

BUILDING DETECTION FROM HIGH-RESOLUTION SATELLITE IMAGERY USING ADAPTIVE FUZZY-GENETIC APPROACH

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ABSTRACT:

We present a technique for extracting the buildings from high resolution satellite imagery using adaptive fuzzy-genetic approach. The technique was inspired from the genetic image exploitation system, GENIE PRO, conducted by Perkins *et al.*, (2005) but brings an important novelty, which is an adaptive-fuzzy module that fine-tunes the genetic algorithm parameters aiming to improve the feature extraction performance. The technique integrates the well known genetic algorithm concepts such as population, chromosome, gene, crossover and mutation into the fundamental image processing concepts. The population is defined as the set of chromosomes, which consists of a predetermined number of image processing operations (genes). The genes are comprised the basic image processing operations. The algorithm is initiated by selecting the training samples for the building and non-building areas from the imagery. The image processing operations are applied in a chromosome-by-chromosome basis to obtain specific attribute planes. These planes are then fed into Fisher Linear Discriminant (FLD) module, which finds an optimal discriminating hyper plane between the building and non-building features. Next, for each chromosome, the fitness values are calculated by analyzing the detection and mis-detection rates. After that the crossover and mutation operations are applied to arbitrary chromosome(s) to create a better population in the next generation by diversifying the current population. At the end of each generation cycle, the crossover and the mutation probabilities are adjusted by the adaptive-fuzzy module for the next generation. The evolutionary process is repeated until a satisfactory level of iteration is reached. Finally, a post-processing operation is performed in order to enhance the extracted building polygons by means of the morphological image processing operations. The approach was implemented on a selected urban area of the city of Ankara, Turkey using the 1-m resolution pan-sharpened IKONOS imagery. The study was found to be quite promising since the building regions were successfully extracted with an approximate detection rate of 90%.

1. INTRODUCTION

Since the largest part of world population lives in urban areas, many critical management issues involving geographical analysis are required such as urban planning, monitoring urban change and growth, civil protection, and environmental impact studies. In urban areas, land cover and land use change rapidly due to the new construction of the buildings, roads, and other man-made objects. In urban planning, monitoring these changes is an important issue and many Geographic Information System (GIS) applications suffer from the lack of timely land use information. Therefore, the maps should be regularly updated with the changes. In order to do that, for many years, the extraction of geographic features has been performed manually by human operators, with high accuracy and reliability. But, this is a very time consuming operation and requires qualified people. For that reason, automated object extraction from high resolution digital imagery has become a key concern for modern geospatial applications.

Recent advances in the quality of satellite imagery and the desire to analyze this data has improved the development of new image processing techniques for automated object extraction. There are many applications in order to be able to efficiently extract individual objects from a scene for the

purpose of spatial analysis and object retrievals from large-scale image databases. In these applications, the items of interest mainly focus on man-made structures, such as buildings and roads as well as the fields and forestry areas.

One of the major research areas in urban remote sensing is the detection of buildings and their corresponding footprints, which are fundamental GIS data components and have been shown to be extremely useful in urban planning, infrastructure development, construction of telecommunication lines, pollution modeling, disaster planning, and many other kinds of urban simulations. In many applications of building detection, airborne remote sensing technology is widely used. One of the frequently used applications utilizing this technology is the detection of the buildings from their shadows from aerial photographs. Huertas and Nevatia (1988) and Irvin and McKeown (1989) focused on the relation between structures and their cast shadows for extracting the building footprints and estimating the building heights. Further, Noronha and Nevatia (2001) performed automatic detection and modeling of buildings from multiple aerial images. They described a system that detects and constructs 3-D models for rectilinear buildings. Rottensteiner and Brieske (2002) presented a methodology for the automated generation of 3D building models from point clouds generated by the airborne LIDAR sensors.

A novel building extraction method from the concept of fitting CSG (Constructive Solid Geometry) primitives to aerial images was proposed by Tseng and Wang (2003). In their study a semi-automatic procedure was adopted for performing high-level operations, such as building detection and model selection interactively by the operator and performing optimal model-image fitting automatically using a least-squares fitting algorithm. In a more recent study conducted by Kim and Nevatia (2004), an approach was developed for detecting and describing complex buildings with flat or complex rooftops by using the multiple, overlapping images. In a method presented by Peng and Liu (2005), the use of monocular urban aerial images without any prior knowledge of illumination was carried out to extract buildings in dense urban areas. An automated extraction procedure for building footprints from airborne LIDAR data was proposed by Wang *et al.*, (2006), who offered a novel Bayesian technique for automatically constructing building footprints from a pre-classified LIDAR point cloud. Lu *et al.*, (2006) developed an approach for the automatic detection of buildings from aerial images using the combined analysis and interpretation techniques that include classification, shape modeling, and fusion.

As in airborne imagery, the recent high-resolution spaceborne images also provide a valuable information data source for the extraction of objects such as buildings. Lee *et al.*, (2003) presented a building extraction approach guided by the classification results using both multispectral and panchromatic Ikonos images. In a different study, a combined fuzzy pixel- and object-based approach was employed for the discrimination of buildings from other urban land cover classes using the pan-sharpened multispectral Ikonos imagery (Shackelford and Davis, 2003). The automatic detection and delineation of the buildings from high resolution space images were carried out by San and Turker, (2004). The proposed approach was developed for updating the buildings of an existing vector database making use of spectral values, Digital Elevation Model (DEM), and model-based extraction techniques. An integrated strategy for automated extraction of buildings from 1-meter resolution satellite imagery of urban areas was demonstrated by Jin and Davis (2005). Kim *et al.* (2006) proposed a new algorithm for extracting building lines from high-resolution satellite images. The approach was based on the extraction of lines from rectangular-shaped building roofs with a relatively large size.

In building extraction, many general purpose supervised learning strategies have been applied using the multi-spectral imagery. The general approach employs purely spectral input vectors, built by the set of intensity values in each spectral channel for each pixel in the image. Although these vectors provide a suitable fixed-dimensionality space, in which the conventional classifiers often work well, it is evident that spatial relationships such as texture, proximity, or shape can be very informative in feature extraction. Therefore, such information can be added to the spectral dimensionality. However, there exists a combinatorial huge choice for these additional vector dimensions (Harvey *et al.*, 2002). To deal with this problem, a hybrid evolutionary algorithm called GENIE (GENetic Image Exploitation) was developed by Perkins *et al.*, (2000), who search a space of image processing operations for a set that can produce suitable feature planes, and a more conventional classifier which uses those feature planes to output a final classification. In a further study, Perkins *et al.* (2005) developed

the system GENIE Pro. As in GENIE, this system was also a general purpose adaptive tool deriving automatic pixel classification algorithms for satellite and aerial imagery, from training input. In particular, GENIE Pro integrated spectral information and spatial cues such as texture, local morphology and large-scale shape information, in a much more sophisticated way.

Recently, the idea of adaptive fuzzy-genetic algorithms, which is based on the adjustment of the selected control parameters or genetic operators, has been found to be quite promising. These algorithms offer the most appropriate exploration and exploitation behavior to avoid premature convergence problem and improve the final result. In Figure 1, an adaptive fuzzy-genetic algorithm model, which was conducted by Herrera and Lozano (2003), is illustrated.

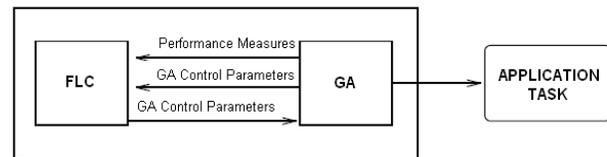


Figure 1. The adaptive fuzzy-genetic algorithm model (Herrera and Lozano 2003).

The objective of this study is to extract building regions from high resolution multispectral satellite imagery using an adaptive fuzzy-genetic approach. To do that, a novel methodology is proposed which is based on a well-known optimization technique (Genetic Algorithms) in cooperation with a conventional supervised image processing approach. Thus, the proposed approach can be considered to be a hybrid feature extraction procedure.

2. STUDY AREA AND DATA

The proposed approach was implemented in a selected urban area of the Batikent district, which is a planned and regularly developed settlement of Ankara, the capital city of Turkey. The area contains various types of buildings having different shapes and usage such as residence, industrial, commercial, social and cultural facilities. Batikent is on the western corridor of Ankara, lying over an area about 10,000,000 square meters. The district was a housing project of the 1980s, which was the biggest mass-housing project accomplished through cooperatives in Turkey.

The input data set comprises the IKONOS pan-sharpened imagery, which was pre-processed for a former study conducted by San and Turker, (2004). The 1-m resolution pan-sharpened image of the study area is shown in Figure 2.



Figure 2. The pan-sharpened image of the study area.

3. THE METHODOLOGY

3.1 Background Information

Before describing the proposed methodology, the fundamental image-based genetic algorithm concepts, which were developed by Perkins *et al.*, (2000), should be clarified first. In this design, the population is generated from a predefined number of chromosomes. The structure of a chromosome consists of a predetermined number of image processing operations (genes), which are the well known image processing operations as well as the spectral distance, spectral similarity, spectral angle and basic textural measures. These operations are randomly initialized from a gene pool that keeps those image processing operations. The structure of a population, chromosome and gene are illustrated in Figure 3.

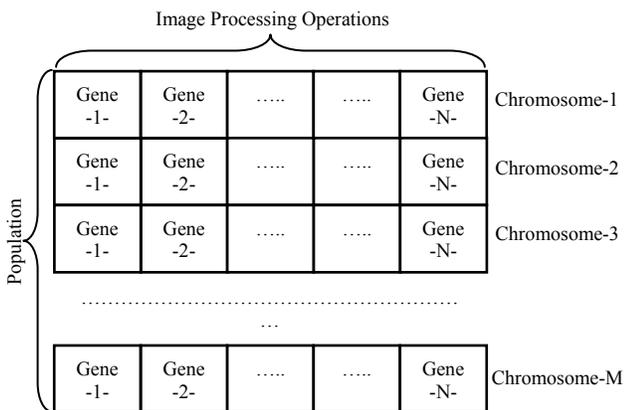


Figure 3. The structure of a population, composed of M chromosomes and N genes in each chromosome.

3.2 The Processing Steps

The processing steps of the proposed methodology for building extraction from high-resolution satellite imagery using the adaptive fuzzy-genetic approach is represented in Figure 4.

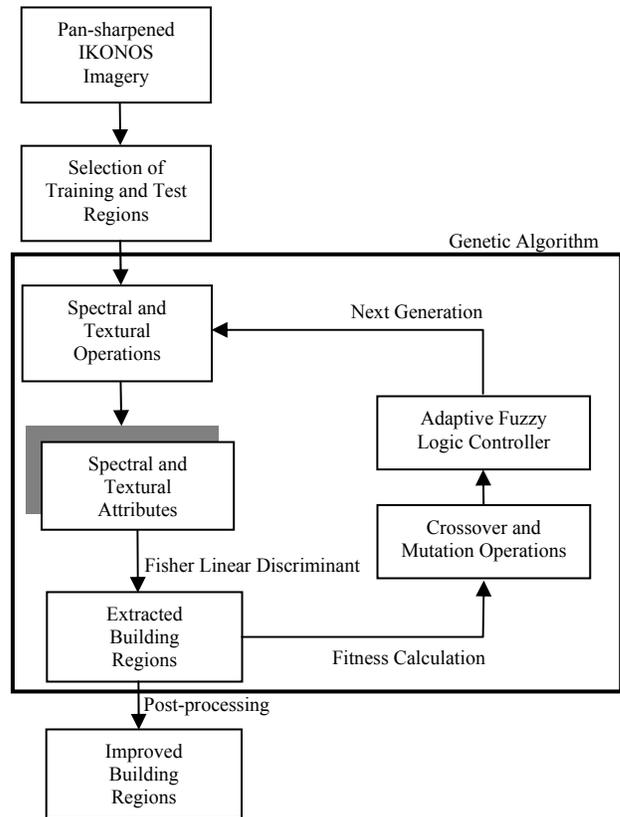


Figure 4. The building extraction methodology.

The methodology is initiated by selecting the training and test regions for both the building and non-building areas from pan-sharpened imagery. Then, the predetermined image processing operations are applied on the pan-sharpened input bands (RGB) in a chromosome-by-chromosome basis to obtain the spectral and texture attributes. For each chromosome, the attributes are stored in separate temporary image planes. Then, these planes are combined to construct a single grayscale image plane by employing a conventional classification algorithm, which is the Fisher Linear Discriminant (FLD). The classifier uses the training data and attempts to find an optimal discriminating hyperplane between the building and non-building features. Next, the fitness values are calculated using the detection and mis-detection rates. The detection rate is computed by the fraction of pixels marked as true that the algorithm gets correct. On the other hand, the mis-detection rate is defined as the percentage of pixels marked as false that the classifier gets wrong. This step is followed by the crossover and mutation operations that are to be applied on an arbitrary chromosome(s) except the one that having the best fitness value (elite chromosome). These operations are aimed to create a better population in the next generation by diversifying the current chromosomes. The single point crossover operation, which is used in this study, simply exchanges the genes of two

chromosomes starting from an arbitrary gene. On the other hand, mutation exchanges an arbitrary gene by a new gene randomly selected from the pool. The crossover and mutation operations are illustrated in Figures 5 and 6, respectively.

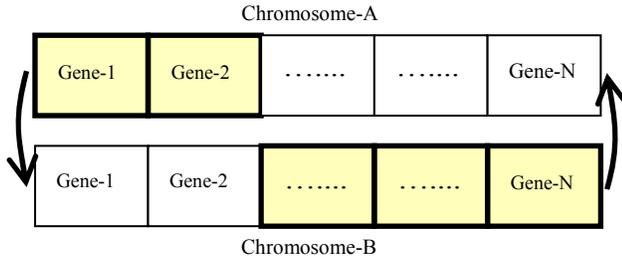


Figure 5. An example crossover operation between two chromosomes, A and B.

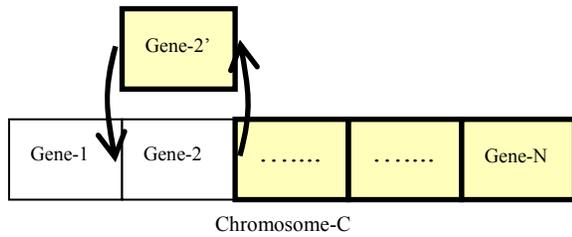


Figure 6. An example mutation operation on a single chromosome, C.

3.2.1 Adaptive-Fuzzy Component

In the adaptive-fuzzy component, the crossover and mutation probabilities are estimated by an adaptive-fuzzy logic controller. The idea behind this is as follows: The crossover and mutation probabilities (P_c and P_m) are increased if it consistently produces a better offspring (new chromosomes). However, P_c is decreased and P_m is increased when $f_{ave}(k)$ (average fitness in k^{th} generation) approaches to $f_{max}(k)$ (maximum fitness in k^{th} generation) or $f_{ave}(k-1)$ approaches to $f_{ave}(k)$. This scheme is based on the fact that it encourages the well-performing operators to destroy the potential chromosomes during the recombination process. According to the study conducted by Liu *et al.*, (2005), two parameters (e_1 and e_2) are introduced to define the fuzzy rules for crossover and mutation operations shown in equations 1 and 2.

$$e_1 = (f_{max}(k) - f_{ave}(k)) / f_{max}(k) \quad (1)$$

$$e_2 = (f_{ave}(k) - f_{ave}(k-1)) / f_{max}(k) \quad (2)$$

Using these parameters, the fuzzy rules are identified in order to describe the relation between the inputs e_1 and e_2 and the output (the step size of the crossover or mutation probabilities), shown in Tables 1 and 2.

CROSSOVER	e_2				
	NL	NS	ZE	PS	PL
e_1	NL	NS	ZE	PS	PL
PL	NS	ZE	NS	PS	PL
PS	ZE	ZE	NL	ZE	ZE
ZE	NS	NL	NL	NL	NL

Table 1. Fuzzy rules for crossover operation.

MUTATION	e_2				
	NL	NS	ZE	PS	PL
e_1	NL	NS	ZE	PS	PL
PL	PS^*	ZE^*	PS^*	NS^*	NL^*
PS	ZE^*	ZE^*	PL^*	ZE^*	NS^*
ZE	PS^*	PL^*	PL^*	PL^*	PS^*

Table 2. Fuzzy rules for mutation operation.

In these tables, the abbreviations NL, NS, ZE, PS and PL represent Negative Large, Negative Small, Zero, Positive Small and Positive Large, respectively. The inputs of the mutation controller (e_1 and e_2) are the same as those of the crossover controller. However, in table 2, the output values illustrated by the asterisk (*) are reduced by 10% compared with the output values given in table 1. The output values specify the step sizes of crossover and mutation rates, which are ΔP_c and ΔP_m , respectively. Using the membership functions defined in Liu *et al.*, (2005), defuzzification process is performed by using the centroid approach and the computed crisp values are used to modify the genetic algorithm parameters presented in equations 3 and 4.

$$P_c(k) = P_c(k-1) + \Delta P_c(k) \quad (3)$$

$$P_m(k) = P_m(k-1) + \Delta P_m(k) \quad (4)$$

After determining the new probabilities, the next generation is initiated with a renewed population. The genetic algorithm runs repeatedly during a predetermined generation cycle, which almost yields an unchanged value of fitness in the extraction of the building regions.

3.2.2 Post-processing Step

Although the extracted buildings reveal the regions that might be the feature of interest, many false alarm areas are likely to appear. In order to eliminate the false alarm areas, a set of morphological image processing operations such as openings, closings are applied to the single grayscale image that is the output of the genetic algorithm. The opening operation generally smoothes the contour of an object, breaks narrow strips, and eliminates thin protrusions. On the other hand, the closing operation not only tends to smooth sections of contours, but also fuses narrow breaks and long thin gulfs, eliminates small holes, and fills the gaps in the contour (Gonzales and Woods, 2002).

4. THE RESULTS

To implement the approach, a software was developed using the MATLAB 7.01 programming tool, which provides a set of powerful image processing modules and a user-friendly programming environment. For building and non-building features, 20 rectangular areas were marked carefully on the pan-sharpened IKONOS image in order to use them in the training phase. Similarly, 20 test regions different from the training rectangles were also selected. In order to make the assessments in the fitness calculation, the building and non-building regions were labeled 1 and 0, respectively.

Next, the parameters of the genetic algorithm were initialized. The population size (number of chromosomes) was set to 20

chromosomes and the number of genes in a chromosome was initiated as 5. Further, the number of temporary planes, the initial crossover and mutation rates were fixed to 4, 0.8, and 0.2, respectively. The above given values of the parameters were chosen through the experience, and have found to work fairly well over many different experiments. The stopping criterion was kept as 20 generations, which was quite sufficient for the algorithm to converge.

In order to find the building regions, the algorithm was executed with two different variants. In the first case, the adaptive fuzzy module was excluded, which means that the crossover and the mutation probabilities were kept fixed. After several runs of the algorithm, the maximum fitness rate of **90.345%** (averaged over 5 runs) was reached within the stopping criterion. The performance curve for the averaged runs is shown in Figure 7.

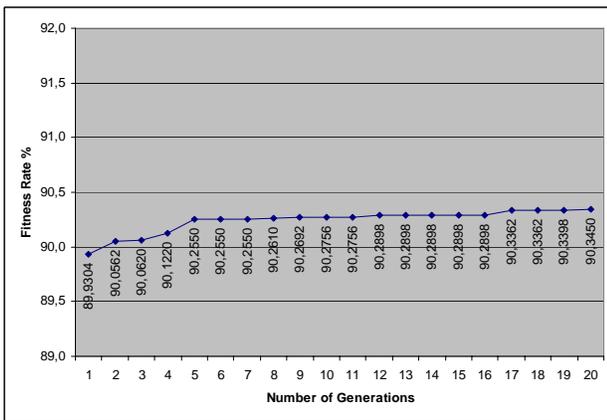


Figure 7. The performance curve of the algorithm without the adaptive fuzzy module.

In the second case, the adaptive fuzzy module was taken into account in the genetic algorithm. That is, the crossover and the mutation rates were changed adaptively with respect to the performance measures. This change was determined by a rule-based fuzzy logic controller mentioned in section 3.2.1. After making a number of experiments, the value of **91.135%** was found to be the maximum fitness rate, averaged over 5 runs. The corresponding performance curve is illustrated in Figure 8.

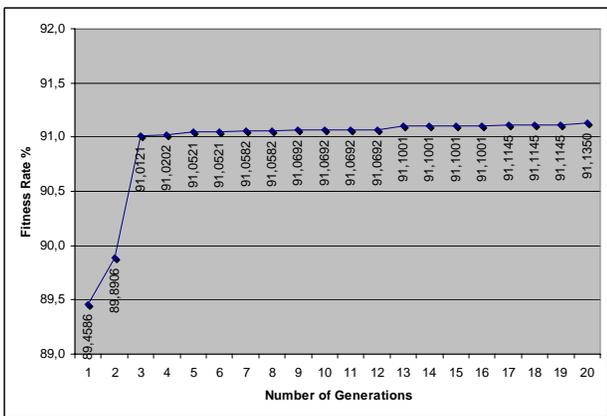


Figure 8. The performance curve of the algorithm with the adaptive fuzzy module.

Figure 9 represents a selected output image, which has a fitness rate of **90.915%** generated from the adaptive fuzzy-genetic approach. The improved building regions, after applying the post-processing stage, are illustrated in Figure 10.

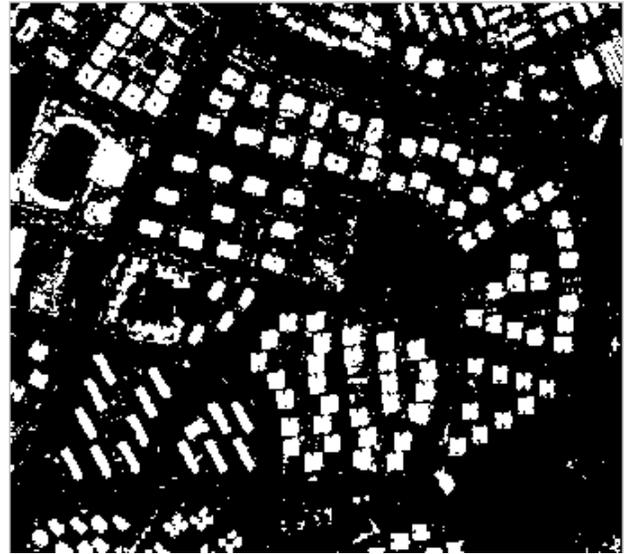


Figure 9. The extracted buildings.

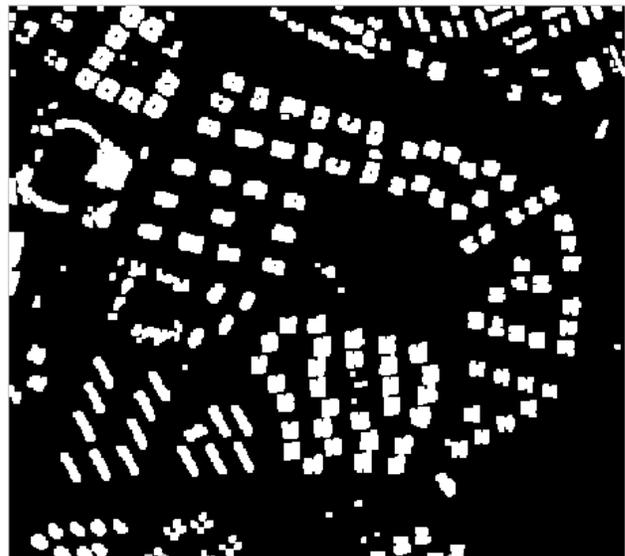


Figure 10. The building regions after post-processing.

5. CONCLUSIONS

In this study, we proposed a novel methodology based on a previous study conducted by Perkins *et al.*, (2005) in an attempt to detect the building regions from the 1-m resolution pan-sharpened IKONOS imagery. In this study, our major contribution is that the genetic image exploration was combined with the adaptive fuzzy-logic based controllers. As expected, the adaptive fuzzy approach was converged more quickly than the conventional approach within a few generations yielding an average fitness rate of 91%. The conventional genetic approach

also yields a detection rate of 90% but the convergence speed can be considerably slow. This is due to the fixed initial probabilities of the crossover and mutation, which highly increase the risk to get trapped in local minimum solution. In addition, the post-processing step was also found to be very useful for eliminating the false alarm areas.

As a future work, high resolution (~ 20-30 cm) digital aerial images will be used to reveal the difference between the two variants of our methodology. In addition, the image processing operators will be enriched in order to boost the detection accuracy. Finally, the post-processing operation will be embedded into a genetic algorithm module that finds the best combination of image enhancement operators.

6. REFERENCES

- Gonzales, R.C. and Woods R.E., (2002), *Digital Image Processing*, 2nd Edition, Prentice-Hall, Inc.
- Harvey, N.R., Theiler, J., Brumby, S.P., Perkins, S., Szymanski, J.J., Bloch, J.J., Porter, R.B., Galassi, M. and Young A.C., (2002), Comparison of GENIE and Conventional Supervised Classifiers for Multispectral Image Feature Extraction, *IEEE Transactions on Geoscience and Remote Sensing*, Vol.40, No.2, pp.393-404.
- Herrera, F. and Lozano, M., (2003), Fuzzy Adaptive Genetic Algorithms: Design, Taxonomy and Future Directions, *Soft Computing Springer-Verlag*, Vol.7, pp.545-562.
- Huertas, A. and Nevatia, R., (1988), Detecting Buildings in Aerial Images, *Computer Vision, Graphics, and Image Processing*, Vol.41, pp.131-152.
- Irvin, R.B. and McKeown, D.M., (1989), Methods for Exploiting the Relationship Between Buildings and Their Shadows in Aerial Imagery, *IEEE Transactions On Systems, Man, and Cybernetics*, Vol.19, No.6, pp.1564-1575.
- Jin, X. and Davis, C.H., (2005), Automated Building Extraction from High-Resolution Satellite Imagery in Urban Areas Using Structural, Contextual, and Spectral Information, *EURASIP Journal on Applied Signal Processing*, Vol.14, pp.2196-2206.
- Kim, T., Lee, T.Y. and Kim, K.O., (2006), Semiautomatic Building Line Extraction from Ikonos Images Through Monoscopic Line Analysis, *Photogrammetric Engineering and Remote Sensing*, Vol.72, No.5, pp.541-549.
- Kim, Z. and Nevatia, R., (2004), Automatic Description of Complex Buildings from Multiple Images, *Computer Vision and Image Understanding*, Vol.96, pp.60-95.
- Lee, D.S., Shan, J. and Bethel, J.S., (2003), Class-Guided Building Extraction from Ikonos Imagery, *Photogrammetric Engineering and Remote Sensing*, Vol.69, No.2, pp.143-150.
- Liu, H., Xu, Z. and Abraham, A., (2005), Hybrid Fuzzy-Genetic Algorithm Approach for Crew Grouping, *Proceedings of 5th International Conference on Intelligent Systems Design and Applications*, ISDA'05, pp.332-337, Wroclaw, POLAND.
- Lu, Y.H., Trinder, J.C. and Kubik, K., (2006), Automatic Building Detection Using the Dempster-Shafer Algorithm, *Photogrammetric Engineering and Remote Sensing*, Vol.72, No.4, pp.395-403.
- Noronha, S. and Nevatia, R., (2001), Detection and Modeling of Buildings from Multiple Aerial Images, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol.23, No.5, pp.501-518.
- Peng, J. and Liu, Y.C., (2005), Model and Context-driven Building Extraction in Dense Urban Aerial Images, *International Journal of Remote Sensing*, Vol.26, No.7, pp.1289-1307.
- Perkins, S., Edlund, K., Esch-Mosher, D., Eads, D., Harvey, N. and Brumby, S., (2005), Genie Pro: Robust Image Classification Using Shape, Texture and Spectral Information, *Proceedings of SPIE*, Vol.5806, pp.139-148.
- Perkins, S., Theiler, J., Brumby, S.P., Harvey, N.R., Porter, R., Szymanski, J.J. and Bloch, J.J., (2000), GENIE: A Hybrid Genetic Algorithm for Feature Classification in Multi-Spectral Images, *Proceedings of SPIE*, Vol.4120, pp.52-62.
- Rottensteiner, F. and Briese, C., (2002), A New Method for Building Extraction in Urban Areas from High-Resolution Lidar Data, *Proceedings of the Photogrammetric Computer Vision, ISPRS Commission III Symposium, PCV'02*, Graz, AUSTRIA.
- San, D. and Turker, M., (2004), Automatic Building Detection and Delineation from High Resolution Space Images Using Model-Based Approach, *Proceedings of the XXth ISPRS Congress, Commission I*, Istanbul, TURKEY.
- Shackelford, A.K. and Davis, C.H., (2003), A Combined Fuzzy Pixel-Based and Object-Based Approach for Classification of High-Resolution Multispectral Data Over Urban Areas, *IEEE Transactions on Geoscience and Remote Sensing*, Vol.41, No.10, pp.2354-2363.
- Tseng, Y. and Wang, S., (2003), Semiautomated Building Extraction Based on CSG Model-Image Fitting, *Photogrammetric Engineering and Remote Sensing*, Vol.69, No.2, pp.171-180.
- Wang, O., Lodha, S.K. and Helmbold, D.P., (2006), A Bayesian Approach to Building Footprint Extraction from Aerial LIDAR Data, *Proceedings of the International Symposium on 3D Data Processing, Visualization, and Transmission*, pp.192-199, NC, USA.