A MODE IDENTIFICATION SYSTEM FOR A RECONFIGURABLE TERMINAL USING TIME FREQUENCY ANALYSIS AND A NON-PARAMETRIC CLASSIFIER

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ABSTRACT

The use of Time Frequency (TF) analysis is proposed as signal processing technique combined with a pattern recognition approach, for identifying the transmission modes in indoor wireless environment with a reconfigurable mobile terminal based on Software Radio techniques. In particular, a Software Radio device is considered aiming at the identification of the presence of two co-existent communication modes as Bluetooth, based on Frequency Hopping - Code Division Multiple Access (FH-CDMA), and IEEE WLAN 802.11b, based on Direct Sequence - Code Division Multiple Access (DS-CDMA). A pattern recognition approach will be presented, where TF analysis is employed for feature extraction, and a multi hypotheses *k* nearest neighbors (*k*-NN) non parametric classifier is used. Results in terms of error classification probability, expressed as relative error frequency, will be provided.

1. INTRODUCTION

The concept of Software Radio (SR) [1] gives the possibility that transmission/reception layer functions can be fully software-defined to support multi-mode, multi-band, multi-standard communications for future generation wireless systems [11]. In this work, the receiving part of a SR device and in particular its physical layer is highlighted and considered. To support multi-standard communications, SR brings to a revolution in the design of a receiver terminal with respect to the conventional radio devices based on the classical heterodyne scheme [1]. In fact, the analog part of an SR receiver is very reduced (only the wideband antenna, the Low Noise Amplifier (LNA) and a Band pass filter [1]) and it should be designed to receive more than one standard and not a particular one [1]. Moreover, the A/D conversion process becomes closer to the antenna and all the signals associated with communication modes present in the radio environment are first sampled at high frequency and then represented in a digital format. After this, the entire processing (usually done in an analog way in conventional terminals) is performed by means of digital signal processing techniques. In the design of a SR terminal problems arise from an hardware, software and signal processing (SP) point of view [1]; in fact, an ideal hardware based SR receiver like that described above is not possible yet with the current technology. In fact, the wideband receiving antenna designing and A/D converters with sufficient quantization levels and sampling frequency are still to come [1], [11]. Therefore, the current solution is to use a radio frequency (RF) conversion stage that brings the received signal at Intermediate Frequency (IF) [1]. In the SP category, one of the most important open issues object of this work and of current research, is mode identification [2], [11]. More precisely, with this term the following operation is considered: a SR based receiver should be able to monitor the channel to recognize the presence of a communication mode by means of digital signal processing techniques [2]. To perform this task the solution of demodulating in parallel a large set of transmission modes at the receiver seems unfeasible. A more suitable solution, explored in this paper and more in general in the SR domain, is to try to identify, at a lower abstraction level, multiple transmission modes directly from the sampled version (provides by the A/D) of the incoming electromagnetic received signal. Once the mode has been identified the receiving operations can be directly carried out, if the software modules (for that standard) are present in the terminal, otherwise downloaded the dedicated libraries from the network [1],[11]. In particular, the proposed method could be practical for those contexts in which multiple transmission modes co-exist on the same bandwidth like those explored in this paper. The term mode identification can involve several things [2]: modulation recognition, air interface type classification, etc. In this work our attention is devoted to the identification of air interface. In particular, for IEEE WLAN 802.11b DS-CDMA [4] and Bluetooth FH-CDMA [3]. The choice to realize a mode recognition algorithm for Bluetooth and IEEE 802.11b is due to the coexistence of the two mentioned modes in the same bandwidth (Industrial, Scientific and Medical band, ISM Band) with the possibility to design a unique RF stage as ideally required for SDR platform [1] and for the grown interest in the market around these two standards for indoor wireless connectivity. This is a case of study for the application of the proposed identification method. However, more in general the proposed method could be employed in all case where signals are superimposed in the same band.

Energy detection [5], is a common method with low processing load to recognize the presence or absence of a signal. Unfortunately, when signals temporally overlapping on the same bandwidth are considered, energy detection can be not sufficiently discriminant. Moreover, the information provided by Energy detection can be not sufficient to perform further steps, for example, in the direction of modulation recognition. A recent work [6] presents the use of a radial basis function neural network with a Power Spectral Density estimation to identify some communication standard standards. No superposition of signals is considered and different RF stages are employed. The European project TRUST (TRansparent UbiquitouS Terminal) presents a system for mode identification for GSM and UMTS standard [2].

In this work, a signal processing method, the TF analysis [7], and a multi hypotheses *k*-NN classifier, as possible solution, is proposed to solve the problem of mode identification. TF analysis allows to extract important features to classify the air interface present in the case under inspection. A *k*-NN technique is here employed because it is able to classify without any a-priori statistical information on the probability density function (PDF) of samples. In this 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. 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, in section 4 conclusion will be drawn.

2. THE PROPOSED METHOD FOR MODE IDENTIFICATION

The following scenario is considered: an indoor WLAN cell, including Bluetooth piconets [3], [4] where an user with his reconfigurable terminal can move around identifying one of the

available transmission modes. The mobile device should detect the presence of DS-CDMA although FH-CDMA is also present and vice-versa. The proposed classification scheme is depicted in Figure 1. The received signal after RF stage and A/D conversion is processed by a TF block. The TF block provides a TF representation where the two modes are well defined in the TF plane. TF allows one to use a compact and robust signal representation. In fact, using TF, signals can be represented in two dimensions: time and frequency. For this reason, TF methods potentially provide an higher discriminating power for signal representation useful for their identification. The features obtained by the Features Extraction module are given to the classification module to perform mode identification.

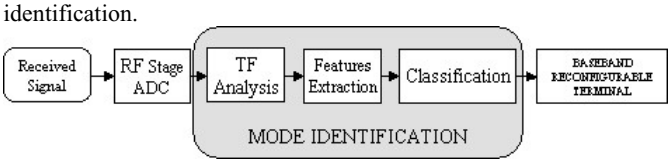


Figure 1: The proposed mode identification scheme.

2.1 Time-Frequency Distribution

As TF distribution, the Wigner transform has been chosen. This transform is the most used. It presents slow computational complexity, a good feature for real-time usage. The Wigner distribution is given by the following expression [7]:

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

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 (IEEE 802.11b and Bluetooth).

The transmitted signal has the following expression in the case of IEEE 802.11b if given in terms of quadrature representation:

$$s_{Wlan}(t)=d(t)\cos(2\pi f_c t)+d(t)\sin(2\pi f_c t) \qquad (2)$$

in this case $d(t)$ is modulated by CCK modulation [4] and its expression is too complex and long to be reported here. However, more details about this can be found in [10]. f_c is the carrier frequency. For Bluetooth:

$$\begin{aligned} s_{Blue}(t) &= (d(t)\cos(\pi t/2T)\cos(2\pi f_c t+n_h\Delta f)+ \\ &+d(t)\sin(\pi t/2T)\sin(2\pi f_c t+n_h\Delta f))*g(t) \end{aligned} \qquad (3)$$

where

$$d(t)=\sum_{k=-\infty}^{+\infty}a_k p(t-kT_s) \qquad p(t)\begin{cases}1 & kT_s<t<(k+1)T_s\\ 0 & otherwise\end{cases} \qquad (4)$$

a_k is the transmitted symbol, $g(t)$ is the Gaussian filter for realizing GFSK modulation [3], T_s is the transmitted symbol duration, Δf is the frequency interval for the hopping (for Bluetooth equal to 1 MHz [3]), n_h is the hop number, and f_c is the carrier frequency. The symbol "*" is the convolution operator.

2.2 Features Extraction

From Wigner transform, it is possible to extract TF features of the received signal observed on a time window T. Three features are considered:

- Feature1: standard deviation of the instantaneous frequency.
- Feature 2: maximum time duration of signal.
- Feature 3: standard deviation of instantaneous bandwidth.

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

$$<\omega>_t=\frac{1}{P(t)}\int \omega P(t,\omega)d\omega \qquad (5)$$

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 [7]. If the signal is considered as a generic band pass signal given by [7] :

$$s(t)=A(t)e^{j\varphi(t)} \qquad (6)$$

where $A(t)$ is the signal amplitude and $\varphi(t)$ is the signal phase. Its instantaneous frequency ω_i is [7]:

$$\omega_i=\varphi'(t)=<\omega>_t \qquad (7)$$

The standard deviation of ω_i :

$$std(\omega_i)=\left(\frac{1}{T}\sum_{t=1}^{T}(\omega_i-\overline{\omega}_i)^2\right)^{\frac{1}{2}} \qquad (8)$$

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

$$\overline{\omega}_i=\frac{1}{T}\sum_{t=1}^{T}\omega_i \qquad (9)$$

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 (IEEE 802.11b) while $std(\omega_i)$ assumes high values in the case of FH (Bluetooth).

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 be presented to the k-NN has been chosen as the maximum value T_M in such set, namely:

$$T_M=\max\{T(\omega)\} \qquad (10)$$

where

$$T(\omega)=\sum_t P_{bin}(t,\omega) \qquad (11)$$

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

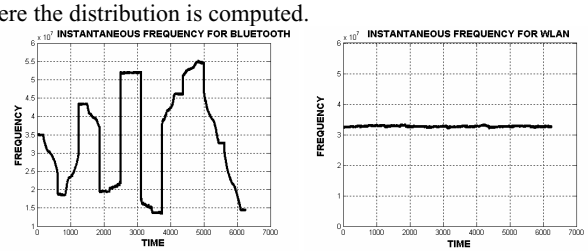


Figure 2. Example of the conditional moment of the first order in case of Bluetooth (FH-CDMA) (left) and IEEE 802.11b (DS-CDMA) (right).

Also the third feature has been obtained from Wigner transform. The second order conditional moment, called mean square bandwidth [7], is computed through the following formula:

$$B^2 = \frac{1}{P(t)} \int_{-\infty}^{+\infty} (\omega - <\omega>_t)^2 P(t,\omega) d\omega \qquad (12)$$

From the values of B^2 the square root is computed to obtain the instantaneous bandwidth of signal. Figure 3 shows the main characteristics of the instantaneous bandwidth: in the Bluetooth case the shape describes the frequency hops of the signal. In each time hopping a change is present because of the instantaneous bandwidth is computed from two different values of hopping, so the value contains the real bandwidth spread of the signal plus the difference between the two frequency hops. In the WLAN signal this behaviour is not present. The standard deviation of the instantaneous bandwidth is then processed obtaining the third feature.

In Figure 4 the two features planes are depicted. Features are organised in couples Feature 1-Feature 2 and Feature 1-Feature 3 and will be presented to the classifier.

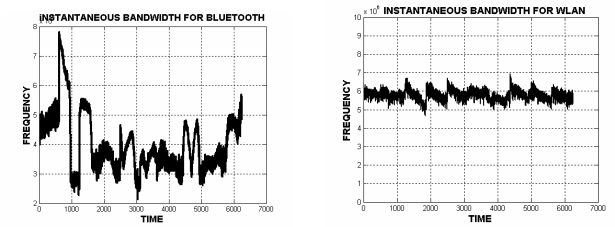
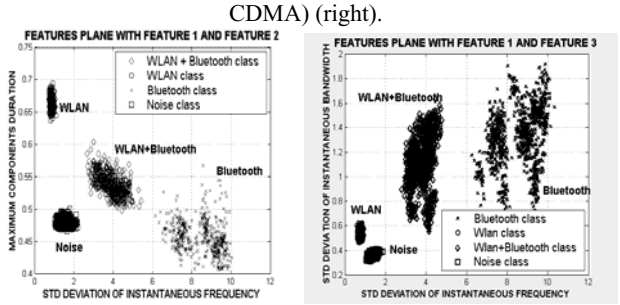


Fig. 3. Example of the conditional moment of the second order in case of Bluetooth (FH-CDMA) (left) and IEEE 802.11b (DS-CDMA) (right).



(a) **(b)**

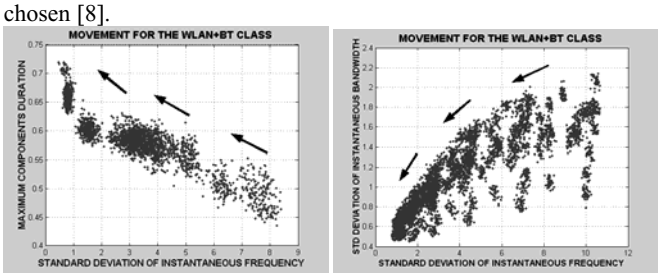
Fig. 4. Feature planes at a Fixed Position: (a) Feature 1 and Feature 2, (b) Feature 1 and feature 3.

2.3 THE CLASSIFIER

A multiple hypotheses test has been performed. In particular four classes have been studied. The classes are divided as below:

- class H_0 : presence of a Additive White Gaussian Noise (AWGN). This class will be indicated as 'Noise'.
- class H_1 : presence of WLAN signal with AWGN and Multipath Fading. It will be indicated as 'WLAN.
- class H_2 : presence of Bluetooth signal with AWGN. And Multipath Fading. It will be indicated as 'Bluetooth'.
- class H_3 : presence of both signals with AWGN and and Multipath. It will be indicated as 'WLAN + Bluetooth'.

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. For example, in Figure 5 the movement of the "WLAN + Bluetooth" using the features grouped in two couples is presented. The same behaviour is for the other classes excepted for Noise one. The first effect is that different classifiers for each user position would be necessary. This is too complex and unfeasible. Therefore, a non-parametric classifiers is used. Moreover, with this technique 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 [8], the *k*-Nearest Neighbors (k-NN) [8], has been chosen. It determines the *k* elements nearest to the pattern to be classified; then the class with more 'votes' among the *k* nearest points is the winner. The best value of *k* has to be experimentally chosen [8].



(a) **(b)**

Figure 5: Movement of the "WLAN + Bluetooth" class employing Feature 1 and Feature 2 (a), Feature 1 and Feature 3 (b).

3. SIMULATIONS AND RESULTS

The system has been set up in Matlab 6.0 environment. The two sources (WLAN and Bluetooth) satisfies all the requirements specified in [3] and [4]. The received signal is translated in IF at 30 MHz with a sample rate of 120 Msample/s to satisfy the Nyquist limit. The number of transmitted bits is equal to 10^5. The channel is indoor multipath with AWGN. Multipath model is Rice fading with delay spread of 60 ns and root mean square (*rms*) delay spread of 30 ns [9]. A path loss term has been inserted; it follows the model proposed in [12]. This is composed by two parts: for distances lower than 8 meters the path loss L_p has a value dependent on frequency *f* and by the distance *d* from the source; for distances bigger than 8 meters L_p is function only of *d*. The formula is shown in (13):

$$LP = \begin{cases} 32.45 + 20\log(f \cdot d) & d \le 8 \\ 58.3 + 33\log(d/8) & d > 8 \end{cases} \qquad (13)$$

where *d* is expressed in meters and *f* in GHz. In our case *f* is fixed at 0.03 GHz (30 MHz). Once the signals are passed through the channel they are directly computed by TF block at intermediate frequency. The Wigner distribution uses blocks with N = 512 samples obtained through a time window T large enough to contain 10 frequency hops. The time hopping is 625 µs [3]. The extraction module stores 10 of TF matrix and it calculates the features as expressed in Section 2.2. The three features has been considered two at a time:

- Case 1: Feature 1 - Feature 2.
- Case 2: Feature 1 - Feature 3.

Features are grouped in these two couples because of their characteristics: the Feature 1 (standard deviation of instantaneous frequency) is the most discriminant, so it is present in the two cases; the Feature 2 (maximum time duration of signal) is used in the first couple, but due to its dependence to the threshold value (through which the "binarization" of TF matrix is computed) it has been changed by the Feature 3 (the standard deviation of instantaneous bandwidth) in the second couple. In both cases a couple of values is used by the k-NN algorithm to classify the mode present. The parameter *k* has been fixed equal to *k* = 25. Due to the user mobility a critical issue arise: the choice of a significant training vector. This problem has been solved considering a training set saved in different user positions. This also has been done for the test samples, which are considered in different points with step lower than 1 meter to simulate the user movement. An indoor room 15m×15m with two Bluetooth and one WLAN access points placed in the room corners

have been simulated. The movement is straight from the Bluetooth source towards WLAN one and vice-versa (Figure 6).

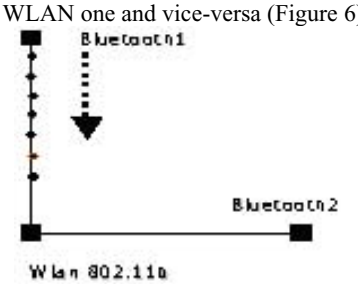


Figure 6: Indoor Simulation environment.

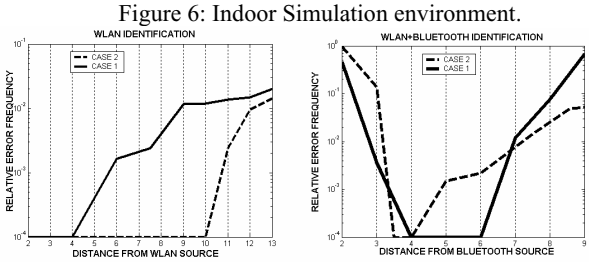


Figure 7: Relative Error Frequency for WLAN identification (left), for WLAN+Bluetooth identification (right).

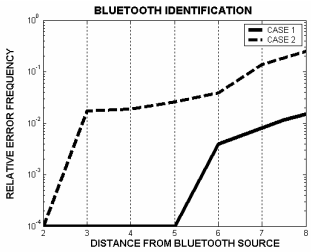


Figure 8: Relative Error Frequency for Bluetooth identification.

Figures 7,8 show the results for the classification of WLAN, WLAN+Bluetooth and Bluetooth (BT) classes in terms of Relative Error Frequency in Case 1 (solid line) and Case 2 (dashed line). The only noise class is always correctly classified. Results are expressed with respect to the relative distance (in meters) from the source. Signal to Noise Ratio (*SNR*) is considered variable with respect to the distance from the Bluetooth source, (Fig. 7 right and Fig 8), or from WLAN source (Fig. 7 left). In fact, the received signal power changes due to the path loss. The noise power is considered as constant. In Figure 7 (left) the Case 2 (dashed line) presents best results. This is due to Feature 3 (present in Case 2), that suffers less than Feature 2 (present in Case 1) from decreasing of *SNR* during the increase of *d.* In fact it isn't directly connected to the amplitude of received signal as Feature 2 (where the threshold, through which the TF matrix is "binarized", is the mean value of the amplitude of WV of the received signal).The WLAN+Bluetooth (Figure 7 right) class is well identified with sufficient values of error rate in the range of 3-7 meters. But, when the user is closer to one of the sources, $d<3$m (closeness of Bluetooth) and $d>7$m (closeness of WLAN), the power level of the source, to which the terminal is closer, is dominant with respect to the power level of the other source. Then the classifier decides for the presence of only one standard instead of two. Also in this case, when the user is close to WLAN source ($d>7\ m$), the best performances are obtained by Case 2 because the threshold has a higher value (due to high amplitude of WLAN signal) and then the components of BT, with their low amplitudes, are lost in the "binarization" of the TF matrix. This doesn't happen close to BT source ($d<3.5\ m$) where the power level of the BT source is comparable to WLAN one, then the "binarization" doesn't hide the FH signal, on the contrary it allows to discriminate more than Features 3 (case 2, dashed line) the presence of two standards. This is confirmed by Fig. 8 where it is shown that the first couple of features (solid line) presents a lower error rate with respect to the Case 2 (dashed line). The results show that the two cases present advantages and disadvantages; in particular the first couple of features has best results in the presence of only BT case and in the presence of both standards, but until 7.5 meters from BT source. Instead, the second couple presents best performances in the presence of the only WLAN signal and in presence of both standards, from 7.5 meters to 10 meters from BT source; the different results, as above explained, are mainly due to the thresholding operation performed to compute the Feature 2. This conclusion presses to explore an algorithm to dynamically modify the threshold, topic which will be dealt with in future works.

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 Bluetooth based on FH-CDMA. The proposed technique combined the use of time frequency analysis and *k*-NN non parametric classifier as solution. Numerical results for indoor environment have been presented. Future works will concern the extension of the model to take in account other indoor standards, the possibility of developing an adaptive technique for the threshold setting to determine the Feature 2, and finally the design of a multi-standard transceiver.

5. ACKNOWLEDGEMENTS

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