Analysis of a serial based digital voice recorder

GCFA

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Version 2.0 (option 2)

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SANS 2005

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I. Abstract

This paper will explore issues with a serially accessed digital voice recorder and in particular the retrieval and analysis of the voice files contained on the device. The device, a "VoiceIt" recorder records files to load later into the Dragon Speech recognition software. Unlike standard disk or USB card devices this hardware is accessed using a 9 pin serial link and does not map as a disk drive. There is a SD card expansion slot, though this is not in current use and there is no facility on the device to undelete files and copy them to the SD card. The analysis will derive around extracting the voice files from the device and copying them to a computer in a forensically sound manner. The device has a delete function independent of the PC and may be used "on the road" to dictate files which are later downloaded to the PC host for conversion into text. The device has had voice files deleted without being written to the PC.

Due to a white noise fingerprint in the wave form, it is possible to map files from an individual digital recorder to that specific hardware device.

II. Document Conventions

When you read this practical assignment, you will see the representation of certain words in different fonts and typefaces. The representation of these types of words in this manner includes the following:

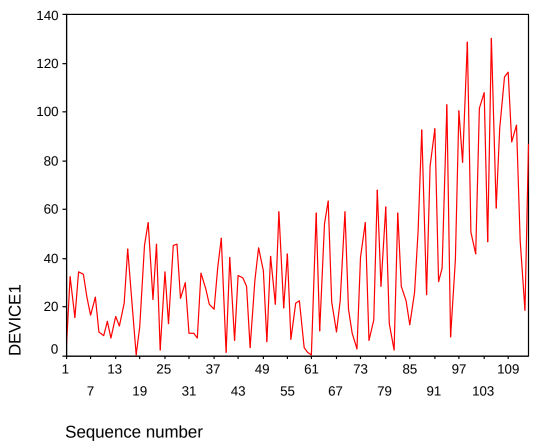
`command`	The representation of operating system commands uses this font style. This style indicates a command entered at a command prompt or shell.
`filename`	The representation of filenames, paths, and directory names use this style.
`computer output`	The results of a command and other computer output are in this style
URL	Web URL's are shown in this style.
Quotation	A citation or quotation from a book or web site is in this style.

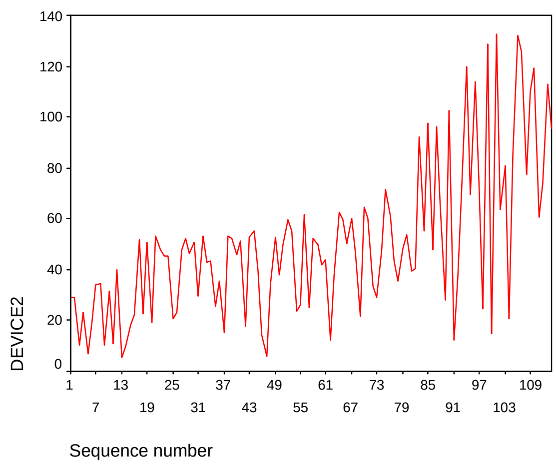
III. Executive Summary

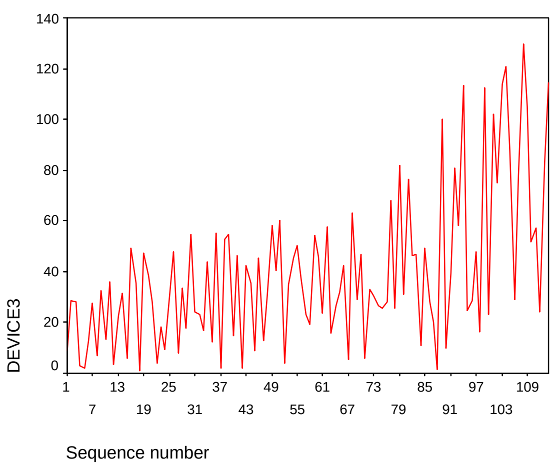
This paper presents a new approach to the detection of forgeries in digital audio and a possible means to forensically match an audio recording to a specific hardware based digital recorder. Either the hardware device that made the recordings or other recordings from the same digital media recorder need to be a available. The method is based on detecting the underlying white noise created by the recording device. This is a unique stochastic characteristic of the hardware recorder. Any forged region of sound may be shown as not demonstrating the standard white noise pattern.

1 Method

The primary test involved an analysis of the startup waveform the for each of the five devices. This was achieved by measuring the amplitude of the signal using a digital oscilloscope and recording the measurements for each of the first 112 ms. A wave file was created and downloaded using the VoiceIT software to obtain these samples.







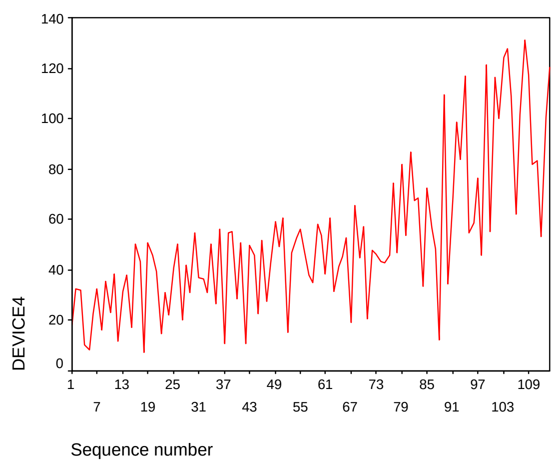
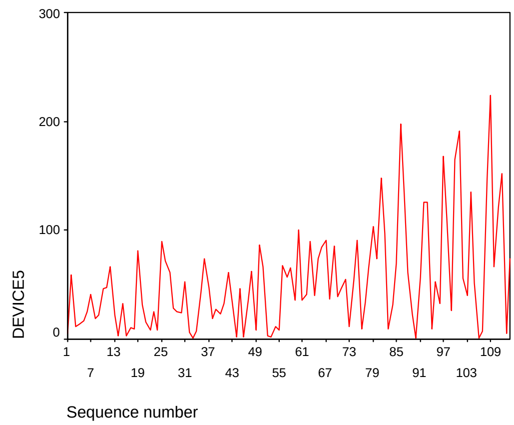


Figure 1 - Time Series Plot of the 5 devices



When visually compared, there are some differences but the overall pattern is similar across all devices.

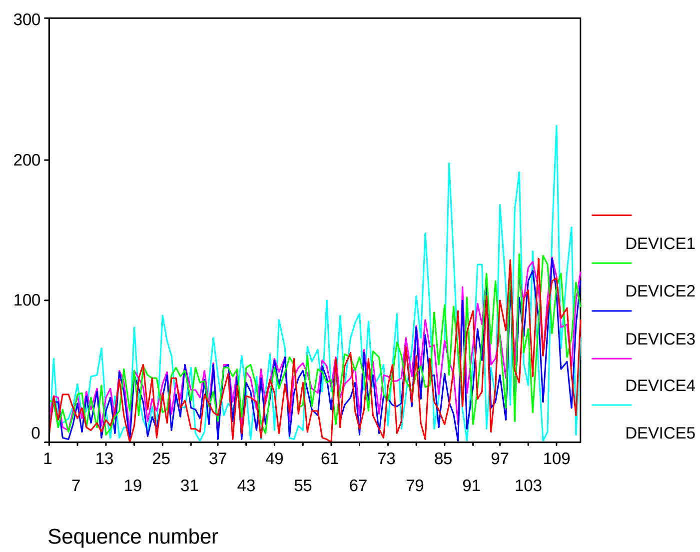


Figure 2 – Aggregated Time Series Plots of Amplitude

In order to confirm that the startup pattern remained constant for each device, five separate downloads were conducted and analysed for the 5th device.

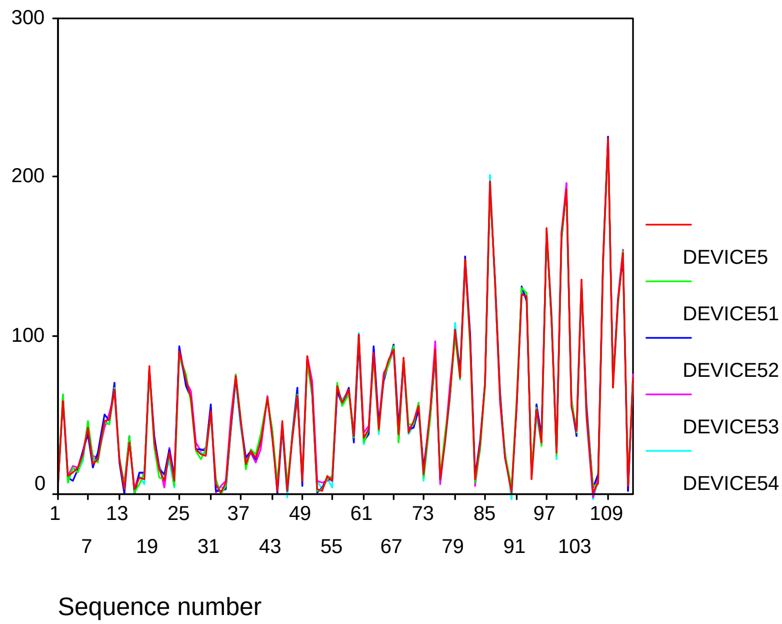


Figure 3 - Aggregated Time Series Plots of Amplitude for device 5

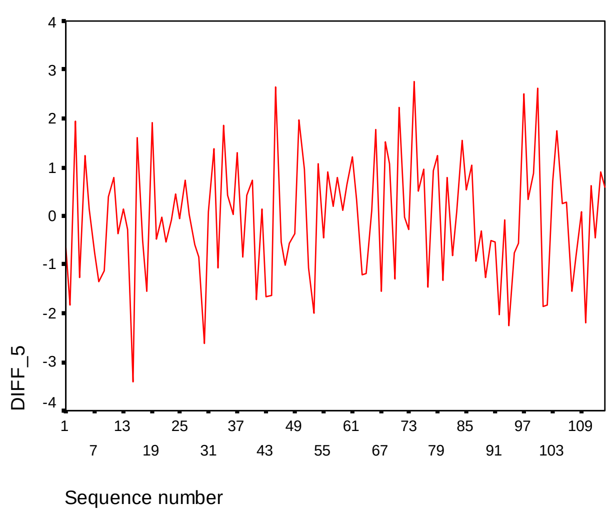


Figure 4 - Residual White Noise associated with Device 5

Looking at the differences from each of the results of the 5th device, the differences obtained when each of the five samples was analysed is attributable to IID white noise. It was shown that the differences are normally distributed about the mean.

Confidence Intervals

Parameter	Estimate	Lower CI	Upper CI	1-Alpha
Mean	-0.02754	-0.25728	0.202192	0.950
Std Dev	1.238102	1.095585	1.42358	

Fitted Normal

Parameter Estimates

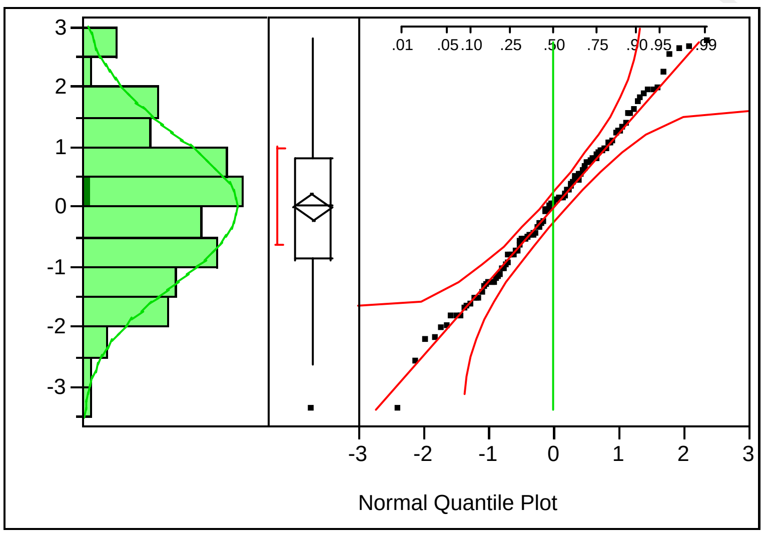
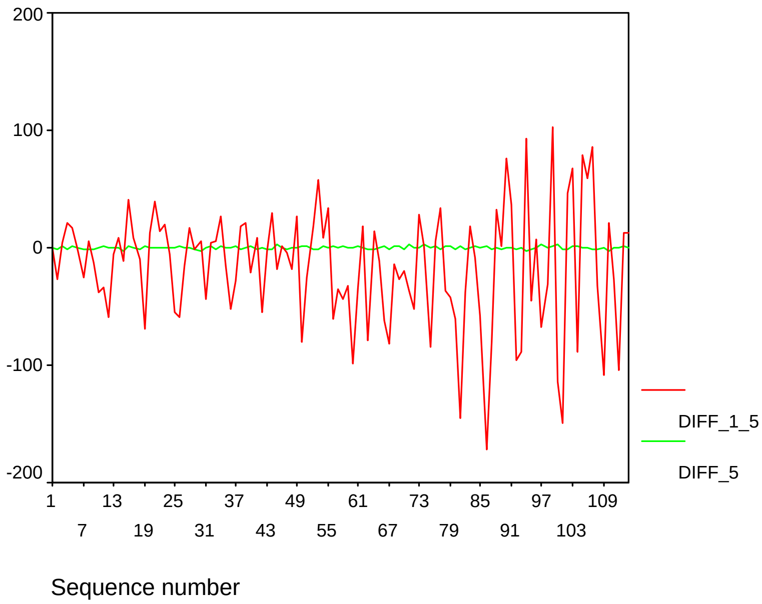


Figure 5 - Normal Plot of Residual White Noise

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	Mu	-0.02754	-0.25728	0.202192
Dispersion	Sigma	1.23810	1.09558	1.423580

Alternatively, a comparison of the differences from the results of separate devices did not demonstrate any similarity of values. In comparing the values from the first and fifth devices, there is a clear difference in the patterns.

Figure 6 – Differenced analysis of Device 1 and device 5



When plotted together, the discrepancies which seemed similar on individual plots are show to be significantly different (as will be upheld using statistical tests later in the paper).

The plot of the discrepancies on the same device are demonstrated to be small and insignificant. This shows us that there is some correlation at the startup stage. From this it is possible to deduce that there is a hardware dependant white noise signature. Each file created with the device may be shown to have the individual white noise signature. Each signature is unique to the individual hardware device.

2 Discussion of Findings

A correlation of the wave function was completed across the five devices and against the same device.

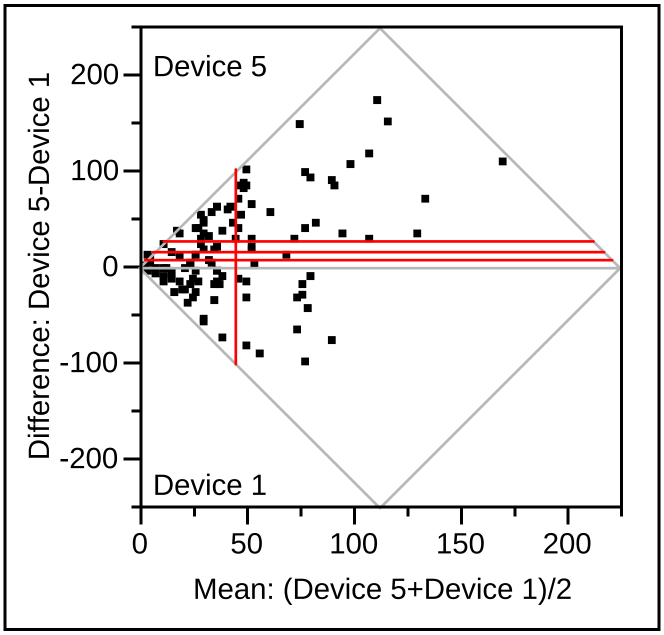
Proximity Matrix					
	Correlation between Vectors of Values				
	DEVICE5	DEVICE51	DEVICE52	DEVICE53	DEVICE54
DEVICE5	.000	.998	.998	.998	.998
DEVICE51	.998	.000	.996	.997	.997
DEVICE52	.998	.996	.000	.996	.996
DEVICE53	.998	.997	.996	.000	.997
DEVICE54	.998	.997	.996	.997	.000
This is a similarity matrix					

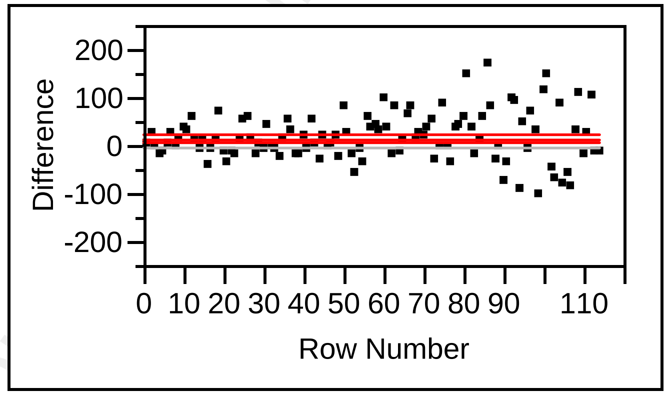
It is clear with a correlation factor between 0.996 and 0.998 from readings taken that there is a common white noise function that is associated with the device.

Proximity Matrix					
	Correlation between Vectors of Values				
	DEVICE1	DEVICE2	DEVICE3	DEVICE4	DEVICE5
DEVICE1	.000	.473	.532	.604	.230
DEVICE2	.473	.000	.430	.544	.148
DEVICE3	.532	.430	.000	.860	.288
DEVICE4	.604	.544	.860	.000	.381
DEVICE5	.230	.148	.288	.381	.000
This is a similarity matrix					

Alternatively, it is also demonstrated (correlation from 0.148 to .860) that there is a variation between the separate devices. The white noise startup function is similar between the 5 devices, but there is enough of a difference that a white noise fingerprint may be determined.

Figure 7 - Matched Pairs, Difference: Device 5-Device 1





Device 5	53.5432	t-Ratio	3.430242
Device 1	37.4354	DF	113
Mean Difference	16.1078	Prob > |t|	0.0008
Std Error	4.69582		
Upper95%	25.4111		
Lower95%	6.80454		
N	114		
Correlation	0.23026		

Wilcoxon Sign-Rank

	Device 5-Device 1
Test Statistic	1069.5
Prob > |z|	0.002

An analysis of the bi-variate matched pairs model for the separate device wave functions demonstrates that there is some correlation (R^2=5.3%) but as may be seen from the Wilcoxon Sign-Rank Test, the wave forms are significantly different at the alpha = 5% level..

This may be compared again with the results of the correlations from the wave functions obtained from the same device (see below). In this case the correlation is high (R^2=99.65%) and the results are not significantly different.

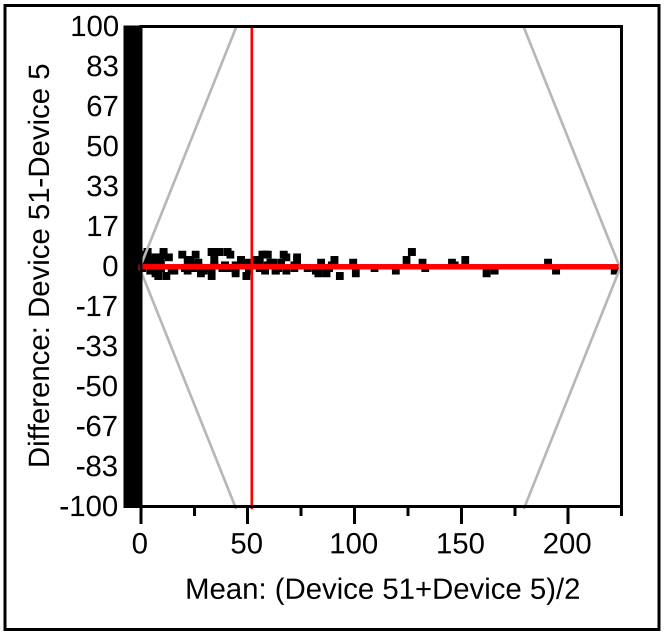
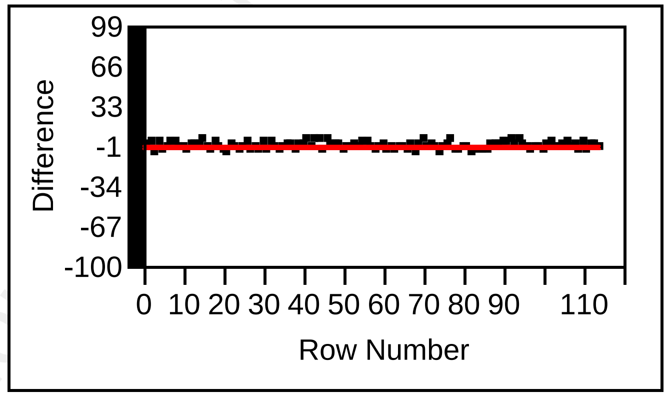


Figure 8 - Matched Pairs - Difference: Device 51-Device 5



Device 51	53.4068	t-Ratio	-0.51836
Device 5	53.5432	DF	113
Mean Difference	-0.1364	Prob > |t|	0.6052
Std Error	0.26314	Prob > t	0.6974
Upper95%	0.38493	Prob < t	0.3026
Lower95%	-0.6577		
N	114		
Correlation	0.99825		

Wilcoxon Sign-Rank

	Device 51-Device 5
Test Statistic	-248
Prob > |z|	0.486

From this result, we can clearly see that there is a device specific signature to the start-up sequence that is mapped into the resulting waveform and thus the file.

This start-up sequence may be used forensically as a hardware fingerprint to prove conclusively that a file originated from a particular hardware voice recorder. This may be necessary in cases where a forgery is suspected as the resultant wave function will not have the same white noise function as that produced by the hardware recorder being tested if the file was not created on the device.

This is demonstrated clearly in the scatterplots.

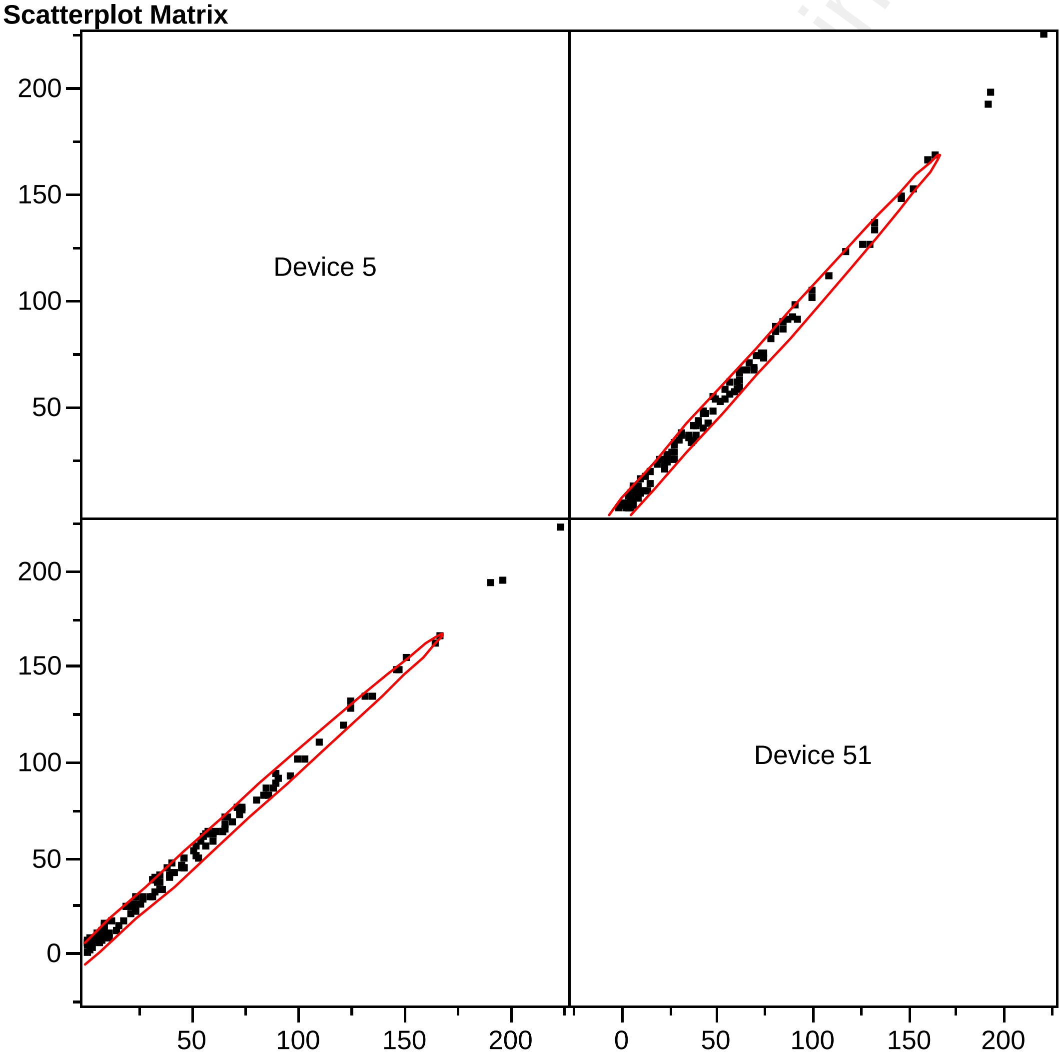
Figure 9 - Multivariate Correlations

	Device 5	Device 51
Device 5	1.0000	0.9982
Device 51	0.9982	1.0000

Partial Correlations

	Device 5	Device 51
Device 5	.	0.9982
Device 51	0.9982	.

Scatterplot Matrix



Pairwise Correlations

Variable	by Variable	Correlation	Count	Signif Prob	Plot Corr
Device 51	Device 5	0.9982	114	0.0000	

Cronbach's Alpha

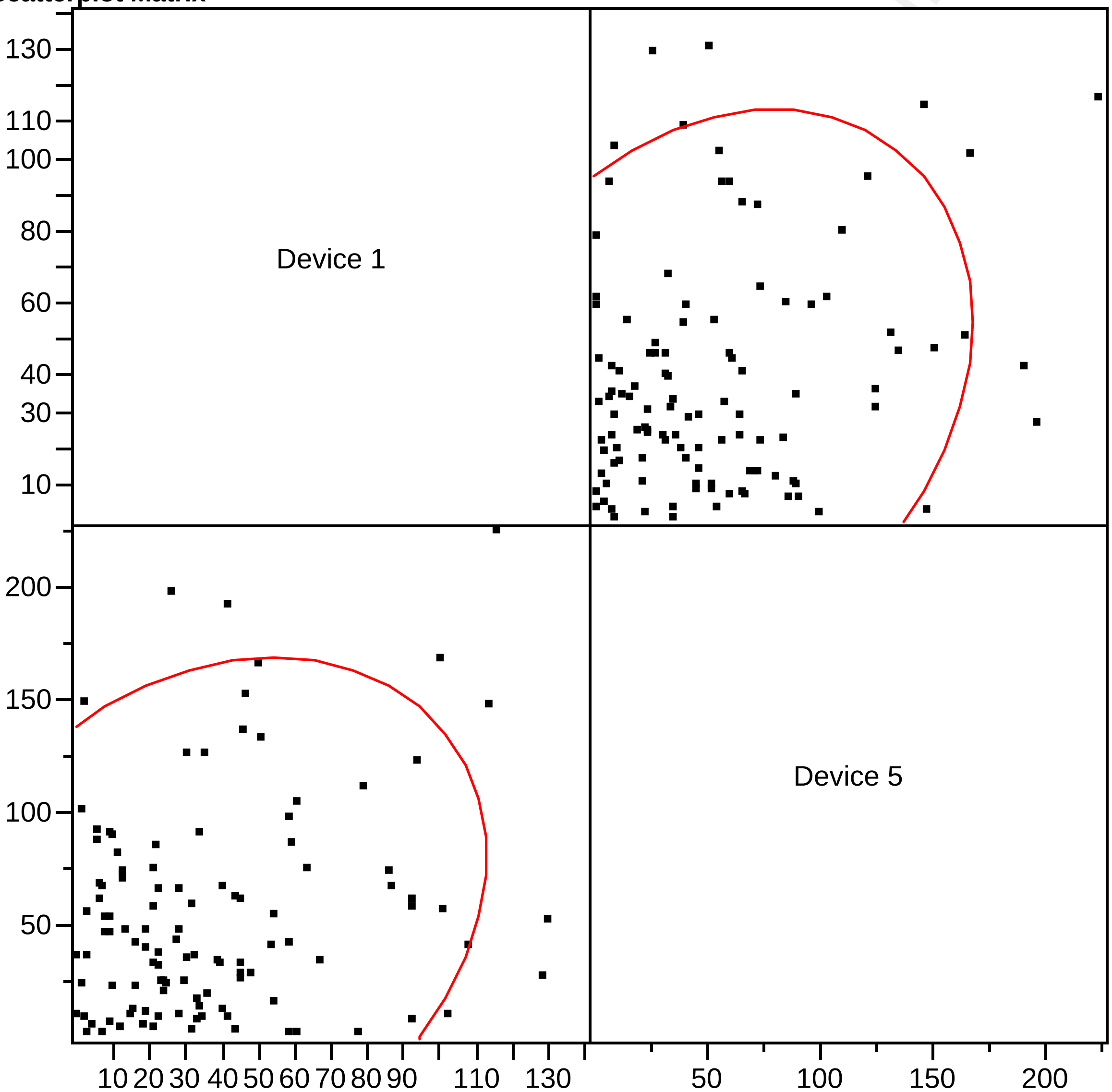
	Alpha	Plot Alpha
Entire set	0.9991	

Excluded Col	Alpha	Plot Alpha
Device 5	.	
Device 51	.	

Multivariate Correlations

	Device 1	Device 5
Device 1	1.0000	0.2303
Device 5	0.2303	1.0000

Scatterplot Matrix



Pairwise Correlations

Variable	by Variable	Correlation	Count	Signif Prob	Plot Corr
Device 5	Device 1	0.2303	114	0.0137	

Cronbach's Alpha

	Alpha	Plot Alpha
Entire set	0.3491	

Excluded Col	Alpha	Plot Alpha
Device 1	.	
Device 5	.	

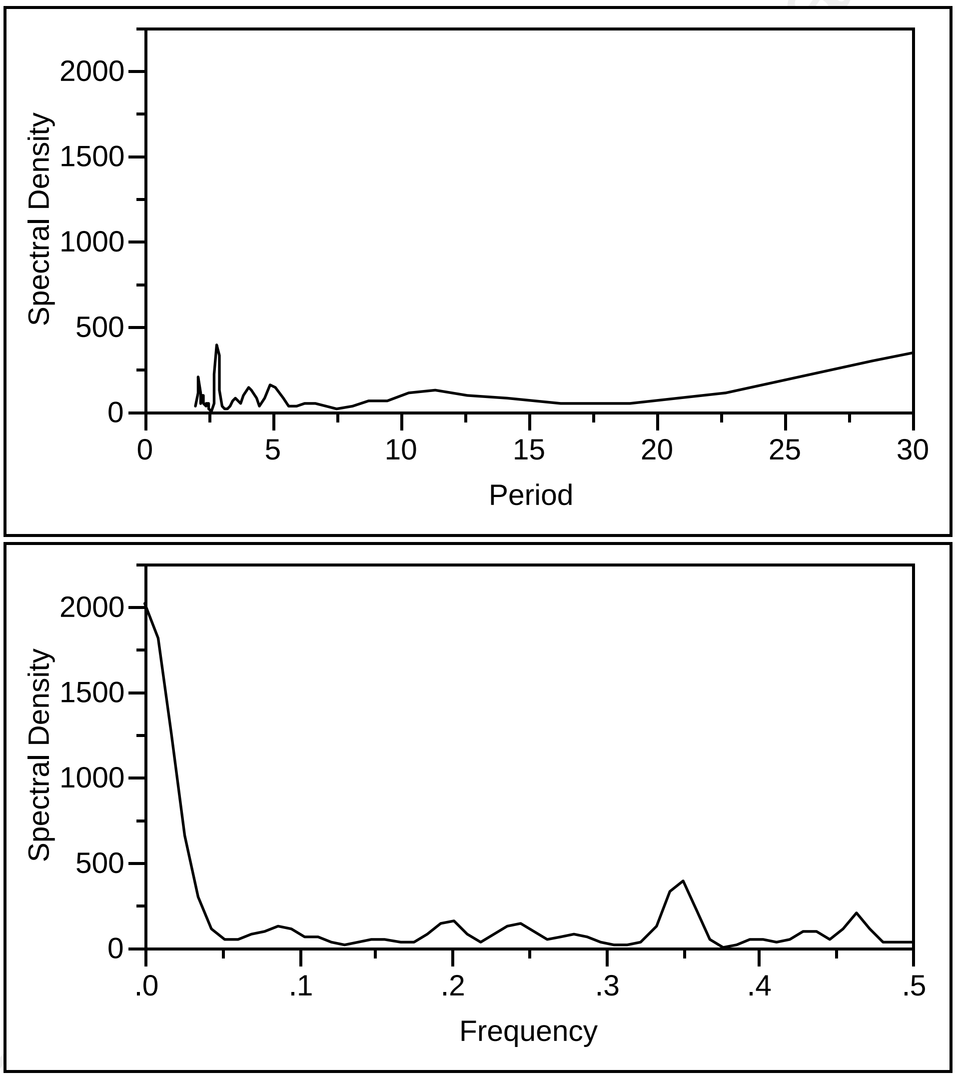
Here we see a significant correlation within the results across recordings on the same device giving a Cronbach's Alpha = 99.91%. This may be compared with the analysis of separate devices. When comparing hardware device 1 and device 5, Cronbach's Alpha is found to be only 34.91% which is not significantly correlated.

The results have demonstrated that there is a strong correlation between wave files produced on the same hardware device. This is contrasted with the ability to significantly demonstrate variation in wave files created on a separate hardware device.

Spectral Densities

By taking the spectral densities of the individual devices, we can create a unique hardware fingerprint based on the individual white noise function of the device.

Figure 10 - Time Series Device 1 - Spectral Density

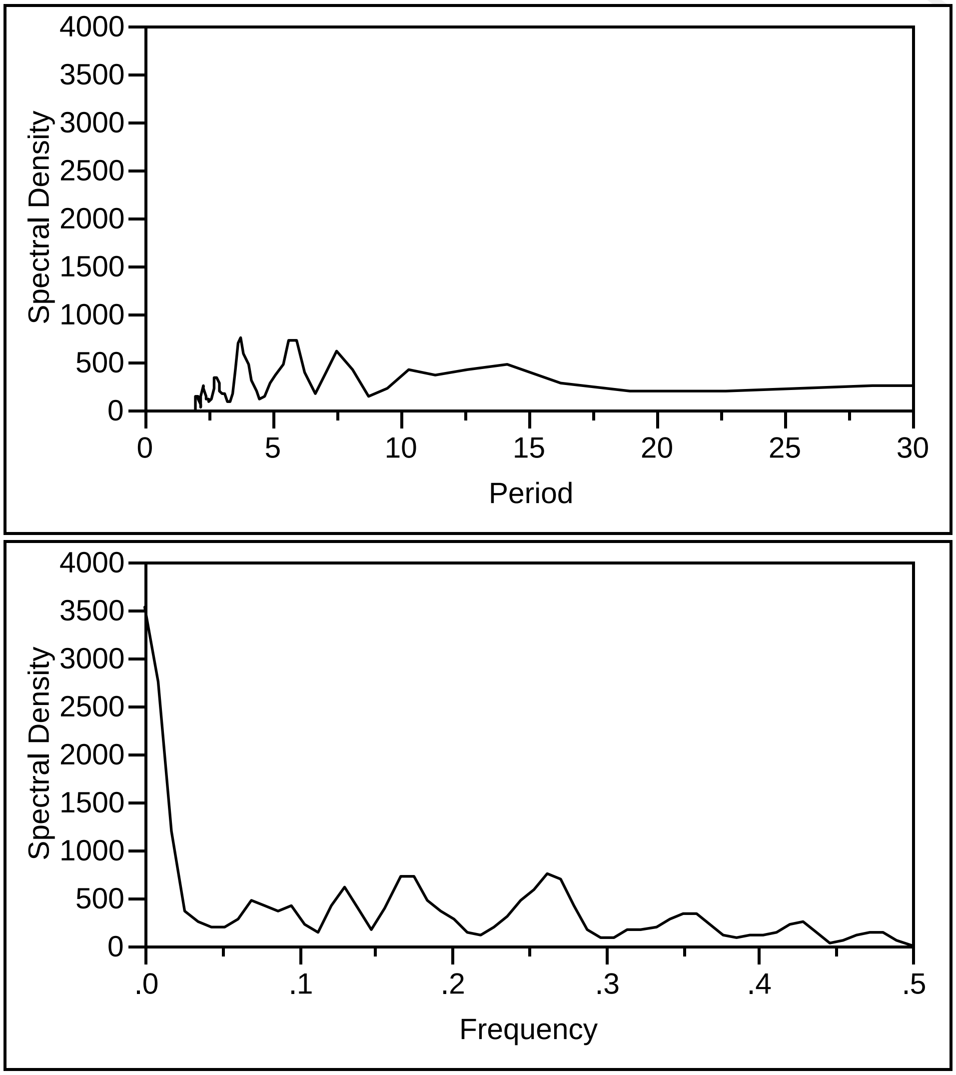


White Noise test

Fisher's Kappa	13.099152
Prob > Kappa	0.0000242
Bartlett's Kolmogorov-Smirnov	0.418624

The spectral density is unique for each hardware device and a fingerprint function may be created for the individual device.

Figure 11 - Time Series Device 5 - Spectral Density

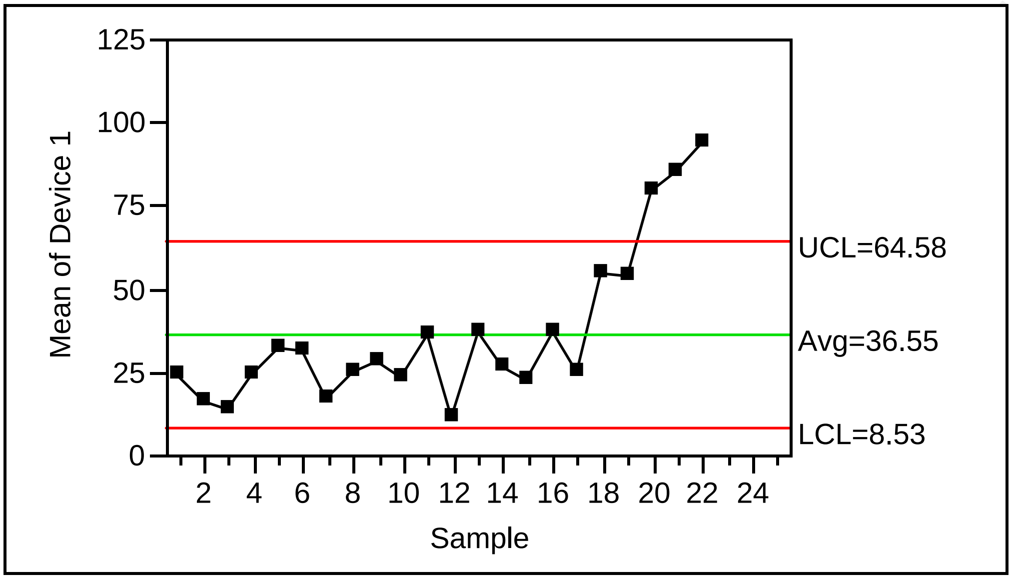


White Noise test

Fisher's Kappa	9.9355812
Prob > Kappa	0.0012104
Bartlett's Kolmogorov-Smirnov	0.236253

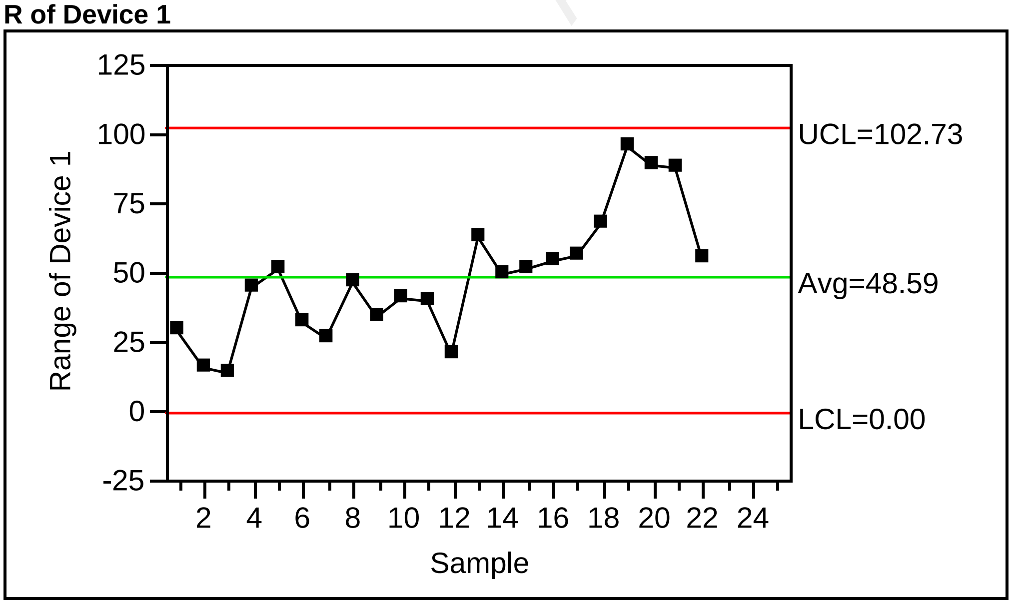
Figure 12 - Variables Control Chart

XBar of Device 1

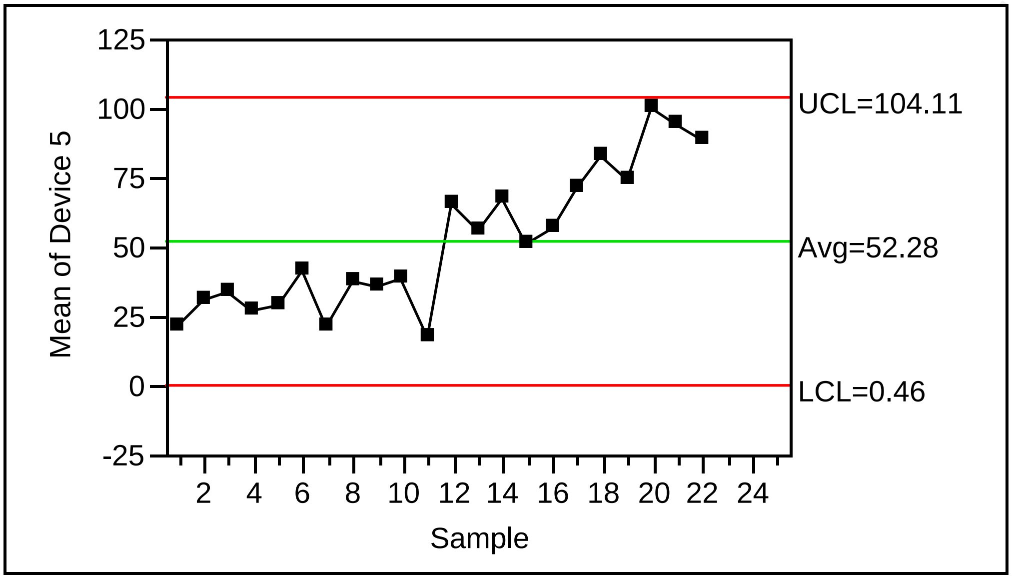


Note: Sigma used for limits based on range.

R of Device 1

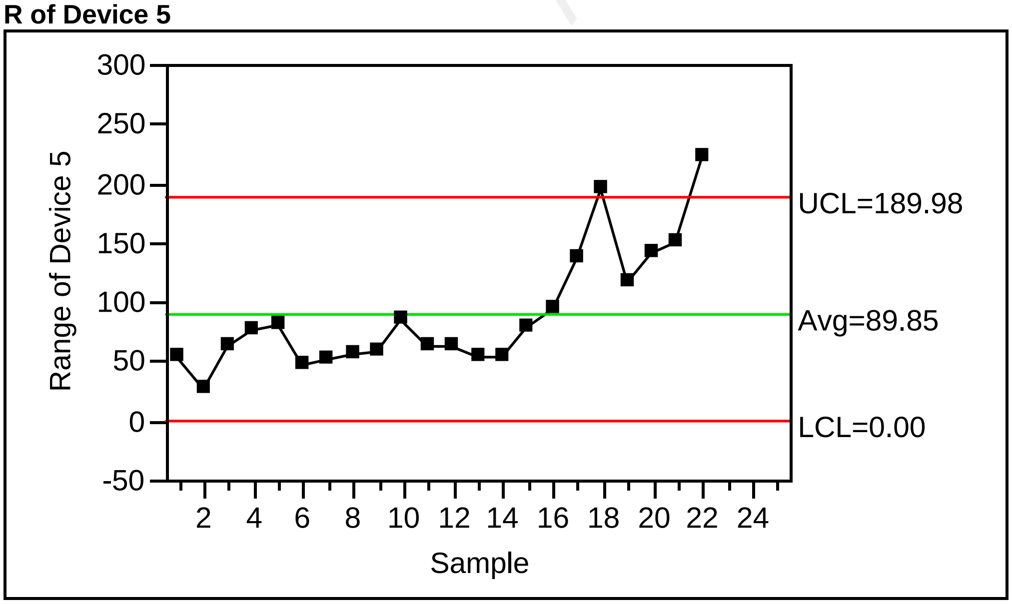


XBar of Device 5



Note: Sigma used for limits based on range.

R of Device 5



The start-up function may be used as a fingerprint against the hardware to determine if the file was created using the specific device.

3 Further Research

Although the tests are significant for the hardware being researched, further work would need to be completed to make these results valid for all hardware based digital recorders. It may also be possible to map wave files to software/ hardware combinations on PC's. This could be the focus of future research.

A test of other devices should also be completed. It would be expected that other devices should satisfy the same white noise differences across a group and it is likely that there it is possible to create signatures for all digital recorders based on this technique. Further research would need to be completed to satisfy this hypothesis beyond reasonable doubt. By testing a sample of the same devices, it is however possible to test this assumption on a case by case basis. This would lead to the testing of a group of devices to prove the white noise function for a device model under investigation.

No compression was used during the test. This is not an issue for wave file based digital recorders, but there may be different results in the case of MP3 or other compression based processes.

4 Conclusions

It has been demonstrated that we can map an individual digital hardware recorder to a specific wave file. This study verified the ability and developed techniques to allow device fingerprinting that use the devices white noise on start-up to link a sound file to a specific hardware recorder.

The techniques apply to a number of different practically useful goals, ranging from distinguishing between device fingerprinting of audio files to the detection of forgeries. The difficulties associated with digital forensic analysis of PDA's and digital hardware recorders have proven to be an obstacle (Frichot, 2004) and other methods need to be developed to ensure the forensically sound acquisition of data.

This study presents another method that may be utilized in forensic analysis of audio files.

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Definitions

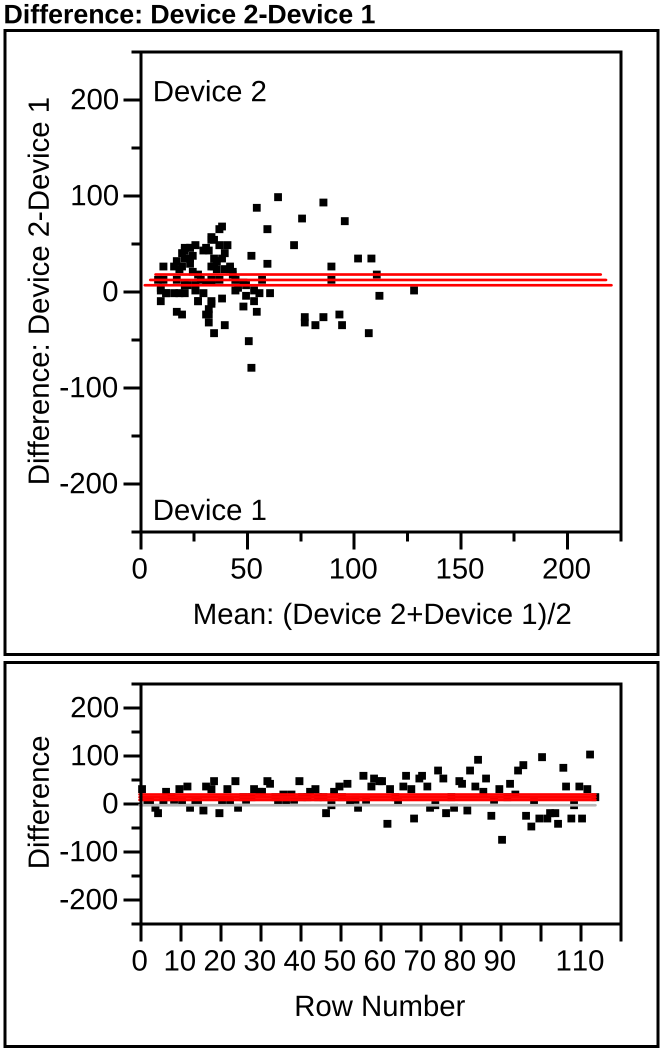
The following table defines abbreviations used in this document:

GIAC	Global Information Assurance Certification
MAC	Modified, Accessed, Created times
SOE	Standard Operating Environment
SANS	SysAdmin, Audit, Network, Security
USB	Universal Serial Bus

6 Appendix

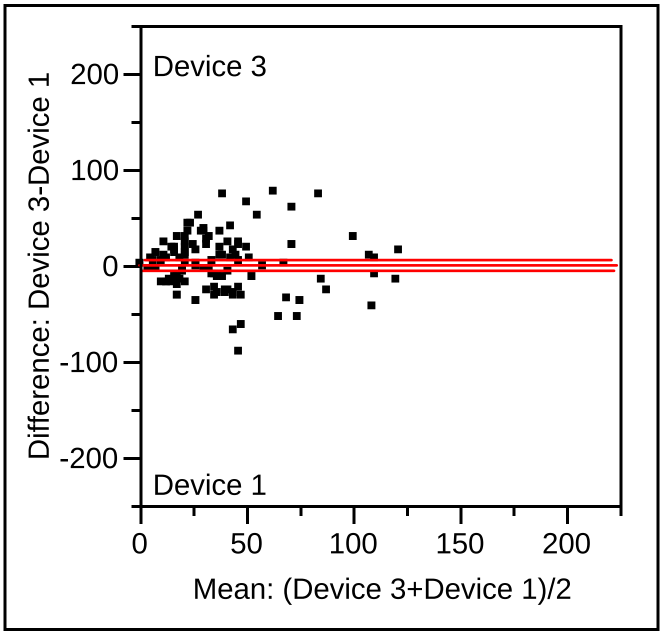
Correlations by Device

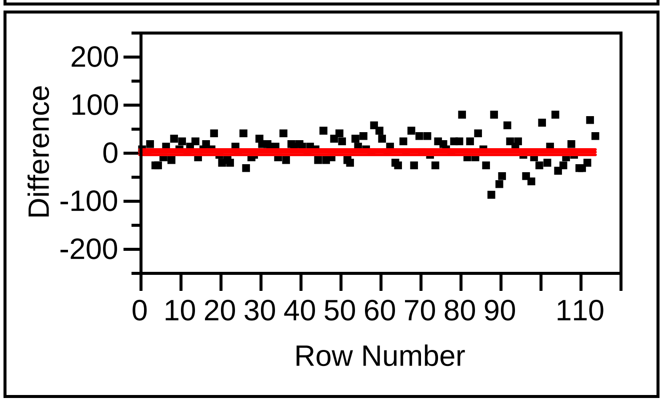
Matched Pairs
Difference: Device 2-Device 1



Device 2	49.8094	t-Ratio	4.219716
Device 1	37.4354	DF	113
Mean Difference	12.374	Prob > |t|	<.0001
Std Error	2.93243	Prob > t	<.0001
Upper95%	18.1837	Prob < t	1.0000
Lower95%	6.56436		
N	114		
Correlation	0.47275		

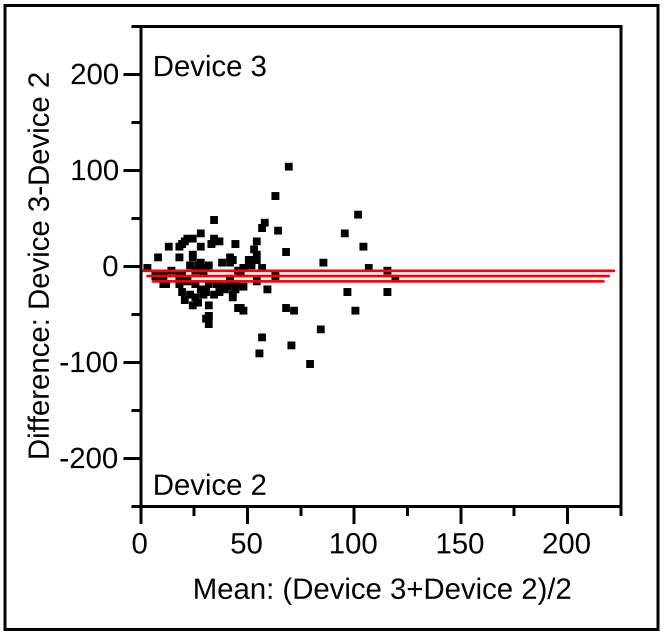
Difference: Device 3-Device 1

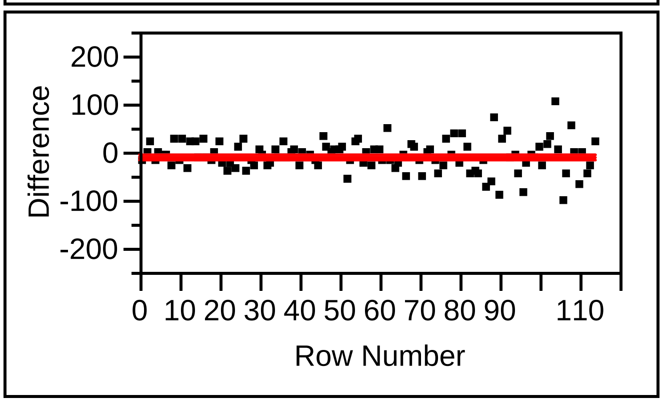




Device 3	39.3934	t-Ratio	0.711586
Device 1	37.4354	DF	113
Mean Difference	1.95807	Prob > |t|	0.4782
Std Error	2.7517	Prob > t	0.2391
Upper95%	7.40968	Prob < t	0.7609
Lower95%	-3.4935		
N	114		
Correlation	0.53169		

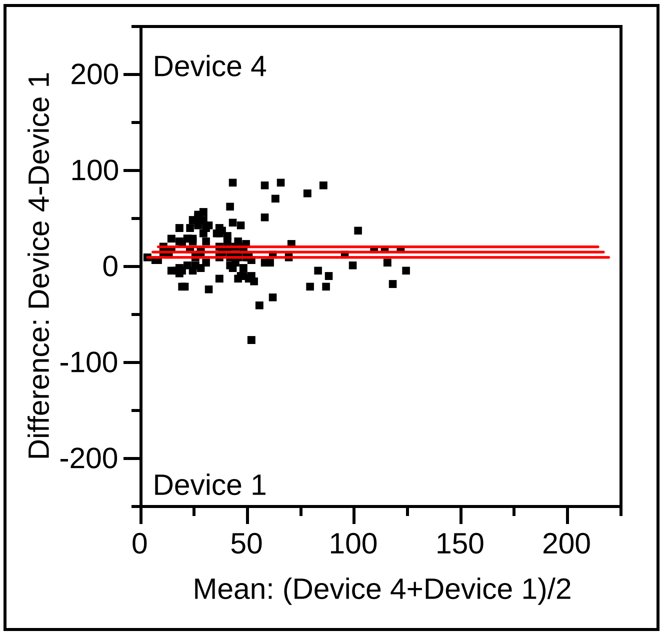
Difference: Device 3-Device 2

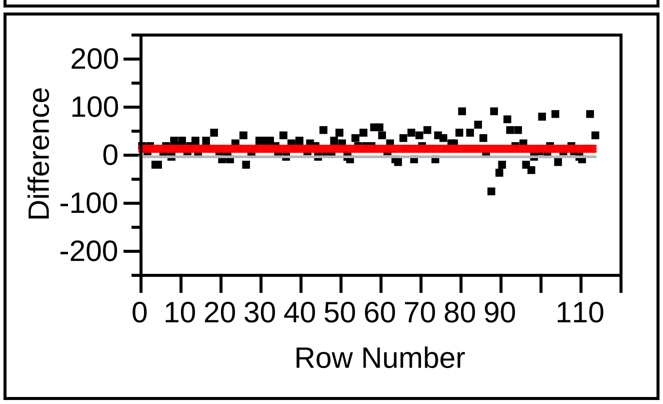




Device 3	39.3934	t-Ratio	-3.49948
Device 2	49.8094	DF	113
Mean Difference	-10.416	Prob > |t|	0.0007
Std Error	2.97643	Prob > t	0.9997
Upper95%	-4.5191	Prob < t	0.0003
Lower95%	-16.313		
N	114		
Correlation	0.43002		

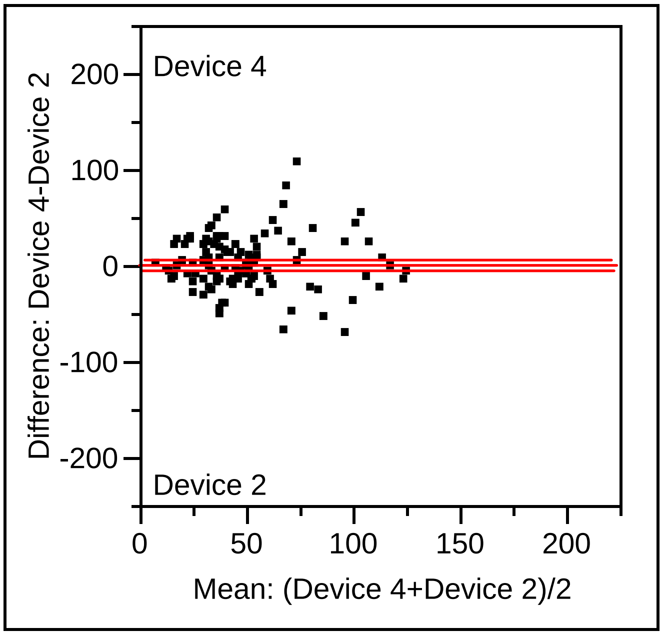
Difference: Device 4-Device 1

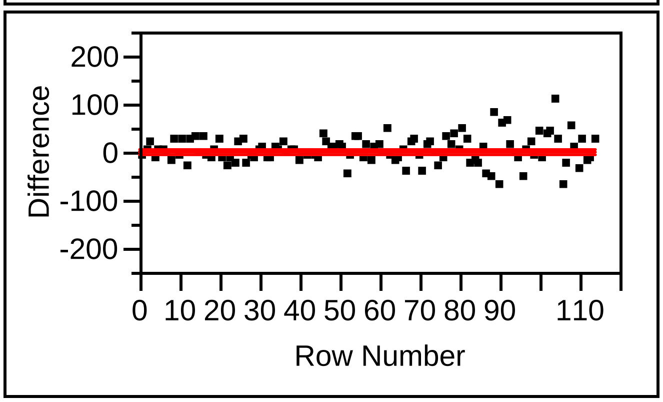




Device 4	52.0595	t-Ratio	5.804449
Device 1	37.4354	DF	113
Mean Difference	14.6241	Prob > |t|	<.0001
Std Error	2.51947	Prob > t	<.0001
Upper95%	19.6156	Prob < t	1.0000
Lower95%	9.6326		
N	114		
Correlation	0.60377		

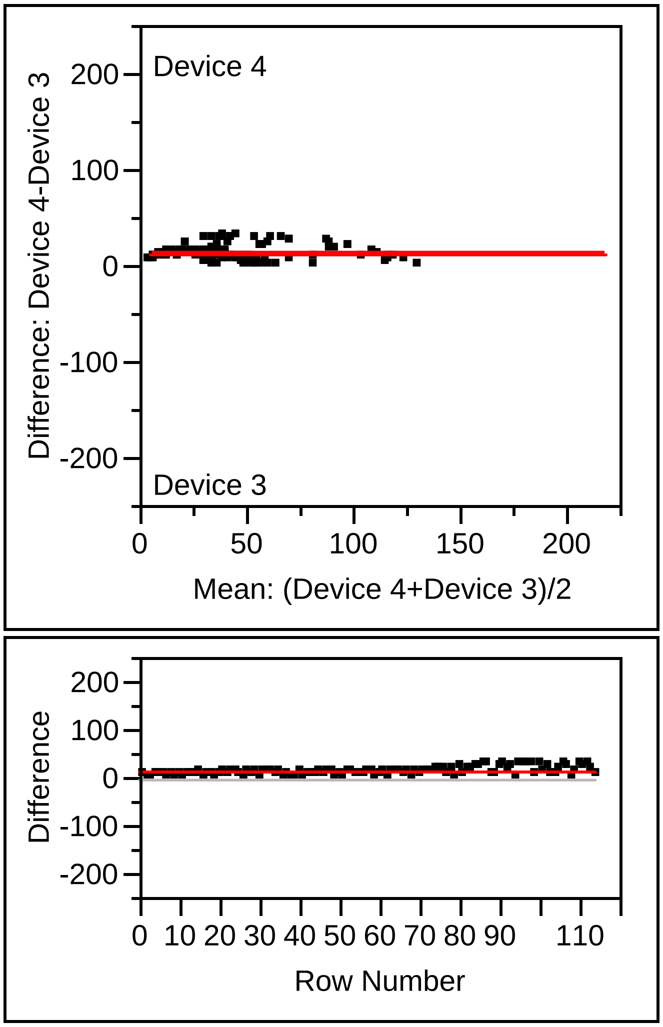
Difference: Device 4-Device 2





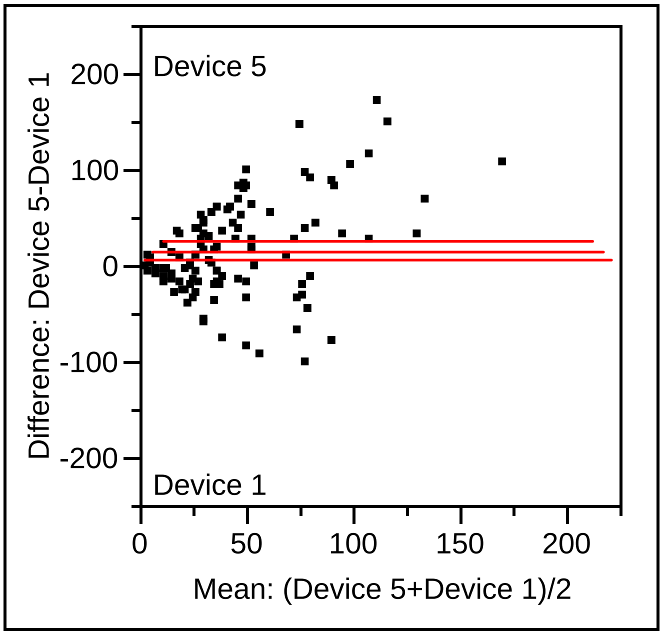
Device 4	52.0595	t-Ratio	0.849546
Device 2	49.8094	DF	113
Mean Difference	2.25009	Prob > |t|	0.3974
Std Error	2.64858	Prob > t	0.1987
Upper95%	7.4974	Prob < t	0.8013
Lower95%	-2.9972		
N	114		
Correlation	0.54381		

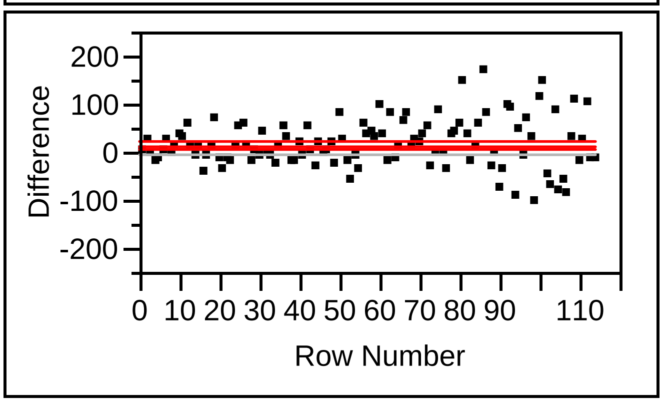
Difference: Device 4-Device 3



Device 4	52.0595	t-Ratio	16.14369
Device 3	39.3934	DF	113
Mean Difference	12.6661	Prob > |t|	<.0001
Std Error	0.78458	Prob > t	<.0001
Upper95%	14.2205	Prob < t	1.0000
Lower95%	11.1117		
N	114		
Correlation	0.95962		

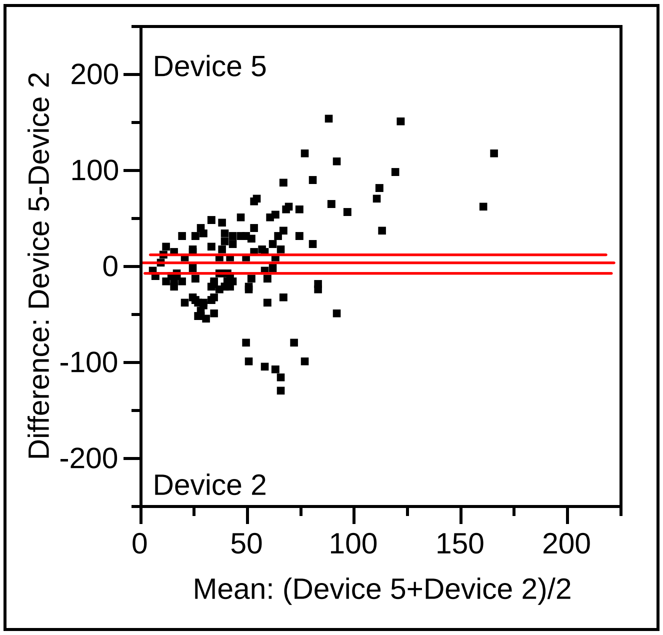
Difference: Device 5-Device 1

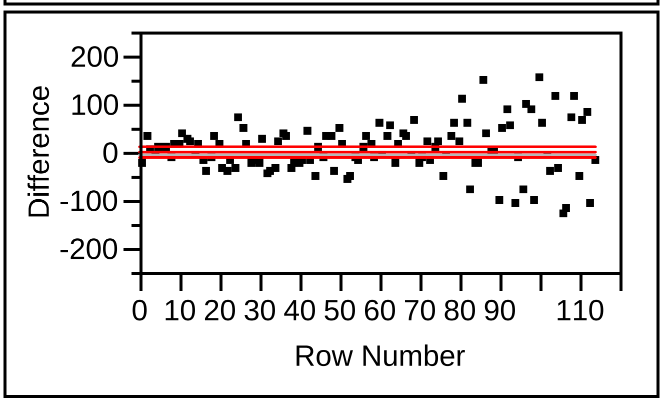




Device 5	53.5432	t-Ratio	3.430242
Device 1	37.4354	DF	113
Mean Difference	16.1078	Prob > |t|	0.0008
Std Error	4.69582	Prob > t	0.0004
Upper95%	25.4111	Prob < t	0.9996
Lower95%	6.80454		
N	114		
Correlation	0.23026		

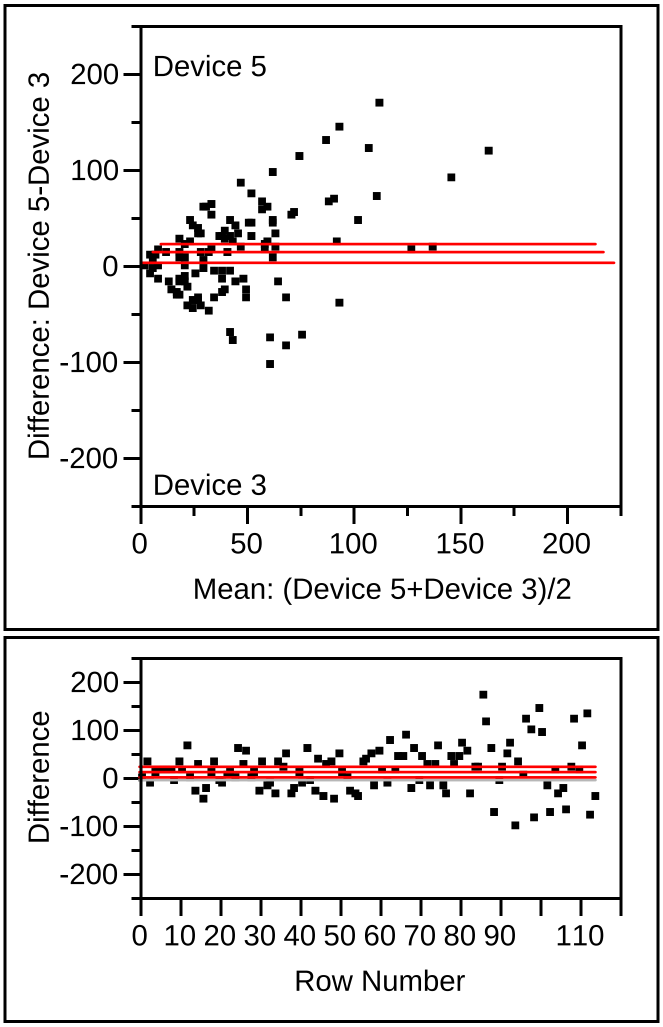
Difference: Device 5-Device 2





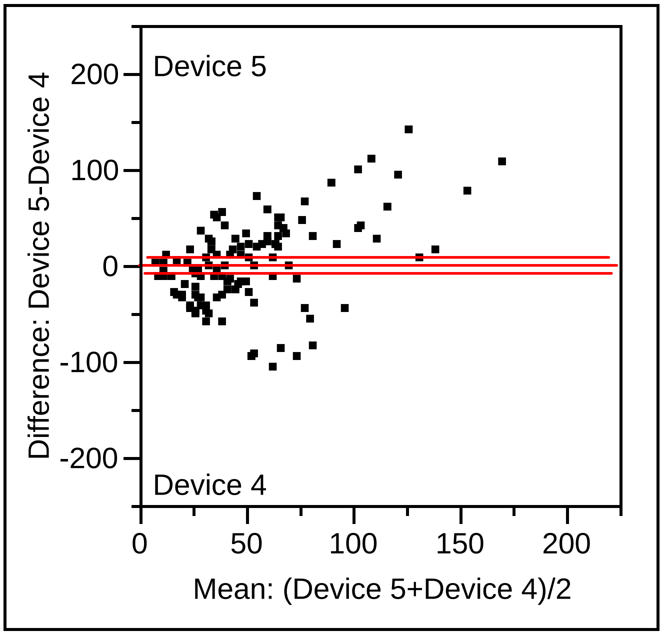
Device 5	53.5432	t-Ratio	0.767057
Device 2	49.8094	DF	113
Mean Difference	3.73377	Prob > |t|	0.4446
Std Error	4.86766	Prob > t	0.2223
Upper95%	13.3775	Prob < t	0.7777
Lower95%	-5.9099		
N	114		
Correlation	0.14809		

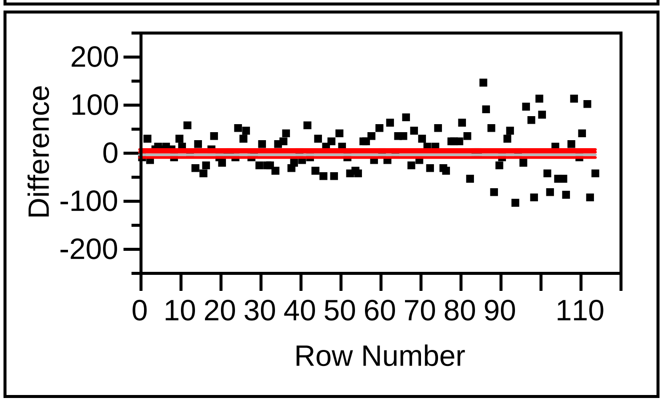
Difference: Device 5-Device 3



Device 5	53.5432	t-Ratio	3.151746
Device 3	39.3934	DF	113
Mean Difference	14.1497	Prob > |t|	0.0021
Std Error	4.48949	Prob > t	0.0010
Upper95%	23.0442	Prob < t	0.9990
Lower95%	5.25525		
N	114		
Correlation	0.28776		

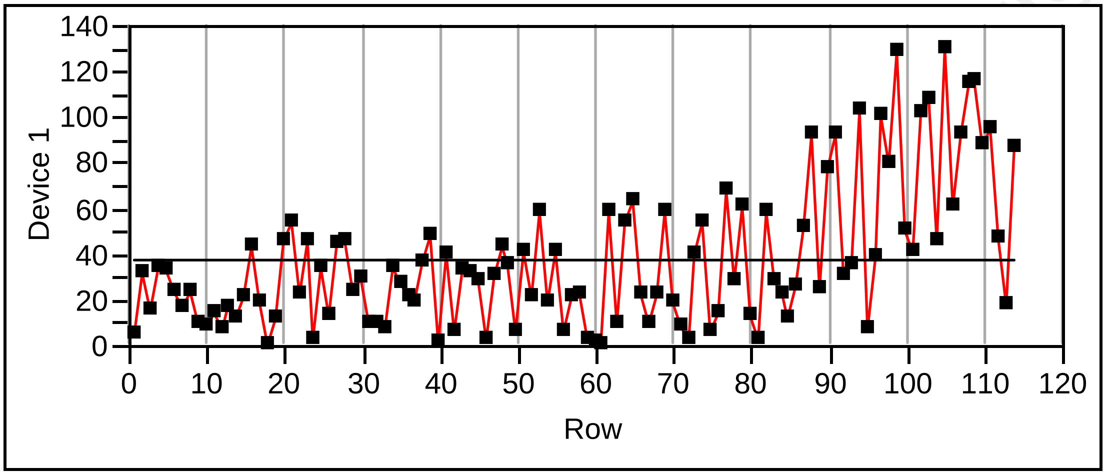
Difference: Device 5-Device 4





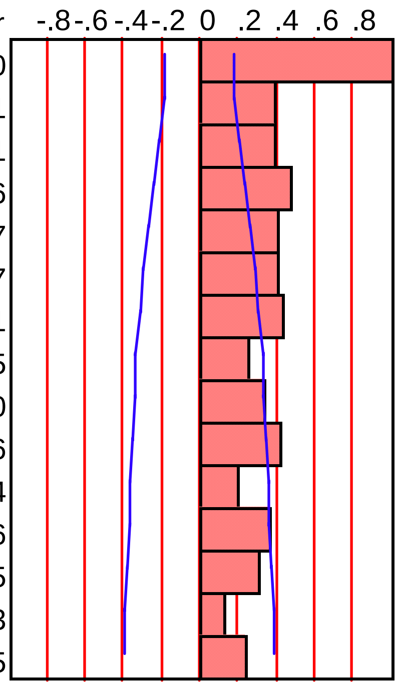
Device 5	53.5432	t-Ratio	0.351713
Device 4	52.0595	DF	113
Mean Difference	1.48368	Prob > |t|	0.7257
Std Error	4.21846	Prob > t	0.3629
Upper95%	9.84121	Prob < t	0.6371
Lower95%	-6.8738		
N	114		
Correlation	0.38138		

Time Series Device 1

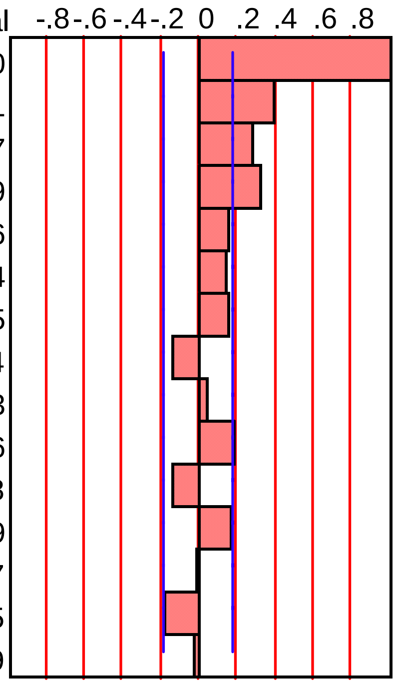


Mean	37.435351
Std	30.905543
N	114

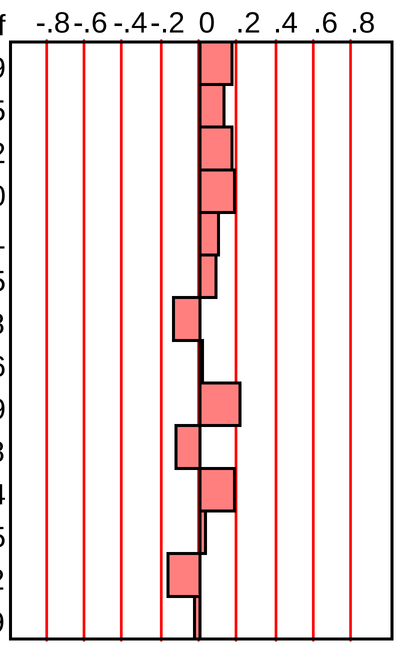
Lag	AutoCorr
0	1.0000
1	0.3981
2	0.3921
3	0.4756
4	0.3987
5	0.3997
6	0.4311
7	0.2455
8	0.3310
9	0.4256
10	0.1934
11	0.3636
12	0.3015
13	0.1303
14	0.2355



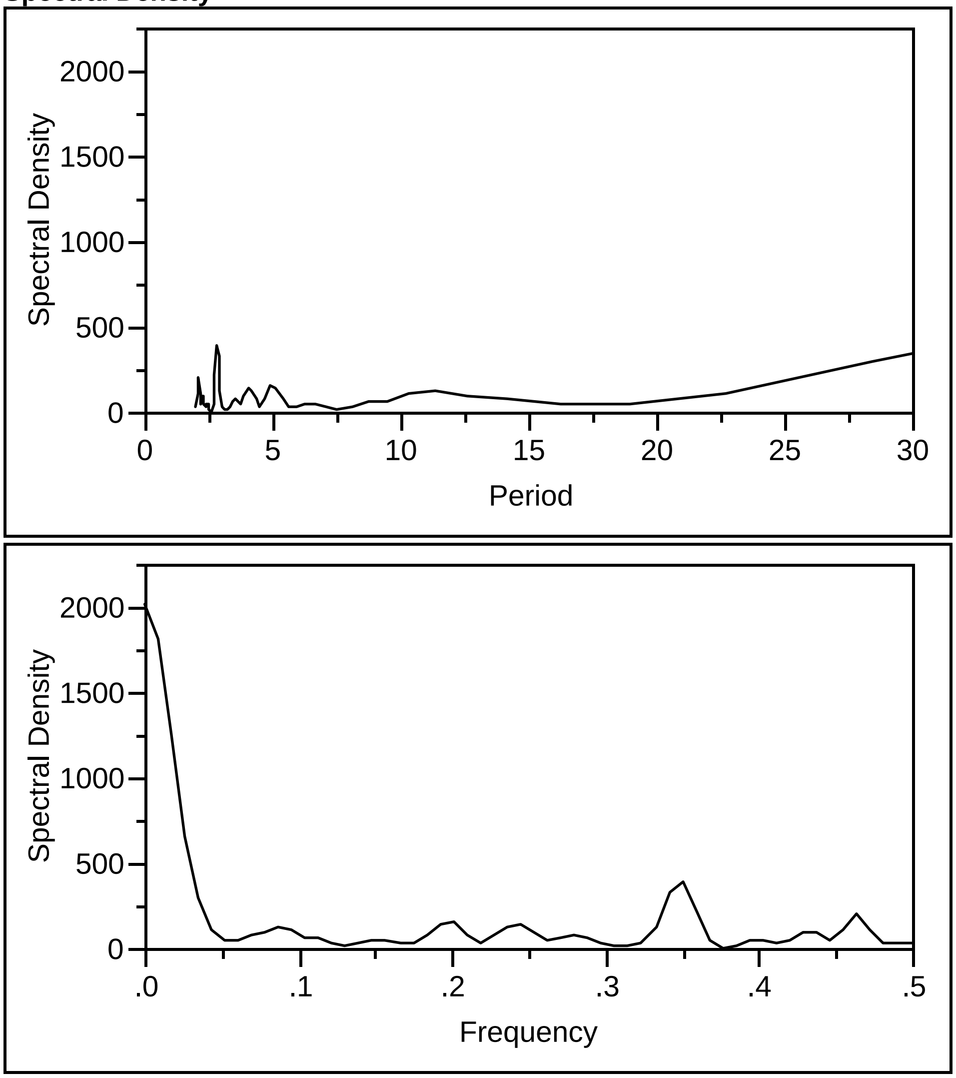
Lag	Partial
0	1.0000
1	0.3981
2	0.2777
3	0.3249
4	0.1486
5	0.1334
6	0.1475
7	-0.1394
8	0.0363
9	0.1756
10	-0.1468
11	0.1619
12	-0.0077
13	-0.1785
14	-0.0239



Lag	AR Coef
1	0.1739
2	0.1325
3	0.1632
4	0.1840
5	0.0911
6	0.0895
7	-0.1348
8	0.0196
9	0.2039
10	-0.1328
11	0.1854
12	0.0275
13	-0.1742
14	-0.0239



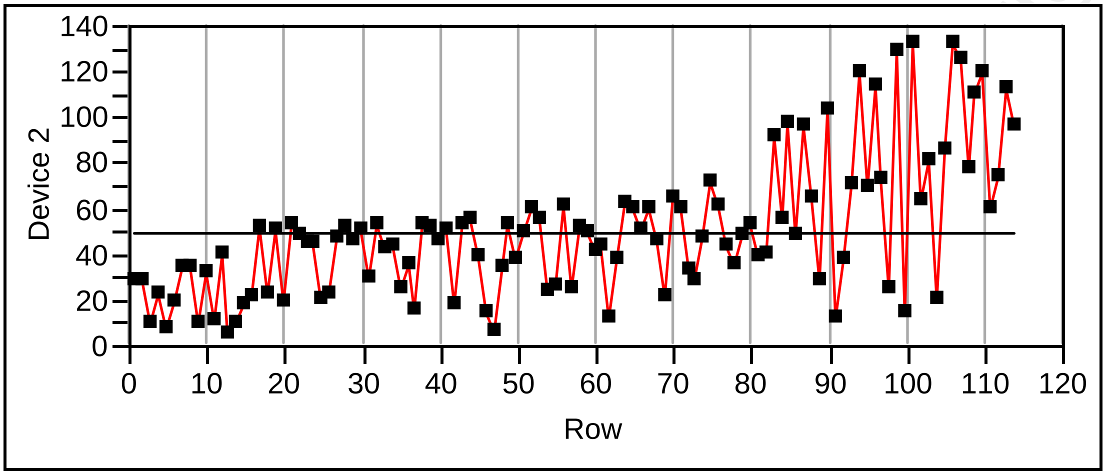
Spectral Density



White Noise test

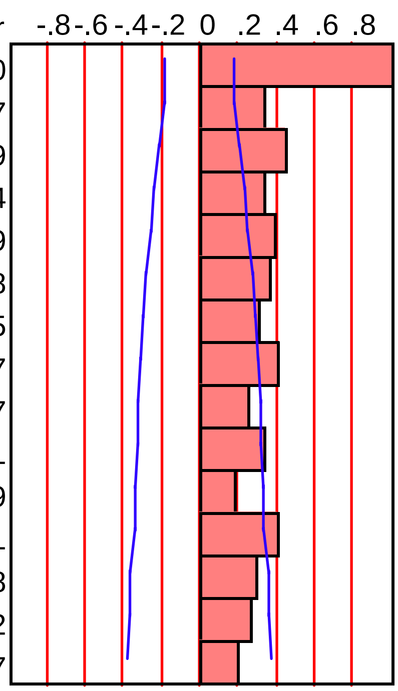
Fisher's Kappa	13.099152
Prob > Kappa	0.0000242
Bartlett's Kolmogorov-Smirnov	0.418624

Time Series Device 2

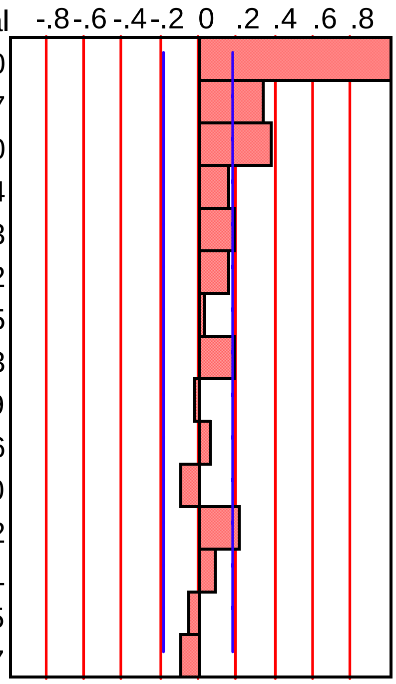


Mean	49.809386
Std	29.776896
N	114

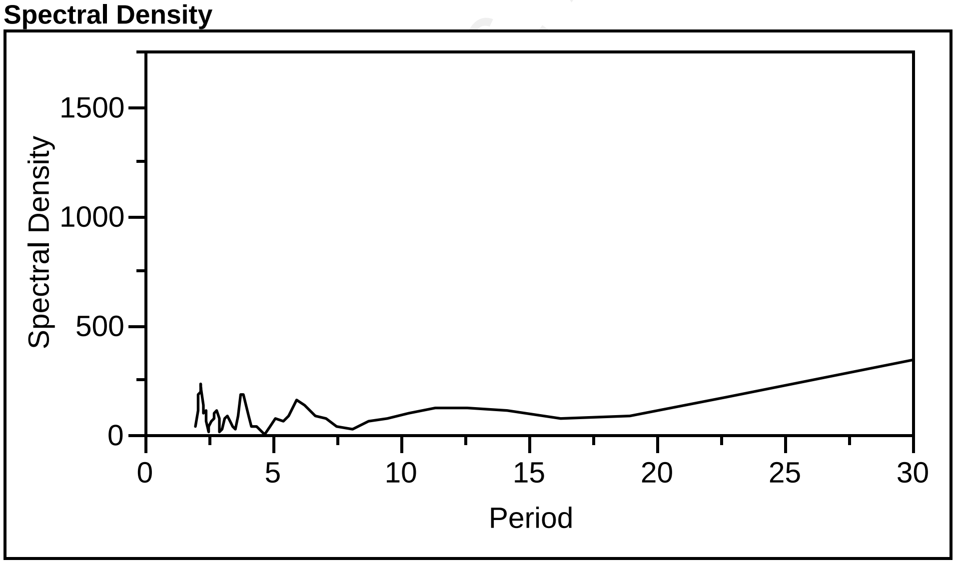
Lag	AutoCorr
0	1.0000
1	0.3337
2	0.4419
3	0.3304
4	0.3869
5	0.3618
6	0.3035
7	0.4097
8	0.2537
9	0.3411
10	0.1799
11	0.4061
12	0.2958
13	0.2602
14	0.2017

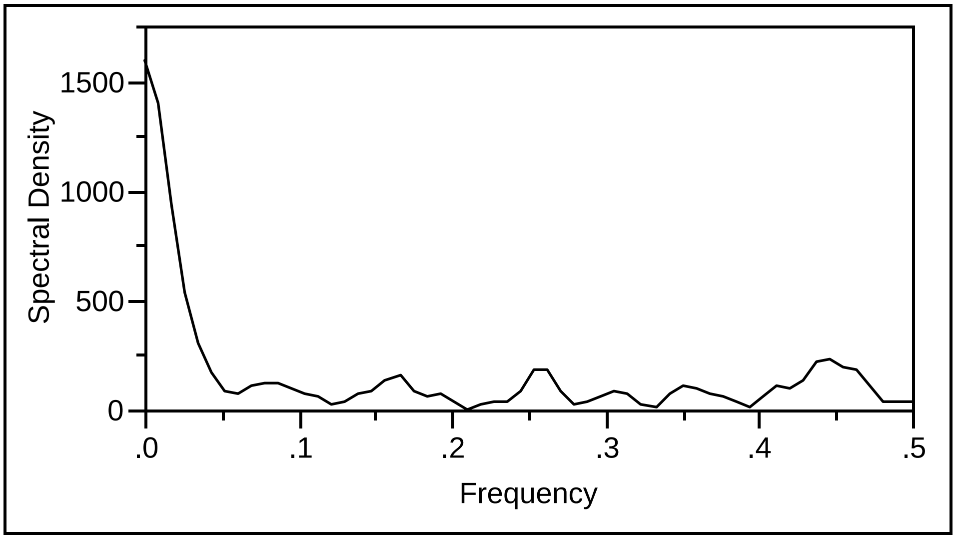


Lag	Partial
0	1.0000
1	0.3337
2	0.3720
3	0.1484
4	0.1813
5	0.1472
6	0.0265
7	0.1883
8	-0.0349
9	0.0546
10	-0.1040
11	0.2052
12	0.0811
13	-0.0525
14	-0.0977



Spectral Density

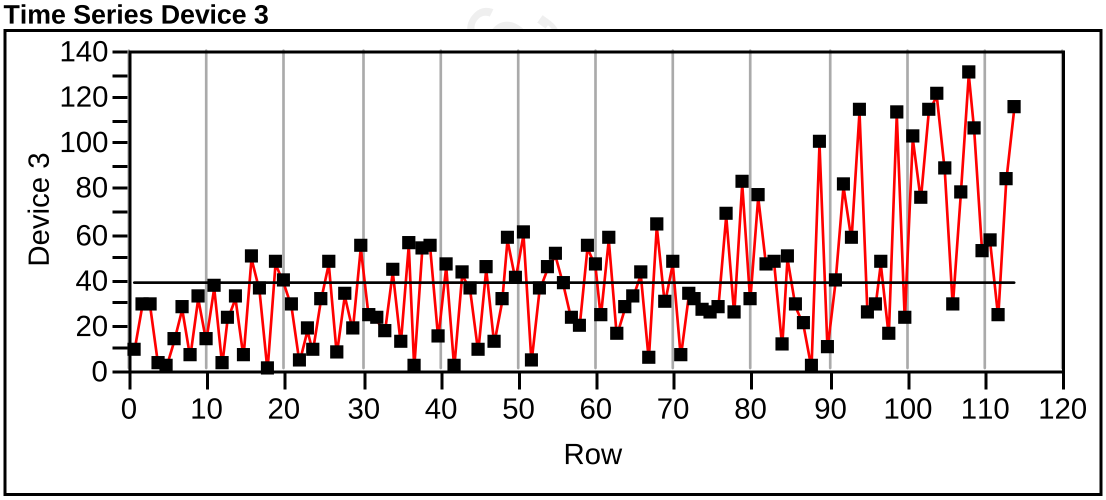




White Noise test

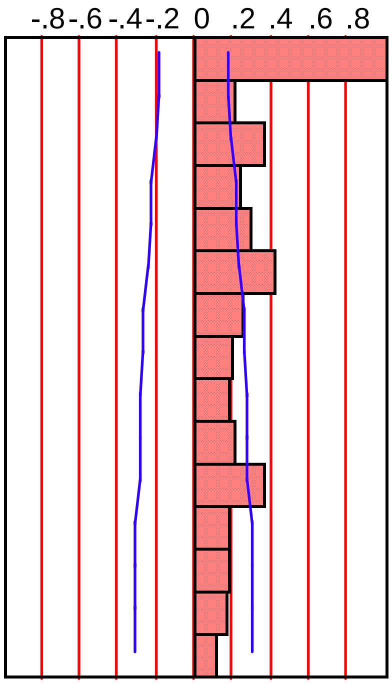
Fisher's Kappa	11.156033
Prob > Kappa	0.0002764
Bartlett's Kolmogorov-Smirnov	0.3501048

Time Series Device 3

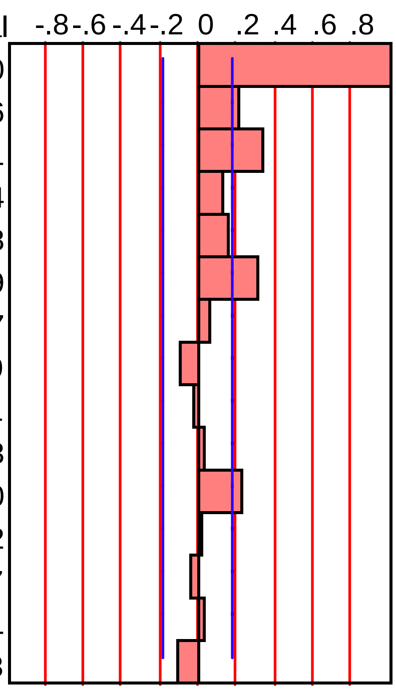


Mean	39.393421
Std	29.489137
N	114

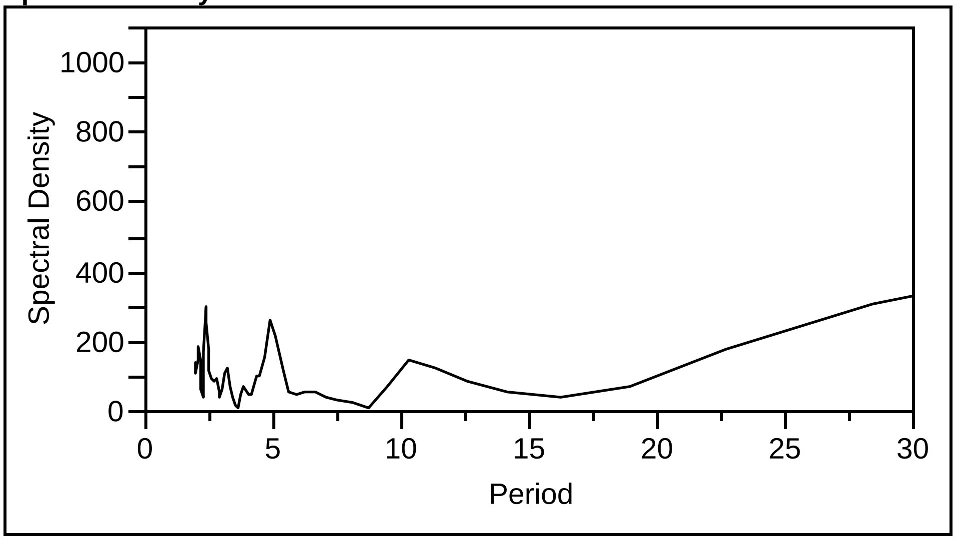
Lag	AutoCorr
0	1.0000
1	0.2136
2	0.3683
3	0.2346
4	0.2937
5	0.4154
6	0.2476
7	0.1905
8	0.1761
9	0.2106
10	0.3704
11	0.1821
12	0.1786
13	0.1652
14	0.1073

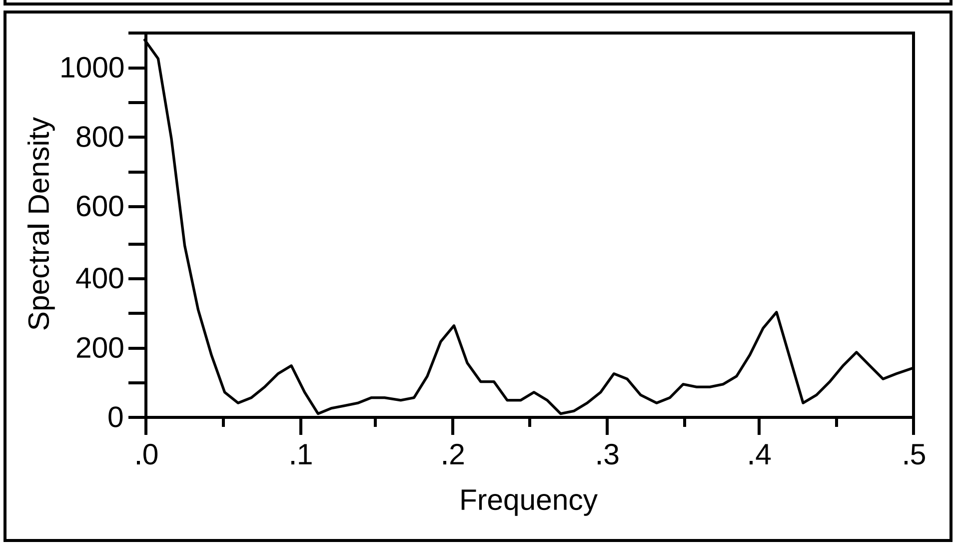


Lag	Partial
0	1.0000
1	0.2136
2	0.3381
3	0.1304
4	0.1508
5	0.3129
6	0.0617
7	-0.0949
8	-0.0301
9	0.0333
10	0.2170
11	0.0092
12	-0.0407
13	0.0271
14	-0.1123



Spectral Density

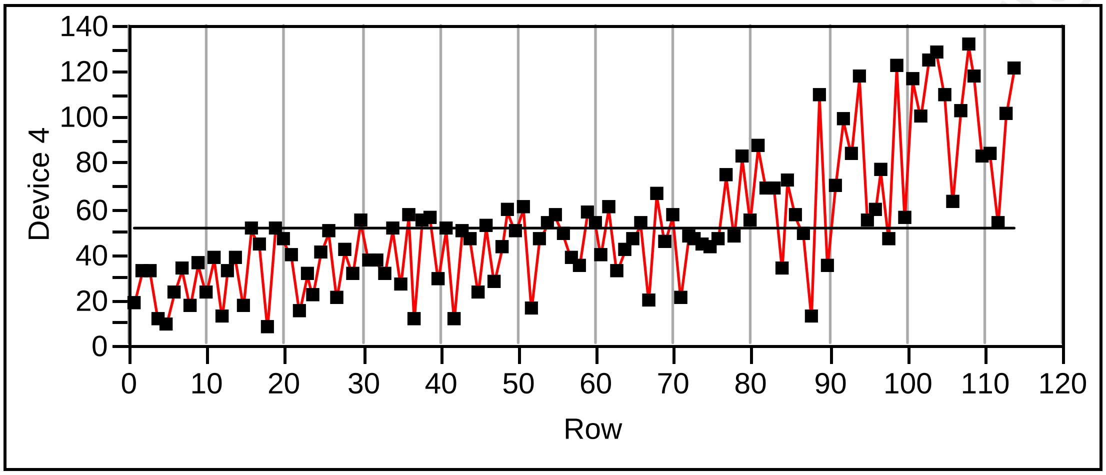




White Noise test

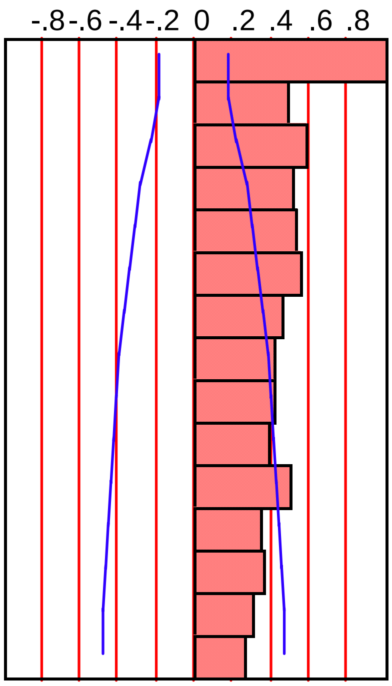
Fisher's Kappa	7.6978653
Prob > Kappa	0.0164113
Bartlett's Kolmogorov-Smirnov	0.2898514

Time Series Device 4

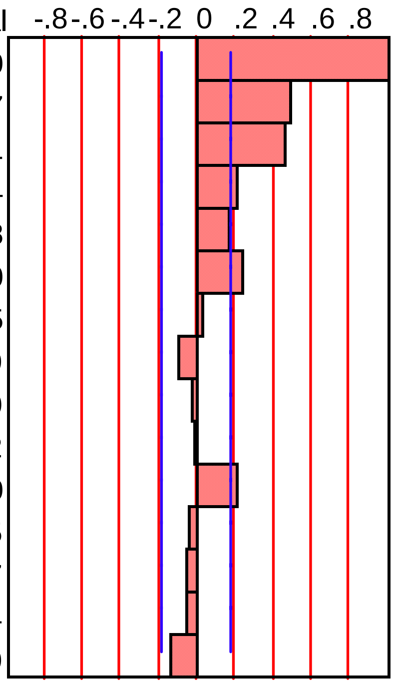


Mean	52.059474
Std	29.163549
N	114

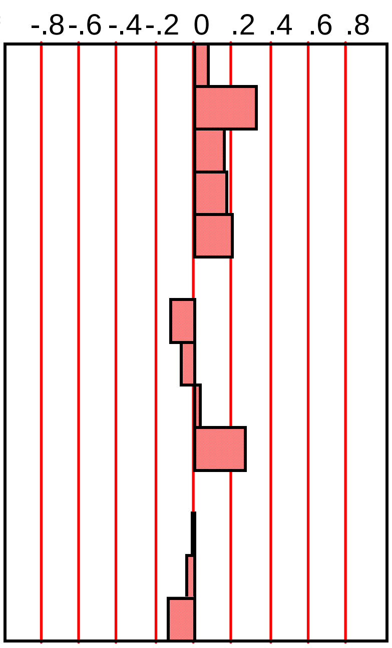
Lag	AutoCorr
0	1.0000
1	0.4877
2	0.5923
3	0.5106
4	0.5272
5	0.5632
6	0.4679
7	0.4202
8	0.4155
9	0.3915
10	0.4973
11	0.3449
12	0.3578
13	0.3102
14	0.2669



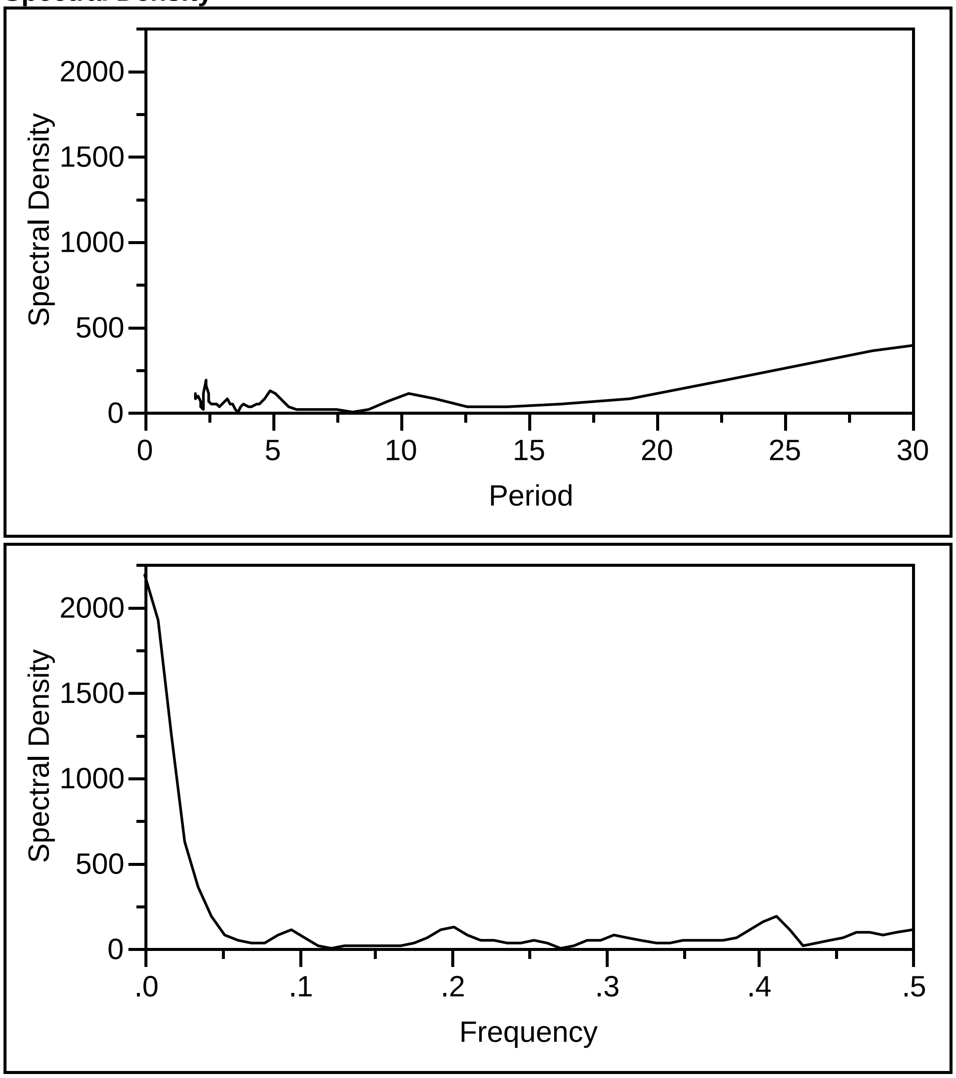
Lag	Partial
0	1.0000
1	0.4877
2	0.4651
3	0.2164
4	0.1718
5	0.2350
6	0.0215
7	-0.1049
8	-0.0250
9	-0.0102
10	0.2110
11	-0.0405
12	-0.0617
13	-0.0504
14	-0.1349



Lag	AR Coef
1	0.0753
2	0.3229
3	0.1541
4	0.1680
5	0.2010
6	0.0015
7	-0.1213
8	-0.0643
9	0.0294
10	0.2595
11	0.0027
12	-0.0128
13	-0.0393
14	-0.1349



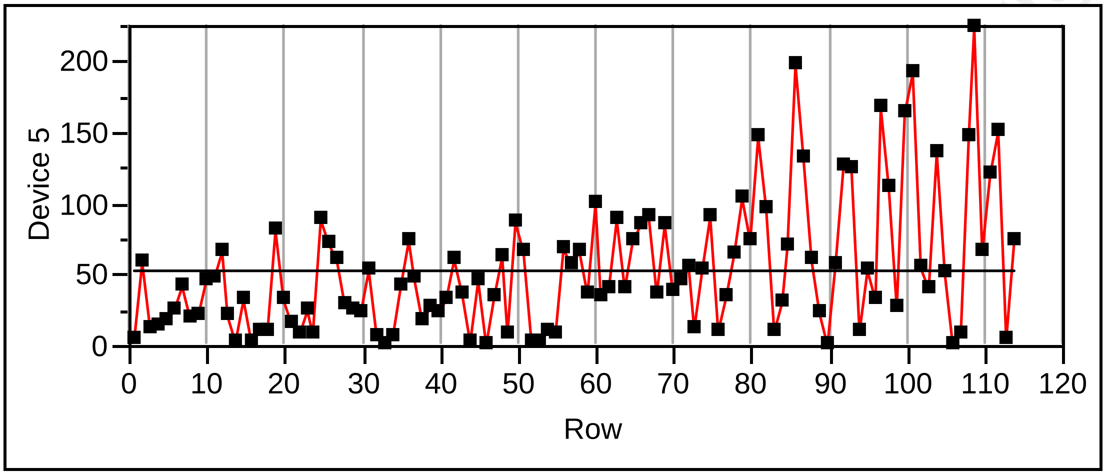
Spectral Density



White Noise test

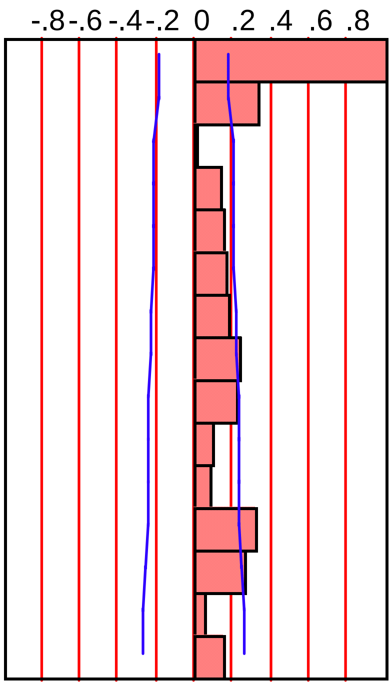
Fisher's Kappa	15.965443
Prob > Kappa	5.3923e-7
Bartlett's Kolmogorov-Smirnov	0.5026617

Time Series Device 5

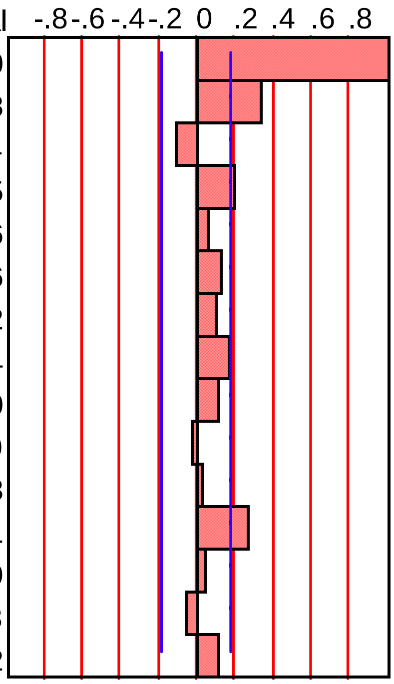


Mean	53.543158
Std	46.956261
N	114

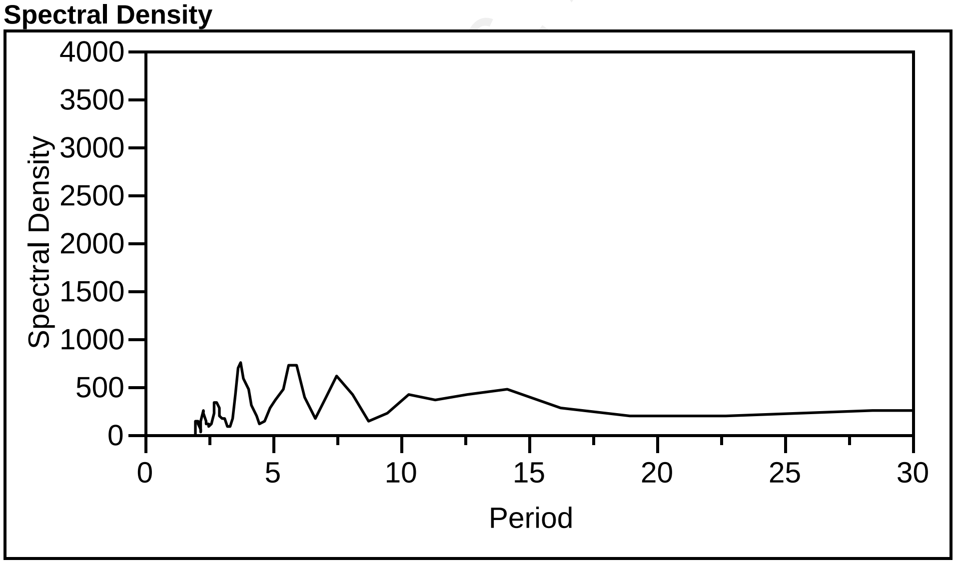
Lag	AutoCorr
0	1.0000
1	0.3318
2	0.0153
3	0.1388
4	0.1575
5	0.1627
6	0.1853
7	0.2376
8	0.2260
9	0.0930
10	0.0773
11	0.3252
12	0.2702
13	0.0604
14	0.1565

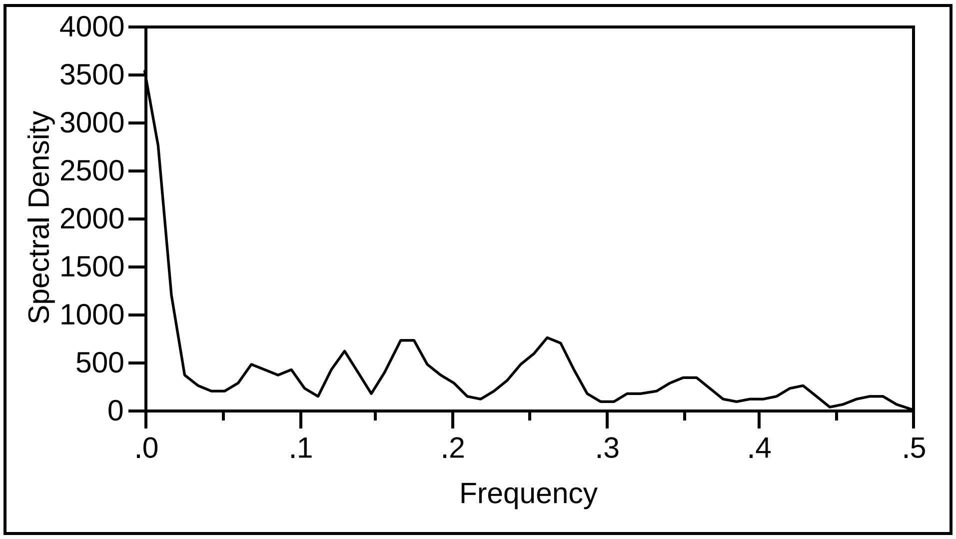


Lag	Partial
0	1.0000
1	0.3318
2	-0.1064
3	0.1915
4	0.0506
5	0.1266
6	0.1032
7	0.1654
8	0.1050
9	-0.0260
10	0.0233
11	0.2691
12	0.0379
13	-0.0523
14	0.1052



Spectral Density

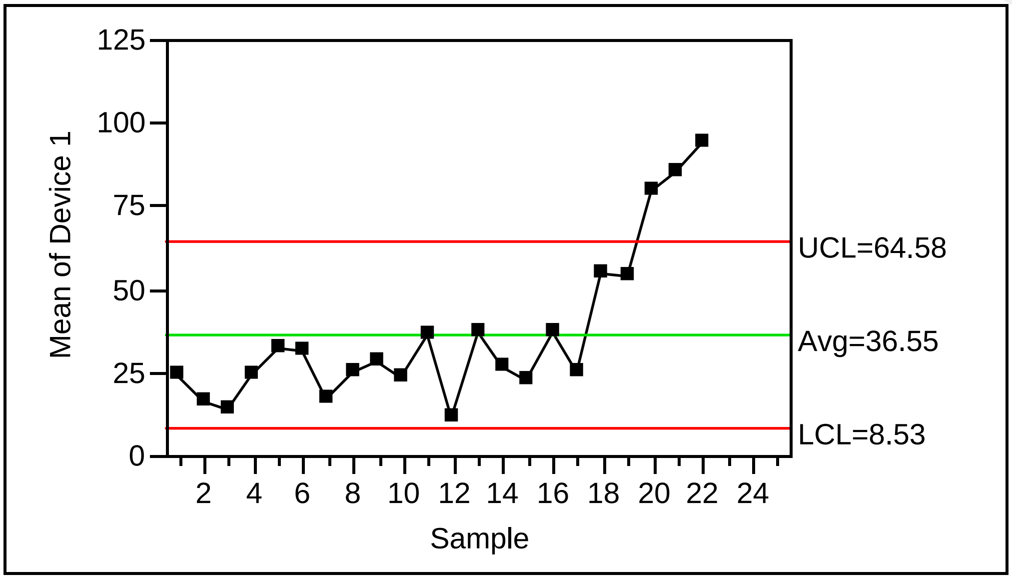




White Noise test

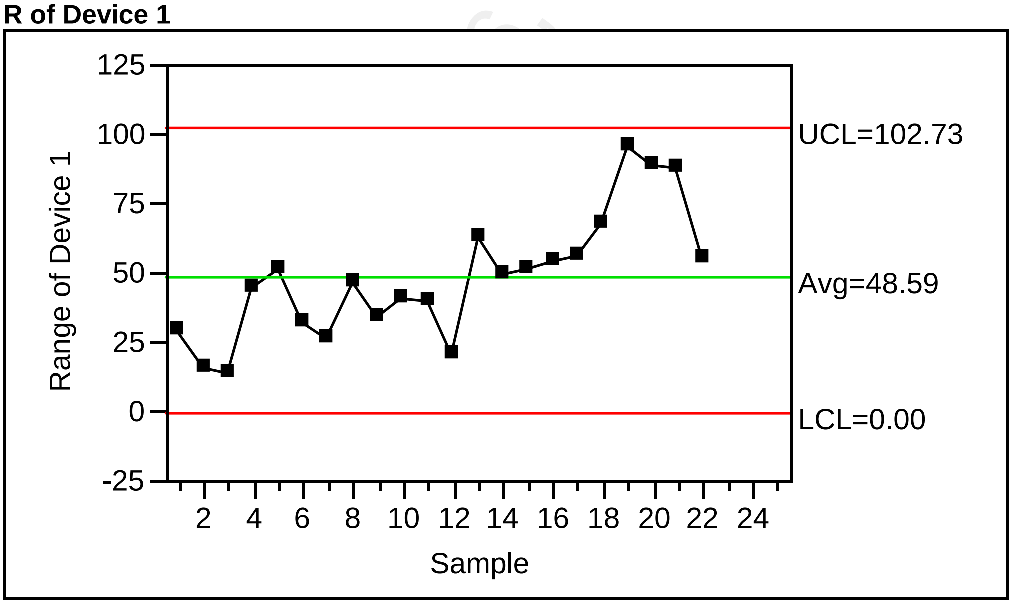
Fisher's Kappa	9.9355812
Prob > Kappa	0.0012104
Bartlett's Kolmogorov-Smirnov	0.236253

Variables Control Chart
XBar of Device 1

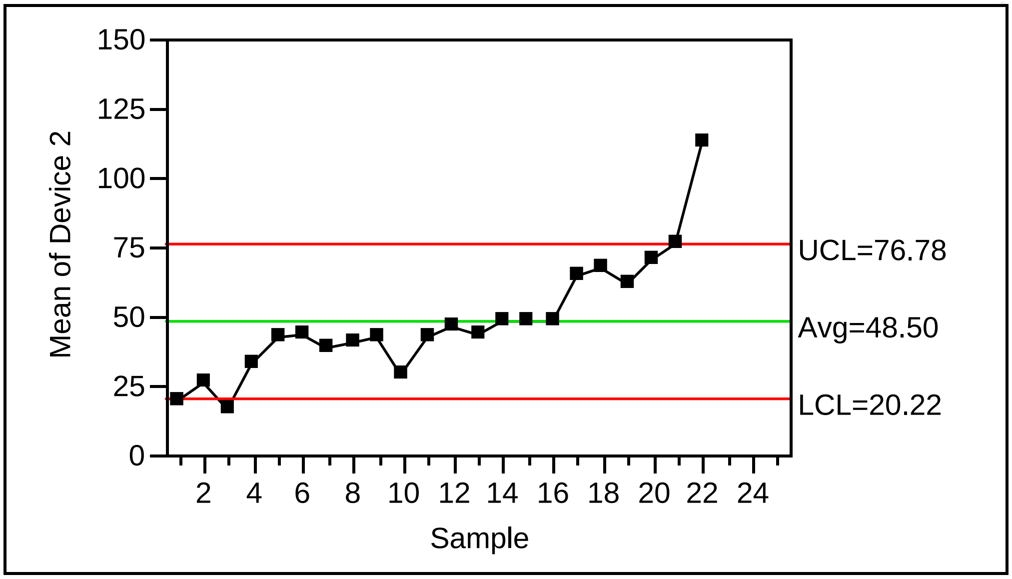


Note: Sigma used for limits based on range.

R of Device 1

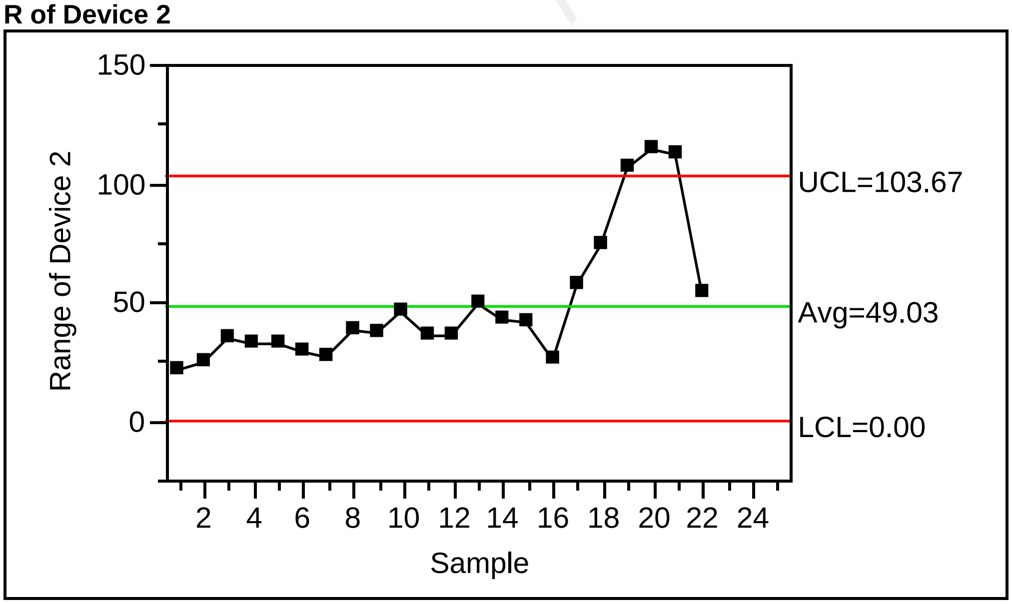


XBar of Device 2

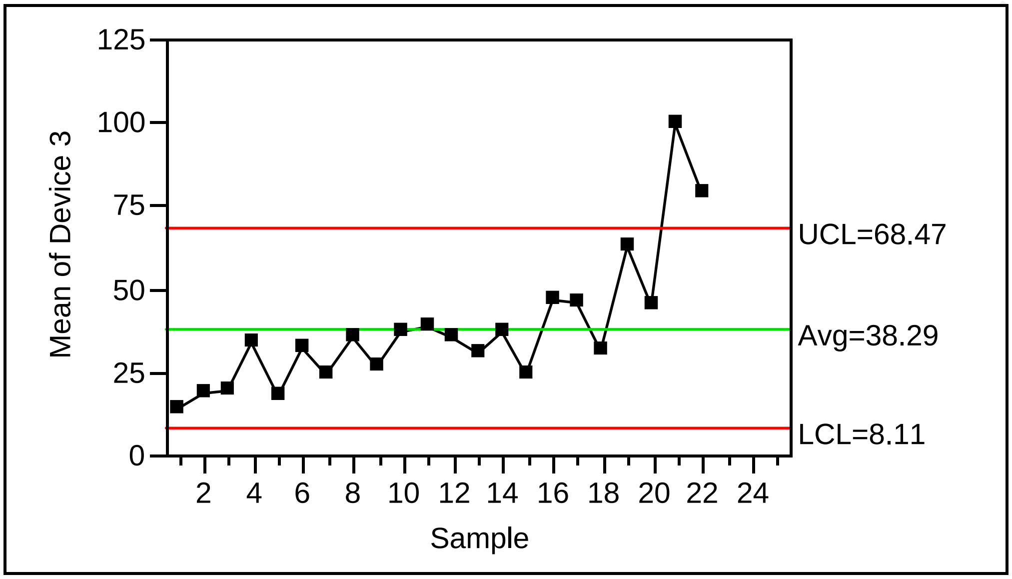


Note: Sigma used for limits based on range.

R of Device 2

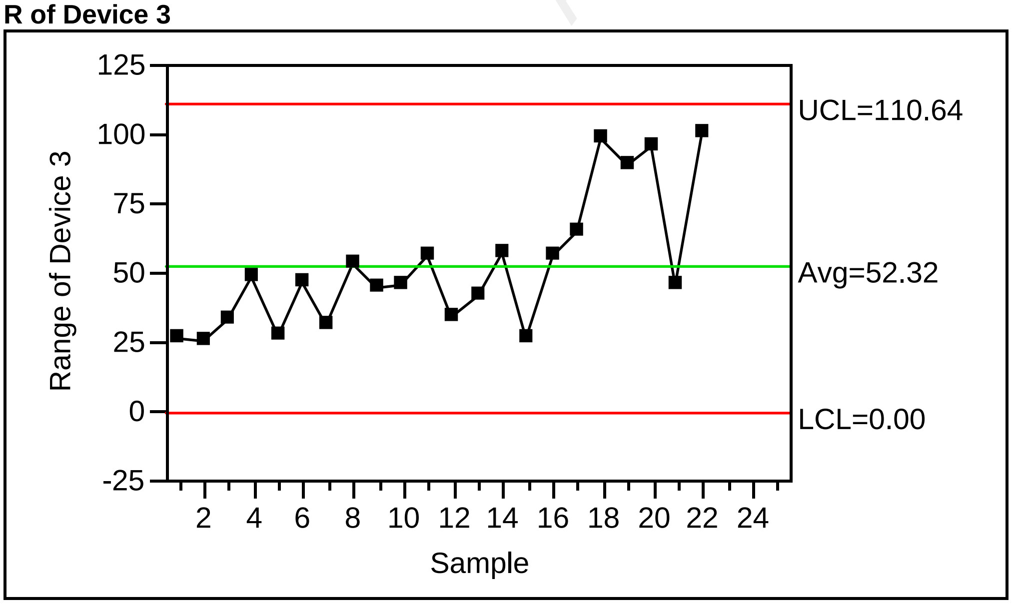


XBar of Device 3

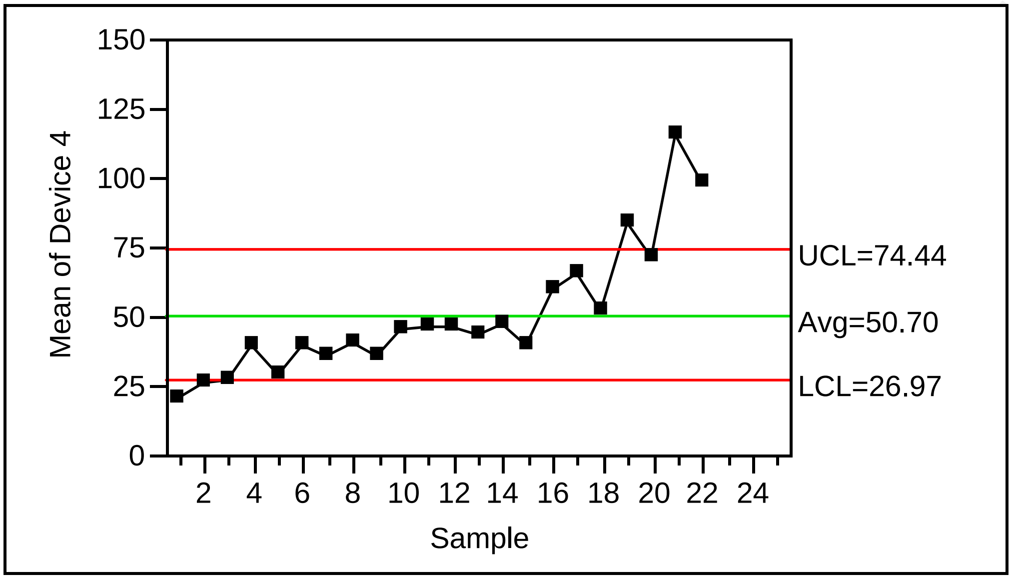


Note: Sigma used for limits based on range.

R of Device 3

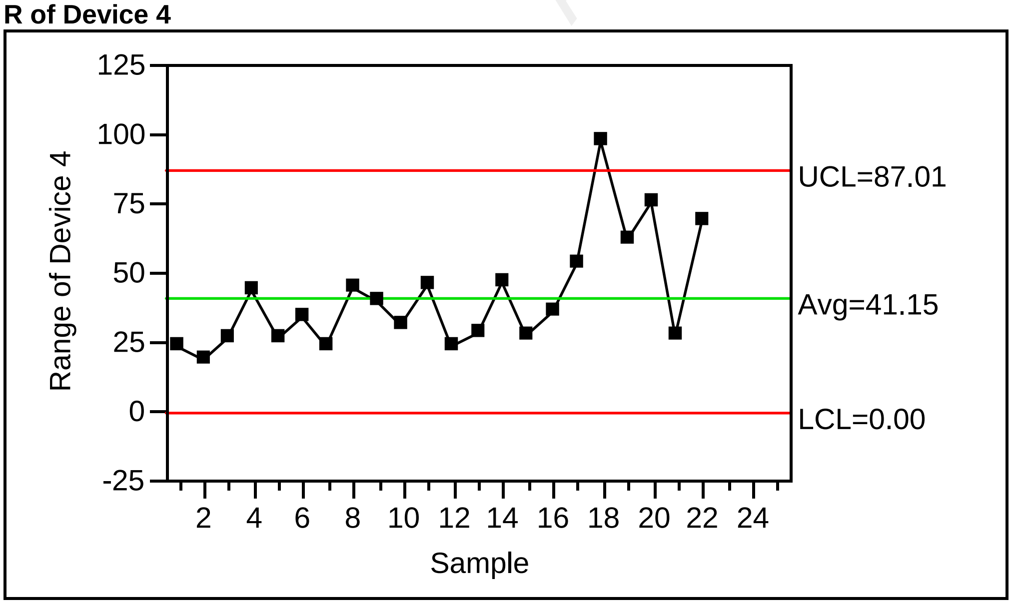


XBar of Device 4

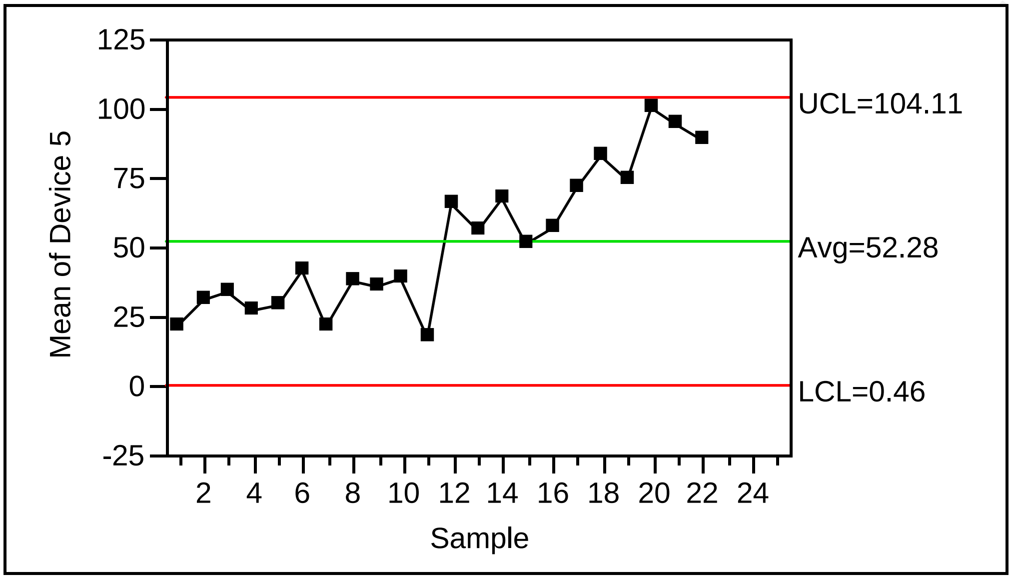


Note: Sigma used for limits based on range.

R of Device 4



XBar of Device 5



Note: Sigma used for limits based on range.

R of Device 5