UNIVERSITY of RWANDA

COLLEGE OF SCIENCE AND TECHNOLOGY

SCHOOL OF ENGINEERING

DEPARTMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING

IMPLEMENTATION OF A REAL-TIME MANUSCRIPT SCANNER SOFTWARE FOR HANDWRITTEN LECTURING DIGITIZATION.

Undergraduate Final Year Project

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3. METHODOLOGY.

3.1. Introduction.

Our idea arose from the fact that a human being is able to remember previous scenes of varying video frames from his/her temporary memory. To illustrate this, let us take an example (refer to Fig. 1. for illustrations): imagine that you are watching a video of an artist drawing a small labelled rectangle on a white paper, using a pen. Then after few seconds, the artist starts drawing a larger curve around that rectangle. As the artist draws the curve, his/her hand will roll over the labelled rectangle he/she previously drew, obstructing it from your perspective (view). Your temporary memory will keep reminding you that still there is a rectangle drawn, even when the artist's hand is obstructing it. Our project will rely on this idea of temporary memory, by providing an algorithm which will be able to compensate for obstructed pixels of a white paper being written on in a sequence of recorded video frames.

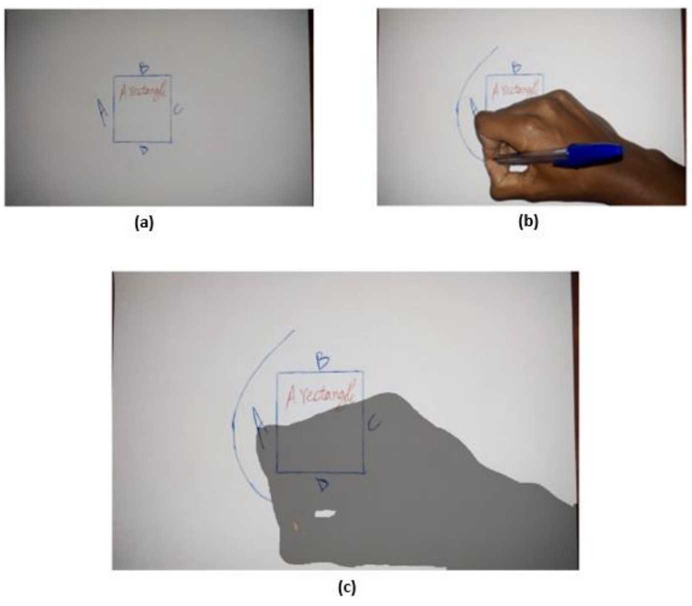


Fig. 1. Illustration of the image stored in a human temporary memory. (a) represents the initial image, (b) represents the obstructed image and (c) represents the perception of the obstructed image, referring to the temporary memory.

Technically, A video is a sequence of images called frames. Each frame is a digital image, a two-dimensional grid of pixels. By that definition, a video of a white paper being written on by someone is a sequence of digital images, where every image shows a state of the white paper throughout the sequence. The main objective of this project will be achieved by enhancing each frame and compensating for the white paper's area obstructed by the writer's syntax, a single input frame will be referred to as “images{n}” where ”n” is the number of the frame (this means that the first frame will be images{1}, the second will be images{2} and son on). As the software will command the camera to capture a video frame (image), the video frame will be processed through three consecutive main processes: Image enhancement, Mask creation and Obstruction removal. In Fig.2., a flow chart for this algorithm is illustrated.

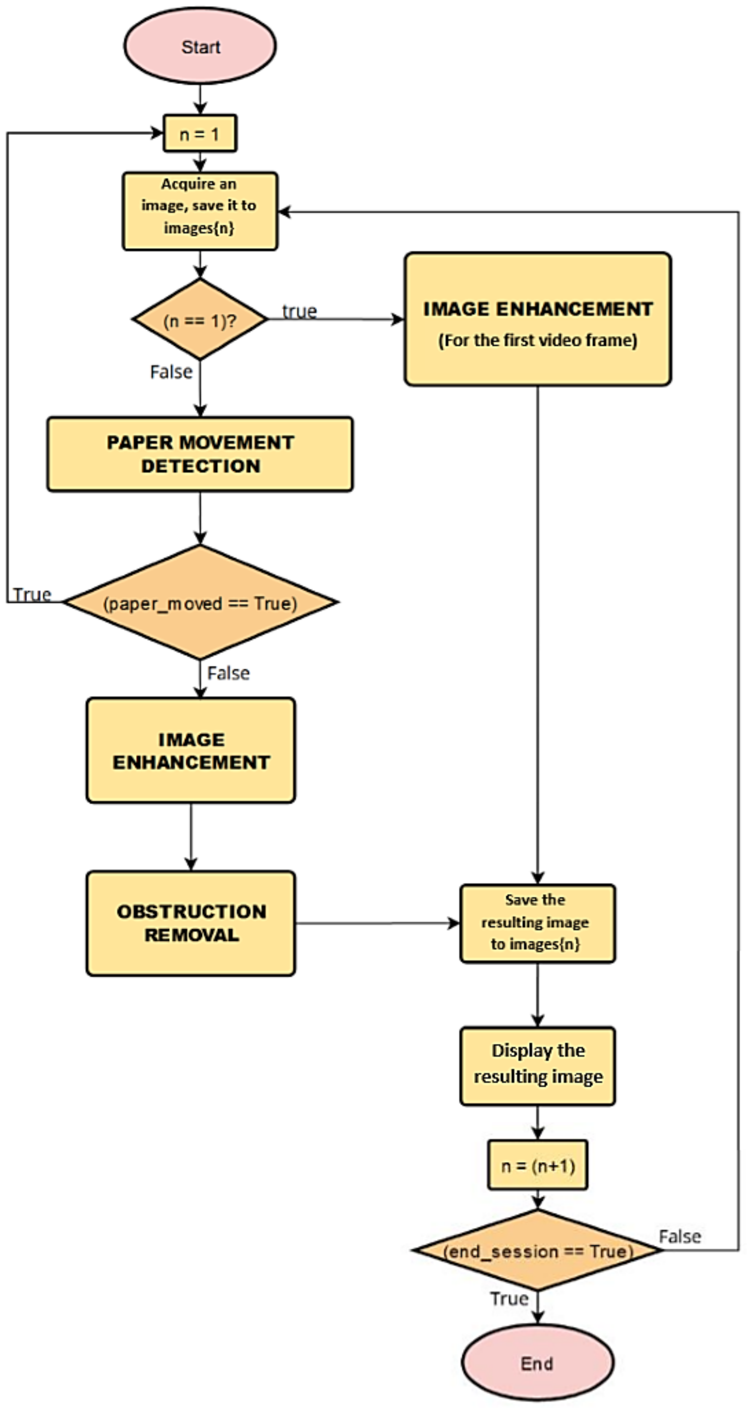


Fig. 2. The Proposed Main Algorithm.

3.3.1. Description of Paper Movement Detection Process

This process will help to ensure that the paper being written on is not being moved with respect to the camera. This will be achieved by computing correlation coefficients of sample data for every two consecutive image frames. A low correlation coefficient will indicate that the paper has moved, thus the algorithm will need to reset, and restart.

3.3.2. Description of the Image Enhancement Process

This process will truncate the input RGB (Red Green Blue) image so as to extract at the maximum the part showing the white paper, enhance the extracted part by increasing the saturation. The purpose of this process is to enhance the colors of the pen strokes inscribed on the white paper. The first frame will undergo its unique enhancement process so as to be transformed into a perfect frame to be a good reference to the next frame for obstruction removal. Fig. 3. illustrates an ideal result of the desired image enhancement process.

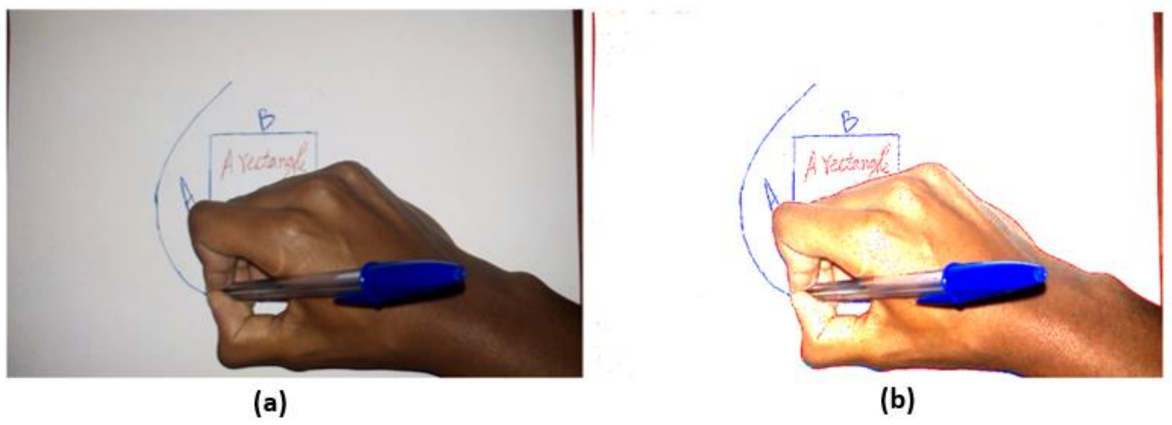


Fig. 3. Image enhancement process: (a) represents the raw image, (b) represents the enhanced image.

3.3.3. Description of the Obstruction Removal Process

This process will threshold the input image. The result will be a binary image, where the obstructed part will be having zero intensity. The binary image will be used in the next task as a mask indicating the obstructed part to be compensated for. Fig. 4. illustrates an ideal desired binary mask.

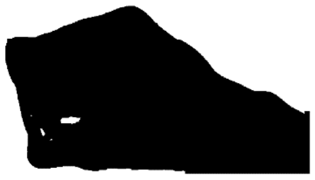


Fig. 4. The Binary Mask created after thresholding.

The process will use the enhanced image and the created mask, process them along with the previous frame, images{n-1} so as to compensate for the obstructed image, and provide a non-obstructed and enhanced image as the output. By using the illustrations from Fig. 5., let's consider the mask as a binary matrix, M and the inverse (the one's complement) of each digit in the mask as Mc. Since the pixels of matrix M where the white paper is obstructed have zero intensities, and the remaining pixels have intensity of 1, element-wise multiplication of matrix M with the enhanced images{n} will give an output with the obstructed part having intensity of zero. Let us call that output matrix, "A". By multiplying (element-wise) the previous image (frame) matrix (the one we called images{n-1}) with the complemented mask matrix, Mc, this will give an output with the non-obstructed part having intensity of zero, but the obstructed part of the white paper will be revealed. Let us call this output image matrix, "B". By adding the matrix B to matrix, A, the result will be the final desired image where the obstruction will have been removed. Fig. 5. and Fig. 6. illustrate well the obstruction removal approach explained above.

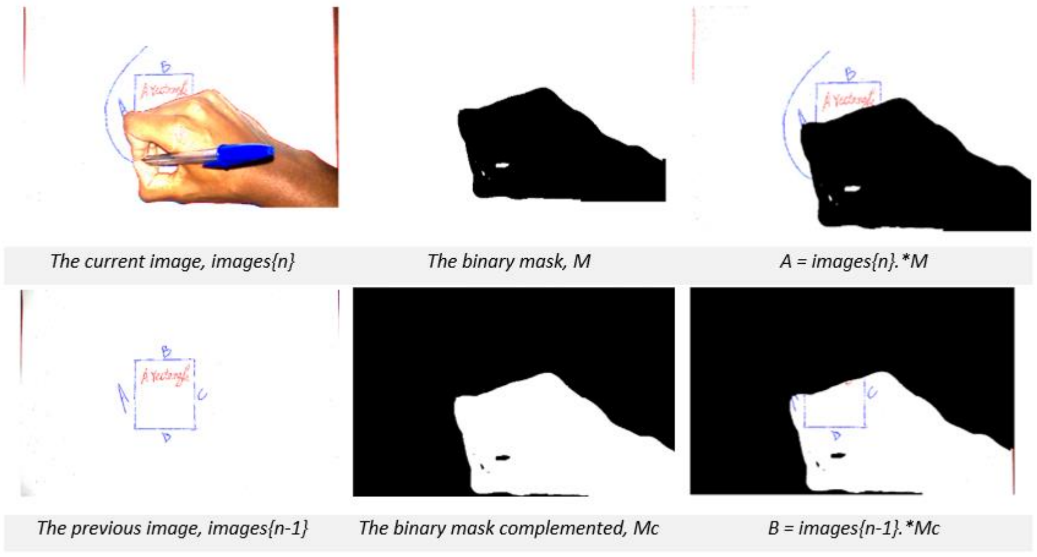

The current image, images{n}
The binary mask, M
A = images{n}.*M
The previous image, images{n-1}
The binary mask complemented, Mc
B = images{n-1}.*Mc

Fig. 5. Obstruction removal processes: Deduction of the obstructed part.

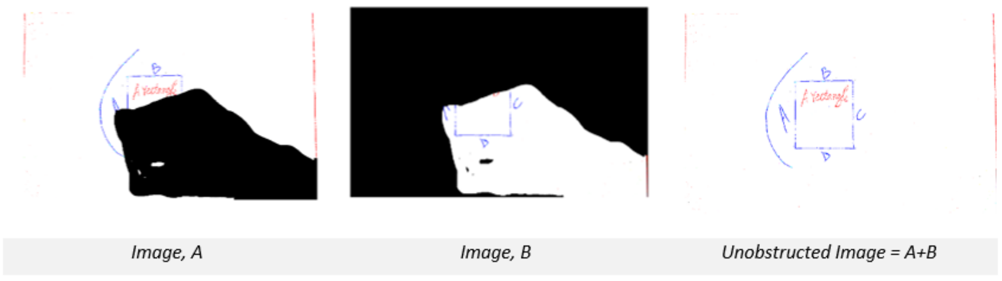


Fig. 6. Obstruction removal: compensating for obstructed pixels.

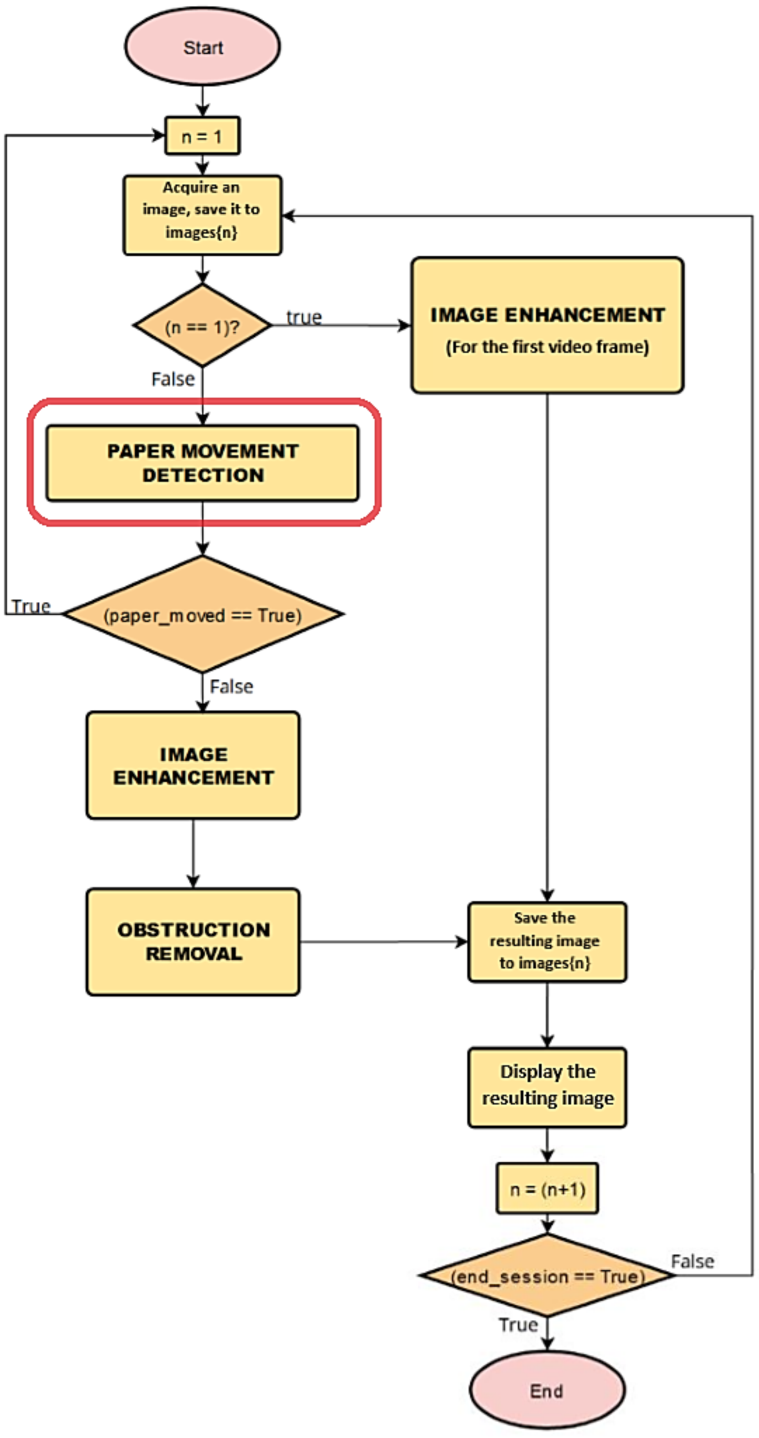


Fig. 7. Indication of where the Paper Movement Detection process belongs to in the Main Algorithm.

4.2.1. Methodology Illustration.

In this section, we are going to illustrate the algorithm of paper movement detection. The flowchart shown in Fig.8. illustrates basic information on the paper movement detection algorithm. Note that the indicated numbers are the number of processes (steps) that are going to be explained.

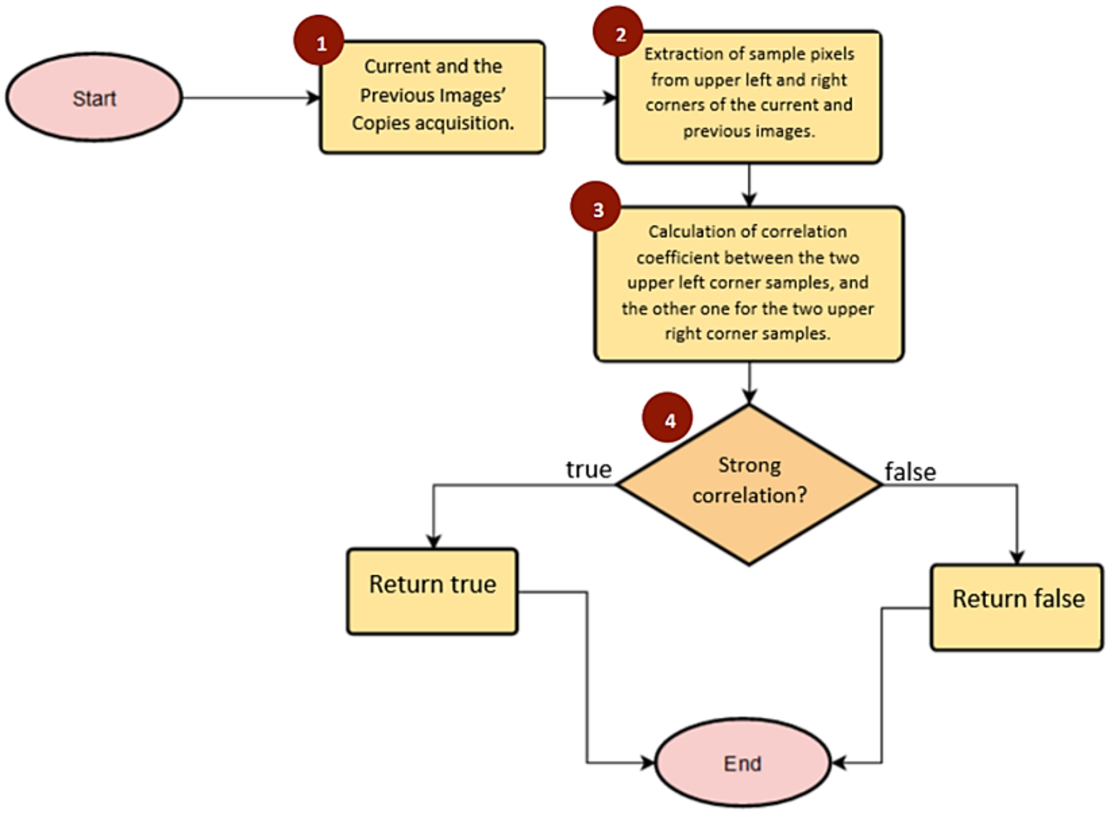

Start
1
Current and the Previous Images' Copies acquisition.
2
Extraction of sample pixels from upper left and right corners of the current and previous images.
3
Calculation of correlation coefficient between the two upper left corner samples, and the other one for the two upper right corner samples.
4
Strong correlation?
true
false
Return true
Return false
End

Fig. 8. Illustration of the proposed Paper Movement Detection algorithm.

Step 1: Current and Previous Images' Copies Acquisition.

In this demonstration, we will assume two images, where one represents a paper positioned well, and another represents the paper moved a bit from its initial position. Here at Step 1, this process will acquire a copy of the current image (frame) and the previous image (frame). It will also trim the images, so as to show the white paper section at maximum, as it is shown in Fig.9.

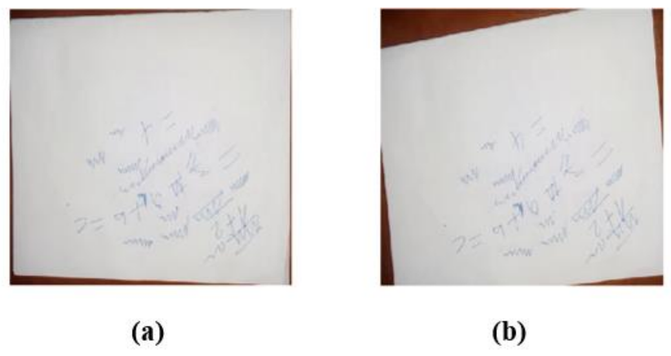


Fig. 9. Illustration of the previous image (a) which was acquired before moving the paper, and the current image, (b), which was acquired after moving the paper.

Step 2: Sample pixels extraction from the upper corners of the two acquired images.

This process will take samples from the upper left and upper right corners of the two images. The extracted segments' height and width will be ten percent of the height and width of their respective images. The acquired corner samples are shown in Fig.10.

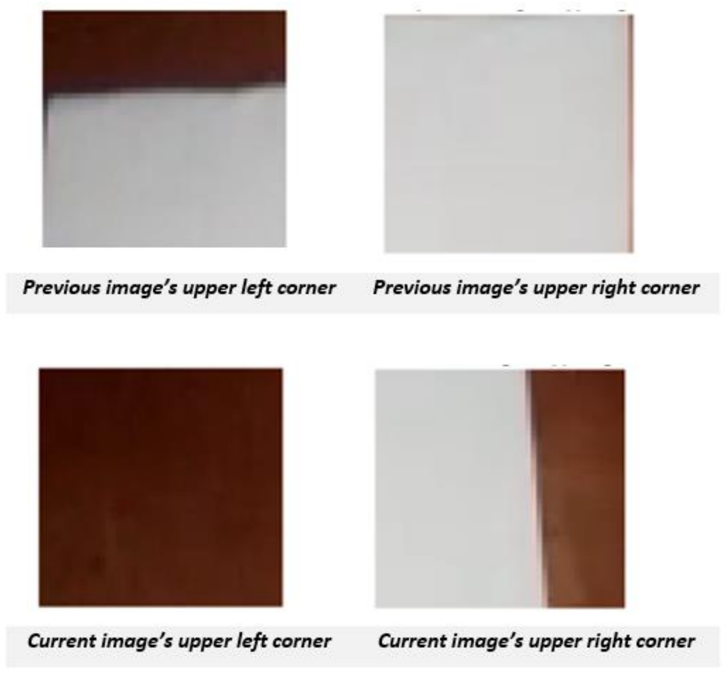

Previous image's upper left corner
Previous image's upper right corner
Current image's upper left corner
Current image's upper right corner

Fig. 10. Acquired samples from each image's upper corners.

Step 3: Correlation coefficients calculations between the equivalent corners of the two acquired images.

To enhance the contrast, this process will first equalize the taken samples. Next, it will transform them into single column vectors, then compute two correlation coefficients: correlation coefficient between upper right corner of current image and the upper right corner of previous image, then correlation coefficient between upper left corner of current image and

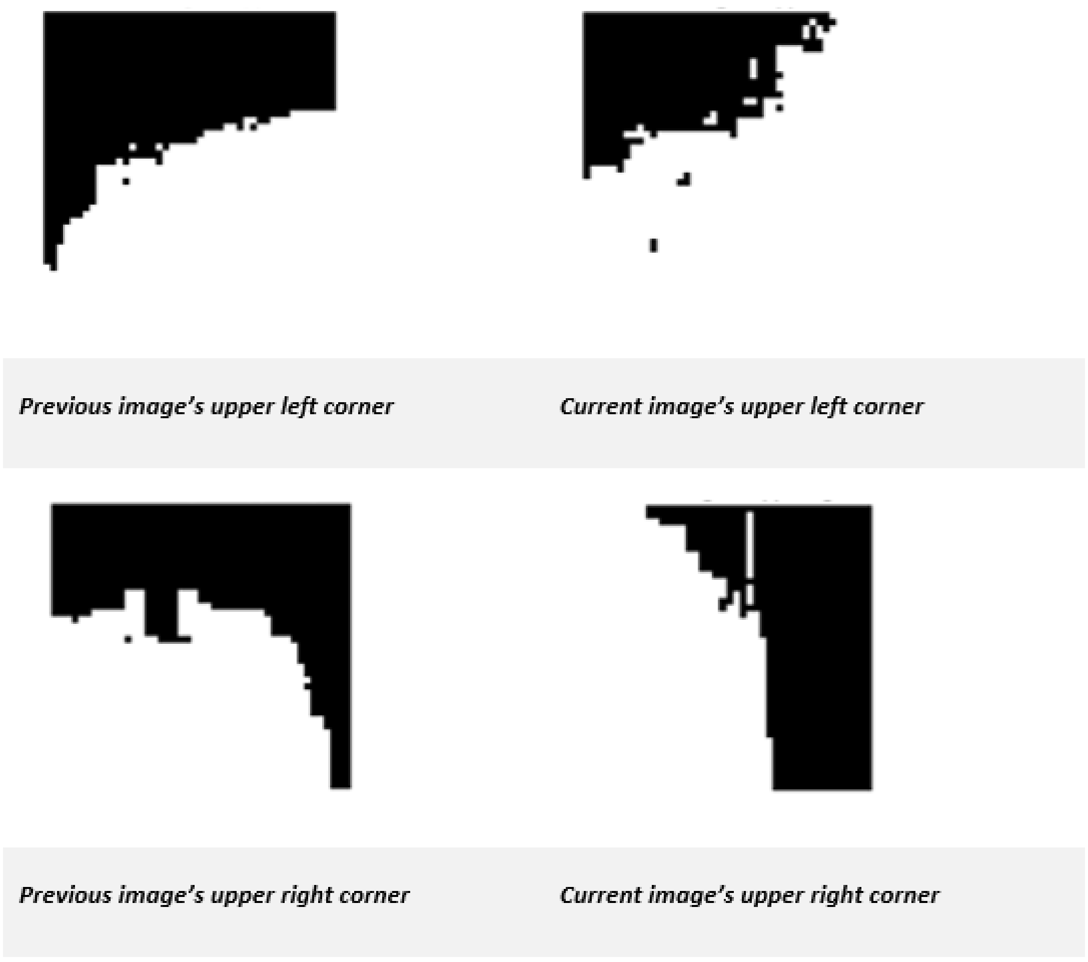

Previous image's upper left corner
Current image's upper left corner
Previous image's upper right corner
Current image's upper right corner

Fig. 11. Results after thresholding the acquired samples.

```
ratio_xor_from_corner1 = 0.1929
ratio_xor_from_corner2 = 0.3034
```

The ”ratio_xor_from_corner1” and ”ratio_xor_from_corner2” provides the fractions of number of pixels that changed, by referring to the samples extracted from the upper left and upper right corners, respectively.

4.2.3. Comparison of Time Usage Between the Correlation-Coefficient-Based Approach and the XOR-Based Approach.

In this section, we are going to compare the time usage of the two approaches: correlation-coefficient-based approach against the XOR-based approach. We will emulate the paper movement detection by using corner samples from images of 1 megapixel to 8 megapixels and graph the time it will take for the computer to process each image using each of the two approaches. For each approach, the computer will execute the step number 3, by considering the corner samples of each image as if they are from the current and the previous images (frames).

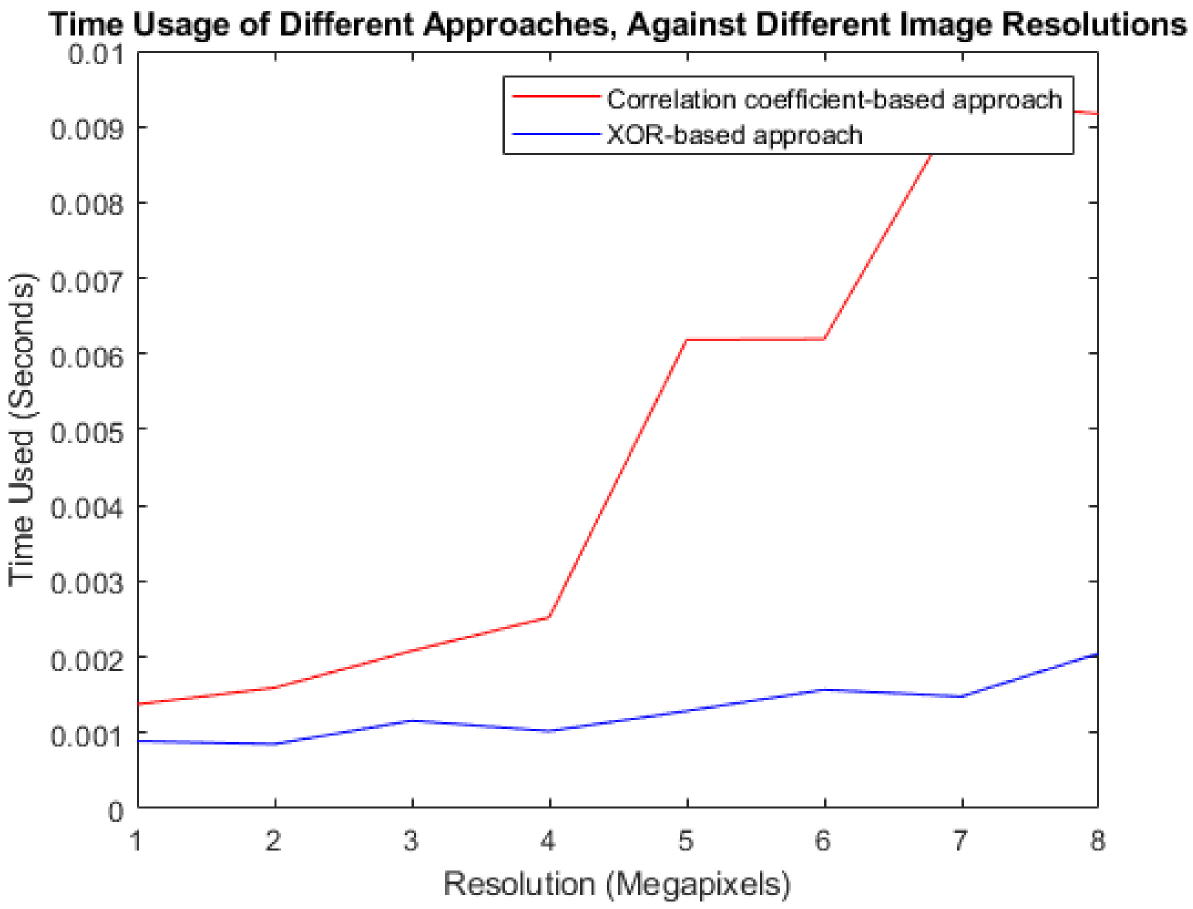


Fig. 12. Time usage of the Correlation-Coefficient-based approach and the XOR-based approach, with respect to different input images' resolutions.

From Fig. 12., it can be seen that the XOR-based approach uses less time than the correlation coefficient-based approach. As we targeted a minimum frame rate of 3 frames per second, about 0.333 seconds has to be allocated to the overall frame processing time. The XOR-based approach was chosen to be implemented since it requires less time which ranges from 0.001 seconds to 0.002 seconds (for input resolutions ranging from 1 megapixel to 8 megapixels), equivalent to the range of 0.3% to 0.6% of the minimum targeted frame processing time (which is 0.333 seconds).

4.3. Algorithm Design for the Image enhancement Process.

To ensure that the pen strokes are enhanced, the system will need to remove noises from the image and then enhance specifically the traces of the pen's ink. Fig. 13. shows a flowchart that indicates where the Image Enhancement process belongs to in the main algorithm.

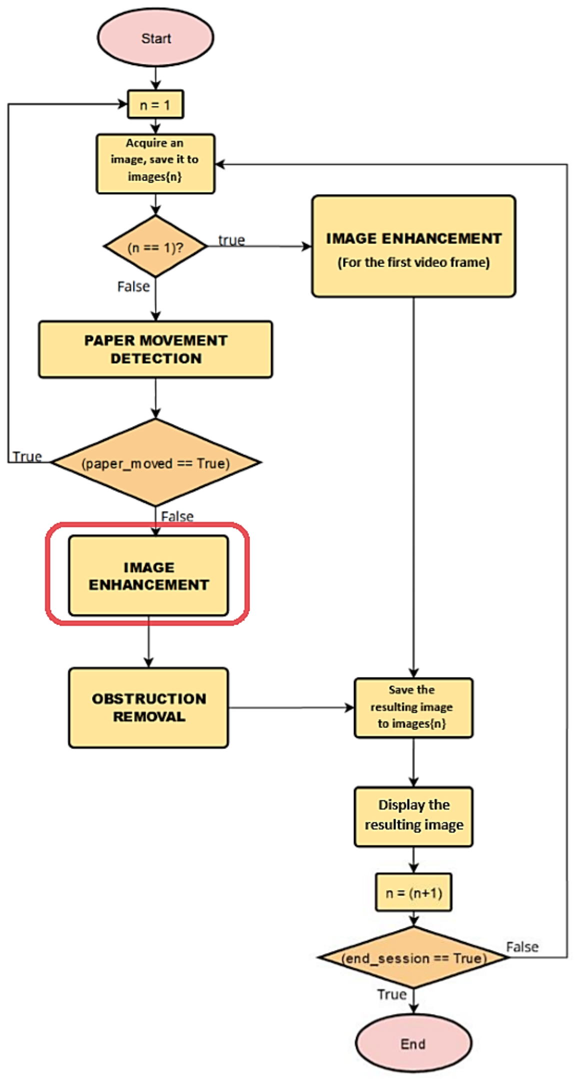


Fig. 13. Indication of where the Image Enhancement process belongs to in the Main Algorithm.

4.3.1. Proposed output of the "Image Enhancement" process:

It is desired that the Image Enhancement process provide an output image with these characteristics:

• The image should be truncated to show at maximum the enhanced white paper,

• The pen strokes on the image should be enhanced, with an increased saturation,

• The first frame will undergo its unique enhancement process so as to be transformed into a white frame and be a good reference to the next frames.

4.3.2. Methodology Illustration.

In this section, we are going to illustrate the algorithm of image enhancement. The flow chart shown in Fig. 14. presents basic information on the algorithm used in this presentation for the process of image enhancement. Note that the indicated numbers are the number of processes (steps) that are going to be explained.

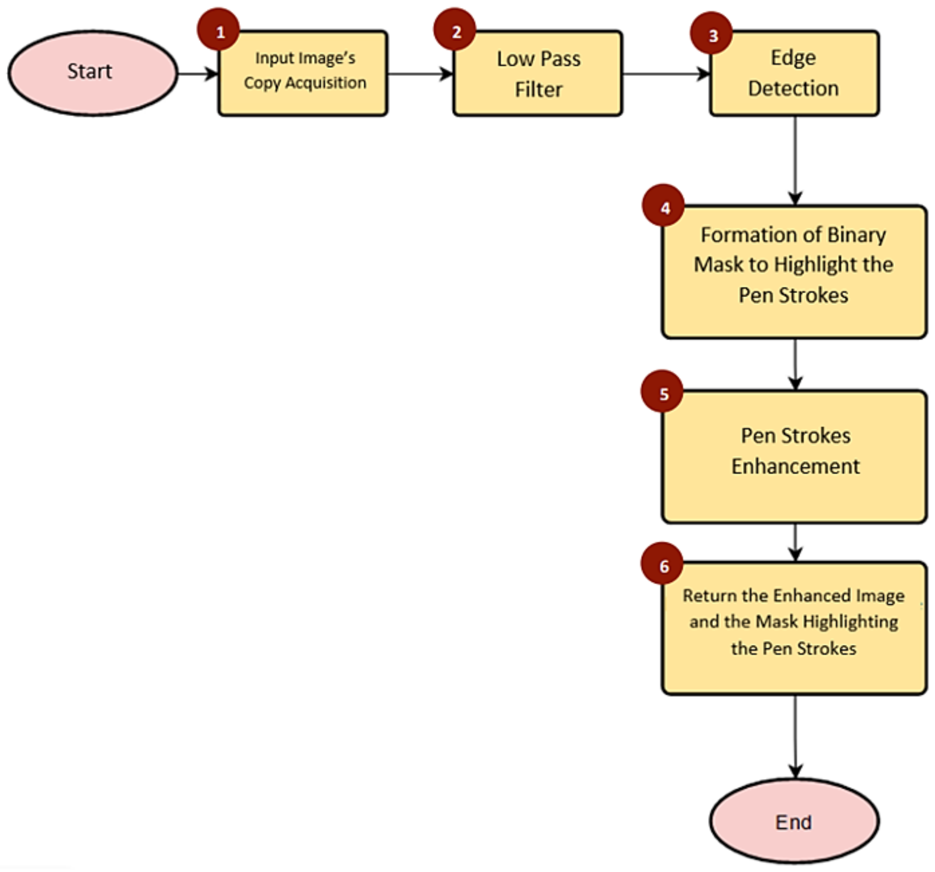

Start
1
Input Image's Copy Acquisition
2
Low Pass Filter
3
Edge Detection
4
Formation of Binary Mask to Highlight the Pen Strokes
5
Pen Strokes Enhancement
6
Return the Enhanced Image and the Mask Highlighting the Pen Strokes
End

Fig. 14. Illustration of the proposed Image Enhancement algorithm

Step 1: Acquisition of the Input Image's Copy.

At this step, the program will acquire a copy of the input image and trim it so as to get at maximum the part that shows the white paper.

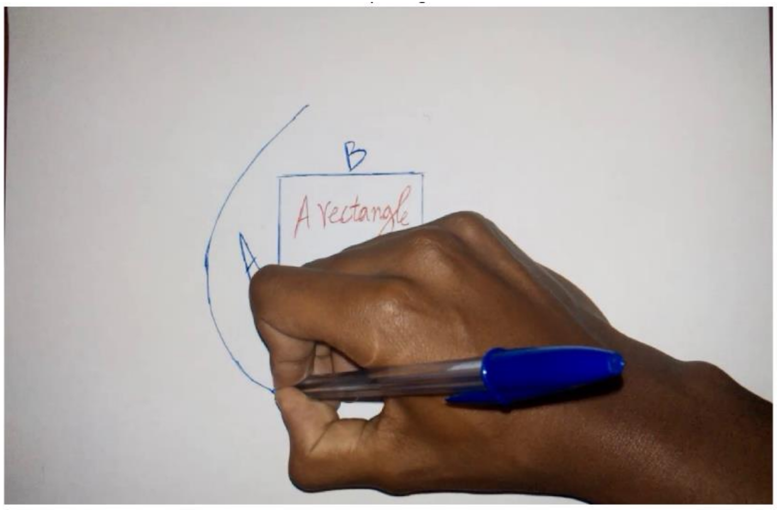


Fig. 15. The acquired input image.

Step 2: Image smoothing using a low pass filter.

This process will use an averaging filter (a low pass filter) to filter out noises in the image after converting it to grayscale. As it was stated in [8, p. 152], a major use of averaging filters is in the reduction of "irrelevant" detail in an image. By "irrelevant" we mean pixel regions that are small with respect to the size of the filter mask. Therefore, noting that the size of the filter matters, this process uses a filter whose height and width are 0.3% of the height and width of the input image (which means that the area of the filter is 0.09% of the area of the input image). That factor of 0.3% was selected after numerous try-and-see image enhancement experimentations.

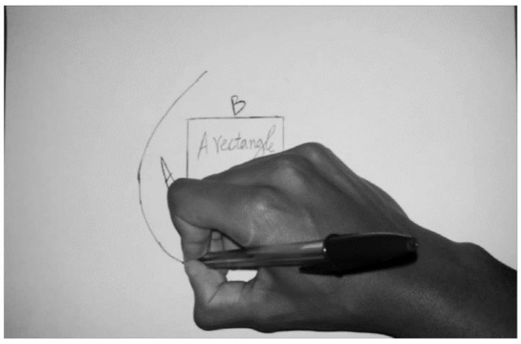


Fig. 16. The input image smoothed after transforming it into a grayscale image.

Step 3: Edge Detection.

This step will use a 3x3 Laplacian filter to detect edges in the image, then threshold the output so as to highlight areas where the ink has traced. Since the pen strokes can have any direction, we need an edge detector that is isotropic. As it is stated in [8, p. 699], the Laplacian detector is isotropic, so its response is independent of direction (with respect to the four directions of the Laplacian mask: vertical, horizontal, and two diagonals).

```
Laplacian_Filter = 3×3
      1      1      1
      1     -8      1
      1      1      1
```

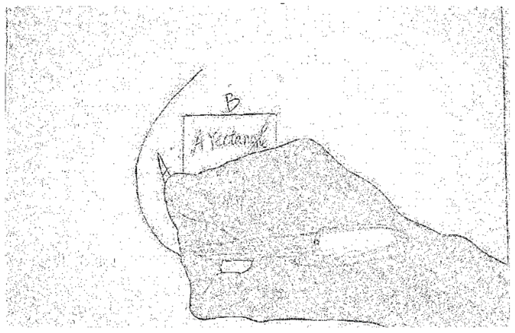


Fig. 17. The detected edges.

Step 4: Formation of a binary mask to highlight the pen strokes.

This step will do a dilation morphological operation so as to remove remaining noises. As it is proved in [8, p. 632], the used structuring element's size matters. Therefore, this process uses a structuring element whose height and width are 0.2% of the height and width of the input image (which means that the area of the filter is 0.04% of the area of the input image). That factor of 0.2% was selected after numerous try-and-see image enhancement experimentations.

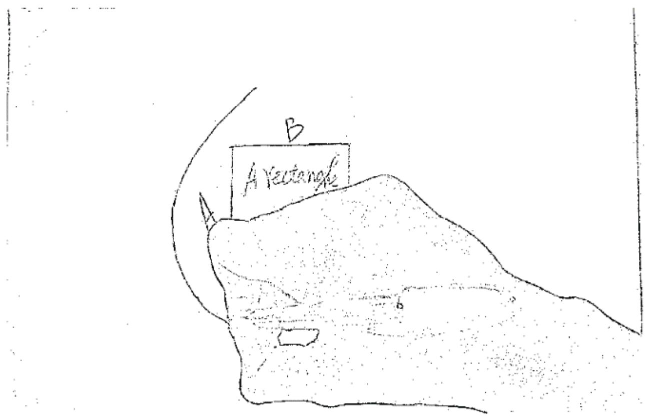


Fig. 18. A binary mask highlighting the pen strokes, excluding noises.

Step 5: Pen Strokes Enhancement.

This process will do an element-wise multiplication between the input image and the created mask (complemented), so as to highlight the pen strokes. To increase the saturation of the pen strokes, the resulting image was converted to the HSI model, and the saturation dimension was multiplied by a relatively large number (10 for our case). After the enhancement, the image was re-converted to RGB for the next steps.

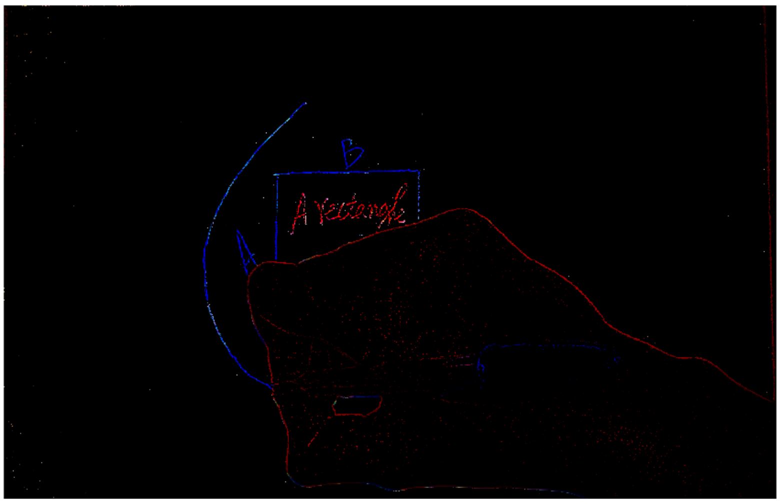


Fig. 19. Pen strokes enhanced.

Step 6: Returning the enhanced image and the binary mask.

This process will set the remaining part (the part which does not represent pen strokes) to higher intensity levels, by multiplying it with a constant. The part is then added to the part that represents pen strokes. After that, it will return the enhanced image and a binary mask to be later used in obstruction removal process, so as to protect pen strokes from being considered as obstruction (see the next topic: Obstruction Removal)

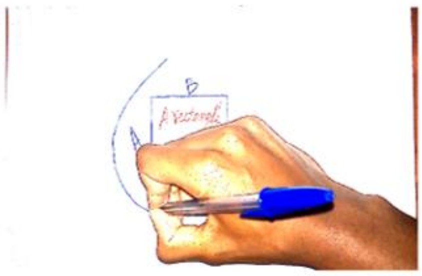
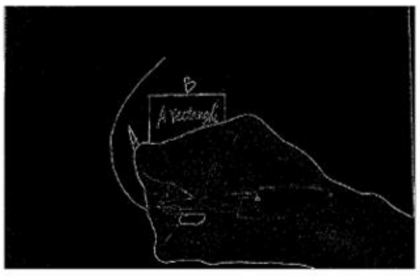
	
Enhanced Image	***Pen strokes binary mask (to be used in the next process: Obstruction Removal)***

Fig. 20. The returned data after the Image Enhancement process.

4.3.3. Algorithm Improvement.

By experimentation, it was found that step 5 (Pen strokes Enhancement) took too much time for execution, due to the conversion from RGB to HSI and vice-versa. The process of RGB-HSI conversion requires complex calculations such as trigonometric and inverse trigonometric functions. These calculations result in low algorithmic efficiency (time efficiency). For this reason, various approaches to improving the RGB to HSI conversion has been proposed, as it can be found in [4]. Given that our case needed to increase only the saturation parameter, we developed our own approach so as to tackle the challenge of time efficiency, as a real-time constraint. The new approach proposed was to divide by three the sum of the Red, Green and Blue components' intensities, so as to get the average intensity for each pixel. Next, the original intensities of the Red, Green and Blue components were compared to the resulting average so as to determine which intensities are major in each pixel. The intensities that were found to be greater than the average were set to the maximum intensity (which is 255), while the intensities that were found to be less than the average were set to the lowest intensity (which is 0). Fig. 21. shows the resulting enhanced image after using this new (improved) approach.

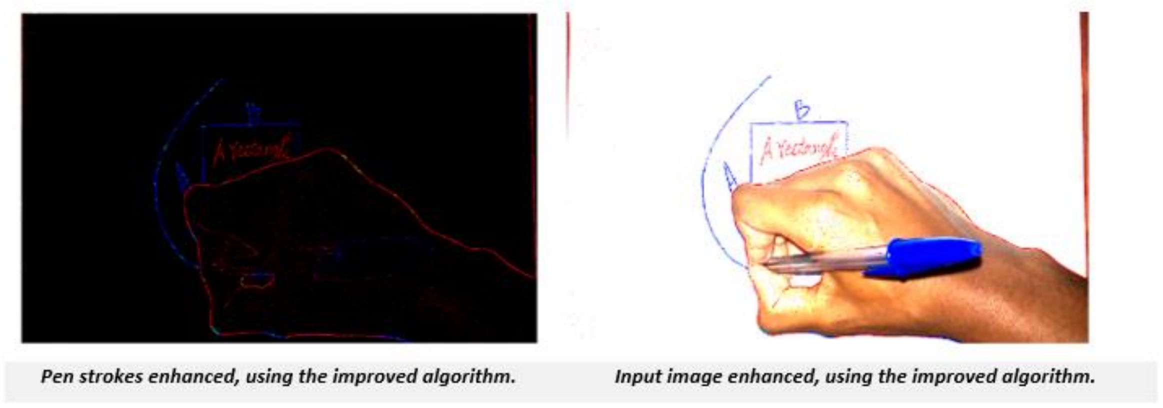

Pen strokes enhanced, using the improved algorithm.
Input image enhanced, using the improved algorithm.

Fig. 21. Results after improving the image enhancement algorithm.

4.3.4. Comparison between the HSI-based approach and the improved approach.

In this section, we are going to compare the time usage of the two approaches: the HSI approach against the improved approach. We will emulate the saturation enhancement process of the system by using sample images of 1 megapixel to 8 megapixels and graph the time it will take for the computer to execute each dataset using each of the two approaches. For each approach, the computer will execute the step number 3, assuming that the given image represents the RGB image to be processed.

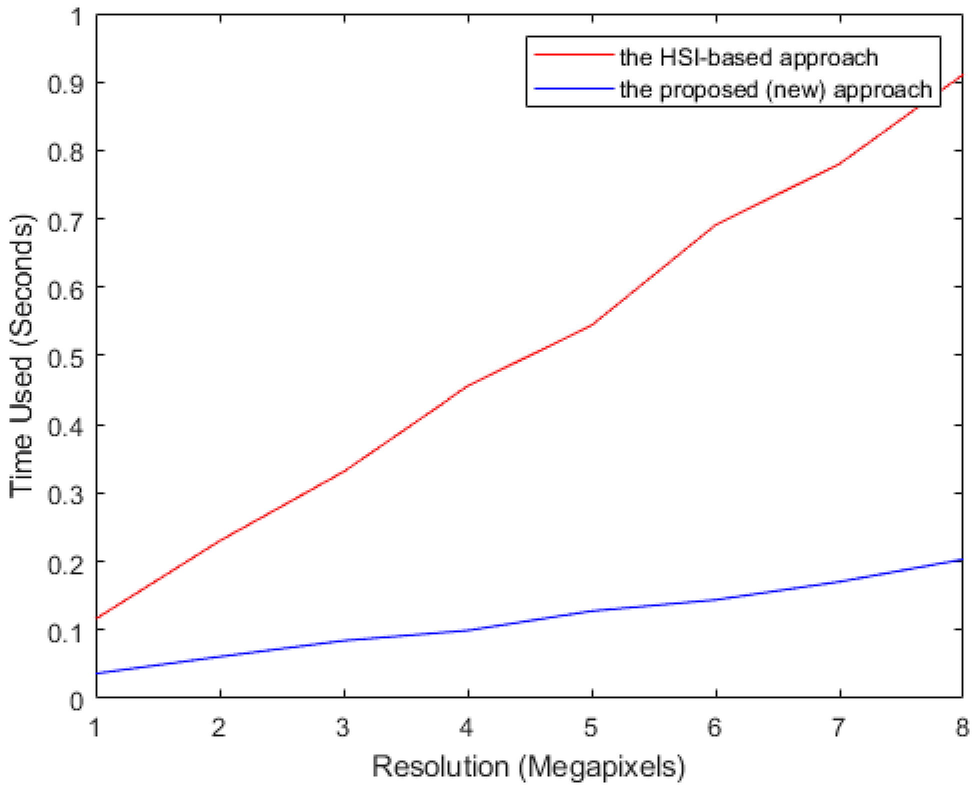


Fig. 22. Comparison between the HSI-based approach and the new (improved) approach.

By referring to Fig.22., the new (improved) approach uses less time than the HSI approach. As we targeted a minimum frame rate of 3 frames per second, about 0.333 seconds has to be allocated to the overall frame processing time. The new (improved) approach was chosen to be implemented since it requires less time which ranges from about 0.04 seconds to 0.2 seconds (for input resolutions ranging from 1 megapixel to 8 megapixels), equivalent to the range of 12% to 60% of the minimum targeted frame processing time (which is 0.333 seconds). The HSI-based approach was rejected as it requires much time that even exceed the minimum targeted frame processing time (which is 0.333 seconds) for resolutions higher than 3 megapixels.

4.4. Algorithm Design for the Obstruction Removal Process.

After the Image Enhancement process, the system will need to compensate for the obstructed part of the input image. Fig. 23. illustrates a flowchart which indicates where the Obstruction Removal process belongs to in the main algorithm.

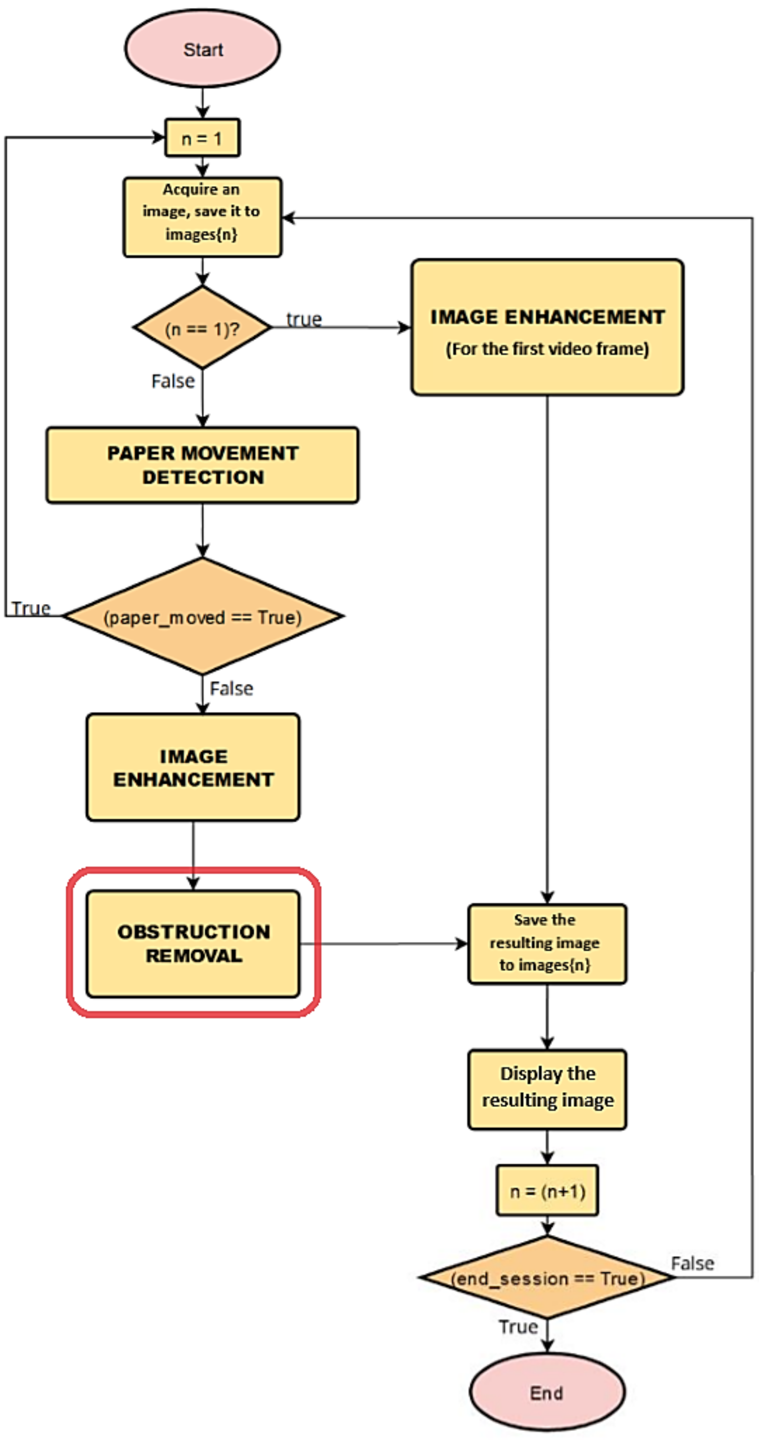


Fig. 23. Indication of where the Obstruction Removal process belongs to in the Main Algorithm.

4.4.1. Methodology Illustration.

In this section, we are going to illustrate the algorithm of obstruction removal. The flowchart illustrated in Fig. 24. shows basic information on the Obstruction removal algorithm that we are going to explain here below. Note that the indicated numbers are the number of processes (steps) that are going to be explained.

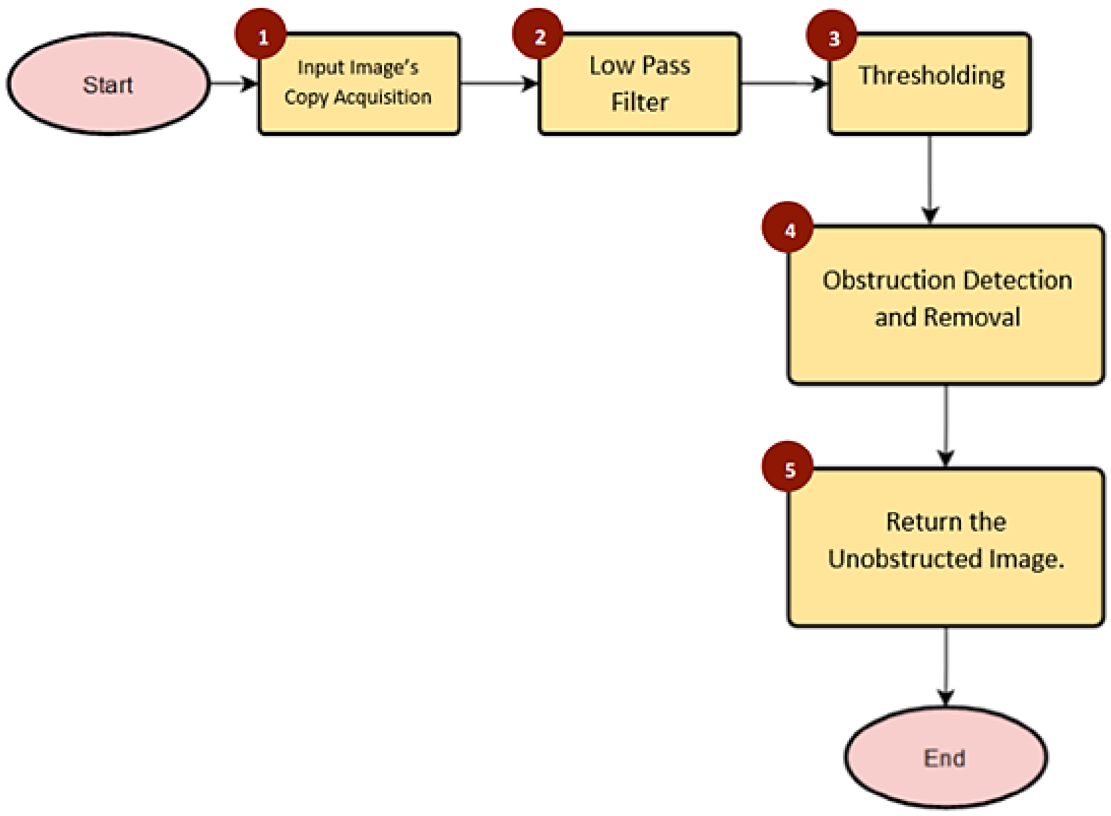

Start
1
Input Image's Copy Acquisition
2
Low Pass Filter
3
Thresholding
4
Obstruction Detection and Removal
5
Return the Unobstructed Image.
End

Fig. 24. Illustration of the proposed Obstruction Removal algorithm

Step 1: Input Image's Copy Acquisition

At this step, the program will read the input image and trim it so as to get at maximum the part that shows the white paper.

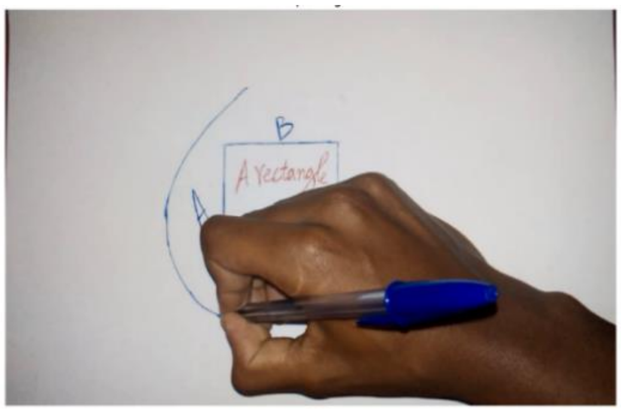


Fig. 25. the input image.

Step 2: Image smoothing using a low pass filter.

This process will use a low pass filter to filter out any object that appears in the image, except only the obstruction (the hand). As it was stated in [8, p. 152], a major use of averaging filters is in the reduction of “irrelevant” detail in an image. By “irrelevant” we mean pixel regions that are small with respect to the size of the filter mask. Therefore, noting that the size of the filter matters, this process uses a filter whose height and width are 1.5% of the height and width of the input image (which means that the area of the filter is 2.25% of the area of the input image). That factor of 1.5% was selected after numerous try-and-see image enhancement experimentations.

The process will use the binary mask from the image enhancement process so as to highlight pen strokes, and make sure that they do not contribute to the obstruction pixels by setting them to the highest intensity value, 255 (This will also prevent the effect of unequal illumination from obstructing the pen strokes). Then the resulting image will be filtered by smoothing.

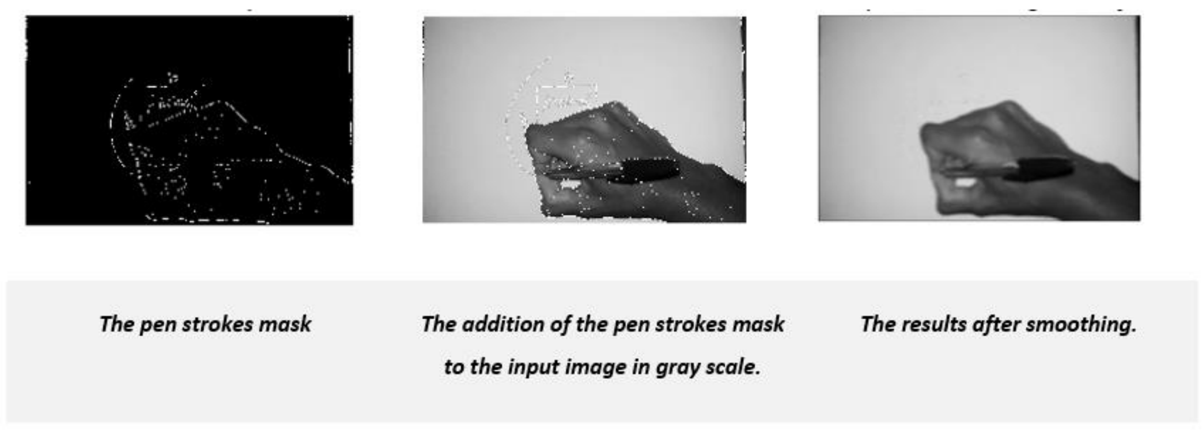
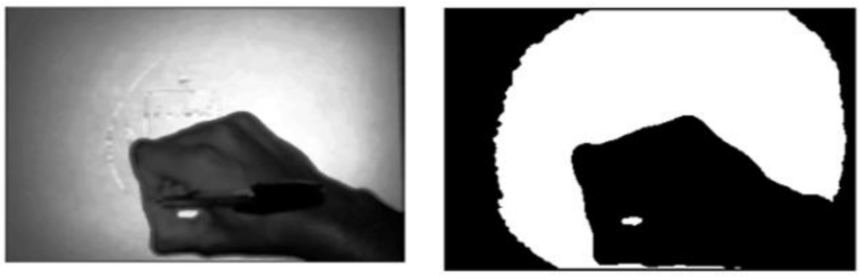

The pen strokes mask
The addition of the pen strokes mask to the input image in gray scale.
The results after smoothing.

Fig. 26. The process that leads to smoothing, ensuring that the pen strokes are protected from obstruction.

Step 3: Thresholding

This process will threshold the smoothed output image from step 2. As various thresholding models rely on contrast enhancement ([6] and [7]), the image equalization will enhance the contrast significantly, so as to prepare the image for the thresholding. By thresholding the image, the process' results will make sure that the obstruction will be represented by 0 intensity pixels.



The equalized image

The Results of thresholding: the Obstruction Mask

Fig. 27. The process of thresholding.

Step 4: Obstruction Removal.

This process will replicate the created obstruction mask into three dimensions so as to multiply (element-wise multiplication) with the input image, thus remove the obstruction by setting the obstruction to zero intensity. The zero intensities will be compensated by the previous frame through addition.

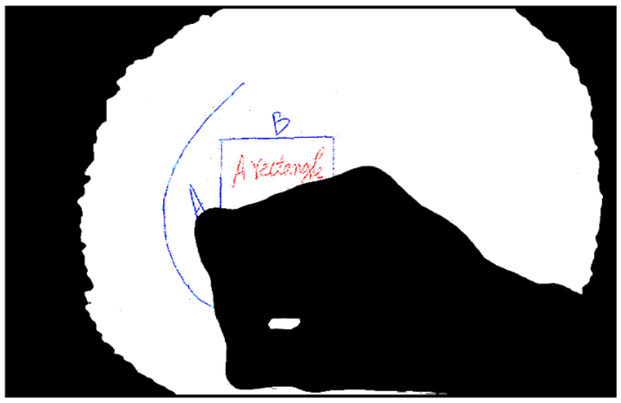
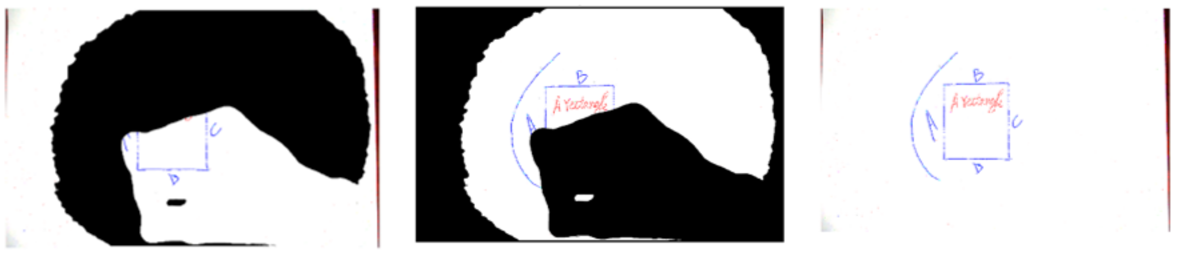


Fig. 28. The obstructed pixels' intensities are set to zero.

Even though the illumination correction is a challenge, all the pen strokes were protected from obstruction. This was due to that, at step 2, we used the pen strokes mask to protect the pen strokes.

Step 5: Return the output image.

This step will return the output unobstructed image to the main program. It will compute the image by compensating the obstructed part by the pixels of the previous image.



(a) The obstructed pixels are acquired from the previous image

(b) The non-obstructed pixels are acquired from the current image

(c) The final obstruction-free image is got as the addition of (a) to (b)

Fig. 29. The final step that generates an obstruction-free output image.

4.5. Frame Rate Related Issues and Code Optimization.

As it is mentioned in the introduction, the goals of this project were set with an envision that it will provide a new alternative for digitized lecturing. Therefore, the time efficiency of the developed algorithms should match with real-time constraints of handwriting. To tackle this challenge of frame rate determination, we referred to the data reported in a forensic related research paper [5]. The objective of that research was to determine the highest speed of handwriting that can be achieved by a person, from a selected sample of people. As it was reported, in undisputed police interview records, the highest speeds observed fell in the range 120–155 characters per minute. By conversion, that range is equivalent to about 2 - 2.58 characters per second. For our case, the targeted frame rate was to be set such that it would at least exceed the highest writing speed expected. Therefore, all the parameters used in the program were tuned so as to match an output frame rate of at least 3 frames per second, for a convenient image resolution. By experimentation, the highest resolution that complied with that constraint was found to be 2 Megapixels. This means that the frame rate would increase if lower resolutions were used, but that would sacrifice the image quality if the resolution was too much lower. The lowest resolution that we found to be tolerable was 0.5 megapixels. Fig. 30. shows a graph that indicates the recorded average frame rate achieved with respect to the resolution of input images. Fig. 31. shows screenshots of outputs of different resolutions. Note how artefacts appears as the input resolution diminishes.

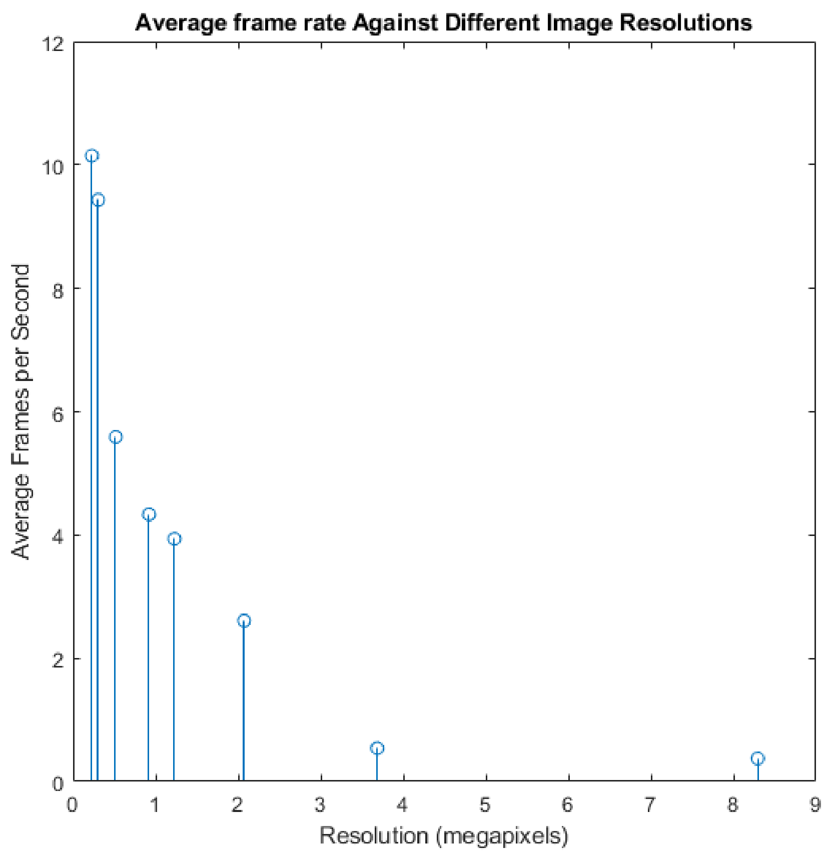
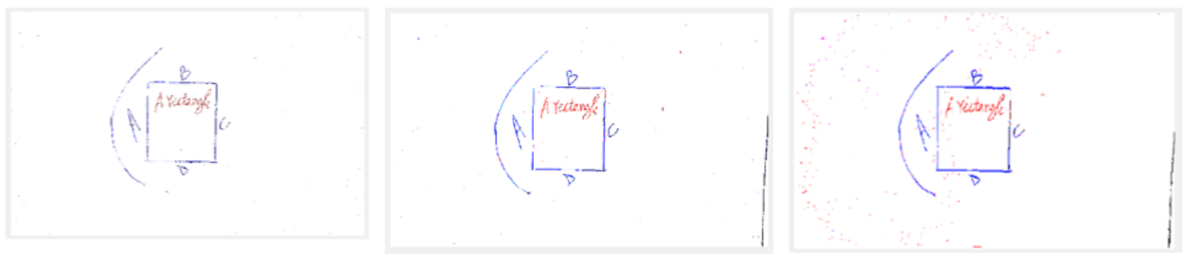


Fig. 30. Average frame rate against different image resolutions. Two Megapixels resolution was found to be the maximum resolution whose output video frame rate would reach in the proposed range.



Output of a 1920x1080 resolution input.	***Output of a 960x540 resolution input.***	***Output of a 640x360 resolution input.***

Fig. 31. Screenshots of outputs of different resolutions. Note how artefacts appears as the input resolution diminishes.

Regarding the code optimization challenge, we had to rely on MATLAB programming language's syntax. As it is suggested in [9], we had to consider two important approaches for MATLAB code optimization: pre-allocating arrays and vectorizing loops. Here, the term "pre-allocation" refers to initializing the variables (arrays) with values before entering a "for" loop that computes and assigns elements to the array. Vectorization in MATLAB refers to techniques for eliminating loops altogether, using a combination of matrix/vector operators, indexing techniques, and existing MATLAB or toolbox functions.

4.5.1. Array pre-allocation Illustration.

To illustrate the concept of array pre-allocation, let us take an example: suppose that, using a for loop, we want to generate a 1x10^8 array, R, of random numbers. Without pre-allocating the array, we would implement our code like this (here the **tic** and **toc** keywords were used to time the execution time):

```
clear R; % we start by clearing the R variable from the memory.
tic; % tic keyword is used to calculate the time of execution.
for k=1:1:10^8
 R(k)=rand(1);
end
toc % toc keyword is used to calculate the time of execution.
```

```
Elapsed time is 17.495172 seconds.
```

```
R
```

```
R = 1×100000000
    0.7940    0.0866    0.4583    0.5840    0.8606    0.4653    0.2677 ⋯
```

By doing different tries, it was seen that it took about 17 seconds for the loop to end its execution.

Let us see the time it will take if we pre-allocate the array, R using the function ones(), so that its elements are initialized as 1s before entering the loop:

```
tic; % tic keyword is used to calculate the time of execution.
R=ones(1,10^8);
for k=1:10^8
 R(k)=rand(1);
end
toc % toc keyword is used to calculate the time of execution.
```

```
Elapsed time is 4.490343 seconds.
```

```
R
```

```
R = 1×100000000
    0.6575    0.4060    0.9396    0.1912    0.2177    0.0114    0.9936 ⋯
```

By doing different tries, It was seen that it took about 3.5 to 4.5 seconds for the loop to end its execution, which is less than the time it took when we did not pre-allocate the R array.

Therefore, in our project, array pre-allocation was a practice followed so as to ensure time efficiency.

4.5.2. Vectorizing loops illustration

Vectorization in MATLAB refers to techniques for eliminating loops, using a combination of matrix/vector operators and indexing techniques. To illustrate this idea, we assume that we have an array, R, whose elements are random decimal numbers, ranging from 0 to 1. We want to threshold the elements of the array, such that the elements of R greater than or equal to 0.5 will be set to 1, and those less than 0.5 will be set to 0. By using a for loop, without vectorizing, our code will be written as given below (here the **tic** and **toc** keywords were used to time the execution time):

```
R=rand(1,10^7);
tic; % tic keyword is used to calculate the time of execution.
for k=1:10^7
    if (R(k) < 0.5)
        R(k) = 0;
    else
        R(k) = 1;
    end
end
toc % toc keyword is used to calculate the time of execution.
```

```
Elapsed time is 0.119271 seconds.
```

By various experimentations, the loop took about 0.1 to 0.15 seconds to finish its execution.

Let us then see the time it will take if we vectorize the loop. The syntax of the loop will even look simpler, since it will take only operators to indicate the loop.

```
R=rand(1,10^7);
display("R array's variables before the loop execution")
```

```
    "R array's variables before the loop execution"
```

```
R
```

```
R = 1×10000000
     0.8910     0.6911     0.7243     0.1794     0.7174     0.4693     0.4250 ⋯
```

```
tic; % tic keyword is used to calculate the time of execution.
R=(R >= 0.5);
toc % toc keyword is used to calculate the time of execution.
```

```
Elapsed time is 0.015905 seconds.
```

```
display("R array's variables after the loop execution")
```

```
    "R array's variables after the loop execution"
```

```
double(R)
```

```
ans = 1×10000000
      1      1      1      0      1      0      0      1      1      0      0      1
1 ⋯
```

Through various experimentation, the time of execution diminished to about 0.01 to 0.03 seconds. Therefore, in our project, loops vectorization was a practice followed so as to ensure time efficiency.

4.6. The Graphical User Interface.

As it was mentioned, this project aimed at developing a computer software for end-users. This means that the image processing algorithms and functions explained above will be executed as the user manipulates an interface that has graphics (buttons, plots of images, sliders, …). MATLAB has an application called “MATLAB App Designer” that allows the development of graphical user interfaces [10]. MATLAB also allows to compile such graphical user interface software into a standalone software for Windows and Mac Operating systems, through MATLAB Compiler [11]. As we were investigating different ways of implementing the image processing algorithms to be used in this project, we also indicated some variables that the user will be able to manipulate through the graphical user interface, depending on the output he/she wishes. As it can be seen on the screenshot below, those variables include the camera, the image trimmer sensitivity and the movement detector sensitivity.

4.6.1. The main components of the graphical user interface.

The figure below shows the first window a user sees when he/she opens our application. The final software can be accessed (with a graphical user interface) through downloading our folder of scripts from [12], add all those files to a local folder, open that folder in MATLAB (version R2021a or later), and run the matApp.m file.

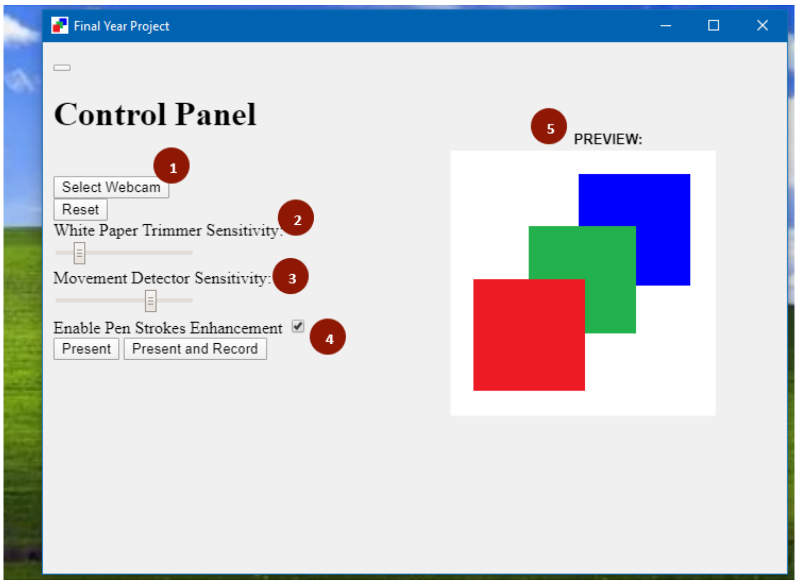

Final Year Project
Control Panel
1
Select Webcam
Reset
2
White Paper Trimmer Sensitivity:
3
Movement Detector Sensitivity:
4
Enable Pen Strokes Enhancement
Present
Present and Record
5
PREVIEW:

Fig. 32. The main components of the graphical user interface.

1. **The "Select Webcam" button:** allows the user to select an installed camera and available resolution and then preview a sample output of the camera on the **"PREVIEW" pane (labelled as 5 on the figure)**. Fig.33. illustrates the required steps of selecting a webcam.

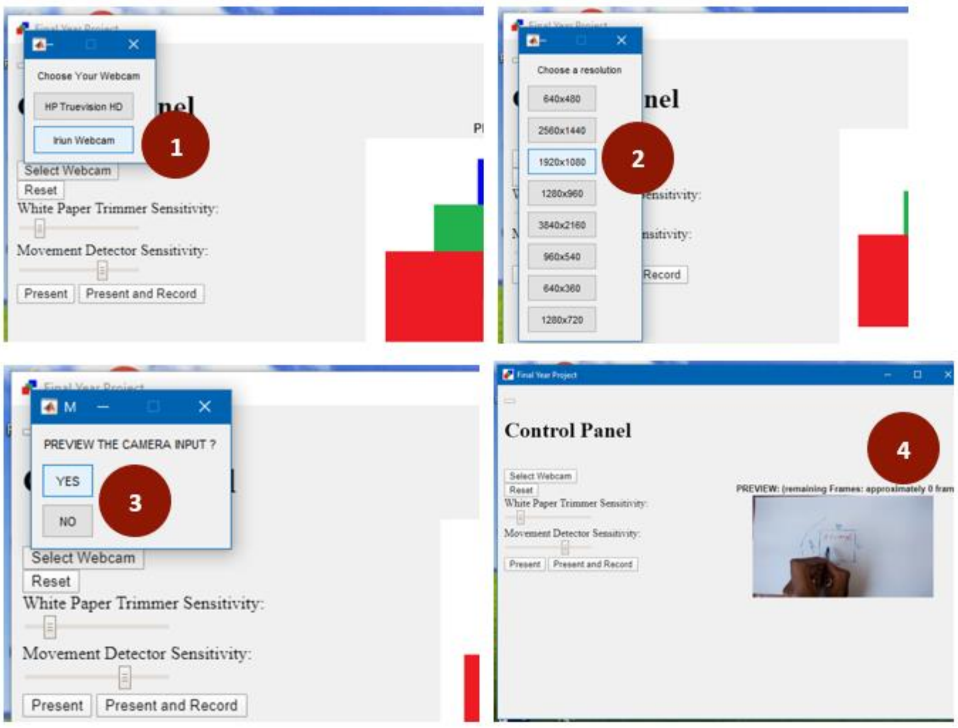
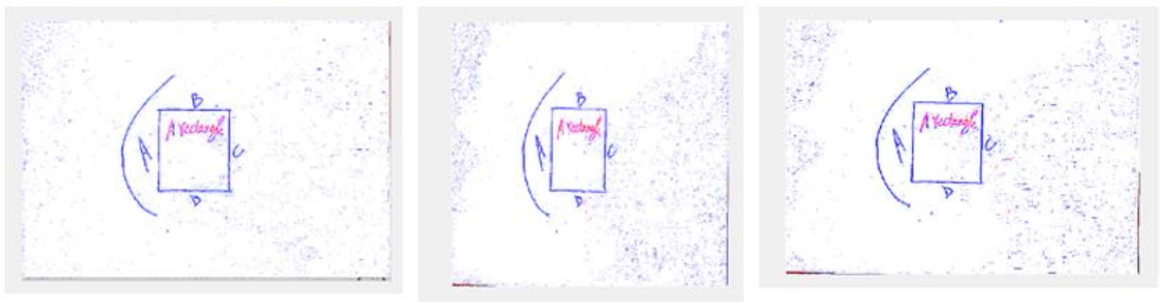


Fig. 33. Process of selecting a webcam. (1: select a webcam by name, 2: select a resolution, 3: choose whether or not you want to preview a video from your selected webcam, 4: Watch a preview for a limited number of frames)



Output of a 1920x1080 resolution input. | Output of a 1280x960 resolution input. | Output of a 960x540 resolution input.

Fig. 34. The output can be impacted by random fluctuation of non-uniform illumination. The screenshots were taken during an experiment done in a low illuminated place.

5.2. The system was not tested on various people with different skin colors.

Due to time limits, the final software was finished late and thus it was tested only on the group members who conducted this research. The only emulation that could be done was to turn the sides of the hand in front of the camera and see if the obstruction would still be removed regardless of the skin color changes. As a result, the system was able to remove the obstruction for inputs with resolutions higher or equal to 1 megapixel. For resolutions lower than 1 megapixel, the system showed some part of the hand's edges as pen strokes. Fig. 35. shows a screenshot taken to illustrate the artefacts, for an input of a low resolution (640x360).

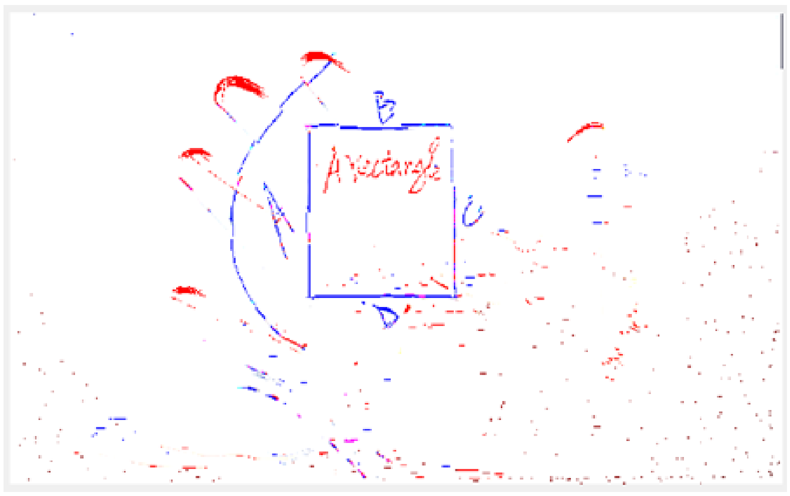


Fig. 35. Artefacts due to failure of obstruction removal process, for resolutions lower than 1 megapixel. (Here we used a resolution of 640x360.)

5.3. The user should always be aware of the camera's perspective with respect to the paper.

The user should know that if a region of the white paper is never exposed to the camera, the software will not be able to figure out the pen inscriptions from that region. It is recommended that the user should place the camera in a way that the line of sight from the camera to the whitepaper will not be obstructed most of the time. The user should also note that the system considers the first frame as an unobstructed reference for removing the obstruction in the next frames. Therefore, the user should not start presenting while the whitepaper is not fully exposed to the camera. This also applies to the case of resetting, when the paper is moved. The software was programmed to dim the intensity and beep twice when the system resets due to paper movement or illumination changes. The user should remove his/her hand from the paper for a second so as to ensure that the image processing loop resets correctly. Fig. 36. shows the resulting output when the first frame is obstructed by the hand.

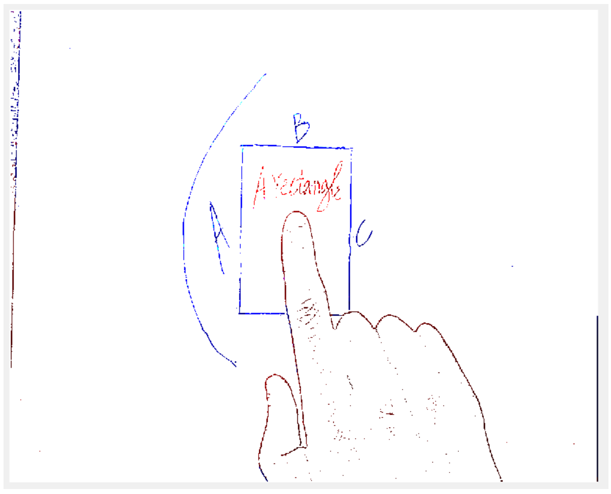


Fig. 36. The resulting output when the first frame is obstructed by the hand.

5.4. Problems related to output video file compression.

MATLAB provides functions that allow combining images into a video file, and other functions that allow a programmer to combine recorded audio samples into an audio file. When it came to combining the video frames together with audio samples into a single file, a compression challenge arose: the output file was extremely huge. We tried the two compressors available on the platform ('DV Video Encoder' and 'MJPEG Compressor'), both did not provide a satisfactory performance, as a video of less than 10 seconds took more than 5 Megabytes, with

A. Appendix A: MATLAB Code used in Illustrating the Main Algorithm's Processes.

A.1. Introduction.

In this section, we are going to provide explanations along with MATLAB codes of the proposed algorithms to deal with the basic parts of our implementation. Those parts include processes of Paper Movement Detection, Image Enhancement and Obstruction Removal. Note that the codes shown here corresponds to the 4th chapter of this report, specifically the 4.2, 4.3 and 4.4 sections. The codes are presented here for illustration purposes only.

A.2. Algorithm Design for the Paper Movement Detection Process.

To ensure that the obstruction can be removed, the system will need to first make sure that the paper has not been moved with respect to the camera's perspective.

A.2.1. Methodology Illustration.

In this section, we are going to illustrate the algorithm of paper movement detection.

Step 1: Current and Previous Images' Copies Acquisition.

In this demonstration, we will assume two images, where one represents a paper positioned well, and other represents the paper moved a bit from its initial position.

Here at Step 1, This process will acquire a copy of the current image (frame) and the previous image (frame). The input images are supposed to be trimmed, thus showing the white paper section at maximum.

```
rawImage1= imread("outImageCr1.png");
rawImage2=imread("outImageCr2.png");
```

Step 2: Sample pixels extraction from the upper corners of the two acquired images.

This process will take samples from the upper left and upper right corners of the two images.

```
cropCornerArea=uint16(10); % area cropped from the corner, in percentage;
rowCr1=1;
```

```
colCr1=1;
[rowCr2 colCr2 d]=size(rawImage2);
total_numberOfRows=rowCr2 - rowCr1 + 1;
total_numberOfColumns = colCr2 - colCr1 + 1;
farthest_row = total_numberOfRows * cropCornerArea / 100 ;
farthest_column = total_numberOfColumns * cropCornerArea / 100 ;
cropCorner1{1}=rawImage1(1:farthest_row,1:farthest_column,:);
cropCorner1{2}=rawImage1(1:farthest_row,end-farthest_column:end,:);
cropCorner2{1}=rawImage2(1:farthest_row,1:farthest_column,:);
cropCorner2{2}=rawImage2(1:farthest_row,end-farthest_column:end,:);
```

Step 3: Correlation coefficients calculations between the equivalent corners of the two acquired images.

To enhance the contrast, this process will first equalize the taken samples. Next, it will transform them into single column vectors, then compute two correlation coefficients: correlation coefficient between upper right corner of current image and the upper right corner of previous image, then correlation coefficient between upper left corner of current image and the upper left corner of previous image.

```
Corner1{1}=histeq(cropCorner1{1});
Corner1{2}=histeq(cropCorner1{2});
Corner2{1}=histeq(cropCorner2{1});
Corner2{2}=histeq(cropCorner2{2});

correlation_from_corner1=corr(double(Corner1{1}(:)),double(Corner2{1}(:)))
correlation_from_corner2=corr(double(Corner1{2}(:)),double(Corner2{2}(:)))
```

Step 4: Returning a result of a test for a high correlation coefficient.

For this process, the program has to decide whether or not the two correlation coefficients satisfy a minimum correlation coefficient. Normally, a correlation coefficient will range from 0 to 1, such that a value near to 1 indicates a high correlation. By experimentation, we found that in different conditions, 0.65 is the minimum coefficient of correlation that resulted when the paper was not moved. Therefore, this process will give a true answer if each of the two correlation coefficients satisfies the threshold condition of being greater than 0.65.

```
Decision_ = ((correlation_from_corner1 > 0.65) && (correlation_from_corner2 > 0.65))
```

A.2.2. Algorithm Improvement.

Given that the calculation of coefficient of correlation takes too much time due to its high computational complexity, we developed a new approach to tackle the challenge of time efficiency, as a real-time constraint. The new approach proposed had to start by thresholding the equalized pixel samples from the papers' upper corners. The process had then to compare the resulting binary patterns using the binary XOR operation. The resulting data would indicate which pixels have changed, and those that didn't change, if the paper had been moved. By experimentation, we found that the maximum percentage of pixels that changed when the paper was not moved was 30%. This was due to the presence of noise that varied in different cases.

```
Corner1{1}= rgb2gray(Corner1{1});
Corner1{2}= rgb2gray(Corner1{2});
Corner2{1}= rgb2gray(Corner2{1});
Corner2{2}= rgb2gray(Corner2{2});

Corner1{1}=imbinarize(Corner1{1},0.5);
Corner1{2}=imbinarize(Corner1{2},0.5);
Corner2{1}=imbinarize(Corner2{1},0.5);
Corner2{2}=imbinarize(Corner2{2},0.5);

xor_from_corner1=xor((Corner1{1}(:)),(Corner2{1}(:)));
xor_from_corner2=xor((Corner1{2}(:)),(Corner2{2}(:)));

sum_xor_from_corner1=sum(xor_from_corner1(:));
sum_xor_from_corner2=sum(xor_from_corner2(:));

ratio_xor_from_corner1 = sum_xor_from_corner1/length(xor_from_corner1)
ratio_xor_from_corner2 = sum_xor_from_corner2/length(xor_from_corner2)
```

A.2.3. Comparison of Time Usage Between the Correlation-Coefficient-Based Approach and the XOR-Based Approach.

In this section, we are going to compare the time usage of the two approaches: coefficient correlation approach against the XOR approach. We will generate different random images of 1 megapixel to 5 megapixels and graph the time it will take for the computer to execute each dataset using each of the two approaches. For each approach, the computer will execute the step number 3, assuming that the given image represents the corner samples of the current and the previous images (frames).

```
i1_MegaPixels=uint8(255*rand(1000,1000,3));
i2_MegaPixels=uint8(255*rand(2000,1000,3));
i3_MegaPixels=uint8(255*rand(3000,1000,3));
i4_MegaPixels=uint8(255*rand(4000,1000,3));
i5_MegaPixels=uint8(255*rand(5000,1000,3));
tic;
corr_Approach(i1_MegaPixels);
t_correlation(1)=toc;
tic;
corr_Approach(i2_MegaPixels);
t_correlation(2)=toc;
tic;
corr_Approach(i3_MegaPixels);
t_correlation(3)=toc;
tic;
corr_Approach(i4_MegaPixels);
t_correlation(4)=toc;
tic;
corr_Approach(i5_MegaPixels);
t_correlation(5)=toc;

tic;
xor_Approach(i1_MegaPixels);
t_xor(1)=toc;
tic;
xor_Approach(i2_MegaPixels);
t_xor(2)=toc;
tic;
xor_Approach(i3_MegaPixels);
t_xor(3)=toc;
tic;
xor_Approach(i4_MegaPixels);
t_xor(4)=toc;
tic;
xor_Approach(i5_MegaPixels);
t_xor(5)=toc;
subplot(1,1,1)
plot(1:1:5,t_correlation,'r',1:1:5,t_xor,'b')
title("Time Usage of Different Approaches, Against Different Image Resolutions")
xlabel("Resolution (Megapixels)")
ylabel("Time Used (Seconds)")
legend({'Correlation coefficient approach','XOR approach'})
```

A.3. Algorithm Design for the Image enhancement Process.

To ensure that the pen strokes are enhanced, the system will need to remove noises from the image and then enhance specifically the traces of the pen's ink.

A.3.1. Proposed output of the "Image Enhancement" process:

The output Image should match these characteristics:

- The image should be truncated to show at maximum the enhanced white paper,
- The pen strokes on the image should be enhanced, with an increased saturation,
- The first frame will undergo its unique enhancement process to be transformed into a white frame and be a good reference to the next frames.

A.3.2. Methodology Illustration.

In this section, we are going to illustrate the algorithm of image enhancement.

Step 1: Acquisition of the Input Image's Copy.

At this step, the program will acquire a copy of the input image, supposing that it is trimmed to get at maximum the part that shows the white paper.

```
inputIm=imread("theImageWithHand.png");
rowCr1 = 1;
colCr1 = 1;
[rowCr2 colCr2 d] = size(inputIm);

total_numberOfRows=rowCr2 - rowCr1 + 1;
total_numberOfColumns = colCr2 - colCr1 + 1;
```

Step 2: Image smoothing using a low pass filter.

This process will use an averaging filter (a low pass filter) to filter out noises in the image after converting it to grayscale. Given that the size of the filter matters, this process uses a filter whose height and width are 0.3% of the height and width of the input image (which means that the area of the filter is 0.09% of the area of the input image). That factor of 0.3% was selected after numerous try-and-see image enhancement experimentations.

```
theRowPeriod = ceil((0.3/100) * total_numberOfRows);
theColPeriod = ceil((0.3/100) * total_numberOfColumns);
global LP_filter_PS
LP_filter_PS = (1/(theColPeriod*theRowPeriod)) * ones(theRowPeriod,theColPeriod);
inputIm_Smoothed=rgb2gray(inputIm);
inputIm_Smoothed = imfilter(inputIm_Smoothed,LP_filter_PS);
```

Step 3: Edge Detection.

This step will use a 3x3 Laplacian filter to detect edges in the image, then threshold the output so as to highlight areas where the ink has traced. Since the pen strokes can have any direction, we need an edge detector that is isotropic, the Laplacian filter.

```
Laplacian_Filter=[1 1 1; 1 -8 1; 1 1 1]
F=[1 1 1; 1 -8 1; 1 1 1] ;
inputIm_Edges=imfilter(inputIm_Smoothed_Gray,F);
inputIm_Edges = histeq(inputIm_Edges);
inputIm_MaskForPenStrokes = (inputIm_Edges < 250);
```

Step 4: Formation of a binary mask to highlight the pen strokes.

This step will also do a dilation so as to remove remaining noises. Given that the used structuring element's size matters, this process uses a structuring element whose height and width are 0.2% of the height and width of the input image.

```
theRowPeriod = ceil((0.2/100) * total_numberOfRows);
theColPeriod = ceil((0.2/100) * total_numberOfColumns);
global Dilution_se
Dilution_se = ones(theRowPeriod,theColPeriod);
pattern = Dilution_se;
inputIm_MaskForPenStrokes=imdilate(inputIm_MaskForPenStrokes,pattern);
```

Step 5: Pen Strokes Enhancement.

This process will do an element-wise multiplication between the input image and the created mask (complemented), to highlight the pen strokes. To increase the saturation of the pen strokes, the resulting image was converted to the HSI model, and the saturation dimension was multiplied by a relatively large number (10 for our case). After the enhancement, the image was re-converted to RGB for the next steps.

```

inputIm_MaskForPenStrokes = uint8(inputIm_MaskForPenStrokes);
my_white_blank = 255*ones(size(inputIm));
inputIm_WhiteArea= inputIm_MaskForPenStrokes.*uint8(my_white_blank) ;
inputIm = uint8(~inputIm_MaskForPenStrokes) .* inputIm;
inputIm_Penstrokes_Unsaturated = inputIm;
inputIMAGE_HSV=rgb2hsv(inputIm);
inputIMAGE_HSV(:,:,2)=inputIMAGE_HSV(:,:,2)*10;
inputIm=hsv2rgb(inputIMAGE_HSV);
```

Step 6: Returning the enhanced image and the binary mask.

This process will add the remaining part (the part which does not represent pen strokes) to the part that represents pen strokes. After that, it will return the enhanced image and a binary mask to be later used in obstruction removal process, to protect pen strokes from being considered as obstruction (see the next topic: Obstruction Removal)

```
outputIMAGE= uint8(inputIm_WhiteArea) + uint8(inputIm*255);
global mypenstroke_mask
mypenstroke_mask = ~inputIm_MaskForPenStrokes;
```

A.3.3. Algorithm Improvement.

By experimentation, It was found that step 5 (Pen strokes Enhancement) took too much time for execution, due to the conversion from RGB to HSI and vice-versa. Given that our case needed to increase only the saturation parameter, we developed our own approach so as to tackle the challenge of time efficiency, as a real-time constraint. The new approach proposed was to divide by three the sum of the red, green and blue components' intensities, so as to get the average intensity for each pixel. Next, the original intensities of the red, green and blue components were compared to the resulting average so as to determine which intensities are major in each pixel. The intensities that were found to be greater than the average was set to the maximum intensity (which is 255), while the intensities that were found to be less than the average were set to the lowest intensity (which is 0).

```
inputIm_average = ...
    inputIm_Penstrokes_Unsaturated(:,:,1)/3+ ...
    inputIm_Penstrokes_Unsaturated(:,:,2)/3+ ...
    inputIm_Penstrokes_Unsaturated(:,:,3)/3;
penstrokes_Saturated = inputIm_Penstrokes_Unsaturated;
penstrokes_Saturated(:,:,1) = 255*uint8(inputIm_Penstrokes_Unsaturated(:,:,1) > ...
    inputIm_average);
penstrokes_Saturated(:,:,2) = 255*uint8(inputIm_Penstrokes_Unsaturated(:,:,2) > ...
    inputIm_average);
penstrokes_Saturated(:,:,3) = 255*uint8(inputIm_Penstrokes_Unsaturated(:,:,3) > ...
    inputIm_average);
outputIm= (inputIm_WhiteArea) + penstrokes_Saturated;
```

A.3.4. Comparison between the HSI-based approach and the improved approach.

In this section, we are going to compare the time usage of the two approaches: the HSI approach against the improved approach. We will generate different random images of 1 megapixel to 5 megapixels and graph the time it will take for the computer to execute each dataset using each of the two approaches. For each approach, the computer will execute the step number 3, assuming that the given image represents the RGB image to be processed.

```
i1_MegaPixels=uint8(255*rand(100000,10,3));
i2_MegaPixels=uint8(255*rand(200000,10,3));
i3_MegaPixels=uint8(255*rand(300000,10,3));
i4_MegaPixels=uint8(255*rand(400000,10,3));
i5_MegaPixels=uint8(255*rand(500000,10,3));
tic;
hsi_Approach(i1_MegaPixels);
t_hsi(1)=toc;
tic;
hsi_Approach(i2_MegaPixels);
t_hsi(2)=toc;
tic;
hsi_Approach(i3_MegaPixels);
t_hsi(3)=toc;
tic;
hsi_Approach(i4_MegaPixels);
t_hsi(4)=toc;
tic;
hsi_Approach(i5_MegaPixels);
t_hsi(5)=toc;

tic;
new_Approach(i1_MegaPixels);
t_new(1)=toc;
tic;
new_Approach(i2_MegaPixels);
t_new(2)=toc;
tic;
new_Approach(i3_MegaPixels);
t_new(3)=toc;
tic;
new_Approach(i4_MegaPixels);
t_new(4)=toc;
tic;
new_Approach(i5_MegaPixels);
t_new(5)=toc;

plot(1:1:5,t_hsi,'r',1:1:5,t_new,'b')
title("Time Usage of Saturation Enhancement Approaches, Considering Image Resolutions.")
xlabel("Resolution (Megapixels)")
ylabel("Time Used (Seconds)")
legend({'the HSI approach','the proposed (new) approach'})
```

A.4. Algorithm Design for the Obstruction Removal Process.

After the Image Enhancement process, the system will need to compensate for the obstructed part of the input image.

A.4.1. Methodology Illustration.

In this section, we are going to illustrate the algorithm of obstruction removal.

Step 1: Input Image's Copy Acquisition

At this step, the program will read the input image and trim it so as to get at maximum the part that shows the white paper.

```
 inputIm=imread("theImageWithHand.png");
 rowCr1 = 1;
 colCr1 = 1;
 [rowCr2 colCr2 d] = size(inputIm);
```

Step 2: Image smoothing using a low pass filter.

This process will use a low pass filter to filter out any object that appears in the image, except only the obstruction (the hand). Given that the size of the filter matters, this process uses a filter whose height and width are 1.5% of the height and width of the input image (which means that the area of the filter is 2.25% of the area of the input image). That factor of 1.5% was selected after numerous try-and-see image enhancement experimentations.

The process will use the binary mask from the image enhancement process to highlight pen strokes, and make sure that they do not contribute to the obstruction pixels by setting them to the highest intensity value, 255 (This will also prevent the effect of unequal illumination from obstructing the pen strokes). Then the resulting image will be filtered by smoothing.

```
 total_numberOfRows=rowCr2 - rowCr1 + 1;
 total_numberOfColumns = colCr2 - colCr1 + 1;
 theRowPeriod = ceil((1.5/100) * total_numberOfRows);
 theColPeriod = ceil((1.5/100) * total_numberOfColumns);
 LP_filter_Hand = (1/(theColPeriod*theRowPeriod)) *
ones(theRowPeriod,theColPeriod);
```

```
global mypenstroke_mask
inputIm_Smoothed=rgb2gray(inputIm);
inputIm_Smoothed(mypenstroke_mask)= uint8(255);
inputIm_Smoothed = imfilter(inputIm_Smoothed,LP_filter_Hand);
```

Step 3: Thresholding

This process will threshold the smoothed output image from step 2. The image equalization will enhance the contrast significantly, to prepare the image for the thresholding. By thresholding the image, the process' results will make sure that the obstruction will be represented by 0 intensity pixels.

```
inputIm_Smoothed_eq=histeq(inputIm_Smoothed);
inputIm_Smoothed_eq_gray = (inputIm_Smoothed_eq);
inputIm_MaskOfObstruction_Binary = imbinarize(inputIm_Smoothed_eq_gray,0.5);
```

Step 4: Obstruction Removal.

This process will replicate the created obstruction mask into three dimensions to multiply (element-wise multiplication) with the input image, thus remove the obstruction by setting the obstruction to zero intensity. The zero intensities will be compensated by the previous frame through addition.

```
inputIm_MaskOfObstruction_Binary=uint8(inputIm_MaskOfObstruction_Binary);
clear Mask_RGB;
Mask_RGB(:,:,1)=inputIm_MaskOfObstruction_Binary;
Mask_RGB(:,:,2)=inputIm_MaskOfObstruction_Binary;
Mask_RGB(:,:,3)=inputIm_MaskOfObstruction_Binary;

outputIm=inputIm.*(Mask_RGB);
```

Step 5: Return the output image.

This step will return the output image to the main program.