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Original Article

A Recently Formulated Individual Control Chart Designed for Quality Control Applications within the Health-care Domain

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ABSTRACT

Quality control charts are based on data that is also used for various statistical analyses, such as regression, time series analysis, and other types of analyses. This implies that the data used to create these charts may contain outliers, potentially compromising their accuracy. To eliminate any potential noise or pollution from the data, a researcher proposed using wavelet shrinkage with a threshold and comparing the resulting data with Shewhart's individual chart. Based on this, a new quality control chart was proposed and built using a universal approach for assessing the level of thresholding, representing the individual chart for wavelet haar with soft and hard thresholding. Following that, a comparison was performed between them as well as with Shewhart's individual chart. This letter's most significant conclusion is that in addition to using two real data points—triglyceride, which was recorded by a laboratory blood analyzer in Al-Jumhuri and at the specialized Center for Cardiology Hospital in Erbil Governorate—it may be possible to use wavelet shrinkage with a threshold to address issues of noise or pollution when Shewhart's individual chart was made and used. Moreover, the wavelet method effectively reduces deviation, as demonstrated in both sets of data.

Keywords: Quality control, individual chart, wavelet process, laboratory testing, deviation

INTRODUCTION

A control chart for laboratory testing typically involves plotting test results over time to monitor variation. It includes a centerline representing the mean and control limits indicating acceptable variation. Outliers beyond these limits may signal process issues. Control charts in laboratory testing offer several benefits, including early detection of process variations, identification of systematic issues, improved quality control, enhanced consistency in results, and the ability to make informed decisions based on statistical analysis.[1]

Quality control charts, also known as statistical process control charts, are tools used to monitor and control processes. They help identify variations and maintain quality standards by plotting data points over time.

Wavelet filters are mathematical functions used in wavelet transformations for signal processing. They analyze signals at different scales and resolutions, allowing for a more detailed examination of both high and low-frequency components. These filters play a crucial role in applications, such as image compression, de-noising, and feature extraction.

Creating a quality control chart with wavelet analysis involves using wavelet transform techniques to analyze and represent the signal characteristics. You can start by applying wavelet transform to your quality data to identify patterns or abnormalities at different scales. Then, plot the transformed data on a control chart to visually assess variations. Implementing this may require specific tools or programming languages with wavelet analysis capabilities.[2]

Quality control charts and wavelet analysis are both tools used in statistical process control, but they serve different purposes.

1. Quality control charts:
   - Purpose: Quality control charts, such as X-bar, individual and R charts, monitor process stability, and detect variations in a production process.

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    - Usage: They are effective for identifying common cause and special cause variations, helping to maintain consistent quality.
2. Wavelet analysis:
    - Purpose: Wavelet analysis is a mathematical technique used for signal processing, revealing patterns at different scales in a dataset.
    - Usage: It is often applied in various fields to analyze time-series data, image processing, and more. In quality control, wavelets can be used to identify patterns or trends at different frequencies in a time series.
    - Quality control charts primarily focus on overall process stability, while wavelet analysis provides a more detailed view of patterns and variations at different scales.
    - Combining both approaches could enhance the understanding of a process. For example, if a quality control chart indicates a shift, wavelet analysis might help identify the specific time scale or frequency of the change.

In summary, quality control charts monitor overall process stability, while wavelet analysis delves into the details of patterns and variations within the data. Integrating these approaches can offer a comprehensive view of process dynamics and help in effective quality management.

MATERIALS AND METHODS

The quality control data, including daily records of white blood cells (WBC) and triglyceride levels, were arranged and analyzed. The data were recorded by a laboratory blood analyzer in Al-Jumhuri and at the Specialized Center for Cardiology Hospital in Erbil Governorate. Using the wavelet shrinkage method to establish a new individual control chart, and then compared results with the traditional individual Shewhart method.

Control

Control the process of monitoring and inspecting a production process to keep conforming to the standards to produce a high percentage of acceptance quality.[1]

Such control typically consists of four steps.[2]

1. Setting quality criteria.
2. Appraising conformity to these standards.
3. Taking action when the requirements are not met.
4. Planning for improvements in the standards.

Quality

Quality generally refers to the standard or degree of excellence of something, often measured against a set of criteria. It can encompass characteristics such as durability, accuracy, effectiveness, or overall excellence in a given context.[2]

Quality Control

Quality control is the use of techniques and activities to achieve, sustain, and improve the quality of a product or service. It involves the integration of the following related techniques and activities.[3]

1. A description of the requirements.
2. The product or service's design to adhere to the requirements
3. Production or installation that complies with the standard in its entirety.
4. Inspection to determine compliance with specifications.
5. Examine the updated specification, if necessary.

On production, quality control is split into two sections.[3]

A. Process control is part of the quality system that deals with keeping an eye on and enhancing the manufacturing process through the study of patterns and indicators of problems with quality or chances to improve quality.

B. Product control: This is an inspection procedure that includes monitoring products both in the field and at the production source. Determining whether or not the product complies with the objectives for product quality is the goal of the control.

Variation

The variation concept is a law of nature, in that no two natural items in any category are exactly the same.

According to Besterfield's[3] idea "the ability to measure variation is necessary before it can be controlled.[3]

Source of Variations

Stochastic (also known as random) and non-stochastic (sometimes known as deterministic) variation are the two different forms of variation.

1. Random sources of variation: There are numerous intricate factors that contribute to this kind of variation, which is difficult to completely eliminate or regulate but is manageable. Some are inherited from the production process, some are unobservable, and there are small processing variations.
2. Variations with assignable causes are those that are observable and whose causes can be accurately determined and removed.[4]

Quality Characteristics

Two major groups of quality attributes are distinguished:[5]

1. Measurable qualities: Features that can be measured and expressed as a number on some continuous scales of measurement are called measurable characteristics, and the control charts utilized for this type are called variable charts.
2. Immeasurable characteristics: Immeasurable characteristics are those that are difficult to quantify or even measure on a continuous scale. The control charts that are used to manage these kinds of characteristics are known as attribute charts.[6]

Quality Control Charts

A quality control chart is a statistical tool used to monitor and control a process over time. It helps identify variations and maintain consistency in production by plotting data points against predetermined control limits.[7]

Walter A. Shewhart of the Bell Telephone Laboratories created the first quality control chart in 1924, and he and his collaborator continued to enhance it. In 1931, he provided a comprehensive explication of control charts.[8]

The Idea of Shewhart

Shewhart used the normal distribution in his chart construction see Fig.1, and statistical inference and sampling theory provided the statistical underpinnings for the creation and application of quality control charts. He came to the conclusion that a distribution's mean and standard deviation can be estimated to convert it into a normal shape.

Question Shewhart posed was whether the production process was proceeding smoothly and organically and whether the points on the chart corresponded to a normal distribution. For these reasons, Shewhart had to build his charts using the normal distribution.[9]

A stable distribution was defined as one where variation does not exceed the set limits more than 0.27% of the time if the process is under statistical control.

To arrive at a definition of a stable distribution, Shewhart used the central limit theorem. The theorem has three aspects which relate to control charts:

A normal distribution curve (Bell shape) is formed by the distribution of averages from individual item averages of a certain population.

Three parallel lines make up Shewhart control charts see Fig.2, and they are as follows:[10]

1. The mean or overall average, of the quality feature being monitored, is represented by the letter T as the center line (also known as the target line) of the control chart.
2. For a process in a state of control, the upper control limit is the greatest allowable deviation from the mean. represented mathematically as:
   $$UCL = T+3\sigma \quad (1)$$
3. For a process in a state of control, the lower control limit is the greatest allowable deviation from the mean. represented mathematically as:
   $$LCL = T-3\sigma \quad (2)$$

Where the horizontal axis represents the sequence of samples (or time), while the vertical axis represents the quality characteristic.

Classification of Control Charts

Control charts may be classified into two main types, which are:[10]

Variables control charts

When the goods produced are measurable (in one of the units of measurement), these charts are utilized in product process control. When creating charts, it is ideally necessary to have a minimum of 25 samples and a minimum of four units for each sample (individual charts excluded). There is only one attribute or characteristic to which variable charts can be used.

a. Individual – chart (or x-chart)
b. Average – chart (or -chart)
c. Standard deviation- Chart (or S-chart)
d. Range - Chart (or R-chart).

Individual – chart (or X-chart)

This chart is used to control the quality of the product. The target line for this chart represents the overall average for all observations of the same process. The (upper and lower) control limits are put at (±3 standard deviation) from the target line.

Attributes control charts

Attributes control charts are statistical tools used in quality control to monitor and control processes that produce discrete or categorical data. Unlike variable control charts that deal with continuous measurements, attributed control charts are designed for attributes or counts, often expressed in terms of proportions or percentages.[11]

Common types of attributed control charts include:

1. P-Chart (Proportion Chart).
2. C-Chart (Count Chart).
3. U-chart.

Uses of Control Charts

Control charts are used in quality control to monitor and maintain the stability of processes over time. Here are a few key applications.[1]

1. Process monitoring:
   - Detecting and identifying any variations or shifts in a process that may lead to defects.
   - Tracking the stability of the process by comparing observed data points with control limits.
2. Quality improvement:
   - Identifying the root causes of process variability or defects.
   - Implementing corrective actions based on insights gained from control chart analysis.
3. Decision-making:
   - Making informed decisions about whether a process is operating within acceptable limits.
   - Determining when to intervene and take corrective actions to prevent defects.
4. Continuous improvement:
   - Facilitating continuous improvement efforts by providing real-time feedback on process performance.

Statistical Analysis

To read and understand the plotted points on the chart and determine whether or not the production process is under statistical control, the person in charge of using quality control charts should be knowledgeable in the science of statistics. Based on this analysis, he will make the following decision:[11]

The control process

A process is said to be under a state of control when all assignable causes have been removed to the point that control chart points stay within the designated bounds. Variation is a natural occurrence when a process is under control.

Out-of-control process

A process that is out of control is one that has changed as a result of assignable reasons. The process is considered to be out of control when a point (subgroup value) exceeds its control limits or when an abnormal pattern of variation arises. This indicates that there are identifiable sources of variance.[1,4]

WAVELETS PROCESS

A wavelet process involves analyzing signals or time-series data using wavelet transformations. Wavelet transforms are mathematical tools that decompose a signal into different frequency components and time scales.

Wavelet processes find applications in various fields, including signal processing, image compression, quality control, and feature extraction. Implementing a wavelet process often involves using programming languages or tools that support wavelet analysis.[12]

Wavelet Types

1. Haar.
2. Beylkin (18) wavelet.
3. Coiflet (6, 12, 18, 24, 30).
4. Daubechies wavelet (2, 4, 6, 8, 10, 12, 14, 16, 18, 20).
5. Binomial-QMF.
6. Mathieu wavelet.
7. Haar wavelet.
8. Legendre wavelet.
9. Villasenor wavelet.
10. Symlet wavelet.

Haar wavelet

A series of "square-shaped" functions that have been rescaled and combined to form a wavelet family or basis is known as a Haar wavelet in mathematics. Wavelet analysis and Fourier analysis are comparable in that they both enable the representation of a target function over an interval in terms of an orthonormal basis.[13]

The Haar sequence is widely used as a teaching example and is now acknowledged as the first wavelet basis see Fig.3. It was and is now acknowledged as the first wavelet basis. It was Alfréd Haar who first proposed the Haar sequence in 1909.

Wavelet Transform

Wavelet transform is a mathematical tool used for signal processing and image compression. It decomposes a signal into different frequency components, allowing both time and frequency information to be analyzed simultaneously. It is particularly useful for handling non-stationary signals with varying frequency content.[14]

Discrete wavelet transform (DWT)

DWT is a specific type of wavelet transform that operates on discrete data. It decomposes a signal into approximation and detail coefficients at different resolution levels. DWT is widely used in signal processing tasks such as image compression, denoising, and feature extraction due to its ability to capture both low and high-frequency components efficiently.[15]

Given a vector of a signal X consisting of 2^j observation where j an integer is. The DWT of X is

$$W = wX \tag{3}$$

Where W is an $n*1$ vector comprising both discrete scaling and wavelet coefficients. The vector of wavelet coefficients can be organized into $j+1$ vectors.

$$W = \left[W1, W2, \ldots, Wj_0, Vj_0\right]^T$$

Where Wj is a length $N_j = N/2^j$ vector of wavelet coefficients (Details) associated with changes on a scale of length $\lambda_j = 2^{j-1}$ symboled as CD, and V_{j0} is a length $N_{j0} = N/2^j$ vector of scaling coefficients (approximation or smoothing) associated with an average on a scale of length $\lambda_{J0} = 2^{J0}$ symboled as CA, and w is an orthonormal $N*N$ matrix associated with the orthonormal wavelet basis chosen.[16]

After each DWT, the approximation coefficients are divided into bands using the same filter as before, with the result that the details are appended with the details of the latest decomposition, at each level, the signal can be reconstructed of the de-noise signal by the inverse transform.[17]

$$X = Ww^T = \sum_{j=1}^{j0} W^T W_j + V_{j0}^T V_{j0} \tag{4}$$

Wavelet Shrinkage

Wavelet shrinkage is a technique used in signal and image processing, particularly with the DWT. It involves thresholding the wavelet coefficients to reduce or eliminate noise while preserving important signal features. By setting small coefficients to zero based on a specified threshold, wavelet shrinkage helps enhance the signal-to-noise ratio and improve the overall quality of the processed data.[16]

The wavelet shrinkage based on thresholding of the wavelet coefficients, well discussed in the next section, attempts to recover a signal $\theta(t)$ from noisy a signal $x(t)$.

$$x(t) = \theta(t) + \zeta(t) \tag{5}$$

Where $\zeta\ (t)$ represents a noise.

Thresholding Method

Thresholding is a method used in signal and image processing to simplify or segment data by setting values above or below a certain threshold to specific levels. In the context of wavelet shrinkage, for example, thresholding involves setting coefficients below a certain threshold to zero, effectively removing noise and retaining relevant information. Various thresholding methods exist, such as hard thresholding and soft thresholding, each influencing how coefficients are modified based on their magnitudes relative to the chosen threshold.[18]

Universal threshold

Given the universal threshold that[19] proposed,

$$\ell^U = \tilde{\sigma}_{(MAD)} \sqrt{2logN} \tag{6}$$

Where N is the data length series, and is the estimator of the standard deviation of details coefficients, which is estimated as:

$$\tilde{\sigma}_{(MAD)} = \frac{MAD}{0.6745} \tag{7}$$

The wavelet coefficients' median absolute deviation at the finest scale, or MAD, is defined as.

$$MAD = median\left[\left|W_{1,0}\right|,\left|W_{1,1}\right|,\ldots,\left|W_{1,\frac{N}{2}-1}\right|\right]$$

So that W_1, t represents the element of the W_1 while the constant is the median of the standard normal distribution.

Thresholding Rules

There are several thresholding rules commonly used in signal and image processing, especially in the context of wavelet shrinkage. Two common types are:[6,20,21]

1. Hard thresholding
2. Soft thresholding.

Choosing the appropriate thresholding rule depends on the characteristics of the data and the desired balance between noise reduction and the preservation of important features.

Soft thresholding

Soft thresholding is a technique used in signal and image processing, particularly in the context of wavelet shrinkage. It involves shrinking or reducing the magnitude of wavelet coefficients by a certain threshold without setting them exactly to zero. The soft thresholding function is defined as follows:[22-25]

$$Wn^{st} = sign\,\{wn\}(|wn| - l|)_{+} \tag{8}$$

Where

$$sign\{Wn\}\begin{bmatrix} +1 & if\ Wn > 0 \\ 0 & if\ Wm = 0 \\ -1 & if\ Wn < 0 \end{bmatrix} \tag{9}$$

And

$$(|wn| - \ell\,|)_{+} = \begin{bmatrix} (|wn| - \ell) & if\,(|wn| - l) \geq 0 \\ 0 & if\ (|wn| - l) < 0 \end{bmatrix} \tag{10}$$

CONSTRUCTION NEW INDIVIDUAL CONTROL CHART BASED ON WAVELET SHRINKAGE

In Fig.4 by addressing the problem of contamination in the data (if any) using the small wave (db2) with soft threshold rule and estimating the level of the threshold method through the (universal) method through which these new charts will be formed and compared with Shewhart's individual chart as summarized in the following diagram.

APPLIED AND RESULTS

This part deals with the formation of the new individual chart using wavelet shrinkage, and it is compared with the Shewhart individual chart to determine the accuracy, efficiency, and suitability of these new individual charts to avoid the weaknesses of the Shewhart individual chart.

The Al-jumhuri Hospital in Erbil Governorate was chosen to obtain data related to our study. The data we obtained related to (WBC) and the ratio of cholesterol in blood for the patients having angina pectoris who are enrolled in the Specialized Center for Cardiology in Erbil in Kurdistan-Iraq. Ready-made programs (Matlab) and (Statgraphics) were used to draw the new individual chart, clarify it, and compare it with the Shewhart individual chart.

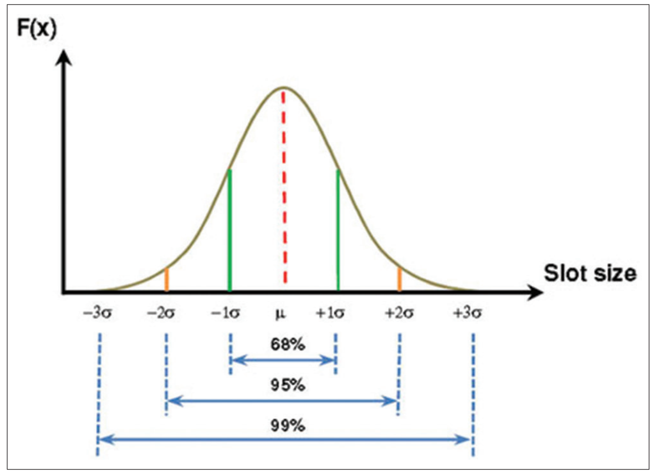

Figure 1: Using central limit theorem

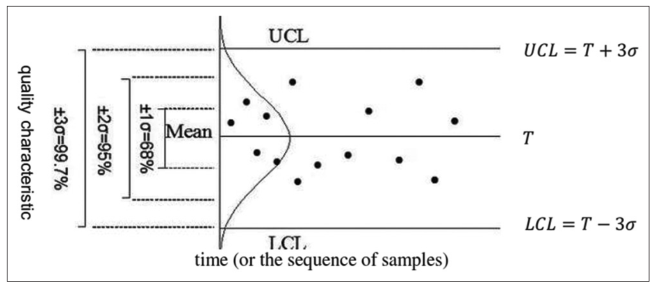

Figure 2: General quality control chart

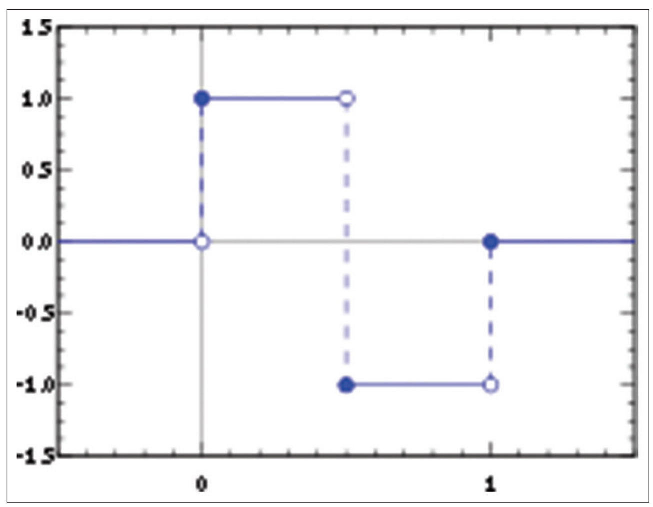

Figure 3: Haar wavelet

WBC Data

WBCs are key components of the immune system, guarding the body against diseases and foreign invaders. Each type

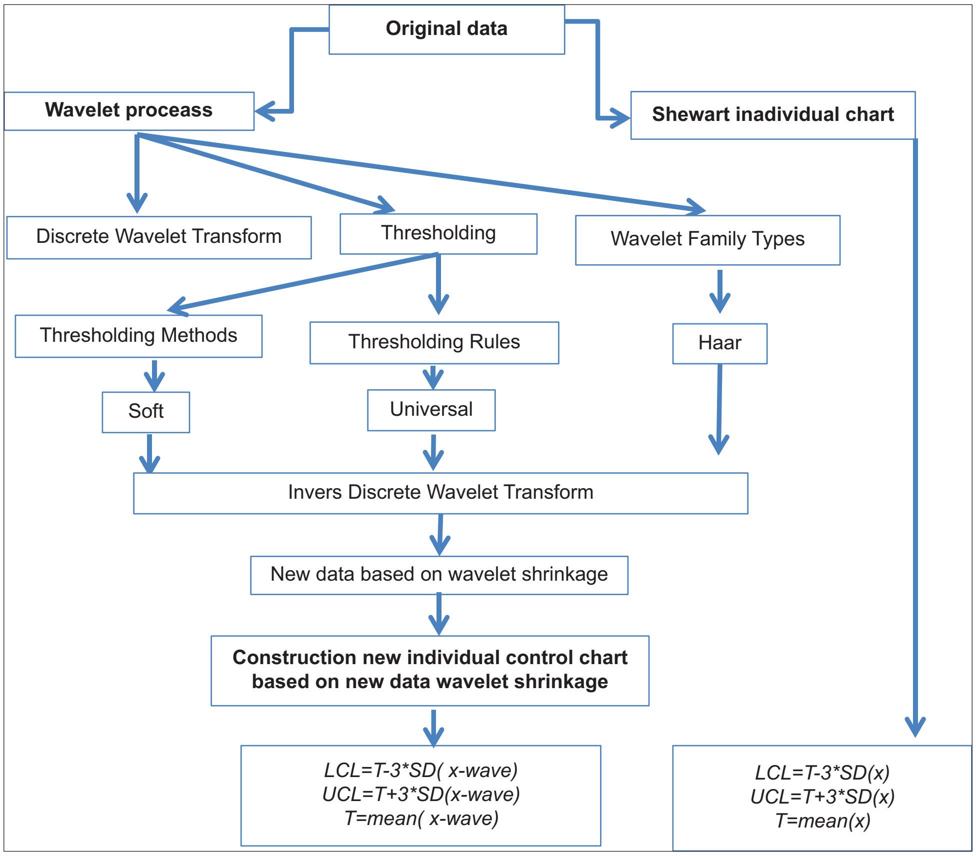

Figure 4: Block diagram for construction individual control chart

plays a distinct role in the immune response; they include neutrophils, lymphocytes, monocytes, eosinophils, and basophils. WBC counts can range from 4000 to 11,000/mL of blood, although this is not always the case. Depending on the reference values used in the laboratory, laboratory findings may differ slightly. WBC count abnormalities can be a sign of a number of illnesses; thus, it is critical to evaluate results in light of the patient's health and medical history. The above-mentioned characteristics were gathered to create charts, and Table 1 shows the outcomes of the laboratory analysis for 200 individuals at the Pathological Analysis Laboratory.

Figure 5's computation and graph demonstrate the presence of outliers. Within the upper and lower tails of the sample, all the data are not located.

Figure 6 shows that lots of the points are outside of the regulated ranges, indicating an issue with the WBC.

In Table 3, the descriptive statistical analysis of WBC data for 200 people shows that the standard deviation is equal to 3.031756, the coefficient of variation is equal to 37%, and the difference between the maximum and minimum values is equal to 18.79.

Table 2 shows the outcomes of the laboratory analysis for 200 individuals at the pathological analysis laboratory WBC after used wavelet process.

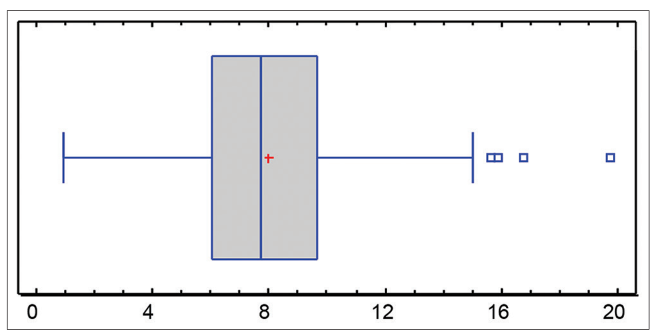

Figure 5: Box-and-Whisker plot for white blood cells

Figure 7's computation and graph demonstrate the presence of outliers. Within the upper and lower tails of the sample, all the data are not located.

Figure 8 shows that few of the points are outside of the regulated ranges, indicating an issue with the WBC based on wavelet shrinkage.

Table 4 shows the descriptive statistical analysis for WBC data based on wavelet shrinkage for 200 people and shows that the standard deviation is equal to 1.51545, the coefficient of variation is equal to 18.9%, and the difference between the maximum and minimum value is equal to 10.7513.

Table 1: White blood cells data

Original data									
6.82	6.03	11.7	6.21	11.35	4.58	10.28	7.25	8.96	6.63
4.68	9.27	10.36	8.36	14.6	13.08	0.94	5.72	5.34	13.6
11.33	6.18	6.41	6.02	5.86	7.34	8.14	7.84	4.96	5.73
6.02	3.42	1.29	6.4	15	8.57	6.77	14.3	9.51	6.78
14.51	7.27	8.29	4.94	5.99	6.19	9.87	6.56	5.09	6.28
5.15	6.35	6.89	7.77	6.5	9.74	8.7	7.88	7.59	8.6
6.8	8.72	7.96	5.26	12.47	9.91	8.73	7.01	3.32	7.7
12.49	5.74	3.42	8.18	5.45	7.93	8.36	5.28	9.69	9.42
7.84	7.18	4.22	9.72	10.42	6.59	6.35	9.75	6.79	7.73
2	6.87	8.17	10.13	2.85	14	5.09	3	5.74	5.82
9.12	4.92	10.61	4.4	6.26	8.33	7.26	5.75	7.74	10.04
9.57	7.76	19.73	4.37	6.38	11.37	7.45	9.11	8.34	5.92
7.36	7.45	4.16	12.11	3	5.2	9.91	8.17	7.87	7.7
7.96	5.96	5.4	10.74	8.84	6.92	16.72	7.06	2.83	9.16
6.85	9.29	10.32	8.26	9.25	11.58	9.85	3.33	12.2	3.41
3.6	9.3	6.8	2.24	6.99	8.29	7.74	8.14	10.3	6.82
10.95	10.29	8	5.85	11.33	8.93	7.41	14.81	7.43	4.68
12.28	7.02	7.25	9.92	15.86	8.5	9.35	15.63	9.23	11.33
7.57	13	6.27	8.03	5.86	3.45	11.14	13.16	10.8	6.02
5.96	11.11	8.24	7.01	8.47	6.59	8.12	6.63	8.88	14.51

Table 2: Descriptive statistical analysis for white blood cells data

Average	7.99175
Standard deviation	3.01756
Coefficient. of variation	37.7584%
Minimum	0.94
Maximum	19.73
Range	18.79

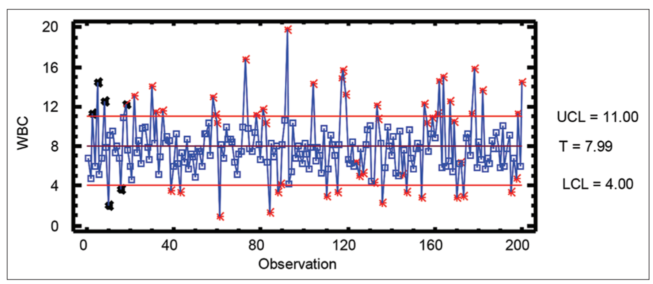

Figure 6: Shewhart individual control chart for white blood cells

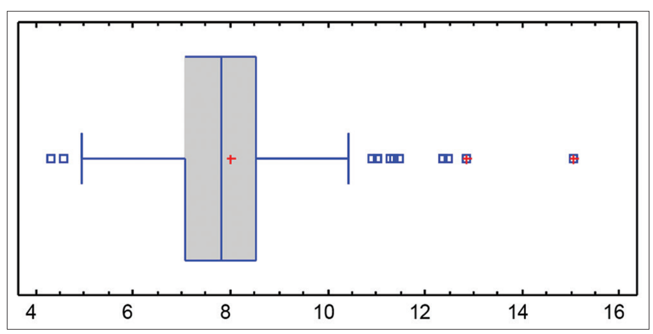

Figure 7: Box-and-Whisker plot for white blood cells based on wavelet shrinkage

Triglyceride Data

One kind of fat in your blood is called triglycerides. Although high levels can increase the risk of cardiovascular problems, they are necessary for energy. Triglyceride levels during a fasting state should normally be within the normal range, which is <150 mg/dL. Still, ideal levels are sometimes far lower for cardiovascular health. Since every person's health situation is different, it is crucial to interpret these values after speaking with a health-care provider. Table 5 shows the outcomes of laboratory analysis for 100 patients in the specialized Center for Cardiology. We gathered the aforementioned criteria to create charts.

Table 7 shows the outcomes of the laboratory analysis for 100 individuals at the Pathological Analysis Laboratory Triglyceride after used wavelet process.

Figure 9 Computation and graph demonstrate the presence of outliers. Within the upper tail of the sample, all the data are not located.

Figure 10 shows that lots of the points are outside of the regulated ranges, indicating an issue with the triglyceride.

Table 6 shows the descriptive statistical analysis for triglyceride for 100 people shows that the standard deviation

Table 3: New data based on wavelet shrinkage

7.9544	6.5844	7.0644	4.9544	9.6881	6.7581	6.9731	7.5969	10.1094	7.9344
7.9544	11.4644	7.0644	8.5344	9.6881	6.7581	6.9731	7.5969	10.1094	11.284
9.1794	9.0244	6.9494	7.9794	5.8031	7.3781	6.9731	7.1319	7.3494	8.2944
7.4894	9.0244	7.1794	7.9794	4.3031	10.2181	6.9731	8.0619	12.8694	8.2944
11.0144	9.0244	7.0644	8.0619	7.3706	7.1231	6.9731	7.1181	8.4494	8.0194
5.2744	9.0244	7.0644	8.0619	7.3706	7.1231	6.9731	7.1181	8.4494	8.0194
7.1094	9.0244	7.0644	8.0619	7.8306	7.1231	6.9731	5.7431	10.3194	8.0194
9.1794	9.0244	7.0644	8.0619	6.9106	7.1231	6.9731	8.4931	6.9194	8.0194
7.2881	7.1294	8.0606	8.0619	5.7094	8.6881	9.0944	7.1181	9.0544	8.0194
5.0681	10.9194	8.0606	8.0619	6.0394	5.5581	9.0944	7.1181	5.1044	8.0194
8.0581	9.0244	8.0606	8.0619	9.5544	7.1231	6.0994	7.1181	7.0794	8.2694
8.0581	9.0244	8.0606	8.0619	15.0544	7.1231	6.0994	7.1181	7.0794	7.7694
7.1181	6.3994	8.0606	12.4919	6.9844	7.6069	9.4119	7.3969	5.9694	8.3388
7.1181	6.3994	8.0606	9.2419	6.9844	7.6069	9.4119	5.9769	8.1894	8.3388
7.1181	7.7294	8.0606	7.7019	8.2194	7.0119	6.9819	10.0569	7.0794	7.5688
7.1181	7.7294	8.0606	7.7019	8.2194	8.2019	4.5819	10.0569	7.0794	7.5688
10.1769	7.7794	7.5794	9.4569	7.7781	12.3544	7.3719	8.3719	10.4394	6.4388
10.1769	7.7794	9.9394	9.4569	7.7781	12.3544	7.8219	8.3719	11.3494	9.4688
7.8719	6.3494	8.7594	9.1119	7.7781	11.0294	7.5969	8.3719	7.0094	5.5188
7.8719	6.3494	8.7594	9.1119	7.7781	8.1194	7.5969	8.3719	7.0094	10.388

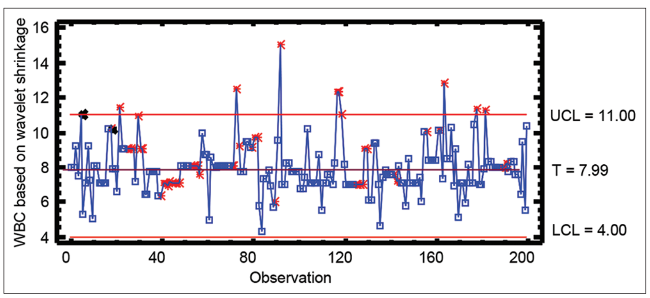

Figure 8: Individual control chart for white blood cells based on wavelet shrinkage

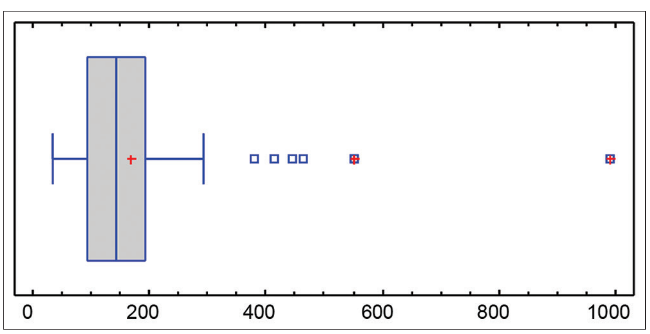

Figure 9: Box-and-Whisker plot for triglyceride

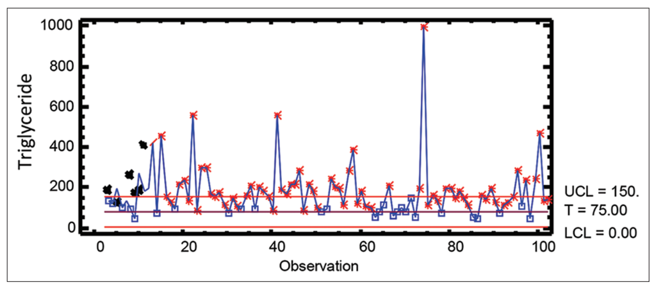

Figure 10: Individual control chart for triglyceride

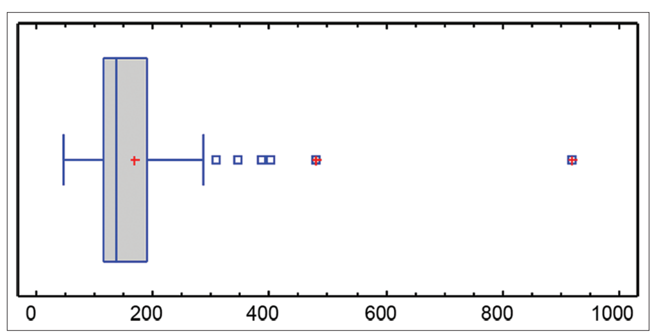

Figure 11: Box-and Whisker plot for triglyceride based on wavelet shrinkage

is equal to 130.47, the coefficient of variation is equal to 77.4259%, and the difference between the maximum and minimum value is equal to 955.0

In Figure 11, computation and graph demonstrate the presence of outliers. Within the upper tail of the sample, all the data are not located.

Table 4: Descriptive statistical analysis for white blood cells data based on wavelet shrinkage

Average	7.99176
Standard deviation	1.51545
coefficient of variation	18.9627%
Minimum	4.3031
Maximum	15.0544
Range	10.7513

Table 5: Triglyceride data

Original data				
124	76	161	44	143
112	294	212	73	106
189	294	209	104	43
95	161	278	201	40
126	150	81	50	155
83	171	210	70	134
35	105	172	94	190
266	63	90	72	123
175	144	73	143	64
190	102	87	45	109
416	86	234	190	117
64	151	198	990	150
446	200	190	108	276
150	88	107	154	100
120	196	277	130	231
85	178	380	63	40
210	146	112	187	235
232	76	176	187	465
130	551	100	143	124
550	180	94	172	135

Table 6: Descriptive statistical analysis for triglyceride data based on wavelet shrinkage

Average	168.51
Standard deviation	130.47
coefficient of variation	77.4259%
Minimum	35.0
Maximum	990.0
Range	955.0

Figure 12 shows that lots of the points are outside of the regulated ranges, indicating an issue with the Triglyceride based on wavelet shrinkage

Table 8 shows the descriptive statistical analysis for Triglyceride for 100 people shows that the standard deviation is equal to 108.524, the coefficient of variation is equal to 64.4023%, and the difference between the maximum and minimum value is equal to 918.75.

Table 7: Triglyceride data after wavelet process

New database on wavelet shrinkage				
128.75	139.75	207.5	94.75	103.25
128.75	287.75	207.5	94.75	103.25
140.75	245.25	207.5	117.75	77.75
116.75	182.25	207.5	144.75	77.75
128.75	131	116.25	79	143
128.75	131	175.25	79	143
48.25	112	151.75	79	143
209.25	112	139.75	79	143
205.75	121.5	116.25	129.25	117.5
205.75	121.5	116.25	101.25	117.5
346.75	121.5	194.75	188.75	117.5
64.75	121.5	194.75	918.75	117.5
387.75	194	176.25	121.25	207.25
161.75	152	163.25	121.25	101.25
136.75	173	275.75	121.25	214.75
136.75	173	308.75	121.25	93.75
242.25	132.25	113	164.75	241.25
242.25	132.25	113	164.75	401.25
128.75	479.75	113	164.75	158.25
478.75	178.75	113	164.75	158.25

Table 8: Descriptive statistical analysis for triglyceride data based on wavelet shrinkage

Average	168.51
Standard deviation	108.524
Coefficient of variation	64.4023%
Minimum	48.25
Maximum	918.75
Range	870.5

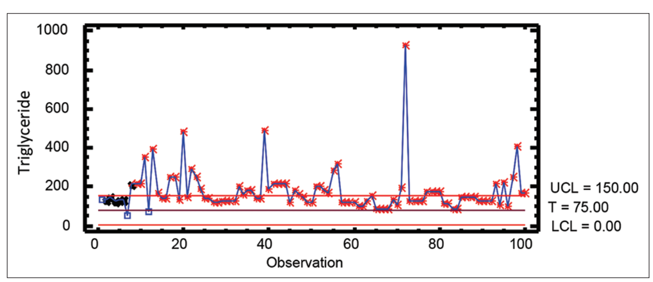

Figure 12: Individual control chart for triglyceride based on wavelet shrinkage

CONCLUSIONS

Our study highlights the potential benefits of employing wavelet shrinkage in enhancing daily control in laboratory tests, specifically those involving WBC and triglyceride measurements. The effectiveness of the wavelet process is evident in both sets of data, demonstrating a significant reduction in deviation. Furthermore, in practical applications, the coefficient of variation becomes more comparable to the data when wavelet shrinking is applied, underscoring its utility in refining the analysis. The observed possibility of utilizing wavelet shrinkage to address outliers or noise when constructing and utilizing individual control charts adds a valuable dimension to quality control methodologies. These findings suggest that incorporating wavelet shrinkage techniques can contribute to improved precision and reliability in laboratory testing, particularly in the context of individual control charts.

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