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REVIEW ARTICLE

IMAGE AND VIDEO COMPLEXITY ANALYSIS UTILIZING IMAGE AND VIDEO COMPRESSION TECHNIQUES

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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 paper presents various metrics used for image and video complexity analysis. For this we have utilized image and video compression method

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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 (Wu *et al*., 2006). 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) (Perkio and Hyv, 2009), picture grouping and arrangement (Guha and Ward, 2012). 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 deal 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.

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Complexity Measures

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

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 me asures of information content of X. The conditional Kolmogorov complexity K(X,Y) of X relative to Yis 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.

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.

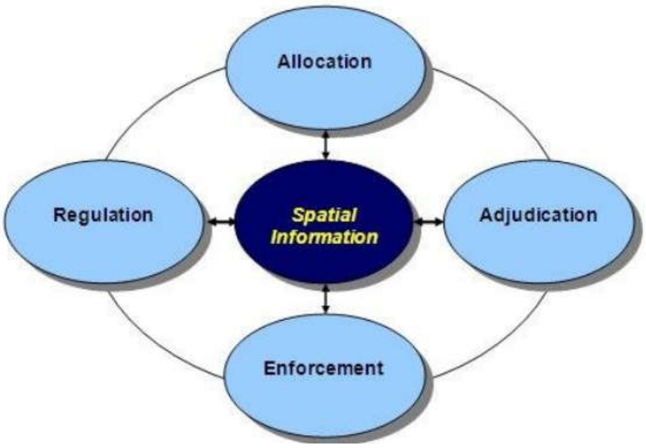

Fig.1. Shows the Spatial Information Metrics

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 (Lewicki and Sejnowski, 2000).

Literature Survey

Honghai *et al.*, 2013. Explore 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.* (2001). 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.*, 2009. 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.* (2014). 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.*, 2011. 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.

MATERIALS AND MAETHODS

In this section we present proposed methodology in detail. The A and B sections presents the proposed system architecture and working. There are various factors through which image complexity can be measured. We propose various mechanisms for analysis of image and video complexity. This section deals with all of the method.

Image Compression

To analyze image complexity various metrics are used. Image compression mechanism is utilized for analysis of complexity. Fig. 2. Shows the architecture of image compression mechanism.

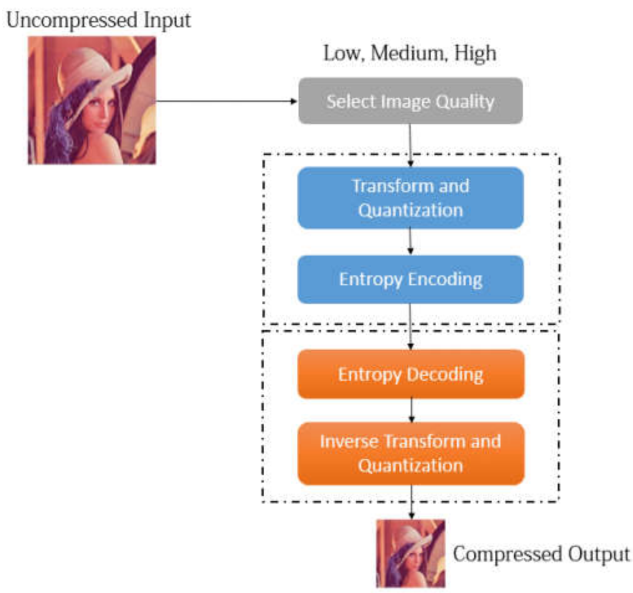

Fig. 2. Architecture of Image Compression

Firstly, the input image is taken which is to be compressed.

Image Quality Selection: Framework asks to select the quality of image which is outputtted. The more is the quality the less will be the compression and vice versa.

Transform and Encoding: Transformation replaces the pixel value information with another vpixel value. It can be one to one or many to many mapping. For encoding, huffman encoding are used. The huffman simply encodes the simialr co-occurrences pixel information based on below menthoned equation.

$$H(S) = \sum_i pi \frac{log_2 1}{pi}$$

Where,

Pi is the probability of symbol Si in S.

$\log_2(1/pi)$ → indicates the information content in Si

Video Compression

For analyzing the complexity of video, video compression technique are used. Its intermediate results shows the complexity of a sequence file. Fig. 3. Shows the video compression architecture.

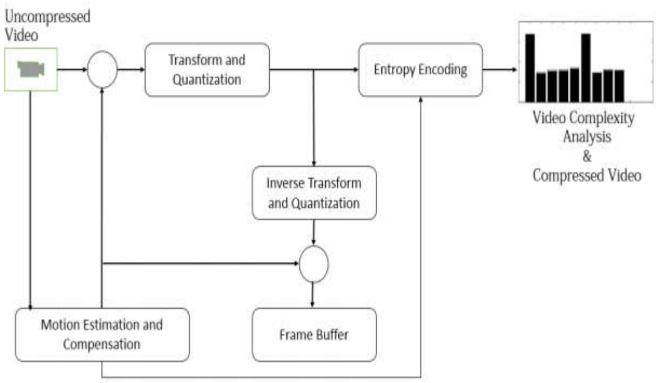

Fig. 3. Architecture of Video Compression

Tansformation and Quantization: The video sequence files are divided into frames. These frames are tansformed using DCT transformation. This step is similar with image transformation and quantization.

Frame Buffer: It is used to store the information of each and every frame of sequence images.

RESULTS

Dataset form images are taken from Google image search while video dataset are sequence of images. Fig. 4. Shows the image dataset description.

Image Complexity Analysis

To analyze image complexity the following metrics are considered.

1. Output Bit Count: Number of bits present in output when image is compressed
2. PSNR: Best measure for complexity analysis, calculate the quality of output image.
3. Bit Saving: The amount of bit saved while compression.

Fig. 4. Image and Video Dataset Description

Fig. 5. Shows the analysis image of above 3 metrics

Fig. 5. Presents 3 metrics for calculating image complexity

Video Complexity Analysis

To analyze video complexity the following metrics are considered.

1. Total Bits per Frame
2. PSNR per frame

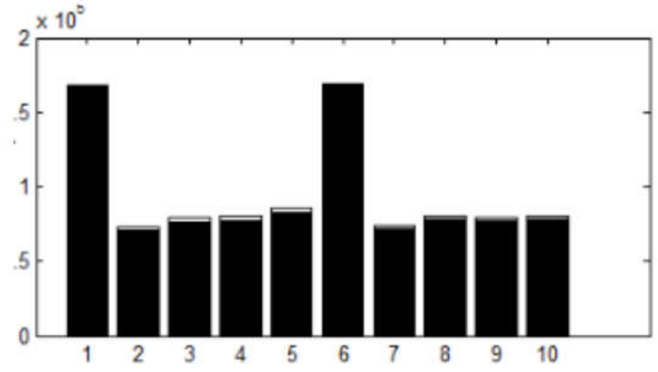

Fig. 6. Count of total bits per frame

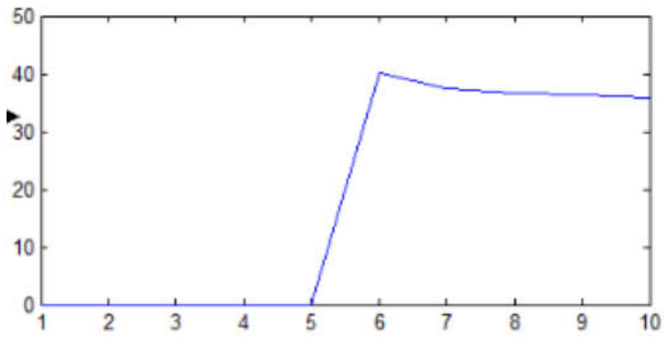

Fig. 7. Count of PSNR value per frame

Analysis of Complexity

In Fig. 5, we can see that the bit saving of image is 73%. That simply means that compression performed is on good quality image. The PSNR is also high, that means the complexity of image is quite good and can be used for various analysis purposes due to its high complexity. In fig. 6. Count of the bits frame is more for frame number 1 and 6, it means that the complexity is high for both of the image sequence. In fig. 7, The PSNR value is more for the image sequence from 5 to 10. It means the quality of sequence file from 5 to 6 is of good quality and hence this is required for any compression to work fine.

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. The key challenge will be finding the complexity of videos, which are present as frame by frame. In this paper we propose a novel mechanism to find image as well as video complexity with various numbers of parameters and comparing them with each other.

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