Color Detection Under Supervised Learning

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Abstract

1 Introduction

2 Proposed Method

2.1 Preprocessing

// cyrus explain boat stuff
Each boat photo we label by hand, marking the color and rectangle around each buoy within about 30 feet from the boat. From each rectangle, we extract the associated color histogram into a 256x256x256 feature vector, where each entry represents the frequency of the RGB color associated with the entry index. We then reduce this feature vector to a vector of size 64x64x64, to make feature vectors less sparse, and to decrease classification time as we are building this for a real time application.

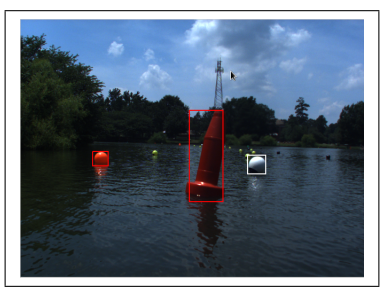

Figure 1: Labelled photo from boat

2.2 Classification

In this project, we run our training data with multiclass SVM and multinomial Naive Bayes, and have excellent results.

We began with SVM beacuse it is a parametric algorithm, thus we do not need to store entire training data set to make predictions on the boat. It is also kernelized, which provides us with the flexibility to create arbitrarily complex boundaries. SVM prediction can be used to calculate confidence values for the decision by taking the distance from the separating hyperplane, which is a useful measurement. SVM does not make any assumptions about the underlying distribution of the data. SVM is a very popular algorithm, so it is very good as a baseline classification algorithm. We used LIBLINEAR for our SVM classification, which utilizes a one-vs-rest multi-class classification scheme [1]. We achieved very good results with LIBLINEAR, as described later, so we decided not to use any kind of SVM kernelization. Using a linear kernel with SVM is preferrable, as it is faster to train and test. Making decisions quickly is essential to this application, as we want to classify colors at the same rate photos are captured (10 Hz).

We also used Naive Bayes because it is simple to implement, and performs well even on small sets of training data. Like SVM, Naive Bayes is parametric, so we do not need to store the entire training data set to make decisions during the real time application. A parametric classifier is essential, as it is impractical to store all training data on the boat to make decisions in real time. Naive Bayes is also very fast in training and testing, which is ideal for this application. The multinomial Naive Bayes classifier works well for classification with discrete features, such as color frequencies of pixels in a certain section of a photo, or word frequencies of a text document (the classic application). We used MATLAB's multinomial Naive Bayes classifier, which performs very well, as described later.

3 Related Work

// tommy majority vote and average color algorithm performance
// cyrus other related work

4 Experimental Results

Using both linear SVM and multinomial Naive Bayes, we achieve excellent accuracy rates, especially compared to current methods discussed in related works. With enough training examples, both methods achieve over 98% accuracy. Naive Bayes performs marginally better, the advantage of Naive Bayes is emphasized when fewer training examples are used. Each average accuracy is calculated by selecting a random training set of size n, then selecting a random testing set of size 130 from the remaining data, then train and test classifiers accordingly. The average accuracy is taken over 10 classification results. Although these results are excellent, we believe one contributing factor to such great results can be attributed to a fairly homogeneous data set. We do not have enough variation in our data set, so classification is easier. This problem, and how we intend to solve it, will be discussed in the future milestones section. Experimental results are shown below.

Table 1: Linear SVM Average Accuracy

EXAMPLES	**ACCURACY**
50	89.08
100	93.77
200	96.92
400	97.85
700	98.38

5 Future Milestones

One problem with our method we have identified is that the data set we are using is from one log, resulting in a very homogenous data set. Within one week from the due date of the progress report, we plan to label at least another 1000-5000 buoys, including many more blue and green buoys, and more buoys in varied lighting conditions. We hope that after running our algorithms on this data set with variation, we have a more realistic classification accuracy, which will perform better during the real application. We also want to try to add a feature which encodes the direction of lighting, to be completed within two weeks. One idea we have as an extension to this color classification project is implementing a segmentation algorithm to identify buoy boundaries under unsupervised learning, then do color classification with or current supervised learning algorithms. We are considering an extension to this project as we have achieved excellent results so far, thus we don't have much room for further improvement for the rest of the semester. We will discuss what we should pursue as a possible extension with the EECS445 staff.

6 Conclusion

References

References follow the acknowledgments. Use unnumbered third level heading for the references. Any choice of citation style is acceptable as long as you are consistent. It is permissible to reduce the font size to 'small' (9-point) when listing the references. **Remember that this year you can use a ninth page as long as it contains *only* cited references.**

[1] Alexander, J.A. & Mozer, M.C. (1995) Template-based algorithms for connectionist rule extraction. In G. Tesauro, D. S. Touretzky and T.K. Leen (eds.), *Advances in Neural Information Processing Systems 7*, pp. 609-616. Cambridge, MA: MIT Press.

[2] Bower, J.M. & Beeman, D. (1995) *The Book of GENESIS: Exploring Realistic Neural Models with the GEneral NEural SImulation System.* New York: TELOS/Springer-Verlag.

[3] Hasselmo, M.E., Schnell, E. & Barkai, E. (1995) Dynamics of learning and recall at excitatory recurrent synapses and cholinergic modulation in rat hippocampal region CA3. *Journal of Neuroscience* **15**(7):5249-5262.

Table 2: Multinomial Naive Bayes Average Accuracy

EXAMPLES	**ACCURACY**
50	92.85
100	96.54
200	97.31
400	98.38
700	98.31