A Review on Various Measures for Finding Image Complexity

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Abstract

The complexity of an image tells many aspects of the image content and is an important factor in the selection of source material for testing various image processing methods. Databases of pictures or videos explained with subjective evaluations constitute basic ground truth for preparing, testing, what's more, benchmarking calculations for target quality appraisal. We propose a few criteria for quantitative correlations of source substance, test conditions, and subjective evaluations, which are utilized as the reason for the resulting investigations and dialog. This review paper presents some of the existing image quality metrics through which image quality can be classified or measured.

Keywords— *Image Quality Assestment, Spatial , Temporal, Video, MPEG, Compression, Decoder and Encoder, PSNR.*

I. INTRODUCTION

The learning of image complexity nature is valuable in numerous applications. It can be utilized to decide the compression level and data transmission portion, as a picture with low quality can be compacted more effectively and requires less transfer speed than a picture with high quality [1]. Moreover, complexity-based similarity measures are used in many high-level image understanding and recognition problems, such as content-based image retrieval. For example, content-based Image Retrieval (CBIR) [2], picture grouping and arrangement [3]. To wrap things up, Image unpredictability is an imperative calculate the plan of image and video quality databases.

Frequently, specialists might want to know the multifaceted nature of an image before compacting it in order to decide the ideal tradeoff between picture compression and picture quality. One approach to get such data, which must be to a great degree quick to process, is to quantify the spatial data (SI) contained in the picture. In this paper, we inspect and review various method such as regular SI measures and compression based image complexity measures, which as far as anyone is concerned has not been done some time recently. We will inspect the impact of determination change on image intricacy and SI.

II. COMPLEXITY MEASURES

In this section, we briefly explain the basic ideas behind Kolmogorov complexity and sparse signal representation.

A. *The Kolmogorov Complexity*

The complexity of image or video is somewhat related to its randomness. Let take a string1 -> 11010100011 is more complex as compared to another string2-> 1010101010, because the string2 contains some regular occurring word whereas in string1 there is no randomness. Kolmogorov Complexity use this type of features.

Given a finite object X, its Kolmogorov complexity K(X) is defined as the length of the shortest program that can
Effectively reconstruct X on an universal computer, such as a Turing machine. K(X) is the ultimate lower bound among all measures of information content of X. The conditional Kolmogorov complexity K(X,Y) of X relative to Y is defined as the length of the shortest program that can generate X when Y is supplied. K(XY) is defined to be the length of the shortest program to generate the concatenated string XY .

The normalized distance is given by formula:

$$NID(x_0, x_1) = \frac{\max\{K(x_0|x_1), K(x_1|x_0)\}}{\max\{K(x_0), K(x_1)\}}.$$

Where,
NID = Normalized Information Distance

X - String1
Y -String2

One of the issues with Kolmogorov complexity is that the briefest depiction of a string can run gradually. Truth be told, it should frequently do as such, for fear that the arrangement of arbitrary strings have an unending calculably enumerable subset. One exceptionally helpful variation of established many-sided quality is the time-limited variant.

B. *Sparse Representation*

The main idea of sparse representation is to represent data with linear combination of very tiny number of basis function.

Sparsely is not so easy to achieve. Wavelets and sinusoidal succeeded in scarifying some of the data from raw dataset, but in practice, it is not like that. In reality the dataset are mixed structures that is hard to be captured by wavelets and sinusoidal alone.

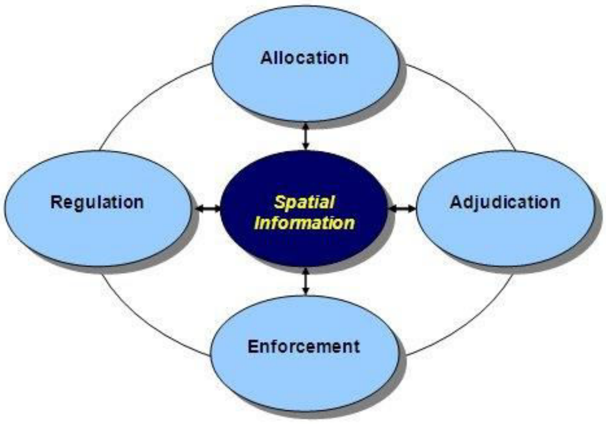

Fig.1. shows the Spatial Information Metrics

Keeping in mind the end goal to accomplish sparsely in such cases, one must join different bases. This prompts to the possibility of over complete word reference - where the number of premise vectors is more prominent than the dimensionality of the info flag i.e. at the point when m < n.

An over complete word reference offers more prominent adaptability in speaking to the basic structures in a flag which prompts to higher sparsely in the change area. Such portrayals likewise have preferences like power to add substance clamor, impediment and interpretation of the information flag [4].

III. LITERATURE SURVEY

Honghai Y et al. [5]. Explorse objective measures of complexity that are based on compression. It shows that spatial information (SI) measures strongly correlate with compression-based complexity measures. Among the commonly used SI measures, the mean of the edge magnitude is shown to be the best predictor. Moreover, It find that compression-based complexity of an image normally increases with decreasing resolution.

Huahui Wu et al. [6]. Video motion and scene complexity characteristics are studied. In particular, 9 different video clips are encoded to MPEG files and the MPEG files are analyzed with statistics measurements. The results of different measurements are compared with a 3-person preliminary user study. The results show that the proposed metric Percentage of Forward or Intra-coded Macrob locks (PFIM) is highly correlated with the user's score of motion characteristics while the proposed metric Average Intra-coded Block Size (IBS) has a more modest correlation with user's score of scene complexity

Jukka Perki¨o et al. [7]. Presents a novel method to estimate the complexity of images, based on ICA. It further use this to model joint complexity of images, which gives distances that can be used in content-based retrieval. It compare this new method to two other methods, namely estimating mutual information of images using marginal Kullback-Leibler divergence and approximating the Kolmogorov complexity of images using Normalized Compression Distance.

Tanaya Guha et al. [8]. Presents a very general method for the computation of a suitable measure of similarity between two images. The proposed measure relies on the parsimony of some suitable representation of one image using the information of the other. Two quite different theories which capitalize on the parsimony of representation are - Sparse representation and Kolmogorov complexity.

Juan Romero et al. [9]. Classifies images gathered from a photography web site, attempting to reproduce the evaluation made by a group of users. For this purpose we use complexity estimate metrics based on the encoding size and compression error of JPEG and fractal compression, which are applied to the original Value channel and to the images resulting from applying Sobel and Canny filters to this channel.

Table I. shows various existing methods, strength and measures for deriving complexity

Ref. No.	Method Used	Data Source	Approach	Strength	Measures for Deriving Image Complexity
5	Compression Based Image Complexity	CSIQ database	It shows that spatial information (SI) measures strongly correlate with compression-based complexity measures. Among the commonly used SI measures, the mean of the edge magnitude is shown to be the best predictor.	Evaluated the correlation between different SI measures and complexity measures, showing that SI mean is the best predictor of image complexity among the three SI measures considered.	Spatial Information
6	MPEG Encoding	Motion Score Video Clip	It shows that the proposed metric Percentage of Forward or Intra-coded Macro blocks (PFIM) is highly correlated with the user's score of motion characteristics while the proposed metric Average Intra-coded Block Size (IBS) has a more modest correlation with user's score of scene complexity.	AICBS method outperforms in measuring video complexity	Average Intra-coded Block Size.
7	Normalized Compression Distance	16 × 16 randomly sampled patches	Presents a novel method to estimate the complexity of images, based on ICA. Further this is used to model joint complexity of images, which gives distances that can be used in content-based retrieval.	Effective for pair-wise similarity measure for natural images.	ICA
8	perceptual similarity measurement, clustering	biology, biometrics, medicine as well as natural textures and scene	It presents a very general method for the computation of a suitable measure of similarity between two images.	accurate experimental results achieved on a diverse collection of datasets	Sparse Representation, Kolmogorov Complexity
9	JPEG Compression	Aesthetic Image	It explores the use of complexity estimates to predict the aesthetic merit of photographs. Author uses set of image metrics and two different classifiers. This approach classifies images gathered from a photography web site, attempting to reproduce the evaluation made by a group of users.	Yields a success rate of 71.34%, which is competitive with the best results reported in literature, 71.44%, using the same dataset.	encoding size and compression error

IV. SUMMARY OF LITERATURE REVIEW

In this paper we have tried to compare various method used for finding complexity of images. Many of them uses spatial information and PSNR value as their measures to find complexity. Both method are capable of deriving complexity of images efficiently and accurately. JPEG, MPEG encoding method used to compress Images and Videos. The main drawback of all the above algorithm is that they work well with images. MPEG compression technique uses AICBS to measure complexity of video but the complexity of video can also be derived by most popular method PSNR via frame by frame scanning of video. Hence further study is needed to accomplish video complexity analysis in a more efficient way.

V. CONCLUSION

To conclude that, finding complexity of images is critical task hence important. In this paper we propose a few criteria for quantitative correlations of source substance, test conditions, and subjective evaluations, which are utilized as the reason for the resulting investigations and dialog.

This paper reviews spatial information and Kolmogorov technique for finding complexity of images. Further Kolmogorov outperforms as compared to spatial information in finding complexity. But there are some other method exists which needs to address in finding out complexity of images as well as videos.

The key challenge will be finding the complexity of vides, which are present as frame by frame. Hence our further research will be towards finding complexity of video files and compare their results.

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