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# Airport Runway Detection Based On Adaboost Algorithm

Abuthahir A[1], Mohana Arasi M[2],Kanya Kumari G E[3] , Nagarajan P[4]

**Abstract—*Automatic detection of airports is particularly essential, due to the strategic importance of these targets. In this paper, a detection method is proposed for airport runways. This method, which operates on large optical satellite images, is composed of a segmentation process based on textural properties, and a runway shape detection stage. In thesegmentation process, several local textural features are extracted. Since the best discriminative features for airport runways cannot be trivially predicted, the Adaboost algorithm is employed as a feature selector over a large set of features. Moreover, the selected features with corresponding weights can provide information on the hidden characteristics of runways. The proposed algorithm is examined with experimental work using a comprehensive data set consisting of large and high resolution satellite images and successful results are achieved*.**

**Keywords:** ***Airport runway detection, Textural features, Segmentation, Adaboost algorithm*.**

## I. INTRODUCTION

Airports are important structures from both economical and military perspective.Economically, as fundamental cargo and passenger transportation stations, airportsserve to attract and retain businesses with national and global ties. Therefore, airportsare a major force in the local, regional, national and global economy, becomingincreasingly significant in terms of financial reasons.The military airports, i.e. airbases, are also critical strategic targets considering theimportance of the aviation branch of a nation's defense forces. Airbases are usedfor not only take-off and landing of crucial bomber and fighter units, but also consequentialsupport operations such as strategic and tactical airlift, combat airdrop andmedical evacuation, promoting the worth of airports. From this point of view, automaticdetection of airports can provide vital intelligence to take well-timed militarymeasures in a state of war.The technological improvements on both computational hardware and pattern recognitiontechniques made identification of airports an attainable objective. Besides,increasing number of countries that have their own satellites renders the problemeven more attractive, by the supplied unbiased data to investigate. These reasonsform the motivation of this paper. In this letter, airport runway detection is undertaken by theAda-boost learning algorithm [14] employed on a large set oftextural features. It is utilized to find the best discriminativefeatures with corresponding weights, which can represent theGenuine local characteristics of the runway texture that cannotbe intuitively identified. In addition, Adaboost does not sufferfrom the curse of dimensionality and a large computationalcost for the extraction of extensive number of features since itdiscovers which features are to be used in the classification andwhich are to be eliminated by its feature selection property. Thisstrategy is based upon finding as many features as possible andletting the Adaboost algorithm judge and decide which featuresare to be used. In this letter, the following features are used:textural features including the mean and the standard deviationof image intensity and gradient; Zernike moments [15] andcircular-Mellin features [16], both of which have been previouslyused in airport detection [3], [4]; and Haralick features[17], commonly used in road detection [7], [18]. Furthermore,other prevalent textural features that have not been previouslyused for airport detection are employed, and they include theFourier power spectrum [19]–[21], wavelets [20], [21], andGabor filters [20]–[23].

## II. METHOD

First, satellite images are divided into nonoverlapping imageblocks of size N by N pixels. N is selected to be 32, whichis specified as appropriate for an airport runway width in1-m resolution images. Throughout the process, these blocks,represented by f(x, y) where x and y represent the coordinatesof the blocks, are considered to be the basic elements, and allfeature extraction and classification operations are executed interms of whether they are a runway or not.

### *A.* Features

Below, a brief information on the usage of the featuresemployed (137 in total) is provided. More detailed informationconcerning these features can be found in the references andabout their employment in airport detection in [24].

• **Basic features (features F1–F4):**Runways are generally auniform gray level and brighter than their surroundings.Thus, the means and the variances of intensity, and thegradient of intensity inside the image blocks can describethe intensity level and variation, respectively.

• **Zernike moments (F5–F13):**Zernike moments [15] arerotation-invariant image moments. The order of a Zernikemoment must have an upper bound to have a feasiblecomputation. In this letter, the Zernike moments of orderfrom 0 to 4, resulting in a total of nine features, areconsidered according to the restrictions in memory andcomputational time.

• **Circular-Mellin features (F14–F23):**Circular-Mellin featuresare also orientation and scale invariant. Thesefeatures take advantage of two parameters, i.e., radialfrequency and annular frequency. Some experimental resultsare given in [16] about the selection of these variablesby a search



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algorithm. The choice of the set of employedcircular-Mellin features was decided based on the parametersgiven in [16].

• **Fourier power spectrum (F24–F33):**The Fourier power Spectrum is used to extract features related to periodicpatterns. The power spectrum of the image block can beexamined in ring- [19] or wedge-shaped [21] regions. Thelatter are orientation dependent, and thus, they were notused. Ring-shaped regions can provide information aboutrepetitive forms. In this letter, power spectrum was dividedinto six equal ring-shaped regions, and the total powerscomprised by each region were considered as features. Inaddition, the maximum value, the average value, and thevariance of the discrete Fourier transform magnitude, aswell as the overall power spectrum energy, were used.

• **Gabor filters (F34–F81):**A dictionary of Gabor Filterswith six orientations and four scales was employed. Theother parameters were chosen according to [23]. Themeans and the variances of the Gabor-filtered outputimages were also used. To make Gabor filter outputsapproximately rotation invariant, the feature vector is cir-cularly shifted so that the scale–orientation pair having themaximum mean is located at the beginning of the vector[12], [21].

• **Haralick features (F82–F97):**Gray-level co-occurrencematrices are calculated [17]. When no prior informationis available, it is common to use offsets (1, 0), (1, -1),(0, -1), and (-1, -1), which correspond to adjacentpixels at 0◦, 45 ◦, 90 ◦, and 135◦, respectively. However,we initially selected the best discriminative window sizefrom a set of different-sized windows (1, 3, 5, 7, and9 pixels). The selected size was adjacent pixels, and weused that size for classification analysis.FourHaralick feature (energy contrast, homogeneity, and correlation)for four offsets (16 features in total) were employed.

• **Wavelet analysis (F98–F121):**These features are expected to provide a quantitative description of the textural properties related to both frequency and spatial domains. A three-level decomposition structure was employed, and the energies and the standard deviations of the four components (low–low, low–high, high–low, and high–high) for the three levels were used as features, giving a total of 24 features.

• **Features in Hue, Saturation, Value (HSV) color space (F122–F137):** Since the runways tend to be in gray tones and colorfulness is a synonym for saturation, it is thesaturation that will most probably provide valuable information. Likewise, the hue is closely related to thedominant wavelength, and although it is not so evident,the dominant wavelength of the color of a runway might beuseful. For these reasons, the mean, the variance, and themean and variance of the gradient magnitude, as well asthe Zernike moment of order 1 and circular-Mellin featurefor both saturation and value components, were employed.Since these two components provide linear information,the common mean and variance formulas still apply. Onthe other hand, since the hue bears angular information,its directional statistics are involved in the mean and variancecalculations. Since the Zernike and circular-Mellin features inherently require magnitudes rather than angles, the hue component is not utilized for these features. Employing features from the HSV color space for runway detection is a novel practice, and it has been shown to be very effective in the experimental analysis.

## III. Adaboost Learning Algorithm

Boosting is a general method to improve the performance of a learning algorithm(Freund, 1999). Adaboost (short for Adaptive Boosting) is a boosting algorithm,which takes a set of weak learners and constitutes a linear combination of them, in anumber of iterations, to produce a strong classifier. A weak learner is a classifier, whichgives weak hypotheses that are insufficient to solve the whole problem alone. These weak learners are often selected as threshold classifiers (Viola, 2001) which decide the output by judging the result of a comparison between input and a threshold. Such athreshold classifier, hj(x), is given in Equation 2.41.

$$hj(xj) = \begin{cases} +1 \ if \ p_i x_j < pj\theta j \\ -1 \text{ otherwise.} \end{cases}$$

.

In this equation xjis the feature, θjis the threshold, pis the parity which decides the direction of inequality and 1 = j = K where K is the number of features. Everyweak learner makes its decision by examining only one feature, so every classifier corresponds to a feature.Training of a weak learner, j, is given in Equation 2.42, and it means determining θj and pjj values that minimizes the classification error on the iteration t.

$$(\theta_j, p_j) = \text{argmin}_{(\theta_j, p_j)}\{\epsilon_{t,j}\}$$

This operation can be achieved simply by searching in intervals min(x) = θ= max(x) and pj= {+1, -1}. The definition of ϵ t,jis given in Equation .where yis the desired output label.

$$D_t\epsilon_{t,j} = \sum_{i:h_j(x_i) \neq y_i} D_{tj}i(i)$$

In this equation is the distribution function over training samples on the titeration. As it can be observed in the complete algorithm of the Adaboost, given in Figure 2.6, this distribution is utilized to emphasize the misclassified samples, forcing the algorithm to focus on the hard examples in the training set. Dt(i) is initialized to uniform.

## IV. EXPERIMENTAL RESULTS

The experiments were carried out with a data set consisting of 57 large satellite images having a size of 14 000 × 11 000 Pixels on average and a resolution of 1 m. Twenty-eight of these images were randomly selected for training, and 29 of them were reserved for testing. Each image was divided into blocksof size 32 × 32, and in this way, 4 205 796 blocks were obtainedfor training. Each block of the training images was labelled as runway (positive) if more than half of its pixels belong tothe runway of an airport and labeled as nonrunway (negative)otherwise. After labeling training images, 5315 runway blocksand 4 200 481 nonrunway blocks are obtained.


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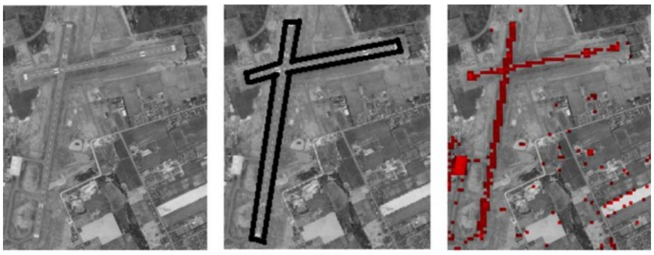
Only 10% ofthe nonrunway blocks are randomly selected and used becauseof memory constraints, whereas all of the runway blocks wereutilized. For the test images, ground-truth data were manuallyformed by marking only the main runways.The following measures were used for performance evaluation:The true positive rate (TPR; Sensitivity), which is the ratioof correctly classified positive labeled blocks to true positiveblocks (indicates how much the algorithm fails to find anExisting airport block). Likewise, the *true negative rate* (TNR;*Specificity*) is the ratio of correctly classified negative labelled blocks to true negative blocks (it indicates the amount thatthe algorithm fails to label a nonairport block as a nonairportblock).There are no parameters required by Adaboost except forthe iteration count, which determines the number of weakclassifiers to be considered. In this letter, 40 iterations wereperformed since an iteration count less than 40 is satisfactoryfor classification accuracy. Fig. 1(a) shows the performanceresults on every iteration for the training set. The *x*-axis indicatesthe number of features (weak learners) utilized, andthe *y*-axis is the corresponding performances (TPR and TNR).With only a few features, the performance increased to over80% and 70% for TNR and TPR, respectively. The performanceincreased to close to 90% in approximately 20 iterations wereconsidered. The performance increase was minor when moreiterations were considered.Each iteration of the Adaboost algorithm corresponds to aweak classifier operating on a single feature. The informationabout which feature was selected at each iteration is provided inTable I, where the names and the parameters of the selected featuresare given with their selection orders, the assigned featureidentification number among the 137 total features,Adaboostweights, and classifier rules, respectively. The threshold valuesof the classifier rules were normalized in order to provide amore explanatory expression. While it is not trivial to state thereasons for every selected feature, some are explicit. For instance,the first selected feature, which is the mean of saturation,denotes how colorful the image block is on the average. Observingthe classifier rule, the weak learner output is positive if theinput is less colorful than 16% of the saturation range. Sinceairport runways are not colorful structures and they tend to bein grayscale, this outcome is consistent with common sense.Likewise, the second selected feature, i.e., the variance of the Intensity gradient magnitude, which is selected multipletimes,denotes variation in the rate of intensity change in a block.Higher values mean that the block must have abruptly changingneighboring pixels and uniform areas at the same time. This isthe case when there is a runway sign or runway edge in a block.Haralick features (correlation andhomogeneity) and the thirdand fourth features in the table are also observed as significantdiscriminative features for runways. The multiple selection ofthe same feature is possible in Adaboost. At first, this may seemto be a redundancy;however, in this way, more sophisticatedclassification rules can be established, because the thresholdsand/or the parities of weak classifiers change at every iterationof training.The performance results for the test set are given in Fig. 1(b).While the TNR was very close to those achieved for thetrainingset, the TPR was slightly lower. The number of iterationsaround 20 gave comparable results with 40 iterations. In fact,due to duplicate selection by Adaboost, these first 20 classifierswere operating on 16 different features. That is to say, afterapproximately 16 features, adding more features did not providesignificant performance improvement. It is a question ofcomputation capacity whether to include remaining features ornot. In our letter, 83% TPR and 91% TNR were achieved forthe entire test set.

We also employed the support vector machine (SVM) classificationwith radial basis function kernel. We considered

(a) (b)

Fig. 2. (a) Original image with an airport inside dashed lines. (b) Detectedrunway blocks shown in red.



(a) (b) (c)

Fig. 3. Closer view of the (a) runway, (b) boundary, and (c) labeled blocks.

16 Adaboost selected features, which were concatenated to form a single vector. It was observed that the performance wasbelow that of Adaboost. We obtained 77% TPR and 86% TNRover the entire test set.In Fig. 2, an example of block labeling is given. Unlike theprevious studies in the literature, the experiment in which theproposed method was used contained a data set of large imagesconsisting of heavily negative samples. In Fig. 3, a closer viewis provided. As shown in Figs. 2 and 3, irrelevant blocks occursuch as roads classified as runways, which were of similargray tone and intensity variation. One way to remove falsepositives is to increase the final acceptance threshold used bythe Adaboost as a strong classifier. In this letter, a sign functionwas used; therefore, it takes threshold 0 when generating thefinal decision. Increasing the threshold would result in highprecision by decreasing false positives; however, it would alsodecrease true positives at the same time, i.e., resulting in a lowrecall. After taking the output of the classifier proposed hereas the region of interest, the false positives can be eliminatedby further processing considering domain information. For example,candidate blocks, which form long and wide elongatedrectangles, can be selected as runways, and others can beeliminated. In addition, by performing a connected componentanalysis, sparse false alarms may simply be eliminated byarea thresholding since they do not form elongated connectedcomponents. It was observed that the algorithm occasionallymisinterprets the highways or other wide roads as runways.Therefore, the interconnected network of these structures canbe analyzed by including road network detection in the method.Another way of determining whether the detected structure is anairport is to search for distinct fundamental airport buildings,such as



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control towers, terminal buildings, or hangars.Employing the Adaboost learning algorithm and the utilizationof features obtained using HSV color space, Gabor filters,Fourier power spectrum analysis, and wavelets are originalways of solving the airport runway detection problem.It was observed in the Adaboost training process that the majority ofselected features (24 out of 40) were new features (see Table I),which means that they are suitable features for runway detection.In fact, there are many textural features, but it is difficultto intuitively state the best discriminative one. Adaboost selects the best feature among a feature set; thus, it may be possible to explain the specific textural properties of runways that are hidden. Haralick features that have been previously used forautomatic road detection applications were also selected by
Adaboost (4 out of 40), which is an expected result due to the similarity of textural properties of roads and runways.The experiments are carried out on a 64-bit MATLAB environment, on a dual Xeon 2.0-GHz workstation with 4 GB ofmemory, running Linux ×64 operating system. Extracting allof the 137 features from a 14000 × 11000 image took approximately115 min, whereas extracting the Adaboost selected 16features to be used for test images took only 58 min. Bearing thesize of the data and the platform in mind, algorithm performedfairly well. After the training, it took 5 s to classify all blocksof a test image. Since nonoverlapping blocks are processed, theproposed system can be run in parallel to extract features forsaving time. As for the SVM, the training took approximately20 s after extracting 16 features, and it took about 1 s to classifyall blocks in a test image. While training the SVM, a problemarose from memory limitations, and it proved difficult to work on large feature vectors. Adaboost does not suffer from memorylimitation and can work with very large set of features; however,the training takes longer than that for the SVM.

## V. RESULT

A method for the detection of airport runways is proposed in this study. This method is based on an approach, which involves a segmentation process and a subsequentgeometric analysis on the aerial image. In the segmentation phase, textural propertiesare considered, and mostly prevalent textural features that are used for segmentationin the literature are employed. In addition to that,employing Adaboost learning algorithm and utilization of features obtained by usingHSV color space, Gabor Filters, Fourier Power Spectrum Analysis and Wavelets, arealso original works for the airport runway detection problem.Segmentation process can also be modified with a multi-class Adaboost learning algorithm,so that it can serve as a general purpose region of interest detector, for amultipurpose automatic target detection system. This improvement provides an efficiencyenhancement due to the unification of the detection of the regions of interest operations for various targets.

## VI. CONCLUSION

A texture-based method for the detection of airport runways has been proposed in this letter. Since it is not a trivial task to select discriminative features for classification, it may be inadequate to intuitively state the discriminative features for the classification of the objects of interest in remotely sensed images. Ada boost provides the most beneficial features that may also bear the nontrivial characteristics of objects. Thus ,it is possible to deduce hidden characteristics of objects, and this represents the twofold benefits of the proposed method. In general, the proposed method may be used for other kinds of objects of interest (targets) to better expose their hidden features. Then, domain information, if available, can be incorporated with selected features for target detection and recognition .Classification can be also modified with a multiclass Ada boost learning algorithm so that it can serve as a general-purpose region of interest detector for a multipurpose automatic target detection system.

## VII. REFERRENCE

[1] P. Gupta and A. Agrawal, “Airport detection in high-resolution panchromaticsatellite images,” J. Inst. Eng. (India), vol. 88, no. 5, pp. 3–9,May 2007.
[2] J. W. Han, L. Guo, and Y. S. Bao, “A method of automatic finding airportrunways in aerial images,” in Proc. 6th Int. Conf. Signal Process., 2002,vol. 1, pp. 731–734.
[3] D. Liu, L. He, and L. Carin, “Airport detection in large aerial opticalimagery,” in Proc. IEEE ICASSP, 2004, vol. 5, pp. V-761–V-764.
[4] Y. Qu, C. Li, and N. Zheng, “Airport detection base on support vectormachine from a single image,” in Proc. 5th Int. Conf. Inf., Commun.Signal Process, 2005, pp. 546–549.
[5] Y. Pi, L. Fan, and X. Yang, “Airport detection and runway recognition inSAR images,” in Proc. IEEE IGARSS, 2003, vol. 6, pp. 4007–4009.
[6] Q. Wang and Y. Bin, “A new recognizing and understanding method ofmilitary airfield image based on geometric structure,” in Proc. ICWAPR,2007, pp. 1241–1246.
[7] J. B. Mena and J. A. Malpica, “An automatic method for road extractionin rural and semi-urban areas starting from high resolution satelliteimagery,” Pattern Recogn. Lett., vol. 26, no. 9, pp. 1201–1220,Jul. 2005.
[8] H.Mayer, S. Hinz, U. Bacher, and E. Baltsavias, “A test of automatic roadextraction approaches,” in Proc. Int. Archives Photogramm., Remote Sens.Spatial Inf. Sci., 2006, pp. 209–214.
[9] S. Hinz and A. Baumgartner, “Automatic extraction of urban road networksfrom multi-view aerial imagery,” ISPRS J. Photogramm. RemoteSens., vol. 58, no. 1/2, pp. 83–98, Jun. 2003.
[10] J. Zhou, L. Cheng, and W. F. Bischof, “Online learning with noveltydetection in human-guided road tracking,” IEEE Trans. Geosci. RemoteSens., vol. 45, no. 12, pp. 3967–3977, Dec. 2007.
[11] M. Ziems, M. Gerke, and C. Heipke, “Automatic road extraction fromremote sensing imagery incorporating prior information and colour segmentation,”in Proc. Int. Arch. Photogramm., Remote Sens. Spatial Inf.Sci., 2007, vol. 36 (3/W49A), pp. 141–148.
[12] M. Mokhtarzade, M. J. V. Zoej, and H. Ebadi, “Automatic road extractionfrom high resolution satellite images using neural networks, texture analysis,fuzzy clustering and genetic algorithms,” in Proc. Int. Arch. Photogramm.,Remote Sens. Spatial Inf. Sci./ISPRS Congr., Beijing, China,2008, pp. 549–556.



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[13] T. Oommen, D. Misra, N. K. C. Twarakavi, A. Prakash, B. Sahoo, andS. Bandopadhyay, “An objective analysis of support vector machinebased classification for remote sensing,” Math. Geosci., vol. 40, no. 4,pp. 409–424, May 2008.
[14] Y. Freund and R. E. Schapire, “A short introduction to boosting,” in Proc.16th Int. Joint Conf. Artif. Intell., 1999, pp. 1401–1406.
[15] A. Khotanzad and Y. H. Hong, “Invariant image recognition by Zernikemoments,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 12, no. 5,pp. 489–497, May 1990.
[16] G. Ravichandran and M. M. Trivedi, “Circular-Mellin features for texturesegmentation,” IEEE Trans. Image Process., vol. 4, no. 12, pp. 1629–1640, Dec. 1995.
[17] R. M. Haralick, K. Shanmugam, and I. Dinstein, “Textural features forimage classification,” IEEE Trans. Syst.,Man, Cybern., vol. SMC-3, no. 6,pp. 610–621, Nov. 1973.
[18] D. Popescu, R. Dobrescu, and D. Merezeanu, “Road analysisbased on texture similarity evaluation,” in Proc. 7th WSEAS/SIP, 2008,pp. 47–51.
[19] M. F. Augusteijn, L. E. Clemens, and K. A. Shaw, “Performance evaluationof texture measures for ground cover identification in satellite imagesby means of a neural network classifier,” IEEE Trans. Geosci. RemoteSens., vol. 33, no. 3, pp. 616–626, May 1995.
[20] S. D. Newsam and C. Kamath, “Retrieval using texture features in highresolution multi-spectral satellite imagery,” in Proc. SPIE Defense SecuritySymp., Data Mining Knowl. Discov.: Theory, Tools, Technology VI,Orlando, FL, 2004.
[21] S. D. Newsam and C. Kamath, “Comparing shape and texture featuresfor pattern recognition in simulation data,” in Proc. SPIE Conf.—SPIEConf. Ser., E. R. Dougherty, J. T. Astola, and K. O. Egiazarian, Eds., 2005,pp. 106–117.
[22] B. S. Manjunath and W. Y. Ma, “Texture features for browsing and retrievalof image data,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 18,no. 8, pp. 837–842, Aug. 1996.
[23] R. M. Rangayyan, R. J. Ferrari, J. E. L. Desautels, and A. F. Frere,“Directional analysis of images with Gabor wavelets,” in Proc. XIII Braz.Symp. Comput. Graph. Image Process., 2000, pp. 170–177.
[24] U. Zöngür, “Detection of airport runways in optical satellite images,” M.S.thesis, Middle East Techn. Univ., Ankara, Turkey, Jul., 2009.
[25] P. Viola and M. Jones, “Robust real-time object detection,” Int. J. Comput.Vision, vol. 57, no. 2, pp. 137–154, Jul. 2001.

## Author Details:

[1]M.E.Applied Electronics, Bannari Amman Institute Of Technology.
[2]Assistant Professor, Dept.of ECE, BannariAmman Institute Of Technology.
[3]Professor, Dept.of ECE, Bannari Amman Institute Of Technology.
[4] M.E. Applied Electronics, Bannari Amman Institute Of Technology.



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