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영상 단말에 전송된 이미지를 이용한 전송 영상 복원

(Reconstruction of Transmitted Images from Images Displayed on Video Terminals)

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요 약

본 논문에서는 영상 단말에 디스플레이되는 영상들을 이용하여 전송된 영상의 원본 상태를 예측하는 복원 알고리듬을 제안한다. 제안한 알고리듬은 카메라를 이용하여 비디오 단말 스크린에 나타나는 영상들을 취득한다. 전송된 영상들은 카메라를 통해 획득된 영상들을 이용하여 예측해야 하지만, 일반적으로 카메라를 통해 획득된 영상들은 영상 출력 장치와 카메라의 특성에 의해 기하학적 왜곡과 컬러 왜곡을 포함하게 된다. 우리는 가중치 선형 모델을 이용하는 컬러 왜곡과 호모그라피를 이용하는 기하 왜곡 보정 알고리듬을 이용하여 이러한 왜곡들을 보정하는 알고리듬을 제안한다. 실험결과, 제안한 알고리듬이 예측한 영상과 원본 영상과의 PSNR이 28 ~ 29 정도로 나타났다.

Abstract

An image reconstruction algorithm is proposed to estimate transmitted original images from images displayed on a video terminal. The proposed algorithm acquires images that are displayed on video terminal screens by using a camera. The transmitted images are then estimated with the acquired images. However, camera-acquired images exhibit geometric and color distortions caused by characteristics of the camera and display devices. We make use of a geometric distortion correction algorithm that exploits homography and color distortions using a weighted-linear model. The experimental results show that the proposed algorithm yields promising estimation performance with respect to the peak signal-to-noise ratio (PSNR). PSNR values of the estimated images with respect to the corresponding original images range from 28 - 29 dB.

Keywords : image estimation, real-time multimedia service, quality measurement, QoS

Ⅰ. Introduction

Wireless communication and the Internet are avenues that offer multimedia services to public users. These multimedia applications include IPTV (Internet protocol television), video phones, DMB (digital multimedia broadcasting), video conferencing, VOD (video on demand), and remote presentation. However, wireless communication and Internet networks suffer from performance degradation due to traffic congestion or channel errors when a link or node transfers too much data. Quality of videos can be influenced by the channel deterioration. These applications can be monitored and assessed in order to improve their QoS (quality of service)[1]. To assess the quality of an image, we typically require information about the original image (which serves as the assessment reference) and a degraded image that is the target of the assessment. The original image is

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※ 본 연구는 지식경제부 및 한국산업기술평가관리원의 산업융합원천기술개발사업(정보통신)의 일환으로 수행하였음. [KI002142, 차세대 모바일 영상서비스를 위한 초경량 비디오 부호화 원천기술개발]
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not usually available to multimedia applications[2]. Furthermore, because real-time multimedia systems do not save displayed images on the end-user device and the images may only be assessed when the images are displayed on-screen, it is difficult to extract information about the degraded image from the end-user device without a special electronic interface. Consequently, real-time multimedia services are currently assessed by subjective methods that are based on visual perception. However, it is nearly impossible to achieve the same measurement values for a sequence of multiple trials because the videos displayed in real-time applications cannot be reproduced. To make subjective evaluations more reliable, statistical analyses must be conducted, which requires a large number of people and expensive evaluations[2]. However, subjective measurement values are considered to be more valid than objective methods such as PSNR (peak signal-to-noise ratio). Recently, several studies have been conducted with the objective of replacing subjective measurements with new objective methods that quantify subjective evaluations. They can be used to assess the quality of subjective measurements based on human visual perception[3~4, 12]. Even though objectification methods are effective for evaluating multimedia service quality, it is difficult to access the original images that are transmitted instead of the images displayed on a screen to the end user. This can be applied to transmit the display videos to other side with other video formats. However, the conventional algorithm was presented to estimate original images from displayed videos[13]. In this paper, we propose an image reconstruction algorithm to estimate original transmitted images for objective quality assessment of network-based video services. The proposed algorithm is one improved algorithm based on the conventional algorithm[13]. In the proposed algorithm, we acquire images displayed on an end-user device using a camera and estimate the transmitted image using the acquired image. The acquired image includes distortions caused by compression and transmission errors, as well as distortions resulting from the imperfections of the display device and camera-screen geometry. Moreover, variations in illumination may significantly affect the quality of acquired images. Due to these and other error-introducing factors, it is impossible to reconstruct the original images perfectly. We exploit the homography between the screen and camera image planes in order to perform geometric calibration. The geometric calibration is based on the conventional algorithm[13]. While the conventional algorithm[13] did not well consider the color mis-match, we make use of a weighted linear model for color calibration. The performance of the proposed algorithm is evaluated using the PSNR and mean opinion score (MOS). We found that the proposed algorithm can accurately estimate original images from images displayed on a screen. In addition, we found that the reconstructed frames are quite good based on the subjective evaluation of MOS test. We found that the proposed algorithm employing the new color calibration is around 0.5~1.5 dB better than the conventional algorithm[13].

In Section Ⅱ, we present the proposed image reconstruction algorithm. Experimental results are shown in Section Ⅲ. Conclusions are presented in Section Ⅳ.

Ⅱ. Proposed Image Reconstruction Algorithm

The key goal presented in this paper is the extraction of a transmitted image using a camera instead of an additional electronic interface. However, the image acquired from the camera is distorted due to several factors. Thus, we must calibrate the acquired image for the purpose of reconstruction of the transmitted image. Geometric and color distortions that are easily perceived by the human eye are given special consideration. In this paper, we consider only two factors: geometric distrotion and color changing. However, the geometric and color calibration algorithms were presented; however, it is not easy to deal with correctly the color mismatch. In this paper, we focus on the weighted linear modeling for the color calibration. In this section, we provide further details regarding the proposed image reconstruction algorithm.

Figure 1 shows the data flow of the proposed approach to estimating transferred images. As shown in Fig. 1, an original image is transmitted to an end-user device through a network. This image is distorted by several types of network errors; thus, the end-user device receives a distorted image. The proposed method aims to reconstruct the transmitted image. However, the proposed system acquires the image displayed on the screen using a camera. The captured image contains both geometric and color distortions. Therefore, geometric and color compensation procedures must be performed in order to eliminate these artifacts and obtain the transmitted image, which we desire to be the same as the transmitted image. We could evaluate the quality of video on the displaying devices. However, it is not easy to achieve high quality image frames by capturing the images on the screen. However, once we acquire the image frame on the screen, we can detect severe quality degradation due to packet loss and so on. However, if high quality image frames can be estimated, the quality of video services can be assessed for many practical applications.

Figure 2 shows a block diagram of the proposed compensation method. First, a predetermined training

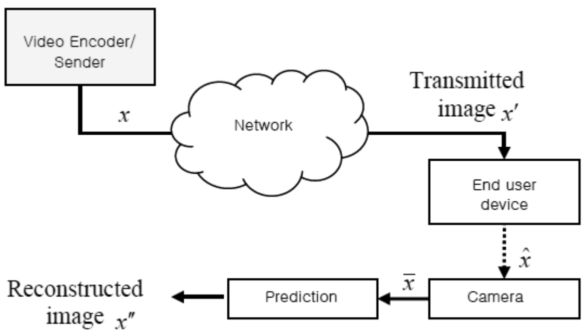

그림 1. 제안하는 알고리듬을 이용한 영상 재구성 과정
Fig. 1. Image reconstruction flow using the proposed algorithm.

image is displayed on the screen, and the image is then acquired using a camera to conduct geometric distortion modeling. The acquired image and training image are used to calculate homography that represents the relationship between the end-user device and the camera. Note that the geometric modeling and calibration are the same to the existing algorithm[13]. After modeling the geometric distortion, three training images are displayed on the screen for color calibration. For color modeling, color offsets for all the three color components are computed with the training data. The images are also acquired using the camera and then compensated using the geometric model calculated above. Geometric and color modeling are performed only once prior to the measurement of image quality as an off-line process. The geometrical screen-to-camera relationship can be represented by homography, and geometric distortion can then be calibrated by transformation based on homography[5]. We assume that camera optics can be modeled by perspective transformation. The presented algorithm is based on the conventional algorithm[13]. However, the proposed algorithm employed a new color calibration algorithm. The color correction is based on weighted offset adjustment for all the color components. Further details on the subject of homography are described in [6].

Given a point (X, Y) on an original image plane on a display screen, it is assumed that the point is observed at a pixel location (x, y) on the camera-image plane. The point can be represented by $x = HX$, where X is the corresponding point on the screen-image plane. Therefore, the homography H is

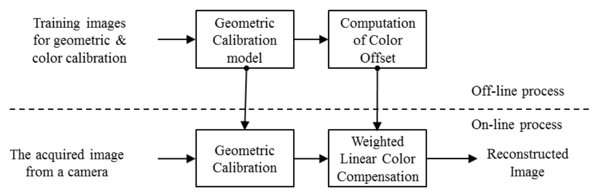

그림 2. 제안하는 컬러 및 기하 보정 알고리듬을 영상 복원에 적용하는 방법
Fig. 2. Block diagram describing the proposed geometric and color-compensation method.

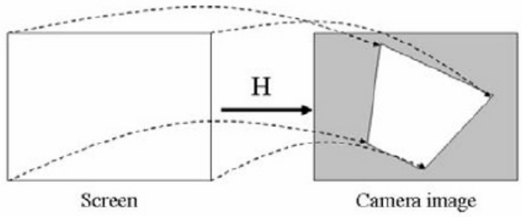

그림 3. 전송된 영상과 촬영된 영상 사이의 형태적 왜곡 (Homography; H)
Fig. 3. Homography H between the transmitted image and camera image.

represented by a 3 × 3 matrix. With multiple corresponding points, the relationship can be expanded into a systematic matrix. The this form can be considered as $A\lambda = B$, where λ can be computed given at least four correspondence points between the screen and camera planes by singular value decomposition (SVD) or the pseudo-inverse method. As shown in Fig. 3, the relationship between the acquired image and displayed image can be represented by homography.

In order to estimate homography, at least four reliable feature points must be available for use in the acquired training image. In this study, the Harris corner detector was used to achieve this objective[7]. The Harris corner detector is a popular interest-point detector due to its invariance to rotation, scale, illumination variation, and image noise. The Harris corner detector is based on the local auto-correlation function of a signal that can be defined by

$$C(x,y) = \sum (I(x,y) - I(x - \triangle x, y - \triangle y))^2$$

The local auto-correlation function measures the local changes of a signal with patches shifted by a small amount in different directions [8]. The shifted image can be expanded by the Tayor expansion. The auto-correlation can be represented by

$$C(x,y) = [\triangle x \, \triangle y] \, Q [\triangle x \, \triangle y]^T$$

where Q represents the intensity structure and its eigen values shows the cornerness that is invariant to rotation, translation and scale.

1. Geometric Calibration

Unless a camera is aligned perpendicular to the screen of the end-user device, images acquired by the camera will contain perspective geometric distortion. It is therefore important to estimate accurate homography parameters in order to correct for distorted images. Thus, we estimate the screen-camera homography H according to the procedure outlined above. Note that the proposed algorithm assumes that the geometric distortion is only caused by the perspective distortion not other factors. Due to the simple modeling, we could observe the barrel and other distortion even with the proposed algorithm.

Once the homography H between the camera and screen has been established, a desirable rectangular image is generated as follows: each pixel in the desirable rectangular image is transformed to a point in the acquired image using H, and the four pixels closest to this point are blended using linear interpolation [11]. In this paper, bilinear interpolation is employed and denoted by:

$$\begin{aligned} I(X,Y) = & (1-q) \times ((1-p) \times I([X],[Y]) \\ & + (p \times I([X],[Y]+1))) \\ & + q \times ((1-p) I([X]+1,[Y]) \\ & + (p \times I([X]+1,[Y]+1))) \\ p = & X - [X] \\ q = & Y - [Y] \end{aligned}$$

where $[X]$ and $[Y]$ represent the largest integers smaller than X and Y, respectively.

2. Color Modeling and Calibration

The colors of images acquired by a camera are typically altered depending on the camera's intrinsic and extrinsic parameters, the characteristics of the display device, illumination conditions, and other factors. Because these artifacts are generated by a variety of factors, it is not easy to separately compensate for all of the distortions [9 - 10]. Thus, we focus on the estimation and elimination of the artifacts. The conventional algorithm [13] employed the table mapping based on the training data; however, the proposed algorithm is based on linear modeling with color component offsets.

In the proposed method, color alternation is compensated for using several parameters obtained using several training images. The training images consist of pure red, green, and blue images. Each image is displayed on a screen and then acquired by a camera. The acquired training images contain geometric distortion. Thus, we first compensate for geometric distortion based on the homography H mentioned above. Next, both the corrected training image and original training image are used for color calibration. The proposed color compensation method assumes that the color distortion can be compensated with color offsets. This is not perfect for all the cases. However, we found that the proposed algorithm can yield moderate accurate color compensation with the simple color offsets.

For pure red training images, red, green, and blue offsets for the red training images are computed by:

$$\begin{bmatrix} \triangle R_{TR} \\ \triangle G_{TR} \\ \triangle B_{TR} \end{bmatrix} = \begin{bmatrix} R_{TR}^{O} \\ G_{TR}^{O} \\ B_{TR}^{O} \end{bmatrix} - \begin{bmatrix} R_{TR}^{A} \\ G_{TR}^{A} \\ B_{TR}^{A} \end{bmatrix}$$

where $(R^{o}{}_{TR},\ G^{o}{}_{TR},\ B^{o}{}_{TR})$ are the red, green, and blue components of the original red training image and $(R^{A}{}_{TR},\ G^{A}{}_{TR},\ B^{A}{}_{TR})$ are the red, green, and blue components of the acquired training image. In the same fashion, the red, green, and blue offsets for the blue training images are computed by:

$$\begin{bmatrix} \triangle R_{TB} \\ \triangle G_{TB} \\ \triangle B_{TB} \end{bmatrix} = \begin{bmatrix} R_{TB}^{O} \\ G_{TB}^{O} \\ B_{TB}^{O} \end{bmatrix} - \begin{bmatrix} R_{TB}^{A} \\ G_{TB}^{A} \\ B_{TB}^{A} \end{bmatrix}$$

where $(R^{o}{}_{TB},\ G^{o}{}_{TB},\ B^{o}{}_{TB})$ are the red, green, and blue components of the original blue training image and $(R^{A}{}_{TB},\ G^{A}{}_{TB},\ B^{A}{}_{TB})$ are the red, green, and blue components of the acquired training image. The red, green, and blue offsets for the green training image are also defined by:

$$\begin{bmatrix} \triangle R_{TG} \\ \triangle G_{TG} \\ \triangle B_{TG} \end{bmatrix} = \begin{bmatrix} R_{TG}^{O} \\ G_{TG}^{O} \\ B_{TG}^{O} \end{bmatrix} - \begin{bmatrix} R_{TG}^{A} \\ G_{TG}^{A} \\ B_{TG}^{A} \end{bmatrix}$$

The color corrected image is compensated by:

$$\begin{bmatrix} R_C \\ G_C \\ B_C \end{bmatrix} = \begin{bmatrix} R_{acq} \\ G_{acq} \\ B_{acq} \end{bmatrix} - \begin{bmatrix} R_{offset} \\ G_{offset} \\ B_{offset} \end{bmatrix}$$

where $(R_{acq},\ G_{acq},\ B_{acq})$ are the color components of the acquired input image and $(R_c,\ G_c,\ B_c)$ are the corrected color components. In the proposed algorithm, the r-, g-, and b-offset values are computed by:

$$\begin{bmatrix} R_{offset} \\ G_{offset} \\ B_{offset} \end{bmatrix} = \begin{bmatrix} W_r \triangle R_{TR} + W_g \triangle R_{TR} + W_b \triangle R_{TR} \\ W_r \triangle G_{TR} + W_g \triangle G_{TR} + W_b \triangle G_{TR} \\ W_r \triangle B_{TR} + W_g \triangle B_{TR} + W_b \triangle B_{TR} \end{bmatrix}$$

where the weighting factor W is defined by:

$$\begin{bmatrix} W_r \\ W_g \\ W_b \end{bmatrix} = \begin{bmatrix} R_{acq}/(R_{acq}+G_{acq}+B_{acq}) \\ G_{acq}/(R_{acq}+G_{acq}+B_{acq}) \\ B_{acq}/(R_{acq}+G_{acq}+B_{acq}) \end{bmatrix}$$

Ⅲ. Experimental Results

In order to evaluate the performance of the proposed algorithm, the PSNR values between transmitted and reconstructed images were quantified. We also performed MOS tests to evaluate the subjective quality of reconstructed images using the proposed algorithm. MOS values were obtained based on the double-stimulus continuous quality scale (DSCQS) presented by the ITU-T Recommendation BT.500-11[11]. Twenty-five people participated in this experiment.

To estimate transmitted images without significant loss of information, the resolution of the camera capturing the images should be higher than that of transmitted original images. Therefore, the CCD camera (Nikon D70) used in this simulation has a resolution of 15041 × 000. Each image used in the experiment was captured at ISO 60, with an exposure

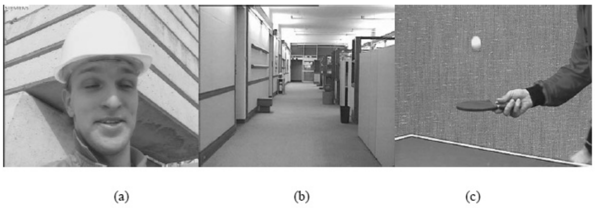

그림 4. 테스트에 사용된 영상들 (a) foreman; (b) hall-monitor; and (c) table tennis.
Fig. 4. Examples of the test images: (a) foreman; (b) hall-monitor; and (c) table tennis.

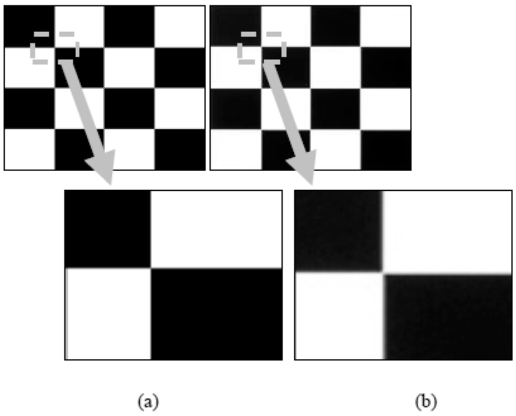

그림 5. 제안하는 기하보정 알고리듬 방법의 성능을 평가하기 위해 사용된 체크무늬 영상: (a) 체크무늬 영상 원본 (b) 보정된 체크무늬 영상
Fig. 5. Check pattern images used to evaluated the proposed geometric compensation: (a) original check pattern image, (b) compensated check pattern image.

time of 1/20 seconds, and with the auto white balance mode set to ON. Note that the format of the tested sequences is CIF (352 × 288). In our experiment, a 17-inch LCD monitor was used as the end-user device. Figure 4 shows three test images that were used in the experiment.

To evaluate the performance of geometric modeling, a check pattern was displayed on the screen of the end-user device. The check-pattern image was then acquired by the camera. The acquired image was transformed into the desired rectified image using the homography H that was computed through off-line processing. Finally, the PSNR for the original pattern image and rectified image was calculated.

Figure 5 shows the check pattern calibrated using

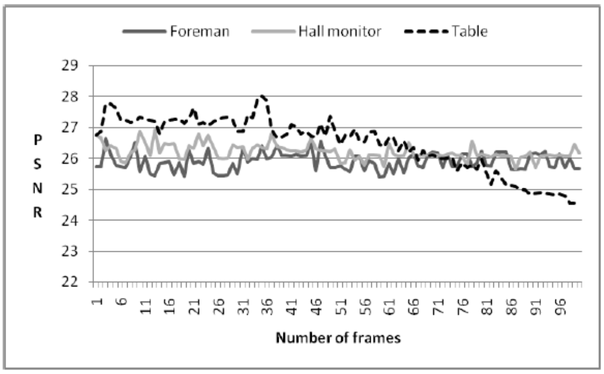

그림 6. 테스트 영상과 기하보정 영상 사이의 PSNR
Fig. 6. PSNR between the test image and the geometric-compensated image.

the proposed algorithm. As shown in the figure, the compensated pattern image appears to be blurred due to the point spread function (PSF) of the camera and monitor. We also found that the geometric compensation has a precision accuracy of approximately ±1 pixels. Figure 6 shows PSNR values for the original test images and their geometric-compensated images. Both test images and compensated images are converted to gray-scale images and their PSNR values are then calculated.

As shown in Fig. 6, the geometric compensation algorithm yields PSNR values of 26 - 27 dB for the test video sets.

Figure 7 shows examples of original, acquired, and reconstructed images using the proposed method. As shown in the figure, the reconstructed image is visually similar to the original image. The reconstructed image appears to be blurred by the PSF characteristics of the screen and camera. A moiré pattern of interference can be also seen between the screen's pixel sampling grid and camera CCD sensor grid. However, we found that the PSNR value of the geometric calibration is highly affected by corner detection error. The PSNR of the proposed algorithm is not as high. However, as shown in Fig. 7, the quality of the warped image using the proposed algorithm is moderately good in quality in terms of a subjective perspective. Because the proposed algorithm uses a camera to estimate the

그림 7. 제안하는 알고리듬 적용 예, 왼쪽부터 원본영상, 카메라로 취득된 영상, 복원된 영상
Fig. 7. An example of the original, acquired, and estimated images from the LCD monitor.

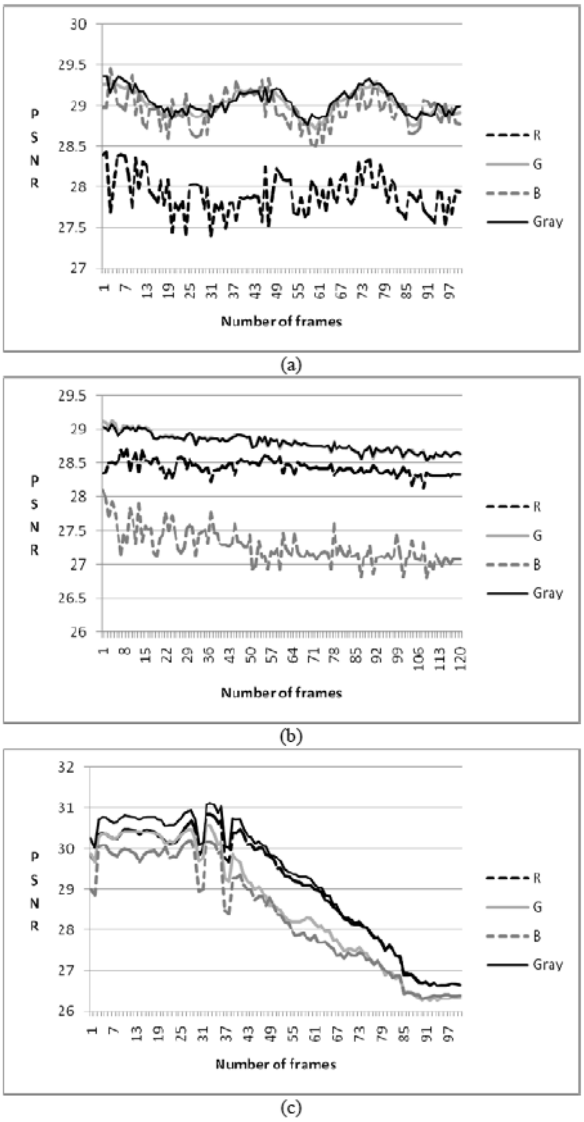

그림 8. 원본영상과 복원영상간의 PSNR 그래프: (a) Foreman, (b) Hall-monitor, (c) Table
Fig. 8. PSNRs of the original and reconstructed images. (a) Foreman; (b) Hall-monitor; and (c) Table.

transmitted image, it is difficult to perfectly reconstruct the transmitted images in terms of the PSNR value. However, based on subjective evaluations, we found that the proposed algorithm performs well in image estimation.

그림 9. 원본 영상과 취득 후 복원된 영상들
Fig. 9. Original, acquired, and estimated images from an LCD monitor.

Figure 8 shows the PSNR values of the R-, G-, B-, and Y- components between original and reconstructed images based on the proposed method. In addition, we also show PSNRs of luminance components as ‘Gray’. As shown in Fig. 8, the experimental results indicate that the proposed reconstruction algorithm yields PSNR values of 28 - 29 dB with three video sets. Because geometric calibration yields PSNR values of 26 - 28 dB, we conclude that PSNR values are improved roughly 2 dB by the use of the proposed color calibration algorithm. In addition, the proposed algorithm is approximately 1dB better than the conventional algorithm [13] due to the new color calibration.

Figure 9 shows several examples of reconstructed images. As shown in the figure, any visual differences are not perceived between the original and reconstructed images.

The proposed method was also evaluated based on MOS tests. Figure 10 shows the MOS values of original and reconstructed images for the "Foreman," "Table tennis," and "Hall monitor" sequences, respectively. In this test, we used 10 frames for each sequence. The x axis represents the number of frames, and the y axis denotes the MOS values. As shown in Fig. 10, the difference in MOS values ranges roughly from 0 to 15. This evaluation indicates that the subjective quality of the image reconstructed by the proposed algorithm is almost the same as that of the original image displayed on a screen.

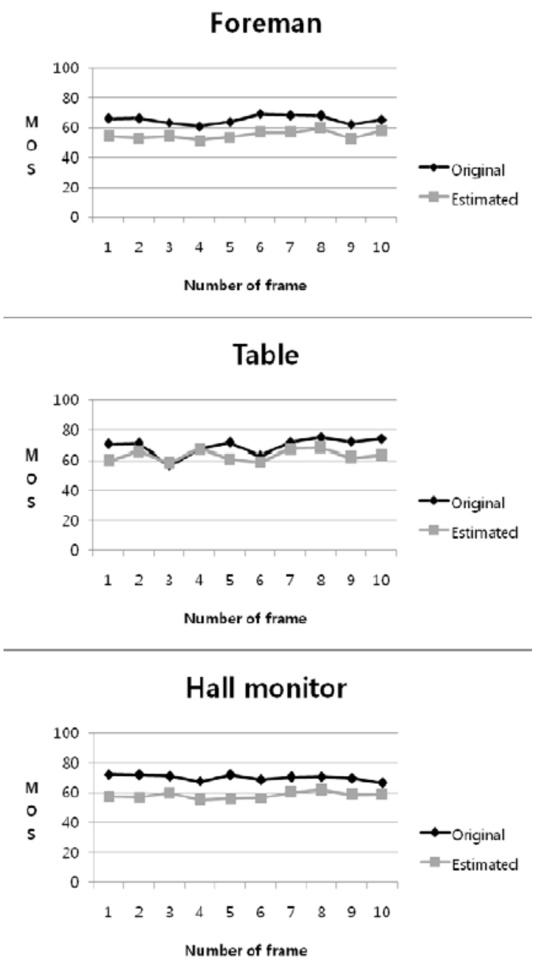

그림 10. 원본 영상과 복원된 영상들의 MOS 값 비교 그래프

Fig. 10. MOS values of original and reconstructed images for three test sequences.

Ⅳ. Conclusions

In this paper, we proposed a transmitted image reconstruction method that can be used to assess quality of video based on human perception or objective evaluation. We proposed an image reconstruction algorithm to estimate original transmitted images from displayed images. In this paper, geometric and color distortions related to the characteristics of cameras and display devices are estimated and compensated. We designed a geometric distortion correction algorithm by exploiting homography and color distortions using a weighted linear model with offset compensation. In the future, the proposed system can be used for real quality evaluation equipments.

감사의 글

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