EFFECTIVENESS OF BOOSTING ALGORITHMS IN FOREST FIRE CLASSIFICATION

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ABSTRACT:

In this paper, it is aimed to investigate the capabilities of boosting classification approach for forest fire detection using SPOT-4 imagery. The study area, Bodrum in the province of Muğla, is located at the south-western Mediterranean coast of Turkey where recent largest forest fires occurred in July 2007. Boosting method is one of the recent advanced classifiers proposed in the machine learning community, such as neural networks classifiers based on multilayer perceptron (MLP), radial basis function and learning vector quantization. The Adaboost (AB) and Logitboost (LB) algorithms which are the most common boosting methods were used for binary and multiclass classifications. The effectiveness of boosting algorithms was shown through comparison with Bayesian maximum likelihood (ML) classifier, neural network classifier based on multilayer perceptron (MLP) and regression tree (RT) classifiers. The pre and post SPOT images were corrected atmospherically and geometrically. Binary classification comprised burnt and non-burnt classes. In addition to the pixel based classification, textural measures including, gray level co-occurrence matrix such as entropy, homogeneity, second angular moment, etc. were also incorporated. Instead of the traditional boosting weak (base) classifiers such as decision tree builder or perceptron learning rule, neural network classifier based on multilayer perceptron were adapted as a weak classifier. The accuracy of the MLP was greater than that of ML, AB, LB and RT both using spectral data alone and textural data. The use of texture measures alone was found to increase classification accuracy of binary and multi-class classifications. The accuracy of the land cover classifications based on either binary or multi-class was maximised using a MLP approach. This was slightly greater than the accuracy achieved using AB and LB classifications. However, it was shown that AB and LB classifications hold great potential as an alternative to conventional techniques.

1. INTRODUCTION

Forest fires, whether natural or initiated by man, have an important influence on the environment, human health (often leading to fatalities) and property. Fires destroy thousands of hectares of the worldwide forests each year, causing soil erosion and desertification processes, long-term site degradation and alteration of hydrological regimes, producing a significant amount of aerosols and carbon gases that may strong influence to the global climate changes. In terms of annual damage, Turkey is one of the most susceptible countries in the Mediterranean region. Turkish Ministry of Forestry reports that the most frequently burned regions in Turkey are Antalya, Balikesir, Çanakkale, Denizli, Isparta, Izmir and Mugla (İm et al., 2006). The information needed for fire management includes fire risk map, fire detection and monitoring (Mazzeo et al., 2007; Cuomo etc. 2001), damage assessment and planning post-fire recovery (Badarinath et al., 2007; Isaev et al., 2002; Phulpin et al., 2002; Yu et al, 2004; Fraser et al., 2003; Sunar and Özkan 2001). Effective management requires the use of new techniques using remote sensing and Geographical Information Systems (GIS). In fire damage assessment, satellite imagery in conjunction with ground observations is the main source of information from which pre-fire vegetation condition can be determined. Pre-fire condition is important both in order to assess potential fire risk and to make rational judgements on the precautionary measures required to avoid potential soil erosion which topographic and meteorological conditions may promote on newly burnt land (Chuvieco and Martin, 1994; İm et al., 2006).

Many remote sensing analyses comprise many digital image processing algorithms from simple spectral or spatial transformations such as image subtracting to complex procedures such as classification. The land cover changes such as fire burnt areas and the degree of severity because of fire can be effectively determined by the change detection approaches, image spectral transformations such as NDVI (Normalized Difference Vegetation Image) or classification methods such as ISODATA and maximum likelihood. The success of the change detection procedures mostly depends on the radiometric and geometric consistencies of the multi-temporal imageries. NDVI in which the vegetation is the primary reflectance object is a commonly used technique. Although change detection and NDVI are effective to extract the biomass and to discriminate the healthy and unhealthy vegetation, the classification phase is vital for the quantitative and qualitative precise analysis of these land covers. Among many supervised and unsupervised classification methods, the approaches based on the artificial intelligence such as artificial neural networks and ensemble algorithms such as boosting are mostly investigated. Boosting method is one of the recent advanced classifiers proposed in the machine learning community, such as neural networks classifiers based on multilayer perceptron, radial basis function

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and learning vector quantization (Freund and Schapire, 1997, 1999). Boosting is an ensemble method aimed to increase the performance of weak classifier by dividing and conquering (Ramalho and Medeiros, 2006). From some points of views these techniques are found superior to the conventional statistical methods. Nowadays, especially the boosting classification methods such as Adaboost and Logitboost are the most attractive ones. These methods are easily programmable and can be easily fused with the artificial neural network classifiers. In this study, the main purpose is to show the capabilities of boosting ensemble methods to determine the burnt severity.

This paper assesses classification accuracy of forest fire with various classification techniques, including the Multi Layer Perceptron (MLP), Maximum Likelihood (ML), Adaboost (AB), Logitboost (LB) and Regression Tree (RT). The grey-level co-occurrence matrix of image processing was also applied successfully to derive textural measures. Three textural measures were extracted from the co-occurrence matrix and used to feedback the classification.

2. STUDY AREA AND DATA

In this study, one of the recent big forest fires occurred in Bodrum, in the province of Muğla, was analyzed (Figure 1). This devastating fire occurred in July 2007 and ruined approximately 1,100 hectares including forestland and agricultural areas while damaging also few settlements in Torba district (Sunar, 2007). Two SPOT-4 multispectral images (pre- and post-fire) dated on 29th June and 14th July respectively, were used (Figure 2).

Figure 1: Study area

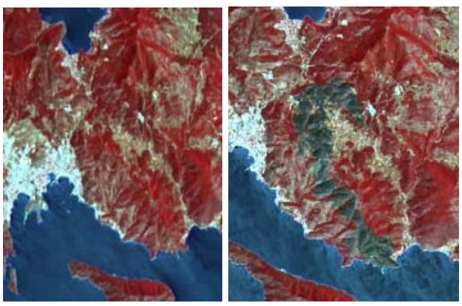

Figure 2: Pre and post-fire SPOT-4 imageries.

3. METHODOLOGY

Pre (dated on 29th June) and post-fire (dated on 14th July) images of SPOT-4 were utilized in order to assess the damages occurred in the area. As a first step, radiometric correction and registration processes were applied and than the burnt areas were determined using digital change detection analysis techniques together with the help of ancillary data. For this purpose, binary and multiclass cases were taken into consideration. For binary classification, burnt and non-burnt classes were constituted. In addition to the pixel based classification, textural measures including, gray level co-occurrence matrix such as entropy, homogeneity, second angular moment, etc. were also incorporated. Adaboost and Logitboost algorithms, the most widely used boosting methods, were tested for the forest fire classification. Instead of the traditional boosting weak (base) classifiers such as decision tree builder or perceptron learning rule, neural network classifier based on multilayer perceptron were adapted as a weak classifier. In order to be able to show the effectiveness of boosting algorithms, Bayesian maximum likelihood classifier, neural network classifier based on multilayer perceptron and regression tree classifiers were also employed.

3.1 Maximum Likelihood classification (ML)

As a statistical classifier, Maximum likelihood is one of the most popular methods of classification in remote sensing, in which a pixel with the maximum likelihood is classified into the corresponding class (Swain and Davis, 1978). The likelihood is defined as the posterior probability of a pixel belonging to that class. For mathematical reasons, a multivariate normal distribution is applied as the probability density function. For more information, Richards and Jia (2006) can be referred.

3.2 Artificial Neural Network (ANN)

Artificial neural networks are a branch of artificial intelligence science. Since 1940s, the theoretical and practical aspects of the artificial neural networks have been investigated. Artificial neural networks are soft-computational systems based on the working principles of biological neural systems, i.e. it is a mathematical model composed of many neurons operating in parallel (Özkan and Sunar, 2003, Berberoğlu et al., 2006). These networks have the capacity to learn the nonlinear and highly complex relationships amongst data and to generalize these relations to the unseen data before. Since the learning skill completely depends on the sample data, ANNs can be seen as non-parametric. They have also easy adaptation capacity to different types of data and input structures. These features make ANNs good solutions for the nonlinear classification problems having arbitrary decision boundaries. Amongst many ANN structures, Multi Layer Perceptron (MLP) with backpropagation learning algorithm is the most common network type (Beale et al., 1996). MLP simply comprises one input layer, one hidden layer and one output layer. The weight values of connections are updated iteratively in terms of error minimization in the backpropagation way. Despite all these advantages of ANN MLP, the construction of the topological design of network and determination of the learning rule parameters and the iteration number are hard tasks and they fully depend on from an application to another.

3.3 Boosting

Boosting (Schapire, 1990) is an ensemble method used for increasing the precision of a weak or base classifier. An ensemble is a set of classifiers whose individual predictions are combined to classify new examples (Dzeroski and Zenko, 2004) with better performance than using a single classifier. These individual classifiers called as weak or base classifiers can be decision tree, perceptron learning rule, binary thresholding a single feature, etc. At each boosting iteration, one weak (base) classifier is constituted and trained using a different sample distribution which depends on the misclassified vectors. These classifiers are then combined by weighted voting into a new final classifier. This combined classification approach improves the performance of classifier and also minimizes the misclassification. Another important advantage of boosting compared to other methods is that it works without fine tuning and no sophisticated nonlinear optimization is necessary. The number of weak classifiers is the only parameter to be tuned that boosting algorithm needs. Moreover, boosting is resistant to overfitting whereas other techniques such as, neural network suffers very often (Ramalho and Medeiros, 2006). As a result of these advantages, boosting method as a classification technique is becoming a widely-used approach. Besides to the machine learning, pattern recognition and bioinformatics areas (Dettling and Bühlmann, 2002), the potentials of boosting classification methods for different problems in the remote sensing area has been recently exploited (Ramalho and Medeiros, 2006; Özkan and Sunar, 2007; Bailly et al., 2007; Chan et al., 2003).

Adaboost (AB) and Logitboost (LB) algorithms are the most common boosting methods. They are very easy to program and adapt for different types of weak classifiers. As the original boosting algorithm was improved to get adaptive boosting (Adaboost) by Freund and Schapire (1997, 1999), the Logitboost algorithm was introduced by Friedman et al. (2000). Logitboost is a boosting improvement instead of Adaboost in order to reduce the training errors linearly which provides bias minimizing and hence improves the generalization. Logitboost relies on the binomial log-likelihood as a loss function (Friedman et al., 2000). This approach is a more natural criterion in classification than the exponential criterion underlying the Adaboost algorithm (Dettling and Bühlmann, 2002). The coding flowchart and more theories can be found in (Friedman et al., 2000; Freund and Schapire, 1997, 1999).

3.4 Regression Tree (RT)

The RT method has become a common alternative to conventional soft classification approaches in recent years particularly with MODIS data (Hansen et al., 2005). A regression tree is a logical model represented as a binary (two-way split) tree that shows how the value of a target variable can be predicted by using the values of a set of predictor variables. The basic concept of a decision tree is to split a complex decision into several simpler decisions, which may lead to a solution that is easier to interpret. A regression tree is constructed by a binary split that divides the rows in an initial node into two groups (child nodes). The same procedure is then used to split the child groups. Tree building begins at the root node that represents all of the rows in the dataset and includes all features in the training dataset. Beginning with this node, the model finds the “best” possible variable to split the node into two child nodes. It analyzes all input predictive variables to determine the binary division of a single variable which best reduces the deviation in response and, therefore, the two most homogeneous stems. This process is repeated until homogeneous divisions, or terminal nodes, are found (Breiman et al., 1984; Verbyla, 1987). Regression tree models can account for non-linear relations between predictor and target variables and allow both continuous and discrete variables as input. The accuracy and predictability of regression tree models have been found to be greater than those of simple linear regression models (De’Ath and Fabricius, 2000; Huang and Townshend, 2003; Pal and Mather, 2003).

4. APPLICATION AND RESULTS

In order to correct pre- and post-imageries radiometrically, simple dark object subtraction method was applied because of lacking an accurate digital elevation model and short time interval between two imageries. After removing the geometric deformations by a second order polynomial transformation through 64 GCPs with a 0.61 rms error, the difference image was produced using NDVI images through NIR and RED channels (Figure 3).

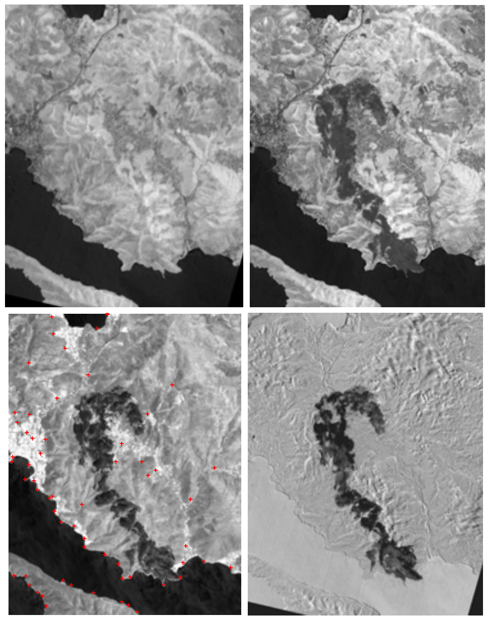

Figure 3: Pre-fire NDVI image (upper left), Post-fire NDVI image (upper right), Distribution of the GCPs used, (lower left), difference image (lower right).

The burnt area of approximately 950 hectares was determined precisely from the highest spectral gradients with the help of ancillary data. Then the binary image of the burnt area was extracted and applied to the pre-fire NDVI image. After ISODATA clustering analysis of the extracted pre-fire NDVI image, a ML classification was applied to determine the approximate biomass areas; mainly as soil (low dense vegetation), green-1 (dense vegetation) and green-2 (high dense vegetation) areas (Figure 4).

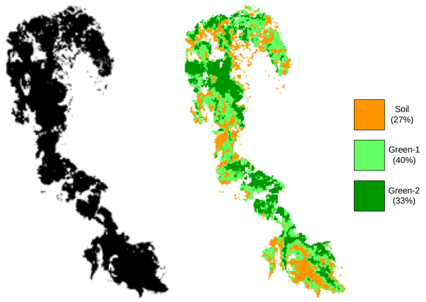

Figure 4: Binary image of the burnt area (left) and ML classification of pre-fire NDVI image (right).

According to this classification, the areas of soil, green-1 and green-2 classes were calculated approximately as 256, 380, 314 hectares, respectively.

In the post-fire image classification phase, totally 4368 train patterns and 9046 test patterns for 6 classes were selected from post-fire imagery. These classes are burnt area, green-1, green-2, soil, urban and sea. Binary and multiclass classification strategies were applied separately. For binary classification, non-burnt classes were constituted from other 5 classes. In addition to the pixel based classification, for textural classification, textural measures including, mean, variance and entropy measures (Eq. 1) based on gray level co-occurrence matrix (GLCM) were also incorporated (Haralick et al., 2007).

$$Mean = \sum_{ij} (i,j) P_{ij}$$

$$Variance = \sum_{ij} [(i,j) - mean]^2 P_{ij} \qquad (1)$$

$$Entropy = -\sum_{ij} P_{ij} \log(P_{ij})$$

where, P_{ij} is the GLCM value. In contradiction to the pixel intensity itself, texture provides information about the spatial correlation among neighboring pixels. These textural measures were computed using 5x5 kernels with shifting 1 pixel in x and y axis.

From artificial neural network structures, Multilayer Perceptron was employed. Levenberg-Marquardt backpropagation selected as the training algorithm was used for updating the synaptic weights and bias values. This learning algorithm was so fast converging and found as the best from a test of sequence of different learning rules such as standard gradient decent with momentum, conjugate gradient methods and one-step secant. The network topology was constituted as one hidden layer of 10 and 15 neurons for binary and multiclass cases. In order to obtain the optimal learning phase, each learning epoch was analysed through test data.

In Adaboost and Logitboost classifications, multilayer perceptron ANN classifiers based on Levenberg-Marquardt backpropagation were employed as the weak classifier instead of conventional decision tree classifiers. Adaboost multiclass algorithm was coded as Adaboost.M2 (Freund and Schapire, 1997). Boosting iteration number meaning the number of weak classifiers ensembled was tuned as 10 for Adaboost and 5 for Logitboost binary applications. For multiclass applications, this parameter was tuned as 5 for Adaboost and 1 for Logitboost. Although the only parameter that must be tuned is the iteration number for boosting methods with decision tree weak classifier, topological and learning rule ambiguities such as number of hidden layers and number of artificial neurons must be adjusted for MLP weak learners.

The classification results of the test data calculated from ML, MLP, Adaboost, Logitboost and RT were given in tables 1-8. In these tables, the abbreviations of PA, UA and OA mean producer, user and overall accuracies, respectively.

	PA		UA	
	B	U	B	U
ML	96.90	100	100	99.20
MLP	99.78	100	100	99.94
AB	99.80	100	100	99.90
LB	99.70	100	100	99.90
RT	95.81	99.95	99.82	98.97

Table 1: PA and UA for test data pixel-based binary classifications (B burnt and U unburnt classes).

Class	1	2	3	4	5	6
ML	98.70	70.40	49.20	94.70	96.90	99.90
MLP	99.60	70.30	83.60	96.10	96.50	100
AB	99.39	70.6	80.83	95.61	96.36	100
LB	99.72	68.03	78.94	95.38	96.81	100
RT	99.49	63.73	56.25	87.06	95.35	100

Table 2: PAs for test data pixel-based multiclassifications.

Class	1	2	3	4	5	6
ML	100	72.1	76.20	88.60	58.60	100
MLP	100	75.80	82.80	88.90	97.80	99.90
AB	100	72.39	81.62	88.65	98.60	99.93
LB	99.94	74.68	81.36	83.10	96.16	99.93
RT	95.91	62.19	73.68	92.40	69.25	99.79

Table 3: UAs for test data pixel-based multiclassifications.

	Binary OA	Multiclass OA
ML	99.40	86.80
MLP	99.96	93.20
AB	99.96	92.58
LB	99.93	92.06
RT	99.14	86.60

Table 4: OAs for test data pixel-based binary and multiclass classifications.

	PA		UA	
	B	U	B	U
ML	97.49	100	100	99.38
MLP	100	100	100	100
AB	100	100	100	100
LB	100	100	100	100
RT	96.70	99.75	98.97	99.19

Table 5: PA and UA for test data textural binary classifications (B burnt and U unburnt classes).

Class	1	2	3	4	5	6
ML	99.72	69.53	51.21	98.27	98.63	99.83
MLP	100	71.24	88.53	98.85	98.18	100
AB	100	71.78	86.29	99.08	97.72	100
LB	99.94	66.95	81.07	97.34	97.95	100
RT	96.70	77.14	55.82	97.34	98.17	99.86

Table 6: PAs for test data textural multiclassifications.

Class	1	2	3	4	5	6
ML	99.17	76.69	77.29	57.23	96.76	100
MLP	100	79.71	84.58	94.90	99.77	100
AB	99.89	76.02	84.69	94.81	100	100
LB	99.83	67.61	81.27	94.40	99.77	100
RT	98.97	71.18	82.36	64.74	97.51	98.12

Table 7: UAs for test data textural multiclassifications.

	Binary OA	Multiclass OA
ML	99.5	87.56
MLP	100	94.66
AB	100	94.28
LB	100	92.68
RT	99.14	88.47

Table 8: OAs for test textural binary and multiclass classifications.

5. CONCLUSIONS

In this study, the classification efficiencies of Adaboost (AB) and Logitboost (LB) boosting algorithms were investigated for the assessment of forest fire damage using SPOT-4 pre- and post- imageries and compared with the Maximum Likelihood (ML), Multilayer Perceptron Neural Network (MLP) and Regression Tree (RT) classification methods. The classification procedure was executed in a manner of both binary and multiclass cases for each classifier.

In the pixel based spectral classification, the binary classification results for all classifiers are very close to each other since the spectral separability between burnt and unburnt classes is very high. The multiclass classification results show that although MLP classifier gives the best performance, the performances of AB and LB classifiers are comparable to that of MLP. RT and ML classifiers, whose performances are the lowest ones, are also comparable to each other.

In the textural classification, texture measures alone increased the classification accuracies of binary and multi-class classifications. For binary case, MLP, AB and LB algorithms have given a hundred percent accuracies. For multiclass case, MLP and AB gave the highest results being comparable to each other. However, the performance of LB was close to others.

Although the accuracy of the land cover classifications based on either binary or multi-class was maximised using a MLP approach, AB and LB classifiers gave slightly lower performances than that of ML. Consequently, it was shown that AB and LB classifications hold great potential as an alternative to conventional techniques.

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