Introducing An Efficient Set of High Spatial Resolution Images of Urban Areas to Evaluate Building Detection Algorithms

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***Abstract*—The present work aims to introduce an efficient set of high spatial resolution (HSR) images to evaluate building detection algorithms more fairly. The introduced images are chosen from two recent HSR sensors (QuickBird and GeoEye-1) and based on several challenges of urban areas encountered in building detection such as diversity in building density, building dissociation, building shape, building size, building alignment, building roof color, building height, and imaging angle. To practically examine the proposed dataset, three-building detection algorithms with different strategies are employed. The results imply the proposed dataset can be helpful to more fairly evaluate each algorithm, so that it indicates where the algorithm can be efficient and successful and where may be encountered with the problems in detecting buildings in urban areas.**

***Keywords*—remote sensing, high spatial resolution, building detection, evaluation, urban area.**

I. Introduction

The recent remote sensing satellite sensors such as QuickBird, OrbView, and the latest GeoEye-1 can provide high spatial resolution (HSR) images [1]. In HSR images, urban objects such as roads, vegetation, green spaces, bare lands, water bodies, and buildings can be found largely. Detecting these objects especially building regions has important applications such as urban mapping and planning, map updating, 3D virtual modeling, disaster management, and change detection [2].

In the recent studies, many diverse algorithms have been proposed to detect buildings from HSR images ([1]–[13]). According to Table I, some different challenges focused on buildings have been encountered during evaluation of the algorithms e.g. diversity in building density ([3]–[7]), building alignment ([3], [4], [5], [7]), building dissociation ([2], [3]), building shape ([1], [2], [3], [6], [7], [8], [9], [10], [11]), building size ([1], [2], [3], [7], [8], [9],[10], [11], [12]), building color ([1], [3], [8], [9], [10], [12], [13]) and building height ([1], [2], [3], [7], [13]). Some of them have used a few images having one or two challenges (e.g. [4], [5], [12], [13]).

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However, all these challenges were not considered together in the above studies. Accordingly, an important question arises whether a low-diverse dataset is solely proper for fairly evaluation of a building detection algorithm.

So, this paper aims to introduce an efficient set of HSR images focused on the challenges of building detection in urban areas in order to more fairly evaluate the building detection algorithms. Based on the aforementioned challenges i.e. building density, alignment, dissociation, shape, size, color and height, the images introduced in this paper are chosen from three different urban areas i.e. the cities of Tehran, Isfahan, Ankara, and two recent HSR sensors, QuickBird and GeoEye-1. In addition, an oblique image is included in this dataset.

TABLE I
DIFFERENT CHALLENGES FOCUSING ON BUILDING CONSIDERED IN RECENT STUDIES

Challenges	Density	Alignment	Dissociation	Shape	Size	Color	Height
[1]	✗	✗	✗	✓	✓	✓	✓
[2]	✗	✗	✓	✓	✓	✗	✓
[3]	✓	✓	✓	✓	✓	✓	✓
[4]	✓	✓	✗	✗	✗	✗	✗
[5]	✓	✓	✗	✗	✗	✗	✗
[6]	✓	✗	✗	✓	✗	✗	✗
[7]	✓	✓	✗	✓	✓	✗	✓
[8]	✗	✗	✗	✓	✓	✓	✗
[9]	✗	✗	✗	✓	✓	✓	✗
[10]	✗	✗	✗	✓	✓	✓	✗
[11]	✗	✗	✗	✓	✓	✗	✗
[12]	✗	✗	✗	✗	✓	✓	✗
[13]	✗	✗	✗	✗	✗	✓	✓

The proposed dataset should be practically examined using different building detection algorithms. In this paper, we test three recent diverse algorithms which strategies are as follows, respectively: 1) the use of spectral indices, clustering, and morphology; 2) the use of clustering and segmentation, and 3) object-based analysis. They require several key parameters to run. However, tuning the parameters is not the aim of this paper. During the evaluation by the proposed dataset, it can be checked where three algorithms are successful or failed to solve the challenges. Accordingly, a mutual comparison of them will also be feasible.

The paper is continued as follows: Next section introduces the efficient set of HSR images that are chosen based on the aforementioned challenges. In section 3, the different algorithms are implemented on the dataset. In this section, two relative metrics are provided to indicate the degree of relative efficiency and relative reliability of the algorithms. The results imply to the high importance of the proposed dataset as an efficient dataset to more fairly evaluate a building detection algorithm. Section 4 is the conclusion of the paper.

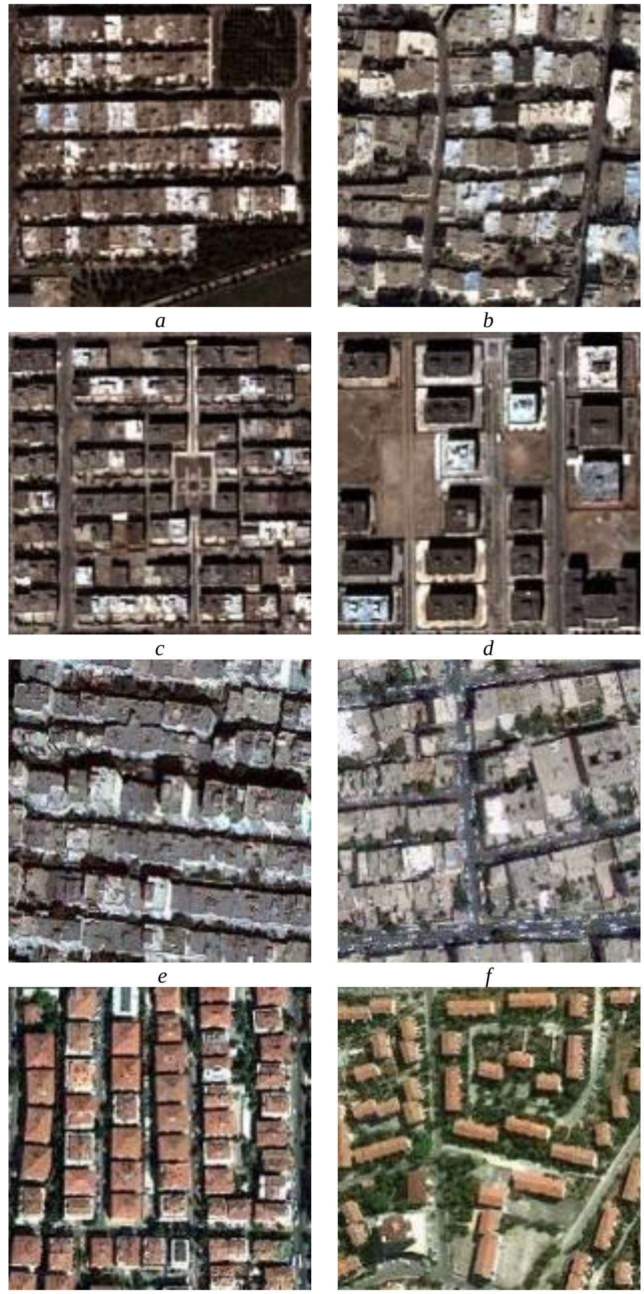
II. Introducing An Efficient Set of HSR Images

Eight regions which are chosen from different urban areas and different recent sensors are shown in Fig. 1a to 1h. They can be downloaded at http://hsrimagery.webs.com/. The first four regions (regions A to D) are the pan-sharpened QuickBird images (0.6 m resolution) and region E is the pan-sharpened GeoEye-1 image (0.5 m resolution at off-nadir mode) of the city of Isfahan. Region F is the pan-sharpened GeoEye-1 image (at nadir mode) of the city of Tehran. Finally, regions G and H are the pan-sharpened QuickBird images of the city of Ankara.

TABLE II
Categorizing Basic Challenges Focusing on Building in the Proposed Dataset

Basic Challenges		Regions
1) Building Alignment	Regular Alignment	A, C
	Irregular Alignment	H
2) Building Density	High Density	B, F
	Low Density	D, H
3) Building Dissociation	Single Buildings	D, G, H
	Blocks of Building	A, B, C, E, F
4) Building Shape	Diverse Shapes	B, F
5) Building Size	Diverse Sizes	B, C, F, H
6) Building Height	Diverse Heights	E
7) Building Roof Color	Similar Reflectance	C, D
8) Imaging Angle	Oblique Image	E

The images proposed in Fig. 1 can be considered as an efficient dataset based on basic challenges of urban areas focused on only buildings (Table II). Challenges such as: 1) Building density; regions D and H have the low density while the other regions are relatively dense. 2) Building dissociation; there are the isolated and single buildings in regions D, G and H and the continuous blocks of building in the other regions. 3) Building alignment; the buildings of regions A, C, E (blocks), D and G (single) have the regular alignment. In regions H, the buildings alignment is irregular. 4) Building shape; all the buildings of regions A, C, and G have rectangular shape. In addition, there are other shapes such as polyhedral, L-like (region B), a few H-like (region D) and the irregular shapes (regions B and F). 5) Building size; there are buildings with different sizes in regions D, H (single), B, C, and F (blocks). 6) Building roof color and brightness; all the building roofs of regions G and H are relatively homochromatic. There is a diversity of roof color such as dark brown, light brown, white, some blue, and even black in the other regions. By contrast, there is similar reflectance and color between building and non-building areas in regions C and D. 7) Building height; there is the diversity of building height in region E as compared with the other regions. 8) Imaging angle; the image of region E is an oblique (off-nadir) image and the others are vertical (nadir).



a *b* *c* *d* *e* *f* *g* *h*

Fig. 1. (a)–(h) regions A to H. The efficient set of HSR images proposed in the paper based on challenges of urban areas focusing on building objects i.e. building density, alignment, dissociation, shape, size, color and height, in addition an oblique image.

III. Experiments and Discussion

A. Implementation and Results

To practically examine the proposed dataset, we aim to implement three different building detection algorithms in all the regions. The first algorithm uses spectral indices, clustering, and morphology, the second one uses clustering and segmentation and the third one uses the object-based classification. In the following, we call them as ICM, CS and OBC, respectively.

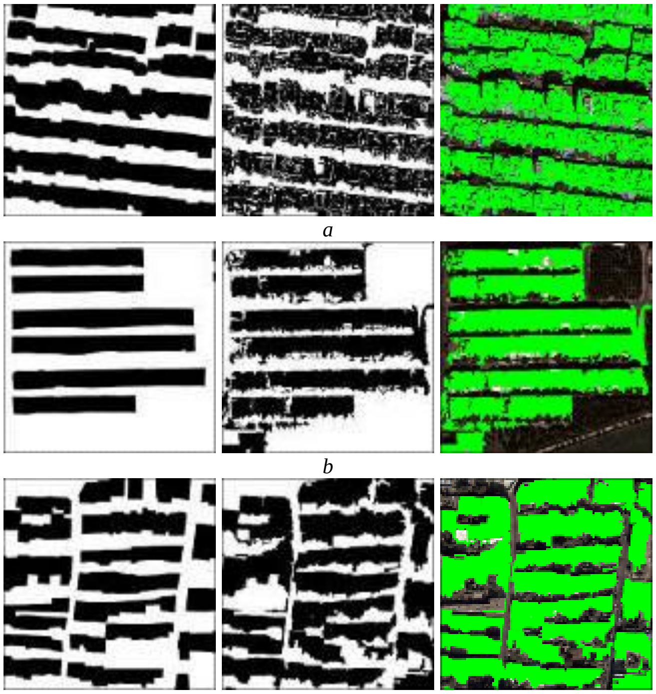


Fig. 2. The best result of buildings detection. a ICM algorithm. b CS algorithm. c OBC algorithm (Left: Reference data. Middle: Detected buildings image. Right: Masked image with detected buildings).

ICM algorithm removes the vegetation, the shadow, the roads and the other artefact of the urban areas using the vegetation index, shadow index, thinning algorithm and area morphological methods, respectively [6]. CS algorithm uses the k-means and fuzzy c-means clustering to remove the non-building areas. Then, the pseudo-building areas can be removed by a region-growing segmentation method [8]. The procedure of the OBC algorithm is as follows: segmenting the image, selecting optimum attributes, and finally classifying the image based on segments [12]. The best and the worst images of buildings detected from each algorithm with their reference data are shown in Fig. 2 and Fig. 3, respectively.

After implementing each algorithm on eight regions, the buildings detected by each are compared with the reference data i.e. the digital map of each region (refer to Fig. 2 and Fig. 3) pixel by pixel. Then, the common metrics such as the detection rate (DR), false negative rate (FNR), reliability (R), false positive rate (FPR) and overall accuracy (OA) which are defined in ([1]–[9], [14]) are utilized to evaluate the algorithms. Tables III, IV, V and Fig. 4 show the evaluation results of the building detection algorithms. A higher DR with a lower FNR indicates the high efficiency of an algorithm in the building detection, and a high R and a low FPR implies the reliability of the produced results.

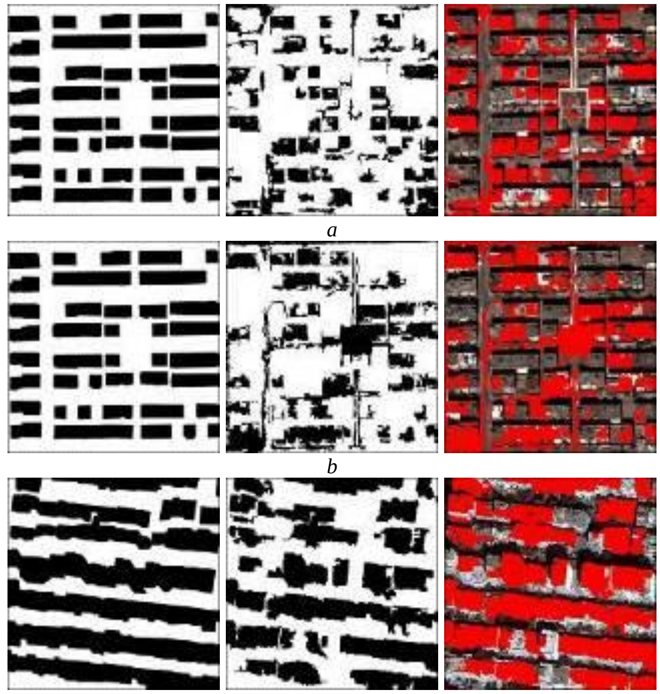


Fig. 3. The worst result of buildings detection. a ICM algorithm. b CS algorithm. c OBC algorithm (Left: Reference data. Middle: Detected buildings image. Right: Masked image with detected buildings).

From the Tables, the DR (FNR) value is between 41%–81% (19%–59%) for the ICM algorithm, 40%–91% (9%–60%) for the CS algorithm, and 73%–93% (7%–27%) for the OBC algorithm. The average DR (FNR) of the algorithms is 66% (34%), 76% (24%) and 86% (14%), respectively. These values generally state CS algorithm is more efficient than the ICM algorithm, and the OBC algorithm is more efficient than the two other algorithms.

TABLE III
THE EVALUATION RESULTS (%) OF ICM ALGORITHM

		DR	R	FNR	FPR	OA
Regions	A	81.13	75.77	18.87	***14.89***	**83.66**
	B	58.61	**78.40**	41.39	15.04	72.25
	C	***40.62***	59.24	**59.38**	18.06	***65.72***
	D	66.50	***47.05***	33.50	25.77	72.24
	E	**81.32**	76.84	***18.68***	**31.89**	75.58
	F	57.50	73.31	42.50	14.90	70.39
	G	74.14	73.22	25.86	22.29	76.10
	H	67.44	58.74	32.56	27.81	70.93
	Mean	65.91	67.82	34.09	21.33	73.36
	STD	13.64	11.36	13.64	6.62	5.27

In addition, the average R of three algorithms is 68% (47%–78%), 61% (34%–75%) and 77% (65%–89%), respectively. The average FPR is 21% (15%–32%), 29% (19%–46%) and 18% (7%–34%), respectively. It can be generally concluded from these values that the building detection outputs of the OBC algorithm are more reliable than the two other algorithms. Furthermore, the reliability of the ICM algorithm is higher than the CS algorithm. The better efficiency and reliability of OBC algorithm may be due to the use of segments instead of single pixels and also the use of non-spectral attributes.

TABLE IV
THE EVALUATION RESULTS (%) OF CS ALGORITHM

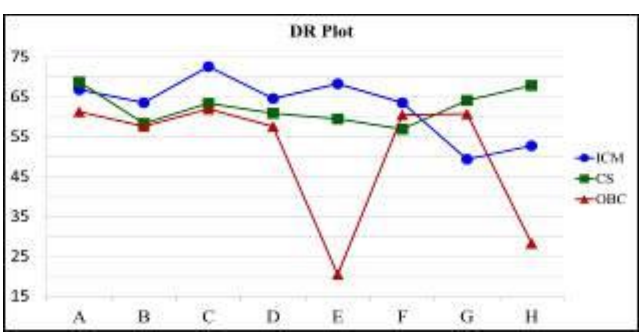
		DR	R	FNR	FPR	OA
Regions	A	**91.39**	73.73	***8.61***	***18.80***	**84.93**
	B	80.76	74.14	19.24	24.19	78.10
	C	***40.05***	50.25	**59.95**	25.62	60.90
	D	67.86	***33.56***	32.14	**45.69**	***57.75***
	E	82.72	**74.61**	17.28	36.60	74.32
	F	79.84	69.09	20.16	25.23	76.87
	G	81.28	71.30	18.72	26.90	76.79
	H	86.87	44.26	13.13	31.38	72.69
	Mean	76.35	61.37	23.65	29.30	72.79
	STD	16.14	16.21	16.14	8.44	9.09

TABLE V
THE EVALUATION RESULTS (%) OF OBC ALGORITHM

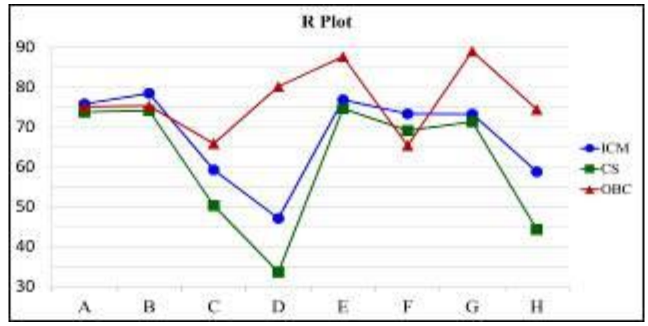
		DR	R	FNR	FPR	OA
Regions	A	91.53	75.11	8.47	17.51	85.80
	B	**92.80**	75.28	**7.20**	28.39	81.83
	C	83.74	65.82	16.26	28.09	76.55
	D	81.73	80.13	18.27	**6.98**	90.13
	E	**72.63**	87.62	**27.37**	13.36	78.72
	F	89.71	**65.33**	10.29	**33.63**	**76.03**
	G	85.36	**88.99**	14.64	8.68	88.63
	H	87.11	74.41	12.89	8.60	**90.45**
	Mean	85.58	76.59	14.42	18.16	83.52
	STD	6.47	8.78	6.47	10.50	6.02

Another conclusion can be drawn from the last column of the Tables is standard deviation (STD) of the evaluation metrics in order to evaluate the stability of the algorithm. The STD of DR, R, and FNR values of the OBC algorithm is very lower than the one of ICM and CS algorithms. Thus, the OBC algorithm can produce DR, R, and FNR values with lower scattering as compared with the two other algorithms. It can also be concluded from a visual comparison between their plots (Fig. 4a, Fig. 4b, and Fig. 4c). The change of slope at OBC algorithm plots is relatively less, while the difference between maximum and minimum values of ICM and CS algorithms is very high. Therefore, it can be said that the OBC algorithm is much more stable than ICM and CS algorithms in DR, R, and FNR metrics.

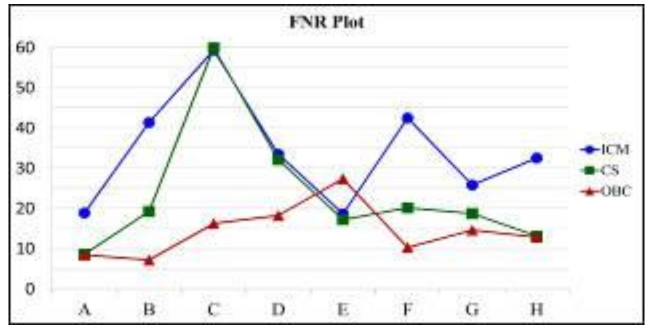
In contrast, the ICM algorithm is more stable than CS and OBC algorithms in FPR and OA metrics (Fig. 4d and Fig. 4e). In addition, the ICM algorithm is more stable than the CS algorithm in all evaluation metrics.



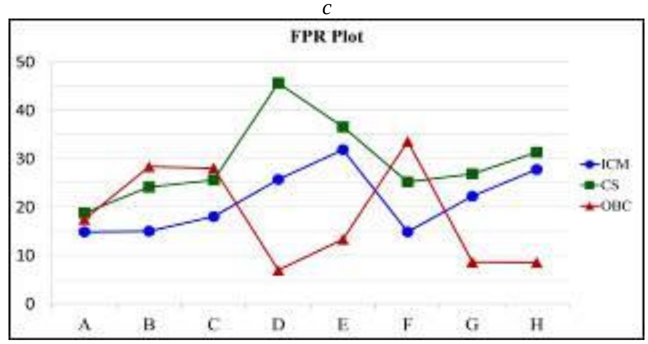
a



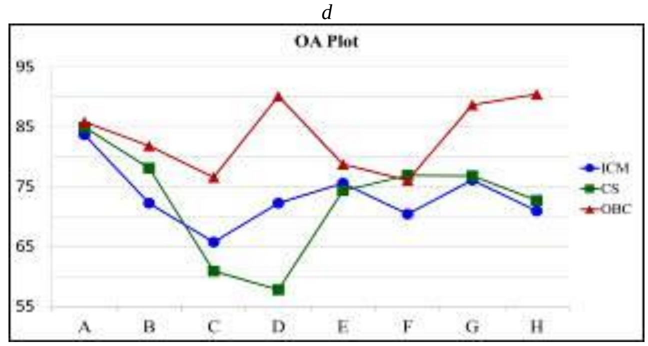
b



c



d



e

Fig. 4. The plot of three algorithms. a DR values. b R values. c FNR values. d FPR values. e OA values (Blue color: ICM algorithm; Green color: CS algorithm; Red color: OBC algorithm).

It is concluded from the above paragraph, the proposed dataset can more fairly evaluate the algorithms whereas a low-diverse dataset cannot. Because the stability of the results of an algorithm cannot be discovered having one or two images. Another point is about the STD of all metrics at each algorithm, so that it can be seen the STD values of all metrics in the OBC algorithm are nearly close together (6 to 10). But one of ICM and CS algorithms are very far each other (5 to 13 and 8 to 16). It means that all plots have different scattering from each other for ICM and CS algorithms. Therefore, two

TABLE VI
THE EVALUATION RESULTS OF THREE ALGORITHMS BASED ON CHALLENGES OF TABLE II

Algorithms	Evaluation Metrics	Challenges											Standard Deviation
		Regular Alignment	Irregular Alignment	High Density	Low Density	Single Buildings	Blocks of Building	Diverse Shapes	Diverse Sizes	Diverse Heights	Similar Reflectance	Oblique Image	
ICM	DR	60.88	67.44	58.06	66.97	69.36	63.84	58.06	56.04	**81.32**	**53.56**	**81.32**	9.42
	R	67.51	58.74	75.86	**52.90**	59.67	72.71	75.86	67.42	**76.84**	53.15	**76.84**	9.47
	FNR	39.13	32.56	41.95	33.03	30.64	36.16	41.95	43.96	**18.68**	**46.44**	**18.68**	9.42
	FPR	16.48	27.81	**14.97**	26.79	25.29	18.96	**14.97**	18.95	**31.89**	21.92	**31.89**	6.37
CS	DR	65.72	86.87	80.30	77.37	78.67	74.95	80.30	71.88	**82.72**	**53.96**	**82.72**	9.30
	R	61.99	44.26	71.62	**38.91**	49.71	68.36	71.62	59.44	**74.61**	41.91	**74.61**	13.77
	FNR	34.28	13.13	19.70	22.64	21.33	25.05	19.70	28.12	**17.28**	**46.05**	**17.28**	9.30
	FPR	**22.21**	31.38	24.71	**38.54**	34.66	26.09	24.71	26.61	36.60	35.66	36.60	5.95
OBC	DR	87.64	87.11	**91.26**	84.42	84.73	86.08	**91.26**	88.34	**72.63**	82.74	**72.63**	6.40
	R	70.47	74.41	70.31	77.27	81.18	73.83	70.31	70.21	**87.62**	72.98	**87.62**	6.66
	FNR	12.37	12.89	**8.75**	15.58	15.27	13.92	**8.75**	11.66	**27.37**	17.27	**27.37**	6.40
	FPR	22.80	8.60	**31.01**	**7.79**	8.09	24.20	**31.01**	24.68	13.36	17.54	13.36	8.81

recent paragraphs state ICM and CS algorithms may produce the unreal and illusive results due to two reasons: 1) DR, R and FNR plots of ICM and CS algorithms are not as stable as the one of OBC algorithm and they have the high scattering. 2) The scattering of all plots of two these algorithms are different from each other.

A. *Discussion on Capability of Dataset*

In order to survey the capability of the proposed dataset in evaluating the algorithms, Table VI shows their evaluation results based on the challenges of Table II. It is noteworthy that the evaluation metric values of each challenge are obtained from the average of values of related regions. For example, the DR value of regular alignment column is the average of the DR values of regions A and C or for blocks of buildings, the average of the one of regions A, B, C, E and F and etc. Referring to Table VI, a more fairly evaluation can be concluded than the previous tables, so that it is able to better show the strength and weakness of the algorithms and to state where an algorithm can be successful or (and) where may be (unsuccessful) encountered with the problems in the detection of buildings.

It can be seen from Table VI; OBC algorithm can more detect buildings than two other algorithms with nearly 22%–27% higher at DR in "regular alignment" challenge. However, the reliability of the three algorithms is approximately the same. In "irregular alignment" challenge, only the ICM algorithm has been confronted with the problems in detecting buildings with the 67% for DR which is 20% lower than the one of CS and OBC algorithms. However, the reliability of ICM and CS algorithms is very lower than the OBC algorithm, with 15%–30% lower for R and 15%–18% higher for FPR. This point indicates the lower reliability of the ICM and CS algorithms in regions with the irregular alignment of buildings.

In "high density" and "diverse shapes" challenges, the ICM algorithm has been extremely confronted with the problems in the detection of buildings with 32%–43% lower (higher) for DR (FNR), while the reliability of CS and ICM algorithms is higher than OBC algorithm so that the minimum commission error of ICM algorithm (15%) and the maximum one of OBC algorithm (31%) belong to two these challenges. In "low density", three algorithms have the same detection rates. But, the lowest reliability of ICM and CS algorithms belongs to this challenge with 53% and 39% for R and 27% and 39% for FPR. While the minimum commission error of the OBC algorithm belongs to this challenge with 8% for FPR.

In "single buildings" and "blocks of buildings" challenges, three algorithms have the DR higher than 60%. The R of the CS algorithm is 50%, and its FPR is 35% in single buildings, while the OBC algorithm has the 81% for R and 8% for FPR.

In the regions with the diversity of building heights and oblique angle, the OBC algorithm has lower efficiency than ICM and CS algorithms, with approximately 10% lower for DR and 10% higher for FNR. However, it can produce more reliable results than two other algorithms, with approximately 10%–13% higher for R and 19%–24% lower for FPR. It implies: "where there are buildings with diverse heights and imaging angle is oblique, OBC algorithm may be confronted with the problems in detecting the buildings but it can be more reliable than two other algorithms. In addition, although ICM and CS algorithms can detect more buildings than OBC algorithm, however, their results may not be as reliable as the results of the OBC algorithm, so that the maximum commission error of the ICM algorithm belongs to these challenges (with 32% for FPR). In addition, the FPR of CS algorithm is also nearly high (37%)".

The lowest DR of ICM and CS algorithms belongs to "similar reflectance" with 54% for DR (46% for FNR), i.e. approximately 30% lower than DR of OBC algorithm. In addition, the reliability of two these algorithms is lower than the OBC algorithm, with 20%–30% lower at R and 4%–18% higher at FPR. Therefore, "where there is similar reflectance between building and non-building areas, ICM and CS algorithms may be confronted with the problems in the reliability detection of buildings.

IV. Conclusion

The paper followed the fact that an efficient dataset is necessary in order to more fairly evaluate a building detection algorithm. Based on basic challenges focused on only building objects in urban areas such as diversity in building density, building alignment, building dissociation, building shape, building size, building roof color and building height and imaging angle, an efficient set of HSR images were introduced. The proposed dataset was able to better indicate the strength and weakness of the algorithms and to state where an algorithm can be successful and where may be encountered with the problems in the detection of buildings. A general conclusion can be drawn from Table VI in relation to the proposed dataset are as follows: 1) the lowest building detection rate of ICM and CS algorithms belongs to where there is similar reflectance between building and non-building areas (with nearly 0.9 for IER). Thus, it can be said, "ICM and CS algorithms may be confronted with the problems in the detection of buildings where there is similar reflectance between building and non-building areas". In addition, the CS algorithm has a nearly lower reliability rate in this challenge (with 0.9 for URR). While the OBC algorithm has good efficiency and reliability in this challenge. 2) the most building detection rate of ICM and CS algorithms belongs to regions with the diversity of building heights and oblique angle (with 0.2 for IER). It is noteworthy that the lowest building detection rate of the OBC algorithm belongs to this challenge (with 0.4 for IER). In contrast, the reliability of the OBC algorithm is higher than two other algorithms (with 0.2 versus 0.5 for URR). Therefore, "in the regions with the diversity of building heights and oblique angle, OBC algorithm may be confronted with the problems in the detection of buildings, however its detection results can have a significant reliability". 3) The lowest and most reliability rate of the ICM algorithm belongs to regions with irregular building alignment and dense area with a diversity of building shapes, respectively (with 0.5 and 0.2 for URR). Of course, in high density area, the ICM algorithm could not detect many buildings (with 0.7 for IER). In contrast, the OBC algorithm has the lowest reliability (0.4 for URR) and the most efficiency (0.1 for IER) in this challenge. It implies "ICM algorithm has a high reliability and low efficiency in the dense area, while the OBC algorithm has a high efficiency and low reliability". 4) CS algorithm has the lowest reliability rate in a dense area (with 0.4 for URR) and the most rate in a low-density area (with nearly 1 for URR). In addition, it could detect many buildings in both regions (with 0.3 for IER). In contrast, the most reliability rate of the OBC algorithm belongs to the low-density areas (close to 0 for URR). Meanwhile, it has a good detection rate in this region. Therefore, "CS algorithm is successful in the dense areas. In the low density areas, it may detect many buildings but with a low reliability, while OBC algorithm has a good efficiency and reliability in this region".

This work discussed more qualitatively on the proposed dataset. Introducing the quantitative metrics based on the proposed dataset to evaluate the building detection algorithms can be the next work of the authors of this paper.

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