Enhancement of Videos Captured Under Low Light Conditions through ICD Approach Using Savitzky-Golay Filter

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Abstract

Primary objective of video enhancement is to process the videos captured under low light conditions, making them more appropriate for precise applications. Different techniques existing for Enhancement of Digital videos provide a multitude of choices to improve the visual quality of dark videos.

Local, global, dark contrast stretching, Adaptive Histogram Equalization are the existing contrast enhancement algorithms periodically result in artifacts or noise effects. These result deceptive details and contrary effects in the videos processed. These shortcomings increase for videos recorded under poor radiance conditions.

We propose an algorithm to overcome these flaws and enhance dark videos, by sharpening edges with more detailed textured regions, and smoothness of flat portion being preserved. This paper contains enhancement of the video contrast based on Intensity Channel Division. Whole process is done by grouping the information with common characteristics after analyzing the contrast of the video frame in the boundary and textured regions. These groups model the relations within the frame, from which the transformation functions are extracted.

The proposed method adapts Savitzky Golay filtering for the transformation function, which applies smooth transformation to the contents of the video frame avoiding the introduction of errors in the frame.

KEYWORDS— Artifacts, Videos, Frames, Intensity Channel Division, Savitzky Golay filter.

I. *Introduction*

It is necessary to improve sub-standards that are recorded in bright or dark environments producing low contrast videos. Several contrast enhancement algorithms have been proposed to step up this problem. For enhancing the intensity of the video frames Histogram Equalization (HE) is one of the widely used techniques. In this process, artifacts are created in smooth regions and do not consider the boundaries degrading the sharpness of the video. Another approach is Adaptive Histogram Equalization (AHE) for contrast enhancement of the video produces over enhancement resulting unnatural videos. To overcome these problems, we opt for enhancing the content of the image.

The first step in the proposed algorithm is to divide the video in to required number of frames. Now every frame is an image. The intensity pair distribution is done for individual frames. In this algorithm, the global properties of HE [3] and local properties of AHE are combined. Here the contrast pairs are formed and the transformation is generated. The obtained output image has artifacts so we select Intensity Channel Division (ICD) and the transformation function for this is generated. But the transformation curve obtained using channel division is not smooth. So Savitzky-Golay filtering is performed to smoothen the curve and is applied on the input frame to obtain an enhanced frame. This process is applied on all frames extracted and hence all the enhanced frames are combined to form an enhanced video.

II. *Extracting Frames from Videos*

An object i.e., a video is considered and is kept in Viplane with .avi extension. This object is read and is assigned with a variable. Getting the number of frames from a video is done using 'obj. No of Frames'. The number of frames which are to be extracted from a video is to be specified by using an iterative process. This process is a counting loop by its nature gives a count i.e., the number of frames that are to be extracted from a video. These frames are written using the MATLAB command 'imwrite'.

This command writes the image data to the file specified by filename, inferring the file format from the extension. The function creates the new file in the current folder. The obtained frames are to be saved with .tif format. For the frame to be saved under this .tif format, it has to be concatenated with the .tif first. Frame and .tif are to be concatenated using 'strcat'. Resulting frames are shown in   Figure 1.
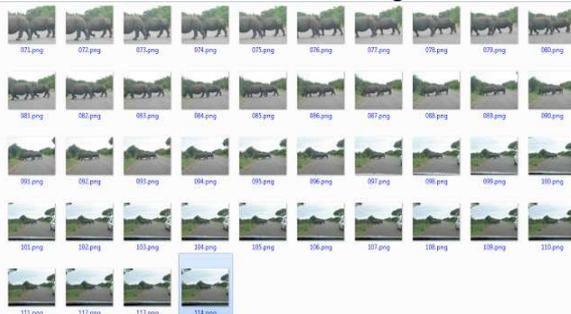

Fig. 1. *Frames from the video rhinos.avi*

III. *Intensity channel division approach*

The proposed algorithm form the informal transformation based on the information extracted from the boundaries and textured regions. Formation of contrast pairs is done using the contrast understanding the relation between two neighboring pixels. The isolated pixels which do not form neighbor with the other pixel are left over and the contrast pairs are piled up in to the Local Contrast Indicator (LCI) function and fusion of such functions in to channels is done to minimize the artifacts. This is channel division process. By this process spreading of inaccurate dynamic range controlling the interference and overlap of the contrast pairs is observed. This results reduction in artifacts and provide maximum enhancement. The transformation function for the region is formed and we apply SGolay filter to the transformation function to remove the noise.

To carry out the proposed algorithm first we transform the frame in to HSV color space which is Hue-Saturation-Value. Next, we apply the proposed algorithm to the V component that is illumination component of the video frame where the H & S are retained. Later the preserved H & S are fused with the enhanced V component to provide enhanced frame.

A. Contrast Pair Distribution

In our algorithm first the intensity pair distribution is formed by extracting both local and global information of the frame. [3] For a given frame the intensity difference is found out between the center pixel and neighboring 8 pixels.

The contrast pair ρ^i_j between two given intensities *i* and *j* is formed as a set of votes for every intensity in the intensity set *(i,......,j)*. We define the set of contrast pairs for a pixel *(x, y)* as

$$P(x,y) = \left\{ \rho_{I(x,y)}^{I(x',y')} \big| (x',y') \in N(x,y) \right\} \qquad (1)$$

where $N(x,y)$ is a set representing 8 neighbours of the center pixel (x,y).

The first four contrast pairs are formed by scanning the three neighbors above the pixel and the one directly to its left. And the other four pairs are formed by scanning the three neighbors below and the one to its right.

The set of contrast pairs of each frame is divided into two classes: edge and smooth. If the intensity difference between the pair intensities exceeds the threshold (10 intensity levels in our process) then it is considered an edge contrast pair, otherwise it is considered as smooth contrast pair.

Transformation function is created using LCI of the contrast pairs. We use the LCI which is normalized since we found that channel division provides higher enhancement than the proposed method. The LCI is formed by grouping the votes formed by the contrast pairs [3]. Here we use an edge contrast pair which reveals the details of the frame. This procedure preserves the flat regions. As a result the accumulation of all the edge contrast pairs generates an LCI function f, defined by

$$f(i) = \sum_{x,y} \sum_{\rho \in P_e(x,y)} \rho(i) \qquad (2)$$

where $f(i)$ is the ith position of the LCI f, which acts like a vector of the accumulated votes from the contrast pairs, x and y are coordinates of the frame, $P_e(x, y)$ is the set of neighboring edge contrast pairs for pixel (x, y), $\rho(i)$ is the ith position in an edge contrast pair of (x, y), i is the intensity index in the range $0 \leq i \leq N$, and N is the maximum number of intensities. Note that, for simplicity, the intensities have been removed from the contrast pair notation for pairs that are identifiable. Furthermore, the edge contrast pairs for the pixel (x, y), i.e., $P_e(x, y)$, are defined by

$$P(x,y) = \left\{ \begin{array}{l} \rho_{I(x,y)}^{I(x',y')} \big| (x',y') \in N(x,y) \\ \wedge \big| I(x,y) - I(x',y') \geq \varepsilon \big| \end{array} \right\} \qquad (3)$$

where (x, y) and (x', y') are the positions of the pixels in the image with intensities $I(x, y)$ and $I(x', y')$, $N(x, y)$ contains the eight neighbors of (x, y), and ε is a constant. Once the LCI is computed, it is integrated and normalized by

$$F(k) = \frac{\sum_{i=0}^{k} f(i)}{\sum_{i=0}^{N} f(i)} \qquad (4)$$

Where $F(k)$ is the kth position in the integrated expansion force F, $f(i)$ is the ith position in the LCI f, k is the intensity index in the range $0 \leq k \leq N$, and N is the maximum number of intensities. Since the transformation function should be monotonically increasing and single-valued, we normalize and project the transformation function T onto the identity transformation I, which is defined by $I(x)=x/N$ for $0 \leq x \leq N$. Then the transformation function can be defined by

$$T(k) = \frac{I(k) + F(k)}{\max(I + F)} \qquad 0 \leq k \leq N \qquad (5)$$

This process is well understood with an example showing a sub image with some pixel values as shown in Figure 2.

170	85	120	200
60	90	100	210
150	180	95	15
9	50	6	56

Intensity Pairs formed are:

(90,170)   (90, 85)   (90,120) (90, 60)
(90,100)   (90,150)   (90,180) (90, 95)

Fig. 2. *Sub image & 8 Neighbours with 8 intensity pairs*

B. Formation of Expansion Force

If the Intensity difference of an Intensity Pair is larger than a pre-selected threshold (10), train of *Expansion Forces* is generated. From the example considered some Expansion forces (difference >10): (90,170), (90, 120)
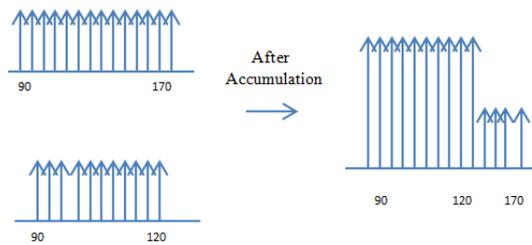

Fig. 3. *Expansion Forces*

Voting between 90,170 and 90,120 are shown as impulses with magnitude one if difference is greater than 10 otherwise zero and after accumulation or integration the net expansion force values are shown as impulses with magnitude 2 between intensity values 90,120 and magnitude 1, between 120, 170 as shown in Figure 3.

C. Formation of Intensity channels

In intensity pair distribution, the contrast pairs belong to different regions. Thus, one accumulation of contrast pairs does not represent the intensity relations and may separate the intensities that should stay together. To overcome this problem, we group the contrast pairs into intensity channels and the transformation obtained from the intensity channels gives better result than the intensity pair distribution because the LCI of each channel affects only its peers. Hence the intensity channels avoid the interference of LCI's that excessively spread the intensities of the group, and consequently compress other intensities [3]. This intensity channels maintains the flat regions in the frame and enhance the textured regions, which avoids the introduction of artifacts.

The intensity channel LCI, $f^i(j)$, for the intensity i is defined by

$$f^i(j) = \sum_{x,y} \sum_{\rho \in P^i_e(x,y)} \rho(j) \qquad (6)$$

where $f^i(j)$ is the jth position in the LCI f^i, x and y are coordinates of the frame, $P^i_e(x, y)$ is the set of the eight neighboring edge contrast pairs for the pixel (x, y) such that the intensity i is within that pair's intensity, and $\rho(j)$ is the jth position in an edge contrast pair of (x, y). Note that i and j vary from zero to the maximum number of intensity levels, i.e., N. Furthermore, the set of edge contrast pairs for the pixel (x, y) and intensity i, P^i_e, is defined by

$$P^i_e(x, y) = \left\{ \begin{array}{l} \rho^{I(x',y')}_{I(x,y)} | (x',y') \in N(x,y) \\ \wedge \left| I(x,y) - I(x',y') \geq \varepsilon \right| \\ \wedge (i = I(x,y \vee i) = I(x',y')) \end{array} \right\} \qquad (7)$$

where (x, y) and (x', y') are the positions of the pixels in the frame with intensities $I(x, y)$ and $I(x', y')$, respectively, $N(x, y)$ contains the eight neighbors of (x, y), and ε is a constant. Finally, the accumulation for each intensity channel LCI, F^i, is computed as in (4), and their transformation functions, T^i, are projected as in (5), by replacing f with f^i, as follows:

$$F^i(k) = \frac{\sum\limits_{j=0}^{k} f^i(j)}{\sum\limits_{j=0}^{N} f^i(j)} \qquad (8)$$

$$T^i(k) = \frac{I(k) + F^i(k)}{\max(I + F^i)} \qquad 0 \leq k \leq N \qquad (9)$$

Finally, the frame is enhanced by

$$I_e(x, y) = \xi(I(x, y)) \qquad (10)$$

where $I(x, y)$ is the intensity of the pixel (x, y) in the original frame, ξ is the final transformation function after smoothing using Savitzky- Golay filtering, and I_e is the enhanced frame.

IV. *Savitzky Golay Filtering* (Curve Fitting Toolbox in Matlab)

Savitzky-Golay filtering can be thought of as a generalized moving average [7]. We derive the filter coefficients by performing an un-weighted linear least-squares fit using a polynomial of a given degree. For this reason, a Savitzky-Golay filter is also called a digital smoothing polynomial filter or a least-squares smoothing filter. Note that a higher degree polynomial makes it possible to achieve a high level of smoothing without attenuation of data features.

The Savitzky-Golay filtering method [2] is often used with frequency data or with spectroscopic (peak) data. For frequency data, the method is effective at preserving the high-frequency components of the signal. For spectroscopic data, the method is effective at preserving higher moments of the peak such as the line width. By comparison, the moving average filter tends to filter out a significant portion of the signal's high- frequency content, and it can only preserve the lower moments of a peak such as the centroid. However, Savitzky-Golay filtering can be less successful than a moving average filter at rejecting noise. The Savitzky-Golay smoothing method used by Curve Fitting Toolbox [6] software follows these rules:

i. The span must be odd.

ii. The polynomial degree must be less than the span

iii. The data points are not required to have uniform spacing

Normally, Savitzky-Golay filtering requires uniform spacing of the predictor data. However, the Curve Fitting Toolbox algorithm supports non-uniform spacing. Therefore, we are not required to perform an additional filtering step to create data with uniform spacing. We can use the smooth function to smooth response data [2]. We can also use optional methods for moving average, Savitzky-Golay filters, and local regression with and without weights and robustness (lowess, loess, rlowess and rloess). The syntax of the smoothing methods is presented below:

Syntax: [7]
yy = smooth(y, span)
yy = smooth(y,method)
yy = smooth(y,span,method)
yy = smooth(y,'sgolay',degree)
yy = smooth(y,span,'sgolay',degree)

V. *Quantitative Analysis*

To evaluate the frame, we use three different metrics: measure of enhancement by entropy, structural similarity. The structural similarity metric was an alternative to intensity based metrics. The structural similarity is based on the assumptions that natural frames are highly structured, since their pixels exhibit strong dependencies, and that the human visual system is highly optimized to recover the structural information from the frame. We estimate the luminance of the frame as the mean intensity such that

$$\mu_I = \frac{1}{N} \sum_{x,y} I(x,y) \qquad (11)$$

where N is the number of pixels in the frame and $I(x, y)$ is the intensity at the position of the pixel (x, y). Instead of using the correlation proposed by Wang et al., we use the ratio of the original frame luminance to that of the enhanced frame. This process allows us to identify the differences in frames, given that the enhanced frame should be brighter than the original, and simultaneously determine the structural Similarities between the frames. Note that the definition by Wang et al. measures only the similarity to the dark frame.

Thus, we define the luminance index by the ratio

$$L(I_o, I_e) = \frac{\mu_{Ie}}{\mu_{Io}} \qquad (12)$$

where I_o is the original frame, I_e is the enhanced frame, and estimate the contrast as the standard deviation of the frame, given by

$$\sigma_1 = \sqrt{\frac{1}{N-1} \sum_{x,y} (I(x,y) - \mu_I)^2} \qquad (13)$$

Similar to the luminance index, we use the ratio of the contrast of the original frame to that of the enhanced frame. Hence, the contrast index is defined by

$$c(I_o, I_e) = \frac{\sigma_{Ie}}{\sigma_{Io}} \qquad (14)$$

Likewise, the structural index is given by the correlation coefficient, which is defined as

$$S(I_o, I_e) = \frac{\sigma_{Io,Ie} + K}{\sigma_{Ie}\sigma_{Io} + K} \qquad (15)$$

where K is a constant to avoid division by zero, and $\sigma_{Io,Ie}$ is

$$\sigma_{Io,Ie} = \frac{1}{N-1}\sum_{x,y}(I_o(x,y) - \mu I_o)(I_e(x,y) - \mu I_e) \qquad (16)$$

where N is the number of pixels of the frames, and $I_o(x,y)$ and $I_e(x,y)$ are the intensities in the *(x, y)* position of each frame. For our evaluation, we do not mix these indices as Wang et al. proposed [3]. Instead, we analyze them separately, which allows us to do a deeper analysis on the enhancement of each frame.

VI. *Results*
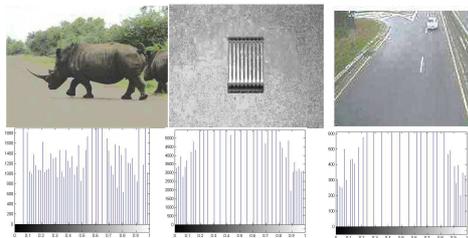
Fig. 4. *One Frame from each Video "Rhinos.avi","Staples.avi","Traffic.avi, Input frames and their histograms*
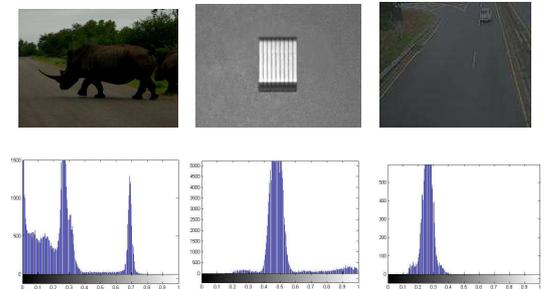
Fig. 5. *Enhanced Frames"Rhinos.avi", "Staples.avi","Traffic.avi", Output frames and their histograms*

Figure 4 and 5 show the outputs of proposed method. i.e., Channel Division using SGolay filter. The methods other than the proposed method have drawbacks in them such as over enhancement, artifacts, unnatural images; lowered boundaries sharpness etc.and the comparison is shown in Figure 6 and represented using quantitative measures. From the quantitative analysis, we observed that our proposed method gave good results.

The Luminance Index for the result of HE for one of the frame is considered and compared to other methods. It is because of over enhancement which is a limitation for that method.

Thus, we used two additional metrics, the Structural Similarity Index and Contrast pair-based metric, to evaluate the enhancement. Considering our proposed metric, it scored better in the "Staples.avi," and "Rhinos.avi" frame. It revealed details in the shadow areas. The proposed method could reveal the details near the objects in frames and maintain the details in other parts of the frame because it created different transformation functions. This behavior is verified in the balance of the luminance, contrast, and structural indices – all of which exhibited high scores for the proposed method.

Overall, the proposed method did a better job in producing frames with means closer to ideal frames—i.e., points closer to the diagonal in the space defined by

the edge and smooth means. Furthermore, the structural similarity indices reveal that the proposed method procured good luminance and contrast indices while maintaining

the structural index the proposed method maintained the frame's structure during the enhancement process and simultaneously increased the luminance and the contrast more than other methods ideal frames—i.e., points closer to the diagonal in the space defined by the edge and smooth means. Furthermore, the structural similarity indices reveal that the proposed method procured good luminance and contrast indices at the same time maintaining

the structural index the proposed method maintained the frame's structure during the enhancement process and simultaneously increased the luminance and the contrast more than other methods as shown in Figure 7.
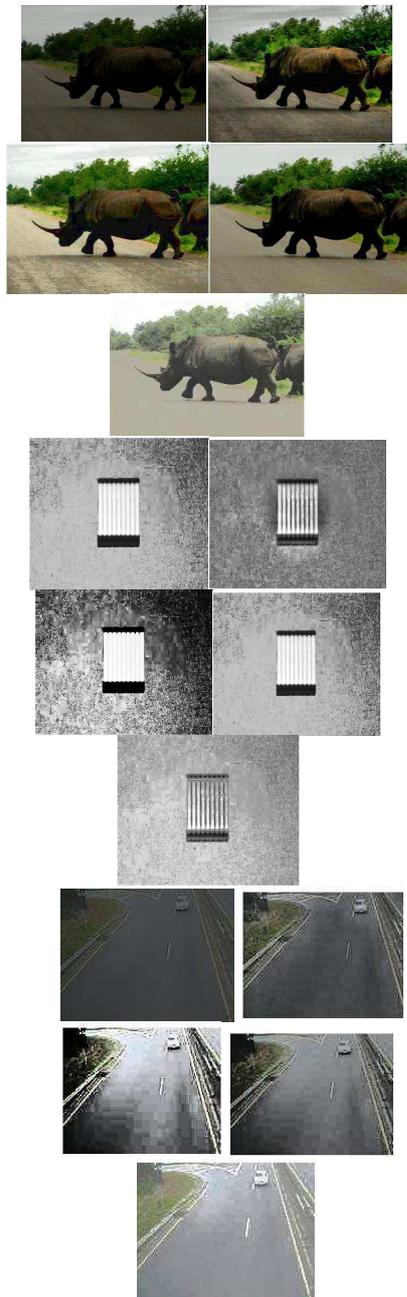

Fig. 6. *Frame number 10 from top to bottom:*
"rhinos.avi","staples.avi","traffic.avi"
a)Input frame   b) Result of HE c)
Result of AHE   d)Result of Intensity Pair
Distribution e) Result of Intensity
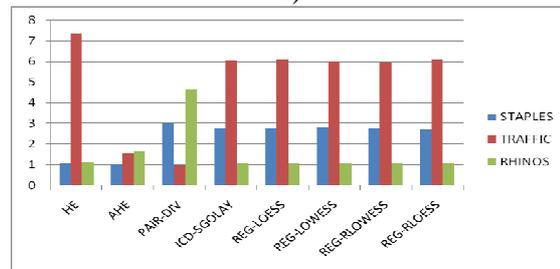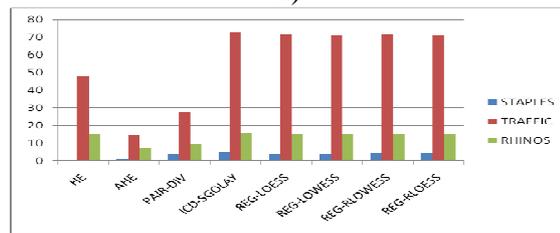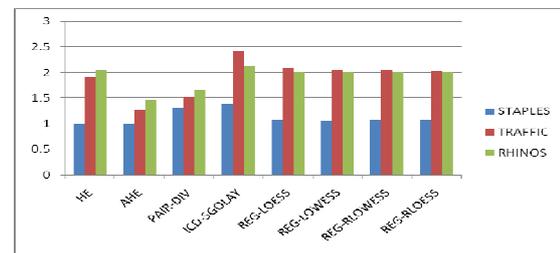*Channel Division with SGolay filter*

a)

b)

c)

Fig. 7 *Quantitave Measures of the results from different frame enhancement methods a) Luminance Index b) Contrast Index c) Structural Index*

VII. *Conclusion*

In this paper, we introduced a content-aware enhancement algorithm that can enhance frames from different environments. The algorithm creates different enhancement functions based on the contents of the frame, thereby improving its enhancement capabilities while reducing the artifacts and other unnatural effects in the resulting frames. The method analyzes the contents through contrast pairs, which are grouped together according to their intensities. Ideally this process increases the enhancement and level of revealed. Ultimately the enhancement is intended to mimic the human visual perception, which is accomplished by Intensity Channel Division with Savitzky – Golay filtered transformation.

The proposed method gave best results because it adapts its transformation functions to the contents of the frame, which avoids the introduction of errors in the image. Once the enhanced frames are obtained they are merged again to form an enhanced video.

References

[1] Adin Ramirez Rivera, Byungyong Ryu, and Oksam Chae, "Content-Aware Dark Image Enhancement Through Channel Division," *IEEE Trans. Image Processing*, vol. 21, no. 9, pp. 3967 – 3980, Sep 2012.

[2] R. Priyakanth, Santhi Malladi, Radha Abburi, "Dark Image Enhancement through Intensity channel division and Region channels using Savitzky – Golay Filter", International Journal of Scientific and Research Publications (IJSRP), Vol.3, Issue No.8, ISSN:2250-3153(Online), Vol.3, Issue No.8, August 2013.

 [3] T.-C. Jen, B. Hsieh, and S.-J. Wang, "Image contrast enhancement based on intensity-pair distribution," in *Proc. IEEE Int. Conf. Image Process*. vol. 1. Sep. 2005, pp. 913–916.

[4] Raman Maini and Himanshu Aggarwal "A Comprehensive Review of Image Enhancement Techniques," Journal of Computing, vol. 2, issue 3, Mar 2010, ISSN 2151-9617, pp. 8-13.

[5] R.C. Gonzalez and R. E. Woods, *Digital Image Processing*, 2nd ed. Upper Saddle River, NJ: Prentice-Hall, 2002.

[6] R.C. Gonzalez, R. E. Woods and S.L. Eddins, *Digital Image Processing using MATLAB*, 1st ed. Upper Saddle River, NJ: Prentice-Hall, 2004.

[7] A. Savitzky and M. J. E. Golay, "Smoothing and Differentiation of Data by Simplified Least Squares Procedures," Analytical Chemistry, vol. 36, no. 8, July 1964, pp. 1627–1639.

[8] Curve Fitting Toolbox For Use with MATLAB®, User's Guide, Version 1.1, 2nd printing, 3 Apple Hill Drive, Natick, MA, The MathWorks, Inc, July 2002, pp. 2-19 – 2-24.