Spectrum Sensing for Cognitive Radio using Multicoset Sampling

Babar Aziz*, Samba Traoré†, Amor Nafkha*, and Daniel Le Guennec* †

*IFSTTAR, LEOST, F-59650 Villeneuve d’Ascq, France
†SUPELEC/IEITR, Campus de Rennes, Avenue de la Boulaiac - CS 47601, F-35576 Cesson-Sévigné cedex, France
babar.aziz@ifsttar.fr, samba.traore@supelec.fr, amor.nafkha@supelec.fr,daniel.leguennec@supelec.fr

Abstract—Spectrum sensing is the very task upon which the entire operation of Cognitive Radio rests. In this paper, we propose a spectrum sensing technique based on the estimates of the spectrum of a multiband signal obtained from its non-uniform compressed multicoset samples. We show that our proposed spectrum sensing method provides accurate results using less data samples. We discuss in detail the effect of false detections on the quality of the reconstructed signal obtained from non-uniform multicoset samples.

Keywords—Non-uniform sub-Nyquist sampling, Multicoset sampling, Cognitive radio, Spectrum sensing.

I. INTRODUCTION

The available electromagnetic radio spectrum is a precious but limited natural resource. Due to this current static licensing approach of spectrum, spectrum holes or spectrum opportunities arise. Cognitive Radio (CR), a new way of looking at wireless communications, has the potential to become the solution to the spectrum under utilization problem, by allowing unlicensed users to access these spectrum holes for transmission [1]. The first cognitive task is to develop wireless spectral detection and estimation techniques for sensing the available spectrum. Spectrum sensing can be defined as the task of detecting the presence or absence of a signal by sensing the radio spectrum. Some popular spectrum sensing techniques are energy detection, matched filter and cyclostationary feature detection that have been proposed for narrow band sensing [2]. All these techniques function by filtering the received signal with narrowband band-pass filters and then sample it uniformly at the Nyquist rate. In these approaches to spectrum sensing, the detection process boils down to a binary hypothesis-testing problem i.e. to detect presence (H1) or absence (H0) of a primary user in the considered band.

It is well known that with the advances in wireless communications, future cognitive radios should be capable of scanning a wideband of frequencies, in the order of few GHz. The usual sampling of a wideband signal needs high sampling rate ADCs, which need to operate at or above the Nyquist rate. The above mentioned spectrum sensing techniques have their respective advantages and disadvantages over one another. But a common drawback is that they operate at Nyquist sampling rate. Since, sampling a wideband at Nyquist rate followed a common drawback is that they operate at Nyquist sampling rate. In these approaches to spectrum sensing, the detection process boils down to a binary hypothesis-testing problem i.e. to detect presence (H1) or absence (H0) of a primary user in the considered band.

To overcome this problem, solutions based on compressive sampling have been proposed in [3]–[5]. In [3], the signal is detected from the estimated spectrum obtained from the compressed samples of the signal. However, spectrum estimation of a signal from its compressed samples is achieved by solving an optimization problem, which is not an easy task. Using the fact that the wireless signals in open-spectrum networks are typically sparse in the frequency domain, in [5], a sensing method based on MUSIC algorithm has been proposed. Authors in [5] claim that the proposed method would bring substantial saving in terms of the sampling rate. However, the performance of the proposed method degrades at low SNRs and also requires more data samples to correctly detect the signal.

In this paper, based on the sparsity of the multiband signals in frequency domain and using non-uniform sub-Nyquist Multicoset sampling of the input signal, we propose a wideband spectrum sensing method for the detection of active bands that would bring substantial saving in terms of the sampling rate. The performance of the proposed method is examined at low SNR values with less data samples and is found to produce accurate results. The impact of the false-detections of the proposed sensing method on the reconstructed signal is also analyzed. The remainder of the paper is organized as follows. In Section II the signal model and problem statement. In Section III, an overview of multicoset sampler is given and the proposed non-uniform spectrum sensing method is presented in Section IV. Numerical results are presented in Section V followed by the empirical evaluation of threshold in Section VI. The impact of the proposed method on the multicoset sampler is discussed in Section VII followed by conclusion in Section VIII.

II. SIGNAL MODEL AND PROBLEM STATEMENT

Let \( x(t) \) be a real valued, finite-energy, continuous-time signal and let \( X(f) = \int_{-\infty}^{\infty} x(t) e^{-j2\pi ft} dt \) be its Fourier transform. We treat a multiband signal model \( M \) in which \( x(t) \) is bandlimited to \( B = [-f_{Nyq}/2, f_{Nyq}/2] \). \( F \) represents the spectral support of the signal \( x(t) \) such that \( F \subset B \). \( F \) consists of at most \( N_B \) frequency intervals (bands) whose widths. Multicoset sampling starts by dividing the entire frequency band into \( L \) narrowband cells, each of them with bandwidth \( B \), such that \( f_{Nyq} = L \times B \) [6]–[8]. These cells are indexed from 0 to \( L-1 \), see Figure 1. The spectral cells which contain part of the signal spectrum are called active cells. The indexes of the active cells are collected into a set \( K \) called the active cells set \( K = \{k_j\}_{j=1}^{q} \) where \( q = \left| K \right| \) is the cardinality operator. For the particular band shown in Figure 1, the set of active cells indexes is \( K = \{k_1, k_2, ..., k_{12}\} = \{1, 2, 4, 5, 8, 9, 10, 11, 14, 15, 17, 18\} \) with \( q = 12 \) and \( N_B = 6 \).

To recover Nyquist rate samples of the received signal from sub-Nyquist Multicoset samples, the knowledge of the number of bands \( N_B \) and \( K \) is of paramount importance [6]. These parameters are indispensable to reconstruct the time domain signal but are unknown to the system. Therefore, based on this
Given the observation band, the objective is to correctly detect the active cells set \( K \) for optimal reconstruction of the non-uniformly sub-Nyquist sampled signal \( x(t) \) and to analyze the impact of false detections of \( K \) on the averaging sampling rate of the system.

\[
\text{Given the observation band, } B = [-\frac{f_{Nyquist}}{2}, \frac{f_{Nyquist}}{2}], \text{ the objective is to correctly detect the active cells set } K \text{ for optimal reconstruction of the non-uniformly sub-Nyquist sampled signal } x(t) \text{ and to analyze the impact of false detections of } K \text{ on the averaging sampling rate of the system.}
\]

III. Multicoset Sampler

A complete block diagram of a Multicoset sampler along with the proposed non-uniform spectrum sensing scheme is shown in Figure 2. The received analog signal is sampled by the multicoset sampler at a rate lower than the Nyquist sampling rate. The multicoset samples are then sent to the non-uniform spectrum sensing block. The non-uniform sensing block performs spectrum detection and computes the parameters \( N_B \) and \( K \) required for signal reconstruction in the reconstruction block.

In this paper, our objective is to study the performance of the proposed non-uniform sensing method. Therefore, we give an overview of the multicoset sampling scheme. Multicoset sampling is a periodic non-uniform sampling technique which samples the input signal \( x(t) \) at a rate lower than the Nyquist rate, thereby capturing only the amount of information required for an accurate reconstruction of the signal. Multicoset sampling starts by choosing an appropriate sampling period \( T \), less than or equal to the Nyquist period associated to \( x(t) \). Then the input signal \( x(t) \) is non-uniformly sampled at \( t_i(n) = (nL + c_i)T \), where \( 1 \leq i \leq p \) and \( n \in \mathbb{Z} \) [9]. The set \( C = \{c_i\} \) contains \( p \) distinct integers from \( \{0, 1, \cdots, L-1\} \) and is termed as the sampling pattern. The parameters \( L \) and \( p \) are selected such that \( L \geq p > 0 \). The process of multicoset sampling can be viewed as first sampling the input signal at a uniform rate with period \( T \) and then selecting only \( p \) non-uniform samples from \( L \) equidistant, uniform samples (see Figure 3). The process is repeated for consecutive segments having \( L \) uniform samples each such that the \( p \) selected samples have a sampling period \( L \). The set \( C \) specifies the \( p \) samples that are retained in each segment of length \( L \) such that \( 0 \leq c_i < c_2 < \cdots < c_p \leq L - 1 \). Multicoset sampler is usually implemented by placing \( p \) ADCs in parallel [10]. Each ADC operates uniformly at a period \( T_s = LT \). The multicoset sampler, therefore, provides \( p \) data sequences for \( i = 1, \ldots, p \), given by

\[
x_i = x(nL + c_i)T = (n + \frac{c_i}{L})T_s \tag{1}
\]

where \( 1 \leq i \leq p \). The average sampling rate of this scheme is \( f_{avg} = \alpha f_{Nyquist} \), where \( \alpha = \frac{p}{L} \). In order to perform recovery the signal \( x(t) \) sampled at sub-Nyquist rate, \( N_B \) and \( K \) must be known to the reconstruction block [6].

IV. Proposed Non-uniform Spectrum Sensing Model

In this section we discuss our proposed Non-Uniform Spectrum Sensing Block (NUSS) (shown in dotted block in Figure 2) to compute the parameters \( N_B \) and \( K \) to allow successful reconstruction of \( x(t) \). The function of each sub block is explained in the subsections to follow.

A. Non-uniform spectrum estimation block

As stated in Section II, our objective is to detect the total number of bands \( N_B \) and the set of active cells \( K \). Since, the input signal \( x(t) \) is under sampled and the samples are not evenly spaced, the usual spectrum sensing techniques like FFT based energy detection and cyclostationarity cannot be used [2]. In order to overcome this hurdle, we treat this scenario as a missing data problem and in this paper we propose to use the Lomb-Scargle method [11] to estimate the power spectral density (PSD) of the non-uniformly sampled signal. Then in the remaining sub blocks of the sensing model, \( N_B \) and \( K \) are computed from this estimated PSD. The Lomb-Scargle periodogram is a well known tool to detect if an unevenly spaced data is due to noise or it contains also the contribution of a signal by providing an estimate of the PSD.
Lomb-Scargle method evaluates the samples, only at times \( t_n \) that are actually measured. Suppose that there are \( N_s \) samples \( x(t_n) \), \( n = 1, ..., N_s \). The PSD estimate obtained from Lomb-Scargle method is defined by (2) (spectral power as a function of angular frequency \( \omega = 2\pi f > 0 \) with \( f \in B = [-\frac{\text{Nyq}}{2}, \frac{\text{Nyq}}{2}] \)).

\[
\hat{\gamma}(\omega) = \frac{1}{2\sigma^2} \left[ \frac{1}{\sum_i \cos^2 \omega (t_i - \delta)} \sum_i (x_i - \bar{x}) \cos \omega (t_i - \delta) \right]^2 + \frac{1}{2\sigma^2} \left[ \frac{1}{\sum_i \sin^2 \omega (t_i - \delta)} \sum_i (x_i - \bar{x}) \sin \omega (t_i - \delta) \right]^2
\]

where \( \bar{x} \) and \( \sigma^2 \) represent the mean and variance of the samples. More detail on Lomb-Scargle method can be found in [11].

B. Moving average filter block

It is observed that the PSD estimate \( \hat{\gamma} \) obtained from the Lomb-Scargle method has a high variance. As a result of which \( N_B \) and \( K \) are not easy to detect if the PSD estimates are used in their original form. Therefore, we use a moving average filter to smoothen the \( \hat{\gamma} \) obtained from the non-uniform sampled data. The moving average filter smooths the incoming \( \hat{\gamma} \) by replacing each data point with the average of the neighboring data points defined within a specified span. This process is equivalent to lowpass filtering with the response of the smoothing given by the difference equation

\[
\hat{\gamma}_s(f) = \frac{1}{2M+1} (\hat{\gamma}(f+M) + \hat{\gamma}(f+M-1) + ... + \hat{\gamma}(f-M))
\]

where \( \hat{\gamma}_s(f) \) is the smoothed value for the PSD at frequency \( f \), \( M \) is the number of neighboring data points on either side of \( \hat{\gamma}_s(f) \), and \( 2M+1 \) is the span. Smoothing is done over a span of \( 2M+1 \) is the span where \( M \) is the number of neighboring data points on either side of \( \hat{\gamma} \). Although this process is simple in operation, but we will show later that the results obtained are quite accurate.

C. Support Detector Block

Once a smooth PSD estimate has been obtained, the spectral support \( F \) is computed with reference to a threshold value, \( \eta \) which is selected as a function of maximum PSD value \( \hat{\gamma}_{\text{max}} \) i.e.

\[
\eta = \lceil \hat{\gamma}_{\text{max}} + \beta \rceil
\]

where \( \lceil \cdot \rceil \) is the floor function. If \( \hat{\gamma}_{\text{max}} \) is normalized such that \( \hat{\gamma}_{\text{max}} = 0 \) dB then \( \eta = \beta \) dB where \( \beta \) is negative valued.

The selection of parameter \( \beta \) plays an important role in the performance of the proposed method and is further explained in Section VI. With reference to the threshold \( \eta \), the number of bands \( N_B \) are computed. The process is illustrated in Figure 4 for a signal with \( N_B = 4 \). The spectral support is calculated using the following equation

\[
F = \bigcup_{i=1}^{N_B} [a_i, b_i]
\]

where \( a_i \) and \( b_i \) represent the crossing points at the threshold \( \eta \), see Figure 4. Once the support \( F \) is found, the set \( K \), can be calculated using (5) as follows

\[
\lceil a_iLT \rceil \leq \{ k_i \} \leq \lceil b_iLT \rceil
\]

where \( 1 \leq i \leq N_B \) and \( T = 1/f_{\text{Nyq}} \). When all the \( k_i \) sets are calculated for each band, the set of spectral indexes \( K \) is computed as

\[
K = \bigcup_{i=1}^{N_B} \{ k_i \} = \{ k_i \}^2_{i=1}
\]

The set \( K \) then is sent to the reconstruction stage to recover \( \hat{x}(t) \), as shown in Figure 2.

V. PERFORMANCE OF THE PROPOSED NON-UNIFORM DETECTOR

In this section, we present some numerical results for our proposed non-uniform spectrum sensing block. For simulations, the wideband of interest is in the range of \( B = [-300, 300] \) MHz, therefore, the Nyquist sampling rate is \( f_{\text{Nyq}} = 600 \) MHz. We consider a multiband signal with \( N_B = 6 \) bands, each with a maximum bandwidth of 10 MHz. Therefore, the input signal is sparse in the frequency domain. For simplicity we assume that the \( N_B \) bands have the same amplitude. 16 QAM modulation symbols are used that are corrupted by the additive white Gaussian noise. Given \( f_{\text{max}} = 300 \) MHz, it is desired to detect \( N_B \) and \( K \) for the input signal which is sampled at a sub-Nyquist sampling rate using the multicest sampler. For the NUSS block, \( \beta \) is set equal to -5 dB. Note that \( \alpha \) is the ratio of the number of non-uniform samples to the number of Nyquist rate samples, i.e. the average sampling rate for the multicest sampler is \( f_{\text{avg}} = \alpha f_{\text{Nyq}} = (p/L)f_{\text{Nyq}} \).

The detection performance is evaluated by computing the probability of correctly detecting the signal occupancy in terms of the number of bands \( N_B \) and the active cells set \( K \) as follows:

\[
P_{d(N_B)} = \Pr \left( \hat{N}_B = N_B \right)
\]

\[
P_{d(K)} = \Pr \left( \hat{K} = K \right)
\]

and the false alarm probability is computed as

\[
P_{fa(N_B)} = \Pr \left( \hat{N}_B > N_B \right)
\]

\[
P_{fa(K)} = \Pr \left( |\hat{K}| > |K| \right)
\]
where \(|\mathcal{K}|\) represents the cardinality of \(\mathcal{K}\). The subscripts \(N_B\) and \(\mathcal{K}\) are used to distinguish the probabilities for the number of bands and the active cells set, respectively. We present both the \(P_d(N_B)\) and \(P_d(\mathcal{K})\), as the correct detection probability of the active cells set is linked to the probability of correct detection of \(N_B\), see equations (5), (6), (7). In order to compute \(P_d\) and \(P_{fa}\), we have performed 1000 iterations at various values of SNR and for different values of \(\alpha\). It should be noted that results in Figures (5-8) are plotted to explicitly show the performance of the NUSS block. Furthermore, the results are compared with the energy detector. The results for energy detector are plotted for \(P_{fa} = 0.01\) [12].

In Figure 5, \(P_d(N_B)\) and \(P_d(\mathcal{K})\) are plotted against varying SNR for \(\alpha = 0.4, 0.5, 0.6\). It is observed that for \(\alpha = 0.4\), after SNR=5 dB our proposed sensing method is able to detect the total bands and the occupied cells with high probability. At \(\alpha = 0.5\) the performance has further increased and we are able to detect with high probability at an SNR=2 dB. With \(\alpha = 0.6\) even better performance is obtained and the results are close to the energy detector \(P_d\). Figure 5 shows that the performance of the proposed sensing model depends on the number of non-uniform samples available to NUSS block for detection. To show this dependency, we have plotted \(P_d(N_B)\) and \(P_d(\mathcal{K})\) for varying values of \(\alpha\) in Figure 6. It is observed that the proposed sensing model behaves rather poorly at \(\alpha = 0.3\) but its performance improves at \(\alpha = 0.4\). At \(\alpha = 0.5\), our proposed sensing model detects with high probability, approaching 1 after \(\alpha = 0.6\). Next in Figure 7, we plot the \(P_{fa}(N_B)\) and \(P_{fa}(\mathcal{K})\) as a function of varying SNR. At low SNR i.e. -1 dB, the values for \(P_{fa}(N_B)\) and \(P_{fa}(\mathcal{K})\) are high, especially for \(\alpha = 0.4\). But as the SNR increases, the \(P_{fa}(N_B)\) and \(P_{fa}(\mathcal{K})\) drop quickly, practically becoming zero at an SNR=3 dB for \(\alpha = 0.5\). \(P_{fa}(N_B)\) and \(P_{fa}(\mathcal{K})\) further decrease when \(\alpha = 0.6\) and matches the performance of energy detector in terms of \(P_{fa}\) beyond 0 dB. As suspected, \(P_{fa}(N_B)\) and \(P_{fa}(\mathcal{K})\) also depend on the number of non-uniform samples available. To explain this, in Figure 8, we have plotted \(P_{fa}(N_B)\) and \(P_{fa}(\mathcal{K})\) for varying values of \(\alpha\) at different SNR values. It is observed that the performance of the sensing model improves with increasing \(\alpha\).

\[ \Delta P = P_d - P_{fa} \]  

(10)

where \(-1 \leq \Delta P \leq 1\) and for an optimal \(\beta\), \(\Delta P\) will be close to 1.

In Figure 9, we have plotted the probability of detection \((P_d\) and \(P_{fa}\)) for spectral indexes \(\mathcal{K}\) against varying values of \(\beta\) at an SNR = 10 dB with \(\alpha = 0.5\). For simplicity of explanation, in this section we only present results for the detection of spectral indexes \(\mathcal{K}\). The signal parameters are...
the same as were in Section V. 1000 Monte-Carlo iterations are performed to empirically find the $\beta$. Furthermore, the PSD estimate obtained from moving average filter of the NUSS block is normalized such that $\hat{\gamma}_{\text{max}} = 0$ dB (see Figure 10, only positive frequencies are shown for simplicity) and therefore equation (4) implies that $\eta = \beta$. It is observed that $P_d(K)$ increases as $\beta$ is increased from -8 dB to -5.5 dB and then decreases drastically as $\beta$ increases beyond -4.5 dB. As observed from the normalized estimated PSD shown in Figure 10, it is clear that if $\beta$ is reduced below -7 dB, the threshold value $\eta = \beta$ approaches the noise floor in the estimated PSD which in turn reduces $P_d(K)$. However, if $\beta$ is increased beyond -4.5 dB, the actual spectral indexes does not match with the detected spectral indexes because of the degradation of the estimated PSD, therefore, resulting in decrease in $P_d(K)$. Through similar reasoning, it can be observed that $P_f(K)$ is high for $\beta$ less than -7 dB and greater than -4.5 dB. As a result $\Delta P$ is maximum for $-7 \leq \beta \leq -4.5$, shown shaded in Figure 9. As a result, $\beta$ value within this range will ideally give $P_d = 1$ and $P_f$ approaching 0.

![Fig. 9. $P_d(K)$, $P_f(K)$ plotted for varying $\beta$ at an SNR = 10 dB. Since $\hat{\gamma}_{\text{max}} = 0$ dB, therefore $\eta = \beta$.](image)

In Figure 11 we have plotted $\Delta P$ against varying $\beta$ values for $\alpha = 0.4, 0.5$ and 0.7 to further investigate the optimal selection of $\beta$. The results are plotted for three SNR values i.e. 0, 5 and 10 dB. From Figure 11(a), we observe that for small $\alpha = 0.4$, maximum values of $\Delta P$ occur between $\beta = -5.5$ dB and $\beta = -4.5$ dB. However, $\Delta P$ never reaches 1 within this range because of small number of samples available to the non-uniform spectrum sensing block and the reconstructed spectrum is noisy as shown in Figure 11(b). $\Delta P$ increases for $\alpha = 0.5$ for the three SNR values as shown in Figure 11(c). Maximum $\Delta P$ is observed for $\beta$ values between -7 dB and -4 dB. This is evident from the improved reconstructed spectrum (see Figure 11(d)) obtained from a higher number of non-uniform samples i.e. $\alpha = 0.5$. As shown in Figure 11(e), even better results are obtained for $\alpha = 0.7$ but at the cost of more samples and a higher sampling rate. It is observed that with $\alpha = 0.7$, for SNR greater than 5 dB $\Delta P = 1$ for beta values between -8 dB and -4 dB. With more samples available to the NUSS block, the reconstructed spectrum is less noisy, thus, allowing a $\beta$ values less than -8 dB to be used (see Figure 11(f)). However, a $\beta = -8$ dB will result in higher

![Fig. 10. Normalized PSD estimate $\hat{\gamma}_s$ obtained from NUSS block. Note that SNR = 10 dB and $\alpha = 0.5$.](image)

![Fig. 11. Selection of optimal value of threshold $\eta$. Since we consider normalized PSD i.e. $\hat{\gamma}_{\text{max}} = 0$ dB, therefore $\eta = \beta$.](image)
false detections for $\alpha = 0.4$ or 0.5. From the results presented in Figures 11(a,c,e), it is observed that $\beta = -5 \text{ dB}$ is within the optimal $\Delta P$ range for the three $\alpha$ and SNR values used. This means that $\beta = -5 \text{ dB}$ establishes a trade-off between $\alpha$ and the detection performance. Therefore, in this paper we have selected $\beta = -5 \text{ dB}$ which provides satisfactory results as was shown in the numerical results in the Section V.

VII. IMPACT ON MULTICOSET SAMPLER PERFORMANCE

In this section, we analyze the impact of false detections performed by the proposed non-uniform sensing method on the reconstruction of $\hat{x}(t)$ shown in Figure 2. The performance is analyzed in terms of the RMSE (Root Mean Squared Error) of the reconstructed time domain signal i.e.

$$RMSE = \frac{\|\hat{x}(t) - x(t)\|_2}{\|x(t)\|_2}$$  (11)

The simulation parameters are the same as were in Section V i.e. $B = [-300, 300] \text{ MHz}$, and the Nyquist sampling rate is $f_{Nyq} = 600 \text{ MHz}$. A multiband signal with $N_B = 6$ bands, each with a maximum bandwidth of 10 MHz is considered.

In Figure 12, RMSE is plotted against SNR values for $\alpha = 0.3$ and 0.4 for non-blind multicoset sampler and blind multicoset sampler. Non-blind multicoset sampler has perfect knowledge about the number of bands $N_B$ and spectral indexes $K$ of the input signal while blind multicoset sampler uses the proposed NUSS block to estimate $N_B$ and $K$. It is observed that for $\alpha = 0.3$, the RMSE for blind multicoset sampler is very high compared to RMSE for non-blind multicoset sampler. This is because of the high number of false detections provided by the NUSS block at $\alpha = 0.3$. However for $\alpha = 0.4$, the performance of the NUSS blocks improves for SNR values greater that 5 dB and it is observed that the RMSE for blind multicoset matches that of the non-blind multicoset sampler. To summarize the performance of the proposed sensing method, we have plotted RMSE against varying values of $\alpha$ for different SNR values in Figure 13. We can see from the RMSE curves for non-blind and blind multicoset samplers that the performance of the proposed non-uniform sensing method is poor at $\alpha = 0.3$ even at high SNR values because of high $P_{fa}(x)$. However, as $\alpha$ increases above 0.3, the performance of the proposed sensing method improves in terms of the RMSE and matches that of the non-blind multicoset sampler.

VIII. CONCLUSION

In this paper, we have proposed a spectrum sensing technique based on non-uniform sub-Nyquist multicoset sampling. We have shown that the proposed sensing model works efficiently and shows high detection and low false alarm probabilities. The performance of the spectrum sensing model improves with increase in number of the non-uniform samples available to the sensing method. Finally, the effect of false detection is shown on the RMSE of the reconstructed time domain signal.

REFERENCES