RECTANGULAR DISCRETE RADON TRANSFORM TOWARDS AN AUTOMATED BUILDINGS RECOGNITION FROM HIGH RESOLUTION SATELLITE IMAGE

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ABSTRACT

This paper presents a new approach titled Rectangular Discrete Radon Transform (RDRT) which is based on the generalization of the classical Radon transform to project the images with rectangular objects instead of straight lines. The RDRT was conceived to accurately locate and automatically recognize Rectangular Buildings from high resolution satellite images. Experimental results demonstrate the efficiency of our method.

Index Terms— Rectangular Discrete Radon Transform, Rectangular Buildings, High Resolution satellite image.

1. INTRODUCTION

In recent years and due to the increase of satellite image resolution, accurately detecting buildings becomes an area of interest which attracts many researchers. Thus, several approaches were realized for this purpose and can be classified on three categories: pixellic approaches that exploit directly the information from the pixels by extracting the contours [1], classifying regions after a pre-segmentation [2,3] or combining photometric, geometric and morphological information in a caractaretics vector[4] , Based Models approaches which, after a segmentation, look for two dimensional models of rectangular, in cross, in “L” or in “U” forms[5], Auxiliar data based approaches which utilises an external data such as cadastral maps on areial images[6] or altimetric description provided by the DigitalElevation Model[7] and finally mixed approaches which combines the advantages of the three previous approaches to improve quality results [8,9]. On the other hand, The Classical Radon transform is defined to be a projection of an image by straight lines.Thus,it transforms a two dimensional image into a parameters space where each line in the initial image gives a peak positioned at the corresponding line parameters[10,11]. Consequently,the classical Radon Transform was widely used in many line detection applications within image processing applications[12,13,14,15,16].The classical Radon transform was also used in extracting buildings from high resolution images in [17] where the authors applied the classical Radon Transformand then used the Forstner operator in the Radon transform parameters space to detect peaks. This approach is dependent on the buildings size to detect peaks. In addition, it needs a post-treatment to extract building contours because it uses the classical Radon Transform which detects only lines. To overcome this inconvenience, we have developped the Rectangular Discrete Radon Transform (RDRT) that extends the classical Radon Transform formalism by projecting an image with rectangular objects. Consequently, a peak in the Radon space denotes the exisctence of a rectangle at the same coordinates in the initial image and the detection of buildings wil be then reduced to the peaks extraction without any post-treatement. This paper is organized as follows: Section 2 presents the definition of the RDRT formalism followed by its automation in section3.Section 4 presents its application on extracting buildings from high resolution images and presents experimental results.In final,we summarize our research and conclude the paper in Section 5.

2. RDRT FORMALISM

Our method is an algebraic transform based on the multiplication of image columns and a selection matrices. Our work is inspired from the Beylkin approach[18] which projects an image with curves following only the horizontal direction. Our RDRT method in counterpart, projects rectangular objects oriented according to an angle $\theta \in [0, 2\pi[$ and translated according to both the horizontal and the vertical directions as shown in the following figure:

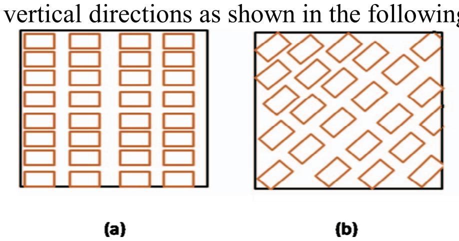

Figure 1:(a): the rectangles follow the horizontal direction (b):the π/4-rotated rectangles.

Let I be a two dimensional image sized of (LXN) where $l, 0 \le l \le L-1$ are the image lines, $n, 0 \le n \le N-1$ its columns and $I(l,n)$ presents a pixel value from the image *I*. A column n is presented by the vector $I(n)$.

$$I(n) = \begin{pmatrix} I_0(n) \\ .... \\ I_l(n) \\ .... \\ I_{L-1}(n) \end{pmatrix} \text{ and the entire image } as \quad I = \begin{pmatrix} I(0) \\ I(1) \\ . \\ . \\ I(N-1) \end{pmatrix}$$

Let the following expression be the RDRT formalism:

$$y_{\theta,l}(n) = \sum_{m=0}^{M-1} R_{\theta,l}(m) \times I(n+m) \qquad (1)$$

$$with\, \theta \in [0, 2\pi[,\ 0 \le l \le L-1,\ 0 \le n \le N-1.$$

The RDRT formalism is based on the multiplication of the *m* lines of the transform matrices $R_{\theta,l}$ and the image columns $I(n)$. $R_{\theta,l}$ are the transform matrices sized of $M \times L$ where each line $m, 0 \le m \le M-1$ selects from the column $I(n+m)$, the pixels contributing to a rectangular projection according to the θ direction. M presents the rows number of the matrix S which is the minimal bounding box of the θ-rotated projection rectangle *A*. The construction of the $R_{\theta,l}$ matrices is performed at first by constructing at the position *l,* the $M \times O$ sized matrix S where the pixels belonging to the *A* perimeter are set to 1 and the remaining pixels to zero. Then, the $R_{\theta,l}$ construction is followed by horizontally translating S over the handling $R_{\theta,l}$ matrix. The translation increases in unit pixel step and wraps back around the beginning of $R_{\theta,l}$ matrix if the translated S exceeds $R_{\theta,l}$ length limit. The figure2 presents a construction example of the matrices $R_{\theta,l}$ where the rectangles are not rotated. It is to notice that there are *L-1* matrices to construct for the rectangular projection.

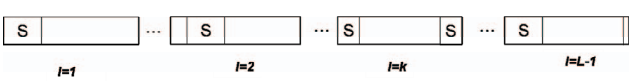

Figure 2:A construction example of the matrix $R_{\theta,l}$

$y_{\theta,l}(n)$ denotes the projection result of a *θ*- rotated rectangle S positioned at *(l,n)*.The column *y(n)* presents then the projection results of the rectangles positioned at the column *n* of the initial image.

$$y_\theta(n) = \begin{pmatrix} y_{\theta,0}(n) \\ .... \\ .... \\ y_{\theta,L-1}(n) \end{pmatrix}$$

A peak positioned at *(l,n,θ)* coordinates testifies of the top left corner of S which presents the delegate of the rectangle object in the image I. The real rectangle position coordinates can be easily determined knowing the position of the top left corner of the θ-rotated rectangle in the matrix S. The following figure shows the results of our method applied on synthetic image.

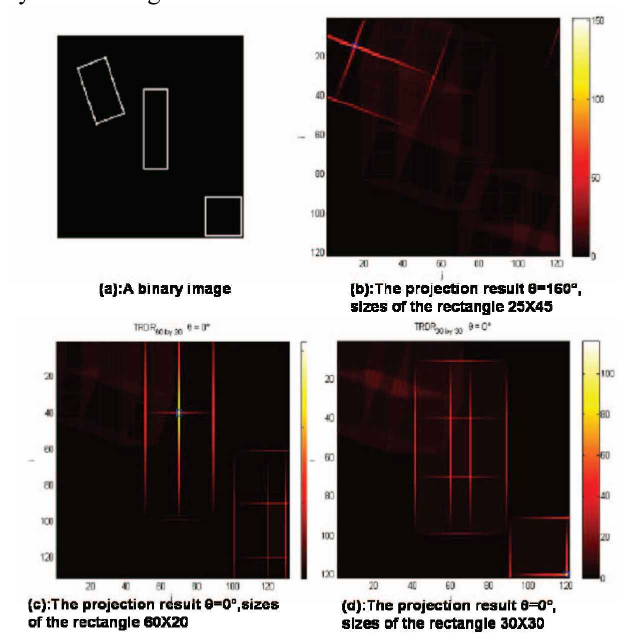

Figure 3: The peaks corresponding to recatngles in Radon spaces

Our method can detect rectangular forms but the dimensions of rectangles to project are set manually. In the next section, we will try to make the Rectangular RDRT fully automatic method in the way that the size of the rectangles in the image will be extracted with the help of the RDRT itself.

3. AUTOMATION OF RDRT

To automate the RDRT, (i.e. the automatic determination of dimensions rectangles in the image), we have used the RDRT method but instead of projecting rectangular objects, we have projected four shapes able of locating the four vertices of the rectangles in the image. For that purpose, we construct a "a model recatngle"where its sizes are chosen arbitrarly.We extract from the model rectangle the four shapes to project. Each presenting a rectangular vertex and the two segments attached to it (figure 4). In another words, we used the right angles as a projection objects.

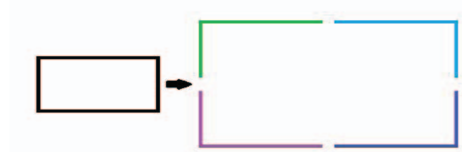

Figure 4:The four shapes to project.

We then project the image with the new projection objects to produce four parameters spaces. The first corresponds to the top left corner, the second to the top right corner, the third to the bottom left corner and the final to the bottom right corner of the rectangles. Consequently, each space contains several peaks giving the location of the right angles of the shapes.Extracting peaks from each space and then calculating the distances between them allows the sizes extraction of rectangles to project in further phase. To ensure that the four peaks belong to the same rectangle, we specified four rules:
Let *(x1,y1),(x2,y2),(x3,y3)* and *(x4,y4)* be successively the coordinates of a peak in the first ,in the second,in the third and in the fourth space. If the rules are verified, then the four peaks are related to a same rectangle.

1. $x1=x2$ and $y1\neq y2$.
2. $y2=y3$ and $x2\neq x3$.
3. $x3=x4$ and $y3\neq y4$. *(2).*
4. $y4=y1$ and $x4\neq x1$.

For each found peak in the first space of RDRT, we look if there are peaks in each of the other spaces that satisfy the rules mentioned above. If the rectangles are not horizontal (i.e. oriented according to an angle $\theta\neq 0$), the detection rules no longer apply. Thus, we have, for each angle of projection, rotated the image according to the angle $-\theta$.All dimensions and orientations resulting from this preprocessing phase will be used for the rectangular projection phase RDRT.

4. EXPERIMENTS

The method developed in this study was applied to extract buildings from a Quickbird image of Strasbourg city with a spatial resolution 0.6 metre/pixel. First, the initial image is pretreated by using the multi-scale mathematical morphological filter[19] to preserve building boundaries while removing noise such as thinner lines and spots.Then, we detect the edges of the original image by means of the Perwitt operator [20]. After that, we extract rectangles sizes and orientations angles as it is shown in the previous section. Finally, we apply the RDRT method on the edges image. The Radon images resulting from this method are $y_{\theta,p,q}$, where *p, q, θ* present respectively the orientation angle,the height and the width of the rectangle to project.To detect the peaks in the Radon images, we have used a local maximas filter. In our tests, the size of the local maxima filter was fixed to be 21x21 taking in consideration the minimum distance between buildings. After selecting the local maximas in all images, we check the peaks coordinates. If more than one peak are at the same position or at a very approximate positions, we select the peak having the highest value. We have tested our approach on five areas. We present here some of our results(**Figure5**,**Figure6**).

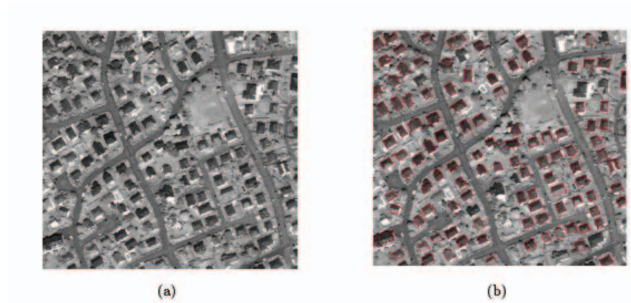

Figure 5: (a) initial image I1.(b) extracted buildings.

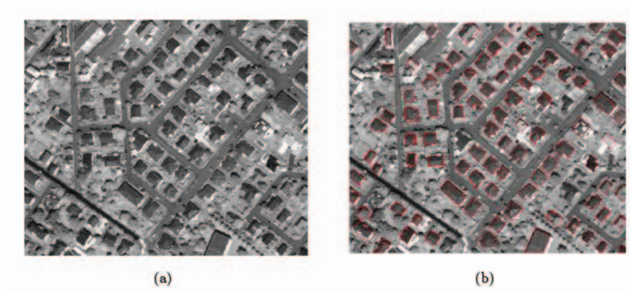

Figure 6: (a): Initial image I2.(b) Extracted buildings

To evaluate our results, we have used the following metrics defined in [4]:
For a quantitative assessment:

$$BER = \frac{BCE}{TB}$$

Where BER is the Building Extraction Rate, BCE is the Correctly Extracted Buildings number and TB is the Total Buildings number existing in the area of test.
And for a qualitative metric, we used these formalisms:

$$exactness = \frac{BCE}{BCE + FA} \tag{4}$$

$$quality = \frac{BCE}{BCE + BPE + BNE + FA} \tag{5}$$

Where BPE is the number of Partially Extracted Buildings, BNE is the number of Not Extracted Buildings and FA is the False Alarms denoting the wrongly identified buildings. The table1 presents the results of the RDRT on each of the five images.

	I1	I2	I3	I4	I5	Total
BCE	100	81	62	43	184	470
BPE	2	0	2	0	3	7
BNE	10	11	14	3	16	54
FA	4	3	3	1	3	14
TB	112	92	78	46	201	527

Table 1: The calculated measures of the RDRT results

We have compared our results with the results of three other approaches. The first was developped using the *R-θ* *signature* [21] which presents a new shape descriptor based on Classical Radon transform, the second "*DCB"*[9] extracts buildings with reference to geodatabase and prior knowldge and the last method *"DRV"* [4] detects buildings with the help of photometric, geometric and morphological informations. The choice of these methods was guided by the similarity between their images characteristics applied on and ours.

methods	BER(%)	Exactness	Quality
DCB	94	0.903	0.855
DRV	91	0.940	0.824
R-θ Signature	83	0.962	0.808
RDRT	90	0.971	0.862

Table2: The results rates of DCB,DRV, *R-θ Signature and* RDRT methods.

Table2 shows that our method has a less buildings extraction rate than the DCB and DRV methods but this result can be improved if the quality of the contour image is perfectly performed since the RDRT process is closely related to the extraction contours results. Nevertheless, our method seems to be more efficient regarded to the quality and the exactness rates. In fact, the RDRT method tends to limit the number of the buildings partially extracted and the false alarms.

5. CONCLUSION

In this work, we have presented a new approach to characterize a rectangular object using the Radon transform and its application in buildings extraction. The results showed that our approach has really good performance in detecting rectangular building shapes especially in term of exactness and quality. In a further work, we ill focus on optimizing RDRT transform which is a time cosumming method and we will try to apply our work on other geometric shapes detection.

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