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

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***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

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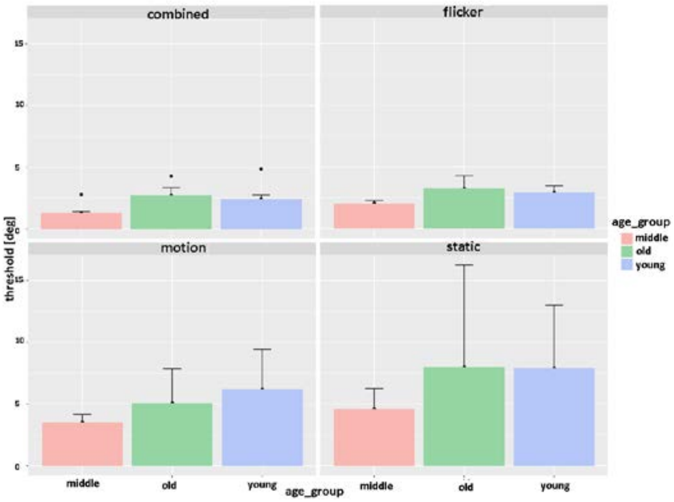

Fig.5 Estimated thresholds for discriminating the shift of the pattern center for the different stimulus types and age groups. The error-bars represent the 95% confidence intervals of the estimates. The black dots in the subplot of the combined condition represent the estimated thresholds if the static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

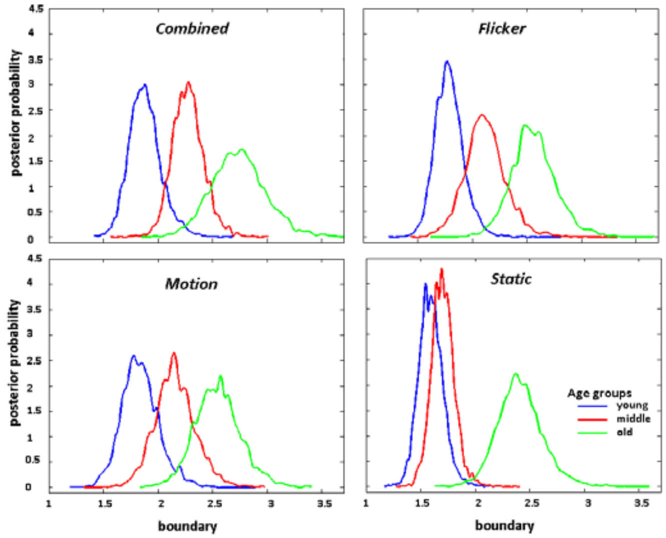

Fig. 6. The estimated distribution of the decision boundary for the three age groups and the different stimulus conditions

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.

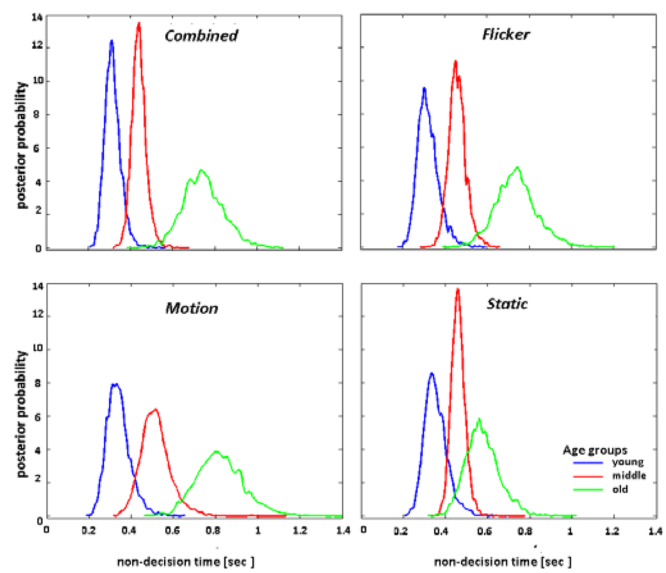

Fig. 7. The distribution of the non-decision time in the HDDM model for the three age groups and stimulus condition.

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.

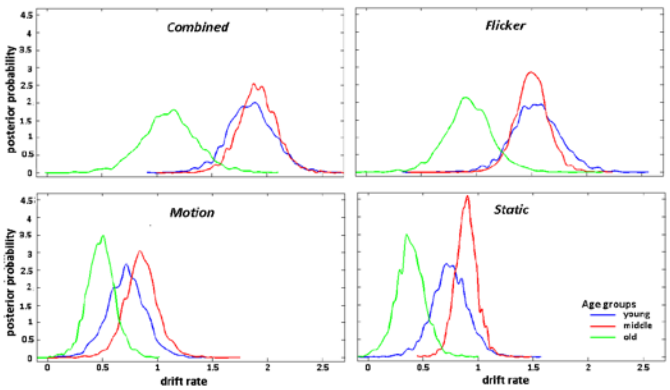

Fig. 8. The distribution of the values for the drift rate in the easy condition for the three age groups and stimulus types

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.

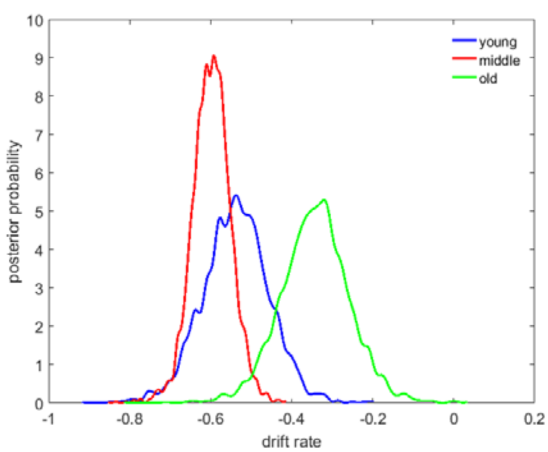

Fig.9. The changes in the drift rate for the three age groups for the difficult condition

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.

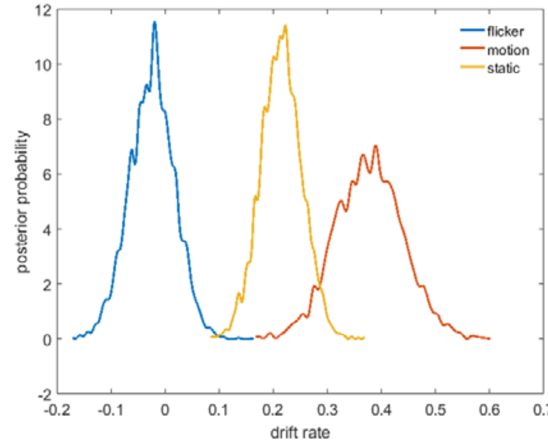

Fig.10. The changes in the drift rate for the motion, static and flicker conditions with respect to the combined condition for the hard task difficulty

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.

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