A novel Entropy based Denoising algorithm on color videos

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Abstract:

Video signals are considered as a sequence of two-dimensional images, projected from a dynamic three-dimensional scene onto the image plane of a video camera. Luminance and chrominance are two attributes that describe the color sensation in a video sequence of a human being. Luminance refers to the perceived brightness of the light, while chrominance corresponds to the color tone of the light. Numerous still images and video denoising algorithms have been developed to enhance the quality of the signals over the last few decades. Traditional fuzzy based denoising algorithm fails to operate the noise on the high resolution images and motion datasets. In this proposed work, a novel noise prediction and elimination based filter model was proposed on the high resolution image datasets with varying features.

Keywords – Video denoise, Frame process, Color video.

I. INTRODUCTION

Image denoising is often used in the field of photography or publishing, where an image was somehow degraded but needs to be improved before it can be printed. For this type of application we need to know something about the degradation process in order to develop a model for it. When we have a model for the degradation process, the inverse process can be applied to the image to restore it back to the original form. This type of image restoration is often used in space exploration to help eliminate artifacts generated by mechanical jitter in a spacecraft or to offset for distortion in the optical system of a telescope. Image denoising finds applications in fields such as astronomy where the resolution limitations are severe, in medical imaging where the physical requirements for high quality imaging are needed for analyzing images of unique events, and in forensic science where potentially useful photographic evidence is sometimes of extremely bad quality. Binary images are the simplest type of images and can take only two discrete values, black and white. Black is represented with the value ‘0’ while white with ‘1’. Note that a binary image is generally created from a grayscale image. A binary image finds applications in computer vision areas where the general shape or outline information of the image is needed. They are also referred to as 1 bit/pixel images. Gray-scale images are known as monochrome or one-color images. The images used for experimentation purposes in this thesis are all gray-scale images. They contain no color information. They represent the brightness of the image. This image contains 8 bits/pixel data, which means it can have up to 256 (0-255) different brightness levels. A ‘0’ represents black and ‘255’ denotes white. In between values from 1 to 254 represent the different gray levels. As they contain the intensity information, they are also referred to as intensity images. Color images are considered as three band monochrome images, where each band is of a different color. Each band provides the brightness information of the corresponding spectral band. Typical color images are red, green and blue images and are also referred to as RGB images. This is a 24 bits/pixel image.

Typical images are corrupted with noise modeled with either a Gaussian, uniform, or salt and pepper distribution. Another typical noise is a speckle noise, which is multiplicative in nature. The behavior of each of these noises[1 - 5].

Noise is present in an image either in an additive or multiplicative form.

\[ w(x, y) = s(x, y) + n(x, y), \text{ while} \]

the multiplicative noise satisfies

\[ w(x, y) = s(x, y) \cdot n(x, y), \]

where \( s(x,y) \) is the original signal, \( n(x,y) \) denotes the noise introduced into the signal to produce the corrupted image \( w(x,y) \), and \((x,y)\) represents the pixel location. The above image algebra is done at pixel level. Image addition also finds applications in image morphing. By image multiplication, we mean the brightness of the
image is varied. The digital image acquisition process converts an optical image into a continuous electrical signal that is, then, sampled. At every step in the process, there are fluctuations caused by natural phenomena, adding a random value to the exact brightness value for a given pixel.

Gaussian noise is evenly distributed over the signal [Um98]. This means that each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value. As the name indicates, this type of noise has a Gaussian distribution, which has a bell shaped probability distribution. Graphically, it is represented as shown in Figure 2 When introduced into an image, Gaussian noise with zero mean and variance as 0.05. Fig 2 illustrates the Gaussian noise with mean (variance) as 1.5 (10) over a base image with a constant pixel value of 100[6].

Speckle noise is a multiplicative noise. This type of noise occurs in almost all coherent imaging systems such as laser, acoustics and SAR(Synthetic Aperture Radar) imagery. The source of this noise is attributed to random interference between the coherent returns. Fully developed speckle noise has the characteristic of multiplicative noise.

Brownian noise comes under the category of fractal or 1/f noises. The mathematical model for 1/f noise is fractional Brownian motion [Ma68]. Fractal Brownian motion is a non-stationary stochastic process that follows a normal distribution. Brownian noise is a special case of 1/f noise.

II. LITERATURE SURVEY

The emergence of wavelet transforms [1] played a prominent role in solving image processing problems such as denoising, image compression, etc. In [2], it has been shown that the difference of information between successive resolutions of an image can be extracted by decomposing the image using a wavelet orthonormal basis. It has been shown that wavelet transform facilitates in depth understanding of the statistical properties of images and applications of wavelets in image compression and texture discrimination have been discussed. In [3], Daubechies presented wavelet theory and different types of wavelet transforms in great detail.

Donoho et al. Proposed denoising by soft or hard thresholding on the coefficients in wavelet domain[4], [5].

For reasons of symmetry h(t,u) is always chosen to be of size m=n where m and n are both odd (often m=n). In physical systems, the kernel h(t,u) must always be non-negative, which results in some blurring or averaging of the image. If the coefficients are alternating positive and negative, the mask is a filter that returns edge information only. The narrower the h(t,u), the better the system in the sense of less blurring. In digital image processing, h(t,u) may be defined arbitrarily and this gives rise to many types of filters. The weights of h(t,u) may be varied over the image and the size and shape of the window can also be varied. These operations are no longer linear and no longer convolutions. They become moving window operations. With this flexibility, a wide range of linear, non-linear and adaptive filters may be implemented[7].

Computing the straightforward convolution of an image with this kernel carries out the mean filtering process. It is effective when the noise in the image is of impulsive type. The averaging filter works like a low pass filter, and it does not allow the high frequency components present in the noise to pass through. It is to be noted that larger kernels of size 5x5 or 7x7 produces more denoising but make
the image more blurred. A trade off is to be made between the kernel size and the amount of denoising. The mean filter is used in applications where the noise in certain regions of the image needs to be removed. In other words, the mean filter is useful when only a part of the image needs to be processed[8-10].

II. PROPOSED WORK

An adaptive filter does a better job of denoising images compared to the averaging filter. The fundamental difference between the mean filter and the adaptive filter lies in the fact that the weight matrix varies after each iteration in the adaptive filter while it remains constant throughout the iterations in the mean filter. Adaptive filters are capable of denoising non-stationary images, that is, images that have abrupt changes in intensity. Such filters are known for their ability in automatically tracking an unknown circumstance or when a signal is variable with little a priori knowledge about the signal to be processed. In general, an adaptive filter iteratively adjusts its parameters during scanning the image to match the image generating mechanism. This mechanism is more significant in practical images, which tend to be non-stationary.

PROPOSED MODIFIED ALGORITHM

Step 1: The sequence normalization is computed using the function:

\[X = \{g(1), g(2), \ldots, g(s)\}\] is the sequence of color sequence sets.

\[Y(i,j) = f(x(i,j)) = \frac{1}{1 + x(i,j)}\]

Step 2: Finding the realistic information entropy \(E(X)\) and Maximum entropy \(E_{\text{max}}(X)\)

\[E(X = x(i, j)) = -p s \sum_{k=1}^{s} Y(i, k) \log(Y(i, k))\]

\[E_{\text{max}}(X) = -p \log(S)\]

Calculate the information diversion using

\[E(X) = |E_{\text{max}}(X) - E(X = x(i, j))|:\]

Step 3: Initialize parameters
For \(r=0,1,2,3,\ldots\) do

Step 4: \(P = P^0 = \mu_{f(x,y)}, x = 0\).

Step 5: \(\mu^{r+1} = \lambda^r (P^r, P^0) - \lambda^r ||\nabla P^r||, \lambda^r\) is a Gaussian parameter

Step 6:
\[P_{r+1} = (P(i, j) + \lambda^r P^0) / (1 + \lambda^r \theta + \lambda^r \mu^r),\]

Step 7: \(P(i, j)^{r+1} = P^r - \theta \nabla^2 i^r\)

Step 8: \(\text{Denoise}^{r+1} = \min\{1/\lambda, ||\text{Denoise}^r + \nabla P(i, j)^r||\}\)

Step 9: End for

Step 10: Terminate criterion : \(r > r_{\text{max}}\), where \(r_{\text{max}}\) is the maximum user defined iteration.

IV. Experimental Results

All experiments are performed with the configurations Intel(R) Core(TM)2 CPU 2.13GHz, 2 GB RAM, and the operating system platform is Microsoft Windows XP Professional (SP2).
Numerous still images and video denoising algorithms have been developed to enhance the quality of the signals over the last few decades. Traditional fuzzy based denoising algorithm fails to operate the noise on the high resolution images and motion datasets. In this proposed work, a novel noise prediction and elimination based filter model was proposed on the high resolution image datasets with varying features. It will be useful to investigate a real-time implementation of this approach so that denoising can be executed before compression. Our approach has the potential to be implemented in real time as all components are block-based; no complex optimization, such as conjugate gradient, is involved in the optical flow estimation.

V. CONCLUSION

7. REFERENCES


