Interpolation Techniques for the Artificial Construction of Video Slow Motion in the Postproduction Process

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ABSTRACT
Motion compensated interpolation (MCI) refers to the process of taking a video sequence, finding motion information, and then using that information to produce interpolated video frames between source frames. In this study, we compare two MCI techniques: adjacent-frame motion compensated interpolation (AF-MCI) and wide-span motion compensated interpolation (WS-MCI). Using reproducible artificially generated video sequences, the methods are quantitatively compared with the objective of optimizing interpolated frame quality relative to control interpolated frames. This is useful because on a large flat-panel display with high resolution (such as HDTV), frame transition coherence becomes a crucial factor in assessing the quality of the user’s viewing experience. To enhance MCI, the encoder should attempt to exploit long-term statistical dependencies, precisely estimate motion by modeling the motion vector field, and superimpose efficient prediction/interpolation algorithms. WS-MCI achieves this. Computer simulations using artificially generated video sequences demonstrate the consistent advantage of WS-MCI over adjacent-frame MCI under increasingly complex source scenes and chaotic occlusion conditions.

Categories and Subject Descriptors
H.5.1 [Information Interfaces and Representation]: Multimedia Information Systems – video; C.3 [Special-Purpose and Application-Based Systems]: Signal Processing Systems; J.5 [Arts and Humanities]: Fine Arts

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Keywords
Frame interpolation, slow motion, high definition, video, postproduction, ambient, video art.

1. INTRODUCTION
Motion Estimation (ME) and Motion Interpolation (MI) are two ordered constituent phases of Motion Compensated Interpolation (MCI). They are fundamental problems in digital video processing and are the subject of much research [17]. Furthermore, image-plane motion estimation is an integral part of motion compensated filtering and compression [18]. The predicted need for increased capabilities for slow motion in the postproduction phase of creative video work in the realm of high definition will also involve the use of related techniques [20].

Typical ME tracks the movement of objects, or parts of objects, from one frame to the next. Chupeau & Salmon [8] used a motion compensation algorithm where all pixels in the interpolated frames are assumed to have at least one motion vector from sets of adjacent frames \{-1→0\}, \{0→1\}, and \{1→2\}. This is known as AF-MCI. In contrast, our novel method always tracks motion across the crucial central time frame gap \{0→1\} into which interpolated frames will be placed. We call this the “sweet spot”.

We know from Physics that an object in motion tends to stay in motion. This means that linear motion is more likely than oscillatory motion, and vectors that span a few frames may be better able to depict object motion as compared to motion vectors that span only one frame. This is especially true since sampling of our analog world into the digital pixels of successive video frames means that each frame cannot capture the scene completely due to quantization and rasterization sampling errors (e.g. precise color at object edges). Moreover, when performing ME, tracking a sum-of-luminance (SOL) value from an adjacent frame to another may lead to erroneous and erratic motion vectors due to the fact that there is not a 1:1 ratio of similar SOL values in one frame to another. In other words, due to quantization and rasterization errors during filming, there is no guarantee that each pixel will map into any other frame. Aside from sampling errors tainting motion information, the AF-MCI method for ME is fallible because it assumes that each pixel has a good chance of being present in each adjacent frame. This assumption is perhaps unfounded because different parts of an object can be obscured,
transformed, blurred, or occluded by another object; and therefore, each pixel will not necessarily appear in each adjacent frame.

A small amount of motion can result in large differences in the pixel values of a scene, especially near the edges of an object. Also, a wider field of view and higher resolution (HDTV) makes it harder to fool the eye, and therefore more difficult to do motion compensation [14]. The effectiveness of MCI will depend on the ME and MI phases as well as on source video scene complexity. MCI is useful in various circumstances. Current NTSC frame rates may be increased to accommodate newer HDTV or multimedia standards. MCI can be used to create new frames for frame rate up-sampling and slow motion video [5]. Although pixel-wise MCI was abandoned more than a decade ago [7], recent hardware advances make it an emerging viable alternative to conventional region-based techniques.

We propose to address some of these problems by using temporal motion compensation that analyzes a “Wide-Span” of multiple frames over time (WS-MCI). Performing ME on SOL values across the sweet spot frame gap for all motion vectors allows us to focus exploitation of available motion information in the time span that is most crucial. Additionally, WS-MCI can determine how an SOL value has moved over a wider span of time. Thereby, it can better ignore movement ‘noise’ between adjacent frames because it does not assume that each pixel is present in every frame. This heuristic reduces quantization and rasterization error creeping into the region-based vectors.

The rest of the paper is organized as follows: Section 2 highlights the importance of slow motion in video aesthetics. Section 3 gives an overview of the MCI process. Section 4 briefly describes related techniques. The methods used in this study are covered in Section 5. The next section presents our results and a discussion of them. Before concluding the paper, we summarize our future work.

2. SLOW MOTION AND VIDEO AESTHETICS

We have argued in [20] that the introduction of video technologies such as large-scale flat-screen displays and high-definition video standards will transform our traditional conception of televisual aesthetics. We maintain, among other effects, that the television image will become more pictorial, approaching the cinematic in ways that video has never been able to match. This trend will see a new televisual aesthetic that emphasizes cinematic (and photographic) visual staples such as the sweeping wide-shot, composition in depth, the play of light and shadow, revelation of patterns and textures, and the manipulation of the time base of the moving image [25].

Changing the time base to depict slow motion is the most difficult technical feat in this array of cinematic visual devices that will be adopted in the emergence of a new video aesthetic. Slow motion was possible to realize in cinema, relying on either over-cranking the camera (running it faster than the 24 frames per second projection speed) or on multiple-printing in postproduction. The latter was of limited utility, typically losing visual quality and impact after the postproduction film speed was slowed by anything larger than a factor of two. However, it was possible to over-crank the camera with a variety of brands and models, and producing slow motion while shooting was a reasonably accessible technique utilized by a wide variety of theatrical, documentary and experimental filmmakers. Nonetheless, most video cameras can not produce slow motion by over-cranking. Further, converting footage to slow motion in video postproduction is often subject to the same problem as film when the action is slowed by greater than a factor of two - the illusion of smooth motion is lost.

Slow motion can be used for a variety of effects, and so its relative difficulty in video production is problematic. Bordwell & Thompson point out that slow motion has been used for such diverse ends as super-realism, fantasy, lyricism, or the visceral treatment of cinematic violence [22]. Zettl has a similar list, maintaining that the technique can allow us to see phenomena more clearly as well as imply a freedom from gravity, the agony of not reaching a goal, or even an increased awareness of subject speed [23]. The authors of this paper have maintained that slow motion will be one of the stylistic foundations of a new “ambient video” form supported by the imminent dissemination of large and high-definition flat-panel home television display units. This new form builds on a long artistic history of the “slow-form” exploration of the moving image. Film and video artists as diverse as Michael Snow (Wavelength), Andy Warhol (Empire and many others), Yoko Ono (Sky), Michael Fricke (Baraka), and Bill Viola (The Greeting and many others) have explored the power of the slowly changing moving image. Growing contemporary interest in the ambient video form is confirmed by the latest SIGGRAPH Call for Works which includes the category: "4D Wall Hung Work". This category is described as: “Works that reside in a frame or on the wall but move”. For instance, a plasma screen with a slowly evolving image, or a projection onto a frame on the wall [24].

Despite the natural attraction of the well-composed slow-moving image, it is not a simple goal to achieve. The current generation of video artists and producers have accessible and relatively inexpensive access to a variety of sophisticated and high quality production and postproduction tools, but slow motion remains a difficult challenge to easily produce.

3. MCI OVERVIEW

A movie is composed of discrete video frames where each frame is a 2D image. Motion estimation uses the source frames to deduce the motion vectors, and interpolation uses that information to produce the new interpolated frames (Figure 1). MCI can be iterated for each time gap in the source video sequence to produce a video sequence with multiple new frames (Figure 2). This results in slow motion if the movie’s frame rate is preserved when viewed. Multiple time gaps, into which interpolated frames are placed, represent multiple iterations of the MCI process. Also, the identities of the frame indices will shift forward in time for each MCI iteration such that the sweet spot spans different pairs of successive frames. In Figure 2, only one new frame is inserted into the video sequence per source frame time gap; however, once motion information is gleaned from the source video, any number of interpolated frames can be produced between source frames (Figure 3).
Figure 1. Motion Compensated Interpolation (MCI) is a process that combines Motion Estimation (ME) and Motion Interpolation (MI). After ME, the interpolation step uses the motion information to produce new video frames that are then combined with the originals to produce the new video sequence.

Figure 2. The goal of Motion Compensated Interpolation (MCI) is to produce new video frames, shown in dotted outlines, that look as though they belong within the original video sequence.

Figure 3. An example of one MCI iteration that shows source video frames and the interpolation sweet spot where the new interpolation frames, shown in dotted outlines, are placed for this particular MCI iteration.

Figure 4. Pixel-wise motion interpolation producing a) one, and b) many motion interpolated frames, shown in dotted outlines.

4. PREVIOUS WORK

Motion estimation represents the major portion of Motion compensation algorithm complexity [14], and many methods have been proposed. Region-based ME is ubiquitous throughout most current MCI methods because of its reduced resource requirements in processing time and memory ([3], [7], [12], and [14]). Some techniques use hierarchical block-based ME that provides better motion information over typical full search block-based ME [5]. Other techniques smooth the motion information field in time and space [5]. Because there is a near-infinite variation in possible real-world video sequences, object-recognition-based ME is not plausible for generic MCI needs. Conversely, pixel-wise MCI may have distinct case-specific advantages that may become more evident as computers become more powerful.

MCI techniques provide the best solution in temporal rate up-conversion. Current techniques include frame repetition and linear interpolation by temporal filtering, but these methods may introduce motion noise and object blurring ([1] and [5]). Objectively comparing MCI techniques using various real-world video conditions is problematic because there is no control for experimental results. Consequently, there is a clear need for a test apparatus to objectively and quantitatively compare and contrast various video processing algorithms [19].
5. METHODS
The quality of video frames can be thought of as a measure of how close a set of interpolated frames approach a set of perfectly interpolated control frames in terms of the colors at each pixel in each frame. To rigorously analyze an MCI algorithm, we created an artificial video sequence to provide a reproducible and controlled sequence of data that could be directly compared to experimental results. For each test run, six artificial video frames, five control intermediate frames, and five experimental interpolated frames were created. The experimental frames were directly compared to the control frames in terms of the sum of their pixel color differences for all interpolated frames. This allowed us to quantitatively assess the quality of a set of experimentally derived interpolated video frames. The average error over all frames yields the metric average-ECCE. This denotes the average experimental-control-color-error.

All objects and scenes in the initial source frame are randomly created in a reproducible manner. This allows for parallel testing and analysis of both AF-MCI and WS-MCI, thus yielding two sets of results that can be directly compared to the control interpolated sequence. Our implementation of the two algorithms assumes a progressive-scan source video sequence. However, these algorithms could be applied to interlaced video if the frames are linearly de-interlaced first [8]. For each experiment, we performed paired t-tests using 40 test runs. The same source video frames were utilized for the two experimental techniques.

5.1 Object and Source Scene Creation
Figure 5 demonstrates the diversity of initial source scenes, and shows the chaotic nature of the "inkblot" object (size and shape) as compared to the simple circle object. Inkblots are created using a collection of dots based on random-walk theory. Because inkblots vary in size and are porous, a few blots can create a scene that is just as challenging to process as a scene with many simple objects (compare Figures 5.d and 5.e).

To allow for SOL tracking that would mimic a natural scene, all objects are given ‘texture’ that doesn’t change from frame to frame. This texture is produced by altering all the colors in each object by some random value that is as much as +/-20 for red, green, and blue. Texture was added so that both experimental MCI algorithms could distinguish between the areas within the same object that have the same SOL values. Moreover, a maximum speed of 40 pixels per frame was imposed. The translation’s magnitude and direction are kept constant across the artificial video sequence.

5.2 Artificial Video Sequence Creation
There is a clear need for a standardized motion compensation algorithm testing apparatus – where each algorithm can be compared and contrasted both quantitatively and qualitatively (see Figure 6). This would allow for problems to be easily recognized, resolved and optimized [11]. An important question is “What are the main factors/variables that are inherent in a high quality viewing experience?” This question can be dealt with by qualitative studies, but an alternative is to compare experimental interpolated frames to control interpolated frames. These control frames can easily be produced in an artificial video sequence because all the objects in the scene have a known location and movement direction.

Random objects are selected (inkblot or circle), assigned random sizes, translations, colors, and positions. Each one is then placed into an image layer which can be manipulated independently of other layers, thus allowing for control over experimental conditions. Object layers are used for constructing an artificial video sequence of frames. The number and type of objects in a scene can be altered to test the efficacy of our two experimental MCI algorithms under different sample video complexities.

We assume that the ‘best’ interpolated frames should be as close as possible to the ideal control interpolated frames. The similarities between control and experimental images can be easily obtained for all the interpolated frames by computing the RGB-error-magnitude for all pixels in a frame and then averaging the frame color-error for all interpolated frames, thus obtaining the average ECCE.

![Figure 5](image)

**Figure 5.** Representative source video frames showing a progression of scene complexity. Each source frame is comprised of randomly positioned, textured, and scaled objects with random motion vectors. Frame a) includes 7 inkblots/circles, b) 7 inkblots, c) 14 inkblots/circles, d) 14 inkblots, and e) contains 21 inkblots.

![Figure 6](image)

**Figure 6.** Our MCI apparatus uses an artificially generated a) source video sequence of 6 frames. These are used to produce both the b) 5 control interpolated frames and experimentally derive the c) 5 experimental interpolated frames. This WS-MCI experimental run uses color interpolation, and the source frames contain 7 random objects (inkblots or circles).

5.3 Pixel-Wise SOL Funneling Hierarchical Search for Motion Field Estimation
Motion estimation is performed using pixel-wise sum-of-luminance (SOL) search [8] that progressively funnels down
through a hierarchy of down-sampled frames, using a decreasing search space at each level (see Figure 7). The SOL value at one pixel is searched for in other frames to find the end point for that pixel’s motion vector. Pixel-wise ME is predictable in resource use, and produces dense and accurate ME information [8]. Multi-resolution representations of video frames have been shown to improve motion estimation [18]. Each frame in the video sequence has its own hierarchy of five images. The lowest resolution is at the top, and the resolution progressively increases towards the bottom image, which is not blurred. As the search goes down the hierarchy of the stack of images, the search size gets smaller, hence the term funneling. Because we are using an artificially generated video sequence, the scene can be controlled to optimize several variables, such as funneling search sizes for each low-pass filtered hierarchy level. The funneling search size used along one side of the 2D search square is 41, 17, 13, 9, and 3 pixels, respectively.

Tracking a pixel’s SOL value from one frame to another may not represent actual movement of a constant color pixel because pixel neighbors are used in the calculation. Searching based on sum-of-luminance decreases the dimensionality of the pixel search to 1D from an RGB value (three dimensions). Because SOL values are fallible due to their color ignorance, using only adjacent source video frames for ME may be slightly more error prone than examining how SOL values move across the sweet spot. This time frame is where the interpolated frames are produced and it contains the most pertinent temporal/spatial information about how SOL values will move. Interpolating along a fitted Bezier curve would be ideal, but pixel-wise SOL motion estimation is not precise. Even under completely controlled conditions, pixels can’t be unerringly tracked because of the error inherent in SOL search. Vector determination is problematic when an object or a portion of it is in a frame, but not in the next. Finding matching/minimal SOL values will produce erroneous vectors for this portion of a scene. Pixel color interpolation allows the effect of this error to be reduced because a pixel color in frame {0} will become the color in frame {1} according to the motion vector for that pixel.

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Figure 7. Motion estimation using the funneling SOL search.

5.4 AF-MCI and WS-MCI
AF-MCI only creates motion fields across single time frame gaps, whereas WS-MCI always creates vectors across the sweet spot (Figure 8). The pseudo-code for WS-MCI ME and MI phases are presented in Figures 9 and 10, respectively. Although both MCI methods use the same source frames to get motion information, adjacent-frame and wide-span MCI differ in their exploitation of motion information within the source video frames. AF-MCI creates only one motion vector that spans the sweet spot; however, all WS-MCI vectors span this crucial time gap. Therefore, WS-MCI more fully exploits the pertinent SOL-migration information across the time gap that is most motion-information rich. Notice that two of the three WS-MCI generated vectors will span a wider time span than those of the adjacent frame method. The wide-span motion vectors can be normalized as though they spanned only one time gap. The advantage is that we can control for the effect of MI between the two algorithms because WS-MCI normalized vectors can use the same interpolation algorithm as does AF-MCI.

For this particular iteration of WS-MCI’s ME phase
Create a 5-level ME hierarchy of 2D-arrayed luminance values for each source frame: [-1], [0], [1], [2]
Populate ME hierarchies with luminance values from each corresponding source frame
Progressively down-sample all hierarchies (the most down-sampled level is at index 4, 0th level is not down-sampled)
Calculate SOL values for all pixels at all hierarchy levels for all hierarchies
Using a progressively smaller search space (from level 4 to 0), tunnel down (looking for the closest SOL values for each pixel) through each ME hierarchy to find the 3 sets of motion information across these frame gaps: [-1→1], [0→1], [0→2]
Normalize the wide-span vectors to the magnitude of 1 frame time gap
For each pixel, combine the 3 motion vectors

Figure 8. Comparison of adjacent-frame and wide-span motion estimation phases (motion information gathering step). AF only finds one set of motion vectors across the sweet spot (a); whereas, WS uses all three (b).
6. RESULTS AND DISCUSSION

Experimental-control-color-error is concerned with pixel RGB values across all experimentally derived interpolated frames compared to control frames, and it will be influenced by a number of factors such as: the object complexity, and the size/complexity of each object in a scene. In Table 1, the scene complexity ranges from 1 circle to 21 inkblots per scene. Experimental and control interpolated frames were created and compared in terms of the sum of their pixel color differences for all interpolated frames and for each run. This allowed us to quantitatively assess the quality of a set of experimentally derived interpolated video frames. We have called this metric the average Experimental-Control-Color-Error (av. ECCE). The column labeled “WS-MCI % benefit” represents the WS-MCI performance advantage compared to AF-MCI for all test runs at a particular scene complexity in terms of their respective average ECCE values.

Table 1. Quantitative comparison of AF-MCI and WS-MCI over a progression of source video scene complexity.

<table>
<thead>
<tr>
<th>scene complexity</th>
<th>runs</th>
<th>Pearson correlation</th>
<th>2 tailed P-value</th>
<th>AF-MCI av. ECCE</th>
<th>WS-MCI av. ECCE</th>
<th>WS-MCI % benefit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 circle</td>
<td>40</td>
<td>0.9850</td>
<td>9.17E-12</td>
<td>1.86</td>
<td>1.58</td>
<td>15.20%</td>
</tr>
<tr>
<td>7 circles</td>
<td>40</td>
<td>0.9812</td>
<td>6.63E-15</td>
<td>10.08</td>
<td>9.27</td>
<td>8.09%</td>
</tr>
<tr>
<td>7 objects</td>
<td>40</td>
<td>0.9982</td>
<td>3.65E-17</td>
<td>18.53</td>
<td>17.57</td>
<td>5.20%</td>
</tr>
<tr>
<td>7 inkblots</td>
<td>40</td>
<td>0.9983</td>
<td>1.13E-19</td>
<td>23.28</td>
<td>22.11</td>
<td>5.02%</td>
</tr>
<tr>
<td>14 circles</td>
<td>40</td>
<td>0.9768</td>
<td>3.11E-08</td>
<td>19.47</td>
<td>18.78</td>
<td>3.54%</td>
</tr>
<tr>
<td>14 objects</td>
<td>80</td>
<td>0.9949</td>
<td>5.07E-11</td>
<td>26.24</td>
<td>25.34</td>
<td>3.43%</td>
</tr>
<tr>
<td>14 inkblots</td>
<td>40</td>
<td>0.9958</td>
<td>2.57E-02</td>
<td>34.40</td>
<td>33.51</td>
<td>2.61%</td>
</tr>
<tr>
<td>21 inkblots</td>
<td>40</td>
<td>0.9865</td>
<td>3.00E-03</td>
<td>44.93</td>
<td>44.46</td>
<td>1.05%</td>
</tr>
</tbody>
</table>

Recall that the AF-MCI and WS-MCI motion estimation at frame \(0\) will be the same for both. It is only between frames \([-1\rightarrow0]\) and \([1\rightarrow2]\) where the difference between the algorithms is apparent. Because both methods use the same interpolation algorithm for dealing with occlusion [8], the effects of the motion fields from \([-1\rightarrow0]\) and \([1\rightarrow2]\) will be small if the object has purely linear motion. The AF-MCI method uses only adjacent frames for determining motion vectors, and this implies that objects have linear motion in time spans that are not between \([0\rightarrow1]\).

MCI results can be influenced if parallel motion vectors that are close together map to the same interpolated pixel location. This problem may present itself as pixels within the same object layer ostensibly disappearing and leaving white space when they are actually occupying the same 2D-position due to quantization. We have controlled for this effect by using the same source data for both experimental methods.

A scene with many objects that are porous and overlapping (e.g. occlusion conditions) is challenging to analyze. Results show that analysis of 1 circle (Figure 11.a) is easier than when considering 7, 14, or 21 random objects of various complexities. The data points in all parts of Figure 11 have a high degree of correlation and most are very close to the best fit line. Moreover, the corresponding P-values in Table 1 suggest that the results are reproducible and significant. The slope and y-intercept of the best-fit line suggest that there is a slight-but-definite benefit to the use of WS-MCI when there are many chaotic objects (e.g. scenes with a flock of birds or blowing leaves).
Table 1 shows that scenes with several simple objects, random objects, or complex objects are all handled better by WS-MCI because P-values remain lower than 0.05. Therefore, we can conclude that WS-MCI treatment is statistically significant and effective. Additionally, the algorithm has the same resource expense as AF-MCI. For this reason, WS-MCI should be considered as part of any new MC algorithm to produce higher quality interpolated frames, or map motion for video compression.

The average ECCE suggests how far away from ideal the results were, and is a metric for MCI analysis. Since 14 inkblots/circles shows approximately the same EC-color-error as 7 inkblots, this supports the intuitive idea that circles are easier to analyze than inkblots. These results suggest that 14 complicated objects drastically increase the analysis difficulty over 14 random objects. Not surprisingly, EC-color-error assay results with 14 and 21 inkblots produced more EC-color-error than 14 inkblots/circles.

7. FUTURE WORK
Pixel-wise ME that uses SOL search does not concern itself with color. In real-world scenes, this will be problematic – especially when an object enters/exits shadows. Future research will focus on making wide-span MCI more robust in terms of object tracking with regards to objects’ colors. Other future studies will consider how WS-MCI might be adapted for video compression for use with HDTV signals, and this will involve testing using natural HDTV video sequences.

Objects in our artificial scenes are moving at constant linear velocity. However, we anticipate that WS-MCI would probably work well with non-linear motion because it looks for how the SOL values lay across the interpolation ‘sweet-spot’ – instead of before it or after it. We plan to explore this topic in our future research.

Furthermore, our preliminary work shows that using backward motion vectors across the sweet-spot produces frames that are more filled-in with sensible colors. This makes sense since backward motion vectors will give more information about pixel movement in the time frame from \(0\rightarrow1\) so this information is equally important as forward motion vectors that traverse the same time span. Using backward vectors may cause more pixels to try to find a position on the interpolated frames. In addition, having more migrating pixels tend to not produce the same amount of overlap as when only forward vectors are used.

8. CONCLUSION
Since the goal of motion estimation and motion interpolation is to produce convincing inter-frames, it is important that we focus the search for quality motion information at the sweet spot. This idea manifests itself in the wide-span motion compensated interpolation algorithm that we have presented in this paper. Using artificial video sequences, we created a test apparatus capable of reproducing source video frames of varying complexity and used it to compare two MCI techniques: AF-MCI and WS-MCI. The resulting measure of average experimental-control-color-errors and paired t-tests show that WS-MCI consistently outperforms AF-MCI for complex video sequences. These results clearly indicate that using WS-MCI on a real-world chaotic scene would be the better choice. Our overall objective is the application of these advanced computational techniques for the creation of enhanced visual and aesthetic effects such as slow motion in the postproduction of high-resolution video on large-screen displays.

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10. REFERENCES


