Indian J. Edu. Inf. Manage., Vol. 1, No. 5 (May 2012) ISSN 2277 - 5374

Digital image compression using sparse matrix

Chandra Sekaran KC[1,*], Kuppusamy K[2]

[1]*Assistant Professor and Head, Department of Computer Science, Alagappa Govt. Arts College, Karaikudi-3, Tamil Nadu, India, Email: ponkccdvk@yahoo.co.in*
[2]*Associate Professor, Department of Computer Science and Engineering, Alagappa University, Karaikudi-3, Tamil Nadu, India, Email: kkdiksamy@yahoo.com*

***Corresponding author**: Assistant Professor and Head, Department of Computer Science, Alagappa Govt. Arts College, Karaikudi-3, Tamil Nadu, India, Email: ponkccdvk@yahoo.co.in

Abstract

The multimedia applications are widely adopting in all the fields and in the day-to-day activities. All multimedia file storages are attempted to store in tiny devices with minimal memory area. The storage process and its functionalities are differs with one another, but the logical processes are same. As per the file storage techniques, the file format is differ one with another. The resource availability, utilizations become a challenging task to the multimedia user. Various research works are carried out in the field of file size minimization especially of images and video. Most of the file format presentation and minimization work carried out in the wavelet algorithms. The same work has been done by the researchers by using mathematical approach in which the digital image is converted into sparse matrix. However, the video compression is not at the appreciated level of the researchers. There are many possible avenues for the researches to reduce the frame image into minimized level in terms of size, storage approach and retrieval process of the application presentations. This research work attempted to reduces the image storage size via the functional process of the reduction mathematical tool approach, such as sparse matrix. In the sparse matrix reduction approach, the video image is converted into frames according to the scaling standards. The frames converted from the original accessible file format into three-dimensional layer based mathematical set. Each frames sequences is named and generated and then compared with transactional mapping set. The transactional binary set, one represents the difference of the pixel value and the zero represents the equivalent pixels. From the transactional matrix, the sparse matrix is generated and compared with the converted three-dimensional matrix. If the sparse is combined with the first conventional sparse that could generate the sequence of next frame. The overall numerical representation of the image and is size after decompression is compared to the original image model and its size.

Key words: Video Compression; Sparse matrix, Image compression

Abbreviation: DNs- Digital numbers.

Introduction

Image compression addresses the problem of reducing the amount of data required to represent a digital image. It is a process intended to yield a compact representation of an image, thereby reducing the image storage/transmission requirements (Quinlan, 1992; Raymond, 1992). Compression is achieved by the removal of one or more of the three basic data redundancies: 1. Coding Redundancy, 2. Interpixel Redundancy, and 3. Psychovisual Redundancy. Coding redundancy is present when less than optimal code words are used. Interpixel redundancy results from correlations between the pixels of an image. Image and video data compression refers to a process in which the amount of data used to represent image and video is reduced to meet a bit rate requirement (below or at most equal to the maximum available bit rate), while the quality of the reconstructed image or video satisfies a requirement for a certain application and the complexity of computation involved is affordable for the application (Zavod za gozdove, 1998). Image compression techniques reduce the number of bits required to represent an image by taking advantage of these redundancies. An inverse process called decompression (decoding) is applied to the compressed data to get the decoding) is applied to the compressed data to get the reconstructed image (Hyyppa, 2004). The objective of compression is to reduce the number of bits as much as possible, while keeping the resolution and the visual quality of the

Indian J. Edu. Inf. Manage., Vol. 1, No. 5 (May 2012)
ISSN 2277 - 5374

reconstructed image as close to the original image as possible.

Image Compression provides a potential cost savings associated with sending less data over switched telephone network where cost of call is really usually based upon its duration (Witten, 2005). It not only reduces storage requirements but also overall execution time. It also reduces the probability of transmission errors since fewer bits are transferred. It also provides a level of security against illicit. This paper addresses the conversion of sequential image into sparse matrix and represented as a numerical way of presentation and re-constructs the image into frame which could be converted as a video.

Pixels towards objects

The strong motivation to develop techniques for the extraction of image objects stems from the fact that most image data exhibit characteristic texture which is neglected in common classifications. The texture of an object can be defined in terms of its smoothness or its coarseness. One field of image processing in which the quantification of texture plays a crucial role is that of industrial vision. These systems are used to assess characteristics of products by measuring the texture of their surface. Most methods are based on the statistical properties of an image as well as the spectral or Fourier characteristics of airborne data, radar or VHR-satellite data which are playing an increasing role in remote sensing. In many cases, image analysis leads to meaningful objects only when the image is segmented into 'homogeneous' areas (Breiman, 1996). Segmentation is not new (Džeroski, 2006), but it is yet seldom used in image processing of remotely sensed data. Efron (1993) state: "Although there has been a lot of development in segmentation of grey tone images in this field and other fields, like robotic vision, there has been little progress in segmentation of colour or multi-band imagery." One reason is that the segmentation of an image into a given number of regions is a problem with a huge number of possible solutions. The high degrees of freedom must be reduced to a few which are satisfying the given requirements.

The image represented in the multi dimensional layer based Digital numbers. The DNs are represented according to the layer. The Image layers are from 1 to 4. The Image extracted with three layer with possible combination (1, 2, 3), 1, 2, 4) etc. These combinational arrays are represented in the same cubical array. this array are converted into to equaling array in two dimension with following attribute procedure (X,Y, layer1 value , layer 2 value, layer 3 value) .

Video → Frames → Digital Numbers → Main

Frame → Sequence of Frame link Values

Compression using sparse Matrix

Table 1. Images pixels are converted as a layer based values

R				G				B		
208	227	47		41	219	227		59	25	199
1	112	80		75	48	241		152	246	160
58	113	190		95	95	80		254	193	34
221	43	232		53	14	25		60	107	53
180	223	222		226	186	84		8	88	224
69	139	194		32	163	26		14	117	91
R				G				B		
208	227	47		41	219	227		59	25	199
11	114	88		98	67	165		144	43	134
123	244	244		187	188	180		134	193	124
221	43	232		53	14	25		60	107	53
180	223	222		226	186	84		8	88	224
69	139	194		32	163	26		14	117	91
R				G				B		
0	0	0		0	0	0		0	0	0
10	2	8		23	19	76		8	203	26
65	131	54		92	93	100		120	0	90
0	0	0		0	0	0		0	0	0
0	0	0		0	0	0		0	0	0
0	0	0		0	0	0		0	0	0

The given image is divided into the frames using the splitter software. This frames are contains with the images which has the equal size. These images pixels are converted as a layer based values which could be presented as first two layers of Table 1. The last set of the rows shows the difference matrix

Indian J. Edu. Inf. Manage., Vol. 1, No. 5 (May 2012)
ISSN 2277 - 5374

Table 2. Ratio of file compression

S. No	Org. File Size	Frames	Compressed File Size
1	691592	70	486500
2	649475	74	407331
3	634692	53	254965
4	539301	65	370047
5	646039	58	248244
6	570093	58	325467

which presented the difference of the images. While storing the video pixels the change of the images are differing in a small motion parts. Those parts alone have the different values compare with the other values. These other values are having zero elements because the image frame is same .While changing the frame and the background the entire change values are differs. The size of the image is presented as single cubical elements using multi dimensional representation using mat lab workspace variables stored in the appropriate variable in the file name.

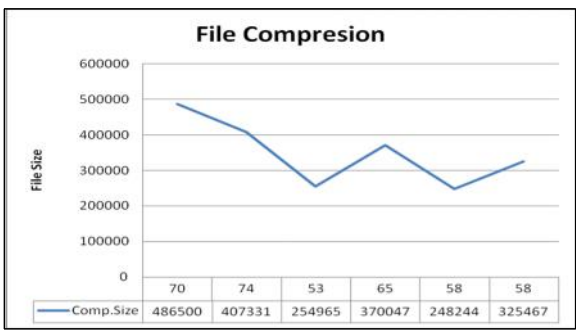

Fig.1. Ratio of file compression

Results and Discussion

The six video files are adopted for the compression process. The video files are converted as frames and the compressed digital values are stored in the files as a mat lab workspace. The table values shows original file size and compressed file size is presented in Table 2.

As per the obtained result the frames and the compressed files are directly proportionate. These values are achieved through the sparse matrix presentation. The file size is high then compressed file size also little bit high (Fig.1). The compression of the file and the number of frames are direly reflects the compressed size.

Conclusion

This video file compression process is converted the video into frames in the jpeg file format. That is divided and presented in the three layer process of (R, G, B) representation. These represented frames are converted and the related values are presented with the master frame and the relational values in the sparse matrix representation. This is the conversational mechanism of the video image into the file storage. However, the recoding process and the image resolutions are not appreciable, therefore other image compression must be evaluated.

References

1. Breiman L (1996) Bagging Predictors. Machine Learning, 26(2), 123–140.
2. Džeroski S (2006) Using decision trees to predict forest stand height and canopy cover from LANSAT and LIDAR data. In: Managing environmental knowledge: EnviroInfo 2006: proceedings of the 20th International Conference on Informatics for Environmental Protection, Aachen: Shaker Verlag, pp. 125-133.
3. Efron B (1993) An Introduction to the Bootstrap. Chapman and Hall, New York.
4. Hyyppa H (2004) Algorithms and Methods of Airborne Laser-Scanning for Forest Measurements. Rational Archives of Photogrammetric and Remote Sensing, Vol.36, 8/W2, Freiburg, Germany.
5. Quinlan JR (1992) Learning with continuous classes. In Proceedings of the 5th Australian Joint Conference on Artificial Intelligence, World Scientific, Singapore, 343–348.
6. Raymond M (1992) Measures. Laser remote sensing: fundamentals and applications. Malabar, Fla., Krieger Pub. Co. 510 p. G70.6.M4.
7. Zavod za gozdove RS (1998) SFS Slovenian Forestry Service: Slovenian forest and forestry, pp.24.
8. Witten I (2005) Data Mining: Practical machine learning tools and techniques with Java implementations. Second Edition.