

Texture Enhancement and Repair for Digital Multimedia Broadcasting

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Abstract—Digital terrestrial television (DTT) has been adopted in many countries for free-to-air broadcasting. Although DTT offers improved picture quality compared to their analog predecessors, impairments induced during transmission still need to be dealt with. In this paper, we focus on texture enhancement and repair in digital multimedia broadcasting (DMB) with application to video recordings from a measurement campaign conducted in a live DMB system in South Korea. First, the texture of the frames of the received video clips is enhanced in terms of contrast and sharpness. Second, texture is repaired by analysing the presence of scene cuts, spatial blocks, and displacement blocks. On this basis, the positions of impaired blocks can be detected and fed into an adaptive Gaussian mixture model to repair the texture. Examples are provided to illustrate the operation of the texture enhancement and repair approaches. Results from a subjective test on the quality of the DMB video clips before and after texture repair are also provided. The analysis of the participants’ quality opinion scores and related box-and-whisker plots support the conjecture that the proposed approaches can significantly improve the received DMB videos if their quality resides in the range between good to poor quality. While this paper focuses on DMB, benefiting from recordings in a live system and the processing in the pixel domain, the proposed approaches can also be applied to other DTT formats.

Index Terms—Digital Multimedia Broadcasting, Sharpness, Contrast, Texture, Subjective Tests, Mean Opinion Scores.

I. INTRODUCTION

Digital terrestrial television uses digital signals to broadcast television programs carrying high quality video and audio. Many related standards have been developed, e.g., digital video broadcasting (DVB), digital multimedia broadcasting (DMB), and DMB+. While radio transmission technologies for such systems have been widely studied, computer vision approaches that can alleviate transmission impairments at the receiver, are less studied. In this paper, we therefore focus on texture enhancement and repair approaches as efficient means to improve video quality of experience (QoE) for DMB. The DMB focus is motivated by having videos available that were recorded in a live DMB system in South Korea and building on our earlier work on the QoE of such videos [1].

Recent years have seen significant progress in learning-based video restoration techniques, including convolutional neural networks (CNN) and transformer-based architectures

that jointly model spatial and temporal artifacts [2]–[7]. Recurrent CNN frameworks such as BasicVSR and BasicVSR++ employ feature propagation and alignment across frames to address temporal inconsistencies and restoration artifacts [2], [3]. More recently, transformer-based approaches have demonstrated strong performance by exploiting long-range temporal dependencies through attention mechanisms [4], [5]. In addition, learning-based methods have been proposed for compressed video quality enhancement, explicitly targeting transmission-induced artifacts using multi-frame fusion and deformable convolution techniques [6], [7]. While these approaches can achieve impressive visual quality, they typically require large-scale training datasets, induce high computational complexity, and use task-specific optimization, which may limit their robustness when encountering unseen transmission impairments.

The work in [8] proposes an image texture enhancement technique using an orthogonal polynomials model along with a transform coefficient analysis and block decomposition. The focus of the processing in the transform domain is directed toward texture brightness adjustment and texture sharpening. In [9], in light of event-based vision [10], event-driven texture enhancement for video super-resolution is proposed. It comprises an event-driven texture branch for refining textures and a motion branch for enhancing temporal consistency. However, as pointed out by the authors, this work is limited to deterministic CNNs and transformer-based backbones among others. In contrast to these works, our approaches operate in the pixel domain with respect to the frames that constitute a video, do not require training, and are hence well suited for real-time and resource-constrained DMB receivers. Further, we go beyond contrast and sharpness enhancements but also correct impaired blocks as blocking causes severe QoE degradation.

Although partial differential equation (PDE)-based approaches are sometimes regarded as classical, recent research has demonstrated their continued relevance for image and video enhancement, particularly due to their mathematical interpretability, stability, and robustness to noise and unseen degradations [11]–[14]. Studies have revisited diffusion- and variational-based models, as well as hybrid formulations com-

binning PDE priors with data-driven components, to achieve edge-preserving enhancement and artifact suppression under challenging conditions [12], [13]. These properties make PDE-based methods attractive for practical video processing scenarios where reliability and low computational complexity are critical. The approaches proposed in this paper leverage these advantages through complex diffusion, extending its applicability to DMB video enhancement and repair.

QoE constitutes a holistic view for assessing video enhancement techniques, as it reflects users' perceptual quality rather than purely signal-based fidelity [15]. Studies have shown that transmission-related artifacts such as blocking, texture distortions, and temporal inconsistencies can significantly degrade perceived video quality, thereby motivating QoE-driven enhancement and repair strategies [16], [17]. Subjective tests further indicate that enhancement techniques are most effective in the mid-quality regime, where artifacts are perceptually salient but the underlying scene structure remains coherent [18], [19]. This observation is consistent with the findings reported in this paper, where texture enhancement and repair yield the largest perceptual gains for video clips with mean opinion scores (MOS) between good and poor quality. These conjectures are also inline with findings of our earlier work reported in [1] where QoE of DMB video clips in the presence of a variety of spatial and temporal impairments was assessed. However, comprehensive details about the algorithms for alleviating such transmission impairments were not provided in this earlier work but were only briefly described for the understanding of the subjective tests. As such, the approaches proposed and detailed algorithms presented in this paper align well with perceptually driven optimization in DMB systems.

In this paper, we focus on computer vision based processing of DMB video clips in the pixel domain regarding texture analysis, texture enhancement, and subsequent texture repair. The proposed approaches and algorithms operate in the pixel domain on a sequence of frames of the considered DMB video clips. It commences with sharpness and contrast enhancement resorting on a bio-inspired simple model of the retina processing and a sharpness filter. On this basis, texture repair is performed analysing the presence of scene cuts, spatial blocks, displacement blocks in the respective frames, determining the positions of displaced blocks, and their repair with the help of an adaptive Gaussian mixture model (GMM). It should be mentioned that GMMs have also been successfully applied in [20] for contrast enhancement and in [21] for texture characterization with application to brain diffusion tensor imaging. As this approach tracks temporal changes between frames including scene cut detection, temporal artifacts are inherently taken care off to some extent. For both components of the texture processing, i.e., enhancement and repair, representative examples are provided to facilitate an understanding of the operation and quality improvements that can be obtained by the suggested approaches. In addition, the results of subjective tests are reported to shed light on the perceived quality achieved by the proposed texture enhancement and repair approaches.

The rest of this paper is organized as follows. Section II describes the overall structure of the texture enhancement and repair procedures. In Section III, the texture enhancement approach is presented including contrast and sharpness analysis along with numerical and visual examples illustrating the obtained quality improvements. In Section IV, the processing involved in repairing spatial impairments in the texture are described while its operation is illustrated by a visual example. In Section V, results of subjective tests on the perceived quality of texture impaired video clips from a live DMB system and their texture repaired counterparts are provided. Conclusions are given in Section VI.

II. OVERALL PROCEDURE

The overall structure of the texture enhancement and repair procedure is shown in Fig. 1. First, let us assume that a video clip is given as a sequence of frames. This format is obtained after video decoding, making the pixel domain accessible for processing. Each frame serves as an input to the texture enhancement and repair procedure. Two subsequent frames and information contained in these frames are used in each processing step, i.e., frame f_k at time k and the preceding frame f_{k-1} at time $k-1$. The texture of each frame is enhanced either by contrast enhancement, sharpness enhancement or both depending on the frame quality. Second, the concealment process for texture repair uses information of a series of three frames, i.e., frames f_k , f_{k-1} , and f_{k-2} .

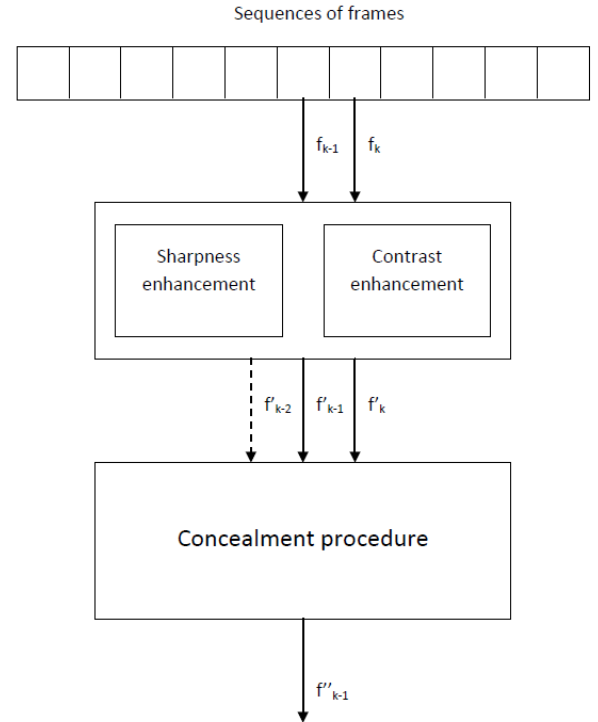


Fig. 1. Overall texture enhancement and repair procedure.

III. TEXTURE ENHANCEMENT

In this work, texture analysis and enhancement is applied to the frames of a video clip and is concerned with contrast and sharpness analysis and the related texture enhancement.

A. Contrast Analysis and Enhancement

The contrast analysis and enhancement resorts on the bio-inspired method reported in [22], which is applied on the color filter array (CFA) image. A simple model considers photoreceptors as sampling device, horizontal cells as spatio-temporal low pass filter, and bipolar cells as transmitter device.

Our contrast enhancement primarily separates the original image into chromatic and luminance components implementing a mosaic process. In digital cameras, a Bayer CFA works as a frequency modulator of the chromatic signals and samples only a single chromatic sensitivity per spatial location. The chrominance is modulated in the border of the Fourier spectrum and the luminance located in the middle of the spectrum is left unchanged. An adaptive nonlinear low pass filter, representing the horizontal cell, is applied only to the luminance information of the separated data. As such, the contrast enhanced data goes through a de-mosaic process, i.e., interpolation of chrominance and integration of its result with enhanced luminance data.

B. Sharpness Analysis and Enhancement

A sharpness filter by way of a negative Laplacian in conjunction with a complex diffusion process [23] is used. The diffusion process tunes and increases the accuracy of sharpness. The linear diffusion equation is given as [23]

$$I_t = c \Delta I, \quad I_{t=0} = I_0, \quad c > 0 \in \mathbb{R} \quad (1)$$

where subscript t represents a natural continuous scale dimension, I_0 is the input (blurred) image at $t=0$, c is a constant diffusion coefficient, and ΔI denotes the Laplacian of the image highlighting areas of rapid pixel intensity changes.

For simplicity, we consider the 1-dimensional case [23]:

$$I_t = c I_{xx}, \quad t > 0, \quad x \in \mathbb{R} \quad (2)$$

$$I(x; 0) = I_0 \in \mathbb{R}, \quad c, I \in \mathbb{C} \quad (3)$$

where I_{xx} is the partial second derivative of the input data with respect to x . We seek the complex fundamental solution $h(x; t)$ that satisfies the relation

$$I(x; t) = I_0 * h(x; t) \quad (4)$$

where $*$ denotes the convolution operator. Furthermore, we write the complex diffusion coefficient in polar form as $c = r e^{j\theta}$ with magnitude r and phase angle θ . Given this problem formulation, the following equation provides a solution, which is implemented in our algorithm:

$$h(x; t) = A g_\sigma(x; t) e^{j\alpha(x; t)} \quad (5)$$

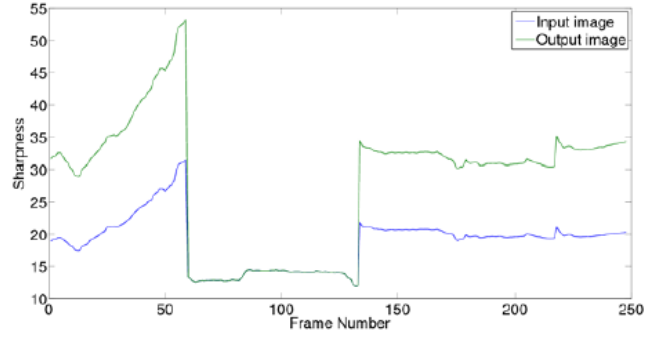


Fig. 2. Sharpness estimation for input and output image of clip “Human”.

where

$$A = 1/\sqrt{\cos \theta} \quad (6)$$

$$g_\sigma(x; t) = \frac{1}{\sqrt{2\pi\sigma(t)}} e^{-\frac{x^2}{2\sigma^2(t)}} \quad (7)$$

$$\alpha(x; t) = \frac{x^2 \sin \theta}{4tr} - \frac{\theta}{2} \quad (8)$$

$$\sigma(t) = \sqrt{2tr/\cos \theta} \quad (9)$$

Here, (5)-(9) follow the solution of the linear complex diffusion equation derived in [23]. In contrast to the original derivation, where the normalization constant includes magnitude and phase, we retain only the real-valued magnitude. As the constant phase does not affect the sharpening behavior, it is omitted. This simplification yields a computationally efficient kernel while preserving the essential diffusion characteristics.

C. Numerical and Visual Examples

Fig. 2 shows the sharpness estimation for the input and output of video clip “Human” progressing from frame 0 to frame 250. It can be observed that engaging the sharpness algorithm improves the sharpness of input frame 0 to around frame 60 and from around frame 140 to frame 250. In the middle part of the video clip, there was no additional enhancement measured. The achieved sharpness enhancement is illustrated by the particular input and output snapshots of the clip “Human” shown in Fig. 3(a)-(b). While the input image may be perceived as somewhat blurred with washed out faces and background, the output image appears sharper and with more contrast. In particular, the foreground face is much crisper and in conjunction with the enhanced background may even give a little 3D impression. Interestingly, the difference between input and output image is rather moderate as shown in Fig. 3(c).

IV. TEXTURE REPAIR

Fig. 4 shows the flow of the processing involved in the texture repair which uses three subsequent frames. In each step, two new frames are processed in the overall procedure, i.e., actual and previously enhanced frame, while the frame enhanced at discrete time $k - 2$ is kept referring to the history. Then, processing is performed on the basis of texture



Fig. 3. Sharpness enhancement of sample frames of video clip “Human”: (a) Input image, (b) Output image, (c) Difference image.

information of these frames such as scene cut and impairment analysis, detection and position of impaired blocks, processing in the impaired patches bank, impaired blocks bank, and non-impaired patches bank, before feeding the outcome to an adaptive GMM [24]. The scene cut and impairment detection algorithms use the current two frames to distinguish scene changes and impairments where spatial blocks and displacement blocks center around impairment features. The process of scene cutting and impairment detection is called “Analysis” in the block diagram. The result of the “Analysis” process constrains the concealment to one scene and extracts the position of the impaired blocks (PIB). The PIB is used as binary image which speeds up the processing time. Three templates in the form of binary images are generated, namely, impaired blocks bank (IBB), impaired patches bank (IPB) and non-impaired patches bank (NPB). Using these three templates, the impaired block information is replaced by the most recent and relevant non-impaired information. The NPB keeps track of recent non-impaired information by implementing an adaptive GMM. The updating of these three templates is shown in Table I.

TABLE I
UPDATE OF TEMPLATES

Template	Updated by
IBB	PIB, GMM, enhanced actual frame
IPB	IBB, GMM, enhanced actual and previous frames
NPB	IBB, enhanced previous frame

A. Visual Example

Fig. 5(a) provides an illustration of the texture repair algorithm in terms of background blocks update and displacement positions. The input image is shown on the left hand side, the background blocks update is shown in the middle column, and the displacement positions are shown on the right hand side. Recall that the texture repair algorithm utilizes information from the previous frame and the frame before that frame as an indication of the impairment that may be present in the actual input image at the current discrete time instant. In this example, the amount of background blocks (blue) is rather

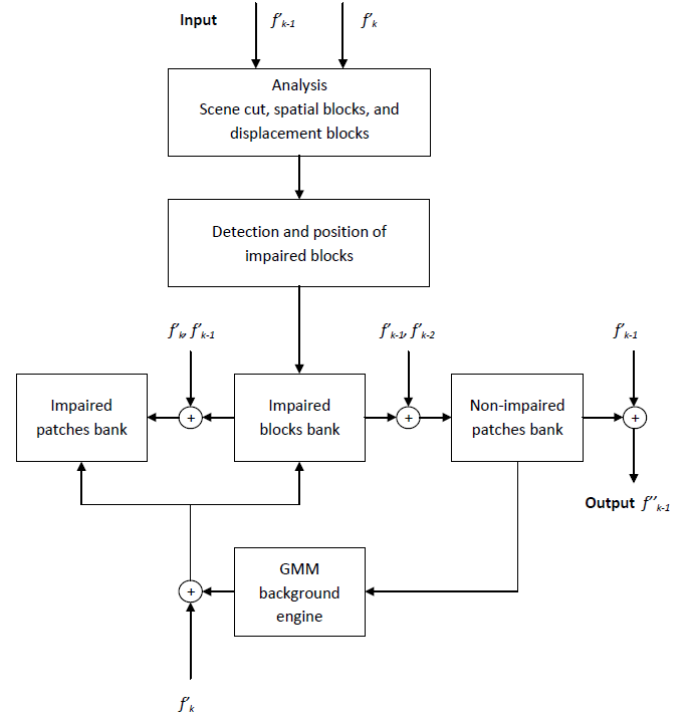


Fig. 4. Block diagram of the texture repair procedure.

large. The information about the blocks and their location are then used to repair the texture of the input image.

Similarly for the displacement positions, the information of the previous frame contained in the pixel domain is used to find the block displacement candidates (green) for each input image. This part of the algorithm helps to reconstruct the face and shoulder of the singer for the considered example. The scene cut algorithm is used to decide if there is an actual change in the scene, e.g., changing from a news speaker to a clip supporting the particular news. In such a case, a sudden change from one scene to a different scene would cause a large number of blocks and displacements if the scene cut algorithm was not used to flag such events.

Figs. 5(b)-(c) provide a comparison of the impaired input

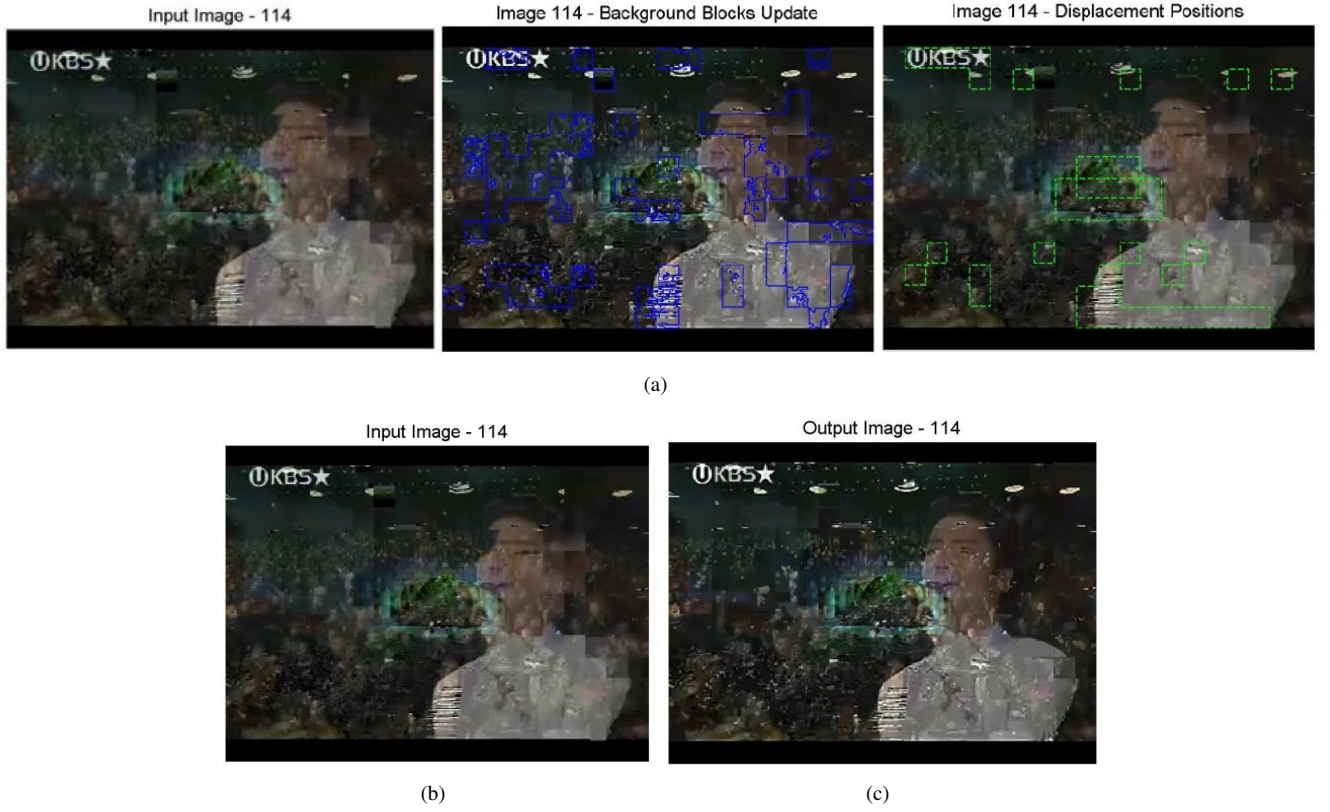


Fig. 5. Illustration of texture repair for video clip frame 114: (a) Input image, background blocks update, and displacement positions, (b) Impaired input image, (c) Image after texture repair.

image with the output image obtained after texture repair. As for the input image, block displacement is clearly visible in the upper part of the face of the singer shifting from the left to the right and causing the left eye (with reference to the viewer) to disappear. In addition, some blocking develops around the shoulder and eye of the singer. The output image shows that the proposed texture repair algorithm is indeed capable of concealing these severe impairments. As such, even for these very severe degradations, which are beyond an acceptable quality level, the proposed algorithms manage to bring the appearance of the singer back to a recognizable shape.

V. SUBJECTIVE TEST RESULTS

A. Test Material

A set of 14 representative test video clips of 10s duration have been selected that were produced from the videos obtained during the field test in the live DMB system in South Korea. These video clips cover a wide range of quality levels.

B. Test Method

Absolute category rating (ACR) was chosen for the assessment of the perceived quality of the presented video clips on a 5-point opinion score scale: (5) Excellent, (4) Good, (3) Fair, (2) Poor, (1) Bad. The subjective tests were organized into two sections: (1) Showing video clips with texture impairments, (2) Showing the related video clips after texture repair. Given that

only a single stimulus is presented at a time without providing a reference for comparison, the chosen subjective test method fits well with the operation of DMB being a broadcasting system with a one-way forward flow.

C. Test Panel

Table II provides demographic information about the test panel that participated in the subjective tests. All participants were from academia with different levels of seniority with the majority coming from East Asia. The participants' task was to rate the quality of video clips that contain texture impairments and the related video clips having undergone texture repair.

TABLE II
DEMOGRAPHIC INFORMATION OF THE TEST PANEL

Size	20 non-expert participants
Age	23 to 50 years with an average of 30.6 years
Gender	4 females and 16 males
Occupation	Bachelor, Masters, Ph.D. students, Postdoctoral fellow
Nationality	7 China, 5 Vietnam, 2 Pakistan, 1 Sri Lanka, 4 Rwanda, 1 Italy

D. Opinion Score Analysis

The opinion scores recorded in the subjective tests for each test video clip were averaged over the number of participants to calculate the MOS. Averaging opinion scores may mask severe incidents that can significantly impact users' perceived

quality, i.e., smoothing it out by the mean. Therefore, box-and-whisker plots are provided to illustrate the distribution, median, and outliers of the recorded opinion scores.

E. Test Results

Fig. 6 shows the MOS in decreasing order for the video clips containing texture impairments (input) and the video clips obtained after texture repair (output). The results indicate that texture repair becomes more beneficial with decreasing quality of the impaired video clips (see also Fig. 7). In case of video clip C14, the entire panel rated the quality as bad before and after texture repair keeping the result bars at MOS=1 (see also results for C14 in Figs. 7-8). In other words, texture repair is not sufficient in such bad conditions and may be preceded by, for example, transport stream syntax repair strategies.

Fig. 8 shows box-and-whisker plots of the opinion scores for the video clips with texture impairments and after their repair. The results indicate that the opinion score distribution of the repaired video clips increasingly shifts toward higher quality for impaired video clips with decreasing quality in the mid-range MOS. Significant improvements are observed for the impaired video clips C07, C11, C12, and C13. Similar as texture repair is insufficient for the bad video clip C14, it is not required for the video clip C01 with opinion scores of the impaired video concentrated at a value of 5 apart from one outlier. In contrast, texture repair may even degrade quality in a video that has already been assessed as being of excellent quality prior any processing.

Overall, the following conjectures can be drawn from the MOS and box-and-whisker plots. If the input video clip quality resides in the range of good to poor quality, texture repair may significantly improve the quality of the input video. This behaviour may be due to the play-out rate of a video clip in frames-per-second which may translate to the texture repair of an individual frame of an excellent video clip not being noticeable but would enhance quality for more severely texture impaired video clips. As such, if the input video clip is approaching excellent or bad quality, respective, texture repair would not provide further improvement or be not sufficient.

VI. CONCLUSIONS

In this paper, we have proposed texture enhancement and repair approaches as means of dealing with impairments induced during transmission of DMB videos. Practical relevance of the work has been secured through considering a set of DMB videos with mixtures of impairments that were recorded during an extensive measurement campaign in a live DMB system in South Korea. First, texture enhancement has been achieved regarding contrast and sharpness resorting on a bio-inspired simple model of the retina processing. Second, texture repair has been dealt with through analysing the presence of scene cuts, spatial blocks, displacement blocks, detection of the impaired blocks, and their subsequent repair engaging an adaptive GMM. The operation of these approaches have been illustrated by visual examples. In addition, the results of subjective tests on the perceived quality of DMB video clips

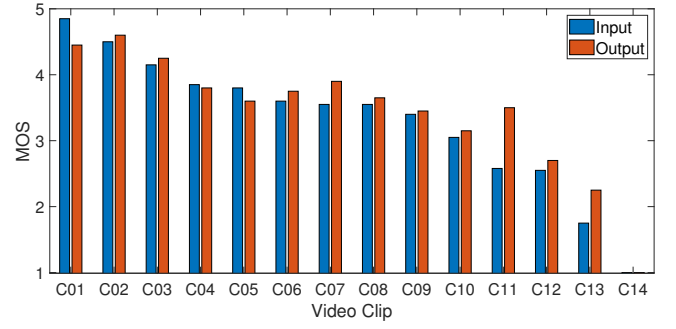


Fig. 6. MOS of video clips before and after texture repair.

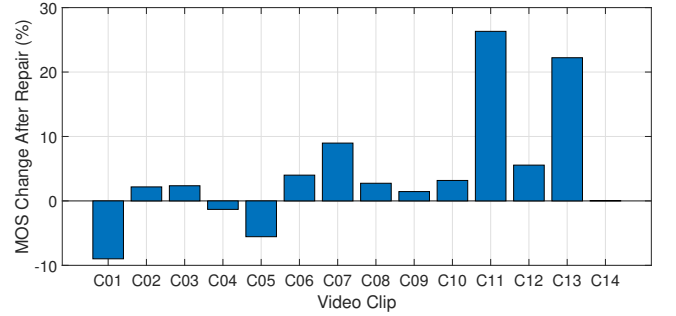


Fig. 7. MOS change of video clips after texture repair in percent.

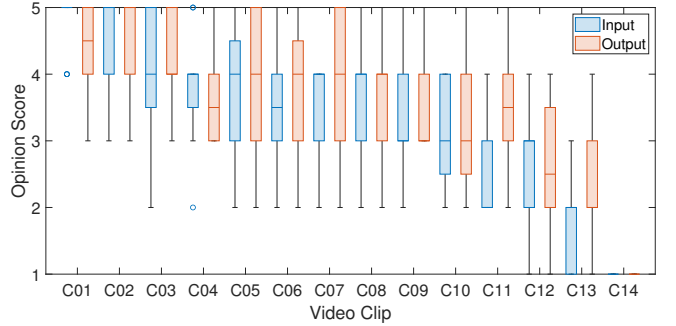


Fig. 8. Box-and-whisker plots of video clips before and after texture repair.

of texture impaired and their repaired counterparts have been presented. It is shown that the proposed texture enhancement and repair approaches can significantly improve perceived quality of received DMB videos that are in the range between good to poor quality. If the received DMB videos are already approach excellent quality or are severely damaged toward bad quality, texture enhancement and repair are not needed or not sufficient, respectively. In the latter case, other impairments such as syntax errors in the DMB transport stream may induce bad quality in the received DMB videos that could be dealt with by syntax repair strategies. Because the proposed approaches operate in the pixel domain of DMB videos, applications to other DTT formats is also supported.

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