submitted to *Medical Physics*

accepted for publication on Sep 2, 2009

Liquid crystal display response times estimation for medical applications

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(Dated: September 4, 2009)

Abstract

Purpose: Accurate characterization of diagnosis instruments is crucial in medical applications such as radiology and clinical neurosciences. While classical CRT medical displays have been replaced almost exclusively with liquid crystal devices (LCDs) the assessment of their temporal properties (response times) is still largely based on heuristic methods, which have not been evaluated thoroughly yet. We introduce a novel approach and show that it improves the accuracy and reliability compared to the common heuristic recommended by ISO 9241-305 substantially for a wide range of settings.

Methods: Our approach is based on disentangling the signal from the modulatory backlight through division (division approach). We evaluated this method in two different ways: First, we applied both methods to luminance transition measurements of different LCD monitors. Second, we simulated LCD luminance transitions by modeling the LCD optical responses according to a physical liquid crystal director orientation model. Simulated data was generated for four different response times, each with four different backlight modulation frequencies. Both the novel and the ISO convolution method were applied to the data.

Results: Application of the methods to simulated data shows a bias up to 46% for the ISO approach while the novel division approach is biased at most 2%. In accordance with the simulations, estimates for real measurements show differences of the two approaches of more than 200% for some LCD panels.

Conclusion: Our division approach is robust against periodic backlight fluctuations and can reliably estimate even very short response times or small transitions. Unlike to the established method, it meets the accuracy requirements of medical applications. In contrast, the popular convolution approach for estimating response times is prone to misestimations of time by several orders of magnitude, and tend to further worsen as advances in LCD technology lead to shorter response times.

Keywords: liquid crystal display, temporal characteristics, response time, estimation, backlight

INTRODUCTION AND PURPOSE

Active matrix liquid crystal displays (LCDs) are not only the most popular type of contemporary computer displays, but are also increasingly used in medical imaging workstations. As recently stated[1], there are special demands on the temporal precision of medical LCDs. Clinical diagnosis tests as well as psychophysical experiments in basic research, often require the accurate control of the presentation duration of visual stimuli. Similarly, visible artefacts for motion stimuli are primary concern of display manufacturers and a large amount of research effort goes into minimizing such artefacts. Radiologists, for instance, need to browse through and analyze large amounts of computed tomography image data sets and often use stack-mode reading (rapid serial presentation) to detect subtle visual differences. Inhomogeneous response times could lead to misleading contrast artefacts and cause the failure to notice important details.

The key parameter for temporal characterizations of LCDs is the "response time" which is the time needed to switch from one luminance level to another. This is usually specified between the 10% level and 90% level of the transition.

Problem statement

We regard the transition as a monotonic function of time $s(t)$ (light transmission function of the liquid crystal). The main problem for determining the response time is that $s(t)$ is modulated by a periodic signal $m(t)$ (usually with a dominant frequency $f_d \geq 100\text{Hz}$). The modulation is due to the pulse-width modulation (PWM) that dims the cathode fluorescent or LED lamps of the display's backlight. It is present even at maximal brightness settings of modern monitors, and its max. amplitude A_{max} typically increases with decreasing backlight luminance. In real world measurement situations, the signal is additionally distorted by additive white noise $\nu(t) \sim N(0, \epsilon)$ with $\epsilon \ll A_{max}$. The measured output $y(t)$ can be modeled by

$$y(t) = m(t)s(t) + \nu(t). \tag{1}$$

Fig. 1(a) to (d) illustrates our assumptions about $y(t)$ for simulated signals.

Furthermore, we assume that the measured data covers the initial plateau level, the transition phase, the target level and at least one period of the modulatory signal at either

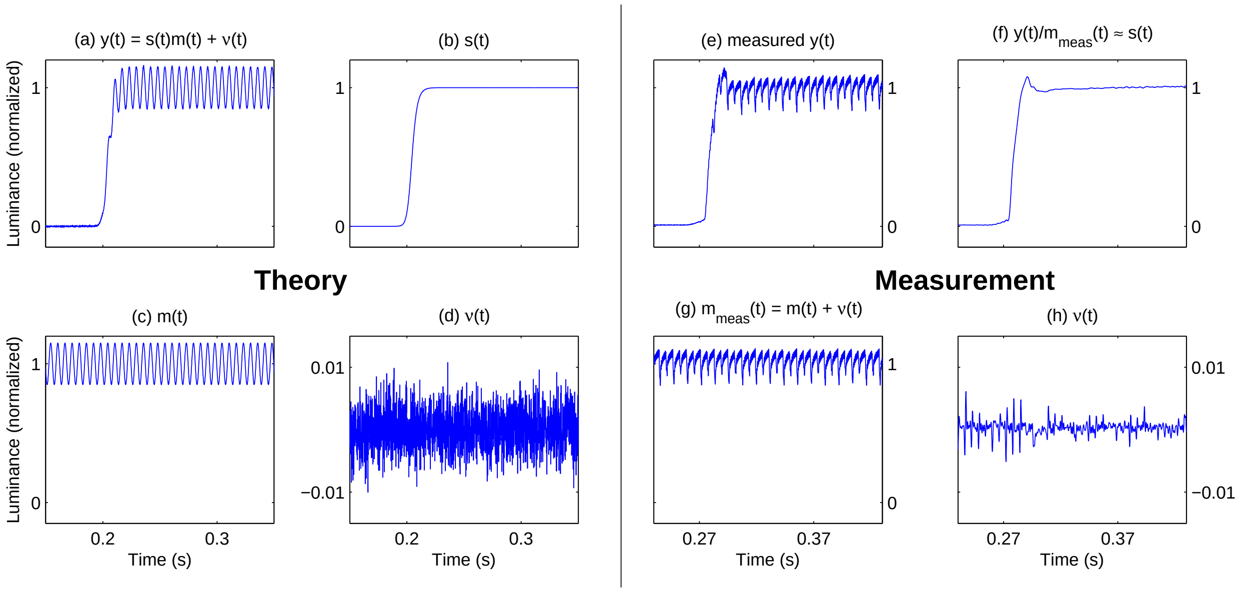

FIG. 1: Sketch of our model of the transition signal ((a) to (d)) and the corresponding decomposition of an actual measurement ((e) to (h)). (e) is a 0% to 100% luminance transition measurement of an Eizo CG222W monitor. (f) was calculated by the division method described in this work. (g) is a 100% constant level measurement of the same monitor. (h) was calculated by dividing two independent constant level measurements (one of them shown in (g)). It is actually the quotient of the two independent measurement noises and represents the type of noise remaining after division (e.g., in signal (f)).

of the two levels.

Our goal is to estimate the response time $t_b - t_a$ between two plateau levels $s_a = s(t_a)$ and $s_b = s(t_b)$ as accurately as possible in terms of bias and variation.

The standard approach: Convolution

For transition problems as stated above, a widely used approach is to determine the dominant (i.e. with max. energy) frequency f_d from the frequency spectrum of $y(t)$ and to filter $y(t)$ with a moving average window w of length $\frac{1}{f_d}$. In the following we refer to this as the *convolution approach*. This approach is the current measurement standard for LCD response times[2,3] and applied in medical display metrology[1].

The main idea of the approach is that, if there is only a finite number of dominant frequencies, ideal filtering would yield $m(t) \rightarrow m'(t) \approx 1$ and $\nu(t) \rightarrow \nu'(t)$ with corresponding $\epsilon' \approx 0$. Therefore, the filtered signal $z(t)$ would be

$$z(t) = \text{convolution}(y, w) \approx s(t) + \nu'(t) \approx s(t). \tag{2}$$

Deficiencies of the convolution approach

The convolution leads to a misestimation of the duration of the transition times. In general, the smaller $s(t)$ or f_d, the larger is its bias (average deviation). As LCD device manufacturers attempt to minimize transition times, this error has increased steadily over the past few years. In our measurements we found differences of more than 200% (see Fig. 2) to our new approach or visual inspection. Averaging over repeated measurements might reduce the variation but is usually not feasible if a large number of transitions need to be examined.

A recently proposed error correction[4] fits a sigmoid function σ to the transition, calculates the convolution of σ for different average windows w, and finally introduces a *correction factor* $k(w)$. This correction, however, fails when transition times are short compared to w (see Becker, 2008[4]). Given recent advancements in reducing transition time with overdrive technology (see Conclusions), such failures become increasingly likely.

Here, we present a method which is fundamentally different from the convolution approach and which also works for arbitrarily short transition times.[13]

METHODS

We try to solve a system identification problem with the output $y(t)$, the unknown system $s(t)$ and the input $m(t)$, which we can determine independently given our assumptions.

In order to estimate $s(t)$ from $y(t)$, our novel *division approach* follows from (1):

$$s(t) = \frac{y(t) - \nu(t)}{m(t)} \approx \frac{y(t)}{m(t)} \tag{3}$$

(for measurement noise $\epsilon \ll A_{max}$). First, $m(t)$ is estimated as described in the next section. After the calculation of $s(t)$ according to (3), the response times are determined as the duration between the 10% and the 90% levels of the transition between l_1 and l_2 according to the standard for LCD response time measurement[2]. In case of the signal exceeding the

90% threshold multiple times, we choose the first occurrence for rising transitions and the last occurrence for falling transitions.

Determination of $m(t)$

Our measurement of $y(t)$ includes the transition of interest between lower level l_1 and upper level l_2 (i.e. $l_1 < l_2$). $m(t)$ is a periodic modulatory signal independent of $s(t)$. Without modulation $A_{max} = 0$ and $m(t) = 1$.

A straightforward method to obtain $m(t)$ is to measure a constant signal $c(t)$ from the same signal source as $y(t)$ (i.e. a plateau level) which should be sufficiently long to cover a full period of its composing frequencies. $m(t)$ is approximated by a measurement $m_{\text{meas}}(t) = m(t) + \nu(t)$. Assuming relatively small noise $\nu(t)$, we set $m(t) \approx m_{\text{meas}}(t)$.

The upper levels l_2 generally tend to have a better signal–to–noise ratio than l_1. Furthermore it avoids $s(t) = 0$, at which $m(t)$ is not defined. In practice, $y(t) = 0$ or $s(t) = 0$ are unlikely due to imperfect black levels of liquid crystals and environmental illumination. If $m(t) = 0$ at any t, we mask out the sample at t, as $s(t)$ is also not defined. However, such cases are very rare (e.g., due to very large A_{max}) and can usually be avoided (e.g., by disabling black frame insertion).

As $c(t)$ contains a full period, certain phase shifts of $m(t)$ must be fully contained in $c(t)$. That is, $c(t)$ needs to be appropriately shifted and either cut or periodically concatenated to length(y).

The phase shift σ of $c(t)$ (in the following shift(c, σ)) could be obtained, for instance, as the maximum of the cross correlation between $c(t)$ and the l_2 level(s) of $y(t)$. It would, however, ignore the transitions as well as all parts of the signal that belong to l_1.

We applied a more precise method instead: We shifted $c(t)$ horizontally point by point and calculated the quotient $q_\sigma = y/\text{shift}(c, \sigma)$. In addition, we calculated a signal z by the conventional convolution method (2). Then we compared each q_σ and z: We chose the optimal shift $\hat{\sigma}$ from all σ so that for the two plateaus l_1 and l_2, the deviation of z and q_σ was minimal.

Fig. 1(e) shows an exemplary measurement of $y(t)$, (g) a constant level measurement of the same monitor, and (f) the resulting signal $s(t)$ after division.

If there is only very small modulation (small A_{max}), neither convolution nor division are necessary, and the division method would leave the signal effectively unchanged. In such a case, the convolution method, however, might randomly choose a dominant frequency from the unspecific noise, which could harm its reliability as it will use very different moving average windows for repeated measurements.

Further improvements: Dynamical low–pass filtering

When the preprocessed signal is not monotonically changing but still fluctuating (e.g., due to remaining noise), the chance of spuriously exceeding a threshold increases with the duration of the transition. This is a general problem for estimating long response times, possibly resulting in lower reliability of the estimates.

Pre–filtering of the measured signals may reduce the variation of the estimated response times. Simple low–pass filters would smooth the signal and filter out some noise, but also get rid of many higher frequencies which are essential part for transitions with short response time, and distortions in the time domain might be the result. In addition, low–pass filters may introduce additional ripple in the time domain.

Instead, we applied a popular approach for optimal FIR filter design[5] to create a low–pass filter that minimizes ripple in the time domain and, as a side effect, leaves the high frequency band periodically permeable. Its pass band stops at frequency f_p and is followed by a transition band of 20 Hz preceding the stop band. In the following, we refer to this filter as an f_p Hz Parks–McClellan low–pass (PMLP).

In an evaluation with simulated signals (described in one of the following sections), we found that PMLPs hardly impair response times for f_p sufficiently greater than the dominant backlight modulation f_d.

As a further improvement of the division approach, particularly for longer response times T, we pre–filtered the measurements with an f_p Hz PMLP where $f_p = f_d + \frac{1}{T_c}$, with T_c as the response time estimated according to the convolution approach. We refer to this approach as *dynamical low–pass filtering* in the following.

LCD MONITOR MEASUREMENTS

We measured luminance transitions of ten LCD monitors (see Table I for a subset). In addition to the transition, the constant signal of the corresponding higher luminance level was recorded. We performed five independent measurements per condition with an optical transient recorder OTR–3[14].

For the measurements, the OTR sensor was placed over a test patch on the monitor, which was running at its native frame rate of 60 Hz. Monitors were set to manufacturers' settings with maximum contrast. For warm-up monitors were turned on for about 1 hour before measurement.

For the convolution approach, we identified f_d from a discrete Fourier transform. For the division approach (with dynamical low–pass filtering), we shifted the constant measurement as described in the Methods section.

Table I contrasts the averages of response time of both approaches. In most cases, the convolution approach estimates longer response times than the division approach. Its average estimate is longer, the shorter the transition.

Fig. 2 shows a transition with a particular large disagreement and indicates that our division approach can avoid convolution induced deviations of over 200%.

Note the different deviations of the two methods for the different monitors. For the Samsung monitor there is almost no average deviation due to its extraordinarily high dominant backlight modulation frequency (> 700 Hz).

None of the monitor specifications reported details about how the response times have been gathered or about which gray levels were measured. Given the large deviations between the different luminance levels which we found within our few measurements, we consider the sparse information given in the monitor specifications to be of very little use.

SIMULATED DATA

We compared the division approach with the established convolution approach by applying both to simulated data, which makes it possible to estimate the error relative to a known ground truth. An established liquid crystal (LC) director orientation model[6] was applied to simulate a monitor luminance transition from a lower to a higher gray level. The optical

TABLE I: Luminance transition times (in ms) of four typical LCD monitors. Selected luminance levels: 0 (black), 50%, and 100 (white). Vertically and horizontally arranged are initial luminance level ("From") and target level ("To"), respectively. Transition times are specified as t_d/t_c, with t_d = transition according to division approach and t_c= convolution approach. The average is calculated over table cells and shown together with manufacturer's typically very vague information about the response times ("specs"; BTB: black to black, GTG: gray to gray).

↓ *From* \ *To* →	0	50	100
BenQ FP91G+ (average 16.1/18.5, specs: 8 (5,6 + 2,4))			
0	—	31.58/32.88	24.80/27.92
50	1.80/3.55	—	17.70/23.15
100	1.85/3.70	18.95/19.60	—
Eizo CG222W (average 8.5/11.1, specs: 16)			
0	—	13.17/14.07	9.48/13.95
50	6.04/7.66	—	6.60/7.96
100	6.67/12.38	9.32/10.50	—
HP LP2480zx (average 8.4/9.3, specs: 12 BTB, 6 GTG)			
0	—	10.63/11.13	7.02/8.35
50	8.12/7.75	—	6.25/7.15
100	8.75/10.60	9.50/10.95	—
Samsung XL30 (average 10.6/10.5, specs: 6 GTG)			
0	—	5.68/5.67	18.65/18.13
50	5.54/5.66	—	19.40/19.00
100	6.47/6.52	8.08/8.05	—

response function of an LC director reorientation from an angle of $\frac{\pi}{16}$ to $\frac{\pi}{2}$ was modeled.

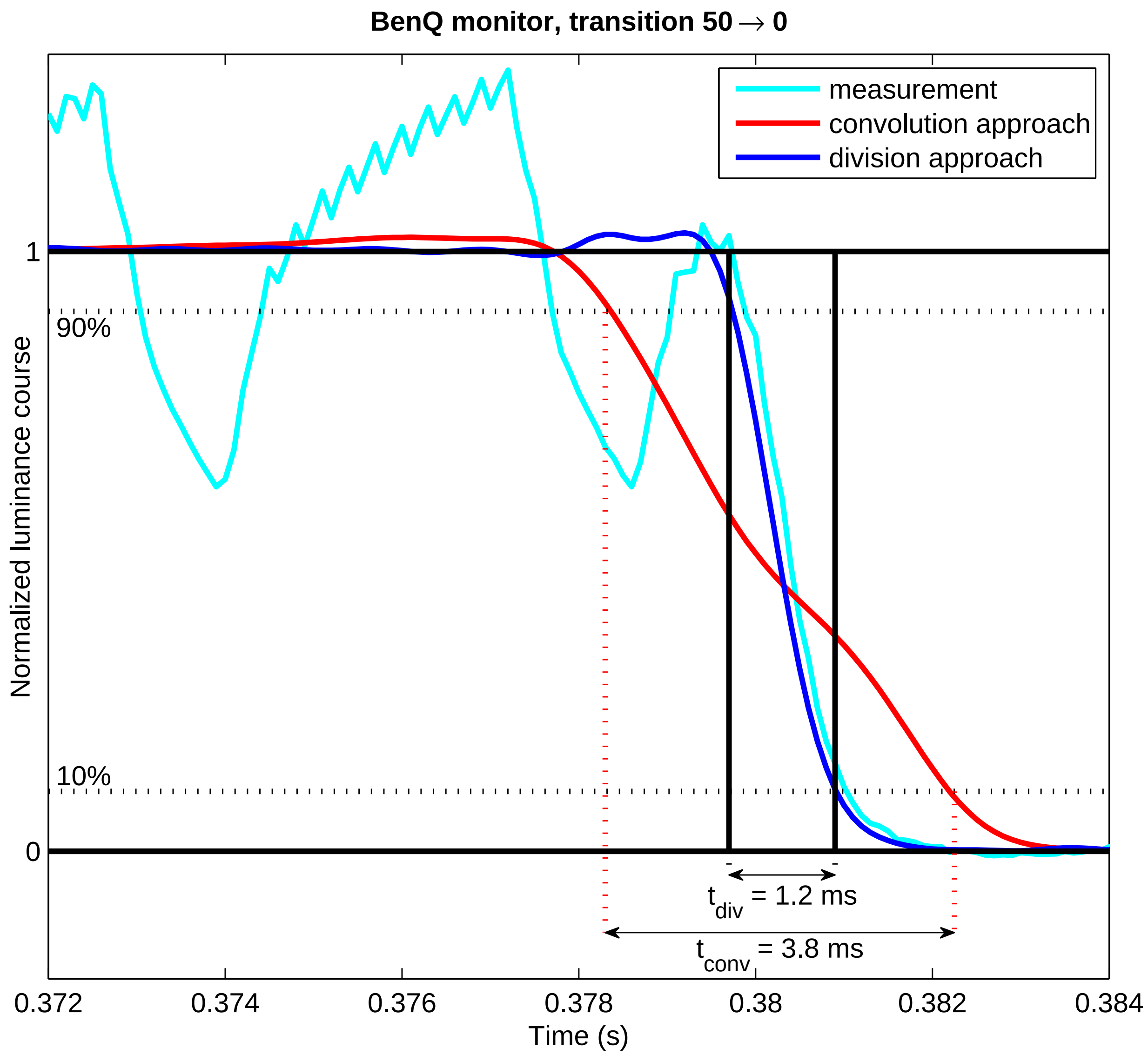

FIG. 2: Comparison of the convolution approach and the division approach for the transition with greatest difference between the two approaches (one of the 50 → 0 transitions of the BenQ monitor). Difference of the two approaches: 1.2 ms vs. 3.8 ms (217%).

150 We simulated a recording of 1 s duration with a transition that exceeds the 10% level after 200 ms and the 90% level $T \in \{5, 10, 15, 20\}$ ms later. An exemplary signal ($T = 10$ ms) is shown in Fig. 1(b).

We simulated the modulatory signal $m(t)$ using sinusoids:

$$m(t) = 1 + A_{max} \sin(2\pi f_d(t - r)) \tag{4}$$

with $A_{max} = 0.15$, $f_d \in \{100, 125, 150, 175\}$ Hz, and a random phase shift $r \in [0, 2\pi]$.

Fig. 1(c) shows an exemplary signal $m(t)$. Note that the division approach works with all periodic signals and not just sinusoids, which were chosen for better control.

Finally, we added white noise ϵ to the signal. Sources of noise in the signal could be the LCD backlight[7] or the measurement devices. In order to estimate realistic noise levels, we took two independent constant level measurements of ten different LCD monitors, and calculated their ratio after performing appropriate phase shifting. In the ideal case only the noise should remain. We obtained white noise with an average variance of $\hat{\epsilon} = 1.94 \cdot 10^{-5}$. The maximal $\hat{\epsilon}$ of the ten measured monitors was $1.44 \cdot 10^{-4}$. For our simulations we chose $\epsilon = 5.76 \cdot 10^{-4}$, which is four times the maximal and about 30 times the average variance. This ensures we have a very conservative estimate of the performance of the method.

The corresponding constant level measurement $c(t)$ was simulated by the same methodology as $m(t)$ (see (4)), but a different random phase shift r was used and a different noise signal was added.

We applied the division approach with a static 800 Hz PMLP and additionally with dynamical low–pass filtering as described in the Methods section.

Fig. 3 summarizes the response time estimations of 200 simulated independent measurements for each of the four true response times T and dominant backlight modulations f_d. The figure shows the relative errors of the estimations (absolute difference between median and T) as well as the quartiles (blue boxes). The box lengths (interquartile ranges, "middle fifty") demonstrate the variation of the data. The quartiles are better for indicating the skewness of some of the distributions than the mean (which was typically very close to the median) and variance.

Yellow bars ("conv") show the bias of the convolution approach, increasing with decreasing T and f_d and ranging up to 46%.

For comparison, we included the pure division approach without low–pass filtering: Orange bars ("div") indicate that the division approach is much more accurate (maximal bias: 2%). The shorter the response time, the larger are the variations. For slow T it tends to underestimate the times since we defined the end of the transition as the first time it exceeds the 90% threshold.

The recommended dynamical low–pass filtering ("div_dyn", red bars) generally reduce both bias and variation.

To sum up, our division approach is robust, more accurate, and avoids the errors for short

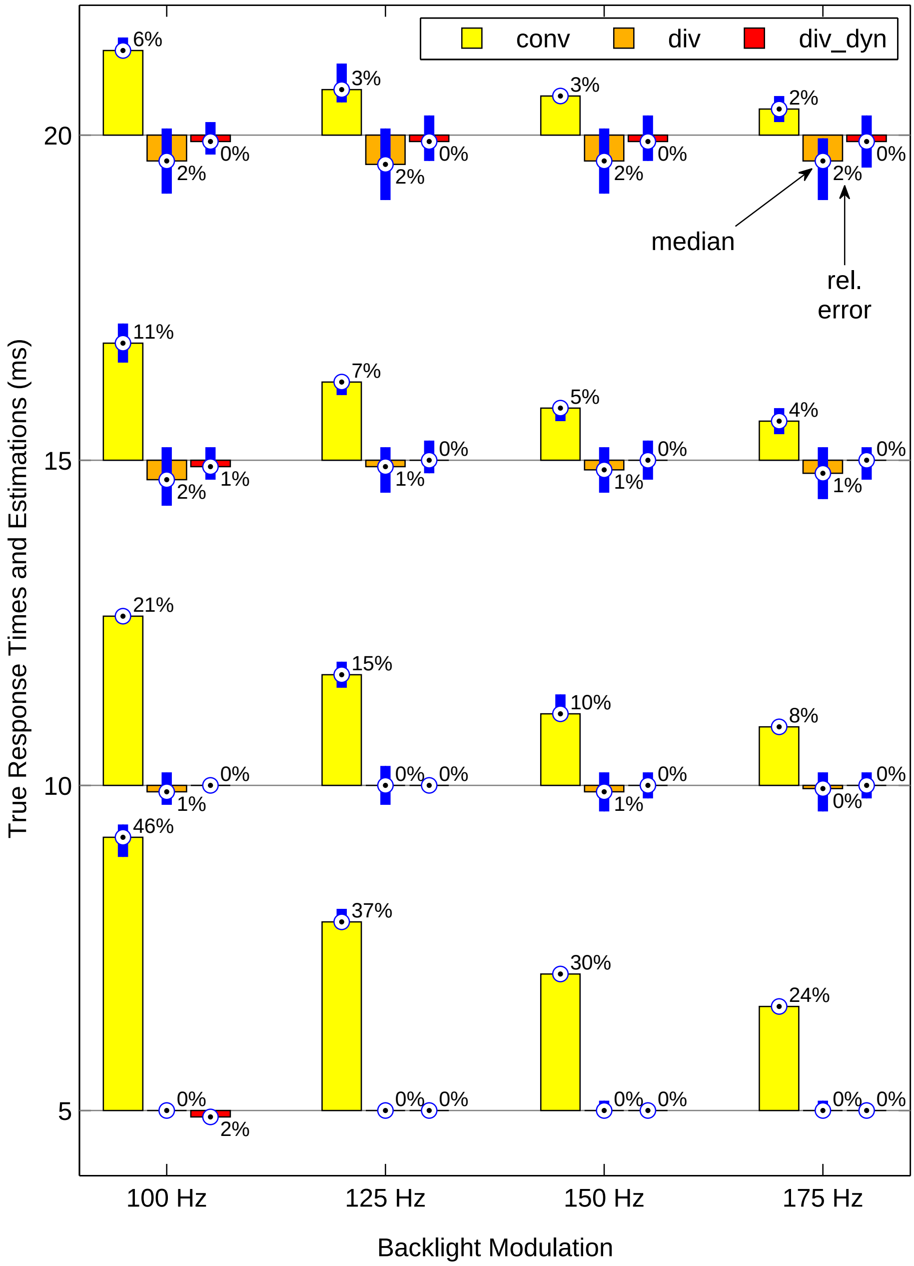

FIG. 3: Comparison of three methods (conv: convolution approach, div: division approach, div_dyn: division approach with dynamical low–pass filtering) applied to simulated data. Black horizontal lines indicate the four true response times, the bars the relative errors (bias). The columns represent the four different dominant backlight frequencies. The narrow blue boxplots contain median (central mark) and 1st and 3rd quartiles (box edges).

response times. For longer response times the application of dynamical low–pass filtering is recommended. Note that the simulations have been performed with extraordinarily strong noise and that real world measurements yield less variations and an increase in robustness.

SMALL TRANSITIONS

In certain applications detecting very tiny visual differences can be crucial; e.g., in computed tomography, the differences of only a few Hounsfield units may correspond to nearby luminance levels of imaging devices.

Transitions between nearby luminance levels are a challenge for both the convolution method and our division approach as the signal-to-noise ratio is much lower. However, as we can infer from the previous section, the critical point for response time methods is the nature of noise signal $\nu(t)$. The convolution method is supposed to eliminate $\nu(t)$ implicitly together with the elimination of the backlight modulations $m(t)$ by the moving average, whereas the division method with dynamical filtering tries to apply specific filters for $\nu(t)$ which keep $m(t)$ unaffected.

In the following, we report simulations as in the previous section, however, using the measured noise $\nu_m(t)$ of the Eizo CG222W monitor. It was obtained by dividing two independent constant level measurements (scaled to the same luminance level as the upper level of the simulated signal). A part of this signal is shown in Fig. 1(h). This procedure makes it possible to mimic the transition behavior of a real monitor without measuring it.

We simulated a small luminance transitions from 50% to 60% as well as from 50% to 55% luminance level. The modulatory signal $m(t)$ and the ground truth transition signal $s(t)$ were generated in the same way as described in the previous section, except that $s(t)$ was scaled and shifted to the intervals $[0.5, 0.6]$ and $[0.5, 0.55]$, respectively. According to the LC director orientation model the shape of the transition would not change but the relative influence of $m(t)$ and $\nu_m(t)$ would increase strongly. The estimated measurement noise $\nu_m(t)$ was randomly phase shifted over the transition for each simulated signal.

Fig. 4 shows the simulation results. For both methods, there is much more variation (and hence, less reliability) compared to the simulated 0%–100% transitions (Fig. 3). In general, the large bias of the convolution method is unchanged (up to 46%, compared to $\leq 2\%$ for div_dyn).

The variations, represented by the interquartile distances (IQD, blue bars) show that for $T = 5$ ms, IQDs for both conv and div_dyn are equally small, whereas for all $T > 5$ ms, the

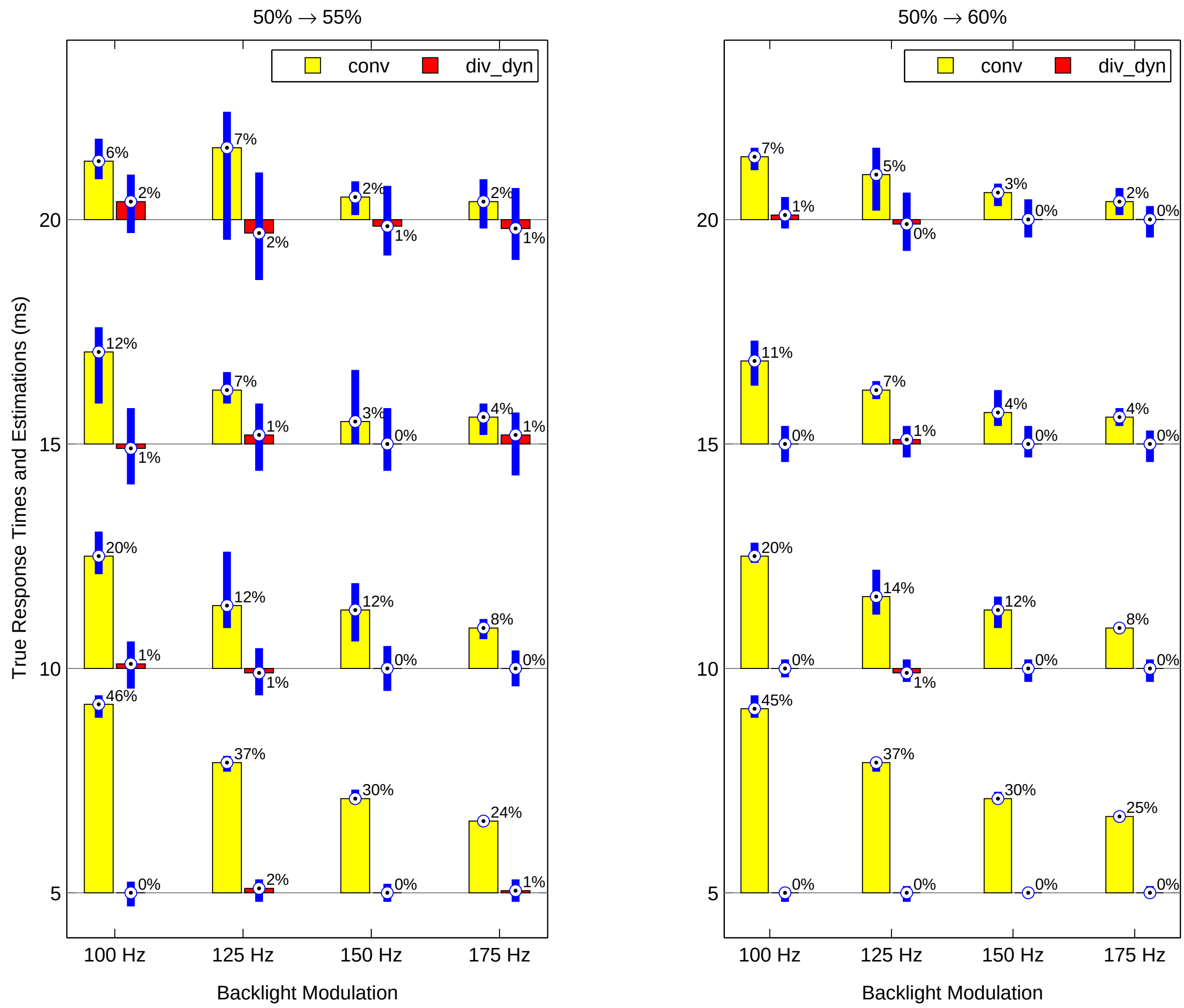

FIG. 4: Small luminance transition (left: 5%, right: 10% difference) simulations with real noise. Notation: see Fig. 3.

IQD maxima are notably higher for conv compared to div_dyn.

Not only does the division approach with dynamical filtering show better accuracy for large transitions (Fig. 3) but it is also superior in terms of accuracy and reliability for small transitions.

While the distribution of the estimated response times for div_dyn is nearly symmetric, the convolution method reveals strong asymmetries for some conditions (for instance, for the 50% → 55% transition, T = 15 ms and f_d = 100 Hz or 150 Hz). This indicates an undesirable dependency of the moving average on the unspecific noise or systematic errors for certain phase shifts of the backlight modulation signal.

CONCLUSIONS

The established convolution approach is prone to misestimations of LCD response times in the order of several magnitudes, which seriously questions its application for the characterization of medical displays. Medical technicians and clinical vision researchers should be aware that it works well only for long response times of large transitions with high frequency backlight modulations.

Our novel approach is simple, robust and avoids the systematic misestimation of transitions times inherent in the widely used convolution approach.

Our division approach also works for more complex periodic modulatory signals. However, a large additive noise amplitude will result in a high variation of the estimated times. For this purpose, we introduced an additional dynamical low–pass filtering procedure to improve robustness.

Furthermore, the division approach appears to perform particularly well for both short transition times and small transitions, which is where the convolution approach fails most seriously.

The shorter the transition, the higher is the chance that the not fully disentangled modulation signal would cut the target level at the wrong time. However, Figures 3 and 4 show that even for relatively slow transitions of 20 ms the relative error is much smaller than that of the convolution approach and the variation is tolerably small.

In order to predict perceptual effects such as motion blur[8] it is necessary to study the complete system including the modulation, which is usually not constantly aligned with the signal (i.e. frame onsets). Our method makes it possible to disentangle both components from only a few measurements, which can be used to simulate the perceptual effects on the complete system by combining the signal with arbitrarily phase shifted versions of the modulation. This supersedes multiple measurements of the complete system.

An additional standard which describes the temporal behavior of LCD monitors is the Motion Picture Response Time[9] (MPRT). Whereas our division method deals with response times according to the liquid crystal response curve (LCRC, signal $s(t)$), the MPRT approach defines response times according to the so-called motion picture response curve (MPRC). However, LCRC and MPRC are related and MPRC can be modeled on the basis of LPRC[10,11]. Therefore, the disentangling procedure introduced in this work might also be of relevance for determining MPRT.

For LCD monitors, there are a few additional issues that should be borne in mind when estimating the actual transition times:

1.) For the assessment of a monitor one would ideally estimate all pairs of transitions between signal levels. So far the ISO standard[2] prescribes neither a unique nor an exhaustive set of electrical input level pairs. The grey-to-grey average response times provided by vendors rarely reference any standard method nor describe their procedure. Therefore the reported values are highly ambiguous and generally should not be trusted. Our own results showed large deviations from the numbers reported in the specifications.

2.) For a fair comparison of transitions times between monitors, the plateau levels should be perceptual lightness levels (e.g., CIE L^*) instead of the gamma dependent (and hence not necessarily perceptually scaled) uncalibrated grey RGB tuples.

3.) While the response time characteristics should be the same for each color channel, each might have a different gamma curve, primary shift or crosstalk[12], so that RGB grey levels could deviate from the whitepoint. Therefore, we recommend to assess only a single channel (e.g., green).

4.) The overdrive technology can reduce the actual response time of the liquid crystal. It briefly applies a higher voltage than that necessary for reaching the desired final level to accelerate the change of the crystal. However, an overdrive mechanism that is not properly fine-tuned could even prolong the time of converging to the desired crystal state by overshooting. This could result in worse perceptual artefacts despite a reduction of the technical 10%–90% response time. We recommend to look for the earliest time when the signal no longer deviates from the target plateau level by more than 10%.

Our novel approach meets the requirements of medical applications with respect to robustness and precision and takes into account the progressively improving transition time properties of modern LCD devices. As recent guidelines for the assessment of display performance for medical imaging systems extensively consider LCD devices[7], we hope our approach will be considered for future temporal characterization specifications for LCDs.

Acknowledgments

The authors would like to thank Ulrich Steinmetz, Jürgen Jost, Roland Fleming, and the two anonymous reviewers for their useful ideas, suggestions, and comments, and particularly Michael E. Becker from Display Metrology & Systems for his collaboration, his measurement assistance, and for providing the measurement device.

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