An Implementation of Image Processing using an Algorithm.

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Abstract: This paper sheds light on the recent least-square (LS)-based adaptive prediction schemes for lossless compression of natural images. Our analysis shows that the superiority of the LS-based adaptation is due to its edge-directed property, which enables the predictor to adapt reasonably well from smooth regions to edge areas. Recognizing that LS-based adaptation improves the prediction mainly around the edge areas, we propose a novel approach to reduce its computational complexity with negligible performance sacrifice. The lossless image coder built upon the new prediction scheme has achieved noticeably better performance than the state-of-the-art coder CALIC with moderately increased computational complexity.

Index Terms—Edge-directed prediction, least-square optimization, lossless image compression, orientation adaptation.

1. Introduction

MULTICHANNEL signal processing has been the subject of extensive research during the last ten years, primarily due to its importance to color image processing. The amount of research published to date indicates a great interest in the areas of color image filtering and analysis. It is widely accepted that color conveys information about the objects in a scene and that this information can be used to further refine the performance of an imaging system. Color images are studied in this paper using a vector approach. The value at each image pixel is represented by a three-channel vector, transforming the color image to a vector field in which each vector's direction and length is related to the pixel's chromatic properties [1]. Being a two-dimensional (2-D), three-channel signal, a color image
requires increased computation and storage, as compared to a grey-scale image during processing. Recognizing that the LS-based adaptation method improves the prediction performance mainly around the edge areas, we propose a novel way of reducing the overall computational complexity. Instead of performing the LS optimization on a pixel-by-pixel basis, we update the predictor coefficients only when the magnitude of the prediction error is beyond a pre-selected threshold. Since the set of the optimal predictors for an edge belongs to the set of optimal predictors for the smooth region, updating the prediction coefficients on an
edge-by-edge basis is enough to achieve the gain offered by LS-based adaptation. Therefore we propose to store the predictor coefficients optimized for an edge and repeat using them until the scanning reaches the next edge event. By modestly increasing the memory requirement, we can achieve significant reduction on the computational complexity. Simulation results have shown that a typical gray-scale image with the size of
512*512 can be compressed within seconds on a common computing machine.

2. Literature Review

The DCT being a linear unitary transform is distributive over matrix multiplication.The earlier approaches to down sampling in the compressed domain start with theproblem stated in the time domain and then carry out its equivalent operation inthe compressed domain. But the down sampling operation directly in the compresseddomain leads to computationally much faster algorithms [12]-[13].The down sampled image obtained by this method contains all the low-frequencyDCT-coefficients of the original image. This in turn, implies that one can obtain an upsampled image by prediction for the original image. This contains all the low-frequencyDCT-coefficients of the original image from the down sampled image [13].In 2002, Dugad and Ahuja have developed an elegant computational model forconverting the DCT blocks of an image to the DCT blocks of its reduced version.Similarly, for image doubling, they could directly convert its DCT blocks to the DCTblocks of the enlarged version. These conversions could be performed by multiplyingthe blocks with a given set of matrices and nally adding the intermediate results tothenal

DCT representations [4].In 2008, LeiWang, JiajiWu, Licheng Jiao, Li Zhang and Guangming Shi proposed ascheme which they called Reversible Integer Discrete Cosine Transform (RDCT). Whichis derived from the matrix factorization theory? In this case PSNR of RDCT basedmethod is higher.Three basic data redundancies can be categorized in the image compression standard.

3. Prior Work

With the proliferation of online photo storage and social medias from websites such as Facebook, Flickr, and Picasa, the amount of image data available is larger than ever before and growing more rapidly every day [Facebook 2010]. This alone provides an incredible database of images that can scale up to billions of images. Incredible statistical and probabilistic models can be built from such a large sample source. For instance, a database of all the textures found in a large collection of images can be built and used by researchers
or artists. The information can be incredibly helpful for
understanding relationships in the world1. If a picture is worth a thousand words, we could write an encyclopedia with the billions of images available to us on the internet.
These images are enhanced, however, by the fact that users are supplying tags (of objects, faces, etc.), comments, titles, and descriptions of this data for us. This information supplies us with an amazing amount of unprecedented context for images. Problems such as
OCR that remain largely unsolved can make bigger strides with this available context guiding them. Stone et al. describe in detail how social networking sites can leverage facial tagging features to significantly enhance facial recognition. This idea can be applied to a wider range of image features that allow us to examine and analyze images in a revolutionary way.

It is these reasons that motivate the need for research with vision applications that take advantage of large sets of images. Map Reduce provides an extremely powerful framework that works well on data-intensive applications where the model for data processing is similar or the same. It is often the case with image-based operations that we perform similar operations throughout an input set, making Map Reduce ideal for image-based applications. However, many researchers find it impractical to be able to collect a meaningful set of images relevant to their studies [Guo. . . 2005]. Additionally, many researchers do not have efficient ways to store and access such a set of images. As a result, little research has been performed on extremely large image-sets.

4. IMAGE DECOMPOSITION

We must have some decision process that determines which positions of each object model are output as hypothetical target locations. To this end, Section II describes a modified Hausdorff measure that uses both the location and orientation of the model and image pixels in determining how well a target model matches the image at each position. Section III then describes an efficient search strategy for determining the image locations that satisfy this modified Hausdorff measure
and are thus hypothetical target locations. Pruning techniques that are implemented using a hierarchical cell decomposition of the transformation space allow a large search space to be examined quickly without missing any hypotheses that satisfy the matching measure. Additional techniques to reduce the search time when multiple target models are considered in the same image are also discussed.

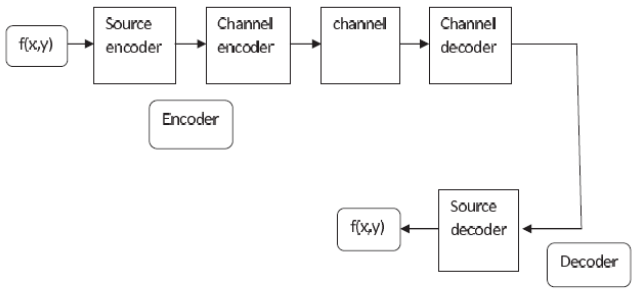
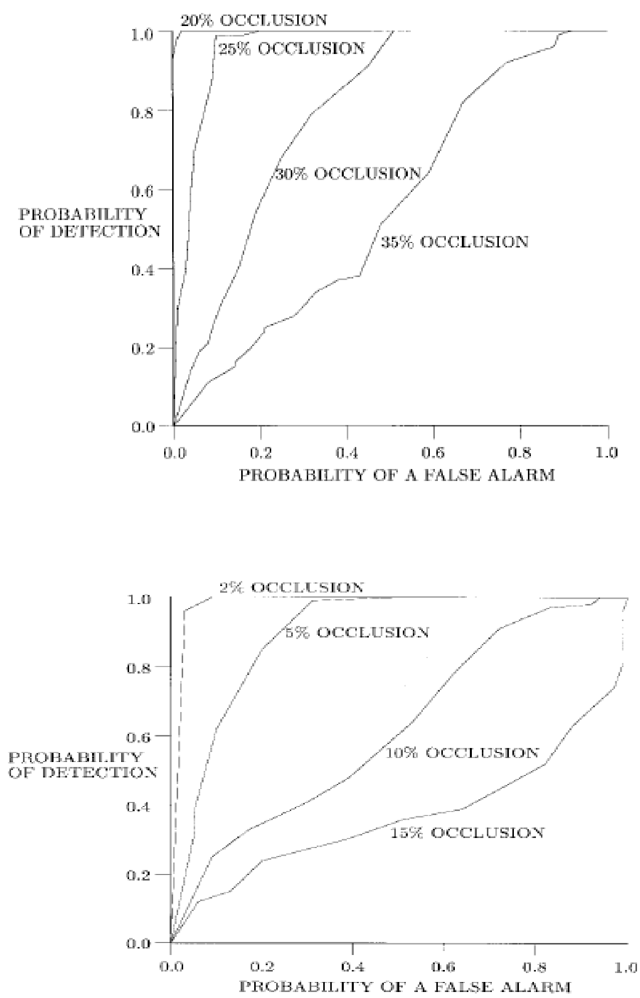


Figure : A general Decomposition system model

5. Simulation and Results

Alternatively, the matching threshold can be set such that it is expected that most or all of the correct target instances that are present in the image are detected. The techniques that have been described here yield an estimate on the probability that a false alarm will be found for this threshold as well as an estimate on the expected number of such false alarms, which will be useful when the probability is not small. More importantly, the likelihood that each hypothesis that we find is a false alarm can be determined by considering the *a priori* probability that the image window of the hypothesis yields a false alarm of the appropriate size as described above. These likelihoods can be used to rank the hypotheses by likelihood and the hypotheses for which the likelihood of being a false alarm is too high can be eliminated.



(b)

Figure shows Receiver operating characteristic (ROC) curves generated using synthetic data. (a) ROC curves when using orientation information. (b) ROC curves when not using orientation information

6. Conclusions

In this paper, we provide an interpretation of the LS-based adaptive prediction from the edge-orientation point of view. Its superior performance is attributed to the edge-directed property of the LS optimization. Based on a better understanding of LS-based adaptation, we propose a novel approach of reducing its computational complexity. The LS optimization is performed only for a fraction of pixels in the image. The performance

and the complexity of our lossless image coder built upon the edge-directed prediction lie somewhere between those of CALIC and TMW. The edge-directed property of the LS optimization has also found other important applications in other image processing tasks such as error concealment [13].

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