

# Heart Functional State Diagnostic Using Pattern Recognition of Phase Space ECG-Images

**Dr. Leonid S. Fainzilberg**

Head of Department

International Research & Educational Center for Information  
Technologies and Systems NAS and EM of Ukraine  
Prospect Akademika Glushkova 42, Kiev-22, UKRAINE, 252022  
Phone: +380 44 2676023, Fax + 380 44 2661570  
E-mail leon@fan.carrier.kiev.ua

**ABSTRACT:** The modern to analysis and interpretation of ECG-data based on them presentation in phase space is considered. This presentation allows to obtain some new features of real ECG which may be used to increase the sensibility of ECG analysis. For selection of suitable diagnostic features we used obtained earlier theoretical results which guarantee usefulness of any feature when the problem of pattern recognition of two classes in statistical statement have to be solved. Decision rules for recognizing the normal and abnormal heart functional state based on selected features was constructed and justified. The experimental results of clinical testing are given.

## PART 1. INTRODUCTION

An important use of pattern recognition and image processing is the development of intelligent technologies in medicine and biomedical application [Strauss, Burger 1995, Shi, Robinson, Duncan 1994, Hui-Huang, Principo 1991]. It is known that the problem of heart state diagnostics is of a great importance. The different instrumental systems for analysis of electrocardiograms, reograms, pulsegrams and others are traditionally using for this purpose in all day medicine.

At the same time, when the problems of computer analysis of electrocardiograms (ECG) are solving, the traditional representation of ECG in time domain  $u = u(t)$  leads to errors in recognition of it's relevant segments (complex and waves). First of all this situation is caused by complexity of analytic description of ECG. Moreover it is known that the boundaries of relevant segments of real ECG usually are fuzzy. In this connection the alternative approaches to the problem of ECG analysis and interpretation have to be studied.

In 1995 we had suggested the new method of creation of phase space ECG-image was considered [Fainzilberg, Potapova 1995]. In this paper we describe the possibility of using these images to solve the problem of heart state diagnostics.

## PART 2. PHASE SPASE ECG-IMAGES

The main idea of phase space ECG-images construction is to transform the scalar signal  $u(t)$  of any tradition leads in each moment  $t$  to vector  $(x(t), y(t), z(t))$  using special computation procedures [Fainzilberg, Potapova 1995]. In this case the signal's values in each discrete time moment  $1, 2, \dots, K$  which is cyclical in time domain are assigned to the sequence  $\{(x_1, y_1, z_1), (x_2, y_2, z_2), \dots, (x_K, y_K, z_K)\}$  of such vectors and create a locus in phase space  $X-Y-Z$  as a specific 3-D curve.

Figures 1 and 2 show the example of real ECG from 12 traditional leads in time domain (Figure 1) and one of the orthogonal projection corresponding phase space images (see Figure 2).

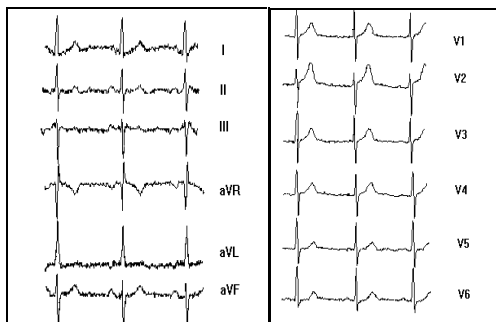


Figure 1: Example of real time domain ECG

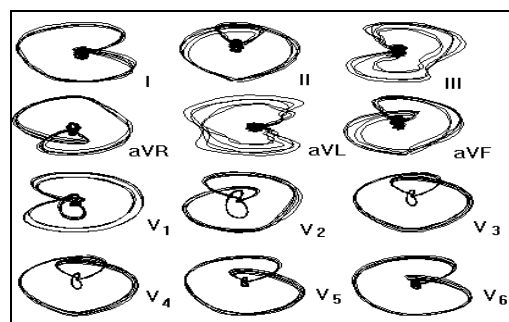


Figure 2: Corresponding phase space images

Any of these images is exposed to the additional computation procedure which allows to estimate the average curve in phase space. This procedure gives us also the values of initial features of phase space ECG-images including the disperse  $D$  of phase space image points regarding to the average curve (see Figure 3), the orientation angle  $A$  as well as the area  $S$  of inner loop of the average curve in phase space (see Figure 4) and some other features.

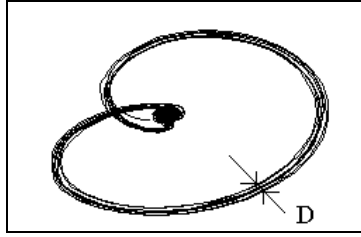


Figure 3: The disperse  $D$  of phase space image

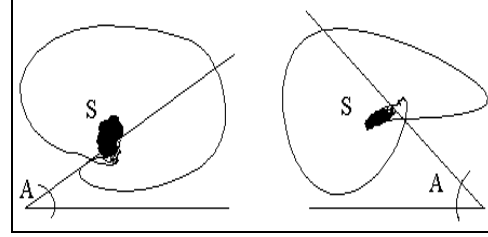


Figure 4: The orientation angle  $A$  and area  $S$  of inner loop of the average curve

It goes without saying that to initial set of features we include only simplest calculating parameters of phase space ECG-images. Using this features it is very attractive to solve the important application problem of human functional state diagnostic. But we may to solve this problem only if these features are useful really.

### PART 3. DIAGNOSTIC FEATURES OF PHASE SPACE ECG-IMAGES

To solve the problem of feature selection for human functional state diagnostic let us use our previous theoretical results regarding to problem of feature selection in statistical pattern recognition of two classes [Fainzilberg 1994, 1996]. This results establish the sufficient conditions of feature usefulness in combination with other features under incomplete *a priori* information about feature distributions.

Let  $V = \{V_1, V_2\}$  be set of two classes,  $x^{(N)} = (x_1, \dots, x_N)$  is initial set of  $N$  features  $x_1, \dots, x_N$ . Let further  $P(V_k)$ ,  $k=1,2$  denotes *a priori* probability for class  $V_k$  and let  $P(x|V_k)$  is the conditional distribution of probability of feature values in class  $V_k$ . In [Fainzilberg 1994] the following two theorems, which will be utilized latter, are introduced.

**Theorem 1 :** Any feature  $x_n$  ( $1 \leq n \leq N$ ) is useful in combination with other  $N-1$  features, i.e. the average probability of error  $P(e)$  is increasing as a result of transformation of full vector  $x^{(N)} = (x_1, \dots, x_N)$  to the reduced vector  $x^{(N-1)}$  which doesn't contain this feature  $x_n$ , if following conditions are fulfilled:

1<sup>0</sup> feature  $x_n$  is differently distributed in classes, i.e. there exist such values of  $x_n$  when

$$P(x_n | V_1) \neq P(x_n | V_2); \quad (1)$$

2<sup>0</sup> feature  $x_n$  and other  $N-1$  features are conditionally independent in both classes, i.e.

$$P(x_n | x^{(N-1)}, V_k) \equiv P(x_n | V_k), \quad k=1,2; \quad (2)$$

3<sup>0</sup> The conditional distributions  $P(x^{(N-1)} | V_k)$  are continuous functions of  $x^{(N-1)}$  and sets  $X_k^{(N-1)} = \{x^{(N-1)} : P(x^{(N-1)} | V_k) \neq 0\}$ ,  $k=1,2$  are connected domains.

**Theorem 2 :** Any feature  $x_n$  ( $1 \leq n \leq N$ ) is useful in combination with other  $N-1$  features, i.e. the average probability of error  $P(e)$  is increasing as a result of transformation of full vector  $x^{(N)} = (x_1, \dots, x_N)$  to the reduced vector  $x^{(N-1)}$  which doesn't contain this feature  $x_n$ , if following conditions are fulfilled:

1<sup>0</sup> feature  $x_n$  is identically distributed in classes, i.e.

$$P(x_n | V_1) \equiv P(x_n | V_2); \quad (3)$$

2<sup>0</sup> feature  $x_n$  and other  $N-1$  features are conditionally independent in one of classes and conditionally dependent in the other class, i.e.

$$P(x_n | x^{(N-1)}, V_1) \equiv P(x_n | V_1), \quad (4)$$

$$P(x_n | x^{(N-1)}, V_2) \neq P(x_n | V_2); \quad (5)$$

3<sup>0</sup> the conditional distributions  $p(x^{(N-1)} | V_k)$  are continuous functions of  $x^{(N-1)}$  and sets  $X_k^{(N-1)} = \{x^{(N-1)} : P(x^{(N-1)} | V_k) \neq 0\}$ ,  $k=1,2$  are connected domains.

We have studied real observations of phase space ECG-images corresponding to two groups of persons: with normal functional state of heart (class  $V_1$ ) and with abnormal functional state of heart (class  $V_2$ ). These observations have shown following properties of the above-mentioned features.

The values of the dispersion  $D$  of the phase space ECG-images from the class  $V_2$  was larger than the values of the dispersion  $D$  from the class  $V_1$ . Of course this property was not valid for some person. Meanwhile the observations have shown that  $P(V_1|D) > P(V_2|D)$  if  $D$  takes small values and  $P(V_1|D) < P(V_2|D)$  if  $D$  takes large values. Therefore feature  $D$  is useful itself and allows to discriminate normal and abnormal human functional state using following simplest decision rule:

$$\begin{aligned} & \text{normal functional state,} && \text{if } D < D_0; \\ & \text{abnormal functional state,} && \text{if } D > D_0, \end{aligned} \quad (6)$$

where  $D_0$  is the threshold which satisfies the following equation :

$$P(D | V_1) / P(D | V_2) = P(V_2) / P(V_1), \quad (7)$$

where  $P(D | V_1)$  and  $P(D | V_2)$  are the conditional distributions of feature  $D$  in classes and  $P(V_2)$  and  $P(V_1)$  are the *a priori* probabilities of these classes.

It is important to note that there exists such domain of values  $D$  where the conditional distributions  $P(D | V_1)$  and  $P(D | V_2)$  are crossing, i.e. concrete person may be in normal or abnormal functional state under identical values of  $D$ . Therefore the recognition of the phase space ECG-images without error using only this feature  $D$  is not possible, i.e. the average error probability  $P_D(e)$  satisfies the following inequality

$$0 < P_D(e) < P_0(e), \quad (8)$$

where  $P_0(e) = \min \{P(V_1), P(V_2)\}$  is the initial probability of error, based only on *a priori* probabilities.

Hence the question comes into being: how to decrease the average error probability in human functional state diagnostic using recognition of the corresponding phase space ECG-images ?

The main goal of following researches is the answering on above question.

The values of the inner loop area  $S$  of the average curve in phase space increase when the functional state of testing person is deteriorating. This fact causes by changing the location of the ST-T complex on ECG regarding to the baseline (see Fig. 5). Hence for any two not equal values of  $S$  the following condition is valid:

$$P(V_1 | S_i) > P(V_1 | S_j) \quad \text{for every } S_i < S_j. \quad (9)$$

However for every  $S$  the conditional probability of the class  $V_1$  was larger than the conditional probability of the class  $V_2$ , i.e.

$$P(V_1 | S) > P(V_2 | S) \quad \text{for every } S. \quad (10)$$

From (10) follows immediately that, in contrast to the feature  $D$ , the feature  $S$  is unuseful as such because the average probability of error decisions  $P_S(e)$ , based on testing of this feature only, is equal to the initial probability of error. In other words the following equation is valid

$$P_S(e) = P_0(e). \quad (11)$$

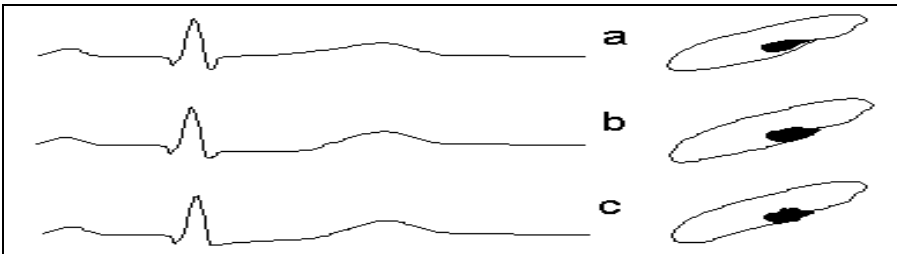


Figure 5: The changing of the inner loop area of phase space ECG-images  
a) normal ECG; b) ECG with ST-depression; c) ECG with ST-elevation

The observations have also shown that the value of  $S$  for concrete person does not change when under some physical or emotion loads the value of  $D$  changes. This property takes place both for class  $V_1$  and  $V_2$ . Hence we may suppose that feature  $S$  and  $D$  are conditionally independent in both classes, i.e.

$$P(S | D, V_k) \equiv P(S | V_k), \quad k=1,2; \quad (12)$$

Then taking into account that for values of  $D$  the condition 3<sup>0</sup> of Theorem 1 is valid certainly and, in accordance to (9) and (12) the other conditions 1<sup>0</sup>, 2<sup>0</sup> of this theorem are satisfied also, we may affirm that feature  $S$  is useful in combination with feature  $D$ . In other word the following inequality takes place:

$$P_{SD}(e) < P_D(e) < P_0(e), \quad (13)$$

where  $P_{SD}(e)$  is the average probability of error decisions based on testing both features  $S$  and  $D$ .

We may recognize the normal and abnormal human functional state using following decision rule:

$$\begin{aligned} \text{normal functional state} & \quad \text{if } D < D_0(S); \\ \text{abnormal functional state} & \quad \text{if } D > D_0(S), \end{aligned} \quad (14)$$

where  $D_0(S)$  is the threshold corresponding to concrete values of feature  $S$  of the average phase space ECG-image.

The optimum values of threshold  $D_0(S)$  is the decision of the following equation :

$$P(D | V_1)P(S | V_1)[P(D | V_2)P(S | V_2)]^{-1} = P(V_2) / P(V_1). \quad (15)$$

In accordance to [Fainzilberg, Potapova 1995] the orientation angle  $\alpha$  of the average curve in phase space is specific to the concrete person. The observances have shown that the conditional distributions of this feature for classes  $V_1$  and  $V_2$  are identical, i.e.

$$P(A | V_1) = P(A | V_2). \quad (16)$$

From (16) follows immediately that the feature  $A$  is unuseful as such because the average probability of error decisions  $P_A(e)$ , based on testing only this feature, is equal to the initial probability of error. In other words the following equation is valid

$$P_A(e) = P_0(e). \quad (17)$$

At the same time we have discovered that features  $A$  and  $S$  are correlated when testing person is in abnormal functional state. Hence the following condition takes place

$$P(A | S, D, V_2) \neq P(A | V_2); \quad (18)$$

So far as above-mentioned interconnection between features  $A$  and  $S$  does not discovers when testing person is in normal functional state, we may suppose that

$$P(A | S, D, V_1) = P(A | V_1). \quad (19)$$

From (18) and (19) in accordance with Theorem 2 follows that unuseful as such feature  $A$  is useful in combination with other two features  $D$  and  $S$ . Hence taken into account (13), the following inequality takes place:

$$P_{ASD}(e) < P_{SD}(e) < P_D(e) < P_0(e), \quad (20)$$

where  $P_{ASD}(e)$  is the average probability of error decisions, based on testing of all features  $A$ ,  $S$  and  $D$ .

Thus the decision rule for recognizing the normal and abnormal human functional state may be derived of follows form

$$\begin{aligned} \text{normal functional state} & \quad \text{if } D < D_0(S, A); \\ \text{abnormal functional state} & \quad \text{if } D > D_0(S, A), \end{aligned} \quad (21)$$

where  $D_0(S, A)$  is the threshold corresponding to the concrete values of features  $S$  and  $A$  of the average phase space ECG-image.

The average probability  $P_{ASD}(e)$  of error decisions based on testing of all features  $A$ ,  $S$  and  $D$  takes the minimum values if the threshold  $D_0(S, A)$  satisfies the following equation :

$$P(D | V_1)P(S | V_1)P(A | V_1) [P(D | V_2)P(S | V_2)P(A | D, S, V_2)]^{-1} = P(V_2) / P(V_1); \quad (22)$$

To increase the sensitiveness of the normal and abnormal functional states diagnostic we suppose some modification of constructed decision rules. This modification consist of using in (6),(14) and (21) instead of the absolute

values of the features  $A$ ,  $S$  and  $D$  the differences of their values obtained before and after special functional loads for testing person.

It goes without saying that in the case of a finite number of observations it is not possible to define the probability distributions of features which are used in (7), (15) and (22). Therefore for estimation of the sub-optimal threshold  $D^0$  (.) in decision rules (6), (14) and (21) we used the offered earlier method of learning to recognize two classes given a finite number of observations [Fainzilberg 1978].

## **PART 4. CONCLUSIONS**

The presentation of ECG-data in phase coordinates gives the additional information to traditional ECG analysis. The offered approach is tested in clinic on more than 400 ECG of patients with a normal and abnormal state of heart. The statistical treatment of these observations has confirmed a hypothesis about usefulness of phase space ECG-images for heart functional state diagnostic. This method allowed us to construct the intelligent information technology using for monitoring of operators in chemical production during their labour activity.

## **REFERENCES**

Fainzilberg L.S. 1978. An approach to the problem of learning to recognize two classes given a finite number of observations. Soviet automatic control (printed in USA), vol. 11, p.p. 38-41.

Fainzilberg L.S. 1994. Interconnection Between Feature Properties and Probability of Error in Statistical Recognition of Two Classes. Proc. of the 12th Int. Conf. on Pattern Recognition (ICPR'94), Jerusalem, Israel, vol. 2, pp. 544-546.

Fainzilberg L.S., Potapova T.P. 1995. Computer Analysis and Recognition of Cognitive Phase Space Electro-Cardio Graphics Image. Proc. of the 6th Int. Conf. on Computer Analysis of Images and Patterns (CAIP'95), Prague, Czech. Republic., pp. 668-673.

Fainzilberg L.S. 1996. Why relevant features may be useless in statistical recognition of two classes. Proc. of the 13th Int. Conf. On Pattern. Recognition (ICPR'96). Vienna, Austria, vol. 2, p.p. 730 - 734.

Hui-Huang H., Principe J.C. 1991. Visualization of epileptic spikes in state space. Proc. Annu. Int. Conf. IEEE Eng. Med. and Biolog., Orlando/ FL, vol 13, p.p. 1191-1192.

Strauss E., Burger P. 1995. 4-Dimensional Modelling of the Human Heart .- Proc. of the 6th Int..Conf.of Computer Analysis of Images and Patterns (CAIP'95), Pragua, Czech. Republic, p.p.376-383.

Shi P., Robinson G., Duncan J. 1994. Myocardial motion and function assessment using 4d images. Visualization in biomedical Computing, v.2359, p.p. 149-159.