What makes a Pollock Pollock: A machine vision approach

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Abstract

Jackson Pollock introduced a revolutionary artistic style of dripping paint on a horizontal canvas. Here we study Pollock's unique artistic style by using computational methods for characterizing the low-level numerical differences between original Pollock drip paintings and drip paintings of other painters who attempted to mimic his signature drip painting style. Four thousands and twenty four numerical image content descriptors were extracted from each painting, and compared using Weighted Nearest Neighbor classification such that the Fisher discriminant scores of the content descriptors were used as weights. In 93% of the cases the computer analysis was able to differentiate between an original and a non-original Pollock drip painting. The most discriminative image content descriptors that were unique to the work of Pollock were the fractal features, but other numerical image content descriptors such as Zernike polynomials, Haralick textures, and Chebyshev statistics show substantial differences between original and non-original Pollock drip paintings. These experiments show that the uniqueness of Pollock's drip painting style is not reflected merely by fractals, but also by other numerical image content descriptors that reflect the visual content. The code and software used for the experiment is publicly available, and can be used to study the work of other artists.

keywords: Pollock, drip paintings, Art, computer vision

Biographical notes: Lior Shamir is an Assistant Professor of Computer Science at Lawrence Technological University. Received his Ph.D in Computational Science and Engineering from Michigan Technological University, and was a research fellow at the National Institute on Aging, National Institute of Health.

1 Introduction

Abstract expressionist Jackson Pollock developed a novel artistic style of dripping paint on a large canvas laid on the floor (Herczyrisky et al., 2011; Cernuschi, 1992). This revolutionary method of painting became an important technique recognized with the abstract expressionism movement. Analysis of Pollock drip paintings has focused on the materials (Lake, Ordonez & Schilling, 2004), dripping techniques (Landau, 1989; Friedman, 1995), fluid dynamics (Herczyrisky et al., 2011), and significant work has also been done using low-level computer analysis of the visual content (Taylor, Micolich & Jonas, 1999; Stork, 2009).

While early work in computer-based analysis of Art was based on retrieval and analysis of captions and metadata (Mattison, 2004; Tsai, 2007), other studies attempted to perform automatic analysis of the visual content of the art (Postma, Herik & Lubbe, 2007; Stork, 2009; Hurtut, 2010). Automatic analysis of visual art has mainly focused on classification of paintings by their creating artists (van den Herik & Postma, 2000; Keren, 2002; Widjaja et al., 2003; Johnson et al., 2008; Shen, 2009; Zujociv et al., 2009) or automatic association of paintings with captions and key words (Barnard & Forsyth, 2001; Lewis et al., 2004; Vrochidis et al., 2008). More recent work also showed that computers can assess the similarities between the artistic styles of painters, and thus automatically associate painters that share similar artistic styles or associated with the same schools of art (Shamir et al., 2010). Other studies also applied computer-based analysis to determine the drawing methods (Kammerer et al., 2007; Roussopoulos et al., 2010). While the vast majority of the work on computer-aided analysis of visual art is based on two-dimensions, three dimensional methods were also used to demonstrate that computer-aided analysis can be applied to aesthetic and scientific analysis of sculptures (Bernardini et al., 2000) and artistic visualization of tree-dimensional objects (Gooch et al., 2001).

Naturally, computer-aided analysis of visual art found an immediate application in art authentication. Perhaps the most visible discussion of computer-aided art authentication focused on Jackson Pollock's drip paintings (Taylor, Micolich & Jonas, 1999; Mureika, Cupchik & Dyer, 2004; Jones-Smith & Mathur, 2006; Taylor et al., 2007; Stork, 2009) due to their high monetary value and the controversial authenticity of some of the paintings, but other applications of computer vision to art authentication include paintings of Eugene Delacroix (Kroner & Lattner, 1998), Pieter Bruegel (Lyu, Rockmore & Farid, 2004), and Vincent Van Gogh (Li et al., 2012).

The human perception of visual art is a complex cognitive task that involves different processing centers in the brain (Zeki, 1999; Ramachandran & Herstein, 1999; Solso, 2000, 1994). A study more specific to the work of Jackson Pollock showed unique physiological and neurological human responses to Pollocks drip paintings (Taylor et al., 2011). While the human eye and brain are limited by what they can sense and perceive (Canosa, 2009), it is possible that computer analysis can provide tools that analyze the visual content in a fashion that allows the detection and quantification of features that cannot be easily noticed or quantified by the unaided human eye. An example is the fractal analysis applied to Pollock's drip paintings, which showed that Pollock's work has a certain degree of fractality that changed during his career (Taylor, 2002). Further work also proposed the possibility that Jackson Pollock's work share mathematical descriptors that are significantly more similar to the work of Van Gogh compared to other painters (Shamir, 2012).

Here we use computer vision algorithms that extract thousands of numerical image content descriptors from Jackson Pollock's paintings, and compare these features to visually similar drip paintings that were not painted by Jackson Pollock in order to identify numerical image content descriptors that are unique to Pollock's signature artistic style. In Section 2 we describe the dataset of paintings used in the experiment, in Section 3 we briefly describe the computer analysis methods, and in Section 4 the experimental results are discused.

2 Image dataset

The dataset includes 26 paintings of Jackson Pollock that were downloaded from various sources via the internet, and used in previous studies (Shamir et al., 2010; Shamir, 2012). The drip paintings that were not painted by Pollock were also downloaded from different on-line sources, but it should be noted that these paintings are not fakes of authentic Pollock's work, but the work of painters that were heavily inspired by Pollock and attempted to produce similar paintings, in most cases for the purpose of selling them as a Pollock-inspired work, but not as original Pollock. A third dataset included 26 drip paintings of Pollock that were painted between 1950 and 1955.

Frames and other visual features that are not the painting itself were removed, and all images were converted to the lossless TIFF image file format. Since the images were downloaded from various sources, their sizes varied significantly. Therefore, all images were normalized proportionally to the size of 640,000 pixels such that the aspect ratio of all images was preserved, and no image content was sacrificed.

3 Image analysis method

The image analysis method used in this study is based on the *wnd-charm* method (Shamir et al., 2008; Shamir, 2008; Shamir et al., 2009a), which was originally developed for computer-aided biomedical image analysis, but its comprehensiveness has been shown to be effective also for quantitative analysis of visual art (Shamir et al., 2010; Shamir, 2012).

Wnd-charm uses a large and comprehensive set of numerical image content descriptors reflecting very many aspects of the visual content such as textures, colors, edges, shapes, fractals, polynomial decomposition of the image, and statistical distribution of the pixel intensities. The set of image features is thoroughly described in (Shamir et al., 2008; Shamir, 2008; Orlov et al., 2008; Shamir et al., 2009a, 2010). The set includes Radon transform features, edge statistics, objects statistics, fractal features, Chebyshev statistics, Gabor filters, Tamura and Haralick textures, Zernike polynomials, Multi-scale histograms, and first four moments. The source code implementing these features is publicly available for free download (Shamir et al., 2008).

To increase the comprehensiveness of the set of image content descriptors, the features are extracted not just from the raw pixels, but also from the image transforms and second-order image transforms, which allow extracting more information from the visual content as demonstrated by previous experiments with general images datasets (Orlov et al., 2008; Shamir et al., 2009b) and specifically with image datasets of visual art (Shamir et al., 2010). The image transforms that are used are Fourier transform, Chebyshev transform, Wavelet (symlet 5, level 1) transform, color transform (Shamir, 2006), hue transform (which is simply the hue component of the HSV triplets), and edge magnitude transform. A detailed description of the image features and image transforms can be found in (Shamir et al., 2008; Shamir, 2008; Shamir et al., 2010).

As done in (Shamir et al., 2010), each image was divided into 16 equal-sized tiles such that the image content descriptors are computed on each of the 16 tiles, providing 16 feature vectors for each painting in the dataset. Since the size of all images used in the experiment is 640,000 pixels, each of the 16 tiles was 40,000 pixels in size.

Once the numerical image content descriptors are computed, each descriptor is assigned with a Fisher discriminant score (Bishop, 2006) that reflects its strength in discriminating between original Jackson Pollock paintings and drip paintings of other painters. The Fisher discriminant score is defined by Equation 1

$$W_f = \frac{\sum_{c=1}^{N}(\overline{T_f} - \overline{T_{f,c}})^2}{\sum_{c=1}^{N}\sigma_{f,c}^2}, \tag{1}$$

where W_f is the Fisher discriminant score, *N* is the number of classes (set to 2 in the experiment described in this paper), $\overline{T_f}$ is the mean of the values of feature *f* in the entire training set, and $\overline{T_{f,c}}$ and $\sigma_{f,c}^2$ are the mean and variance of the values of feature *f* among all training images of class c.

The purpose of the Fisher discriminant scores is to rank the different numerical image content descriptors by their ability to differentiate between Pollock and non-Pollock drip paintings. That is, a numerical image content descriptor that has unique values when computed from Pollock original work will be assigned with a high weight compared to image content descriptors that do not have different values for Pollock and non-Pollock paintings, and therefore do not reflect the differences between original drip paintings of Jackson Pollock and the work of other painters who attempted to replicate his signature artistic style.

After the Fisher discriminant scores are computed for all content descriptors, 75% of the least informative image content descriptors are rejected. The purpose of rejecting 75% of the features is to ignore non-informative image content descriptors that were assigned with a low weight, but their combined impact on the score can be significant due to the high number of non-informative features.

When a feature vector of a test image is classified, a simple Weighted Nearest Neighbor rule is used such that the Fisher scores are used as the weights of the 25% of the

remaining numerical image content descriptors. That is, the Fisher discriminant scores are used not only to filter non-informative features, but also to assign weights to the other image features that determine the impact of the feature on the classification decision. The classification decision for a given test image is then made by a majority rule of the individual classification decisions of the 16 tiles of that image, as discussed in (Shamir et al., 2010). This classification method is described more thoroughly in (Shamir et al., 2008, 2010). The source code of *wnd-charm* is publicly available, and can be downloaded at
http://vfacstaff.ltu.edu/lshamir/downloads/ImageClassifier.

4 Results

To test if the computer can automatically differentiate between genuine Pollock drip paintings and Pollock-inspired paintings we used 20 paintings from each class for training, and the remaining six for testing. The experiment was repeated 40 times such that in each run different paintings were randomly allocated for training and test sets. Since each image in the dataset was separated into 16 equal-sized tiles as explained in Section 3, if a certain image was allocated to the training or the test sets all its tiles were allocated to that set to prevent bias caused by automatic matching of tiles allocated for testing to tiles taken from the same image but allocated to the training set.

The classification accuracy was determined by the number of genuine Pollock paintings that were classified automatically by the algorithm as Pollock paintings added to the number of the Pollock-inspired drip paintings classified automatically as Pollock-inspired, divided by the total number of test samples. The final classification accuracy was the average accuracy of all 40 runs, and the Fisher discriminant scores were also averaged across all runs.

Experimental results show that the computer algorithm has 93% of accuracy in automatically identifying a genuine Pollock over a Pollock-inspired drip paintings, suggesting that Pollock's style is unique, and is different from the work of other artists despite their attempts to mimic his work and produce paintings that are visually as similar as possible to Pollock's drip painting signature style. The numerical image content descriptors that have the strongest discriminative power between Pollock and non-Pollock drip paintings are specified in Figure 1. For the sake of the simplicity of the visualization, the figure includes only descriptors with Fisher score greater than 1.0.

As the figure shows, a broad range of numerical image content descriptors differentiate between original Pollock and non-original Pollock drip paintings. Clearly, the fractal features that were used in the experiment (Chen, Daponte & Fox, 1989) provided the strongest discriminative signal between genuine Pollock paintings and Pollock-inspired drip paintings, which is in agreement with previous studies (Taylor, Micolich & Jonas, 1999; Taylor, 2002). In addition to the fractal features, the graph also shows that Haralick textures and Zernike polynomials extracted from the different image transforms also provide strong discriminative signal between Pollock and non-Pollock drip paintings. Chebyshev statistics and the first four moments of the statistical distribution of the pixels computed on the Fourier transform of the paintings also provide strong discriminative signal, demonstrating that the difference between original Pollock drip paintings and Pollock-inspired drip paintings is not reflected by merely the fractality of the work. The fact that fractals are not the only features that distingiush between an original and non-original Pollock drip paintings is in agreement with the results of Stork (2009), who showed that te use of non-fractal features elevated the classification accuracy from near randomness to 81%.

The imperfect accuracy can be explained by the fact that the dataset of Pollock paintings included drip paintings painted during a relatively long period of time, from the early 1940's to the mid 1950's. Since Pollock's style changed significantly throughout his life (Taylor, 2002), the dataset of Pollock and Pollock-inspired drip paintings introduces a certain variance.

To reduce the variance in the artistic style of Pollock's drip paintings we performed a similar experiment, with the difference that the dataset of original Pollock drip paintings was replaced with the set that contained just Pollock's paintings painted in the first half of the 1950's. In that experiment, the classification accuracy between the original Pollock paintings and the Pollock-inspired art was 100%, and the numerical content descriptors with the strongest discriminative signal are specified in Figure 2. Like with Figure 1, the graph does not include all content descriptors, but just the content descriptors with Fisher discriminant scores greater than 3.

As the graph shows, the discriminative power of the image content descriptors is substantially higher than in Figure 1. Also, the fractal features extracted from the Fourier transform of the Chebyshev transform provided a very strong classification signal compared to the other image content descriptors. Additionally, Zernike polynomilsl, Haralick textures, and Chebyshev statistics also provide strong classification signal. Like the results of Figure 1, the experiment shows that Pollock's drip paintings painted during te 1950's are not unique merely in the sense of fractals, but also by several other numerical image content descriptors that reflect the visual content of the art.

5 Conclusion

The human perception of visual art is a complex cognitive process, and is highly difficult to quantify or analyze manually in a systematic and objective fashion. Here we used a comprehensive machine vision analysis to compare numerical image content descriptors computed from genuine Jackson Pollock work and the work of other painters that attempted to follow his drip painting signature style. The analysis shows that the numerical image content descriptors in Pollock's work are different from the Pollock-inspired drip paintings. This analysis demonstrates that Pollock's work is unique, and attempts to mimic his work failed to follow his unique signature style.

The analysis also shows that the uniqueness of Pollock's artistic style is reflected by a broad range of numerical image content descriptors. These descriptors include fractals, which provide the strongest discriminating signal, but also polynomial decomposition of the image such as Zernike and Chebyshev statistics, as well as Haralick textures and the first four moments of the pixel intensity distribution in different image transforms and multi-order image transforms.

The comprehensiveness of the method allows it to be used for similar experiments with other painters for identifying unique features in the artistic style of other painters. The source code and software used for the experiment described in this paper is available for free download at
http://vfacstaff.ltu.edu/lshamir/downloads/ImageClassifier.

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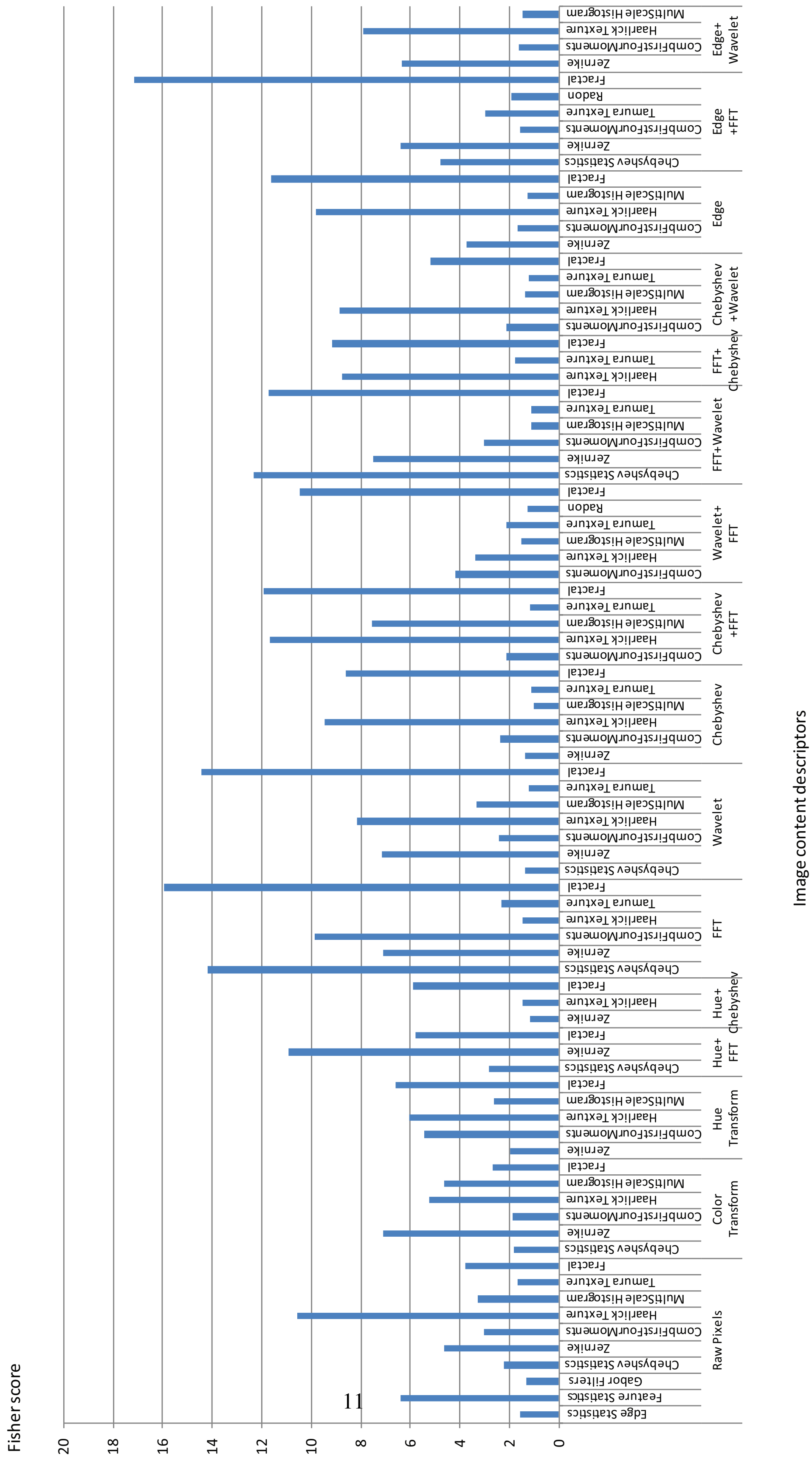

Figure 1: Fisher discriminant scores reflecting the power of the different numerical image content descriptors in discriminating between original Pollock drip paintings and Pollock-inspired drip paintings

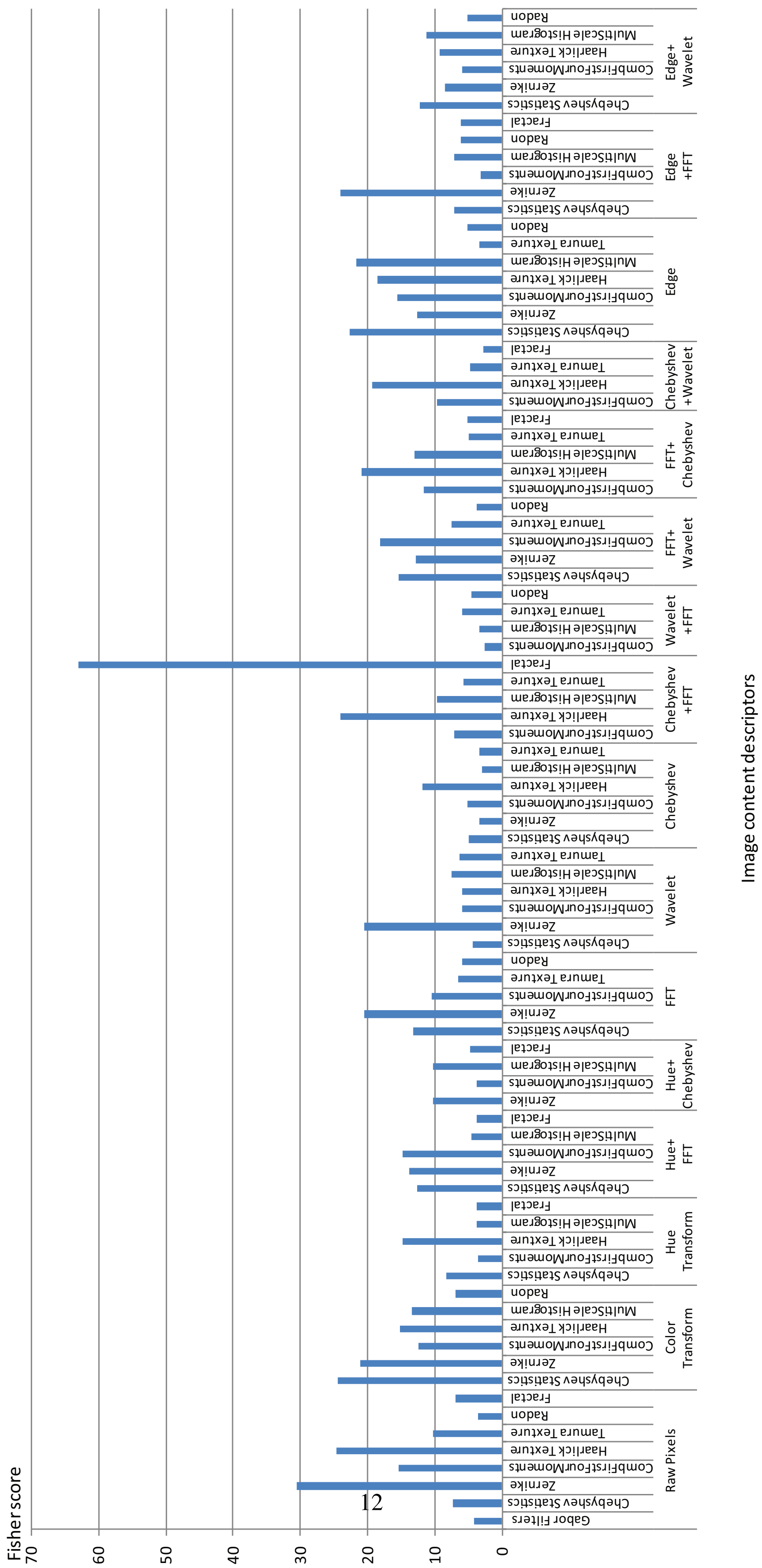

Figure 2: Fisher discriminant scores reflecting the power of the different numerical image content descriptors in discriminating between original Pollock drip paintings painted in the early 50's and Pollock-inspired drip paintings