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임의의 부분 노이즈제거를 지원하는 윤곽선 매칭의 색인 구축 방법

김범수*

An Index-Building Method for Boundary Matching that Supports Arbitrary Partial Denoising

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요 약

윤곽선 이미지를 시계열로 변환하는 작업은 빠르고 상호작용 방식이 매우 중요한 대용량 이미지 데이터베이스에서도 윤곽선 매칭 수행을 가능 할 수 있게 만든다. 최근 연구에서는 윤곽선 이미지를 시계열 데이터로 변환하여 부분 노이즈제거를 고려하면서 빠르게 매칭을 수행하려는 시도가 있었다. 본 논문에서는 성능 향상을 위해 임의의 노이즈제거를 위해 임의의 모든 노이즈제거 매개 변수를 고려한 색인 구축 방법을 제안한다. 이는 가능한 모든 노이즈제거 매개 변수에 따른 부분 노이즈제거를 고려해야하기 때문에 어려운 문제이다. 본 논문에서는 다차원 색인인 R*-tree를 사용하여 모든 가능한 노이즈제거 매개 변수에 의한 최소 경계 영역(MBR)을 구성하여 효율적인 단일 생성 알고리즘을 제안한다. 다양한 실험 결과, 제안한 색인 기반 매칭 방법은 검색 성능을 최대 46.6 ~ 4023.6 배나 향상시킨다.

ABSTRACT

Converting boundary images to time-series makes it feasible to perform boundary matching even on a very large image database, which is very important for interactive and fast matching. In recent research, there has been an attempt to perform fast matching considering partial denoising by converting the boundary image into time series. In this paper, to improve performance, we propose an index-building method considering all possible arbitrary denoising parameters for removing arbitrary partial noises. This is a challenging problem since the partial denoising boundary matching must be considered for all possible denoising parameters. We propose an efficient single index-building algorithm by constructing a minimum bounding rectangle(MBR) according to all possible denoising parameters. The results of extensive experiments conducted show that our index-based matching method improves the search performance up to 46.6 ~ 4023.6 times.

키워드 : 시계열 데이터, 윤곽선 매칭, 시계열 매칭, 부분 노이즈제거, 색인

Keywords : Time-series data, Boundary matching, Time-series matching, Partial denoising, Indexing

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Ⅰ. Introduction

Efforts have recently been made by Kim et al.[1] to solve the boundary matching problem that supports *partial denoising*. Fig. 1 depicts the overall framework of partial denoising boundary matching. To improve the matching performance, the lower bound of the partial denoising distance is given, and this distance is optimized. Their work addresses boundary matching considering *partial noise*, which is a limited amount of noise embedded in a boundary image. The partial noise varies with level, position, and length on a boundary image. In the case of query images, partial denoising is simple as it is performed only once by preprocessing. On the other hand, in the case of data images, it is a challenging problem since all possible partial noises from the data images have to be considered. To solve this problem, Kim et al.[1] first define the *partial denoising time-series* that is a time-series obtained by removing the partial noise from a boundary time-series and then compute the similarity distance, i.e., *partial denoising distance*, between all possible partial denoising time-series and the query time-series. Finally, their proposed *partial denoising boundary matching* enables identification of similar boundary images regardless of the denoising position with the denoising length and the denoising level given by users.

In this paper, we propose an index-building method that supports arbitrary partial denoising for faster matching. In an index, it is not trivial since computing partial denoising for obtaining similar boundary images are needed for every change in the denoising level and the denoising length, respectively; that is, it incurs severe overhead. Thus, the index-based partial denoising boundary matching that supports arbitrary denoising parameters in a large image database is a challenging problem.

To enable support for arbitrary partial denoising, we use a multidimensional index, i.e., R^*-tree[2], and define *arb-MBR* that contains all low-dimensional points transformed from partial denoising time-series – generated by changing not only the denoising position but also the denoising level and the denoising length – and then present a single index-building algorithm by constructing *arb*-MBR; that is, we do not build indexes for every change in the denoising parameters, we simply

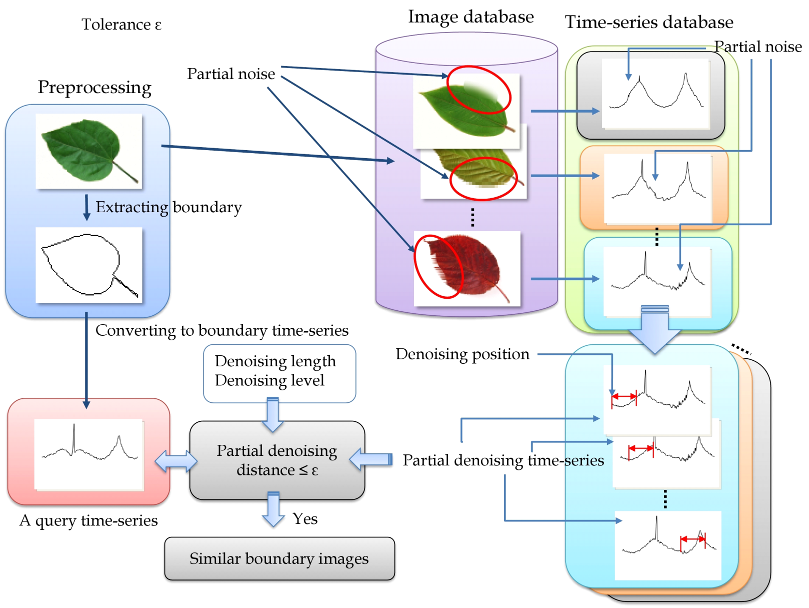

Fig. 1 The overall framework of partial denoising boundary matching[1].

build a single index that stores *arb*-MBR. The single index-building algorithm, however, has high computational complexity since it has to transform all possible partial denoising time-series into low-dimensional points for constructing *arb*-MBR.

Through extensive experiments, we show the superiority of the proposed index-based approach to partial denoising boundary matching for supporting arbitrary denoising parameters and compare its elapsed time with that of the previous method. On the basis of this result, we believe that our index-based method is a practical and interactive way of realizing boundary matching for supporting arbitrary partial denoising.

The remainder of this paper is organized as follows. Section 2 discusses existing work related to time-series matching, image matching, and partial denoising boundary matching. Section 3 outlines the concept of its index-based solution. Section 4 evaluates the performances of the proposed approach through experiments. Section 5 summarizes and concludes this paper.

Ⅱ. Related Work

2.1. Time-Series Matching

Time-series matching methods can be classified into two categories[3]: *whole matching*, where the lengths of the data time-series and the query time-series are all identical, and *subsequence matching*, where the lengths of the data time-series and the query time-series are different.

Index-based time-series matching is also classified into these two categories. Whole matching proposed by Agrawal et al.[4] first stores an MBR containing low-dimensional points into an index, after transforming data time-series into low-dimensional points, and then finds data time-series similar to the query time-series on the index. Subsequence matching proposed by Faloutsos et al.[3] is a generalization of whole matching. Subsequence matching first divide data time-series into sliding windows and store MBRs constructed using their low-dimensional points in an index. Finally, they obtain subsequences similar to the query time-series on the index. In this paper, we focus on the application of whole matching to boundary matching.

2.2. Image Matching

Shape-based matching is important for many applications such as industrial inspection, fingerprint matching, and tumor recognition[5, 6]. There have been many research efforts on shape matching[5, 6, 7, 8]. As the representative shape-based matching, there is the shape matching method using the shape context, i.e., shape context matching[5, 6]. The shape context is represented as the histogram between the distance and the angle from a selected point to all other points on the contours of a shape[5]. This feature is invariant to image scaling, translation, and rotation[6]. Shape context matching, however, does not use any index mechanism. We use the centroid contour distance(*CCD*) function[1, 6, 9], which is the simplest method for representing one-dimensional shapes, as a shape feature to exploit time-series matching techniques instead of shape features such as edge, curvature, and region. Specifically, *CCD* maps a shape feature, i.e., boundary time-series, to a time-series of length n as follows: it first evenly divides 360° into n equal-sized angles ($\triangle\theta = 2\pi/n$), where the direction is from the centroid to the boundary, and then computes the distance of each point on the boundary from the centroid. Thus, this *CCD* function enables transformation of an image domain problem into a time-series domain problem.

For shape-based image matching in a large image database, there have also been many attempts to use indexing techniques[7, 8, 10]. In general, multi-dimensional indexes such as k-d-b tree[11], R^*-tree, and MVP-tree[12] are used to perform image matching in a large image database[8]. Recently, several studies have been conducted using a vocabulary tree as a text retrieval approach for index-based image matching[10, 11, 13, 14]. These indexing methods predominantly use shape features that have region characteristics in an image. In this paper, however, such methods are not suitable since we deal with boundary features, which do not have region characteristics, to solve the partial denoising problem in boundary matching.

2.3. Patial denoising Boundary Matching

This subsection explains the concept underlying partial denoising boundary matching in more detail and defines the notations applied to formalize it. Partial denoising is an interesting problem since the partial noise can distort the matching results in boundary matching[1]. In this paper, partial denoising boundary matching is focused on similar boundary matching rather than on partial noise detection; that is, it is not important where exactly the partial noise lies on the boundary. We focus on finding similar boundary images regardless of partial noise.

Partial denoising boudnary matching requires the denoising level *d* and the denoising length *l* from the user. To solve a problem of supporting arbitrary denoising parameters, we apply a multidimensional index. If, however, *d* and *l* are changed at every matching by the user, a new index has to be constructed using these respective values. That is, the user may use different *d* and *l* depending on the application and purpose of matching, in which case an index has to be constructed each time using each pair of *d* and *l*. For example, if the number of *d*'s and *l*'s is 10, then 100 indexes have to be constructed. Thus, the existing solution incurs substantial storage space and update maintenance overhead owing to the use of multiple indexes. In this paper, we propose a single index-based approach that solves the index maintenance overhead problem by supporting arbitrary denoising parameters in a very large databases.

Table 1 summarizes the notations used in this paper. As shown in the table, $\widetilde{X}_p^{d,l}$, called by *partial denoising time-series*, is a boundary time-series replaced by the noise-removed subsequence instead of its subsequence *X*[*p*:*p*+l-1] using the moving average transform[9]. *PDD(X,Y,d,l)* is a similarity measure that is the minimum distance from a query time-series to all possible partial denoising time-series. We call it *partial denoising distance*.

Table. 1 List of notations.

Notation	Definition
d	Denoising level
l	Denoising length
p	Denoising position
%	A modular operator
X	A boundary time-series of length *n*, $\{x_o, x_1, \cdots, x_{n-1}\}$
X[i;j]	Subsequence of *X*, including entries from the *i*th one to *j*th
X	A set of boundary time-series
D(*X*,*Y*)	The Euclidean distance between *X* and *Y*, $\sqrt{\sum_{i=0}^{n-1} \lvert x_i - y_i \rvert^2}$
$\widetilde{X}_p^{d,l}$	A boundary time-series replaced by the noise-removed subsequence instead of its subsequence *X*[*p*:*p*+*l*-1] using the moving average transform[9], $\tilde{X}_p^{d,l} = \{\tilde{x}_{p,0}^{d,l}, \tilde{x}_{p,1}^{d,l} \ldots, \tilde{x}_{p,n-1}^{d,l}\}$, $\tilde{x}_{p,i}^{d,l} = \begin{cases} \text{if } i \in \{p\%n, \ldots, (p+l-1)\%n\}, \\ \qquad x_i^{d,l} = \frac{1}{d}\sum_{j=i}^{i+d-1} x_{j\%n} \\ \text{otherwise, } x_i \end{cases}$, where $0 \le p \le n-1$ and $2 \le d \le n-1$.
PDD (*X*,*Y*,*d*,*l*)	a similarity measure that is the minimum distance from a query time-series to all possible partial denoising time-series, $\min_{p=0}^{n-1} D(X, \widetilde{Y}_p^{d,l})$
F(*X*)	An *f*-dimensional point transformed by using the low-dimensional transformation PAA $F(\cdot)$, $\{\breve{x}_0, \breve{x}_1, \cdots, \breve{x}_{f-1}\}$, $\breve{x}_0 = \frac{1}{\omega}\sum_{j=\omega i}^{\omega(i+1)-1} x_j$, where $\omega = \frac{n}{f}$.
M(X)	An n-dimensional minimum bounding rectangle (MBR) that bounds all boundary time-series contained in X, i.e., an MBR [*L*,*U*] whose lower-left and upper-right points are *L* and *U*, respectively
M_F(X)	An *f*-dimensional MBR that bounds all *f*-dimensional features transformed by using $F(\cdot)$ in X

Ⅲ. Proposed Index-based Solution

In index-based partial denoising boundary matching, there are three main ways to support arbitrary denoising parameters: 1) only support arbitrary denoising level, 2)

Algorithm $BuildArbitraryIndex\left(\mathcal{T}\right)$

Input: Time-series database $\mathcal{T}$

for each data time-series $T \in \mathcal{T}$ **do**
  Make an f-dimensional MBR $\mathbb{M}_F\left(\cdot\right)$ that is initially empty;
  for each denoising length $l \in [2, n-1]$ **do**
    for each denoising level $d \in [2, n-1]$ **do**
      for each denoising position $p \in [0, n-1]$ **do**
        Make a partial denoising time-series $\widetilde{T}_p^{d,l}$ from T;
      end-for
    end-for
  end-for
  Construct a set $\widetilde{\mathcal{T}}$ of all partial denoising time-series;
  Construct a set of f-dimensional points from $\widetilde{\mathcal{T}}$ by using the low-dimensional transformation $F(\cdot)$;
  Construct arb-MBR $\mathbb{M}_F\left(\widetilde{\mathcal{T}}\right)$ by bounding all f-dimensional points;
  Make a record $< T\text{-}ID, \mathbb{M}_F\left(\widetilde{\mathcal{T}}\right) >$, and store it into the index;
end-for

Fig. 2 An index-building algorithm for boundary matching considering arbitrary partial denoising.

only support arbitrary denoising length, and 3) support both 1) and 2). To support arbitrary denoising level, we can construct an MBR considering the partial denoising time-series generated by all possible denoising levels. Likewise, to support arbitrary denoising length, we also can construct one considering those generated by all possible denoising lengths. These two methods enable users to obtain pseudo-optimal results by querying the given denoising length or denoising level several times. These methods, however, still have the overhead problem of building multiple indexes; that is, for index-based partial denoising boundary matching, we have to build as many indexes as denoising lengths and denoising levels, respectively. Consequently, we propose an index- based approach to partial denoising boundary matching that supports arbitrary denoising level and denoising length by using a single index.

In this paper, to support arbitrary denoising level and denoising length in a single index by using a multi-dimensional index, i.e., R*-tree, we construct a low-dimensional MBR considering all possible denoising levels and denoising lengths. We first define the set of arbitrary partial denoising time-series as follows:

Definition 1. Given X, the notation of $\widetilde{X}$, called the *set of arbitrary partial denoising time-series*, is defined as a set of $n\cdot(n\text{-}2)\cdot(n\text{-}2)$ partial denoising time-series, $\left\{\widetilde{X}_p^{d,l} | 0 \le p \le n-1 \text{ and } 2 \le d, l \le n-1\right\}$, considering all possible denoising levels and denoising lengths. We then denote $\widetilde{X}_p^{d,l}$ of $\widetilde{X}$ as the *arbitrary partial denoising time-series* $\widetilde{X}$.

Next, we define an MBR that bounds all low-dimensional points transformed from partial denoising time-series in the set of arbitrary partial denoising time-series and define as follows:

Definition 2. Given X, let a low-dimensional point $F\left(\widetilde{X}_p^{d,l}\right)$ be transformed from a partial denoising time-series $\widetilde{X}_p^{d,l}$ in the set of arbitrary partial denoising time-series, i.e., $\widetilde{X}$ by $F(\cdot)$. We then define *arb-MBR*, $\left\{F\left(\widetilde{X}_p^{d,l}\right) | 0 \le p \le n-1 \text{ and } 2 \le d, l \le n-1\right\}$, as an MBR that bounds all low-dimensional points and denote it as $\mathrm{M}_f(X\%)$.

To use *arb*-MBR in index-based partial denoising boundary matching, we prove that using *arb*-MBR incurs no false dismissal as follows:

Theorem 1. Given two boundary time-series X and Y, if the distance $D(F(X), \mathrm{M}_F(\widetilde{\mathrm{Y}}))$ between the low-dimensional point *F(X)* and *arb*-MBR MF($\widetilde{Y}$) satisfies the lower bounding condition of the distance $D(X, \widetilde{Y})$

between X and the arbitrary partial denoising time-series $\widetilde{Y}$ of $\tilde{\mathrm{Y}}$, then Eq. (1) holds.

$$\forall p, D\left(F(X), \mathrm{M}_F\left(\tilde{\mathrm{Y}}\right)\right) \leq D\left(X, \tilde{Y}\right) \quad (1)$$

Proof. We first note that following Eq. (2) holds since, excepting that Y is replaced with the partial denoising time-series $\widetilde{Y}$, Eq. (2) is identical to Lemma 1 in Faloutsos et al.[3].

$$\forall p, D\left(F(X), F\left(\tilde{Y}\right)\right) \leq D\left(X, \tilde{Y}\right) \quad (2)$$

Meanwhile, Eq. (3) can be derived from Eq. (7) in Kim et al.[1].

$$\forall p, D\left(F(X), \mathrm{M}_F\left(\tilde{\mathrm{Y}}\right)\right) \leq D\left(F(X), F(\tilde{Y})\right) \quad (3)$$

Thus, Eq. (1) of the theorem trivially holds by Eqs. (2) and (3).

On the basis of Theorem 1, we propose a single index-building algorithm that supports arbitrary denoising parameters in partial denoising boundary matching. Fig. 2 shows an index-building algorithm to support arbitrary denoising parameters. the index-building algorithm uses two additional loops for the denoising level d and the denoising length l; that is, in Lines 3-9, we generate partial denoising time-series with each denoising position by changing the denoising level d and the denoising length l, respectively. In Line 10, we construct the set of arbitrary partial denoising time-series. In Lines 12-13, we finally construct *arb*-MBR by using low-dimensional points transformed from all partial denoising time-series and store them in the index.

To use our index-building method, we propose an index-based matching algorithm. The inputs are a query time-series Q, a given tolerance ε, the denoising level d, and the denoising length l. The outputs are data time-series similar to the query time-series. We first transform the query time-series to an f-dimensional point by using the low-dimensional transformation $F(\cdot)$ and then construct an f-dimensional range query using $F(Q)$ and the tolerance ε. Next, we evaluate the range query on the multidimensional index and construct a set of candidate time-series that are potentially similar to the query time-series. This candidate set contains false alarms as well as the true similar time-series. Finally, we perform a post-processing step that discards false alarms by retrieving the real data time-series from the database and computing their partial denoising distance from the query time-series.

Ⅳ. Experimental Evaluation

In our experiments, we used the synthetic boundary dataset used by Kim et al.[1]. This dataset consisted of 102,590 boundary time-series of length 360 including nine different partial noises created by changing the length and the position from each original image, all collected from the Web. To generate the partial noise, we used the Gaussian noise model[15]. Although we only used ten thousand original images[1, 9, 16], we actually extracted more boundaries than that number using the *CCD* method since one image might contain multiple boundary objects.

We performed the experiments in the following environment. The hardware platform was an IBM compatible PC equipped with a 2.0GHz Intel Core 2 Duo CPU, 2.0GB RAM, and 500GB hard disk. The software platform was the CentOS 6.3. We used the C/C++ language to implement the index-building and matching algorithms. As the multidimensional index, we used the R^*-tree and set its index and data page sizes to 4,096 bytes. In addition, we used PAA as the low- dimensional transformation and extracted 72 features each time-series using it.

We compare the elapsed times of the boundary matching algorithms that supports arbitrary partial denoising. Fig. 3 presents the performance results by varying the tolerance ε on the fixed denoising level d and denoising length l. (Note that the Y-axis is log-scale.) These results can be controlled by changing ε for range queries in the matching algorithms. BAI is an index-based matching algorithm using our proposed index-building algorithm. NIV-OG is the naive matching algorithm proposed by Kim et al.[1] and NIV-OP is the optimized algorithm of NIV-OG. As shown in the figure, BAI incurs the more performance degradation when the number of similar boundary images is between 1 and 10. This means that the matching performance of our index-based matching algorithm is very sensitive to the tolerance. On the other hand, in the case of NIV-OG and NIV-OP, their matching performance shows no change since the similarity distance is computed to all possible data time-series. Thus, for our index-based matching algorithm, it is very important to determine the appropriate tolerance. We leave the solution of this problem as a future study. In the experimental results, BAI improves that by 1.2 to 4023.6 times compared with NIV-OG and NIV-OP.

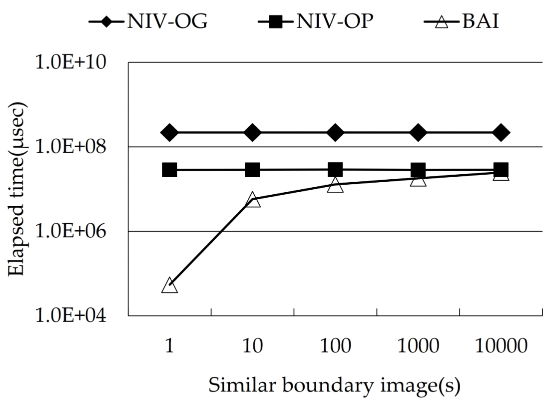

Fig. 3 Comparison of the matching performance by varying the tolerance (*d*=24, *l*=72).

Fig. 4 shows the scalability of the matching algorithms. As shown in the figure, the performance results show linear scalability of all algorithms. This means that, as the number of data time-series increases, our algorithms are suitable for handling a large image database. Thus, we can obtain the results in just a few seconds even on a large boundary database. In the experimental results, BAI improves the matching performance by 5.0 to 46.6 times compared with NIV-OG and NIV-OP. As a result, we can confirm that our index-based matching algorithm provides an efficient way of performing partial denoising boundary matching on a large boundary database.

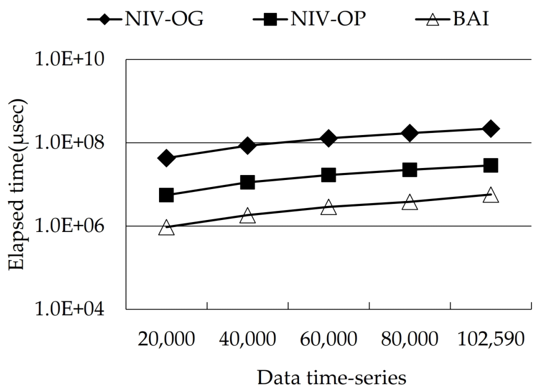

Fig. 4 The scalability of partial denoising boundary matching algorithms(*d*=24, *l*=72).

Ⅴ. Conclusions

In this paper, we solved the overhead problem incurred in supporting arbitrary denoising parameters for partial denoising boundary matching using a multidimensional index. The contributions of the paper could be summarized as follows. First, we proposed an efficient index-based approach that supports arbitrary partial denoising in boundary matching using R^*-tree and PAA as the low-dimensional transformation. Second, we formally proved its correctness. Third, through experiments, we showed that the index-based matching algorithms were superior to the existing matching algorithms. The experimental results also indicated that the index-based matching algorithms outperformed the existing matching algorithms by orders of magnitude.

We plan to use other similarity measures instead of the Euclidean distance and may find the optimal denoising level and denoising length. We believe that the significant improvement in matching performance makes the proposed algorithms suitable for recent smart devices with constrained resources such as CPU power and memory.

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