BOĞAZİÇİ UNIVERSITY

IE 423

Project Part 3

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Introduction

The structure formed by bringing the yarns together is called fabric. Fabrics are formed by passing the yarns which are perpendicular and parallel to each other from above and below each other. The properties of the fabrics differ according to which kind of fabric you use. Natural fabrics have better properties in terms of health than others. Linen is a natural fiber and a flax-based textile that is predominantly used for homeware applications. While linen is similar to cotton, it is made from fibers derived from the stems of the flax plant instead of the bolls that grow around cotton seeds. Linen fabric is very durable and flexible thus it is used in upholstery. Linen has a lint-free fabric structure. Its structure is heat resistant. Because it is airy and comfortable, it is also used in bedspreads. Products such as pants, clothes made of Linen Fabric should generally be preferred in summer months.

Because of the fibrous structure of linen fabric, the process needs to be followed very carefully. Unlike other fabrics, flaws in linen fabrics are more pronounced. The resulting fabric defects cause greater damage to woven fabrics. Therefore, the quality of the fabrics should be examined in detail during the production phase. Nowadays, image processing technology for the detection of these errors has become widespread. With this technology, the type of error is determined and then the variable causing the error is eliminated in the system, the material used and other elements of the system according to the type of error. The quality of the products produced in this way increases and also the customer satisfaction and the brand value of the company increases.

There are about 20 known defects in the textile sector that may occur on the fabric. All of these errors are due to different reasons. These are the most encountered and the reasons are.

1. Horizontal lines: This fabric defect is defined by irregular lines that run from side to side. Horizontal lines are generally caused by the faults in the bobbin (the barrel used to hold the yarn in place) and the irregular thread tension

2. Shade variation: One of the more obvious visual defects that can be found on raw textiles, shade variation is defined by a difference in depth of shade and color from roll to roll or piece to piece. Shade variation in the fabric is caused by the mixing of fabrics used in production, the variations in the production process with regard to time and speed, improper cutting, bundling and/or numbering and unequal fabric stretching.

3. Drop stitches: One of the most common quality issues found in raw textiles, drop stitches are holes or missed stitches that appear randomly in the fabric. Drop stitches are typically caused by: Incorrect set-up of yarn carriers, slubs and knots, yarn overfeeding or underfeeding and the loose stitching during the production process

As can be seen from the above, these errors can be caused by the system, the material used or the employees. For companies that make millions of production per day, it is very important to detect these errors and find solutions in a short time. Late detection of these defects may result in defects in all products produced on the same production line, and manufacturers may suffer major economic losses. In a factory where millions of products are produced, it is almost impossible to detect these errors by human hands in a short time, so technology support is required. Nowadays, various image processing methods have been developed in order to detect these fabric defects quickly. Thanks to this technology, faults on the fabric are detected in a short time and solutions of the faults are found quickly.

Background information

Fabric defect detection has importance in terms of sectoral quality. Automatic systems are developed on the defect detection, and many methods are developed to obtain high precision with image processing studies. Defects decrease the profits of manufacturers and cause undesirable loses. Several methods are used to detect the defects. In old times, manufacturers have tried to detect detection as manually but this method caused exhaustion and this was not efficient ,succesful rate was about 70% . As computer sciences are improved , detection become more easier and some several methods are used in this field. In finding the faults and testing the system performance real fabric images are used and some of them are more efficient. Approaches which are used to detect the faults of textile are :

1- Spatial Filtering
2- Fourier Transform
3- Gabor Transform
4- Deep Neural Networks

Spatial Filtering :

Spatial filtering is an image processing technique used to vary the density of a pixel according to the density of neighboring pixels. Using spatial filtering, the image is transformed to a nucleus of a certain height and width (x,y), defining both the area and weight of the pixels that will change the value of the image in the first image. The corresponding operation is to combine the input image with the filter function to produce the new filtered image. Mathematical operation is a product in frequency space. Spatial filtering can be characterized as a "shift and multiply" process: the core shifts over the first image that forms a mask and multiplies its value by the corresponding pixel values of the image. The result is a new value that replaces the central value of the mask in the new image.

Fourier Transform:

Fourier transform translate the calculations between time domain and frequency domain knowledge, as well asit is a very useful method for analysing periodic signals due to the algorithmic structure of the Fourier transform. Domain and Fourier transform is a very suitable technique for analysing periodic signals because of certain desirable properties, including noise immunity and translation invariance. Fourier transform is a well-known technique that relates the frequency and time. It characterized the objects as complex valued functions in two dimensional structures, and all of these processes are performed in frequency domain. In parallel, a magnitude spectrum is formed, magnitude spectrum contains information about the Periodicity and directionality of the pattern, also periodical and directional disturbance can change the peaks in spectrum. These differences lead to identify the deformity on signal or patterns .Periodic structure of fabrics makes Fourier transform suitable for use during the detection process. Fourier transform will also have a regular, crystalline structure of isolated peaks. A defect on the fabric has expanded over a region in the magnitude spectrum. In the same way, sizes, shapes and spread of defects change the peaks of magnitude spectrum to higher or lower frequencies values. Therefore, the spectrum gives ideas about the regularity of fabric patterns and the features that assist to define defects

Gabor Transform

Gabor filters are used for texture analysis in both spatial and frequency domain.It is a popular a method which is also used in Fabric defect detection systems. Large sets of Gabor filter gives advantages to characterize all differentiation in different directions. However, it cause to make hard computations and too much features will lead to information pollution. Therefore, more efforts are needed to study the methods of designing Gabor filters for detecting fabric defects.

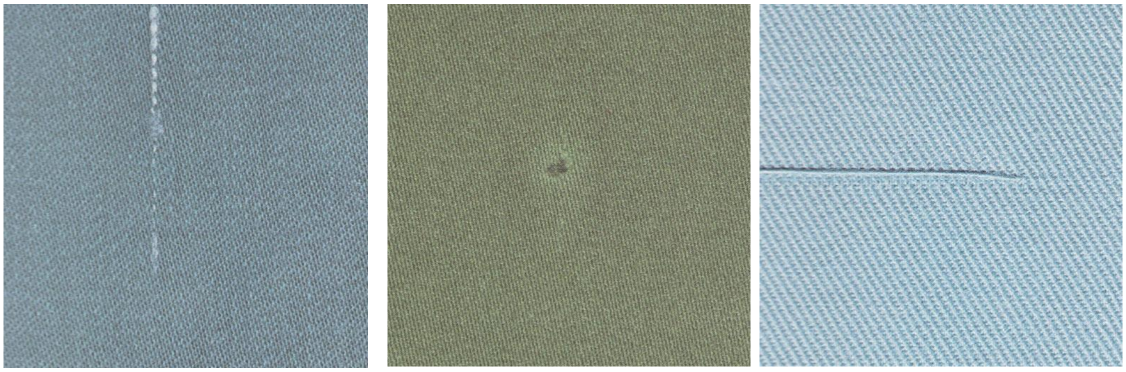
Deep Neural Networks

The most commonly used algorithms are Deep Neural Networks. Deep learning enables nonlinear transformation of data and can model complex relationships with multi-layered structures rather than basic structures. Also, the deep learning model has great advantages in learning attributes. Data can be represented with richer information by attribute learning by this model, which will improve classification performance. However, since this methods requires high theorotical knowledge , we cannot utilize these in our defect detection approaches.

Among all these methods, we have decided to use Gabor Transformation as our preprocessing tool due to its wide range of usage and easiness to implement. On top of this transformation, we have developed some statistical methods to detect anomaly as described throughtout the report.

Approach

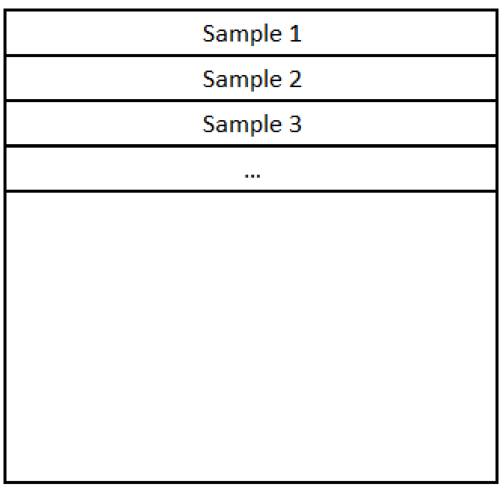
After understanding the nature of the dynamics of the linen manufacturing process, and making literature research regarding the process monitoring, we have decided to think about our approach to the problem. Firstly, we have transformed original images to grayscale to better understand the patterns and irregularities. After obtained grayscale images, we have used Gabor filter as a preprocessing tool. Actually, first we haven't applied Gabor filter and directly used statistical process control charts to detect mean shifts and variability shifts. However, we haven't identified the defects well from these control charts. Therefore, we decided to Gabor filter and obtained great improvements. To identify the out of control points, we have used two types of control charts. To detect mean shift, we used x-bar chart and to detect variability changes we have used s chart instead of r chart since sample size is greater than 10. As we are dealing with image data, we had to decide how to determine samples in our problem. To decide this, we have analyzed defects in images and focused on their shapes and patterns. Generally, there are three types of defects which are horizontal, vertical and spherical as seen below.



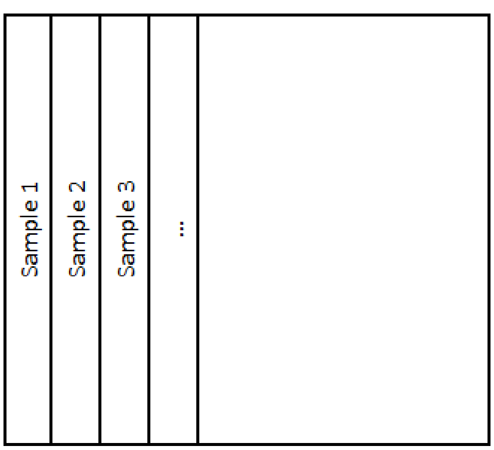
Vertical Defect Example Spherical Defect Example Horizontal Defect Example

Therefore, we selected our samples as three types.

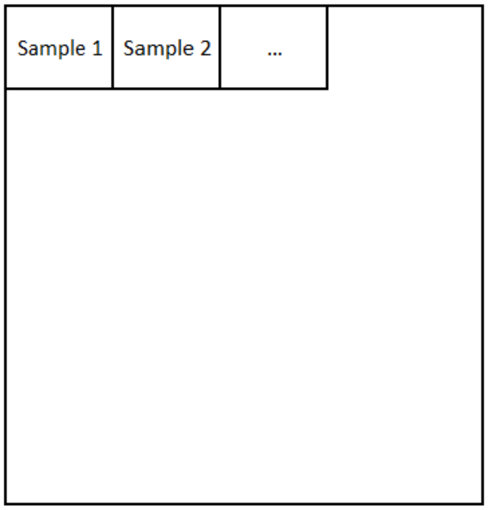
- Horizontal sample with size 512



- Vertical sample with size 512



- Windows with size 64



The size of the windows are determined after trying many possibilities and analyzing their performances by looking at the altered images and corresponding control charts.

Initially, we have used 3-sigma control limits for out control charts but it didn't give good results for all images. So, we started to change control limits to detect problematic points better. After changing control limits, we have obtained great improvements for some images. For example, in some images, defective points were marked as problematic with some other unproblematic points. To overcome this, we tried to widen control limits so that only the most extreme points can be identified. However, this caused defects in some images not to be identified although they were determined as problematic previously. So, to adjust the control limits dynamically according to the behaviour of each image, we have added a multiplier to control limits. This multiplier includes a range of the pixel values of an image and control limits widen as range increases and narrows as range decreases. This is because, when we have an image with a high range than extreme points can be identified even if the control limits are wide. We have tried lots of combinations with this range of information and put the best one in terms of overall performance. Such changes are also applied to s chart limits to achieve the best control limits.

Whenever an irregularity is obtained, that pixel's value is changed to zero, which is a black point so that one can see the problematic points by comparing it with the original image. Also, control charts are also plotted after each image. Generally, our code has given good results in terms of detecting anomaly but sometimes it has marked some too little points as out of control. Since these points will not be considered as a defect, this can be a false alarm. To overcome this, we have applied a median filtering-like method that controls too little marked points and eliminates them.

Result

We processed images and detect anomalies. We plotted original images and anomaly-detected images in order to analyze the accuracy of our anomaly detection method. As a result, our model catches all the manufacturing errors. In the examples, there are so many types of errors. Some of them have shapes like a horizontal line, vertical line or a circle. Instead, our method catches all types with a negligible error. But in Figures 1 and 16, our method detected some irrelevant pixels as an anomaly. Since linens have patterns with pixels that have significant differences, our method detected some of them as anomalies.

In our method, we used two techniques, one searches with columns and other searches with windows. In Figures 5 and 10 errors are detected by the column search technique and others are detected by window search method. In image 12, there is a brightness in the left-down corner. Because of that output has black pixels there.

Linens which have patterns with high pixel value difference have more deviation hence the difference between upper and lower limit are higher. Also detecting small errors is harder because the method can color black some part of patterns or can miss errors because the difference between limits is high. Hence, upper and lower limits should be assigned with a good approach to have better outputs.

Consequently, we observe that our method gave use good outputs and detects errors accurately.

Conclusions and Future Work

In general, we had difficulties to make our algorithm works for all images appropriately since each image has its own characteristics and patterns. Even though we have constructed our algorithm flexible to a different type of image, it has some weaknesses in detecting some irregularities as we can see in image 1. To figure out this issue, we can split our data as training and test, and apply our algorithm with train data to learn the general patterns excluding much of the effect of extreme points. In this way, our control charts might be more accurate.

After analyzing the output of our algorithm, we have seen that the photographic quality of the image has also effect on the defect detection quality. For example, in image X, we see that at the left bottom there is a large anomaly detected region due to the general brightness of that area. So, if we increase the quality of the image, we can increase detection quality, too.

Reference

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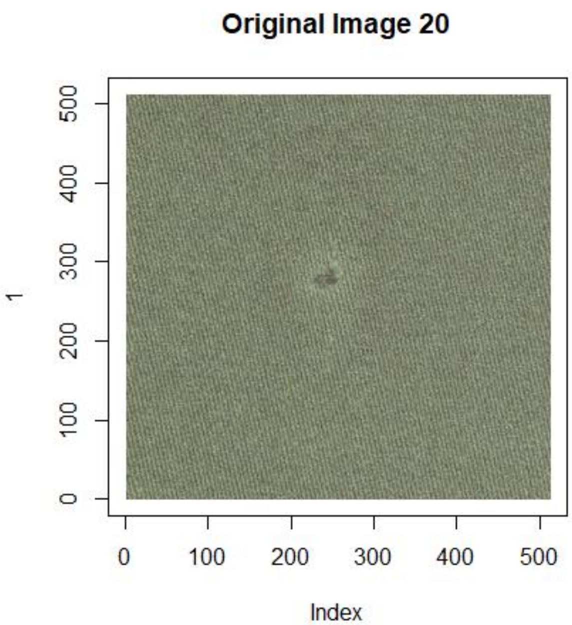
Appendix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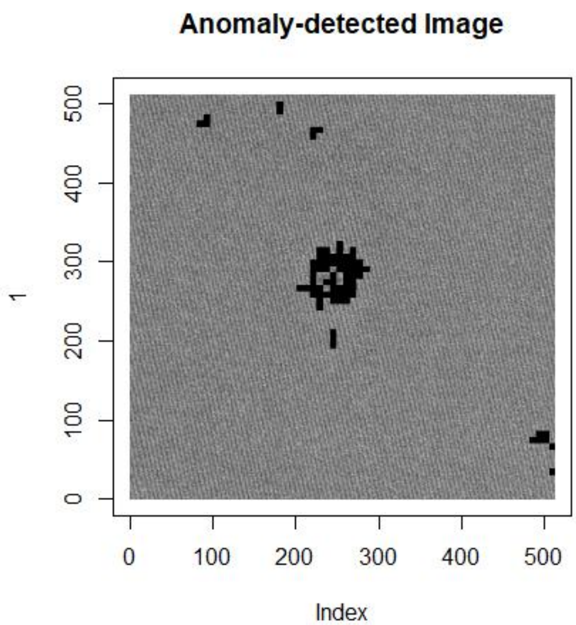
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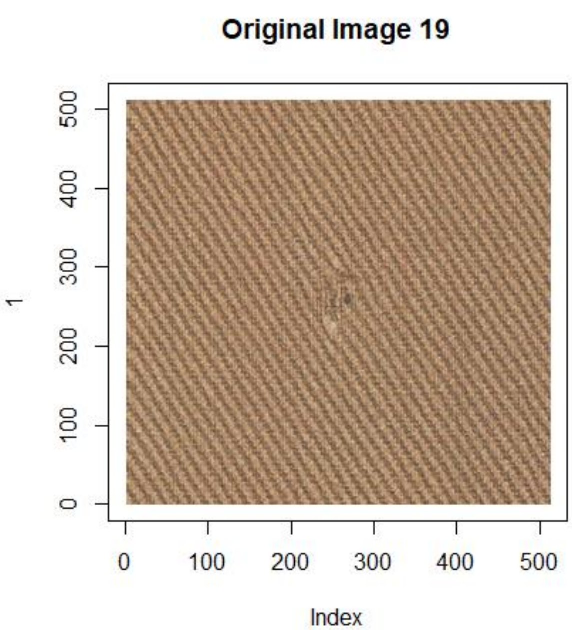
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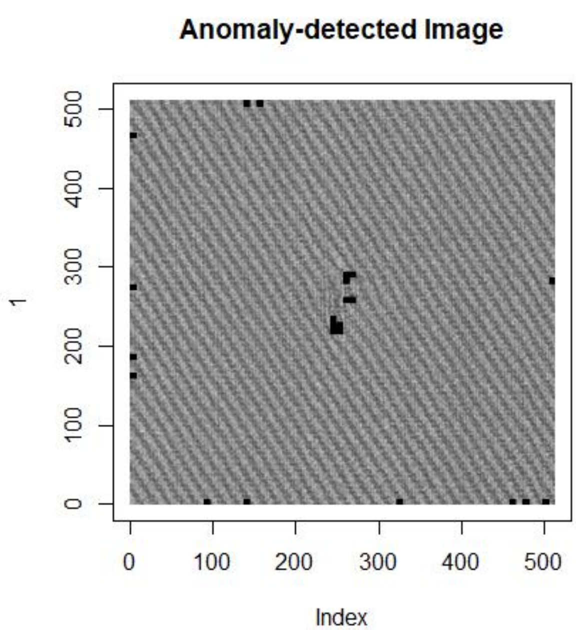
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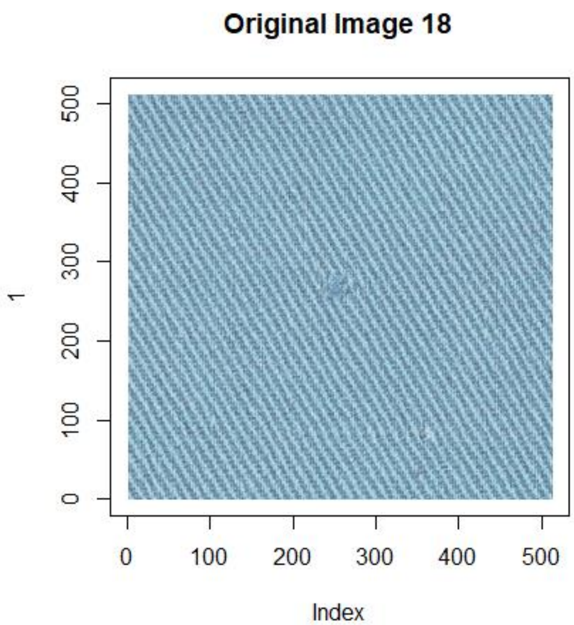
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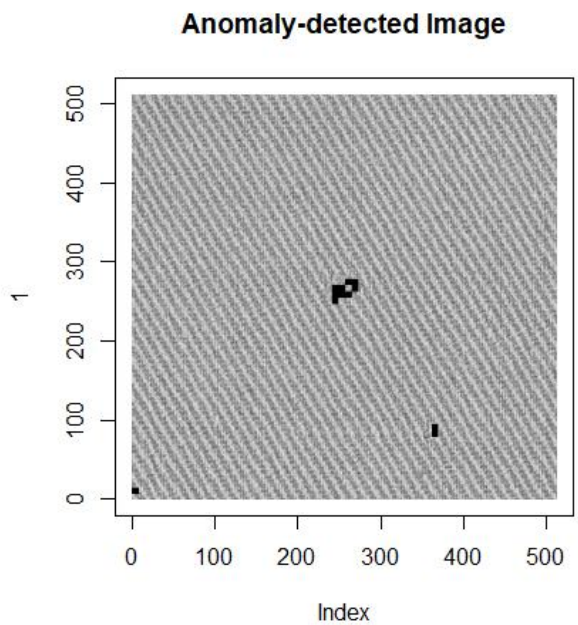
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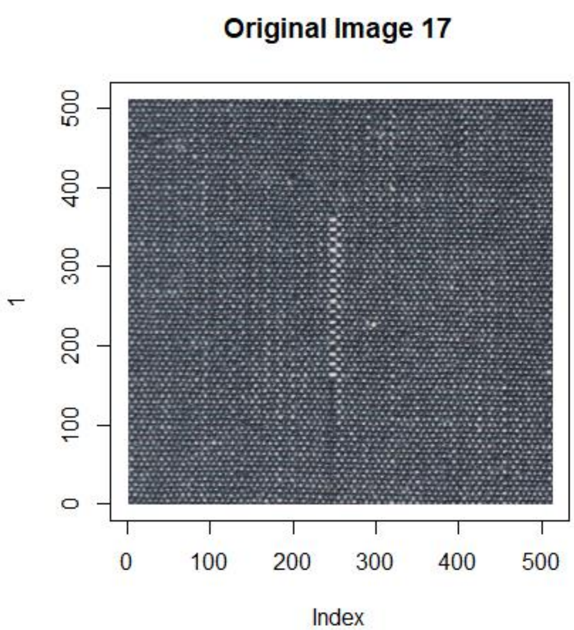
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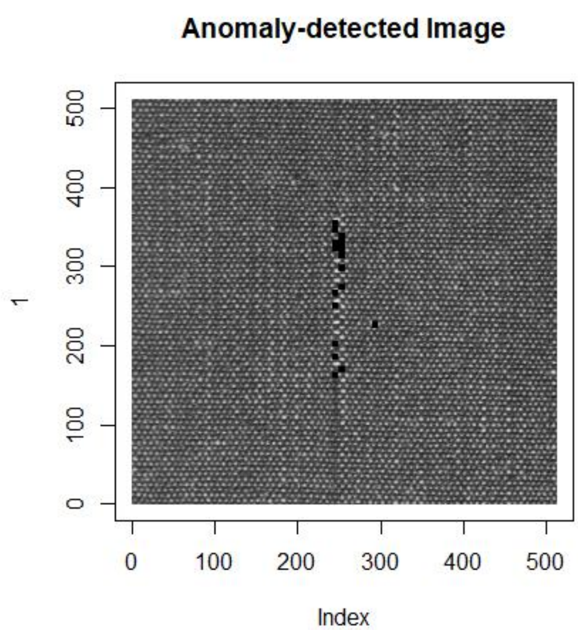
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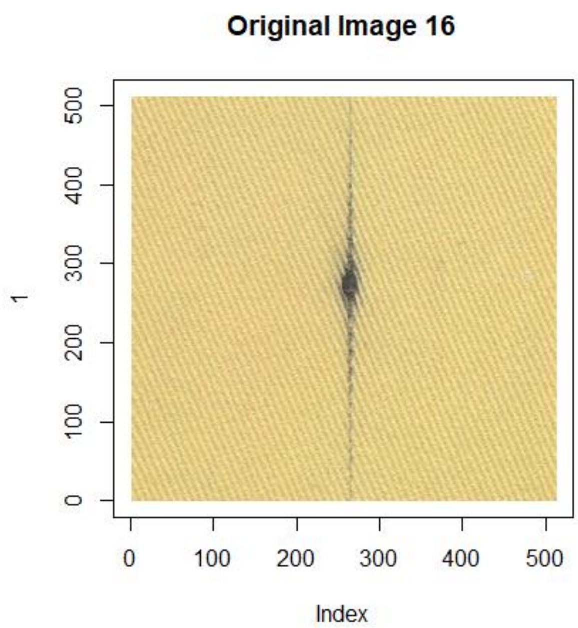
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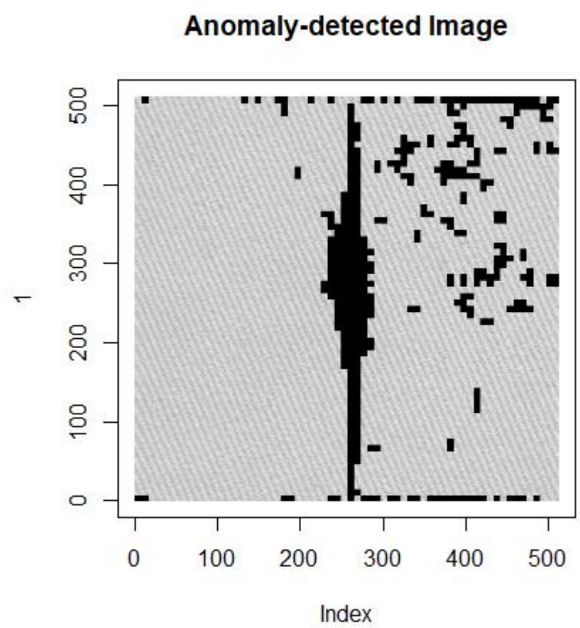
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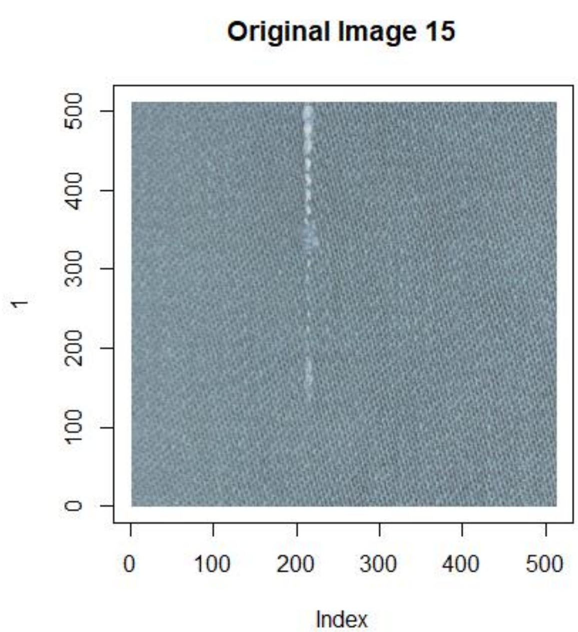
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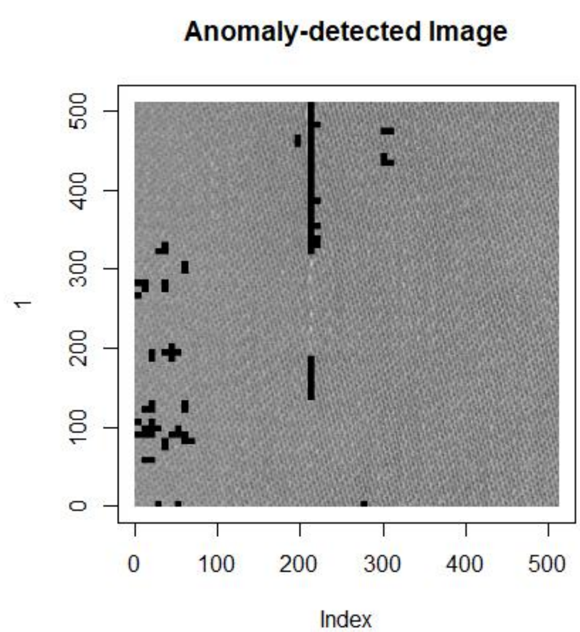
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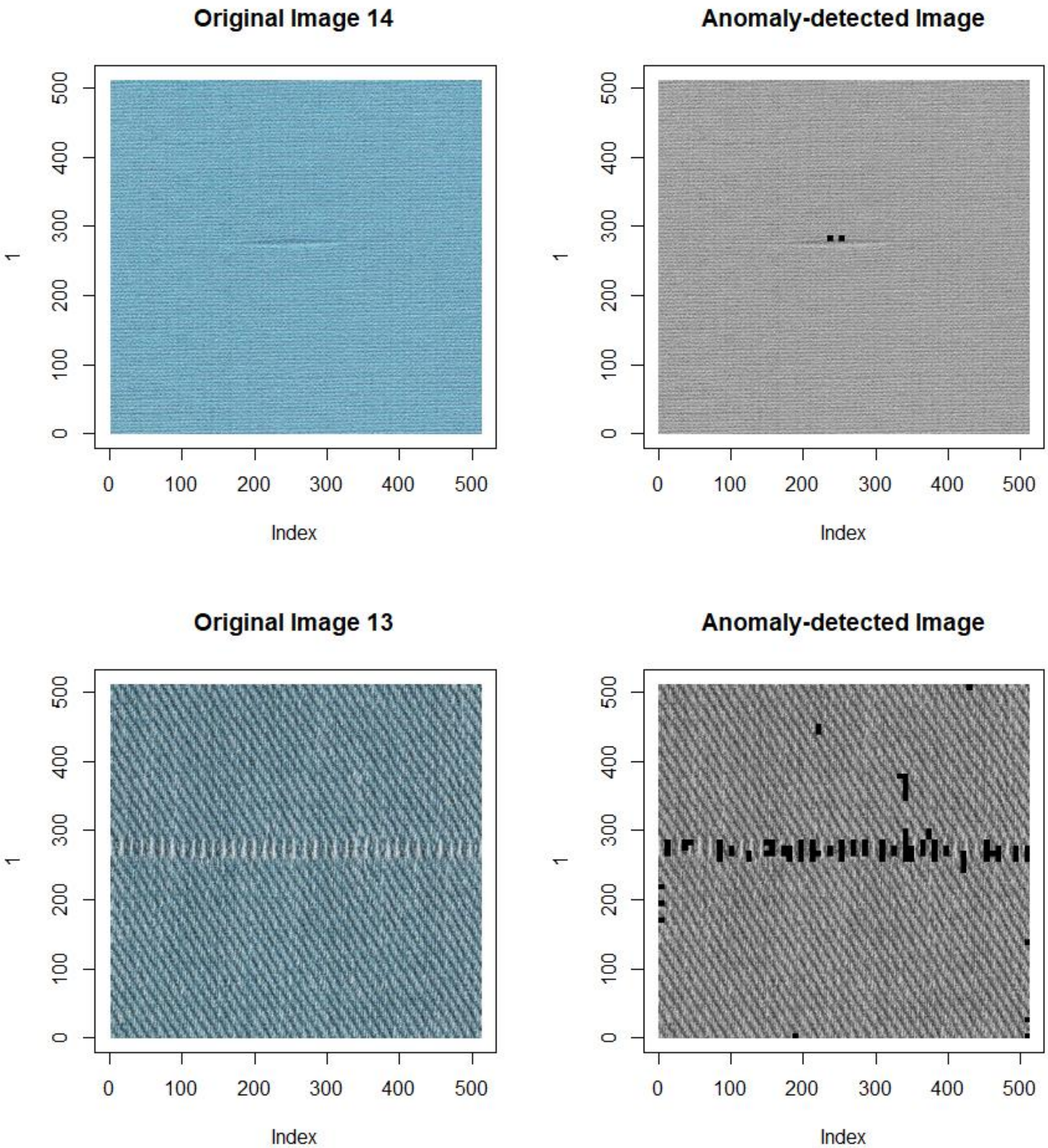
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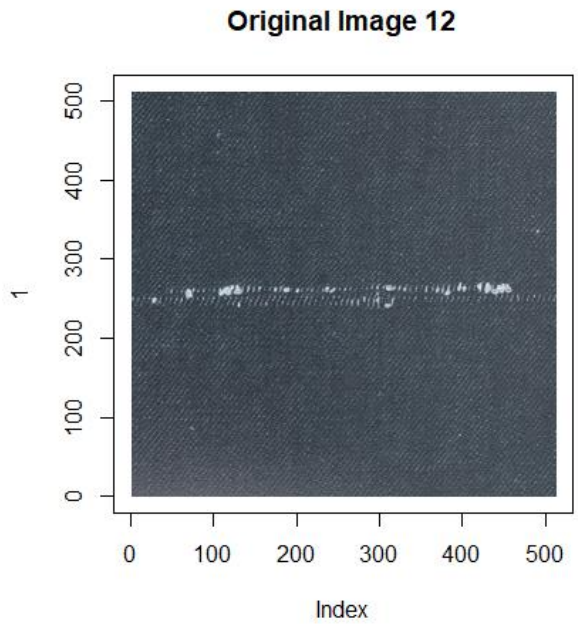
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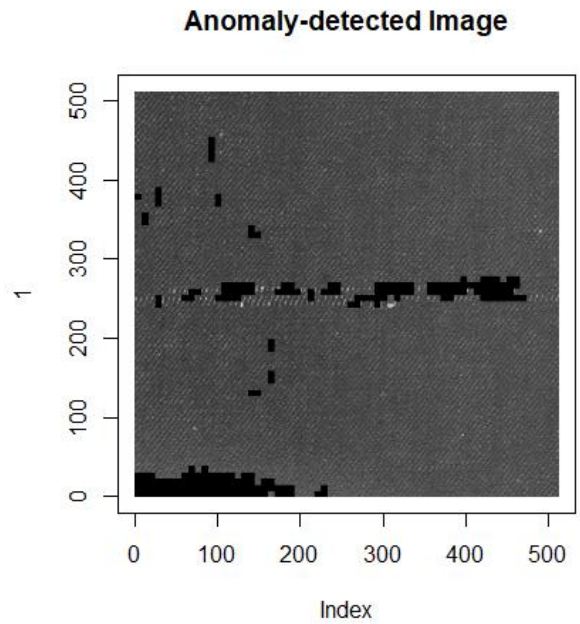
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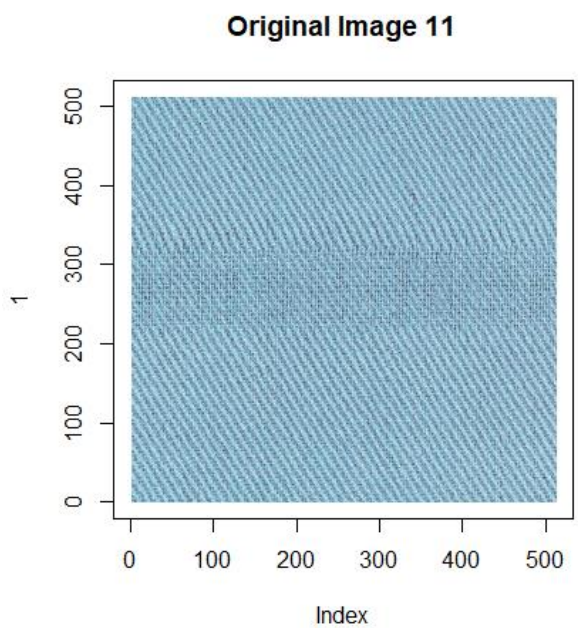
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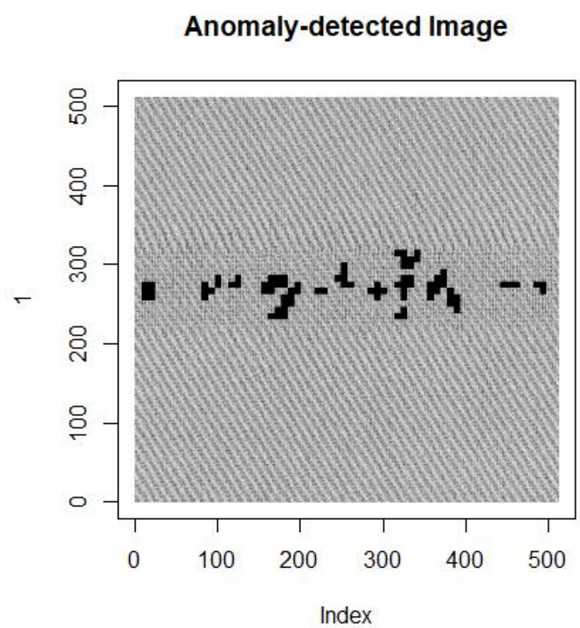
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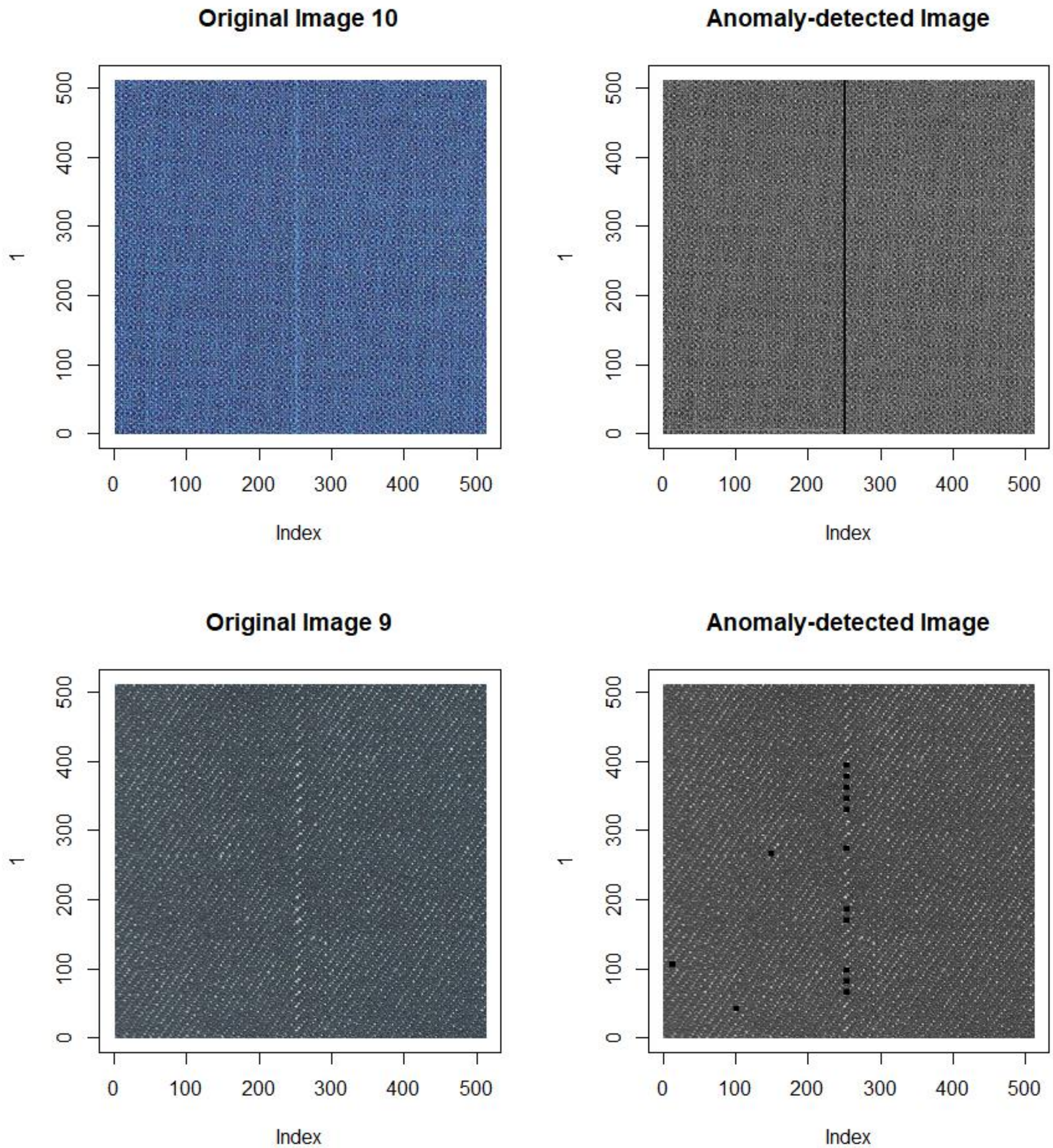
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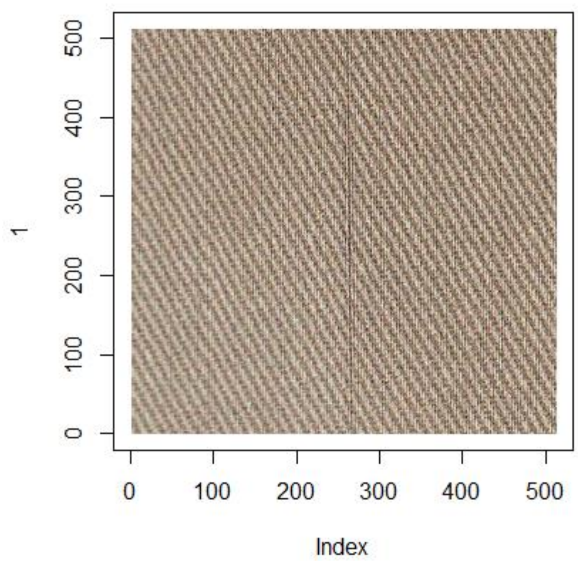

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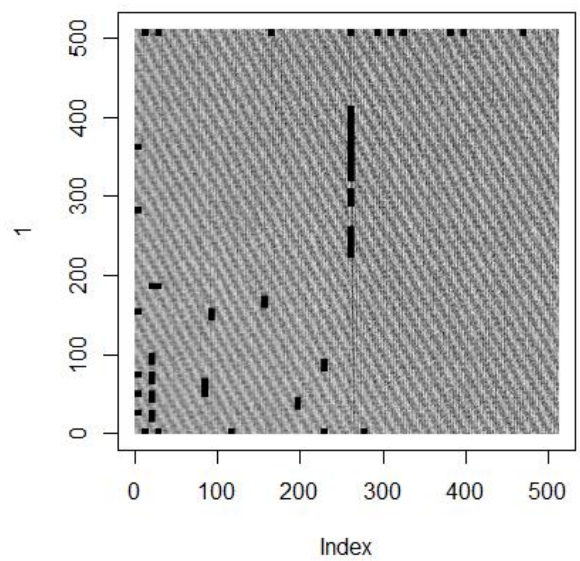

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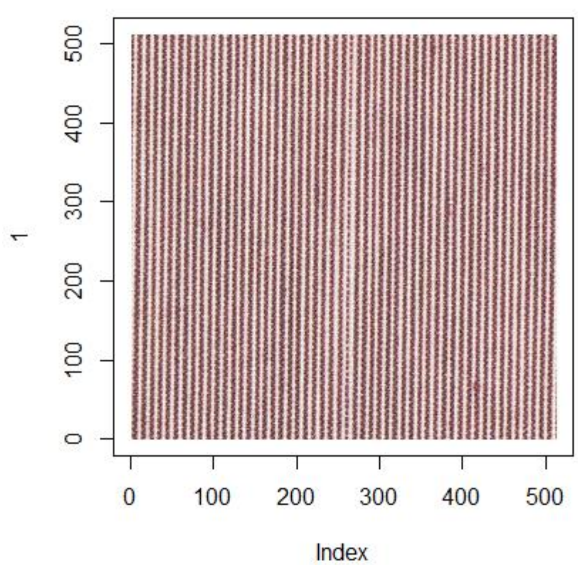

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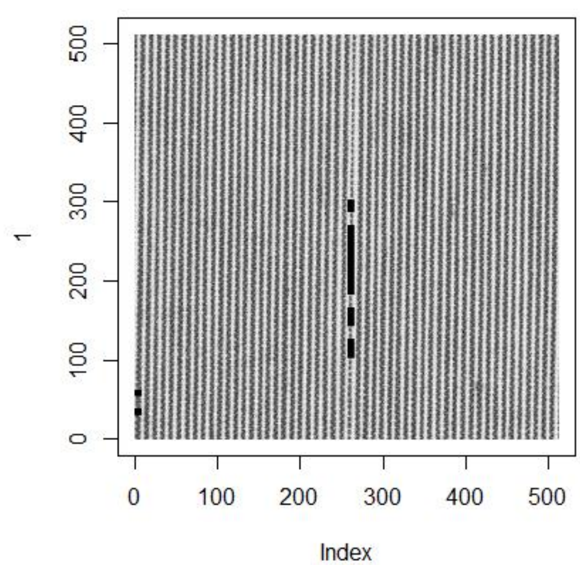

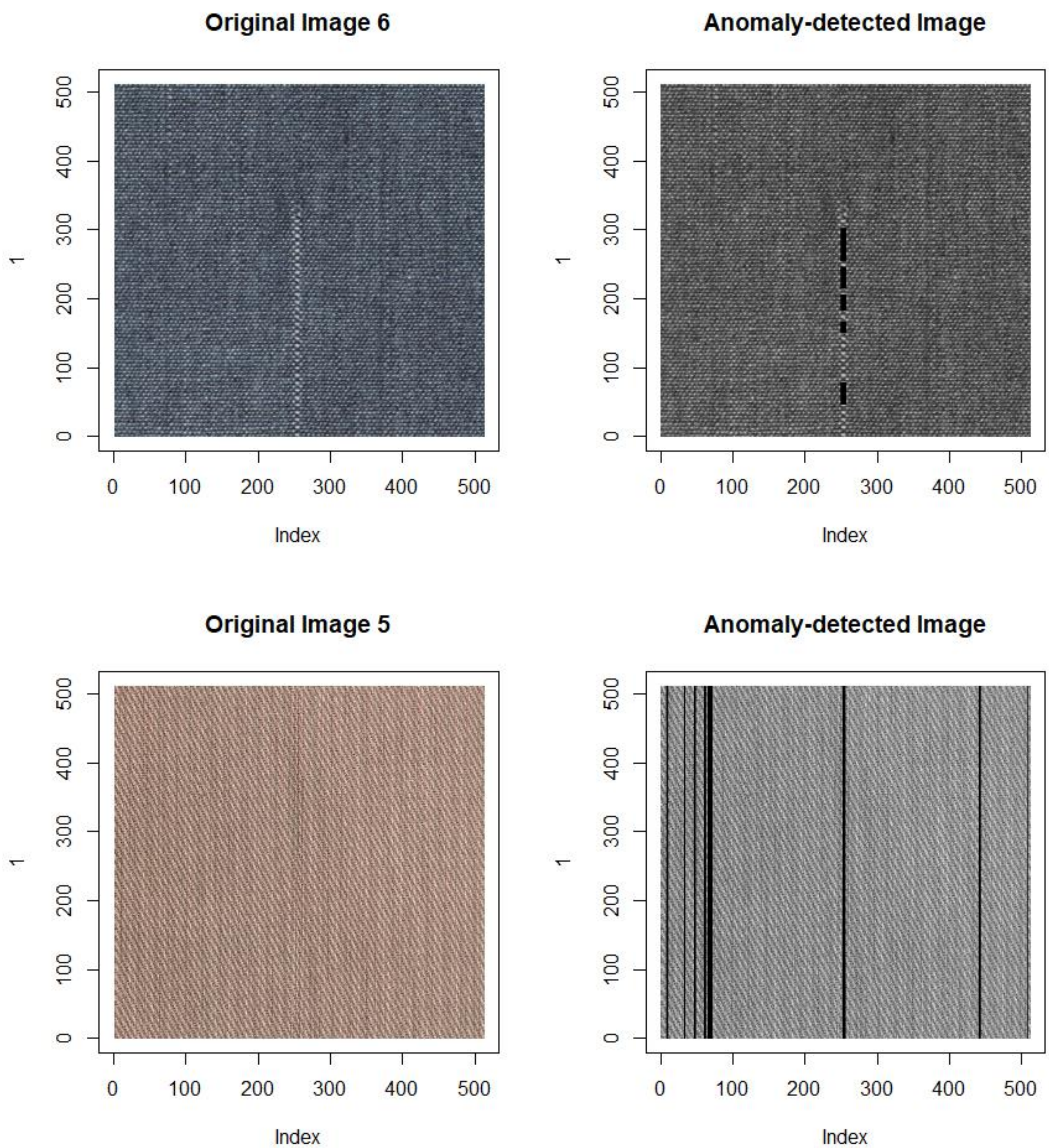
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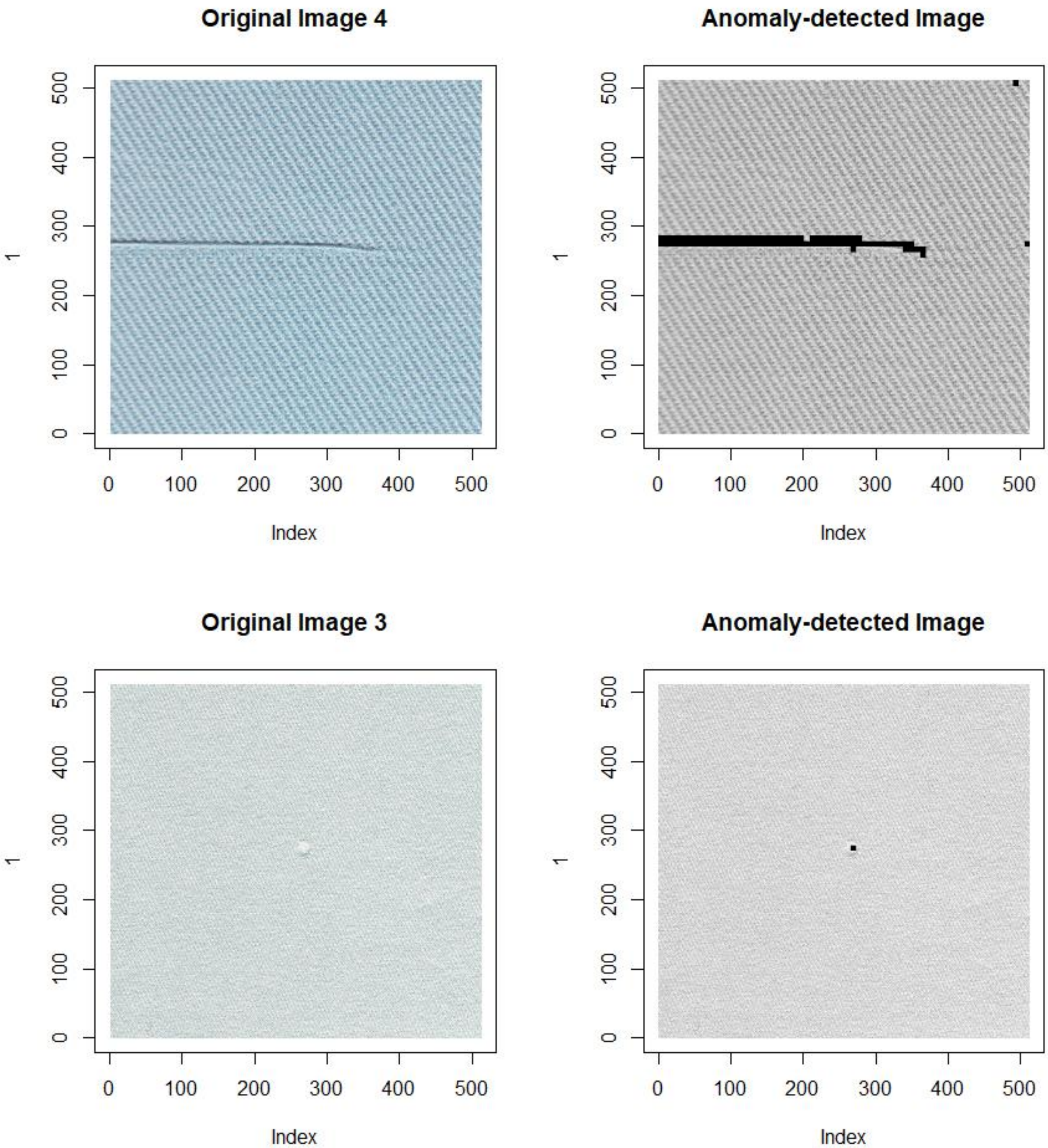
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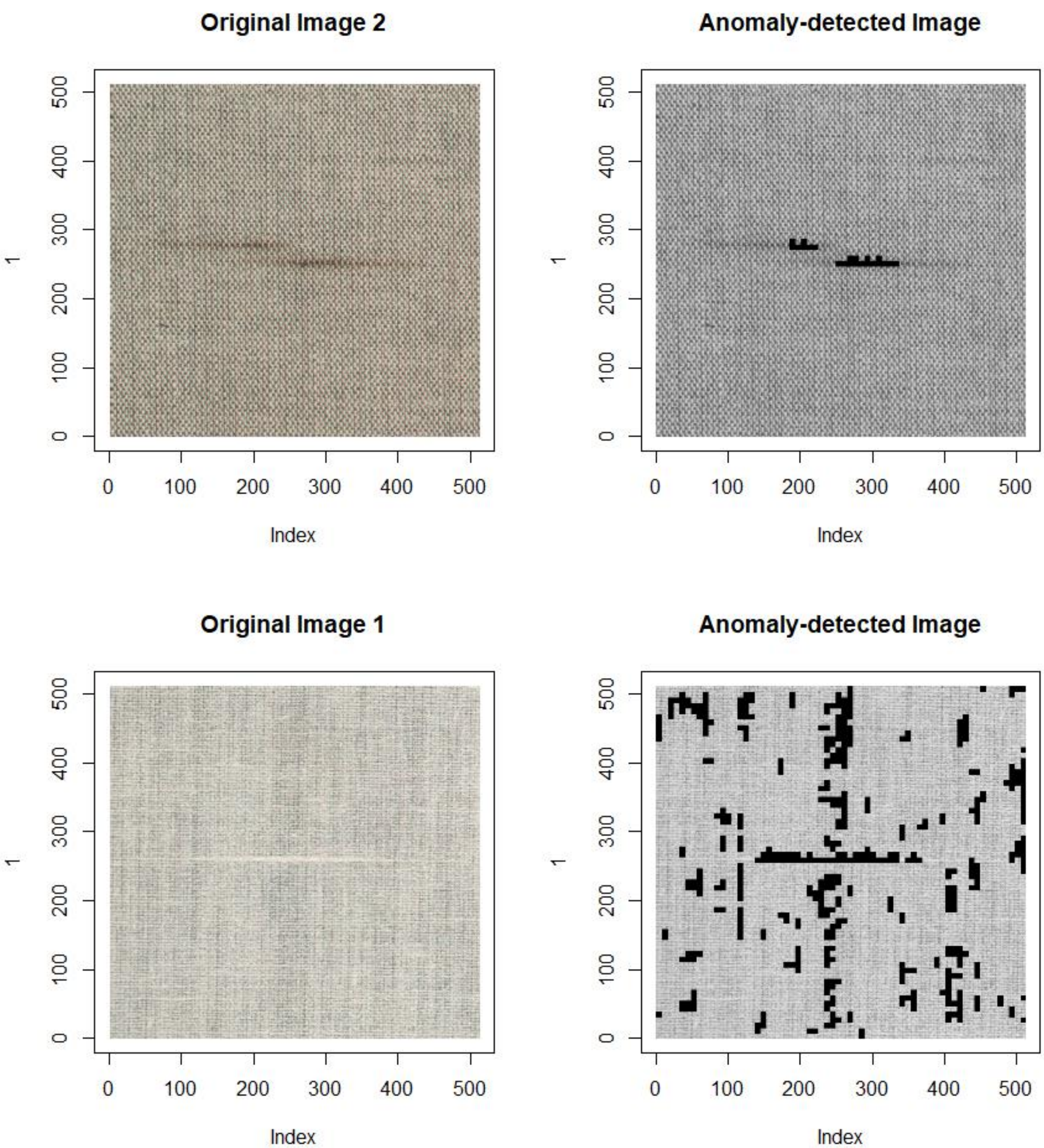
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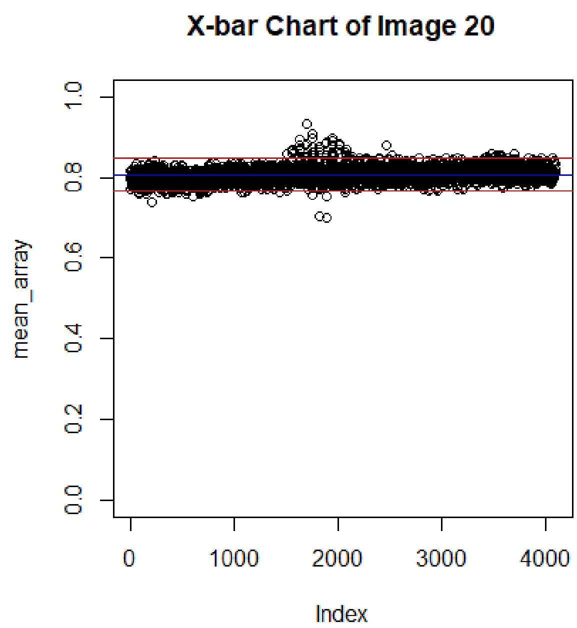
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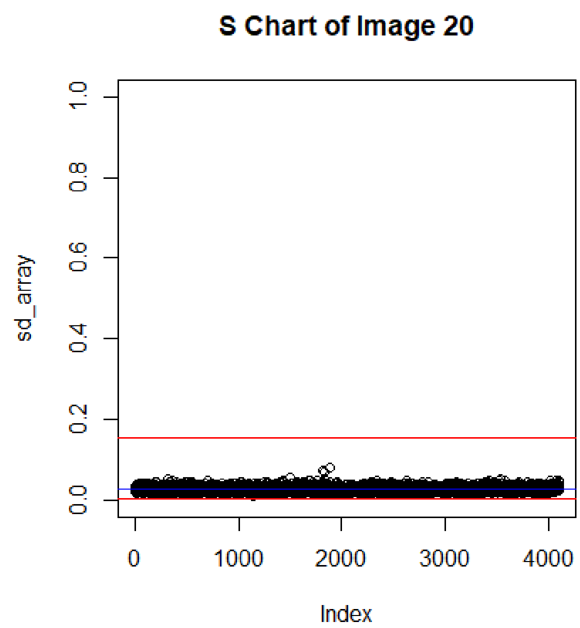
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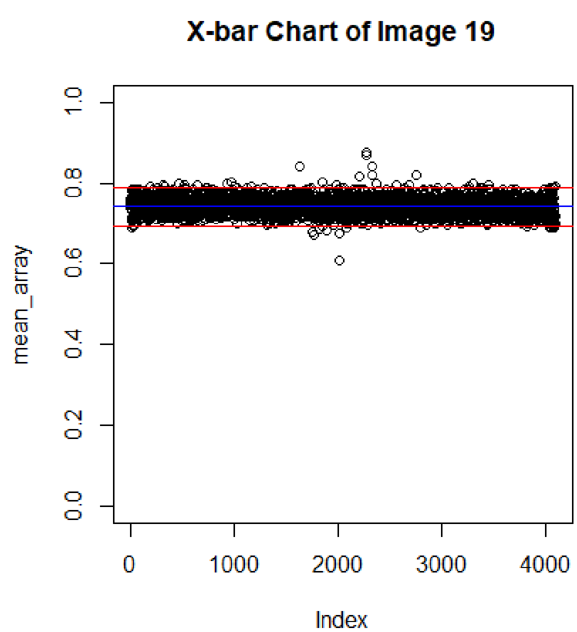
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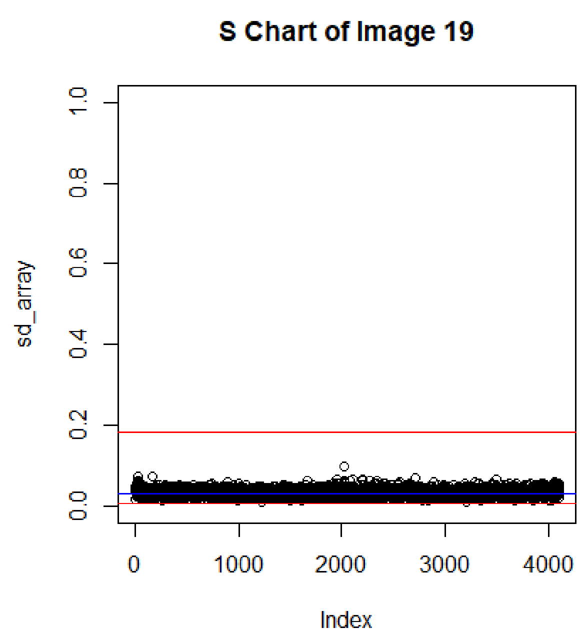
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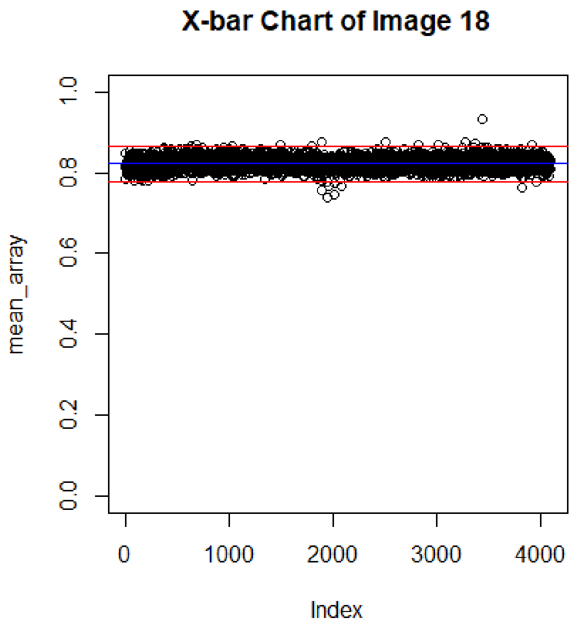
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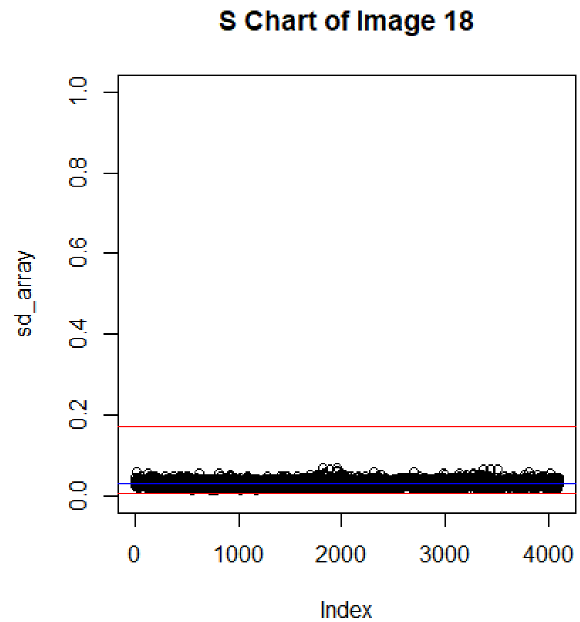
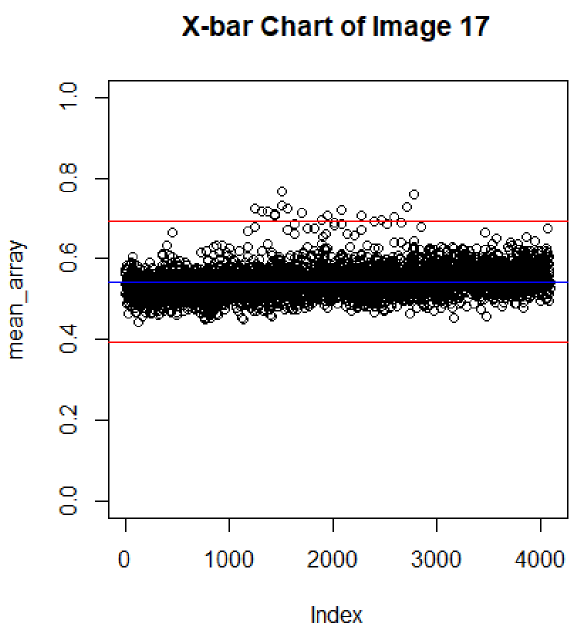
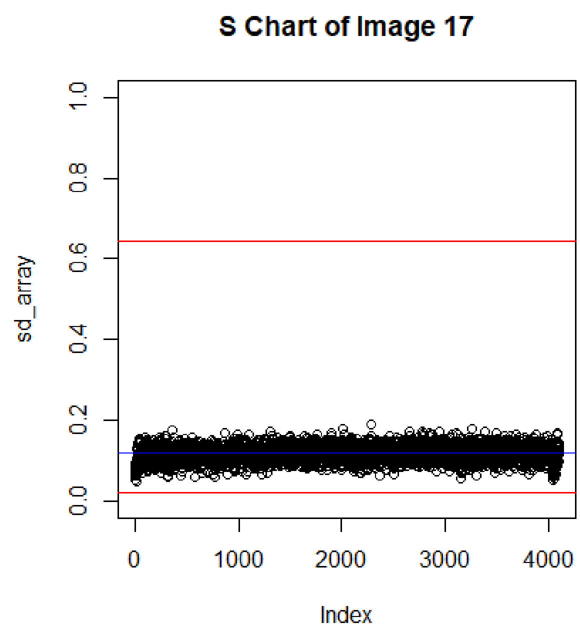
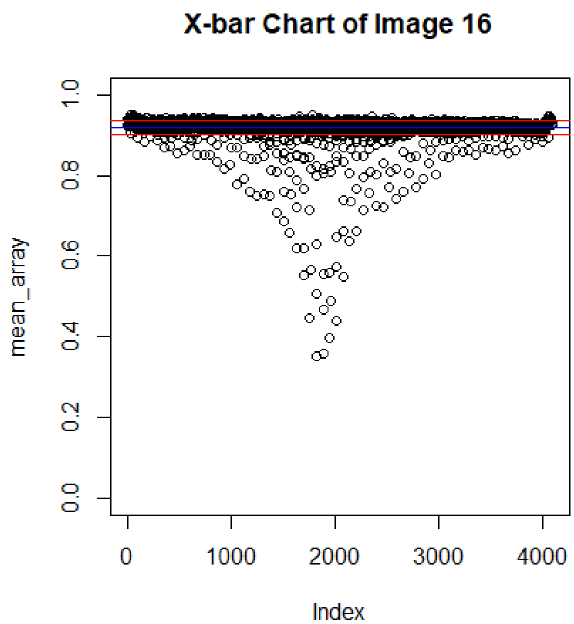

S Chart of Image 18
sd_array
1.0
0.8
0.6
0.4
0.2
0.0
0
1000
2000
3000
4000
Index


X-bar Chart of Image 17
mean_array
1.0
0.8
0.6
0.4
0.2
0.0
0
1000
2000
3000
4000
Index


S Chart of Image 17
sd_array
1.0
0.8
0.6
0.4
0.2
0.0
0
1000
2000
3000
4000
Index


X-bar Chart of Image 16
mean_array
0.0
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0.4
0.6
0.8
1.0
0
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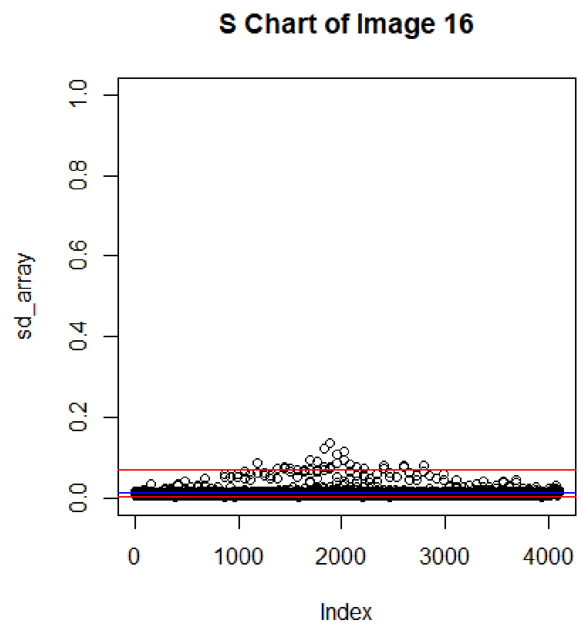
2000
3000
4000
Index


S Chart of Image 16
sd_array
0.0
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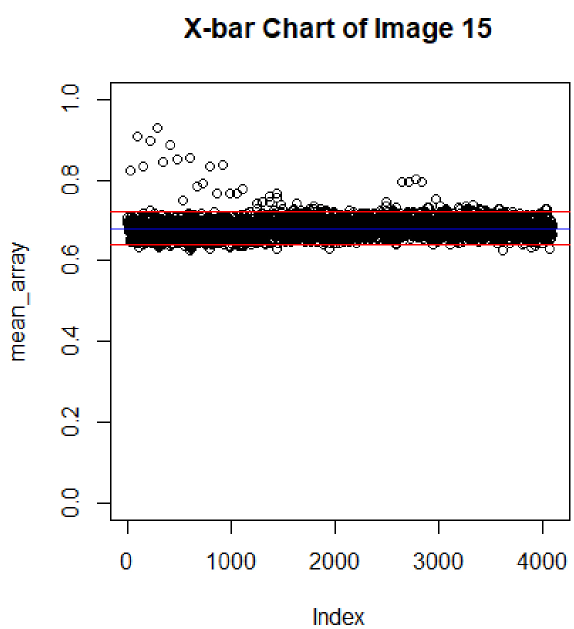
0.4
0.6
0.8
1.0
0
1000
2000
3000
4000
Index


X-bar Chart of Image 15
mean_array
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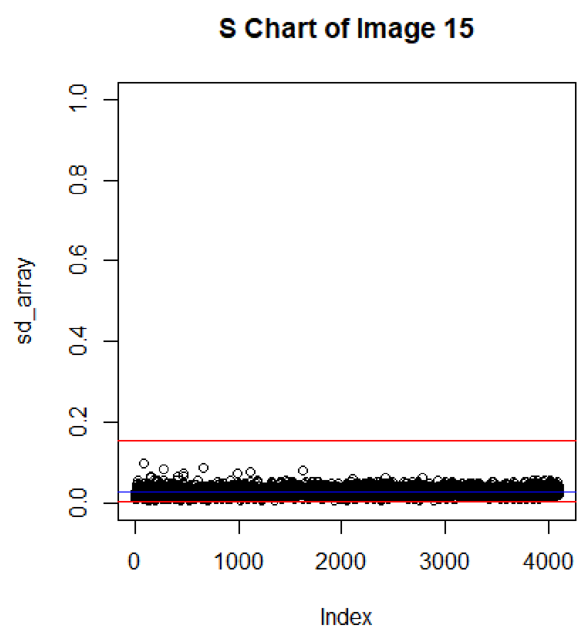
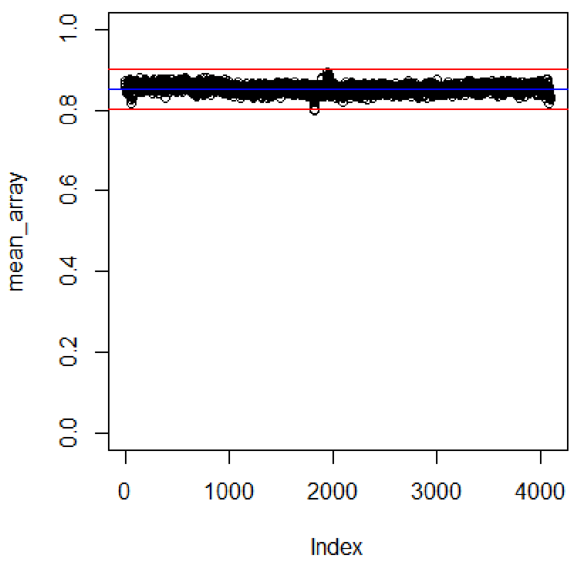
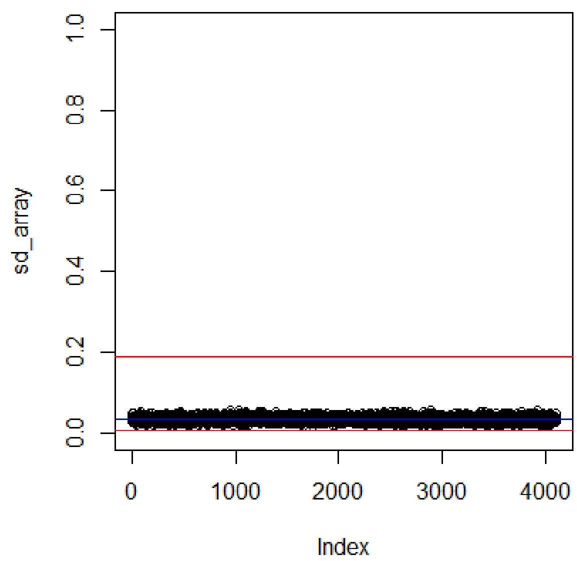
0.2
0.4
0.6
0.8
1.0
0
1000
2000
3000
4000
Index


S Chart of Image 15
sd_array
0.0
0.2
0.4
0.6
0.8
1.0
0
1000
2000
3000
4000
Index

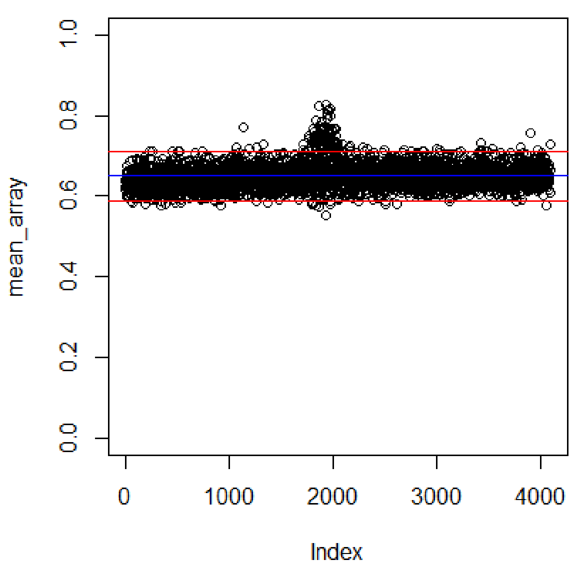
X-bar Chart of Image 14



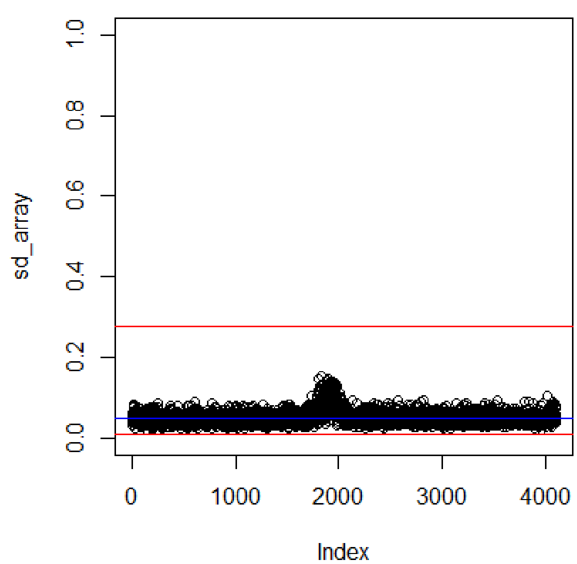
S Chart of Image 14

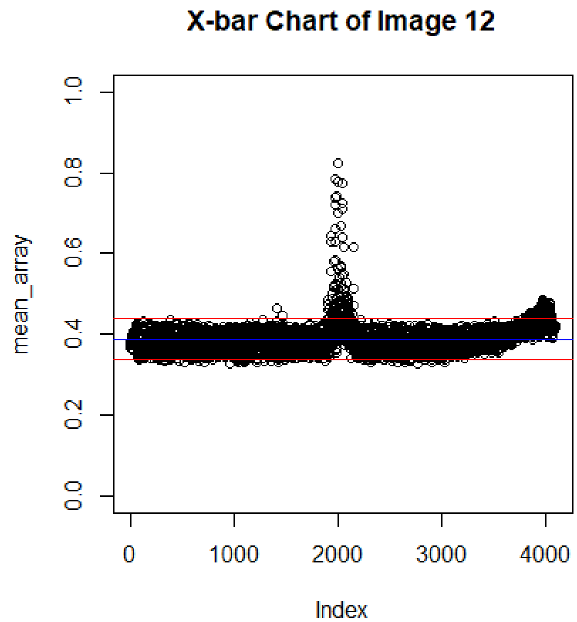


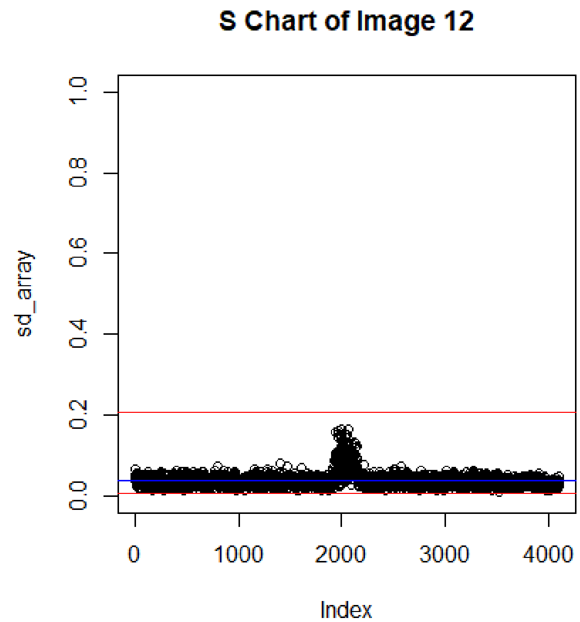
X-bar Chart of Image 13

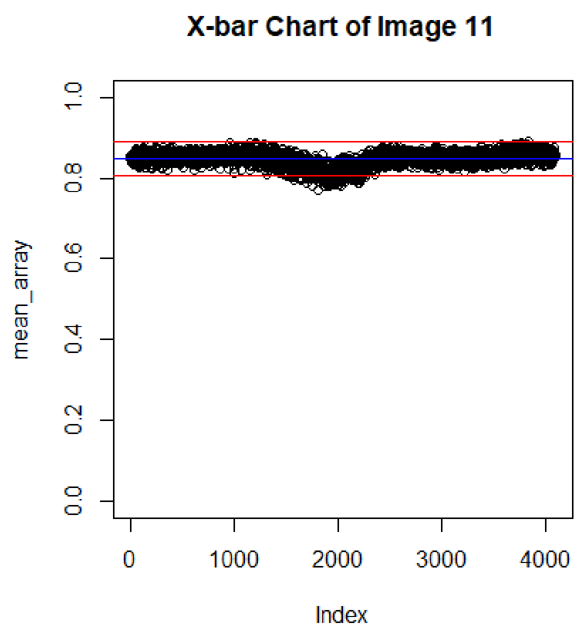


S Chart of Image 13




X-bar Chart of Image 12
mean_array
0.0
0.2
0.4
0.6
0.8
1.0
0
1000
2000
3000
4000
Index


S Chart of Image 12
sd_array
0.0
0.2
0.4
0.6
0.8
1.0
0
1000
2000
3000
4000
Index


X-bar Chart of Image 11
mean_array
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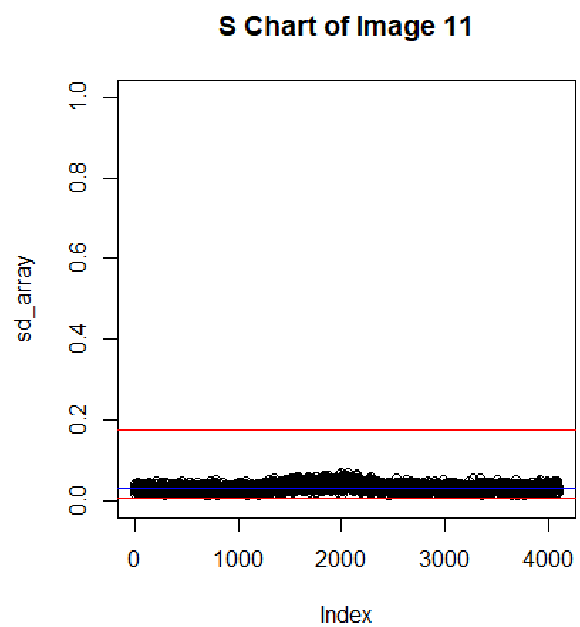
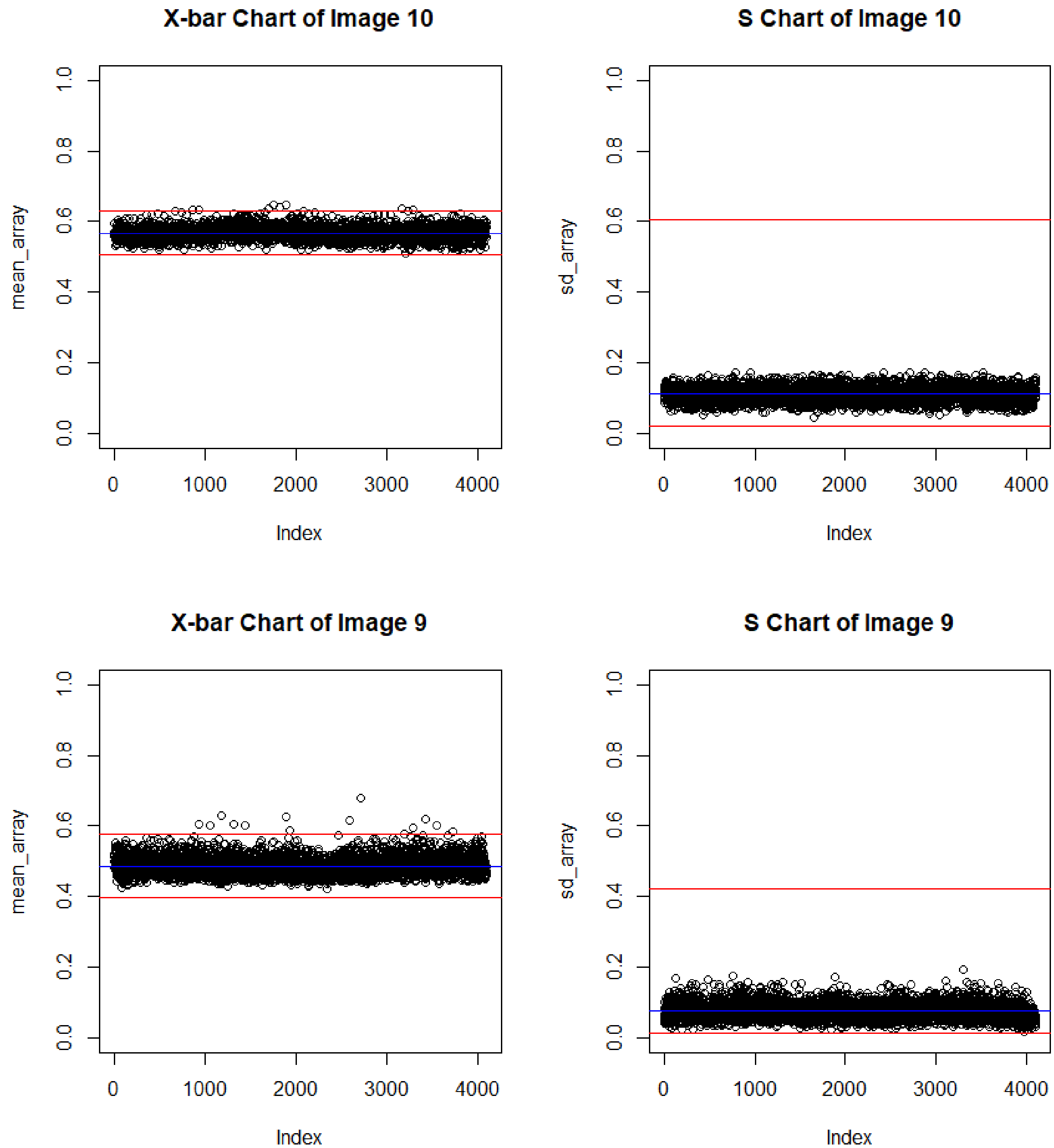
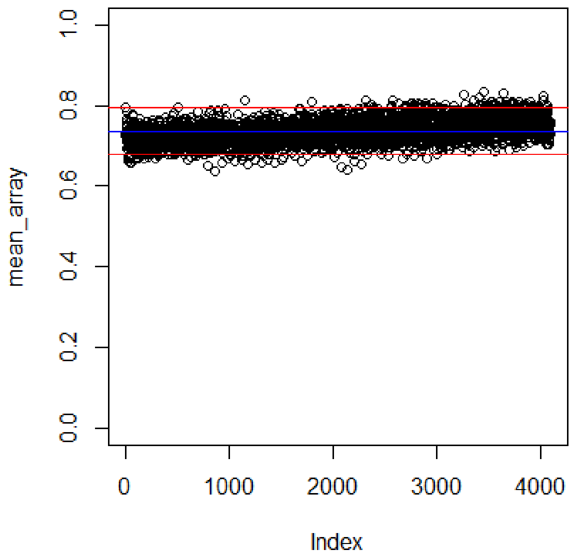
0.2
0.4
0.6
0.8
1.0
0
1000
2000
3000
4000
Index

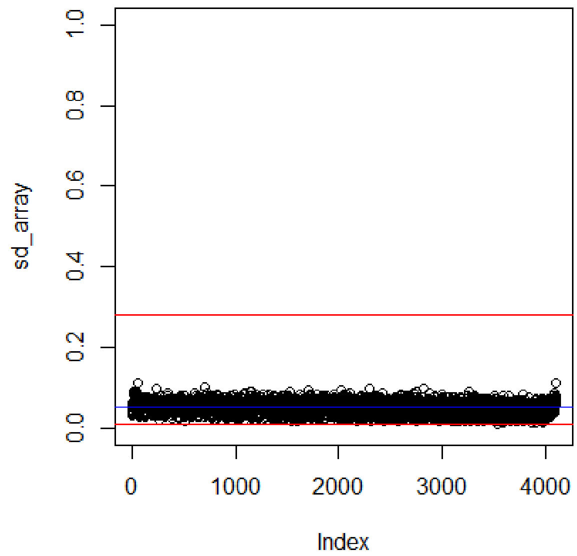

S Chart of Image 11
sd_array
0.0
0.2
0.4
0.6
0.8
1.0
0
1000
2000
3000
4000
Index


X-bar Chart of Image 10
S Chart of Image 10
X-bar Chart of Image 9
S Chart of Image 9
mean_array
sd_array
Index
0.0
0.2
0.4
0.6
0.8
1.0
0
1000
2000
3000
4000

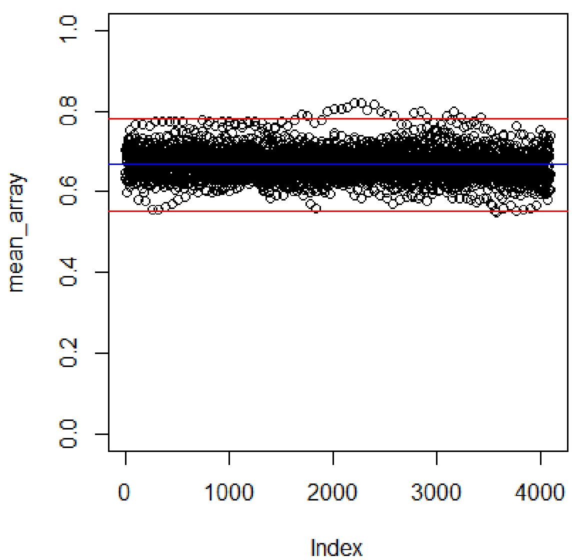
X-bar Chart of Image 8



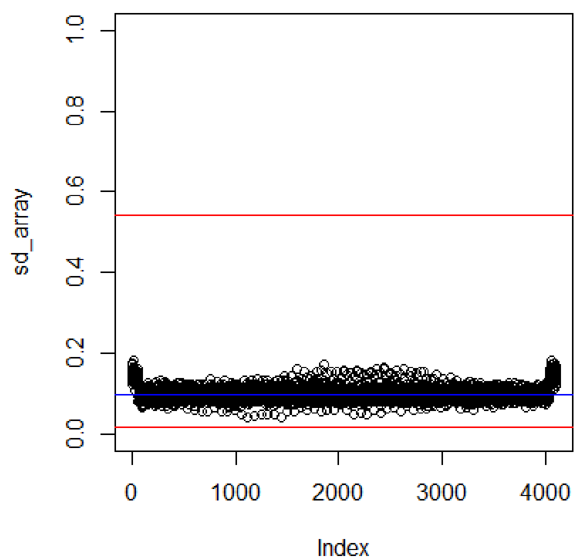
S Chart of Image 8



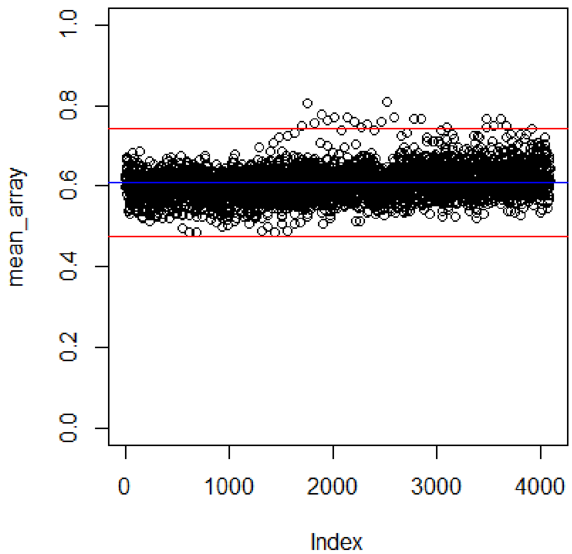
X-bar Chart of Image 7



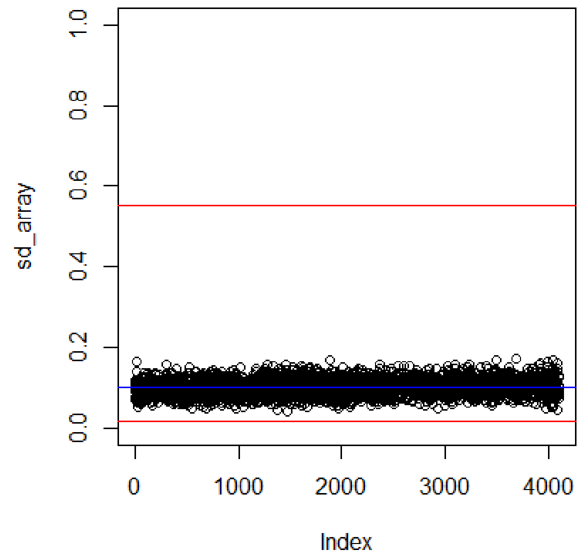
S Chart of Image 7



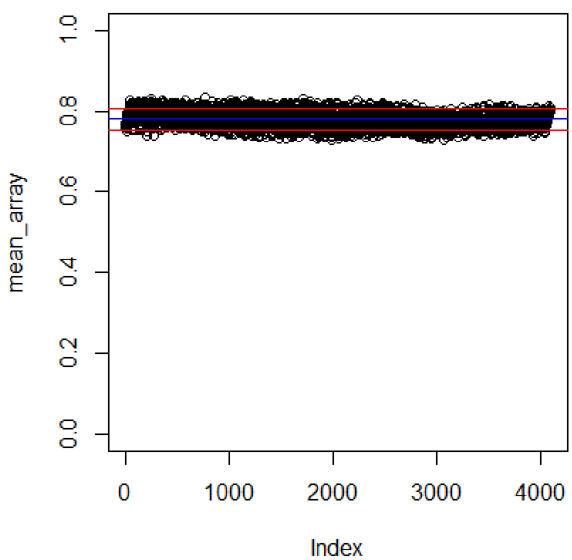
X-bar Chart of Image 6



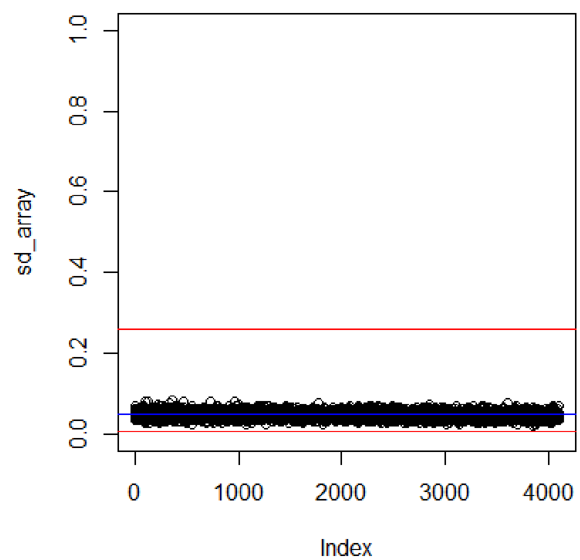
S Chart of Image 6

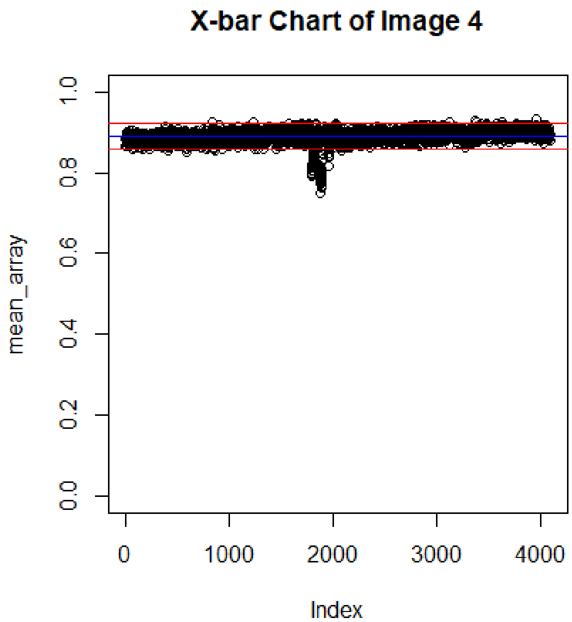


X-bar Chart of Image 5



S Chart of Image 5




X-bar Chart of Image 4
mean_array
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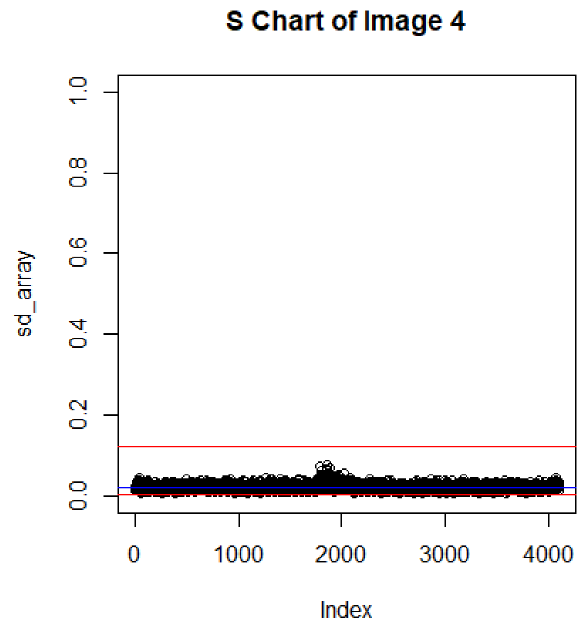
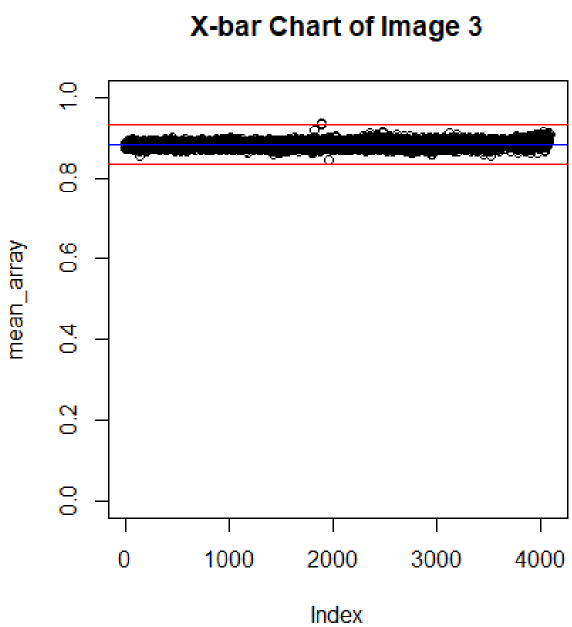
0.2
0.4
0.6
0.8
1.0
0
1000
2000
3000
4000
Index


S Chart of Image 4
sd_array
0.0
0.2
0.4
0.6
0.8
1.0
0
1000
2000
3000
4000
Index


X-bar Chart of Image 3
mean_array
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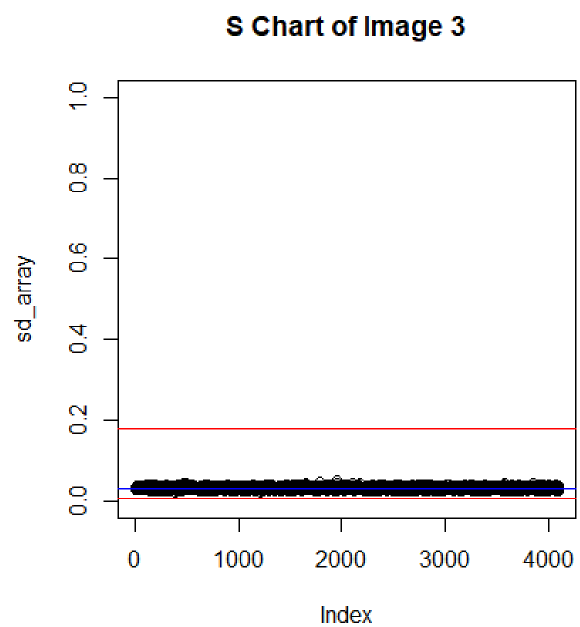
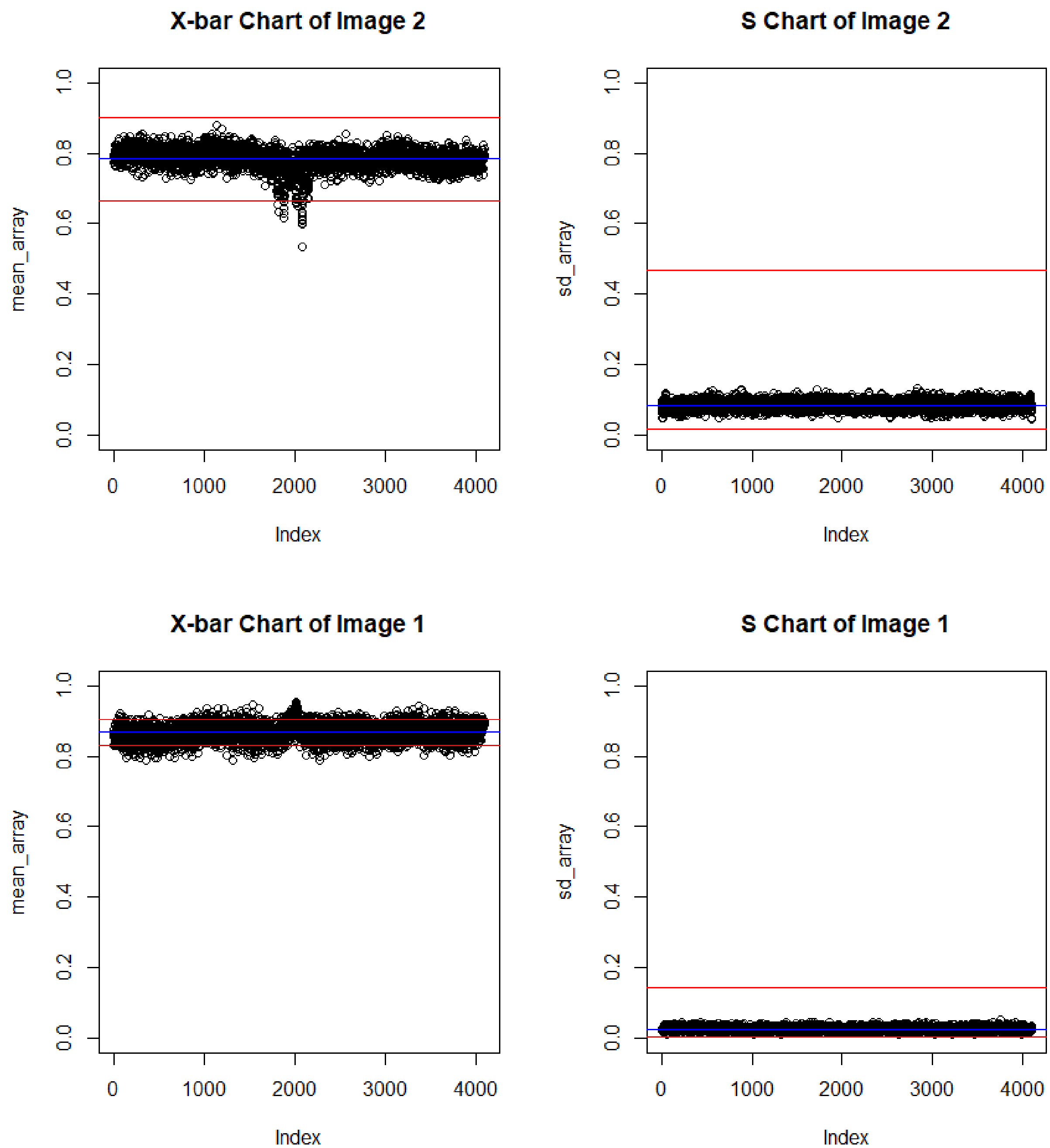
0.2
0.4
0.6
0.8
1.0
0
1000
2000
3000
4000
Index


S Chart of Image 3
sd_array
0.0
0.2
0.4
0.6
0.8
1.0
0
1000
2000
3000
4000
Index



X-bar Chart of Image 2
S Chart of Image 2
X-bar Chart of Image 1
S Chart of Image 1
mean_array
sd_array
Index
0.0
0.2
0.4
0.6
0.8
1.0
0
1000
2000
3000
4000