# ON CALCULATION OF CHAMFER DISTANCE AND LIPSCHITZ COVERS IN DIGITAL IMAGES

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**Abstract.** We study the chamfer distance transformations of binary digital images and corresponding Lipschitz covers of grayscale images. Validity of the double scan algorithm in arbitrary dimension is proved.

**Keywords:** chamfer distance, Lipschitz cover, top-hat procedure, background elimination

### **1** Introduction

Distance transformation is an operation with a lot of applications in image processing and in analysis of spatial patterns. Special distance transformations, e.g. chamfer or city block distance, can be calculated especially easily by a sequential double scan algorithm [3,9]. The same algorithm can be used for the calculation of the lower Lipschitz cover of a grayscale image [7] that is equivalent to a grayscale opening by a cone [4]. The Lipschitz cover can be applied for the elimination of a slowly varying image background by subtraction of the lower Lipschitz cover (a top-hat procedure).

The distance is usually defined as a symmetric function that is positive for distinct points. If we relax these assumptions we obtain a function called quasi-distance that can be useful to model *e.g.* directional positional relations in images [1], or real situations like uphill and downhill paths. We will show that the quasi-distance can also be calculated by the double scan algorithm. Moreover, the notion of quasi-distance can simplify description and validation of the double scan algorithm that inherently contains the measurements of the quasi-distance to the preceding image elements during the scan.

#### 2 Chamfer quasi-distance in digital images

The elements of the *n*-dimensional digital image are arranged in a regular lattice and they can be indexed by  $\mathbb{Z}^n$ .

The digital image is a function  $f: X \to \mathbf{R} \cup \{-\infty, +\infty\}$ , where  $X \subset \mathbf{Z}^n$ . The binary image is a digital image with range in  $\{0,1\}$ .

**Definition 2.1**: Chamfer mask M is a digital image with a finite domain D(M) such that  $M \ge 0$  and  $M(\mathbf{0}) = 0$ .

The path from x to y,  $x, y \in X$  is a sequence of vectors  $v_1, v_2, ..., v_m \in D(M)$  such that

$$x-y=\sum_{k=1}^m v_k \ .$$

Chamfer quasi-distance between  $x, y \in X$ ,  $X \subset \mathbb{Z}^n$ , is

$$d_{M}(x, y) = \inf_{\{v\}} \sum_{k=1}^{m} M(v_{k}), \qquad (1)$$

where sequence of vectors  $v_1, v_2, ..., v_m \in D(M)$  is path v from x to y.

The chamfer quasi-distance, defined in (1) fulfills  $d_M(x,x)=0$ ,  $d_M(x,y)\ge 0$ ,  $d_M(x,y)+d_M(y,z)\ge d(x,z)$ . Related chamfer quasi-norm  $n_M(x)=d_M(x,0)$  is positively homogeneous  $n_M(ax)=an_M(x)$  for  $a\in\mathbb{Z}$ ,  $a\ge 0$ .

The notion of quasi-distance is more general than notion of distance:

a) d is symmetric, i.e.  $d_M(x, y) = d_M(y, x)$  iff M is symmetric: M(x) = M(-x).

b)  $d_M(x, y) = 0$  does not imply  $x \neq y$  iff there is  $x \neq 0$  such that M(x) = 0.

c)  $d_M(x, y)$  attains infinite value for x, y that can not be connected by vectors from D(M).

**Definition 2.2**: Let  $x, y \in \mathbb{Z}^n$ . Then  $x <_L y$  lexicographically iff there is  $0 \le j \le n$  such that  $x_j < y_j$  and  $x_k = y_k$  for k > j. Let us define the two intervals bounded by **0** from one side  $\mathbb{Z}^{n-} = \{x \in \mathbb{Z}^n, x <_L 0\}, \mathbb{Z}^{n+} = \{x \in \mathbb{Z}^n, x >_L 0\}$ .

**Definition 2.3**: Let f be a function and let d be a quasi-distance on D(f), then f is d-Lipschitz function with respect to d iff for every x, y from D(f)

$$f(x) - f(y) \le d(x, y). \tag{2}$$

Let f be a function. Then the greatest d-Lipschitz function  $f(x)-f(y) \le d(x, y)$  is called the lower d-Lipschitz cover of f. Lipschitz condition (2) represents continuity in discrete spaces.

#### **3** Chamfer distance transformation algorithms in **2D**

The distance transformation converts a binary digital image into a gray-level image with pixels having value of the distance to the nearest feature. It can be achieved using only local operations of a small neighborhood of a pixel. The chamfer distance transformation of a binary image can be computed either by a sequential algorithm or by a parallel algorithm.

In next section we assume  $X \subset \mathbb{Z}^2$ . Then we can denote a pixel of the image as  $a_{i,j} = f(i, j)$ . Computing algorithms for the chamfer distance transformation in arbitrary dimensions are very similar and you can find them in [2].

The parallel algorithm uses a parallel chamfer mask (Fig.1) and is defined by the recurrent relation

where *u* is a vector,  $u = (u_1, u_2)$ , *m* is the width of the image, *n* is the height of the image,  $i \in \{1, ..., m\}, j \in \{1, ..., n\}$ .

Algorithm stops on fixpoint, it means if  $a_{i,j}^{k+1} = a_{i,j}^k$  for all *i*,*j*.

We used in (3) the value m+n that represents the infinity in the algorithm, because any real distance in the image is less than m+n.

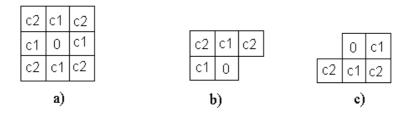


Fig. 1: 3 x 3 chamfer masks: a) parallel chamfer M, b) forward sequential  $M^-$ , c) backward sequential  $M^+$ .

The sequential algorithm presented in [8] has two steps: forward and backward scan. Both of these scans use its own chamfer masks  $M^-$  and  $M^+$  (Fig.1), with the signs in the sense of lexicographical order, defined in **2.2**. The coefficients  $c_1$  and  $c_2$  represent the gradient step in horizontal and vertical directions and in diagonal direction, respectively. Usually  $c_1 = 1, c_2 = \sqrt{2}$  or if we require that these values are natural numbers,  $c_1 = 2, c_2 = 3$ . A more precise calculation also with larger chamfer masks is possible to find in [6].

The first forward scan (with output matrix  $(a_{i,j}^1)$ ) begins from the upper left corner of the image and scans the rows all over the image to the bottom right corner. The second backward scan (with output matrix  $(a_{i,j}^2)$ ) has the opposite direction of the scanning from the bottom right corner to the upper left corner:

$$\begin{aligned} a_{i,j}^{1} &= 0 & \text{if } a_{i,j} = 0, \\ a_{i,j}^{1} &= \inf\{m+n\} \cup \{a_{i+u_{1},j+u_{2}}^{1} + M^{-}(u) \mid u \in D(M^{-}) \setminus \{0\}, (i+u_{1},j+u_{2}) \in D(f)\} \\ & \text{if } a_{i,j} = 1, \\ a_{i,j}^{2} &= \inf\{a_{i,j}^{1}\} \cup \{a_{i+u_{1},j+u_{2}}^{2} + M^{+}(u) \mid u \in D(M^{+}) \setminus \{0\}, (i+u_{1},j+u_{2}) \in D(f)\}. \end{aligned}$$

In the computation of the value of  $a_{i,j}^1$  we use the value of  $a_{i+u_1,j+u_2}^1$ , but we already have these values from previous computation for all  $u \in D(M^+)$ , because  $u <_L 0$ . Analogous situation is in the second backward scan.

This algorithm can be easily extended for the calculation of the lower *d*-Lipschitz cover of a grayscale image [7]:

$$a_{i,j}^{1} = \inf\{a_{i,j}\} \cup \{a_{i+u_{1},j+u_{2}}^{1} + M^{-}(u) \cdot slope | u \in D(M^{+}) \setminus \{0\}, (i+u_{1},j+u_{2}) \in D(f)\},\$$
$$a_{i,j}^{2} = \inf\{a_{i,j}^{1}\} \cup \{a_{i+u_{1},j+u_{2}}^{2} + M^{+}(u) \cdot slope | u \in D(M^{+}) \setminus \{0\}, (i+u_{1},j+u_{2}) \in D(f)\},\$$

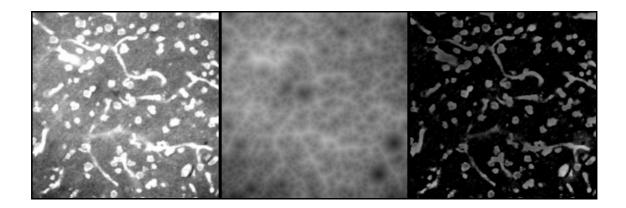
where *slope* is a parameter controlling gradient in the resulting image.

A similar algorithm computes the upper *d*-Lipschitz cover:

$$a_{i,j}^{1} = \sup\{a_{i,j}\} \cup \{a_{i+u_{1},j+u_{2}}^{1} - M^{-}(u) \cdot slope \mid u \in D(M^{-}) \setminus \{0\}, (i+u_{1},j+u_{2}) \in D(f)\},\$$
$$a_{i,j}^{2} = \sup\{a_{i,j}^{1}\} \cup \{a_{i+u_{1},j+u_{2}}^{2} - M^{+}(u) \cdot slope \mid u \in D(M^{+}) \setminus \{0\}, (i+u_{1},j+u_{2}) \in D(f)\}.$$

The Lipschitz cover is a very useful tool for the elimination of a slowly varying image background. There are some examples in the figures (Fig.2, Fig.3).

In 24-bit (or 32-bit) colored pictures the same algorithm is used for every color channel.



*Fig. 2: An original microscopic image (on the left), the Lipschitz lower cover (in the middle) and the image after using a Lipschitz top-hat filter (on the right).* 

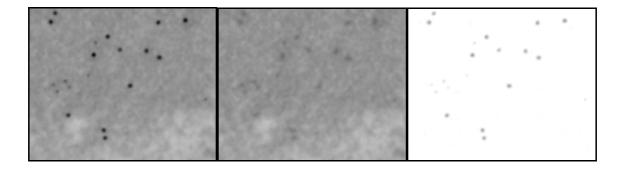


Fig. 3: An original electron-microscopic image of immunogold labels (on the left), the Lipschitz lower cover (in the middle) and the image after using a Lipschitz top-hat filter (on the right).

### 4 Chamfer distance in digital image of arbitrary dimension

Now we will assume that  $X \subset \mathbb{Z}^n$ , n > 0. It can be proved that the lower *d*-Lipschitz cover of *f* is

$$g(x) = \inf_{y \in D(f)} (f(y) + d(x, y)).$$
(4)

The sequential algorithm for the distance transformation scans the image elements in the lexicographic order calculating the lower  $d_{M^+}$ -Lipschitz cover h of the image f taking the minimum of  $h(x + y) + M^+(y)$  for  $x + y \in D(f)$ ,  $y \in D(M^+)$ ,  $y <_L 0$  and of f(x) in the first step and then scans the image elements in the anti-lexicographic order calculating lower  $d_{M^-}$ -Lipschitz cover g of the image h, taking minimum of  $g(x + y) + M^-(y)$  for  $x + y \in D(f)$ ,  $y <_L 0$  and of h(x) in the second step.

According to the following theorem the result of the double scan algorithm is the lower chamfer quasi-distance Lipschitz cover of the digital image.

**Theorem 4.1**: Let f be an image and M a chamfer mask. Let  $M^+$  and  $M^-$  be chamfer masks such that  $M^+(x) = M(x)$  if  $x <_L 0$  and  $M^+(x)$  is not defined if  $x >_L 0$ ,  $M^-(x) = M(x)$  if  $x >_L 0$  and  $M^-(x)$  is not defined if  $x <_L 0$ . A lower  $d_M$ -Lipschitz cover of f is a lower  $d_{M^-}$ -Lipschitz cover of a lower  $d_{M^+}$ -Lipschitz cover of f.

**Proof**: Let g be a lower  $d_M$ -Lipschitz cover of f, then  $g(x) = \inf_{y} (f(y) + d_M(x, y))$ . The

path  $\{v_k\}$  (4) minimizing  $d_M(x, y) = \inf_{\{v_k\}} \sum_{k=1}^m M(v_k)$  can be partitioned between  $\mathbb{Z}^{n+}$  and  $\mathbb{Z}^{n-}$ :

$$d_{M}(x, y) = \sum_{k=1}^{m} M^{+}(y_{k}) + \sum_{k=1}^{m} M^{-}(y_{k})$$

and the statement of the theorem follows from

$$g(x) = \inf_{z} \left( \inf_{y} \left( f(y) + d_{M^{+}}(z, y) \right) + d_{M^{-}}(x, z) \right).$$

**Proposition 4.2**: Let *d* be a quasi-distance. The distance transformation of a binary digital image *b* is an image  $DT_{b,d}$  such that  $D(DT_{b,d}) = D(b)$ ,

$$DT_{b,d}(x) = \inf_{b(y)=0} d(x, y).$$

It is easy to see that  $DT_{b,d}$  is a lower *d*-Lipschitz cover of the function  $g \circ b$ , g(0)=0, g(1)=1. Then by the theorem 4.1 the double scan algorithm calculates also the chamfer quasi-distance transformation of the binary image.

### 5 Conclusion

The chamfer distance relatively well approximates the Euclidean distance and is widely used because of its relatively small computational requirements as it imposes only 2 scans of the *n*-dimensional image independently of the dimension of the image. A more precise approximation [5] requires  $2^n$  scans in *n*-dimensional image, hence for n > 2 the algorithms for Euclidean distance transformation that are separable in dimension and require *n*-scans are preferable [4].

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#### References

- [1] Bloch I.: *Fuzzy spatial relationships for image processing and interpretation: a review.* Image and Vision Computing 23 (2005), 89-110.
- [2] Borgefors G.: *Distance transformations in arbitrary dimensions*. CVGIP 27 (1984), 321-345.

- [3] Borgefors G.: Distance transformations in digital images. CVGIP 34 (1986), 344-371.
- [4] Breu H., Gil J., Kirkpatrick D., Werman M.: *Linear time euclidean distance transform algorithms*, IEEE Trans. PAMI 17 (1995), 529-533.
- [5] Danielsson P.-E.: Euclidean distance mapping. CVIP 14 (1980), 227-248.
- [6] Fouard C., Malandain G.: Automatic calculation of chamfer mask coefficients for large masks and anisotropic images. Rapport de recherche (2003).
- [7] Moreau P., Ronse C.: *Generation of shading-off in images by extrapolation of Lipschitz functions*. Graphical Models and Image Processing 58 (1996), 314-333.
- [8] Rosenfeld A., Pfaltz J. L.: Sequential Operations in Digital Picture Processing. (1966), 33-61.
- [9] Rosenfeld A., Pfaltz J. L.: *Distance functions on digital pictures*. Pattern Recognition 1 (1968), 33-61.
- [10] Sternberg S. R.: Grayscale morphology. CVGIP 35 (1986), 333-355.