A Simple Approach of Data Fusion Algorithms for Image Content Enhancement and Shadow Removal

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Abstract— **Several situations in image processing simultaneously require high spatial and high spectral information in a single image. Since the instruments are not capable of providing such information either by design or because of observational constraints, one possible solution for this is data fusion. The fused image is formed to improve image content and to make it easier for the user to detect, recognize, and identify targets and increase his situational awareness. In this paper, we have proposed and implemented three novel fusion algorithms, namely the averaging method, the PCA algorithm and the gradient domain algorithm to automatically combine images of a scene captured under different illumination. We have developed a hierarchical approach to improving the efficiency of gradient-domain compositing, a technique that constructs seamless composites by combining the gradients of images into a vector field that is then integrated to form a composite. A unique characteristic of the algorithm is its ability to extract and maintain the meaningful information in the enhanced image while recovering the surrounding scene information by fusing the background image. The results of the algorithms are analyzed and compared. The study also examined a method of shadow correction for color images using the concept of image fusion.**

Keyword - Context, fusion, gradient, shadow correction.

I. INTRODUCTION

IMAGE fusion is a process of combining relevant information from two or more images into a single image. The fused image should have more information which is useful for human or machine perception. The image fusion techniques allow the integration of different information sources. The fused image can have complementary spatial and spectral resolution characteristics. Beyond providing digital tools for artists for creating surrealist images and videos, the fusion methods can also be used for practical applications. Surrealism is the practice of producing incongruous imagery by means of unnatural juxtapositions and combinations. For example, the non-realistic appearance can be used to enhance the context of nighttime traffic videos so that they are easier to understand. The context is automatically captured from a fixed camera and inserted from day-time image.

Content enhancement (CE) is used in numerous applications such as surveillance and civilian or military image processing. Content enhancement aims to detect, recognize and track objects such as people and cars from the image while being aware of the existing surroundings.

Moreover, CE helps analyses background information that is essential to understand object behavior without requiring expensive human visual inspection. One way of achieving content enhancement is fusing a low quality image (i.e., foreground image) and a high quality image (i.e., background image) at the same viewpoint. However, extracting the important features from the foreground image and combining them efficiently with the environmental context from the background image still remains a challenging problem.

Here we implement some novel image fusion techniques to automatically combine images of a scene captured under different illumination and also to perform shadow correction. We demonstrate that, compared with previous methods, our algorithm has a number of advantages. A unique characteristic of the gradient domain algorithm is its ability to extract and maintain the meaningful information in the enhanced image while recovering the surrounding scene information by fusing the background image. As a result, the overall algorithm performs in a near optimal way to enhance the perceptive quality of the fused images.

The rest of the paper is organized as follows. In Section II, the methodology adopted for implementing fusion algorithms is described. Section III provides a brief framework for weighted average fusion Section IV, describes the Principal Component Analysis (PCA) algorithm. A novel optimization approach using the gradient domain algorithm is discussed in Section V. Shadow correction approach and experimental results are presented in Section VI and Section VII, respectively. Finally, conclusion and future work are made in Section VIII.

II. METHODOLOGY

We implement the proposed work in MATLAB 7.0.1 with Image Processing Tool Box. The block diagram implementation is as shown:

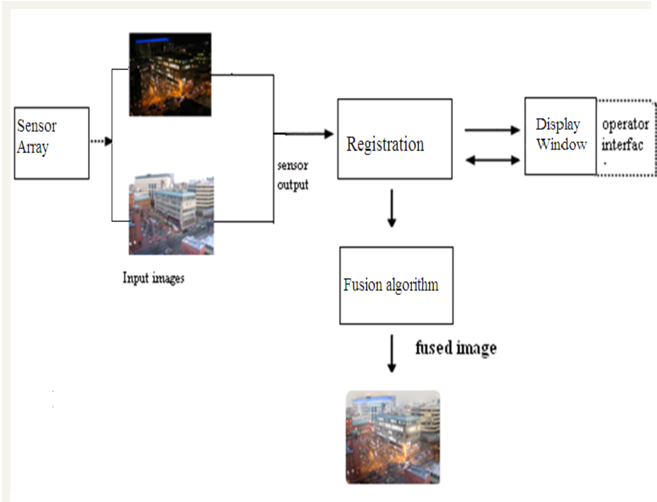

Fig. 1. Block diagram showing implementation of fusion of two images of the same scene captured at different instants of time.

Here we use sensor array which is high resolution digital camera to capture 'n' number input images. Here, the simplest case of fusion with two input images is shown. The input images are captured at different instants of time under different illumination (one a night time image and the other a day time image) and are stored in registration block. The registration block may be a digital computer. Later these input images are sent to fusion algorithm block where the two images are fused to obtain a single image which contains the positve characteristics of both the images using different fusion methods. The main idea of work is to exploit information available from fixed cameras to create content-rich images

III. AVERAGING METHOD

Averaging algorithms are common, when implemented in large networks of wirelessly connected elements. We extend the notion of "Increasing Correctness" (IC) which was defined for cycle-free graphs, to general graphs. An averaging algorithm that is IC has meaningful outputs at each iteration. This makes it possible to stop the algorithm at any time, and use the output values computed up to that time. The concept of averaging when extended to image and data fusion;, say the weighted average fusion, the fusion algorithm consists of two main components. First, the detailed wavelet coefficients are composed using weighted combination:

$$DF = w1D1 + w2D2 \qquad (1)$$

where $D1$ and $D2$ are the wavelet coefficients of two source images, and DF are the composite coefficients. $w1$ and $w2$ are the weights for these two input images, respectively. Because of their different physical meaning, the approximation and detail images are usually treated by the combination algorithm in different ways. As we deal with the asymmetrical fusion in which the salient objects are from the foreground image and the surrounding context is from the reference background image, a better option is to give more importance to the regions of interest in the foreground image. This is to make sure that no information in the foreground image is lost in the enhanced image. Hence, the composite approximation image AF can be computed by:

$$AF = IA1 + (1 - I)A2 \qquad (2)$$

where I is the importance map of which the values are constrained between 0 to 1. Finally, the fused image is obtained by taking an inverse wavelet transform.

IV. THE PCA ALGORITHM

PCA (Principal Component Analysis) is a general statistical technique that transforms multivariate data with correlated variables into one with uncorrelated variables. These new variables are obtained as linear combination of the original variables. PCA has been widely used in image encoding, image data compression, image enhancement and image fusion. When this technique is used in image fusion, it is performed on the images with all its spectral bands. William Krebs has used this method in many of his experiments (Krebs and Sinai, 2002, McCarley and Krebs, 2000, Krebs et al., 2001). There are two ways researchers have used PCA to fuse images. The first one assigns the first principal component (PC) band to one of the RGB bands the second to another RGB band in a false color technique. The second method separates the first and second PCs to intensity and hue in an HSV image and is described in more detail later. PCA is theoretically the optimal linear scheme, in terms of least mean square error, for compressing a set of high dimensional vectors into a set of lower dimensional vectors and then reconstructing the original set. It is a non-parametric analysis and the answer is unique and independent of any hypothesis about data probability distribution. However, the latter two properties are regarded as weakness as well as strength, in that being non-parametric, no prior knowledge can be incorporated and that PCA compressions often incur loss of information.

PCA uses the eigenvectors of the covariance matrix and it only finds the independent axes of the data under the Gaussian assumption. For non-Gaussian or multi-modal Gaussian data, PCA simply de-correlates the axes. When PCA is used for clustering, its main limitation is that it does not account for class reparability since it makes no use of the class label of the feature vector. There is no guarantee that the directions of maximum variance will contain good features for discrimination.

PCA simply performs a coordinate rotation that aligns the transformed axes with the directions of maximum variance. It is only when we believe that the observed data has a high signal-to-noise ratio that the principal components with larger variance correspond to interesting dynamics and lower ones correspond to noise.

V. THE GRADIENT DOMAIN ALGORITHM

We developed a hierarchical approach to improving the efficiency of gradient-domain compositing, a technique that constructs seamless composites by combining the gradients of images into a vector field that is then integrated to form a composite. While gradient-domain compositing is powerful and widely used, it suffers from poor scalability. Computing an n pixel composite requires solving a linear system with n variables; solving such a large system quickly overwhelms the main memory of a standard computer when performed for multi-megapixel composites, which are common in practice. Instead, we can perform gradient-domain compositing approximately by solving an O(p) linear system, where p is the total length of the seams between image regions in the composite; for typical cases, p is $O(\sqrt{n})$. We achieve this reduction by transforming the problem into a space where much of the solution is smooth, and then utilize the pattern of this smoothness to adaptively subdivide the problem domain using quad trees.

Our approach allows us to perform panoramic stitching and image region copy-and-paste in significantly reduced time and memory while achieving visually identical results. Image stitching is used to combine several individual images having some overlap into a composite image. The quality of image stitching is measured by the similarity of the stitched image to each of the input images, and by the visibility of the seam between the stitched images.

In order to define and get the best possible stitching, we introduce several formal cost functions for the evaluation of the quality of stitching. In these cost functions, the similarity to the input images and the visibility of the seam are defined in the gradient domain, minimizing the disturbing edges along the seam. A good image stitching will optimize these cost functions, overcoming both photometric inconsistencies and geometric misalignments between the stitched images. This approach is demonstrated in the generation of panoramic images and in object blending. Comparisons with existing methods show the benefits of optimizing the measures in the gradient domain.

Gradient domain technique preserves important local perceptual cues while avoiding traditional problems such as aliasing, ghosting and haloing. We present several results in generating surrealistic images and in increasing the information density of low quality nighttime images.

VI. SHADOW CORRECTION

We have performed shadow correction for color images by performing fusion of output fused image with foreground image. To get an optimised shadow corrected output image we need to perform fusion 'n' number of times depending on quality of image and amount of shadow introduced.

VII. RESULTS AND DISCUSSION

A fused image should be "visually pleasing", i.e., it should have very few aliasing, ghosting or haloing artifacts and it should maintain smooth transition from background to foreground. Our method achieves this by using the underlying properties of integration. We show how this can be used for synthetic as well as natural indoor and outdoor scenes.

In many applications, the human perception of the fused image is of paramount importance. Therefore, we choose multi-time and multi-season images, apply the algorithm, and visually evaluate the enhanced image in comparison with the previously proposed fusion methods, including the weighted average (WA) method, and principal component analysis.

We have developed a scheme for asymmetrically fusing multiple images preserving useful features to improve the information density in a picture. We show an example of outdoor scene combined from a day and a night picture (see Fig.2 - right image). Notice the dark regions of the night image are filled in by day image pixels but with a smooth transition.

Fig. 2: Automatic context enhancement of a night time scene.

An approach to automatically combining a daytime and nighttime picture would be to use a pure pixel substitution method based on some importance measure, referring to the averaging method. This works well only when the source images are almost identical (e.g. two images of the same scene with different focus as in Fig. 2. For example, when combining day-night images, one need to deal with high variance in daytime images and with mostly low contrast and patches of high contrast in night images. Taking the average simply overwhelms the subtle details in the nighttime image, and presents 'ghosting' artifacts around areas that are bright at nighttime. Furthermore, juxtaposing or blending pixels usually leads to visible artifacts (e.g. sudden jumps from dark night pixels to bright day pixels) that distract from the subtle information conveyed in the night images. Fig. 3 (bottom row) shows a comparison between gradient domain method and averaging method. Averaging (right image) leads to ghosting, while gradient domain (left image) leads to visible transitions. The shadow corrected output image is also shown.

Fig. 3: Enhancing a dynamic scene. (Top row) A high quality daytime image, a nighttime reference, and with a foreground person, (Bottom row) The image obtained after processing gradient domain fusion and averaging algorithms the final output of our shadow correction algorithm.

Our approach to gradient domain method is inspired by some recent methods that work in the gradient space rather than intensity space. While gradient-domain compositing is powerful and widely used, it suffers from poor scalability. Still the image reconstructed from integration the gradients achieves a smooth blend of the input images, and at the same time preserves their important features. However our method may cause observable color shifts in the resulting images, especially when the segmented foreground occupies a substantially large portion in the result. This phenomenon unfortunately has been a common problem of gradient-based approaches and can be observed in most previous works. There are two major reasons that cause the color shifting. First of all, a valid vector field is not guaranteed to be maintained when modifying it with non-linear operators. The gradient field of the resulting image computed by our method is only an approximation of the desirable one. Secondly, in some cases, it is difficult to maintain the perception of high contrast in a single image because the day and night time images are captured at significantly different exposure times.

VIII. CONCLUSION AND FUTURE WORK

Using the different fusion schemes, we exploit useful information available from the fixed cameras to create context rich images. The main contribution of this work is that it provides a precise and robust statistical model to perform an automatic content enhancement task. Future work will concentrate on combining our optimization method with higher-complexity fusion rules. A possible extension to our work will be to maintain a valid vector field when modifying the gradient image. This requires using analytical operators to approximate our non-linear mask and blending function. This remains an active area of research and we hope to use better reconstruction algorithms in the future. Separating intrinsic and color images, then applying our algorithm on intrinsic images and fusing them back with the color images could be another possible solution.

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