International Journal of Enhanced Research in Science, Technology & Engineering
ISSN: 2319-7463, Vol. 5 Issue 6, June-2016

Comparative Analysis of Medical Image Compression Techniques and their Performance Evaluation for Telemedicine

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ABSTRACT

In this paper a comparative analysis of different types of medical image compression techniques have been made for the telemedicine application. We find that lossless techniques are not much feasible for large data compression while the lossy compression techniques can compress a huge amount of data selectively to improve the over all compression ratio. The emphasis is done on the recent trends of compression. The wavelet transform based techniques (JPEG 2000) have shown better results in comparison to DCT based techniques (JPEG) due to manifold properties of Wavelet Transform over DCT. The results of the above techniques have been compared and performance evaluation in done on the basis of compression ratio, MSE, SNR, PSNR for medical images.

Key Words: Telemedicine, JPEG (Joint Photographic Experts Group), JPEG2000, DWT (Discrete Wavelet Transform), DCT (Discrete Cosine Transform), SNR, MSE (Mean Square Error), PSNR.

1. INTRODUCTION

Analysis and compression of medical images is an important area of Biomedical Engineering, especially for Telemedicine. This may be more useful and can play an important role for the diagnosis of sophisticated and complicated images through consultation [1]. As medical images (large size and huge volumes require much transmission time) are to be transmitted over networks at large distances for the use of telemedicine, hence it is necessary that they must be transmitted in compressed and secure form for the reliable, improved and fast diagnosis [2]. The difficulty, however, in several applications lies on the fact that, while high compression rates are desired, the applicability of the reconstructed images depends on whether some significant characteristics of the original images are preserved after the decompression process has been completed [3].

In medical image compression, diagnosis is effective only when compression techniques preserve all the relevant information needed without any appreciable loss of information. This is the case with lossless compression techniques while lossy compression techniques are more efficient in terms of storage and transmission needs. In lossy compression, image characteristics are usually preserved in the coefficients of the domain space in which the original image is transformed [4]. The other approach for lossy compression may be region of interest based. The goal of such a lossy compression method that aims at maximization of the overall compression ratio is to compress each region separately with its own compression ratio, depending on its significance, so as to preserve the important features. Hence, such a strategy that exploits the feature of interest of region may be more useful and compact providing better compression ratios and fast processing [5].

1.1 State of the Art

Various algorithms for lossy and lossless image compression have been proposed in the literature till now, such as predictive coding [Kobayashi1974], sub-band coding [Woods, 1991], vector quantization [Cosman, 1996], segmented image coding [Christopoulos, 1997], neural networks [Dony, 1995] and fractal coding [Fisher, 1995] [6][7][8]. Among the several im age compression techniques during the recent years, the wavelet transform has got more importance due to its manifold characteristics i.e. high compression ratio, lossless to lossy, multi-resolution in nature and applicable to variety of medical images. Wavelet transforms use different basis functions that lead to the desirable property of characterizing and localizing signal features simultaneously in both spatial and frequency domains. JPEG -2000 outperforms JPEG standard in almost every aspect [9].

2. DIS CRETE COSINE TRANSFORM CODING

The key to the JPEG compression process is a mathematical transformation known as the discrete cosine transform. It takes a set of points from the spatial domain and transforms them into an identical representation in the frequency domain. The DCT can be used to convert spatial information into frequency or spectral information, with X and Y-axes representing the frequencies of the two signals in two different directions. The pictorial representation for DCT based compression algorithm is

shown in figure 1.

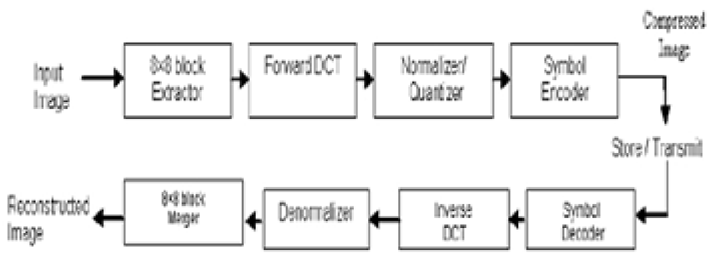

Fig. 1: JPEG Encoder and Decoder

The N × N Cosine transform of matrix T, is defined mathematically as-

$$T(u.v) = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\alpha(u)\alpha(v)\cos[(2x+1)u\pi/2M]\cos[(2y+1v\pi/1N]$$

Where

$$\alpha(u) = \begin{Bmatrix} \sqrt{\frac{1}{M}}, & u=0 \\ \sqrt{\frac{2}{M}}, & u=1,2,\ldots\ldots..M-1 \end{Bmatrix}$$

Similarly for a(v) is used to map an image into a set of transform coefficients which are then quantized and coded. One of the first thing that shows up when examining the DCT algorithm is that the calculation time required for the each element in the DCT is heavily dependant on the size of the image matrix. One of the consequences is that it is virtually impossible to perform a DCT on entire image. Therefore DCT implementation typically breaks the image down into smaller, more manageable blocks. The JPEG selected an 8-by-8-block size of their DCT calculation. To further improve calculations, we take advantage of alternative definition of DCT function: DCT = C * [8 × 8 block extracted image] * C^T ; Where C is the 8 × 8 DCT coefficient matrix and * denotes matrix multiplication.

2.1. Quantization

DCT is a lossless transformation that does not actually perform the compression. The action used to reduce the number of bits required for storage of the DCT matrix is referred to as "Quantization". Quantization is simply the process of reducing the number of bits needed to store an integer value by reducing the precision of the integer. The JPEG algorithm implements the quantization using a quantization matrix. For every element position in the DCT matrix, a corresponding value of quantization matrix gives the quant um value. The quantum value indicates what the step size is going to be for that element in the compressed rendition of the picture, with values ranging from 1 to255. The quantization is done according to formula:

$\hat{T}(u,v) = \text{round}\left[\frac{T(u,v)}{Z(u,v)}\right]$, Where T(u,v) is the DCT transformed image and Z(u,v) is the normalization matrix. By

choosing extraordinarily high step sizes for most DCT coefficients, we get excellent compression ratios and poor picture quality. By choosing low step sizes, compression ratios will begin to decrease but picture quality would be excellent.

2.2 Algorithm for Jpeg Compression

1. The first step in JPEG compression process is to subdivide the input image into non-overlapping pixel blocks of size 8 x 8.

2. They are subsequently processed from left to right, top to bottom. As each 8 x 8 block or sub -image is processed, it's 64 left pixels are level shifted by subtracting $2^{(m-1)}$, where 2^m is the number of gray levels.
3. Now its DCT is computed. The resulting coefficients are then simultaneously normalized and quantized.

4. After each block's DCT coefficients are quantized, the elements of T(u, v) are reordered in accordance with a zig-zag pattern. Now the non-zero AC coefficients are coded using a variable length code.

3. WAVELET CODING

The key to the JPEG 2000 compression process is a mathematical transformation known as the wavelet transf orm. Wavelet coding techniques are based on the idea that the coefficient of a transform that de -correlates the pixels of an image can be coded more efficiently than the original pixels themselves. The computed transform converts a large portion of the original image to horizontal, vertical and diagonal decomposition coefficients with zero mean and Laplacian-like distribution. The principal difference between the wavelet-based system and the transform coding system is the omission of the transform coder's sub-image processing stages. Because wavelet transforms are both computationally efficient and inherently local (i.e. their basis functions are limited in duration), subdivision of the original image is unnecessary. This eliminates the blocking artifact that characterizes DCT - based approximation at high compression ratios. The wavelet - coding scheme is shown in figure 2.

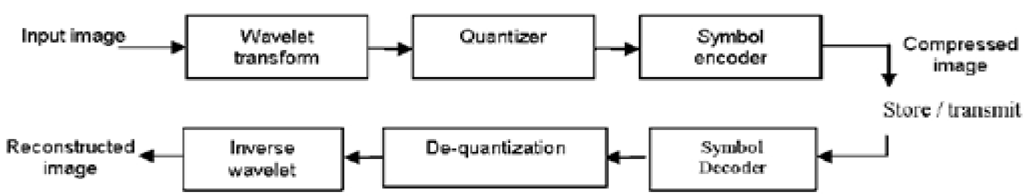

Fig. 2: Wavelet Encoder and Decoder

3.1. Wavelet Selections and Quantizer Design

The ability of the wavelet to pack information into a small number of transform coefficients determines its compression and reconstruction performance. The wavelets chosen as the basis of the forward and inverse transforms in figure2 affect all aspects of wavelet coding system design and performance. They impact directly the computational complexity of the transforms and the system's ability to compress and reconstruct images of acceptable error. Another factor affecting wavelet coding computational complexity and reconstruction error is the number of transforms decomposition level. The number of operations, in the computation of the forward and inverse transform increases with the number of decomposition levels. The largest factor affecting wavelet coding compression and reconstruction error is coefficient quantization. The effectiveness of the quantization can be improved significantly by introducing an enlarged quantization interval around zero, called a dead zone, or adapting the size of the quantization interval from scale to scale. In either case, the selected quantization intervals must be transmitted to the decoder with the encoded image bit stream.

3.2. Discrete-time Wavelet Transform

Discrete wavelet transform contains the same number of pixels as the original image. In addition its local statistics are relatively constant and easily modeled, secondly many of its values are close to zero which makes it an excellent candidate for image compression and thirdly both coarse and fine resolution approximations of original image can be extracted from it. The wavelet series expansion of function f(x) relative to wavelet ?(x) and scaling function F(x) is:

$$f(x) = C_{jo}(k)\Phi_{jo,k(x)} + \sum_{j=jo}^{\infty}\sum_k d_j(k)\Psi_{j,k(x)}$$

Where j0 is an arbitrary starting scale. The $C_{j0}(k)$'s are normally called the approximation or scaling coefficients and $d_j(k)$'s are referred to as the detail or wavelet coefficients. The wavelet series expansion maps a function of a continuous variable into a sequence of coefficients. If the function being expanded is a sequence of numbers, like samples of a continuous function f(x), the resulting coefficients are called the discrete wavelet transform of f(x). For this case, the series expansion defined in equation(3) becomes the DWT transform pair:

$$W_{\Phi(J0,K)} = \frac{1}{\sqrt{M}}\sum_x f(x)\Phi_{jo,k(x)}$$

In two dimensions, a two-dimensional scaling function, f(x, y) and three-dimensional wavelets, $?^H(x, y)$, $?^V(x, y)$ and $?^D(x, y)$ are required. Each is a product of a one-dimensional scaling function f and corresponding wavelet ?. These wavelets measure functional variations - intensity or gray - level variations for images along different directions: $?^H$ measures variations along columns, $?^V$ responds to variations along rows, and $?^D$ corresponds to variations along diagonals. The discrete wavelet transform of function f(x, y) of size M X N is then defined by:

$$W_{\varphi(jo,m,n)} = \frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\varphi_{jo,m,n}(x,y)$$

$$W_{\psi(j,m,n)}^{i} = \frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\psi_{j,m,n}^{i}(x,y)$$

where i□ □ {H ,V , D} and index i identifies the directional wavelets. f(x,y) is obtained via the inverse discrete wavelet transform given by:

$$f(x,y) = \frac{1}{\sqrt{MN}}\sum_m\sum_n W_{\varphi(jo,m,n)}\varphi_{jo,m,n}(x,y) + \frac{1}{\sqrt{MN}}\sum_{i=H,V,D}\sum_{j=jo}^{\infty}\sum_m\sum_n W_{\psi}^{i}(j,m,n)\psi_{j,m,n}^{j}(x,y)$$

4. MS E, SNR & PSNR

Techniques commonly employed for image compression result in some degradation of the reconstructed image. A widely used measure of reconstructed image fidelity for an N x M size image is the mean square error (MSE) and is given by -

$$\text{MSE}=\frac{1}{NM}\sum_{i=0}^{n-1}\sum_{j=0}^{m-1}[|f(i,j) - f^*(i,j)|^2] \text{ and}$$

$$\text{RMSE} = \sqrt{\text{MSE}}$$

Where f (i, j) is the original image data and is the compressed image value. SNR is used more commonly in the image - coding field. So, the SNR that is used corresponding to above error equation (9) is defined in equation (10). Another quantitative measure is the PSNR, based on the root mean square error of the reconstructed image is given by equation (11).

$$\text{SNR} = 10\log\left\{\frac{\sum_{i=0}^{N-1}\sum_{j=0}^{M-1} f(i,j)^2}{\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}[f(i,j)-f(i,j)^*]^2}\right\}$$

$$\text{PSNR} = 10\log\left(\frac{(255)^2}{\text{MSE}}\right)$$

5. RESULTS AND DIS CUSSIONS

We take CT brain and chest images for the compression. All these images are compressed by using DCT and wavelet techniques of different anatomical structures. In the first case, for CT brain images, we have got several compression ratio levels at different MSE, SNR and PSNR as shown in table 1. We have plotted these results in figure 3(a,b,c,d) showing the comparative performance of JPEG and Wavelet Coding. We find that the compression ratios are far better in the case of Wavelet coding than the JP EG. At lower compression ratio we find that the MSE, SNR and PSNR are good in the case of DCT coding but as the compression ratio increases, these factors detoriates and become poorer and poorer while in the case of wavelet coding these factors impro ve with the increase of compression ratio which is the requirement of image compression for the telemedicine application.

Table 1: Comparative Analysis of CT-brain Images using JPEG & Wavelet Transform
JPEG Compression Wavelet Compressio

Image Sequence	Compression Ratio (Max.)	MSE	SNR (dB)	PSNR (dB)	Compression Ratio (Max.)	MSE	SNR (dB)	PSNR (dB)
9580801	40	147.0	18.82	26.45	52	383.42	14.66	22.29
9580802	41	151.44	18.19	26.32	55	381.52	14.18	22.32
9580803	41	143.78	18.50	26.55	57	394.50	14.12	22.17
9580804	45	128.94	19.45	27.02	63	327.37	15.40	22.98
9580805	52	112.55	18.42	27.61	76	254.27	15.89	24.08
9580806	55	107.52	19.18	27.81	83	219.97	16.08	24.71
9580807	56	106.73	19.08	27.84	83	211.05	16.12	24.89
9580808	56	105.69	19.27	27.89	83	211.05	16.27	24.89
9580809	55	107.96	19.17	27.79	82	232.85	15.84	24.46
9580810	74	66.31	22.52	29.91	125	114.76	20.14	27.53
9580811	78	63.7	22.52	30.08	136	97.47	20.68	28.24
9580812	79	63.21	22.56	30.12	136	96.09	20.74	28.31
9580813	73	65.72	22.53	29.95	114	107.97	20.38	27.80
9580814	77	62.19	22.77	30.19	120	95.27	20.92	28.34
9580815	81	60.72	22.73	30.29	129	83.25	21.36	28.93
9580816	88	59.38	22.57	30.39	142	68.46	21.95	29.77
9580817	104	57.9	22.17	30.50	185	42.04	23.56	31.89
9580818	125	55.64	18.34	30.67	240	26.04	21.64	33.97

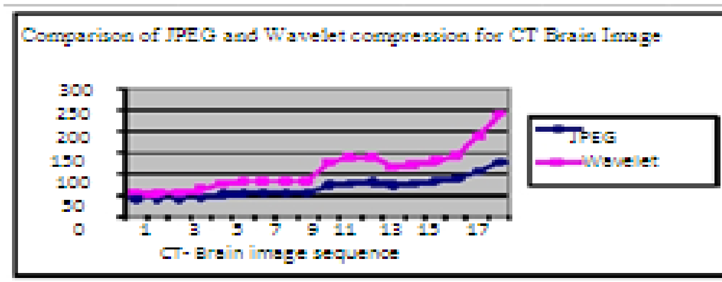

Fig. 3(a) JPEG and Wavelet compression ratio Results for CT Brain image (anatomical structure)

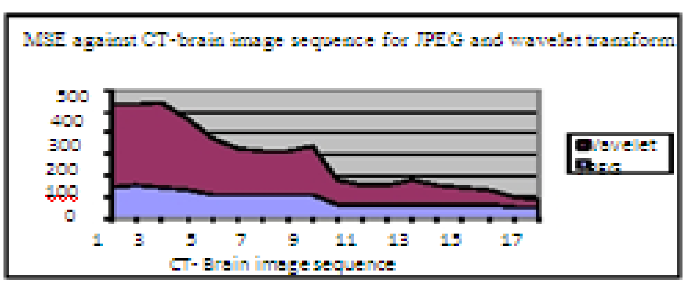

Fig. 3(b) JPEG and Wavelet MSE results for CT Brain image (anatomical structure)

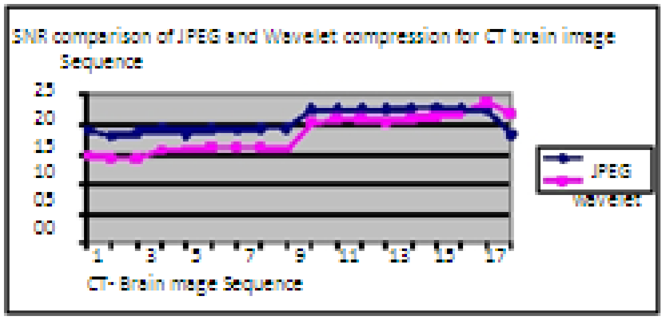

Fig.3(c) Comparison of JPEG and Wavelet SNR (dB) Results for CT Brain Image

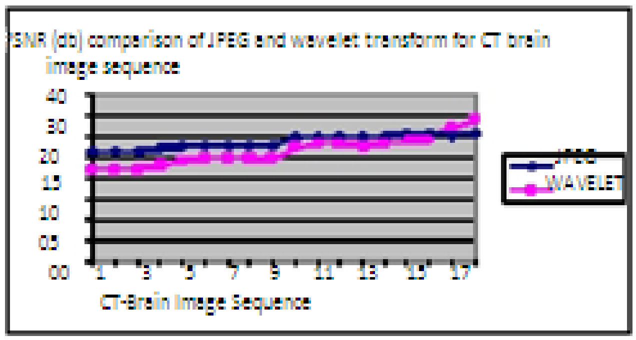

Fig. 3: (d) Comparison of JPEG and Wavelet Compression PSNR Results for CT Brain Image

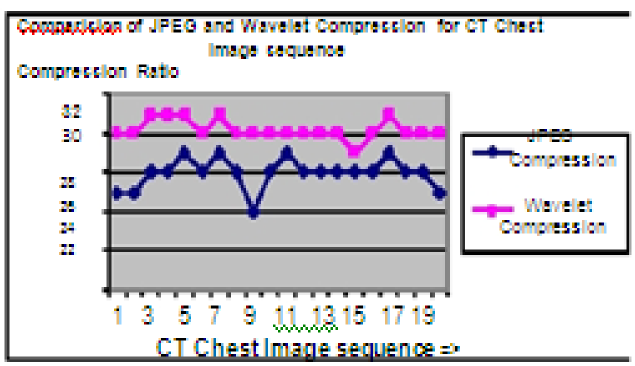

Fig. 4: (a) JPEG and Wavelet Compression Ratio Results for CT Chest Image sequence

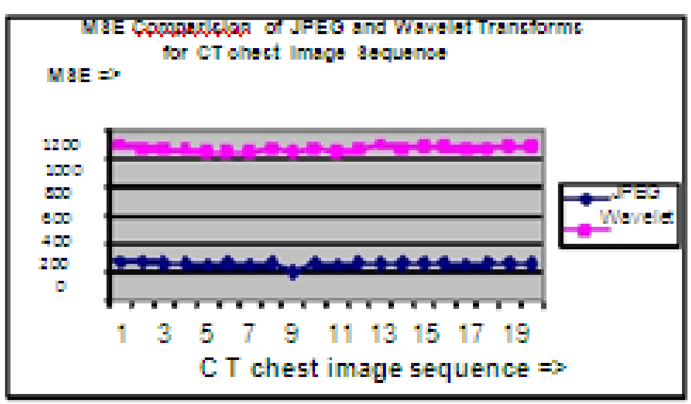

Fig. 4: (b) JPEG and Wavelet MSE results for CT Chest Image sequence

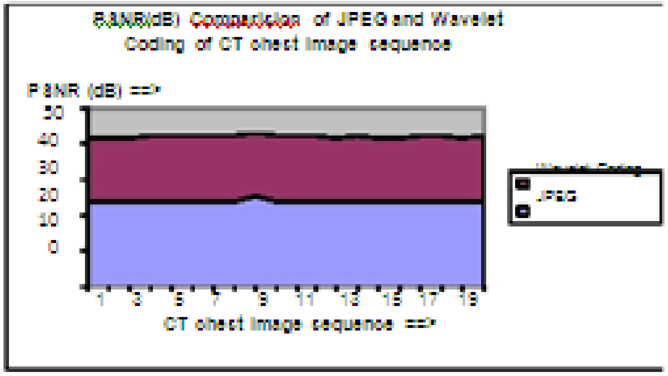

Fig. 4: (c) PSNR (dB) results for CT Chest Image of JPEG and Wavelet Compression

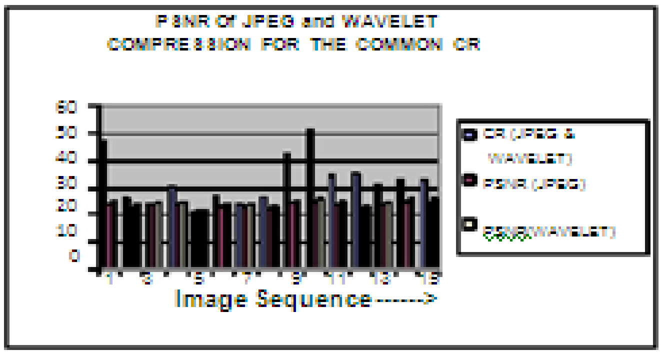

Fig. 5: Combined Performance for PSNR of JPEG and Wavelet Compression for Common CR

Also we get a very high compression ratio 240:1 for the case of wavelet coding as compared to the DCT coding 125:1 table 1. In the second case, table 2 and figure 4(a,b,c) where CT Chest image is analyzed, we find that at lower compression ratio 30:1 the MSE, SNR and PSNR are all better in the case of DCT as compared to wavelet coding. Now in the third case where the analysis is made for the common compression ratio figure 5, we find that for the same compression ratio, the PSNR of wavelet-compressed image is higher than the DCT compressed image. Hence in all the respects for higher compression ratios the results of wavelet compression proves better and better than DCT compression.

CONCLUSIONS

From the above results, we conclude that wavelet compression can be used at higher compression ratios without information loss than JPEG compression for CT images. The wavelet algorithm introduces less image errors, which yields higher PSNR. We have found that in terms of image quality, the wavelet algorithm is either equivalent or better than JPEG algorithm for these images. Our results illustrate that we can achieve higher compression ratios for brain images than chest images i.e. the anatomical structure and its complexity have an effect on image compression ratios. Furthermore, we also observe that by using JPEG compression for chest images the PSNR values obtained are higher than those achieved by using wavelet compression. For a lower compression ratio, JPEG compression yields higher quality image than wavelet compression. From the numerical values obtained we observe that for chest images the PSNR is equal to 24dB for compression ratio up to 31:1 by using JPEG compression, whereas for brain image the PSNR is equal to 22 to 34 dB for compression ratio between 52 to 240:1 by using wavelet compression. The degree of compression is dependent on anatomical structures and complexity of diagnostic information in the image, so careful consideration must be given to the level of compression ratio before archiving clinical images for telemedicine otherwise essential information will be lost and the purpose will not solve. Therefore, as a conclusion we can say that the wavelet transform has better compression ratios and image quality as compared to DCT so far as the medical image compression is concerned.

ACKNOWLEDGEMENTS

It is my pleasure to express sincere thanks to Dr. Gopal Ranjan, Director General, College of Engineering Roorkee and Dr. R. S. Anand, Department of Electrical Engineering, IIT Roorkee for providing their constant support and guidance for this

work to be completed.

JPEG COMPRESSION					WAVELET COMPRESSION			
Image sequence	Compression ratio (max.)	MSE	SNR(db)	PSNR(db)	Compression ratio (max.)	MSE	SNR(db)	PSNR(db)
365401	27	271.68	15.11	23.79	30	1099.00	9.25	17.72
365402	27	264.02	15.52	23.91	30	1075.08	9.62	17.82
365403	28	258.07	15.48	24.01	31	1060.19	9.55	17.88
365404	28	253.12	15.44	24.09	31	1058.02	9.45	17.88
365405	29	248.50	15.35	24.18	31	1040.56	9.32	17.96
365406	28	250.76	15.03	24.19	30	1048.37	9.01	17.93
365407	29	248.48	14.98	24.18	31	1039.98	8.95	17.96
365408	28	253.56	15.18	24.09	30	1067.82	9.12	17.85
365409	26	198.23	15.61	25.16	30	1033.06	8.64	17.99
365410	28	253.12	14.86	24.09	30	1071.52	8.83	17.83
365411	29	249.78	15.03	24.16	30	1048.68	8.98	17.92
365412	28	253.29	14.64	24.09	30	1057.48	8.63	17.88
365413	28	256.37	14.78	24.04	30	1094.81	8.67	17.74
365414	28	250.53	14.60	24.14	30	1070.48	8.50	17.84
365415	28	255.48	14.68	24.06	29	1078.63	8.64	17.80
365416	28	253.70	15.08	24.08	30	1082.35	8.97	17.78
365417	29	248.25	15.04	24.18	31	1058.16	8.91	17.88
365418	28	252.42	15.29	24.11	30	1066.75	9.13	17.85
365419	28	252.95	15.34	24.10	30	1077.87	9.22	17.80
365420	27	251.34	15.54	24.13	30	1088.32	9.38	17.79

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