LCD MOTION BLUR MODELING AND SIMULATION

Stanley H. Chan and Truong Q. Nguyen

ECE Dept, UCSD, La Jolla, CA 92092-0407
{h5chan, nguyent}@ece.ucsd.edu
Website: http://videoprocessing.ucsd.edu

ABSTRACT

Liquid crystal display (LCD) devices are well known to have slow response due to the physical limitations of the liquid crystals. Therefore, fast moving objects in a scene are often seen blurred on an LCD. In order to reduce motion blur, an accurate LCD model and an efficient deblurring algorithm are needed. However, existing LCD models are inadequate to reflect the human eye tracking limitation. Also, the spatial-temporal equivalence in LCD models is widely used but not proven directly in the 2D discrete spatial domain. In this paper, we study the human eye tracking limit by reviewing a number of papers in the cognitive science literature. We provide both theoretical and experimental arguments to support our findings. Also, we prove the spatial-temporal equivalence rigourously and verify the results using real video sequences.

Keywords— LCD, motion blur, simulation, modeling

1. INTRODUCTION

Liquid crystal display (LCD) devices are well known to have slow response due to the physical limitations of liquid crystals (LC). LC are organic fluids that exhibit both liquid and crystalline like properties. They do not emit light by themselves, but the polarization phase can be changed by applying electric fields [1]. A common circuit used in LCD to control the electric fields is known as the thin film transistor (TFT) [2]. Although TFT responds quickly, it takes some time for the LC to change its phase. This latency is known as the fall time if the signal is changing from high to low or the rise time if the signal is changing from low to high. Since the fall and rise time are not infinitesimal, the step response of an LC exhibits a sample-hold characteristic.

Compared to LCD, traditional cathode ray tube (CRT) displays do not have the sample-hold characteristic. When a phosphor is exposed to electrons, it starts to emit light. As soon as the electrons leave, the phosphor stops emitting light. The latency of a phosphor is typical between 20μs to 50μs [2]. However, for a 60 frame per second video sequence, the time interval between two frames is 16.67ms. Therefore, the latency of a phosphor becomes negligible compared to the frame interval.

There are a number of LCD motion blur reduction methods, such as back light flashing [3], black frame insertion [4], full frame insertion [5, 6], and motion compensated inverse filters (MCIF) [7, 8]. Besides the methods, there are also efforts in exploring the motion blur measurements, such as [9, 10]. Yet, most of these methods are based on experimental results, in a sense that there are not many systematic studies of the LCD model and analysis.

The authors would like to acknowledge the support of the Croucher Foundation scholarship, as well as the support of Samsung Information Systems America Inc. (SISA).

1.1. Related works

Klompenhouwer and Velthoven [7] studied the LCD motion blur as a combination of both LCD response and human visual system (HVS). They derived an LCD model in the frequency domain. However, frequency domain may not be the best domain to analyze motion blur because a video sequence is intrinsically a spatial-temporal volume [11]. It is more intuitive to study the motion blur in the spatial-temporal domain directly.

In [12], Pan, Feng and Daly showed a fundamental equation of LCD motion blur (Equation (7) of [12]). However, a limitation of this equation is that the integration has to be performed in the temporal domain. Because of this, the time step of the integration should be made small. Otherwise, the integration cannot be approximated using a finite sum. In order to make the time step small, we need to interpolate intermediate frames. However, temporal interpolation can be time consuming. If the integration time step is 1/10 of the time interval of frames, then 10 intermediate frames are needed. Therefore, the simulation of motion blur will be difficult unless there is an alternative method. As we will show in Section II, an alternative method can be derived based on the spatial-temporal equivalence.

Another limitation of Pan's paper is that they implicitly assumed that the human eyes are able to track objects perfectly. This is not true in general because our eyes only have limited range of tracking speed. This finding is reported by He et al [13]. However, He et al did not explain the cause of such a limit. Also, they did not justify their MCIF design from a human perceptual perspective.

The most relevant paper to our work is [14]. Klompenhouwer drew a connection between the spatial and temporal aperture in a somewhat different - and very elegant - manner. However, a precise numerical approximation scheme for evaluating the continuous time integration in the discrete spatial domain is not pursued. Also, Klompenhouwer's paper is focused on the unit step input signal (which is a 1D signal), but the theory presented in this paper is focused on general 2D video sequences.

1.2. Objectives

The purpose of this paper is to address the following questions: (1) Why is it valid to model the LCD blur (temporal problem) as a spatial average problem? (2) How to evaluate the LCD blur equation (Equation (7) of [12])? (3) How does eye tracking limit affect the LCD motion blur model?

The organization of the paper is as follows. In Section II we discuss the LCD motion blur model and the main theorem about the spatial-temporal equivalence. The eye tracking assumption will also be discussed in later parts of this section. In Section III, we show numerical simulation results to verify the theoretical findings. Last, a conclusive remark is given in Section IV.

978-1-4244-7493-6/10/$26.00 ©2010 IEEE

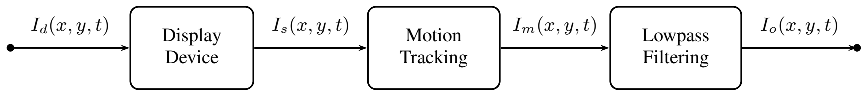


Fig. 1. Block diagram of the perception chain: Display device (CRT or LCD) and Human visual system (HVS)

2. LCD MOTION BLUR MODEL

2.1. LCD model

For completeness, we provide a brief introduction to the LCD motion blur model. Most of the material presented in this subsection is due to Pan, Feng and Daly [12]. We will emphasize a few implicit assumptions made in [12].

When an image is displayed on an LCD, the image is first distorted by the sample-hold characteristics of the LCD. Then the human visual system (HVS), which consists of eye tracking and a low pass filtering mechanism, will further distort the observed image. This chain of processes can be seen in Fig. 1.

Let $I_c(x,y,t)$ be a frame sampled at time t and suppose $I_c(x,y,t)$ has a motion vector (v_x, v_y). Let $h_D(t)$ be the step response of the display, where the subscript D can either be CRT or LCD. By Pan, Feng and Daly [12], the image shown on the display is

$$I_s(x,y,t) = \int_{-\infty}^{\infty} h_D(\tau) I_c(x+v_x(t-\tau), y+v_y(t-\tau), t-\tau)d\tau. \quad (1)$$

An implicit assumption used in [12] is that the human eye tracking system is perfect, meaning that the eyeball is able to capture any motion at any speed. Based on this, the motion compensated image (formed on the retina) becomes

$$\begin{aligned} I_m(x,y,t) &= I_s(x-v_xt, y-v_yt, t) \quad \text{[perfect motion tracking]} \\ &= \int_{-\infty}^{\infty} h_D(\tau) I_c(x-v_x\tau, y-v_y\tau, t-\tau)d\tau. \end{aligned} \quad (2)$$

Now assume that there is no low pass filtering of the HVS, then the observed signal becomes

$$I_o(x,y,y) = \int_{-\infty}^{\infty} h_D(\tau) I_c(x-v_x\tau, y-v_y\tau, t-\tau)d\tau. \quad (3)$$

If the step response of LCD are given by a boxcar signal, that is $h_{LCD}(t) = 1/T$ for $0 \le t \le T$ and $= 0$ for otherwise, then the image shown by an LCD is

$$I_o^{LCD}(x,y,t) = \frac{1}{T}\int_0^T I_c(x-v_x\tau, y-v_y\tau, t-\tau)d\tau. \quad (4)$$

The integral (4) can be evaluated by integrating over time $0 \le t \le T$. However, for a digital video sequence the signal $I_c(x-v_x\tau, y-v_y\tau, t-\tau)$ is available only for a few instants t_k, where $k = 1, 2, \cdots$. Therefore, it is never possible to compute the integral exactly. In the following subsections, we will discuss a numerical method that approximates the temporal integration accurately. But before we do so, we would like to provide some intuitive arguments to the readers.

Fig. 2 shows a sequence of the sampled images from a video. When integrating (4), we are essentially taking average over the pixel values at a fixed position but different time instants. Since all frames are identical to each other (assume perfectly motion compensated), we can approximate the average over different time instants as a spatial average over the pixel's neighborhoods. In this sense we can transform the temporal average into a spatial average problem.

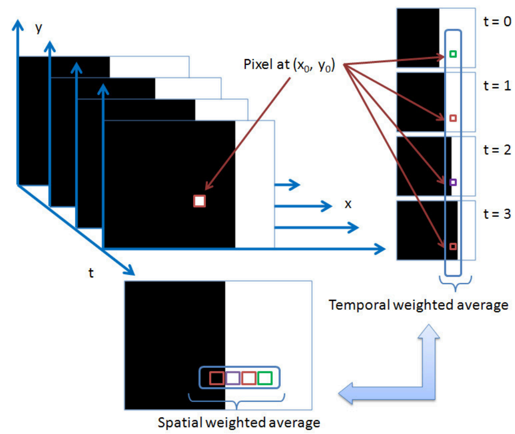


Fig. 2. Illustration of integrating (4) - we first fix a position (x_0, y_0) and consider the pixel values at different times $t = 0, \ldots, 3$. The average is taken over the time, so it is the average across the four marked pixels on the right hand side. But since these four frames are identical to each other (after a motion compensation), the temporal average value is the same as the spatial average value.

2.2. Evaluating the Integral

Definition 1. *Given the velocities (v_x, v_y) and decay time T, and let $K \gg \max\{v_xT, v_yT\}$ be a very large displacement made by v_x and v_y in time T, and K should be a common multiple of v_xT and v_yT, we define two sequences*

$$\mathcal{S}_x = \left\{k,\ s.t.\ \frac{kv_xT}{K} \text{ is an integer, where } k \text{ is an integer.}\right\}$$

$$\mathcal{S}_y = \left\{k,\ s.t.\ \frac{kv_yT}{K} \text{ is an integer, where } k \text{ is an integer.}\right\}$$

Define $\overline{\mathcal{S}} = Sort\{\mathcal{S}_x, \mathcal{S}_y\} = \{k,\ s.t.\ k$ is taken from $\mathcal{S}_x$ and $\mathcal{S}_y$ and k is sorted in an acending order$\}$.

Define the weights $h(i,j)$ using the following algorithm:
For a given $k > 0$,

- *If $s_k \in \mathcal{S}_x$, then $i \leftarrow i+1$, and $h(i,j) = (s_k - s_{k-1})/K$,*
- *If $s_k \in \mathcal{S}_y$, then $j \leftarrow j+1$, and $h(i,j) = (s_k - s_{k-1})/K$,*
- *$h(0,0) = s_1$.*

Theorem 1. *Let T be the hold time of an LCD. Assume that $I_c(x,y,t) \approx I_c(x,y,t+\delta t)$ for $\delta t < T$. Let $K \gg \max\{v_xT, v_yT\}$ be an integer multiple of v_xT and v_yT. Let M and N be the largest integer smaller than $v_xT\frac{K-1}{K}$ and $v_yT\frac{K-1}{K}$ respectively. That is*

$$M = \left\lfloor v_xT\frac{K-1}{K} \right\rfloor \quad \text{and} \quad N = \left\lfloor v_yT\frac{K-1}{K} \right\rfloor,$$

where $\lfloor\cdot\rfloor$ is the floor operator. Then the integral (4) can be evaluated *as*

$$I_o^{LCD}(x,y,t) = \frac{1}{T}\int_0^T I_c(x - v_x\tau, y - v_y\tau, t-\tau)d\tau \approx \sum_{i=0}^{M}\sum_{j=0}^{N} I_c(x-i, y-j, t)h(i,j), \quad (5)$$

where $h(i,j)$ is defined in Definition 1.

Proof. We first explain the assumption that $I_c(x,y,t) \approx I_c(x,y,t+\delta t)$ if $\delta t < T$. Digital video is a sequence of temporally sampled images of a continuous scene. Unless the scene contains extremely high frequency components such as a checkerboard pattern, typically the correlation between frames is high. Since no intermediate image is captured between two consecutive frames, we assume that $I_c(x,y,t) \approx I_c(x,y,t+\delta t)$ if $\delta t < T$. Other assumptions about the intermediate images are also possible, such as a linear translation from frame $I_c(x,y,t)$ to $I_c(x,y,t+T)$. For simplicity we assume that $I_c(x,y,t)$ holds until the next sample arrives.

Using this assumption we have

$$I_o^{LCD}(x,y,t) = \frac{1}{T}\int_0^T I_c(x - v_x\tau, y - v_y\tau, t-\tau)d\tau \approx \frac{1}{T}\int_0^T I_c(x - v_x\tau, y - v_y\tau, t)d\tau. \quad (6)$$

Let $K \gg \max\{v_xT, v_yT\}$ be an integer multiple of v_xT and v_yT. Also let the finite difference interval $\Delta\tau = \frac{T}{K}$. Then the integral in (6) can be approximated by finite sum

$$\begin{aligned} I_o^{LCD}(x,y,t) &\approx \frac{1}{T}\int_0^T I_c(x - v_x\tau, y - v_y\tau, t)d\tau \\ &\approx \frac{1}{T}\sum_{k=0}^{K-1} I_c(x - v_x k\Delta\tau, y - v_y k\Delta\tau, t)\Delta\tau \\ &= \frac{1}{K}\sum_{k=0}^{K-1} I_c\left(x - k\frac{v_xT}{K}, y - k\frac{v_yT}{K}, t\right). \quad (7) \end{aligned}$$

Now assume that $I_c(x,y,t)$ is a digital image at a particular time t. Since the image is composed of a finite number of pixels and each pixel has a finite size, we have $I_c(x,y,t) = I_c(x+\Delta x, y+\Delta y, t)$ if $|\Delta x| < 1$ and $|\Delta y| < 1$. Therefore, the above sum can be broken into a few groups, and within each group the values are identical. By considering $\mathcal{S}_x$, $\mathcal{S}_y$ and $\mathcal{S} = \{s_1, s_2, \ldots\}$ as in Definition 1, we have

$$\begin{aligned} I_o^{LCD}(x,y,t) &= \frac{1}{K}\sum_{k=0}^{K-1} I_c\left(x - k\frac{v_xT}{K}, y - k\frac{v_yT}{K}, t\right) \\ &= \frac{1}{K}\sum_{k=0}^{K-1} I_c\left(x - \left\lfloor k\frac{v_xT}{K}\right\rfloor, y - \left\lfloor k\frac{v_yT}{K}\right\rfloor, t\right) \\ &= \frac{1}{K}\Big[\sum_{k=0}^{s_1-1} I_c(x,y,t) + \sum_{k=s_1}^{s_2-1} I_c(x-i_1, y-j_1, t) + \ldots \\ &\quad + \sum_{k=s_P}^{K-1} I_c(x-i_N, y-j_N, t)\Big], \end{aligned}$$

where (i_k, j_k) are indices whose increment is determined by finding out whether s_k is in $\mathcal{S}_x$ or $\mathcal{S}_y$ (see Definition 1).

Using the definition of $h(i,j)$ in Definition 1, we can further simplify the above expression as

$$\begin{aligned} &I_o^{LCD}(x,y,t) \\ &\approx \frac{1}{K}\Big[\sum_{k=0}^{s_1-1} I_c(x,y,t) + \sum_{k=s_1}^{s_2-1} I_c(x-i_1, y-j_1, t) + \ldots \\ &\quad + \sum_{k=s_N}^{K-1} I_c(x-i_N, y-j_N, t)\Big], \\ &= \sum_{i=0}^{M}\sum_{j=0}^{N} I_c(x-i, y-j, t)h(i,j), \end{aligned}$$

where $M = \lfloor v_xT\frac{K-1}{K}\rfloor$ and $N = \lfloor v_yT\frac{K-1}{K}\rfloor$. □

As we explained before, the importance of Theorem 1 is that the *temporal* problem is transformed into a *spatial* problem. Therefore, the temporal motion blur can now be treated as spatial blur problem.

2.3. Example

To illustrate the meaning of the parameters in the theorem, we show an example. Suppose an image is subejcted to a diagonal motion of $v_x = 180$ pixel/sec and $v_y = 180$ pixel/sec. The video is playing at 60 fps and so $T = 1/60$ sec. Since $\max\{v_xT, v_yT\} = 3$, we may define $K = 6$ (K can be any integer multiple of $\max\{v_xT, v_yT\}$). Let $k = 0,1,2,3,4,5$, then $i = 0,1,2$ and $j = 0,1,2$, $M = 2$ and $N = 2$.

We define $S_x = \{0,2,4,6\}$ and $S_y = \{0,2,4,6\}$. Concatenate and sort $\mathcal{S}_x$ and $\mathcal{S}_y$ we have $\mathcal{S} = \{0,2,4,6\}$. Therefore, we have

- $h(0,0) = (2-0)/6 = 1/3$,
- $h(1,1) = (4-2)/6 = 1/3$,
- $h(2,2) = (6-4)/6 = 1/3$,

and $h(i,j) = 0$ for otherwise.

2.4. Discussion

Before we proceed further we would like to point out a few interesting observations.

First, in coherence to what we discussed before the derivation, the above model shows that the perceived LCD blur is a temporal average, but it can be approximated by a spatial average.

Second, the skewness of $h(i,j)$ is determined by the direction of the motion. If $v_x = v_y$ (as in our example), then $h(i,j)$ becomes diagonal; If $v_x = 0$, then $h(i,j)$ becomes vertical; If $v_y = 0$, then $h(i,j)$ becomes horizontal. In these three special cases, all the non-zero entries of $h(i,j)$ are identical because the points are sampled uniformly on the Cartesian grid. But if the direction is not horizontal, vertical or diagonal, then entries of $h(i,j)$ cannot be identical. A point closer to the line segment is larger than if it is farther from the line segment.

Third, magnitude of the motion determines the length of the filter $h(i,j)$, hence the blurriness of the perceived image. If there is no motion, then $h(i,j) = 1$ and so there will be no blur. However, if the motion is large, then $h(i,j)$ will be long and so the averaging effect will be strong.

Fourth, compared to a 60Hz LCD monitor, a 240Hz LCD monitor shows better perceptual quality because it refreshes 4 times faster than a 60Hz monitor. This effect can be reflected by reducing the hold time T and hence the length of the filter $h(i,j)$.

2.5. Eye Tracking

In the above derivation, it was assumed that the eye tracking is perfect, meaning that the eye is able to track at any speed. However, this is not valid. In [13], He et at demonstrated that by truncating the FIR filter of motion blur to its first zero, the MCIF gives the better results than without truncating. Therefore, limiting the eye tracking speed should improve the modeling. We now point out some papers in cognitive science literature that justifies this finding.

1. Westerink and Teunissen [15] conducted two experiments about the relation between perceptual sharpness and the picture speed. In their first experiment, they asked the viewers to track a moving image with their heads stay at a fixed position (referred to as the fixation condition). The conclusion is that the perceived sharpness drops to a minimum score when picture speed is beyond 5 deg/s.
2. Bonse [16] studied a mathematical model for temporal subsampling. They mentioned that there is a maximum eye tracking velocity of 5 to 50 deg/s, which had been experimentally justified by Miller and Ludvigh [17].
3. Glenn and Glenn [18] studied the discrimination of human eyes on televised moving images of high resolution (300-line) and low resolution (150-line). Their results showed that it is harder for human eye to discriminate high resolution from low resolution images if the speed increases.

The conclusion of these findings is that when picture motion increases, the perceptual sharpness decreases. In some experiments, the maximum picture speed is found to be 5 deg/s for fixation condition. Beyond this threshold, our eyes are unable to capture visual content from the image.

The maximum tracking speed implies that the LCD model has to be written as

$$\begin{aligned} I_m(x,y,t) &= I_s(x-u_xt, y-u_yt, t) \\ &= \int_0^T h_D(\tau) I_c(x - v_x\tau - (u_x - v_x)t, \ldots \\ &\quad \ldots y - v_y\tau - (u_x - v_x)t, t-\tau)d\tau. \end{aligned} \tag{8}$$

where u_x and u_y are the eye tracking speed. If the picture speed is low, then our eyes are able to capture the visual content, and hence $u_x = v_x$ and $u_y = v_y$. However, if the picture speed is beyond the threshold, then the difference $(u_x - v_x)\tau$ accounts for the images that we cannot see.

The consequence of the maximum eye tracking speed is the maximum size of $h(i,j)$. One of the main applications for LCD modeling is to design inverse filters to compensate the motion blur, such as [7], [19] and [20]. Since $h(i,j)$ can be regarded as a low pass filter, the inverse filter of $h(i,j)$ must be a high pass filter. If the motion is large, then the frequency bandwidth of $h(i,j)$ is narrow and hence the inverse filter can be unstable. Since eyes cannot track a fast moving object anyway, it is not reasonable to model a long $h(i,j)$ and inverse filter the image. Instead, it is more appropriate to limit the span of $h(i,j)$ as

$$h(i,j) = \begin{cases} h(i,j), & \text{if } i \le L \text{ and } j \le L, \\ 0 & \text{else }, \end{cases}$$

where L is the maximum length of the line segment, and is a constant depending on the particular display system.

2.6. Numerical Implementation of Theorem 1

Algorithm 1 is a pseudocode for numerically implementing Theorem 1. The algorithm consists of four steps. In the first step, motion vectors have to be computed. This can be done via any motion estimation algorithms available in the literature, for example full search, three step search [21], directional methods [22], or hybrid methods [23]. The second step is to define the blur kernel $h(i,j)$ according to definition (1), based on the motion vector information. Note that each $h(i,j)$ is only defined locally, meaning that one motion vector defines one $h(i,j)$. So a motion vector field corresponds to a collection of $h(i,j)$. In step 3, $h(i,j)$ is limited to a finite length and width for modeling the eye tracking property. Last, the output can be computed via a discrete convolution shown in Equation (5).

Algorithm 1 Compute $h(i,j)$ and $I_o^{LCD}(x,y,t)$

Fix a time instant t, and LCD decay time T.
Step 1: Use motion estimation algorithm to detect (v_x, v_y).
Step 2: Define weights $h(i,j)$ according to Definition 1.
Step 3: Set $h(i,j) = 0$, if $i > L$ or $j > L$ for some L.
Step 4: Compute $I_o^{LCD}(x,y,t)$ using via discrete convolution in Equation (5).

3. EXPERIMENTS

3.1. Comparison between Spatial and Temporal Integration

To verify Theorem 1, we compare the simulated motion blur using the temporal integration (Equation (4)) and spatial integration (Equation (5)). To correlate these simulation results to experiments, we refer to [24], where the authors experimentally demonstrated the spatial-temporal equivalence for black-and-white bars.

Fig. 3 shows four simulation results [1]. For each video sequence, two consecutive frames are collected, and the relative motion is computed using a full search algorithm [21]. 10 motion compensated frames are inserted via standard H.264 MC algorithm. This is to simulate a continuous time signal. The temporal integration is calculated as the average of the 10 motion compensated frames, and they are shown in the third row of Fig. 3. On the other hand, the spatial integration is calculated using Theorem 1, where $h(i,j)$ are determined from the given motion vector information.

To measure the discrepancy of spatial integration to the temporal integration, a PSNR value is computed for each of the sample image. As shown, on average the PSNR is higher than 40dB, which implies a small difference between the two images.

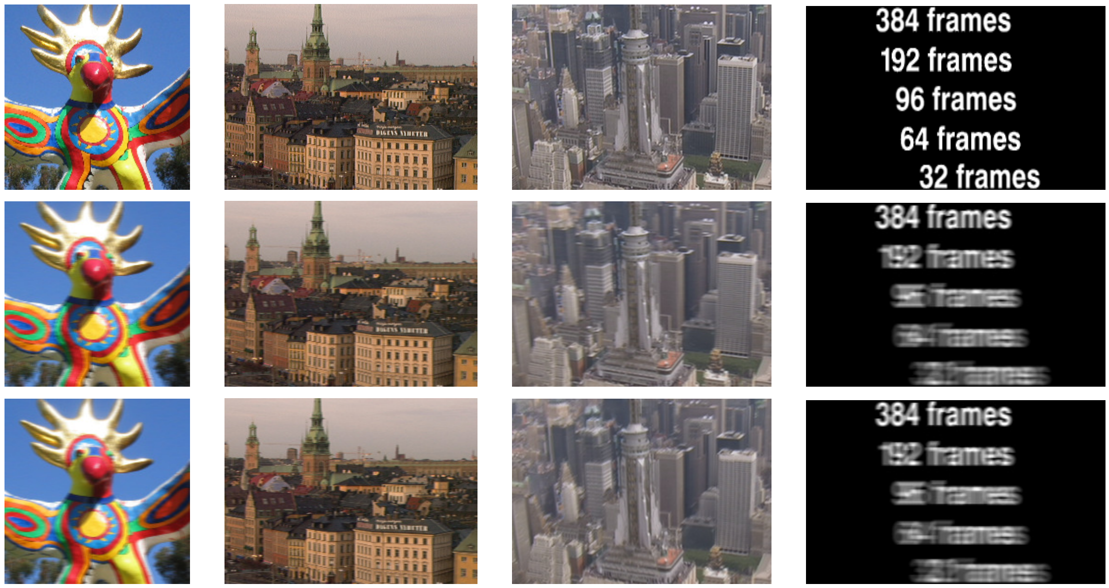
Image	Size	Maximum MV	PSNR
A	200×200	4.35	42.45dB
B	640×480	3.71	41.34dB
C	320×240	7.23	41.10dB
D	300×600	10	40.81dB

Table 1. Comparison between spatial integration and temporal integration. Maximum MV refers to the maximum motion vector in the image. PSNR is computes as the difference from the spatial integration to the temporal integration.

3.2. Maximum Length L

As we discussed in Section II, the point spread function cannot be infinitely long, and so there is an upper limit to the length of $h(i,j)$. In this experiment, we try to determine this upper limit from a human subjective perspective.

[1] Results are available online at `http://videoprocessing.ucsd.edu/~stanleychan`



A B C D

Fig. 3. Simulation results of spatial and temporal integration. Top row: original input image; middle row: simulated blur using spatial integration; bottom row: simulated blur using temporal integration.

There are three video sequences in this experiment. Given an estimate of the point spread function using Algorithm 1, we truncate it using different length L. Then following the procedure suggested in [20], inversely synthesized signals can be generated. Here the conjugate gradient problem is solved using a damped LSQR [25] with damping constant $\lambda = 10^{-1}$. Maximum number of iteration is set to be 100, and tolerance level is set to be 10^{-6}.

Fig. 4 shows a few cases of setting different maximum length L. When L increases, it can be observed that more artifacts is introduced. To measure these artifacts, we calculate the average total variation metric around neighborhood pixels:

$$e = \Big(\frac{1}{MN} \sum_{i,j} |X(i+1,j) - X(i,j)|^2 + |X(i,j+1) - X(i,j)|^2 \Big)^{1/2}. \tag{9}$$

The value of e for the images shown in Fig. 4 is listed in Table 2.

L	Video 1 Shield	Video 2 Stockholm	Video 3 Black White
1	0.0465	0.0546	0.0478
2	0.0589	0.0764	0.0504
3	0.0655	0.0895	0.0533
4	0.0896	0.1205	0.0608
5	0.1010	0.1279	0.0581
6	0.1146	0.1412	0.0620

Table 2. Average total variation error around adjacent pixels increases when maximum length L increases.

The maximum length L is determined by a human visual subjective test. The testing procedure follows ITU-R BT. 1082, Section 8 [26]. 18 human viewers were invited to the experiment. For each of the three video sequences, there are six levels of the maximum lengths ($L = 1, \ldots, 6$). $L = 1$ means $h(i,j)$ has length of 1, which in turn implies no processing. $L = 6$ means $h(i,j)$ is at most length 6, and so there are substantial processing. Each time the viewer will be presented a reference and a processed video sequence simultaneously. They were asked to tell whether the processed one shows any distracting artifacts. If they replied not, then L will be increased until the level such that noise are appealing. The videos are played on a PC with 2.8GHz CPU, 8GB DDR2 RAM, ATI Radeon 2600 XT 512MB video card. The video sequences are uncompressed, 60 frames per second.

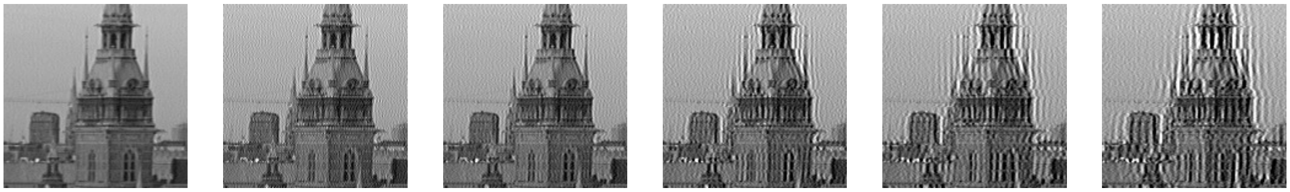
Subjective Test to determine optimal L			
	Video 1 Shield	Video 2 Stockholm	Video 3 Black White
mean	4.19	3.89	3.39
std	0.67	0.65	0.90

Table 3. The subjective tests to determine the optimal length L.

The mean and variance of the best L determined by the subjective test is shown in Table 3. It can be observed that on average $L = 4$ is the optimal length. It is also interesting to point out that some viewers report the video sharpest at the optimal length.

4. CONCLUSION

This paper has two contributions. First, we proved the equivalence between temporal and spatial integration. The equivalence allows us to simulate the LCD blur efficiently in the spatial domain, instead of a time consuming integration in the temporal domain. Experiments verified that computing the LCD motion blur in the spatial domain is as accurate as computing it in the temporal domain. Second, we studied the limit of eye movement speed. Based on a number of papers in the cognitive science literature, we showed that perceptual quality reduces as picture motion increases. Beyond certain speed limit, human eyes cannot retrieve any useful content from the picture. Consequently, we showed that it is more reasonable to limit the length of the LCD motion blur FIR filter. We also found the optimal length of the filter by visual subjective tests.



$L = 1$ $L = 2$ $L = 3$ $L = 4$ $L = 5$ $L = 6$

Fig. 4. Video 2 Stockholm. The sequence is processed using [20], with different truncation of L.

5. REFERENCES

[1] Shin-Tson Wu and Deng-Ke Yang, *Fundamentals of Liquid Crystal Devices*, Wiley, Sep 2006, ISBN-13: 978-047001542.

[2] Erik Reinhard, Erum Arif Khan, Ahmet Oguz Akyuz, and Garrett Johnson, *Color Imaging Fundamentals and Applications*, A K Peters, 2008.

[3] N. Fisekovic, T. Nauta, H. Cornelissen, and J. Bruinink, "Improved motion-picture quality of am-lcds using scanning backlight,," *Proc. IDW*, pp. 1637–1640, 2001.

[4] Sunkwang Hong, Brian Berkeley, and Sang Soo Kim, "Motion image enhancement of LCDs," in *Proc. International Conference on Image Processing*. IEEE, 2005.

[5] BW. Lee, K. Song, DJ. Park, Y. Yang, U. Min, S. Hong, C. Park, M. Hong, and K. Chung, "Mastering the moving image: Refreshing TFT-LCDs at 120 hz," in *SID Symposium Digest of Technical Papers*. SID, 2005.

[6] N. Mishima and G. Itoh, "Novel frame interpolation method for hold-type displays," in *Proc. International Conference on Image Processing*, 2004, vol. 3, pp. 1473–1476.

[7] M. Klompenhouwer and L. Velthoven, "Motion blur reduction for liquid crystal displays: Motion compensated inverse filtering," in *Proceedings of SPIE-IS&T Electronic Imaging*. SPIE, 2004.

[8] F. H. Heesch and M.A. Klompenhouwer, "Spatio-temporal frequency analysis of motion blur reduction on LCDs," in *in International Conference on Image Processing*, 2007, vol. 4, pp. 401–404.

[9] Michael E. Becker, "Motion blur measurement and evaluation: From theory to the laboratory," *SID Symposium Digest of Technical Paper*, vol. 38, no. 1, pp. 1122–1125, May 2007.

[10] Sylvain Tourancheau, Kjell Brunnstrom, Borje Andrrn, and Patrick Le Callet, "Motion blur estimation on lcds," in *SID International Symposium, Seminar and Exhibition*, Los Angeles, 2008.

[11] Yonatan Wexler, Eli Shechtman, and Eli Shechtman, "Space-time completion of video," *IEEE Transcations on Pattern recongition and Machine Intelligence*, vol. 29, pp. 1–14, March 2007.

[12] Hao Pan, Xiao-Fan Feng, and Scott Daly, "LCD motion blur modeling and analysis," in *Proc. International Conference on Image Processing*. IEEE, 2005.

[13] Haiyan He, Velthoven L.J., E. Bellers, and J.G. Janssen, "Analysis and implementation of motion compensated inverse filtering for reducing motion blur on lcd panel," in *Digest of Technical Papers. International Conference on Consumer Electronics, 2007. ICCE 2007*, 2007, pp. 6.3–1.

[14] Michiel A. Klompenhouwer, "Comparison of LCD motion blur reduction methods using temporal impulse response and MPRT," *SID Symposium Digest of Technical Papers*, vol. 37, pp. 1700–1703, 2006.

[15] Joyce Westerink and Kees Teunissen, "Perceived sharpness in complex moving images," *Display*, vol. 16, no. 2, pp. 89–97, 1995.

[16] Thomas Bonse, "Visually adapted temporal subsampling of motion information," *Signal Processing: Image Communication*, vol. 6, pp. 253–266, 1994.

[17] J.W. Miller and E. Ludvigh, "The effect of relative motion on visual acuity," *Survey of Ophthalmology*, vol. 7, pp. 83–116, 1962.

[18] W. Glenn and K. Glenn, "Discrimination of sharpness in a televised moving image," *Displays*, vol. 6, pp. 202–206, 1985.

[19] Shay Har-Noy and Truong Q. Nguyen, "LCD motion blur reduction: A signal processing approach," *IEEE Trans. on Image Processing*, vol. 17, pp. 117–125, Feb 2008.

[20] Stanley Chan and Truong Q. Nguyen, "Fast LCD motion deblurring by decimation and optimization," in *International Conference on Acoustics, Speech and Signal Processing 2009*, 2009.

[21] Yao Wang, Jorn Ostermann, and Ya-Qin Zhang, *Video Processing and Communications*, Prentice Hall, 2002.

[22] Yoon Kim, Kang-Sun Choi, Jae-Young Pyun, Byung-Tae Choi, and Sung-Jea Ko, "A novel de-interlacing technique using bidirectional motion estimation," in *Computational Science and Its Applications*, Heidelberg, 2003, vol. 2667 of *Lecture Notes in Computer Science*, p. 971, Springer Berlin.

[23] Stanley Chan, Dung Vo, and Truong Nguyen, "Subpixel motion estimation without interpolation," in *IEEE International Conference on Acoustics, Speech and Signal Processing*, 2010, available at `http://videoprocessing.ucsd.edu/~stanleychan`.

[24] Xiaofan Feng, Hao Pan, and Scott Daly, "Comparison of motion blur measurement in lcd," *SID Symposium Digest of Technical Papers*, vol. 38, no. 1, pp. 1126–1129, May 2007.

[25] Christopher C. Paige and Michael A. Saunders, "Lsqr: An algorithm for sparse linear equations and sparse least squares," *ACM Transactions on Mathematmal Software*, vol. Vol 8, no. 1, pp. 43–71, March 1982.

[26] Report 1082-1, "Studies toward the unification of picture assessment methodology," Tech. Rep., ITU, 1986.