A SOFTWARE PACKAGE FOR EXG ANALYSIS

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ABSTRACT: The Dynamic CNV (DCNV) paradigm is an extension of the classical CNV paradigm with a biofeedback design. The experiment results in creation of the new cognitive phenomenon denoted as the electroexpectogram (EXG) which relates to the classical conditioning theory. The EXG is observed from the human brain using this experimental design. The DCNV Research Tool (DCNVrt) is a Windows package performing a physiology research, organizing the DCNV experiment. The software is written in LabVIEW (data-flow, graphical environment). It is used for acquisition and extraction of event-related potentials (ERP), processing of the anticipatory components and is convenient for presentation of statistical results. It is tested at the Institute of Physiology at the University of Skopje, Macedonia, and intended for exploitation in the field of clinical research of neurological disturbances. Further extension of the work towards a fuzzy DCNVrt is also presented at the end of the paper.

KEYWORDS: anticipatory potential, CNV, DCNV, electroexpectogram, ERP, event-related potential, evoked potential, EXG, LabVIEW

1. INTRODUCTION

Brain potentials are divided into spontaneous and event-related. The spontaneous potentials result from the regular brain activity and are also known as EEG potentials. The event-related potentials (ERP) result from external brain excitation (event) and can be divided into *evoked* and *anticipatory*. Evoked potentials appear after the excitation, as a reflex of the brain. Anticipatory potentials appear before the corresponding event and represent the expectation of the event, usually via a motor preparation process for it in the brain. The most prominent example of the expectation-related potential is the contingent negative variation (CNV) potential. It is extracted from subject's EEG within the CNV experiment, originally proposed by Walter et al. [9]

The CNV experiment is based on the CNV paradigm which applies two brain stimuli (S_1 and S_2, usually audio) to the subject within a constant interstimulus interval (ISI). S_1 is a warning signal and S_2 is an imperative stimulus that the subject has to react to. The subject's reaction is applied to the experiment to prevent subject's concentration from lowering. The procedure is repeated tens of times, during which an ERP produced in the EEG trace between the stimuli shapes itself toward a specific CNV wave. After 10-20 trials the ERP usually shows both components - the evoked (short) potential due to S_1 as well as the anticipatory (late, expectancy) potential together with the preparatory potential prior and due to S_2.

The DCNV (Dynamic CNV) experiment is an extension of the CNV experiment as defined above. The extension is actually a closed loop (bio-feedback) which enables switching S_2 ON and OFF the due to fulfilling certain conditions in the experiment's environment, thus forcing a cyclic process of building and degrading of the CNV wave. The subject is not informed about the dependence of the stimuli, so the expectation of appearance (absence) of S_2 during the experiment corresponds to the learning process. That enables the learning process to be easily modeled.

The CNV wave (extracted ERP) can be qualified by its parameters: amplitude, slope, etc. After the experiment, a statistical curve of the qualifying parameter (any one of the above) is drawn across the trials. This statistical curve is denoted as the *electroexpectogram* (EXG) [1] and presents directly the subject's cognitive capabilities. As the current research at the Institute of Physiology (Faculty of Medicine, Skopje, Macedonia) indicates, the future clinical research at the Clinic of Neurology is expected to demonstrate distinctive differences in this statistics between different categories (healthy and patients with neurological disturbances, or different age groups, etc).

As a paradigm, the DCNV completely corresponds to the classical Pavlov-type conditioning paradigm. The only difference between the two experiments is the advantage of the DCNV paradigm collects a bigger body of evidence about the classical conditioning paradigm, by giving the expectation process in the brain, a phenomenon which is not evident in Pavlov's experiment.

The paper is organized as follows. Section 2 gives the details of the DCNVrt experiment setup. Section 3 overviews the software. Section 4 gives an overview of the fuzzy version of DCNVrt, i.e. the initial results of the investigation of the implementation of the fuzzy paradigm in this domain. Section 5 gives concluding remarks of the work presented in the paper.

2. THE DCNV PARADIGM EXPERIMENTAL SETUP

This section presents an overview of the experimental setup for the application of the DCNVrt.

The software package DCNVrt is written completely in LabVIEW ("G" from National Instruments) and it embraces the acquisition, signal processing and analysis of an EEG and EOG traces (latter used for validation of the EEG against artifacts), as well as reporting. The hardware used in the experiment consists of a precise Low-Pass amplifier for μV ranges, an AT-MIO-E card from National Instruments, a sound card for applying the stimuli and a button with a TTL interface (Figure 1).

The system acquires two differential analogue channels, the EEG and the EOG. The excitation is of type audio, S_1 being a short (0.5s) 1kHz warning beep and S_2 being a longer (3.2s) 2kHz imperative beep. It is essential that the subject does not know the nature of the signals or the number of the stimuli during the measurement. One acquisition process lasts for 7s. The process is buffered and hardware–timed. The signal S_1 happens at time t=1s after the initialization of the acquisition, whereas S_2 is turned on at time t=3s if needed.

The subject has to react upon hearing S_2 by pressing the button and immediately stopping it. This is prevention from falling asleep and lowering of concentration. The number of trials in the experiment is set to maximum 100 successful (120 trials total). The *gap* between two consequent trials varies from 12-15s to avoid timing determinism.

After three consequent detections of CNVs detected, S_2 is turned OFF and the subject *learns to forget* the imperative stimulus thus lowering the value of the CNV-qualifying parameter. S_2 is turned ON again when in three consecutive trials no CNV is detected, and so on. The EOG trace is used for automatic validation of the EEG trace against artifacts defined as voltage sequences longer and higher than preset thresholds. There is a second manual criterion applied, where the operator can reject current EEG if artifacts are recognized visually. Rejection of such trials is necessary since the process of extraction of the ERP uses a cumulative iterative FIR filter that averages the acquired signal by ensemble, so every artifact that passes it will influent the extracted ERP till the end of the experiment.

During the experiment, the subject learns about the number, nature and order of the stimuli, thus demonstrating the process of learning by shaping the ERP wave toward the expected CNV.

3. THE DCNVrt SOFTWARE PACKAGE

Figures 2-9 shown below are screen captions of the DCNVrt software package. This section gives explanations of the figures as well as of the options that DCNVrt offers.

The main panel (Figure 2) shows the EEG signal acquired in the current trial, the extracted CNV potential and its linearized model, as well as the required measurements and calculated values. The green (right most) vertical marker on the CNV Morphology represents the reaction time of the subject.

The yellow LED in the upper left corner of the *REJECT* button is ON for 3s after the end of the current acquisition allowing the operator for that period of time to reject it if significant artifacts are noticed on the EEG strip.

Patient Data is saved as a header in an ASCII data file. *Options* start and stop the experiment. Maximum 120 trials can be performed (limit of subject's patience) but 100 successful are required. Measured values are the absolute offset (ref_0) and the reaction time (R_t). The calculated values are the amplitudes of the CNV wave at S_1, $S_2 - A(S_1)$ and $A(S_2)$, having calculated the latencies of both stimuli, as well as the difference of the maximum and the minimum of the difference ISI – APP (APP is the energy of the CNV wave in the ISI and the slope of the same calculated from the linearized model). *Gain* relates to the amplification, and c and d are parameters of the optimal cumulative filter for CNV extraction. The optimal filter is defined as follows [5]:

$$CNV_i = d \cdot CNV_{i-1} + c \cdot EEG_i$$

or explicitly as:

$$CNV_n = \sum_{i=0}^{n} d^i \cdot EEG_i$$

The stability of the filter is obviously achieved by keeping $d<1$, and $d<c$ secures dominant influence of the current EEG sequence in the current CNV extraction.

The *complete report* is retrieved from an ASCII file containing all recorded, processed and analyzed data. The reporting panels are shown on Figures 3-9).

- The *first* option gives the main report page containing the CNV evolution and the electroexpectogram (Figure 3).
- The *second* option gives the complete EEG history across all valid (not rejected) trials (Figure 4).
- The *third* option gives the complete CNV wave evolution during the experiment (Figure 5).
- *Option 4* shows a table containing all measured and calculated parameters across the valid trials (Figure 6).
- The *fifth* option detects the CNV cycles and their individual extremes as well as the experiment extremes (Figure 7).
- The *sixth* option gives enlarged graphs of the first two couples of CNVs and NOT-CNVs (Figure 8). It is strongly believed they give the best "view" of the cognitive process of learning the nature and order of the excitation (the environmental circumstances).
- The *last* option allows the opportunity of zooming individual CNV morphologies and exploring their shapes (Figure 9).

The software package written in LabVIEW's dataflow works under Windows NT4/95. DCNVrt is a completely hardware-synchronized software. The on-board clock of the acquisition card times the acquisition. The audio stimulation performed through the sound card is based on WAV strings prepared in the memory prior to the start of the experiment and triggered by the clock too. The reaction time is measured by the on-board counter, started by a digital output from the card issuing pulse at the same moment with the start of S_2 and stopped by the user press or the time-out pulse applied again by the same digital line.

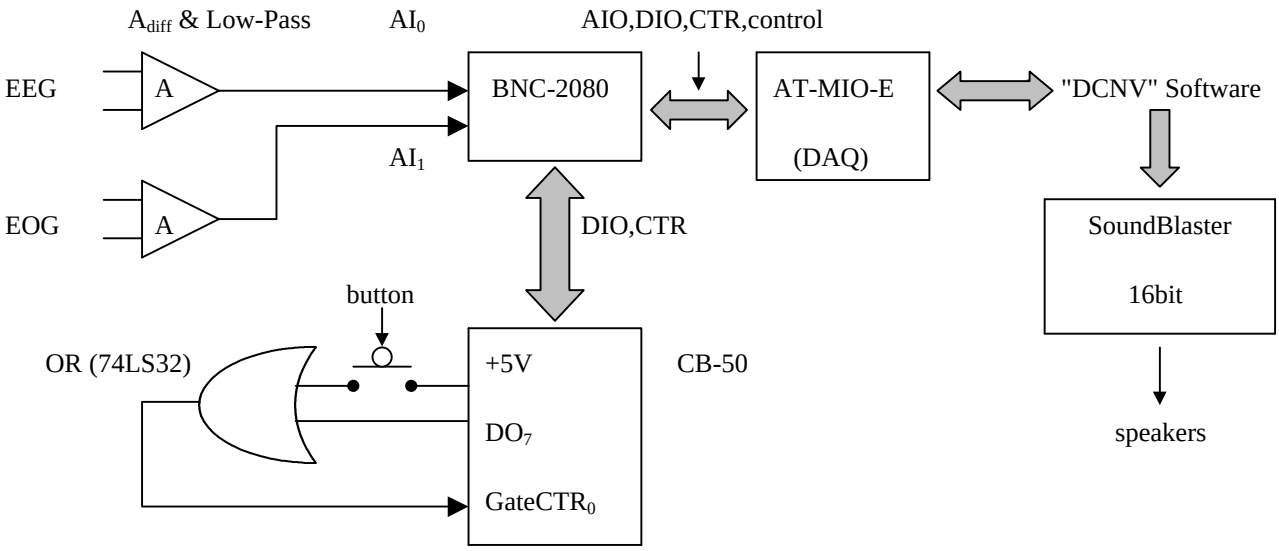


Figure 1: Hardware configuration of the DCNV experiment

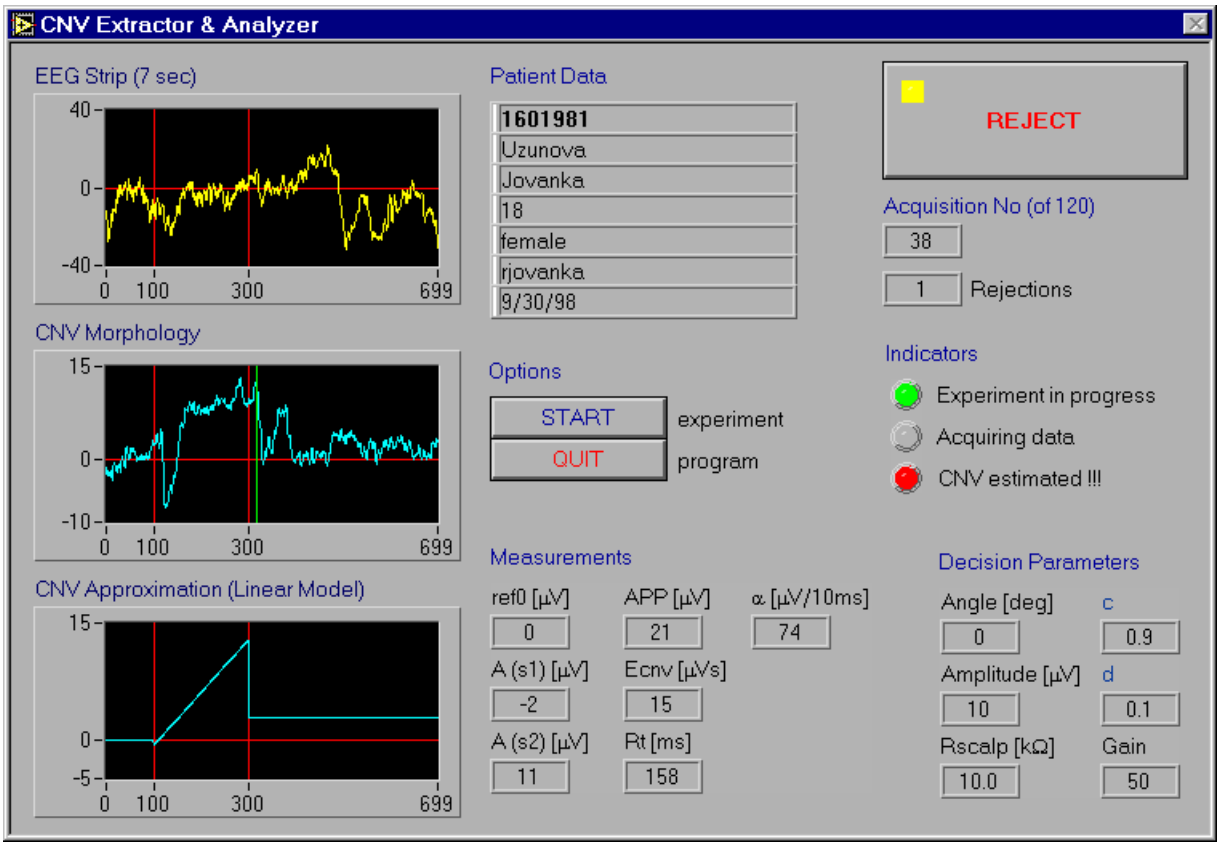


Figure 2: Main panel

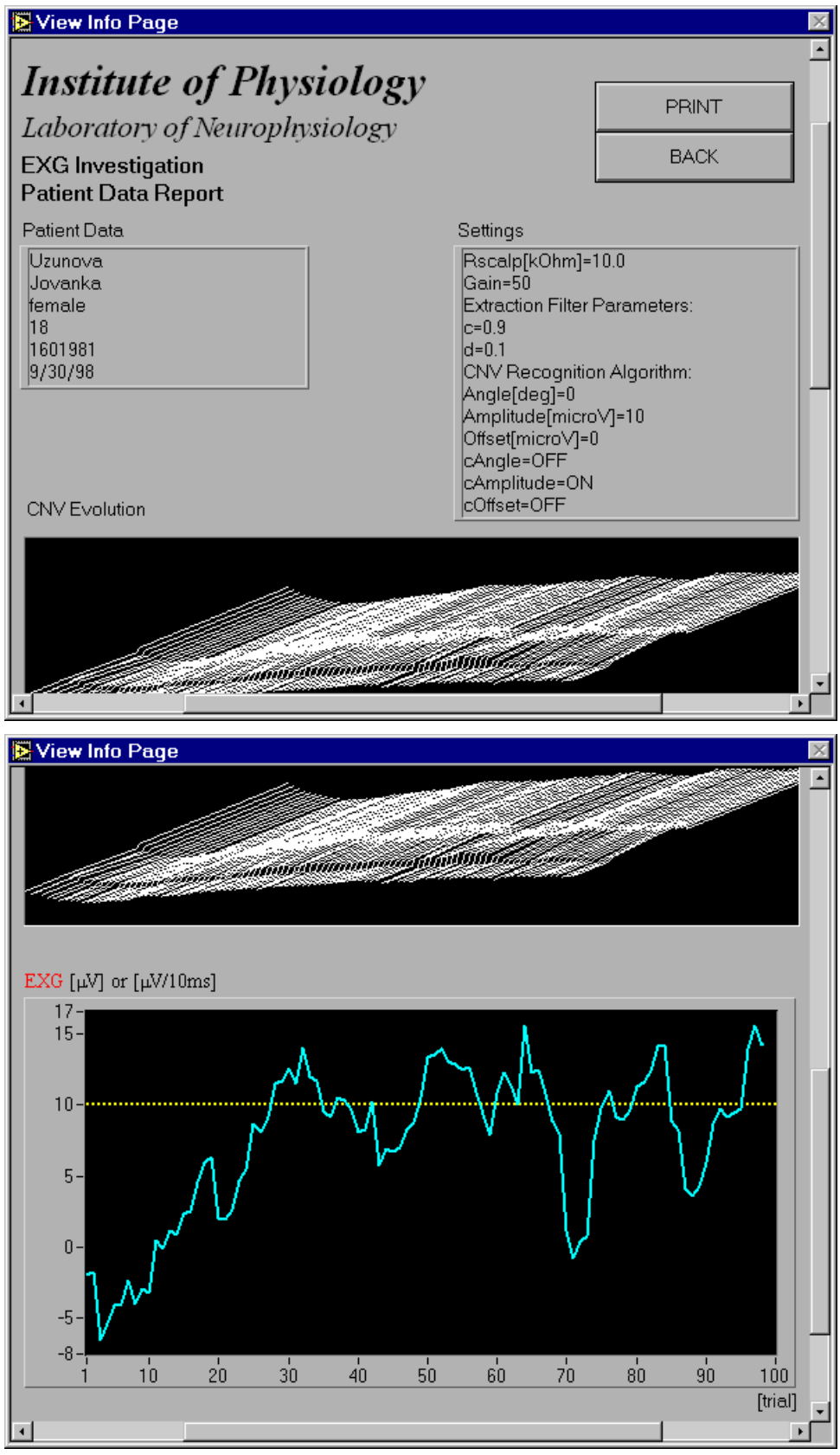


Figure 3: Main report page of DCNVrt

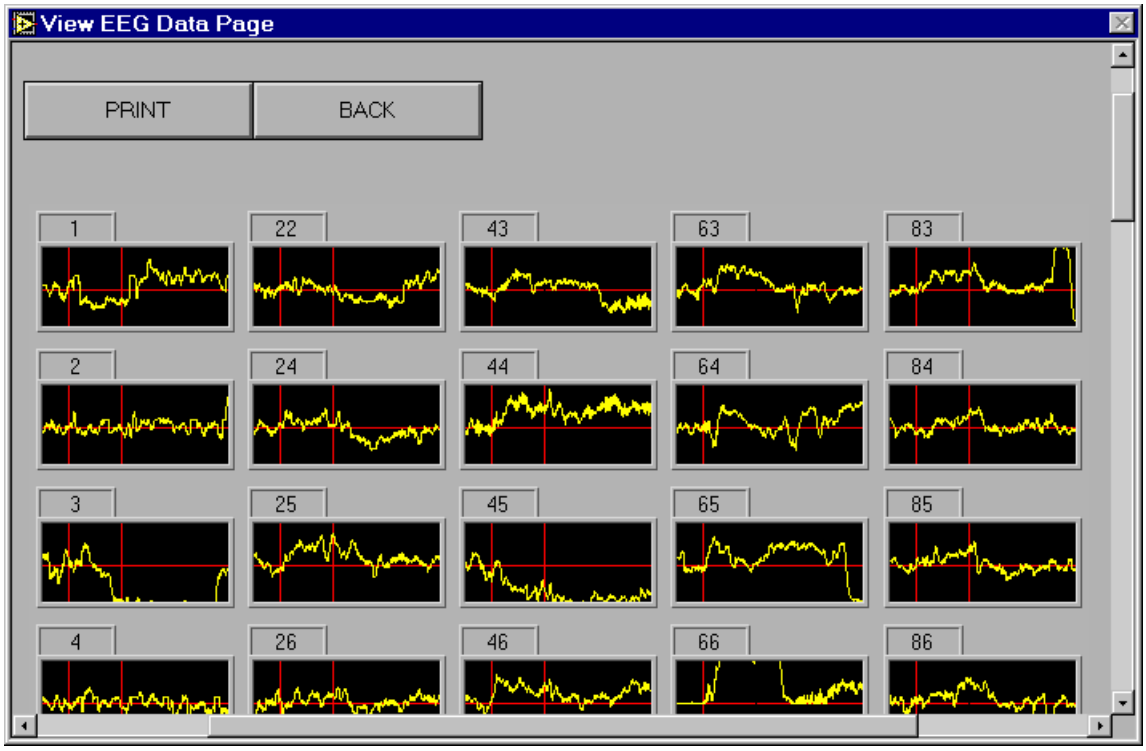


Figure 4: EEG history of all valid trials

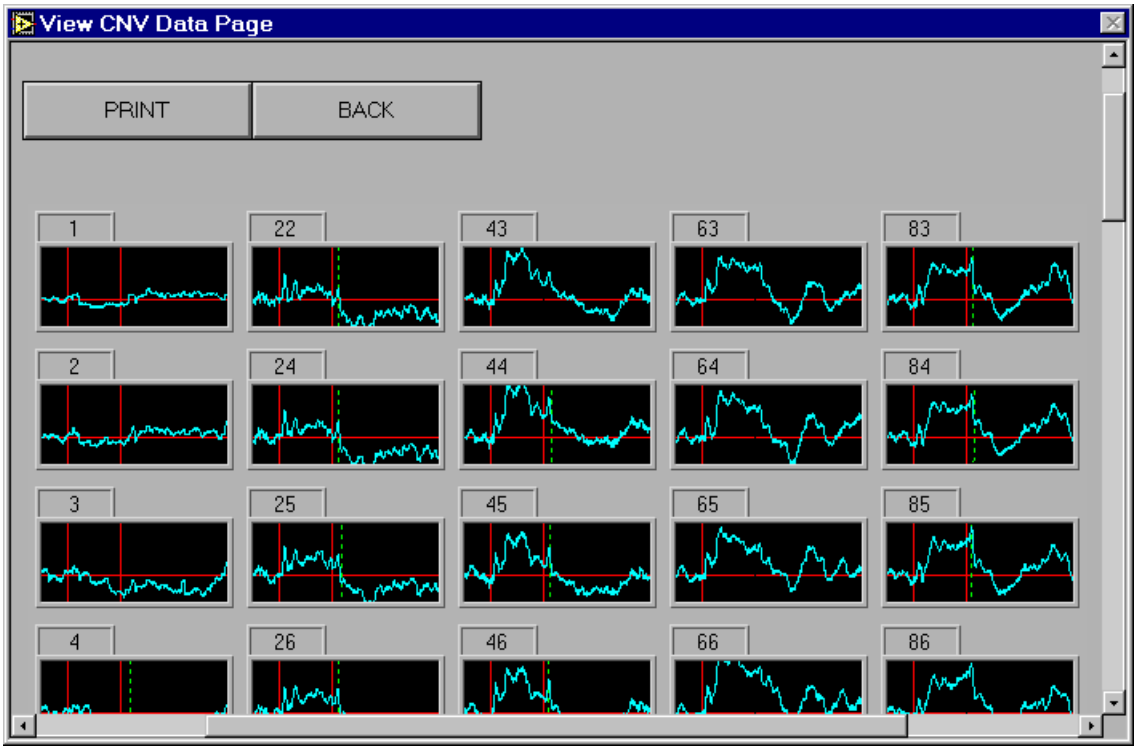
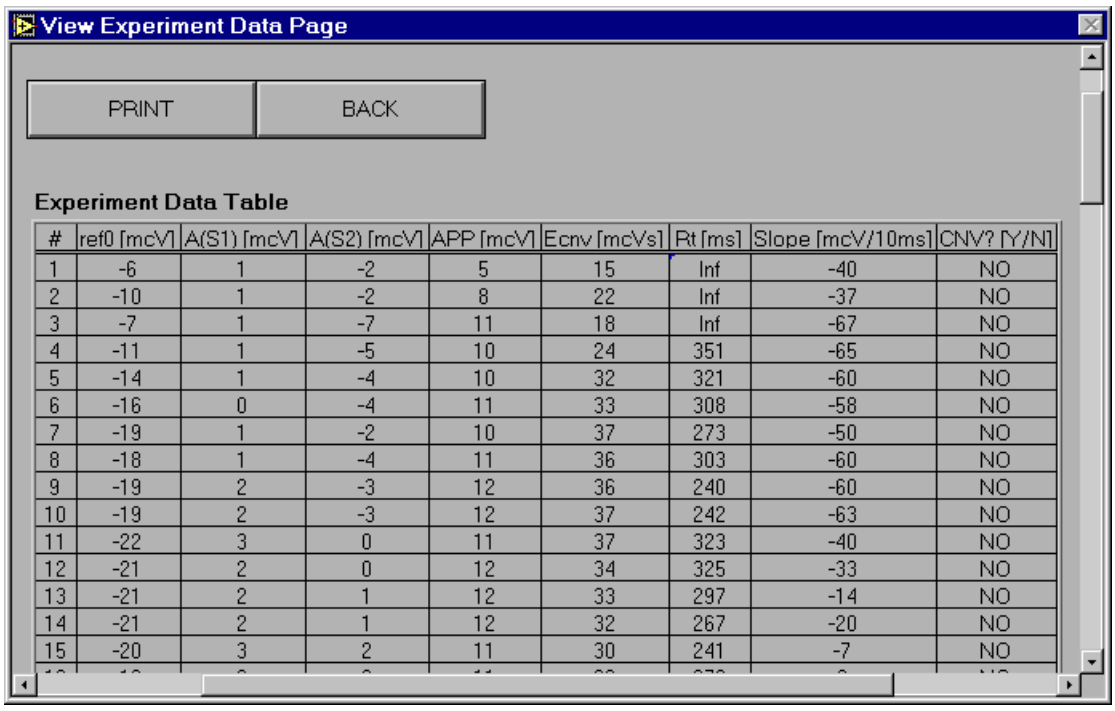
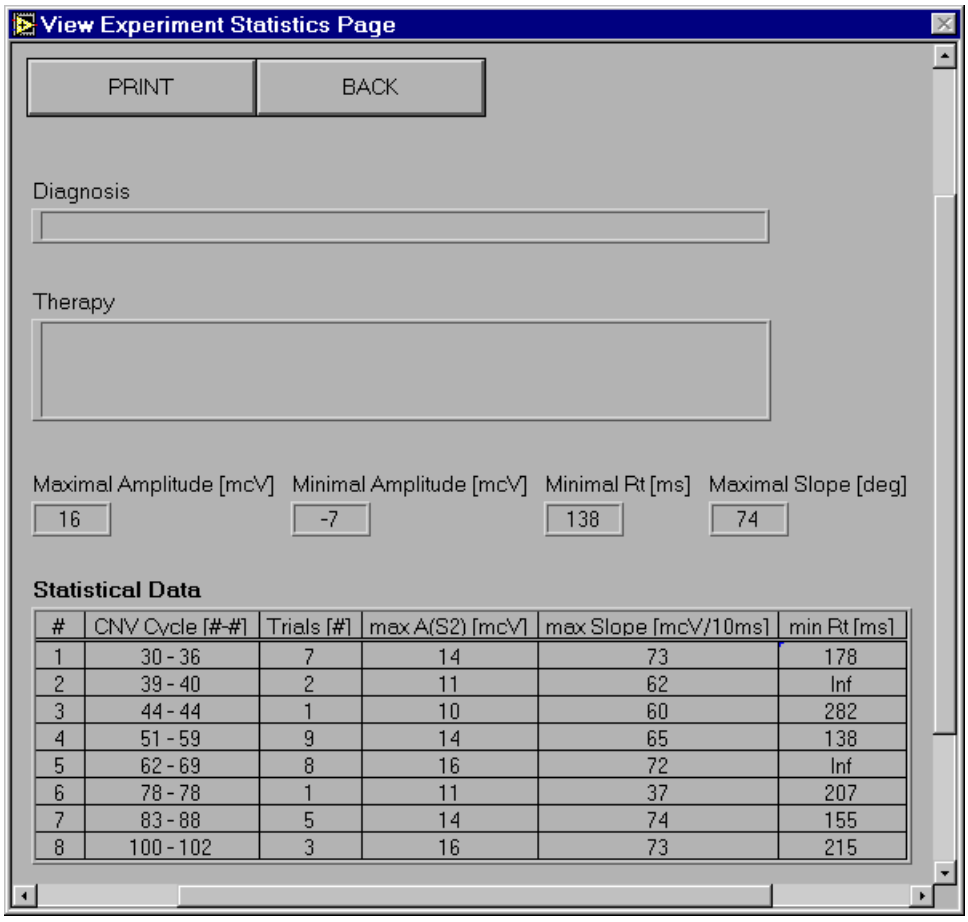


Figure 5: CNV evolution across all valid trials



#	ref0 [mcV]	A(S1) [mcV]	A(S2) [mcV]	APP [mcV]	Ecnv [mcVs]	Rt [ms]	Slope [mcV/10ms]	CNV? [Y/N]
1	-6	1	-2	5	15	Inf	-40	NO
2	-10	1	-2	8	22	Inf	-37	NO
3	-7	1	-7	11	18	Inf	-67	NO
4	-11	1	-5	10	24	351	-65	NO
5	-14	1	-4	10	32	321	-60	NO
6	-16	0	-4	11	33	308	-58	NO
7	-19	1	-2	10	37	273	-50	NO
8	-18	1	-4	11	36	303	-60	NO
9	-19	2	-3	12	36	240	-60	NO
10	-19	2	-3	12	37	242	-63	NO
11	-22	3	0	11	37	323	-40	NO
12	-21	2	0	12	34	325	-33	NO
13	-21	2	1	12	33	297	-14	NO
14	-21	2	1	12	32	267	-20	NO
15	-20	3	2	11	30	241	-7	NO

Figure 6: Table of measured and calculated trial parameters



#	CNV Cycle [#-#]	Trials [#]	max A(S2) [mcV]	max Slope [mcV/10ms]	min Rt [ms]
1	30 - 36	7	14	73	178
2	39 - 40	2	11	62	Inf
3	44 - 44	1	10	60	282
4	51 - 59	9	14	65	138
5	62 - 69	8	16	72	Inf
6	78 - 78	1	11	37	207
7	83 - 88	5	14	74	155
8	100 - 102	3	16	73	215

Figure 7: Table of CNV cycles and their and experiment's extremes

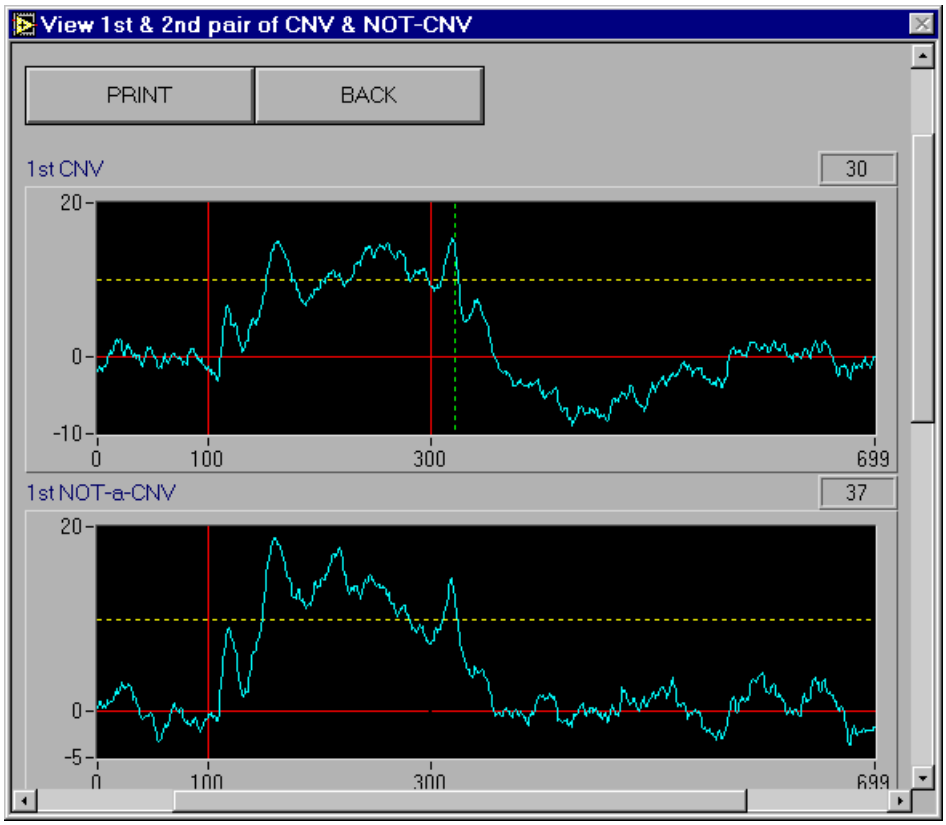


Figure 8: First two couples of CNVs and NOT-CNVs

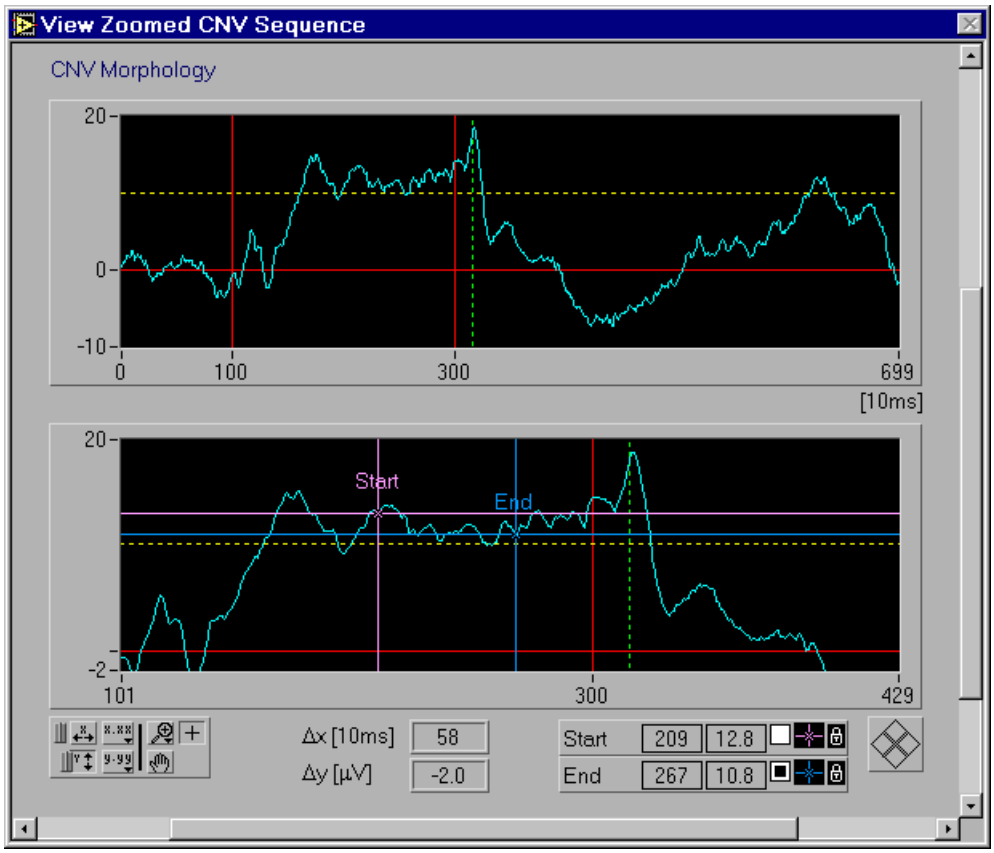


Figure 9: A zoomed CNV morphology

4. TOWARDS FUZZY DCNVrt

4.1. Motivation

In many fields of medical sciences, neurophysiology included, the definitions of certain phenomena are rather vague, if any. Most of the time the definitions are given in a form of assertions vaguely explaining selected features of the problem at hand. Having seen lots of samples indicating existence/absence of an observed phenomenon, experts are able to perform classification following some learned, implicit rules, despite the fact that there no well-defined parameters that can be measured and inferred upon.

Asked to comment whether a certain waveform in terms of the parameters of the ramp-model [5] is a CNV, an CNV expert gave the following a statement:

"If the angle φ, the difference *a-reff*$_0$, and the amplitude *A* are *large enough*, then the wave is a CNV."

Statements like this one are motivating a fuzzy approach in solving the problem of defining and classifying waveforms, since they account for the fuzziness of the natural language.

4.2. The fuzzy approach and its uniqueness

Taking into account the CNV expert's "definition" of the CNV waveform (in terms of the natural language statement from Subsection 4.1., in an ill-defined manner), we define the fuzzy memberships for j, *a-reff*$_0$ and A to be continuous functions. These consist of three linear segments. Two constant segments are equal to *0* and *1*, and the third segment "connects" them, thus forming an angle a with the positive part of the variable range axis. Parameter d is the value that maps to 0.5. Since the membership functions are piece-wise linear, the membership values are easy to compute. For the universes of discourse of each of the variables, we use the range of all the values that parameters can assume. The values a and δ (see Fig. 3) for each of the variables are set to the values that CNV expert suggested as minimal in all the observed waveforms (with and without CNV). They are given in Table 1 of the appendix.

Based on the defined membership functions for all the variables, we construct a membership function μ over the Cartesian product of the universes of j, *a-reff*$_0$ and A, as given below:

$$\mu(x, y, z) = \text{median}\{\mu_j(x), \mu_{a\text{-}reff0}(y), \mu_A(z)\},$$

where x, y, and z are the measured parameters of the waveform. After a given input triplet is evaluated, we take its *0.5*-cut to represent the CNV waves.

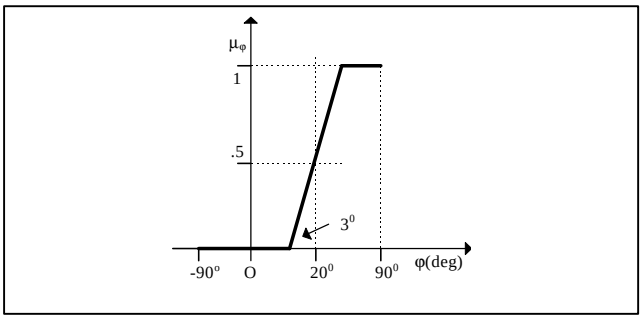


Figure 10. Graph of the membership function for the variable φ (α=3^0 and δ=20^0)

Table 1. The parameters of the membership functions for φ, *a-reff*$_0$ and A

Variable	Universe [units]	a[deg]	d[units]
φ	[-90,90][deg]	3	20
a-reff$_0$	[-30,30][μV]	5	9
A	[0,30][μV]	2	11

4.3. Experimental Results

The results of the implementation of the fuzzy detection system are presented in this section. These results are compared with the results obtained by using a neural network approach towards the same goal [8].

For the purpose of testing the automatic CNV detection system, a CNV expert was asked to evaluate 50 waveforms that were filtered from the subject's EEG. The expert made decisions upon the waves on the basis of their waveform, instead of using the wave parameters. The fuzzy decision algorithm guided the experiment. Upon comparing the results of the fuzzy approach with expert's classification, a mismatch was detected in *5* out of *50 (10%)* cases. This is two times better than in the case of artificial neural networks [7]. By lowering the cut-level of the fuzzy decision module to *0.45*, the mismatch occurs in only two of the cases (*4%*).

However, we should not take for granted the fact that for this data set the fuzzy approach work better. Fuzzy approach static, and low mismatch ratio is the result of minor calibrations done. The fuzzy approach is easy to implement, and very promising, [8]. The neural network performance is also satisfactory. Trained with larger data sets, the neural network is expected to provide better results, since the implicit interpolation it performs is certainly a better approximation to the human expertise then the piece-wise linear membership functions of the fuzzy system.

5. CONCLUSION

The EXG is a manifestation of the expectation process and the learning process taking place in the human brain during the DCNV paradigm. In this paper we have presented the DCNVrt software package, as a tool for investigating EXG of a subject. DCNVrt performs as expected and produces reports with information suitable for further statistical analysis.

The experiments during the test phase indicated that different categories of subjects (healthy adults, groups of people with distinctive neurological disturbances, younger children) may produce different EXGs. EXGs tend to show significant similarities within the groups, which implies potential use in diagnostics.

6. REFERENCES

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