The Meaning-Switch - Investigation of Precognition in an Operationally Closed System

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Authors*: Matthias Braeunig, Tilmann Faul

Project Leader: Walter von Lucadou

T.REG Systems Research
Bötzenstr. 3, D-79219 Staufen /Germany

&

University Medical Center Freiburg,
Department of Environmental Health Sciences,
Evaluation Research in Complementary Medicine,
Breisacher Str. 115 B, D - 79106 Freiburg, Germany

Abstract:

We investigate the effect of a human operator intention on the sampling of random bits from a Triggered Random Event Generator (T.REG). The device that has been constructed in a previous study, allows for the local environment to be coupled with the process. Binary events are sampled from an electronic random stream of states and acoustic feedback is given on the cumulative hit rate. A case is being made for operational closure: The subject can – in principle – direct the course of events, if there is intrinsic knowledge about the random stream. This knowledge is considered a systemic property of the arrangement giving rise to memory and self-organization that cannot be accessed or controlled from the outside.

In an intention task experiment a sample of 22 self-selected subjects are instructed to generate sequences of rising feedback tones. By using a special push button, called Meaning- or M-switch, the participant can decide on the meaning of hits and misses by inverting down-runs that are pre-cognitively intuited and create a mean shift. Still, the null hypothesis of random sampling is maintained.

We extract the statistical properties of the bit sequences and compare the results with their theoretical expectation and with a pseudo random generator also built into the system. M-switch gain is assessed with respect to the reconstructed un-inverted sequence of scores. The M-switch application is investigated in terms of psychological variables capturing the distinctive switching behavior of the participant. Finally, a matrix of physical and psychological measures is checked for excess correlation.

* Contact Info:
matthias.braeunig@uniklinik-freiburg.de,
tilmann.faul@uniklinik-freiburg.de

Contents

1 Introduction

1.1 Conception and setup

In experiments involving a physical RNG and an intention task to deviate the outcome of the generator, psycho-kinetic (PK) effects may occur as a systemic interaction between the physical process and the local operator, her intentions, or a global field property. However, in conventional experiments of this type the nature of such connection is never put into question. As a methodological improvement for testing possible local interactions and operational closure (OC) we have developed the *Triggered Random Event Generator (T.REG)* *(*[Braeunig&Faul2006] and [DE102005009190]). We attempt to make the connection between the device and the environment explicit, using triggers drawn from the operator's physiology who is thus becoming an integral part of the process, without loosing the fundamental properties that are characteristic for a true physical random processes.

In theory there may be two factors responsible for the generally weak and unstable (ie. non-reproducible) effects observed in RNG-experiments that involve operator intention:

1. Postulating some degree of operational closure by which the observed part and the observing part cohere into a systemic 'whole', it is impossible to separate the experimental setup from extraneous interaction. It simmply cannot be confined within the laboratory space as the interaction remains uncontrolled and ever changing – leading to decline effects – due to diffusion of the causal chain;
2. A second type of system may be separable to a high degree, but its random source produces merely 'trivial' randomness, i.e. independent variates, unperturbed by any agent or influence, thus being robust against local environmental changes. Such arrangement is similar to algorithms producing pseudo randomness with defined statistical properties. Robustness is a requirement for commercial applications of randomness, as in cryptography or simulations, but fails to respond to systemic interactions.

These two arguments suggest a re-design that links the operator with the generation of random events in a well-defined and sustained manner. We achieved this goal by taking physiological measurements on the participant to elicit the events from a random stream of states. The systemic relations are closed with a feedback channel, facilitating a self-organizing dynamic. Under normal conditions the null hypothesis of random sampling has to be maintained, ie. the interaction must not lead to systematic bias under un-informed sampling.

By installing a trigger feedback loop, in which sampling of binary events (bits) takes place on triggers contingent on some physiological property of the observer-agent, the subject is made an integral part of the process. This is exemplified by an experimental design in which EEG measured at the forehead of the subject generates trigger pulses for sampling from a random stream of binary states. A running score value (the random variable) is calculated from a fixed number of consecutive bits and the deviation from theoretical expectation is played on earphones to the subject as feedback. This construction does not violate the null hypothesis: the sampling of events is still expected to be random (binomial distribution) as long as no internal knowledge about the state of the random stream exists. Nevertheless there is a possibility for anomalous sampling, in which the sequence generated from the triggers may not be random anymore, or to put it differently, the entropy in the sequence may be reduced. In such a case, internal organization must be held responsible for the effect as a consequence of systemic, or operational closure.

The T.REG system is illustrated in Fig. 1, showing an (electronic) random source on the left and a sampling mechanism in the center of the picture. The subject is included as an agent providing EEG modulated triggers that drive the sampler. An acoustic feedback tone is produced after a block of bits has been sampled from the random stream of states. The pitch is moving according to the cumulative deviation of the score from theoretical expectation.

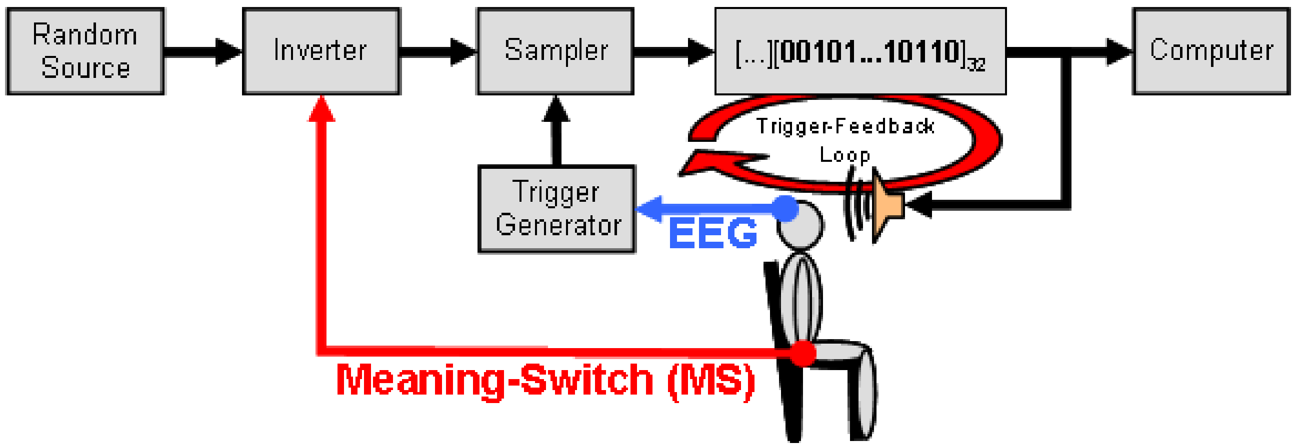

Fig. 1: T.REG setup with EEG modulated triggers and Meaning-switch.

Subjects can operate a switch that defines the level of the input states. If it is pressed the sampled states are inverted, giving the subject the possibility to define what is considered to be a hit according to some pre-stated intention. Hence it is called the Meaning-switch (or M-switch for short), as it can actually switch the meaning of events. If a down-run of feedback tones is anticipated, the pressing of the M-switch can turn the sequence of tones into an up-run, corresponding to a mean shift of the score values.

The question to be investigated in this study is how subjects use the M-switch to alter the sequence of events, and if the operationally closed design of this RNG-experiment enhances psycho-kinetic performance in the direction of the pre-stated intention. If the systemic nature of interaction leads to stable alterations of randomness in the output sequences, it could potentially provide an explanation for the riddle of the decline effect.

1.1 Technical details

The T.REG platform uses an electronic digital circuit written in Verilog® Hardware Description Language. Its FPGA chip loads our design version v.17c4 enabling the operation of the device. Compared to the design version of our first project documented in [Braeunig&Faul2006], a number of technical improvements have been implemented, that we list here briefly:

- 32-bit blocking for score and M-switch count
- bit level access to random and M-switch data
- computer programmable channel settings
- built-in triggered pseudo REG (PREG)
- hardware error handling
- fast USB output to computer

The data header includes information about the loaded design version and channel settings. Header and raw data are transferred and recorded in hexadecimal ASCII codes. A sample output is shown in Table 1.

The blocking of bits has been reduced to 32-bit words (it was 200 bits before) but the total number of bits generated per trial remained 300,000 bits, or 9375 records per channel. With equal binomial probability of sampling either a high (1) or low (0) state, the score is in the range of [0,32] with a theoretical mean of 16 and a variance of 8. The choice of 32-bit blocking was mainly motivated by convenience of representation as integer type (4 bytes), a requirement of the test bench when testing for randomness.

As signal source for the trigger generator we used a formerly developed one-channel EEG platform based on the OpenEEG project [Hansmann2005]. The amplified EEG voltage is measured with an active electrode at the forehead of the participant, driving a voltage controlled oscillator (VCO). The oscillator has a center frequency of 1 KHz and a linear characteristic of 320 Hz/V (for details see [Braeunig&Faul2006], p. 22, Fig. 16). The EEG itself is not recorded, as it is not our primary focus. However, since the EEG voltage modulates the VCO frequency with a known characteristic, the time differences between records in the variable `timer` are a measure of that frequency, and the EEG voltage can be reconstructed with a mean resolution of 1/32 KHz, or 31.25 samples per second.

Description	***Output***

Header
Setting EEG-VCO
Setting feedback channel
Setting other channels...
	`# Design altium17c4`
	`# RX Main     : 00 0A`
	`# RX Channel 1: 01 01 11 00 00`
	`# RX Channel 2: 02 41 11 00 00`
	`# RX Channel 3: 03 81 11 00 00`
	`# RX Channel 4: 04 21 00 00 00`
	`# RX Channel 5: 05 31 00 00 00`
	`# RX Channel 6: 06 11 00 12 21`
	`# RX Channel 7: 07 00 00 00 00`
	`# RX Channel 8: 08 00 00 00 00`
	`# ch score word timer ms mword fbv`

First data block
(record 1)
	`1 12 CAAF983D 013C 00 00000000 82`
	`2 18 2D9FFBFE`
	`3 12 401D9FFD`
	`4 13 56931FEE`
	`5 05 82240001`
	`6 0E 3A252F0A`

Second data block
(record 2)
	`1 14 EFB97D42 013E 00 00000000 86`
	`2 0C 32D40869`
	`3 0C B230036A`
	`4 12 5A6FC47A`
	`5 06 400C0016`
	`6 0E C30B18D3`

Table 1: Sample output of the T.REG for first two blocks with 6 data channels

1.2 Pseudo REG (PREG)

The electronic noise that is produced by the device is the primary source of entropy, and the true physical states for the sampling of random bits are not reproducible across subjects. As a practical solution to inter-subject reproducibility we implemented another hardware generator using a *Linear Feedback Shift Register* (LFSR) [wiki:LFSR] that generates a pre-defined sequence of bits from a seed value. Its implementation is a useful device for reproducing a pseudo random sequence on which the effect of the M-switch can be tested. The seed value for this generator has been determined in a search run for sequences with mean and variability of deviation scores matching exactly their expectation values (namely μ=0 and Chi-squared=N). This procedure used a sliding window of the appropriate length, N=9375, shifted over a long period of bits. About 60 suitable seeds could be found in this way. In order to make both experimenters blind as to which exact random walk the built-in sequence would take, we agreed on a protocol that one experimenter (mb) screened visually the sequences of all the seeds and created a subset of 'well-behaved', good seed values. These seeds were transferred to the other experimenter (tf) who let a computer program choose one of them to be hard-coded in the design. So neither of the two experimenters was able to tell the course that the pseudo random walk resp. feedback tones would take.

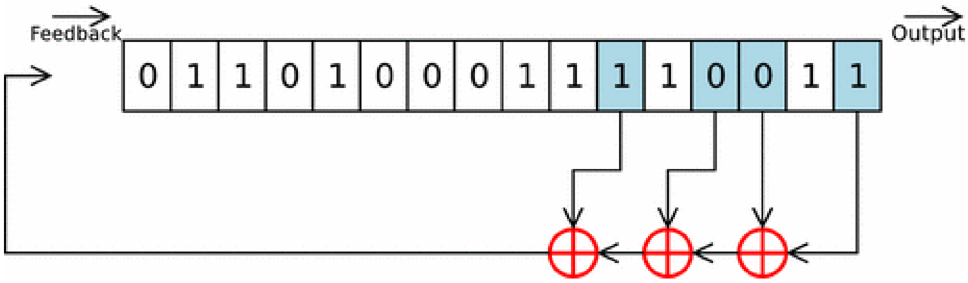

Fig. 2: A Fibonacci-type Linear Feedback Shift Register (LFSR) generator implemented in hardware for pre-recorded targets.

The tap numbers used for our Fibonacci LFSR generator are (32,31,30,10) [TapSequence2002]. The next bit is shifted in from the left, starting at the seed value, and obtained by modulo-2 addition (XOR) and right-shift of the respective polynomial coefficients $a_0 = a_{32} \wedge a_{31} \wedge a_{30} \wedge a_{10}$ generating a maximum length sequence with period (2^{32}-1) [wiki:MaxLengthSeq], which is much longer than the 300,000 bits extracted during the experiment. See Appendix 6.3 Pseudo REG (PREG) Sequence for details.

The pseudo REG is activated as the feedback device only in the last experimental trial (the others are true physical trials). Nevertheless, the individual triggers of the subjects elicit events as before but now as the exact same pre-defined sequence of bits and their corresponding feedback tones. Subjects could, however, modify the sequence with the M-switch and thus yielding different end results. Because of the same input for all participants with a mean deviation fixed at zero, the M-switch application is directly comparable in inter-subject trials and the final score value is the gain. The variance, as a quadratic measure, is not affected by this inversion.

1.3 Computer interface

Since the T.REG experimental platform does event counting and feedback generation in real time within its hardware, no post-processing of data takes place during experiment. The output is recorded from the USB device as-is on a laptop computer. Data acquisition and trial enumeration is controlled by a versatile measurement program `gentreg` that takes as input the id-name of an operator and various options about the number and type of trials one wishes to run. First the program is loading the prepared design file into the FPGA chip. In its default and experimental mode, the configuration is programmed with EEG modulated triggers and 6 channel settings. After presenting a welcome screen with instructions (see Appendix II, p. 45), the program cycles through the trials and prepares the output files. On each trial it presents a status window with a progress bar (Fig. 3). When the operator pressed the green start button, it initiates a trial with feedback tones audible on phones and the progress bar is moving to the right until it reaches 100% (9375 data blocks). The purpose of the progress bar is to provide the subject with information on how long the trial is going to take. When finished it starts over to the next trial with a new status window waiting for another start button press, until it eventually stops after the last trial. A screen with summary information terminates the session.

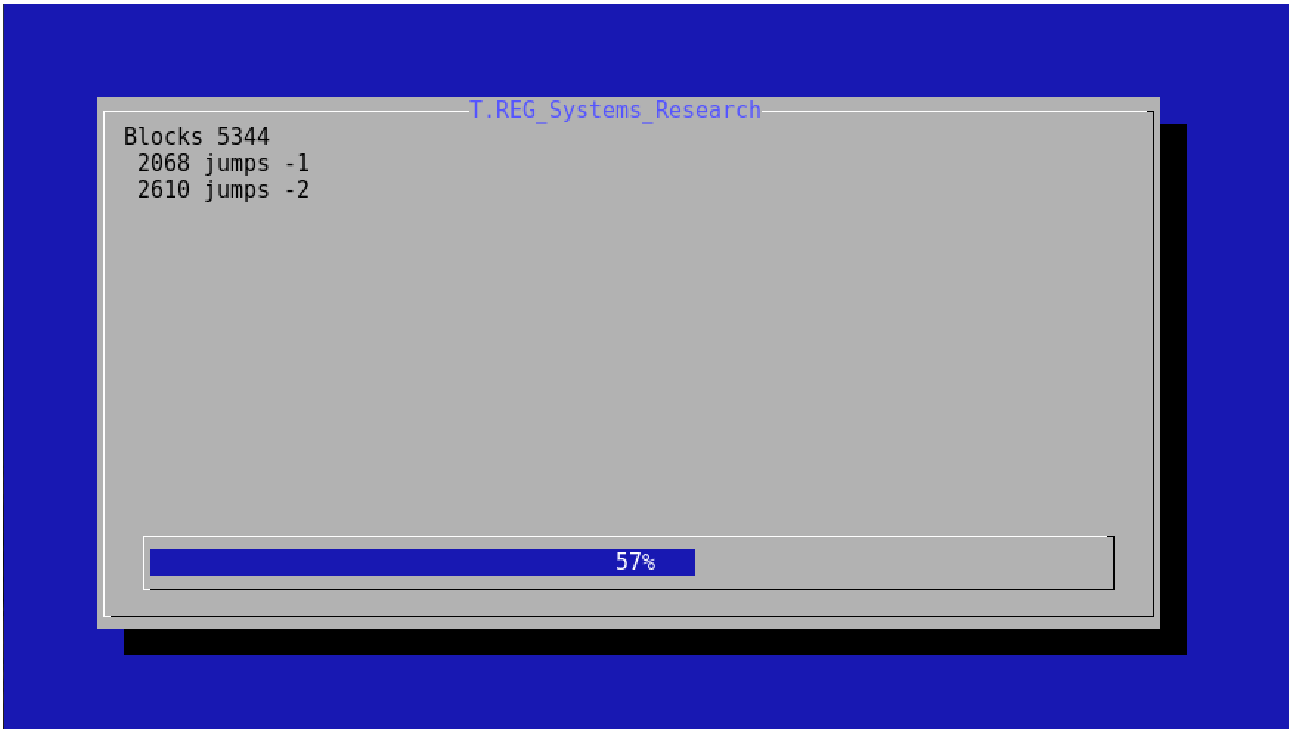

Fig. 3: Progress display during measurement with run-time information about the number of blocks generated and jumps locations in the feedback signal.

As has been detailed in our first report about the construction of the T.REG [Braeunig&Faul2006], the feedback tones are contained within a window with a lower and upper bound. An over- or under-run occurs, when the cumulative deviation score leads to a feedback beyond those limits. In that case the participant hears a sudden change in the pitch towards the center of the scale and the jump block number and its type is printed on the screen: A positive (negative) jump reflects a tone reset from the upper (lower) edge of the window. Although subjects usually correlate the event of a jump in the feedback tone with its printing on screen, they rarely take notice of it as it happens.

2 Experiments

2.1 Hypotheses

The experiment has been registered with an officially recognized authority[1]. Details of the protocol, definitions and hypotheses, can be found in the Appendix, chapter 6.1 Registration on p. 43.

2.2 Participants and procedures

Experiments have been conducted with the aim of obtaining at least 20 complete data sets from subjects. Participants were a self-selected sample of co-workers and friends at the office after several announcements had been issued. Each subject performed in a run of 10 separate trials with identical intention task, namely trying to generate sequences of increasing feedback tones, equivalent to generating more hits than misses. Subjects received written instruction (see Appendix 6.2, p. 45) about the intention task, and how to operate the M-switch and start button.

After attaching the EEG clip to the subject's forehead and adjusting the headphones the measurement program was started on a laptop computer, running a fully automated procedure until the experimental run terminated. For this period of time the experimenter (mb) left the room until he was called back in by the subject. The procedures generated an electronic protocol of the session that was subsequently printed. The subject's experience was recorded on the protocol in anecdotal form.

Most of the participants reported that listening to the feedback and trying to influence the outcome was fun. They were well aware that tones originated in their own activity (of generating trigger impulses). While some of them related the tones to feelings within their own body - high pitch tones felt more in the head and low pitch in the belly - others compared the experience with a football match seeing their team advancing when tones increased and scoring a goal when an overrun (jump) occurred in the feedback. Most of them had visual associations, like birds flying to the sky, when the pitch went high. When keeping up their intention almost all subjects reported using some kind of visualization. The jumps[2] implicit in the sequences had a strange effect on some participants, making them feel like Sisyphus rolling the same stone over and over again. Others said, that the jumps (which are also shown on the screen) were actually helpful in counting their success.

M-switch usage was reportedly more diverse. Since it required motor activity and conscious engagement it entailed a different mode of awareness. Several subjects remarked that there was “no effect” of pressing the M-switch – an observation that is based in the independence and equal probability of up and

1 The protocol was registered at the *Institut für Grenzgebiete der Psychologie und Psychohygiene e.V. (IGPP) with Dipl. Psych. Eberhard Bauer* prior to running the experiment.

2 Jumps arise when the feedback tone is passing over a threshold at either very high or very low pitch and then are reset to a medium level. Typically 3-4 jumps occur in a run.

down runs. This fact also explains why some subjects thought they could just do away with the M-switch and rely on the EEG triggers alone. However, the majority of subjects reported making frequent use of the M-switch and generally considered it “a good tool” to enhance their success rate.

2.3 Control trials

In order to firmly establish the randomicity of events under “un-informed” sampling we have been running control trials with triggering from a source that is not capable of intentionality. This proof is the basic corner stone for the null hypothesis. Two sets with the same total number of trials as in the experimental condition are recorded without intervention of the experimenter in an automatic mode of the measurement program, using only fixed frequency triggers. The triggers are generated from a digital circuit within the T.REG in two modes: fixed interval triggers alternate between a long and a short time interval (proportion 7:1), while fixed regular triggers follow in the same time intervals (1ms). In both cases, again, the mean frequency is 1 KHz. The purpose of these two modes is to demonstrate independence from time intervals[3]. The sets of trials are then concatenated to form two data sets that are analyzed with the '*DieHarder*' *Random Number Test Suite* (see 3.2 Tests for randomness on p.13).

3 The combined independence from time intervals and null hypothesis is a relevant test to the experimental condition, where time intervals between triggers are not fixed.

Oops. Was that what I was expecting?
-- Louise Matthews (during the practicals of 'Statistical Practice in Epidemiology Using R'), SPE Course, Tartu (May 2005)
fortunes::fortune("expecting")

3 Data Analysis

The following subsections describe the steps taken to arrive at conclusions about the hypotheses outlined in Appendix 6.1 (p.43). In addition we conducted post-hoc analysis not included in the Appendix (marked in the text as 'post-hoc') in order to learn from the data and to generate further hypotheses for future experiments.

We start with a description of the data format and basic variables. Next we describe the tests for randomness by which we probe the basic assumption about the random number generator. Then we investigate individual performance of the subjects with respect to the main physical variable. The effect of the Meaning-switch is discussed with an exploratory analysis into the factors involved in button activity. We conclude our analysis with a correlation matrix approach to detect excess correlation between psychological and physical variables.

3.1 Data base

The experiment took place during a three weeks period in January 2008, followed by a day of control measurements one month later. Raw data is stored in hexadecimal ASCII files and read into objects suitable for processing in R Statistical Computing Language [R2008] and the Lattice Graphics package [Sarkar2007]. The package odfWeave [Kuhn2009] was used for processing R code embedded into this report.

After collecting data from 26 participants we rated the quality of the recording into three groups (A-C) next to the control category (X). Syntactically correct and complete data sets were rated into category A, while usable but incomplete or otherwise defective recordings were rated B, and unusable data sets were rated C. Only data sets of category A and X were considered for analysis (Table 2).

Category	A	B	C	X
Number of trials	220	30	3	402

Table 2: Number of trials in each category.

A total of 220 trials are rated category A, corresponding to 22 participants who contributed 10 trials each. Recordings from three participants had procedural errors, the data was incomplete and thus discarded (B). One recording yielded only three trials and was unusable (C).

A single trial consisted of 9375 blocks of data, of which the feedback channel (ch1) was selected for further analysis (Table 1). The primary variables were then combined with meta information about the subject and the specifics of the experimental run to form a sub-settable data base object from which all relevant information can be extracted. The following table summarizes the main variables:

```
age :  int [1:2062500] 26 26 26 26 26 26 26 26 26 26 ...
block :  int [1:2062500] 1 2 3 4 5 6 7 8 9 10 ...
dt :  int [1:2062500] 371 371 371 371 371 371 371 371 371 371 ...
fbv :  int [1:2062500] 127 125 124 132 132 132 128 128 129 130 ...
index :  int [1:2062500] 1 1 1 1 1 1 1 1 1 1 ...
med :  int [1:2062500] 2 2 2 2 2 2 2 2 2 2 ...
mf :  Factor w/ 2 levels "f","m": 1 1 1 1 1 1 1 1 1 1 ...
ms :  int [1:2062500] 0 0 0 0 0 0 0 0 0 0 ...
mword : Class 'hexmode'  num [1:2062500] 0 0 0 0 0 0 0 0 0 0 ...
name :  Factor w/ 26 levels "alexandra","andrea",..: 9 9 9 9 9 9 9 9 9 9 ...
partno :  int [1:2062500] 1 1 1 1 1 1 1 1 1 1 ...
score :  int [1:2062500] 15 14 15 24 16 16 12 16 17 17 ...
score0 :  int [1:2062500] 15 14 15 24 16 16 12 16 17 17 ...
timer :  int [1:2062500] 224 309 2536 419 354 265 211 188 208 230 ...
timestamp :  int [1:2062500] 1199961740 1199961740 1199961740 1199961740
1199961740 1199961740 1199961740 1199961740 1199961740 1199961740 ...
trial :  int [1:2062500] 0 0 0 0 0 0 0 0 0 0 ...
word : Class 'hexmode'  num [1:2062500] 2.75e+09 8.39e+08 1.36e+09 3.21e+09
2.22e+09 ...
yog :  int [1:2062500] 2 2 2 2 2 2 2 2 2 2 ...
```

Table 3: Main variables and factors for analysis – name: type [length] data ...

Here `score` is the bit-sum of variable `word`, and `ms` ("M-switch score") is the bit-sum of variable `mword`, where the latter variables are 32-bit words of the samples and M-switch, respectively, in hexadecimal integer representation. The variable `timer` holds the clock count for each record which is a non-constant integer. The names `index`, `partno` and `trial` are factors that differentiate between trials and participants. The other names are individual factors used for splitting the data base according to certain criteria (Table 3).

Similar data objects have been created for the two control runs with similar variable and factor names as in the experimental runs.

3.2 Tests for randomness

As the first step of analysis we tested for the general null hypothesis $\mathbf{H}^*$ that our generator performs as a "good" RNG (stated in Appendix 6.1). The notion of 'randomness' is a convention related to certain properties that a sequence of symbols must possess, and it does not matter, for instance, whether that sequence has its origin in a true physical process or is generated by an algorithm[4]. The hypothesis relates to the case, when sampling in the T.REG is un-informed, i.e. the triggers are independent and not informed by feedback. This is a fundamental prerequisite for the experiment, as the process should not exhibit any internal bias or systematic deviations when sampled through an independent trigger mechanism. Control runs were thus recorded with a fixed frequency sampling rate producing two sets of 200 and 202 trials. The single

4 Random sequences from pseudo-RNGs (algorithms), or PRNG, have the practical advantage of being deterministic, their implementation is portable and they run fast on modern computers. For many applications, such as cryptography or simulation, this is enough. The sequences produced by the T.REG should be indistinguishable from known good PRNGs.

bit information in variable `word` (4 byte integers) is converted[5] to binary files of size 7,575,000 and 7,500,000 bytes, respectively. Three tests are performed on this data:

1. Visual inspection by noise sphere plots (post-hoc);
2. Dieharder tests and comparison with a known good RNG;
3. ENT random tester, evaluating entropy, serial correlation and other measures (post-hoc).

All control data should qualify in this respect, while experimental data may or may not pass the same set of tests.

As a first simple inspection of the random sequences we applied the Noise Sphere Test described in [Pickover1995]. In this visual test consecutive integers in polar coordinates are printed as dots in the three projections of a 3D sphere. Variations in density, indicative of local attractors and biases, are easily spotted in these plots. However, our data showed no such deviations and the phase space is evenly populated (Fig. 4).

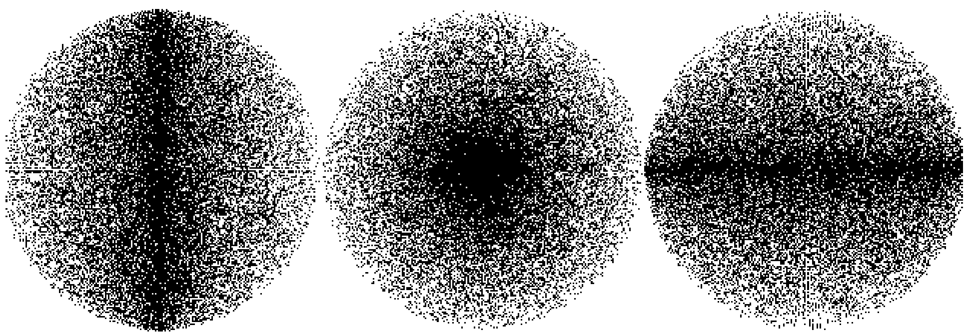

Fig. 4: Visual test with 'Noise Sphere Plot' of random integers [Barber1996]. Data for this plot is taken from the first control trial with interval triggers.

Next, the data was tested with the *DieHarder Test Suite* [Brown2008]. This collection of tests is an extension and sophistication of the well-known '*Diehard Battery of Tests of Randomness*' by [Marsaglia1985], implementing many more and newer tests which have become recently available. These numerical tests are sensitive to non-randomness in the data and generators with poor performance, for example having internal correlation, would fail in several or most of the tests. However, failing in some tests – even for known good generators – is not uncommon, and in fact unavoidable. One of the best generators in this respect is the Mersenne-Twister mt19937 [Matsumoto1998] which is widespread in statistical applications and readily available through the GNU Scientific Library (GSL) [Galassi2009]. The DieHarder Test Suite links against the GSL and the mt19937 can be used as gold standard for comparison with the T.REG[6]. Fortunately most tests could be tailored to take a smaller

5 The conversion to binary must preserve the original bit order.

6 Note that it does not matter whether we compare a true physical RNG (the T.REG) with a pseudo RNG, such as the mt19937, as long as it does not recycle. The Mersenne-Twister

number of samples, or to generate lesser test p-values, without losing their general validity. These parameters could be set individually for each test to take as much of the random data available and to generate the same amount in the mt19937. Where it was not possible to secure the validity of the test, the test was skipped.

Table 4 gives a detailed account of the parameters used in the Dieharder tests. The parameter `tsamples` is the number of samples drawn from the source to produce one in `psamples` number of test P-values. As these P-values are uniform random variables themselves, a combined Kuiper P-value is computed for their distribution. The test is passed if this combined P is neither too small nor too close to 1. Tests results with less than 10 `psamples` should be regarded as preliminary.

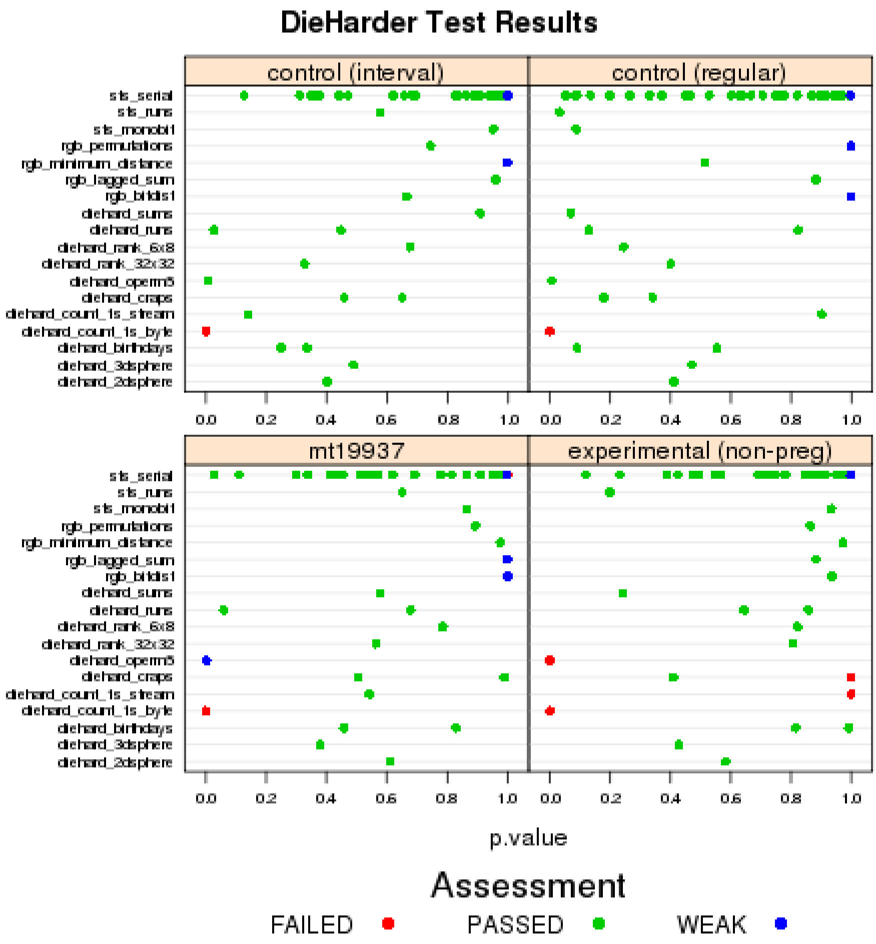

Fig. 5: Combined P-values and assessment for control, experimental data and the GSL Mersenne-Twister (mt19937).

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algorithm, however, was shown to possess an 'astronomically' long period, 2^{19337} in fact, and there is no danger that this limit will ever be reached in computational applications. If any, the limitation is rather on the side of the limited amount of T.REG data available, as the concatenation of 200 trials (60 Mbits) does not nearly provide enough data for many of the tests.

The tests were run on the two control data sets, on the experimental data and - for comparison - on the mt19937. The results are best visualized in a dot plot, in which each dot represents the combined Kuiper P-value obtained for a number of P-samples in the particular test (Fig. 5).

It turns out that the control runs passes 18 out of 25 available tests. With the limitation of the amount of data it is not unusual to find a few weak test results. One of the tests, the *diehard_count_1s_byte*, has been a failed for all four data sets. Even the mt19937 fails that test. This test requires a particularly high number of test samples (more than 100,000), but was only given about a half of that. We are therefore lead to consider the alternative that this test is unreliable for our purpose, and had better been excluded from the list.

In fact, four tests fail in the mt19937, which may be an indication of too few samples in these tests. Running the full battery of tests on this generator with the default parameters (many more samples) shows no problems (result shown in Appendix 6.4). On the other hand, also four (different) tests are failed by the experimental data, that are passed in control. In contrast, this is not an alarming sign, as we would allow and even welcome the experimental condition to fail and therefore reject the null hypotheses. The fact that control shows no indication of a serious problem is the important message here and leads us to believe, that the T.REG performs as a “good” RNG for un-informed sampling.

test_name	**ntup**	**tsamples**	**psamples**
diehard_birthdays	0	100	48
diehard_birthdays	0	48	100
diehard_operm5	5	16949	100
diehard_rank_32x32	0	588	100
diehard_rank_6x8	0	3030	100
diehard_count_1s_stream	0	64000	20
diehard_count_1s_byte	0	51200	6
diehard_2dsphere	2	8000	1
diehard_3dsphere	3	4000	1
diehard_sums	0	100	1
diehard_runs	0	50000	37
diehard_craps	0	18750	25
sts_monobit	1	18750	49
sts_runs	2	18750	49
sts_serial	1	18750	49
sts_serial	2	18750	49
sts_serial	3	18750	49
sts_serial	4	18750	49
sts_serial	5	18750	49
sts_serial	6	18750	49

test_name	ntup	tsamples	psamples
sts_serial	7	18750	49
sts_serial	8	18750	49
sts_serial	9	18750	49
sts_serial	10	18750	49
sts_serial	11	18750	49
sts_serial	12	18750	49
sts_serial	13	18750	49
sts_serial	14	18750	49
sts_serial	15	18750	49
sts_serial	16	18750	49
rgb_bitdist	12	18750	3
rgb_minimum_distance	5	10000	25
rgb_permutations	5	18750	16
rgb_lagged_sum	0	50000	18

Table 4: Test names and parameters used in the Dieharder Test Suite

After having established this main result about the quality of T.REG data, we wish to measure parameters that quantitatively describe the amount of randomness implicit in the data base. These measures are taken on a trial-by-trial basis[7] in the three conditions (1 experimental, 2 control) which can then be compared with each other. The software tool that served our purpose is the 'ENT random tester' at http://fourmilab.ch/random/ [Walker1998]. The program calculates the entropy, chi-squared, mean value, a Monte Carlo value for Pi, and a serial correlation coefficient (or dependence on predecessor) for the single bit stream. The entropy (information content, or compressibility) is of particular interest, as we could expect deviations for the experimental trials. However, the distributions of the five randomness measures seem to be all very similar, which indicates that entropy reduction in experimental trials is weak or non-existent and may occur only selectively.

7 Measures are taken on non-PREG trials only, excluding all pseudo sequences (from PREG).

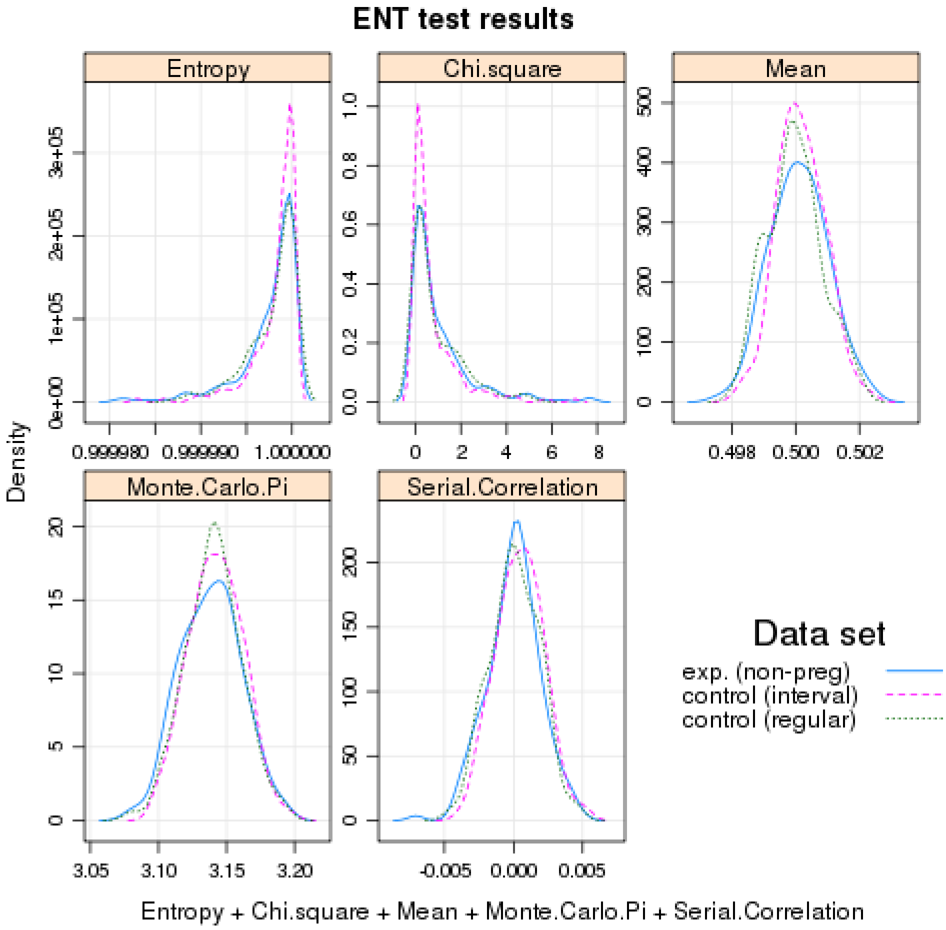

Fig. 6: Measures of randomness for non-PREG trials show no particular deviations between the three groups.

Noting that the measures are all very similar, we finally give the output of ENT for all available data in the control data set with regular triggers:

```
Value Char Occurrences Fraction
  0          29989942   0.499832
  1          30010058   0.500168

Total:       60000000   1.000000

Entropy = 1.000000 bits per bit.

Optimum compression would reduce the size
of this 60000000 bit file by 0 percent.

Chi square distribution for 60000000 samples is 6.74, and randomly
would exceed this value 0.50 percent of the times.

Arithmetic mean value of data bits is 0.5002 (0.5 = random).
Monte Carlo value for Pi is 3.142134400 (error 0.02 percent).
Serial correlation coefficient is 0.000449 (totally uncorrelated = 0.0 .
```

3.3 Physical variables

The sampling of bits from the random stream of states produces a score value for the “number of ones”, or hits, in a record of n bits. Under the null hypothesis of equally probable sampling the theoretical distribution for this hit count follows the binomial ***B(n=32, p=.5)*** distribution with mean 16 and a variance of 8. By construction (due to symmetrizer in hardware) the asymptotic duty cycle in each state is exactly ½ but the probability for hitting may vary due to the participants performance in the task. There are two factors that have an influence on the outcome: The triggers provided by the subject (his or her EEG signature) determine which state is sampled. Second, the participant can invert states with the M-switch, thus altering the mean value by shifting the cumulative score in both directions. In a pseudo-REG trial, which is always the last in a series of ten trials, the first of the two factors is not in effect, as the EEG triggers can elicit only the pre-determined target that is the same for all participants. On the other hand, inversion by itself cannot affect the variance because of its mathematical nature as a quadratic measure[8].

	Trials in the two types of generators	
	Non-PREG (9/10)	**PREG (1/10)**
Triggered sampling	M/V	-/-[9]
Meaning-switch	M/-	M/-

Table 5: Mean (M) and Variability (V) affected by OC and RNG type.
The available amount of data is 9:1 for true random trials (non-PREG).

Both factors rely on the concept of operational closure (OC) in the T.REG, which is a structural characteristic that fully involves the participant in the M-switch- and trigger-feedback loop. Thus an effect is defined as a significant deviation in mean and/or variance. However, the null hypothesis $\mathbf{H_0}$ states that no such effect occurs and sampling is un-informed about the internal state (i.e. no anticipation).

We attempt to test the null hypothesis by calculating the Z-values with respect to theoretical expectation for both mean and variance. The standardized variance, here called *variability Z*, is proportional to the *Chi-Squared Excess* X^2-1 . The Chi-Squared measure can be calculated exactly (an integer value) and has the advantage of being additive without renormalization. As a Z-value it is an easily graspable effect measure.

8 Inversion cannot affect variance, or the Chi-square measure. This statement is true for fully inverted (M-switch pressed) records. Scores resulting from partially pressed records, usually on the fringe of a pressed period, will minimally alter the variance. See a discussion in chapter 3.3.2 Definition of gain below.

9 It is evident that triggered sampling alone cannot alter the PREG sequence. In practice, this case in the table will only be met when M-switch has not been used at all, which incidentally occurred once (trial 9 in participant 26) in the experimental data, thus yielding the default results.

In a sequel to this topic we finally investigate the gain, which is defined as the difference in score between the inverted and the reconstructed un-inverted sequence. The gain measures how much of the negative or positive mean shift in a trial has been achieved due to M-switch (inversion). However, its expectation value (under the null hypothesis of un-informed M-switching) generally depends on the mean value of the sequence and on the number of inverted bits (`pb`, see below). In PREG trials the gain is the mean value itself, as the un-inverted sequence for a trial has been chosen to zero mean. But in non-PREG trials with arbitrary sampling the expectation value of the gain has to be subtracted from the measured gain in order to obtain the net effect.

A sufficiently trained statistician can read the vagaries of a Q-Q plot like a shaman can read a chicken's entrails, with a similar recourse to scientific principles. Interpreting Q-Q plots is more a visceral than an intellectual exercise. The uninitiated are often mystified by the process. Experience is the key here.

-- Department of Mathematics and Statistics, Murdoch University StatsNotes: fortunes::fortune("shaman")

3.3.1 Evolution of mean value

First we look at the final mean value of trials that are evaluated for each participant and their evolution across the experiment as observed in PREG and non-PREG trials. The global mean value over the whole data set is a natural outcome of summing up all individual results.

The mean value of the scores $\bar{x}=\sum_i^n x_i/n$ is standardized with respect to theoretical expectation as Stouffer Z-value:

$$Z_{mean}=\frac{1}{\sqrt{n}}\sum_i^n \frac{x_i-\mu}{\sigma}=\sum_{trials}^N z_i/\sqrt{N}$$

where for individual trials n=9375 is the number of records, and N is the number of trials combined into a final Z. With 22 subjects passing 10 trials each, a matrix of 22x10 mean or Z-values is obtained that can be further aggregated.

The total Z-value for the mean in non-PREG trials (N=198) is Z_{NP}=-0.518, and for PREG trials (N=22) it is Z_{PR}=1.469. A post-hoc two-tailed t-test for the differences of score in the groups yields

```
Welch Two Sample t-test

data:  score by factor(trial == 9, labels = c("non-preg", "preg"))
t = -1.5569, df = 254252.3, p-value = 0.1195
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-0.023095639  0.002646884
sample estimates:
mean in group non-preg     mean in group preg
              15.99892               16.00915
```

With P=0.119 this result is not significant and does not allow for separating the groups, so they must remain indistinguishable. It is instructive, however, to take the distribution of either group into account and note that the mean for PREG trials is shifted in the direction of intention, while non-PREG trials seem to behave almost as expected by $\mathbf{H_0}$:

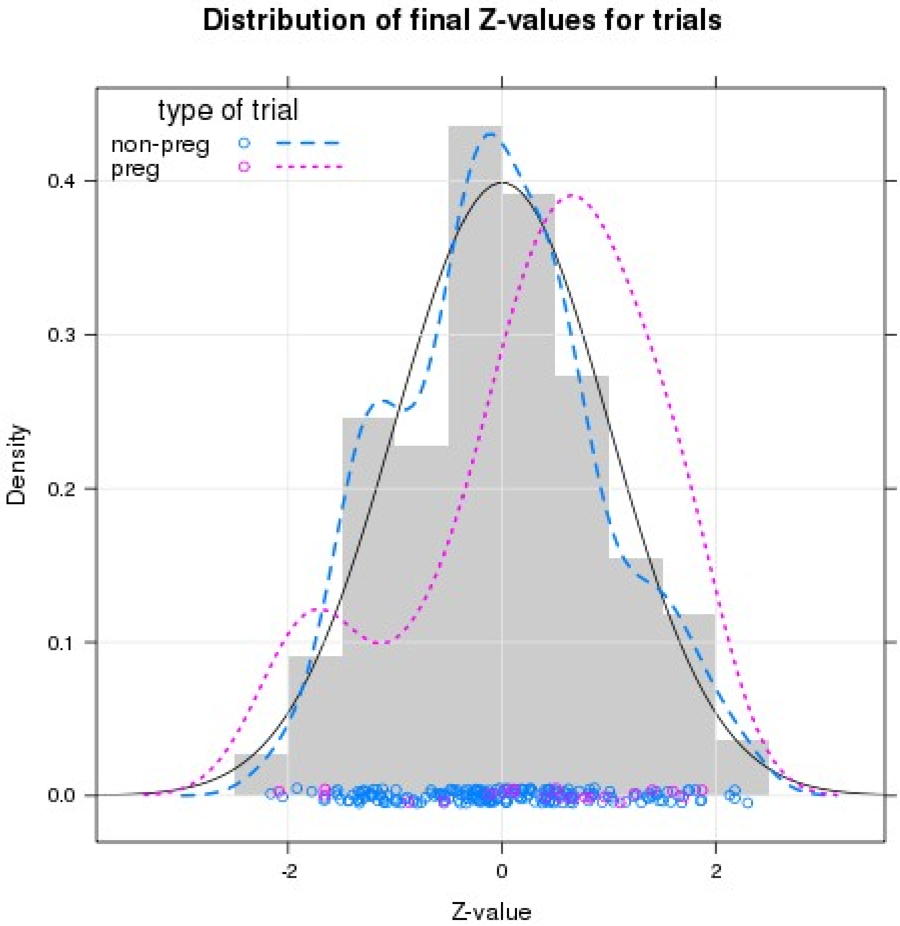

Fig. 7: Density plot showing mean shift for trials. The histogram shows the relative counts for all trials and the solid line is their normal expectation.

This same difference between the two groups is seen more clearly in a Q-Q-plot where the data is plotted against the theoretical quantiles, and reference lines are drawn through 25% and 75% percentage points (Fig. 7). Although the PREG trials are fewer than non-PREG by 1:9, the distributions are clearly separated. For PREG the distribution is shifted towards a greater mean (location change), and both distributions appear to be slightly tilted to the right, indicating scale change. Interestingly, a departure from the normal distribution is observed for PREG at the lower end, where trials tend to approach the expected statistic.

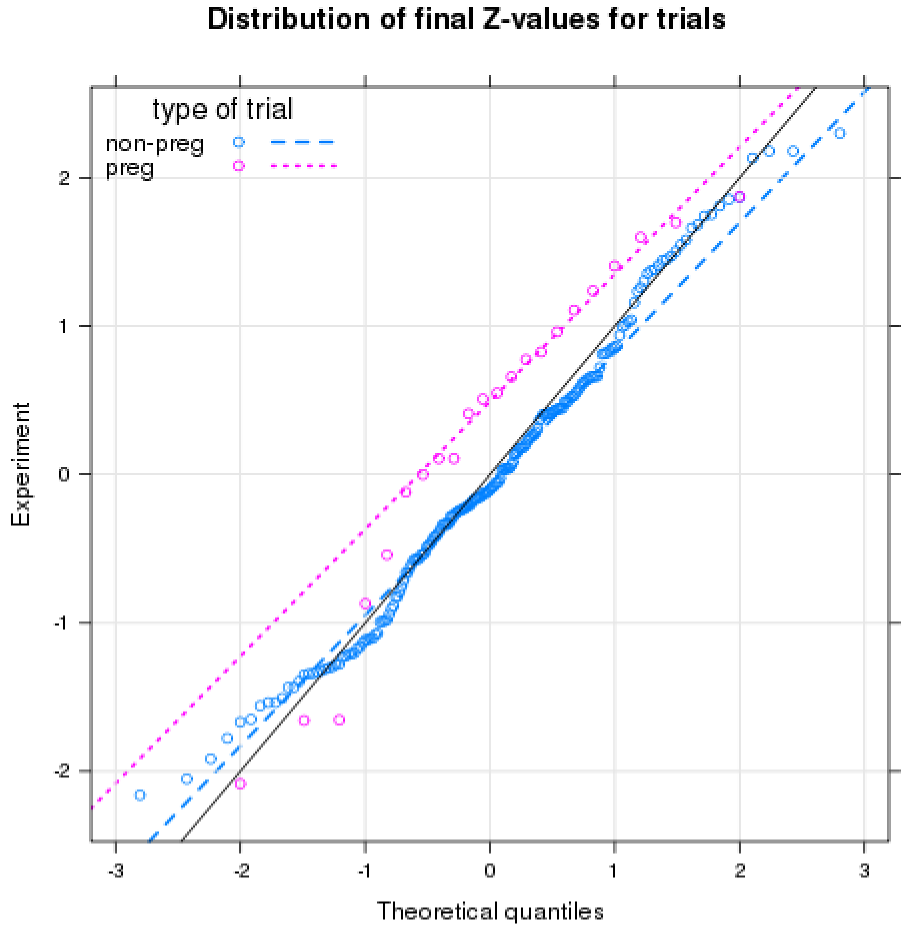

Fig. 8: Q-Q-plot for mean values, comparing PREG and non-PREG trials with theoretical quantiles. The shift shows as location change for PREG. Tilted lines indicate scale change. Note departure from normal distribution for low Z-values in PREG.

3.3.2 Definition of gain

In order to evaluate the net effect of M-switching on the sequence we need to know the difference to the corresponding un-switched (un-inverted) sequence. This can always be achieved by reconstructing the un-inverted sequence, `score0`, from the measured scores and subtracting it. The information about the single bit sequence and which bits had been inverted is readily available (in variables `word` and `mword`). The individual gain per record is thus defined as $score - score_0$, or in terms of mean values $mm - mm_0$ for the trial gain.

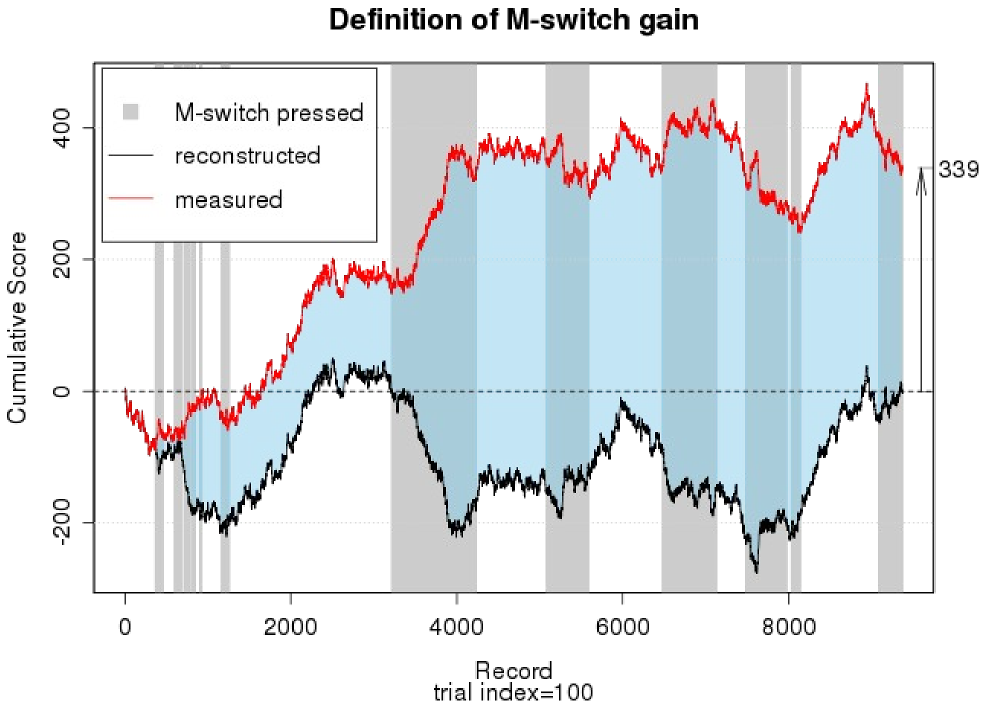

Fig. 9: Evolution of cumulative score (upper curve) for a PREG trial with stripes indicating M-switch application. Note the final mean is zero in the reconstructed curve (lower). The difference between both curves is the gain.

However, this is not enough. A non-zero mean of the un-inverted sequence leads to an expected shift, if the Meaning-switch is randomly applied on the sequence. The null hypothesis of un-informed M-switch predicts that the mean is shifted proportional to the number of inverted bits, `pb` (for pressed bits see chapter 3.4 M-switch variables below). The two quantities, gain and expected gain, are defined as $mm - mm_0$ and $-2*(mm_0-16)*pb/N\cdot n$, respectively[10], where N denotes the number of records per trial and n is the number of bits per record, thus the number of bits per trial, N*n, is 300,000. The net gain (per record) is the difference of the two, or

$$net\ gain = (mm - mm_0) + 2\,(mm_0 - 16)\cdot pb/(N*32\text{bits})$$

Multiplication by the number of records, N, yields the net gain per trial, or the effective amount of bits that the sequence was shifted, a positive (negative) gain indicating hits (misses). We can verify this reasoning for PREG trials, where the mean of the un-inverted sequence, `mm0`, was fixed at the expectation value (i.e. 16): the net gain per trial is then the measured total score

$$net\ gain_{preg} = \sum^{N} score = N\cdot(mm-16)$$

10 For expected gain the factor (-2) is a consequence of inversion. The contribution is negative, because we start from the reconstructed, or un-switched sequence.

We would consider an increase in gain over the course of (9+1) trials as a sign for individual learning, i.e. the subjects “learned” how to cope with the task and how to “operate” the T.REG in order to achieve higher gain. For testing this '*Individual Learning Hypotheses*', $\mathbf{H_L}$, we looked at the trial mean of net gain and fitted a linear regression line to the data, excluding the last (PREG-)trial from the fitted data, but extending the prediction to stretch out beyond the last non-PREG trial.

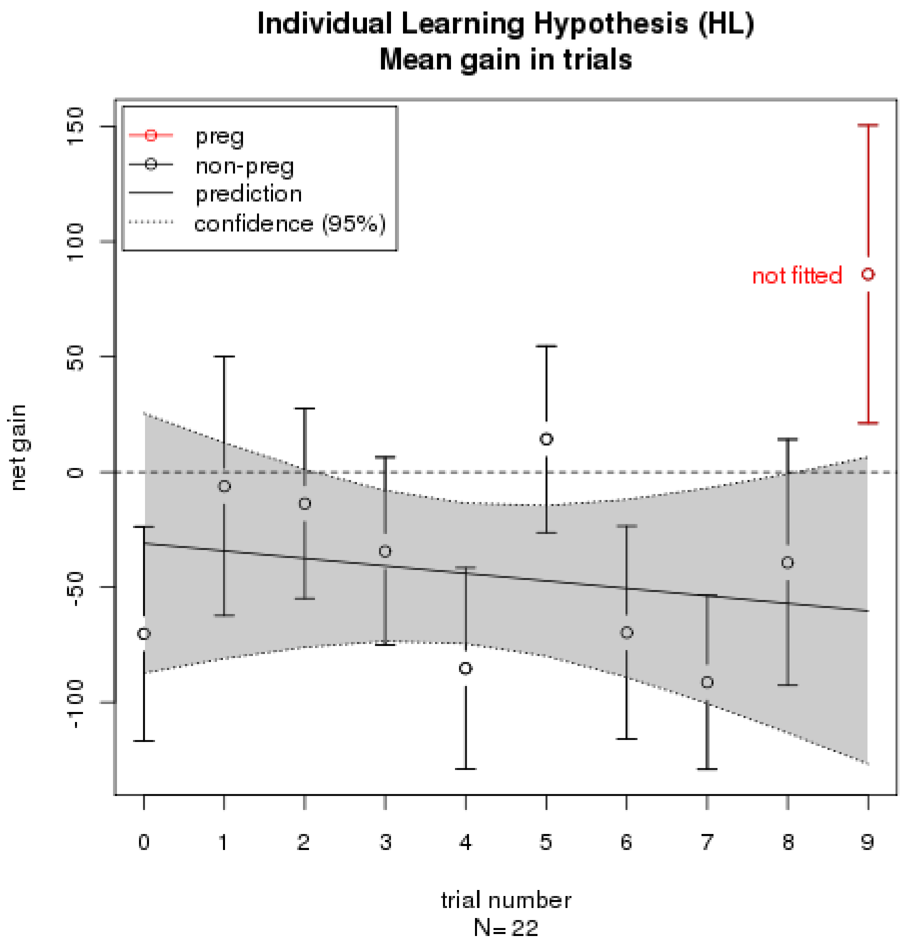

Fig. 10: Mean of net gain in trial sequence, with first order prediction and confidence band for non-PREG. Note that PREG trials were not included in the fit.

It turns out that the regression itself is non-significant, with negative intercept and slope, indicating a weak tendency to miss rather than increase the gain. The PREG trial (#9) has positive gain and lies outside and above the 95% confidence band for non-PREG, which would have slightly lifted the regression line to a positive slope when included in the fit. Therefore the net gain shows a similar tendency as the final Z-values discussed above. At this point we have to reject the hypothesis that gain increases with the trial sequence number.

On the other hand, if we are looking at participant's net gain in both types of trials, non-PREG and PREG, in the order in that they occurred, we can see a slight positive gain and increase only for PREG trials. But the large confidence bands do not really allow to separate between them. So we must also reject the '*Morphogenetic Learning Hypothesis*', **H_M**, that the overall gain increases with the participant sequence number.

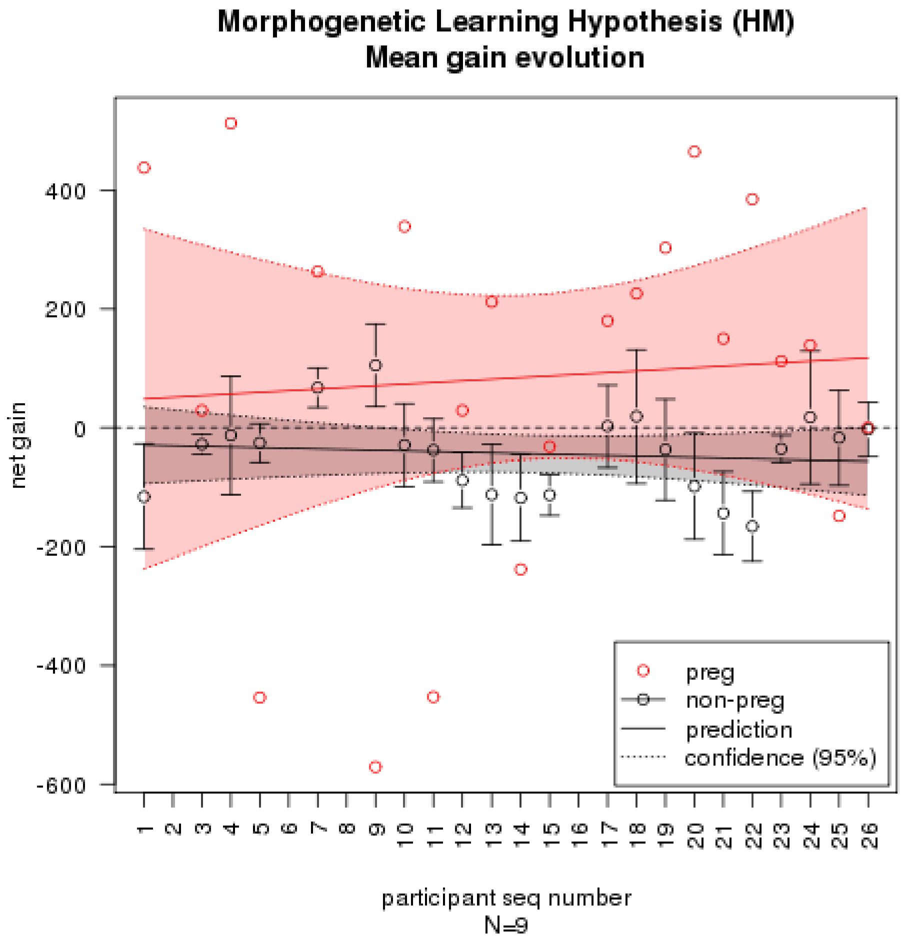

Fig. 11: Mean of net gain in participant sequence, with first order prediction and confidence bands for PREG and non-PREG trials separately.

3.3.3 Variability

The score value is in the range of 0..32 hits per record with a mean of 16. For symmetrical probability p=1/2 and n=32 draws the theoretical distribution B(n,p) has a spread or variance of np(1-p)=n/4. The validity of the theoretical assumption of equal probability is motivated by the fact that the electronic symmetrizer inherent in the construction of the binary states assures equal asymptotic duty cycle.

However, the design of the T.REG is such that probability p may depend on the triggering of events. The triggering by an extraneous process not only alters the hit rate or mean value but may also influence the variance measure. M-switch application, on the other hand, does not affect the variance (see Table 5 on page 19). Thus the variance measure is really relevant only in non-PREG trials where the score is generated through triggers rather than being fixed through a pre-defined sequence.

The variance is calculated as the square of the Z-values for scores, which are distributed as Chi-squared with N degrees of freedom.

$$excess = \sum_{i=1}^{N} (X^2 - 1) = \sum_{i=1}^{N} (z_i^2 - 1) = X_N^2 - N$$

The Chi-squared excess can be transformed into a Z-value itself by approximation with the normal distribution

$$Z_{var} = \frac{X_N^2 - N}{\sqrt{2N}}$$

which will subsequently be called *Variability* Z-Value. The variability is evaluated on a trial-by-trial basis. The total variability for all 198 non-PREG trials across participants is Z_{var}=0.24. The distribution of variability for trials is close to normal which is, again, best seen in a normal Q-Q-plot:

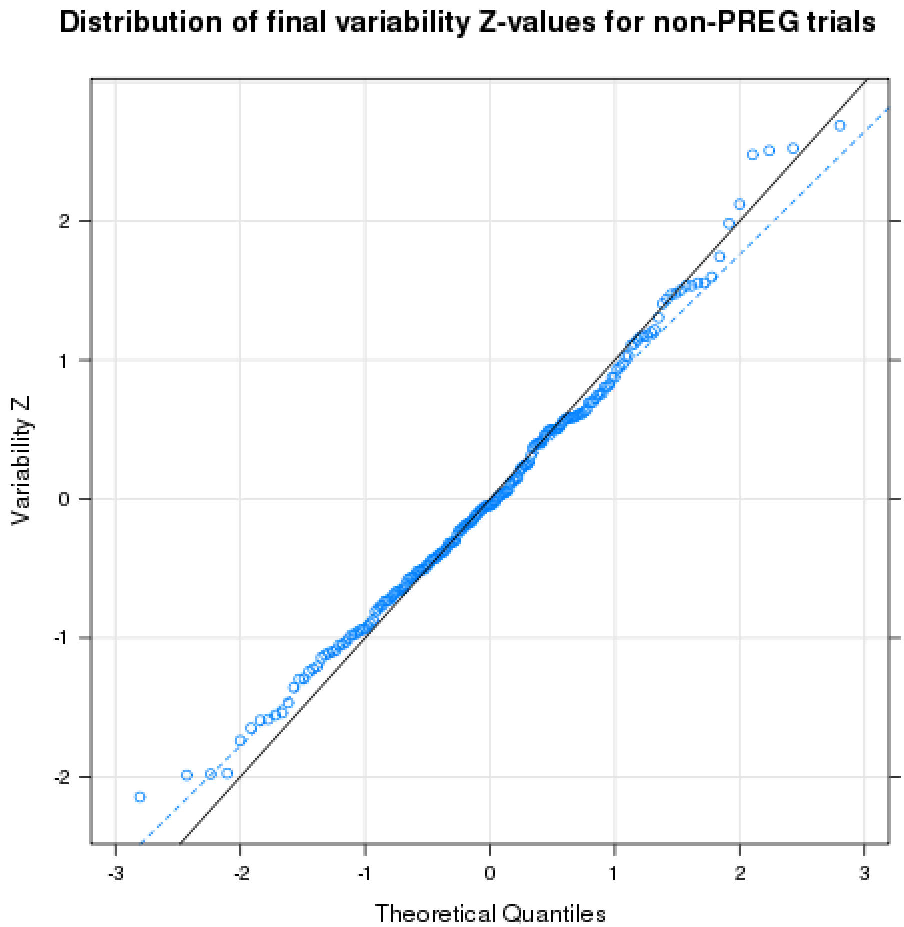

Fig. 12: Q-Q-plot for the distribution of trial variability shows that data is close to normal and follows a straight line that is tilted to the right, indicating scale change.

In conclusion to this brief analysis of the variability it can be said, that no indication of anomalous behavior is observed in the data. Therefore the triggering of events seems to have little or no influence on the distribution of trial variance and fails to reproduce a finding from our previous study [Braeunig&Faul2006]. It should be noted, however, that this type of assertion does not take into account the order in which events occurred in a trial, or that the trials themselves occurred. Further investigation might nevertheless show localized effects that cancel out in the trial as a whole.

3.4 M-switch variables

Based on the M-switch counter variable, `ms`, the number of bits inverted per record, useful experimental variables can be defined that are evaluated in each trial. These variables are descriptive of the switching behavior of participants and provide insight into potential psychological factors.

The following Table 6 lists these variables together with their operational definitions. The mathematical definitions for these variables involve *run length encoding* (RLE) and summation over runs and run lengths of the pressed state.

Variable	Short name	Definition
pn	Pressed number	Number of M-switch presses
pl	Pressed length	Number of pressed records
pb	Pressed bits	Number of pressed bits
pg	Pressed gain	Number of successful presses (positive gain)
pb/pn	Bits per press	Pressed bits per press (“duration”)
pb/pl	Bits per record	Pressed bits per record

Table 6: M-switch variables based on ms>0.

However, the reader shall be aware of the fact that we are looking at records of 32 bits of which less than the maximum number of bits may have been inverted. The table focuses on the pressed state, i.e. a state in which the M-switch was active (held down) for at least one bit and the M-switch counter is positive (`ms>0`). There is a complementary set of records at which no M-switch activity was present (`ms=0`). This definition of the pressed state is straight forward but somewhat over-estimates records with less than the full number of inverted bits. A more balanced definition is in fact `ms>16` (where 16 is the median) which counts *partially pressed records* (PPR) with fewer than 16 bits pressed as unpressed. Whether we employ the former definition or the balanced one is generally of little practical importance as PPR usually occur as boundary records of a longer fully pressed period, with the exception that isolated PPR sporadically occur in trials with a very high number of presses. We proceed without discussing this subtle distinction further and indicate the pressed definition where necessary.

The two primary variables are the number of pressed periods, `pn`, and the number of pressed bits within those periods, `pb`. The value of `pb` is the exact number of inverted bits which is equivalent to the sum of M-switch scores (ms). This number is limited by the total length (in bits) of a trial and by the number of M-switch presses pn: Its maximum, pb_{max}, is 32x9375 (300,000) bits for a single fully inverted trial (pn=1). Theoretically the maximum number of inversions is 32x9375/2 (150,000), for which every second bit has to be inverted and thus pb_{max}=pn. However, in a blocked design, where presses are evaluated on a record basis, pn_{max} is half of the trial length, or 9375/2 records. The experimental numbers are of course much lower. Fig. 13 shows that the number of presses, pn, is generally around 10 per trial, but there is one participant with a higher and two with a much higher average (200 and 510 presses).

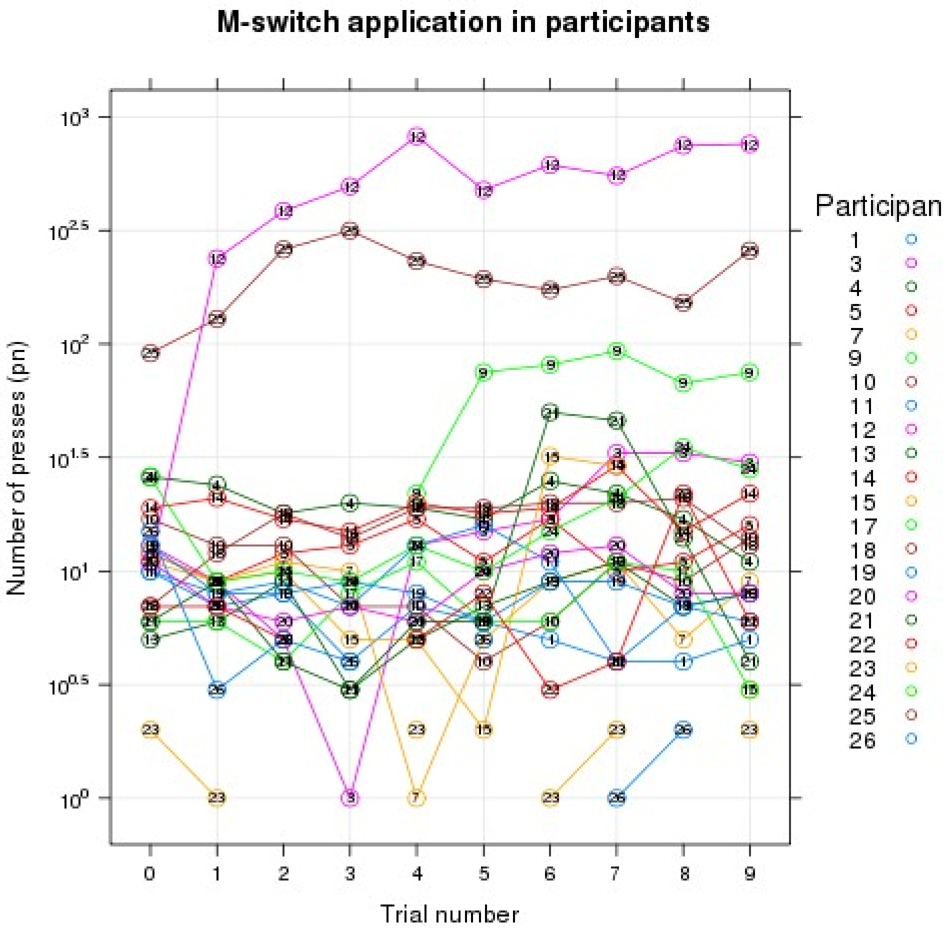

Fig. 13: Trial sequence for the number of presses reveals two participants with an extremely high M-switch press rate (note logarithmic scale).

The ratio of pressed bits per press, or pb/pn, is a useful measure of how many bits in a trial have on average been inverted in an M-switch press. It presents, therefore, a measure of “duration” and reveals participants that used the button for very short periods. While the average duration for most of our participants lies around 10,000 bits (or 312 records) per press, those with short presses had only 200-500 bits per press[11]. The following box-plot reveals that participants remain mostly consistent within their 'pattern' of using the Meaning-switch which can be seen as a psychological trait of dealing with the random sequences.

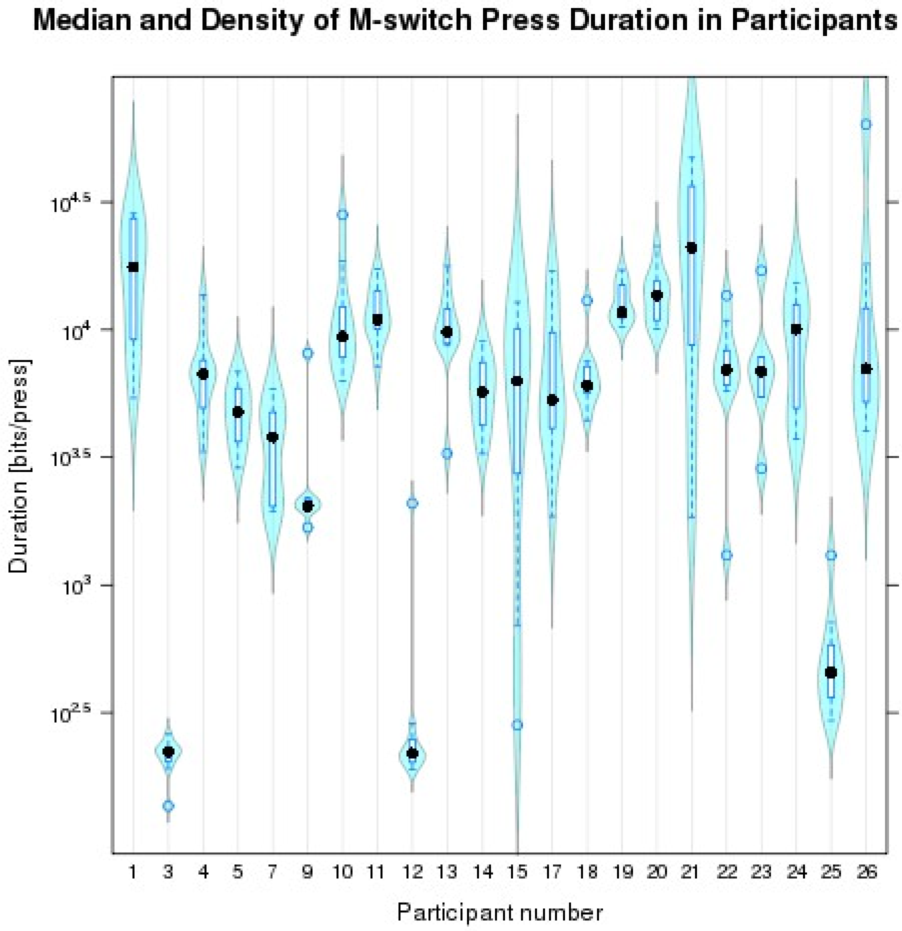

Fig. 14: M-switch duration is on average 10,000 bits per press with some outliers.

It seemed therefore reasonable to consider the number and the duration of presses as primary variables describing the distinct M-switching behavior in participants. The consistency of M-switch application is best seen in a scatter plot revealing three different domains: Most subjects applied the M-switch in a consistent manner covering a central region in the plot; second, two participants (no. 12 and 25) had a high press number and consequently a short duration; a third subject (no. 3) was identified to have mistaken the M-switch for a change-over switch instead of a push-button, whose presses have been

11 At normal sampling frequency of 1 KHz this would take less than a second. However, as the VCO trigger mechanism may have stalled (due to saturation) the actual time duration may have been longer. Information about real time duration is contained in the `timer` variable.

very short, but as many as in the first group. Another subject (no. 15) had been more diverse and tried out many different possibilities.

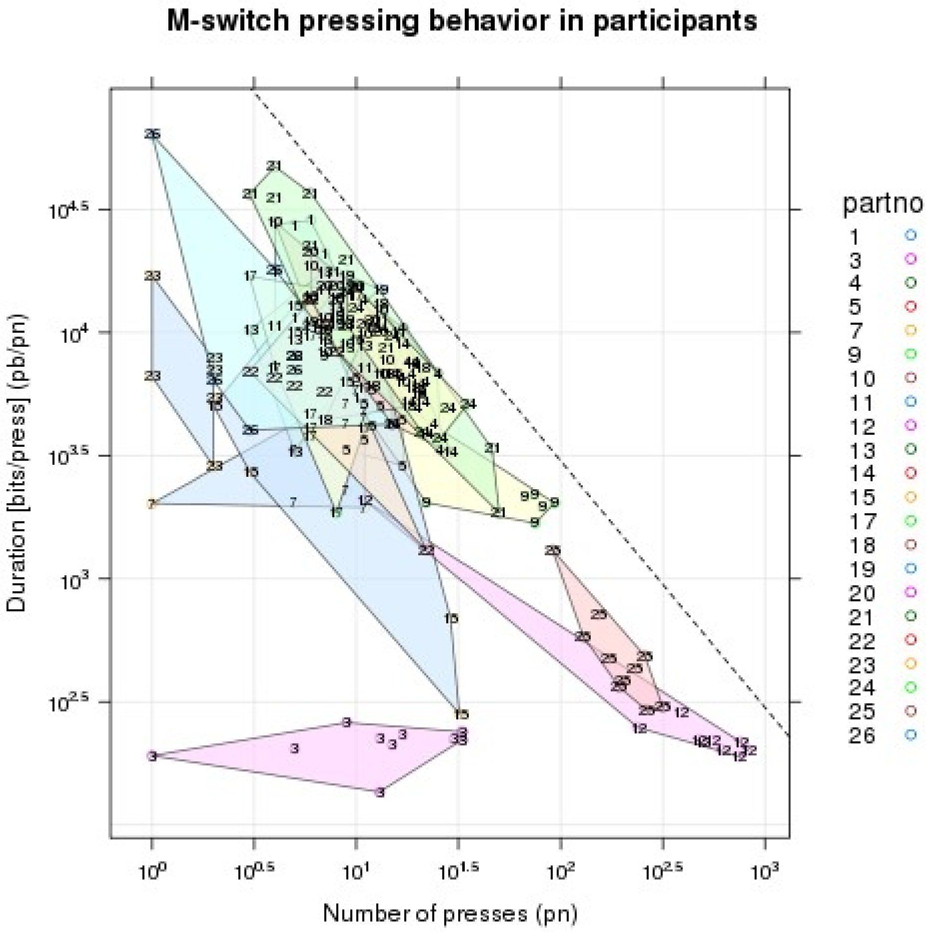

Fig. 15: Domains of trial means of bits per press and pressed number. M-switch behavior is consistent within participants (note logarithmic scale in pn).

In a cluster analysis we identified those participants and categorized them according to the Euclidean distance of their (inverse) duration values that allows to select each of the groups. With most of the subjects in group 1 the main cluster contains 18 out of 22 participants, while the other four clusters pertain to single participants. These clusters are being used in an analysis of the cumulative score value near and around the point where the M-switch button action took place (see next chapter).

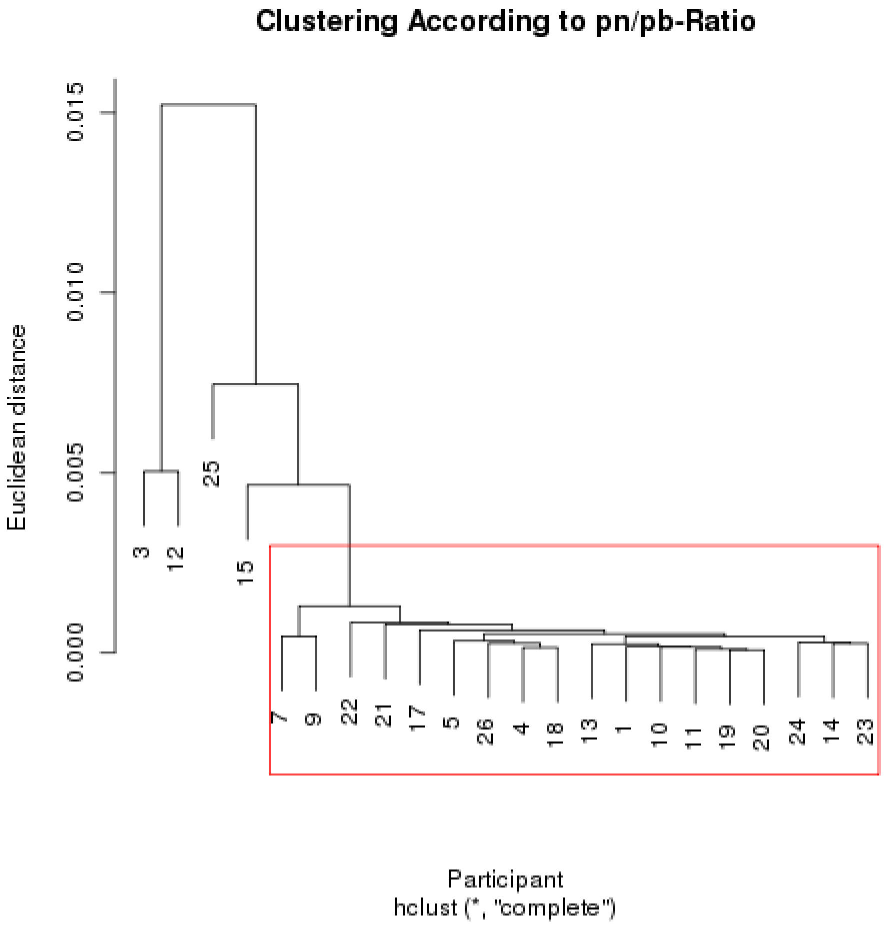

Fig. 16: Participants in cluster 1 form the main group.

3.5 M-switch synchronization

To give an example of how psychological factors might affect the M-switch behavior of participants we have to refer back to Fig. 9 on page 23: Each M-switch period is marked by a run in the variable ms>0 (gray strips) that defines the onset of either holding the M-switch down (pressed) or releasing the M-switch. Superposing all such records with a window around the button action, i.e. a press or release of the push button, the cumulative score can be fixed at a value of zero for that record observing the evolution of the cumulative score before and after the event.

Of course, one would assume a random walk on either side of the button action if the application of M-switch was totally un-informed. However, the cumulative score itself is the source of feedback given to the participants as tones, who had been instructed to increase them in whichever way they liked. It is therefore not surprising that the cumulative score reflects the course of events before a button action took place, if activity was a reaction to past events. On the other hand, anticipating the sequence after the button action becomes also visible.

Of the many different ways that we can visualize M-switch behavior around button action we follow the clustering described above, superposing all button actions for press and release in one of the clusters and displaying the cumulative score as the mean over all sequences. The number of contributing button actions differs according to the number of presses, `pn`, in each of the groups.

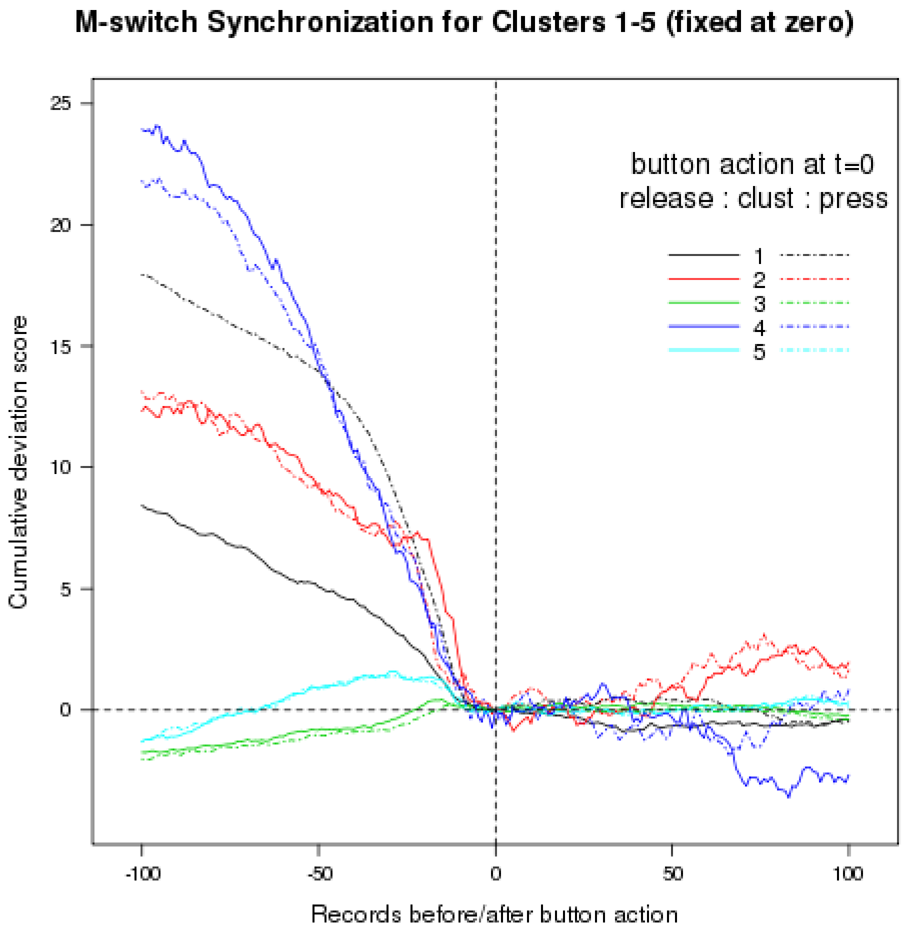

Fig. 17: Synchronization of M-switch activity shows a strong effect in cumulative score before button action, which is seen as a genuine psychological factor.

The synchronization plot shows, that the cumulative score follows a steep descent prior to button action which demonstrates pressing and holding the M-switch when the feedback was on a downward slope. Release of the M-switch button is similar in this respect and follows much in the same pattern, except for cluster 1 (the main group) where a clear division between pressing and releasing behavior becomes evident. In this cluster, subjects seem to be more reluctant to pressing – which is active – than to releasing the M-switch button. The overshoot in cumulative score thus produced prior to M-switch action is lower and closer to zero in the clusters 3 and 5 (pertaining to subjects #12 and #25, respectively) which is due to their extremely short run length of presses and releases that is well below the window size (100 records) used in the sync plot. In cluster 2 (participant #3), however, the pressed duration is much shorter than the runs lengths for releases, which has been discussed already above. Nevertheless, the two synchronized curves remain basically in parallel.

On the other hand, the cumulative score after the M-switch action, to the right of the synchronization point, does not seem to show any anomalies. In fact, M-switch synchronization shows that the reaction is to past events and does not lead to an increased performance in the task.

To complement the picture of distinct M-switch behavior in the clusters it is instructive to investigate the density of run lengths of M-switch button presses and releases that can be translated directly into M-switch duration seen in Fig. 18.

The density of run lengths, or duration in records for the pressed and un-pressed (released) M-switch state shows that only cluster 1 fills the window of 100 records used in the synchronization plot. The other clusters mostly reach a maximum at a much lower run length (note logarithmic scale), beyond which the cumulative score essentially follows a random path.

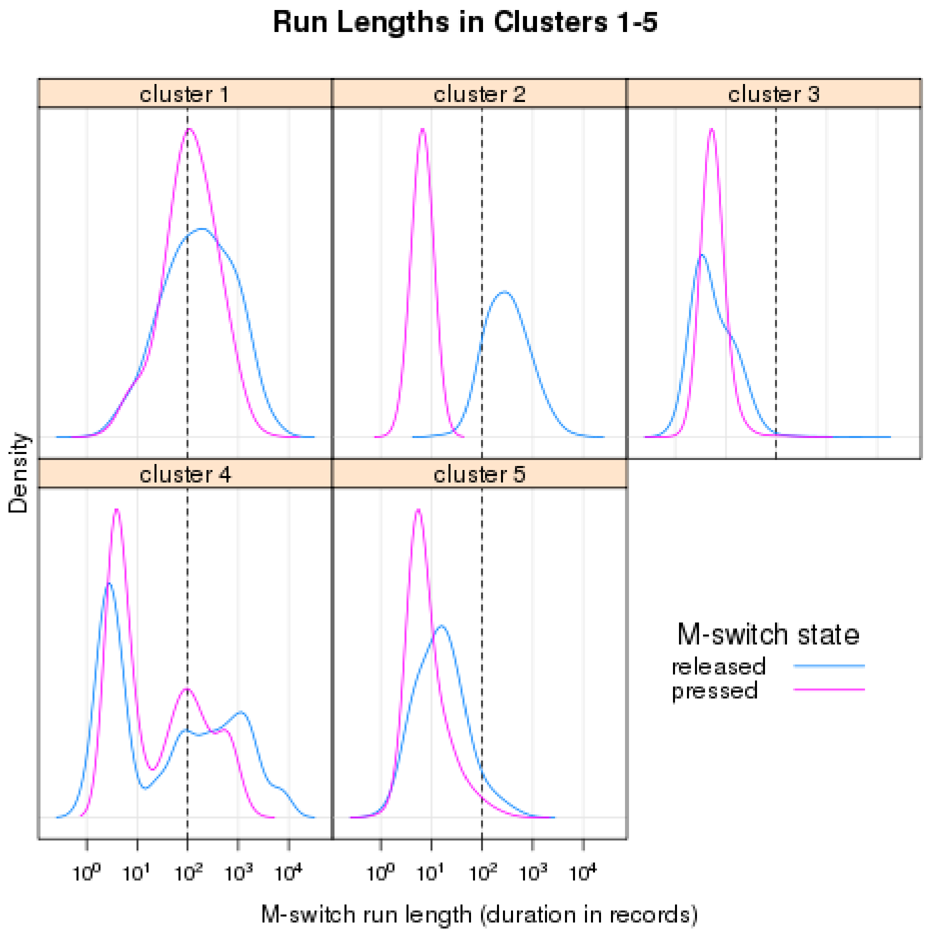

Fig. 18: Distributions of run lengths of M-switch pressed and released states. Dashed vertical line marks window size in synchronization plot.

The random walks in the synchronization plot before button action can be described with a linear model, taking into account the intercept (a), a linear slope (b) and a square-root law (c), where the latter coefficient describes the 'overshoot' due to psychological reaction of the participant:

$$Y = a + b \cdot T + c \cdot \sqrt{|T|}, \text{ where } T = t - \tau$$

The parameter T is the number of records before the button action, t, shifted by a time lag, $\tau = 8$, that can be interpreted as reaction time, corresponding to about 0.25 seconds. The fit parameters of the model have been used as psychological variables in the correlation analysis (see next chapter).

3.6 Random Correlations Analysis

As a last step in the analysis we investigate the number of significant correlations between two sets of variables. As a matter of fact such correlations do always appear as convoluted random variables. The Model of Pragmatic Information (MPI) of Walter von Lucadou suggests that psycho-physical systems show an excess of such correlations between physical and psychological measurement variables as a consequence of generalized entanglement (see [Lucadou2006]and [Lucadou2007]).

The method of determining the number of significant correlations is straight forward once the variables themselves have been determined. It may be questionable, however, if the distinction between what constitutes a physical or a psychological variable is possible in a system that is said to be operationally closed. The separation between these two sets contradicts the idea that the T.REG incorporates structural constraints in its trigger-feedback- and M-switch-loops that render any distinction of causal factors rather artificial[12].

This does not mean that variables cannot be defined at all, as we have seen throughout this report. The variables that have been dealt with so far include statistical moments of `score` and measures of M-switch activity, such as the numbers of button presses and inverted bits. More variables that have not been discussed yet were analyzed in the course of our investigations (whose details we skip for reasons of space). In short, these measures include auto-correlations of the scores, and timing information gained from timer variable and time stamps collected concurrently with the primary variables. These latter variables are related to the EEG-voltage measured at the participant's forehead and timing parameters collected during the experiment. A detailed list of the variables used in the final correlation analysis is given in Table 7 and 8 in Appendix 6.5 .

The variables are grouped according to the general recipe that variables based on `score` are considered to be physical measures, while those based on `ms` (M-switch score) or `timer` are considered to be psychological in nature. An exception are variables such as the model fit parameters of the cumulative

12 It may be worth discussing if the variable (or observable) definitions themselves are behind any 'experimenter effects' that are often observed in psycho-physical systems, where no obvious interference takes place during experiment, but is introduced through the experiment design and post-hoc analysis methods.

score in M-switch synchronization and the net gain, which are also considered to be psychological. All variables are evaluated for non-PREG data on a trial-by-trial basis and the two groups then correlated with each other using Pearson's rank statistic (rho). The resulting table of correlation test P-values has a dimension of 24x9 and yields a number of 17 (7.9%) significant correlations at 5% significance level.

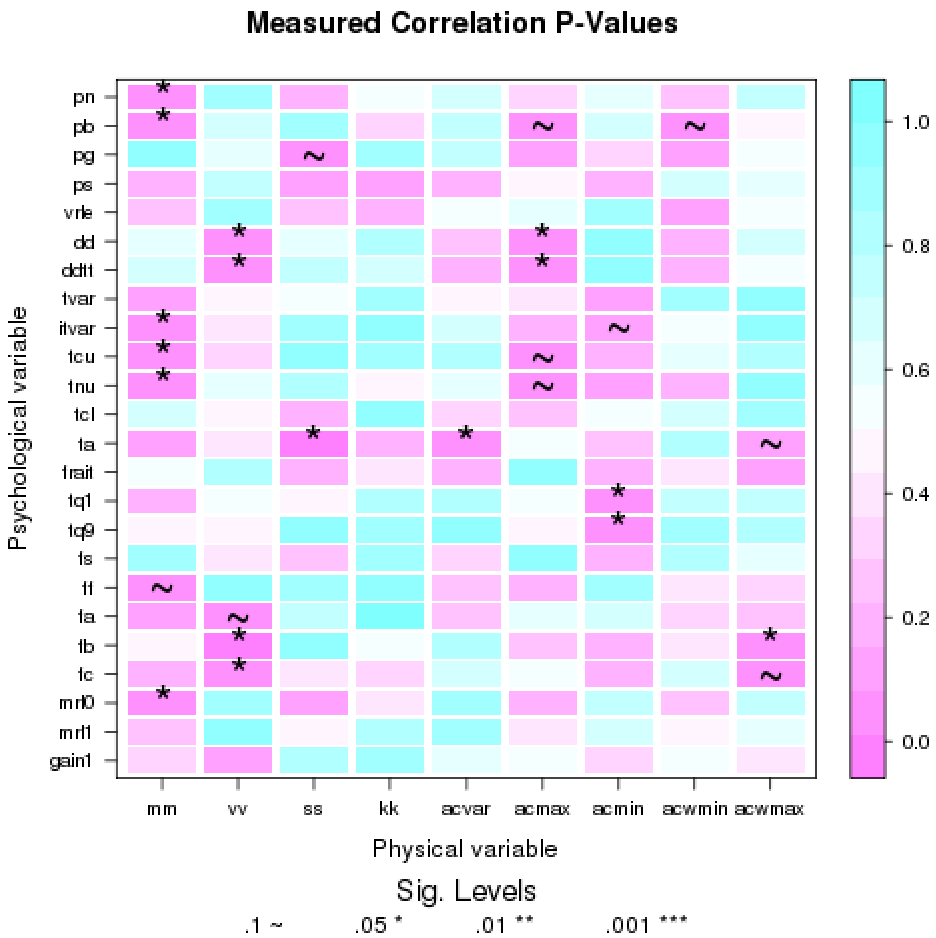

Fig. 19: Matrix of correlation P-values for psychological and physical variables (in set E). Stars mark significant correlations at the 5% level.

In order to assess the importance of this finding we need to compare it with the distribution of correlation counts. Two methods have been employed: The first is to perform random permutations on the `score` variable across all trials and then to re-compute the derivative variables. The correlation matrices thus produced are then analyzed in the same way as the measured matrix. The second method is to generate a random `score` vector from the theoretical binomial distribution. Our tests showed that both methods yielded consistent results so that we restrict our discussion to the first method.

Following the approach outlined in [Lucadou2006], a Z-value for the difference of the number of significant correlations, $C-C_0$, is computed according to the formula

$$Z_{sig}=\frac{C-C_0}{\sqrt{2\cdot C_0(1-C_0/N)}}$$

where C denotes the number of significant correlations in the experimental correlation matrix and C_0 denotes the number of significant correlations in the simulated (dummy) matrix, and N is the dimension, or size of the matrix.

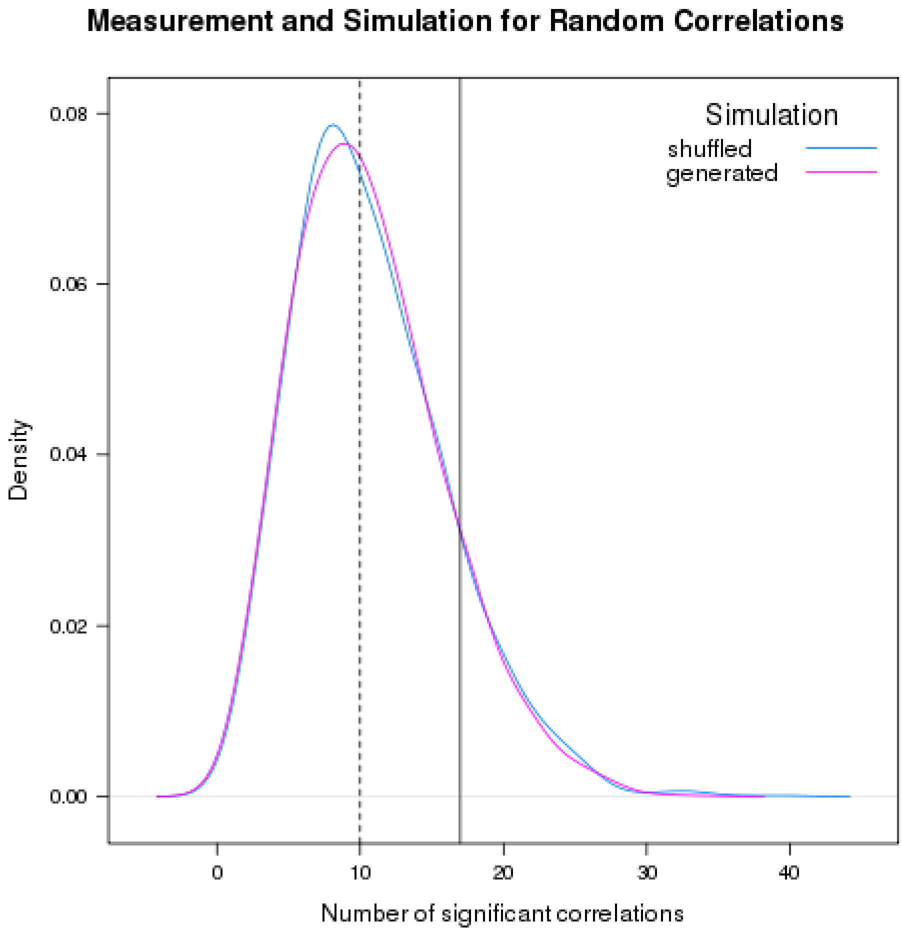

Fig. 20: Distribution of the number of significant correlations for 3,000 simulations each with variable set E. The dashed line marks the median of the simulation and the solid line the experimental number of significant correlations.

The median of the number of significant correlations for both types of simulation is 10. Taking this as the standard, or expected value, we conclude a Z-value of $Z_{sig}=1.6$. Conversely, if Z_{sig} is calculated with each simulated correlation matrix, it's mean Z-value is 1.86 ± 0.03, while it's median remains the same. Thus, for a one-sided test the finding is just significant with

P=0.031, suggesting an increased number of significant random correlations in the measured data set.

Different sets of variables have been tried out for the correlation table. It turned out (Fig. 23 in Appendix 6.5) that the method depends critically on the choice variables, as the number of significant correlations is sensitive to the variables in the sets. While seeking to expand the variable sets in order to achieve a high dimensionality of the correlation matrix, duplicate variables have to be removed from the variable list, to not artificially increase the correlation count. Similarly, variables that are mere transformations of otherwise included (primary) variables, such as the duration pb/pn, shall be removed, too. All these steps reduce the correlations excess, so that we remain with the result above as the most conservative estimate. The bar-plot below demonstrates these facts in our several attempts of defining a core variable set.

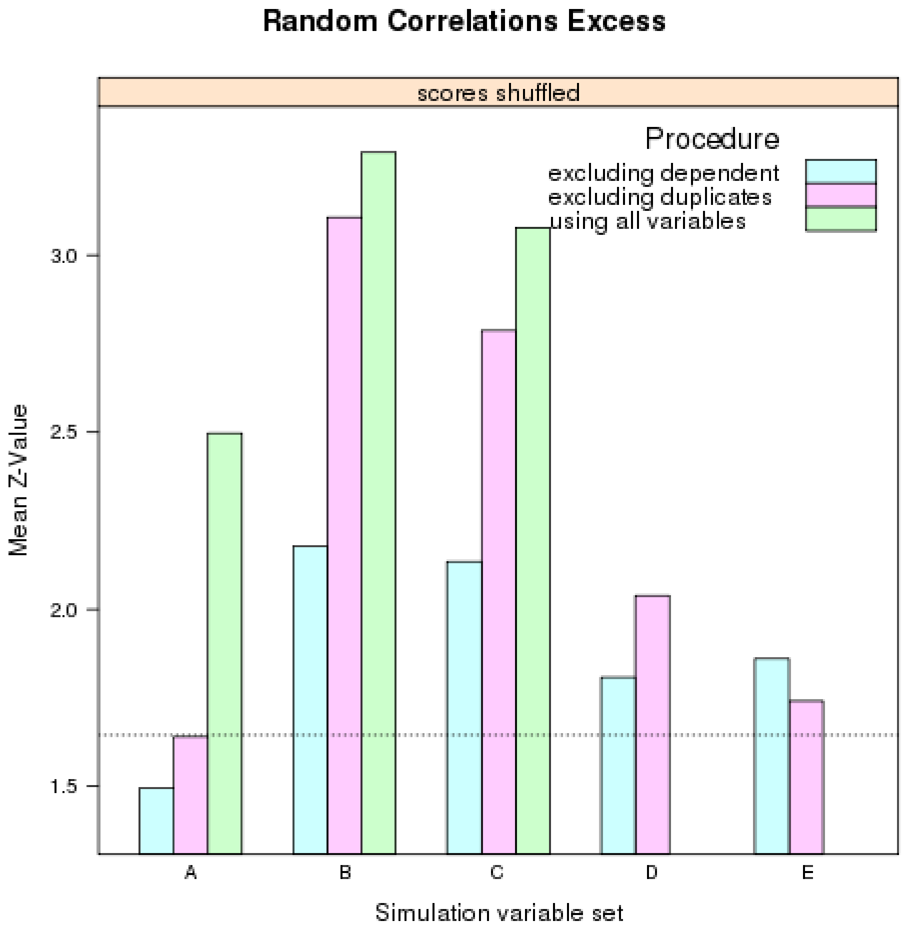

Fig. 21: Test results are sensitive to variable selection. In the final and most stringent choice (here variable set E), Z-values fall just within the 95% limit.

The choice of variables for describing the process in terms of physical and psychological parameters faces a certain dilemma: On one side, variables should carry as much information as possible, that is not already covered by any other variable. On the other hand, a causal relationship cannot be distinguished from 'entanglement' correlations when the variables are orthogonal. Therefore a careful choice has to be made to find non-orthogonal variables that do correlate to a certain degree among each other within their own group, and gather substantial information about the process. This excludes duplicate variables, that are strong correlates, as well as variables that are mere transformations of other variables that are already in the set. Our variable sets A-E demonstrate this 'learning curve' which was finally concluded with variable set E.

4 Project Summary

The T.REG is a Triggered Random Event Generator, which has been developed as a device that couples an electronic noise process with the local environment, and in particular with a human subject capable of intentionality, in order to investigate the effect of operational closure in a psycho-physical system. In this second project we have technically improved the initial design of the T.REG including the Meaning-switch (M-switch), which is a means to let the participant decide on the meaning of hits and misses by pressing or releasing a push-button that inverts the sequence of sampled binary events.

Fully automated experiments have been run with 22 subjects who participated in 10 trials, generating 3,000,000 binary events each. About the same amount of data has been generated in two control experiments, using a deterministic trigger source. A number of pre-stated and -registered hypotheses and further post-hoc analyses have been performed on the data, that investigate the statistical properties of the hit counts (scores) and binary sequences for deviations from randomness, mean and variability shift, correlation, and for psychological factors involved in the application of the M-switch.

Randomness is the key requirement for the null-hypothesis of 'un-informed' sampling. This is why we used fixed frequency trigger pulses in control trials, where there can be no intentionality or feedback. Three kinds of tests – the visual noise sphere test, the DieHarder suite including 18 carefully designed tests for randomness, and the ENT random tester – all showed no indication of a violation of our basic assumption, that the T.REG performs as a good random number generator under un-informed sampling, which was an expected result. However, also the experimental data – with intentionality and feedback – are similarly random in this respect: they cannot be distinguished from control, although a few tests failed in DieHarder, indicating subtle non-randomness. These indications could not be confirmed with ENT.

Further investigations are concerning the experimental data set only. The physical measures of mean and variability remained within mean chance expectation (MCE), which underpins the null hypothesis that no anomalous sampling is taking place. In particular, a significant effect in variability from a previous experiment could not be replicated.

Single trials from a pseudo-random event generator (PREG), with pre-defined standard properties, that all participants had passed as part of the 10 trials, showed a slight mean shift as compared to the true physical trials (non-PREG). This leads to the interesting conclusion, that people might be able to distinguish a pseudo-random sequence from a non-deterministic one, or – since any shift could have only been produced by M-switch application – enables them to act pre-cognitively. The difference was, however, non-significant, so that we cannot reject the null that this finding is by chance alone.

This idea is, however, also supported by the definition of gain, which is the difference in score between the by M-switch partly inverted and the reconstructed un-inverted sequence. Although the 'Individual Learning

Hypothesis' (**H_L**), that gain increases with trial number (or experience) could not be validated – because a regression was not significant - the opposite effect was found: Gain was generally negative and decreasing with trial number. The last PREG trial had positive gain, which is suggesting a similar tendency as found in the mean values.

There was not enough power to separate PREG from non-PREG conditions in terms of gain. For the 'Morphogenetic Learning Hypothesis' (**H_M**) the gain for non-PREG remained near zero (chance expectation), while gain in PREG was increasing across subjects. Again, the tendency was in the hypothesized direction, but the regression lines were non-significant and the error bars were too large to exclude a chance effect.

The application of the Meaning-switch was analyzed in detail, revealing distinctive and consistent behavior in all participants, that lead to a clustering into 5 groups: Cluster 1 contained 18 participants who consistently used the M-switch on average 10 times per trial for a duration of 10,000 bits (312 records) per press, which is about 10 seconds (at 1KHz sampling frequency). The exceptions were single participants in clusters 2-5, who consistently either applied the M-switch at much higher pace (200-500 presses), or for a very short duration (a misconception), or creatively trying out all of the above (one participant).

The M-switch analysis lead to a number of interesting psychological observations and variables, in particular about the relationship between intentionality and the participant's reaction to past events (feedback) – the implicit assumption that the past course of events, or decline of score and feedback, will continue into the future. This was evidenced by M-switch synchronization, that revealed different reaction patterns in the five analyzed clusters. These patterns could be successfully described with a square-root regression model, whose parameters were used as psychological variables in the correlation analysis.

Finally an attempt was made to separate physical from psychological variables and to investigate the Pearson rank statistic between them for an excess of significant correlations. In the final and most conservative variable set we found 17 significant (at 5% level) correlations in a matrix of 24x9 variables, while simulations suggested an expectation of only 10 (median). This result was significant in a one-sided hypothesis test (P=0.031), supporting the hypothesis of 'generalized entanglement'. However, the correlation analysis method itself was found to be sensitive to the set of variables, and any evidence in favor for 'entanglement correlations' may be explained as variable selection bias.

In view of the non-significant deviations from randomness it was impossible to identify subjects with a special capacity to affect the score, hit rate or variance, in the intended and pre-stated direction. Although two participants showed extraordinary performance in M-switch application, no further attempt has been made to run additional experiments.

4.1 Acknowledgments

The researchers wish to thank Fundação Bial, Portugal, for generously funding this project under contact number 98/06, which made it all possible.

We extend our thanks to all our participants who not only took interest in the experiments, but supported us actively with their time and patience.

The University Medical Center in Freiburg, at the Institute for Environmental Health Sciences provided laboratory space and facilities during measurements.

Finally we like to thank Dr. Walter von Lucadou of WGFP e.V. for helpful discussions and support as the project leader.

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6 APPENDIX

6.1 Registration

Registration of an experiment of this type before execution is considered good scientific practice, as it reveals the hypotheses and standards applied. The following letter was sent by email to a recognized authority and is available to everyone interested in the background of this research project.

Registration of Experiment with Dipl.-Psych. E. Bauer (IGPP/Freiburg)

BIAL PROJECT 98/06: The Meaning-Switch - Investigation of Precognition in an Operationally Closed System

Definition1: The T.REG is an FPGA hardware implemented triggered random event generator. Triggers are impulses drawn from regular or irregular, in particular non-deterministic sources.

Definition2: The Meaning-switch, or M-switch is a device for deliberately altering the meaning of hits (and misses) by inverting the random stream of states, sampled by the T.REG and operated by the participant. The gain in an M-switch trial is defined as the difference in mean of deviation scores between the inverted and corresponding un-inverted sequence.

Definition3: PREG is a deterministic LSFR Pseudo-REG running as an alternative setting of the T.REG. It is based on a seed value and triggered in the same way as the true random event generator. Its primary use lies in a comparison of inter-subject M-switching behavior.

HYPOTHESES

H* According to the DieHarder Battery of Tests, the T.REG performs as a "good" Random Number Generator. This basic hypothesis will be tested with fixed trigger pulses.

From exploratory analysis of a previous experiment [1] there is evidence for increased variability (Z=2.587) in a T.REG setup featuring EEG modulated triggers and M-switch. The current study investigates the M-switch as a necessary ingredient in an operationally closed system composed of a T.REG with EEG modulated triggers. With the M-switch the hit rate can be augmented but not the variance.

We adopt H* and formulate the preliminary null hypothesis H0* that the T.REG performs equally well under the setup described above. As a consequence, mean and variability should not be increased above chance level. This is a testable statement formulated as H0 Mean and variability of scores do not deviate from Mean Chance Expectation (MCE) in a T.REG with EEG modulated triggers and M-switch.

This and all other hypotheses will be tested at a confidence level of 5% (two-tailed) using theoretical expectation values.

Alternatives:

H1 The overall mean value in all subjects is increased due to the effect of the M-switch.

H2 The overall variability in all subjects is increased due to operational closure in the above stated setup.

HL Individual Learning Hypothesis: In intra-subject trials the gain is positively correlated with the trial sequence number.

HM Morphogentic Learning Hypothesis: In inter-subject trials, the gain for PREG is positively correlated with the subject sequence number.

Furthermore the MPI [2] hypothesis of excess correlation is tested in a matrix of physical and psychological variables, to be extracted from the application of M-switch and timing information.

METHOD

The hit rate, or score, is based on 32 bit words. Bits are generated at a mean frequency of 1KHz modulated by the subject's EEG voltage measured at the forehead. (The EEG is not recorded.) A push button (aka Meaning-switch) can deliberately be applied by the subject inverting the meaning of hits and misses in the output sequence. Detailed information on switching periods is recorded along with full bit words. Acoustic feedback on cumulative deviation scores is given on headphones. The subjects run all ten trials in an automated procedure without interference of the experimenter.

PREG trial

The last (tenth) trial in an experiment is using a pre-defined PREG (not a true REG). Both experimenters are blind to the exact display of the sequence. The blinding is lifted after all experiments are completed. The PREG seed value is chosen to produce a sequence that matches the expectation of zero mean and variability Z exactly. It is the same for all subjects.

MEASUREMENT PROTOCOL

Subjects are invited to the lab on a day-by-day schedule in a two weeks period with the aim of gathering 20 complete and in form identical datasets. Quality of datasets is rated into categories A-C for formal correctness: Defective datasets (C) are discarded from analysis, usable but incomplete data (B) is included only if hypothesis testing of category A data is critical (plausibility analysis).

Data is recorded in an automated procedure for ten trials giving the subject full control over starting each trial and M-switch. A screen with instructions is presented to the participant (also available on paper - see attached document). Trials are started on button press. In between trials the participant can take a short break, time is recorded. The procedure stops after ten trials. A measurement protocol of each session with summary information is generated.

References

[1] Braeunig, M. & Faul, T. High Performance REG Array with Simultaneous Read-Out - Exploration of a new REG design, involving self-selective amplification and EEG triggered read-out for PK studies, BIAL Summary Report, 2006

[2] von Lucadou, W., in: Sheehan, D. P. (ed.) Self-Organization of Temporal Structures --- A Possible Solution for the Intervention Problem, FRONTIERS OF TIME: Retrocausation - Experiment and Theory, AIP, 2006, 863, 293-315

6.2 Instructions

The following text (originally in German) was presented to the subjects prior to and available during the experiment. It was also presented on screen in the measurement program. The subject could ask questions of comprehension.

WELCOME TO THE T.REG EXPERIMENT
You are participating in an interactive experiment that generates seeming random sequences of tones. There is no risk in what you do, and you cannot do anything "wrong". Please proceed with the instructions below. We thank you very much for your cooperation and patience!

Instructions
You will be given 10 equal experiments of about 5 minutes duration each. It is up to you when to begin a run by pressing the green start button once. After each run you can take a break if you need a pause.

You are wearing headphones and an electrode clip is connected to your forehead. In a moment you will hear a sequence of rising and falling tones, that are concurrently generated by the signals measured at your forehead. From the very beginning you are an integral part of a system that listens to what it generates - tones. Your task is to make the tones rise, ie. generating ever higher frequencies. When they reach an upper or lower threshold and jump back to the center of the scale, don't worry or be discouraged and continue your efforts. You are completely free in your strategies of how you try to achieve this. For example, you may prefer hard concentration, using your will power, or simply relaxing in a meditative poise. There is no wrong as everything that happens is just you with yourself. Just keep up the intention to raise the tones.

At times you may find that -contrary to your intention- the tones fall rather than rise. If you foresee such a period in which the tones drop rather than rise, you can reverse its direction anytime by holding the red Meaning-switch button pressed, and vice-versa release the button, when you want it the other way again. Use your intuition as to when you press the M-switch button and use it as much as you like to improve your result.

The experiment will start immediately after you pressed the green button.
Try it now!

Good luck!!

6.3 Pseudo REG (PREG) Sequence

The Pseudo-REG (or PREG) is a *Fibonacci-type Linear Feedback Shift Register* (*LFSR*) implemented as hardware inside the T.REG and activated as the feedback channel (ch1) through a particular setting. The seed value has been carefully chosen so that the mean and variance of the sequence match the expectation values $\sum_{i=1}^{n} x_i / n \equiv n \cdot p = 16$ and $SS/n \equiv n \cdot p \cdot (1-p) = 8$ exactly.

For completeness we give here the steps to an algorithm that generates this sequence outside of the T.REG (using a GNU linux computing environment). The sequence can be reproduced by running a C-program as follows:

1. Download and install `lfsr-generator` software from http://lfsr-generator.sourceforge.net/
2. Run the source code generator:

   ```
   lfsr-generator --length=32 --taps=32,31,30,10 --shift-amounts=1 --shift-left >shift_lfsr.c
   ```

   ```
   lfsr-generator --header >shift_lfsr.h
   ```
3. Save the following main program in `lfsr.c`:

   ```
   #include <stdio.h>
   #include "shift_lfsr.h"

   int main( int *argc, char **argv)
   {
     const unsigned int init = 0xc83788b8;          // PREG seed
     unsigned int i = 0;                            // step count
     unsigned int v = init, x, c;                   // registers, count
     unsigned int recs=9375, bits=32;               // constants
     do {
       v = shift_lfsr(v);                           // update
       if( ++i%bits == 0) {                         // word
           x = v;                                   // copy register
           for(c = 0; x; c++) x &= x - 1;           // Kernighan's way
           printf("%d\t%#x\n", c, v);               // score, hex
       }
     } while (i < bits*recs  && v != init);
   }
   ```
4. Compile the sources:

   ```
   gcc -O3 -s lfsr.c shift_lfsr.c -o lfsr
   ```
5. Run the executable and save output in `preg`:

   ```
   ./lfsr >preg
   ```
6. Proof that scores meet the expectation values for mean and variance:

   ```
   gawk '{s+=x=$1;ss+=(x-16)^2}END{print"N="NR,"mean="s/NR,"var="ss/NR}' preg
   ```

   N=9375 mean=16 var=8

6.4 DieHarder test of the Mersenne-Twister (mt19937)

Running the test suite on the mt19937 with default parameters allows for more tests than those used in the comparison chart (see 3.2 Tests for randomness). We give here the results of the mt19937 alone, showing no problem in the tests that were previously marked as weak or failing.

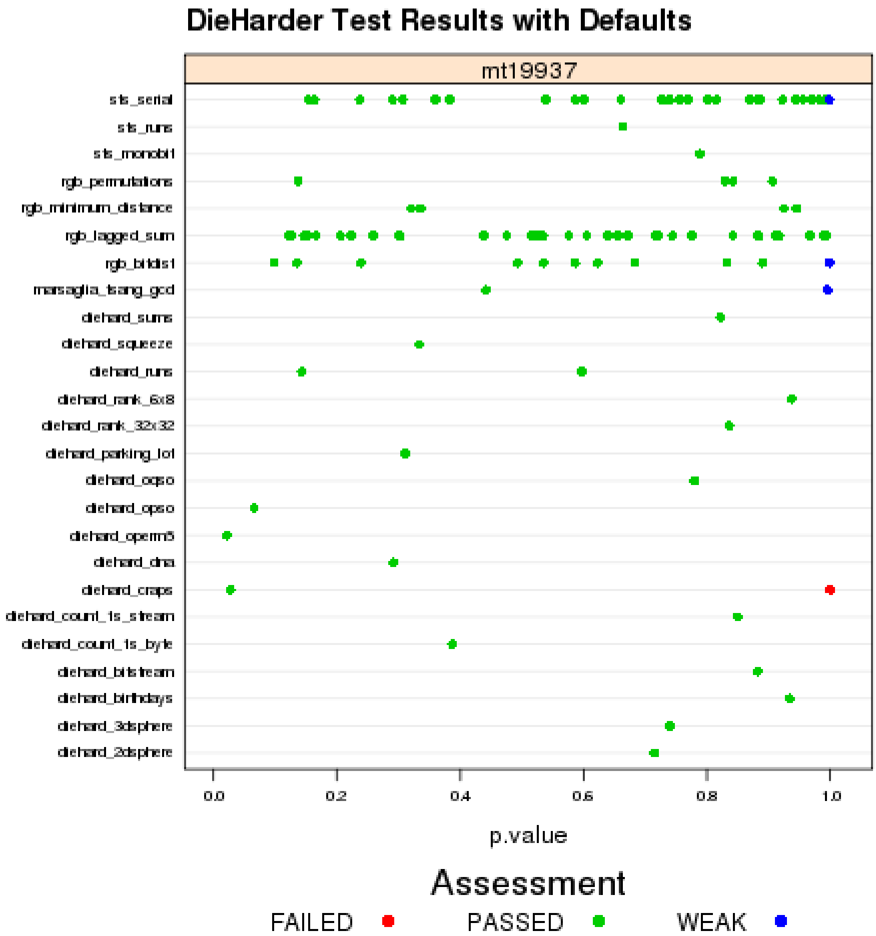

Fig. 22: Performance of the GSL Mersenne-Twister (mt19937).

6.5 Variable descriptions

The measured variables thus identified have been used for correlation. The following two tables separate between psychological and physical variables.

Note that variable gain1 (net gain discussed in 3.3.2 Definition of gain) is considered to be a psychological rather than a physical variable, as it had been based on the number of pressed bits (pb) and compensated for mean shift.

Acronym	Description
pn	number of M-switch presses
pb	number of pressed (inverted) bits (max. 300,000)
gain1	net gain (compensated for mean of score)
pg	number of M-switch presses with positive net gain
ps	pressed start, number of records between start and first M-switch press
lvr	logarithm of variance of run lengths of ms>0
vrle	variance of run lengths of ms>16, later used to replace lvr
dd	time between trials
ddtt	time before first press, or dd–tt
tvar	variance of timer
itvar	variance of 1/timer (variance of reconstructed EEG voltage)
tcu	record count with high 1/timer value replacing log fold tcu0 in simulation
tcu0	logarithm of record count with high 1/timer value
tcl	record count with low 1/timer value replacing tcl0
tcl0	logarithm of record count with low 1/timer value
tnu	counting number of occurrences of high 1/timer value
tnl	counting number of occurrences of low 1/timer value
ta	first root in auto-correlation of timer
frait	first root in auto-correlation of 1/timer
tq1	10% quantile of timer
tq9	90% quantile of timer
fs	slope of linear model for 1/timer vs. score
ff	slope of linear model for 1/timer vs. fbv
fa	intercept term in M-switch synchronization
fb	slope term in M-switch synchronization
fc	sqrt term ('overshoot') in M-switch synchronization
mrl0	mean run length un-pressed
mrl1	mean run length pressed

Table 7: Psychological variables based on M-switch and timer.

Acronym	**Description**
`mm`	mean value of `score`
`vv`	variance of `score`
`ss`	skewness of `score`
`kk`	kurtosis of `score`
`acvar`	variance of auto-correlation values of `score`
`acmax`	maximum auto-correlation value of `score`
`acmin`	minimum auto-correlation value of `score`
`acwmin`	lag in records where `acmin` occurs
`acwmax`	lag in records where `acmax` occurs

Table 8: Physical variables based on score.

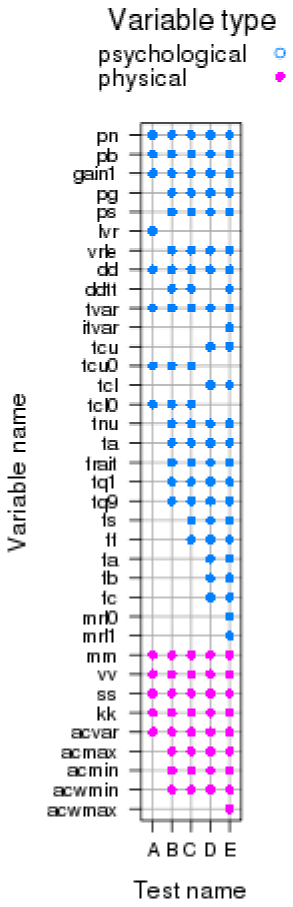

Fig. 23: Choice of variables used in the correlation analysis.
The test names A-E denote the variable sets.