In a cooperative spectrum sensing method and system for locating primary transmitters, each of secondary users transmits to a corresponding one of cognitive radio (CR) base station location information thereof and a received signal strength indicator (RSSI) value generated thereby in response to sensing power signals from the primary transmitters. The CR base stations transmit the location information and the RDDI values of the secondary users to a data fusion center such that the data fusion center obtains the number and locations of the primary transmitters based on the location information and the RSSI values received thereby using a learning algorithm to thereby reconstruct a power propagation map of the primary transmitters.
PROCESS RSSI VALUES FROM CR BASE STATIONS \( \sim S21 \)

PROVIDE \( M \) BASIS FUNCTIONS \( \phi \) SO AS TO OBTAIN BASIS MATRIX \( \Phi \) \( \sim S22 \)

DEFINE ITERATION INDEX \( k \), AND COMPUTE COVARIANCE \( \Sigma \) AND MEAN \( m \) WITH \( \alpha_j = 1, \beta = 1 \) AND \( k = 1 \) \( \sim S23 \)

LET \( k = k+1 \), UPDATE \( \alpha_j^{-1} \) AND \( \beta^{-1} \), AND COMPUTE AGAIN COVARIANCE \( \Sigma \) AND MEAN \( m \) \( \sim S24 \)

DELETE BASIS FUNCTIONS \( \phi \) WHOSE CORRESPONDING WEIGHTS ARE LESS THAN \( \gamma \), AND UPDATE \( M, \Phi, \Sigma \) AND \( m \) \( \sim S25 \)

UPDATE REPEATEDLY \( \mu_j \) AND \( s_j \) FOR \( L \) TIMES \( \sim S27 \)

\[ k \geq K, \text{AND} \]

\[ (Q(k) - Q(k-1))/Q(k-1) \lt \text{CONDITIONAL PROBABILITY THRESHOLD} \]

\( \sim S26 \)

YES

RE-COMPUTE \( \alpha_j^{-1}, \beta^{-1}, m \) AND \( \Sigma \), AND RECONSTRUCT POWER PROPAGATION MAP \( \sim S28 \)

NO

FIG. 2
COOPERATIVE SPECTRUM SENSING
METHOD AND SYSTEM FOR LOCATIONING
PRIMARY TRANSMITTERS IN A
COGNITIVE RADIO SYSTEM

CROSS-REFERENCE TO RELATED
APPLICATION

This application claims priority to Taiwanese Application
No. 1001119421, filed on Jun. 2, 2011.

BACKGROUND OF THE INVENTION

1. Field of the Invention
The invention relates to wireless communications, and
more particularly to a cooperative spectrum sensing method
and system for locationing primary transmitters in a cognitive
radio system.

2. Description of the Related Art
Cognitive radio (CR) aims at improving the spectrum utili-
zation in wireless communications. In a CR system, second-
ary users, such as customer premise equipments (CPEs), are
permitted to utilize vacant spectra in frequency, time and
space without causing interference with primary users.

To establish geo-location information of primary users in a
CR system, each CPE is required to incorporate a positioning
unit, such as a global positioning system (GPS) positioning
device, for obtaining GPS information thereof. However,
CPEs are likely to be sparsely and randomly distributed in
space. In this case, base stations (BSs) of the CR system may
use compressive sensing to obtain spectrum sensing signal
strengths and locations of the CPEs, thereby reconstructing a
data propagation map of the primary users as proposed in an
article by E. Candes, J. Romberg, and T. Tao, entitled “Robust
Uncertainty Principles: Exact Signal Reconstruction from
Highly Incomplete Frequency Information,” IEEE Trans.
on Information Theory, No. 2, vol. 52, pp. 489-506, February
2006. Although compressive sensing allows perfect signal
reconstruction at a random sampling rate lower than that
defined by Nyquist theorem, compressive sensing fails to
obtain the number of the primary users when directly applied
to spectrum sensing and locationing of the primary users.

Furthermore, a CR system with sparse samples, which has
been proposed in an article by Juan Andres Bazerque and
Georgios B. Giannakis, entitled “Distributed Spectrum Sens-
ing for Cognitive Radio Networks by Exploiting Sparsity,”
IEEE Trans. on Signal Processing, vol. 58, no. 3, pp. 1847-
1862, March 2010, is directed to estimate the locations and
power propagation map of primary users. However, since
basis weights are estimated, such a CR system cannot ensure
accurate location estimation. If the accuracy of location esti-
mation is improved, the amount and complexity of computa-
tion will increase, thereby adversely affecting processing
speed and protection for the primary users.

Therefore, improvements may be made to the above tech-
niques.

SUMMARY OF THE INVENTION

Therefore, an object of the present invention is to provide a
coop erative spectrum sensing method and system for loca-
tioning primary transmitters in a cognitive radio system that
can overcome the aforesaid drawbacks of the prior art.

According to one aspect of the present invention, there is
provided a cooperative spectrum sensing method for location-
ing primary transmitters in a cognitive radio (CR) system.
Each of the primary transmitters transmits a power signal.

The CR system includes a number (N) of secondary users,
which are randomly located in a predetermined area and are
divided into a plurality of sets, and a plurality of CR base
stations disposed in the predetermined area and correspond-
ing respectively the sets of the secondary users. The coop er-
ative spectrum sensing method comprising the steps of:

a) configuring each of the secondary users to obtain loca-
tion information thereof, generate a received signal strength
indicator (RSSI) value in response to sensing the power sig-
als from the primary transmitters, and transmit the location
information and the RSSI value such that each of the CR base
stations receives and collects the location information and the
RSSI values from a corresponding set of the secondary users;

b) configuring each of the CR base stations to transmit the
location information and the RSSI values collected thereby to
a data fusion center through a backbone network such that the
data fusion center receives the location information and the
RSSI values associated with all the secondary users; and

c) configuring the data fusion center to obtain the number
and locations of the primary transmitters in the predetermined
area based on the location information and the RSSI values
received thereby using a learning algorithm to thereby recon-
struct a power propagation map of the primary transmitters in
the predetermined area.

According to another aspect of the present invention, there
is provided a cooperative spectrum sensing system for loca-
tioning primary transmitters in a predetermined area. Each of
the primary transmitters transmits a power signal. The coop er-
ative spectrum sensing system comprises:

a number (N) of secondary users randomly located in the
predetermined area and divided into a plurality of sets, each of
the secondary users including a positioning module for
obtaining location information thereof, being adapted for
sensing the power signals from the primary transmitters to
generate a received signal strength indicator (RSSI) value, and
transmitting the location information and the RSSI value;

a plurality of cognitive radio (CR) base stations disposed in
the predetermined area and corresponding respectively the
sets of the secondary users, each of the CR base stations
receiving and collecting the location information and the
RSSI values from a corresponding set of the secondary users;

and

da data fusion center communicating with each of the CR
bas stations through a backbone network.

Each of the CR base stations transmits the location infor-
mation and the RSSI values collected thereby to the data
fusion center through the backbone network such that the data
fusion center receives the location information and the RSSI
values associated with all the secondary users.

The data fusion center is configured to obtain the number
and locations of the primary transmitters in the predetermined
area based on the location information and the RSSI values
received thereby using a learning algorithm to thereby recon-
struct a power propagation map of the primary transmitters.

BRIEF DESCRIPTION OF THE DRAWINGS

Other features and advantages of the present invention will
become apparent in the following detailed description of the
preferred embodiment with reference to the accompanying
drawings, of which:

FIG. 1 is a schematic view showing the preferred embodi-
ment of a cooperative spectrum sensing system for location-
ing primary transmitters according to the present invention;
FIG. 2 is a flow chart illustrating how a data fusion center
of the preferred embodiment obtains the number and loca-
3

tions of the primary transmitters and reconstructs the power propagation map of the primary transmitters;

FIG. 3 is a three dimensional simulation plot showing an example of an original power propagation map for three primary transmitters constructed based on a conventional power path loss model;

FIG. 4 is a three dimensional simulation plot showing a power propagation map reconstructed by the preferred embodiment under the same conditions as those of the example of FIG. 3; and

FIG. 5 is a plot illustrating the relationships between the average mean squared error and measurement rate for the prior art and the preferred embodiment.

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENT

Referring to FIG. 1, the preferred embodiment of a cooperative spectrum sensing system for locating primary transmitters 1, for example, TV transmitters, in a predetermined area according to the present invention is shown to include a number (N) of secondary users 2, for example, notebook computers, cell phones, etc., in the predetermined area, a plurality of cognitive radio (CR) base stations 3 in the predetermined area, and a data fusion center 4. Each primary transmitter 1 transmits a primary signal. In this embodiment, the predetermined area is an area of 60 Kms×60 Km.

The secondary users 2 are divided into a plurality of sets. Each secondary user 2 includes a positioning module (not shown), such as a GPS positioning module, for obtaining location information thereof, and is adapted for sensing the power signals from the primary transmitters 1 to generate a received signal strength indicator (RSSI) value. Each secondary user 2 transmits the location information and the RSSI value.

The CR base stations 3 correspond respectively to the sets of the secondary users 2. As such, each CR base station 3 receives and collects the location information and the RSSI values from a corresponding set of the secondary users 2 through a control channel.

The data fusion center 4 communicates with each CR base station 3 through a backbone network.

Each CR base station 3 transmits the location information and the RSSI values collected thereby to the data fusion center 4 through the backbone network such that the data fusion center 4 receives the location information and the RSSI values associated with all the secondary users 2.

The data fusion center 4 is configured to obtain the number and locations of the primary transmitters 1 in the predetermined area based on the location information and the RSSI values received thereby using a learning algorithm to thereby reconstruct a power propagation map of the primary transmitters 1 that is regarded as an important basis for determining whether the vacant spectra can be utilized by the secondary users 2. In this embodiment, the data fusion center 4 is a cloud computing center. In addition, the learning algorithm is a sparse Bayesian learning algorithm.

FIG. 2 is a flow chart illustrating how the data fusion center 4 obtains the number and locations of the primary transmitters 1 in the predetermined area and reconstructs the power propagation map of the primary transmitters 1 in accordance with the sparse Bayesian learning algorithm.

In step S21, to alleviate large variation occurring in the RSSI values due to barriers, for example, high buildings or mountain terrain, the data fusion center 4 processes the RSSI values received thereby so that those of the RSSI values greater than a predetermined value (P_mob) are respectively updated with differences with the predetermined value (P_mob) and that those of the RSSI values not greater than the predetermined value (P_mob) are updated with zero. For example, the predetermined value (P_mob) is equal to about the receiving sensitivity of a TV receiver, such as −76 dBm. Thus, the processed RSSI values become not less than zero.

In step S22, initially, the data fusion center 4 provides a number (M) of basis functions (Φk) that are randomly distributed in the predetermined area. The RSSI values processed in step S21 form a vector (y) that is represented by the following expression: t=(t1, t2, . . . , tN), which is modeled by the following expression (1):

\[ t = \Phi \theta + e \]

where \( \Phi \) denotes a basis matrix consisting of the basis functions (\( \Phi_k \)) and is represented by the following expression (2):

\[ \Phi_{N \times M} = \begin{bmatrix} \phi_1(x_1) & \phi_2(x_1) & \cdots & \phi_M(x_1) \\ \phi_1(x_2) & \omega & \cdots & \omega \\ \vdots & \vdots & \ddots & \vdots \\ \phi_1(x_N) & \omega & \cdots & \omega \end{bmatrix} \]

where \( x_i (i=1, \ldots, N) \) denotes the location of the i-th one of the secondary users 2 and is represented as \( x_i = (x_i, y_i) \) and \( X_i = (x_i, y_i) \), \( w \) denotes a weighting coefficient vector and is represented by the following expression: \( w = (w_1, w_2, \ldots, w_M) \), and \( n \) denotes a shadowing effect vector and is represented by the following expression: \( n = (n_1, n_2, \ldots, n_M) \).

In this model using Bayesian compressive sensing, the expression (1) also can be represented in a linear regression form by the following expression (3):

\[ t = \gamma(x_i, w) + e \]

where \( \gamma(x_i, w) \) is the weighted sum of the M basis functions (\( \phi_k(x_i) \)) at the position of \( x_i \), and can be represented by the following expression:

\[ \gamma(x_i, w) = \sum_{j=1}^{M} w_j \phi_j(x_i) \]

In addition, \( w_j (j=1, \ldots, M) \) is initially given with a prior probability of

\[ \mathcal{N}(0, \sigma^2) \]

and \( e_i (i=1, \ldots, N) \) is a zero-mean Gaussian random variable with variance \( \sigma^2 \). Preferably, the weighting coefficient vector (\( w \)) that maximizes the likelihood function represented by the following expression (4) should be found.

\[ p(y|x, M) = \sum_{w \in \mathbb{W}} p(y|x, w) p(w|M) \]

Thus, the prior probability to the weighting coefficient vector (\( w \)) can be represented by the following expression (5):

\[ p(w|x, M) = \frac{1}{M} \sum_{i=1}^{M} \mathcal{N}(w|x_i, \sigma^2) \]

where hyperparameters \( \alpha_1 \) denotes the precision of the corresponding \( w_i \) and \( \alpha_2 = (\alpha_1, \alpha_2, \ldots, \alpha_M)^T \). When \( \alpha_1 \) is initialized with a very small value, which is equivalent to setting most coefficients in the weighting coefficient vector (\( w \)) to zero, the weighting coefficient vector (\( w \)) can be easily restrained to be sparse in advance. Consequently, an approximately L_1-norm
sparse estimation of $w$ can be obtained by iteratively computing a mean ($\mu$) and a covariance ($\Sigma$) of a posterior distribution of $w$ represented by the following expression (6):

$$ p(w|x, \alpha, \beta, M) \propto \exp \left\{ \frac{-D}{2\beta} \right\}, $$

where $D$ is defined as $\frac{1}{2\beta} \left[ (x, \mu) - \log(\Sigma)^{-1} \right]$. $\mu$ is defined as the location of an $m$th one of the primary transmitters $I$ and is represented by $\mu = (\mu_1, \mu_2, \ldots, \mu_m)$, and $\beta$ is a scale parameter and denotes a power decaying rate for the $m$th one of the primary transmitters $I$. Thus, $\mu = (\mu_1, \mu_2, \ldots, \mu_m)$ and $\beta = (\beta_1, \beta_2, \ldots, \beta_m)$. As a result, the log marginal likelihood function becomes

In step S23, an iteration index (k) is defined. The covariance ($\Sigma$) and the mean ($\mu$) are computed initially with $\alpha^{-1} = 1$, $\beta^{-1} = 1$, and $k = 0$.

In step S24, the iteration index (k), $\alpha^{-1}$, and $\beta^{-1}$ are updated respectively with k+1.

In step S25, the basis functions ($\phi$, $\psi$) whose corresponding weighting coefficients ($w$) are less than a predetermined weight threshold ($\eta$), for example, $\eta = 2$, are deleted. The number ($M$) of the basis functions ($\phi$, $\psi$) is updated based on the remaining basis functions ($\phi$, $\psi$) such that the basis matrix ($\Phi$) and $A$ are updated, thereby updating the covariance ($\Sigma$) and the mean ($\mu$).

In step S26, it is defined that $Q = \log \left( p(t|x, \Phi, \Sigma) \right)$, and it is determined whether $k$ is not less than a predetermined threshold (K), for example, K = 30, while $(Q(k) - Q(k-1)) < 10^{-4}$.

In step S27, $\mu$, $\Sigma$, and $w$ are updated repeatedly for L times, for example, $L = 3$, based on the basis matrix ($\Phi$) and mean ($\mu$) updated in step S25 using

In this embodiment, $\delta$ is a learning rate greater than zero, for example, $\delta = 12$. Thereafter, the flow goes back to step S24.

In step S28, $\alpha^{-1}$, $\beta^{-1}$, and $\Sigma$ are re-computed. In this case, $m$ serves as $w$, and the number ($M$) updated in step S25 serves as the number of the primary transmitters $I$ in the predetermined area, and the power propagation map of the primary transmitters $I$ is reconstructed based on $P_{t,n}^{d_{n},i}$, $\Sigma$, and $w$.

FIG. 6 is a dimension simulation plot showing an example of an original power propagation map for three primary transmitters $I$ constructed based on a conventional power path loss model, i.e.,

$$ P_{t}(d) = P_{t0} - 10 \log(d) + W, $$

where $n$ is the path loss exponent, $d$ is the close-in reference distance, $d$ is the separation distance, $P_{t}(d)$ is the reference path loss, and $W$ is a zero-mean Gaussian random variable. In this example, the predetermined area is an area of 60 Km x 60 Km. The transmitting power ($P_{t}$) of each primary transmitter $I$ is 50 dBm, $d = 1$ Km, $P_{t}(d) = 88.9113$ dB, $n = 3$, and $W = 2$.

FIG. 4 is a dimension simulation plot showing a power propagation map reconstructed by the preferred embodiment under the same conditions as the above example. In this simulation, $N = 3K$, the measurement rate is 0.075, $L = 3$, and $M = 20$. From the reconstructed power propagation map of FIG. 4, the number of the primary transmitters $I$, $\mu$, and $\Sigma$ are obtained, and match those in original power propagation map of FIG. 3.

FIG. 5 is a plot illustrating the relationships between the average mean squared error and measurement rate for the prior art, i.e., the conventional l1-norm method, and the preferred embodiment. It is apparent that the sparse Bayesian learning algorithm of the preferred embodiment has a superior reconstructed capability compared to the conventional l1-norm method even though the number of measurements is below the theoretical lower bound for the conventional l1-norm method.

In sum, the cooperative spectrum sensing system of the present invention can accurately estimate the number and locations of the primary transmitters $I$. In addition, the computational complexity is reduced through deletion of the basis functions performed in the sparse Bayesian learning algorithm.

While the present invention has been described in connection with what is considered the most practical and preferred embodiment, it is understood that this invention is not limited to the disclosed embodiment but is intended to cover various arrangements included within the spirit and scope of the broadest interpretation so as to encompass all such modifications and equivalent arrangements.

What is claimed is:

1. A cooperative spectrum sensing method of detecting primary transmitters in a cognitive radio (CR) system, each of the primary transmitters transmitting a power signal, the CR system including a number (N) of secondary users, which are randomly located in a predetermined area and are divided into a plurality of sets, and a plurality of CR base stations disposed in the predetermined area and corresponding respectively the sets of the secondary users, said method comprising the steps of:

   a) configuring each of the secondary users to obtain location information thereof, generate a received signal strength indicator (RSSI) value in response to sensing the power signals from the primary transmitters, and transmit the location information and the RSSI value such that each of the CR base stations receives and
collects the location information and the RSSI values from a corresponding set of the secondary users; b) configuring each of the CR base stations to transmit the location information and the RSSI values collected thereby to a data fusion center through a backbone network such that the data fusion center receives the location information and the RSSI values associated with all the secondary users; and c) configuring the data fusion center to obtain the number and locations of the primary transmitters in the predetermined area based on the location information and the RSSI values received thereby using a learning algorithm to thereby reconstruct a power propagation map of the primary transmitters in the predetermined area.

2. The cooperative spectrum sensing method as claimed in claim 1, wherein the data fusion center is a cloud computing center.

3. The cooperative spectrum sensing method as claimed in claim 1, wherein the RSSI values generated respectively by the secondary users are processed to form a vector (t), which is modeled

\[ \Phi(t) \in \mathbb{R}^{1 \times 
 \begin{bmatrix}
 \phi(t_1) & \phi(t_2) & \cdots & \phi(t_N)
 \end{bmatrix}
\]

wherein \( \Phi \) denotes a basis matrix and is represented as

\[ \phi(t_i) = \begin{bmatrix}
 \phi_1(t_i) \\
 \phi_2(t_i) \\
 \vdots \\
 \phi_{m}(t_i)
\end{bmatrix}
\]

where \( \phi_1, \cdots, \phi_m \) denote \( m \) basis functions uniformly distributed in the predetermined area, \( x_i = (x_{i1}, \cdots, x_{iN}) \) denotes the location of an \( i \)-th one of the secondary users and is represented as \( x_i = (x_{i1}, \cdots, x_{iN}) \), \( w \) denotes a weighting coefficient vector and is represented as \( w = (w_1, w_2, \cdots, w_N)^T \), and \( n \) denotes a shadowing effect vector and is represented as \( n = (n_1, n_2, \cdots, n_N)^T \).

4. The cooperative spectrum sensing method as claimed in claim 3, wherein \( w_i, i = 1, \ldots, M \) is initially given with a prior probability of

\[ \gamma_{ij} \sim \text{Beta}(\alpha, \beta) \]

and \( \epsilon_j, j = 1, \ldots, N \) is a zero-mean Gaussian random variable with variance \( \sigma_j^2 \).

5. The cooperative spectrum sensing method as claimed in claim 4, wherein \( \phi_j(x_j) \) is substantially a two dimensional Laplacian function and is represented as

\[ \phi_j(x_j) = \frac{1}{2\sigma_j} \exp \left( -\frac{D}{\sigma_j} \right) \]

where \( D \) is defined as \( \sqrt{(x_{ij} - x_{ji})^2 + (x_{ik} - x_{ki})^2} \), \( \mu_j \) is defined as the location of an \( j \)-th one of the primary transmitters and is represented as \( \mu_j = (\mu_{j1}, \mu_{j2})^T \), and \( \sigma_j \) is a scale parameter and denotes a power decay rate for the \( j \)-th one of the primary transmitters.

6. The cooperative spectrum sensing method as claimed in claim 5, wherein:

- the learning algorithm is a sparse Bayesian learning algorithm; and

- further includes the sub-steps of:

- c-1) configuring the data fusion center to process each of the RSSI values received thereby so that those of the RSSI values greater than a predetermined value \( P_{\text{th}} \) are respectively updated with differences with the predetermined value \( P_{\text{th}} \) and that those of the RSSI values not greater than the predetermined value \( P_{\text{th}} \) are updated with zero;
- c-2) configuring the data fusion center to initially provide the number \( M \) of the basis functions \( \{ \phi_j \} \) uniformly distributed in the predetermined area so as to obtain the basis matrix \( \Phi \) associated with the locations of the secondary users;
- c-3) configuring the data fusion center to define an iteration index \( k \) and compute a covariance \( \Sigma \) and a mean \( m \) initially with \( \alpha_0 = 1, \beta = 1 \) and \( k = 0 \), wherein \( \Sigma^{-1} = (\Phi \Phi^T + \alpha_0 \Sigma)^{-1} = m = \beta_0 \Phi^T + \lambda \Lambda \)-\text{diag}(\alpha_j), which is an \( M \times M \) diagonal matrix;
- c-4) configuring the data fusion center to update respectively the iteration index \( k \), \( \alpha_j \), and \( \beta_j^k \) with \( k + 1 \),

\[ m_k^j = m_k^{j-1} + \frac{m_k^{j-1} - \Phi(t_{j,k-1}) \mu_k}{\gamma_{jj}}, \]

\[ N = \sum_{j=1}^{N} \gamma_{jj}, \]

wherein \( \gamma_{jj} = 1 - \alpha_j \Sigma_{jj} \) and \( \Sigma_{jj} \) is a diagonal term of the covariance \( \Sigma \), and compute again the covariance \( \Sigma \) and the mean \( m \) with the updated iteration index \( k \), \( \alpha_k \), and \( \beta_k \); and
- c-5) configuring the data fusion center to delete the basis functions \( \{ \phi_j(x_j) \} \) whose corresponding weighting coefficients \( w_j \) are less than a predetermined weight threshold \( \eta \), and update the number \( M \) of the basis functions \( \{ \phi_j(x_j) \} \) based on the remaining basis functions \( \{ \phi_j(x_j) \} \) such that the basis matrix \( \Phi \) and \( A \) are updated, thereby updating the covariance \( \Sigma \) and the mean \( m \); and
- c-6) configuring the data fusion center to compute \( Q(k) \), wherein \( Q = \text{log} p (t|X, w, \beta, \mu, s, M) \) and update repeatedly \( \mu_j \) and \( s_j \) for predetermined times based on the basis matrix \( \Phi \) and mean \( m \) updated in step c-5) using

\[ Q = \sum_{j=1}^{N} \frac{\partial Q}{\partial \rho_j} \mu_j \rho_j + \frac{\partial Q}{\partial \rho_j} s_j \rho_j + \frac{\partial Q}{\partial \rho_j} \mu_j \rho_j + \frac{\partial Q}{\partial \rho_j} s_j \rho_j \]

upon detecting that \( k \) is less than a predetermined index threshold or that \( (Q(k) - Q(k-1))/Q(k-1) \) is not less than a conditional probability threshold, wherein \( \delta \) is a learning rate greater than zero;
- c-7) repeating steps c-4) to c-6) until \( k \) is not less than the predetermined index threshold while \( (Q(k) - Q(k-1))/Q(k-1) \) is less than the conditional probability threshold; and
- c-8) configuring the data fusion center to re-compute \( \alpha_k^j, \beta_k^j, m, \Sigma \), wherein \( m \) serves as \( w \) and the number \( M \) updated in step c-5) serves as the number of the primary transmitters in the predetermined area, and reconstruct the power propagation map of the primary transmitters based on \( P_{\text{th}}, \Sigma, \Phi, \mu_j, M \) and \( w_j \).
7. A cooperative spectrum sensing system for locationing primary transmitters in a predetermined area, each of primary transmitters transmitting a power signal, said cooperative spectrum sensing system comprising:

a number (N) of secondary users randomly located in the predetermined area and divided into a plurality of sets, each of said secondary users including a positioning module for obtaining location information thereof, being adapted for sensing the power signals from the primary transmitters to generate a received signal strength indicator (RSSI) value, and transmitting the location information and the RSSI value;

a plurality of cognitive radio (CR) base stations disposed in the predetermined area and corresponding respectively the sets of the secondary users, each of said CR base stations receiving and collecting the location information and the RSSI values from a corresponding set of secondary users; and

da data fusion center communicating with each of said CR base stations through a backbone network;

wherein each of the CR base stations transmits the location information and the RSSI values collected thereby to said data fusion center through the backbone network such that the data fusion center receives the location information and the RSSI values associated with all the secondary users; and

wherein said data fusion center is configured to obtain the number and locations of the primary transmitters in the predetermined area based on the location information and the RSSI values received thereby using a learning algorithm to thereby reconstruct a power propagation map of the primary transmitters.

8. The cooperative spectrum sensing system as claimed in claim 7, wherein said data fusion center is a cloud computing center.

9. The cooperative spectrum sensing system as claimed in claim 7, wherein the RSSI values generated respectively by said secondary users are processed to form a vector (t), which is modeled using linear regression as

\[ t = \Phi \omega_n + \epsilon \]

wherein \( \Phi \) denotes a basis matrix and is represented as

\[
\Phi_{MxN} = \begin{bmatrix}
\phi_1(x_1) & \phi_2(x_1) & \ldots & \phi_M(x_1) \\
\phi_1(x_2) & \phi_2(x_2) & \ldots & \phi_M(x_2) \\
\vdots & \vdots & \ddots & \vdots \\
\phi_1(x_N) & \phi_2(x_N) & \ldots & \phi_M(x_N)
\end{bmatrix}
\]

where \( \phi_1, \ldots, \phi_M \) denote M basis functions uniformly distributed in the predetermined area, \( x_i (i = 1, \ldots, N) \) denotes the location of an \( i^{th} \) one of the secondary users and is represented as \( x_i = (x_{i1}, x_{i2}) \), \( w \) denotes a weighting coefficient vector and is represented as \( w = (w_1, w_2, \ldots, w_M)^T \), and \( \epsilon \) denotes a shadowing effect vector and is represented as \( \epsilon = (\epsilon_1, \epsilon_2, \ldots, \epsilon_N)^T \).

10. The cooperative spectrum sensing system as claimed in claim 9, wherein \( w_j (j = 1, \ldots, M) \) is initially given with a prior probability of

\[ N(0, \sigma_j^2) = \frac{1}{\sqrt{2\pi \sigma_j^2}} \exp \left( -\frac{t^2}{2\sigma_j^2} \right) \]

and \( \epsilon_i (i = 1, \ldots, N) \) is a zero-mean Gaussian random variable with variance \( \beta^{-1} \).

11. The cooperative spectrum sensing system as claimed in claim 10, wherein \( \phi_j(x_1) \) is substantially a two dimensional Laplacian function and is represented as

\[ \phi_j(x) = \frac{1}{2\pi} \exp \left( -\frac{D}{\sigma_j^2} \right) \]

where \( D \) is defined as \( \sqrt{(x_{i1}-\mu_{i1})^2 + (x_{i2}-\mu_{i2})^2} \), \( \mu_i \) is defined as the location of an \( i^{th} \) one of the primary transmitters and is represented as \( \mu_i = (\mu_{i1}, \mu_{i2}) \), and \( \sigma_j \) is a scale parameter and denotes a power decaying rate for the \( j^{th} \) one of the primary transmitters.

12. The cooperative spectrum sensing system as claimed in claim 11, wherein the learning algorithm is a sparse Bayesian learning algorithm such that said data fusion center is configured in accordance with the sparse Bayesian learning algorithm to perform

a first operation, where each of the RSSI values received by said data fusion center is processed so that those of the RSSI values greater than a predetermined value (P_{stop}) are respectively updated with differences with the predetermined value (P_{stop}) and that those of the RSSI values not greater than the predetermined value (P_{stop}) are updated with zero,

a second operation, where the number (M) of the basis functions (\( \Phi(\Phi_M) \)) are initially provided and are uniformly distributed in the predetermined area so as to obtain the basis matrix (\( \Phi(\Phi_M) \)) associated with the locations of said secondary users,

a third operation, where an iteration index (k) is defined, and where a covariance (\( \Sigma(\Sigma_M) \)) and a mean (m) are computed initially with \( \alpha_j = 1, \beta_j = 1 \) and \( k = 0 \), wherein \( \Sigma = \Sigma(\Phi(\Phi_M) + \Lambda)^{-1} + \mu - \beta_0 \Sigma^{-1} \Lambda \) and \( \Lambda = \text{diag}(\alpha) \), which is an \( M \times M \) diagonal matrix,

a fourth operation, where the iteration index (k), \( \alpha_j^{-1} \) and \( \beta_j^{-1} \) are updated respectively with \( k+1 \),

\[ \frac{m_j}{\gamma_j} + \frac{\| \epsilon_j - \Phi \omega_n \|^2}{N \| \gamma_j \|} \]

where \( \gamma_j = 1 - \alpha_j \Sigma_j \) and \( \Sigma_j \) is a diagonal term of the covariance (\( \Sigma(\Sigma_M) \)), such that the covariance (\( \Sigma(\Sigma_M) \)) and the mean (m) are computed again with the updated iteration index (k), \( \alpha_j^{-1} \) and \( \beta_j^{-1} \), where the basis functions (\( \phi_j(x_1) \)) whose corresponding weighting coefficients (\( \omega_j \)) are less than a predetermined weight threshold (\( \gamma \)) are deleted to thereby update the number (M) of the basis functions (\( \Phi(\Phi_M) \)) based on the remaining basis functions (\( \Phi(\Phi_M) \)) such that the basis matrix (\( \Phi(\Phi_M) \)) and A are updated, thereby updating the covariance (\( \Sigma(\Sigma_M) \)) and the mean (m), and

where Q(\( k \)) is computed, wherein \( Q_k = \ln P(t|X,w,\mu,s,M) \), and \( \mu_i \) and \( s_j \) are updated repeatedly for predetermined times based on the updated basis matrix (\( \Phi(\Phi_M) \)) and mean (m) using

\[
\begin{bmatrix}
\mu_{i1}(k) \\
\mu_{i2}(k) \\
\mu_{i1}(k-1) \\
\mu_{i2}(k-1)
\end{bmatrix} = \begin{bmatrix}
\frac{\partial Q}{\partial \mu_{i1}} \\
\frac{\partial Q}{\partial \mu_{i2}} \\
\frac{\partial Q}{\partial \mu_{i1}} \\
\frac{\partial Q}{\partial \mu_{i2}}
\end{bmatrix}
\]

upon detecting that \( k \) is less than a predetermined index threshold or that \( (Q(k) - Q(k-1))/Q(k-1) \) is not less than a conditional probability threshold, wherein \( \delta \) is a learning rate greater than zero,
a fifth operation, where the fourth operation is performed repeatedly until \( k \) is not less than the predetermined index threshold while \((Q(k)-Q(k-2))/Q(k-1)\) is less than the conditional probability threshold, and a sixth operation, where \( \alpha^{-1}, \beta^{-1}, m \), and \( \Sigma \) are re-computed, wherein \( m \) serves as \( w \) and the number \( (M) \) updated in the fourth operation serves as the number of the primary transmitters in the predetermined area, such that the power propagation map is reconstructed based on \( P_{\text{sub}} \), \( \beta \), \( \Sigma \), \( M \) and \( w \).