State Description of Wireless Channels Using Change-Point Statistical Tests

Dmitri Moltchanov, Yevgeni Koucheryavy, and Jarmo Harju

***Abstract*— Wireless channels are characterized by highly dynamic time-varying nature often manifesting non-stationary behavior. In this paper we consider the state of a wireless channel in terms of the piecewise covariance stationary signal-to-noise ratio (SNR) process and parameterize it using the probability distribution function of the received SNR and lag-1 autocorrelation coefficient of the corresponding autocorrelation function (ACF). In order to discriminate the state of a wireless channel when its characteristics vary in time we apply methods of statistical process control. Particularly, we use exponential weighted moving average (EWMA) change-point statistical test to detect shifts in the mean value of SNR process. The proposed approach is tested using artificial traces and SNR measurements of IEEE 802.11b wireless channel. Obtained results demonstrate that changes in wireless channel characteristics can be timely detected in real-time. The proposed approach is useful in cross-layer environment where higher layers often need explicit information about the current state of the wireless channel.**

***Index Terms*– Wireless, non-stationarity, EWMA test.**

I. INTRODUCTION

Due to movement of a mobile user and movement of different objects in a radio channel, the propagation path between the transmitter and the receiver may vary from simple line-of-sight (LOS) to very complex ones. As a result, any metric used to represent the quality of a wireless channel is characterized by time-dependent stochastic behavior. Insufficient signal-to-noise ratio (SNR) at a certain instant of time may result in incorrect reception of the channel symbol possibly leading to an erroneously received bit. Techniques such as forward error correction (FEC) and automatic repeat request (ARQ) may allow to recover from these errors locally. However, even in presence of ARQ and FEC, bit errors may still propagate to higher layers resulting in loss of protocol data units (PDU) at those layers. On the other hand, when the channel quality is locally good, ARQ and FEC may lead to inefficient usage of available bandwidth.

To ensure acceptable quality of the wireless channel, some wireless access technologies incorporate features allowing to control power of the transmitter such that the target bit error rate (BER) is maintained. This capability, known as power control, may lead to various undesirable effects including 'cell breathing' in CDMA systems or increase in interference with neighbor cells in TDMA systems. These effects should be avoided whenever possible. Another way to maintain the acceptable quality of wireless channels is to dynamically change correction capability of FEC schemes at the data-link layer. FEC procedures use proactive approach eliminating the influence of bit errors in advance introducing error correction redundancy. This redundancy is exploited at the receiver to recover from bit errors. The major advantage of FEC techniques is that they do not introduce delays allowing unrecovered information to be lost. There is a number of papers exploring the correcting effect of FEC codes for different conditions of wireless channels (see [7], [8] among others).

The state of the wireless channel is usually represented in terms of the stochastic process, where the stochastic variable of interest is either SNR or a certain function of it. Basically, two types of processes are widely used to describe the state of wireless channels. These are SNR (see [9], [2], [12] among others) or PDU error processes (see [3], [17], [6] among others). Latter models aim at determining the performance of a wireless channel at a certain layer of the protocol stack in terms of incorrectly received PDUs. Although PDU error models can be directly measured, the major advantage of these models is that they can be derived from the SNR model at the physical layer [7], [4]. From this point of view, PDU error models are seen as an extension of SNR models. Due to this reason, to represent the state of the wireless channel, SNR process is often sufficient and will be further used in this paper.

Most papers that considered performance of information transmission over wireless channels either implicitly or explicitly assumed covariance stationarity for wireless channel statistics. Recently, important observations of wireless channel characteristics have been published in [5]. Authors found their GSM bit error traces to be non-stationary and proposed an algorithm to extract covariance stationary parts. They further used doubly-stochastic Markov processes to model these parts separately. The modeling trace is finally obtained by concatenation. Among other conclusions, authors suggested that a given bit error trace can be divided into a number of concatenated covariance stationary traces. Since the bit error probability is a function of the SNR value, we can expect the same property for SNR observations. Despite of important conclusions made in [5], authors failed to develop theoretical basis for their change detection algorithm. In this paper in order to discriminate the state of the wireless channel in terms of the covariance stationary SNR segments, we propose to use well-known statistical methodology based on sequential change-point statistical tests.

The rest of the paper is organized as follows. In Section 2 we review propagation characteristics of wireless channels and models used to capture them. Setup of experiments that are used to gather SNR statistics is described in Section 3. Model for SNR process is introduced in Section 4. Sequential statistical tests for detecting changes in parameters of stochastic observations are reviewed in Section 5. Particularly, EWMA change-point statistical test is proposed there. Numerical results are given in Section 6. Conclusions are drawn in the last section.

II. DESCRIPTION OF WIRELESS CHANNELS

To determine parameters of a stochastic process, such as mean and variance, based on only one, sufficiently large realization we usually assume ergodicity for stochastic observations. The sufficient condition for a stochastic process to be

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ergodic is $\lim_{i\to\infty} K(i) = 0$, where $K(i)$, $i = 0, 1, \dots$, is its ACF. The concept of stationarity is another advantageous property of stochastic processes. It is of paramount importance in context of stochastic modeling. Practically, if some observations are found to be non-stationary, their stochastic modeling is rarely feasible. A process is said to be strictly stationary if all its M-dimensional distributions are the same. Only few real-life processes are strictly stationary. A process is said to be weakly (covariance) stationary, if the mean of all its sections is the same and ACF depends on the time shift only, i.e. $K(t_1, t_2) = K(i)$, $i = t_2 - t_1$.

III. SETUP OF EXPERIMENTS

In this paper we use SNR observations of IEEE 802.11b wireless local area network (WLAN) channel operating according to distributed coordination function (DCF) of IEEE 802.11 in DSSS mode at 11Mbps. In order to gather SNR statistics we carried out a number of experiments in office environment as described below.

According to the setup experiments shown in Fig. 1, there were two entities involved in communication. These are the mobile node, called *tester node*, and the access point (AP). SNR capturing software was installed on mobile node. The communication between AP and the tester node was of interest. The tester and AP were in non-LOS (NLOS) and LOS environments as explained below. To capture SNR traces we used Network Stumbler software (version 0.4.0, [10]). This program is capable of capturing the SNR value, averaging it over 0.5 second intervals.

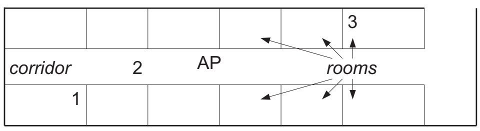


Fig. 1. Testbed for SNR measurements.

All experiments were carried out in office environment as shown in Fig. 1, where reference points denote places where measurements were carried out, AP denotes the placement of AP transceiver. Note that the tester node, when in points 1 and 3, is in NLOS environment with respect to the transceiver of AP. The distance between reference point 1 and AP is shorter than that between reference point 3 and AP. Reference point 2 corresponds to LOS environment. The experiments were carried out as follows. Mobile station was at a certain reference point for some time and then was moved to another reference point. SNR was uninterruptedly measured during the course of each experiment.

IV. MODEL FOR SNR PROCESS

A. Statistical Characteristics

Consider statistical characteristics of the SNR process when a mobile station is in stationary position. We concentrate our attention on two statistical characteristics. These are the histogram of relative frequencies of the SNR process and the corresponding ACF. These two properties of the SNR process were found to produce the major impact on the performance of higher layers [7], [4]. In what follows, results for reference point 1 are demonstrated. Results for other reference points are qualitatively similar.

Sequences of SNR observations for two experiments are shown in Fig. 2. Respective histograms of relative frequencies of these SNR observations and their approximations by normal probability density functions (pdf) are shown in Fig. 3, where $f_{i,E}(\Delta)$, $i = 1, 2, \dots$ is the relative frequency corresponding to the is histogram bin, m is the number of histogram bins, $\Delta = (\max_{\forall i} Y(i) - \min_{\forall i} Y(i))/m$ is the length of the histogram bin, $\max_{\forall i} Y(i)$ and $\min_{\forall i} Y(i))$ are the maximum and minimum values of the SNR, respectively. Approximations shown in Fig. 3 allow us to assume that SNR values are approximately normally distributed. χ^2 statistical test carried out with the level of significance set to 0.1 has shown that statistical data belongs to the normal distribution.

Empirical normalized ACFs (NACF) of two SNR traces are shown in Fig. 4 using solid lines with circles. One may notice that the memory of the process is short and limited to several lags. In what follows we propose to approximate such a behavior using a single geometrical term, e.g. $y(i) = K_Y(1)^i$, $i = 0, 1, \dots$, where $K_Y(1)$ is the lag-1 autocorrelation coefficient. In Fig. 4 approximating functions are denoted by solid lines. These functions exactly capture lag-1 autocorrelation coefficient of the empirical processes and do not significantly overestimate or underestimate the autocorrelation coefficients for larger lags.

In what follows we assume that when a mobile station is in stationary position, SNR observations compose realization of covariance stationary stochastic process with normal marginal distribution and non-negligible positive short-term autocorrelations. This assumption is supported by first- and second-order statistical characteristics shown in Fig. 3 and Fig. 4, respectively.

B. Model for SNR Process

In order to model SNR traces we propose to use autoregressive process of order one, often denoted by AR(1). A process is said to be autoregressive of order one if it is generated using the following recursion

$$Y(n) = \phi_0 + \phi_1 Y(n-1) + \epsilon(n), \qquad n = 0, 1, \dots, \quad (1)$$

where ϕ_0 and ϕ_1 are some constants, $\{\epsilon(n), n = 0, 1, \dots\}$ are independently and identically distributed random variables having the same normal distribution with zero mean and variance $\sigma^2[\epsilon]$.

If a process given by (1) is covariance stationary we have

$$E[Y] = \mu_Y, \quad \sigma^2[Y] = \gamma_Y(0), \quad Cov(Y_0, Y_i) = \gamma_Y(i), \quad (2)$$

where μ_Y, $\gamma_Y(i)$, $i = 0, 1, \dots$, are some constants.

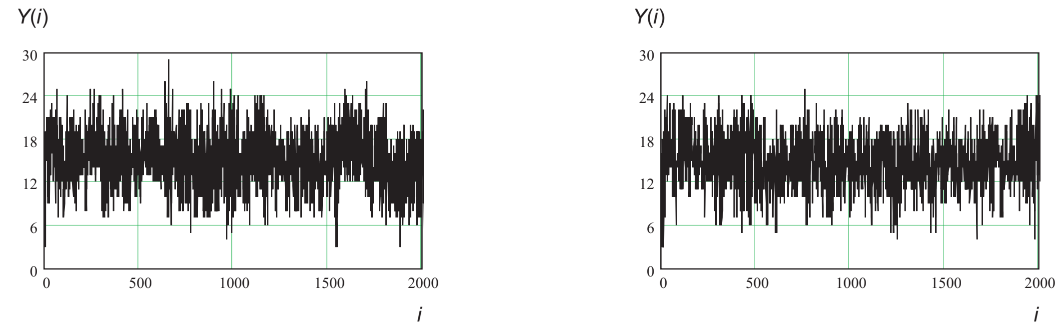
Mean, variance and covariance of AR(1) are related to ϕ_0, ϕ_1 and $\sigma^2[\epsilon]$ as

$$\mu_Y = \frac{\phi_0}{1-\phi_1}, \quad \sigma^2[Y] = \frac{\sigma^2[\epsilon]}{1-\phi_1^2}, \quad \gamma_Y(i) = \phi_1^i \gamma_Y(0). \quad (3)$$

Parameters of AR(1) models can be found as follows

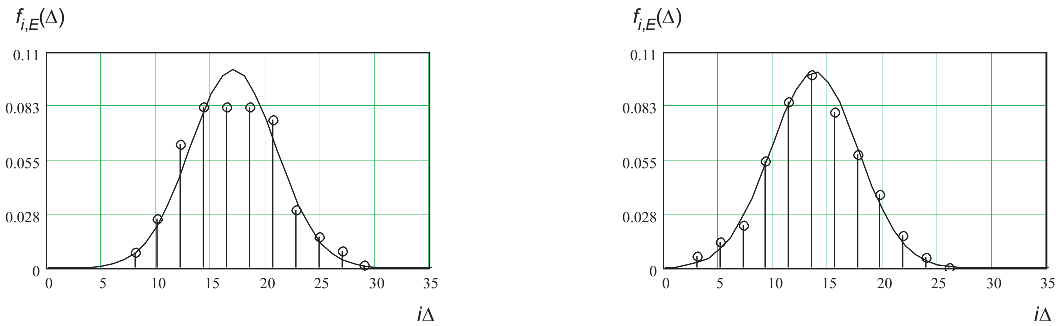
$$\begin{cases} \phi_1 = K_X(1) \\ \phi_0 = \mu_X(1-\phi_1) \\ \sigma^2[\epsilon] = \sigma^2[X](1-\phi_1^2) \end{cases}, \quad (4)$$

where $K_X(1)$, μ_X and $\sigma^2[X]$ are point estimates of lag-1 autocorrelation coefficient, mean and variance of SNR observations, respectively.



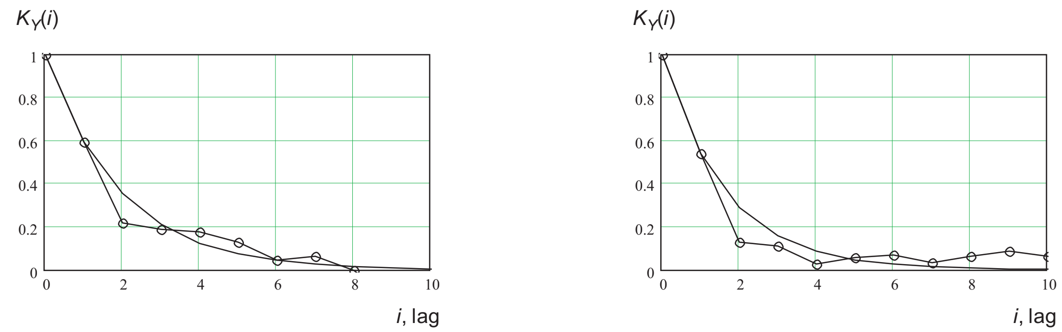
(a) Experiment 1 (b) Experiment 2

Fig. 2. Sequences of SNR observations for two experiments.



(a) Experiment 1 (b) Experiment 2

Fig. 3. Histograms of SNR observations and their approximations.



(a) Experiment 1 (b) Experiment 2

Fig. 4. NACFs of SNR observations and their approximations.

V. Change-point Sequential Tests

A. The Methodology

In order to differentiate between rapid fluctuations of the SNR around a constant mean and changes in the mean value of the SNR process we propose to use the so-called change-point sequential statistical tests. There is a number of change-point detection algorithms developed to date. The common approach to deal with this task is to use control charts including Shewhart charts [15], cumulative sum (CUSUM, [11], [16]) charts, or exponentially weighted moving average (EWMA, [13], [14]) charts. These charts were originally developed in statistical process control (SPC) where they are successfully used to monitor the quality of production.

The idea of control charts is to classify all causes of deviation of a certain parameter of the process from its target value into two groups. These are common causes of deviation and special causes of deviation. Deviation due to common causes is the effect of numerous disturbances affecting a given process. They are inherent part of a process. Special causes of deviation are not the part of the process, occur accidentally and affect the process significantly. Control charts signal the point at which special causes occur using two control limits. If observations are between them, the process is 'in-control'. If some observations fall outside, the process is classified as 'out-of-control'.

For detecting changes in SNR statistics the following interpretation of causes of deviation is taken. We assume that common causes of deviation are those resulting from small-scale propagation characteristics (see [12], Ch. 5). Special causes are those caused by movement of a user including large-scale changes of the distance between the transmitter and a receiver or shadowing of the signal by obstacles (see [12], Ch. 4). The whole procedure is as follows. Initially, a control chart is parameterized using estimates of parameters of the SNR process. When change in the controlled parameter occurs, a new process is considered as in-control and the control chart has to be re-parameterized according to statistics of this process.

B. Change in the Mean Value

Assume that k observations $\{Y(n), n = 0, 1, \dots, k-1\}$ of a certain stochastic process have the same distribution F_0. In general, the change point statistical test refers to testing the null hypothesis, H_0, that a currently observed observation k has distribution F_0 against alternative hypothesis, H_1, that this observation has distribution F_1. Formally, it is written as

$$H_0 : F_Y(k) = F_0, \qquad H_1 : F_Y(k) = F_1, \tag{5}$$

where $F_Y(k)$ is the distribution of observation k.

The latter case in (5) represents situation when a change occurs in a distribution and can be rewritten as

$$\begin{aligned} &H_0 : F_Y(i) = F_0, \qquad i = 1, 2, \dots, k, \\ &H_1 : F_Y(i) = \begin{cases} F_0 & i = 0, 1, \dots, k-1, \\ F_1 & i = k. \end{cases} \end{aligned} \tag{6}$$

It is often assumed that distributions F_0 and F_1 are known except for some parameters of F_1. Control charts are used for detecting changes in these unknown parameters. In our case the form of distributions F_0 and F_1 and parameters of F_0 are known in advance (can be estimated from statistical data) and the unknown parameter is the mean value of F_1. Therefore, the task is to detect change in the mean value of the SNR process resulting in following test

$$\begin{aligned} &H_0 : E[Y(i)] = \mu_0, \qquad i = 0, 1, \dots, k, \\ &H_1 : E[Y(i)] = \begin{cases} \mu_0, & i = 0, 1, \dots, k-1, \\ \mu_1, & i = k. \end{cases} \end{aligned} \tag{7}$$

where μ_0 and μ_1 are the mean values prior and after change, respectively.

The major problem of change-point statistical tests is that they often require observations to be realizations of independently and identically distributed random variables. However, SNR observations are not necessary independent but can be correlated. Autocorrelation makes classic control charts less sensitive to changes in the mean value. For detecting change in the mean of autocorrelated processes two approaches have been proposed. According to the first approach, control limits of charts are modified to take into account autocorrelation properties of observations. The idea of the second approach is to fit observations using a certain time-series model of autoregressive integrated moving average (ARIMA) type and subsequently control residuals. The shift in the mean value of observations is transferred to residuals that are monitored. If the model fits empirical data well, residuals are uncorrelated and control charts for independent observations can be used.

Performance of change-point statistical tests for autocorrelated data has been compared in [18]. It was shown that the residuals-based approach performs well when the autocorrelation is negative. When the autocorrelation is positive, modified control charts on initial observations perform better. This is mainly due to the fact that changes in the mean value of original observations are only partially transferred to residuals and the transfer of the change is different for positive and negative autocorrelations [1]. Due to these reasons, we use the first approach.

C. EWMA Control Charts

Let $\{Y(n), n = 0, 1, \dots\}$ be a sequence of SNR observations. The value of EWMA statistic at the time n, denoted by $L_Y(n)$, is given by

$$L_Y(n) = \gamma Y(n) + (1-\gamma) L_Y(n-1), \tag{8}$$

where parameter $\gamma \in (0, 1)$ is some constant.

The first value of EWMA statistics, $L_Y(0)$, is usually set to the mean of $\{Y(n), n = 0, 1, \dots\}$ or, if unknown, to the estimate of mean. As a result, for on-line real-time test there should always be a certain 'warm-up' period involving estimation of the mean.

In (8) $L_Y(n)$ extends its memory not only to the previous value but weights values of previous observations according to constant coefficient γ. In (8) this previous information is completely included in $L_Y(n-1)$. To show it, let us rewrite $\{L_Y(n), n = 0, 1, \dots\}$ statistics recursively, starting from $L_Y(0) = Y(0)$

$$\begin{aligned} &L_Y(0) = Y(0), \\ &L_Y(1) = \gamma Y(1) + (1-\gamma) Y(0), \\ &L_Y(2) = \gamma Y(2) + \gamma(1-\gamma) Y(1) + (1-\gamma)^2 Y(0), \\ &\dots. \end{aligned} \tag{9}$$

Since for any constant n the following holds

$$\gamma \sum_{i=0}^{n-1} (1-\gamma)^i + (1-\gamma)^n = 1, \tag{10}$$

it is easy to see that (9) converges to

$$L_Y(n) = \gamma \sum_{i=0}^{n-1} (1-\gamma)^i Y(n-i) + (1-\gamma)^n Y(0). \tag{11}$$

EWMA charts take central part among other control charts. Although, according to (8), the most recent value always receives more weight in computation of $L_Y(n)$, the choice of γ determines the effect of previous observations of the process on the current value of EWMA statistics. Indeed, when $\gamma \to 1$ all weight is placed on the current observation, $L_Y(n) \to Y(n)$, and EWMA statistics degenerate to initial observations. As a result, EWMA control chart behaves like Shewhart one. Contrarily, when $\gamma \to 0$ the current observation gets only a little weight, but most weight is assigned to previous observations. In this case, EWMA control chart behaves similar to CUSUM one. Summarizing, EWMA charts give more flexibility at the expense of additional complexity in determining one more parameter γ.

Assume now that given observations $\{Y(n), n = 0, 1, \dots, N\}$ are taken from strictly stationary process whose all sections are independently and identically distributed random variables with the same distribution, mean $E[Y]$ and variance $\sigma^2[Y]$. In fact, (8) defines a new stochastic process as a function of initial observations and this process has different statistical characteristics compared to those of $\{Y(n), n = 0, 1, \}$. Given that $L_Y(0) = E[Y]$, the mean of the process is

$$E[L_Y(n)] = E[Y](1 - (1-\gamma)^n) + (1-\gamma)^n E[Y], \tag{12}$$

that converges to constant $E[L_Y] = E[Y] = \mu_Y$ as $n \to \infty$.

The variance of $\{L_Y(n), n = 0, 1, \dots\}$ is given by

$$\sigma^2[L_Y] = \sigma^2[Y] \left(\frac{\gamma}{2-\gamma} \right) (1 - (1-\gamma)^{2n}). \tag{13}$$

Using (13) control limits for EWMA charts are computed as follows

$$E[Y] \pm k\sigma[Y]\sqrt{\left(\frac{\gamma}{2-\gamma}\right)(1-(1-\gamma)^{2n})}, \quad (14)$$

where k is a design parameter whose values are tabulated in the literature.

According to (14) out-of-control behavior is signaled when $L_Y(n)$ at some point in time is less than $(E[Y] - C(n))$ or greater than $(E[Y]+C(n))$. Note that in (14) upper and lower control limits are time-varying in nature. However, when $n \rightarrow \infty$ it is easy to see that

$$\lim_{n\rightarrow\infty}\left(\frac{\gamma}{2-\gamma}\right)(1-(1-\gamma)^{2n} = \frac{\gamma}{2-\gamma} \quad (15)$$

and constant control limits $E[Y] \pm k\sigma[Y]\sqrt{\frac{\gamma}{2-\gamma}}$ can be used.

Assume now that given SNR observations $\{Y(n), n = 0, 1, \dots, N\}$ are taken from covariance stationary process with mean $E[Y]$ and variance $\sigma^2[Y]$ and can be well represented by AR(1) process in the form $Y(n) = \phi_0 + \phi_1 Y(n-1) + \epsilon(n)$. If $L_Y(0) = E[Y]$, observing (12) it is easy to see that $E[L_Y] = E[Y] = \mu$ when $n \rightarrow \infty$. When $n \rightarrow \infty$ approximation for variance of $\{L_Y(n), n = 0, 1, \dots\}$ is given by [18]

$$\sigma^2[L_Y] = \sigma^2[Y]\left(\frac{\gamma}{2-\gamma}\right)\left(\frac{1+\phi_1(1-\gamma)}{1-\phi_1(1-\gamma)}\right), \quad (16)$$

where ϕ_1 is the parameter of AR(1) process.

Control limits are then given by

$$E[Y] \pm k\sigma[Y]\sqrt{\left(\frac{\gamma}{2-\gamma}\right)\left(\frac{1+\phi_1(1-\gamma)}{1-\phi_1(1-\gamma)}\right)}, \quad (17)$$

where k is a design parameter whose values are tabulated in the literature.

To parameterize EWMA control charts a number of parameters have to be provided. Firstly, parameter γ determining the decline of the weights of past observations should be set. The values of k and γ determine the wideness of control belts for a given process with a certain $\sigma^2[Y]$ and ϕ_1. These two parameters affect behavior of the so-called average run length (ARL) curve that is usually used to determine efficiency of a certain change detection procedure. ARL is defined as the average number of observations of in-control process up to the first out-of-control signal. The ARL is the function of both k and γ. Different parameters of k and γ for a given ARL, $\sigma^2[Y]$ and ϕ_1 are provided in [18], [19]. Finally, $E[Y]$ and $\sigma^2[Y]$ are not usually known in practice and must be estimated from empirical data. Therefore, estimates of $E[Y]$ and $\sigma^2[Y]$ should be used in (17).

VI. Numerical Results

A. Artificial Traces

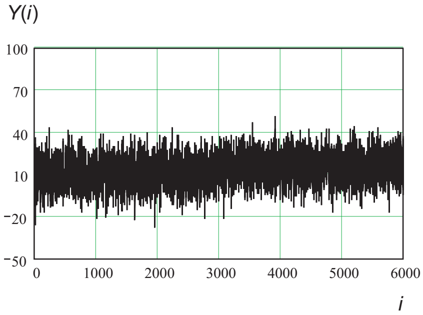
Firstly, let us consider performance of the change detection algorithm using artificial traces. Traces were generated as follows. First 3000 observations were generated according to AR(1) model with a certain mean μ_0. Next 3000 observations were generated according to AR(1) model with different mean μ_1. Variance, σ^2, and lag-1 autocorrelation coefficient, $K(1)$, were kept constant for each trace. Two subtraces were concatenated to obtain a single artificial trace. Using this algorithm we generated two artificial traces with the following parameters: $\mu_0 = 10$, $\mu_1 = 15$, $\sigma^2 = 10$, $K(1) = 0.0$ for trace 1 and $\mu_0 = 10$, $\mu_1 = 15$, $\sigma^2 = 10$, $K(1) = 0.4$ for trace 2. Time series of generated traces are shown in Fig. 5. One may observe that due to the same variance and lag-1 autocorrelation coefficients prior and after the change, the change in the mean value is almost not noticeable for both traces. To detect shifts in the mean value EWMA change-point statistical test was then applied to these traces.

Results of EWMA change-point statistical test for different parameters of γ are shown in Fig. 6. The warm-up period used to compute parameters of empirical observations was set to 50 observations. For all values of γ parameter k was set to 3. However, in general, usage of different values of γ requires different values of k to match a given ARL. Behavior of in-control ARL for our traces is shown in Fig. 7. Since ARL is also function of the variance and the mean value of observations, these curves are only suitable for presented observations. Note that $k = 3$, $\gamma = 0.01$ corresponds to 3326.68 in-control ARL for trace 1 and 1198.60 in-control ARL for trace 2. Parameters $k = 3$, $\gamma = 0.001$ corresponds to 5138.14 in-control ARL for the trace 1 and 3075.59 in-control ARL for trace 2. However, one can observe from Fig. 6 that changes in the average value of traffic observations are detected for all values of k and γ and no false alarms occurred.

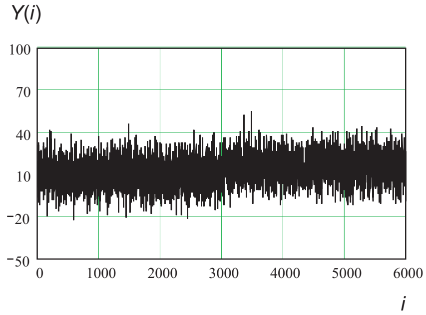
B. SNR Measurements

Let us now apply the proposed EWMA test to SNR observations. Two SNR traces were obtained as explained below. According to the course of the first experiment, the tester node was stationary at the reference point 1 (see Fig. 1) for approximately 30 minutes and then was moved to the reference point 2, where it was also stationary for a long time. The full time-series of SNR observations is shown in Fig. 8(a). One can see that the change in the mean value of SNR observations occurs around 1000th observation. According to the second experiment, the tester node was in the stationary position at the reference point 1 for approximately 40 minutes. Then, it was moved to the reference point 3 skipping the reference point 2. The node was then at the reference point 3 for a long period of time. The full time series of SNR observations is shown in Fig. 8(b). The change in the average value of SNR observations occurs around 1200th observation.

Results of EWMA change-point statistical test for trace 1 are shown in Fig. 9(a), Fig. 9(b). The warm-up period used to compute parameters of empirical observations was set to 50 SNR observations (25 seconds). Note that for all γ the parameter k was set to 3. It was found that usage of tabulated (theoretical, [19]) values of k and γ corresponding to relatively small values of in-control ARL (< 100) usually leads to many out-of-control signals even when the tester node is in the stationary state. One of the reasons is that the monitored process may not be exactly covariance stationary and may occasionally contain some extreme observations (outliers). These observations are of local significance only and may not affect the future evolution of the monitored process. Since the test is real-time in nature, each out-of-control signal starts a new warm-up period. During this period new average value and control limits are estimated and the process cannot be monitored. From this point of view we should detect only those changes that occur 'for sure'. During experiments, it was found that value $k = 3$ provides a good choice for any value of γ in the range $\gamma \in (0.001, 0.1)$. One can observe from the Fig. 9 that the change in the average value of SNR

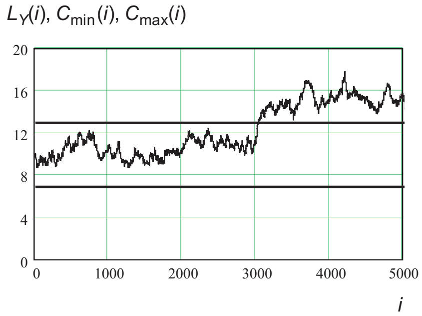


(a) Trace 1: $\mu_0 = 10$, $\mu_1 = 15$, $K(1) = 0.0$

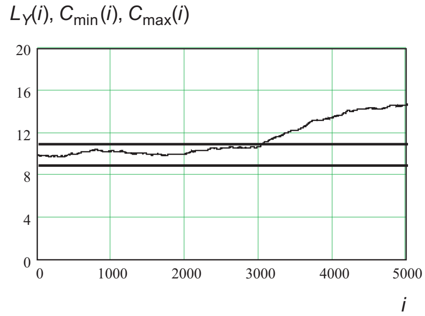


(b) Trace 2: $\mu_0 = 10$, $\mu_1 = 15$, $K(1) = 0.4$

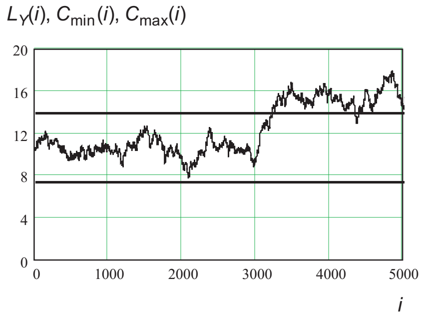
Fig. 5. Time series of artificially generated traces.



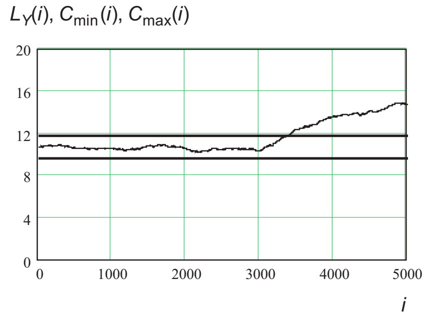
(a) Trace 1, $\gamma = 0.01$



(b) Trace 1, $\gamma = 0.001$

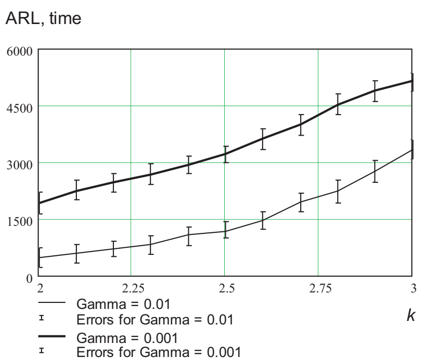


(c) Trace 2, $\gamma = 0.01$

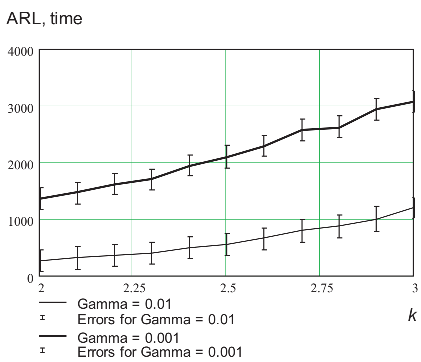


(d) Trace 2, $\gamma = 0.001$

Fig. 6. EWMA charts for generated traces.

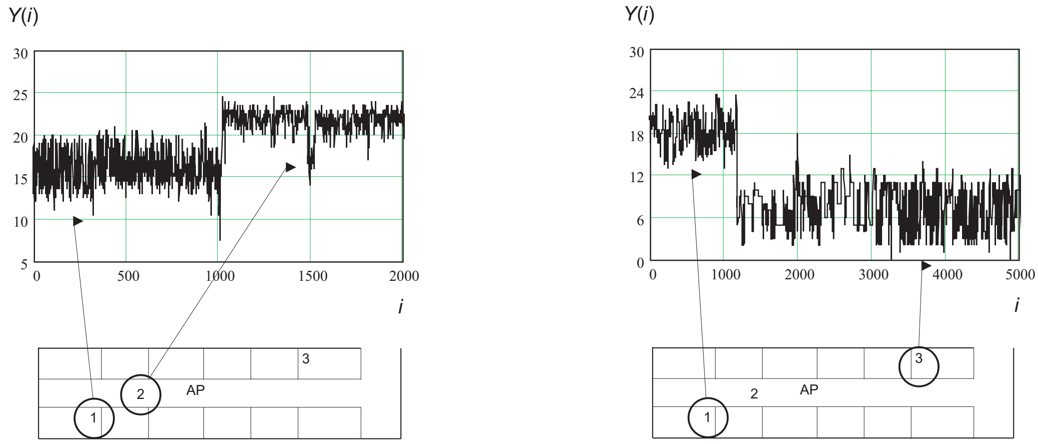


(a) Trace 1: $\mu_0 = 10$, $\sigma^2 = 10$, $K(1) = 0.0$



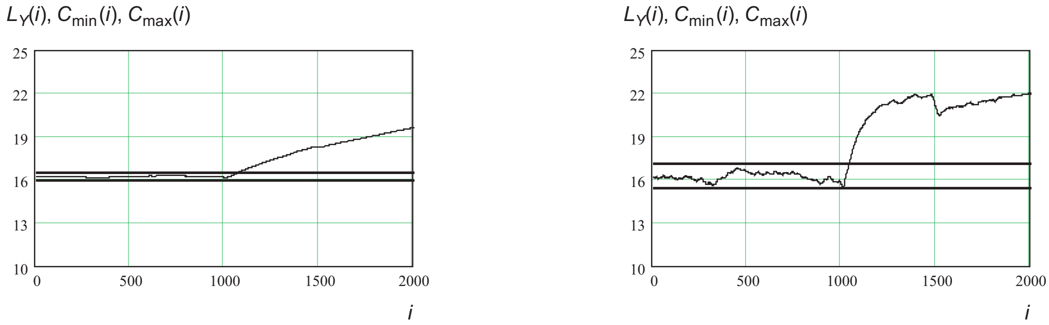
(b) Trace 2: $\mu_0 = 10$, $\sigma^2 = 10$, $K(1) = 0.2$

Fig. 7. In-control ARL curves for generated traces.



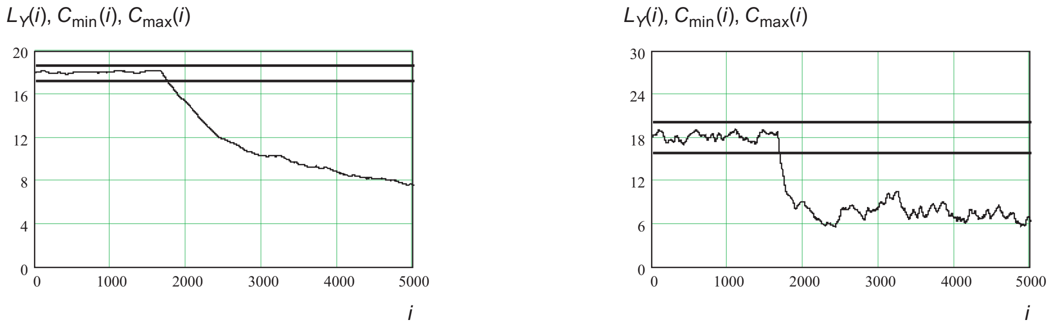
(a) Trace 1 (b) Trace 2

Fig. 8. Time series of SNR observations.



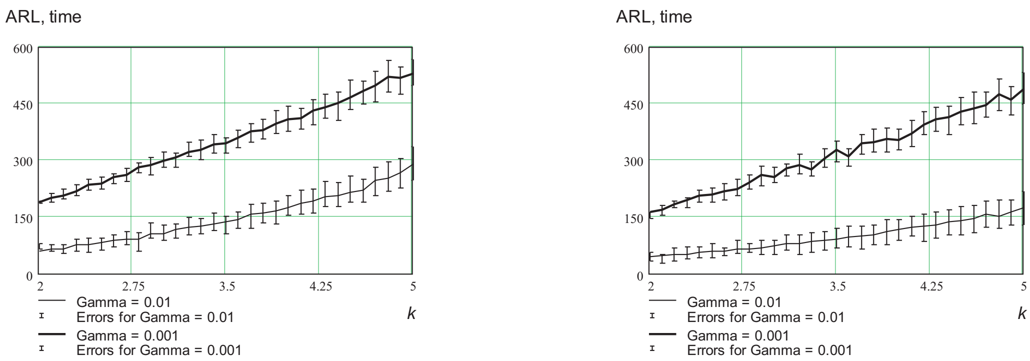
(a) EWMA chart, $\gamma = 0.001$ (b) EWMA chart, $\gamma = 0.01$

Fig. 9. SNR observations and EWMA chart for reference points 1 and 2.



(a) EWMA chart, $\gamma = 0.001$ (b) EWMA chart, $\gamma = 0.01$

Fig. 10. SNR observations and EWMA chart for reference points 1 and 3.



(a) Trace 1: $\mu = 16$, $\sigma = 5$, $K(1) = 0.65$ (b) Trace 2: $\mu = 24$, $\sigma = 13$, $K(1) = 0.81$

Fig. 11. In-control ARL curves for our measurements.

observations is successfully detected for all values of k and γ and no false alarms occurred.

Results of EWMA change-point statistical test for trace 2 are shown in Fig. 10(a), Fig. 10(b). For all values of γ parameter k was set to 3. The warm-up period was constant and set to 50 observations. One can observe from Fig. 10 that the change in the average value of SNR observations is successfully detected for all values of k and γ and no false alarms occurred. Behavior of in-control ARL for our traces and different values of γ and k is shown in Fig. 11.

VII. CONCLUSION

To discriminate the state of a wireless channel in terms of the covariance stationary SNR processes we proposed to use EWMA change-point statistical test. To represent SNR process when a mobile user is in the stationary state we use AR(1) model. EWMA test is applied to detect a point at which the mean value of the SNR process changes. Presented results demonstrate that the proposed test is able to quickly detect points at which change in the mean value of SNR observations occur. Although some modifications are required, we believe that the proposed approach can be also used for detecting changes in parameters of PDU error observations.

Possible applications of the proposed algorithm include real-time cross-layer parameters adaptation system, where the proposed test may signal points at which change in wireless channel statistics occur. In response to these signals, layers of the protocol stack of the wireless channel may perform appropriate actions including changes in the transmitted signal strength, error correction capability of the FEC code, type of the ARQ scheme, etc.

The choice of the smoothing parameter that affects wideness of control limits is still an open issue. Our experiments have shown that theoretically-computed parameters corresponding to relatively small values of in-control ARL may lead to many out-of-control signals. This is due to a number of reasons including imperfect modeling, inaccurate estimation of parameters, presence of outliers, etc. Optimal length of warm-up is another question that remains open. In this context, the aim of the future work is to optimize the proposed test for on-line implementation.

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