IDENTIFICATION OF TYPICAL GDV-PICTURES OF FINGERS ON THE BASIS OF ANALYSIS OF THEIR FRACTAL DINAMICS

K.G. Korotkov, R.I. Polonnikov

Saint Petersburg Institute of Fine Mechanics and Optics, Saint Petersburg Institute of Informatics and Automation of the Academy of Sciences of Russia.

A new method of analysis of fractal dynamics, which realizes conversion and compression of the data obtained with the help of "GDV-Camera" firmware complex, is studied. The techniques of picture typification and classification are developed on which basis the converted and compressed data are subject to a discriminant analysis. System MathCad operators' notation is used in the work mainly.

Introduction

It is well known [1,2] that electrical self-activity of the organism generated by complex nonlinear and nonequilibrium dynamic systems are fractal by its nature, i.e. possessing the scale invariance property. The same nature have the processes of induced electrical activity and, in particular, the processes which enable the GDV-images of fingers. The fractal structures of this kind processes may be investigated in different ways. May be studied Statical Images, i.e. the resulting picture of Gas Discharge Visualization as a photograph or a television shot. However, another way may be used – "dynamic" investigation, i.e. examination of "genesis" of the same image, by means of fragmentation of this shot into a number of lines-ovals (pic.1) enclosed one into another, and investigation of an energy component of each discrete value of the corresponding oval (its brightness) and, what is especially important, analysis of its information component, a certain length of radius-vector crossing some discrete values (pic.2). Here the length is the number of illuminated pixels – image elements, crossed by the radius-vector, drawn at a fixed angle to a chosen oval [3]. The length defined in such a way would depend upon the angle of radius-vector, drawn from a fixed image center. This line-oval image dissector gives an opportunity to examine dynamics of the process of image formation in time and space. We used the decomposition of GDV-image into 8 lines-ovals, each of which was also digitized according to 0,35156 ^{0} degree of rotation of radius-vector. As a result, two vectors $F1^{<j>}$ and $F2^{<j>}$, sized 1024 x 1 each, are formed for each of the ovals. At that, F1 – characterizes the energy component, and F2 – the information component, j – is the number of oval evaluated within the limits 0…7 (j $\in$ 0,1,..7). Using the operation of columns connection, the two data matrixes F1 and F2, sized 1024 x 8 each, containing the information about the GDV-image, may be created. These data will be converted and compressed according to the method of fractal dynamics analysis.

The method of analysis of fractal dynamics.

This method was developed for the EEG analysis [4] and later applied for the analyze of the GDV-images of fingers [5]. The core of the method is the investigation of the dynamic power spectra of the initial process's fragments. For the purpose of their description the two-parameter mathematical models are constructed, where one of the parameters is the energetic, and the other – informational. The estimation of the parameters on the basis of nonlinear regression is constructed and the dynamics of their change from one fragment to the other is monitored. These changes are evaluated by means of singular decomposition of the corresponding matrixes. The final result of these conversions and estimates may be compactly presented in terms of a certain resulting vector sized 6 x 1. The two vectors of this kind are formed as a result of F1 and F2 matrixes conversion and compression respectively.

Let us discuss the method's realization in more details.

1. Conversion and structuring of the initial data.

F1 and F2 matrix columns undergo the operation of folding into a matrix sized 128 x 8. For example, $F1^{<0>}$ null column of F1 matrix fold into A0 matrix:

$A0 = \text{fold}\,(F1^{<0>})$

Schematically the fold operation is shown on the diagram:

$$F1^{<0>} = \begin{bmatrix} f_{1,1} \\ f_{1,2} \\ . \\ . \\ f_{1,1024} \end{bmatrix} \longrightarrow \begin{bmatrix} f_{1,1} & f_{1,129} & f_{1,257} & \cdot & \cdot & f_{1,897} \\ f_{1,2} & f_{1,130} & f_{1,258} & \cdot & \cdot & f_{1,898} \\ . & . & & . & . & . \\ . & . & . & . & . & . \\ f_{1,128} & f_{1,256} & f_{1,384} & \cdot & \cdot & f_{1,1024} \end{bmatrix} = A0$$

As a result of this procedure instead of F1, F2 matrixes we get A0, A1, A2,…A7 and B0, B1,…B7 matrixes respectively.

2. Fast Fourier transformation (FFT) of the columns of A and B matrixes.

$C0^{<i>} = FFT\,(A0^{<i>})$, $i = 0..7$,

$D0^{<i>} = FFT\,(B0^{<i>})$, $i = 0..7$

Here the symbol <i> means the number of the corresponding column of the matrixes A0, B0.

These conversions result in vectors with the complex components, which determine spectral constituents of the processes. It is worth mentioning that in case we take up such a procedure in MathCad program, because of the property of complex conjugacy of the constituents MathCad system deduce in fact only a half of their number. This means that with the $A0^{<i>}$ vector dimension equal to 128, $C0^{<i>}$ will include 64 constituents only.

3. Calculation of the power spectra.

To get the required power spectrum of the segment of $A0^{<i>}$, or $B\,0^{<i>}$ oval, it is necessary determine respectively:

$CM^{<i>} = |\,C0^{<i>}\,|^2$, $i = 0..7$,

$DM^{<i>} = |\,D0^{<i>}\,|^2$, $i = 0..7$

Examples of the specific power spectra of the required processes are shown on fig.3,4. It is obvious from the pictures that the power spectra change considerably from one segment of an oval to the other and from an oval to another oval, respectively. In order to describe these changes mathematically within fractal approach it is necessary to use the model of spectral envelope which is usually applied in such cases.

4. Evaluation of parameters of the model of power spectral envelope.

The simplest model of such class is the following:

$$M\,(n) = k \cdot n^{-\beta} , \qquad (1)$$

where n is the component's number in the power spectrum proportional to its frequency,

k and β – energy and information parameters subject to evaluation.

Let us take into consideration a simple formula [1] linking the fractal degree d and the fractal index β:

$$d = \frac{5-\beta}{2} \qquad (2)$$

It is also advisable to remember that digitization frequency f_d of the process and frequency of the corresponding n-spectral constituent f_n are connected by the following relation:

$$f_n = \frac{n}{m} \cdot f_d , \qquad (3)$$

where m is the number of components in $A0^{<i>}$, $B0^{<i>}$ vector. In our case we have m=128, this is why if f_d =128 is chosen, $f_n = n$.

For the estimation of k and β parameters it is necessary to solve the task of non-linear regression which can be easily reduced to the linear at the first stage. Let us demonstrate the procedure. As usual, comparing the object (here it is the corresponding power spectrum) to the model we receive the system of equations:

$CM^{<i>}{}_n = k \cdot n^{-\beta}$, n = 0..63, (4)

where $CM^{<i>}{}_n$ is the n-component of $CM^{<i>}$ vector. Applying logarithm to the both parts of (4) we get:

$\ln(k) - \beta \cdot \ln(n) = \ln(CM^{<i>}{}_n)$ (5)

Let $x1_{0,i}{}^{A0} = \ln(k_{0,i}{}^{A0})$, $x2_{0,i}{}^{A0} = \beta_{0,i}{}^{A0}$,

$$XA0^{<i>} = \begin{bmatrix} x1^{A0}{}_{0,i} \\ x2^{A0}{}_{0,i} \end{bmatrix} , \quad U = \begin{bmatrix} 1 & -\ln(2) \\ 1 & -\ln(3) \\ . & . \\ . & . \\ 1 & -\ln(30) \end{bmatrix} , \quad VA0^{<i>} = \begin{bmatrix} \ln(CM^{<i>}{}_2) \\ \ln(CM^{<i>}{}_3) \\ . \\ . \\ \ln(CM^{<i>}{}_{30}) \end{bmatrix} ,$$

then in the vector-matrix form we receive the following systems of equations:

$U \cdot XA0^{<i>} = VA0^{<i>}$, i = 0..7 , (6)

for which we would have the next solutions:

$XA0^{<i>} = (U^{T} \cdot U)^{-1} \cdot U^{T} \cdot VA0^{<i>}$, i = 0..7 (7)

For the computational convenience let us assume:

$VA0 = [\ VA0^{<0>}\ VA0^{<1>}\ VA0^{<2>} \ldots VA0^{<7>}]$,

i.e. VA0 is a matrix of 28 x 8 in size, then the decision matrix is given by :

$XA0 = (U^{T} \cdot U)^{-1} \cdot U^{T} \cdot VA0$ (8)

Having transposed it (upper index T) we receive $XA0^{T}$ matrix, where the column with zero number includes the evaluation logarithms of parameter k:

$$XA0^{T})^{<0>} = \begin{bmatrix} x1^{A0}{}_{0,0} \\ x1^{A0}{}_{1,0} \\ . \\ . \\ x1^{A0}{}_{7,0} \end{bmatrix} , \qquad (9)$$

and, accordingly, the column with number one is the evaluation vector of parameter β:

$$(XA0^{T})^{<1>} = \begin{bmatrix} \beta^{A0}{}_{0,0} \\ \beta^{A0}{}_{1,0} \\ . \\ . \\ \beta^{A0}{}_{7,0} \end{bmatrix} \qquad (10)$$

Taking into account that in (9) by definition each component is

$x1_{i,0}^{A0} = \ln(k_{i,0}^{A0})$, (11)

it is not difficult to get the evaluation vector:

$$K0 = \begin{bmatrix} \exp(x1^{A0}{}_{0,0}) \\ \exp(x1^{A0}{}_{1,0}) \\ . \\ . \\ \exp(x1^{A0}{}_{7,0}) \end{bmatrix} \qquad (12)$$

Thus, for A0 matrix all the estimates of parameters of model (1) are received in the form of vectors (10) and (12). In the same way, using the relations (6)-(12) it is possible to get the estimates of the required parameters k and β for the rest matrixes A1…A7, B0…B7. Arranging the received evaluation vectors into the corresponding matrixes, let us find the next four matrixes of evaluation of the parameters:

$$\beta A = \begin{bmatrix} \beta^{A0}{}_{0,0} & \beta^{A1}{}_{0,1} & . & . & \beta^{A7}{}_{0,7} \\ \beta^{Ao}{}_{1,0} & \beta^{A1}{}_{1,1} & . & . & \beta^{A7}{}_{1,7} \\ . & . & . & . & . \\ . & . & . & . & . \\ \beta^{Ao}{}_{7,0} & \beta^{A1}{}_{7,1} & . & . & \beta^{A7}{}_{7,7} \end{bmatrix}, \qquad (13)$$

$$KA = \begin{bmatrix} \exp(x1^{A0}{}_{0,0}) & . & . & . & \exp(x1^{A7}{}_{0,7}) \\ \exp(x1^{A0}{}_{1,0}) & . & . & . & \exp(x1^{A7}{}_{1,7}) \\ . & . & . & . & . \\ . & . & . & . & . \\ \exp(x1^{A9}{}_{7,0}) & . & . & . & \exp(x1^{A7}{}_{7,7}) \end{bmatrix}, \qquad (14)$$

$$\beta B = \begin{bmatrix} \beta^{B0}{}_{0,0} & \beta^{B1}{}_{0,1} & . & . & \beta^{B7}{}_{0,7} \\ \beta^{Bo}{}_{1,0} & \beta^{B1}{}_{1,1} & . & . & \beta^{B7}{}_{1,7} \\ . & . & . & . & . \\ . & . & . & . & . \\ \beta^{Bo}{}_{7,0} & \beta^{B1}{}_{7,1} & . & . & \beta^{B7}{}_{7,7} \end{bmatrix}, \qquad (15)$$

$$KB = \begin{bmatrix} \exp(x1^{B0}{}_{0,0}) & . & . & . & \exp(x1^{B7}{}_{0,7}) \\ \exp(x1^{B0}{}_{1,0}) & . & . & . & \exp(x1^{B7}{}_{1,7}) \\ . & . & . & . & . \\ . & . & . & . & . \\ \exp(x1^{B9}{}_{7,0}) & . & . & . & \exp(x1^{B7}{}_{7,7}) \end{bmatrix} \qquad (16)$$

It is worth recalling that the family of matrixes A (A0…A7) is generated by the data matrix F1, and the family B (B0…B7) – by the data matrix F2. The four matrixes found (13)-

(16) contain valuable information about the fractal dynamics of the processes studied – about genesis of GDV-images of fingers. This is why these matrixes may be called the information matrix.

5. Conversions of the information matrixes.

The goal of these conversions is the necessity to find some integral estimates which could serve as the most informative features of the investigated GDV-image of finger and could help to solve the problem of identification of this image's type. Such estimates have been found. There are three of them for each information matrix (13) – (16):

- integral average,
- normalized standard deviation,
- maximal singular number.

Let us study these estimates in more detail in terms of βA matrix. If we determine a mean value for each column of this matrix:

$\beta A_m{}^i = \text{mean}\ (\beta A^{\langle i \rangle})\ , \quad i = 0..7,$ (17)

we would receive a vector of means for all the columns:

$$\beta A_m = \begin{bmatrix} \beta^0{}_{cp} \\ \beta^1{}_{cp} \\ . \\ . \\ \beta^7{}_{cp} \end{bmatrix} \qquad (18)$$

For this vector (18), in its turn, it is possible to find a mean value, which can be called "integral mean":

$\beta A_{int.m} = \text{mean}\ (\beta A_m),$ (19)

where mean is the operator defining the estimate of mean value of βA_{cp}. vector components. The normalized standard deviation is determined as the ratio of standard deviation to integral mean:

$$\beta A_{\text{н ско}} = \frac{stdev(\beta A_{cp})}{mean(\beta A_{cp})}\ , \qquad (20)$$

where the operator stdev determines the standard deviation of βA_m vector. Any information matrix may be presented in terms of βA matrix as:

$\beta A = Q\ \Sigma\ W^T\ ,$ (21)

where Q and W are the unitary matrixes, and matrix Σ is diagonal, moreover its diagonal elements σ_{ii} are non-negative square roots of the characteristic values of $\beta A^{\cdot} (\beta A)^T$ matrix, and, hence, are defined uniquely. The columns of Q matrix are the characteristic values of $\beta A^{\cdot} (\beta A)^T$ matrix, and the columns of W matrix – the characteristic values of $(\beta A)^{T\cdot} \beta A$ matrix. Both systems of characteristic vectors are organized in accordance with the distribution of the characteristic values (for instance, in ascendancy). Diagonal elements of Σ matrix – σ_{ii} are called singular numbers of βA matrix. The columns of Q and W matrixes are named, respectively, left and right singular vectors and the decomposition (21) is called singular decomposition. The latter possesses [6] a remarkable property: any matrix is conditioned ideally relative to the problem of calculating singular numbers, however, at that it can be poorly conditioned relative to the problem of evaluation its characteristic values. The vector of diagonal elements (singular numbers) of βA matrix in the MathCad pack is determined through the operator svds:

$$Z\beta A = \mathrm{svds}\ (\beta A) \qquad (22)$$

and, hence, the maximal value of singular number is found in the following way:

$$Z\beta A_{max} = \max\ (Z\beta A) \qquad (23)$$

Drawing some conclusions we may say that as a result of the analysis of fractal dynamics, compact integral estimates brought together in Table 1 are obtained.

Table 1.

Integral fractal estimates of the GDV-grams.

Energy Estimates (F1)	**Information Estimates (F1)**	**Information estimates (F2)**	**Energy estimates (F2)**
$KA_{int.m}$	$\beta A_{int.m}$	$\beta B_{int.m}$	$KB_{int.m}$
$KA_{н\ сао}$	$\beta A_{н\ ско}$	$\beta B_{н\ ско}$	$KB_{н\ сао}$
ZKA_{max}	$Z\beta A_{max}$	$Z\beta B_{max}$	ZKB_{max}

The estimates placed in the 1st and the 3rd columns, as shown by the practice of their application, represent the GDV-image in the best way when the problem of identification of its type according to the classification of types proposed by K.G.Korotkov [7] is being solved. Therefore, therein after the following evaluation vector is used:

$$O\ I = [\beta B_{int.m}\ ,\ \beta B_{н\ ско}\ ,\ Z\beta B_{max}\ ,\ KA_{int.m}\ ,\ KA_{н\ сао}\ ,\ ZKA_{max}\ ] \qquad (24)$$

This fact states that from the total number of combinations of 12 to 6, equal to 924, one optimal combination is chosen, meaning minimum of errors of the image type identification.

The method of identification of the images type.

Five types (classes) of GDV-images of fingers proposed by K.G. Korotkov, obtained with the help of “GDV-Camera” apparatus were evaluated: K, R, L, N, S (pic.5,6). A standard discriminant analysis procedure in STATGRAPHICS program was applied. The components of vector (24) were used as the informative features. 11 objects were taken for each class. Two ways of identification were investigated:

- using the arrangement of types (classes) into groups,
- without grouping the classes.

Classes were distributed between two groups as follows: R, L, N and S, K. The result of identification of objects using the educative sample for the first group:

L-type – 81 % of correct identifications,

R-type – 90,9 % of correct identifications,

N-type – 100 % of correct identifications.

Group average result – 90,9 % of correct answers. For the second group, using educative sample, 100 % of correct identification was achieved.

If we do not distribute the types of objects into the groups, we would have five classes of objects and the following result of correct identification was received:

L-type – 63,64 %,

R-type – 72,73 %,

N-type – 100%,

S-type – 72,73%,

K-type – 72,73%,

which gives an average percent of correct identifications – 76,36 %.

The coefficients for the five classifying functions are reduced to CC matrix:

$$CC = \begin{bmatrix} 98.293 & 245.829 & -0.0016 & -0.3941 & 0.0058 & 0.0281 \\ 97.3856 & 271.194 & -0.0013 & -0.3393 & 0.006 & 0.0199 \\ 103.539 & 214.084 & -0.0017 & -0.3881 & 0.0101 & 0.0264 \\ 96.666 & 175.942 & -0.0016 & -0.2491 & 0.0226 & 0.018 \\ 81.217 & 239.942 & -0.0004 & -0.2559 & 0.0049 & 0.0129 \end{bmatrix}$$

The value of the classifying function CF is determined as the product of CC matrix by vector (24) plus CONST vector calculated from the analyzed data:

$$\text{CONST} = \begin{bmatrix} -106.247 \\ -111.209 \\ -102.897 \\ -89.744 \\ -82.1125 \end{bmatrix}, \qquad \text{CF} = \text{CC} \cdot \text{OI} + \text{CONST} \tag{27}$$

To make decision of classifying the object it is necessary to keep with the rule:

$$\operatorname{Arg} \max_{j} CF_j\,, \qquad j = 1..5 \tag{28}$$

This means that a maximal component of CF vector is being found and its number points to the number of the class, to which the program refers the object. In our case there were the following numbers of classes: 1st – L, 2nd – R, 3rd – N, 4th – S, 5th –K. For example, according to the results of MathCad-program work, one of the 55 investigated objects had OI vector equal to:

$$\text{OI} = \begin{bmatrix} 1.444 \\ 0.348 \\ 147.3 \\ 92.83 \\ 0.583 \\ 964.1 \end{bmatrix},$$

which, in compliance with (27), gives the next value for the classification of CF function:

$$\text{CF} = \begin{bmatrix} 109.849 \\ 109.665 \\ 108.544 \\ 103.443 \\ 105.912 \end{bmatrix},$$

whence it follows that max(CF) = 109.849, which means that the object is referred to the 1st class (L-type) by the program. This result is correct. In general, the results of identification may be considered satisfactory.

Conclusion.

The method proposed, as well as the algorithm and the complex of programs, written in MathCad and STATGRAPHICS packages language, give an opportunity to solve a practical problem of automatic identification of GDV-image type with a satisfactory reliability. It is worth mentioning that the results achieved are not considered to be possible down to the limit (for the fidelity of identification). There are yet some unused reserves, and also the ways of their realization. At the same time, the level achieved is characterized by the following important features (novations):

- the information component of image is actively equipped (uncovered and used), optimally combined with the energy component,

- in the process of solving the problem the main emphasis was laid not on the upgrading of the identification algorithms, but on the preparation of data intended for identification: data structuring, fractal dynamics analysis, selection of informative features, which at the same time provided with powerful data compression, the latter in itself is very important not only for the medical purposes, but also for the purposes of telemedicine,

- programs realizing the method are written in the language of a well-known MathCad package, which gave an opportunity to spare the time and reserves of programmers considerably on the stage of method's processing; at that, the main mathematical instrument was vector-matrix analysis and mathematical statistics [6,8].

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