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Cellular Urban Descriptors of Lowland Urban Model

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Abstract
Shape analysis of city growth is an essential means to develop a comprehensive city plan and the key elements of shape analysis are shape descriptors. Recently, many cellular urban models have been developed including the special models for lowland cities. Shape descriptors are the indices used for output of such urban models. Shape descriptors play a very important role in model fitness, calibration, validation as well as interpretation of the model outcome. This paper proposes the usage of image features that are commonly used in the field of image processing and computer vision as urban shape descriptors.
The cellular urban descriptors can be classified into geometric and multi-scale features. The geometric urban descriptors related with the shape of the city or development cluster of the city can be computed based on connected component or boundary of the cluster. Multi-scale urban descriptors take into account the role of development index of each cell. Determination of each cellular urban descriptor is described using urban development terminology. Special urban model for lowland cities is clarified and relationships of urban descriptor are investigated.

Introduction

Shape analysis has a broad range of applications in urban planning and design, from urban spatial pattern, urban form and sprawl until landscape configuration. Evolution of the physical growth of cities has been shaped by geography, environment, socio-economic and political power of society. Classification of cities according to their various urban forms has always been an important influence on the way cities are planned and conserved. Similar types of urban forms may have similar characteristics that can be used for planning.

Shape analysis of city growth is also an essential means to develop a comprehensive city plan and the key elements of shape analysis are shape descriptors. To measure the urban sprawl and urban development, shape analysis is one of the main factors. For example, a bigger city may increase the average travel time to work for the residents and lower the quality of life of the city population in general. The measurement of the average travel time is directly related to the diameter of the city and the city development. Most of denser city populations and high land values happen in the city center rather than in other areas. The density and land value may be represented roughly by an urban development index. City diameter and urban development indices are few examples of urban descriptors.

Aside from common descriptors of development index and city diameter, fractal dimension has been proposed as urban descriptors in several papers [Batty (1991)]. Recently many urban models have been developed including the special models for lowland cities. All of these models have characteristics of using cellular grid array as the spatial basis. Shape descriptors play very important role in model fitness, calibration, validation as well as interpretation of the model outcome. The operation of a cellular grid array is reminiscent of a well-defined field in computer vision and image processing.

In all of shape analysis models, shape descriptors are the indices used for output of such urban models. Each model proposed one or two descriptors separately without any integration. Additional descriptors may be added at the cost of reliability and computational cost since they may come from different sets of data or defined separately from the original descriptors. In addition, the reason to select those descriptors is simply due to common practices. This paper proposes the usage of image features that are commonly used in the field of image processing and computer vision as urban shape descriptors.

The significant contribution of this paper is the integration approach of the determination of the cellular urban descriptors. Only a single assessment is needed to obtain all the descriptors. The proposed approach does not only reduce the computational cost of the descriptors such that all the cellular urban descriptors can be computed at each simulation time. It also improves the reliability and validity of the descriptors since they all come from a single source of data.

The paper is organized as follows. The next section describes the heart of this paper on determination of the urban cellular features which is divided into geometric and multi-scale features. After that a special urban model for lowland cities is explained briefly. The relationships of urban cellular descriptor were investigated from the numerical experiments and reported for demonstration purposes. Finally conclusions are drawn in last section

Urban Cellular Descriptors

We suggest the usage of image features that are commonly used in the field of image processing and computer vision as urban shape descriptors. Since we are dealing with a cellular urban model, it may be better to call them cellular urban descriptors. Determination of each cellular urban descriptor is described using urban development terminology.

The cellular features can be classified into two types: geometric features, and multi-scale features. The geometric features are related with the city shape characteristics (the connected component), while the multi-scale features are associated with the development index of the city. Each of these features can be measured over time.

Geometric Features

The geometric features are related with the shape of the city or development cluster of the city. The explanation below is related to the way the features are calculated. Except for the fractal dimension which is calculated for the whole city, the cellular features below are calculated for each development cluster of the city.

Connected component

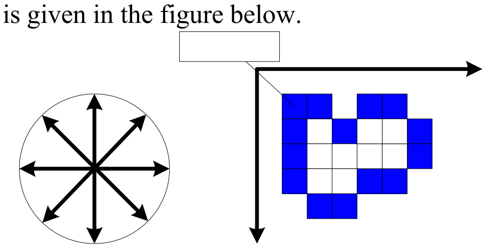
Based on the development cluster, the number of clusters and area of each development cluster are used as cellular features. The area of a development cluster A is the total number of developed cells in the cluster. Neighbor is defined as the adjacent cells, which are only at the first layer. Since development cluster is defined based on the adjacent neighbors, and urban simulation may have several clusters and some clusters may join up together (or split up under a negative development index). Newly developed cell which is not adjacent from its center of consideration will create a new development cluster consisting of a single cell. After some time, this single cell cluster may grow or be connected with other clusters and make a greater area.

Contour Following

The boundary of a development cluster is an internal digital contour which can be extracted using the contour following method. The boundary of a development cluster is the active zone of a growing cluster. Consequently, measurement toward the contour boundary of development cluster is a very important task. Several cellular features are measured based on the contour boundary of a development cluster.

Measuring the length of the contour boundary of a development cluster gives the perimeter of the cluster, P.

Scanning the city matrix to look for the developed cell and tracking the boundary of the development cluster will give the contour boundary. The tracking boundary of the cluster is called contour following. It is done by finding any cell on the edge of the development cluster and then track around successive cells on the edge, store the directional change (quantified at single cell step) required to follow the edge until the original starting cell is reached. The directional change of the contour is called *chain code*. Using the chain code, many cellular features can be computed directly, without necessity to reconvert the development cluster into an array format. Contour representation of development cluster is also fast to compute and reduces the amount of storage to represent the cluster boundary if we encode the directional change as a single array of chain code. The directional change is stored as number 0-7. Each code represents one step change in direction between adjacent developed cells. Example of a chain code for a simple object is given in the figure below.



We call the edge of the development cluster the *perimeter* or *surface* of this cluster. Representing the edge of development cluster as a close curve, we can measure the length of this boundary curve. The Perimeter of the development cluster can be acquired faster by chain code from the contour following, as suggested by Fairhurst (1988) as

$$P = CCode_{event} + CCode_{odd}\sqrt{2}$$

Where $CCode_{event}$ and $CCode_{odd}$ is the summation of event and odd chain code respectively. Change in step in direction 0, 2, 4, 6 are called even direction, while direction 1, 3, 5, 7 are the odd directions. Transition one unit of an even direction has 1 unit distance, while transition of 1 unit in odd direction corresponds to ◊2-unit distance.

Knowing the coordinate of the contour boundary, we can also compute the center of gravity of the development cluster as

$$c.g_x = \frac{\sum x}{A} \text{ and } c.g_y = \frac{\sum y}{A}$$

The center of gravity is the basis to compute the radius of the development cluster. Taking the development cluster as part of city cluster (or even the city as a whole), the center of gravity is a point representative of the cluster center.

Area and Perimeter

There are two approaches to derive the cellular features. One is based on a circular shape and another is based on a rectangular shape. Both approaches are presented in this section. Based on the area and perimeter of the development cluster, several cellular features can be derived. $\textit{Perimeter to area ratio} = \frac{P}{A}$ measures the compactness of the city. For a circle, the value is $4D^{-1}$. In later chapters we can see that this ratio has a very important role to measure the city growth.

$\text{Thinness ratio} = \frac{4\pi\,\text{A}}{\text{P}^2}$ is the index to measure the circularity of city shape. For a circle, the value of thinness ratio is one. Another similar way to measure circularity of city shape is through index $\text{Circularity} = \frac{\text{P}^2}{\text{A}}$, which is equal to 4 for a circle. Still another index for measuring thinness and circularity is called

$$\text{Thinness circularity ratio} = \frac{\text{P} - \sqrt{\text{P}^2 - 4\pi\text{A}}}{\text{P} + \sqrt{\text{P}^2 - 4\pi\text{A}}}$$

The value of thinness circularity ratio is one for a circle because the value of the square root is zero.

When we look for the equivalent of a circle diameter, we have an index

$$\text{Equi. circular diameter} = \sqrt{\frac{4A}{\pi}}.$$

The above derived cellular features are based on a circle as the basis shape. Russ (1999) proposes to use rectangle as the basis shape and called it fiber or ribbon shape, where the area is equal to length times the width and perimeter is equal to double summation of length and width. Then, the three indices below is the result

$$\text{Fiber length} = \tfrac{1}{4}\left(P - \sqrt{P^2 - 16A}\right)$$

$$\text{Fiber width} = \frac{\text{A}}{\text{Fiber length}}$$

$$\text{Fiber elongation} = \frac{\text{Fiber length}}{\text{Fiber width}}$$

Distances

The *diameter*, D, is measured as a maximum line chord connecting two points of the contour boundary. Hence, the diameter is the largest distance between the two points in a development cluster and the maximum line chord represents the major axis of the city shape. It does not necessarily mean that the maximum line chord will pass through the center of gravity.

A sequence of distances of contour boundary from the center of gravity is called a signature. The minimum signature represents the *minimum radius*, $r_{\min}$ while the *maximum radius* $r_{\max}$ is the maximum signature. The *mean radius*, r_{mean} is the summation of signature divided by the perimeter. It is measured as the average distance from the center of gravity to the contour boundary.

Deriving from the above distance based-features, and area, we can obtain many ratios such as

$\text{Elongation} = \frac{\text{r}_{\max}}{\text{r}_{\min}}$ which can also measure the process of growing or increasing in length of the city shape.

The complexity radius is defined as comparison between area and the average distance from the center of gravity. To make the index dimensionless, the distance is squared.

$$\text{r}_{\text{complex}} = \frac{\text{A}}{\text{r}^2_{\text{mean}}}$$

In the case of circle, the value of $r_{complex} = \pi$, is constant.

Taking a similar idea that area of a circle is $A = \frac{1}{4}\pi D^2$, we can define another index

$$\text{Roundness} = \frac{4A}{\pi D^2}$$

The value of the roundness index is 1 in case of a circle. Note that complexity radius and roundness derive from the same analogy of circular shape. Since the radius is measured from the center of gravity while the diameter does not necessarily pass the center of gravity, then the two indices are, in general, independent.

Curvature

When the boundary of a development cluster is represented by a contour curve, one of the extremely important concepts to express the local geometric nature of a curve is curvature. Curvature specifies how fast the tangent vector change its orientation along the curve, which can be obtained from a parametric curve $\left(x(t), y(t)\right)$ by

$$curvature(t) = \frac{\dot{x}(t)\ddot{y}(t) - \dot{y}(t)\ddot{x}(t)}{\left(\dot{x}^2(t) + \dot{y}^2(t)\right)^{3/2}}$$

The value of curvature can be positive, zero or negative indicating local concavity of the curve. When the curve is followed using a clockwise direction, the positive curvature indicates the concave portion of the curve, while negative curvature signify the convex section of the curve. Zero curvature is hinted at a straight line segment of the curve. Constant curvature represents an arc of a circle. Curvature is invariant to rotation, translation and reflection of the original curve, but it is varied by scaling.

Fractal Dimension

When the city boundary is determined, both in real world and in simulation, the shapes are not regular. Magnifying the contour, it becomes rough and tends to be fractal in shape, though not necessarily self similar. Fractal dimension may be used to describe the roughness of the city shape. Fractal dimension is the rate at which the perimeter of an object increases as the measurement scale is reduced (Russ, 1999). There are several ways to compute the fractal dimensions and they may not produce the same result. Thus, when we compare the city shape, it is important to have a consistent method. One of the most widely used methods to calculate fractal dimension is the box counting algorithm. The rough idea is to partition the matrix into square boxes size LxL and counting the number of boxes N containing at least a small portion of the developed cell. By altering the scale of the boxes' size, we can obtain a graph of Log N by log L and the tangent of the graph produces the fractal dimension (Costa and Cesar, 2001).

Multi-Scale Features

The above-mentioned geometric cellular features are connected with the shape of the city or the development cluster. The value of the development index of each cell was not considered. The focus of cellular features in this section, however, is in the role of the development index.

Maximum development index, ϖ is the simplest cellular feature related to the development index. It measures the highest development that can be reached within certain simulation time steps.

Let us define a histogram of development index. The bin represents the value of development index from 1 to maximum development index, ϖ . The value of the histogram is the *histogram probability* defined as the total number of cells that has the development index value equal to the bin value, $n\langle s(x,y)=i\rangle$, divided by the area of the city.

$$p_i = \sum_{i=1}^{\varpi} \frac{n\langle s(x,y)=i\rangle}{A}$$

The height of the histogram represents the relative frequency of how many cells have the value of the development index. Since the total number of cells is equal to the area of the city, the sum of all histogram probability from 1 to maximum development index is equal to one.

The *average development index* is defined as the total value of development index for the whole city divided by the city area, which can also be calculated using histogram probability as

$$\bar{s} = \frac{\sum_{i=1}^{A} s_i(x,y)}{A} = \sum_{i=1}^{\varpi} i.p_i$$

Considering the average development index as the first central moment, we can also take the second central moment, or the *variance of development index*

$$\mathrm{var}_s = \frac{\sum_{i=1}^{A} \left(s_i(x,y) - \bar{s}\right)^2}{A} = \sum_{i=1}^{\varpi} (i-\bar{s})^2 .p_i$$

then the entropy is calculated as

$$entropy = -\sum_{i=1}^{\varpi} p_i \log(p_i)$$

Cellular Urban Model for Low land Cities

Lowland cities are usually located on flat ground with a fluctuating water level. Flood and storm water are commonly regarded as the most frequent and widespread natural hazard for such places. In connection with urban development, the improvement regulation of land use and zone management is one of the most comprehensive and long-term solution for the hazard mitigation. The overall aim is to reduce the risks involved in the present occupation of flood-prone land and to deter further invasion of such area [Smith and Ward (1998)]. To make such land use and zone management effective, an urban development model is needed. These models' factors are usually taken from some kind of descriptors of the model, be it from surveys or from the physical characteristics of the urban development. This paper presents the descriptors based on some image processing technique to be able to determine the shape of the city.

Numerous papers have been done on urban modeling using cellular automata; the novelty of this paper is the use of image processing techniques to generate the urban descriptors to define the urban model. Moreover, an urban model for lowland cities has not yet been developed; this is another uniqueness of this paper. The next section presents the case study used to get the urban cellular descriptors described in the paper. A comparison of urban descriptors between the real image and the raster image is also done.

Case Study

To be able to calculate the cellular urban descriptors, several aerial photographs of the Iwaki Newtown in Fukushima, Japan was used.

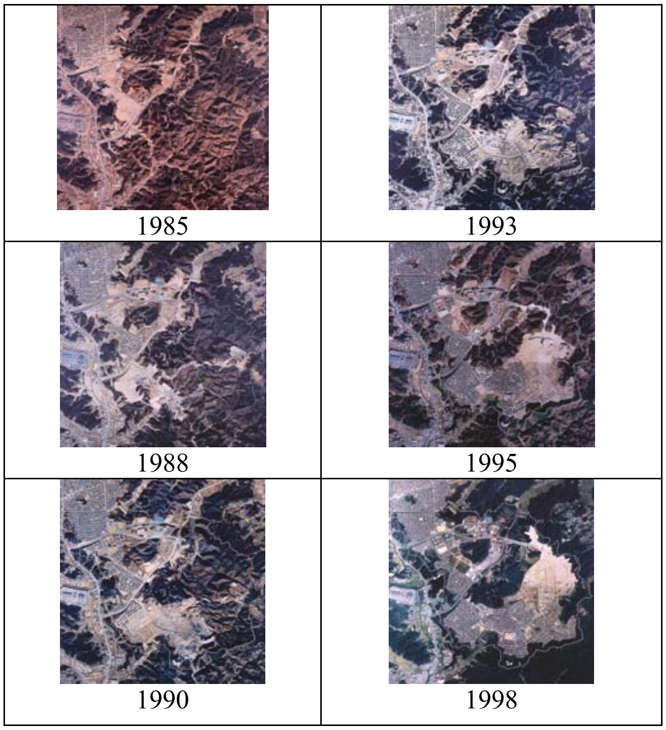


Figure 1. Aerial Photographs of Iwaki Newtown from 1985 – 1998

Figure 1 shows the aerial photographs of the Iwaki New town from 1985 to 1998. It can be seen that development of the Iwaki Newtown grew in different stages as shown in the density of the figures from 1985 to 1998.

The next figure shows development contours captured to get the cellular descriptors. A computer program was made to be able to capture the contours from the aerial photographs to the computer. It can be seen that about 95% of the image was captured into the computer using the developed computer program. The black color shows the developed area while the green color shows the undeveloped area for the image in question. It can be seen from the raster images that development slowly took place in the area. Development was from the north going to the south as well as from the southwest going to the east north east direction.

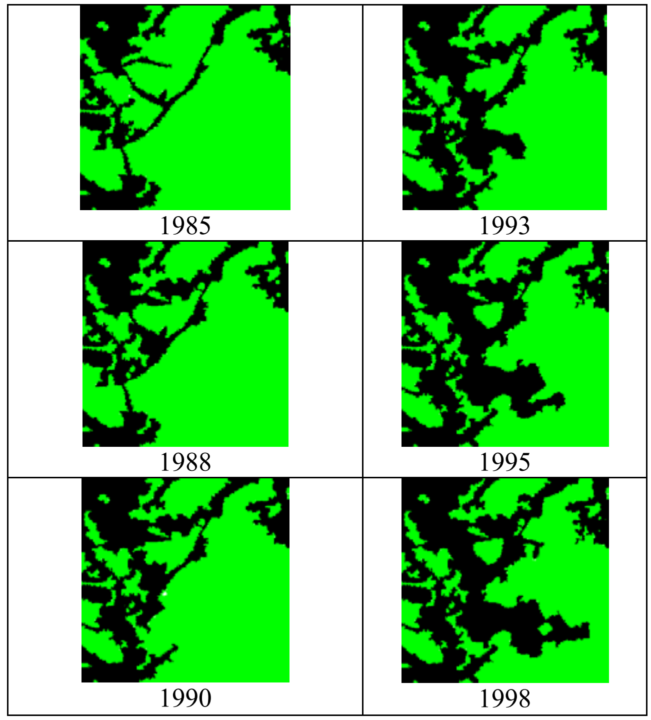


Figure 2. Contour shape captured from the aerial photograph to the computer.

The next step in the case study was the calculation of the cellular urban descriptors based on the raster images. The calculated urban descriptors are shown in Table 1. The computation of the cellular descriptors was done using the models in the previous section. It can be seen that all the indices of a city shape are obtained for each analysis year. If we see the first row of the table, the area in pixels, it can be seen that the developed area in Iwaki Newtown increased during the six year period. It can also be visually verified in the aerial photographs shown in Figure 1. Multi-scale cellular features are not computed due to lack of actual data.

To have an objective view of the calculated urban descriptor and the actual shape index, the calculated area and the actual developed area was compared. The units of the area for the actual new town (ha) were different from that of the calculated area (in pixels), so a converter was estimated using ordinary least square method to be able to compare the two areas. Figure 3 shows the comparison of the developed area and the area descriptor. It can be seen that the area descriptor has only overestimated the original area by less than 10%.

Table 1.The Urban Cellular Descriptors from 1985-1998

Year	1985	1988	1990	1993	1995	1998
Area (pixels) :	16989	20013	22646	25668	29447	30849
Perimeter (Contour) :	2286	1887	2062.43	2336.98	2602.74	2739.8
Fractal Dimension:	1.75	1.79	1.822	1.81	1.819	1.827
Aspect ratio	18.03	6.17	7.924	10.75	24.644	57.204
Bending Energy :	666.	540	614.75	680	775.875	819.625
Center of gravity (contour) X:	71	73	74.78	80.84	90.78	96.59
Center of gravity (contour) Y:	117	121	131.54	135.74	138.52	137.88
Circularity:	322	164	178.937	206.843	233.789	246.365
Compactness :	0.14	0.08	0.087	0.089	0.09	0.09
Complexity radius :	2.71	2.93	3.318	3.811	4.047	4.135
Elongation:	0.01	0.02	0.023	0.02	0.018	0.017
Equiv. circular diameter:	143.	166.11	173.974	183.354	192.077	196.963
Fiber length:	14.38	23.55	23.59	23.05	22.66	22.62
Fiber width:	1128	920.16	1007.62	1145.44	1278.71	1347.28
Maximum radius :	187	188.79	194.53	192.98	188.02	183.63
Mean curvature:	0.39	0.38	0.404	0.396	0.405	0.408
Mean radius :	77.25	85.88	84.646	83.236	84.613	85.84
Min radius :	10.41	30.56	24.55	17.95	7.63	3.21
Roundness:	0.18	0.24	0.269	0.299	0.328	0.345
Thinness Circular Ratio:	2285	1886.94	2061.937	2336.487	2602.25	2739.304
Radius of Gyration:	11905.	10518	10156	9803	9600	9861

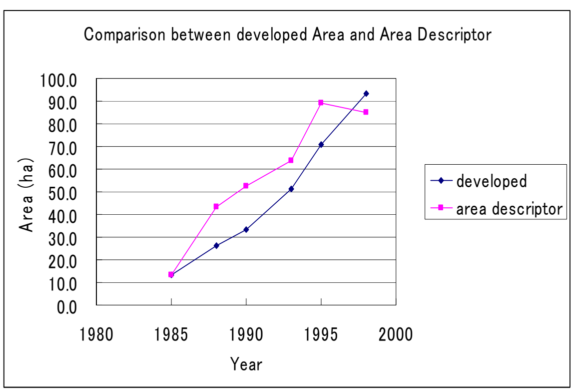


Figure 3. Comparison between the Developed area and the Area descriptor

Conclusion

We have proposed an integrated approach to determine cellular urban model descriptors. They have been used intensively in the field of image processing and computer vision but not as urban shape descriptors. Our proposed approach needs only single scan to get all the descriptors, which significantly reduce the computational cost and improve reliability of the descriptors. The determination of the urban cellular descriptors has been clarified and the relationships of urban cellular descriptor through the numerical experiments of lowland urban model were reported to demonstration the integration approach.

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