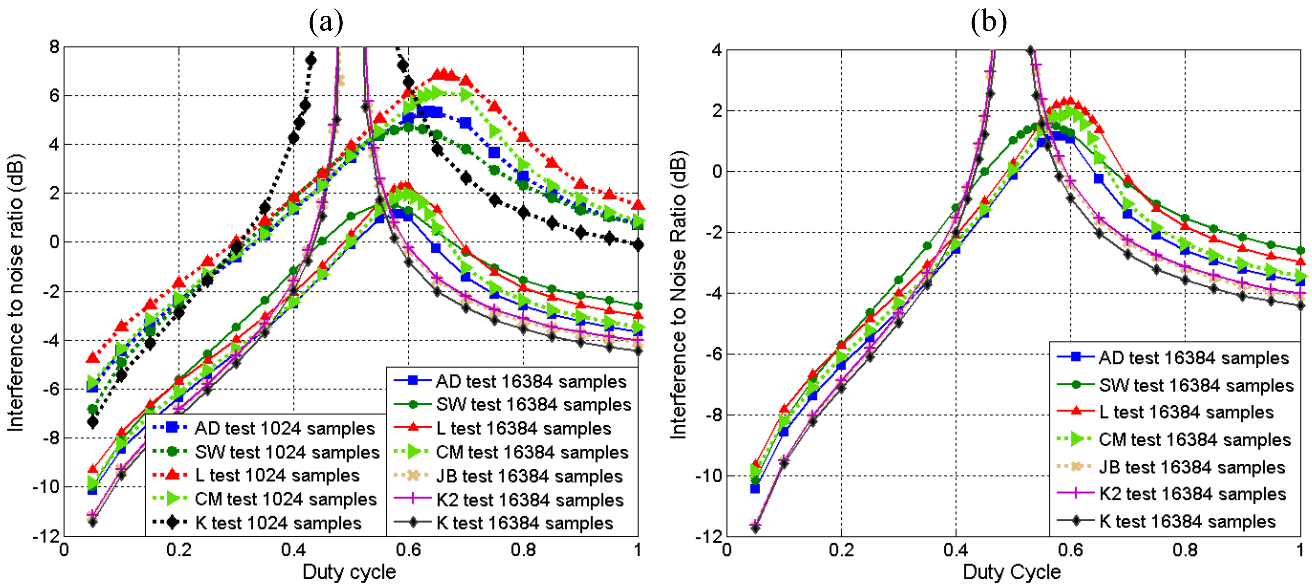
4.1. Pulsed Sinusoidal Signal

It is widely known [7–11] that a pulsed sinusoidal interfering signal of 0.5 duty cycle cannot be detected by the Kurtosis test as this signal has a Kurtosis equal to 3, independently of the frequency of the interfering signal. Hence, a study of different alternatives to detect non-Gaussian signals is performed. Figure 6a shows the performance of different normality tests for sample sizes of 1,024 samples (dotted lines) and 16,384 samples (solid lines). The performance is measured in terms of the required INR to obtain a ROC curve with a $P_{det} = 0.9$ for a $P_{fa} = 0.1$. In order to get reliable results, performance has been calculated as the average of 2^{15} Monte-Carlo simulations. In the following figures, some tests are not plotted due to its poor performance, as it is usually the case of Skewness, Lin-Mudholkar and chi-square tests.

Figure 6. Normality test performance in the detection of a pulsed sinusoidal interference of 1,024 samples (dotted line) and 16,384 samples (solid line) (Figure 6a), and a chirp signal of 16,384 samples (Figure 6b) as a function of signal's duty cycle. Both graphs represent the INR value required to obtain a ROC curve with a $P_{fa} = 0.1$ for $P_{det} = 0.9$. SW test has the best performance around duty cycle = 0.5, followed by AD test for 1,024 samples, while AD tests presents the best performance for 16,384 samples since SW test performance is degraded due to averaging. For low or high duty cycles the K test outperforms. JB and K2 tests results can not be used with 1,024 samples. Parameters f_0 and φ_0 are selected at random for the pulsed sinusoidal interference, while are defined as $f_0 = 2 \times 10^{-5}$ and $f_N = 0.15$ with N =16,384; and $\varphi_0 = 0°$ for the pulsed chirp interference. Results obtained from a Monte-Carlo set of 2^{15} simulations.

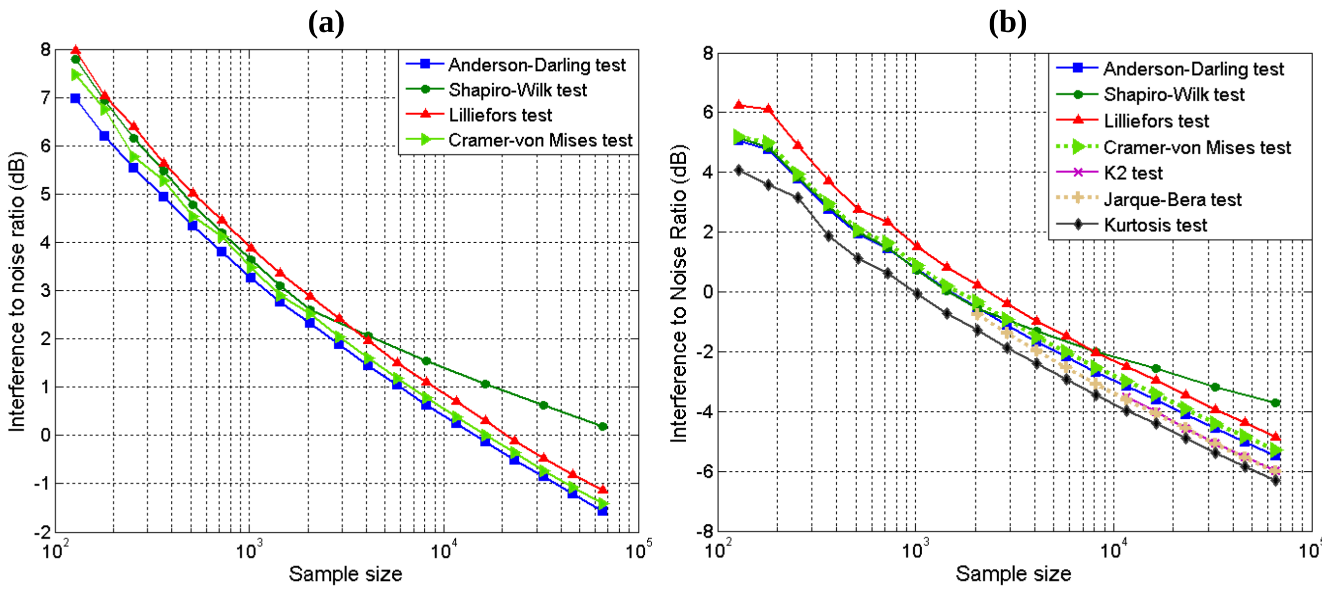


Best normality tests to detect pulsed sinusoidal interfering of duty cycle around 0.5 are the AD, the SW, the CM and the L tests, with improving performance as the sample size increases. These four ECDF based normality tests perform in a similar manner, having a better performance the SW test for shorter sample sizes and the AD test for longer sample sizes. The CM and L tests have a performance in between the other tests for large duty cycle.

For duty cycle values different from 0.5 and nearby values, however, Kurtosis test and Kurtosis-related tests outperform. In Figure 6a Kurtosis and Kurtosis related tests for have a peak around 0.5 that narrows with increasing sample size. Performance of JB and K2 test are worse than the Kurtosis alone, since these two tests depend also on the Skewness parameter which is zero in the analyzed signal.

In Figure 7a the performance of the AD, SW, L and CM normality tests in the detection of a pulsed sinusoidal signal of exactly 0.5 duty cycle is compared as a function of the sample size. K, JB and K2 tests are not present in Figure 8 since they cannot detect sinusoidal signals of 0.5 duty cycle. AD, L and CM tests follow almost the same trend while SW test has a different trend for sample lengths of 4,096 and above since blocks of 2,048 samples have to be averaged to ensure a good performance of the test.

Figure 7. Normality test performance in the detection of a 0.5 duty cycle pulsed sinusoidal interference (Figure 7a) and a chirp interfering signal (Figure 7b) as a function of the signal's sample size. Both graphs represent the INR value required to obtain a ROC curve with a $P_{fa} = 0.1$ for $P_{det} = 0.9$. In the 7a graph Kurtosis test is not present, and AD test has the best performance as sample size increases while in the 7b graph Kurtosis algorithm has the best performance followed by the Kurtosis based normality tests (JB and K2). In both cases SW test performance does not improve as fast as the others above 2,048 samples due to averaging and CM test has a slightly worse performance than AD test. Parameters f_0 and φ_0 are selected at random for the pulsed sinusoidal interference, while are defined as $f_0 = 2 \cdot 10^{-5}$ and $f_N = 0.15$ with N =16,384; and $\varphi_0 = 0°$ for the pulsed chirp interference. Results obtained from a Monte-Carlo set of 2^{15} simulations.

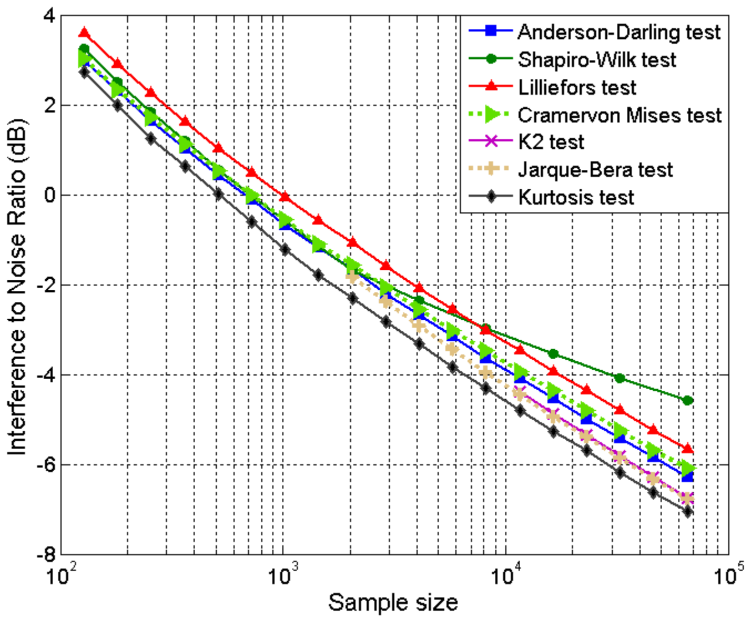


4.2. Chirp Interfering Signal

The performance of all the normality tests in the detection of an interfering chirp signal with a variable duty cycle is very similar to the case of the detection of a pulsed sinusoidal signal. In fact, a 0.5 duty cycle blind spot is still present for Kurtosis algorithm and Kurtosis-based normality tests. Figure 6b presents K, K2, JB, AD, SW, L, and CM test performance in the detection of a pulsed chirp signal as a function of the duty cycle, showing the similarities commented previously. Furthermore Figure 6a (solid lines) and 6b shows similar trends for the different normality tests and duty cycles, even the INR values of the tests are almost the same in both figures.

In the case that the signal has a duty cycle of 1, the best detection algorithm is the Kurtosis test followed by the Kurtosis-based and Skewness-based tests. Figure 10 shows the INR trend Vs. sample size: The AD, L, CM, K, JB and K2 tests follow almost the same trend, while SW test has a different trend for sample length of 4,096 and above, as in Figure 8. JB and K2 tests start taking values of INR at 2,048 and 11,585 number of samples respectively as these tests are not considered valid for a lower sample size (see Section 3). The K, JB and K2 tests are shown (since as the duty cycle of the chirp is 1 and not 0.5 as in Figure 7a).

Figure 8. Normality test performance in the detection of a PRN interference as a function of the signal's sample size. Graphs represent the INR value required to obtain a ROC curve with a $P_{fa} = 0.1$ for $P_{det} = 0.9$. Kurtosis test has the best performance, followed by JB and K2 tests. Best ECDF test performance is obtained with the AD test followed by the CM test. SW test performance does not improve as the rest for large sample size due to averaging. Results obtained from a Monte-Carlo set of 2^{15} simulations.

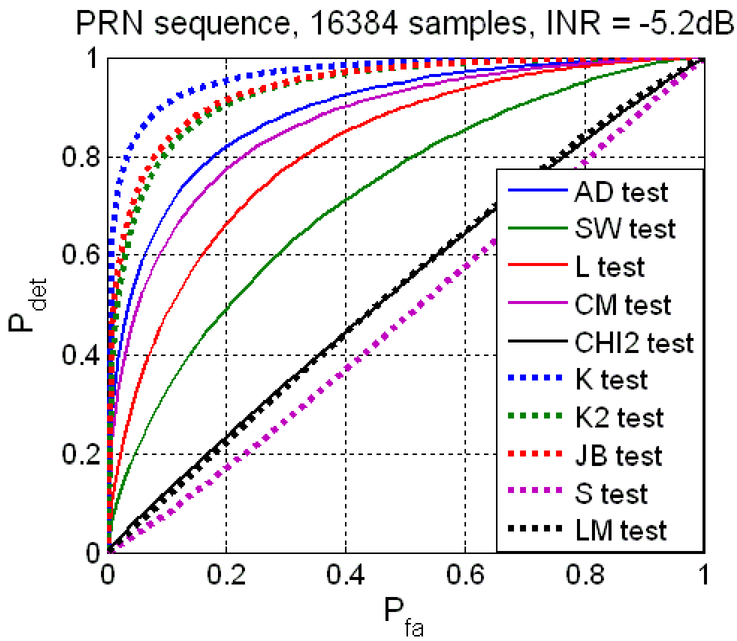


4.3. Pseudo-Random Noise Interfering Signal

Figure 8 shows the performance of the different tests Vs the sample size. The Kurtosis test achieves the best performance in the detection of this kind of interfering signal, followed by JB and K2 tests. Hence, Kurtosis-based tests perform better than ECDF-based tests (AD, L, CM, SW) in the detection of PRN signals. Performance of ECDF-based tests is quite similar to the sinusoidal and chirp interfering signals, obtaining the best results with the AD and the SW tests for lower sample sizes, and with the AD and CM tests for higher sample sizes.

Figure 9 shows the ROC curves of the normality tests performance in the detection of a PRN signal of 16,384 number of samples; in this figure, Kurtosis gets a value of $P_{det} = 0.9$ for $P_{fa} = 0.1$. In this figure it is clearly shown that Kurtosis outperforms for the same INR as the rest of normality tests, followed by the two Kurtosis-based and Skewness-based tests (JB and K2 tests) which have almost the same behavior. The four ECDF based tests (AD, CM, L and SW tests) have a worse performance. The worst performance is obtained by the S, LM and CHI2 tests. S and LM tests fail as the interfering signal Skewness is zero. CHI2 test has a lesser performance in the RFI detection than the ECDF-based tests and Kurtosis based tests, therefore it is not recommended in the RFI detection.

Figure 9. Normality tests performance in the detection of a PRN interference signal. Sample size is 16,384 and INR is −5.2 dB. It is appreciated the difference in performance between the Kurtosis and the rest of tests. Also, bad performance of the Skewness, LM and CHI2 tests is shown.



4.4. Telegrafic Interfering Signal

For this type of interfering signal, depending on the actual message transmitted the performance of the different normality test is quite variable. In this study, three different interfering signals have been used, called messages 1, 2 and 3. Message 1 is a plain text file (very low randomness), message 2 is a zipped file and message 3 is a jpg file (high level of randomness, as redundancy is eliminated). In Figures 10 and 11 ROC curves of message 1 are presented as a function of the sample size and the INR, respectively. As for other kinds of interfering signals increasing the sample size increases the probability of RFI detection, and the normality tests performance degrades with decreasing INR (Figure 11). In Figures 10 and 11 it is shown that Kurtosis and Skewness-based tests are far better than AD, CM and L tests; and that the SW test has a better performance than the rest of the ECDF tests even for a large sample size.

In Figures 12 and 13 ROC curves of the three different messages are presented. Figure 12 presents the normality test performance in the detection of the three different messages with the same INR and the same sample size. Message 1 is relatively easy to detect by any normality test due to its statistical nature (plain text file with high redundancy) while messages 2 and 3 are undetectables for INR = −20dB due to the low redundancy of these messages (compressed data). Figure 13 presents the normality test performance in the detection of the messages 1, 2 and 3 with a higher INR = −5.2 dB, showing that the best normality tests to detect this low redundant telegraphic signal is again the Kurtosis. In fact, the relative performance of the normality tests is exactly the same as the PRN case.

Figure 10. Normality tests performance in the detection of a telegraphic interference signal. ROC curves of the different tests are presented as a function of the sample size, setting the INR to −16 dB. The best normality tests for detecting message 1 varies depending of the sample size, for 2,048 samples is the SW test, while for 1,024 samples are the JB and the K2 tests (highest P_{det} with a low P_{fa}), as both values of Kurtosis and Skewness are non-zero. Results obtained from a Monte-Carlo set of 2^{15} simulations.

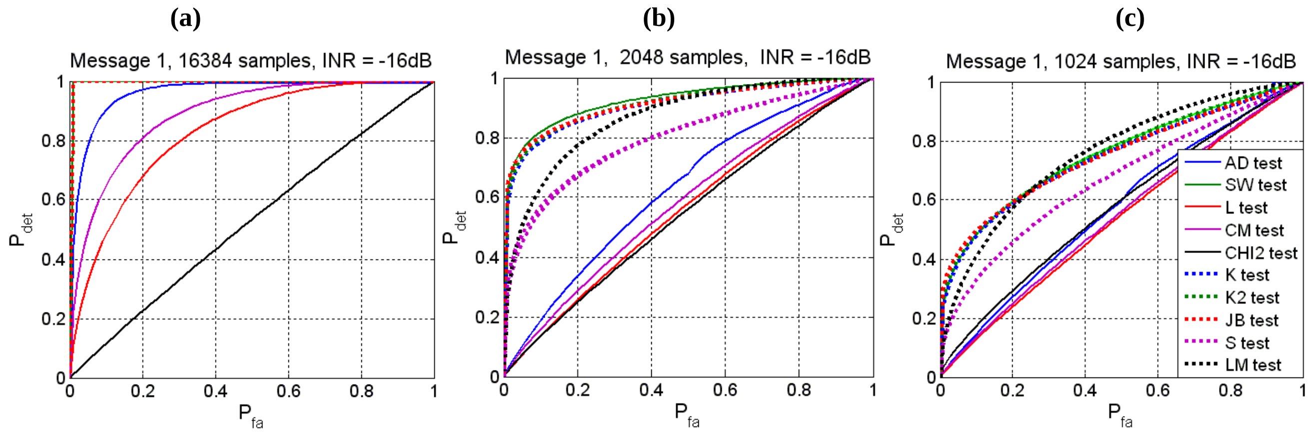


Figure 11. Normality test performance in the detection of a telegraphic interference signal (Message 1). ROC curves of the different tests are presented as a function of the INR, setting the sample size to 2,048. Like in Figure 10, the best normality tests for detecting message 1 is the SW test (highest P_{det} with a low P_{fa}). Results obtained from a Monte-Carlo set of 2^{15} simulations.

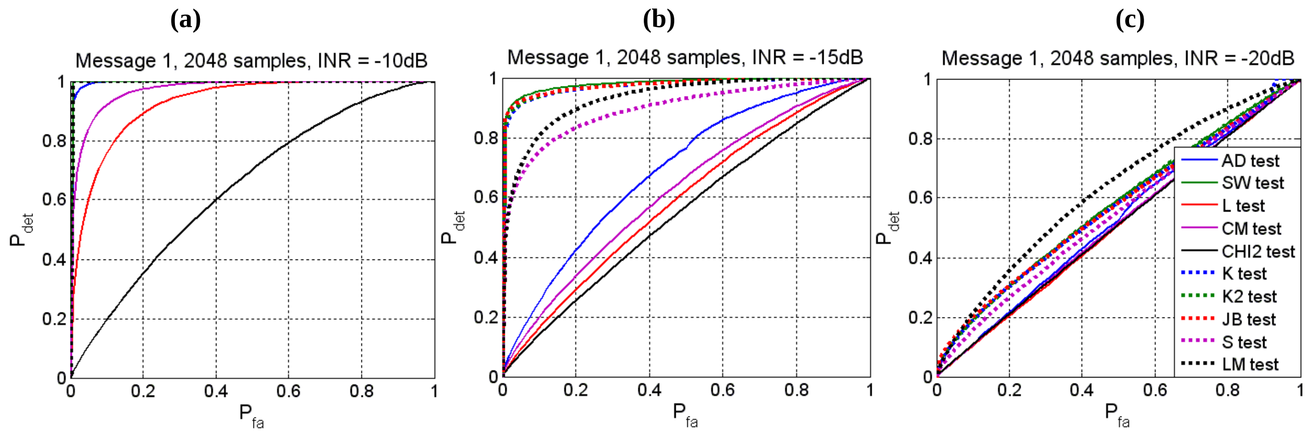


Figure 12. Normality test performance in the detection of a telegraphic interference signal. ROC curves of the different tests are presented in function of 3 different messages, setting the sample size to 16,384 and INR to −20 dB. The best normality tests for detecting message 1 is JB and K2 tests as both values of Kurtosis and Skewness are non-zero. In the cases of message 2 and 3, both compressed data (zip and jpg archives), −20 dB is a very low INR to detect these messages so, in Figure 13, INR is set to -5.2dB. Results obtained from a Monte-Carlo set of 2^{15} simulations.

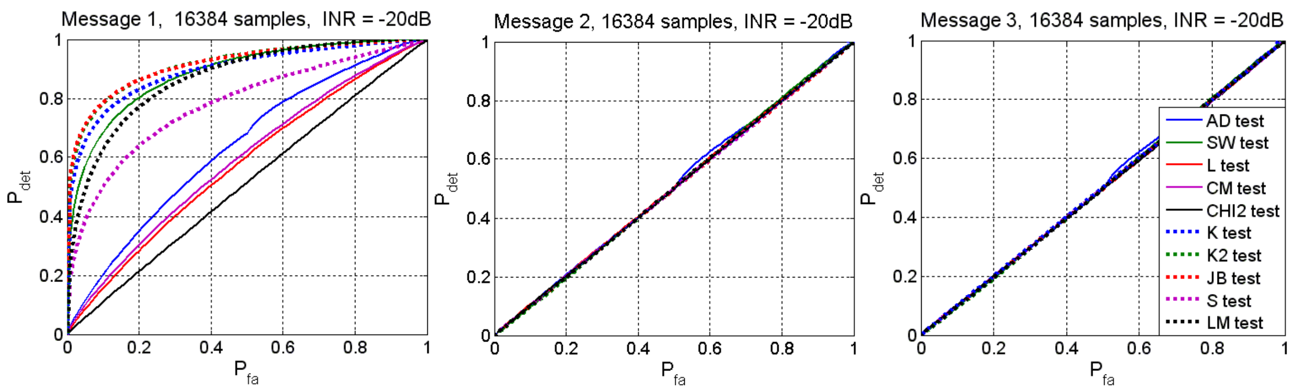
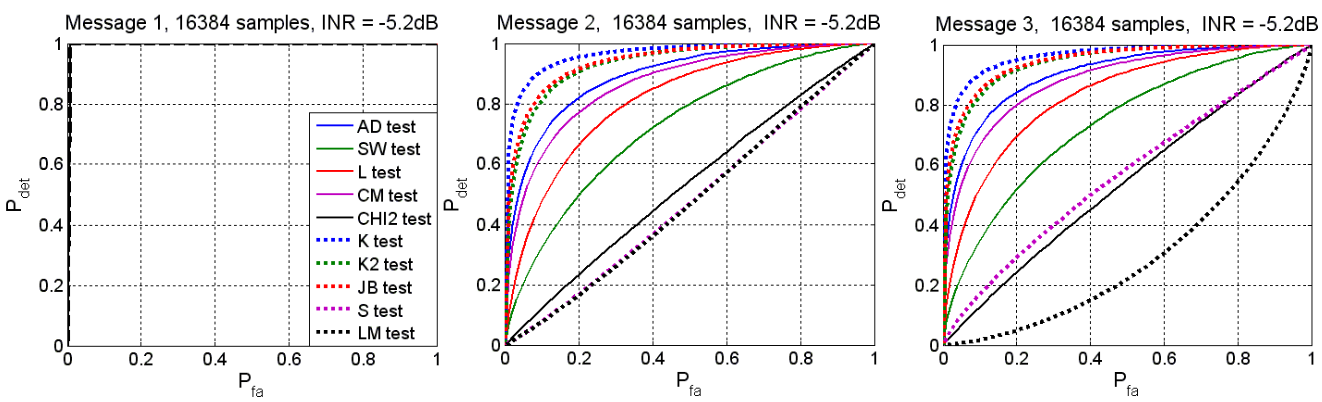
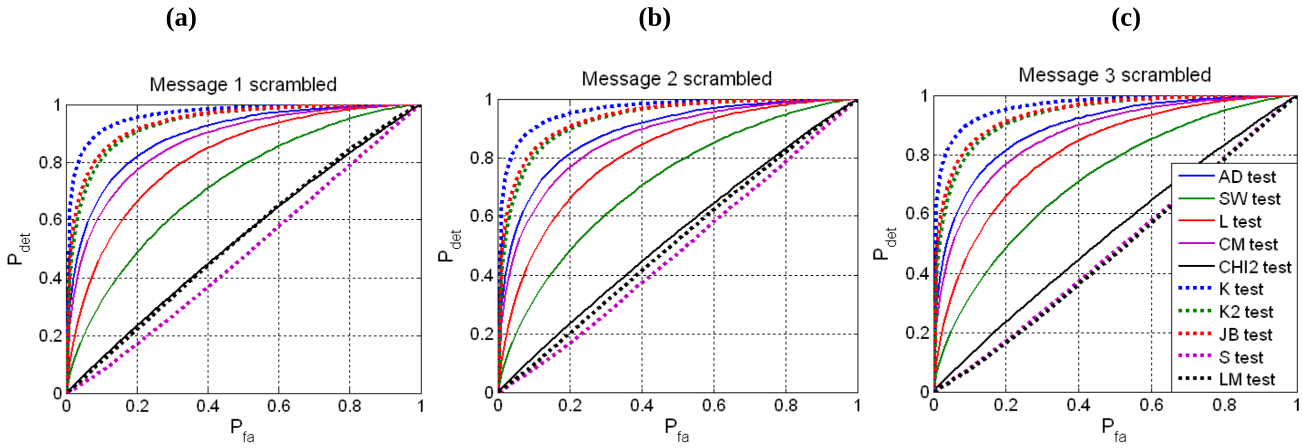


Figure 13. Normality test performance in the detection of a telegraphic interference signal. ROC curves of the different tests are presented in function of 3 different messages, setting the sample size to 16,384 and INR to −5.2 dB. Message 1, is easily detectable for all the normality tests due to its elevated Messages 2 and 3, both compressed data (a zip and a jpg archives), Kurtosis seems to be the best detection algorithm. Results obtained from a Monte-Carlo set of 2^{15} simulations.



To simulate message scrambling and encryption, all 3 messages are scrambled by means of an XOR operation between original message and the PRN code previously studied in this work. Results obtained are shown in Figure 14 which has to be compared with the result obtained in Figure 9. The high similarity between Figure 9 and the result of the test detection of the scrambled signal of all three messages and the PRN signal (Figure 14), shows that the scrambling process usually employed in communications makes the detection of RFI more difficult.

Figure 14. Normality test performance in the detection of a telegraphic interference signal. ROC curves of the different tests are presented in function of 3 different messages scrambled with PRN signal shown in Figure 9, setting the sample size to 16,384 and INR to −5.2 dB. It can be observed that all ROC curves are almost equal for each interfering signal, deducing that if the telegraphic signal is encrypted or scrambled, it can be treated as a spread spectrum signal. Results obtained from a Monte-Carlo set of 2^{15} simulations.



5. Conclusions

In this study the performance of ten different normality tests has been analyzed in terms of their capability to detect radio-frequency interference in microwave radiometry. These tests have been first validated in terms of sequence length and number of quantization bits in the absence of interference. Their capability to detect sinusoidal, chirp, PRN and telegraphic signals has then been analyzed.

It has been shown that the Kurtosis is the best RFI detection algorithm for almost all kinds of interfering signals, although it is known that it has a blind spot for sinusoidal and chirp interfering signals of 0.5 duty cycle.

Skewness-based algorithms (S and LM) usually have a lower performance than other tests as the Skewness of PRN, sinusoidal and chirp interfering signals is almost zero. However nonscrambled telegraphic signals present a higher Skewness parameter leading to a better performance of the S and LM tests than in case of sinusoidal, chirp, PRN and telegraphic scrambled signals.

Kurtosis-based normality tests (JB and K2 tests) have a good performance if both the Kurtosis and the Skewness are high enough. However, since Skewness is usually almost zero, both tests have a performance slightly worse than the Kurtosis test, except in the case of nonscrambled telegraphic interfering signals. Their performance is very similar, although the JB test has always a slightly better performance. In any case, as K, both tests present a blind spot detection for sinusoidal and chirp interfering signals of 0.5 duty cycle.

The four Empirical Distribution Function based normality tests: Anderson-Darling (AD), Lilliefors (L), Cramer-von Mises (CM), and Shapiro-Wilk (SW) tests have a similar performance for PRN, sinusoidal and chirp interfering signals. For a low sample size AD and SW tests work better that the CM and L test, but as sample size increases, SW test performance degrades in front of CM and L tests, as SW test must be averaged above 2,048 sample size to obtain a correct performance.

As compared to the other normality tests, CHI2 normality test has a poor performance, therefore is not recommended to use in RFI detection algorithms.

In summary, the Kurtosis is the best RFI detection algorithm for almost all kinds of interfering signals, although it has a blind spot for sinusoidal (chirp) signals of 0.5 of duty cycle. The AD test is a complementary normality test that covers this blind spot, and has a very good performance for all the studied sample sizes. The combination of the Kurtosis and the AD tests seems capable to detect most types of RFI. The performance of the detection tests improves with the sample size and depends on the duty cycle of the pulsed RFI.

Future research will be devoted to the optimum combination of these statistical analysis with time and frequency blanking methods, since these methods outperform statistical analysis in some specific cases for example low duty cycle pulsed sinusoidal signals (short pulses are easily detected in time domain), or high duty cycle pulsed sinusoidal signals or a continuous wave (a tone is easily detected in frequency domain).

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