Drift diffusion modeling of response time in heading estimation based on motion and form cues

Nadejda B. Bocheva, Bilyana Z. Genova, and Miroslava D. Stefanova

Abstract**—** Decision making in perceptual tasks is considered as a process of accumulation of evidence for a particular response that depends on the task difficulty, the instruction, and the non-decision processes. We performed a study on discrimination of simulated heading direction based on form and motion cues with different age groups in a task where the observers determined the time to respond. In the single-cue conditions, the stimuli were either radial Glass patterns supposed to provide information similar to motion streaks in real motion or moving radial patterns. In the combined condition the motion and form information provided consistent information about the simulated heading as the dots in the Glass patterns moved along trajectories parallel to the orientation of the dot pairs. When compared to optimal cue combination, the accuracy performance in combined condition greatly exceeded the predictions. Applying a hierarchical drift diffusion modeling on the reaction time and the observers' responses we showed that the conditions requiring temporal integration increase the time for the non-decision processing, while the information reliability changes the rate of evidence accumulation for a particular response. Moreover, age affects the amount of necessary evidence for making a decision and the non-decision time. The rate of evidence accumulation in elderly is lowered in conditions requiring spatial information integration.

Keywords**—**Cue combination, Decision making, heading, form, motion.

I. Introduction

The survival of the individual greatly depends on the ability to make context-dependent perceptual decisions in ambiguous and uncertain situations. The process of decision making has attracted a lot of interests and efforts both of theorists and experimentalists. The mathematical description of these processes relies on the idea that the observed behavior represented by the response time and performance accuracy could be decomposed in latent processes, e.g. [1]. The perceptual decision is regarded as a process of accumulation of evidence for a certain alternative and the initiation of response as soon as a decision boundary for this decision is reached. Two major classes of models exist that differ in the way they describe the process of evidence accumulation. In the race models like the Linear Ballistic Accumulator Model [2] it is assumed the process of evidence accumulation is independent for each alternative. In the drift diffusion models [3] a single process of evidence accumulation for the two alternatives is supposed and it is represented as the difference in the evidence for each of them. The accumulation of evidence is regarded as a stochastic noisy diffusion process. The quality of the sensory information affects the rate of evidence accumulation, while the instruction or personal traits like being more cautious could affect the width of the decision boundary between the two alternatives. The unequal probability of occurrence or reward as well as response biases might affect the relative position of the starting point of evidence accumulation with respect to the upper and lower decision boundaries. This implies that changing the richness of the available information will modify the rate of evidence accumulation.

Several studies have shown improvements in subjects' ability to discriminate among stimuli in the presence of multiple cues and could well be described by combining the available information in an optimal way e.g. [4], [5], [6]. If optimal, in the multi-cue conditions, the performance is based on the sum of the information available in the single-cue conditions. However, in a recent study [7] that examines cue combination of visual and vestibular information in heading perception in a task where the subjects determined the time to response no gain was observed in the multisensory condition as compared to the single cues. The authors showed that the subjects still optimally combined the available evidence but the drop in performance with regard to the predictions of optimal cue combination was due to the decrease in the response time in the combined condition. They raised the question of evidence accumulation in the process of decision making when the reliability of the information varies in time.

In the present study, we investigated the process of integration of form and motion information in heading in a task when the response is initiated by the observers in choosing between two alternatives. We used radial Glass patterns to provide form information about heading. These patterns contained pairs of dots positioned in such a way that their orientation is directed towards a common point corresponding

This work was supported by the National Science Fund - Bulgaria under Grant DN02/3/2016 "Modelling of voluntary saccadic eye movements during decision making"

Nadejda Bocheva. Author is with the Institute of Neurobiology, Bulgarian Academy of Sciences, Sofia 1113, Bulgaria (phone: +359-979-2364; e-mail: nadya@ percept.bas.bg).

Bilyana Genova Author is with the Institute of Neurobiology, Bulgarian Academy of Sciences, Sofia 1113, Bulgaria (e-mail: b.genova@abv.bg).

Miroslava Stefanova Author is with the Institute of Neurobiology, Bulgarian Academy of Sciences, Sofia 1113, Bulgaria (e-mail: mirad_st@abv.bg).

to the focus of expansion during the self-motion of the observer on a straight trajectory. The perception of structure in Glass patterns is supposed to proceed in two stages – a local one to determine the correspondence of dots in a pair and a global one to extract the global form.

Glass patterns are regarded as providing similar information as the motion streaks occurring during real motion. Reference [8] showed that neurons in area MT and MST in macaque responded in a similar way to Glass patterns and to globally coherent motion. Reference [9] showed that the local power spectrum of the Glass patterns possess anisotropy similar to the anisotropic changes in the local power spectrum of moving patterns. Several studies have demonstrated an interaction between the form information provided by the Glass patterns and motion information. For example [10] showed that when a sequence of stationary Glass patterns is presented in succession the form information preceded the motion information in discriminating concentric, radial and translation patterns. Their results suggest temporal summation of the form information in the dynamic Glass patterns that strongly influence the processing of information in the motion areas.

Reference [11] showed strong influence of the orientation of the pairs in a Glass pattern on the perceived motion direction and apparent speed with larger effects at conflict angles between the motion direction and orientation about 30°. The perceived motion direction depended on the ratio of the strength of the pattern and motion signals.

Reference [12] showed that when the form and the motion information provided by radial Glass patterns are in conflict, the perceived direction of heading determined by the focus-of-expansion of the moving pattern is shifted away and the information provided by the motion and form cues is optimally integrated. They claimed that these results imply that the form and motion cues are treated as independent sources of information for heading perception. The results were interpreted as interaction of form and motion information at both local level where the orientation of the pairs in the Glass patterns changes the perceived motion direction of the dots and at a global level where the focus-of expansion is determined as a combined estimate from its position based on the motion and form information.

In the present study we separately estimated the ability of the observers to discriminate the shift in the heading direction simulated from radial Glass patterns or from moving radial patterns and their performance in the case when the form information in the Glass patterns coincided with the information from motion in a task in which the observers determine the time to response. In addition, we used a sequence of static Glass patterns that were partially replaced during their presentation in order to separate the contribution of spatial and temporal integration. Our pilot studies indicated that the performance in the combined condition greatly exceeded the predictions of the traditional models of optimal cue combination. For this reason, we choose quite impoverished conditions for the single-cue stimuli. Using a hierarchical drift diffusion model on the accuracy and response time data we were able to separate the contribution of the stimulus manipulations on the process of decision making. In addition, we studied the effect of aging on the decision making in heading discrimination depending on the available form and motion information.

II. Methods

A. Stimuli

Four different types of stimuli were generated. All of them contained 50 dots that formed radial patterns and occupied a circular area of 13.5 cm diameter. In the static condition the dots were grouped in 25 pairs. Eighteen pairs created a radial Glass pattern with a center shifted either to the left or to the right of the pattern middle-point; the rest 7 pairs were randomly oriented. Therefore, the coherence of the Glass patterns was 72%. In the flicker condition a sequence of static radial Glass patterns of 72% coherence, similar to those in the static condition was generated. Each pair of dots in a pattern had a lifetime of 100 ms and was randomly repositioned after the end of its lifetime. However, on every frame only one-third of the dots changed position, thus no coherent flicker of the whole pattern occurred as the initial lifetime of the dots was uniformly distributed in the first three frames. In the motion condition the 36 dots (72%) moved towards a common center on straight radial trajectories, while the rest 14 dots moved in random directions. As in the flicker condition, the lifetime of the dots was 100 ms and the initial lifetimes were uniformly distributed in the first free frames so that on every frame of the stimulus presentation only one-third of the dots changed position. All dots had equal speed of 3.6 deg/s, thus for their lifetime they travelled a path of 26’ length. The combined condition resembles the flicker condition as it contains 25 pairs of dots forming radial Glass pattern with 72% coherence and with limited lifetime of 100 ms. However, unlike the flicker condition, in the combined condition during its lifetime each pair of dots moved on a trajectory parallel to the orientation of the dots in the pair with a speed of 3.6 deg/s. In all conditions, when a dot or a pair was repositioned, it preserved its identity as a signal or noise.

Example of a single frame of the stimuli from the motion condition and the static condition are shown in Fig. 1. A single frame of a stimulus from the combined or flicker condition looks like the one for the static condition.

Fig.1 Single frame from stimulus from the motion (left) or static (right) condition.

The radial Glass patterns or moving patterns simulated 7 different heading directions shifted to the left or to the right of the stimulus center. As the stimuli differed from the patterns created during self-motion on a straight path, in the sequel we will use the term “pattern center” to represent the focus of expansion of the radial patterns, though we will discuss the results with regard to heading estimation. The simulated shifts of the pattern centers were from 0.67 to 4.69 cm with a step of 0.67.

B. Procedure

The observers performed a single-stimulus two-alternative forced choice task.

Each stimulus presentation started with a warning signal and a presentation of a red fixation point of 0.8 deg at the center of the screen. After 500 ms the dot disappeared and the stimulus was presented at the middle of the screen. The task of the observers was to continue fixating and to determine whether the pattern center was shifted to the left or to the right of the screen center. When they made a choice, the observers had to make a saccade towards the perceived pattern center and to press the left or the right mouse button depending on their choice.

Each experiment started with a demonstration of the stimulus sequences.

Each experimental condition: stimulus type and shifts of the pattern center were presented to each subject 20 times. The stimuli were generated offline. Their maximal duration could be 3.3 s. In case the subject could not make a decision during this time, the stimulus disappeared and the screen remained gray until the subject made a response.

The eye movements of the participants were recorded by Jazz novo eye tracking system (Ober Consuting Sp. Z o.o.). These eye movement recordings are not analyzed and included in the present paper.

The stimuli were presented on a gray background with a mean luminance of 25 cd/m^2. The stimuli were viewed binocularly from a distance of 57 cm and were presented on the computer screen operated in refresh rate 60 Hz and resolution 1280×1024 pixels, 21” Dell Trinitron with Nvidia Quadro 900XGL graphic board.

C. Subjects

35 observers participated in the experiments classified in three age groups: 12 young (19 to 34 years, median=23 years); 11 middle aged (36 to 52 years, median=44 years); 12 old (57 to 84 years, median =72).

D. Statistical methods

All statistical analyses of the study were performed using R [13]. Generalized linear mixed linear or probit regressions were performed using lme4 package [14]. Both types of regressions involved fixed and random factors with general form of the type:

$$\boldsymbol{\eta} = \mathbf{X}\beta + \mathbf{Z}b + \delta ,$$

where $\boldsymbol{\eta}$ is linear predictor related to the mean response vector $\mathbf{y}$ through a link function , $\mathbf{X}$ and $\mathbf{Z}$ are fixed-effects and random-effects design matrices of the explanatory variables, β is the fixed-effects vector, b is the random-effects vector and δ is a model offset vector. For the mixed linear regression the link function that related the outcome variable $\mathbf{y}$ to $\boldsymbol{\eta}$ is the identity, and thus, the response variable is assumed to be normally distributed. For the mixed probit regression the link function is the inverse of the cumulative distribution function of the standard normal distribution $\boldsymbol{\eta} = \Phi^{-1}(\mathbf{y})$. The probit model assumes that random errors have a multivariate normal distribution (e.g. [15])

The package car [16] was used to analyze the interactions in the fitted models and to represent in a more compact way the significance of the main effects and interaction terms. It provides Wald’s χ2-test [17].

III. Results

A. Response time

We will consider first separately the effects of the experimental conditions on the response time and accuracy of the observers from the different age groups. Fig. 2 shows the distribution of the response times of the observers for the different stimulus types and age groups. The figure clearly shows that the older observers needed more time to make a decision about the shift of the pattern center from the screen middle-point. Moreover, the distribution of their response times is much broader that the distributions for the other age groups suggesting larger individual differences. In addition, the distributions of response times for either group or condition look normal. This observation was confirmed by Shapiro-Wilks test showing that the null hypothesis of normality could not be accepted for any of the distributions of the response time at p=.01.

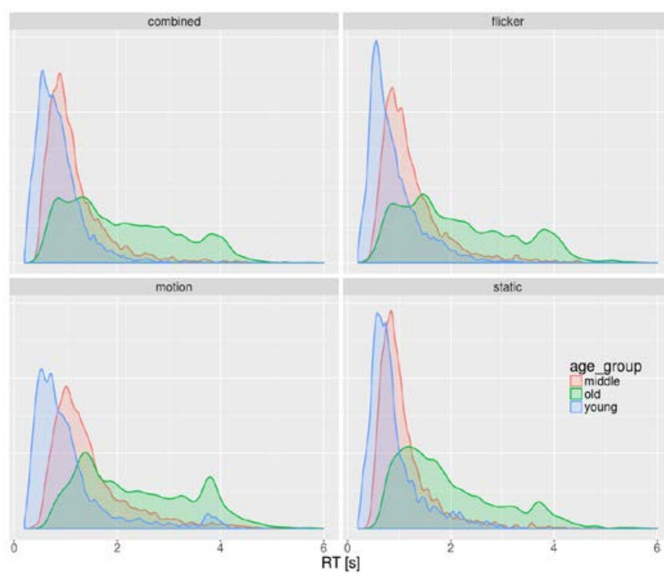

Fig. 2 Distribution of the response times for the different age groups and stimulus types

In order to compare the effect of the experimental conditions on the response time for the different age groups we applied a linear mixed model regression on the log-transformed values of the response times in an effort to reduce the effect of the violation of normality assumption. We used the absolute shift of the pattern center as a continuous predictor and the stimulus type and age group as categorical predictors. As random factors we considered uncorrelated random intercept and random slope within observers. The results of the analysis show a significant effect of the position of the pattern center on the response times (Wald's $\chi^2(1)$ =46.8; p<.01) due to the decrease in the response time with the shift of the position away from the screen center. This effect is similar for all age groups confirmed by the insignificant interaction between the shift of the pattern center and the age group (Wald's $\chi^2(2)$ = 1.76; p=.41). However, such a decrease in response time was not observed for the motion condition and is less apparent for the static condition than for the combined and flicker conditions. This difference resulted in significant interaction between the stimulus type and the shift in the pattern center (Wald's $\chi^2(3)$ = 213.43; p<.01)

The age-group significantly affected the response time (Wald's $\chi^2(2)$ =44.81; p<.01) - the response times were shortest for the younger group and longest for the elderly. The stimulus type also significantly affected the response times (Wald's $\chi^2(3)$ = 1651.17; p<.01) with longest times obtained for the motion condition and shortest - for the static condition. The difference between the stimulus conditions is greater for the middle age group and least - for the younger participants leading to a significant interaction between the age groups and the stimulus type (Wald's $\chi^2(6)$ =229.04; p<.01). This effect is illustrated in Fig. 3.

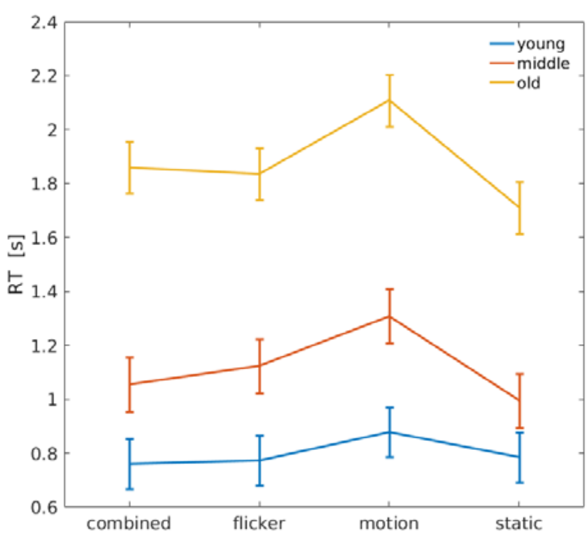

Fig.3. Averaged response times for the different age groups and stimulus types. The error bars represent the 95% confidence intervals of the estimates

B. *Performance accuracy*

We analyzed also the effect of the experimental factors on the ability of the observers to discriminate the relative shift of the pattern center. The proportion of responses "the center is shifted to the right" is presented on Fig. 4 for the three age groups and the different stimulus types. It is clear that the performance is worse in the single-cue conditions i.e. for the static and motion type. It is also evident that the young and the older observers are quite similar in their performance while the middle age group outperformed the other groups.

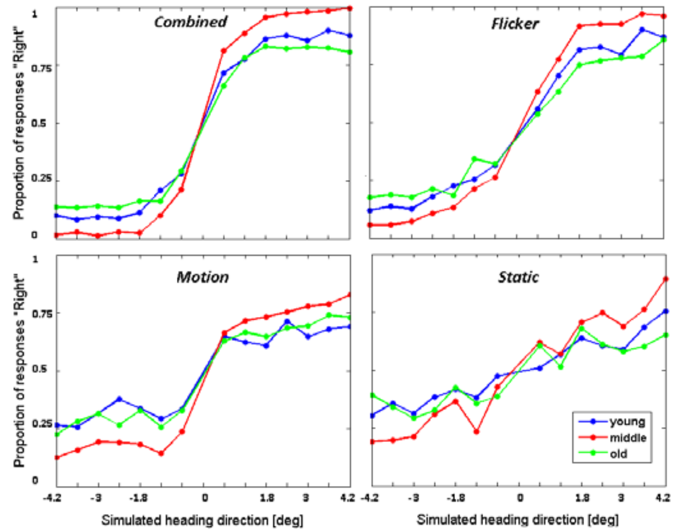

Fig. 4. The average proportion "center shifted to the right" for the three age groups in the different stimulus conditions

To evaluate the effect of the experimental factors on the performance of the observers we applied a generalized mixed effects probit regression on the subject's responses with factors - relative shift of the pattern center as a continuous predictor and the age group and stimulus type as categorical predictors. An independent random slope and intercept were assumed for the different observers. The results of the analysis show significant main effects of the shift (Wald's $\chi^2(1)$ = 138.24; p<.01) and of the stimulus type (Wald's $\chi^2(2)$ = 8.62; p<.05). There was a significant interaction between the shift and the age group (Wald's $\chi^2(2)$ =7.98; p<.05) and between the shift and the stimulus type (Wald's $\chi^2(3)$ =1683.98; p<.01) confirming the observation that the sensitivity to pattern center position varies between the age groups and stimulus types. We estimated the threshold for discriminating the position of the pattern center for the three age groups and stimulus types using the slope of the probit regression. The confidence intervals of the thresholds were estimated by using a bootstrap estimation based on 200 samples. The predicted thresholds based on optimal cue combination of the static and motion information was also obtained from the equation (1):

$$\sigma^2_{comb} = \frac{\sigma^2_{motion}\sigma^2_{static}}{\sigma^2_{motion} + \sigma^2_{static}},$$

where σ^2_{motion} and σ^2_{static} are the variances of the motion and static cues determining the discrimination thresholds.

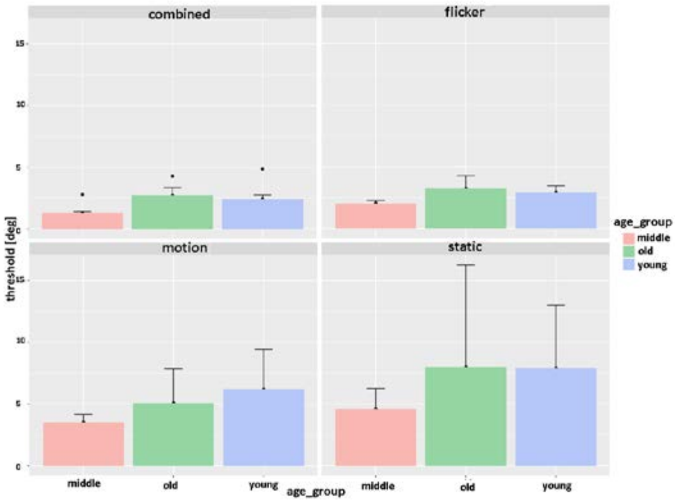

Fig.5 Estimated thresholds for discriminating the shift of the pattern center for the different stimulus types and age groups. The error-bars represent the 95% confidence intervals of the estimates. The black dots in the subplot of the combined condition represent the estimated thresholds if the static and motion cue are optimally combined

These data are presented in Fig. 5. The performance in the combined condition greatly exceeds the predicted performance based on the optimal cue combination from the single cue condition. The discrimination performance in the flicker condition is significantly improved as compared to the motion or static conditions but for all age groups it is lower than in the combined condition. Highest thresholds (lowest sensitivity) are observed for the static condition. The thresholds obtained in our study seriously exceed those obtain in other studies of heading perception for the motion condition. This can be due to the stimulus conditions used in the present study - very short motion trajectories due to the limited lifetime of the moving dots, low speed, and low number of moving dots, no speed gradient and no depth information. It is interesting to note also that the young observers as a group show lower sensitivity to differences in pattern position than the older group for the motion condition.

C. Relation between accuracy and response time

To understand better the performance of the observers we applied hierarchical drift diffusion model HDDM [18] to relate the accuracy and the response time of the subjects in the different experimental conditions. The model is based on the drift-diffusion model [19]. This type of models assumes that information supporting decisions is represented by noisy observations, and the decision-making is considered as a process of stimulus information accumulation or evidence over time.

HDDM model uses prior information about the parameters of the drift diffusion process based on the values reported in 23 existing studies of different decision-making tasks [20]. The hierarchical structure of the model allows the determination of the posterior group parameters and the individual parameters for each subject and condition from the distribution of the group estimates.

We selected a model based on the assumption that both the decision boundary and the non-decision time depend on the age group and the stimulus type and on their interaction. For the drift rate we included as predictors in the model in addition to these factors a variable that represents the change in the difficulty of the task related to the magnitude of the shift of the pattern center from the screen middle-point. We considered all the cases when the absolute value of the shift was less or equal to 2.68 deg as difficult and the rest of the cases as easy. In the modeling of the parameters of the drift diffusion model we used a within subject model with the combined condition as baseline for the stimulus type. We did not assume any bias for the starting point *z* of evidence accumulation, or any differences in it for the different age groups or stimulus types as we used accuracy-coding and there are no reasons that the observers would be more keen to give correct than incorrect answers or vice versa. We did not include any parameters related to the inter-trial variability. For the drift rate we were not able to evaluate the effect of the task difficulty due to the magnitude of the shift separately for each age group and stimulus type. We were able only to estimate the relative change in the drift rate for the hard condition (we used the easy condition as baseline) for the different stimulus types with respect to the combined condition. We specified that the outliers in the data were 5%.

The model parameters were estimated with Markov Chain Monte-Carlo (MCMC) chain of 50K with 2K burn-in to achieve chain stabilization. The visual inspection of the traces for each model parameter and each subject showed that they appeared stationary, and the autocorrelation is nearly zero. In addition, a posterior predictive analysis was performed to evaluate whether the model captures important characteristics of the data. Five hundred posterior samples were used to simulate a different data set for each parameter value and the summary statistic of the simulated and the experimental sets were compared. In all cases, the simulated values fall into the 95% credible interval.

The inclusion of different boundaries for the different stimulus types might be questionable. Our reasoning was that even though the task difficulty is expected to change the drift rate in the diffusion model, in more difficult conditions the observers might be more uncertain and would become more cautious. Indeed, our modeling results confirm the assumption that the boundary threshold will change depending on the stimulus type. Fig. 6 shows the distribution of the estimated boundary parameters for the three age groups and the different stimulus types.

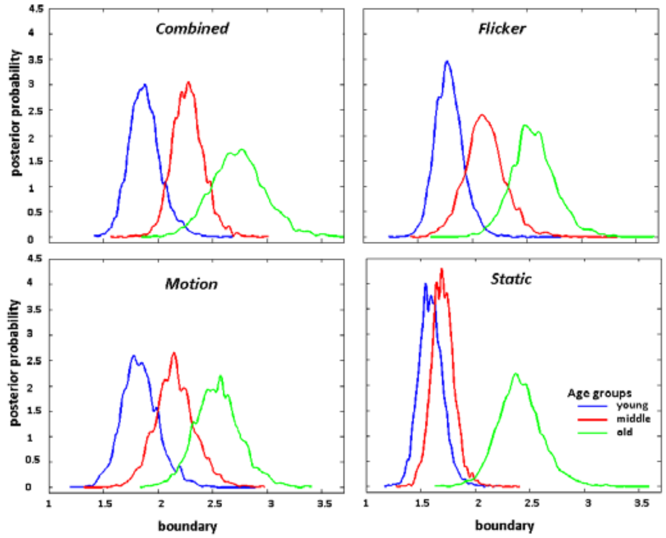

Fig. 6. The estimated distribution of the decision boundary for the three age groups and the different stimulus conditions

We estimated the probability that the boundary estimates for the different age groups and conditions differ. These comparisons can be seen in Tables 1 and 2. The results show that the elderly group needed more accumulated evidence before making a decision that is reflected in significantly larger values for the decision threshold boundary as compared to the young and middle group. The stimulus type affected predominantly the threshold boundary for the middle-aged group. However, contrary to our expectation that the threshold boundary will depend on the task difficulty, the major difference in the thresholds is due to the shrinkage of the boundary for this group in the static condition as compared to the other conditions. This may reflect the fact that only in this condition the available information does not change with time.

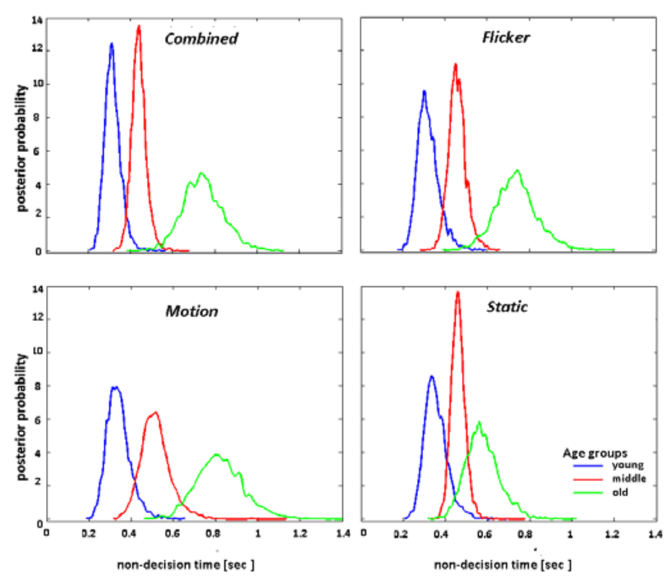

Fig. 7. The distribution of the non-decision time in the HDDM model for the three age groups and stimulus condition.

Fig. 7 shows the differences in the non-decision time associated with stimulus encoding and motor response preparation for the different age groups and conditions. As could be seen from the figure and Tables 1 and 2, the younger observers in all conditions needed less non-decision time and only in the static condition the probability of having longer time than the middle group is low, implying that they differ insignificantly. It should be noted that the results for the three age groups differ less in the static condition. The non-decision time differs only for the elderly observers with a probability of 96% that the non-decision time in the motion condition exceeds the non-decision time in the static condition.

Table1. The probability of differences between the estimated parameters of the HDDM model for the different stimulus type and age groups. The stimulus types are coded as m for motion, s – for static, f – for flicker and c – for combined condition. The age groups are coded as Y – for young, M – for middle, and O – for old

	Decision boundary			Non-decision time			Drift rate		
	Y	M	O	Y	M	O	Y	M	O
m>f	.58	.55	.48	.59	.78	.72	.003**	.004**	.03*
m>s	.90	.98*	.69	.42	.78	.96*	.44	.40	.71
m>c	.42	.30	.27	.63	.85	.71	.000***	.001***	.01*
f>c	.31	.25	.28	.52	.64	.49	.14	.04*	.27
f>s	.88	.98*	.71	.31	.48	.90	.998**	.998**	.98**
c>s	.95*	.998**	.85	.27	.32	.91	1.0***	1.0***	.99**

Table 2. The probability of differences between the parameters of the HDDM model between the age groups for the different stimulus types. The stimulus types are coded as M for motion, S – for static, F – for flicker and C – for combined condition. The age groups are coded as Y – for young, M – for middle, and O – for old

	Decision boundary			Non-decision time			Drift rate		
	Y>M	Y>O	M>O	Y>M	Y>O	M>O	Y>M	Y>O	M>O
M	.10	.007**	0.8	.02*	.0***	.001**	.26	.86	.97*
S	.22	.0002***	.002**	.06	.01*	.08	.20	.96*	.997**
F	.07	.002**	0.6	.02*	.0002***	.003**	.56	.98*	.98*
C	.03*	.002**	0.46*	.01*	.0***	.001**	.41	.99*	.994**

For the drift rate we were able to evaluate the effect of stimulus type and the age group and their interaction only for the easy condition, while the effect of the task difficulty was estimated with respect to the combined easy condition for each age group and relative to the combined condition for the different stimulus types irrespective of the age group. The distributions of the drift rates for the different age groups and stimulus type are shown in Fig. 8 for the easy condition.

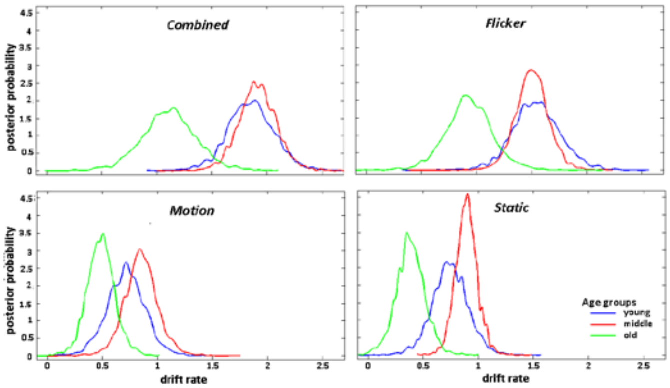

Fig. 8. The distribution of the values for the drift rate in the easy condition for the three age groups and stimulus types

Tables 1 and 2 and the figure show that drift rate of evidence accumulation is higher for the middle group as compared to the elderly, while the probability that the drift rate for the younger group is higher than the middle group is relatively low. An interesting result is that the probability of higher drift rate of the younger observers in comparison to the older group is less than 90% for the motion condition. The results also show that the accumulation of evidence in the two single-cur conditions – motion and static do not differ. In the flicker condition the drift rate for the younger and older observers is similar to that in the combined condition while for the middle group there is a probability of 96% that the drift rate is higher in the combined than in the flicker condition.

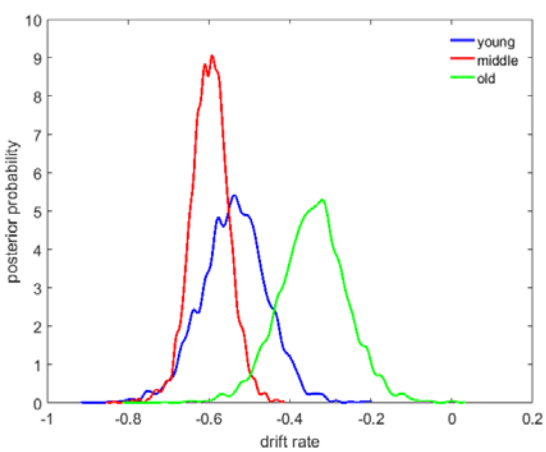

Fig.9. The changes in the drift rate for the three age groups for the difficult condition

The mean change in the drift rate for the three age groups for the hard condition was -.54 ±0.06, -.60±0.08 and -.34±0.08 for the young, middle and old group (Fig. 9) suggesting that the task difficulty reduces the drift rate and this reduction is lesser for the older group. The probability that these values are different significantly exceeds 95% only when the values are compared with the older group suggesting significantly less effect of the task difficulty for this age group.

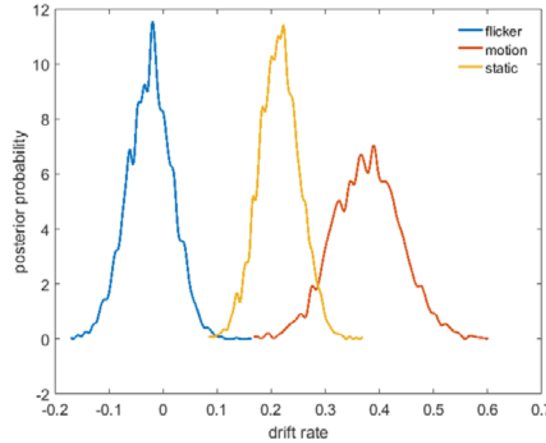

Fig.10. The changes in the drift rate for the motion, static and flicker conditions with respect to the combined condition for the hard task difficulty

The results (Fig. 10) also suggest that the task difficulty has similar effect for the flicker condition as compared to the combined condition and significantly larger effect for the static and motion condition. However, the effect is positive implying that in comparison to the flicker and combined condition the shift of the pattern center away from the midpoint does not reduce the drift rate with the change in the task difficulty.

IV. Discussion

The results of the presents study show that in comparison to the single-cue conditions – motion or static simulating heading, the discrimination of the pattern center greatly improves when the two cues provide consistent information. Shortest response times and lowest sensitivity were observed for the static condition. There are several reasons for this: the distance between the dots in a pair was very large (2°) and exceeds the receptive field size of the neurons in V1 where the local spatial integration is supposed to take place [21]. The density of the dots is also low and this may affect both the local and the global level of spatial integration. It could create spurious pairings. In addition, the observers have tighter decision boundary for this condition.

The motion condition is also impoverished with respect to natural conditions for heading. The trajectory of the individual dots is too short, no depth information is provided, the density of the dots is not high and no speed gradient is present. While at [22] showed that the presence of speed gradient does not provide a strong cue for localizing the center of motion of the patterns, in [23] provided evidence that the amount of depth variation and number of texture elements in the scene, the location and amount of the visual field stimulated, and the position of the focus of expansion within the stimulus are important factors in heading determination from optic flow. In our impoverished conditions the position of the pattern center had little effect on the response time and could not be considered as a factor changing the task difficulty.

Our data show that the sequential presentation of static Glass patterns that partially overlap on every frame significantly improves the ability of the observers to judge to location of the pattern center. While the random repositioning of the dots induced apparent motion in random directions and might be expected to introduce significant noise, its effect seems to be cancelled which suggest temporal integration of the spatial information. The possibility of temporal integration in dynamic Glass patterns of different type has been emphasized in [10]. They have shown that the form information in the dynamic Glass patterns is temporally summated over ten frames and the performance improvement may be a result of the presences of multiple signals. In a similar vein, [24] showed that temporal integration improves heading estimation. In their study three types of noise were added to an optic flow stimuli: noise, uncorrelated in space and time as each dot path was randomly shifted in space and time on every frame; temporally correlated noise where the trajectory of motion of each dot was shifted by a random amount but remained the same during stimulus presentation and perturbation of the position of the heading diraction randomly on the successive frames that would prevent noise reduction by spatial integration. Their results suggest greater decrease in the performance when spatial integration is ineffective in noise reduction. In addition, their findings suggest that the temporal integration occurred for a limited time – up to about 200 ms.

Our data for the combined condition contradict the predictions of optimal cue combination as performance is significantly better than expected. This result also differs from the findings at [7] that the performance in multisensory condition worsens when the observers determine the moment of making choice. Even though the response time in our study in the combined condition is less than for the motion condition, the observers performed much better than in the single-cue conditions or as predicted by optimal cue combination of the motion and static cues. Their modeling of the drift rate in multisensory combination when subjects determined the response moment also predicts different drift rates than the ones we obtained from the HDDM (1.234, .614, and 1.026 for the middle, old and young observers based on the model of [7] and 1.911, 1.110, and 1.855 – from HDDM modeling).

One possibility to explain the excessive performance in the combined condition is to assume that the two cues are highly correlated even though [12] claim that form and motion could be regarded as independent cues in heading estimation from moving Glass patterns. In [27] the conditions when the performance could exceed the prediction of optimal cue combination were considered. Their analysis shows that this could happened when the correlation ρ of the two cues is positive and $\rho > \frac{2\sqrt{r_1 r_2}}{(r1 + r2)}$, where r_1 and r_2 are the reliabilities determined as the reciprocal of cue variance for the two cues. This case would imply negative weight for one of the cues and such a case has not but observed experimentally. A negative weight could be expected when the correlation is greater than either $\sqrt{\frac{r_1}{r_2}}$ or $\sqrt{\frac{r_2}{r_1}}$. In our study the reliability of the motion and the static cue are very similar which would suggest that the correlation should exceed or be very close to 1.

The static condition differs from the rest of conditions used in our study in one important aspect – the information about the pattern center is fixed in the static condition, while the other tasks are of the type expanded judgement tasks [25] in which a new representation of stimulus elements in the sequence must be integrated with the memory representation of the preceding stimulus representation. As discussed in [25], little is known about the dependence of the memory process on the complexity of the stimulus elements, the time needed for it and how it might take place, the weight given to the recent information. It is unclear whether the variability of the internal noise in the cognitive representation of the stimulus is equivalent to the variability in the sequence of stimulus elements. It seems likely that the variability introduced in the decision process is higher in the expanded judgement tasks. In this case, the drift rate would be expected to be lower as compared to the static case. However, our results contradict this expectation as in the combined and the flicker case the drift rate for all age groups is significantly higher than in the static condition. Another possibility is that the dynamic noise introduced by the sequential stimulus presentation delays the time at which evidence accumulation begins [26]. This would delay the leading edge of the response time distribution. Indeed, such a trend in visible in Fig. 2 for the motion as compared to the static condition, but not for the flicker and combined condition.

The single cue conditions – static and motion provided very impoverished information about the heading direction. It is possible that the perceptual stimuli in these conditions provide equal evidence for the two alternative choices in most trials. Apparently, in our experimental conditions for the flicker and combined stimuli, the sequential presentation of the stimuli speed-up the process of decision-making. Thus, instead of increasing the variability of the accumulated evidence, a more appropriate explanation of our findings is the assumption that the reliability of the evidence improved with time due to spatial or temporal integration. The temporal integration could be considered as increasing the number of samples providing evidence for the position of the pattern center.

A final point is related to the process of perceptual decision making and ageing. Several studies, including our own work [28] showed that certain aspects of motion integration processing deteriorate with aging. In addition, spatial and temporal processing also decline with age [29, 30].The results of the present study suggest that the elderly could compensate some of these deficiencies by using greater amount of evidence for making a choice and longer non-decision times. In this way they could achieve a performance that resembles the performance of the younger observers. However, the larger decision boundary could not explain the equivalent drift rate of evidence accumulation in the easy condition for the older and the younger observers. This does not seem to be due to the slower speed of motion as our previous study [28] showed greater differences in noise tolerance between younger and older observers at the slower speed when the noise added to the stimuli was spatially and temporally uncorrelated. The similarity in the drift rate might be due to a mechanism of determining heading direction that is not based on wide-field radial structure of the local motion directions. As shown in [31], the localization of the center of motion in a radial optic flow pattern is not necessarily based on precise computation of radial motion direction, but could be estimated by circular template mechanism that minimizes a global motion error relative to the visual motion input.

The results of the present study suggest that the elderly observers might have difficulties integrating the information in space as they were unable to benefit from the relative shift of the pattern center in the periphery that would allow easier discrimination of the left and right positions. In addition, both the non-decision time and the drift rate for the elderly group differ significantly from the younger one in the static condition.

References

[1] M. Stone, “Models for choice reaction time”, *Psychometrika*, vol. 25, pp. 251-260, 1960.

[2] S.D. Brown, A., Heathcote, “The simplest complete model of choice response time: linear ballistic accumulation”, *Cogn Psychol*., vol. 57(3), pp. 153-178, 2008 .

[3] R. Ratcliff , “ A diffusion model account of response time and accuracy in a brightness discrimination task: Fitting real data and failing to fit fake but plausible data”, *Psychonomic Bulletin & Review*, vol. 9, pp. 278–291, 2002.

[4] D. C. Knill, J. A. Saunders, “Do humans optimally integrate stereo and texture information for judgments of surface slant?” *Vision Res*, vol. 43, pp. 2539–2558, 2003

[5] M. O. Ernst, M. S. Banks. “Humans integrate visual and haptic information in a statistically optimal fashion”. *Nature*, vol. 415, pp. 429–433, 2002

[6] J. M. Hillis, S. J. Watt, M.S. Landy, M.S. Banks, “Slant from texture and disparity cues: Optimal cue combination”. *Journal of Vision*, vol. 4, pp. 967–992, 2004.

[7] J. Drugowitsch, G. C. DeAngelis, E.M. Klier, D. E. Angelaki , A. Pouget, “ Optimal multisensory decision-making in a reaction-time task”, Elife. Jun 14;3. doi: 10.7554/eLife.03005, 2014.

[8] B. Krekelberg, S. Dannenberg, K. P. Hoffmann, F.,Bremmer, J. Ross, “Neural correlates of implied motion”. *Nature*, vol. 424, pp. 674–677, 2003

[9] H. Barlow, B. Olshausen, “Convergent evidence for the visual analysis of optic flow through anisotropic attenuation of high spatial frequencies”, *J Vis*, vol. 4(6), pp. 415-426, 2004

[10] J-F Nankoo, C. R. Madan, M.L.Spetch,D. R. Wylie,” Perception of dynamic Glass patterns”, *Vision Res*., vol. 72,pp. 55-62, Nov. 2012.

[11] J Ross, “The perceived direction and speed of global motion in Glass pattern sequences”, *Vision Res*., vol. 44 (5), pp, 441-448, 2004

[12] D.C. Niehorster, J.C.K. Cheng, L. Li ,“Optimal combination of form and motion cues in human heading perception”, *J. Vision*, vol. 10, no. 11, pp.20-20, Sep. 2010.

[13] R Core Team. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL http://www.R-project.org/, 2014

[14] D. Bates, M. Maechler, B. Bolker, St. Walker. “Fitting linear mixed-effects models msing lme4”. *Journal of Statistical Software*, 67(1), 1-48. doi:10.18637/jss.v067.i01, 2015

[15] M. Razzaghi. “The probit link function in generalized linear models for data mining applications”. *Journal of Modern Applied Statistical Methods*,vol. 12, no. 1, pp. 164-169, 2013.

[16] J. Fox, S. Weisberg.”An {R} Companion to Applied Regression”, Second Edition. Thousand Oaks CA: Sage. URL: http://socserv.socsci.mcmaster.ca/jfox/Books/Companion, 2011

[17] A. Agresti. Categorical Data Analysis. Wiley, New York, NY, 2002

[18] T.V. Wiecki, I. Sofer, M.J. Frank, “HDDM: Hierarchical Bayesian estimation of the Drift-Diffusion Model in Python”. *Front. Neuroinform*, vol.7, pp.1–10, Aug.2013,doi:10.3389/fninf.2013.00014.

[19] R. Ratcliff, J.N. Rouder, “Modeling response times for two-choice decisions”,*Psychol. Science*, vol. 9, pp.347–356, 1998.

[20] D. Matzke, E.-J. Wagenmakers,”Psychological interpretation of the ex–Gaussian and shifted Wald parameters: a diffusion model analysis”, *Psychon. Bull. Rev.* vol. 16, pp.798–817, 2009.

[21] M. A. Smith, W. Bair, J. A. Movshon, “Signals in macaque striate cortical neurons that support the perception of glass patterns”, *J Neurosci*., vol. 22(18), pp. 8334-8345, 2002.

[22] S.A. Beardsley, L.M. Vaina, “Psychophysical evidence for a radial motion bias in complex motion discrimination”, *Vision Res.* vol. 45, no.12, pp.569–1586, 2005.

[23] J.A. Crowell, M.S. Banks, “Ideal observer for heading judgments”, *Vision Res.*, vol. 36, pp.471–490, 1996.

[24] E.M. Sikoglu, F.J. Calabro, S.A. Beardsley, L.M. Vaina, “Integration mechanisms for heading perception”. *Seeing and Perceiving*. vol.23(3), pp. 197-221. doi: 10.1163/187847510X503605, 2010

[25] R. Ratcliff, Ph. Smith, S. Brown, G. MacKoon. “Diffusion decision model: Current issues and history”. *Trends in Cognitive Science*, vol. 20, no. 4, pp. 260-281, 2016

[26] R. Ratcliff, Ph. Smith. “Perceptual discrimination in static and dynamic noise: The temporal relation between perceptual encoding and decision-making”. *J Exp Psychol Gen*., vol. 139, no. 1, pp/ 70–94. doi: 10.1037/a0018128, 2010

[27] I. Oruc, L. T. Maloney, M.S. Landy,” Weighted linear cue combination with with possibly correlated error”, *Vis. Res.*, vol.43, pp.2451-2468, 2003.

[28] N. Bocheva, D. Angelova, M. Stefanova, “Age-related changes in fine motion direction discriminations “, *Experimental Brain Research*, vol. 228, no.3, pp. 257-278, 2012.

[29] E. Roudaia, P. J. Bennett, A.B. Sekuler, K.S. Pilz, “Spatiotemporal properties of apparent motion perception and aging“. *J Vision*, vol. 10 (14), pp. 1–15, doi:10.1167/10.14.5, 2010

[30] K. S., Pilz., M. Kunchulia, K. Parkosadz, M. H. Herzog, “Ageing and visual spatiotemporal processing.“, *Experimental Brain Research*, vol. 233 (8), pp. 2441–2448, doi:10.1007/s00221-015-4314-9, 2015

[31] S. A. Beardsley, L. M. Vaina, “How Can a Patient Blind to Radial Motion Discriminate Shifts in the Center-of-Motion? “J Comput Neurosci, vol. 18, pp 55–66, 2005

First A. Author (M’76–SM’81–F’87) and the other authors may include biographies at the end of regular papers. Biographies are often not included in conference-related papers. This author became a Member (M) of **INASE** in 1976, a Senior Member (SM) in 1981, and a Fellow (F) in 1987. The first paragraph may contain a place and/or date of birth (list place, then date). Next, the author’s educational background is listed. The degrees should be listed with type of degree in what field, which institution, city, state or country, and year degree was earned. The author’s major field of study should be lower-cased.

The second paragraph uses the pronoun of the person (he or she) and not the author’s last name. It lists military and work experience, including summer and fellowship jobs. Job titles are capitalized. The current job must have a location; previous positions may be listed without one. Information concerning previous publications may be included. Try not to list more than three books or published articles. The format for listing publishers of a book within the biography is: title of book (city, state: publisher name, year) similar to a reference. Current and previous research interests ends the paragraph.

The third paragraph begins with the author’s title and last name (e.g., Dr. Smith, Prof. Jones, Mr. Kajor, Ms. Hunter). List any memberships in professional societies other than the **INASE**. Finally, list any awards and work for **INASE** committees and publications. If a photograph is provided, the biography will be indented around it. The photograph is placed at the top left of the biography. Personal hobbies will be deleted from the biography.