A MODE IDENTIFICATION PROCEDURE FOR SOFTWARE DEFINED RADIO TERMINALS IN CASE OF SUPERIMPOSED SIGNALS

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ABSTRACT

In this work, a mode identification system for superimposed signals in the same band is presented. More precisely, a signal processing technique, namely the Wigner-Ville distribution, combined with non parametric (k-Nearest Neighbors and Parzen) and Neural Network classifiers is proposed for identifying the transmission modes in an indoor wireless environment. A reconfigurable terminal based on Software Defined Radio technology is considered aiming at the identification of the presence of two co-existent communication modes such as Bluetooth, based on Frequency Hopping - Code Division Multiple Access, and IEEE WLAN 802.11b, based on Direct Sequence - Code Division Multiple Access. Results in terms of error classification probability, expressed as relative error frequency, will be provided with a comparison among the classifiers.

1. INTRODUCTION

The Software Defined Radio (SDR) paradigm [1] defines the enabling technology that allows one to realize the so called reconfigurable terminals (RT) by software-defining their communication layers [2]. By definition SDR devices should support multi-mode, multi-band and multi-standard communications in future generation wireless system [3] with an high level of adaptability, flexibility and reconfigurability.

This work deals with the physical layer of a SDR based RT. To support multi-mode communications, SDR brings a revolution in the receiver's design with respect to the conventional radio devices based on heterodyne schemes [1], [4]. In fact, SDR based receiver should have a very reduced analogical part based on a unique Radio Frequency (RF) stage which is composed by the Antenna, Low Noise Amplifiers (LNA) and Filters [1], [4] with the A/D conversion process closer to the antenna. All the signals captured by RF part, are first sampled at high frequency and then converted in a digital format [4]. After, the entire processing (usually done in an analogical way in conventional terminals) is performed by means of digital signal processing techniques. In the design of RT, the problems lies at hardware, software and signal processing (SP) level [1]. In fact, SDR based receiver, as described above, is not yet feasible with the current technology. For example, it's not possible to design a wideband antenna to receive multi band modes and A/D converters with sufficient quantization and sampling frequency as required in SR applications [1]. Therefore, the current solution aims to use a radio frequency (RF) conversion stage that brings the received signal at Intermediate Frequency (IF) [1]. In case of multi band communication, antenna arrays or different RF stages can be also employed [15].

However, to design SDR based receiver with the characteristics describe above, one of the most important open issue, that this paper deals with, is the mode identification [5], [9] and [19]. More precisely, SDR receiver should be able to monitor the radio channel in a certain frequency range (as wide as possible) and recognize all possible communication modes, employing digital signal processing techniques. The solution of demodulating in parallel a large set of transmission modes is infeasible at the receiver and it introduces an high level of complexity in the hardware receiver structure. A more suitable solution, explored in this paper, is to try to identify at a lower abstraction level, multiple transmission modes directly from the sampled version of the signal before decoding and extracting the modulated information contained in the signal itself. Once the available mode/s is/are identified, SDR receiver should set up all necessary procedures at base-band processing to support it/them.

In general, a mode identification procedure can involve several aspects [2]: modulation recognition, air interface type classification, etc. Moreover, communications modes can be superimposed in the same band or separated. In the first case the identification process is more difficult because they interfered each other. In this work, the attention is devoted to analyze this case employing signal processing techniques.

The identification of two co-existent Spread Spectrum access methods is analysed; in particular, IEEE WLAN 802.11b DS-CDMA [7] and Bluetooh (BT) FH-CDMA [6] are considered. These two standards operate in the same bandwidth (Industrial Scientific Medical, ISM Band). The choice of these modes is due to the possibility to design an unique RF conversion stage, and the growing interest in the market around them for wireless connectivity especially, for the communication in the coexistent environment [3], [16]. In the state of the art, Energy detection [8], is a common method with low processing load to recognize the presence or absence of a signal. Unfortunately, when signals are temporally overlapped on the same bandwidth, the energy detection may not be not sufficiently discriminant. Consequently, the information are not sufficient to perform further steps for mode identification. A recent work [6] presents the use of a radial basis function neural network with a Power Spectral Density estimation to identify the communication standards. No superposition of signals is considered and different RF stages are employed. The European project TRUST (European research project transparent Ubiquitous terminal) presents a system for mode identification for GSM and UMTS standard [2].

In this work, a pattern recognition approach based on Time Frequency (TF) signal analysis, non parametric an Neural Networks classifiers is proposed to solve the problem of mode identification in the case of two superimposed standards, namely WLAN IEEE 802.11b and BT. As TF tool, the Wigner-Ville Distribution (WVD) [10] has been chosen: it allows one to extract important features to classify the air interface present in the case under inspection. As classifiers non non parametric and neural networks techniques are here employed because they are able to classify without any a-priori statistical information about the probability density function (PDF) of features. In the case of study such kind of information (PDF) is not available due to the user mobility as it will be explained in the sub-section 2.3, so the use of *k*-Nearest Neighbors (k-NN), Parzen Windows, Feed Forward Back Propagated Neural Network (ffbpnn) and Support Vector Machine (SVM) are considered. The present paper is so organized: in section 2 the proposed identification method is explained, in section 3 numerical results will be presented and discussed, conclusions will be drawn in section 4.

2. PROPOSED METHOD

The following scenario is considered: an indoor WLAN cell, including BT piconets [6], [7] where a user with his RT can move around identifying one of the available transmission modes. The mobile device should be able to detect the presence of two standards: DS-CDMA and FH-CDMA. The proposed classification scheme is depicted in the following figure.

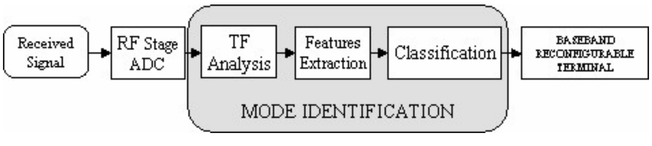


Figure 1. The proposed mode identification scheme

2.1 Time-Frequency Distribution

The received signal after RF stage and A/D conversion is processed by a TF block. The TF block provides a representation which allows one to use a compact and robust signal visualization in two dimensions: time and frequency. For this reason, TF methods potentially provide higher discriminating power useful for signal identification. As TF distribution, the Wigner-Ville transform has been chosen. This transform is the most used. It has low computational complexity, a good feature for real-time usage. The Wigner-Ville distribution is expressed by the following expression:

$$W(t,\omega) = \frac{1}{2\pi}\int y^*(t-\tfrac{1}{2}\tau)\,y(t+\tfrac{1}{2}\tau)\,e^{-j\tau\omega}\,d\tau \tag{1}$$

the integral ranges from -∞ to ∞ and $y(t)$ in our case is the sampled version of the received signal. It is band-limited and contains the two superimposed modes (WLAN and BT).

2.2 Features Extraction

From Wigner-Ville transform, it is possible to extract TF features of the received signal observed on a time window *T*. Two features are considered [10]:

- Feature 1: standard deviation of the instantaneous frequency.
- Feature 2: maximum time duration of signal.

To obtain the first feature from a given TF distribution $P(t,\omega)$ the first conditional moment is computed as:

$$<\omega>_t = \frac{1}{P(t)}\int \omega P(t,\omega)\,d\omega \tag{2}$$

where $P(t)$ is the time distribution and the integral ranges from -∞ to ∞. In our case $P(t,\omega)$ is the Wigner distribution of the received signal. $<\omega>_t$ is the average of frequency at a particular time *t* and it is considered as the instantaneous frequency [10] . If the signal is considered as a generic band pass signal given by [10] :

$$s(t) = A(t)e^{j\varphi(t)} \tag{3}$$

where $A(t)$ is the signal amplitude and $\varphi(t)$ is the signal phase. Its instantaneous frequency ω_i is [10]:

$$\omega_i = \varphi'(t) = <\omega>_t \tag{4}$$

The standard deviation of ω_i :

$$std(\omega_i) = \left(\frac{1}{T} \sum_{t=1}^{T} (\omega_i - \overline{\omega}_i)^2 \right)^{\frac{1}{2}} \tag{5}$$

where $\overline{\omega}_i$ is the mean value of ω_i computed on the time window *T*, given by:

$$\overline{\omega}_i = \frac{1}{T} \sum_{t=1}^{T} \omega_i \tag{6}$$

From Figure 2 one can see that it is reasonable to obtain a low value of $std(\omega_i)$ when the first conditional moment is quite constant as in the case of DS (WLAN) whereas $std(\omega_i)$ assumes high values in the case of FH (BT).

The second feature is obtained on the basis of the following considerations. In case of DS, frequency components are continuous in time for a duration that depends on the length of the time observation window *T* used to compute the distribution. Instead, for FH signal, a discontinuity in time can be observed due to the presence of different frequency hops. Therefore, it is possible to obtain an empirical discriminating feature based on the time duration of the signal. To obtain such data the following operations are performed:

1. From the chosen transform a binary TF matrix $P_{bin}(t,f)$ is obtained, by a threshold. The values of this matrix represent presence (element equals to 1) or absence (element equals to 0) of signal at a given time *t* and at a given frequency *f*.
2. The threshold has been chosen in an empirical way. After a trial and test procedure, its value has been chosen as the mean value of the TF matrix;
3. Once $P_{bin}(t,f)$ has been obtained, the elements of each row, i.e. for each frequency, are summed up to obtain the length in time of the signals component at a certain frequency.

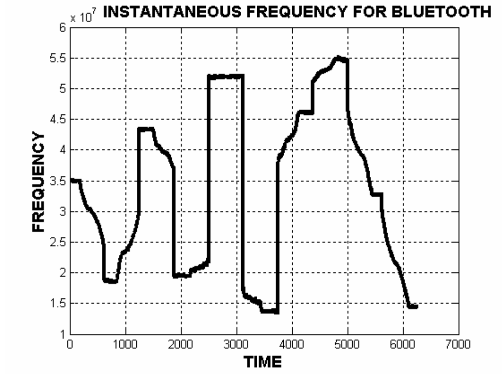
With these operations the duration of the components for each frequency, $T(\omega)$, is obtained. The feature to presente to the *k*-NN or Parzen has been chosen as the maximum value T_M in such set, namely:

$$T_M = \max\{T(\omega)\}. \tag{7}$$

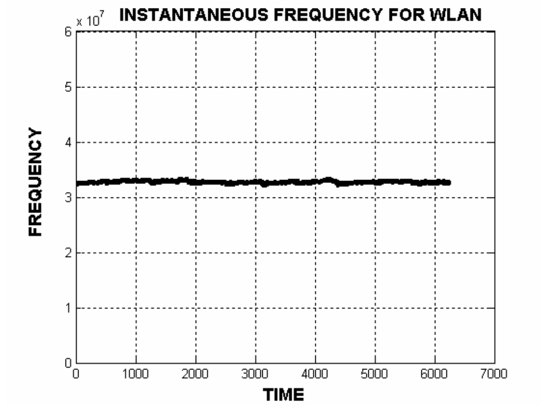
where

$$T(\omega) = \sum_t P_{bin}(t,\omega) \tag{8}$$

where the summation is done over the entire length of the window where the distribution is computed.



(a)



(b)

Figure 2. Example of the conditional moment of the first order in case of BT (FH-CDMA) (a) and IEEE 802.11b (DS-CDMA) (right).

2.3 The Classifier

A multiple hypotheses test has been performed. In particular four classes have been studied:

- class H0: presence of a Additive White Gaussian Noise (AWGN). This class will be indicated as ‘Noise’.
- class H1: presence of WLAN signal with AWGN and Multipath Fading. It will be indicated as ‘WLAN’.
- class H2: presence of BT signal with AWGN and Multipath Fading. It will be indicated as ‘BT’.
- class H3: presence of both signals with AWGN and Multipath. It will be indicated as ‘WLAN + BT’.

The extracted features to discriminate the four cases depend on the user distance from the signal source; as consequence, the four classes move in the feature plane with respect to the user movement. The first effect is that different classifiers for each user position would be necessary [11]. This is too complex and unfeasible. Therefore, non-parametric and neural classification tools will be used [11]. With the first a theoretical model of experimental distribution is not necessary because the classification is carried out without any a-priori statistical information of samples. Between the various non parametric classifiers the *k*-Nearest Neighbors (k-NN) and Parzen approach have been chosen and their performances have been evaluated. Both perform an estimation of PDF in a particular region whose dimension can be variable (k-NN) or fixed (Parzen) [11]. The former computes the estimation considering a fixed (*k*) number of training samples through the entire features space, then the estimation window becomes larger in low density areas and smaller in high density areas. Instead the Parzen algorithm fixes the dimension of the estimation window so the samples number changes with respect to density, that is the dual procedure of k-NN.

For the k-NN the best value of *k* has to be experimentally chosen, while the window size for Parzen approah is obtained after a minimization of the Integrated Mean Square Error (IMSE) [11] :

$$IMSE = \int E\left\{\left[\hat{p}(X) - p(X)\right]^2\right\} dX \qquad (9)$$

where $\hat{p}(X)$ is the estimated PDF of samples *X*, while $p(X)$ is the real PDF. Imposing $\partial IMSE/\partial r = 0$, the optimal dimension r^* of kernel (through which the PDF is estimated) is:

$$r^* = \left[\frac{n\Gamma\left(\frac{n+2}{2}\right)}{\pi^{n/2}(n+2)^{n/2}|A|^{1/2}\int \alpha^2(X)p^2(X)dX}\right]^{\frac{1}{n+4}} \times N^{-\frac{1}{n+4}} \qquad (10)$$

where *n* is the dimension of features space, *A* is a parameter of the kernel function, *N* is the number of training samples, *Γ* the gamma function and

$$\alpha(X) = tr\left\{\frac{\nabla^2 p(X)}{p(X)} A\right\} \qquad (11)$$

The eq. (11) will be used in simulations to compute the optimal window dimension.

The chosen neural networks are feed forward back-propagation neural networks (f.f.b.p.n.n.) and Support Vector Machines (SVMs). A f.f.b.p.n.n has been trained by the back-propagation supervised [21] method. In particular, the learning algorithm is the "Batch Gradient Descent with Momentum", so the synaptic weights and biases are updated at the end of the entire training set [20]. Moreover, with the Momentum version not only the local gradient is considered but also the previous values of the cost function: acting as a low-pass filter, the Momentum allows the network to ignore some local minima.

The second classifier, the SVM, has a Radial Basis Function (RBF) as kernel, due to the characteristics of the features space, which is composed of non-separable classes [22]. The equation for the kernel is given by the following formula:

$$K(x_i, x_j) = \exp(-\gamma \cdot \| x_i - x_j \|^2), \qquad \gamma > 0 \qquad (12)$$

As in the case of this paper, the classical problem of linear Support Vector Machines is modified by inserting positive slack variables ξ_i, i=1,…,l [22] to introduce a further cost when necessary. So the constraint that has to be satisfied by the training data becomes:

$$\begin{aligned} & y_i \cdot (w^T \phi(x_i) + b) \geq 1 - \xi_i \\ & for \quad \xi_i \geq 0, i = 1.....l \end{aligned} \qquad (13)$$

Then the problem of finding the hyperplane is:

$$\min_{w,b,\xi}\left\{\frac{1}{2}w^T w + C\sum_i \xi_i - \sum_i \alpha_i \left\{y_i\left(x_i w + b\right) - 1 + \xi_i\right\}\right\} \qquad (14)$$

where l is the training-set dimension, x_i is the training vector, $y_i \in \{-1,1\}$ are the training labels, w is the vector normal to the hyperplane, $\phi(x)$ is the mapping function and C is a parameter added to the ξi.

To obtain the best classifier the parameters have to be optimized. The grid-search approach has been chosen to find the values of C and γ (RBF exponent, (12)).Both classifiers present as input a vector $\underline{v}$ whose components are the features (6) and (7):

$$\underline{v} = [std(\omega_i), T_M] = [v_1, v_2] \qquad (15)$$

The output is a two-bit variable with one of the four possible values: presence of WLAN (DS-CDMA), presence of Bluetooth (FH-CDMA), presence of both, presence of noise only.

3. SIMULATIONS AND RESULTS

Results in terms of Relative Error Frequency are here presented. For the trials, a power class three for Bluetooth and a 25 mW power level for WLAN is considered. The number of transmitted bits is equal to 10^3. The simulation model of the physical level of the two standards has been set up in MATLAB/Simulink environment, following all the specifications given by and. Moreover, a scenario with a single user has been considered: an IEEE 802.11b access point and a Bluetooth piconet are presented. An indoor environment (a 15m×15m room) with sources placed in the room corners is considered as described in [12], [14]. The simulation foresees a user, provided with an SDR mobile handset, who arbitrarily moves in the room and has to classify the standards available. The channel model is a downlink indoor channel at 2.4 GHz with multipath fading and AWGN noise (more details can be found in [19]). During the simulations, Signal to Noise Ratio (SNR) is considered variable with respect to the distance as the received signal power changes due to the path loss. Once the signals are passed through the channel, they are converted to intermediate frequency, and then the A/D conversion is performed to a sample rate of 120 MSample/s to satisfy the Nyquist limit. The intermediate frequency has been chosen to be equal to 30 MHz. Then the received signal is computed by the TF block. The WVD distribution uses blocks with N = 512 samples obtained by a time window *T* long enough to contain 10 frequency hops. The time hopping is 625 μs [6]. The extraction module stores 10 TF matrices and calculates the features as defined in the previous section. The values are passed to the classifiers whose implementation requires the following steps: training, testing and evaluation.

The numerical characteristics, explained above, are exactly the same of the system proposed in [19]. The differences are the chosen classifiers, *k*-NN, Parzen and Neural Networks. As consequence, different identification results, which are compared together, have been evaluated: in the following figures, the Relative classification Error Frequency is shown for each class using the two non parametric classifiers and the TF distribution and they are plotted together the results provided by Support Vector Machine and the feed forward back propagated neural network.

The only noise class is always correctly classified. The number of neighbors training samples for *k*-NN has been chosen to be 159. The Figure 4 and Figure 5 show the classification of WLAN and Bluetooth class by using the four classifiers here presented. It is worth mentioning the improvement obtained for Bluetooth class with the *k*-NN where the relative error frequency is lower than 10^{-3} for the whole range covered by standard (10 m). This is due to high performances of the *k*-NN than neural networks with classes with elevated spread as Bluetooth, [23]. For WLAN class, the error rate with non parametric classifiers is worse than with the neural networks and SVM due to lower ability of *k*-NN and Parzen to identify overlapping classes. The Figure 6 shows the error frequency for WLAN+Bluetooth case with respect to distance from Bluetooth; the particular behaviour of the system is due to the fact that when terminal is near a source, the transmitted power is too high to discriminate the two modes present. In these cases, the non parametric approach allows one to obtain the same performances with respect to the neural classifiers.

Some considerations can be done for *k*-NN and Parzen approach: both don't assume any prior knowledge, fundamental feature in applications like that considered in this paper. Regarding the *k*-NN, using *k* equal to 159 as fixed, the classifier presents an high bias, this means that also using a very large number of training samples (ideally ∞) the performances cannot reach the optimal classification rate and the classifier loses local information. But the advantage, as reported in [17], is that the variance can decrease and the decision boundaries are smoothed so the global classification outcomes do approximate those of posterior probability. The same considerations can be done for the Parzen approach: by increasing the window width we have an higher training error, but most likely better generalization performances. Another drawback can be identified for these two classifiers: the computational complexity: either Parzen and *k*-NN suffer of course of dimensionality [18] and moreover with large *k* or window width the computational cost in the testing phase is high.

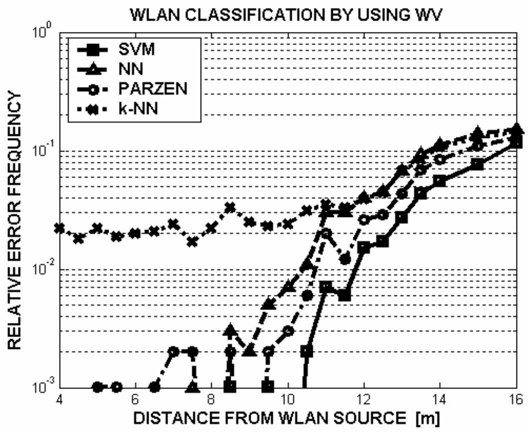


Figure 4 Error rate for WLAN classification

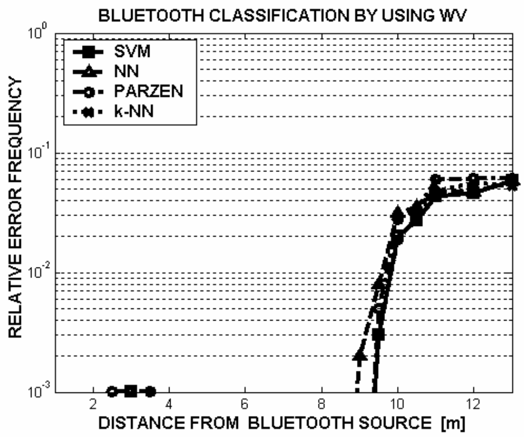


Figure 5 Error rate for Bluetooth classification

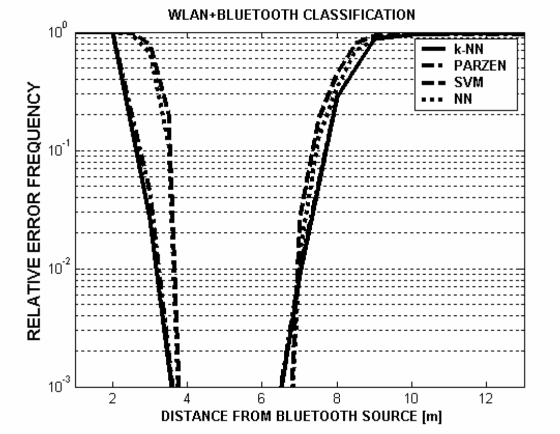


Figure 6 Error rate for WLAN+Bluetooth classification

4. CONCLUSION

In this work a method for mode identification has been proposed and discussed. Two co-existent communication modes have been considered: IEEE 802.11b based an DS-CDMA and BT based on FH-CDMA. The proposed technique combines the use of TF analysis and non parametric, k-NN, Parzen and Neural Networks classifiers as possible solutions. Numerical results for indoor environment have been presented with a comparison of the classifiers and a couples of features. They show that the four configurations, except that WLAN case, present the same performances. The results are promising for all cases and the on-going research is devoted to explore the use of other kinds of TF distribution, classifiers and features to improve the identification ability of the proposed system.

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