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Spectrum Sensing Detection Techniques for Overlay Users

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ABSTRACT

Spectrum allocated Agency (FCC) is currently working on the concept of white space users "borrowing" spectrum from free license holders temporarily to improve the spectrum utilization, i.e known as dynamic spectrum access (DSA). CRN systems can utilize dispersed spectrum, and thus such approach is known as dispersed spectrum cognitive radio systems.

This project provides a tradeoff between a false alarm probability (P_f) and the signal to noise ratio (SNR) value of any spectrum detector to have a certain performance. Moreover, the performance of the cyclostationary detector (CD) and the matched filter detector (MF) is better than the energy detector(ED) especially at low signal to noise ratio values.

Unfortunately, the cyclostationary spectrum sensing method, performance is not satisfying when the wireless fading channels are employed. In this project we provide the best trade off for spectrum usage for over lay users.

I. Introduction

What has motivated cognitive radio technology, an emerging novel concept in wireless access, is spectral usage experiments done by FCC. These experiments show that at any given time and location, much of the licensed (pre-allocated) spectrum (between 80% and 90%) is idle because licensed users (termed primary users) rarely utilize all the assigned frequency bands at all time. Such unutilized bands are called spectrum holes, resulting in spectral inefficiency. These experiments suggest that the spectrum scarcity is caused by poor spectrum management rather than a true scarcity of usable frequency [1]. The key features of a cognitive radio transceiver are radio environment awareness and spectrum intelligence. Intelligence can be achieved through learning the spectrum environment and adapting transmission parameters [2, 3].

The dynamic spectrum access (DSA) allows the operating spectrum of a radio network to be selected dynamically from the available spectrum. DSA is applied in cognitive radio networks, which has a hierarchical access structure with primary and secondary users as shown in Fig. 1 The basic idea of DSA is to open licensed spectrum to secondary users (which are unlicensed users) while limiting the interference received by primary users (which are licensed users)[2,3,4]. This allows secondary users to operate in the best available channel opportunistically. Therefore, DSA requires opportunistic spectrum sharing, which is implemented via two strategies

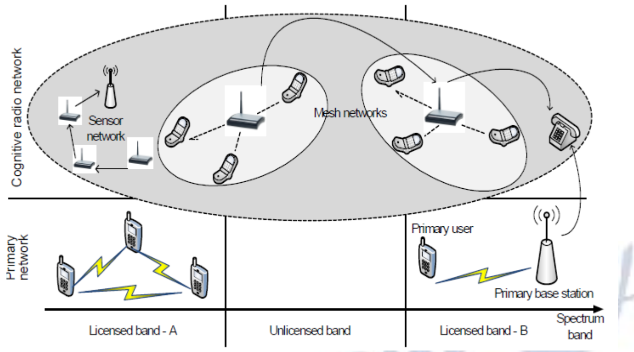


Figure 1: A basic cognitive radio network architecture.

1.1 Spectrum Sensing

The purpose of spectrum sensing is to identify the spectrum holes for opportunistic spectrum access [4, 5]. After available channels (spectrum holes) are detected successfully, they may be used for communications by a secondary transmitter and a secondary receiver. Spectrum sensing is performed based on the received signal from the primary users. Primary users have two states, idle or active. With the presence of the noise, primary signal detection at a secondary user can be viewed as a binary hypothesis testing problem in which Hypothesis 0 (H_0) and Hypothesis 1 (H_1)are the primary signal absence and the primary signal presence, respectively .Based on the hypothesis testing model, several spectrum sensing techniques have been developed[6].

II. Overview of the Paper

In section 3 we discuss the previous work methods and drawbacks, in section 4 we discuss proposed work, in that basic system model and computationally efficient energy detection (CE-ED) techniques were evaluated by use of Receiver Operating Characteristics (ROC) curves over additive white Gaussian noise (AWGN) and fading (Rayleigh & Nakagami-m) channels. Results show that for single user detection, the energy detection technique performs better in AWGN channel than in the fading channel models. The performance of cooperative detection is better than single user detection in fading environments. In section we discuss the results and Conclusions and along with Future work.

III. Previous Work

3.1 Spectrum Sensing Techniques

Spectrum sensing techniques include energy detection, matched filter, cyclostationary feature detection, and eigenvalue detection.

3.1.1 Energy detection: This measures the energy of the received signal within the pre-defined bandwidth and time period. The measured energy is then compared with a threshold to determine the status (presence/ absence) of the transmitted signal [6]. Not requiring channel gains and other parameter estimates, the energy detector is a low-cost option. However, it performs poorly under high noise uncertainty and background interference [7].

3.1.2 .Matched filter: This detector requires perfect knowledge of the transmitted signal and the channel responses for its coherent processing at the demodulator [4, 6, 8]. The matched filter is the optimal detector of maximizing the signal-to-noise ratio (SNR) in the presence of additive noise. Since it requires the perfect knowledge of the channel response, its performance degrades dramatically when there is lack of channel knowledge due to rapid changes of the channel conditions.

3.1.3. Cyclostationary feature detection: If periodicity properties are introduced intentionally to the modulated signals, the statistical parameters of received signal such as mean and autocorrelation may vary periodically. Such periodicity of statistical properties is used in the cyclostationary detection [7]. Cyclostationary properties of the received signal may be extracted by its input-output spectral correlation density. The signal absence status can be identified easily, because the noise signal does not have cyclostationary properties. While this detector is able to distinguish among the primary user signals, secondary user signals, or interference it needs high sampling rate and a large number of samples, and thus increases computational complexity as well[9].

In order to avoid the difficulties of previous spectrum sensing detection techniques, we propose a computationally efficient energy detection (CE-ED) techniques. I.e. improved energy detection technique under both low and high SNR values, Logical selective method and sequential forward search method.

IV. Proposed Spectrum Sensing Detection Technique

4.1. System Model of Spectrum Sensing

Primary users are in either idle state or active state. With the presence of the noise, the signal detection at the receiver can be viewed as a binary hypothesis testing problem[8] in which Hypothesis 0 (H_0) and Hypothesis 1 (H_1) are the primary signal absence and the primary signal presence, respectively. The nth, $n = 1, 2$.........., sample of the received signal, $\mathbf{y}(n)$, can be given under the binary hypothesis as :

$$y(n)=\begin{cases} w(n) & :H_0 \\ x(n)+w(n) & :H_1 \end{cases} \qquad (1)$$

where x = hs.

The complex signal, **s** has real component s_r and imaginary component s_i, i.e., $\mathbf{s} = s_r+js_i$.

The AWGN samples are assumed to be circularly symmetric complex Gaussian (CSCG) random variables with mean zero (E{$\mathbf{w}(n)$} = 0) and variance $2\sigma_w^2\left(\mathrm{Var}\{w(n)\}=2\sigma_w^2\right)$ where E{·} and Var{·} stand for mean and variance, respectively, i.e., $w(n)\sim\mathcal{CN}\left(0,2\sigma_w^2\right)$. A noise sample is denoted as $w(n) = w_r(n)+jw_i(n)$ where $w_r(n)$ and $w_i(n)$ are real-valued Gaussian random variables with mean zero and variance σ_w^2, i.e., $w_r(n)$, $w_i(n)\sim\mathcal{N}\left(0,\sigma_w^2\right)$.

The channel gain is denoted as h = h_r+ jh_i. The channel gain can be assumed as a constant within each spectrum sensing period and can be written as

$$y(n)=\theta x(n)+w(n) \qquad (2)$$

where $\theta = 0$ for $\mathcal{H}_0$ and $\theta = 1$ for $\mathcal{H}_1$.

4.1.1 Improved energy detection under low SNR model:

Three signal models, S1, S2 and S3 which are given and can be considered in the energy detection. For S1 and S2 signal models, the distribution of Λ is modeled exactly Under $H0$, the false-alarm probability is with the upper incomplete Gamma function. Under $H1$, the detection probabilities are with the Marcum-Q function and with the upper incomplete Gamma function for S1 and S2, respectively. However, none of these functions have closed-form inverse functions, and thus there is no closed-form expression for the detection threshold λ when a false-alarm or detection probability is given even with AWGN channel[9,11]. This problem becomes more complicated when the fading effect is considered. Although there are rigorous expressions for the average detection performance over some particular fading channels in the literature, such expressions may not help for the parameter optimization (e.g., optimizing detection threshold). Since S1 and S2 signal models have different set of expressions, results of one model cannot be derived from those of the other model. Moreover, the distribution of Λ cannot be modeled exactly for S3[11,12].

To solve all these problems, the CLT approach can be used as a unified approach of accurately approximating the distribution of Λ in the three signal models.The distribution of Λ can be approximated as a normal distribution for sufficiently large N as

$$\Lambda \sim \begin{cases} \mathrm{N}\left(N\left(2\sigma_w^2\right), N\left(2\sigma_w^2\right)^2\right) & :\mathrm{H}_0 \\ \mathrm{N}\left(N\left(2\sigma_w^2\right)(1+\gamma), N\left(2\sigma_w^2\right)^2(1+2\gamma)\right) & :\mathrm{H}_1\ with\ S1\ or\ S3 \\ \mathrm{N}\left(N\left(2\sigma_w^2\right)(1+\gamma), N\left(2\sigma_w^2\right)^2(1+\gamma)^2\right) & :\mathrm{H}_1\ with\ S2 \end{cases} \qquad (3)$$

Under the low-SNR assumption $(i.e.; \gamma \ll 1)$,the signal has little impact onthe variance of the test statistic under H_1 , as used in the Edell model, Berkeley model and Torrieri model which are well-known Gaussian approximations for the test statistic under H_1 [12, 13]. Thus, (3) can be accurately approximated for any of the three signal models as

$$\Lambda_{low} \sim \begin{cases} \mathrm{N}\left(N\sigma^2, N\sigma^4\right) & :\mathrm{H}_0 \\ \mathrm{N}\left(N\sigma^2(1+\gamma), N\sigma^4\right) & :\mathrm{H}_1 \end{cases} \qquad (4)$$

where $\sigma=\sqrt{2}\sigma_w$. The false alarm probability P_f and the missed-detection probability $P_{md}(\gamma)$ can be evaluated as

$$P_f=\frac{1}{2}Erfc\left(\frac{\lambda-N\sigma^2}{\sqrt{2N}\sigma^2}\right) \qquad (5)$$

And

$$P_{md}(\gamma)\approx 1-\frac{1}{2}Erfc\left(\frac{\lambda-N\sigma^2(1+\gamma)}{\sqrt{2N}\sigma^2}\right), \qquad (6)$$

respectively, where where $Q(z)=\frac{1}{2}Erfc\left(\frac{z}{\sqrt{2}}\right)$ and Erfc(·) is the complementaryerror function defined as $Erfc(z)=\frac{2}{\sqrt{\pi}}\int_z^{\infty}e^{-t^2}\,dt$ [4]. Since the detection probability, $P_d(\gamma)=1-P_{md}(\gamma)$, relates to the cumulative distribution function (CDF)of the test statistic.

The ROC curve, AUC, and the total error rate are used as the performance measures. The ROC curve is a measurement for the sensitivity of a detector used in a binary classifier system [12]. In signal-detection theory, the ROC (or the complementary ROC) curve is a graphical plot of $P_d(\gamma)\left(or\ P_{md}(\gamma)\right)$ versus P_f as the discrimination threshold λ varies. The ROC curves of spectrum-sensing detectors have highly non-linear behavior, and they are, in general, convex[9,10,11]. In wireless communications, $P_d(\gamma)$ depends on the received instantaneous SNR, which is a function of the mobile radio channel gain. Therefore, the average detection probability (or average missed-detection probability) over fading channels is important for plotting the ROC curve.

4.1.2 Logical Selective method based on Fusion center

Performance of an energy detector used for cooperative spectrum sensing is investigated. Single cooperative node, multiple cooperative nodes and multi-hop cooperative Sensing networks are considered. Two fusion strategies, data fusion and decision fusion, are analyzed. For data fusion, upper bounds for average detection probabilities are derived. For decision fusion, the detection and false alarm probabilities are derived under the out-of generalized "*k*- -*n*" fusion rule at the fusion center by considering errors in the reporting channel[10,11]

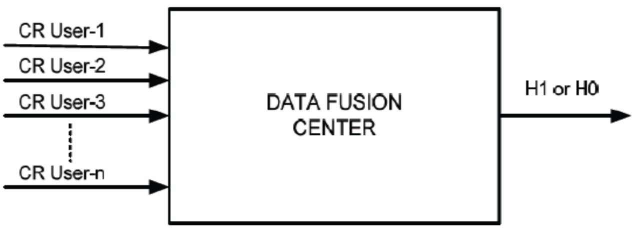


Fig:2 Data fusion center

In decision fusion, each cooperative node makes one-bit hard decision on the primary user activity: '0' and '1' mean the absence and presence of primary activities, respectively. Then, each reporting channel is with a narrow bandwidth. Capability of complex signal processing is needed at each cooperative node. The fusion rule at the fusion center can be OR, AND, or Majority rule, which can be generalized as the "*k*-out-*of*-*n*" *rule*. The decision device of the fusion center with *n* cooperative nodes can be implemented with the *k*-out-*of*-*n rule* in which the fusion center decides the presence of primary activity if there are *k* or more cooperative nodes that individually decide on the presence of primary activity[8,9]. When *k* = 1, *k* = *n* and, $k=\lceil n/2\rceil$ where $\lceil . \rceil$ is the ceiling function, the *k*-out-of-*n* rule represents *OR* rule, AND rule and Majority rule, respectively.

It is assumed that the decision device of the fusion center is implemented with the k out- of-n rule (i.e., the fusion center decides the presence of primary activity if there are k or more cooperative nodes that individually decide the presence of primary activity). When k = 1, k = n and $k=\lceil n/2\rceil$, the k-out-of-n rule represents OR rule, AND rule and Majority rule, respectively. In the following, for simplicity of presentation, p_f and p_d are used to represent false alarm and detection probabilities, respectively, for a cooperative node, and use p_f and p_d to represent false alarm and detection probabilities, respectively, in the fusion center.

4.1.3. Improved sub nyquist sampling method for spectrum sensing

The received signal x(t) is assumed to be an analog wideband sparse spectrum signal, band limited to $[0,B_{max}]$. Denote the Fourier transform of x(t) by X(f). Depending on the application, the entire frequency band is segmented into L narrowband channels, each of them with bandwidth B, such that $B_{max} = L \times B$. It is assumed that the signal bands are uncorrelated with each other. The channels are indexed from 0 to L − 1. Those spectral bands which contain part of the signal spectrum are termed active channels, and the remaining bands are called vacant channels[11,12]. Denote the number of such active channels by N. The indices of the N active channels are collected into a vector

$$b=[b_1,b_2,\ldots,b_N] \tag{7}$$

which is referred to as the active channel set.

In the considered system, N and b are unknown. However, we know the maximum channel occupancy which is defined as

$$\Omega_{\max}=\frac{N_{\max}}{L} \tag{8}$$

where $N_{max} \geq N$ is the maximum possible number of occupied channels. Figure 1 depicts the spectrum of a multiband signal at the sensing radio, which contains L = 32 channels, each with a bandwidth of B = 10 MHz. The signal is present in N = 6 channels, and the active channel set is b [8].

The problem is, given B_{max}, B and Ω_{max}, to find the presence or absence of the signal in each spectral band or equivalently find the active channel set, b, at a sub-Nyquist sample rate.

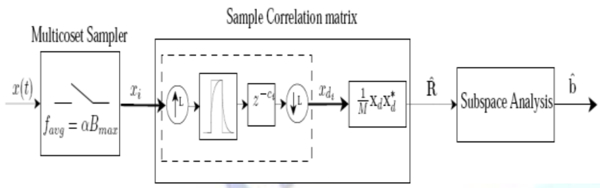


Figure 3. Proposed wideband spectrum sensing model.

The proposed model for wideband spectrum sensing is illustrated in Figure 3. The analog received signal at the sensing cognitive radio is sampled by the multicoset sampler at a sample rate lower than the Nyquist rate. The sampling reduction ratio is affected by the channel occupancy and multicoset sampling parameters. The outputs of the multicoset sampler are partially shifted using a multirate system, which contains the interpolation, delaying and down sampling stages. Next, the sample correlation matrix is computed from the finite number of obtained data. Finally, the correlation matrix is investigated to discover the position of the active channels by subspace methods [9, 10, 12].

V. Results and Conclusion

Improved CE-ED METHOD:

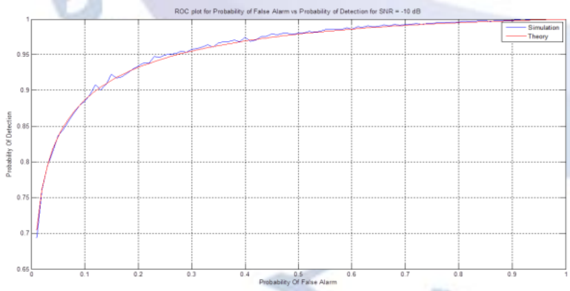


Fig 4:Probability of false Vs Probability of Detection

As the probabilty of false alarm increases the probability of detection also increases

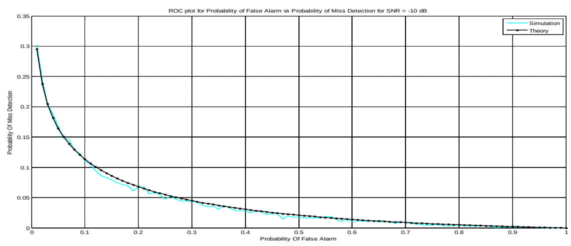


Fig 5:Probability of false Vs Probability of Miss detection

As the probability of false alarm increases the probability of miss detection decreases

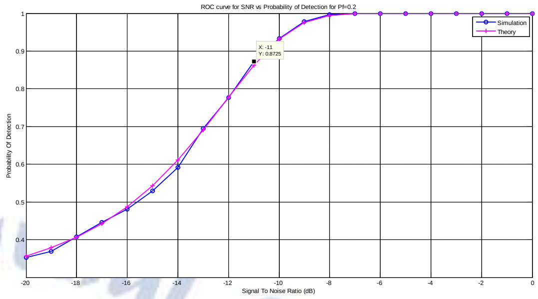


Fig 6:Probability of Detection Vs SNR

As probability of detection increases SNR also increases

LOGICAL SELECTIVE METHOD:

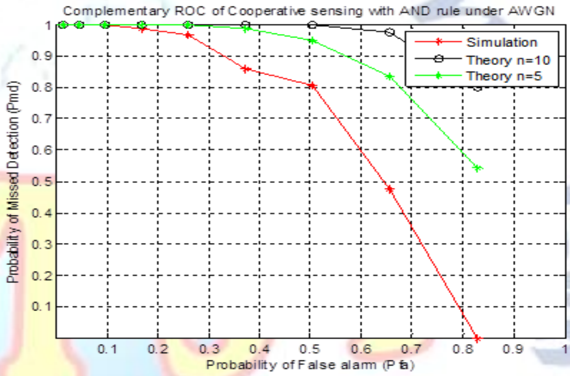
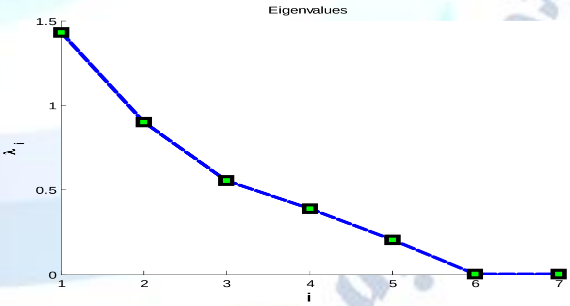
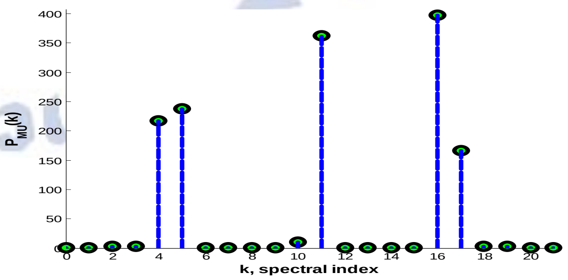


Fig 7: Spectrum sensing with AND rule

The PM (increased detection performance) rapidly improves with increasing average SNR.

Improved sequential Forward search Method:





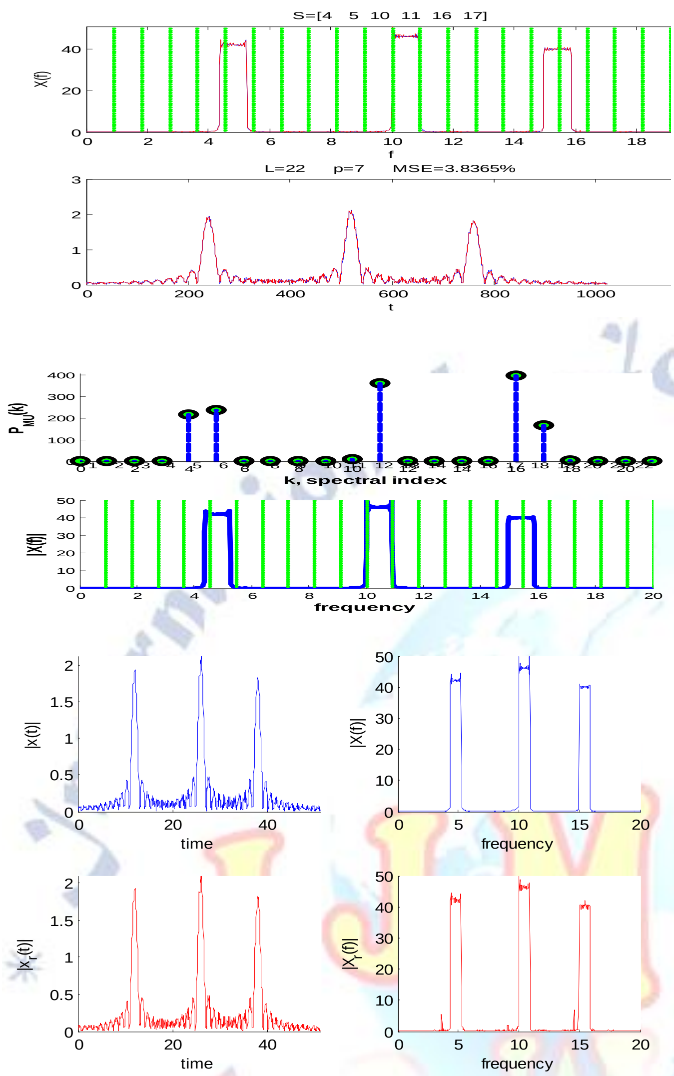


Fig 8: Performance of wideband spectrum sensing under sub nyquist sampling method

Several significant values correspond to active channels are appeared where their locations specify the estimated active channel set. The other channels are interpreted as the vacant channels and can be used by the cognitive system to transmit.The results show that even in low SNR with taking enough number of samples a perfect detection is possible.

In the standardization process of vehicular networks, channel models are required to evaluate and select the proposed physical layer modulation and coding schemes. Analytical and simulation results are provided to support the theoretical formulations and derivations. The presented results show that spectrum sensing and access in vehicular communication can be improved by modeling the wireless environment precisely. IN a cognitive radio network (CRN), in-band spectrum sensing is essential for the protection of legacy spectrum users, with which the presence of primary users (PUs) can be detected promptly, allowing secondary users (SUs) to vacate the channels immediately. For in-band sensing, it is important to meet the detectability requirements, such as the maximum allowed latency of detection (e.g., 2 seconds in IEEE 802.22) and the probability of misdetection and false-alarm. From the presented result it is clear that a channel model composed of mixed distributions is useful for designing vehicular wireless. We studied the performance of cooperative spectrum sensing and signal detection base on hard decision combining technique in data fusion centre compared with non-cooperative one.

In cooperative technique, OR and AND rules are employed and evaluate the system performance by using probability of detection (Pd) and SNR as metric. The OR rule decides H1 when at least one CR user forward bit-1 while the AND rule decides H1 when all CR users forward their bit-1 to data fusion centre. The numerical results show that cooperative technique has better performance compared with non cooperative one and employing OR rule can improve probability of detection than AND rule and non cooperative signal detection at different SNR values. Cooperative technique is more effective when received SNR in cognitive radio users is low due to fading and shadowing. Non cooperative technique achieves the same detection probability value (optimal value) as cooperative technique when received SNR is greater than 10 dB, Furthermore, a minimum of 15 collaborated users relatively in cognitive radio system can achieve optimal value of detection probability. However, it depends on the threshold value used in signal detection.

VI. Future Scope

In future, we would like to explore other types of feature detection and evaluate their performance comparatively with energy detection. In-band sensing of wireless micro-phones should be another subject of our future work.

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