Parikh Matrices for the Reverse Neighbour search on a set of Circles with Digital Image Processing

S. Rukmani Devi[1] ,
Ph.D., Research Scholar (Part-Time),
Bharathiyar University,
Chennai,Tamil Nadu, India.

Dr. P.Selvaraju[2]
Professor & Head, Department of Computer Science,
VeltechMutiTech College of Engineering,
Chennai, Tamil Nadu, India.

Abstract:This paper is with Parikh matrices for finding reverse neighbours for a known object in a digital image. In this paper, the discussion is about a simple RN weighted Parikh matrices to locate the exact neighbours of a known object in the image q to locate reverse neighbour of the object in that image. The work in this paper is compared with R-Trees and its variants with a range searching or the neighbours of a digital image using Parikh matrices.

Index Terms: Parikh Matrices, RN, Objects, circles, Images.

I. INTRODUCTION:

1.1 Digital Images Representation:

An image set as a twodimensional function, *f(x,y)*, where the coordinates are *x* and *y* in the spatial(plane). At the level of image point with the amplitude of *f* is the pair of coordinates *(x,y)* is called the intensity of the image. When *(x,y)* and the values of *f* are all set of quantities called the digital image[13].

Sampling and quantization of an image is represented as a matrix of real numbers. An image with the pair of coordinates*f(x,y)*that has rows and columns. The values of coordinates *(x,y)*is discrete and the coordinates at the origin are *(x,y)* = (0,0) and the next coordinate values are *(x,y)* =(0,1).

f(x,y)=

$$\begin{pmatrix} f(0,0) & f(0,1) & \ldots\ldots & f(0,N-1) \\ f(1,0) & f(1,1) & \ldots\ldots & f(1,N-1) \\ . & . & . & \\ . & . & . & \\ . & . & & . \\ f(M-1,0) & f(M-1,1) & \ldots\ldots & f(M-1,N-1) \end{pmatrix}$$

Figure: 1 M X N Digital Image as Matrix Form

1.2 Neighbours of a Pixel object in a DigitalImage:

A pixel *p* at coordinates *(x,y)* has four horizontal and vertical neighbours whose coordinates are given by

(x+1,y), (x-1,y), (x,y+1), (x,y-1)

This set of pixels are called 4- neighbours of p. Each pixel is a unit of distance from *(x,y)* some neighbours of *p* lies outside the digital image if *f(x,y)* is on the border of the image. The four diagonals of *p* have coordinates *(x+1,y+1), (x+1,y-1), (x-1,y+1), (x-1,y-1)* are denoted by $N_D(p)$.

1.3 Reverse Shortest Neighbours and its Variants:

A broad approach for solving RSN algorithm and R-Tree for a set of circles is based on RSN and its variants. The fundamental concept behind the shortestneighbour relation is not symmetric. For example, if *P* is an object in the image1 that is the shortestneighbour of object *q* in the same image1, the *q* need not be the neighbour of *P*. Hence it is symmetric. Similarly, the K-shortestneighbour relation is not symmetric. For a given object *q*, the neighbour of *q* differ from the set of all objects for which *q* is shortestneighbour called reverse shortestneighbours of object *q* in the image.

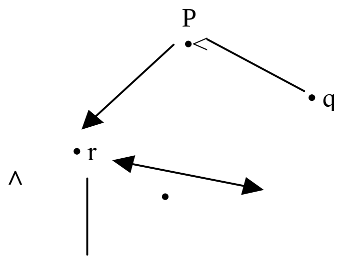


Figure:2 Shortest neighbour node need not be symmetric.

From this fig:2, we believe that the distance among any two objects $p=(p_x,p_y)$ and $q=(q_x,q_y)$ is $d(p,q)=(q_x-p_x)^2 + (q_y-p_y)^2$acknowledged as the distance.

1.4 Formal definition:

From the set of *S* collections of objects, an object *q* and the aim is to find out the shortest Neighbour SN (q) is defined as
SN(q)={rЄS| for all pЄS: d(p,r)<+d(q,p)}

1.5 Variants:

There are two variants for RSNAlgorithm. 1. Monochromatic 2. Bichromatic.

The RSN algorithm consists of a set of objects in the image: *Blue and Red.Blue* must determine the *Red* objects for which the object is the closest *Blue* object. Let *B* represent the set of *blue* objects in an image and *R* represent the set of *red* objects. Consider the *blue* as an object *q* in an image. Then, *RSN (q)={rЄR | for all pЄB : d(r,q)<+d(r,p)}*. This illustration is called Bichromatic. All the objects in the above representation is the same category in monochromatic. RSN problem for both Bichromatic and monochromatic are same. For a *Blue* object in an image, only the *red* objects in the image is the distance to the closest *Blue* object.

1.5.1 Proposition:

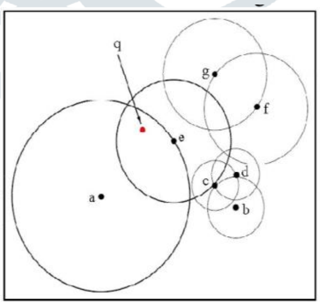
For any object in the image RSN (q) have at most 6 objects in the monochromatic. In Bichromatic, the size of the set RSN (q) is boundless. A proof is found in [1]. From a viewpoint, the output of RSN algorithm is bounded. An RN algorithm is output sensitive since it affects the efficiency. RN algorithm supports Static vs. Dynamic. To insert or delete objects of an image from the set *S* is referred to Dynamic. In contrast, the case when the set *S* is not customized is called Static. All dynamic problems are capable to handle insertions and deletions efficiently without changing the entire data structure.

II. RN using circle objects in the image lies on the circle:

R- Trees are usually used in spatial and multimedia databases to hold special types of algorithms such as exact match, partial match and the shortestneighbour algorithm on the geometric objects. The popular shortest neighbour algorithm is the reverse neighbour algorithm that focuses on the inverse relation among objects. Reverse shortestneighbour algorithm process is performed using R-trees. Given an object *p* in the image, finding the set of circles near the object is the SN – algorithm. The reverse shortestneighbour search finds all the objects in the image whose shortest neighbours are the object which is the inverse relation. That is, a reverse shortest neighbour (RSN) algorithm *q* is to locate all the objects for which *q* is their shortestneighbour.

2.1 Definition:

Given a set of objects *p* and an object *q*, a reverse shortestneighbour algorithm is to locate the set of objects RSN so that for any object in an image*pЄP*and*rЄRSN*, *dist(r,q)<=dist(r,p)*. Korn and Muthukrishnan [5] answer RSN algorithm by pre calculating a circle of each object *p* such that the shortestneighbour of *p* lies on the perimeter of the circle. Circles are indexed by an R – Tree called RSN – Tree. The difficulty of RSN algorithm is condensed to an object location algorithm on RSN – Tree that returns all circles contain *q*. The intermediate nodes have the minimum bounding rectangles (MBR) of basic objects along with the maximum distance from every



object

Fig: 3 The Objects *a*and *e* are the Reverse ShortestNeighbour of *q*

from every object in the Stanoi et. al[6] eliminates the need for pre-computing the shortest neighbour of all data objects by utilizing this algorithm divides the shortest neighbour of all data objects into space around *q* in six regions of equal size S_0 to S_5. O_1 is the shortest neighbour of *q* in region S_0 but it is not the RSN because O_0 present closer to it than *q*. There is no RSN of *q* in S_0 and the algorithm does not need to consider other objects in this region. Based on this property,

RSN algorithm expressed in two steps:

1. For each of the six regions a Shortest Neighbouris found. These entire Neighbournode form a candidate list.
2. A SN algorithm is issued for each object in the candidate list and the algorithm discards the objects from candidate list for which q is not the shortest neighbour.

In a given object *p*, finding those circles for which *q* is their shortestneighbour called the reverse shortest neighbours. Circle intersection can be found in *O(k)* time. Finally, for each object p in candidate list, a Boolean range algorithm with range dist*(p,q)* is issued. A Boolean range algorithm is different from the conventional range algorithm that it terminates when it finds the first object. The object for the Boolean range query does not return any object of the RSNs of *q*.

III. RSN weighted Parikh Matrices with Image objects:

3.1 Parikh Matrices:

The notion of Parikh Matrix of an object over the number of objects was introduced by Mateescu et al in 2000[10]. The Parikh Matrix mapping or a Parikh Matrix uses upper triangular Square matrices, with non-negative integer entries. 1's on the main diagonal and 0's below it. The set of all such triangular matrices is denoted by *M* and the subset all matrices of dimension $k>=1$ is denoted by M_k.

For pixels *p,q*and *z*with coordinates*(x,y), (s,t)*and*(v,w)*, respectively, *D* is the distance function or metric if

a) $D(p,q) >=0$ ($D(p,q) = 0$ iff $p=q$),
b) $D(p,q) =D(q,p)$, and
c) $D(p,z) <= D(p,q) + D(q,z)$

3.2.1Euclidean Distance:

The Euclidean Distance between *p* and *q* is defined as $D_e(p,q) = [(x-s)^2 + (y-t)^2]^2$ This distance measure having the distance less than or equal to some value *r* from *(x,y)* are the pointscontained in a disk of radius *r* centered at *(x,y).*

3.2.2 City-Block distance or D_4 Distance:

The D_4 Distance between *p* and *q*is defined as $D_4(p,q) = |x-s| + |y-t|$

3.2.3 Chessboard Distance or D_8 Distance:

The D_8 Distance between p and q is defined as

D_8 (p,q) = max(|x-s|. |y-t|)

3.2.4 Distance Measures for a set of objects in the image with Parikh Matrices:

Let S be the set of objects in an image defined by the Parikh Matrix *M*. There are 3 types of distances on a set S and perform comparison of objects through these distances[11].

Let $a,b \in S$, $a=x_1x_2\ldots x_n$, $b=y_1y_2\ldots yn$ $(x_i,y_i \in \{x,y\})$be the two distinct objects. Then,

3.2.5 Hamming Distance:

The hamming1 distance $d_H(a,b)$ equals the number of different objects between *a* and *b*. Formally,

$$d_H(a,b)= \sum_{i=1}^{n} (x_i \oplus y_i)$$

where :∑ *∑ ⊕ {o,1} is defined by

$aa=bb=0; a \oplus b = b \oplus a=1.$ ⊕ ⊕

3.2.6 Rank Distance:

The rank distance $d_R(a,b) = \sum |ord_a(x) - ord_b(x)| \; x \in a$Where $ord_u(x)$ represents the position of the object *x* in the set *u* that are counted from left to right.

3.2.7 Amiable Distance:

The amiable distance$d_A(a,b)$ is defined as, if $a=\alpha x1\beta x2\beta\ldots\alpha xn\ \beta xn+1$,

$b= \alpha y1\beta y2\beta\ldots\alpha yn\ \beta yn+1$

Then

$$d_A(a,b) = 1/2\sum_{i=1}^{n+1}$$

3.2.8 Proposition:

d_A is a distance and $d_a\ (a,b) \in N.\ (a,b \in S)$.

Theorem:

Let $a,b \in S$. Then

1. $d_R(a,b) = 4k$, where k is the shortest path length between a and b.
2. $d_A\ (a,b) <= d_H(a,b) <= d_R(a,b)$

4. Conclusion:

A RN – weighted Parikh Matrices with digital image have been proposed to make things easier RSN – algorithm for a known set of pixel objects in a digital image in format of circles. The nature of circle intersection and therefore makes the search for the shortest neighbour to an object is simpler. With the Parikh Matrices of a set of digital image pixel objects that lies on the circles using RSN, the reverse shortestneighbours can be determined. In this paper, the study is to initiate Parikh Matrices using digital image pixel objects with reverse shortestneighbours. Many issues remain to be explored. The role of RSN algorithm in Parikh Matrices using digital image objects can be explored more.

References:

[1]M.Smid, Closest point problems in computational geometry from In J.R.Sack and J.Urratia, editors, Handbook on Computational Geometry, Elsevier Science Publishing. 1997.

[2] K. Fukunaga and P.M. Narendra, A Branch and bound algorithm for computing K nearest neighbors, IEEE Trans. On Computers (TOC), C-24(7): 750-753, July 1975.

[3] G.R. Hjaltason and H.Samet, Distance browsing in spatial databases, ACM TODS, 24(2): 265-318, June 1999.

[4] N. Roussopoulos, S.Kelley, and F.Vincent. Nearest Neighbor Queries, In Proc. Of ACM – SIGMOD, Pages 71-79, San Jose, CA, May 1995.

[5] Flip Korn, and S. Muthukrishnan,Influence sets based on Reverse Nearest Neighbor Queries, Technical Report, AT & T Labs Research, 2000.

[6] IoanaStanoi, Divyakant Agarwal, Amr EL Abbadi, Reverse Nearest Neighbor Queries for Dynamic Databases, In ACM SIGMOD workshop on research issues in Data mining and Knowledge Discovery, 2000.

[7] A. Singh, H. Ferhatosmanoglu, and A.S.Tosun. High dimensional reverse nearest neighbor queries, In CIKM 2003.

[8] Atanasiu. A, Martin-Vide. C, Mateescu. A, On the Injectivity of the Parikh Matrix Mapping, Fundamental Informaticae, 49(2002) 289-299.

[9] Virgil NicholaeSerbanuta, On Parikh Matrices, Ambiguity and Prints, IJFCS, Nov-2008.

[10] A. Mateescu, A.Salomaa, K.Salomaa, S.Yu, A sharpening of the Parikh Mapping, Theoret. Informatics Appl., 35(2001) 551564.

[11] Atanasiu.A,"Binary amiable words", Int. J. Found. Comput. Sci., 18, 387-400.

[12] K.G.Subramanian and Angmiin Huey, Parikh Matrices of words, Int. Conf on research trends in Applications of mathematics, 2010.

[13] Rafael C.Gonzalez, Richard E.Woods, Digital Image Processing, Second Edition, Prentice – Hall of India private Limited, 2007.

[14] A.Salomaa, Criteria for matrix equivalence of words, Theoretical Computer Science,411(16-18), 2010: 1818-1827.

[15] K.G.Subramanian,K.Mahalingam,

R.Abdullah, A.K.Nagar, Binary Images, M-vectors and Ambiguity, J.K. Agarwal et al. (Eds.): IWCIA 2011, Lecture Notes in Computer Science 6636, 2011: 248 -260.