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Applications of Neighborhood Sequence in Image Processing and Database Retrieval

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Abstract: In this paper we show how the distance functions generated by neighborhood sequences provides flexibility in image processing algorithms and image database retrieval. Accordingly, we present methods for indexing and segmenting color images, where we use digital distance functions generated by neighborhood sequences to measure distance between colors. Moreover, we explain the usability of neighborhood sequences within the field of image database retrieval, to find similar images from a database for a given query image. Our approach considers special distance functions to measure the distance between feature vectors extracted from the images, which allows more flexible queries for the users.
Key Words: Database retrieval, Image database, Image processing, Segmentation
Category: H.2.8 H.3.3 I.4.6 I.5.3

1 Introduction

Since the first proposal of Rosenfeld and Pfaltz on mixing the 4- and 8- neighborhoods for better approximation properties [Rosenfeld and Pfaltz, 1968] the investigation of theory of neighborhood sequences grows rapidly [Hajdu et al., 2004] [Hajdu et al., 2005c] [Das et al., 1987] [Hajdu et al., 2005a] [Nagy, 2003] [Fazekas et al., 2002] [Hajdu et al., 2005b] [Hajdu and Hajdu, 2004] [Hajdu et al., 2003] [Fazekas, 1999] [Fazekas et al., 2005]. However, the actual applicability of these theories has not yet been revealed. In this paper, we summarize some former practical results regarding measuring distance using neighborhood sequences [Hajdu et al., 2004] [Hajdu et al., 2003], and show how new application schemes can be derived from them also in another field.

To begin with showing applicability, we begin with recalling some methods for indexing and segmenting color images using neighborhood sequences [Hajdu et al., 2004] [Hajdu et al., 2003]. The proposed procedures are based on well-known algorithms, but now we use digital distance functions generated by neighborhood sequences to measure distance between colors. The application of such distance functions is quite natural and descriptive, since the color coordinates of the pixels are non-negative integers. An additional interesting property of neighborhood sequences is, that they do not generate metric in general, so we can obtain many distance functions in this way. We describe our methods for RGB images in details, but other image representations also could be considered. Moreover, the proposed methods can be applied in arbitrary dimensions without any difficulties.

Image database retrieval is a developing field with growing interest [Santini, 2001] [Lew, 2001] [Chang, 1997] [Chang and Lee, 1991] [Carson et al., 1999] [Elmasri and Navathe, 1994] [El-Kwae and Kabuka, 2000] [Grosky, 1990]. In case of a query image, many features (color, texture, distribution of segments, etc.) can be considered to find similar images in a database. A usual procedure is to extract similarity values and compose similarity vectors according to these features. Then some measurement is applied to calculate the norm of the similarity vectors (that is the distance between the query image and the images in the database). Such a norm can be the weighted Euclidean one applied e.g. in Oracle9i. In this paper we propose a new method to calculate the norm of the similarity vectors. Our approach is based on neighborhood sequences, and we will show that for some purposes it allows more flexible queries for the users to make than the classic methods.

2 Neighborhood Sequences

In this chapter, we recall the basic concepts and properties of neighborhood sequences (NS). For more details, see [Danielsson, 1993] [Das et al., 1987] [Fazekas, 1999] [Fazekas et al., 2002] [Hajdu and Hajdu, 2004] [Hajdu et al., 2005a] [Hajdu et al., 2003] [Kiselman, 1996] [Rosenfeld and Pfaltz, 1968] [Yamashita and Ibaraki, 1986].

In [Rosenfeld and Pfaltz, 1968] Rosenfeld and Pfalz introduced the concepts of octagonal distances by mixing the 4- and 8-neighborhood relations in 2D. In [Yamashita and Ibaraki, 1986] Yamashita and Ibaraki introduced the concept of general periodic NS in $\mathbb{Z}^n$, which was generalized further to non-necessarily periodic sequences in [Fazekas et al., 2002].

2.1 General Neighborhood Sequences

Let $n \in \mathbb{N}$ and two points $p, q \in \mathbb{Z}^n$. $\mathrm{Pr}_i(p)$ indicates the ith coordinate of point p. Further let $m \in \mathbb{N},\ 0 \leq m \leq n$. The points p and q are m-neighbors if the following two conditions hold:

- $|\,\mathrm{Pr}_i(p) - \mathrm{Pr}_i(q)| \leq 1$ for all $1 \leq i \leq n$
- $\sum_{i=1}^{n} |\,\mathrm{Pr}_i(p) - \mathrm{Pr}_i(q)| \leq m$

The sequence $B = \{b(i)\}_{i=1}^{\infty}$, where $b(i) \in \{1, \ldots, n\}$ for all $i \in \mathbb{N}$ are called an n-dimensional neighborhood sequence. That is the ith element of the sequence prescribes that we can move to $b(i)$-neighbors at the ith step.

If there exists $l \in \mathbb{N}$ so that $b(i + l) = b(i)$ for all $i \in \mathbb{N}$, then B is called a periodic neighborhood sequence with period l. The brief notation of a periodic B neighborhood sequence with period l is $B = \{\overline{b(1)b(2)\ldots b(l)}\}$. For example $B = \{\overline{112}\}$ means the sequence $\{112112112\ldots\}$. In case the period length is 1, B is called a constant neighborhood sequence. The set of nD periodic neighborhood sequences is denoted by S_n.

If we can obtain a periodic neighborhood sequence from a $B \in S_n$ omitting its first finitely many elements, then we call B an ultimately periodic neighborhood sequence, and denote it by $B \in UP_n$. The brief notation of an ultimately periodic neighborhood sequence is $B = \{b(1)\ldots b(k)\overline{b(k+1)\ldots b(l)}\}$. That is if we remove the first k element of B, we obtain a periodic neighborhood sequence with period length $l - k$. More details on ultimately periodic sequences can be found in [Hajdu et al., 2005a].

In this paper we will only use neighborhood sequences for our purposes in 3D case. Our approach in image processing and also in database retrieval can be extended in arbitrary dimension.

2.2 Distance Measurement

Let p and q be two points in $\mathbb{Z}^n$ and $B \in S_n$. The sequence of points $p = p_0, p_1, \ldots p_m = q$, where p_{i-1} and p_i are $b(i)$-neighbors, are called B-path from p to q with length of m. The shortest B-path is the B-distance between p and q, denoted by $d(p, q; B)$.

In [Fazekas et al., 2002] an algorithm is given for calculating the distance by neighborhood sequences. It can be summarized as follows.

1. Let $x = (x_1, x_2, \ldots x_n)$ the nonascending ordering of $|\,\mathrm{Pr}_i(p) - \mathrm{Pr}_i(q)|$ for all $1 \leq i \leq n$.
2. In every step the first $b(i)$ elements of x should be decremented by 1.
3. x should be resorted nonascendingly.

4. Steps from 2 to 4 should be repeated until every items in x are 0.

The distance functions generated by neighborhood sequences are not metrics in general. This is the triangular-inequality ($d(p, q; B) \leq d(p, r; B) + d(r, q; B)$ with $p, q, r \in \mathbb{Z}^n, B \in S_n$) does not always hold as it is shown in Example 1.

Example 1. Let $p = (0, 0), r = (1, 1), q = (2, 2) \in \mathbb{Z}^2$ and $B = \{\overline{21}\} \in S_2$ 2D periodic neighborhood sequence. Then $d(p, r; B) = d(r, q; B) = 1$, because 2-neighborhood steps are used. On the other hand, q can be reached from p in three steps, that is $(d(p, r; B) = 3)$ [see Fig. 1].

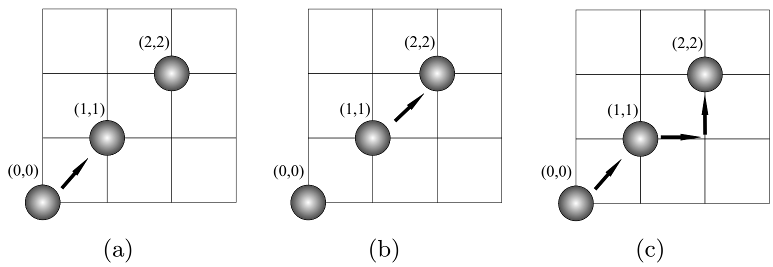


Figure 1: Example for the neighborhood sequence is not a metric; (a) $d(p, r; B) = 1$, (b) $d(r, q; B) = 1$, (c) $d(p, q; B) = 3$.

With the following result of [Nagy, 2003] we can decide whether the distance related to B is a metric on the nD digital space, or not [Fazekas et al., 2005].

Theorem 1. *[Nagy, 2003] Let $A \in S_n$, and for every $i \in \mathbb{Z}^+$ and $j \in \{1, \ldots, n\}$ put $A^{(j)}(i) = \min(A(i), j)$. Then $d(A)$ is a metric if and only if*

$$\sum_{i=1}^{k} A^{(j)}(i) \leq \sum_{i=t}^{k+t-1} A^{(j)}(i)$$

for any $k, t \in \mathbb{Z}^+$.

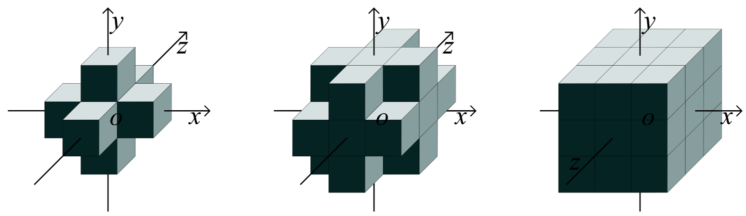
2.3 Neighborhood Sequences for Retrieval Purposes

To prove the applicability of neighborhood sequences in image retrieval, we will fix some common image features to determine image similarity. Namely, we will focus on color, shape and texture. These features are usually described with high dimensionality, from which scalar similarity values can be derived, and thus a special 3D domain can be obtained. Using the quantitative information of the independent similarities of these features we make a common similarity measurement by neighborhood sequences. For this approach, we use two special families of the generalized 3D ultimately periodic sequences, introduced in [Hajdu et al., 2005a]. Here, a neighborhood can contain a finite class of vectors (and is not restricted to the direct neighbors).

Classic NS (CNS) The first family contains the following neighborhoods.

$N_1 = \{\mathbf{O}, (0, 0, \pm 1), (0, \pm 1, 0), (\pm 1, 0, 0)\}$,
$N_2 = N_1 \cup \{(0, \pm 1, \pm 1), (\pm 1, 0, \pm 1), (\pm 1, \pm 1, 0)\}$ and
$N_3 = N_2 \cup \{(\pm 1, \pm 1, \pm 1)\}$.

Note that these neighborhoods are based on the well known 6-, 18- and 26 neighborhood, respectively. We denote this classic subset of neighborhood sequences by CNS_3 [see Fig. 2].



(a) (b) (c)

Figure 2: Neighborhoods used for CNS_3; (a) N_1, (b) N_2, (c) N_3.

Subspace NS (SNS) The next family of neighborhood sequences consist the following neighborhoods:

$N_x = \{\mathbf{O}, (\pm 1, 0, 0)\}$, $N_y = \{\mathbf{O}, (0, \pm 1, 0)\}$, $N_z = \{\mathbf{O}, (0, 0, \pm 1)\}$,
$N_{xy} = N_x \cup N_y \cup \{(\pm 1, \pm 1, 0)\}$,
$N_{xz} = N_x \cup N_z \cup \{(\pm 1, 0, \pm 1)\}$,
$N_{yz} = N_y \cup N_z \cup \{(0, \pm 1, \pm 1)\}$ and
$N_{xyz} = N_{xy} \cup N_{xz} \cup N_{yz} \cup \{(\pm 1, \pm 1, \pm 1)\}$.

Each of these neighborhoods spans a 1D, 2D or 3D subspace of $\mathbb{Z}^3$, respectively, thus the set of the sequences generated by them is denoted by SNS_3 [see Fig. 3]. With the sequences of these neighborhoods we can explicitly prescribe which coordinate(s) are allowed to change at a step, while CNS_3 sequences let as prescribe the number of the changeable coordinates only. Note that $\mathrm{CNS}_3 \subset \mathrm{SNS}_3$, nor $\mathrm{SNS}_3 \subset \mathrm{CNS}_3$ and $N_{xyz} = N_3$.

Mixed NS (MNS) The third family of neighborhood sequences is the mixture of the CNS_3 and SNS_3 so the allowed neighborhoods are the followings:

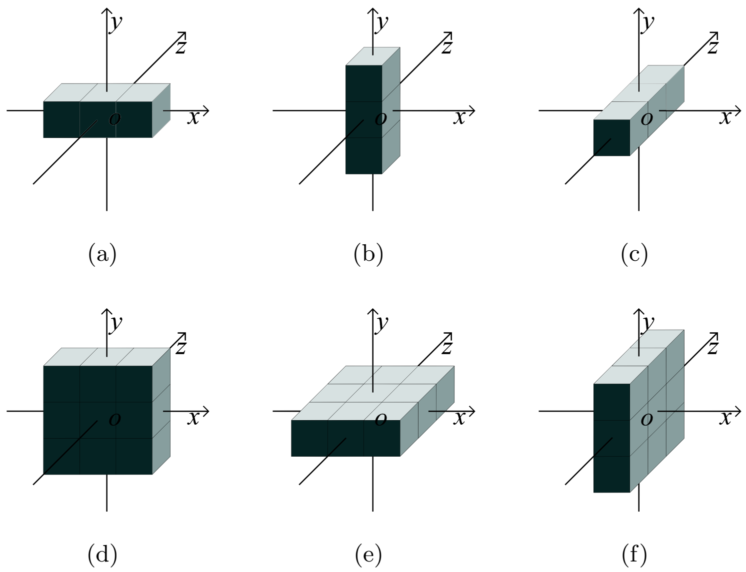


Figure 3: Neighborhood used for SNS$_3$; (a) N_x, (b) N_y, (c) N_z, (d) N_{xy}, (e) N_{xz}, (f) N_{yz} (for N_xyz see [Fig. 2(c)].

$$N_1,\ N_2,\ N_3,\ N_x,\ N_y,\ N_z,\ N_{xy},\ N_{xz},\ N_{yz}.$$

The set of the mixed sequences is denoted by MNS$_3$. Note that the definition of the three sets is extendable in arbitrary dimensions. Thus e.g. for the MNS case, we can compose neighborhood sequences as $N = \{M_1, ..., M_k, \overline{M}_k + 1, ..., M_l\}$ where $M_i \in \{N_1,\ N_2,\ N_3,\ N_x,\ N_y,\ N_z,\ N_{xy},\ N_{xz},\ N_{yz}\}, \quad i = 1, ..., l$.

3 Distance Measurement in RGB Cube

Segmenting color images is primarily based on the comparison of the color of the pixels. In image processing, we usually work with three color components as red, green and blue. This is denoted by RGB color model. In our investigations every component is an integer in $[0, 255]$. That is the 24-bit RGB cube, the domain between black $= (0, 0, 0)$ and white $= (255, 255, 255)$. We consider the points in this domain as colors. Thus we can measure distance between colors by neighborhood sequences, see [Hajdu et al., 2003] [Hajdu et al., 2005b]. The corresponding sequence has to be selected carefully to achieve the desired result.

3.1 Image Segmentation

We recall three segmentation methods from [Hajdu et al., 2004] [Hajdu et al., 2003]:

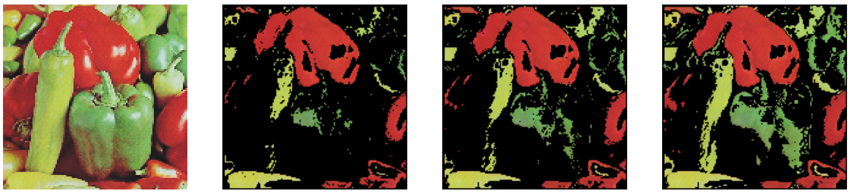
– *fuzziness*,

– *region growing*,

– *clustering*.

Further, we give a tool to help user to select the most suitable neighborhood sequence.

Fuzziness The procedure selects those pixels which are within a given distance k from one or more initially fixed seed colors. The implementation of this method for a fixed distance function can be found in Adobe® Photoshop®, where it is referred as *Fuzziness* option. [Fig. 4] shows that the result of the fuzziness method highly depends on the chosen seed color(s), threshold and neighborhood sequence.



(a) Original (b) (c) (d)

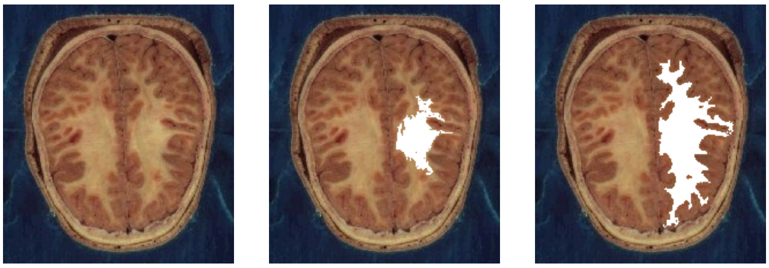
Figure 4: Fuzziness from the initial seed colors (■ = $(204, 56, 56)$, ■ = $(102, 153, 102)$, ■ = $(204, 204, 102)$); (a) Original, (b) $B = \{\overline{1}\}$, (c) $B = \{\overline{1112}\}$, (d) $B = \{\overline{311}\}$, the threshold value is set to $k = 40$.

Region growing Using fuzziness method, it is not guaranteed that the resulting regions are connected, see [Gonzalez and Woods, 1992]. To obtain connected regions we can add the distance function used in fuzziness method to a region growing method. With region growing method we get the connected pixels within distance k from the initially fixed seed points color [see Fig. 5]. The connectedness can be satisfied by arbitrary neighborhood.

Clustering Our approach is based on an algorithm for indexing color images based on cluster analysis, see [Gonzalez and Woods, 1992]. In this method the elements of the RGB cube are classified into clusters using a suitable distance measurement. We use neighborhood sequences as distance functions. For k-means clustering results see [Fig. 6].

3.2 Help Tools

A quantitative analysis of the proposed clustering method can be obtained by considering a suitable measure, like the specialization of the uniformity measure



(a) Original (b) (c)

Figure 5: Region growing of a medical picture; (a) Original, (b) region growing with $B = \{\overline{1}\}$, (c) $B = \{\overline{3}\}$; the bound for the color distance is $k = 70$ in both cases.

(a) Original (b) (c)

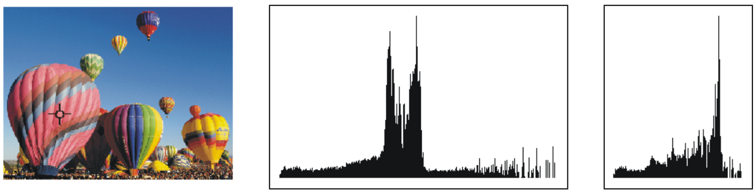
Figure 6: Clustering into 6 colors ( ); (a) Original, (b) $B = \{\overline{12}\}$, (c) $B = \{\overline{23}\}$.

of Levine and Nazif, see [Levine and Nazif, 1985].

Fuzziness histogram We present a tool that is to give a guideline to help with finding the optimal neighborhood sequences and threshold values for the method introduced above. This type of histograms can be assigned to the fuzziness method, and might be useful especially in region growing. The kth column of the histogram illustrates the amount of the pixels whose distance from the seed color(s) is exactly k. The shape of the histograms highly depends on the chosen neighborhood sequence. A “faster” neighborhood sequence results a shorter histogram, but significant differences may occur in the modality, as well [see Fig. 7].

The difference between two histograms can be measured by suitable histogram measures [Cha and Srihari, 2002].

Global histogram Another help tool may be the histogram, which is obtained as follows. The kth column of the histogram indicates the number of the pixel pairs of distance k. As the method depends only on the chosen neighborhood sequence we refer this histogram as global histogram. Similarly to the fuzziness histogram, distance measurements can be calculated. In the following example



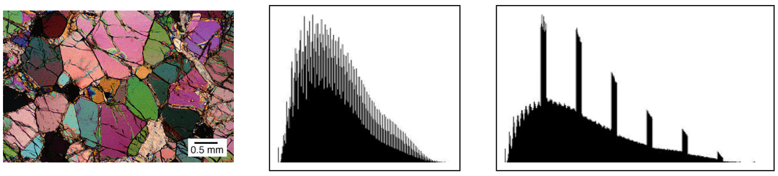
(a) (b) (c)

Figure 7: Fuzziness histograms for the marked initial seed color, using different neighborhood sequences as distant functions; (a) Original image, (b) $B = \{\overline{1}\}$, (c) $B = \{\overline{3}\}$.

the obtained histogram nicely reflects the values in the period of the neighborhood sequence [see Fig. 8]. In case of [Fig. 8c] we used the periodic neighborhood sequence B with period length 50. The elements of B we can get as follows:

$$b(i) = \begin{cases} 3 \text{ if } 1 < i \leq 10, \\ 1 \text{ if } 10 < i \leq 50. \end{cases}$$

The brief notation of the formula above is $B = \{\overline{3^{10}1^{40}}\}$. Fuzziness and global histograms are produced similarly, but in the latter case the first node has no particular importance.



(a) (b) (c)

Figure 8: Global histograms for using different neighborhood sequences as distant functions (a) observed image, (b) $B = \{\overline{123}\}$, (c) $B = \{\overline{3^{10}1^{40}}\}$.

4 Neighborhood Sequences in Database Retrieval

To store and retrieve multimedia data form databases is an important investigation area [Santini, 2001]. The result of the retrieval procedure highly depends on the method how we compare two images. For image retrieval purposes we will concider three features. These are color, shape and texture, denoted by c, s and t, respectively. There are standard ways to assign similarity values to each of c, s, t features of the database images in case of a query image. The norm of the difference vector of two feature vector can be referred as the distance of two image represented by their feature vectors.

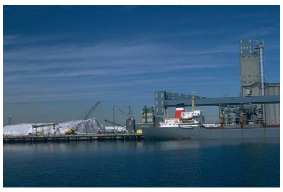
When comparing with an existing database system, we will assign the x, y and z Cartesian coordinates to the c (color), s (shape), and t (texture) values, respectively, for better understanding. Thus we will use the neighborhood notation N_c, N_s, N_t instead of N_x, N_y, N_z and so on with the other SNS neighborhoods. Thus we will have the following neighborhoods: N_1, N_2, N_3, N_c, N_s, N_t, N_{ct}, N_{st}, N_{cs}, N_{cst}.

For example we want to select such images that are quite close in color and texture to the input image. The most important features should be achieved within the least steps, while non-important features should need more steps. Applying these considerations, a possible neighborhood sequence answer is $B_1 = \{\overline{N_{ct}^3 N_s^{40}}\}$. In this case we allow 3 steps in the c and t directions first, then s can be changed for 40 steps. The periodicity of B_1 guarantees that we do not exclude vectors having larger values than 3 in either their c or t coordinates, though, they will be reached only after applying more periods. See [Fig. 9] for the matches ranked by their distance from $\mathbf{O}$, the query image.

(a) Query

(b) 39

(c) 44



(d) 44

(e) 44

Figure 9: Query result for $B_1 = \{\overline{N_{ct}^3 N_s^{40}}\}$; (a) query image, (b-e) retrieved images and their norm.

Against Oracle [iMe, 2002] [Ora, 2000] we can formulate queries which include time factor with permuting the elements of the sequence. [Fig. 10] shows the result of the example of separating the c and s elements of the neighborhood sequences used above. The meaning of this change is: "selecting the images that are close *first* in color *then* in texture and shape to the query image". The result can be seen in [Fig 10] and the resulting neighborhood sequence is $B_2 = \{\overline{N_c^3 N_t^3 N_s^{40}}\}$. We can use MNS_3 neighborhood sequences if we do not know which feature to prefer to get the best result. E.g. "we need the images which are close in color or in texture". The result can be seen in [Fig 11] and the resulting neighborhood sequence is $B_3 = \{\overline{N_c^3 N_t^3 N_2^2}\}$.

(a) Query

(b) 42

(c) 47

(d) 48

(e) 48

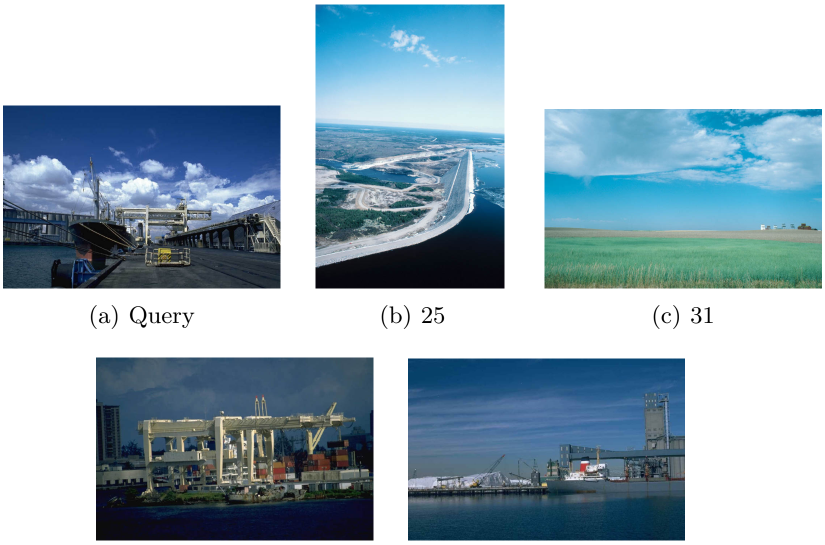
Figure 10: Query result for $B_2 = \{\overline{N_c^3 N_t^3 N_s^{40}}\}$; (a) query image, (b-e) retrieved images and their norm.

5 Conclusions

The most indexing and segmentation methods are based on the classical Euclidean metric. In image processing and image retrieval it is often more suitable to use not only metrical distance functions in $\mathbb{Z}^n$. Distances generated by neighborhood sequences nicely meet this condition. In this paper we presented some tools that may help with choosing the most suitable neighborhood sequence.

In image database retrieval the distance functions generated by neighborhood sequences give a novel approach to formulate more flexible queries. The technique is not limited to image databases; it can be used in other retrieval applications and with arbitrary features, as well.

We note that our aim is not to decide about the suitability of the similarity vectors extracted by Oracle, and so a quantitative analysis (based on e.g. some



(a) Query (b) 25 (c) 31

(d) 50 (e) 72

Figure 11: Query result for $B_3 = \{\overline{N_c^3 N_t^3 N_2^2}\}$; (a) query image, (b-e) retrieved images and their norm.

precision/recall measures [Smeulders et al., 2000]) would not be reasonable here. Moreover, as we recommend an approach for supporting new queries, no existing database has been scored accordingly. If we would make such a scoring (which exhausting work is out of our scope now), then the quantitative analysis would become useless in the lack of a valid possibility for comparisons. Moreover, the general freedom that our approach allows for phrasing queries, would make it extremely difficult to set up a fixed, objective scoring of a database without further restrictions.

In the paper we showed that neighborhood sequences are capable to be used in different types of applications. Beside the theoretical results, they have true practical use.

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