# INTERCEPTION AND FURTIVITY OF DIGITAL TRANSMISSIONS

Gilles BUREL[1], André QUINQUIS[2], Stéphane AZOU[3]

***Abstract:*** *The development of digital communications creates new challenges for spectrum surveillance. Similarly, modern signal processing techniques and increasing available computational power make communication discretion ever more difficult. In this paper, we present recent methods based on time-frequency analysis and on statistical analysis of fluctuations, that are useful for detection and identification of transmissions in a non-cooperative context. Furthermore, promising research concerning the use of chaotic signals to develop furtive transmission systems is also presented.*

***Keywords****: Digital transmissions, Interception, Time-frequency analysis, Furtivity, Chaos, Spectrum surveillance, Spread spectrum, Unscented Kalman filters*

## I. Introduction

The proliferation of high performance digital transmission devices has enhanced the role of collecting and securing information in order to provide intelligence on the enemy's intentions and capabilities without revealing one's own intentions. The modern concept is that interception and furtivity of transmissions is an important part of an overall military strategy which concentrates on collecting information through interception of enemy communications while maintaining the capability of discretely operating one's own data transmissions.

However, these considerations are not restricted to the military domain. Indeed, the development of wireless transmissions (e.g. wireless indoor domestic networks or cellular telephones) points out the need of mastering interception techniques (to protect transmissions, or for spectrum surveillance) as well as the need of research on furtive and secure transmissions.

In this paper, we present an overview of some researches about interception and furtivity of transmissions developed in our laboratory.

In Section 2, we show how modern mathematical tools such as time-frequency analysis, can be adapted for the detection and analysis of classical narrow band digital transmissions. Experimental results show that a high attenuation of interferences can be obtained, thus enhancing discrimination capabilities.

However, digital transmissions are not always narrow-band. Indeed, a technique that is often used to hide transmissions in noise is spread spectrum. In Section 3, we show that spread spectrum signals can be detected and demodulated in a non cooperative context, even at a very low signal to noise ratio. Once demodulated, the spread spectrum signal becomes narrow-band, and techniques presented in Section 2 can be used for further analysis.

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From the opposite point of view, the existence of methods to detect and analyze classical digital transmissions points out the need to develop new modulations, in order to transmit signals which are more difficult to intercept. One promising idea is the use of chaotic signals produced by non-linear oscillators, as detailed in Section 4.

Hence, our research has two complementary objectives: being able to detect and analyze digital transmissions, and, simultaneously, ensuring highest discretion of one's own transmissions.

## II. Detection and analysis of narrow-band signals

### *Introduction*

Nowadays digitally modulated signals such as ASK (Amplitude Shift Keying), PSK (Phase Shift Keying) among others are very important for telecommunications systems. Such signals can be found in many civilian as well as military applications such as: interference identification and spectrum management, identification of non-licensed transmitters, electronic warfare, surveillance and threat analysis, control of communication quality, etc.

In COMmunication INTelligence (COMINT) applications, the modulation types are considered as signal signatures. Therefore, the modulation recognition is an essential key to demodulate as well as to decode and understand the transmitted message.

In the last two decades, many researchers have been interested by automatic recognition and identification algorithms for communication signal. In fact, since 1990, many algorithms have been proposed [3]. The main differences among these algorithms are their sensitivity to Signal to Noise Ratio (SNR), the type of modulation that they can deal with, and the applications where they can be used.

Generally, modulation algorithms consist of various steps depending on the field of interest. First of all, if we are only interested in modulation types, a simple modulation classifier can deal with this case. Once the modulation type has been classified, one may seek other features for signal identification purpose. For example, one can seek for a state number, a symbol duration among others.

To distinguish the different versions of modulation, algorithms often enclose the computation of state number. For instance, many studies aim at distinguishing the different MPSK or the different MFSK versions [15]. With regard to the symbol duration, we can quote the methods based on the level crossing, the derivation or a wavelet transform, for example. On the other hand, it seems that the carrier frequency is a main feature in many applications.

Most of the Frequency-domain estimation methods are based on the signal spectrum. The performances of such methods depend on the estimation techniques (Welch, …) and the estimation window (such as Hamming, Hanning, …). Indeed, the experimental studies show that this technique is sensitive to noise. To increase the robustness of the approach, new methods based on recent developments are possible.

### *Time frequency distributions (TFD)*

Most TFDs of current interest are members of Cohen's bilinear class which can be generated by Fourier transformation of a weighted version of the ambiguity function (AF) of the signal to be analyzed. That is, if *TFR(t,f)* is a bilinear TFD of the signal *x(t)*, then

$$TFR(t,f) = \iint A(\tau,F)\phi(\tau,F)e^{-j2\pi(\tau f + Ft)}d\tau dF$$

with $A(\tau,F)$ the ambiguity function of the signal:

$$A(\tau,F)=\int x^{*}\left(t-\frac{\tau}{2}\right)x\left(t+\frac{\tau}{2}\right)e^{j2\pi Ft}dt$$

If $\phi(\tau,F)=1$ we obtain the classical Wigner-Ville distribution (WVD). Different choices of the kernel function $\phi$ are possible to obtain many TFDs. In recent years, it has become apparent that no single kernel can give adequate performance for a large class of signals; hence, there has been increasing interest in signal-dependent or adaptive TFRs (ATFRs). It was proposed [4] an ATFR based on kernels with Gaussian radial cross sections:

$$\Phi(r,\psi)=\exp\left(-\frac{r^2}{2\sigma^2(\psi)}\right)$$

The function $\sigma(\psi)$ controls the spread of the Gaussian at radial angle $\psi$ ; we will call $\sigma(\psi)$ the *spread function.* The angle $\psi$ is measured between the radial line through the point $(\tau,f)$ and the $\tau$ axis: $\psi=\arctan\frac{f}{\tau}$.

A high quality time-frequency representation results when the kernel is well matched to the component of a given signal. The radial Gaussian kernel is adapted to a signal by solving the following optimization problem:

$$\max_{\Phi}\int_0^{2\pi}\int_0^{\infty}\left|A(r,\psi)\Phi(r,\psi)\right|^2 r\,dr\,d\psi$$

where $\Phi(r,\psi)$ is subject to :

$$\frac{1}{4\pi^2}\int_0^{2\pi}\int_0^{\infty}\left|\Phi(r,\psi)\right|^2 r\,dr\,d\psi=\frac{1}{4\pi^2}\int_0^{2\pi}\sigma^2(\psi)d\psi\le\alpha,\quad \alpha\ge 0$$

By focusing the volume under the optimal kernel, the parameter $\alpha$ controls the trade-off between interference suppression and smearing of the auto-components.

The shape of a radial Gaussian kernel is completely parameterized by the spread function; so, finding the optimal kernel $\Phi_{opt}$ for a signal is equivalent to find the optimal function $\sigma_{opt}(\psi)$ for the signal. The algorithm includes four stages (Fig. 1)

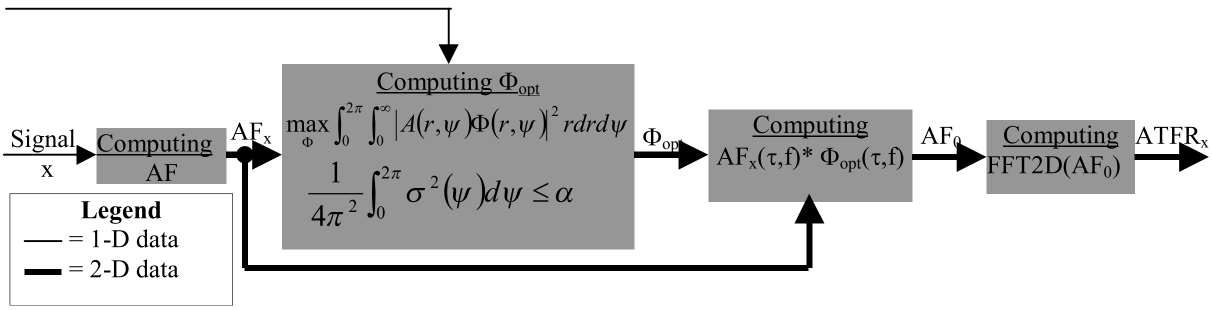


**Fig. 1** - *Adaptive time-frequency representation algorithm*

In the first stage, the AF of the signal is computed. In the second stage the optimization problem is solved for the optimal kernel. Next, we compute the product between AF of the signal $x$ and $\Phi_{opt}$ obtained as result of the second stage. Finally, we compute the bi-dimensional *Fast Fourier Transform* (FFT2D) in order to obtain the adaptive time-frequency distribution of the signal $x$.

This distribution has many attractive qualities; the most important (in this context) is the time-frequency interference suppression. So, we may imagine many applications, such as the time-frequency signal analysis or the signal classification using the most adapted kernel function as a discriminative element.

The limitation of this method is that it designs only one kernel for the entire signal. So, for signals with characteristics that change over time, it is necessary to use a procedure that adapts the kernel each time in order to achieve optimal local performance. Moreover, the choice of the parameter $\alpha$ is another problem that appears in practice.

To obtain the optimal local performances, we apply this procedure on short slide window over the signal. That is, we adapt the kernel for all the sequences obtained by windowing. Let us name this new transformation as «Short ATFR». Furthermore, we prefer the use of this transform, because it is well adapted for real-time problem.

### *Comparative results*

In order to compare the presented method with the classical TFRs we consider an FSK signal (Frequency Shift Keying) with eight frequency steps, presented in figure 2. We show also his ideal time-frequency distribution.

In figure 3, we show the results obtained by applying the described time-frequency distributions and we observe the superior performance of the ATFR. The SPWVD (Fig. 3.a) precludes some interference terms, but affects the time-frequency support which is not well conserved. Another problem with this distribution is the choice of the smoothing windows, that is hard in practice. Moreover, between atoms 3 and 4, respectively 5 and 6 strong interference terms appear. The same comment can be formulated when using CWD (Fig. 3.b). Even if CWD uses a kernel with Gaussian shape (like ATFR), the results are unwell, because this kernel has a fixed position in the ambiguity plane, unadapted to the signal.

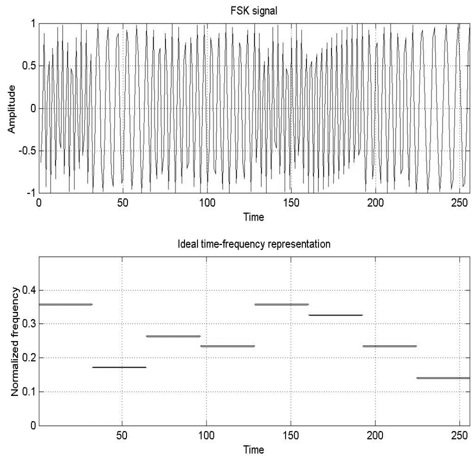


**Fig. 2:** *FSK signal and its ideal time-frequency representation*

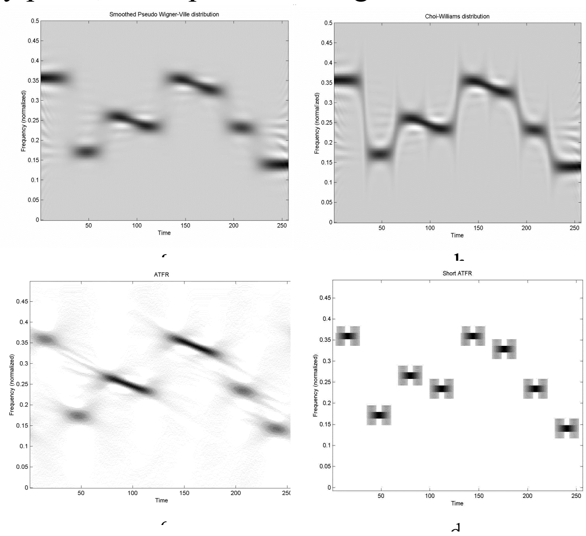


**Fig. 3** - *Comparison of time-frequency distributions. From left to right and top to bottom: (a) Smoothed pseudo Wigner-Ville distribution with g window width 33 and h window width123; (b) Choi Williams distribution with smoothing parameter $\sigma$=3.5; (c) ATFR with $\alpha$=2; (d) Short ATFR of volume $\alpha$=25 and window width 32*

The results obtained by the ATFR use denote the quality of this transformation: ATFR precludes almost all interferences and better preserves the time-frequency support (Fig. 3.c). Ideally, a TFR should have the same nonzero support, i.e., duration and bandwidth, as the signal under analysis. These properties state that if a signal starts at time $t_1$ (and at a frequency $f_1$) and stops at time $t_2$ (and frequency $f_2$), then an ideal TFR should start and stop at the same time-frequency point. These properties ensure the fidelity of the signal approximation in the time-frequency plane. Furthermore, we can accurately estimate the signal characteristics.

In order to evaluate the support conservation capability of the TFR, a set of quality parameters is introduced :

1) *Degree of time support conservation (DTSC)*: this parameter is defined for a certain time-frequency atom and represents the time support of this atom. We prefer to use the DTSC normalized at the support of entire signal. That is : $DTSCn = \frac{dt}{T}$ where *dt* is the temporal support and T is the number of samples of the signal.
2) *Degree of frequency support conservation (DFSC)*: this parameter is defined as the frequency support of a time-frequency atom; we prefer to use the DFSC normalized at the sampling frequency ($F_s$). $DFSCn = \frac{df}{F_s}$
3) *Interferences attenuation factor (IAF)*: this parameter represents a quality measure of the interference time-frequency suppression, defined by $IAF = \frac{E_u}{E_i}$ where $E_u$ is the energy of auto-terms and $E_i$ the energy of interference terms. In the ideal case, this factor must be ∞.

Table 1 shows the obtained parameters for each transformation, as well as their ideal values. We observe the high performances of the short ATFR, provided by the kernel adaptation over time. In figure 3.d we demonstrate the superiority of Short ATFR facing ATFR (that computes a single kernel for the entire signal).

| TFRs | DTSCn | DTFCn | IAF |
|---|---|---|---|
| Ideal | **0.125** | **0** | ∞ |
| Smoothed pseudo Wigner-Ville | 0.0947 | 0.029 | 1.5 |
| Choi-Williams | 0.1 | 0.034 | 1.02 |
| ATFR | 0.0512 | 0.022 | 3.1 |
| Short ATFR | 0.0893 | 0.011 | 157.27 |

***Table 1*** *- Time-frequency distribution performances*

We observe the superior performances of the ATFR facing classical interference terms suppression methods, but its quality is poorer than the short ATFR; this result illustrates the benefits of the kernel time adaptivity.

### *Conclusion*

The novel approach precludes almost all the interference terms and, simultaneously, better keeps the time and frequency resolution. There are two major drawbacks: first, the choice of the kernel volume parameter is sometimes difficult to do and supposes more knowledge about the signal spreading in time and frequency. On the other hand, the adaptive Gaussian kernel designed in the ambiguity plane works only with signals having multiple components of the same nature.

Furthermore, we can improve the performances of this approach using the locally kernel design. Our future work will be devoted to this, by experimenting the time-frequency distributions using adaptive signal expansion for the linear modulations, and using the warping operators for the non-linear ones.

# III. Interception of hidden spread spectrum transmissions

### *Introduction*

Spread spectrum signals have been used for secure communications for several decades. Nowadays, they are also widely used outside the military domain, especially in Code Division Multiple Access (CDMA) systems [12]. Due to their low probability of interception, these signals increase the difficulty of spectrum surveillance.

Direct-Sequence Spread Spectrum transmitters (DS-SS) use a periodical pseudo-random sequence to modulate the baseband signal before transmission. In the context of spectrum surveillance, the pseudo-random sequence used by the transmitter is unknown (as well as other transmitter parameters such as duration of the sequence, symbol frequency and carrier frequency). Hence, in this context, a DS-SS transmission is very difficult to detect and demodulate, because it is often below the noise level.

The research work developed in our laboratory aims at:

1. detecting the presence of a spread spectrum transmission in a non-cooperative context
2. then, estimating the transmitter parameters (including its spreading sequence).

Once the spreading sequence has been estimated, a classical spread-spectrum receiver can demodulate the signal.

### *Blind detection of a spread spectrum transmission*

In a DS-SS transmission, the symbols $a_k$ are multiplied by a pseudo-random sequence which spreads the bandwidth. At the output of the receiver filter, the downconverted signal is:

$$y(t) = s(t) + n(t) = \left\{ \sum_{k=-\infty}^{+\infty} a_k h(t - kT_s) \right\} + n(t)$$

where *s(t)* is the spread-spectrum signal (variance $\sigma_s^2$), *n(t)* is the noise (variance $\sigma_n^2$), and *h(t)* stands for the spreading waveform (more precisely, it is the convolution of the pseudo-random sequence with the transmission filters and the channel).

In a cooperative context, the pseudo-random sequence, as well as the carrier and symbol frequencies, are known by the receiver. The receiver correlates the received signal with the pseudo-random sequence, in order to retrieve the symbols. In a non-cooperative context, these parameters are unknown. Furthermore, classical second order detection methods are useless, because the autocorrelation function of a DS-SS signal is similar to the autocorrelation of a white noise. The method we have developed for blind detection of a DS-SS transmission hidden under the noise level is based on fluctuations of correlation estimators [6]. The received signal is divided into non-overlapping windows of duration $T$ (the exact value of $T$ does not matter; ideally, the window should contain a few symbols, but the methods works over a large range of values). Within each window, we compute an estimation of the correlation:

$$\hat{R}_{yy}^{(m)}(\tau) = \frac{1}{T} \int_0^T y(t) y^*(t - \tau) dt$$

where $m$ is the window's index. Using $M$ windows, we can estimate the second order moment of the estimated autocorrelations:

$$\rho(\tau) = \frac{1}{M} \sum_{m=1}^{M} \left| \hat{R}_{yy}^{(m)}(\tau) \right|^2$$

This is a measure of the fluctuations of the autocorrelation estimator.

If no signal is hidden in the noise (i.e. $y(t)=n(t)$ ), we can predict the average value and standard deviation of the fluctuation curve $\rho(\tau)$. For simplicity, let us consider the case of a receiver filter with flat frequency response in [-$W$/2, +$W$/2] and zero outside. In that case, we can prove [6] that the theoretical average value and standard deviation of the fluctuations are:

$$m_\rho^{(n)} = \frac{1}{TW}\sigma_n^4$$

$$\sigma_\rho^{(n)} = \frac{m_\rho^{(n)}}{\sqrt{M}}$$

Hence, is no signal is hidden in the noise, the curve $\rho(\tau)$ should remain around $m_\rho^{(n)}$ and has a very low probability to go above $m_\rho^{(n)} + 4\sigma_\rho^{(n)}$.

If a signal is hidden in the noise, we can prove that its contribution to the fluctuation curve is negligible, except for values of $\tau$ which are multiples of the symbol period. In this later case, the average value of its contribution is:

$$m_\rho^{(s)} = \frac{T_s}{T}\sigma_s^4$$

Then the ratio between the mean value of the peaks created by the DS-SS signal (if there is one such signal hidden in the noise), and the standard deviation of the fluctuations due to the noise is:

$$\frac{m_\rho^{(s)}}{\sigma_\rho^{(n)}} = \sqrt{\frac{M}{2}}T_s W \frac{\sigma_s^4}{\sigma_n^4}$$

The reader must not be surprised to see a ratio between a mean and a standard deviation: indeed, it is this ratio which is significant to determine if the peaks due to the DS-SS signal may be hidden by the fluctuations due to the noise (see the display below). This equation shows that the performances of our method can always be improved by increasing the number of windows M (at the expense of longer computation time).

Figure 4 shows an example of the detector output. The curve represents $\rho(\tau)$ (i.e. the fluctuations of the correlation estimator), as a function of $\tau$ (in $\mu s$). The two horizontal lines show $m_\rho^{(n)}$ (the predicted average value of the fluctuation if noise only were present) and $m_\rho^{(n)} + 4\sigma_\rho^{(n)}$.

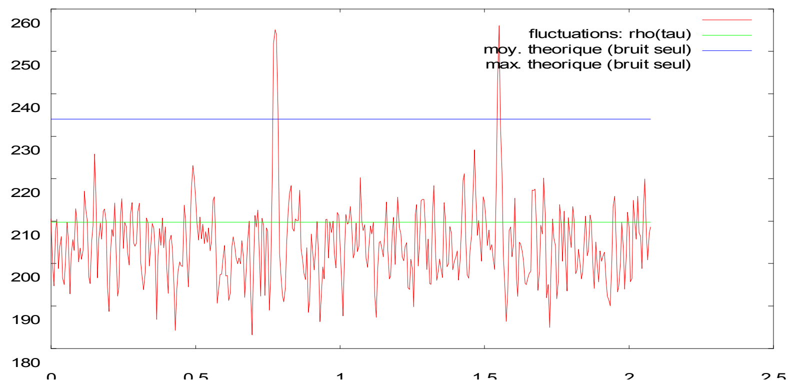


**Fig. 4** - *Example of detector output*

We can clearly see that peaks are present, and that they go far above the theoretical upper bound. Hence, there is no doubt that a spread spectrum signal is hidden in the noise. Indeed, there was, here, a signal hidden 8dB below the noise level. Furthermore, the distance between the peaks provides an estimation of the symbol period Ts.

***Blind estimation of the spreading sequence***

Once a spread spectrum transmission is detected, the problem is to estimate the spreading sequence. The method we have developed is based on eigenanalysis techniques. The received signal is divided into temporal windows, the size of which is the symbol period (this period has been estimated from the distance between the peaks on the fluctuations curve). Each window provides a vector which feeds the eigenanalysis module. Let us carefully examine the structure of the signal (Fig. 5). Since the window duration is equal to the symbol period, a window always contains the end of a symbol (for a duration $T_s - t_0$ ), followed by the beginning of the next symbol (for a duration $t_0$), where $t_0$ is an unknown desynchronization. Hence, the presence of the signal will contribute to align the subspace spanned by the first and second eigenvectors with the subspace spanned by vectors $\vec{h}_0$ and $\vec{h}_{-1}$ shown on figure 6.

One method [7] consists in trying to identify these vectors from the subspace: the sequence can be reconstructed from the two first eigenvectors, and that useful information, such as the desynchronization time, can be extracted from the eigenvalues. Another, slower, but more robust method [5], consists in first performing a blind synchronization (the criteria is maximization of the first eigenvalue), and then estimating the spreading sequence from the first eigenvector.

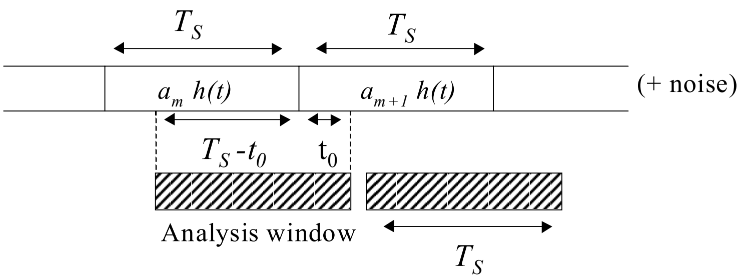


**Fig. 5** - *Structure of the signal*

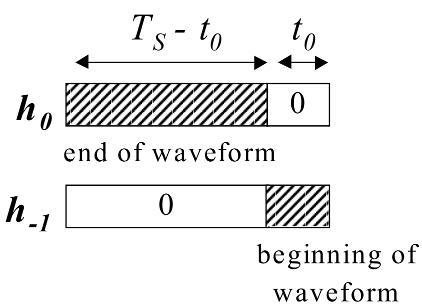


**Fig. 6** - *Generating vectors*

Experimental results show that the method can provide a good estimation, even when the received signal is far below the noise level. Fig. 7 shows the estimated and true sequences. It is clear that the binary sequence can be recovered from the sign of the estimation. Here, the signal was hidden 8dB below the noise.

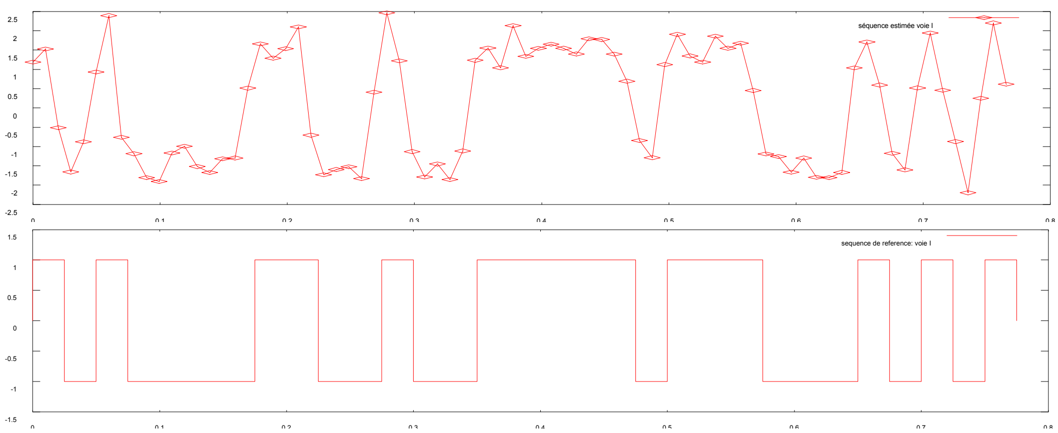

**Fig. 7** - *Estimated spreading waveform (top) and true spreading sequence (bottom)*

# IV. Furtive transmissions based on chaotic signals

### *Introduction*

Since the results of Pecora and Caroll [14] about the synchronization capabilities of chaotic systems, there has been tremendous interest worldwide in the possibilities of exploiting chaos in communication systems. Due to its random-like behavior and its wideband characteristics, a chaotic dynamical system can be very helpful for discretion purposes. Chaos not only spreads the spectrum of the information signal but also acts as an encryption key. Thus, without knowledge of the type of nonlinearity on which the transmission is based (the chaotic dynamic), it will be extremely difficult for the unauthorized user to access the information. Furthermore, such signals are potentially robust against channel imperfections such as multipath propagation or jamming. As a result of their sensitive dependence on initial conditions, chaotic systems are able to produce large sets of uncorrelated signals. This extreme sensitivity can be demonstrated by giving two very close initial states to a chaotic map ; After a few iterations, the two resulting sequences will look completely decorrelated. This can be observed even for very simple (one-dimensional discrete-time) chaotic dynamical systems. The large signal set generated is an attractive feature in a multiple access transmission context. Another advantage of a chaos-based communication system is a less complicated circuitry in comparison with conventional spread spectrum approaches. Consequently, the weight and volume requirements of the devices are reduced and efficiency is increased. It may be possible to put a complete transmitter or receiver on one small chip.

Currently, most of the previously mentioned advantages are only projected advantages, as noted in [17]. Nevertheless, the spectacular success of the recent research on communications with chaos is strong evidence that future nonlinear devices will actually have many of these advantages.

### *Methods for chaos-based digital communications*

Many different chaotic modulations have been proposed since the work of Pecora and Caroll. These techniques may be classified into the following main families : Chaos Shift Keying (CSK), Differential CSK (DCSK), Chaotic Masking, Direct-Sequence/Frequency Hopping Spread Spectrum, Predictive Control and Chaotic Pulse Position Modulation. Some of these methods are overviewed in [8][9]. A detailed explanation is available in [16].

In a chaos-based digital communication system, the information to be transmitted is mapped to chaotic waveforms. As in conventional communication schemes, the transmitted symbols are recognized at the receiver using either *coherent* or *noncoherent* demodulation techniques. The first solution is based on a chaotic synchronization process, in order to recover the original chaotic signal from the noisy received signal. To do so, a precise knowledge about the transmitter is required, including its chaotic dynamic. Conversely, a noncoherent demodulator relies on statistical properties of the received signal only. Such an approach has the advantage of robustness against channel imperfections (noise, multipath, Doppler) but it is not particularly suited for discretion purposes, as a limited knowledge about the transmitter is sufficient to recover the data symbols.

As demonstrated in [14], in the noise-free case, two coupled identical chaotic systems (the *master* and the *slave*) are able to synchronize, that is the slave will asymptotically reproduce the driving signal, for arbitrary initial conditions. However, in practice, we have to cope with disturbed channels or parameter mismatch between chaotic oscillators. As a consequence, a perfect synchronization becomes impossible and even a rough approximation of the original signal is not that easy. Moreover, the synchronization is lost and recovered (partially) every time the transmitted symbol is changed.

Usually, a low signal-to-noise ratio is a necessary condition to secure the transmission. For practical applications, the modulation scheme and especially the chaotic synchronization method have to be chosen carefully to avoid severe performance degradations in this context. We believe that chaotic Direct-Sequence Spread Spectrum (DS-SS) [10] or Chaotic Pulse Position Modulation (CPPM) [18] are very promising methods to succeed in getting competitive well secured digital communication systems. These two approaches allow multiple users to operate simultaneously in time over the same frequency band by using chaotic codes (Code Division Multiple Access).

***Chaotic Direct Sequence Spread Spectrum transmission system***

A Chaotic DS-SS (CD3S) transmitter has a structure similar to that encountered in a standard DS-SS transmitter. The only difference is that the pseudo-noise (PN) code is replaced with a chaotic code. Hence, each data symbol is multiplied by a different portion of the spreading code, due to its aperiodicity. A possible structure for a CD3S transmitter is illustrated by figure 8. Here, chaotic markers, whose length is identical to the processing gain (number of chips of the spreading sequence per data symbol), are regularly inserted in order to synchronize the receiver. The wideband chaotic signal is then upsampled and a shaping filter is applied before modulating a sinusoidal carrier.

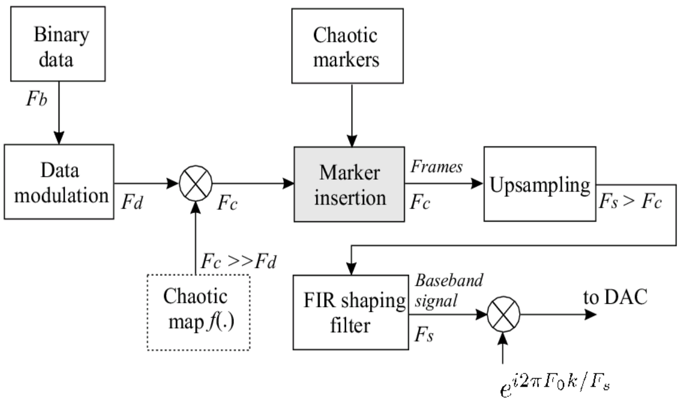


**Fig. 8**- *Block diagram of a Chaotic DS-SS transmitter*

A recent study carried out in our laboratory, about communicating with a CD3S system underwater [1], have led to encouraging results. Two demodulators currently under investigation are described below.

- *Master-Slave CD3S demodulator* (Fig. 9): Though very basic, this kind of demodulation, initially proposed by Milanovic et al. [13], performs well if the spreading chaotic map is properly selected (favorable correlation properties). Here, the original spreading code is estimated owing to a master-slave coupling. Then, symbol decision is just given as the sign of the output of a correlator, operating over symbol duration. Figure 11 shows the Bit Error Rate performance of this demodulator on an Additive White Gaussian Noise (AWGN) channel.
- *Dual Unscented Kalman Filtering (UKF) CD3S demodulator* (Fig. 10): This original scheme, detailed in [2], uses recent results on state space adaptive filtering [11] to achieve the chaotic synchronization. A dual estimation algorithm is implemented to track simultaneously the state of the received chaotic signal and the corresponding dynamic model (the symbol is an unknown parameter of the dynamic model). Symbol decision is

made according to the sign of the averaged output of the second filter over symbol duration. Figure 12 illustrates BER performance of this scheme on AWGN channel.

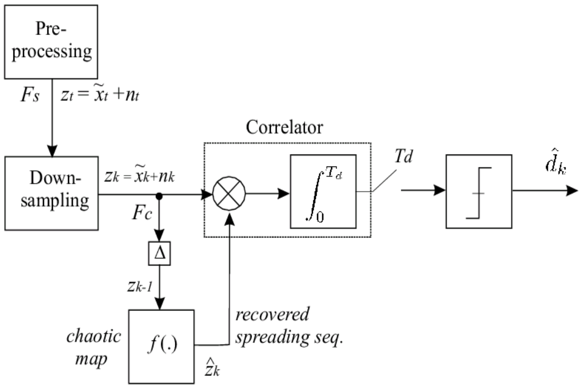


**Fig. 9** – *Block diagram of the Master-Slave CD3S demodulator*

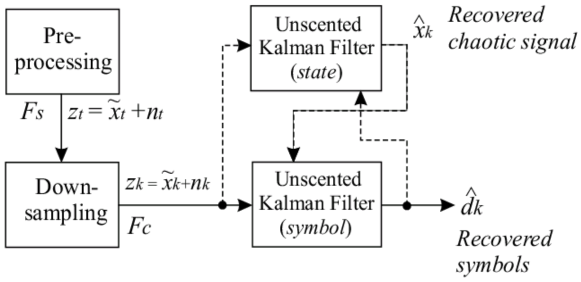


**Fig. 10** - *Block diagram of the dual UKF CD3S demodulator*

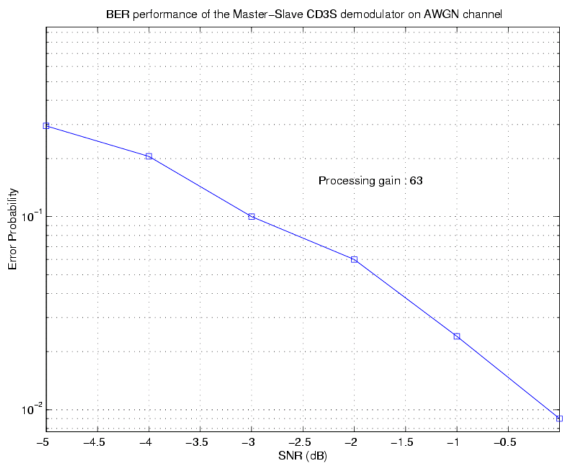


**Fig. 11** – *BER performance of the Master-Slave cd3s demodulator (processing gain: 63)*

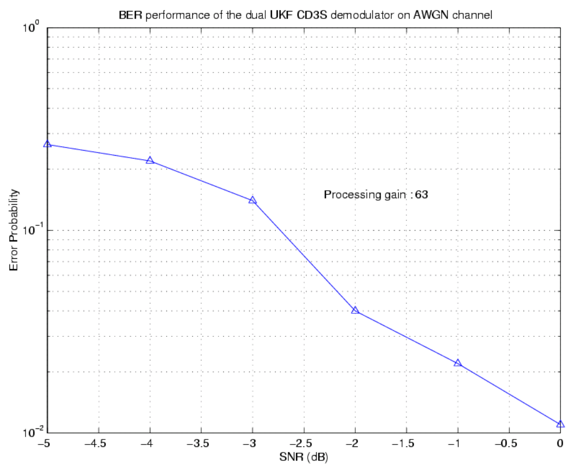


**Fig. 12** – *BER performance of the dual UKF cd3s demodulator (Processing gain: 63)*

# V. Conclusion

In this paper, we have shown that adaptation of modern mathematical tools, such as time-frequency analysis, statistical analysis of fluctuations, unscented Kalman filters, offer promising results, both on the interception and furtivity aspects. While research about these aspects is still mainly confined to the military domain, it is likely to play an increasing role in the civilian domain in a near future, due to the high demand for privacy of communications, as well as to the need of efficient regulation and control.

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