Current results of experiments with GDV images

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Abstract
Recently developed technology for recording the human bioelectromagnetic field (BEM) using the Gas Discharge Visualisation (GDV) technique provides useful information about the human BEM. We use statistical analysis and machine learning to interpret the GDV coronas of fruits and human's fingers in order to verify three hypotheses:
(A) the GDV images contain useful information about the object/patient ,
(B) the human BEM can be influenced by some outside factors, and
(C) the map of organs on fingertips' coronas makes sense.
We performed several independent studies, which we here briefly describe: recording coronas of berries of different grapevines, detecting the influence of drinking the tap water from ordinary glass and energetic glass K2000, detecting the influence of natural energy source in Tunjice near Kamnik, Slovenia on the human BEM, verifying the influence of mobile phones with or without energetic protection on the human BEM, and establishing the relation between energetic diagnoses of an extrasense healer and GDV images. All studies, as well as some other studies described elsewhere, gave significant results and therefore support all three hypotheses.

1. Introduction

Machine learning technology (Mitchell, 1997) is well suited for the induction of diagnostic and prognostic rules and solving small and specialized classification, diagnostic and prognostic problems. Recently developed technology for recording the human bioelectromagnetic field (BEM) using the Gas Discharge Visualisation (GDV) technique (Korotkov, 1998) provides useful information about the human BEM. This technique is also known as Kirlian's effect which appears when exposing the object/patient to high-voltage high-frequency electromagnetic field.

The *Crown TV* camera, which is part of the GDV equipment (Korotkov, 1998), records the coronas of fingers as GDV images (bitmap images). However, the problem is the interpretation of the GDV images. By using machine learning we could eliminate that problem by means of automatically generating classification rules from GDV images. For that purpose the Kirlian images need to be described with a set of parameters. Parameters are calcuated with a computer program *GDV Analysis* (Korotkov, 1998), which comes with the camera. It is also possible to generate the corona of the whole human body from coronas of all ten fingertips. The program is based on a map, developed by Mandel (1986). This map defines regions (sectors) of each finger's corona to be related with specific organ or organ system in the body. Korotkov (1998) and his team slightly modified this map.

In the past we already performed several independent studies (Kononenko et al., 1999): recording coronas of apple skin, relating the coronas of females' fingertips with the state of menstrual cycle, detecting the influence of different T-shirts on the human BEM, studying effects of the art of living programme on the BEM of its participants (Trampuž et al., 1999).

We have recorded coronas of fruits and human fingers with the Kirlian camera. The recorded coronas are then processed and described by a set of numerical parameters. Then we use machine learning algorithms to interpret the GDV coronas in order to verify three hypotheses: 1. The GDV images contain useful information about the plant/person. 2. The human bioelectromagnetic field can be influenced by some outside factors, such as special T-shirts. 3. The map of coronas of fingers according to Chinese medicine does make sense.

We performed several independent studies, reported in this paper in the following sections: verifying the influence of mobile phones with or without energetic protection on the human BEM, establishing the relation between energetic diagnoses of an extrasense healer and GDV images, recording coronas of berries of different grapevines, detecting the influence of drinking the tap water from ordinary glass and energetic glass K2000, and detecting the influence of natural energy source in Tunjice near Kamnik, Slovenia, on the human BEM.

2. The influence of mobile telephones on human bioelectromagnetic field

We recorded coronas of all ten fingertips of five groups of persons that were carrying the mobile telephone above their heart for a period of one hour under different conditions: without any protection, with two different energetic protections, with placebo protection and a control group without mobile telephones. Results indicate that mobile telephones negatively affect the human BEM field, that energetic protection of Minnie Hein works well while the placebo protection doesn't work, and that energetic protection of Milan Mladženović not only eliminates the bad influence of mobile telephones but also strengthens the human BEM.

2.1 The purpose of the study

The purpose of our study was to make a comparative analysis of the effects on human's bioelectromagnetic field (BEM), potentially caused by mobile telephones. The data about person's BEM was gathered by recording coronas of all ten fingertips using the Kirlian camera Crown-TV. Pictures for each person were taken three times – the first time before wearing the turned-on cellular phone, the second time after the phone was worn for half an hour, and the third time after wearing the telephone for one whole hour. Trying to reveal influences of cellular telephones under many different circumstances, we designed five different scenarios. According to them, people were divided into five groups:

- control group of 17 people - subjects without cellular telephones;
- 19 people, wearing cellular phones without any protection against possible effects on their BEM;
- 14 people, wearing cellular phones and Electro-Magnetic Field Shield, invented by therapist Minnie Hein from Peru; the Electro - Magnetic Field Shield consists of small bottle that contains essences (water with alcohol, coded in a similar way like in homeopathy);
- 18 people, wearing cellular telephones that were equipped with protection of Milan Mladženović from Belgrade; the protection is made up from ferromagnetic material, that was bioenergetically

coded;
- 16 people, wearing cellular phones with fake protection - small plate that looked identical to protection of Milan Mladženović; the purpose of this group was in observing a possible placebo-effect.

In all cases, the cellular telephone was worn in the height of human's heart - it was hung around the neck, using the string. The gathered data was statistically processed. The paper describes used methods and results.

2.2 Measurements and preparation of data

The measurements

Gathering of data was the first and also the most extensive step in our study. It was organised in five picture-taking sessions. The measurement procedure was standardised and was the same for every collaborating volunteer. All volunteers were asked to turn their cellular phones off at least three hours before our recording session and keep them turned off till the beginning. Considering this it was presumable that the first measurement of particular volunteer, made without his cellular phone, was not yet influenced by any possible effects that cellular phones might have on BEM. After first measurement, the volunteer's phone was turned on and pictures after thirty-minute and sixty-minute intervals would be taken with phones worn in the height around the heart. In this manner we three times recorded coronas of all ten fingertips of each of 84 volunteers.

Data processing

For statistical analysis of the gathered data, the pictures had to be transformed into numerical values. This was done with program GDV-Analysis, that accompanies the Crown-TV. GDV-Analysis transforms pictures into numerical parameters, that describe the characteristics of fingertip coronas. We used only parameters that in previous studies proved to be important (Kononenko et al., 1999;2000; Trampuž et al., 1999):

1.	Area of GDV-gram.
7.	Number of separated fragments in the image.
8.	Average area of the fragments.
10.	Relative area of corona.
17.1.-17.9	Areas in the sectors of particular finger.

Because the telephone was worn in the height of the human's heart, we decided to observe only 22 parameters out of 79 in sectors 17.1. - 17.9. that according to finger coronas map correspond only to those parts of body, that might have been influenced by cellular phones. Herein are included 4 sectors for heart, 2 sectors for throat with thyroid gland and 2 sectors for brain, dorsal spine, blood circulation, lymph, chest, head, pineal gland and respiratory system. We also defined additional, potentially significant parameters:

- CW - corona width;
- parameters, describing relative percentual changes of parameters 1, 7, 8, 10 and CW.

In the next step the average of parameters 1,7,8,10,CW and their percentual counterparts over all ten fingers for every particular person was calculated. To observe the relative change of every parameter for a given person in sixty-minute interval, we also calculated the difference between average values of these parameters after sixty-minute period and the parameters, describing person's corona before wearing the cellular telephone.

Table 2.1 displays the average differences of values of parameters. Table includes two parameters that describe particular corona sectors and have turned out to be the most important. These two parameters are 3R-6 (sixth sector on third finger of the right hand), that according to coronas map corresponds to heart and 1R-4, that corresponds to throat and thyroid gland.

Table 2.1: Differences between values of important parameters in one hour period for five groups

param.	*control group*	*group with phone*	*placebo group*	*group w/shield from M. Hein*	*group w/shield from M. Mladženović*
1	226.1	115.0	15.4	252.0	504.2
7	0.87	0.16	0.04	-0.16	-0.58
8	-769.5	-224.9	-255.2	-165.8	289.5
10	0.189	-0.056	-0.248	0.082	0.226
%1	0.063	-0.001	-0.003	0.064	0.123
%7	-0.123	-0.107	-0.116	-0.102	-0.181
%8	-0.214	-0.139	-0.124	-0.104	0.019
%10	-0.038	-0.112	-0.110	-0.038	-0.007
CW	1.033	0.131	-0.273	1.044	2.071
%CW	0.075	0.011	-0.012	0.055	0.125
3R-6	68.2	-144.5	-50.7	21.3	124.2
1R-4	248.1	-27.4	-230.3	84.0	250.6

Parameters 1, %1, 10, %10, CW and %CW indicate that

- there is a similar negative effect of mobile phones on the human BEM in groups with mobile phone and in placebo group;
- results in control group are similar to those in group with the shield of Minnie Hein, indicating that shield influences the human BEM in a way that neglects the effect of mobile phones;
- the shield of Milan Mladženović has positive effect - not only that it neutralises the effect of cellular phones, but it also strengthens the human BEM;
- parameters 3R-6 and 1R-4 imply similar findings: placebo protection has no effect, cellular phones negatively affect the human BEM, both shields are effective, and besides the shield of M. Mladženović has an amplifying effect.

2.3 Statistical analysis

To estimate whether the parameters' changes were significant, we used Student's t-test. The significance level α was chosen to be 0,05. The majority of these tests have indicated insignificant changes. The probable cause is in too big standard deviations of parameters' values. This problem could be alleviated with greater number of people in each group. Significance has mostly manifested inside group of people, wearing cellular phones, equipped with the shield of M. Mladženović. The BEM of subjects, belonging to this group, have been significantly increased.

T-tests between different classes were also performed in order to find out, whether the differences between values among all possible pairs of classes were great enough to consider results significant enough in comparison to their deviation. Most of these tests also showed insignificant changes between 5*4/2=10 pairs of groups. But in spite of that, results of parameters 10, 1R-4, 3R-6 and CW indicate that:

1. the control group and group with the shield of Minnie Hein are similar - there are no significant changes between them;
2. the placebo group had worse BEM than the control group - indicated by significant changes of parameter 1R-4 (and partially by almost significant parameters 3R-6, 10 and CW);
3. the control group and group with the shield of Milan Mladženović are similar - there are no significant changes between them;
4. the group with cellular phone had worse BEM than the control group - indicated by significant change in parameter 3R-6 (and partially by almost significant 1R-4 and 10);
5. the placebo group had worse BEM than group with the shield of Minnie Hein – partially indicated by almost significant change in parameters 10 and 1R-4 (and slightly by indicated significance of CW);
6. the group with the shield of Minnie Hein is similar to the group with the shield of Milan Mladženović - there are no significant changes between them;
7. the group with telephone had worse BEM than group with the shield of Minnie Hein - indicated by almost significant change in parameter 3R-6 (this test showed the least significance);
8. the placebo group had worse BEM than the group with the shield of Milan Mladženović - indicated by significant changes in 1R-4, 3R-6 and CW (and partially by almost significant change in 10)
9. the group with telephone is similar to the placebo group - there are no significant changes between them;
10. the group with telephone had worse BEM than group wearing the shield of Milan Mladženović - indicated by significant change in 3R-6 (and partially by almost significant changes in 1R-4 and CW, and slightly by indicated significance of 10)

2.4 Analysis of merged groups

To alleviate an unwanted effect of too great deviation in calculated results, we decided to merge groups/classes that were related. Herewith we reduced the number of classes to three and gained greater number of subjects in

new group	composed of these previous groups	number of people
W - people without telephone	control group (this group remained the same)	17
T - people with telephone	people with telephone + placebo group	35
S - people with shielded telephone	people with shield of Minnie Hein + people with shield of M. Mladženović	32

Table 2.2: Structure of three new classes, gained from previous five classes.

two classes. Table 2.2 shows the structure of new classes and the number of examples in each class.

We processed the data in three groups in the same way as before. Although Student's t-tests inside particular class showed no significant changes, there were some significant differences, showed by t-tests between 3 pairs of classes. Significant changes of parameters 10, 1R-4, 3R-6 and CW indicate that:

- groups S and W are similar, because there are no significant differences;
- group T had worse BEM then W - indicated by significant change in parameters 1R-4 and 3R-6 (and partially by almost significant 10 and CW);
- group T had worse BEM than group S - implied by significant change in parameters 1R-4 and 3R-6 (and partially by almost significant 10 and CW).

3. Relation between energetic diagnoses and GDV images

We recorded coronas of all ten fingertips of 110 persons for whose the extrasense healer provided the energetic diagnosis. We used machine learning to interpret the GDV coronas in order to verify three hypothesis: (a) the GDV images contain useful information about the patient, (b) the map of organs on coronas of 10 fingers does make sense, and (c) the extrasense healer is able to see by himself (with his natural senses) the energetic disorders in the human body. The results support all three hypotheses.

3.1 The measurements and preparation of data

The first stage of the research involved recording coronas of all ten fingertips of patients. Parameters calculated from coronas (GDV images), were then used as attributes for machine learning algorithm. We recorded 150 patients, but due to technical problems only 110 cases were useful. Recording was made with Crown TV camera. It's a digital camera connected to a computer. It captures corona image directly into a bitmap image, which is very suitable for image analysis.

We calculated a set of parameters from each corona image. Each training instance was presented with a set of 634 attributes (parameters), which is too many attributes for only 110 cases. Evidently this large set of attributes had to be reduced in order to expect some positive result from machine learning. Namely with altogether 634 attributes and only 110 cases there is a high probability that certain irrelevant attributes will seem to be very relevant just by chance. Attribute reduction is explained later in this article for each experiment separately.

On the other hand, we also needed the classification class for each case (patient). Here we engaged an extrasense healer. We recorded his observations on audio tapes. The observations were made for all organs of the whole body. The diagnosis for one patient contains the description of the state for 65 organs/parts of organs/glands (e.g. small brain, stomach, left and right kidney, thyroid gland, etc.), 8 parts of the body (e.g. arms, head, neck, legs etc.), 8 physical/psychical functions (e.g. respiration, digestion, concentration, sleeping etc.), and 17 possible diagnoses in terms of classical medicine (e.g. rheumatism, cold, headache, hameorrhoids etc.). For each organ and part of the body the state can be either OK, energetic blockage, strong energetic blockage, incorrect function, no function or damaged. This gives 7 classes, which is too much for our learning conditions (634 attributes, 110 cases). Therefore we decided to distingwish only between 2 classes. The first class is 'no blockage' (OK) but all other classes were joined into second class, called 'blockage'.

3.2 Machine learning of diagnoses

We performed 5 experiments:

(A) The first experiment: 239 attributes, 110 cases

We used all 110 cases. We had to somehow reduce the number of attributes. Here we excluded a large subset of attributes that represent a part of corona sector area and seem pretty irrelevant at first sight. 239 attributes remained. Further on we decided to run our experiment ten times on 10 diagnoses (learning problems) that were best according to their class distributon. We used *C5.0* learning algorithm for building decision trees, a descendant of C4.5 (Quinlan, 1993). We used 10-fold cross validation and calculated the average accuracy of ten decision trees. The results showed about 10% improvement of accuracy compared to the default classifier (that classifies all instances into the majority class) for five diagnoses: duodenum, throat, blood circulation, neck, and cervical spine.

(B) The second experiment: 79 attributes, 110 cases

Here we tried to additionaly reduce the number of attributes. Knowing (according to fingertip corona map) that each diagnosis is directly connected to some sector of fingertip corona, we used only attributes that measure areas of corona sectors (79 attributes). All other experiment conditions remained unchanged. The result was rater similar to the result of the first experiment.

(C) The third experiment: 79 attributes, 71 cases

Here we focused on the quality of the data. We excluded patients with generally weak coronas. This cases show general lack of energy, but do not provide enough information about specific organs (Korotkov, 1998). Only 71 cases remained useful. All other experiment conditions remain unchanged from the second experiment. The result showed larger improvemnts of accuracy from previous experiments, especialy for two diagnoses: taste (20% improvement) and duodenum(15% improvement).

(D) The fourth and fifth experiment: 2 to 10 atributes, 71 cases

To additionaly reduce the set of attributes, we used only attributes that are relevant for some diagnose according to medical doctor's opinion. The set of parameters greatly decreased (from 2 to 5 attributes per diagnosis in the fourth experiment and up to 10 attributes in the fifth experiment). Other conditions remained unchanged. The results didn't show any improvement in accuracy.

3.3 Estimating the quality of attributes

The analysis of the trees that were generated in the third experiment (which gave best results) shows interesting match with medical doctor's opinion. Namely, for this stage of the study we used a map of relations between diagnoses and attributes, which was supplied by an independent medical doctor. Also an interesting phenomena could be noticed. That is, *the best classification results were achieved where the root (best) attribute matches with doctors selection*. For example: All 10 trees generated in 10-fold cross validation for diagnose duodenum, had a 'duodenum attribute' in root. There is less than 2.6% of chance that this is just a coincidence. Also all 10 trees generated for diagnose taste contain 'lymph attribute' in root, which is also relevant according to doctor's opinion.

Further on we estimated the quality of attributes. We used the Gain Ratio estimate (Quinlan, 1993). All parameters for estimation were the same as in the third experiment (71 cases, 79 attributes). We decided to compare the attributes, proposed by the medical doctor, with 10 best estimated attributes. There was a significant match with doctor's opinion in 6 out of 10 learning problems. Here are some examples. A set of 10 best estimated attributes for diagnose duodenum contains 'duodenum attribute' in the first place and 'lymph attribute' in the third place. Both are relevant to duodenum according to doctor's opinion. When estimating parameters for taste, all 3 parameters from doctor's selection are among 10 best estimated attributes. The probability of coincidence is here less than 6%. The diagnosis 'heart' had 'heart attribute' in the first place. The probability of coincidence is less than 5.1%. The diagnosis 'lungs' diagnose had 'throat attribute' as best estimated. Little brain and blood circulation diagnoses had 2 attributes from doctor's selecton among 10 best estimated.

And finally, we performed the estimation on the whole set of 634 attributes. *The results here confirmed results from previous estimates.* We describe some exmples. Estimation for 'duodenum' diagnosis gave 2 relevant attributes among 10 best estimated. Coincidence probability is less than 0.4%. Estimation for 'taste' diagnosis gave also 2 relevant attributes among 10 best estimated. Coincidence probability is less than 0.6%. 'Heart' diagnosis gave 'heart attribute' as best estimated. Coincidence probability is less than 0.7%. Finally, 'little brain', 'lungs', and 'liver' diagnoses had one relevant attribute among 10 best estimated.

3.4 Conclusions and further work

Machine learning experiments show that our numeric parameters, calculated on corona images, aren't sufficient for exact diagnosis. Two basic reasons seems to be inaccurate recording of corona images and too little training instances (patients). In spite of all, it also turned out that corona images contain useful information for diagnostics. Namely, for all diagnoses we managed to increase the classification accuracy for at least 10% according to default classifier (that classifies all instances into the majority class).

Attribute estimation and tree analysis show that we had better success with machine learning where the set of most informative attributes matches with medical doctor's selection of attributes for that specific diagnosis.

We can conclude that *the corona images contain useful information for diagnostics*, but there is a problem with 'extracting' this infomation. Namely, the whole process of data capturing is very sensitive to noise. And after all, it is very difficult to select a small set of informative attributes from a large set of noisy parameters, especially when you have such a small training set.

4. Recording coronas of grapevine berries

The aim of the study was to determine, whether Kirlian camera can record any useful information by recording coronas of berries. We used nine sorts of grapevines, two reedvines for each sort (healthy and infected by different viruses), obtained from plants of Biotechnical Faculty in Ljubljana. We recorded 20 berries for each reedvine. We used only 14 basic numeric attributes (see Section 3, the absolute area of corona was excluded due to different sizes of berries of different sorts).

We used two machine learning algorithms in order to distinguish different sorts and infected from noninfected reedvines from numerical description of coronas of their berries. The naive Bayesian classifier assumes the conditional independence of attributes given the class and calculates for each new instance the probability of each class (Kononenko, 1993). Assistant-R builds decision trees and uses a non-myopic algorithm ReliefF for the estimation of the quality of attributes (Kononenko et al., 1997). We measured the classification accuracy and the information score (Kononenko and Bratko, 1991). The latter measure eliminates the influence of prior probabilities and appropriately treats probabilistic answers of the classifier.

We tried to solve various problems:
(a) distinguishing infected 'Pinela' from noninfected 'Pinela', 2 classes, 30 examples in each class;
(b) distinguishing 'Malvazija' without symptoms and 'Malvazija' with symptoms of phytoplasma; 2 classes, 20 examples in each class;
(c) distinguishing all nine sorts of grapevines, 40 examples in each class;
(d) Volovnik'+'Zweigeld' (not infected with GLRaV viruses) and 'Sladkocrn'+ 'Klarnica' (infected with GLRaV viruses); 2 classes, 80 examples in each class;
(e) distinguishing two cultivars: 'Volovnik' and 'Zweigeld', 2 classes, 40 examples in each class.

For each problem we randomly split the set of all examples in 70% for training and 30% for testing. This process was repeated 10 times and average results and standard deviations for the naïve Bayesian classifier are presented in Table 4.1. Results for Assistant-R are similar.

Table 4.1: Results of the naïve Bayesian classifier in different classification problems for grapevine data.

problem	prior pr. (%)	class. accuracy (%)	inf. score (bit)
nine cultivars	11.1	35.7 ± 3.1	1.09 ± 0.07
‘Volovnik’ : ‘Zweigeld’	50	77.5 ± 9.2	0.45 ± 0.15
infected : non-infected ‘Pinela’	50	70.0 ± 11.1	0.30 ± 0.13
infected : non-infected with GLRaV	50	71.0 ± 5.5	0.35 ± 0.06
‘Malvazija’ with : without phytoplasma	50	88.3 ± 8.0	0.73 ± 0.16

In all tests, the classification accuracy is significantly higher than the prior probability of the classification. For example, in the case of all nine cultivars, the classification accuracy is 35.7%. Since all nine classes are of the same size, a prior probability for each class is 1/9=11.1%, which is more than three times lower than the classification accuracy. Because of this, the information score is very high. The classification is quite successful also in the cases of classification of grape berries according to their sanitary status. In these cases, the prior probability is 50% while the classification accuracy ranges between 70% and 88.3% which is indeed unexpectedly high.

5. Drinking water from ordinary and 'energetic'glass K2000

We performed an experiment with drinking water from ordinary glass and so called 'energetic' glass K2000, which is somehow coded with positive information/energy. K2000 was invented by Vili Poznik from Celje, Slovenia. He uses orgon technology (methodology) in order to encode information into glass.

We recorded each of 34 volunteers three times in three days: without drinking water, 15 minutes after drinking water from ordinary glass, and 15 minutes after drinking water from energetic glass K2000. The persons didn't know which glass is ordinary and which is energetic. We used tap water and the water was left 15 minutes in the glass before it was consumed. For each person we recorded coronas of all ten fingertips. We calculated 15 basic parameters for coronas of each finger and we averaged their values over all ten fingers. We used the following parameters:

1.. Absolute area of corona.
2.. Noise, deleted from the picture (depends on the first setting in the program).
3.. Form coefficient.
4.. Fractal dimension.
5, 6.. Brightness coefficient and deviation.
7.. Number of separated fragments in the image.
8, 9.. Average area of fragments and its deviation.
10.. Relative area of corona
11.. Relative coefficient of glow inside the inner oval.
12-15.. Relative coefficient of image glow for 25, 50, 75 nad 100% area (from the whole area)

We calculated average values and standard deviations for each parameter and for each glass: the difference between the value after drinking water from the given glass minus the value before drinking the water (see Table 2). The results indicate that water from K2000 increases the coronas (parameters 1, 8 and 10-15) and decreases the fragmentation (parameter 7), while that from ordinary glass slightly decreases the coronas and, to the lower extend than K2000, decreases the fragmentation.

To evaluate the significance of differences between the glasses we used the paired one-tailed t-test. We calculated the differences and st. deviations between the values of parameters of two glasses. The differences together with t-values and significance levels are given in Table 5.1. With the exception of parameter 7, parameters 1,8 and 10-15 show significant differences (significance level greater than 0.99)

Table 5.1: Statistical analysis for drinking water from two glasses

parameter	average difference	standard deviation (s)	t = r/s * sqrt(n)	significance level
1	856,61	1199,00	4,17	>0,99994
2	284,60	614,84	2,70	0,9931
3	15,02	42,27	2,07	>0,9596
4	0,14	0,48	1,76	0,9216
5	0,61	4,36	0,82	0,5878
6	-0,67	4,34	-0,90	0,6319
7	-1,49	4,74	-1,83	0,9328
8	563,74	944,61	3,48	>0,99933
9	13,08	44,94	1,70	0,9109
10	0,21	0,35	3,45	>0,99933
11	0,02	0,03	3,49	>0,99933
12	0,08	0,14	3,46	>0,99933
13	0,09	0,15	3,55	>0,99953
14	0,07	0,14	3,11	>0,99806
15	0,03	0,05	2,82	>0,9949

For machine learning analysis we used C4.5 system for building decision trees (Quinlan, 1993). We wanted to distinguish ordinary glass from K2000. We had 68 examples and we performed two experiments: using all 15 attributes and using only attributes 1,7,8, and 10. The average classification accuracy, obtained by 10-fold cross validation, was 76.2%, when all atrtibutes were available, and 81.0%, with four selected attributes. In the latter case, most of the times the decision tree contained only attribute 8 (average area of fragments).

6. Natural energy source in Tunjice

In this study we wanted to evaluate the effect of the natural energy source in Tunjice near Kamnik, Slovenia on the human BEM. The coronas of all ten fingertips were recorded for 71 visitors of Natural Healing Garden Tunjice. Each visitor was recorded before and after the 45 minutes visit of the Healing Garden. Due to mistakes and noise in recordings we used for the analysis the coronas of only 50 persons. The coronas of each finger were described with 15 basic attributes (see Section 3) and for each person they were averaged over all ten fingers.

Table 6.1: Statistical analysis for natural energy source in Tunjice

Parameter	***difference***	***st. deviation***	t
1	-1734,8	4058,6	3,02
7	0,47	2,13	-1,56
8	-1254,8	3867,1	2,29
10	-0,299	1,172	1,80
CW	-0,628	9,605	2,86
%1	-0,0748	0,2762	1.91
%7	0,3110	0,2746	-8.01
%8	-0,0234	0,3045	0.54
%10	0,0578	0,2560	-1.59
%CW	-0,0774	0,2527	2,17

In this study we used only parameters 1,7,8,10, which in previous studies proved to be important, and we defined some additional parameters: corona width (CW), and procentual counterparts for parameters 1,7,8,10 and CW. We calculated average difference of values and standard deviations for each parameter: the difference between the value before visiting the Garden and after the visit. To evaluate the significance of differences we used the paired one-tailed t-test. The average values and standard deviations together with t-values are given in Table 6.1. Procentual counterpart of parameter *i* is indicated by *.%i*. All values of *t* absolutely greater than 2.01 indicate the significant change at the significance level alpha = 0.05.

The results show that the number of fragments (parameter 7) is significantly decreased and that coronas are significantly thicker (parameter CW). Areas of coronas are almost significant (parameter 1).

7. Conclusions and further work

The studies described in this paper, as well as other studies performed in the past, show that the GDV records, described with a set of parameters, contain useful information and they are not only noise.

Results of the study with mobile telephones reveal that:

- cellular phones influence the human BEM in a way that coronas become reduced, more fragmented and incomplete;
- the group of people with telephone and the placebo group are similar, therefore the placebo shield has no effect;
- the control group is similar to the group with the shield of Minnie Hein, indicating that the shield works well – it neglects the effect of the mobile telephones;
- the shield of Milan Mladženović also has not only a protective influence on the human BEM, but also a stimulating and strengthening effect.

Although the results from statistical analysis indicate correctness of these conclusions, the majority of results is not significant. A probable reason for that is the insufficient quantity of data. However, results that are statistically significant support conclusions described above. Because of too large deviations, presumably caused by insufficient number of people in five groups it might be sensible to repeat this study on greater population.

Our results in the study with extrasense healer do support all tree hypoteses:
(a) The corona contains useful information for diagnosis,
(b) the map of organs on the fingers' coronas makes sense,
(c) the extrasense therapist does see the energetic state of the patient and is able to diagnose patient with this information.
To obtain a more reliable confirmation of the three hypotheses, however, a much wider study is necessary, which is currently not possible with our modest resources.

The classification accuracy on different problems with grapevine data is significantly higher than if the classifier would be random. This means that coronas of grapevine berries contain useful information about cultivar and about their sanitary status. We used only parameters that were independent of the size of grape berries. However, there is a possibility to introduce new parameters that may contain additional useful information. We plan to verify this hypothesis and further improve the methodology in order to make it useful for classification of grape cultivars and their diseases.

The results of the study with water show significant positive efect of drinking water from energetic glass K2000. Although, till now, there is no physical explanation for coding the information into glass, the effects are obviously measurable. In order to make the study more reliable, we plan to perform also a double-blind experiment with slightly modified scenario so that persons will be recorded several times: immediately before drinking and 15 and 30 minutes after drinking the water.

The result of the study in Tunjice indicates that the visit of the Natural Healing Garden positively influences the human BEM. Coronas are larger and less fragmented. In order to obtain more reliable conclusions we plan to record coronas of a control group of people, that shall visit another place (for example a walk in a forest) in the same manner as they visited the Healing Garden. The comparison should show whether the Healing Garden has greater influence than ordinary gardens.

We plan to continue studies, described in this paper, and we plan to investigate also some other phenomena:

Water drops: We are trying to distinguish different kinds of water: ordinary tap water, water from various springs, water charged by a healer and water charged with various vibrations. Preliminary experiments show that it is very difficult to reliably measure the corrona's of water drops.

Energetic Influence' on human BEM: We plan to measure the effect of glass bowls (coded with a certain information by Vili Poznik in a similar manner as 'energetic' glasses K2000), the effect of 'energetic' symbols and 'energetic' chairs etc.

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