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ASSESSMENT TECHNIQUE USING WAVELET TRANSFORM FOR IMPROVISING THE SCREEN CONTENT IMAGE QUALITY

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Abstract

Within the confines of this article, we advocate for the utilisation of wavelet transforms in teleconferencing environments as a means of improving the overall video quality. This can be accomplished by increasing the number of participants in the conference. The fundamental concept behind this is to use a collection of high-quality, professionally captured facial images as examples for the purposes of training, and the collection should include as many unique faces as is practically feasible. Images are often changed to make the skin tones and contrast of the facial regions more appealing to the viewer gaze. Adjustments are made to the colouring of a new picture so that the colour distribution in the face region will be comparable to that of the training pictures. This method is very effective when it comes to computation, and it also makes it much simpler to automate the process of making enhancements. The results of user research experiments are presented here, which demonstrate how the suggested method can improve the viewer perception of the video overall quality. The experiments were carried out to determine how the suggested method can accomplish this.

Keywords:

Wavelet Transform, Screen Content, Image Quality

1. INTRODUCTION

There is a wide variety of filters available, the most common of which are spatial and spatial frequency domain filters. Other types of filters also exist. To be more specific, wavelet denoising filters and other spatial frequency domain filters that are used to decrease noise in degraded gamma images have disadvantages when compared to spatial domain filters [1]. These filters are used to decrease noise in degraded gamma images. Noise can be reduced with the help of these filters. The acquisition of the denoised gamma image in techniques that are based on filters in the spatial frequency domain requires many parameters, and the setting of the value requires more sophisticated methods [2].

Because of how easily they can be implemented to lessen the impact of noise distribution, academics make extensive use of spatial domain filters. This is because the procedure generally involves doing nothing more complicated than setting up a new matrix [3]. In addition, many researchers have developed novel noise reduction filters and enhanced the efficiency with which previously developed noise reduction filters can be applied to images that have been damaged [4].

Filters in the spatial domain, such as Wiener, median, and Gaussian filters, are frequently used to minimise the noise distributions in deteriorated images [5]. By adjusting the mask of a new matrix that is n by m in size, these filters make it possible to restore definition to a photograph that had previously lost its sharpness. These filters are helpful in that they concentrate the signal intensity while preserving the edge signal of the image.

Spatial domain filters are useful for cutting down on background noise [6] because they improve the quality of the signal while also decreasing the amount of image distortion that occurs. In addition, the Wiener and median filters are frequently combined to generate a hybrid filter. This hybrid filter is then applied to images of low quality to improve the way they look. The median-modified Wiener filter, also known as the MMWF, is a technique for reducing the distribution of noise. In this approach, the median value of the mask matrix is used instead of the average value of the mask matrix, which is the value that is considered by the Wiener filter [7].

The noise distribution in X-ray images can be evaluated with the help of these filters, which are utilised quite frequently, and the level of noise can be reduced with their help [8] [9]. On the other hand, the application of such filters to images used in nuclear medicine has only been the subject of a relatively modest number of studies. The purpose of this research was to ascertain whether it is advantageous to make use of images that have a greater degree of screen sharpness [10] [11].

The colour of a image that is being used as an input can be altered by selecting the appropriate grouping to use as a target in the process of colour correction. They demonstrated that the method is effective for improving the colour accuracy of outdoor landscapes, provided that the user is present to select a suitable cluster to work with. This is a prerequisite for the method success. On the other hand, the problem of how face images are interpreted was not addressed, and it is not obvious how their method could be modified to work with video.

2. PROPOSED MODEL

In the field of mathematics, the action of moving data from one location to another is referred to as a transformation. When images are processed and analysed, a broad variety of transforms are used. Some of these transforms reveal information about the spatial frequency at which the grey levels in a image change. On the other hand, the primary objective is to eradicate any correlation that may exist between the information contained in the different image sections. The geographic and frequency information of the initial data is preserved by both the wavelet and Haar transforms, even though they achieve this goal in very different methods.

In a nutshell, a transformation is the process of translating one collection of image data to another mathematical region by using an equation that represents a transformation. This translation takes place using an equation that represents a transformation. On the other hand, those colour transformations transferred information from one colour space to another in such a way that there was an exact one-to-one match between each input and output pixel.

This is accomplished by mapping the information from one colour space to another. The image data is mapped from the spatial domain to the frequency domain, which is also known as the spectral domain. In general, the transformations operate by moving from the spatial domain to the frequency domain. With this mapping, each number in the output (which is in the frequency domain) is equal to the sum of all of the pixels located in the input (which is located in the spatial domain) (Fig. 1).

Fig.1. Transform Process

These transformations are helpful in a broad variety of scientific and commercial applications, one of which is the processing of digital images, for example. When referring to the continuous form, it is more common practise to use the discrete (sampled) forms of quantities that were originally specified. This is because discrete forms are easier to work with. It requires a significant amount of processing capacity due to the enormous amount of data that is contained within an image as well as the numerous arithmetic operations that are necessary for the discrete transforms. These two factors combine to make it necessary to perform many arithmetic operations. Because of the substantial improvements that have been made in recent years to processing speed, the amount of RAM that is available, and the storage capacity that is available on discs, it is now much simpler to put these transformations into practise than it was in the past. By decreasing the size of most of the image pixels and separating the image various frequency ranges, image transforms can assist in minimising the amount of superfluous image duplication that occurs.

It is essential to pay attention to the frequencies that are present in images because high frequencies correlate to the image more intricate details, whereas low frequencies correlate to the image more prominent characteristics. It is for this reason that it is important to pay attention to the frequencies that are present. When an image is broken down into its component frequencies by means of a transform, the pixels that correspond to high frequencies can be quantized with a higher degree of precision than the pixels that correspond to low frequencies, which should be quantized with a lower degree of precision, if they are quantized at all. Discarding data that is not directly connected to the successful preservation of essential aspects of an image allows a transform to successfully compress an image in this fashion. The key to this compression method is to focus on preserving the image most essential aspects.

2.1 FOURIER TRANSFORM

The Fourier transform is the one that is employed the most frequently and is the one that is recognised the best. This is because it produces the most accurate results. Since that time, the Fourier transform has been used in a broad variety of fields, including the field you are currently working in, which is computer imaging, as well as in the field of mechanical engineering for the purpose of vibration analysis. In mathematics, the process of decomposing periodic functions or signals into the total of a collection of sine and cosine functions can be accomplished through the application of a technique known as a Fourier series (or complex exponentials).

We can determine the weight of the sinusoidal terms in an image by using this transform, which allows us to reduce the image to a two-dimensional sum of sinusoidal terms. If the input data is a $N \times N$ image, you can use the equation to determine the discrete Fourier transform in two dimensions (2-D DFT).

$$F(u,v)=\frac{1}{N}\sum_{r=0}^{N-1}\sum_{c=0}^{N-1}I(r,c)e^{-j\frac{2\pi}{N}(ur+vc)} \tag{1}$$

The j is used to indicate the imaginary coordinates of a complex integer because the natural logarithmic function, e, has a basis of 2.72. Euler identity is evidence that the basic functions have an oscillating nature. This is shown by the fact that the identity evaluates to 1.

$$e^{jx} = \cos x + j\sin x \tag{2}$$

The expression for the Fourier transform can be written as.

$$F(u,v)=\frac{1}{N}\sum_{r=0}^{N-1}\sum_{c=0}^{N-1}I(r,c)\left[\cos\begin{pmatrix}\frac{2\pi}{N}(ur+vc)\\ -j\sin\frac{2\pi}{N}(ur+vc)\end{pmatrix}\right] \tag{3}$$

The fact that this particular instance of $F(u,v)$ has real parts that correspond to cosine terms and imaginary parts that correspond to sine terms adds an additional layer of complexity to the situation.

After applying a transformation, the original image can be reconstructed using the transformation inverse by applying the transformation again. Equation obtained by performing the Fourier transform backwards.

$$F^{-1}\left[F(u,v)\right]=\frac{1}{N}\sum_{r=0}^{N-1}\sum_{c=0}^{N-1}I(r,c)e^{j\frac{2\pi}{N}(ur+vc)} \tag{4}$$

$F^{-1}[]$ stands for the transform that goes in the opposing direction. By solving this equation, which demonstrates how the transform coefficients $F(u,v)$ are used as weights, the function $I(r,c)$ can be expressed as a weighted sum of the basic functions. This sum can be expressed as a weighted sum of the basic functions. Through the utilisation of the inverse Fourier transform, the negative exponents of the fundamental functions are transformed into their corresponding positive forms.

2.2 DISCRETE COSINE TRANSFORM

The sinusoidal basis functions are utilised by both the cosine transform and the Fourier transform; however, the cosine transform does so in a fashion that is analogous to that of the Fourier transform. The cosine transform is built on a foundation of more straightforward cosine functions, in contrast to the sine transform, which is built on more complicated sine functions. To be more specific, the expression for the 2-dimensional discrete cosine transforms, also known as the DCT, appears like this for a image that contains $N \times N$:

$$C(u,v)=\alpha(u)\alpha(v)\sum_{r=0}^{N-1}\sum_{c=0}^{N-1}I(r,c)\begin{bmatrix}\cos\dfrac{(2r+1)u\pi}{2N}\\ \cos\dfrac{(2c+1)v\pi}{2N}\end{bmatrix} \tag{5}$$

This transformation only makes use of the cosine function, its calculation involves only the application of elementary mathematical ideas (not complex ones). The JPEG image compression method can be followed all the way back to its first iteration because the cosine transform is an important part of the method. It is responsible for a significant portion of the compression process and can be found at the very beginning of the method.

In the field of digital image processing, basis matrices are frequently visualised in the form of images and are consequently referred to as basis images. Within these basis images, the various values that are contained within the basis matrix are represented by varying degrees of grey that are scattered throughout the image.

The primary advantage that the discrete cosine transform (DCT) provides when used as a data-compression tool is its capacity to condense the information that is present in correlated incoming data onto the first few transform coefficients. This is the DCT primary contribution to the field of data compression.

2.3 WAVELET TRANSFORM

Wavelets have an average number of zero, and the length of time they can exist for is always rigorously limited. Because the energy of a wavelet is concentrated over a relatively short period of time, it is possible to make efficient use of a wavelet for analytical purposes by employing it as a tool.

Wavelets are a specific kind of waveform that can be compared to the sine waveforms that are utilised in Fourier analysis. Wavelets are also known as wavelet transforms. There is no way to ever quantify the scope of sinusoids (both negative and positive) accurately. On the other hand, wavelets are characterised by a high degree of inconsistency and irregularity, in contrast to the consistency and predictability of sinusoids.

The concept of windowing can be applied to the way that wavelet analysis works by making use of a variety of different sized regions. If we use lengthier time periods for our wavelet analysis, we will be able to obtain more granular information about low frequencies.

On the other hand, if we use shorter time periods, we will be able to obtain more granular information about high frequencies. When analysing signals that have abrupt transitions, it is conceivable that a chaotic wavelet is superior to a smooth sinusoid in certain circumstances.

- **Scaling**: Scaling refers to the process of expanding (or contracting) a wavelet, which is a straightforward process that can be described by the term itself. to avoid using colloquial expressions like stretching, we introduce the scale factor, which is commonly denoted by the symbol a.

Wavelets can be manipulated in a variety of ways by utilising a scale factor in their calculations. It is said that the wavelet has a more compressed appearance when the scale factor is diminished. The impact that the magnitude of the factor has can be understood very quickly.

2.4 DISCRETE WAVELET TRANSFORM

By selecting scales and positions that are based on powers of two, we have the incredible ability to substantially increase the efficiency and precision of our research. This is a remarkable capability (so-called dyadic scales and positions). We can conduct such an investigation because of a tool called the discrete wavelet transform (DWT).

The information that is present at extremely low frequencies is often the single most essential component of a transmission. This is especially true in many situations. It is the distinguishing characteristic that distinguishes the transmission as being unique to itself. On the other side, the high-frequency information may be responsible for the subtleties of the flavour. Think about how a person sounds when they communicate and how their voice sounds.

Even if the high-frequency aspects of the conversation were removed, it would still be feasible to understand what was being said. Within the realm of wavelet analysis, discussions of estimations and other subjects with a greater degree of nuance are commonplace. In the interest of keeping things as straightforward as possible, the approximations consist of the signal large-scale and low-frequency components. The finer elements are comprised of the higher frequencies and smaller scales of the individual components.

- **Multiple-Level Decomposition:** In the same way that the image on a geographical map contains information that is not redundant because of the changing of the scale, the wavelet is important as a method for multiresolution analysis because it decomposes the image into multiple levels of independent information when the scale is changed. This makes the wavelet an important tool for multiresolution analysis.

It is possible to divide a single signal into many low-resolution sub-signals by repeatedly iterating the decomposition process and decomposing consecutive approximations. Decomposing consecutive approximations is a method that can be used to achieve this goal. The term wavelet breakdown tree is used to suggest to the specific structure being discussed here.

Based on this information, we are able to separate each image into a total of four different components: a low-information version, a high-detail version, and two additional low-detail versions of the original image along the horizontal and vertical directions, respectively. It was not feasible to recreate several aspects of the original image by using this technique of decomposition; however, those aspects have been preserved in the transformed levels.

The wavelet transform is the most useful transform for working with images, sounds, or any other kind of pattern because it provides a powerful time-frequency representation. This transformation can be applied to any kind of pattern. The wavelet transform is responsible for providing it, which is why this is the case.

- **Number of Levels:** The fact that this research is carried out in an ongoing manner means that there is a probability that it will never be completed. Further dissection of the details is possible only up to the point where each detail represents a distinct sample or image. Beyond that point, there is no further possibility of dissection. In actual practise, you will base your decision on the characteristics of the signal or on some other pertinent parameter, such as entropy, to determine the optimal number of levels to use.

2.5 WAVELET RECONSTRUCTION

With the assistance of the discrete wavelet transform, we were shown how to perform signal and image analysis as well as decomposition. This period is sometimes referred to as the investigation stage or the deconstruction stage. The second element of the narrative centres on the procedure of reassembling those components into the original signal while keeping all the data intact. Reconstruction or fusing are two other names that may be used to allude to this method. The utilisation of inverse discrete wavelet transforms (IDWT) is the method by which synthesis can be accomplished.

Upsampling and filtering are essential steps in the process of studying wavelets, whereas downsampling and filtering are required steps in the process of reconstructing a wavelet. Adding additional zeros in between the signal original portions is what is meant by the term up sampling, which refers to the process of up sampling a signal.

3. RESULTS AND DISCUSSION

Our training collection now includes approximately 400 different frame examples that were pulled from the internet and added to it. It functions effectively for people whose complexions range from light to dark. to construct a Gaussian mixture model consisting of five distinct components, we make use of an EM methodology. Figure 4 presents an illustration that exemplifies each of the categories in a manner that is representative of it. It is important to keep in mind that the images you are currently viewing are not necessarily the most outstanding examples of their respective classifications.

to save time and effort on the computations, we keep track of the changes in intensity across the globe at a rate of one change recorded every two seconds. The utilisation of the RGB channels allows for the recording of colour tones to be successfully accomplished. If there is a discernible shift in the overall luminance of an image, the tone mapping function will need to be recalculated for each colour channel before it can be saved to a lookup database for subsequent application.

The process of colour tone mapping is broken down into a series of rapid table searches that are detailed in the following frames. Our technique only requires 5% of the central processing unit time to render a 320x240 movie at 30 frames per second when applied to a computer with 3.2 gigahertz of processing capacity.

Table.1. RMSE

Frames	FT	DCT	WT	DWT	MLD	WLR
10	0.409	0.550	0.890	0.682	0.804	0.689
20	0.687	0.912	0.627	0.966	1.014	0.779
30	0.455	0.385	0.636	0.587	0.723	0.562
40	0.592	0.949	0.486	0.827	0.922	0.667
50	0.304	0.366	0.549	0.773	0.849	0.651
60	1.083	1.076	1.078	1.080	1.084	1.083
70	0.836	0.882	0.971	1.021	1.036	0.879
80	1.019	1.116	1.444	1.034	1.049	1.935
90	0.524	0.708	0.520	0.817	0.890	0.732
100	0.489	0.707	0.687	0.908	0.939	0.950
110	2.930	6.737	1.076	1.031	1.135	1.779
120	0.956	1.088	1.009	0.880	0.906	2.899
130	0.965	1.061	1.044	1.059	1.005	1.035
140	1.094	1.086	1.581	1.054	1.032	2.989
150	0.679	1.097	0.904	0.840	1.014	0.829
160	0.960	1.033	0.942	0.930	0.935	0.937
170	1.381	2.147	1.039	1.107	1.046	3.680
180	0.740	1.086	1.935	1.049	1.087	0.898
190	1.025	1.079	1.087	0.975	1.085	0.888
200	0.889	1.206	0.950	0.906	1.273	0.958

Table.2. RRSE

Frames	FT	DCT	WT	DWT	MLD	WLR
10	0.691	0.930	1.504	1.142	1.338	1.165
20	1.284	1.726	1.164	1.839	1.932	1.470
30	0.591	0.513	0.864	0.807	0.999	0.759
40	0.660	1.064	0.542	0.930	1.038	0.745
50	0.381	0.459	0.644	0.962	1.059	0.816
60	1.250	1.242	1.245	1.246	1.251	1.250
70	0.984	1.038	1.143	1.202	1.220	1.035
80	1.115	1.225	1.610	1.140	1.152	2.136
90	0.587	0.793	0.583	0.911	0.994	0.821
100	0.529	0.822	0.807	1.076	1.117	1.122
110	3.680	6.211	1.318	1.259	1.394	2.220
120	1.161	1.322	1.226	1.066	1.093	3.524
130	1.316	1.450	1.429	1.452	1.379	1.413
140	1.267	1.257	1.842	1.219	1.190	3.511
150	0.889	1.490	1.210	1.149	1.393	1.130
160	1.099	1.182	1.064	1.050	1.059	1.072
170	2.028	3.671	1.109	1.317	1.138	6.665
180	0.868	1.280	2.287	1.236	1.281	1.056
190	1.180	1.243	1.252	1.122	1.250	1.018
200	1.135	1.488	1.190	1.155	1.704	1.224

Our method has been evaluated with a sizable sample size of diverse individuals utilising a wide range of video recording devices. The next part of this article will cover the findings of our research on users, which can be found in the following portion. The encoding of colour tones that is shown in Figure 1 is something that can be acquired through experience. The two videos are used for finding the efficacy of these models as in Table.3-Table.6.

Table.3. MAE

Image	FT	DCT	WT	DWT	MLD	WLR
Video 1	0.416	0.560	0.906	0.694	0.818	0.701
	0.699	0.928	0.638	0.983	1.031	0.793
	0.463	0.392	0.647	0.598	0.736	0.572
	0.602	0.966	0.494	0.841	0.938	0.679
	0.309	0.372	0.559	0.787	0.863	0.663
Video 2	1.102	1.095	1.097	1.099	1.103	1.102
	0.851	0.897	0.988	1.039	1.054	0.895
	1.037	1.135	1.469	1.052	1.067	1.969
	0.533	0.720	0.529	0.832	0.906	0.745
	0.497	0.720	0.698	0.924	0.955	0.967

Table.4. MSE

Image	FT	DCT	WT	DWT	MLD	WLR
Video 1	2.981	6.855	1.095	1.049	1.155	1.810
	0.972	1.107	1.027	0.895	0.922	2.949
	0.981	1.079	1.062	1.077	1.022	1.053
	1.113	1.105	1.609	1.072	1.050	3.041
	0.691	1.116	0.920	0.855	1.032	0.843
Video 2	0.977	1.051	0.959	0.946	0.951	0.953
	1.405	2.185	1.057	1.126	1.064	3.744
	0.753	1.105	1.969	1.068	1.106	0.914
	1.043	1.098	1.106	0.992	1.104	0.903
	0.905	1.227	0.967	0.922	1.295	0.975

Table.5. MAPE

Image	FT	DCT	WT	DWT	MLD	WLR
Video 1	0.703	0.946	1.531	1.161	1.361	1.185
	1.306	1.757	1.184	1.871	1.966	1.496
	0.601	0.522	0.879	0.821	1.016	0.772
	0.671	1.083	0.552	0.946	1.056	0.758
	0.388	0.467	0.655	0.979	1.078	0.831
Video 2	1.272	1.264	1.266	1.268	1.273	1.272
	1.001	1.056	1.163	1.223	1.241	1.053
	1.134	1.246	1.639	1.160	1.172	2.174
	0.597	0.807	0.593	0.926	1.011	0.835
	0.538	0.837	0.821	1.095	1.136	1.141

Table6. PSNR

Image	FT	DCT	WT	DWT	MLD	WLR
Video 1	41.74	44.32	39.34	39.28	39.42	40.26
	39.18	39.35	39.25	39.09	39.11	41.59
	39.34	39.48	39.45	39.48	39.40	39.44
	39.29	39.28	39.87	39.24	39.21	41.57
	38.91	39.52	39.23	39.17	39.42	39.15
Video 2	39.12	39.20	39.08	39.07	39.08	39.09
	40.06	41.74	39.13	39.34	39.16	44.78
	38.88	39.30	40.33	39.26	39.30	39.08
	39.20	39.26	39.27	39.14	39.27	39.04
	39.16	39.51	39.21	39.18	39.73	39.25

The finished images have a tone that is significantly warmer and slightly brighter than the originals due to the incorporation of coloured lights into the setting. This can be seen in comparison to the originals. This is because the lights were initially whitish in colour when they were first turned on. The newly remastered version of the film is, in virtually every way imaginable, a significant step up from the version that was previously available.

4. CONCLUSION

This paper has implemented a cutting-edge method that we refer to as learning-based colour tone mapping to enhance the visual experience that is delivered by online meetings. The term learning-based colour tone mapping was coined by our group. We take a different strategy than other people do because, in addition to modifying the level of brightness, we also alter the colour tone of the image. This sets our method apart from those of other people. During investigation, we put a number of different cameras to the test to evaluate the efficacy of our methodology. According to the findings of the user research that we carried out, the implementation of our strategy led to a substantial improvement in the way that individuals rated the quality of the videos they viewed.

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