HIGH QUALITY ENHANCEMENT OF LOW RESOLUTION COLOUR IMAGES

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Abstract: A new adaptive method is developed for the enhancement of subsampled colour images. The system uses edge information in the luminance channel to aid the reconstruction of the chrominance signals such that edges between the luminance and the chrominance channels are well aligned. A technique exploiting the luminance information effectively is developed. The method is computationally efficient. Simulation results are presented to demonstrate the superior performance of the new technique.

1. INTRODUCTION

Sub-sampling of chrominance signals is extensively used in image communications and coding systems. For example, the well known “PEGs”, MPEG [4] and JPEG [5] video and image compression standards subsample the chrominance signals prior to transform coding. Because of the lossy nature in the subsampling process, visible colour artifacts will inevitably occur. Traditional interpolation algorithms often produce less than satisfactory results, in that jagged edges and false colours will appear. In order to lessen the visual distortion introduced by the subsampling process, it is necessary to develop good algorithms to reconstruct the full resolution images from the subsampled signals.

The most commonly used techniques for image magnification are interpolation based. The simplest technique is the nearest neighbor (zero order) interpolation [8]. However, the magnified images produced by this technique often appear “blocky”, i.e., the pixels are visible as large blocks. This undesired effect is more striking when the zooming factor is high. Using higher order interpolations can generate smooth images. A commonly used approach is the bilinear interpolation [8, 9], which linearly interpolate along each row of the image, and then linearly interpolate the result along the column direction. Even smoother images can be produced by using cubic spline interpolation [9, 10]. However, these methods smooth flat as well as edge areas, important visual features such as sharp edges and thin lines are smoothed over by the interpolations and the magnified images appear “blurry”. Therefore, the results of these methods are often unsatisfactory.

Researchers have proposed various improved algorithms for image magnification. For example, Huang and Chen [11] proposed a hybrid interpolation filtering method. Unser et al [12] developed more accurate spline interpolation algorithms. Schultz and Stevenson developed a Bayesian approach to image enlargement [13], and Jensen and Anastassiou [14] used an edge fitting model to enlarge images. The main goal of these methods is to preserve the visual integrity in detail areas of the magnified image, because interpolations blur the magnified image.

Recently, colour image processing has attracted increasing research interest [15]. Researchers have investigated the problem of enhancing sub-sampled chrominance signal [3, 16]. Here the problem is slightly different from enhancing a single gray scale image. Of the three channels in a colour image, the luminance channel is not sub-sampled and contains the full resolution information. It is only in the chrominance channels that sub-sampling is performed. Therefore, to enhance the chrominance signal, one can exploit the correlation between the luminance and the chrominance channels. In [3], a method based on Bayesian estimation was introduced which used the full resolution luminance channel to determine and maintain the correct edge information to recover full resolution chrominance signals. However, the method was iterative and computationally very inefficient. A computationally very efficient method based on pattern matching and look-up table was recently introduced to enhance sub-sampled colour images [16], however, this method did not utilize the luminance channel.

In this paper, we present a new adaptive learning approach to the construction of high quality images from subsampled signals. Edge information is extracted from the luminance channel to “guide” the adaptive learning so that edges are aligned between the channels. Simulation results show the method is fast, and can recover excellent quality full resolution images from sub-sampled signals.

The organization of the paper is as follows. Section 2 briefly describes a chrominance sub-sampling image format, the YC&Cr 9 format. Section 3 describes the new adaptive learning based chrominance enhancement technique and its implementation details. Section 4 presents simulation results based on both subject and object image quality measures and a brief conclusion is given in section 6.

2. THE YC&Cr9 SUBSAMPLING FORMAT

YC&Cr is a colour space developed by the organization responsible for the international standard of digital coding of television pictures (CCIR) [1] and designed to isolate luminance information from chrominance.
information. In this colour space, \( Y \) contains the luminance information, \( C_b \) and \( C_r \) contain the chrominance information as well as some luminance information. The relation between the more familiar RGB space and \( YCbC_r \) is as follows:

\[
\begin{align*}
Y &= 0.299 R + 0.587 G + 0.114 B, \\
C_b &= -0.169 R - 0.331 G + 0.500 B, \\
C_r &= 0.500 R - 0.419 G - 0.081 B.
\end{align*}
\]

Because human visual system is less sensitive to degradation in chrominance information, the chrominance images are often sub-sampled to reduce the number of bits needed to represent a colour image. One standard method is called \( YCbC_r \) [2]. This method sub-samples the chrominance signals \( C_b \) and \( C_r \) by a factor of 4 in both dimensions. Each \( 4 \times 4 \) neighborhood of pixels have one \( C_b \) and one \( C_r \) values.

Fig.1 shows the location of the sub-sampled pixels (indicated by shaded squares) in the chrominance primaries for the \( YCbC_r \) representation. In this work, we follow the format of [3], i.e., the upper left-most \( C_b \) and \( C_r \) values are used as the representative value for their respective sampling neighborhood. The luminance signal \( Y \) is unchanged. Assuming each sample of \( Y, C_b \) and \( C_r \) is represented by an 8-bit number, each pixel of the image is represented by 9 bits on average, therefore the name \( YCbC_r \).

\( YCbC_r \) format is lossy. Using traditional methods to expand sub-sampled chrominance information often results in jagged edges and false colours. Newer methods, such as the one described in [3], improved the quality of reconstructed image but were generally computationally too complicated to be useful in many practical applications. This paper presents a new method for recovering full resolution colour image from \( YCbC_r \) representation. The new method is also applicable to images containing subsampled information in other colour spaces such as YIQ and YUV.

### 3. Enhancement of Subsampled Chrominance Signal Exploiting Luminance Information

Adaptive learning systems, especially, those appear in the form of artificial neural network [6], have attracted extensive research interests in the past decade. The intrinsically adaptive and parallel nature of these systems make them well suited for solving difficult and complicated signal processing problems. In a recent work [7], we have developed a technique based on a single layer perceptron with linear units for the reconstruction of full resolution colour images from subsampled signals. In [7], only subsampled chrominance information was used to construct the adaptive system. This work extends the work of [7] by exploiting the information in the full resolution luminance component.

One of the problems associated with the reconstruction of full resolution chrominance signal from subsampled information is edge misalignment. In colour spaces such as \( YCbC_r \), most of the energy is concentrated on the luminance component \( Y \), and edge patterns appear in the luminance component should provide very useful information for the reconstruction of chrominance signal.

![Fig. 1. Location of Chrominance Sub-samples](image)

![Fig. 2 Schematic of the learning phase](image)

#### 3.1 Resolution Enhancement via Adaptive Learning

The schematic of the new method is illustrated in Fig. 2 and 3, here the neural network is a feedforward linear network (we don't find a nonlinear network particularly useful in the sense they do not give better performance than their linear counterparts, plus, linear network has the advantage that it has no local minimum in its error surface, it is guaranteed to converge and computationally simple). For easy explanation, we shall use the upper left \( 4 \times 4 \) image block to illustrate the process. In the learning stage, inputs come from two sources, the first is the \( 4 \) subsampled pixels from \( C \) (shown as shaded small square in the Figures), the second is a binary pattern generated from the upper left \( 4 \times 4 \) blocks of the \( Y \) component. Here it is important to note that we can not use the gray scale values of the \( Y \) component because this way it may alter the colour information of the image. What is important here is to provide the network with the edge pattern information to guide the reconstruction of the \( C \) component. Details on how to generate the binary edge pattern will be described in the next subsection. The upper left \( 4 \times 4 \) block of the \( C \)
A binary pattern will only be generated when the magnitude of the gradient of the block \( G \) in (5) is large enough. In order to generate binary edge patterns that are suitable for learning, they have to be in a form that encodes the pattern numerically. Although they may be many different solutions, we have developed a method that was found to work very well.

These binaries can be simply generated by first calculating the mean of this \( 4 \times 4 \) block, then a pixel of the block is replaced by +1 if the pixel is greater than the mean and -1 if the pixel is less than the mean. However, such patterns may be too noisy and give no clear indication of the edge information. We generate the edge pattern in the following way. Let \( b(i, j) \) be the corresponding edge pattern to \( y(i, j) \):

\[
\begin{align*}
  & \text{If } G > T_G \quad b(i, j) = \begin{cases} 
  -1, & \text{if } |y(i, j) - m| < -T_m \\
  0, & \text{if } |y(i, j) - m| < T_m \\
  +1, & \text{if } |y(i, j) - m| > T_m 
\end{cases} \\
  & \text{If } G < T_G \quad b(i, j) = 0
\end{align*}
\]

where \( m \) is the mean of the block, \( T_G \) and \( T_m \) are two pre-set thresholds determined experimentally. We found the choice of these two values is not very sensitive and setting \( T_G = 25 \) and \( T_m = 32 \) work well.

4. SIMULATION RESULTS

Computer simulations were performed to evaluate the performance of the new method. For a large set of natural scene colour images, the algorithm performs very well based on subjective viewing judgment and objective quality measurement. Some of the typical results are presented here. A system trained using the USC image Peppers is used to test other two USC images, Lena and Splash. These images are well known in the image processing community and their scene contents and colours are very different. The original full colour 24-bit images were subsampled to create \( YC_bC_r \) image. An adaptive system, consists of two networks, one for the \( C_b \) and one for the \( C_r \) channel were trained using data from the Peppers image. We tested two different network architectures, one is linear three layer feedforward network of the size 20-8-16 and the other is a linear single layer network with 20 input and 16 output units. It was found that single layer network worked as well as the three layer ones. The results presented here are those of single layer networks.

To measure the performance of the new method objectively, we use a recently introduced colour image
quality metric, the S-SCIELAB system [17] that is suitable for measuring the visual quality of colour images. Fig. 4 shows the distribution of the S-SCIELAB ΔE errors of Lena image. It is seen our new method give better performance. This is also demonstrated by calculating the old fashion mean squared error (mse). The mse values are 51.4, 39.1 and 28.4 for YCbCr9, Gaussian smoothing and the new method, respectively.

A sub-image of Lena is shown in Fig. 5 and Splash is shown in Fig. 6 (Note, if these images are printed in black and white, please see the colour version on the Web on the URL given above). Notice that in both cases, blockiness and false colours exist in the YCbCr images, whilst Gaussian smooth filtering can remove blockiness, false colours (black shadows) still exist along the edge areas. The new technique was not only able to eliminate the blockiness but also remove the false colours.

5. CONCLUDING REMARKS

We have described in this paper a new adaptive method for the enhancement of low resolution colour images. Simulation results are presented to demonstrate its good performance. We demonstrated that a simple single layer linear network suffice in providing excellent image quality. The method is computationally simple and can be easily incorporated into many practical imaging systems.

6. REFERENCES

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17. X. Zhang and B. A. Wandell "A spatial extension to CIELAB for digital color image reproduction", SID 96 Digest, pp. 731-34

Fig. 4 Distribution of S-SCIELAB ΔE errors
Fig. 5 Sub-image of Lena
(a) Original
(b) YCbCr9
(c) Gaussian Smoothing
(d) New method

Fig. 6 Sub-image of Splash
(a) Original
(b) YCbCr9
(c) Gaussian Smoothing
(d) New method