

# Assessment of New Building Recognition Technique Based on Monte Carlo Simulation from LIDAR Data

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## Commission I, WG I/2

**KEY WORDS:** Building Representation, Building Description, Building Recognition, MCS

### ABSTRACT:

Building can be classified into many categories and/or classes which can be identified efficiently from images. The classes can include usage, types, shapes, or any other specific categories. The classification of buildings to predefined classes is called building recognition. This is usually based on the fact that building consumes region in the image and these region boundaries can be used to process and create building descriptors to be used in a building libraries to be utilized in the classification procedure. These building descriptors parameters are then used in creating the libraries to be used in the recognition technique which can be represented in both the spatial and frequency domains.

This research paper will consider building boundary as building representative and use Monte Carlo Simulation (MCS) capabilities for investigating building descriptors. MCS is used to generate random variables with pre-specified distribution to identify the boundary of the region of interest through identifying the boundary of this building or area.

The building boundary can be described by the ratio between its inside generated random values and total generated random values in the boundary image. This research concentrates on investigation the optimum number of generated random variables to be used as building descriptors for buildings recognition. This descriptor will identify the building regardless of its orientation or scale. This means that the descriptor will not be affected or sensitive to the direction or the scale of the building and therefore it can be applied to any type of images without any geometrical corrections. This non sensitivity of the proposed MCS descriptor is the motivation for the assessment of this technique for building recognition. In the paper two different classification techniques will be used for the assessment of this new descriptor for building recognition. The first one is the minimum distance classifier. The second is the optimum statistical classifier that will produce the Probability Density Function (PDF) of building recognition.

The assessment methodology for testing this recognition technique will be conducted by using Sequential Monte Carlo Simulation (SMCS) based on Bayes theorem to get the probability density function. Conclusions and recommendations are given with respect to the suitability, accuracy, and efficiency of this method.

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## 1. INTRODUCTION

Buildings, trees and roads are the most popular features to be extracted from LIDAR data. The exact identification of objects can be determined with the aid of knowledge database that contains most probable objects existing in the application field [Ruel et al., 2007]. Object recognition is one of these database approaches that has many applications especially in military field, such as live monitoring change detection for targets or features [Butkiewicz et al, 2007]. Object recognition is based on building specific descriptors and having an efficient classification technique. Objects can be described in both spatial and frequency domains. There are many classification techniques that can be used in object recognition such as minimum distance classifier, and Bayes classifier [Gonzalez et al., 2004].

Monte Carlo Simulation (MCS) is one of the classification techniques that can model many processes by using random numbers [Huber, 1997]. Srivastava; (2000) succeeded in recognizing and identifying military objects from LIDAR data based on MCS recognition technique. Kim et al.; (2005) presented an effective 3-D target recognition technique based on MCS. Hundelshausen and Veloso; (2007) introduced a new approach called Active Monte Carlo Recognition (AMCR). The algorithm is not simple and based on Sequential Monte Carlo Simulation (SMCS). The SMCS divides the recognition process into two steps, prediction step and updating step. The updating step uses the Bayes theorem for calculating the posterior density function for the recognition process. These techniques are sophisticated and time consuming. This research paper introduces an object recognition technique based on MCS using random number generators. This technique is applicable for all object types. This paper takes buildings as objects of interest for the assessment of the proposed recognition technique.

## 2. OBJECT RECOGNITION

Object recognition is the process of classification of objects to predefined class or classes. Object recognition process consists of

three main sub-processes. First, is object representation, second process is object description, and last is object classification.

### 2.1 Object Representation

The object can be represented by its external characteristics and/or internal characteristics [Gonzalez et al., 2004]. Object can be considered as region; with the external characteristic of the region as the region boundary and; the internal characteristic of the region as the region texture. The texture is formed by pixels properties that form the region as gray levels. The gray levels are height value for the range image and intensity values for the intensity image. Texture representation is critical when dealing with library of reference objects and object with different texture characteristics. The similarity of the gray level characteristics is important for object matching. The object of interest has to have the same texture type as the library objects. Then the best way to represent the object is the object boundary. The object boundary can be calculated as binary image that contains only foreground pixels that form the object boundary and the remaining pixels are the background.

### 2.2 Object Description

As mentioned before the object can be represented by boundary and texture. The object parameters are the parameters that describe the object representatives. They are called object descriptors. The boundary can be described by its diameter, area, signature, major axis, minor axis, and basic rectangle. These descriptors are called boundary spatial domain descriptors. The texture can be described through two main descriptors, statistical moments and moment invariant descriptors [Gonzalez et al., 2004]. The object descriptors should not be sensitive to neither scale nor orientation since an object of interest may be chosen from image with arbitrary scale and orientation.

### 2.3 Object Classification

There are two main trends for classifying an object. The first one is based on mathematical

calculations between two or more parameters. The parameters are the vectors for object descriptors. This is called decision theoretic methods. The second one is based on similarity computation between two or more parameters. The parameters are the vectors descriptors but in this case they are in symbolic forms. This is called structural recognition [Gonzalez et al., 2004]. The most commonly used methods are minimum distance classifier and optimum statistical classifier (Bayes classifier) methods. These two methods are based on decision theoretic methods algorithm. This is based on calculating the decision functions. The decision functions can be represented as  $d_1(x), d_2(x), d_3(x), \dots, d_W(x)$  where  $x$  is the object vector with dimensions  $n \times 1$ ,  $W$  is the total number of classes and the decision functions, and  $d^s$  are the decision functions. The decision functions represent the relation between the vector of an object of interest and the vectors of different classes.

### 2.3.1 Minimum Distance Classifier

This method tends to assign objects to the corresponding pattern class by the minimum distance classifier matching. Equation 1 represents the mathematical model for calculating the decision functions of minimum distance classifier method [Gonzalez et al., 2004].

$$d = \text{sqrt}(\text{sum}(\text{abs}(VB - \text{repmat}(X, p, 1)).^2)) \quad (1)$$

Where:  $VB$  : the matrix containing the class vectors (population matrix) of dimension  $n \times p$

$X$  : the vector of object descriptors of dimension  $n \times 1$

$p$  : the total number of classes

$d$  : the distance vector (decision function) of dimension  $p \times 1$

$\text{repmat}$ : indicating to the replication of object vector to match with population matrix

$X$  is classified to the class of the vector that is corresponding the minimum distance. The decision functions for this method are obtained for every object descriptor type.

### 2.3.2 Optimum Statistical Classifier

This method is called the Bayes classifier. This method merges all descriptors for each class and for the object of interest to calculate mean value and covariance matrix for each item. These parameters are used to calculate the decision function for the object of interest relating to each class. Equation 2 illustrates the mathematical model of decision function calculation [Gonzalez et al., 2004].

$$d_j(x) = P(x/w_j)P(w_j) \quad (2)$$

Where:  $j$  : 1, 2, ...,  $W$

$P(x/w_j)$  : the PDF of the pattern vectors of class  $w_j$

$P(w_j)$  : the probability (scalar) that class  $w_j$  occurs.

The PDF of the pattern vectors is assumed to follow the Gaussian distribution, and then  $P(x/w_j)$  can be calculated by using Equation 3 [Gonzalez et al., 2004].

$$P(x/w_j) = \frac{1}{(2\pi)^{n/2} |C_j|^{1/2}} e^{-\frac{1}{2}[(x-m_j)^T C_j^{-1}(x-m_j)]} \quad (3)$$

Where:  $m_j$  : the mean vector of the pattern population of class  $w_j$

$C_j$  : the covariance matrix of the pattern population of class  $w_j$

For each class the population matrix is containing all the corresponding vectors of class descriptors.

The logarithmic function is monotonically increasing, and then  $\ln$  is used to find the decision function (Equation 4) [Gonzalez et al., 2004].

$$\begin{aligned} d_j(x) &= \ln [P(x/w_j)P(w_j)] \\ d_j(x) &= \ln P(x/w_j) + \ln P(w_j) \\ d_j(x) &= \ln P(w_j) - \frac{n}{2} \ln 2\pi \\ &\quad - \frac{1}{2} \ln |C_j| \\ &\quad - \frac{1}{2} [(x - m_j)^T C_j^{-1}(x - m_j)] \end{aligned} \quad (4)$$

The value  $(\frac{n}{2} \ln 2\pi)$  is constant, so it can be removed, and then the Equation 4 can be reduced to Equation 5 [Gonzalez et al., 2004].

$$d_j(x) = \ln P(w_j) - \frac{1}{2} \ln |C_j| - \frac{1}{2} [(x - m_j)^T C_j^{-1} (x - m_j)] \quad (5)$$

The object is classified to the class that gives the maximum decision function.

### 3. MONTE CARLO DESCRIPTORS

This research will assess the efficiency of new spatial domain descriptors based on MCS. Random values will be generated inside the boundary image. These random values will have a uniform distribution. This distribution will be controlled by Probability Density Function (PDF) as shown in Equation 6 where  $a$  and  $b$  are the distribution parameters. These parameters are used for calculation the mean and variance (Equation 7) [Gonzalez et al., 2004].

$$P_z(z) = \begin{cases} \frac{1}{b-a} & \text{if } a \leq z \leq b \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

Where:

$$m = \frac{a+b}{2} \quad (7)$$

$$\sigma^2 = \frac{(b-a)^2}{12}$$

Random values will be segmented into two groups. The first group is the random values tlocated inside the object boundary. The second group is the total generated random values. The ratio between the number of random values inside the object boundary and the number of all generated random values will represent the ratio of object area with respect to the total area of the image [Leclercq V., 2007]. The number of random values inside the boundary and the ratio will be used as boundary descriptors. This is called MCS descriptors.

### 4. LIBRARY OF CLASSES

This research uses building as a study object as a first step to evaluate the new recognition technique. LIDAR data introduces two types of images; range image that based on height information of LIDAR footprint and intensity image that based on the intensity of LIDAR footprint [Al-Durgham, 2007]. Figure 2 and Figure 2 show the intensity and height images of the area of interest. Selected buildings were chosen from the height image, each building is assumed to represent a separate class. The classes are the buildings with different shapes. The recognition technique is applied to classify each building to its correct class. Figure 3 shows the selected buildings that form the classes' library.

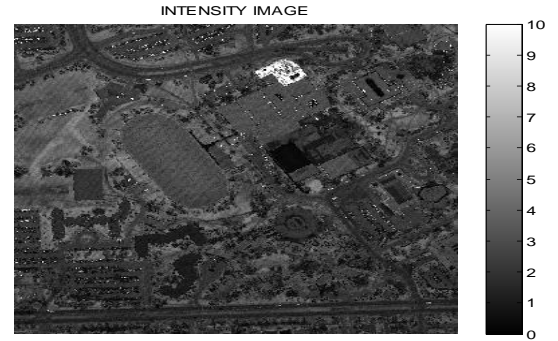


Figure 1: The Intensity Image

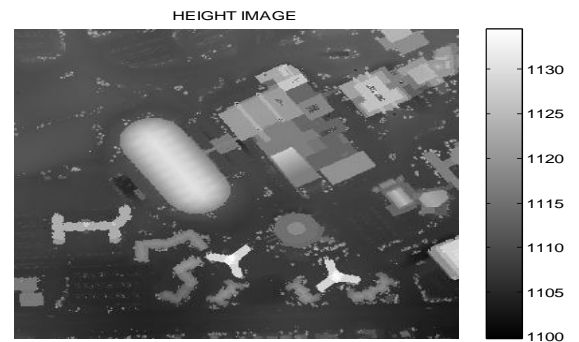


Figure 2: The Height Image

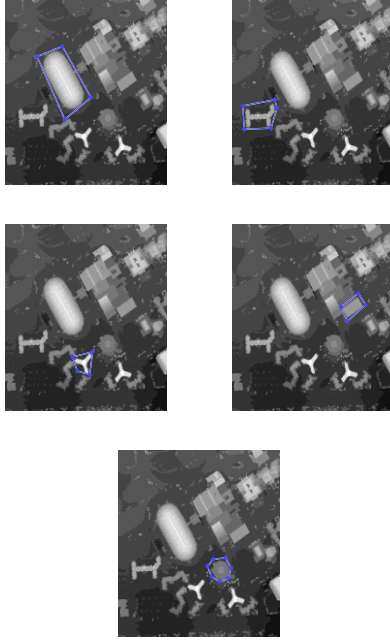


Figure 3: The Selected Buildings

#### 4.1 Building Representation

The selected buildings are represented by their boundaries (Figure 4).

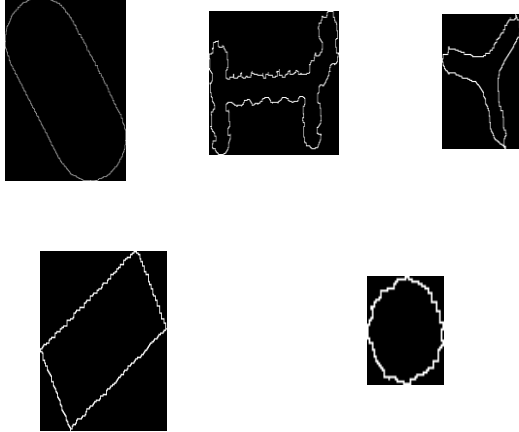


Figure 4: Buildings' Boundaries

#### 4.2 Building Descriptor

Each building boundary is described by two different descriptors based on MCS. The first descriptor is one value for each building. This descriptor is equal to the ratio between the number of generated random values inside the building boundary and the number of total generated random values in the boundary image. This research fixes the total number of

generated random values for each building related to the boundary image dimension for each building (Equation 8).

$$NRAND = M * N/2 \quad (8)$$

Where:  $M, N$  : Boundary image dimension

Table 1 shows the Monte Carlo Descriptors (MCD) for each building. These descriptors form the library of buildings related to the first type of MCD. This library is consisting of one vector.

Table 1: First Type Monte Carlo Descriptors

Building	B1	B2	B3	B4	B5
Ratio	0.4632	0.2672	0.2311	0.3777	0.5878

The total number of generated random values is changed for each building to generate the second type of MCD (Equation 9).

$$NRAND = M * N/L \quad (9)$$

Where:  $L$  : Depend on length of first vector

This descriptor contains many vectors each vector with different length. Equation 10 represents the relation between the lengths of the vectors.

$$Vec_{Len} = Vec_{len-1} + 1 \quad (10)$$

Where:  $Vec_{Len}$  : the length of current vector  
 $Vec_{Len-1}$  : the length of previous vector

Each vector contains the MCD from  $L$  equals two to  $L$  equals the length of first vector plus one. Tables from Table 2 to Table 6 show the second type of MCD for library buildings.

Table 2: Second Type MCD for B1

V1	V2	V3	V4	V5
0.4651	0.4622	0.4663	0.4650	0.4668
0.4974	0.5036	0.5048	0.5048	0.5007
0.5177	0.5252	0.5193	0.5194	0.5191
0.5347	0.5355	0.5354	0.5371	0.5392
0.5418	0.5460	0.5478	0.5435	0.5415
	0.5439	0.5508	0.5490	0.5474
		0.5505	0.5571	0.5574
			0.5503	0.5518
				0.5658

Table 3: Second Type MCD for B2

V1	V2	V3	V4	V5
0.2642	0.2628	0.2631	0.2591	0.2607
0.2866	0.2819	0.2836	0.2876	0.2861
0.2944	0.2917	0.2921	0.2933	0.2964
0.2928	0.3054	0.3076	0.3067	0.2969
0.3033	0.3177	0.3076	0.3048	0.3057
	0.3058	0.3065	0.2993	0.3110
		0.3182	0.3125	0.3112
			0.3146	0.3143
				0.3026

Table 4: Second Type MCD for B3

V1	V2	V3	V4	V5
0.2293	0.2351	0.2343	0.2296	0.2329
0.2617	0.2348	0.2506	0.2417	0.2590
0.2557	0.2655	0.2552	0.2585	0.2541
0.2654	0.2532	0.2567	0.2755	0.2612
0.2742	0.2488	0.2717	0.2584	0.2680
	0.2795	0.2542	0.2761	0.2824
		0.2872	0.2638	0.2810
			0.2749	0.2867
				0.2803

Table 5: Second Type MCD for B4

V1	V2	V3	V4	V5
0.3846	0.3782	0.3798	0.3826	0.3813
0.4095	0.4143	0.4106	0.4180	0.4095
0.4209	0.4281	0.4215	0.4318	0.4316
0.4274	0.4346	0.4300	0.4356	0.4492
0.4474	0.4311	0.4689	0.4563	0.4400
	0.4498	0.4444	0.4458	0.4606
		0.4488	0.4652	0.4656
			0.4505	0.4565
				0.4641

Table 6: Second Type MCD for B5

V1	V2	V3	V4	V5
0.5488	0.5478	0.5671	0.5565	0.5478
0.6304	0.5594	0.5812	0.5522	0.5899
0.6686	0.6145	0.6300	0.6415	0.6261
0.6087	0.6208	0.6498	0.6498	0.6546
0.6406	0.7159	0.6290	0.6087	0.6522
	0.5952	0.6831	0.6628	0.6763
		0.6029	0.6377	0.6879
			0.6739	0.6696
				0.6908

These descriptors form the library of buildings related to the second type of MCD.

## 5. BUILDING RECOGNITION

Figure 5 shows the building recognition algorithm based on MCD.

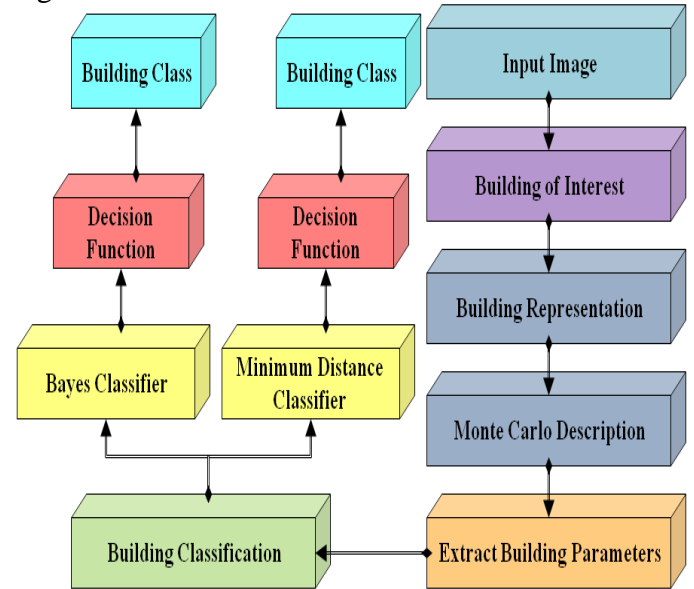


Figure 5: Building Recognition Algorithm

### 5.1 Input Image

The input image is prepared for this project from the height image of the study area after changing the geometric characteristics by increasing the image scale. The scale parameters is different in X and Y directions. The image of the study area is of size 1200 x 1200. The input image is of size 2399 x 1800 after increasing the image scale by scaling factor equals one and half in X direction and two in Y direction (Figure 6).

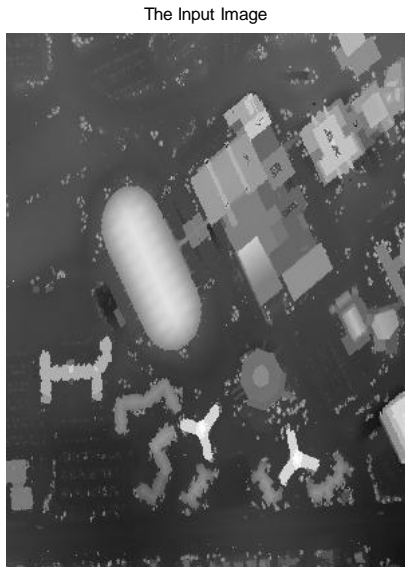


Figure 6: The Input Image

## 5.2 Recognition Results

The recognition technique is applied for all five buildings as shown in section 4. This process is repeated by using two different MCD with two different classification techniques (minimum distance classifier and Bayes classifier).

### 5.2.1 Minimum Distance Classifier Results

The following figures from Figure 7 to Figure 11 show the recognition results for each building using minimum distance classifier technique and first type of MCD. The building of interest in each step is recognised to the class that gives a minimum decision function.

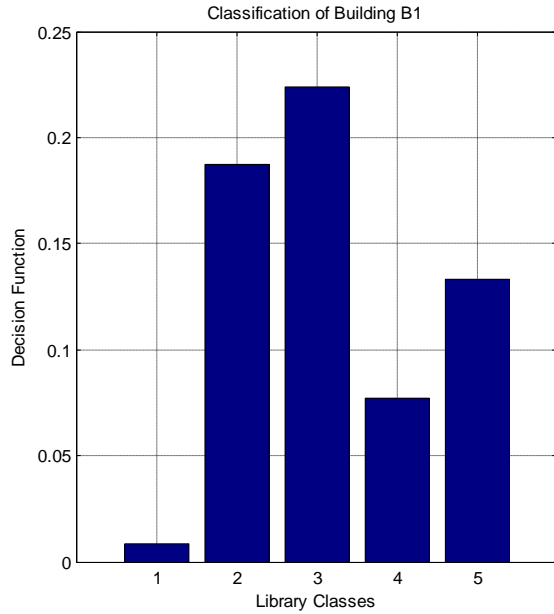


Figure 7: Recognition of First Building MCD1

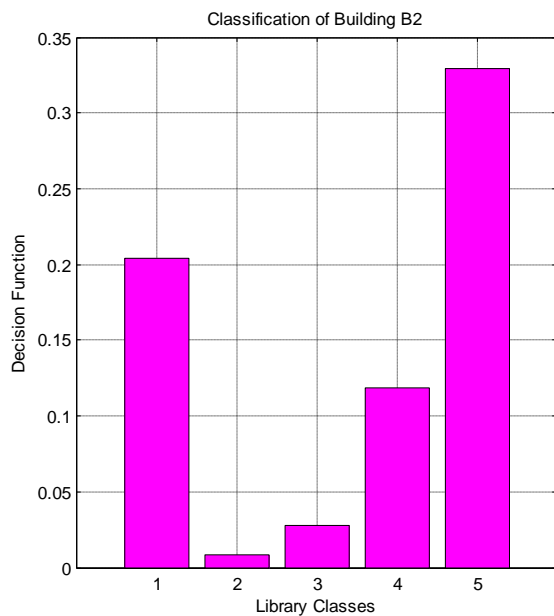


Figure 8: Recognition of Second Building MCD1

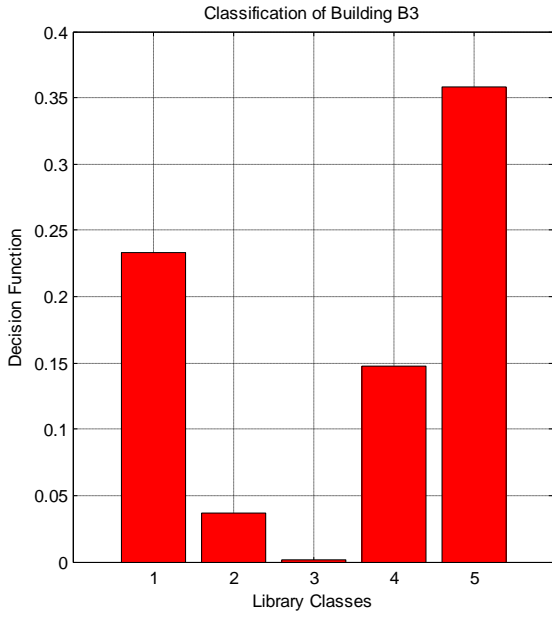


Figure 9: Recognition of Third Building MCD1

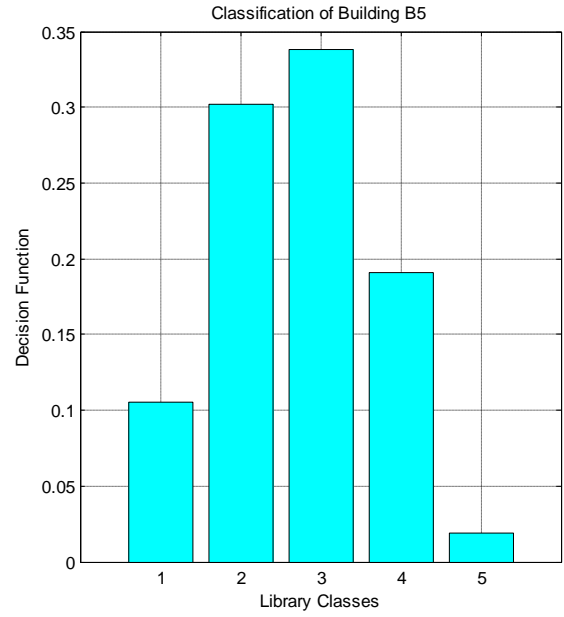


Figure 11: Recognition of Fifth Building MCD1

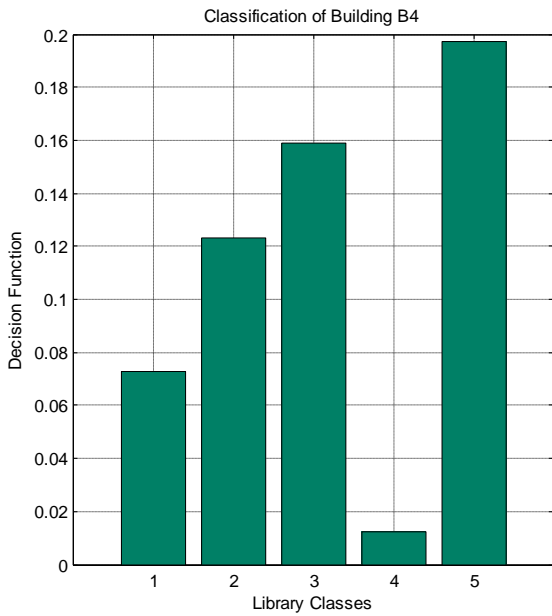


Figure 10: Recognition of Fourth Building MCD1

The following figures from Figure 12 to Figure 16 show the recognition results in case of second type of MCD using minimum distance classifier technique.

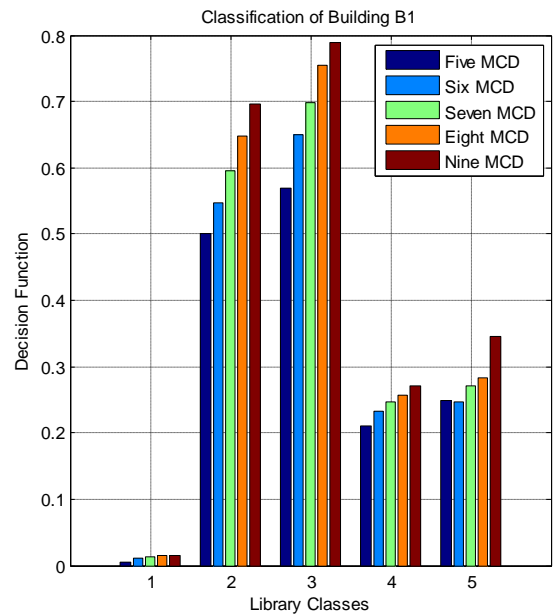


Figure 12: Recognition of First Building MCD2



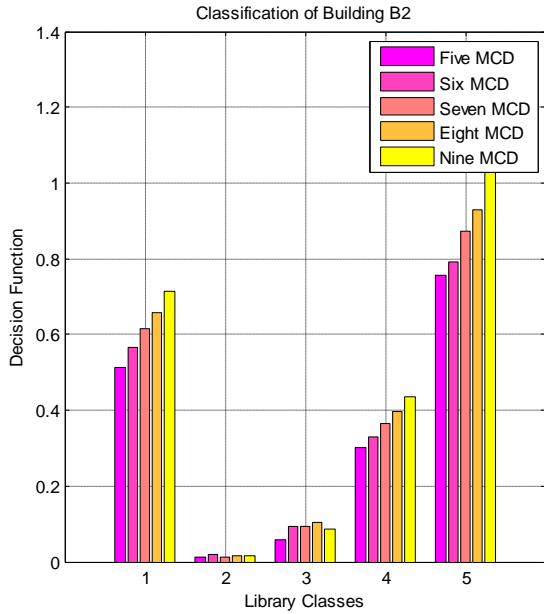


Figure 13: Recognition of Second Building MCD2

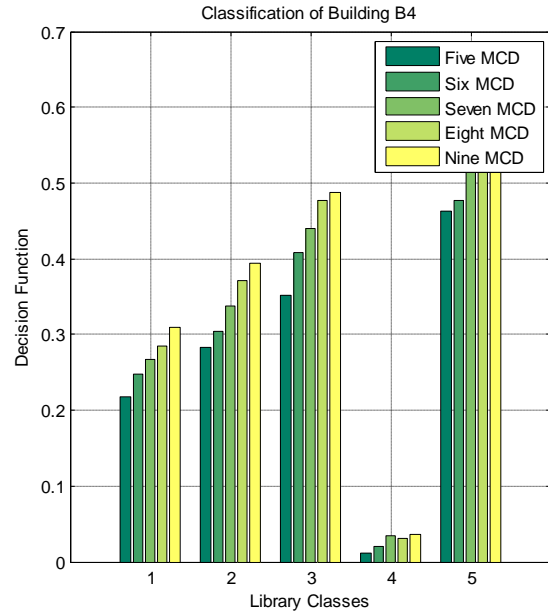


Figure 15: Recognition of Fourth Building MCD2

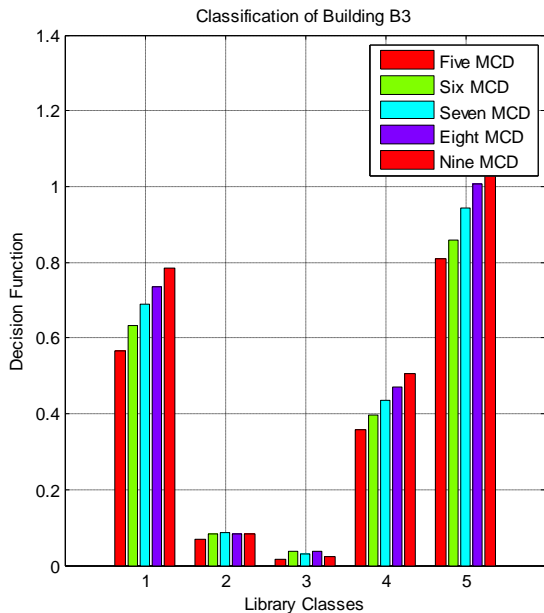


Figure 14: Recognition of Third Building MCD2

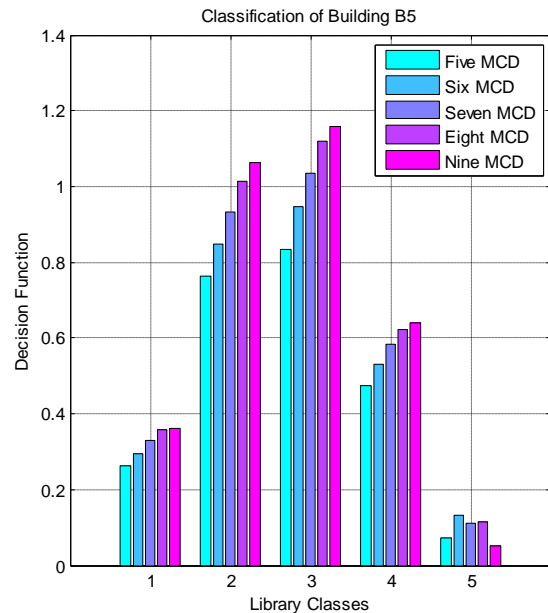


Figure 16: Recognition of Fifth Building MCD2

### 5.2.2 Bayes Classifier Results

Bayes classifier is used only when there are many object descriptors available as mentioned in section 2.3.2 it merges object descriptors. Then, it can be used with the second type of MCD since in this case MCD for each building are composed of five descriptors. The following figures from Figure 17 to Figure 21 show the recognition results for selected buildings. The

building of interest is recognised to the class that gives a maximum decision function.

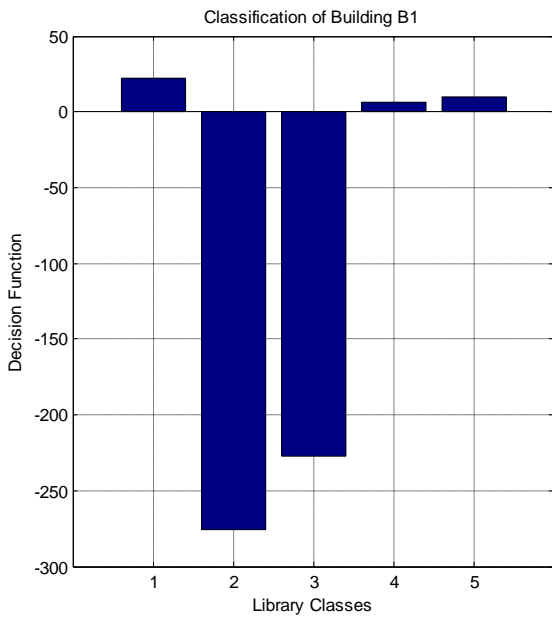


Figure 17: Recognition of First Building

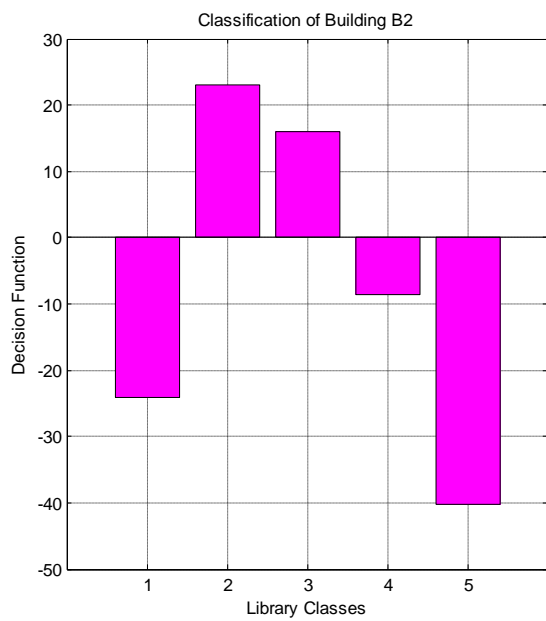


Figure 18: Recognition of Second Building

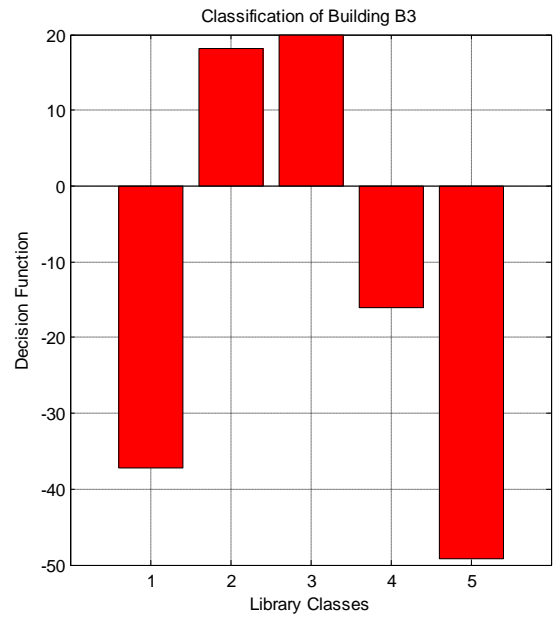


Figure 19: Recognition of Third Building

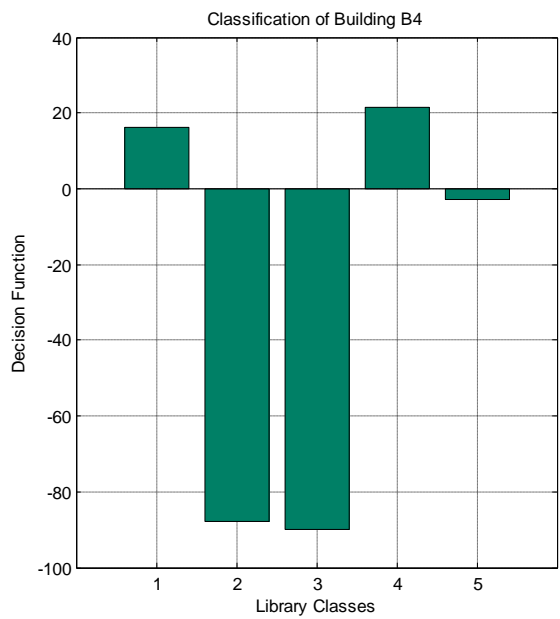


Figure 20: Recognition of Fourth Building

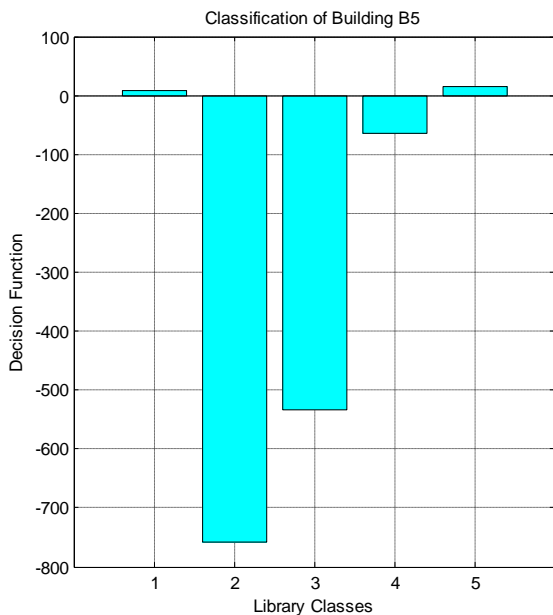


Figure 21: Recognition of Fifth Building

## 6. SUMMARY AND CONCLUSIONS

Monte Carlo Simulation (MCS) succeeded in modelling building descriptors. Monte Carlo Descriptors (MCD) are based on random number generators with specific distribution function, then they are considered as the simplest way to describe buildings. MCD describe the building regardless the scale of the building image.

MCD combined with minimum distance classifier technique can form an effective new building recognition technique as shown in section 5.2.1. These techniques succeeded in recognize all buildings of interest to their correct classes. The recognition process succeeded with using two different classification techniques as shown in section 5. Then MCD are considered as efficient building descriptors.

This research paper introduced and assessed the new efficient, suitable and accurate recognition technique based on Monte Carlo Simulation descriptors.

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