Proposition of an Unexploited Multiple Access Technique

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Abstract

Continual growth in number of telecommunication network users encourages engineers to bring solutions to avoid overload and conflict. The situation is remedied by multiple access techniques and protocols. In fact, several ideas were applied with success to overcome difficulties. Basically, these ideas are based on discrimination in time, frequency, space and modulating code or time management. Within the context, we propose in this paper a new technique which helps us to avoid the conflict between users and manage optimally the information convoy. The basic idea for the new technique, baptized on the occasion by FAT (Fundamentals Agreement Technique), is to develop every signal and to convert it into a form with fundamentals as components. Of course emission and reception parts are in agreement about fundamentals to allow signals recovery later.

Keywords: *Access protocols, genetic algorithms, multiaccess communication, optimization, signal processing.*

1. Introduction

In actual time, the number of users of communications services is in continual growth, while security requirements became more and more imperative. So, engineers and researchers study the problem continuously to bring solutions.

The problem lies in the fact that once summed then discrimination between different signals, carried by transmission channel, is impossible unless ingenuity is employed.

So, with TDMA technique, we can discriminate from time by sending alternately and during period of time, only one signal. By duality, we can differentiate each signal from other if there spectra not overlap and we refer to this by FDMA. Moreover, when we know that users are scattered within a certain area, it seems useful to separate signals spatially, in order to increase the network capacity. This technique is known under SDMA. Another idea consists in modulation of each signal with another called code. The codes are orthogonal to allow decoding and signals recovery in reception side. We know this technique as CDMA [1]–[10].

All multiple access techniques aim to increase number of users. In the same perspective and independently of these techniques, we carry out a new approach by introducing simple idea. In fact, it seems interesting if we consider every signal as a combination of some predefined functions or fundamentals. The signal will be then replaced by simple coefficients which weight his basic components and there combinations, i.e. fundamentals.

Obviously, emitter and receiver are in agreement on fundamentals. The agreement is the key for efficient recovery of original signal. At emitting part, instead of sending out signal, we convey only simple coefficients. A reverse process at receiving part allows signals regeneration.

Because number of fundamentals is finite, then we will put every signal into the closest polynomial form using an optimization technique. Since the problem is not convex, stochastic optimization technique, like Genetic Algorithm, will ensure better solutions [11]–[18]. In this connection, genetic algorithm is easy to implement, with constraints integration and without derivatives information need.

Once solution done, the regenerated signal will be close to the original signal and accuracy is in proportion of number of developing terms and depends on number of fundamentals.

2. Statement

The main idea is to replace original signal by the following approximate form called ‘‘substitute signal’’:

$$s_a(t) = \sum_{i=1}^{i=n} a_i \prod_{j=1}^{j=m} y_j^{bj}(t) \qquad (1)$$

For accuracy checking, we define relative error by:

$$er = \frac{\left\| \int s_a(t) - \int s(t) \right\|}{\left\| \int s(t) \right\|} \qquad (2)$$

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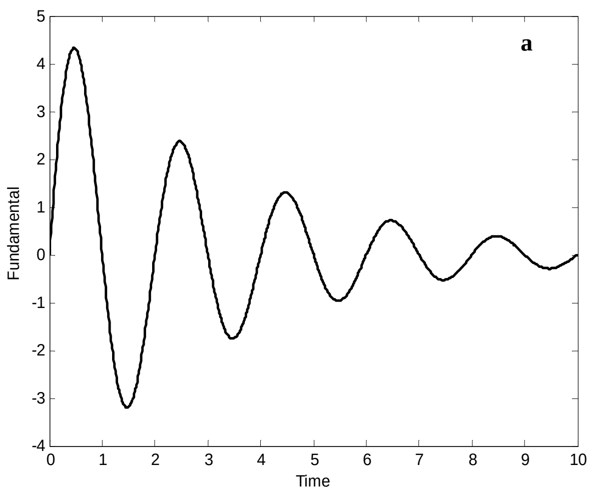
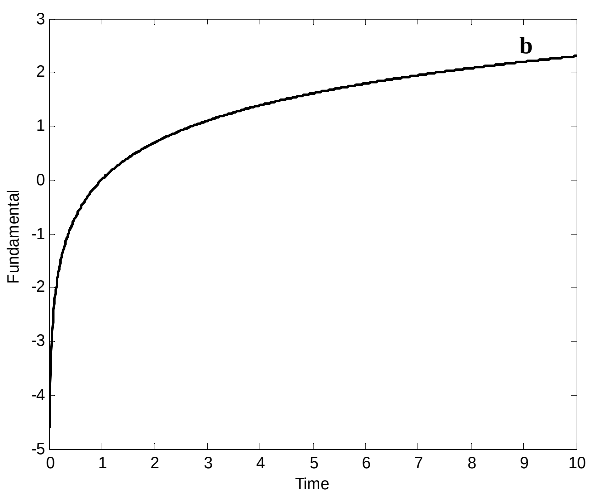
Where:
Σ: summation operator
Π: multiplication operator
$s_a(t)$: substitute signal
s(t): original signal
e_r: relative error
i: term index
j: fundamental index
n: number of terms
m: number of fundamentals yj(t)
$y_i(t)$: fundamental function
b_j: power parameter
a_i: linear parameter

a_i, b_j: are the unknowns to determine

Here we present on Fig. 1 some forms of basic fundamentals:





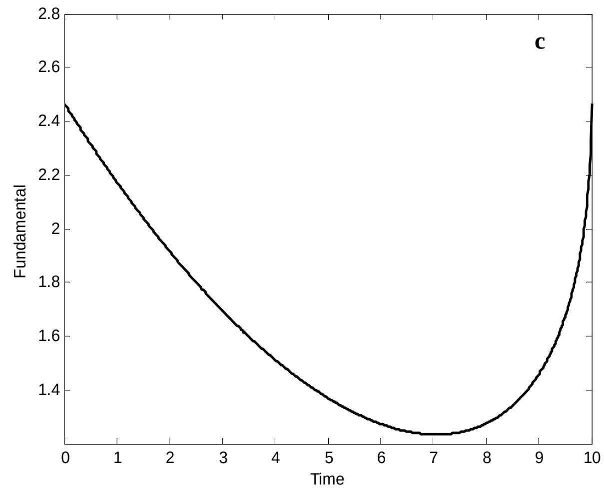


Fig. 1. Some fundamentals forms
a. Exponential-sine function
b. Logarithm function
c. Arccosine-arcsine function

The emitter and receiver are in agreement about fundamentals. The more the number of these functions is large, the more is accuracy. We can say the same thing about the number of polynomial terms.

Now we can say that the solution consist of finding the closest substitute to signal by acting on a_i and b_j. Find the closest substitute amounts to minimize relative error er. So, it is a question of optimization.

Now, without too much math and proofs, it is obvious that for the same data, many solutions exist because the problem is subject to local optimum plurality. So, the classic optimization methods fail in resolution process. Moreover, the number of unknowns is too large to attempt a standard approach.

The best alternative that we consider is then genetic algorithm, which is more appropriate to find best solution for a_i and b_j coefficients.

To sum up, the problem is an optimization one, where we must minimize distance between the signal and its substitute as:

$$er_{min} = \min(er) = \min \frac{\left\| \int s_a(t) - \int s(t) \right\|}{\left\| \int s(t) \right\|} \qquad (3)$$

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Obviously, er is the fitness or cost function to be minimized using genetic algorithm. The variables to determine are then a_i and b_j. We will now give some definitions about GA and especially continuous one, more suitable for our case.

3. Genetic algorithm

The genetic algorithm (GA) is an optimization and search technique based on the principles of genetics and natural selection. A GA allows a population composed of many individuals to evolve under specified selection rules to a state that maximizes or minimizes the fitness or the cost function [11]–[18].
The method was developed by John Holland. Since then, many versions of evolutionary programming have been tried with varying degrees of success. Some of the advantages of a GA include that it:

- Optimizes with continuous or discrete variables
- Doesn't require derivative information
- Searches simultaneously from a wide sampling of the cost surface
- Deals with a large number of variables
- Is well suited for parallel computers
- Optimizes variables with extremely complex cost surfaces, i.e. they can jump out of a local optimum
- May encode the variables so that the optimization is done with the encoded variables
- Works with numerically generated data, experimental data, or analytical functions

These advantages are intriguing and produce stunning results when traditional optimization approaches fail miserably.
The traditional methods are tuned to quickly find the solution of a well-behaved convex analytical function of only a few variables. For such cases the calculus-based methods outperform the GA, quickly finding the minimum while the GA is still analyzing the costs of the initial population. However, many realistic problems do not fall into this category as our case, where we deal with many variables and many solutions exist. From here, we resort to GA to overcome difficulties and to extract the best solution.
If one is attempting to solve a problem where the values of the variables are continuous and want to know them to the full machine precision, in such a problem each variable requires many bits to represent it. If the number of variables is large, the size of the chromosome is also large. Of course, 1s and 0s are not the only way to represent a variable. We could, in principle, use any representation conceivable for encoding the variables. When the variables are naturally quantized, the binary GA fits nicely. However, when the variables are continuous, it is more logical to represent them by floating-point numbers. In addition, since the binary GA has its precision limited by the binary representation of variables, using floating point numbers instead easily allows representation to the machine precision.

This continuous GA also has the advantage of requiring less storage than the binary GA because a single floating-point number represents the variable instead of Nbits integers. The continuous GA is inherently faster than the binary GA, because the chromosomes do not have to be decoded prior to the evaluation of the cost function. The flowchart in Fig. 2 provides an overview of a continuous GA.

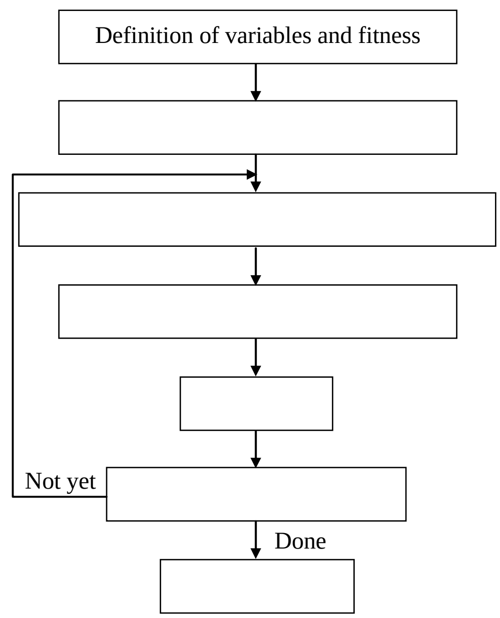

Fig. 2. Flowchart of continuous genetic algorithm

The goal is to solve our optimization problem where we search for an optimal (minimum) solution in terms of the variables of the problem. Therefore we begin the process by defining a chromosome as an array of variable values to be optimized.

Although the values are continuous, a digital computer represents numbers by a finite number of bits. When we refer to the continuous GA, we mean the computer uses its internal precision and round-off to define the precision of the value.

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4. Results

In order to establish the efficiency of our approach, we will now give some obtained results. First results deal with emission of three (03) signals. We carry out simulation under condition of three (03) terms developing and four (04) fundamentals which we express as follow:

$y_1(t) = t^4$
$y_2(t) = \sin(3t^2)$
$y_3(t) = t/\cos(t)$
$y_4(t) = e^{3t}/t$

First signal is given by expression:
$s(t) = t^2 \log(t^2) - t^{2.7} + t + 1$

On Fig. 3 we give the original signal and its best obtained substitute for a relative error er = 0.1254. Table 1 sum up linear and power coefficients (a_i and b_j).

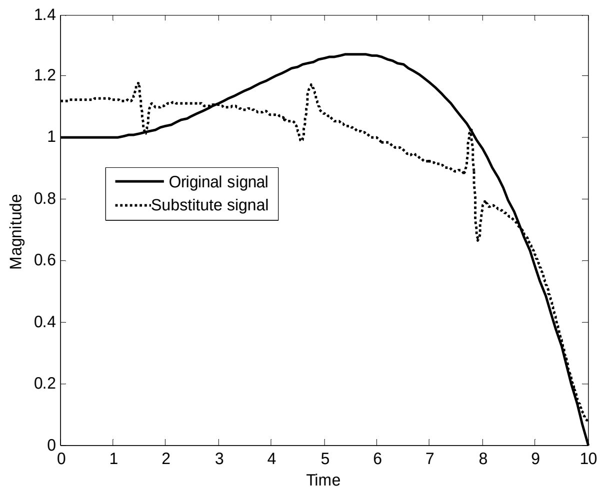

Fig. 3. Original signal and its substitute

Table 1: Linear and power coefficients

		Fundamentals/power coefficients			
Terms	Linear coefficients	1st	2nd	3rd	4th
1st	0.10372	-0.51413	0.10168	1.73870	-3.58984
2nd	0.49680	-2.52615	-0.00011	1.15997	-1.03663
3rd	0.52043	0.08723	-0.01193	-0.00284	-4.34880

Second signal take form as:
$s(t)= 5e^{-0.5t} \sin(\pi t^{1.5}) + 5(1- e^{-2t})$

After GA-based optimization, we reach a relative error er = 0.1530 between the original signal and its optimal substitute. The latter are shown on Fig. 4 while Table 2 contains the corresponding linear and power coefficients.

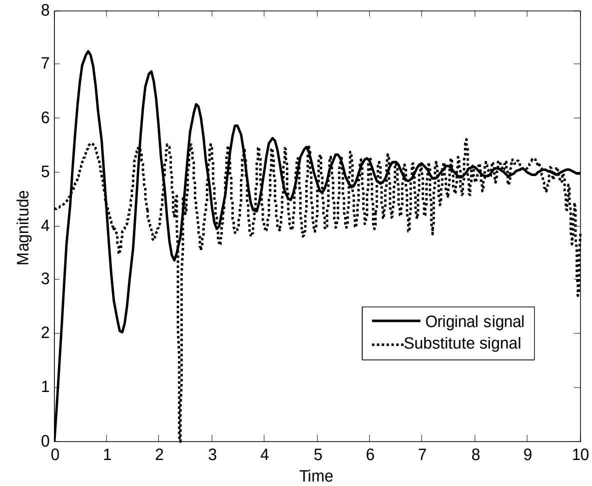

Fig. 4. Original signal and its substitute

Table 2: Linear and power coefficients

		Fundamentals/power coefficients			
Terms	Linear coefficients	1st	2nd	3rd	4th
1st	0.52442	-1.42035	2.41816	0.11871	-0.76123
2nd	4.02999	0.57366	0.01854	-0.01561	-0.41203
3rd	-0.24242	0.21711	2.48672	-1.94683	0.58349

Third signal is identified with:
$s(t) = t^{0.5} \cos(\pi t^{1.5}) + t^{1.5} - 2t + (2t/(t-11)) + 9.5$

Simulation gives rise to Fig. 5, where we can see original signal and optimal substitute, and to Table 3 where linear and power coefficients, which generate a relative error er = 0.1606, are collected.

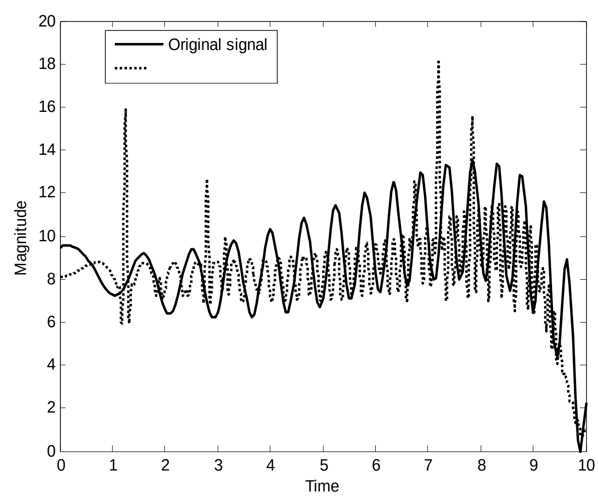

Fig. 5. Original signal and its substitute

Table 3: Linear and power coefficients

		Fundamentals/power coefficients			
Terms	Linear coefficients	1st	2nd	3rd	4th
1st	1.90513	-1.07584	-0.25580	-2.73165	-2.99007
2nd	6.42272	0.93756	0.24192	0.70478	-4.65376
3rd	-0.24482	-3.33890	0.74475	0.70738	2.22865

Until now, we have exposed the problem and justify our approach by very conclusive examples concerning three signals. In fact we proved that instead sending the three signals as they are, we send only their linear and power coefficients, thing which allow to more signals to be carried. Linear and power coefficients will be then convoyed by means of carrying signals. At reception, the reverse process permits regeneration of linear coefficients, power coefficients and substitutes consequently. As ever, the necessary condition is the agreement on fundamentals between receiver and emitter.

Now, we will see the effect of different parameters on results and we begin with number of terms.

4.1 Influence of terms number

The application concerns a sine signal:

$s(t) = \sin(\pi t)$

that we must develop with following fundamentals:

$y1(t) = e^{-0.3t} \sin(\pi t)$

$y2(t) = \log(t)$

$y3(t) = (\arccos(t))^2 + (\arcsin(t))^2$

Number of terms is fixed to three (03) at first time and to six (06) at second time. On Fig. 6 and Fig. 7 we give successively the signals and their best substitutes for 3 and 6 terms developing. Moreover, we give on Table 4 and Table 5 linear and power coefficients which weight fundamentals. Relative error for the first application is of er = 0.2235 and of er = 0.1671 for the second one.

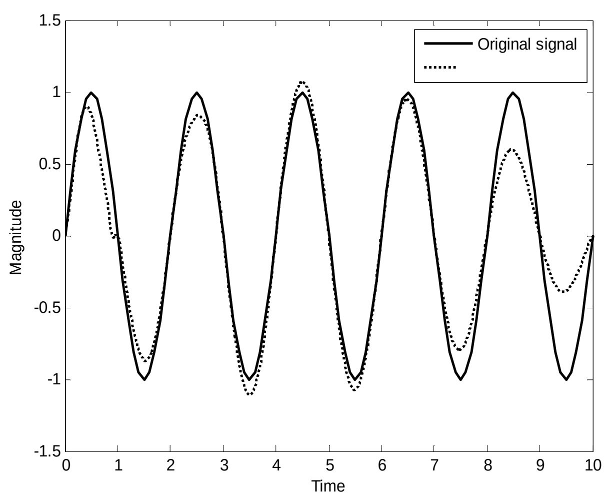

Fig. 6. Original signal and its substitute

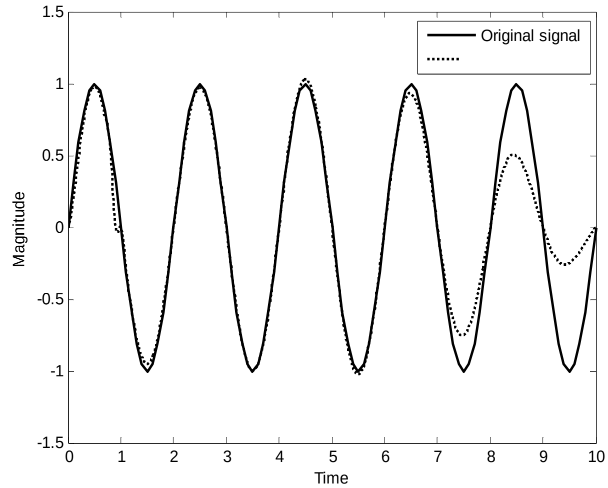

Fig. 7. Original signal and its substitute

Table 4: Linear and power coefficients

		Fundamentals/power coefficients		
Terms	Linear coefficients	1st	2nd	3rd
1st	2.87592	1.00504	3.43212	-0.56699
2nd	1.32387	0.99344	0.27681	-1.57620
3rd	-1.67805	2.49597	0.61114	0.34159

Table 5: Linear and power coefficients

		Fundamentals/power coefficients		
Terms	Linear coefficient	1st	2nd	3rd
1st	0.70323	3.64952	1.80546	1.40411
2nd	-0.02170	1.43745	0.51778	-1.36595
3rd	0.29733	2.45342	2.67951	0.29091
4th	1.39774	1.00390	0.01883	1.86711
5th	1.15259	0.99626	1.07395	-2.52932
6th	0.03819	1.00975	1.44148	0.68444

With respect to relative error, it appears clearly that more is number of terms more is precision, thing which remain obvious.

4.2 Influence of fundamentals number

Now we will consider number of fundamentals and its influence. The results are presented for logarithm form signal:

$s(t) = \log(t)$

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The signal was developed for first application using the two (02) following fundamentals:
y1 (t) = t
y2 (t) = t^3

In second application we added a third fundamental with exponential form as:
y3 (t) = e^t

Number of terms is fixed to 3.
Fig. 8 and Fig. 9 show original signals and their obtained substitutes for two (02) and three (03) fundamentals cases. Afterwards, we will give on Table 6 and Table 7, optimal linear and power coefficients. Relative error for the first application is of er = 0.0184 and of er = 0.0127 for the second one.

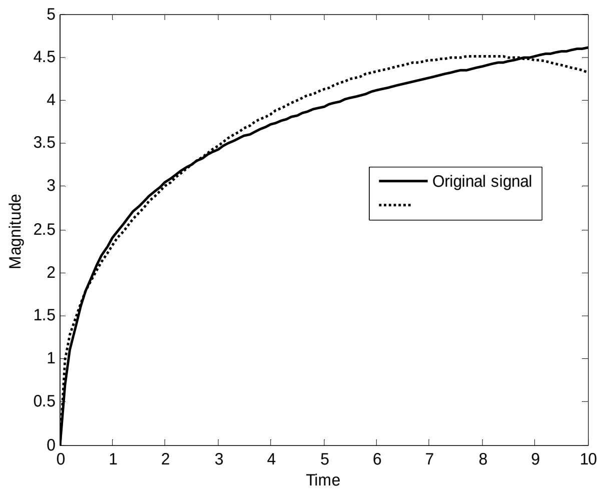

Fig. 8. Original signal and its substitute

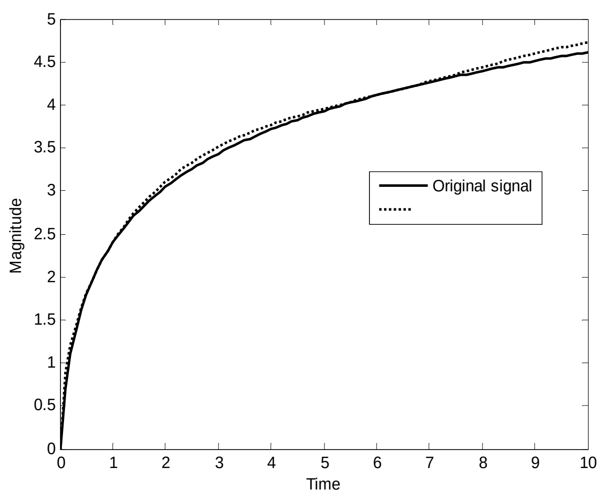

Fig. 9. Original signal and its substitute

Table 6: Linear and power coefficients

Terms	Linear coefficients	Fundamentals/power coefficients	
		1st	2nd
1st	-1.17854	3.35530	0.02306
2nd	4.03360	0.06247	0.11576
3rd	1.47215	0.14005	0.05135

Table 7: Linear and power coefficients

Terms	Linear coefficients	Fundamentals/power coefficients		
		1st	2nd	3rd
1st	0.59513	1.6525	0.58062	-0.07345
2nd	0.35549	3.4259	3.46236	-1.28160
3rd	3.77431	0.3001	0.05452	-0.06867

Visibly and with regarding relative error, we can deduce that the accuracy is in proportion to number of fundamentals.

4.3 Influence of fundamentals choice

Now, we are going to establish the connection between precision and the choice of fundamentals. With this aim in view, we present results relate to parabola form signal:
s (t) = (t^2 – 5t + 6.25)/10

The developing is carried out within six (06) terms and for the first application, we take fundamentals as:
y1 (t) = t e^t
y2 (t) = x e^x, x=t^2

while for second application, we take:
y1 (t) = t
y2 (t) = t^2

Fig. 10 and Fig. 11 show original signals and their obtained substitutes. Subsequently, we will give on Table 8 and Table 9 optimal linear and power coefficients.

After calculation, we get the best relative errors er = 0.4450 for the first application and er = 0.1064 for the second one.

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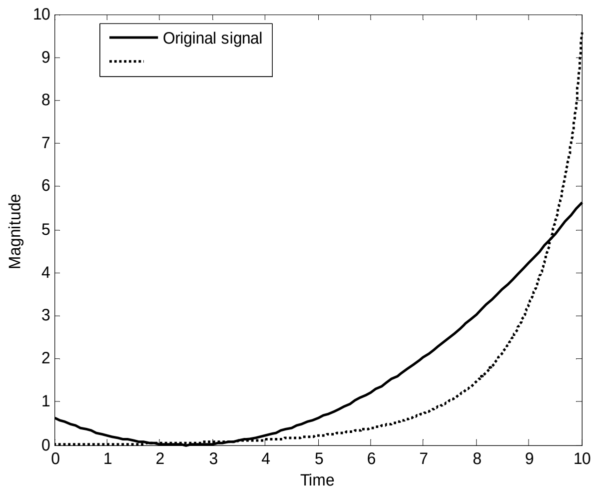

Fig. 10. Original signal and its substitute

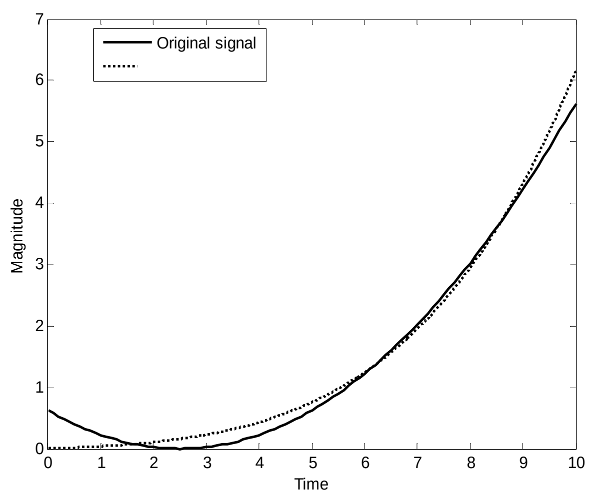

Fig. 11. Original signal and its substitute

Table 8: Linear and power coefficients

		Fundamentals/power coefficients	
Terms	Linear coefficients	1st	2nd
1st	3.86676	0.40410	0.00838
2nd	1.09270	0.25186	0.63739
3rd	0.36876	0.73290	1.16795
4th	2.92942	0.42886	0.05077
5th	-0.54625	0.04034	0.47805
6th	1.86313	0.60902	0.03831

Table 9: Linear and power coefficients

		Fundamentals/power coefficients	
Terms	Linear coefficients	1st	2nd
1st	1.35383	2.11444	1.17892
2nd	0.31204	-0.37311	0.67658
3rd	0.58706	0.53333	1.59174
4th	1.37342	0.59166	1.89827
5th	-0.14731	0.42490	0.69917
6th	2.68010	0.68292	0.92114

As we can see on figures, the regenerated signals or substitute signals are very close to original signals. This means that our implemented code is well adapted to take care of the new multiple access technique.

5. Conclusion

Through the article, we treat a new multiple access technique with aim of increase network capacity. The new technique is based on signal developing concept at emission.

So, instead signal itself convoy, only its corresponding coefficients will be sent. At reception, the regeneration of the original signal is easy and ensures fidelity and confidentiality.

In fact, it is clear that agreement between emission and reception avoid decoding and constitute a guaranty against intrusion. Moreover, it is obvious that we can increase the number of users, if we predefine fundamental components of signals prior to their emission. Therefore, we help receiver to rebuild these signals more quickly and processing time will be then reduced considerably.

Our new multiple access technique seems very interesting because it bring supplementary solution to network saturation and complement the existing techniques. The conceived GA-based code generates very convincing results and prompts us to continue with the prospect of technique improvement.

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