CLASSIFICATION-BASED SPATIAL ERROR CONCEALMENT FOR IMAGES

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ABSTRACT

This paper presents a new, classification-based spatial error concealment algorithm for images. The proposed scheme takes advantage of two state-of-the-art concealment schemes and adaptively selects a better suitable concealment scheme for each corrupted block. Using a Support Vector Machine (SVM) classifier, our proposed approach outperforms the prior art in terms of the concealment quality and has moderate computational complexity.

1. INTRODUCTION

Due to various kinds of noise and failures, part of a compressed image can be damaged or lost during transmission or storage. The widely used block-based visual coding systems have prompted a need of block-based error concealment on the decoder side. A number of concealment approaches have been proposed in recent years [1][2][3]. The smoothness and continuity properties in spatial or frequency domain, the repeating patterns, and other properties of visual data have been exploited to recover corrupted blocks from the survived surroundings. In this paper, we focus on the spatial domain block-based error concealment.

Through a benchmarking effort on existing error concealment approaches that will be detailed in Section 2, we have observed that different approaches are suitable for different image characteristics of a corrupted block and its surroundings, and none of the existing approaches is an all-time champion. This motivates us to explore a classification-based concealment approach that can combine the better performance of two state-of-the-art schemes in literature. For each corrupted block, we propose in Section 3 to use the survived surrounding pixels to determine which of the candidate concealment schemes would give better concealment quality. As shall be seen later in Section 4, the overall concealment quality by our approach can outperform each candidate scheme alone. The classification-based approach also helps us keep the computational complexity low. This is because some state-of-the-art scheme has rather high complexity; our approach spends computation power more strategically by performing expensive computations only when they offer potential gain in concealment quality.

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2. MOTIVATIONS

Prior Work Early explorations on spatial domain image concealment were reviewed in [1]. Among them, the multi-directional interpolation (MDI) approach performs pixel domain interpolation along eight possible edge directions and considers the cases of both single edge and multiple edges. The projection-onto-convex-sets (POCS) approach constrains the feasible solution set based on such priori information as smoothness and neighborhood consistency. And the maximally smooth recovery (MSR) method makes use of the smoothness property of visual signals and formulates the concealment as a constrained energy minimization problem.

Two recent works by Zeng et al. [2] and Li et al. [3] demonstrated performance improvement on classic images such as Lena over the earlier approaches. The geometric-structure-based error concealment (GSB) by Zeng et al.[2] is a spatial directional interpolation scheme, which makes use of the local geometric information extracted from the surroundings. Two nearest surrounding pixel layers of a corrupted block are converted to a binary pattern to reveal the local geometric structure and to classify the block as flat or non-flat. For flat blocks, projective interpolation of [4] is applied. And for non-flat block, the edges inside the lost block are estimated by pairing significant transition points and the lost pixels are recovered by bilinear interpolation along the edge directions.

The orientation adaptive sequential interpolation (OASI) scheme by Li et al. [3] employs a linear regression model. It first estimates the local characteristics from a neighborhood of about four layers of uncorrupted pixels, and then uses the model parameters obtained to estimate each individual missing pixel from its surrounding pixels. More specifically, the interpolation can be characterized by

$$S = \sum a_k S_k \,, \tag{1}$$

where S is the missing pixel to be estimated, and $\{S_k\}$ are N pixels surrounding S. The interpolation coefficients $\{a_k\}$ forms a vector **a**, which can be determined using the classical least square method from an M-pixel neighborhood M_n with $M > N$:

$$\boldsymbol{a} = (C^T C)^{-1} C^T \boldsymbol{y} \ . \quad (2)$$

Here, $\boldsymbol{y}$ is an Mx1 vector representing M pixels in the training area M_n; C is an MxN matrix, and each of its M rows consists of N neighbors around the corresponding pixel in $\boldsymbol{y}$. When $C^T C$ is singular, a_k is set as $1/N$.

Performance Benchmarking Since GSB and OASI employ quite different "philosophies" toward concealment, it was not conclusive from literature which one is better. We attempt to address this issue through a benchmarking effort, which also sheds light on the design direction of a new concealment algorithm that can outperform the existing approaches.

We use a collection of images with different characteristics to evaluate the performance of the five above-mentioned algorithms [1]. We compare both the quality of concealed images in terms of PSNR and the computational complexity in terms of the concealment speed. The speed is evaluated on a 1.20GHz Pentium-4 PC. Due to space limitation, we only show the comparison result for the case of 25% block loss. The lost blocks are in checkerboard pattern shown in Figure 1, and each lost block has a size of 8x8. The results of other loss patterns are similar.

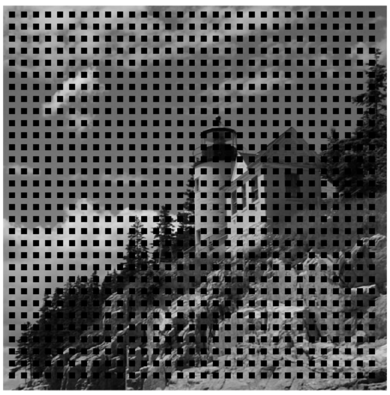

Figure 1. "Bassharbor" image shown with 25% block loss in checkerboard pattern.

As can be seen from Table 1, the GSB and OASI approaches significantly outperform other three classical approaches on these natural images. However, none of the two gives the best performance for all images, which indicates that the image characteristics of the blocks that each of the existing concealment approaches is best suited for are considerably different. This motivated us to go one step further and assemble a concealed image in which each concealed block is the better one selected between the GSB and OASI concealment results. As shown in the last column ("Better-2") of Table 1, this endeavor gives a higher overall concealment quality than using GSB or OASI alone. The detailed selection is shown in Figure 2, where the white blocks indicate that OASI has better performance than GSB for concealing the corresponding blocks, and the black blocks indicate that GSB is better.

Table 1. Concealment quality in terms of PSNR (dB) for 25% block loss in checkerboard pattern. For each image, the scheme achieving the best performance among the first five schemes is highlighted with shade and bold font.

	MDI	POCS	MSR	GSB	OASI	Better-2
Lena	32.28	29.49	29.20	34.43	**35.12**	35.73
Babara	27.41	23.35	27.14	29.26	**30.79**	31.63
Bassharbor	29.47	28.12	28.83	**30.69**	30.37	31.18
Elaine	33.39	32.58	30.41	35.17	**35.93**	36.34
Nickel	27.12	25.19	24.98	**29.15**	28.55	30.50

Table 2. Computation speed (seconds) for concealing the Lena image with a loss of 25% blocks. The scheme achieving the best performance is highlighted with shade and bold font.

	MDI	POCS	MSR	GSB	OASI
Lena	3.03	219.58	0.59	**0.56**	7.12

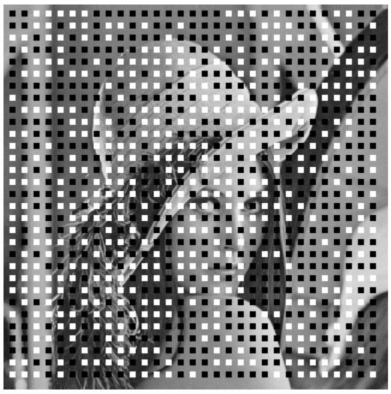

Figure 2. Performance comparison of GSB and OASI on Lenna: white blocks indicate that OASI has better concealment performance than GSB, and black blocks indicate GSB is better.

The Need of Classification We have to, however, realize that picking the better one among the two is non-trivial in practice. This is because a concealment system would not have the original undamaged image to compare with. Available to a concealment system are only the survived pixels that surround each corrupted block. If we could establish before-hand the connection between the image characteristics of the survived surrounding pixels and the concealment performance that which one between

[1] The images used in this paper can be found at http://www.ece. umd. edu/~minwu/public_paper/icip03_image/ . The size of the "Nickel" image is 256x256, and the other images are 512x512.

GSB and OASI is better for the corrupted blocks, we could estimate which scheme is likely to perform better based only on the knowledge of survived pixels. This leads to our proposing a general classification-based concealment framework. Developing concealment schemes under this framework would help us not only improve the concealment quality, but also speed up the concealment. This is because according to our benchmarking result in Table 2, some high-performance schemes such as OASI have computational complexity of about a magnitude higher than other schemes such as GSB. Using classification-based concealment allows us to perform expensive computations only when they can offer potential gain in concealment quality.

3. PROPOSED CLASSIFICATION-BASED BLOCK CONCEALMENT

3.1 Support-Vector-Machine (SVM) Classifier

We formulate the choice of concealment schemes for each block as a supervised classification problem. Each error concealment method is considered as a class, and a feature vector is extracted from the pixels that surround an image block. In the training stage, we collect a number of feature vectors from training images, and label every feature vector $\boldsymbol{x}_i$ with a ground-truth class corresponding to the best concealment method for the associated block. We train the classifier using these feature-class pairs.

We adopt Support Vector Machines (SVM) classifiers, as it can be boiled down to a convex quadratic programming problem with global optimal solutions in training and often exhibits good generalization performance [5]. For our two-class pattern classification problem that decides between the GSB and OASI concealment approaches, we start with a linear SVM. The linear SVM determines a linear discriminant function (parameterized by a vector $\boldsymbol{w}$ and a scalar b) that gives the maximum separation margin between the two classes of training data (equivalently to minimizing $||\boldsymbol{w}||^2$). More specifically, we look for $\boldsymbol{w}$ and b to minimize $||\boldsymbol{w}||^2$ subject to the following constraints:

$$Y_i\,(\,\boldsymbol{w}^T\boldsymbol{x}_i + b\,) - 1 + \xi_i \geq 0\,, \qquad (3)$$

where $\boldsymbol{x}_i$ is the i th training feature vector, $Y_i \in \{-1,1\}$ the class index, and $\xi_i \geq 0$ the slack variable [5].

Nonlinear classification functions can be obtained by replacing a dot-product term in the SVM training by an appropriate kernel function, which is equivalent to mapping feature vectors to a higher dimensional space and then find a linear SVM classifier in this new space [5]. It is interesting to explore as future work what kernel function gives the best performance for our classification problem. An effective alternative, as used in our work and detailed below, is to partition the feature space into several subsets and find a linear discrimination function for each subset.

3.2 Algorithm Details

Selection of Training Data To ensure the reliability of training data, we select the training data only from the blocks on which the GSB and OASI schemes have significant performance difference. In addition, since the GSB and OASI schemes may use different set of pixels surrounding a block, the feature vectors derived for classification should come from the union of the sets of pixels used by these two schemes. For example, GSB often uses two surrounding layers to extract the geometric structure information, while OASI uses four surrounding layers to compute the interpolation coefficients. The classification region should therefore include four surrounding layers of pixels. For block size of 8x8, 192 pixels are involved in classification.

Construction of Feature Vectors A feature vector should include the information that distinguishes the two classes. While the pixel values can be used directly as features, they often pose high computational complexity and require a sophisticated kernel function to ensure linear separability. We propose a lower-dimension feature vector derived from pixel values as the follows. We first convert the four surrounding layers of pixels into a vector through a circular scanning order from outer layers to inner ones. We then partition the vector into segments of m pixels, and use “1” to indicate a busy segment and “0” a flat segment. For example, 192 pixels surrounding an 8x8 block can be reduced to a feature vector of length 28. For every 7 pixels, if the difference between the minimum and maximum values exceeds a threshold, we use “1” to represent these 7 pixels, and “0” otherwise.

Classification and Concealment via SVM We use the mySVM toolkit [6] to accomplish the classification task. mySVM is an implementation of SVM based on the optimization algorithm of SVM^{light} in [7]. To facilitate finding a reliable boundary separating the two classes over a wide range of feature values, we partition the feature space into n subsets according to the weight of a feature vector (i.e., the number of 1’s) and find one linear discriminant function for each subset. As each discriminant function has 29 parameters, we arrive at a total of $29n$ parameters at the end of the training process. n=5 is used in our experiments.

To conceal a block in a test image, we construct a feature vector in the same way as in training, and feed it into the appropriate one of the n trained SVM classifiers according to the vector’s weight. The classification result will then determine which concealment scheme to use.

4. EXPERIMENTAL RESULTS

We use the images of “Lena”, “Babara”, and “Bassharbor” to train the classifier, and use the images of “Elaine”, “Baboon”, “Bellflower”, and “Nickel” for testing. The concealment performance is summarized in Table 3. We can see that our proposed classification scheme outperforms both GSB and OASI, which are two best schemes in literature. Even with our simple feature selection and classification, we have achieved quality improvement of up to 0.4dB in PSNR over the best performance by the existing approaches. The only exception is the “Nickel” image, for which the proposed scheme can improve the visual quality for some blocks as shown in Figure 3, but has an overall PSNR of about 0.1dB worse than GSB. This is due to some special patterns in the “Nickel” image, which requires a richer feature and more sophisticated classification to yield more accurate classification result.

Table 3. Error concealment result on images with 25% block loss in checkerboard pattern. The scheme achieving the best performance for each image is highlighted in shade and bold.

		GSB (dB)	OASI (dB)	Classif.-based (dB)	Classif. Accuracy
Training	Lena	34.43	35.12	**35.51**	82.8%
	Barbara	29.26	30.79	**30.83**	82.0%
	Bassharbor	30.69	30.37	**30.84**	79.4%
Testing	Elaine	35.17	35.93	**36.18**	86.8%
	Baboon	26.11	26.48	**26.54**	70.9%
	Bellflower	33.27	33.70	**33.74**	66.3%
	Nickel	**29.15**	28.55	29.03	59.4%

5. CONCLUSIONS AND EXTENSIONS

In this paper, we have presented a new, classification-based spatial error concealment algorithm for images. Our proposed scheme takes advantage of two state-of-the-art concealment schemes and adaptively selects the best suitable one for each corrupted block. Using a multi-subset linear SVM classifier, our proposed approach has outperformed the prior art in terms of the concealment quality and relatively low computational complexity.

Our proposed framework of classification-based error concealment is general and can be extended in many directions. For example, we can incorporate more than two candidate concealment schemes, and explore different feature selections and other classification tools.

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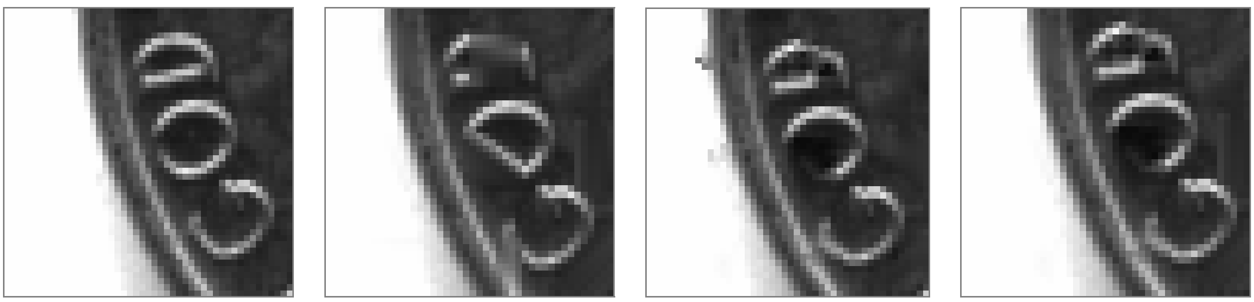

(a) (b) (c) (d)

Figure 3. Concealment results on the “Nickel” image: (a) zoomed-in view of the original image, (b) by the GSB concealment scheme with notable artifacts on the letters, (c) by the OASI concealment scheme with notable artifacts on the rim of the nickel, and (d) by the proposed classification-based scheme with reduced artifacts than GSB and OASI.