Finding Image Features Associated with High Aesthetic Value by Machine Learning

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Abstract. A major goal of evolutionary art is to get images of high aesthetic value. We assume that some features of images are associated with high aesthetic value and want to find them. We have taken two image databases that have been rated by humans, a photographic database and one of abstract images generated by evolutionary art software. We have computed 55 features for each database. We have extracted two categories of rankings, the lowest and the highest. Using feature extraction methods from machine learning we have identified the features most associated with differences. For the photographic images the key features are wavelet and texture features. For the abstract images the features are colour based features.

Keywords: Evolutionary Art, Genetic Art, Feature Extraction, Feature Selection.

1 Introduction

A major goal of evolutionary art is to generate aesthetically pleasing images or images of high aesthetic value. In most evolutionary art systems aesthetic judgments are made by humans, either directly or indirectly. An open problem in evolutionary art is how to have the computer make the aesthetic judgments automatically and only generate images of high aesthetic value. For many reasons solving this problem has proved to be extraordinarily difficult. Among other things, peoples tastes in art vary widely and it is difficult to get consensus among humans on what constitutes a pleasing image.

Constructing computational models of aesthetics is very challenging. There have been a number of proposals, but the models are not very useful. One approach has been to find and study images that people like and to try to determine their underlying characteristics and this is the approach that we have adopted.

In this paper we use two image databases that have been rated by humans and use machine learning techniques to explore the differences between high and low rated images. The first database consists of digital photographs, the second consists of abstract images generated from an evolutionary art system. The photo database has been used in an earlier study [2]. We use the same low level features

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Rating 2.33

Rating 3.17

Rating 6.00

Rating 6.90

Fig. 1. Low ranked (top line) and high ranked (bottom line) photos

as [2]. These features were selected because they were relatively easy to compute and had the potential to be discriminating for good and bad photos.

1.1 Goals

Our overall goal is to determine whether we can get some insight into the image features associated with aesthetically pleasing images by analyzing good and bad images as rated by humans. In particular:

1. What are the features that distinguish bad and good photographs?
2. What are the features that distinguish bad and good abstract images?
3. Are there any significant similarities and differences between the above two groups?
4. Can the selected features be related to an analysis of good and bad images as performed by a photographer/artist?