Detection under Noise Using Component Improvement Strategy

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Abstract Inaccuracy in signal detection due to presence of noise in signal is responsible for fading/interference, this noise needs to be reduced for optimal signal detection, and detection must be accurate enough to minimize the risk of false alarm. A noise reduction model was developed to improve signal detection using component improvement strategy. The system was implemented on MATLAB software package. It can be seen from the results that for a given probability of false alarm (P_{FA}), the detection performance increases monotonically with the ENR based on the balanced probability of not meeting target of 0.5. It can be generally concluded from the results of the study that signal detection could be fully enhanced with the application of six sigma component-based improvement system. This is an indication that component-based sigma improvement system played a significant role in signal detection performance.

Keywords Signal, Detection, Components, Improvement

1. Introduction

With a growing technology of mobile phones, people will always carry these devices anywhere and at anytime. Mobile phones, however, tend to cause interruptions because of the noise coming from the ringtone or the message tone that have been set by the users [1]. In some places such as prayer halls, library, meeting rooms, examination halls and hospitals, the use of hand phones is strictly forbidden because there is need to maintain silence [2]. Mobile phones need to transmit and receive the radio frequency (RF) signal in order to operate. This means there are possibility of jamming (make the system become stuck or in-operable) these RF signals in mobile phone in restricted areas. Jamming of communication signal is illegal in many countries, even when confined to privately owned spaces or secure facilities [3]. Shielding might be used to block RF signals from the required area, but

it is expensive and requires maintenance. It will also prevent user to use phone during emergency. The best way to monitor phone usage is to develop phone detectors that will not interfere or shield any active signal from the mobile phones of legitimate users, rather than to detect unauthorized phones usage and alert the people around. However, the signal detection must be accurate enough to minimize the risk of false alarm (FA) [4,5]. The cost of developing an accurate (robust) detector may be high as also the cost of missing a target [5,6]. The presence of noise in signal is responsible for fading/interference [7, 8] and inaccuracy in signal detection [9-11]. This noise needs to be reduced for optimal signal detection [10, 12, 13]. However, there is a need to establish a balance between improved signals and noise reduction systems such that the cost of detection and risk of missing the target will be carried out at a minimum possible cost. These include detection-interpolation scheme [13], penalty function technique [14], minimax noise variance estimation [15], performance improved nonlinear detector of spread spectrum receiver [16], nonparametric dynamic model for monitoring changes in signal detection performance [17], synthetic antenna array concept for signal detection enhancement [18], algorithm based on sparsity hypotheses [19], successive interference cancellation architecture and channel decoding to treat the co-channel interference [20], Dynamic Spectrum Access (DSA,) [21], and orthogonal frequency division multiplexing scheme for fading/interference mitigation [7,8]. Apart from Broumandan [18] that carried out research on enhancement of signal detection using synthetic antenna array concept, scanty studies were identified in applying the component-based circuitry for the enhancement of signal detection. However, there is need to reduce false alarm which are mostly caused by noises. Increased false alarm may be dangerous in the security settings. In this study, a noise reduction model was developed to improve signal detection by reducing false alarm using component improvement strategy. Sigma-based component improvement strategy is scanty utilized in detection improvement modeling in the modern time. The utilization

of the strategy in this study will determine how promising the system would be in the field of signal detection improvement and also how effective can it be in reducing the effects of noises on the signal detectability of a detector.

2. Materials and Methods

Detection performance of the detector was affected by both internal noises (noise in circuit components) and external noises (noises due to environmental conditions, which are, humidity, temperature, barriers, etc.) presence of noise in signal is responsible for fading/interference. All these lead to inaccuracy in signal detection. The stated noises have ability to influence detection performance in two principal ways: detector detected signal and it was true detection, P_D ; and detector detected signal and it was false detection, P_{FA} .

Meanwhile, detection circuitry reported by Nicholas [22] with deficiencies of low coverage, weak detection and

accuracy modeling is shown in Fig. 1. In Fig. 2, the improved detector by Lawal [23] is given to include buzzer and microcontroller circuitries. The latter showed an improvement in terms of detection coverage and lead time but deficient in detection ability modeling.

Figure 1. Detector Circuitry

Figure 2. Detector Circuit with Buzzer and Microcontroller

Figure 3. Decision Region and Probability

2.1. Modeling of Signal Detection

In cell-phone signal detection system, certain parameter range is looked into; on which trial is made in deciding whether a target (signal) is present, H_1 or target (signal) is absent H_0 . Each hypothesis maps into a point in the observation space corresponding to a set of N observations: $r_1, r_2, r_3, \dots, r_N$, and can be expressed in vector form r [5].

The two known conditional probability densities $[P(r/H_1)]$ and $[P(r/H_0)]$, are the probabilistic transition mechanism points generators. They are used to develop decision rules or hypothesis, either H_0 or H_1 (Fig. 3). Therefore, each time the experiment is conducted one of four scenarios can happen:

$P(H_0 : H_0) = \text{Prob. (decide } H_0 \text{ when } H_0 \text{ is true), Prob. of correct non-detection}$

$P(H_0 : H_1) = \text{Prob. (decide } H_0 \text{ when } H_1 \text{ is true), Prob. of missed detection } P_M$

$P(H_1 : H_1) = \text{Prob. (decide } H_1 \text{ when } H_1 \text{ is true), Prob. of detection } P_D$

$P(H_1 : H_0) = \text{Prob. (decide } H_1 \text{ when } H_0 \text{ is true), Prob. of false alarm } P_{FA}$

From the stated scenarios, the first and third alternatives correspond to correct choices, while the second and fourth alternatives correspond to errors. The method of processing received data r depends on the selected decision criterion.

In this study, the two criteria of interest, P_D and P_{FA} , were utilized on using Bayes' and/or Neyman-Pearson (NP) approaches. The primary approaches to simple hypothesis testing are classical, based on Neyman-Pearson theorem [4], and Bayesian, based on minimization of Bayes risk [4-6,12]. Based on the selected criteria nature of the cell-phone signal detector, modified Neyman-Person criterion based on Bayes' risk was utilized to optimize signal detection system.

In Neyman-Pearson (NP) approach to cell-phone signal detection, the realization of a random variable whose

probability density function (PDF) is either $N(0,1)$ or $N(1,1)$ is observed when the detector is on test. The notation $N(\mu, \sigma^2)$ denotes a Gaussian PDF with mean μ and variance σ^2 . For a sustainable hypothesis testing on μ then the problem is to choose between two competing hypotheses expressed as follows [4]:

$$H_1: \mu=1, H_0: \mu=0 \quad (1)$$

Where H_0 is referred to as the null hypothesis and H_1 as the alternative hypothesis. The PDFs under each hypothesis with the difference in means may cause the PDF under H_1 to be shifted to the right. A reasonable approach might then be to decide H_1 if $x[0] > 1/2$. This is because if $x[0] > 1/2$, the observed sample is more likely if H_1 is true, or if $x[0] > 1/2$. This is equivalent (as given in Figure 3) to:

$$p(x[0]; H_1) > p(x[0]; H_0)$$

Then detector compares the observed datum value with $1/2$, the latter called the threshold.

With this scheme, two types of errors can be identified. If H_1 is decided but H_0 is true, that is a Type I error. On the other hand, if H_0 decided but H_1 is true, then a Type II error is made. The errors, $P(H_i; H_j)$ indicates the probability of deciding H_i when H_j is true. Then,

$$P(H_1; H_0) = \Pr\{x[0] > 1/2; H_0\}$$

These two errors are unavoidable to some extent but may be traded off against each other. The Type I error probability $P(H_1; H_0)$ is decreased at the expense of increasing the Type II error probability $P(H_0; H_1)$. It is not possible to reduce both error probabilities simultaneously. A typical approach then in designing an optimal detector is to hold one error probability fixed while minimizing the other (Figure 3). Let choose to constrain $P(H_1; H_0)$ to fixed value, say α . The problem of Eq. 1 can be viewed as an attempt to distinguish between the hypotheses:

$$H_0: x[0] = w[0], H_1: x[0] = s[0] + w[0]$$

Where $s[0] = 1$ and $w[0] \sim N(0,1)$, then the signal detection problem arise. Deciding H_1 when H_0 is true can be thought of as a false alarm. As a result, $P(H_1; H_0)$ is referred to as the probability of false alarm and is denoted by P_{FA} . To design the optimal detector there is need to

minimize the other error $P(H_0; H_1)$ or equivalently to maximize $1 - P(H_0; H_1)$. The latter is $P(H_1; H_1)$ and in keeping with the signal, detection problem is called the probability of detection, denoted by P_D . This setup is termed the Neyman-Pearson (NP) approach to hypothesis testing or to signal detection. The objective function is to maximize $P_D = P(H_1; H_1)$ subject to the constraint $P_{FA} = P(H_1; H_0) = \alpha$. Based on the stated illustration P_{FA} can be constrained by choosing the threshold γ since

$$\begin{aligned} P_{FA} &= P(H_1; H_0) \\ &= \Pr\{x[0] > \gamma; H_0\} \\ &= \int_{\gamma}^{\infty} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}t^2\right) dt \\ &= Q(\gamma) \end{aligned}$$

Meanwhile, the goal of a detector is to decide either H_0 or H_1 based on an observed set of data $\{x[0], x[1], \dots, x[N-1]\}$. Let R_1 be the set of values in R^N that map into the decision H_1 or $R_1 = \{x : \text{decide } H_1 \text{ or } H_0\}$.

The set of points in R^N that map into the decision H_0 is the complement set of

$$R_1 \text{ or } R_0 = \{x : \text{decide } H_0 \text{ or } H_1\}.$$

Clearly, $R_0 \cup R_1 = R^N$ since R_0 and R_1 partition the data space. The P_{FA} constraint then becomes

$$P_{FA} = \int_{R_1} p(x; H_0) dx = \alpha \quad (2)$$

Now there are many sets R_1 that satisfy Eq. 2, the goal is to choose the one that maximizes

$$P_D = \int_{R_1} p(x; H_1) dx. \quad (3)$$

The NP theorem indicates how to choose R_1 for a given $p(x; H_0)$, $p(x; H_1)$, and α [4], Neyman-Pearson, NP theorem maximize P_D for a given $P_{FA} = \alpha$.

Then decide H_1 if

$$L(x) = \frac{p(x; H_1)}{p(x; H_0)} > \gamma \quad (4)$$

Where the threshold γ is found

$$\int_{\{x: L(x) > \gamma\}} p(x; H_0) dx = \alpha$$

As stated earlier, internal and external noises have effects on the probability of signal detection. With special attention to internal noises-White Gaussian Noise (WGN), then general signal detection problem becomes:

$$H_0 : x[n] = w[n] \quad n = 0, 1, \dots, N-1$$

$$H_1 : x[n] = A + w[n] \quad n = 0, 1, \dots, N-1$$

Where the signal is $s[n] = A$ for $A > 0$ $w[n]$ is WGN with variance σ^2 . The previous illustration (Eqs. 2-4) is a special case where $A = 1$, $N = 1$, and $\sigma^2 = 1$. The current problem is a test of means of a multivariate Gaussian PDF. This is because:

$$\text{under } H_0, x \sim N(0, \sigma^2 I), \text{ while}$$

$$\text{under } H_1, x \sim N(A, \sigma^2 I),$$

where $\mathbf{1}$ is the vector of all ones. Hence, equivalently,

$$H_0 : \mu = 0,$$

$$H_1 : \mu = A\mathbf{1}.$$

This parameter test of the PDF interpretation is used in describing the signal detection problem. Then the signal detector decides H_1 if

$$\frac{\frac{1}{N} \exp\left[-\frac{1}{2\sigma^2} \sum_{n=0}^{N-1} (x[n] - A)^2\right]}{(2\pi\sigma^2)^{\frac{N}{2}}} > \gamma \cdot \frac{1}{\frac{1}{N} \exp\left[-\frac{1}{2\sigma^2} \sum_{n=0}^{N-1} x^2[n]\right]}$$

This is similar to Eq. (4).

Taking logarithm of both sides results in

$$-\frac{1}{2\sigma^2} \left(-2A \sum_{n=0}^{N-1} x[n] + NA^2 \right) > \ln \gamma$$

This simplifies to

$$\frac{A}{\sigma^2} \sum_{n=0}^{N-1} x[n] > \ln \gamma + \frac{NA^2}{2\sigma^2}.$$

Since, $A > 0$, then

$$\frac{1}{N} \sum_{n=0}^{N-1} x[n] > \frac{\sigma^2}{NA} \ln \gamma + \frac{A}{2} = \gamma'. \quad (5)$$

The signal based NP detector compares the sample mean $\bar{x} = (1/N) \sum_{n=0}^{N-1} x[n]$ to a threshold γ' [25]. This is

intuitively reasonable since $\bar{x}$ was thought of as an estimate of A. If the estimate is large and positive, then the signal is probably present. How large the estimate must be before willing to declare that a signal is present depends upon concerns that noise only may cause a large estimate [26].

Therefore noises can be reduced by adjusting γ' with larger threshold values to control P_{FA} , thereby increasing P_D .

The detection performance was tested using the statistic:

$$T(x) = 1/N \sum_{n=0}^{N-1} x[n]$$

The means and variances are [4,5]:

$$\begin{aligned} E(T(x); H_0) &= E\left(\frac{1}{N} \sum_{n=0}^{N-1} w[n]\right) \\ &= \left(\frac{1}{N} \sum_{n=0}^{N-1} E(w[n])\right) \\ &= 0. \end{aligned}$$

Similarly, $E(T(x); H_1) = A$ and

$$\begin{aligned} \text{Var}(T(x); H_0) &= \text{var}\left(\frac{1}{N} \sum_{n=0}^{N-1} w[n]\right) \\ &= \left(\frac{1}{N^2} \sum_{n=0}^{N-1} \text{var}(w[n])\right) \\ &= \frac{\sigma^2}{N} \end{aligned}$$

Similarly, $\text{Var}(T(x); H_1) = \frac{\sigma^2}{N}$

This expressed uncorrelated noise samples. Thus,

$$T(x) \sim \begin{cases} N(0, \frac{\sigma^2}{N}), \text{under } H_0 \\ N(A, \frac{\sigma^2}{N}), \text{under } H_1 \end{cases}$$

We have then

$$\begin{aligned} P_{FA} &= \Pr\{T(x) > \gamma'; H_0\} \\ &= Q\left(\frac{\gamma'}{\sqrt{\sigma^2/N}}\right) \end{aligned} \quad (6)$$

and

$$\begin{aligned} P_D &= \Pr\{T(x) > \gamma'; H_1\} \\ &= Q\left(\frac{\gamma' - A}{\sqrt{\sigma^2/N}}\right) \end{aligned} \quad (7)$$

P_D can be related directly to P_{FA} by noting that the Q function is monotonically decreasing since $1 - Q$ is a CDF, which is monotonically increasing. Thus, Q has an inverse denoted as Q^{-1} . As a result, the threshold was found from Eq. (5) as [4,5],

$$\gamma' = \sqrt{\frac{\sigma^2}{N}} Q^{-1}(P_{FA})$$

$Q(x)$ is the probability of exceeding a given value (target) as:

$$Q(x) = \int_x^\infty \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}t^2\right) dt$$

From which,

$$Q(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}x^2\right) dx$$

Then inverse, complementary Cumulative Distribution Function (CDF);

$$Q(x)^{-1} = \int_{-\infty}^x \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}t^2\right) dt$$

and

$$\begin{aligned} P_D &= Q\left(\frac{\sqrt{\sigma^2/N} Q^{-1}(P_{FA}) - A}{\sqrt{\sigma^2/N}}\right) \\ &= Q\left(Q^{-1}(P_{FA}) - \sqrt{\frac{NA^2}{\sigma^2}}\right). \end{aligned} \quad (8)$$

It is seen that for a given P_{FA} the detection performance would increase monotonically with NA^2/σ^2 , which is the signal energy-to-noise ratio (ENR) [4,5]. Based on hypothesis test, it was observed that the value of a test statistic T while decide H_1 if $T > \gamma'$ and H_0 otherwise is expressed as:

$$T \sim \begin{cases} N(\mu_0, \frac{\sigma^2}{N}), \text{under } H_0 \\ N(\mu_1, \frac{\sigma^2}{N}), \text{under } H_1 \end{cases}$$

where, $\mu_1 > \mu_0$

hence, we wish to decide between the two hypotheses that differ by a shift in the means of T .

However, if $T = \bar{x}$, then detection performance is characterized by the deflection coefficient d^2 [4].

This is defined as

$$\begin{aligned} d^2 &= \frac{(E(T; H_1) - E(T; H_0))^2}{\text{var}(T; H_0)} \\ &= \frac{(\mu_1 - \mu_0)^2}{\sigma^2} \end{aligned} \quad (9)$$

In the case $\mu_0 = 0$, $d^2 = \mu_1^2 / \sigma^2$ is interpreted as a signal-to-noise ratio (SNR). The dependence of detection performance on d^2 was verified by

$$\begin{aligned} P_{FA} &= \Pr\{T > \gamma'; H_0\} \\ &= Q\left(\frac{\gamma' - \mu_0}{\sigma}\right) \\ P_D &= \Pr\{T > \gamma'; H_1\} \end{aligned}$$

$$\begin{aligned}
 &= Q\left(\frac{\gamma' - \mu_h}{\sigma}\right) \\
 &= Q\left(\frac{\mu_0 + \sigma Q^{-1}(P_{FA}) - \mu_h}{\sigma}\right) \\
 &= Q\left(Q^{-1}(P_{FA}) - \left(\frac{\mu_h - \mu_0}{\sigma}\right)\right)
 \end{aligned}$$

And using Eq. (9), we have

$$P_D = Q\left(Q^{-1}(P_{FA}) - \sqrt{d^2}\right) \quad (10)$$

Since, $\mu_1 > \mu_0$, the detection performance is monotonic with the deflection coefficient:

$$d^2 = NA^2 / \sigma^2$$

Each point on the curve corresponds to a value of (P_{FA}, P_D) for a given threshold γ' . If γ' increases, P_{FA}

decreases but P_D increases. This performance is summarily called the Receiver Operating Characteristics (ROC). The ROC adequately supported the detection probability relations:

$$P_{FA} = P_r\{\text{detect}, H_0\}$$

$$P_D = P_r\{\text{detect}, H_1\}$$

Alternative way we used to summarize signal detection performance is by plotting P_D against P_{FA} .

The improvement on probabilities of signal detection P_D was further achieved by utilizing Total Quality Instrumentation Management (TQIM) on the components responsible for signal detection, which are capacitors, transistors, resistors, antennae, etc. (Fig. 2). Improvement strategies based on one-, two-, three-, four-, five-, or six-quality sigmas (δ) were utilized on the components together [24]. With the new arrangement, eqn. (10) then becomes:

$$P_D = Q\left(Q^{-1}(P_{FA} \delta) - \sqrt{d^2}\right) \quad (11)$$

The signal detection improving sigma (δ) was capable of reducing probabilities of false alarms by removing noises in the system. There is need to test the efficacy of this model by experimenting a detection system. The analysis based on alternative way of determining signal detection performance by plotting P_D against P_{FA} was utilized in this study.

2.2. Model Testing

Information on cell-phone signal detector of the type shown in Fig. 2 was used. The experimental data obtained were hypothetically presented based on general detector behaviours with probabilities of false alarm ranging from 0 to 1. This indicated that when false alarm is 0, there is full (accurate) signal detection and if false alarm is 1, then detector is not functioning well. Accuracy of detection was improved upon by reducing false alarm through gradual removal of noises. Reduction of false alarms was carried out

by introducing component based sigma improvement strategies varied from one (1) to six (6) sigma under homogeneous behaviour of the system. In this arrangement, the range 0.69 to 0.0000034 would have reduced circuitry system failure probabilities [24]. The probability of exceeding the given value (target) $Q(x)$ was also assumed a failure range, 0 – 1. The distance (d) between means of the two densities of hypothesis (H_0, H_1) was taken in the range 0.5 to 2.0 in step of 0.5. Analysis of the optimized detection system was carried out on MATLAB computer software to determine the effect of sigma improvement system on the signal detection performance. The detection results generated based on stated variation of input parameters are presented in Figs. 4-10 for detection performance probabilities.

3. Results and Discussion

The results based on balanced probability of not exceeding the target of 0.5 were generated to illustrate performance of the system in terms of signal detection enhancement ability of the system with the deployment of signal sigma circuitry systems as improvement tools. Fig. 4 shows probability level of signal detection improvement with change in difference between the means of signal present and signal absent scenarios, at the probability of not exceeding the target (0.5). It can be seen from the stated results (Fig. 4) that for a given probability of false alarm (P_{FA}), the detection performance increases monotonically with the ENR. The results of the experiment indicated a conformance with the outcomes of previous studies [4,5].

Figure 4. Detection without Sigma Improvement System

Figs. 4-10 revealed detection outcomes when component based sigma improvement circuitry was imposed on the system. The results obtained when detection system was treated with component-based improvement system based on single sigma (Fig. 5) indicated a slightly improved signal detection probability over untreated results given in Fig. 4 which served as control.

Figure 5. Detection with One-Sigma Improvement System

Figure 6. Detection with Two-Sigma Improvement System

Figure 7. Detection with Three-Sigma Improvement System

Figure 8. Detection with Four-Sigma Improvement System

Figure 9. Detection with Five-Sigma Improvement System

Figure 10. Detection with Six-Sigma Improvement System

Steadily and more satisfactorily improved signal detection performance was noticed and demonstrated by considerably monotonically increase in signal strength as the system was moving from two sigma (Fig. 6), three sigma (Fig. 7), four sigma (Fig. 8), five sigma (Fig. 9) to six sigma (Fig. 10). The outcomes generally revealed that signal detection could be fully improved with the application of six-sigma component-based improvement system.

4. Conclusions

The presence of noise in signal is responsible for fading/interference and inability to detect the signal accurately. The noise needs to be reduced for optimal signal detection. Detection must be accurate enough to minimize the risk of false alarm. A noise reduction model was developed to improve signal detection using component improvement strategy. The system was implemented on MATLAB software package. The detection circuit was developed to take care of deficiencies in the previous detection circuitries in the area of signal detection strength/probability through incorporation of component-based sigma improvement system. Signal detection strength modeling was developed using the improvement system under noises. Noises are classified as internal and external noises. Internal or thermal noises due to components' temperature were considered in the study. Two methods of noise reduction were utilized, namely Gaussian mean-shifts of the hypothesized data and components' sigma quality-based improvement strategy. It can be generally concluded from the results of the study that: though the hypothesized Gaussian mean-shifts brought improvement in signal detection by reducing noises in the system, but there was better improvement in signal detection with the application of components' six sigma quality strategy. The deployment of six sigma system may demand high quality component-based circuitry. One cannot conclude yet on the strength of signal detection until thorough analysis of the components quality is carried out. Therefore, determination of signal detection strength would demand balancing the cost of component quality with strength of signal being detected. Detection accuracy based on signal strength improvement through component quality cost could be a good research area in future.

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