin{aligned} A &= a_1, a_2, \cdots, a_i, \cdots, a_I \\ B &= b_1, b_2, \cdots, b_i, \cdots, b_I \end{aligned} \tag{1}$$

These two patterns, A and B, can be depicted in an $i-j$ plane as shown in (Figure 1), where two patterns are represented along the i-axis and j-axis, respectively, and their matching stages are by a sequence of points $S(k)$, where $S(k) = (i(k), j(k))$.



(Figure 1) DTW mechanism for time alignment

To normalize these two signals with a N-stage decision process, a sequence of decision functions can be expressed as :

$$D_{(k, x_k)} = \sum_{k=1}^{N} C_k(q_k, x_k) \tag{2}$$

where C_k is a contribution function at k^{th} stage for the decision vector q_k and the state vector $x_k(a_i, b_j)$

DP matching seeks to find the optimum function $D(k, x_k)$ at the kth stage :

$$D_{(k,x_k)} = \underset{q_k}{Optimum} \left[D_{(k-1, x_{k-1})} + C_k(q_k, x_k) \right] \tag{3}$$

In the context of the DTW algorithm, this problem of determining the optimal sequence corresponds to finding a minimum sequence of warping function $F(i_{(k)}, j_{(k)})$, which is normally composed of two components :

$$F_k = d_{(i_k, j_k)} \times w_{(i_k, j_k)} \tag{4}$$

where $d_{(i_k, j_k)}$ is the k^{th} occupancy cost and $w_{(i_k, j_k)}$ is the corresponding weight.

Then the optimal objective function at the k^{th} stage, D_{f_k}, is given as :

$$D_{f_k} = \underset{F_k}{Min} \left[D_{f_{k-1}} + F_k \right] \tag{5}$$

The optimal value of this function will be the result of the sequence of recursive functions :

$$D_{f_k} = \underset{F}{Min} \sum_{l=1}^{k} \left[\frac{\sum_{l=1}^{k} d_{i_l j_l} \times w_{i_l j_l}}{\sum_{l=1}^{k} W_l} \right] \tag{6}$$

This is expanded as follows.

① Initial condition :

$$D_{f_1} = d(f_1) \times w(f_1) \tag{7}$$

② DP-equation :

$$D_{f_k} = \underset{F_k}{Min} \left[D_{f_{k-1}} + d(f_k) \times w(f_k) \right] \tag{8}$$

③ Time-normalized distance :

1) Other elastic matching methods include *the peak matching technique, a finite state machine approach and regional correlation.*

$$D_{i_k,j_k} = \frac{1}{N} D_{f_k} \tag{9}$$

where $N = \sum_{l=1}^{k} w(f_l)$

One of the major important features of the DTW processing is that the k^{th} decision function, F_k, does not require any decision variables for the previous stages other than F_{k-1} :

It only depends on the value of F_{k-1} and a number of the present decision variables, which implies a considerable complexity reduction for solving the whole optimization problem otherwise requiring all possible combinations of every variable.

2.2 DPM Implementation

Sakoe and Chiba [9] provided a practical solution for Equation (6), which originally was proposed for speech recognition. Since then, this method has been extended for use in signature verification and has been widely accepted for practical applications in this field [2, 4, 7, 8, 10, 12, 14].

- **Restrictions on the warping function**

To provide a safeguard against unusual deviations during the warping process and to keep a desirable warping gradient, two conditions are imposed on the warping function :

① Adjustment window (see (Figure 1))

$$| i(k) - j(k) | \cdot r \tag{10}$$

where r is an adequate value for the window size.

This is to prevent unusual deviations from the warping function, which is based on the assumption that the normal time-axis fluctuation does not cause an excessive timing difference.

② Slope constraint

An appropriate slope constraint is imposed to keep the warping gradient from an undesirable time warping (see Figure 2).

(a) p = 1/2 (b) p = 0 (c) p = 1 (d) p = 2

(Figure 2) DTW slope constraint

Let the pattern at k^{th} stage, (i_k, j_k), be a simplified term, (i, j), then Equation (9) becomes : [2]

(a) $p = 1/2$

$$D_{ij} = Min \begin{bmatrix} D_{(i-1,j-3)} + 2d_{(i,j-2)} + d_{(i,j-2)} + d_{(i,j)} \\ D_{(i-1,j-2)} + 2d_{(i,j-1)} + d_{(i,j)} \\ D_{(i-1,j-1)} + 2d_{(i,j)} \\ D_{(i-2,j-1)} + 2d_{(i-1,j)} + d_{(i,j-1)} \\ D_{(i-3,j-1)} + 2d_{(i-2,j)} + d_{(i-1,j)} + d_{(i,j)} \end{bmatrix} \tag{11}$$

(b) $p = 0$

$$D_{ij} = Min \begin{bmatrix} D_{(i,j-1)} + d_{(i,j)} \\ D_{(i-1,j-1)} + 2d_{(i,j)} \\ D_{(i-1,j)} + d_{(i,j)} \end{bmatrix} \tag{12}$$

(c) $p = 1$

$$D_{ij} = Min \begin{bmatrix} D_{(i-1,j-2)} + 2d_{(i,j-1)} + d_{(i,j)} \\ D_{(i-1,j-1)} + 2d_{(i,j)} \\ D_{(i-2,j-1)} + 2d_{(i-1,j)} + d_{(i,j)} \end{bmatrix} \tag{13}$$

(d) $p = 2$

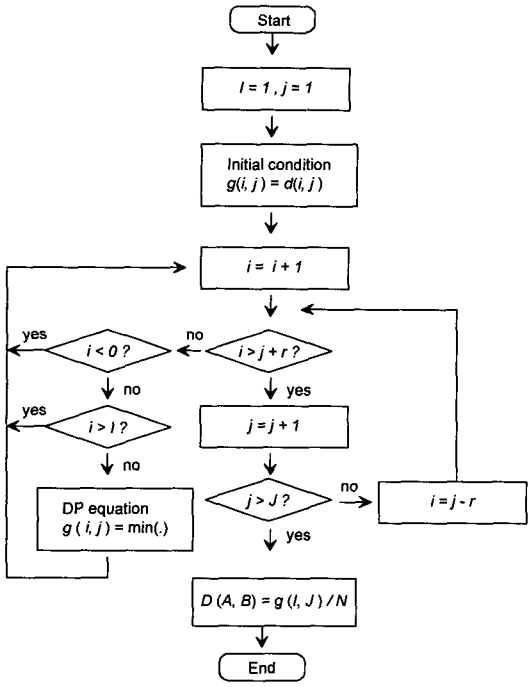
$$D_{ij} = Min \begin{bmatrix} D_{(i-2,j-3)} + 2d_{(i-1,j-2)} + 2d_{(i,j-1)} + d_{(i,j)} \\ D_{(i-1,j-1)} + 2d_{(i,j)} \\ D_{(i-3,j-2)} + 2d_{(i-2,j-1)} + d_{(i-1,j)} + d_{(i,j)} \end{bmatrix} \tag{14}$$

For practical use in signature verification, it is usually applied as a case of slope constraint $p=0$ as in Equation (12) as, apart from the fact that this provides the simplest and the fastest implementation owing to the least constraint (see (Figure 2)), the slope constraint on the warping function has been noted to be merely time-consuming [7][3].

Sakoe and Chiba [9] gave an example of practical implementation of DTW, which is depicted in (Figure 3). In the figure, the flow of the DTW solution for Equation (6) is diagrammed from the initialization according to Equation (7) to the time-normalization as in Equation (9). Unlike Equation (6), which uses variable "k", for indexing from the first stage, 1, to the final stage, "K", this implementation uses two indices, "i, j", to iterate "J" times the DP-equation (8) (see (Figure 1)) for the sequential solution. The ajustment window size is applied as variable "r".

2) Sakoe gave two types of slope constraint, the symmetric and asymmetric forms. Here only the former is concerned for convenience' sake. No significant effect has been noted with respect to the types.

3) Only a small constraint may introduce a minor benefit with a relatively heavy system latency.



(Figure 3) DTW implementation

2.3 Experimentation

An experiment was performed to investigate how the nature of signatures affects the performance of DTW. It was relevant to the issue about the vulnerability of the DTW mechanism to relatively variable signature patterns.

For this experiment, the data base consists of two contrasting types of signature sample groups :

① Group I has the members who have relatively "stable" signature patterns.

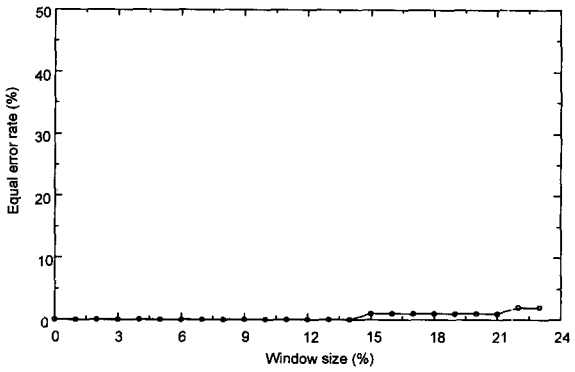
② Group II members have relatively "unstable" patterns in signature writing.

Group I has a membership of 15 writers and Group II 24. A total of 50 signatures was collected from each member in five sessions. Each individual donated ten signatures in each session. Random forgeries, i.e., signatures generated by others, were used for the forgery samples, on the same grounds.

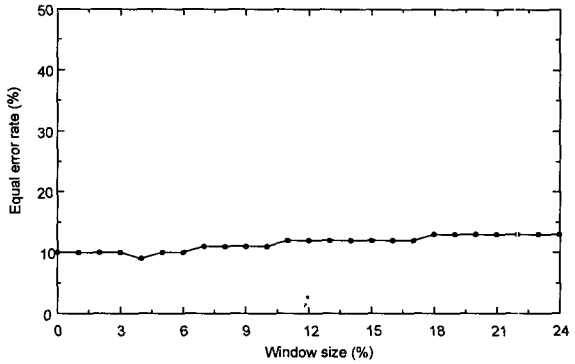
To eliminate effects arising from the variation of magnitude and orientation, a precise normalization process in the spatial domain was performed (refer to Section 3.2.3).

The performance in terms of the equal error rate was measured as a function of the adjustment window size applying the $f(x, y)$ function.

(Figure 4) is the DPM performance result from Group 1 and (Figure 5) is from Group 2.



(Figure 4) Group I DPM result



(Figure5) Group II DPM result

From these results, it has been observed that the nature of signature samples has a considerable effect on the DTW performance :

① For Group 1, in which each member has a stable signature pattern, DTW has ideally functioned at zero error rates with smaller window sizes. Increasing the window size over 14% has caused the degradation of the error rate performance.

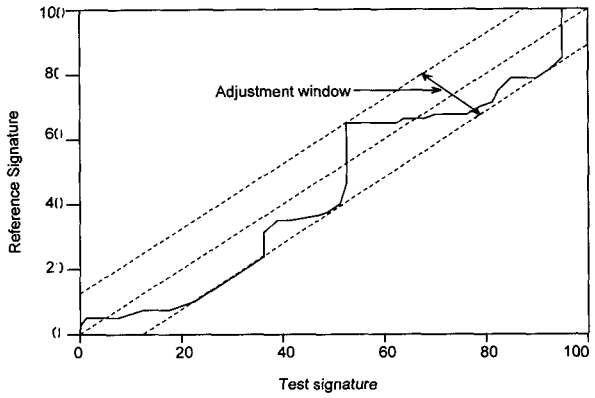
② For Group 2, in which most members have variable signature patterns, the DPM performance has been considerably degraded. The window size of 4% has recorded the best result at the equal error rate of 9%, which is slightly better than the results of 10% with neighbouring window sizes.

To understand how the nature of signature samples affects the DTW performance, further investigations are carried out in the following sections.

2.4 Warping Mechanism

To investigate the time warping mechanism, a graphical illustration of DTW functioning was carried out for each of the two groups.

Unlike Group 1, in which the DTW functioning for most members showed the typical warping trajectory as in (Figure 1) many members of Group 2 showed a malfunctioned DTW trajectory as in (Figure 6).



(Figure 6) Group II DTW result

It was observed that when the time domain fluctuation exceeds a certain limit (in this experiment, it was about 5 % of the whole duration of a signature signal), the time warping mechanism often loses its correct trajectory, begins to malfunction and ends up trailing along one boarder of the adjustment window until it finds a possible optimum point which has a better solution for DP-function (Equation (8)) than the points on the boarder. For Group 2, the fluctuation mostly originates not from a monotonic and continuous shift on the time axis (the pre-conditions for DTW [9]) due to a natural variation during the signature generation but from random noise owing to the excessively variable nature of the signature pattern. Once the DTW function for Group 2 loses the trajectory due to random noise, it takes longer to correct its trajectory than is the case in Group 1 in which the original trajectory can be found in the near vicinity of the spot where the function is lost.

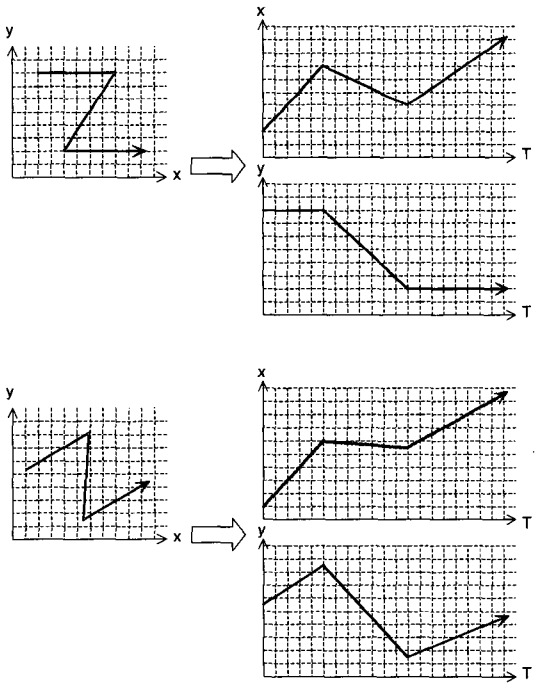
This implies that, under worst conditions, the DTW function can become a compensation function which randomly keeps relaxing the time domain fluctuation according to a window limit until the situation becomes better, which results in a random compensation and accordingly degrades the DTW performance. This malfunctioning in those cases can be enlarged as the window size increases.

2.5 Discussion

From the experiments in the previous sections in this chapter, the following have been observed :

① Applying precise normalization as preprocessing results not only in an error rate performance improvement but also in a smaller optimal window size, which implies that normalization helps reduce the variation of a pattern.

In this regard, it is strongly implied that the "time domain fluctuation" in on-line signature verification originates not only from the natural variation during signature generation due to temporal pauses and hesitations of the writer as usually referred to [8] but also from the attitude variation, including the change of the relative placement and orientation of the signature, during signature collection in the context that normalization in this study mainly corrects such variations. (Figure 7) illustrates an example where the same pattern in the spatial domain is projected on the time axis as different patterns owing to an attitude variation. In the figure, the left hand side is for the spatial domain where a pattern is differently oriented and the right hand side is for the time domain where the pattern is projected as different patterns according to the orientation on the time axis, T.



(Figure 7) Time variation from attitude variation

② Inherently variable patterns which do not satisfy the preconditions of continuity and monotonicity for DTW significantly degrade the DTW performance even though they have been precisely normalized.

③ Generally, for the precisely normalized signatures, the

larger adjustment window over the optimum size negatively affects the performance.

These observations lead to a further investigation using the modified DTW, which adopts a forward-seeking strategy, as described in the following section.

3. Development of Modified DPM

The problem in the DPM application to signature verification in the preceding sections, which applied the implementational version proposed by Sakoe and Sato [9], was that many writers have an unstable pattern of signature writing, which confuses the DTW mechanism. In this section, a different approach from the opposite perspective to investigate the DTW function is performed by applying a heuristic (forward seeking) implementation of DTW under the assumption that the applied patterns satisfy the preconditions for the DTW function, i.e., the patterns have only a monotonic and continuous shift on the time axis. Under such ideal conditions, there is little necessity of DTW functioning for all cases at the preceding stage (see Equation (8)) as the function is continuously increasing.

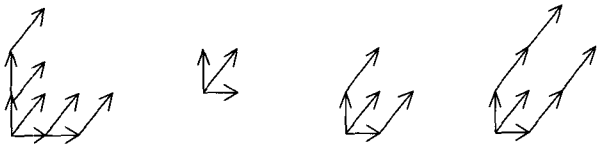
- Algorithm

If the optimal objective function at the $k-1^{th}$ stage, D_{fk-1}, has been correctly selected, and the function satisfies the necessary conditions of continuity and monotonicity for DTW [9] and it does not have an abnormal (excessive) fluctuation[4] on the time axis,

then Equation (8) can be alternatively expanded as :

$$D_{f_k} = D_{f_{k-1}} + \underset{F_k}{Min}\,[d(f_k) \times w(f_k)] \tag{15}$$

A slope constraint then can be imposed as in (Figure 8) to maintain a normal time warping gradient, which corresponds to the slope constraint for Sakoe's version as in (Figure 2).



(a) p = 1/2 (b) p = 0 (c) p = 1 (d) p = 2

(Figure 8) MDTW slope constraint

4) This was assumed for DTW mechanism in Sakoe and Chiba [9] and became the ground for implementing the adjustment window condition.

For the practical application, it is implemented as follows :

(a) $p = 1/2$

$$D_{t_k j_k} = D_{i_{k-1} j_{k-1}} + Min\begin{bmatrix} d(i_{k-1}+3, j_{k-1}+1) + d(i_{k-1}+2, j_{k-1}+1) + d(i_{k-1}+1, j_{k-1}+1) \\ d(i_{k-1}+2, j_{k-1}+1) + 2d(i_{k-1}+1, j_{k-1}+1) \\ d(i_{k-1}+1, j_{k-1}+2) + 2d(i_{k-1}+1, j_{k-1}+1) \\ d(i_{k-1}+1, j_{k-1}+3) + 2d(i_{k-1}+1, j_{k-1}+2) + d(i_{k-1}+1, j_{k-1}+1) \end{bmatrix} \tag{16}$$

(b) $p = 0$

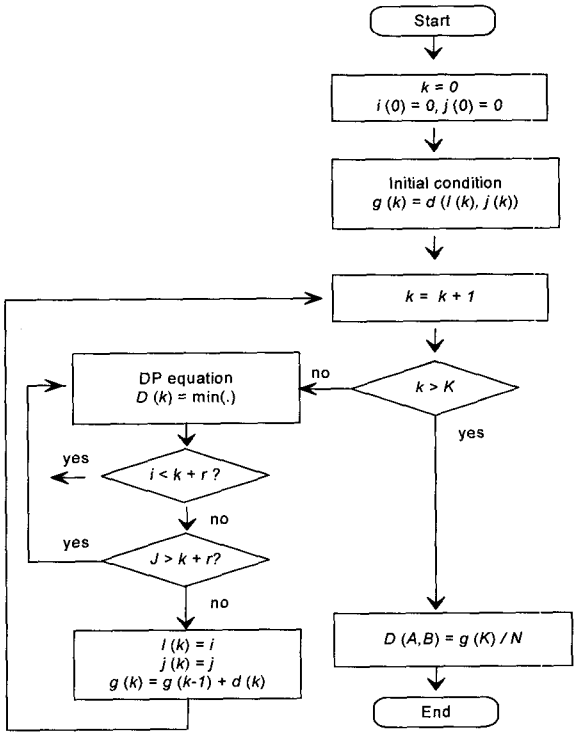
$$D_{t_k j_k} = D_{i_{k-1} j_{k-1}} + Min\begin{bmatrix} d(i_{k-1}, j_{k-1}+1) \\ d(i_{k-1}+1, j_{k-1}+1) \\ d(i_{k-1}+1, j_{k-1}) \end{bmatrix} \tag{17}$$

(c) $p = 1$

$$D_{t_k j_k} = D_{i_{k-1} j_{k-1}} + Min\begin{bmatrix} d(i_{k-1}+1, j_{k-1}+2) \\ d(i_{k-1}+1, j_{k-1}+1) \\ d(i_{k-1}+2, j_{k-1}+1) \end{bmatrix} \tag{18}$$

(d) $p = 2$

$$D_{t_k j_k} = D_{i_k j_{k-1}} + Min\begin{bmatrix} d(i_{k-1}+2, j_{k-1}+3) \\ d(i_{k-1}+1, j_{k-1}+1) \\ d(i_{k-1}+3, j_{k-1}+2) \end{bmatrix} \tag{19}$$



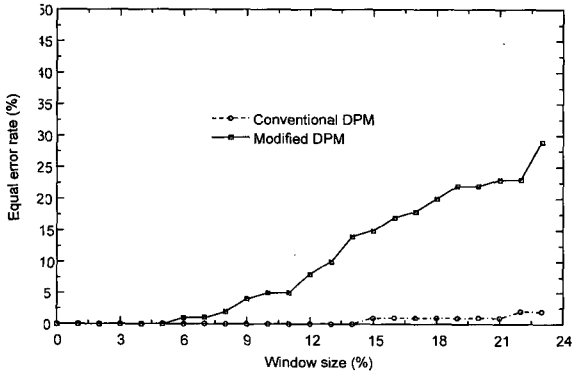
(Figure 9) MDPM implementation

Equation (15) in the modified DPM (MDPM) version, firstly, has a strong point compared to Equation (8) in the conventional DPM (CDPM) as it requires only one DTW process at each decision stage while the conventional one requires this process as many times as the window size. Hence, this alternative method can reduce the computational complexity.

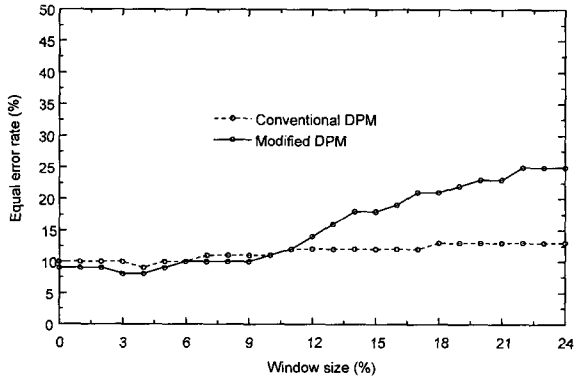
(Figure 9) diagrammatically illustrates the practical implementation of this modified DPM method.

4. Experimentation

To compare the performances of both DPM methods, the same error rate performance tests were applied to the modified DPM (MDPM) for the two groups. (Figure 10) is the result for Group 1 and (Figure 11) is for Group 2.



(Figure 10) Group I MDPM result



(Figure 11) Group II MDPM result

For both of the two groups, the modified DPM (MDPM) method has shown an equal or better performance compared to the conventional DPM (CDPM) method with smaller window sizes while it has a considerably degraded performance with larger window sizes.

For Group 1, MDPM as well as CDPM has recorded a zero error rate : for stable signature patterns, MDPM performs well as CDPM does. But its performance becomes degraded as the window size increases.

For Group 2, the best performance has been recorded by MDPM with the window size of 4 percent : for unstable patterns, MDPM has a slightly better performance than CDPM with smaller window sizes.

As for CDPM, the original data, the position function $f(x, y)$, has the best result and the second time derivative of the position signal, the acceleration function, has the worst performance, which corresponds with the previous assumption for CDPM that the derivative loses the information included in the original signal as the derivation process is repeated, which consequently causes the performance degradation.

Through all experiments, MDPM has shown equal or better performance than CDPM. The observations on the verification performance with regard to relevant parameters all correspond with those for CDPM.

5. Conclusion

During the experiments for CDPM, it was observed that applying precise normalization such as preprocessing results in both an improvement in error rate performance and a smaller optimal window size. Accordingly, it was thought that the time domain fluctuation can also originate from the attitude variation during signature collection as the normalization process mainly reduces this geometrical variation.

The results from the for MDPM, which has been proposed for stable patterns satisfying the preconditions for DPM, applied under the same conditions as for CDPM, have also confirmed these implications as all the results have corresponded to the previous results for CDPM. Some results have even emphasized the assumed trends, e.g., if normalization is more precisely carried out, the optimal window size is reduced.

At this stage, it is worth recalling that the principal function of DPM is to eliminate the timing differences between two differently originating pattern signals.

The previous experiments have suggested three major factors which cause the timing differences :

① The temporal variations during signature generation due to temporal pauses and hesitations of the writer.
② The geometrical variations due to attitude variations

during signature collection including the change of the relative placement and orientation of the signature.

③ The random variations which do not satisfy the preconditions of continuity and monotonicity for DTW.

The results from the experiments have shown that :

① The temporal variations are ideally applied to DTW. Patterns which are affected only by these variations produce a good DTW result (See the experimental results for Group 1).

(2) The geometrical variations due to attitude change can be removed by using precise normalization, which correspondingly improves the error rate performance.

③ The random variations cannot be corrected. Patterns which are severely affected by these variations produce the worst DTW results (See the experimental results for Group 2). Their influence can be minimized by reducing the adjustment window size.

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