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An objective method of measuring texture preservation for camcorder performance evaluation

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ABSTRACT

This paper presents a method for evaluating the performance of camcorders in terms of texture preservation, taking into account the contrast sensitivity function of human visual system. A quality metric called texture preservation ratio (TPR) is the outcome of the method. It quantifies to what extent texture structures are preserved in a video recorded by a camcorder. In our experiments, we used the dead leaves chart to simulate a scene with textures of different scales. The dead leaves chart is known as a good target for testing purposes because it is invariant to scaling, translation, rotation, and contrast (exposure) adjustment. Experimental results have shown the following observations on five tested camcorders from three different vendors: 1) the TPR value decreases monotonically with respect to the motion speed; 2) the TPR value increases monotonically with respect to the lossy compression bitrates. Thereby, our study has confirmed TPR as a useful indicator for measuring a camcorder's performance in terms of preserving textures.

Keywords: Texture preservation, video quality assessment, dead leaves chart, spectral frequency ratio, compression bitrate, motion, contrast sensitivity function

1. INTRODUCTION

Camcorders are video capturing and recording devices.[1] Digital camcorders are camcorders producing digital video files as the output. A digital camcorder is normally composed of three main components: the lens system, the image sensor, and the recorder. The lens system is in charge of light gathering and focusing on the image sensor. The image sensor converts light into electronic signals representing the scene. The recorder is a video encoder compressing the raw video signal into a digital file on a storage media like a memory card or a hard disk.

All the three components of a camcorder can cause quality loss in recorded digital videos. For instance, a loss of focus of the lens system can cause a blurred image, high thermal noises in the imaging sensor can lead to a highly noisy video, and a low-bitrate video encoder can produce noticeable blockiness and aliasing effect. While different components can produce different kinds of visual quality loss, their influences on the final visual quality of the recorded video are often mixed in a very complicated way, thus making it a challenging task to assess the performance of camcorders based on the final visual quality of recorded videos. Among all the visual quality performance factors, blurring and noise are widely studied. These two factors are closely related. Improving one factor often leads to compromise of the other. A common practice of balancing the two visual quality factors is to apply a denoising filter only to relatively smooth region or adapt the level of denoising according to an estimation of the local structure.[2] Another related visual quality factor is about how well texture regions in a video are preserved. As important local structures in digital videos, they can be heavily blurred if denoising filtering is applied to them, which will normally cause a clearly visible deterioration of visual quality. Motion can also cause loss of texture due to the averaging effect of neighboring pixels in both spatial and temporal domains. Therefore, it is important to assess to what extent textures are preserved by a camcorder when we evaluate its overall performance in terms of producing high-quality videos. In this paper we propose an objective method to achieve this goal.

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Compared with still digital cameras,[3–9] quantitative performance evaluation of digital camcorders is a less studied topic in the literature. This is not very surprising because many techniques used for measuring still digital cameras can be applied to digital camcorders in exactly the same way by taking each video frames as a still picture. The added complexity due to the temporal domain is often handled by averaging the measurement on a number of sampled frames. However, since object motion plays a key role in visual quality of recorded videos, a good measurement of the performance of a camcorder should relate the quality measurement to the level of motion. Generally speaking, a camcorder that can still maintain a high quality for digital videos with fast object motion is considered as a good camcorder. The need of including object motion in the loop calls for performance evaluation methods tailored to digital camcorders.

The performance evaluation of still cameras and digital camcorders has a very close link to image and video quality assessment,[10,11] but there is also a clear difference: in the former case we have access to the devices under test so the quality of the images/videos can be linked to the physical settings of the devices and the environmental conditions, but in the latter case we are normally oblivious to the imaging devices so the main focus is the digital images/videos themselves. This is a very important difference because for evaluating cameras/camcorders the images/videos can be made in a strictly controlled environment. Standard printed test charts or physical objects are widely used in performance evaluation of cameras/camcorders to ensure a fair comparison among different cameras/camcorders.[12]

In some previous work,[3,4,6] some methods of evaluating the texture preservation capability of images produced were developed based on a special test target called the dead leaves chart, which was originally proposed by Matheron in 1968 for mathematical morphology.[5,13] The dead leaves chart was chosen because it simulates a scene with textures of different scales and it is variant to many image processing operations. The main idea behind those methods is to measure the level of texture preservation by analyzing the spatial frequency response (SFR) of the images produced by still cameras. The SFR was computed simply by first computing the two-dimensional Fourier transform of an image of the dead leaves chart produced by the camera under study and then comparing its radial power spectral density (PSD) with that of the chart itself. The dead leaves chart is generated by computer and then printed out, so its PSD can be considered as known with a calibrated printer.

This paper extends the above-mentioned methods on digital still cameras to digital camcorders with essential add-ons for handling motion, lossy video compression and the human visual system (HVS). In our method, a quantitative metric is obtained by averaging the (relative) PSD of the recorded video weighted by the contrast sensitivity function (CSF) of the HVS. We call this metric *Texture Preservation Ratio* and TPR in short. A higher TPR value implies a higher fidelity in terms of maintaining the PSD of the printed test chart and thus is expected to reflect a better capability of the camcorder to preserve most textures in the chart. This expectation was confirmed by experiments on five camcorders from three different vendors. A monotonic link between the TPR value and the motion speed and the lossy compression bitrate was also observed in our experiments. Therefore, TPR proves to be a useful indicator for performance evaluation of digital camcorders.

The rest of the paper is organized as follows. In the next section, the proposed method for measuring the texture preservation ratio is introduced. In Section 3, the experimental setup and the process of collecting recorded videos are described in detail. Section 4 reports our data analysis of the recorded videos and interpretation of the experimental results. Conclusions and future work are briefed in the last section.

2. PROPOSED METHOD FOR MEASURING TEXTURE PRESERVATION

Due to the complexity of the video capturing and recording process, we chose to consider a camcorder as a black-box system. A printed test chart is used to measure how well textures can be preserved by a camcorder under test. As other researchers working on digital still cameras, we also choose the dead leaves chart as the test target, which is known as a well-suited test target due to its invariance to scaling, translation, rotation and contrast (exposure) adjustment. In the following two subsections we first briefly review the dead leaves model as a target scene and then proceed to the definition and computation of the proposed texture preservation ratio.

2.1 The dead leaves chart as the target scene

The dead leaves chart is generated by a stochastic image model simulating overlapped and occluded objects as commonly found in natural scenery. Following the model, a image is generated by placing shapes of the same kind (called leaves, but not necessarily look like real leaves) with random radii and random grey scales at random positions onto a canvas until the entire canvas is fully covered. When the probability density functions of the random variables involved are properly chosen, the power spectrum of the resulting image is very close to a power function. The image can then be printed out and used as a physical test target.

For the dead leaves chart used in this paper, we follow the specifications of Cao et al.:[6]

- Leaves are disks.
- The disk radius r is a random variable whose probability distribution is proportional to $1/r^3$ in the interval from the minimum radius to the maximum one.
- The disk center is uniformly distributed on the canvas.
- Each disk is filled by gray scale is a uniformly distributed random variable on the interval $[0.25 \times 255, 0.75 \times 255]$.

An image generated by the above dead leaves model has the following important properties:

- statistical rotation invariance,
- statistical scale invariance,
- statistical shift invariance,
- having all levels of contrast up to the maximal difference on the selected gray scale interval $[0.25 \times 255, 0.75 \times 255]$,
- the power spectral density following a power law,
- having many sharp edges (caused by occlusion).

In the above list of properties, the word "statistical invariance" means that the statistical properties of the image (in term of the PSD) does not change w.r.t to those geometric operations (which happen very often in the process of video capturing and recording).

2.2 Proposed metric TPR

The TPR metric is calculated in the following way: 1) shooting the printed test chart, 2) calculating the PSD of each frame relative to the PSD of the original printed test chart, 3) weighting the relative PSD with the CSF of the HVS to get a scalar value, and 4) pooling the results of all frames into a single value. Here, the 1-D radial PSD of a video frame is calculated by summing the normal PSD with the same radius. The range of the radial frequencies is from 0 to 0.5 cycles per pixel.

The human visual system's CSF is used to consider different contributions of different frequency components to the overall visual quality perceived by human eyes. The CSF quantifies the sensitivity to image contrast depending on the frequency of the stimulus signal. It has been extensively measured by many psychological experiments since the 1960s.[14,15] Experiments have revealed that the CSF depends on both spatial and temporal frequencies, and the chrominance CSF differs from the luminance one. The CSF also changes according to the background illumination level, but it remains fairly stable under photonic lightening conditions. In this paper, we used the luminance CSF because the test chart is colorless. We also ignored the variation caused by temporal frequencies to simplify our method, meaning that we assume a zero temporal velocity. The experimentally measured CSF curves are not easy to use in computer algorithms due to the need for both interpolation and extrapolation, so we chose an analytic model proposed in Ref. 16 which has the following form:

$$A(f) = 75 \cdot f^{0.8} \cdot e^{-0.2f}, \tag{1}$$

where f is the spatial frequency of the visual stimuli given in cycles/degree on human retina. The function has a maximal value 102 at about $f = 4.0$ cycles/degree, and is almost zero for frequencies above 60 cycles/degree indicating the spatial frequency limit of the human visual system.

Given a video recording of the dead leaves test chart, we define the spatial frequency response (SFR) of the video as follows:

$$\mathrm{SFR}(f) = \frac{s(f)}{s_0(f)}, \tag{2}$$

where $s(f)$ is the average PSD of the recorded dead leaves chart in selected frames of the video* and $s_0(f)$ is the reference PSD of computer generated dead leaves image that was printed to create the physical chart.† In this paper we mainly consider distortion of texture details due to object/camera motion and lossy compression. Therefore, we add two more variables into $s(f)$ to get $s(f|b, v)$, where b denotes the compression bitrate and v denotes the average motion of the dead leaves chart in the video. In this case, the relevant spatial frequency response becomes

$$\mathrm{SFR}(f|b, v) = \frac{s(f|b, v)}{s_0(f)}, \tag{3}$$

where $s(f|b, v)$ is the PSD of the test video compressed with a bitrate b and the average motion speed of the chart in the video is v pixels/second.

Finally, we introduce the *texture preservation ratio* (TPR) as the normalized mean spectral frequency response, weighted by the contrast sensitivity function $A(f)$ of the human visual system. The TPR value is defined as follows:

$$\mathrm{TPR}(b, v) = \frac{\int \mathrm{SFR}(f|b, v) A(f)\, \mathrm{d}f}{\int A(f)\, \mathrm{d}f}. \tag{4}$$

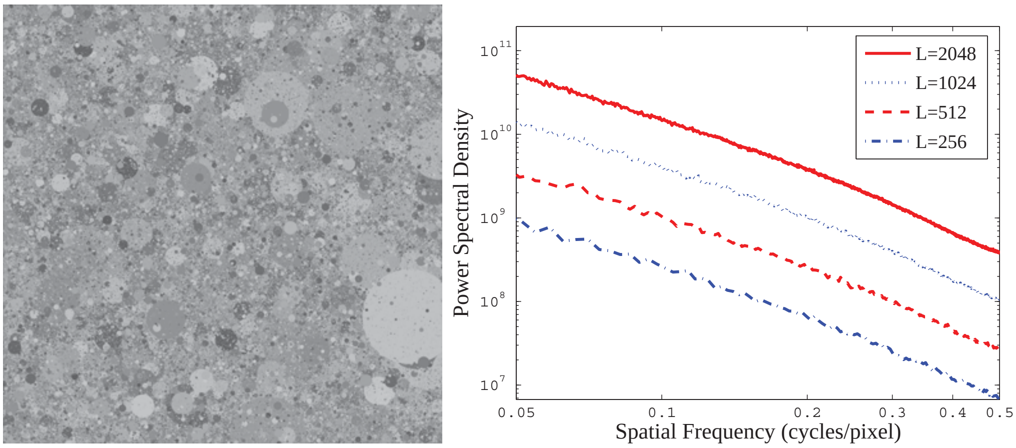
When the spatial frequency is discrete, the integrals are replaced by weighted sums of integrands evaluated at the discrete sample frequencies $\{f_i\}$, thus giving a discrete edition of TPR:

$$\mathrm{TPR}(b, v) \cong \frac{\sum_i \mathrm{SFR}(f_i|b, v) A(f_i)}{\sum_i A(f_i)}. \tag{5}$$

The range of TPR value is $[0, 1]$ since $\mathrm{SFR}(f_i|b, v)$ is always between 0 and 1. The single scalar value TPR reflects the quantity of preserved textures of the dead leaves chart region recorded in the video under study. A larger TPR value corresponds to a better capability of preserving textures. The TPR value is expected to decrease as the motion speed increases and/or the compression bitrate decreases.

*Each video frame normally covers a larger scene, not only the dead leaves chart. So to calculate the PSD, we first extract the recorded dead leaves chart from a number of selected video frame, then calculate PSD for each extracted region and finally do the pooling (averaging). To simplify our discussion, in the following part of this paper when we talk about a video, we actually mean the averaging dead leaves chart recorded in all frames. Note that the averaging is not done for all frames because in some frames the geometric distortion of the recorded dead leaves chart is relatively high.

†In principle, we should use the PSD of the incident light reflected by the printed dead leaves chart illuminated by the environmental lightning. But this is difficult to measure, so we decided to use the PSD of the computer generated dead leaves image to define the TPR metric (as if we used a perfectly linear printer, a perfectly linear paper and an environmental illuminant with a uniform PSD, and the dead leaves chart was perfectly illuminated in a uniform manner). Despite the over-simplification, our experimental results have shown that the TPR metric works well.



(a) (b)

Figure 1. (a) An $N \times N$ image generated by the dead leaves model and (b) its PSD with size $L \times L$.

3. EXPERIMENTAL SETUP

3.1 Dead leaves chart generation

The disks for the dead leaves chart were generated following the description in Sec. 2.1, initially for a large square image of linear size $N = 2^{15} = 32768$. This large image was lowpass filtered using a box filter of size $s \times s$ and subsampled to yield an anti-aliased dead leaves image of size $L = N/s$. The lower bound for the radii of the disks in the dead leaves image was set such that the resulting disks, printed on paper and recorded by a digital camcorder, are smaller than one pixel of the camcorder image sensor array. Here $r_{\min} = N/4096$. The maximal radius is set such that the corresponding maximal disks are about the size of the entire image. We followed the choice of Cao et al. in 6 to choose $r_{\max} = 497 r_{\min}$. The resulting $L \times L$ image was printed out on a calibrated high-resolution printer (Epson Stylus Photo R3000 Inkjet) to make the test chart with a physical size of $21cm \times 21cm$. The printing resolution is 300 DPI (dots per inch). The printer was calibrated to behave linearly in the range of the gray scale selected to produce the dead leaves image.

3.2 Camcorders tested

Five camcorder models from three vendors were tested with interlacing mode in our experiments:

- Three camcorder models from Panasonic: HDC SD800, HDC SDX1, and HDC TM80, with four recording (quality) modes (all with full HD resolution 1920×1080) HA 1920 (17 Mbps VBR), HG 1920 (13 Mbps VBR), HX 1920 (9 Mbps VBR), and HE 1920 (5 Mbps VBR).
- One camcorder model from JVC: GZ HM 445, with four recording (quality) modes (all with full HD resolution 1920×1080) UXP (24 Mbps VBR), XP (17 Mbps VBR), SP (12Mbps VBR), and EP (4.8Mbps VBR).
- One camcorder model from Canon: HFM46, with five recording (quality) modes MXP (1920×1080, 24 Mbps VBR), FXP (1920×1080, 17 Mbps VBR), XP (1440×1080, 12 Mbps VBR), SP (1440×1080, 7 Mbps VBR), and LP (1440×1080, 5 Mbps VBR).

The video compression format of all tested camcorders is MPEG-4 AVC/H.264.

3.3 Video recording

According to the intention of the proposed TPR metric, its value should decrease if the texture structures are partly destroyed due to the loss of some medium- and/or high-frequency components. Both object motion and lossy compression can cause loss of texture. It is reasonable to expect that the faster the object motion is and the higher the compression ratio is (i.e., the lower the bitrate is), the more loss of texture will occur and thus the lower the TPR value. To study how the TPR value changes with respect to both motion speed and compression bitrate, we designed our experiments to record a number of videos by fixing all other settings of the camcorders under study, but changing the object motion speed and the compression bitrate only. To avoid dependence on an object detection and tracking algorithm in our data analysis phase, we chose to move the camcorders to create uniform global motion. This was achieved by fixing the camcorder on a tripod and rotating the camcorder by an electronic motor with a speed control. The compression bitrate was changed by switching to different quality modes supported by the camcorders.

In our experiments, the camcorders and the motor were both mounted on a tripod in a shooting distance of about 1.5 meters from the printed test chart. The dead leaves chart was fixed on a light beige wall, and the camcorders were focused on the dead leaves chart. The videos were made so that the test chart occupies no more than 30% of the whole video field to reduce possible negative influence of geometric non-uniformity of the camcorders. The motor does not have an accurate speed control, but only a continuous voltage adjuster. Therefore, the actual speed was estimated in the video analysis stage from the distance the pattern moved from frame to frame. To have sufficient videos to get the relationship between TPR and motion speed, we recorded from 15 to 30 videos for each compression bitrate (recording/quality mode) of each camcorder model. All recording/quality modes supported by the five camcorders were tested.

To minimize the influence of automatic components to the results, we switched off all such functions including auto focus, auto white balancing and auto iris control, auto image stabilizer, wind cut (for reducing the noise caused by wind), auto brightness adjustment, backlight compensation. The shutter time was also fixed to have the uniform exposure time so that the comparison among different settings is valid.

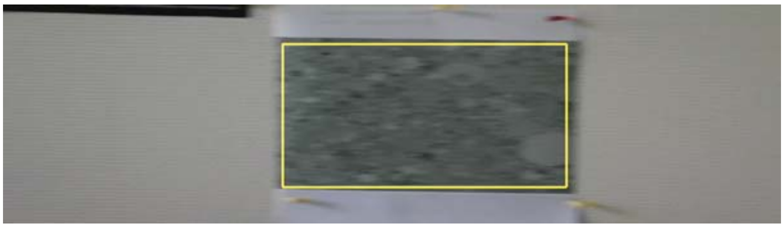
For each tested camcorder, the video recording process proceeded as follows:

- Step 1: Capture a video of the printed dead leaves chart under each recording mode when the camcorder is still.
- Step 2: Switch on the motor to let the camcorder rotate with a particular speed on the tripod.
- Step 3: Capture a video under each recording mode by starting the recording when the dead leaves chart appears in lens until it starts moving out of the scene. A remote control was used to avoid shake when the recording process was started. For camcorders without remote control, the video started a few seconds earlier to make sure the motion is stable when the chart appears in the field of view.
- Step 4: Adjust the voltage of the motor to change the rotation speed of the camcorder and repeat step 3 until videos are made for all desired rotation speeds.
- Step 5: Change the recording mode of the camcorder and repeat Steps 3 and 4 until all recording modes are tested.

3.4 Video analysis

Since all videos were recorded in interlacing mode, the two fields in each frame were not recorded at the same time. Therefore, if we take the whole frame as a single shoot to calculate the TPR value, the mismatch between the two fields can cause inaccuracy. As a result, we decided to handle the two fields separately as if they were independently recorded. The vertical resolution of each field thereby is halved, so the ratio between the horizontal and vertical frequencies becomes 2, which is considered to calculate the radial frequency correctly. The PSDs of all fields are calculated to get the TPR value of each video according to Eqs. (1) to (5).

The video analysis process can be described by the following steps:



(a)

(b)

Figure 2. Region of interest in one field of the interlaced video (a) and the extracted dead leaves target (b).

- Step 1: Localize the region of interest (i.e., the dead leaves chart) in each field. Then, select those fields for which the dead leaves chart appears near the center of the field. Figure 2 shows an example field in one of the videos we processed. The background has been removed and only the region of interest framed in the yellow rectangle is kept. The extracted dead leaves chart, i.e., the region inside of the yellow rectangle, is shown in the sub-figure below. Note that the vertical resolution is halved so circles become ellipses.
- Step 2: Compute the PSD of the extracted target from videos, i.e., $s(f_i|b, v)$ for frequencies $\{f_i\}$ between 0 and 0.5 cycles/pixel.
- Step 3: Compute the relative SFR using Eq. (3), i.e., $s(f_i|b, v)/s_0(f)$.
- Step 4: Multiply the relative SFR with the CSF, then sum and normalize the resulting values over all frequencies $\{f_i\}$, yielding the TPR value (see Eq. (5)). Figure 1 gives an example of a weighted SFR. In this example the camera used was Panasonic HDC TM80 with recording mode HA1920, and the resulting texture preservations ratio is 0.2083 at the speed of 1471 pixels/second.

Note that the frequencies in the CSF of the HVS are given in cycles/degree but the frequencies of the PSD of digital videos are given in cycles/pixel. To weight the PSD by the CSF, we need to align the units. To this end, we assume the recorded video is viewed on a 20.4-inch computer monitor with a resolution of 1920×1200. The viewing distance is assumed to be 50cm. Based on such a setting, 1 cycle/degree on a human observer's retina is equivalent to 0.0618 cycles/pixel on the monitor. The peak of CSF in Eq. (1) is around the highest frequency (0.5 cycles/pixel). The peak of the CSF in Eq. (1) is at the highest frequency (0.5 cycles/pixel).

4. EXPERIMENTAL RESULTS

Figure 4 shows the PSDs of four videos recorded with the Panasonic SD800 camcorder without motion. The PSDs in the four recording modes are plotted for the full range of frequencies. They significantly differ from each other for frequencies above 0.25 cycles/pixel, as shown in the right sub-figure. Similarly, Figure 5 shows the PSDs (high-frequency part only) of videos recorded by the other four camcorders. One can see that for all the three Panasonic camcorders the PSD drops when the bitrate decreases, i.e., when changing the recording mode from HA to HG, HX, and last to HE. For the Canon and JVC camcorders the PSDs obtained under differing recording modes are similar. While the PSDs do not seem to sufficiently differ from each other, Figure 6 shows

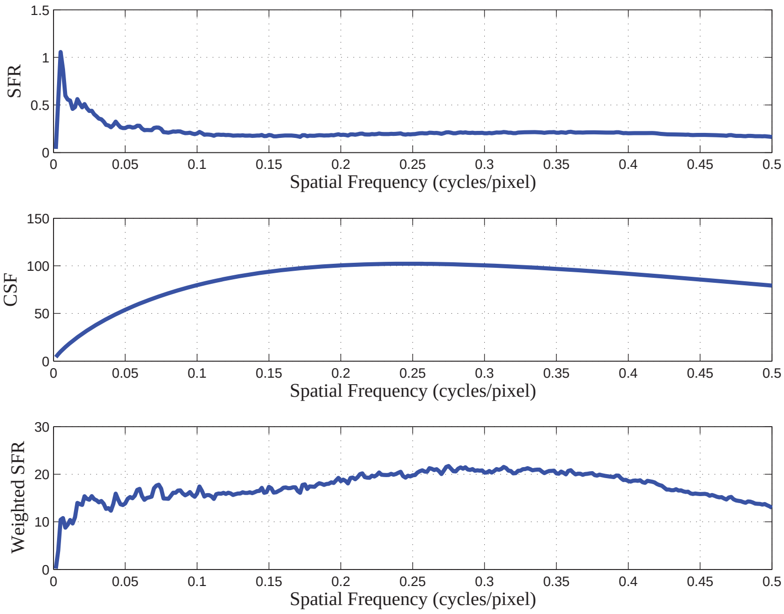
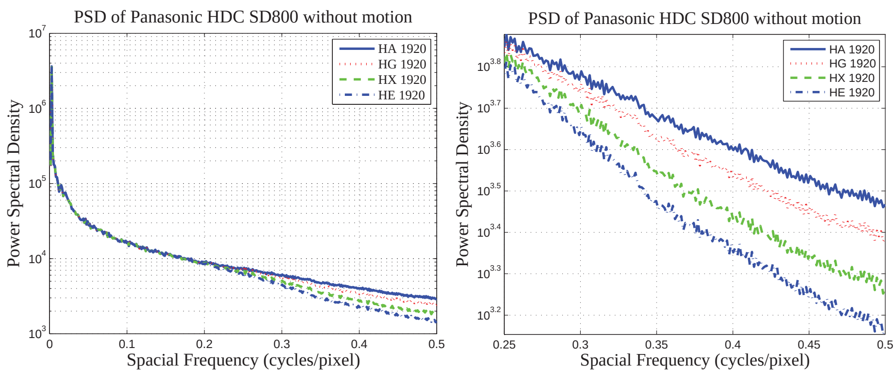


Figure 3. The relative SFR (top) multiplied with the CSF (middle) yields the weighted SFR (bottom). In this example the camera used was Panasonic HDC TM80 with recording mode HA1920, and the resulting TPR value is 0.2083 at the speed of 1471 pixels/second.



(a) (b)

Figure 4. The PSD of the Panasonic SD800 camcorder without motion (a) and the close-up of the high-frequency part of the PSD (b).

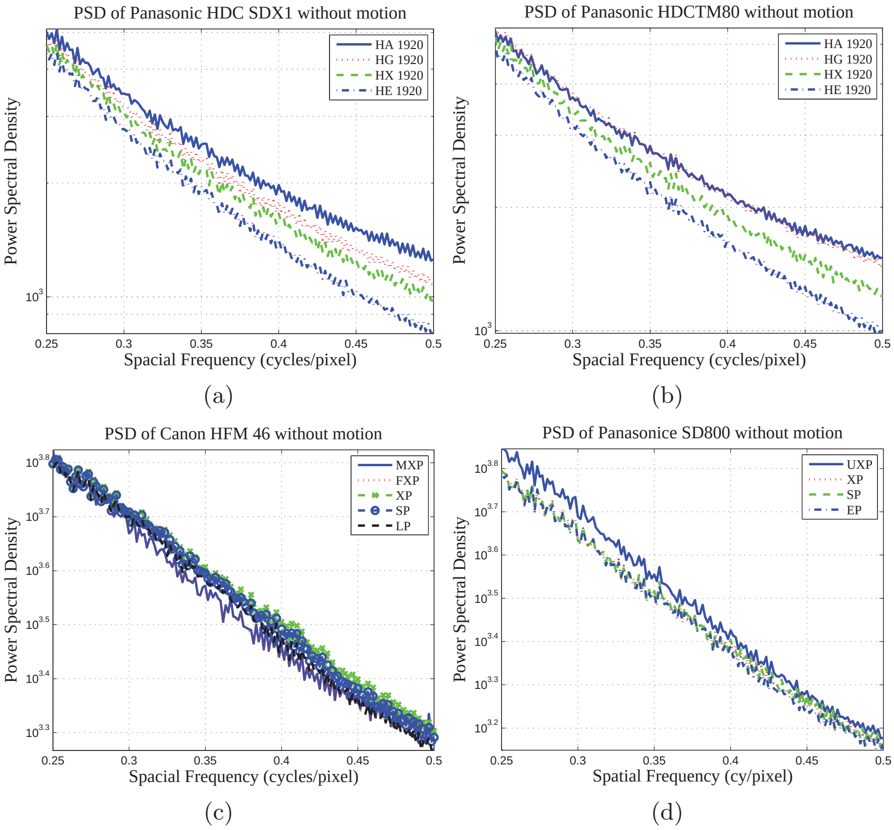


Figure 5. The PSD curves of the other four camcorders at high frequencies.

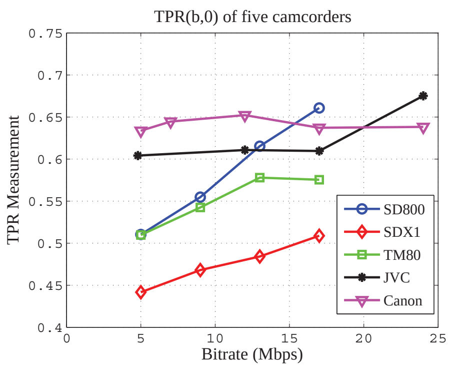


Figure 6. The TPR measurements of the five camcorder models when there is no motion, i.e., when $v = 0$.

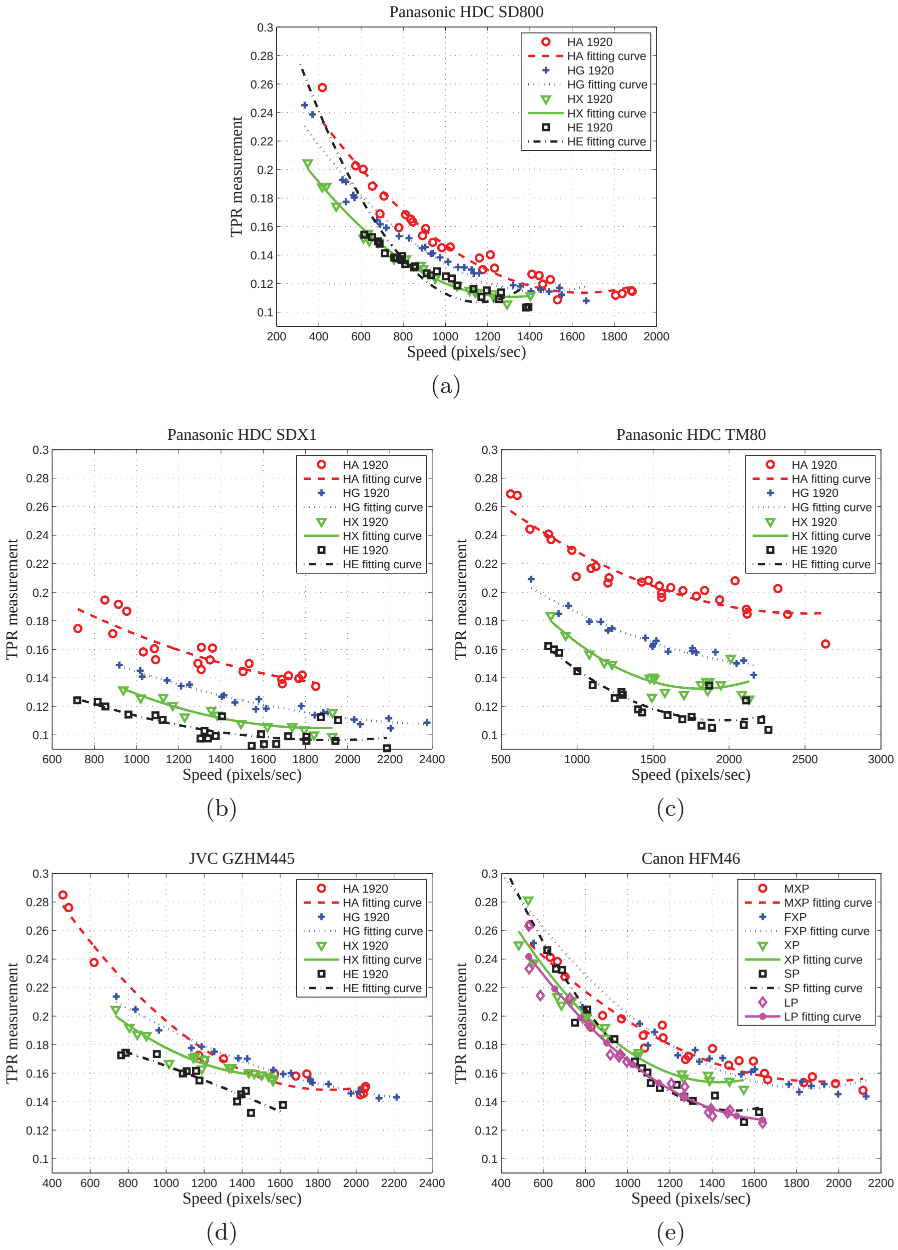


Figure 7. The fitting curves of TPR values obtained for all the five camcorders. All these fitting curves monotonically decrease with respect to the motion speed and the decreasing rate also drops while the motion speed becomes high.

that the TPR value is generally increasing with respect to the compression bitrate for all the five camcorders. This confirms the expected monotonic relationship between the TPR value and the lossy compression bitrate.

Figure 7 shows the relationship between the TPR value and the motion speed of all tested camcorders. For all five tested camcorders and all recording modes the TPR values are plotted with variable object motion from about 400 to 2500 pixels/second. A quadratic curve is fitted to match each recording mode of each camcorder. We could not make any video with a motion speed below 400 pixels/second because the motor we used has a dead zone of the driving voltage.

These results show that up to some measurement noise the TPR curve can reflect the motion speed in a monotonic manner. Note that for the minimal speed around 400 pixels/second the TPR value is only half of the TPR value without motion (Fig. 6), which implies that even slow motion can introduce a significant loss of texture structures for all the five camcorders. This can probably be attributed to the common use of denoising filter in all camcorders.

5. CONCLUSION

In this paper we studied the problem of how to measure a camcorder's capability of preserving textures in recorded videos. A metric called TPR (Texture Preservation Ratio) is proposed as a quantitative measurement. The TPR value is defined by weighting the radial power spectral function of the recorded video by the human visual system's contrast sensitivity function. Some experiments were run on five camcorder models from three vendors to study how the TPR value changes with respect to the motion speed and the lossy compression bitrate. The results showed that the TPR values has a monotonic relationship with both the motion speed and the lossy compression bitrate. Our experimental results confirmed that the TPR metric is a useful quantitative indicator for evaluating the texture preservation capability of camcorders.

While the TPR has been proved to be a useful indicator of texture preservation, there do exist some major limitations. The first one is about the controlled experimental environment, which is an essential element of this kind of performance assessment of physical devices. In our experiments, we tried our best to control the environmental lighting and the physical settings of the test chart, the camera and the motor, but it is very difficult to exactly reproduce these experimental settings. This means that exactly reproducing our experimental results may not be possible, although we expect that the TPR value will still maintain a monotonic relationship with respect to the motion speed and the lossy compression bitrate. In addition, it remains unclear how stable the experimental results will be for other camcorder models and instances of the same model. The simplified CSF we used in the experiments ignores frequencies in temporal domain, which may cause deviation between the TPR value and the actual degree of texture loss in recorded videos.

There are a number of research directions that can be done based on the reported work. First of all, we plan to run more experiments with different experimental settings and more camcorders, in order to clarify the stability of the TPR value to different aspects of the experimental setting. We will also repeat the experiments on different instances of the same model to see how consistent they behave in terms of preserving textures. Secondly, the use of temporal and chroma CSFs will also be investigated to clarify the role of temporal velocity and colors in the perceived loss of textures in the recorded videos. Thirdly, we will study if taking the live output of the camcorder can break the black-box model we used into two parts so that the relationship between the TPR value can be more accurately linked to lossy compression bitrate. Fourthly, our current research lack evidence about human users' perceived loss of texture, so we are also planning to run some subjective tests to offer possible golden standards to the objective TPR values. Fifthly, the use of printed test charts makes the experiments rather complicated, so we will also study if and how we can replace the printed test charts by monitor based digital charts. The last but not the least, we will also see how we can generalize our work on texture preservation to other performance factor of camcorders.

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