LEARNT HORIZON FILTER: A MACHINE LEARNING APPROACH

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ABSTRACT: *In digital image, the sky colour detection has number of applications. It includes, but not limited to lighting correction, image enhancement, horizon alignment, scene indexing and others. This article tackles the problem of pixel based sky colour detection from the machine learning point of view. Rather than creating complex filters, the setup in this article uses simple pixel classification approach by the offline trained classifiers. From the machine learning set, four classifiers are used, including: Random Forests, Multi-layer Perceptron, Radial Basis Function and the Bayesian Network. The experimental evaluation is presented on a dataset of 1000 images. Experimental results show the feasibility of the Multilayer Perceptron for sky detection. It is also found that the Multilayer Perceptron classifier has 8% higher detection performance compared to the Random Forest classifier and the Radial Basis function classifier. The Random Forest classifier however has 9% higher performance compared to the Bayesian classifier and approximately equal to the Radial Basis function. This research work not only presents colour based sky detection, but also contributes and benefits the colour based object detection in general*

Keywords: Static Filter, RGB, nRGB, Sky Color Detection, Horizon detection.

INTRODUCTION

Due to its number of contributions, the analysis and detection of sky colour in images has gained large attention and is among the most important subject matters in color based analysis of digital images [1]. The sky colour segmentation and detection in images is augmenting number of computer vision applications. These applications ranges from scene lighting adjustment, image colour enhancement, horizon alignment in aerial applications, weather analysis to scene indexing and image retrieval applications [2]. In a colour digital image, a set of pixels patch represent a sky color, if it is corresponding to a sky locus in the outdoor scene image. In an image, a pixel is part of a sky patch if the patch is the image representing the earth's atmosphere [1]. The success in the detection of sky region in a digital image will facilitate a variety of image understanding, enhancement and manipulation tasks. The outdoor scenes contain sky colour in the area of blue tone, half white and somewhere, other components are also present. The challenges for sky detection algorithms are the different clouds, air planes, trees, seas and other confused sky-like backgrounds. The sky colour can be detected from the image pixel values and due to this unique property; processing speed of the pixel based algorithm is fast as compare to the region based detection techniques. Generally, colour based detection is independent of image size, angle of pixel and orientation [3]. Pixel based sky detection is significantly dependent on the lightning conditions, due to this reason its strength is limited in uncontrolled environments.

The Algorithm in [4] takes advantage of the adaptive relocation and colour analytical processing for the segmentation and extraction of the sky patch. The authors in [5] use chromatic, shape and position features as an input for sky detection in an image claiming the superior performance compared to the state-of-the-art in. In [6], the authors develop sky colour based solar exposure pplication, segmenting the out-door environmental images under varying lighting conditions.

Luo et. al. [7] models a physical phenomenon associated with the sky/horizon color and their method achieves an excellent over-all performance.

In this paper, we investigate sky color detection from the machine learning point of view. We believe that such thorough analysis has never been undertaken and that this greatly contributes to the state-of-the-art. We investigate color based sky detection and evaluate the four machine learning approaches: Random Forests, Multi-layer Perceptron, Radial Basis Function and the Bayesian Network. For experimental analysis, we use the dataset DS. Experimental results show the feasibility of the Multilayer Perceptron for color based sky detection. It is also found that the Multilayer Perceptron classifier has 8% higher F-measure which is 0.73 than Random Forest classifier and Radial Basis function classifier. F-Measure of Random Forest classifier is 0.65 which is 9% higher than Bayesian classifier and almost equal to Radial Basis function which 0.65. The research benefits the colour based object detection in general.

CLASSIFICATION

A random forest is the mixture of different decision trees. The main concept of Random Forest approach is presented by Tin Ho [8]. The random forest has high accuracy than the decision trees classifier. In random forests, the classifier is trained on a number of decision trees. After that, each tree votes for the input results. The numbers of votes are calculated in the end and each tree uses a dissimilar bootstrap example. A bootstrap example is a random subsection (small part) of the training data sample. During processing, data points might be nominated frequently i.e. collection with addition. A random number of bootstrap might be accordingly used.

Artificial neural networks are based on the same principle the working neurons of the human brains processing the information [9]. Neural networks are greatly used in various fields of technologies. The word Multilayer perceptron means that there are various hidden layers, such that they can form a network of hierarchy. The input layer, is comparatively simple. It has one neuron per input value. The neurons in first layer are linked to each neuron of the second layer. Therefore the mainstream calculation for neural network is done by hidden layers. Weights are assigned to each neurons between the layers.

Each hidden layer are multiplied and summed up by the joining values from the previous joining layer. The total sum of hidden layer is than given to the activation function. The resultant value of neuron is collected, based on the activation function.

The activation function gives a limit for the classification of the substances. There are various types of activation functions. The activation functions mostly used are step function and logic functions.

Bayesian networks [10], also known as belief networks (Belief Network), or a directed acyclic graph model, is a probabilistic graphical model, first proposed in 1985 by Judea Pearl.

Bayesian network representing random variables is a directed acyclic graph of nodes {X1, X2,……….., Xn}, which may be observable variable, or hidden variables and the unknown parameters.

Assuming a direct impact on the node E to node H, i.e. E → H, then use the arrow H from the point E to establish the node E to node H of directed arc (E, H), weights (i.e., the connection strength) with the conditional probability P (H | E) is represented as shown in equation 1.

$$P\left(\frac{H}{E}\right) = \frac{P\left(\frac{E}{H}\right)P(H)}{P(E)} \quad 1$$

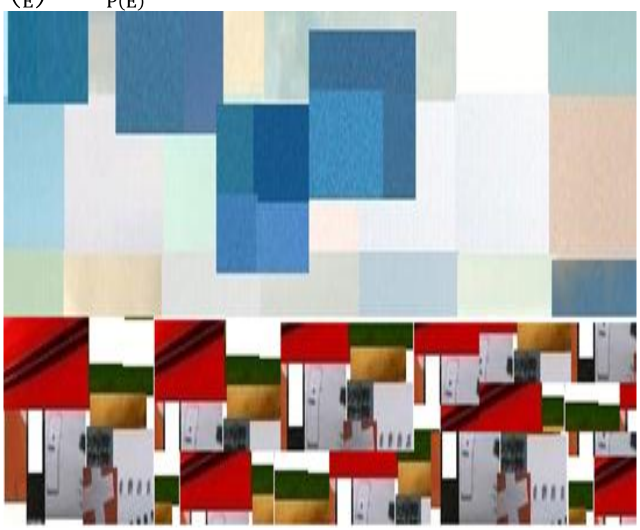

Figure 1: Training image for the dataset DS1

Radial Basis Function (RBF) [11] is similar to neural networks. In computer vision field, RBF plays an important role. RBF has unique characteristics and best approximation of radial basis function in SVM as the input samples can be mapped to a high dimensional feature space to solve some of the original linearly inseparable problems.

RBF network comprises three layers [12], where each layer has a completely different role. Perceived by some input layer units, they will connect the network with the external layer. The second layer is hidden layer, its role is to perform non-linear transformation from the input space to the space between the hidden layer. Output layer is linear, it provides for acting on the active mode in response to the input layer.

In this paper, we investigate and evaluate machine learning based sky filters for sky detection. As such we investigate and evaluate the four machine learning approaches: Random Forests, Multi-layer Perceptron, Radial Basis Function and the Bayesian Network. The experimental evaluation is presented on dataset DS. Experimental results show the feasibility of the Multilayer Perceptron for sky detection. It is also found that the Multilayer Perceptron classifier has 8% higher F-measure which is 0.73 than Random Forest classifier and Radial Basis function classifier. F-Measure of Random Forest classifier is 0.65 which is 9% higher than Bayesian Function classifier and almost equal to Radial Basis function which 0.65. The research also benefits the colour based object detection in general.

EXPERIMENTAL EVALUATION

The dataset DS1 used for recognition of sky is created by [13]. We performed our experiments, training and testing using the DS1. The DS1 contains 1000 images. The images used for training the classifier are called training images (see Figure 1). The images used for testing are called the mask images of original images as depicted in Figure 2. Figure 3 shows the original images from DS1.

Figure 4 shows the result of applying the random forest classifier. First row shows original images, second row shows the result of the random forest (Black pixels show non-sky) on DS1. Figure 5 shows the experimental evaluation of our Random Forest classifier on the dataset DS1. The Accuracy of Random forest classifier is 0.80, Precision is 0.55, Recall is 0.79 and F-measure is 0.65.

Figure 2: Mask images of original images used in the experiments

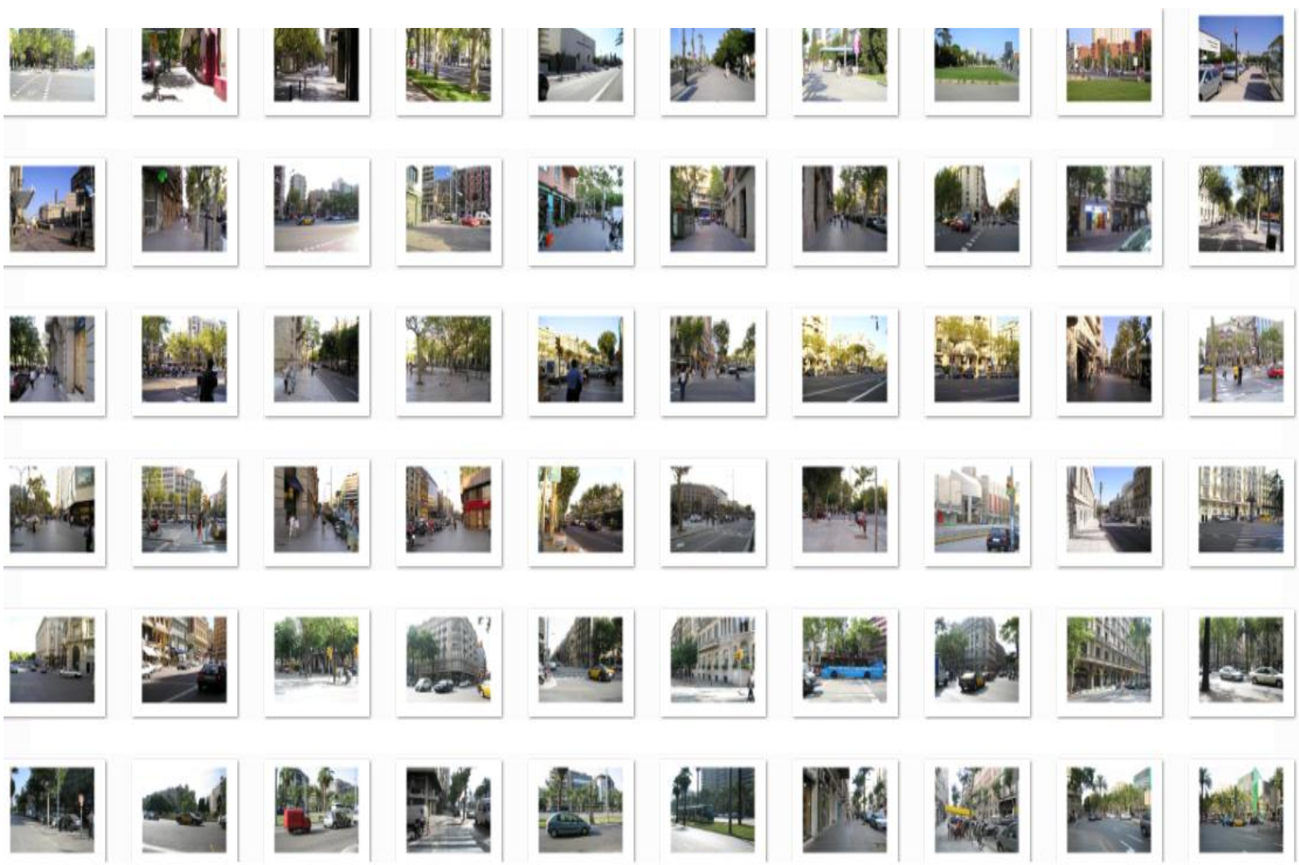

Figure 3: Original images for testing used in the experiments

Figure 4: Result of applying the random forest classifier. First row shows original images, second row shows the result of the random forest (Black pixels show non-sky) on DS1.

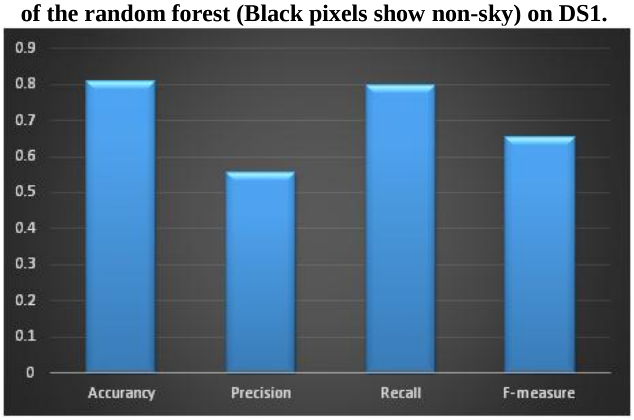

Figure 5: Evaluation Result of Random Forest classifier on DS1

Figure 6 shows the result of applying the Multilayer Perceptron classifier. First row shows original images, second row shows the result of the Multilayer Perceptron (Black pixels show non-sky) on DS1

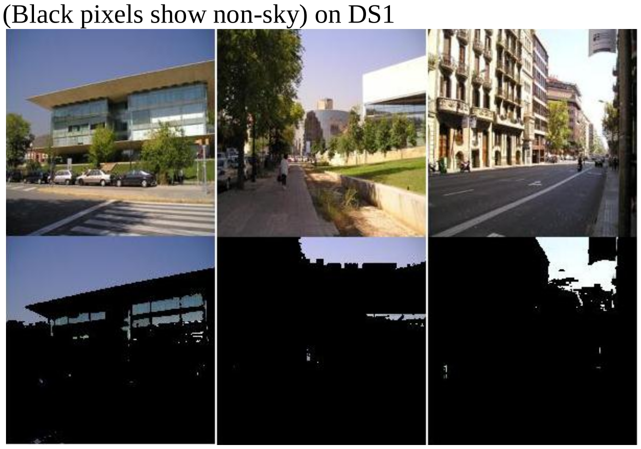

Figure 6: Result of Multilayer Perceptron classifier on DS1. First row shows original images, second row shows the result (Black pixels show non-sky) on DS1.

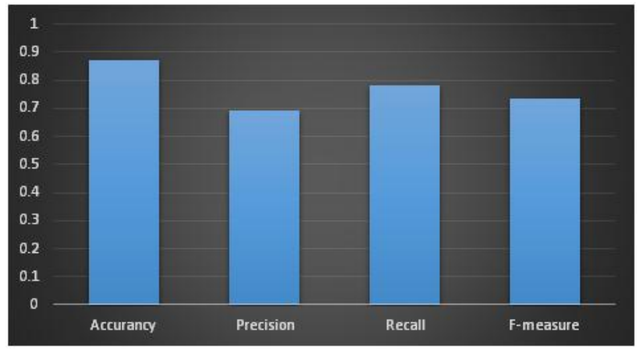

Figure 7: Evaluation of Multi-layer Perceptron classifier on the dataset DS1.

Figure 7 shows the experimental evaluation of the Multilayer Perceptron. The Accuracy of Multilayer Perceptron classifier is 0.87, Precision is 0.69, Recall is 0.78 and F-measure is 0.73.

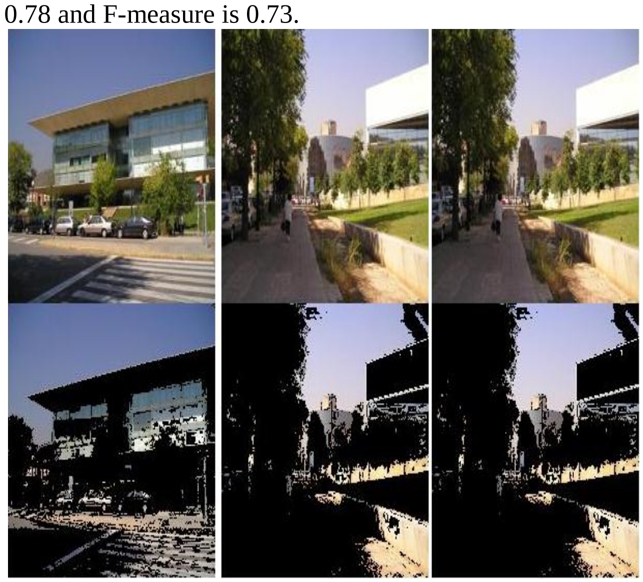

Figure 8: Result of applying the Bayesian Network classifier. First row shows original images, second row shows the result of the Bayesian Network (Black pixels show non-sky) on DS1

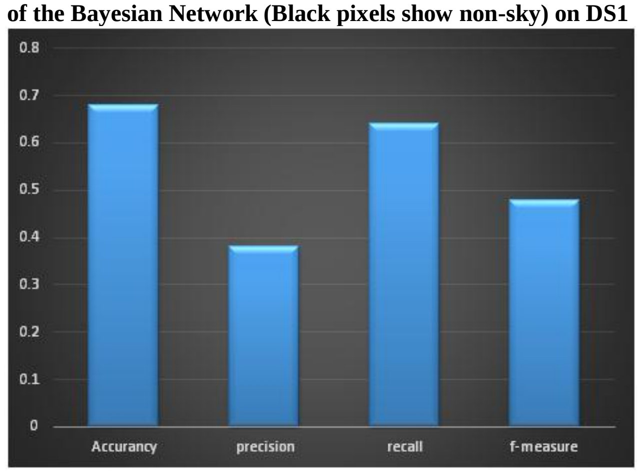

Figure 9: shows the experimental evaluation of our Bayesian Network classifier on the dataset DS1.

Figures 8 and 9 shows the result of applying the Bayesian network on the dataset DS1. The Accuracy of Bayesian Network classifier is 0.67, Precision is 0.38, Recall is 0.64 and F-measure is 0.47.

Figure 10: Result of applying the Radial Basis function classifier. First row shows original images, second row shows the result of the Radial Basis function (Black pixels show non-sky) on DS1

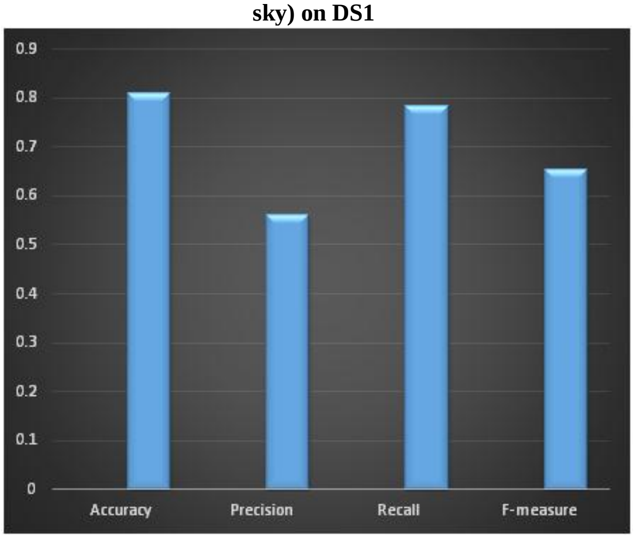

Figure 11: The experimental evaluation of our Radial Basis Function classifier on the dataset DS1.

Figures 10 and 11 show the result of applying the Radial Basis Function on DS1. The Accuracy of Radial Basis function classifier is 0.81, Precision is 0.56, Recall is 0.78 and F-measure is 0.65.

ANALYSIS AND COMPARISON

For visualization purposes, some of the other images from the dataset DS1 and the result of applying the four classifier filters are shown in Figure 12. Figure 13 shows the F-measure of four classifiers. From the figure 4.19 we conclude that Multilayer Perceptron classifier has 8% higher F-measure which is 0.73 than Random Forest classifier and Radial Basis function classifier. F-Measure of Random Forest classifier is 0.65 which is 9% higher than Bayesian Function classifier and almost equal to Radial Basis function which 0.65. Thus the results show the feasibility of the Multilayer Perceptron for sky detection.

Figure 12: First column: Original Images, Second Column: Random Forest, Third Column: Multilayer Perceptron, Forth Column: Bayesian Network, Fifth Column: Radial basis Function

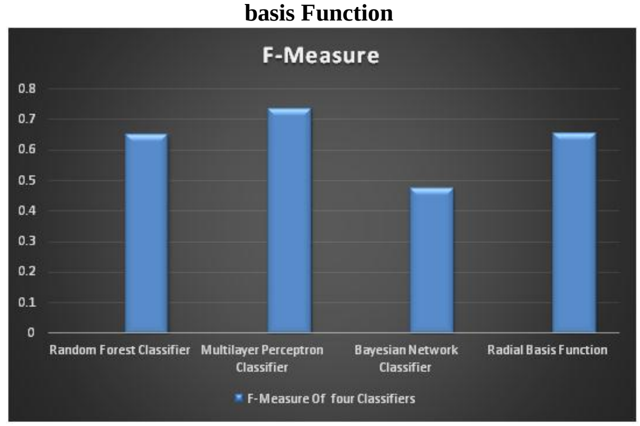

Figure 13 F-Measure Evaluation Results of four classifiers on DS1.

CONCLUSION

In this paper, we investigated and evaluated machine learning based sky filters for sky detection. As such, we investigate and evaluate the four machine learning approaches: Random Forests, Multi-layer Perceptron, Radial Basis Function and the Bayesian Network. The experimental evaluation is presented on dataset DS. Experimental results show the feasibility of the Multilayer Perceptron for sky detection. It is also found that the Multilayer Perceptron classifier has 8% higher F-measure which is 0.73 than Random Forest classifier and Radial Basis function classifier. F-Measure of Random Forest classifier is 0.65 which is 9% higher than Bayesian Function classifier and almost equal to Radial Basis function which 0.65. The research also benefits the colour based object detection in general.

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