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Video Scaling Estimation Technique

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CONTENTS

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Margaret H. Pinson and Stephen Wolf[1]

Digital video compression algorithms are being deployed that spatially stretch or shrink the video picture. Although small changes in spatial scaling are not usually noticeable to viewers, objective video quality measurement systems may be adversely impacted if the spatial scaling is not corrected. This report describes an algorithm that can be used to automatically measure the amount of spatial scaling present in a video system. This algorithm obtains satisfactory computational complexity by (1) separating the searches for horizontal & vertical scaling factors, (2) using image profiles rather than full images, and (3) using random rather than exhaustive searching techniques.

Key words: calibration; objective; random search; spatial scaling; video quality

1. INTRODUCTION

Digital video compression algorithms are being deployed that do not preserve the spatial dimensions, or scaling, of the input video picture. For instance the picture may be stretched or shrunk in the horizontal direction. There are several possible reasons for the presence of spatial scaling in today's digital video systems. Video compression designers may be trying to preserve bits by shrinking the image size slightly, the video system may be designed for display on computer monitors where preserving image size is not an issue, or there may be errors in the spatial sampling used for the video system. Whatever the case, small changes in spatial scaling are not usually noticeable to viewers or if they are noticed, viewers may feel that the spatial scaling has little impact on quality. However, objective video quality measurement systems may be adversely impacted if the spatial scaling is not corrected before the quality measurements are performed. For instance, even a small uncorrected spatial scaling of several percent will cause a common objective measurement such as peak signal to noise ratio (PSNR) to show a large impairment.

This report describes an algorithm that can be used to automatically measure the amount of spatial scaling that is present in a video system. This algorithm is used in conjunction with algorithms that are designed to measure spatial registration (i.e., spatial shift) and temporal registration (i.e., temporal shift) since these calibration problems commonly coexist with video systems that perform spatial scaling. Every effort has been made to make the composite search algorithm computationally efficient. This report presents the algorithm in sufficient detail for

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implementation by an automated measurement system. Results are also presented that give the performance of the algorithm for video streams that have digital video impairments.

2. PROBLEM SPECIFICATION

The primary goal of the algorithm is to find the amount of vertical and horizontal scaling that is present in a processed (i.e., output) video stream when compared to an original (i.e., input) video stream. However, other calibration problems that are present in the processed video stream (e.g., spatial and temporal registration) complicate the estimation of spatial scaling. Thus, for typical video systems, finding the amount of spatial scaling in a processed video stream involves at least five interrelated estimation problems:

- Temporal registration – Estimating the temporal shift of the processed video stream with respect to the original video stream.
- Horizontal scaling – Estimating the stretch or shrinkage in the horizontal direction of the processed video picture with respect to the original video picture.
- Horizontal shift – Estimating the shift in the horizontal direction of the processed video picture with respect to the original video picture.
- Vertical scaling – Estimating the stretch or shrinkage in the vertical direction of the processed video picture with respect to the original video picture.
- Vertical shift – Estimating the shift in the vertical direction of the processed video picture with respect to the original video picture.

There are other potential calibration problems with the processed video stream (e.g., luminance gain, luminance level offset) that may affect the estimation of the above five quantities. However, to adequately address all unknown quantities simultaneously would result in a prohibitively slow search. Therefore, reasonable calibration values will be selected for these other unknown quantities. These assumptions will limit the scope of the search to the aforementioned five dimensions.

However, even an exhaustive five dimension search would require a prohibitive amount of memory and time on today's computers. A 10 second video sequence (a standard length scene for video quality testing purposes) of 525-line / NTSC video stored uncompressed in double precision (a common precision of computing) requires 840 MB of memory for just the luminance (Y) image plane. Consider two such video sequences (original and processed) and the need to search over several seconds of temporal shift, perhaps ±20 pixels of spatial shift, and many combinations of spatial scaling to determine the optimal "alignment" of the processed sequence with the original sequence. Computers would need to improve by several orders of magnitude in CPU speed unless the size of the search is significantly reduced.

This algorithm uses several approximations to reduce the search space. The search is split into two independent searches. One search seeks the horizontal scaling; a second search seeks the vertical scaling. Each two-dimensional video image is transformed into two one-dimensional arrays by computing profiles of the image. A horizontal image profile for horizontal scaling estimation is computed by averaging each column of image pixels, and a vertical image profile for vertical scaling estimation is computed by averaging each row of image pixels. This reduces the order of magnitude of the search from $O(n^5)$ to $O(n^3)$ (spatial shift, spatial scale, temporal shift). A randomized search is performed over the remaining three dimensions instead of an exhaustive search to further speed computations.

A deterministic non-exhaustive search could also be used to speed computations. This would involve designing a deterministic heuristic (i.e., a simple rule or educated guess) to guide the search. However, randomized algorithms are preferable to deterministic algorithms when it is difficult to specify a heuristic that will guarantee good behavior. Randomization does not improve the worst case run-speed. However, heuristic algorithms will exhibit poor behavior when given certain inputs, whereas randomized algorithms will only exhibit poor behavior from an unfortunate series of pseudo-random numbers. Randomized algorithms are particularly valuable in situations like this search where the advantages of good choices are more important than the disadvantages of bad choices.

3. ALGORITHM DESCRIPTION

The same core algorithm is used to independently estimate the horizontal and vertical scaling. This section will present that core algorithm in terms of the horizontal scaling estimation.

3.1. Horizontal Scaling Search

NTSC (525-line) and PAL (625-line) video sampled according to ITU-R Recommendation BT.601 (henceforth abbreviated Rec. 601) may have a border of pixels and lines that do not contain a valid picture. The original video from the camera may only fill a portion of the Rec. 601 frame. Some digital video compression schemes further reduce the area of the picture in order to save transmission bits. To prevent non-picture areas from influencing the spatial scaling algorithm, they must be excluded.

Table 1 gives reasonable default values for the border of invalid pixels around the edge of common image sizes. Pixels in this invalid region will be discarded by the search algorithm. Images in common intermediate format (CIF), source input format (SIF), and quarter resolution versions of these (QCIF and QSIF) typically do not have an invalid border, so no pixels are discarded.

Table 1. Default Invalid Border for Common Video Sizes

Video Type	**Rows**	**Columns**	**Invalid Top**	**Invalid Left**	**Invalid Bottom**	**Invalid Right**
NTSC (525-line)	486	720	20	24	18	24
PAL (625-line)	576	720	16	24	16	24

Let Y_n be the n^{th} luminance image in a video sequence containing N images. For interlace video, Y_n is the n^{th} of N fields; for progressive video, Y_n is the n^{th} of N frames. Let $Y_n(v,h)$ be the coordinates of a pixel, where v is the vertical row index and h is the horizontal column index, and the upper-left coordinate of the image is $v = 1$, $h = 1$. Compute the horizontal profile of each image (i.e., average each column) and join the profiles together into a single profile array, $P(h,n)$.

$$P(h,n) = \frac{1}{C}\sum_{v=1}^{C} Y_n(v,h), \qquad (1)$$

where C is the total number of rows in each column of the image after eliminating the invalid border shown in Table 1. Apply (1) to the original video sequence to create $P_o(h,n)$; and to the processed video sequence to create $P_p(h,n)$. For simplicity, we will assume that the original and processed video sequences both contain N images in time.

We will perform a three dimensional search for horizontal scaling, horizontal shift, and temporal shift by comparing P_o with P_p. Adjusting horizontal shift and time shift requires simple shifts of P_p with respect to P_o. Adjusting horizontal scaling requires profiles in P_p to be stretched or shrunk. Let us define the function *resample* that is used to perform this spatial scaling, or resampling:

$$P_r = resample(P,r), \qquad (2)$$

where r is the amount by which all profiles in P should be scaled. Here, r is an integer denoting the amount of scaling such that $r/1000$[2] is the multiplication factor by which each profile is scaled or resampled. The function *resample* resamples each profile in P separately. The function *resample* applies an anti-aliasing (lowpass) FIR filter, assuming zero samples before and after the ends of the array to be resampled, and retains the center portion of the filtered array. Thus, the array returned, P_r, is of the same dimensions as the input array. The FIR filter used before resampling was designed by minimizing the weighted mean squared error between the ideal brick wall lowpass filter and the actual filter. The weighting function comes from a 10 point Kaiser window with a beta of 5.

Notice that some samples at the top and bottom of P_r will now become invalid if function *resample* shrinks the profiles (i.e., r is less than 1000). When profiles in P_r are shifted vertically (i.e., to find the horizontal shift), even more pixels at the top and bottom of P_r will become invalid. The maximum number of invalid pixels, I, in each column can be found using (3).

$$I = maxsearch\_h_s + ceiling(C * maxsearch\_r/1000), \qquad (3)$$

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[2] Factors larger than 1000 may be used for more precision in the scaling calculation.

where $maxsearch\_h_s$ is the maximum horizontal shift to be searched; function *ceiling* rounds a value up to the nearest integer; and *maxsearch_r* is a constant corresponding to the maximum difference in scaling to be considered, expressed as a deviation from 1000. For example, $maxsearch\_r = 50$ would indicate r varying from 950 to 1050, which corresponds to searching scaling factors from 95% to 105%.

Each combination of horizontal scaling, horizontal shift, and temporal shift must be evaluated separately. The evaluation criteria calculation takes four steps. First, apply the horizontal scaling to P_p,

$$P_{p,r} = resample(P_p, r). \tag{4}$$

Second, take a difference between the original profile array, P_o, and the scaled processed profile image, $P_{p,r}$, after adjusting for horizontal shift (h_s) and temporal shift (n_s),

$$D(h,n) = P_o(h,n) - P_{p,r}(h+h_s, n+n_s). \tag{5}$$

Third, take the standard deviation over each column of the array $D(h,n)$, excluding samples within I of the top or bottom of each column (i.e., because these samples might be invalid),

$$T(n) = stdev\ (\ D(h,n)\ ),\ \text{for}\ h = I\text{+1 to}\ C\text{-}I. \tag{6}$$

Here, n ranges from ($1+maxsearch\_n_s$) to ($N-maxsearch\_n_s$) rather than from 1 to N, where $maxsearch\_n_s$ is the maximum temporal shift that will be examined in the search. We define the optimal alignment point for some horizontal scaling r, horizontal shift h_s, and temporal shift n_s to be the point where the standard deviation of the difference between the original and processed profiles is minimized. However, due to the nature of digital video systems (e.g., some of which drop video frames, repeat video frames, present video frames with errors etc.), not all processed video frames will align with original video frames for one temporal shift n_s between the processed and original sequences. Therefore, a function is required to discard many of the processed frames that are not temporally aligned at temporal shift n_s. This function is represented as,

$$V = below25\%(T(n)), \tag{7}$$

where *below25%* sorts the values in array $T(n)$ from low to high, and computes the average of all values that are less than or equal to the 25th percentile. The net effect of this function is to discard the worst 75% of the matched processed and original image pairs and only consider the 25% best matched pairs.

V in (7) is a function of horizontal scaling (r), horizontal shift (h_s), and temporal shift (n_s). The horizontal scaling, horizontal shift, and temporal shift that minimize V from (7) will be used as the estimates of the actual values for the processed video sequence. However, an exhaustive search over those three dimensions would be prohibitively time consuming. Therefore, a randomized search strategy is used instead.

The strategy contains two stages. The first stage searches randomly and uniformly across the entire search space. The second stage refines the results of the first stage. It uses a 3-

dimensional Gaussian distribution to focus the search in the vicinity of the current best point in space. Each time a new best point is identified, the search is recentered about that point.

Let us define five variables: W, min_W, min_h_s, min_r, and min_n_s. $W(r,h_s,n_s)$ will hold V for each horizontal scale r, horizontal shift h_s, and temporal shift n_s. Initialize $W(r,h_s,n_s)$ to NaN (Not-A-Number). min_W will hold the minimum V, whose value will be associated with horizontal scale min_r, horizontal shift min_h_s, and temporal shift min_n_s. Initialize min_W to infinity. Note that r will range from (1000 – $maxsearch\_r$) to (1000 + $maxsearch\_r$), h_s will range from -$maxsearch\_h_s$ to +$maxsearch\_h_s$, and n_s will range from –$maxsearch\_n_s$ to +$maxsearch\_n_s$. Finally, let us choose *TRIES*, the number of evaluations to be performed before the algorithm declares that a solution has been found. A default value of *TRIES* = 3000 seems to work well and is the recommended setting.

For a number of evaluations equal to *TRIES* / 5, choose values for r, h_s, and n_s randomly over the range to be searched, using a uniform distribution of random values.

$$r = round\,(1000 - maxsearch\_r - 0.5 + ((maxsearch\_r * 2 + 1) * rand)), \qquad (8)$$

$$h_s = round\,(-maxsearch\_h_s - 0.5 + ((maxsearch\_h_s * 2 + 1) * rand)), \qquad (9)$$

$$n_s = round\,(-maxsearch\_n_s - 0.5 + ((maxsearch\_n_s * 2 + 1) * rand)), \qquad (10)$$

where *rand* is a random number generator that yields numbers from the uniform distribution over the range (0, 1).

For each randomly chosen coordinate (r,h_s,n_s), compute V as shown in (7) which will give the value for $W(r,h_s,n_s)$. Update the values of W, min_W, min_h_s, min_r, and min_n_s as shown in (11) and (12).

$$W(r,h_s,n_s) = V \qquad (11)$$

$$\text{If } V < min\_W, \text{ then } min\_W = V,\ min\_r = r,\ min\_h_s = h_s, \text{ and } min\_n_s = n_s. \qquad (12)$$

If a coordinate (r,h_s,n_s) is chosen twice, the calculation of V is skipped. Duplicate coordinates are detected by testing whether $W(r,h_s,n_s)$ contains NaN. Duplicate coordinates are counted in the number of evaluations to be tried.

After *TRIES* / 5 iterations, the coordinate (min_r, min_h_s, min_n_s) will be a fairly close estimate of the actual coordinate. Perform an additional *TRIES * 4 / 5* iterations as shown above but with a modified distribution of random values. The new random distribution increases the likelihood of the chosen coordinate being closer to the current best point in the search space.

$$r = min\_r + round\,(6 * rand\_norm) \qquad (13)$$

$$h_s = min\_h_s + round\,(2 * rand\_norm) \qquad (14)$$

$$n_s = min\_n_s + round\,(2 * rand\_norm) \qquad (15)$$

In (13)-(15), *rand_norm* is a random number generator that yields a normal distribution with zero mean and unity variance. If the coordinate (r,h_s,n_s) is outside the range to be searched, then another random coordinate is chosen instead. The long tails of the normal distribution help prevent the algorithm from locking in on a local minimum rather than the global minimum. The quick handling of duplicate coordinates allows *TRIES* to be set to a large number without negatively impacting run speed. Note that (13)-(15) continually recenter the search about the current best point in the search space.

After the specified number of iterations, the value *min_r* is returned as an estimate of the horizontal scaling. The values min_h_s and min_n_s will not be considered any further as more precise algorithms for estimating these calibration quantities (after spatial scaling is corrected) are already available and standardized [1] [2].

3.2. Vertical Scaling Search

The vertical scaling search is conducted identically to the horizontal scaling search, except that (1) is changed to (16), to accommodate the change in scaling orientation.

$$P(v,n) = \frac{1}{R}\sum_{h=1}^{R} Y_n(v,h) \tag{16}$$

where R is the total number of columns in each row of the image after eliminating the invalid border shown in Table 1. This creates the vertical profile of each image (i.e., average each row) and joins the profiles together into a single image, $P(v,n)$. After the specified number of iterations, the value *min_r* is returned as an estimate of the vertical scaling. Thus, the searches for horizontal and vertical scaling are conducted separately.

3.3. Error Resiliency

Tests performed on a limited set of video clips indicated that the use of a randomized rather than exhaustive search does not seem to have a significant impact on the algorithm's estimate of spatial scaling. The randomized search from (13), (14), and (15) effectively conducts a localized exhaustive search, combined with a limited search for more distant scaling / shift / time possibilities. However, the averaging of columns or rows in (1) and (16) discards a significant amount of information from the image sequence. When combined with impairments in the video sequence, an incorrect spatial scaling estimate can result. This is not because the randomized search reaches a false minimum, but rather because the actual minimum of the profiled spatial-temporal image indicates an erroneous scaling. Therefore, the spatial scaling algorithm should ideally be applied to several different video sequences that have been passed through the same video system. If the majority of these scaling results from several different sequences indicate one scaling number, then the user can be more confident that this answer is correct. If the spatial scaling results from different sequences are not identical, the user should compute the median result to select the final horizontal and vertical scaling numbers.

A visual inspection of the final scale-corrected images may be another good method of checking the spatial scaling results for a processed video sequence. However, an accurate visual inspection will require that the processed video sequence be fully calibrated with respect to spatial registration and temporal registration. Any errors in these calibration values will invalidate the visual inspection. If the video sequence in question contains repeated frames or dynamic time warping (i.e., time varying video delays), then obtaining two time-aligned frames can be quite difficult. It is suggested that the viewer use a video sequence that is either still or nearly still for this visual check.

4. RESULTS

Identical scaling results for multiple sequences indicate a high degree of confidence that the scaling results are accurate. Scaling results that vary widely indicate ambiguity. Most video systems fall in between these two extremes and produce a single scaling factor for many of the sequences but adjacent scaling factors for some sequences, with errors distributed according to a normal distribution. Video systems that contain transmission errors or other severe impairments can result in a wide, more uniform distribution of scaling factors for different sequences.

This automated scaling estimation algorithm was checked by examining 2506 individual video clips processed through a variety of video transmission systems that do not appear to contain any spatial scaling (horizontal or vertical). This lack of scaling was checked visually by displaying the difference between the luminance planes of a fully calibrated processed image and the corresponding original image. These video clips were not used to train or develop the algorithm.

Figure 1 and Figure 2 depict the distribution of vertical and horizontal scaling estimates, respectively, calculated automatically for the 2506 individual video clips. Figure 3 shows the cumulative distribution function of the distance between individual clips' scaling and 1000. When examining these figures, please recall that 1000 indicates "no scaling". 85.28% of the individual clips' vertical scaling estimates were within ±2 of 1000 (i.e., in the range [998,1002]); and 95.65% of the individual clips' horizontal scaling estimates were within ±2 of 1000. Overall, 83.16% of these individual clips had both vertical and horizontal scaling estimates within ±2 of 1000. 89.27% of individual clips' vertical scaling estimates were within ±3 of 1000 (i.e., in the range [997, 1003]); and 96.97% of individual clips' horizontal scaling estimates were within ±3 of 1000. Overall, 87.79% of these individual clips had both vertical and horizontal scaling estimates within ±3 of 1000.

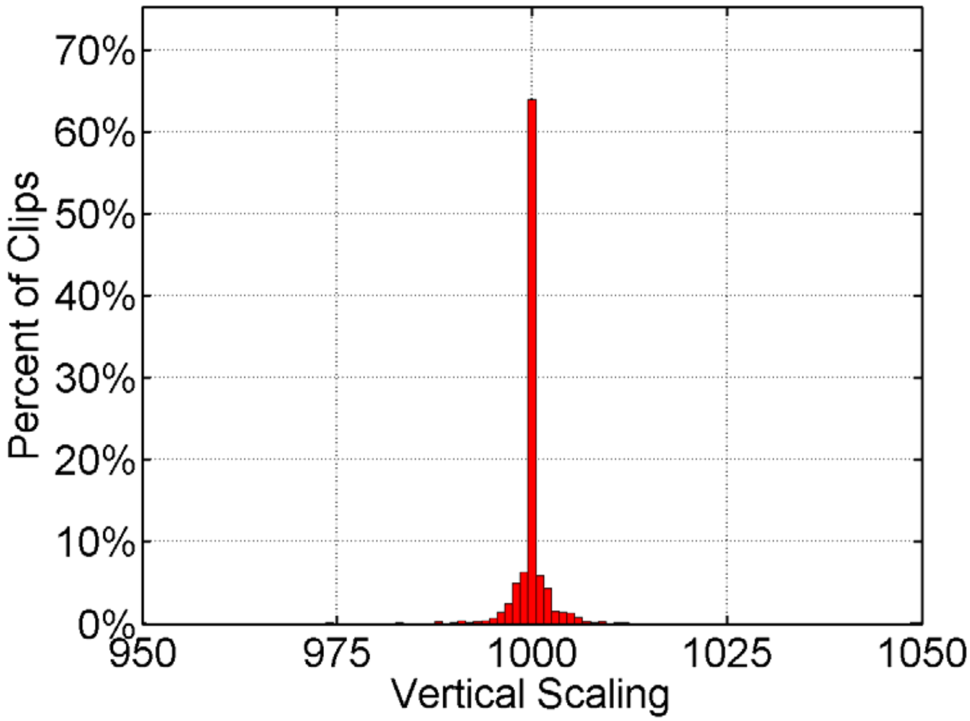

Figure 1. Histogram of vertical scaling results for 2506 un-scaled clips.

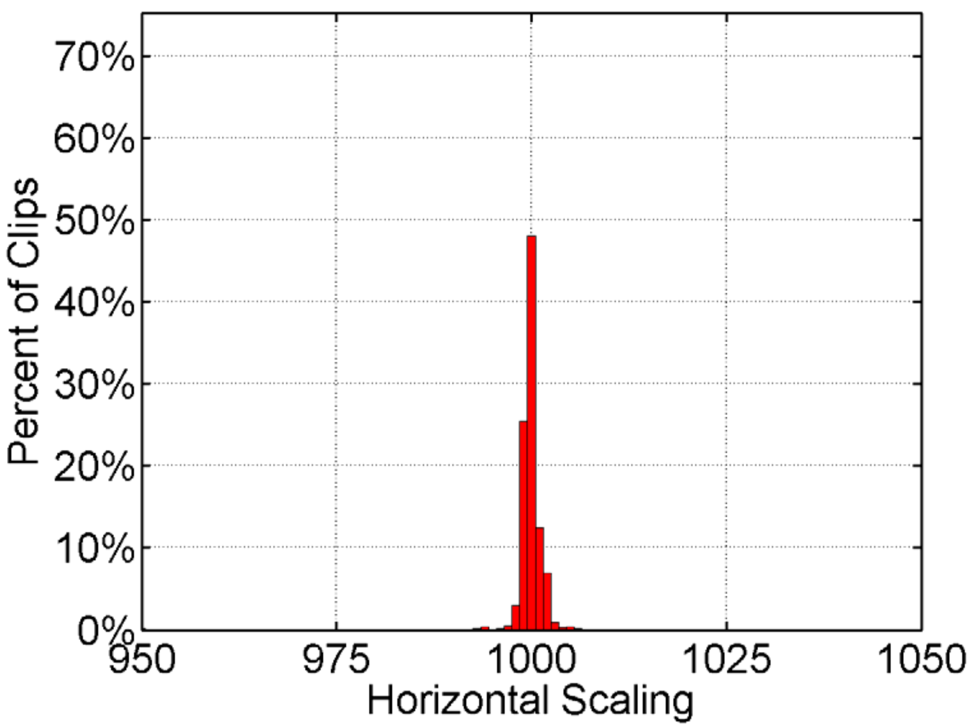

Figure 2. Histogram of horizontal scaling results for 2506 un-scaled clips.

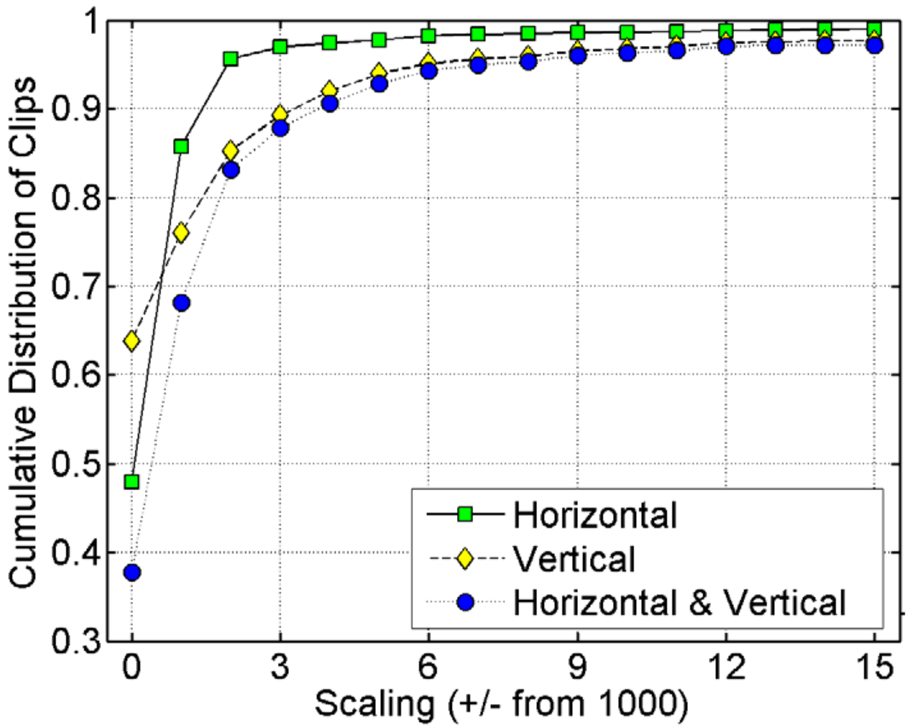

Figure 3. Cumulative distribution of the individual clips' scaling.

When results are filtered across scenes for each video system (i.e., the median of the individual clips' vertical and horizontal scaling estimates, where each clip has been passed through the same video system), the accuracy of the algorithm increases. The aforementioned 2506 individual video clips are associated with 290 video systems. Figure 4 and Figure 5 depict the distribution of these vertical and horizontal scaling estimates, respectively, calculated with median filtering on these 290 video systems. Figure 6 shows the cumulative distribution function of the distance between systems' scaling and 1000. Now, 88.54% of the vertical scaling estimates were within ±2 of 1000; and 98.42% of the horizontal scaling estimates were within ±2 of 1000. Overall, 87.75% had both vertical and horizontal scaling estimates within ±2 of 1000. 92.89% of the vertical scaling estimates were within ±3 of 1000; and 98.82% of the horizontal scaling estimates were within ±3 of 1000. Overall, 92.10% had both vertical and horizontal scaling estimates within ±3 of 1000. These statistics show an overall improvement over the individual clip statistics.

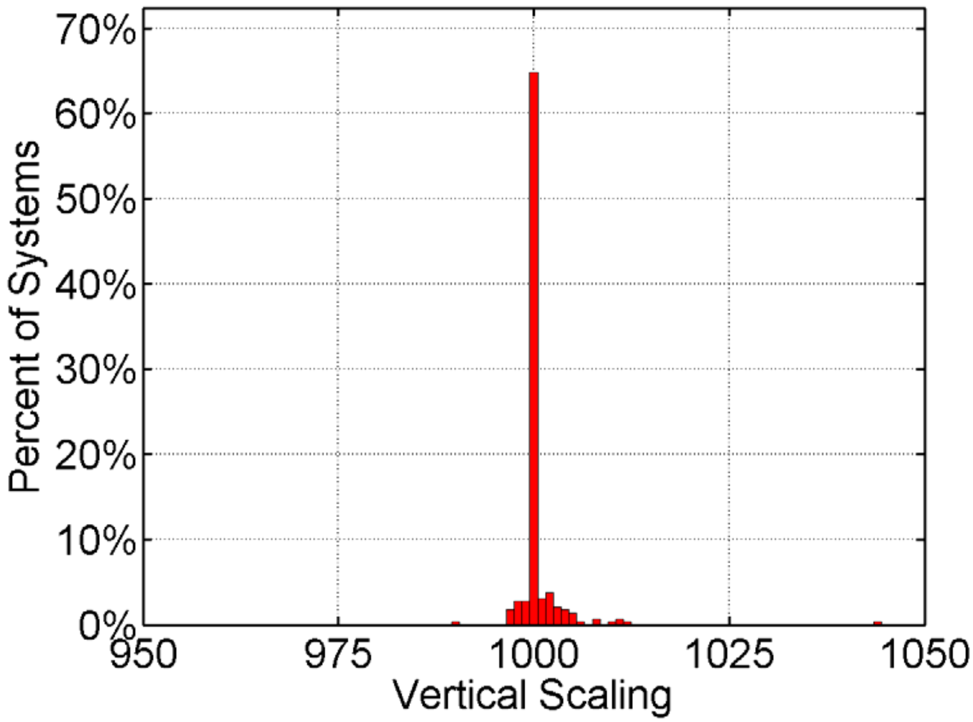

Figure 4. Histogram of vertical scaling results with median filtering.

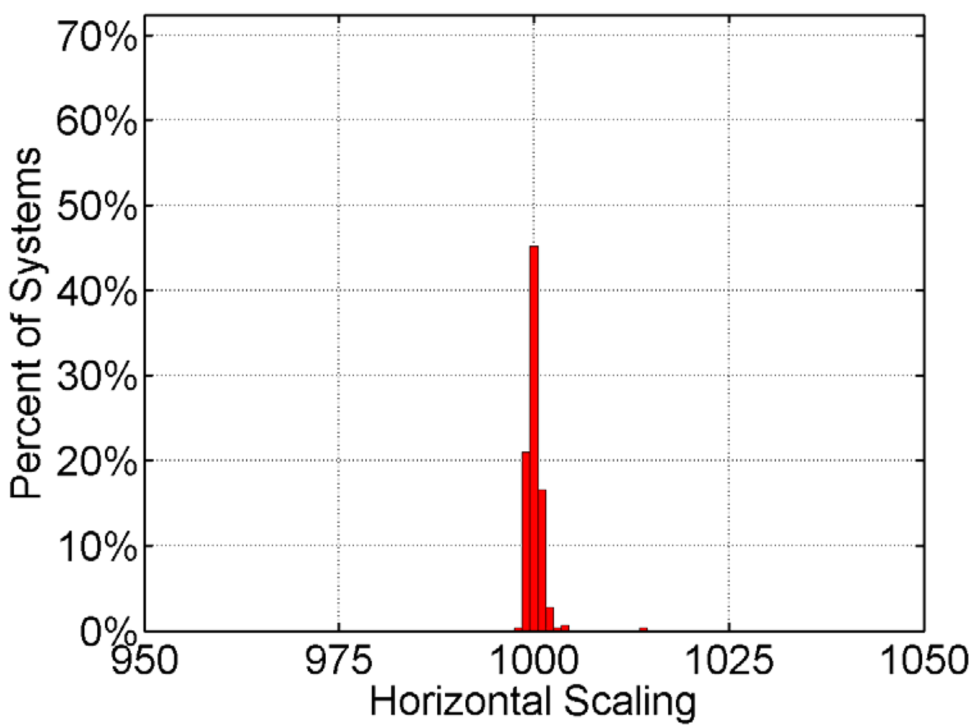

Figure 5. Histogram of horizontal scaling results with median filtering.

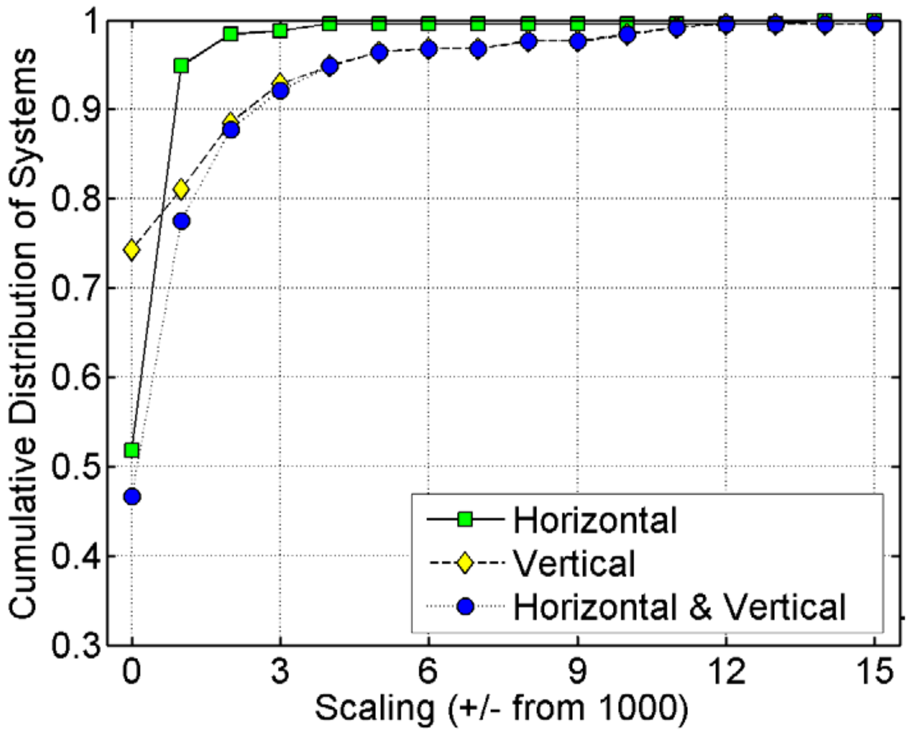

Figure 6. Cumulative distribution of video system's scaling.

Notice that a significant number of the video systems represented in Figure 5 had results that indicated horizontal scalings of 998, 999, 1001, and 1002. The 998 and 1002 scalings indicate a 1.44 pixel stretching or shrinking across a 720 pixel wide image. These horizontal scalings are often too small to be reliably detected via manual examination when digital video system impairments (such as blurring or encoding artifacts) are present in the processed video stream. Because these small scaling factors cannot be easily verified, the user is advised to consider scaling factors that are within plus or minus 3 of 1000 to be indicative of a video system that does not spatially scale images.

The performance of the scaling algorithm was also analyzed using video clips passed through seven transmission systems that exhibited known video scaling. Some of these clips were used to train or develop the algorithm. Figure 7 contains histograms for the clips passed through the three video systems that contained vertical scalings. System 5 was a 22 kbits/s video transmission system that contained serious impairments. These serious impairments caused the scaling algorithm to produce unreliable results for three of the six video sequences. System 6 depicts a tight, reliable grouping. Some clips indicated a vertical scaling of 1011 and others 1013, where the majority of clips indicated the actual vertical scaling of 1012 (confirmed using visual examination). This tight spread of scalings around the correct answer is the most common error distribution for systems that have small amounts of impairments, whereas the error distribution shown for system 7 is more typical of low quality video systems.

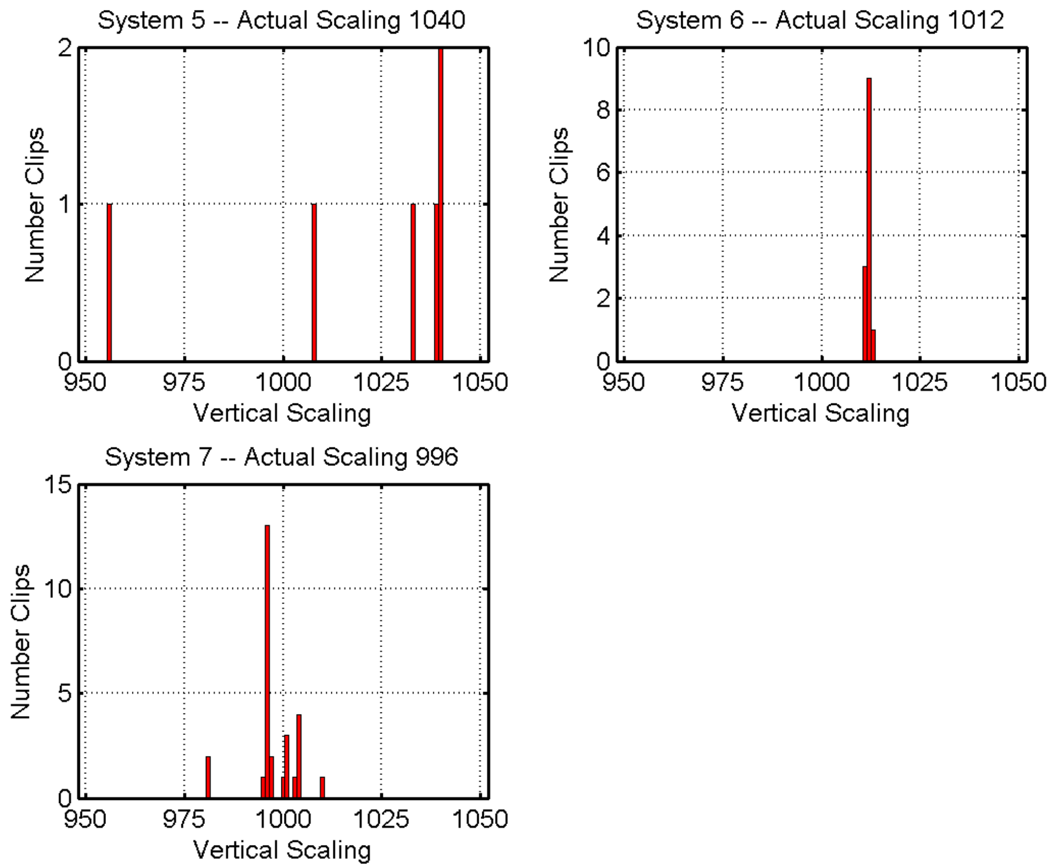

Figure 7. Histograms of typical vertical scaling results.

Figure 8 contains histograms for the clips passed through the seven video systems, all of which contained horizontal scalings. These seven histograms show a range of responses of the scaling algorithm when applied to different video systems. System 3 used CIF images (352 columns by 288 rows). The small image size and high levels of impairments contributed to the increased variability of results from individual clips. System 4 was a video system that was tested both with and without transmission errors. Clips containing serious transmission error impairments are responsible for the unreliable spread of vertical scalings. Notice that all 13 scenes used to analyze system 6 indicated an exact horizontal stretch of 1002. Although the proximity of this scaling to 1000 may tend to indicate no scaling, the conclusive presence of a vertical scaling factor of 1012 (see Figure 7), combined with all scenes being in perfect agreement on the 1002 horizontal scaling, is indicative of an actual horizontal scaling factor of 1002. Visual examination of these scenes agreed with the scaling numbers produced by the automated algorithm.

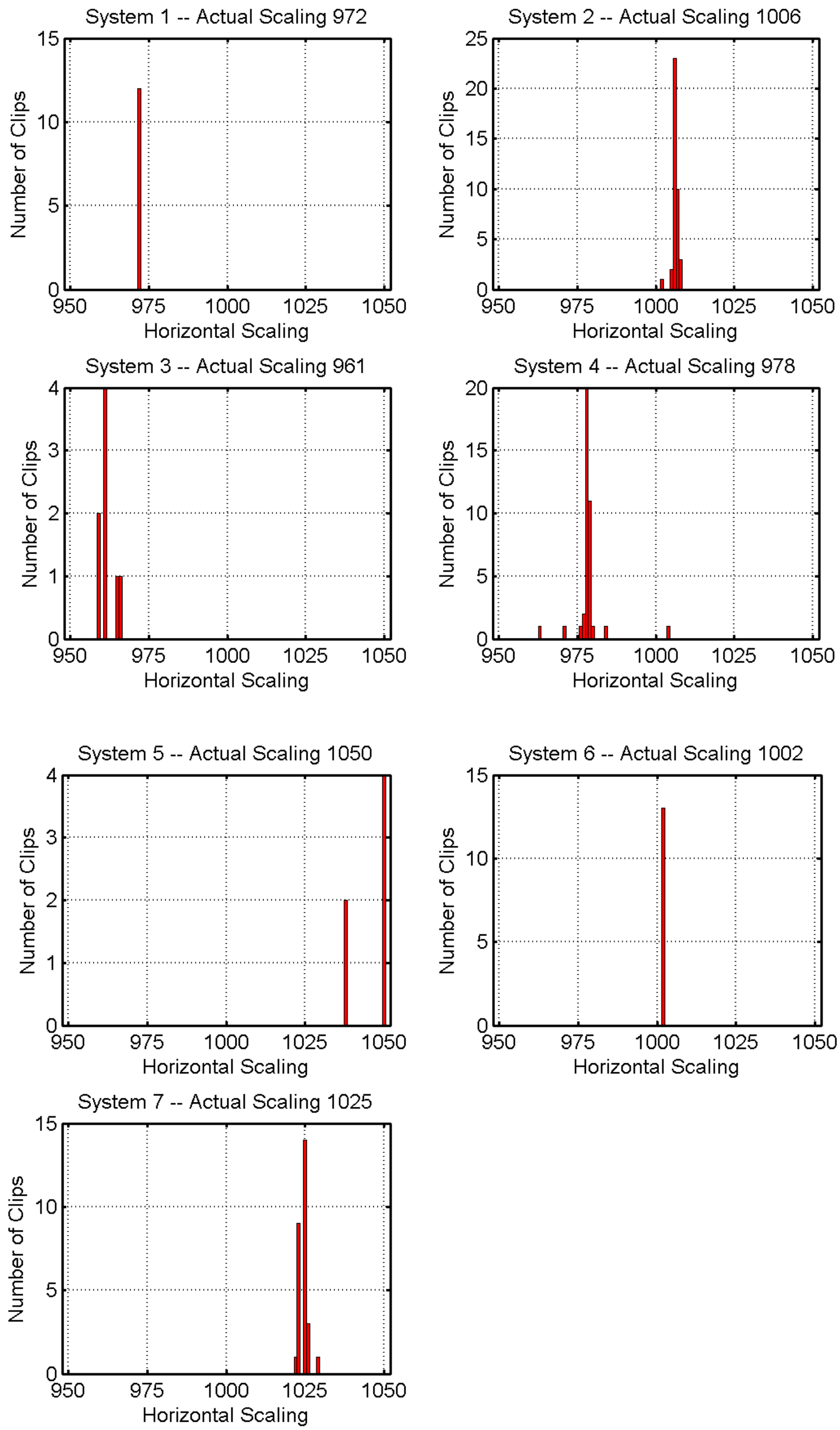

Figure 8. Histograms of typical horizontal scaling results.

5. CONCLUSION

We have presented an automated algorithm for estimating the spatial scaling introduced by video transmission systems. This algorithm obtains satisfactory computational complexity by (1) separating the searches for horizontal & vertical scaling factors, (2) using image profiles rather than full images, and (3) using random rather than exhaustive searching techniques.

This automated algorithm obtains reasonable reliability when the results from multiple video clips are jointly analyzed. Although some combinations of scenes and video impairments produce erroneous results, the use of multiple clips mitigates the impact of these errors on the overall scaling factors that the algorithm produces. However, the scaling estimation algorithm is not sufficiently robust to be recommended as a fully automated solution. The horizontal and vertical image profiling process that was necessary for efficient computations may discard too much information. Thus, a visual verification as to the correctness of the scaling factors produced by the algorithm is advised. The user is also advised to consider scaling factors that are within ±3 of 1000 to be indicative of a video system that does not spatially scale images.

6. REFERENCES

[1] S. Wolf and M. Pinson, "Video quality measurement techniques," NTIA Report 02-392, June 2002. Available: www.its.bldrdoc.gov/n3/video/documents.htm

[2] ANSI T1.801.03 – 2003, "American National Standard for Telecommunications – Digital transport of one-way video signals – Parameters for objective performance assessment," American National Standards Institute.

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14. SUPPLEMENTARY NOTES

15. ABSTRACT (A 200-word or less factual summary of most significant information. If document includes a significant bibliography or literature survey, mention it here.)

Digital video compression algorithms are being deployed that spatially stretch or shrink the video picture. Although small changes in spatial scaling are not usually noticeable to viewers, objective video quality measurement systems may be adversely impacted if the spatial scaling is not corrected. This report describes an algorithm that can be used to automatically measure the amount of spatial scaling present in a video system. This algorithm obtains satisfactory computational complexity by (1) separating the searches for horizontal & vertical scaling factors, (2) using image profiles rather than full images, and (3) using random rather than exhaustive searching techniques.

16. Key Words (Alphabetical order, separated by semicolons)

calibration; objective; random search; spatial scaling; video quality

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