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A Methodology for Investigation the Change in Visual Detection of Motion in the Elderly

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Abstract

The current research is focused on constructing tools for modelling and analysis of changes in motion perception that occur with age. Created software tools allow conducting psychophysical experiments for estimating the sensitivity to motion direction of two age groups. The results were analysed and compared to evaluate the major changes in cognition with age. The differences in visual motion integration and in the decision-making strategies were assessed by a procedure for objective scenario estimation. In the framework of this procedure a trajectory detector estimates and classifies useful statistics for each test. A special measure is proposed for estimation of the temporal characteristics of the random scenario that determines the correctness of observer's decision. The interpretation of the results reveals new information about the age-related characteristics of visual processing of motion information. Moreover, it allows detecting subjects with significant degradation of visual processing.

1 Introduction

The complex process of ageing has been investigated intensively in the last years by scientists from very different fields – medical, biological, social, economic, etc. Understanding the age-related changes in the brain is important for improving the quality of life of the elderly by developing appropriate interventions and ways to slow-down and/or to postpone the deterioration in the cognitive functioning and task performance. It also provides knowledge about brain plasticity and adaptability at the neurobiological, cognitive and behavioural levels. The present study investigates the differences in visual motion perception between two age groups – younger (mean age 19.5) and older (mean age 73.9). Motion information is important for many everyday tasks like navigation, collision avoidance, figure-ground segregation, three-dimensional shape recovery, etc. These tasks are of vital significance for the survival of the individual. Therefore, the study of differences in the perception of motion of the two age groups may reveal some of the brain mechanisms that compensate the impairment of visual functions with aging.

The experiments were focused on the age-related changes in the sensitivity to motion direction of dynamic stimuli. The task of the observers was to indicate whether the mean direction of motion appeared to the left or to the right of the vertical. A fixed proportion of moving elements translated in random directions, while the direction of motion of the rest is taken from uniform distribution centred slightly to the left or to the right from the vertical. In order to perform the task

the observers have to integrate the motion direction of multiple elements. However, the task performance also depends on their ability to ignore the irrelevant information provided by the noisy elements. Age-related deficits in task performance may be expected due to the increase in the internal noise in the ageing visual system [1] or to the impaired attentional capacities of the elderly people [2] and to their inability to scale attention to the scope of relevant stimuli [3].
The experimental design used in the study resembles the classification image paradigm [4],[5] and [6] for a recent review. In a typical experiment of this type the observers classify signals presented against an additive background noise in a numerous number of trials. The noise present in the correctly classified trials and in the incorrectly classified trials is analyzed in order to reveal the perceptual "template" used for solving the task e.g. to infer the stimulus features that determine the perceptual decisions. The classification image paradigm is also useful for estimating the internal noise in the task performance [7]. Our stimuli could be described as a signal modulated by noise in the presence of background noise. This stimulation increases the perceptual load and allows not only to evaluate the perceptual abilities of the subjects, but also to reveal differences in performance due to attentional processes and different decision strategies. To achieve this goal, however, we need to create new approaches and tools of analysis. The main aim of the present paper is to present these new analytical procedures for assessing the age-related differences in discrimination of global motion direction.
Details of our experimental design and its relation to the classification image paradigm will be given in the next chapter. Perception ability investigation is a challenging problem. It requires the development of appropriate tools to obtain accurate statistical estimates of the perception of relevant information from both age groups. The specialized stochastic scenario generator was developed as a valuable tool for easy scenario generation changing noise distributions and their parameters. It is described in the third chapter. To analyze the results of the tests two samples were introduced – frame statistics and trajectory statistics. These statistics describe in some sense the objective reality i.e. what the subjects see on the monitor. The chosen statistics are explained in the fourth chapter. The processing of statistics data with joined data of subjects' answers gives us some knowledge about the human motion information processing and about the change in the cognitive processes with age. The used methods and the interpretation of results are given in the fifth chapter. The summary of the paper and data analysis are included in the conclusion of the paper.

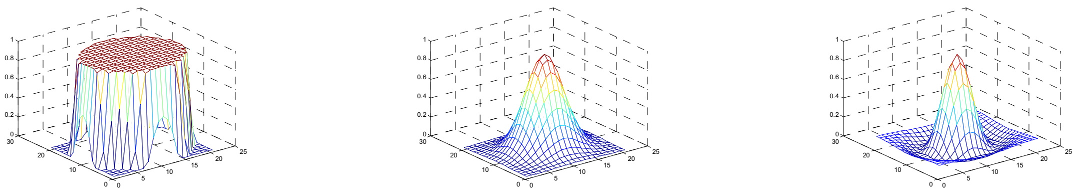
2 Experiment Description

The subject sat at a distance of 114 cm from the computer screen (21" Dell Trinitron with Nvidia Quadro 900XGL graphic board). The monitor operated in a 1280 x 1024 resolution mode. A chin-rest was used to maintain a fixed distance to the screen. The refresh rate of the monitor was 85 Hz. The observation was binocular.
The number of participants in each group is 9. The age of the younger subjects is in the interval 16-24 years, 6 of them are male. The age of older participants varies between 66 to 82 years, 4 of them are male. All participants have normal or corrected to normal vision and have passed eye examination. None of them reported having any major health problems. The younger subjects gave their responses by pressing a mouse key, while the older subjects gave an oral response and their answer was recorded by the experimenter. Each observer took part in 5000 trials, the last 500 of which were the same as the first 500. So, there are 4500 unique trials. The stimuli consisted of 25 frames movie sequences showing 48 moving elements. Elements were isotropic Laplacian-of-Gaussians with radius $r = 0.5$ deg and $\sigma = 0.125$ deg. The elements moved in a circular aperture with radius of 7.0 deg, positioned in the middle of the computer screen. The stimuli were generated and presented with the help of Psychophysics Toolbox [8], which is used for user controlled scenario visualization with strict time constraints.

Due to the complexity of the problem and its dependence on numerous factors several special measures were introduced. An initial normalization of the participants in the test is carried out aiming to reach one and the same level of correct responses in participants' answers ~ 75 per cent.

3 Scenario Generator

Stochastic generator is designed to produce easily a video stream of random moving elements with chosen stochastic characteristics. A typical task in a classification-image experiment is to discriminate between two patterns in the presence of noise. In our experiment the patterns are defined as top-down movement at a mean angle of -10^0 and $+10^0$. The stochastic generator creates a number of elements in each frame of the video flow, divided in two groups – the group of elements with restricted directions of motion and the group of stimuli with randomly generated motion directions. We will label the elements of the first group "signal" and the elements of the second – "noise". The input parameters of the generator characterize the number, type of the stimuli and stochastic characteristics of the elements:
nDots - Specifies the number of the signal elements with generated trajectories;
rDots - Specifies the number of noise trajectories generated with random directions;
DotType - Sets the visual type of the generated stimuli. Three different visualization patterns are realized – elements with equal (flat) intensity, elements with Gaussian distributed intensity and elements with complimentary to LOG distribution of intensity. They are depicted on fig. 1:



a) element with flat intensity (equal point intensity)   b) Element with Gaussian distributed intensity   c) Element with complimentary to LOG (Laplacian Of Gaussian) distribution of intensity

Fig. 1 Visualization patterns of the moving elements

dotRadius - size of the element; positive number, depending on the dot type;
Direction - the direction of translation in degrees;
Speed - the displacement of the element between two frames in pixels;
Area - Aperture size (in pixels);
FrameN - number of frames for the sequence;
Data_flag selects the variant of realization: 1 - Noise; 2 - Signal; 3 Signal + Noise.
The chosen parameters in the experiment are as follow: *DotType* is complimentary to LOG distribution of intensity; *dotRadius* is 16 pixels; *Area* is 550 pixels, *Speed* is equal to 10 pixels per a frame.
The total number of elements in a motion sequence was 48 and it remained constant for all frames and for all observers. The starting positions of the elements were uniformly distributed in the aperture. The stochastic characteristic of each element remained constant for a trial. If an element went outside the circular aperture the new one was generated at a new random position in the aperture, but with the same motion characteristics. The number of signal elements (respectively noisy complementing elements) is determined adaptively at the initial normalization step and it is unique for each participant.
The generated video frames were presented on fig. 2.

Several types of scenario uncertainty were introduced. First of all, every frame was randomly generated. Even in the case of constant parameters of the chosen distributions, the concrete realization (a frame) was unique. To preserve the opportunity to regenerate the same scenario, the initial values of the seeds of random generators were registered.
The group of the noisy elements was generated with random start positions (uniformly distributed) of each element and random direction (also uniformly distributed). The *Speed* is constant.
The group of the signal elements was generated in more complex manner. They had two different additional types of uncertainty – in direction and in velocity.

Fig. 2 A frame from generated video flow

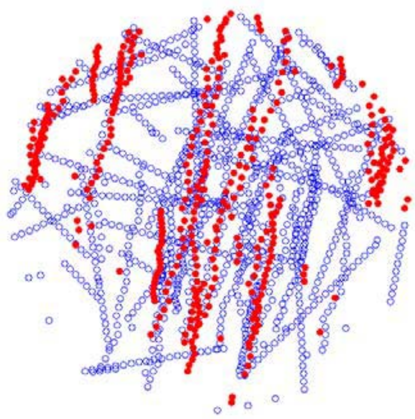


Fig. 3 The fused image of a scenario with 25 frames

The parameters of direction uncertainty were as follows:
NoiseD - the range of the noise distribution of the direction - in degrees;
NoiseDtype - noise distribution for direction with two alternatives – uniform and normal distributions and two forms of evaluation: generation for each frame or ones for the whole trial (25 frames).
The velocity uncertainty was introduced in a similar way. The mean velocity of the signal and noise elements in all trials was 6.4 ang. deg/sec.
The chosen parameters for signal stimuli in the experiment were as follow: *NoiseD* range is equal to [-30^0, $+30^0$]; *NoiseDtype* was uniformly distributed, generated for each frame; the range of velocity uncertainty was equal of [-50%, +50%] of the value of *Speed*, the value of velocity was generated uniformly in the beginning and it was constant for the test. The realized scenario consisted of signal trajectories that changed their direction from frame to frame and have unique speed.
If we have used only the noise elements, the experimental design would have been similar to the reverse-correlation methods used in physiology to describe the functional characteristics of the neurons [9]. This approach was applied also successfully by Gosselin & Schyns in psychophysical studies [10]. If we have used only the signal dots in the movie sequences for the discrimination task, our experimental design will closely resemble the study of Thomas & Knoublach [11]. They have used a temporal luminance modulation perturbed by uniform noise; the distribution of directions of the signal elements in our study was randomly perturbed on every frame due to the random generation of the directions and the relatively little number of signal elements. Our stimulation is more complex because we wanted to study not only the integration abilities of the visual system in processing motion information, but also to characterize the observer's strategies in conditions of high perceptual load.

Our experiment may be described as a discrimination task between two dynamic patterns. Under the word "dynamic" we consider stochastic realization of random process with given (constant) parameters. Every scenario includes multiple instances – 25 frames (1s video stream). On the fig. 3 the information of all 25 frames was superimposed and depicted.
Let describe the experiment mathematically. A dynamic linear process (trajectories in the experiment) can be described in the discrete Markov form:

$$s(t+1)=\Phi(t)s(t)$$

Here s is n-dimensional state vector, Φ is known system behaviour model, described by transition matrix. The equation will be reshaped to correspond to noisy stimuli as follows:

$$\begin{pmatrix} x_{t+1} \\ y_{t+1} \\ v_x \\ v_y \end{pmatrix} = \begin{pmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x_t \\ y_t \\ v_x \\ v_y \end{pmatrix},$$

where $x_{t=1}$ and $y_{t=1}$ are realizations of uniform distribution in the aperture circle; $v_{x,t=1}=Speed*cos(\Theta)$, $v_{y,t=1}=Speed*sin(\Theta)$; Θ are realizations of uniform distribution in the range [0^0, 360^0] and $\Delta t=1$. If the condition $Area<\sqrt{x_{t+1}^2+y_{t+1}^2}$ is fulfilled the trajectory restarts in a similar to the first frame way, preserving the generated angle α.
In the case of signal stimulus, the equations will be different:
$x_{t+1}=(Speed+\mu)*cos(\Theta+v_{t+1})+x_t$
$y_{t+1}=(Speed+\mu)*sin(\Theta+v_{t+1})+y_t$
Here μ is a realization of uniform distribution in the range *[0.5, 1.5]*; Θ is randomly chosen from the pair $-10^0,+10^0$; v_{t+1} is realization of uniform distribution in the range $[-30^0, +30^0]$ for the frame $t+1$.

4 Statistics

In this part we have to deal with several non-trivial problems like: 1. What kind of statistics to collect? 2. If we calculate plausible trajectories how to overcome the combinatorial problem? 3. How to analyse the collected statistics?
The perception of directed motion of elements in a stream of images is related to the discovery of close/linked elements in adjacent frames or to trajectory detection. Moreover, the observer's task is to detect multiple identical or nearly identical directed trajectories among many others chaotic ones. That is why we propose an analysis based on the trajectory detection. One estimate, which may influence observers' decisions, is the number of trajectories (or linked elements) in a scenario. We chose two types of statistics to collect. The first one consists of every pair of elements in two consecutive frames, closer than a fixed distance. Based on the physiological data about human visual system, we assume that for every couple of frames the perception is determined as an average of all directions of the paired elements. This statistic was called frame statistics, because it describes most of the elements' relations between successive frames. The boundary limits of elements' affiliation to this statistic are given on fig. 4, where α and β are corresponding minimal and maximal distance between two successive stimuli A and B.
The frame statistic is gathered in n different bins for each of $2*\pi/n$ directions. For our experiment the frame statistic is a matrix with $24*n$ size, where n is equal to 32.
The main drawback of this statistic is that it is based on a very short interval of time and ignores the temporal integration of motion information by the human visual system.
The second statistic, called trajectory statistic, tries to overcome the pointed drawback. We collected all possible trajectories with different lengths, the elements of which satisfied the limitation depicted on fig. 4. This is a very loose definition of a trajectory that may include even

elements that do not move along a straight line, or even in a strip. The occurrence of additional trajectories is depicted on fig. 5. There are two generated trajectories, every one of which consists of four elements – A1, A2, A3, A4 and B2, B3, B4, B5 (blue trajectories). Here the subscript indicates the frame number to which the element belongs. If the distances between elements Ai and Bi+1 (i = 1,...,4) satisfy the condition shown on fig. 4, the observer may perceive the red trajectories in the picture. Moreover, the rule on fig. 4 does not reject any trajectory, realized as a combination of nearby positioned elements from both trajectories like A1, B2, B3, B4,...; A1, A2, B3, B4,...; etc.
The calculation of this statistic is not an easy task due to unlimited increase in the number of trajectories in some scenario realizations. The attempt to reduce the escalating number of trajectories using additional constraint on the position of the elements (regarding that a trajectory contains only elements, located in a strip with limited width– fig. 6) was not fruitful. The number of scenarios with enormous number of trajectories was reduced insignificantly.

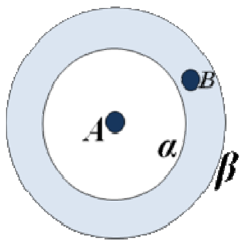


Fig. 4 Linked elements rule ($\alpha < AB < \beta$)

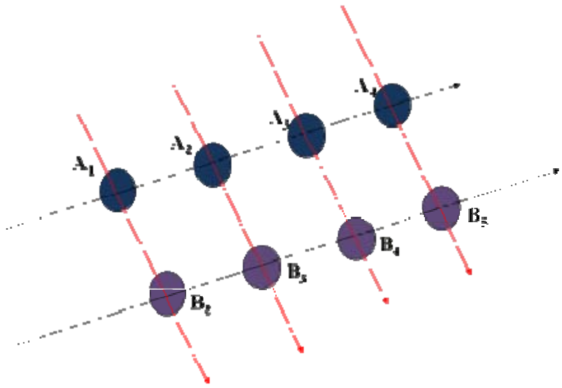


Fig. 5 Additional trajectories in the case of close trajectories

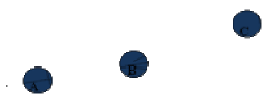


Fig. 6 Additional limitation on the stimulus

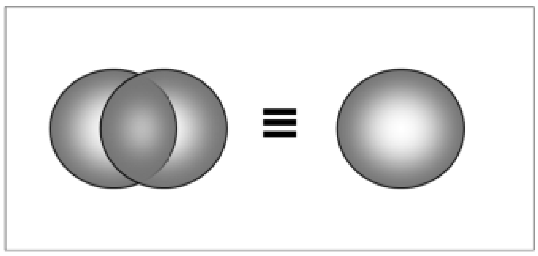
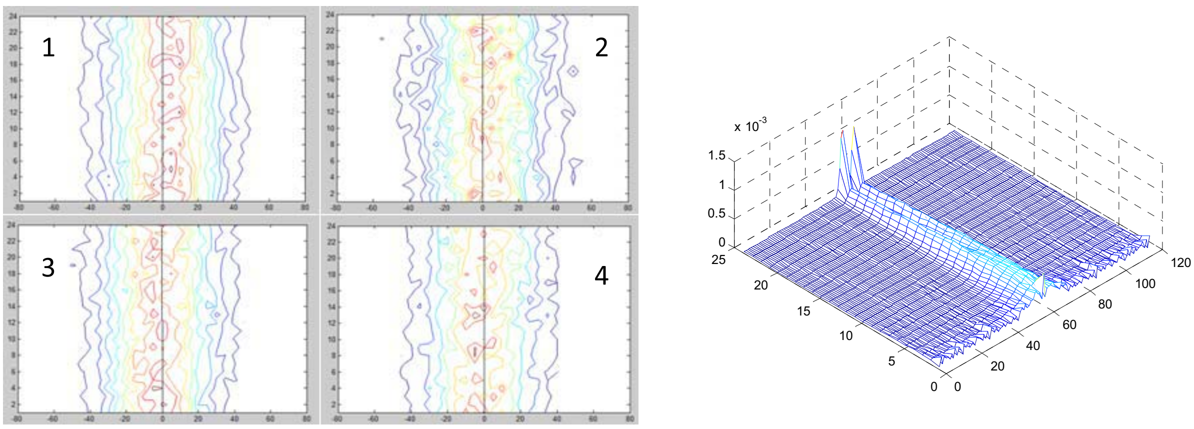


Fig. 7 The partially occluded stimulus are merged

The careful analysis of the generated trajectories shows that enormous number of trajectories occurs in the case when two randomly generated trajectories are almost collinear and very close. It was difficult to believe that the random generation of two trajectories onto one and the same place is probable, but not impossible and it happens ones or more times in the tests for almost every participant in experiments. The solution of the problem was very simple, but robust. We merged every pair/triple/... of overlapping elements in a frame and regard them as one in trajectory analysis (fig. 7). The explanation of our simplification may find additional supporting arguments due to the exposition time of a frame (40ms) and persistence of human vision. On fig. 8 the frame and trajectory statistics for one subject are shown.
To demonstrate the usefulness of the selected statistics a test was conducted. The classification image was calculated from the frame statistics, using Ahumada definitions [4]. Classification image is a linear discriminator in two hypothesis test. It is a special case of the classical

discriminant analysis [12], when stimulus pdf's are symmetric with respect to the vertical axis and the signal is corrupted by additive Gaussian noise. The classification image is calculated as linear combination of four components $\alpha_{s,r}$ for the trials segregated by the signal s (left – l or right - r) and the observer's response r (correct - c or incorrect - i). If both stimuli are equally frequent and the error rates are equal, the combination rule, originally used by Ahumada, is: $CI = \alpha_{l,i} - \alpha_{l,c} + \alpha_{r,c} - \alpha_{r,i}$.
The most power components of the resulting image are placed in the field of the signal (fig. 9) which may be regarded as a confirmation of usefulness of the selected statistic for describing the dynamics of the perceptual template applied by the subjects.



a) frame statistic – contour image (1 – right correct detection, 2 – right incorrect detection, 3 – left correct detection, 4 – left incorrect detection

b) trajectory statistic for all trials

Fig. 8 The proposed statistics

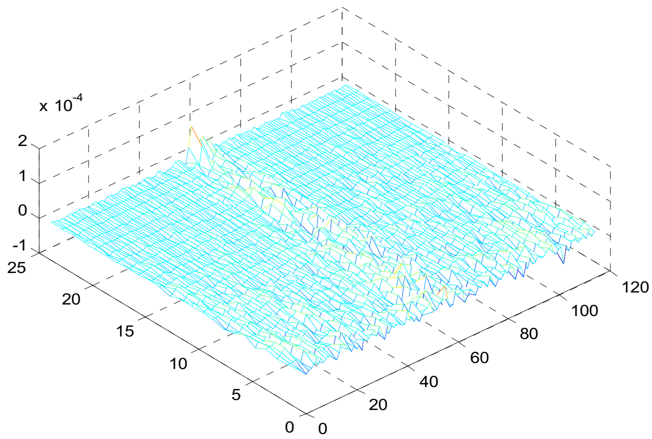


Fig. 9 Classification image (by Ahumada)

5 Data Analysis

Scenario analyzer detects any correlation between collected statistics and corresponding response of the observer. In this way we seek to answer the question what is the minimal duration of motion sufficient for the younger and older subjects to make the correct decision about the mean motion direction. Another important goal is to understand how a person integrates signals in the time window and detects motion in a specific direction based on the information gathered at the

actual locations of the stimuli. The most important part of the study is the detection of differences between members of "younger" and "older" groups.
We will examine the frame distributions of the mean direction (frame statistic - Fig. 8a) for different cases – correct left detection Fig. 8a-1, incorrect left detection Fig. 8a-2, correct right detection Fig. 8a-3, incorrect right detection Fig. 8a-4. The integrated results for one of participants are displayed on fig. 10. This picture reveals how the particular decision strategy of a tested person is changing in time.

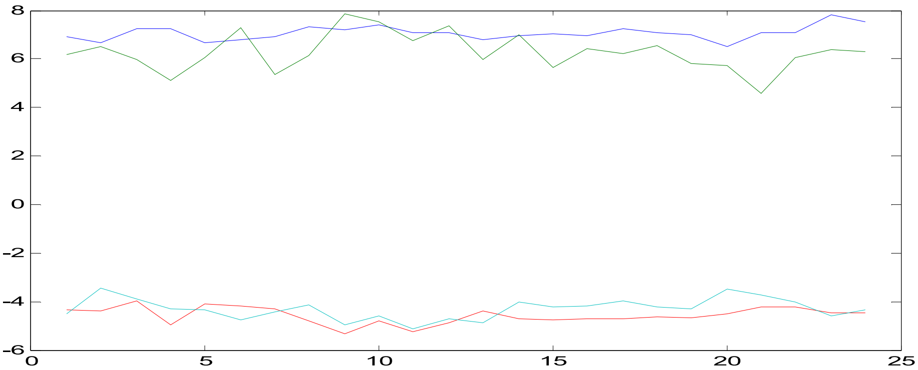


Fig. 10 Frame distributions of the mean direction (blue – correct right detection, green – incorrect right detection, red – correct left detection, cyan – incorrect left detection)

The trajectory statistic is used to assess the impact of the noise. On 3D image of this statistic a distinct area can be seen, where the distributions of the left and right trajectories are clearly distinguishable (fig. 8b). In this area, the observers have information (according trajectory statistic) to take correct decision. To determine the size of this zone it is necessary to evaluate the point (threshold) at which the unimodal distribution transforms to bimodal (fig. 11, fig. 12). For robust threshold determination a 2D Gaussian smoothing filter is applied in advance. The thresholds were evaluated for trials with participants' correct results and for trials with the incorrect ones.

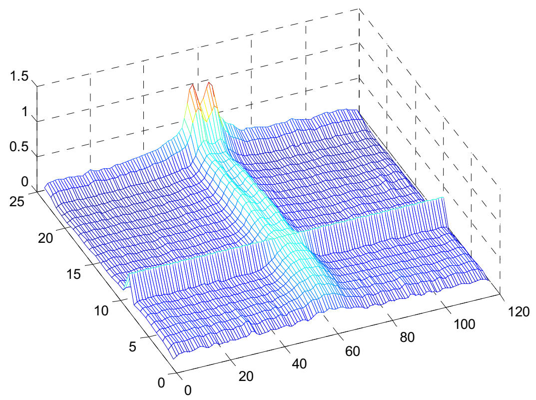


Fig. 11 Trajectory statistic – threshold detection

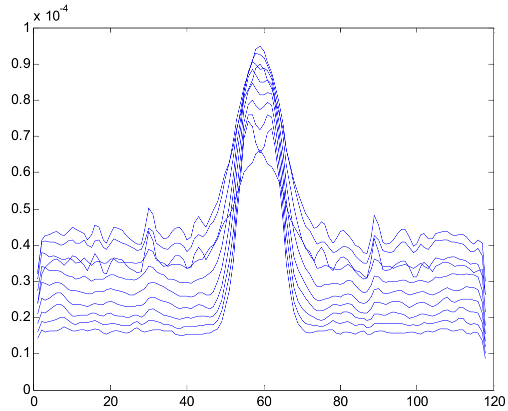


Fig. 12 Determination of the transition from unimodal distribution to bimodal

The summarized results for both groups are given in Table 1. The results show that there are objective reasons to make a wrong decision – the zone of unimodal distribution in the case of incorrect decision is always bigger than that in the case of correct decision. The two age groups have similar temporal thresholds for the correct responses; however, the older group shows greater variability among its members. The difference in the thresholds for correct and incorrect decisions for the older group is smaller (e.g. 5.6 vs. 5.7) than that for the younger group (e.g. 5.6 vs. 6.3). This could be explained by the prior normalisation of the performance for each participant. Usually the younger participants reach the level of 75 per cent correct answers with smaller number of signal elements. The smaller samples fluctuate more around ideal distribution when the number of realizations goes to infinity.

Table 1

YOUNG	CORRECT	INCORRECT	OLD	CORRECT	INCORRECT
b	7	8	**2**	7	5
c	5	5	**3**	5	5
d	5	7	**4**	5	5
emy1	5	5	**7**	5	6
epy1	5	7	**8**	5	7
imy1	6	7	**11**	8	7
k	5	6	**12**	4	4
mdy1	6	5	**13**	6	7
tpy1	6	7	**j**	5	6
mean	**5.6**	**6.3**		**5.6**	**5.7**

We chose one representative from each group with approximately the same performance in the prior normalization test ("c" from "younger" group and "7" from "older" group) and gathered statistics on the fluctuation of their responses over time. For this purpose, the total number of experiments (4500) was divided in 9 blocks of 500 trials. The results are shown in fig. 13, 14 and 15.

The threshold fluctuation shows that in almost all cases the information about the motion direction, estimated by the temporal threshold in the trajectory statistics, was more in the case of correct answers than that in the case of wrong ones (the corresponding thresholds are lower for correct answers). The outcome of this experiment is that random generated stimuli almost always help the observer to make correct decision (7 versus 2 cases).

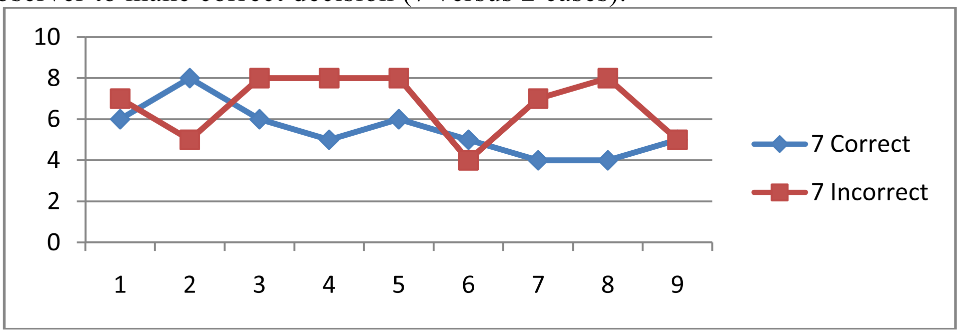


Fig. 13 Threshold fluctuation in time for participant "7"

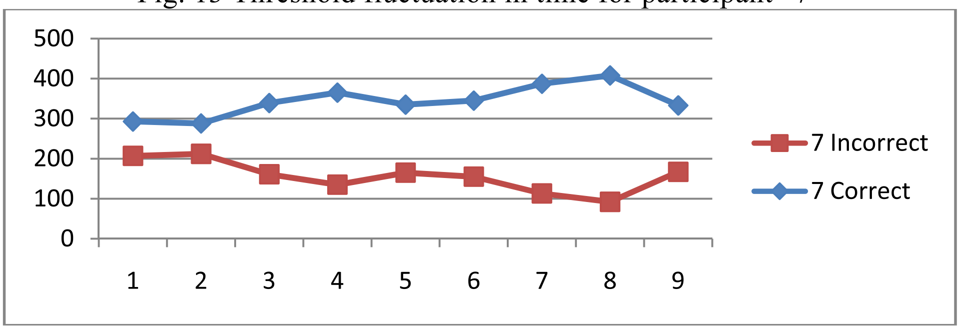


Fig. 14 Variability in the number of correct and incorrect responses in time for participant "7"

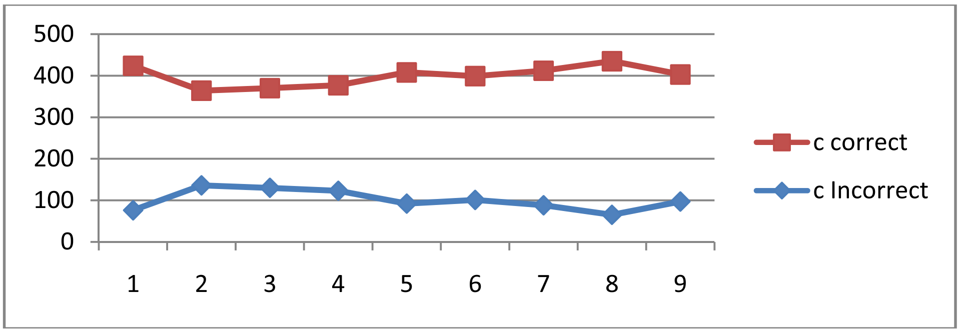


Fig. 15 Variability in the number of correct and incorrect responses in time for participant "c"

On the next two figures the variability in the number of the correct and incorrect responses in the different blocks for the same subjects- younger – fig. 14 and older – fig. 15 are displayed. The younger person has greater variability in his performance during the course of the experiment, which can be explained by a change in the decision strategy of the observer in the course of the experiment. The older subject preserves almost the same level of fluctuation in task performance. It is very interesting to compare positive trends in representatives of the both groups. First of all, the positive trend in both cases means that there exists self-learning process mostly in accommodation to the task conditions and information processing (there is no feedback about correctness of answers). The positive trend is more visible for the younger subject, which indicates his greater potential.

6 Conclusion

This paper presents a study of the age-related changes in visual information processing. The results of the study provide a good description of the trends in the cognitive processes associated with ageing in performance of perceptual tasks. This makes them a useful tool to characterize the process of ageing and to seek association between the behavioural data and the physiological changes in the brain. The analytical procedures presented in this study and the interpretation of the results reveals new information about the age-related characteristics of visual processing of motion information. Moreover, it allows detecting subjects with significant degradation of visual processing and this may serve as a signal to initiate a search for the source of degenerative processes for that person.

Many classical statistical methods were used in this study. But it should be noted that the major contribution of the work is in the suggested procedure for objective scenario estimation. The procedure consists of three major steps – trajectory detector, collecting frame and trajectory statistics and calculation of the information threshold. Trajectory detector discovers what is displayed objectively to the observers. The suggested trajectory statistic collects trajectory records from each trial. But the most important suggestion is the proposed threshold (transition point from unimodal to bimodal distribution, or a threshold segregating the statistic in two parts – the first one where the existing evidence is not enough to make a correct decision and the second where it provides enough information. This allows us to construct a good estimator to what extent the generated noise influences over observers' decision.

The psychophysical studies have the potential not only to describe human performance but also, when combined with other data, to be used as a valuable diagnostic tool to separate normal ageing from degenerative processes. For this purpose it is important to select and to test methods that allow, based on the data from psychophysical experiments, to access the individual differences of the subjects and their deviation from the age group they belong to.

In order to be used as a diagnostic tool of degenerative processes, this approach should be tested in longitudinal studies with large set of subjects and combined with other tests on the cognitive abilities.

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