Age-related slowing in detection and visual discrimination under varying presentation times

CARMEN MORET-TATAY,[1] LENIN-GUILLERMO LEMUS-ZU N~IGA,[2] DIANA ABAD TORTOSA,[3] DANIEL GAMERMANN,[4] ANDREA VA ZQUEZ-MART INEZ,[5] ESPERANZA NAVARRO-PARDO[6] and J. ALBERTO CONEJERO[7]

[1]Universidad Cat olica de Valencia, San Vicente M artir, Spain [2]Instituto Universitario de Tecnolog ıas de la Informaci on y Comunicaciones, Universitat Polit ecnica de Val encia, Spain [3]Facultad de Psicolog ıa, Universitat de Val encia, Spain [4]Instituto de F ısica, Universidade Federal do Rio Grande do Sul, Brazil [5]Sede Guayaquil Departamento Comunicaci on Social, Universidad Polit ecnica Salesiana, Ecuador [6]Universitat de Val encia, Spain [7]Instituto Universitario de Matem atica Pura y Aplicada, Universitat Polit ecnica de Val encia, Spain

Abstract

The reaction time has been described as a measure of perception, decision making, and other cognitive processes. The aim of this work is to examine age-related changes in executive functions in terms of demand load under demand varying presentation times. Two tasks were carried out where a signal detection and a discrimination task were performed by young and older university students. Furthermore, a characterization of the response time distribution by an ex-Gaussian fit was carried out. The results indicated that the older participants were slower than the younger ones in signal recognition and discrimination. Moreover, the differences between both processes for the older participants were higher, and they also showed a higher distribution average except for the lower and higher presentation time. The results suggest a general slowdown in both tasks for age under different presentation times, except for the cases were presentation times were lower and higher. Moreover, if these parameters are understood as a reflection of executive functions, these findings are consistent with the common view that age-related cognitive deficits present a decline in this function.

Keywords: signal detection, discrimination, age-related differences, distribution components

Human beings process information almost instantly. One of the most studied ways to do that is through the visual system. In particular, this process is characterized by its complexity, where its processing speed is closely related to the execution of other superior cognitive processes, and in particular, with the ageing process. In this way, a slowing in visual processing speed has been described for decades (Owsley, 2011), as well as some effects on the quality of vision (Nguyen-Tri et al., 2003, Shahidi and Yang, 2004). Many factors have been described as responsible for vision changes in the elderly (Betts, Sekuler, A. B., & Bennett, 2007; Herbert et al., 2002, Sekuler et al., 2000). However, this is a subject of interest as the studies suggest that the slowed visual processing is not inevitable, or in other words, homogeneous in the older adults. Furthermore, on an applied level, this issue is fundamental in daily life, where we have to interact quickly and effectively with our environment.

Most of the research works in this field employed response times (RTs) and percentage of errors or successes as a dependent variable. However, in the literature (Thorpe, Fize, & Marlot, 1996) it has been pointed out that measuring this processing in terms of RTs presents several difficulties, because this variable also includes response execution. Furthermore, the role of variability should be taken into account (Myerson, Robertson, Hale, 2007) as well as the role of perception, decision, and motor response stages that have been highlighted in this measure in the literature (Luce, 1986). The RT usually has been described as a sensitivity measure for some cognitive process (Moret-Tatay, et al., 2014). Not surprisingly, the RT has turned into a common dependent variable in most cognitive assessment tests. However, beyond the aforementioned theoretical concepts, the RTs usually present positively skewed data distribution that obstructs data analysis. One option is to perform a distributional analysis of the data. In the case of positively skewed data, an appealing possibility for this distribution is the ex-Gaussian distribution function (Balota, & Yap, 2011; Lacouture, & Cousineau, 2008; Luce, 1986; MorenoCid et al., 2015; Moret-Tatay et al., 2014; Ratcliff and Murdock, 1976). Furthermore, this option can be a useful tool when dealing with high variability in the data. The effects of age on a task and how RTs are affected, is the subject of much discussion in the literature. Many authors have shown that RT distributions of older students have longer distribution tails than the younger students (Fozard, Thomas, & Waugh, 1976; Smith, Poon, Hale, & Myerson, 1988).

The Ex-Gaussian characterization can be described through three parameters: μ, σ and τ. Here it is important to remember that, i) The average of the ex-Gaussian distribution in terms of its components' parameters is $M = \mu + \tau$ and its variance is $S^2 = \sigma^2 + \tau^2$, ii) Do not confuse the τ parameter as a skewness measure. In the second point, the ratio of τ / σ has been proposed. This ratio will follow the same tendency as the ex-gaussian skewness ($\gamma_1 = 2\tau^3 / S^3$). It has been described as a perceptual portion of an RT (Hohle, 1965) a decision component (Luce, 1986) and more recently, related to attentional factors, a defective effort control mechanism or attentional lapses (Gu, Gau, Tzang, & Hsu, 2013; Moreno-Cid et al., 2015; Moret-Tatay et al., 2014; Moret-Tatay et al., 2016). In particular, Leth-Steensen, Elbaz, & Douglas (2000) did find main differences in the τ parameter, not in σ or μ, while comparing ADHD children to their age-matched control counterparts. However, most researchers have been cautious in the interpretation of parameters (see, Sternberg, & Backus, 2015). The ageing concept has also been studied for word recognition under this alternative procedure (McAuley, Yap, Christ, & White, 2006; Spieler, Balota, & Faust, 1996). Taking this into account, it has also been suggested that the μ and τ parameters were higher for the older adults than the younger adults (Madden, Gottlob, Denny, Turkington, Provenzale, Hawk, & Coleman, 1999). The authors in this field concluded that the older group requires more attentional demands. However, a study of simulation (Matzke, & Wagenmakers, 2009) argued that the relationship of the ex-Gaussian distribution parameters to specific cognitive processes was not precisely straightforward. This study also suggests that it is not possible to separate general slowdown processes from decision making processses. Further research in this area is necessary.

As mentioned before, the speed of cognitive processing is essential to understand developmental changes. The literature has shown evidence with regards to how cognitive processing speed declines with age. Some previous research suggests that cognitive speed changes from childhood to adolescence (Luna, Garver, Urban, Lazar, & Sweeney, 2004), it reaches its peak speed in adulthood and declines in the later stages of life (Lima, Hale, S., & Myerson, 1991). Moreover, a mathematical model was proposed (Cerella, & Hale, 1994), regarding changes in the speed of information processing into a U-shaped function across life span. A large body of theories and models regarding this subject have been proposed in cognitive science (Schaie, & Willis, 2010). Two of the most widespread models are the processing speed theory (Salthouse, 1996) and the executive theory (West, 1996) that state a general slowing of processing speed is a major contributor to age-related decline. The first one stipulates that speed processing is critical for age but it is not an exclusive variable. This theory highlights two main statements: relevant cognitive operations are too slow and this may interfere in the processing simultaneous information. On the other hand, the executive theory involves higher-order functions of control and coordination of more basic or fundamental cognitive operations that are sensitive to age, assuming a qualitative change with age (in contrast to the quantitative speed difference cied before). In other words, a specific cognitive process is more affected than another or a different strategy is applied. For this reason, a distinction between these accounts is proposed by correcting for the quantitative slowing effect by a transformation into z-scores (Faust, Balota, Spieler, & Ferraro, 1999). The logic underneath is that a significant age and task interaction after correction for the generalized slowing would point to an age-specific change over and above the decline in speed. Moreover, the authors stipulated that this type of analysis offers an appropriate control over Type I errors for Group per Condition interactions over a wider range of condition.

Finally, an according to McCabe, Roediger, McDaniel, Balota, & Hambrick (2010), all the different approaches have a point in common: individual differences in attentional processing. In addition, other research works have (Ratcliff, Thapar, Gómez, & McKoon, 2004; Ratcliff, Thapar, & McKoon, 2001; Ratcliff, Thapar, & McKoon, 2006; Ratcliff, Thapar, & McKoon, 2010) emphasized the role of conservative strategies in the seniors. Furthermore, this tradeoff was supported by studies carried out on the brain. Following also this line of rasoning with regards to parameters in terms of its interpretation to executive funtions, one might expect an increase of them for age group as well as difficulty of the task (e.g., the demand load or the characteristics of the stimuli, as different presentation times) Therefore, the first objective would be to examine the role of age-related changes in executive functions in terms of demand load. Secondly, the role of presentation times would be evaluated on participant's performance. In this way, the strategy proposed in this work is to assess differences between perception or motor response stages and discrimination tasks in RT through an analysis of ex-Gaussian components.

Method

Participants

The two experiments were carried out in two age groups. Firstly, a sample of 30 university students in a doctoral programme, who all took part voluntarily (15 women and 15 men with an average age of 29.93 years and SD=4.25). While in the second group, a sample of 30 senior students at a university program took part voluntarily (22 women and 8 men with an average age of 69.32 years and SD=3.86). It was not necessary to assess specifically the cognitive performance of older participants as it was a required condition for participation in the program of the Senior University. Two participants from the senior sample were eliminated due to an error rate higher than 40%. All the participants had normal vision or corrected to the normal, were native Spanish speakers and did not report cognitive nor neurological disorders.

Materials

For both experiments (as it is shown in figure 1), when the trial experiment started, a fixation point appeared in the center of the screen (250 ms). In experiment one, a black square was shown at different presentation times (250, 1000, 1500, 2000 and 2500 ms), with each stimulus being randomly presented. Participants were encouraged to press the M button as soon as the stimulus was shown on the screen. A total of 120 stimuli were randomly shown. The logic underneath is identical as the one stipulated in classical studies (Poner and Boier, 1971): a detection task has little uncertainty about when the response-related signal will occur, rather than the colour matching task. Thus, in experiment two, a red or a blue square were shown at different presentation times (250, 1000, 1500, 2000 and 2500 ms), as in experiment one, being randomly presented. The participants were instructed to press an M button to indicate whether the stimulus was red, and press another button (the Z button) if the stimulus was blue. A total of 240 stimuli were randomly presented: 120 blue squares and 120 red squares.

--INSERT FIGURE I AROUND HERE--

Procedure

Participants were tested in a quiet, dimly illuminated room. They were organized in groups of three or four people. The presentation of stimuli and the recording of RTs were controlled by a Windows operating system through the DMDX software (Forster, & Forster, 2003). The participants were also instructed to respond as quickly as possible while maintaining a reasonable level of accuracy for both experiments. The session lasted approximately 40 minutes. The whole session consisted of two experimental tasks: a go-no go detection task and a yes-no matching task. The stimuli for both experiments were presented as counterbalanced blocks as in the previous literature (Moret-Tatay, & Perea, 2011). Participants (old and young groups) were divided into two groups. The first group started with experiment one and the following experiment was number two. The second groups did it the other way round.

Design and data analysis

Type of stimuli (black, red and blue) was manipulated as within group variables, Group (Old and Young) was included as between-subject factor in the ANOVA. The statistical package used was the Statistical Package for the Social Sciences (SPSS) version 20.
In the ANOVA for latency analyses, a trimming technique was carried out: the RTs less than 250 and higher than 1500 ms were excluded (less than the 6% of the data set) as well as error trials. This cut-off point was adopted for consistency with earlier studies (Moret-Tatay, & Perea, 2011; Perea, Moret-Tatay, & Carreiras, 2011; Perea, MoretTatay, & Panadero, 2011). Here it is important to bear in mind that the percentage trimmed was similar for both groups. The classical analysis of variance (ANOVA) was conducted on the basis of homogeneity of variance (Levene test over 0.05) and was performed using a mixed design 2 (Group) X 3 (Type of stimuli) X 5 (Presentation times). Bonferroni pairwise post-hoc analysis and z-score transformation were carried out.

Results

The statistical analysis was performed using the SPSS statistical software version 20. In the ANOVA for latency analyses, the RTs less than 250 to 1500 ms were excluded (less than the 6% of the data set) as well as error trials. This cut-off point was adopted for consistency with earlier studies (Moret-Tatay, & Perea, 2011; Perea, Moret-Tatay, & Carreiras, 2011; Perea, Moret-Tatay, & Panadero, 2011). Bear in mind that the percentage trimmed was similar for both groups.The classical analysis of variance (ANOVA) was conducted on the basis of homogeneity of variance (Levene test over 0.05) and was performed using a repeated measures 2 (Group) X 3 (Type of stimuli) for repeated measures. Table 1 presents the average reaction times (ms), error rates and standard deviation for each group and condition.

Each data set was fitted to an ex-gaussian distribution. The fits were performed with the maximum likelihood method: assuming that each reaction time in a data set comes from this distribution, one calculates the parameters μ, σ, and τ that will maximize the probability of obtaining the observed RTs. To perform the fits a Python Script was written that uses the ExGUtils library (Gamermann, 2013). All numerical calculations were done in python and C languages. In order to evaluate uncertainties in the parameters, the bootstrap method was used (Felsenstein, 1985). The method comprises the following steps: from each dataset a new set with the same size is constructed by sampling with replacement. To each new set the fit is performed. This was repeated 500 times and the average and standard deviation from these fits are the values in table 3. The standard deviation is used as uncertainty in each parameter.

Results

The older participants were slower than the younger participants in all categories, both signal detection (the detection of black stimuli) and discrimination task (the discrimination of red and rejection of blue stimuli). As expected, RT were shorter for the detection task (M =322.04 ms) than the discrimination (M =511.53 ms) and rejection task (M =523.82 ms). The ANOVA on these different tasks reached statistical significance: $F_{(2, 116)} = 476.10$; MSE =11214.22; $p < 0.001$;η^2 =.89. As mentioned before, the older participants showed longer RTs than the younger ones in the detection task (M =355.1 vs M =288.99 ms), as well as in the discrimination (M=563.08 vs M =459.99 ms) and rejection task (M =577.73 vs M =469.91 ms). More precisely, there was an interaction between age group and task: $F(2, 116) = 13.52$; MSE =2909.49; $p < 0.001$; $\eta^2 = .19$. On the other hand, the differences for RT on different presentation times (250, 1000, 1500, 2000 and 2500 ms) were generally higher for the shorther presentations (see table 1) and these were statistically significant: $F_{(4,232)} = 7.06$; MSE =5373.41; $p < 0.001$; $\eta^2 = .11$. No intereactions were found across age ($p > 0.05$). However, after a transformation of RT into z-scores, an interaction between type of task and age was found: $F_{(2, 116)} = 4.09$; MSE =1.36; $p < 0.05$; $\eta^2 = .06$. Bonferroni pairwise comparisons indicated that differences on the RTs for the task (detection, discrimination and rejection) and different presentation times (250, 1000, 1500, 2000 and 2500 ms) reached statistical significance across age (all $p < 0.05$). Figure 2 depicts the z-score districution in terms of group and presentation times.

Finally, the participants were more accurate in the detection task (M =99 %) than the discrimination (M =96.6 %) and rejection task (M =96.4 %). These differences only reached the statistical significance for task (detection, discrimination and rejection of the stimuli): $F_{(2, 116)} = 95.66$; MSE =.02; $p < 0.05$). Bonferroni pairwise comparisons did not indicate differences across age groups ($p < 0.05$).

--INSERT TABLE I AROUND HERE—

--INSERT FIGURE II AROUND HERE—

Secondly, we proceeded to characterize the RTs by an ex-Gaussian fit. As mentioned before, we fitted the ex-gaussian distribution by the maximum likelihood method and obtained the uncertainties in these values by bootstraping. Table 2 and 3 show the different parameters obtained by the fitting procedure and their uncertainties and figure III shows the graphical representation of the histograms together with its fit, for each condition. When we want to fit an ex-Gaussian distribution, we have to find the optimal values for the parameters μ, τ and σ that better describe the experimental data. Assessing the goodness of a fit requires specifying the residual variance (χ^2 /degrees of freedom). Smaller values are preferable and they show a better fit.

--INSERT TABLE 2 AND 3 AROUND HERE—

--INSERT FIGURE III AROUND HERE—

If we focus on the uncertainties (errors) from table 3, we could compare the parameters for the different conditions, regarding the uncertainties as a confidence interval length for each parameter. For this, we proceeded with the standard z-test[1] . In table 2 and 3 one can see the results for the comparison of parameters in groups. As expected, in the case of task, both young and older participants showed shorter parameters for the detection than the discrimination task. Moreover, young people also presented lower parameters than the older group, expect for some cases with regards σ and the shortest and longest presentation times for τ.

Conclusions

As expected, the older participants were slower than the younger ones, as can be concluded from the distribution components. The main conclusions can be summarized as follows: i) The young participants showed shorter reaction times for signal detection and discrimination task ii) Differences between signal detection and discrimination task were higher for the older participants than the younger iii) In terms of parameters, the older participants showed a higher distribution average and a higher τ parameter, except for the lowest and highest presentation time.

Discussion

The difference between the signal detection and the discrimination task was higher for the older participants, both in terms of classical RT, and parameters. This supports the processing speed theory (Salthouse, 1996) where speed processing is critical for processing information over the cascade of processing stages involved. In this way, if the previous stages take longer, the following stages might be decreased too. Precisely, the latencies between both processes were higher than in the younger participants. On the other hand, several authors (Lemus-Zúñiga, Navarro-Pardo, Moret-Tatay, & Pocinho, 2015; Myerson, Hale, Wagstaff, Poon, & Smith, 1990; Moret-Tatay, et al., 2014; Navarro-Pardo, Navarro-Prados, Gamermann, & Moret-Tatay, 2013) argued whether the older participants showed more variability because of lapses of attention. The results suggest that older participants are not only slower in the early stages of signal recognition and in discrimination: the latencies between both processes were higher than in the younger participants. Given these results, we can conclude that both processes were slower, producing an overall delay in comparison with younger subjects, as conceived by some cognitive theories. Focusing on the τ parameter, it is possible to conclude that older participants might display a poorer attentional or executive performance. Furthermore, after varying the presentation times, also differences were found across task and ageing, suggesting a different pattern across age. This suggests that the attentional alert system might also slow down with age. Moreover, the lack of differences on the τ parameter in the lowest and higest presentation times for the matching task illustrate the importance of considering, not only the type of load involved in the task performed, it also the level of other interferences, such as times presentations. As stipulated in the literature even with other techniques, the perceptual has an imperant role in this field (Reingold, Charness, Pomplun, & Stampe, 2001). In this way, future lines of research should address this issue in order to examine any problem on encoding due to perceptual slowing (which is less of a problem with other longer presentation times), as well as the load of interference for the longer time exposures across age.

On the other hand, several authors (Ratcliff, Thapar, Gómez, & McKoon, 2004; Ratcliff, Thapar, & McKoon, 2001; Ratcliff, Thapar, & McKoon, 2006; Ratcliff, Thapar, & McKoon, 2010; Ratcliff & Murdock, 1976; Schmiedek, Oberauer, Wilhelm, Süß, & Wittmann, 2007) have pointed out that the cognitive slowing with age might be more frequently due to changes in strategy. Moreover, these changes in strategy were supported by evidence regarding structural limitations in brain connectivity (Forstmann, Tittgemeyer,Wagenmakers, Derrfuss, Imperati, & Brown, 2011). These changes in strategy might explain not only a shift in the RT, but also the differences between samples in terms of parameters. However, as noted by Matzke and Wagenmakers in 2009, in this kind of analysis we focus on general slowdown, more than strategies. A distinction between these accounts has been addressed though a transformation into zscores. In the present study, the interaction in the results (age x task) after correction for the generalized slowing suggests an age-specific change over and above the decline in speed. Finally, we would like to hightlight that decomposing response times into ex-Gaussian parameters has been shown to be a more sensitive approach. As Faust, Balota, Spieler, & Ferraro (1999) pointed out, this might represent the cognitive arquitecture. However, this variable also presents some problems, such as its positively skewed distribution. According to Gu, Gau, Tzang, & Hsu (2013), the ex-Gaussian distribution model not only might be a solution to this problem, it also provides important clinical meaning for attention lapses. Even if caution is advised in this interpretation after studies of shape invariance (Sternberg, & Backus, 2015), we would like to enphaseize its benefits as a complement measure of variability.

Footnote [1] : We evaluate the statistical $z=abs(p_1-p_2)/\sigma$, where p_1 and p_2 are the parameter we want to compare for two different groups and σ is the combined variance (uncertainties, $\sigma^2 = S_{12}+ S_{12}$) in the parameters. With this, we can evaluate the p-value as the probability that the observed difference in the parameters is less or equal to the expected difference due to statistical fluctuations, assuming that both parameters come from the same population. The p-value is then, two times the right tail left by a gaussian distribution with average 0 and variance σ^2.

References

Balota, D. A., & Yap, M. J. (2011). Moving beyond the mean in studies of mental chronometry the power of response time distributional analyses. *Current Directions in Psychological Science*, *20*(3), 160-166.

Betts, L. R., Sekuler, A. B., & Bennett, P. J. (2007). The effects of aging on orientation discrimination. *Vision research, 47*(13), 1769-1780.

Cerella, J., & Hale, S. (1994). The rise and fall in information-processing rates over the life span. *Acta psychologica*, *86*(2), 109-197.

Forster, K. I., & Forster, J. C. (2003). DMDX: A Windows display program with millisecond accuracy. *Behavior Research Methods, Instruments, & Computers*, *35*(1), 116-124.

Forstmann, B. U., Tittgemeyer, M., Wagenmakers, E. J., Derrfuss, J., Imperati, D., & Brown, S. (2011). The speed-accuracy tradeoff in the elderly brain: a structural model-based approach| NOVA. The University of Newcastle's Digital Repository.

Fozard, J. L., Thomas, J. C., & Waugh, N. C. (1976). Effects of age and frequency of stimulus repetitions on two-choice reaction time. *Journal of Gerontology*, *31*(5), 556-563.

Gu, S. L. H., Gau, S. S. F., Tzang, S. W., & Hsu, W. Y. (2013). The ex-Gaussian distribution of reaction times in adolescents with attention-deficit/hyperactivity disorder. *Research in developmental disabilities*, *34*(11), 3709-3719.

Herbert, A. M., Overbury, O., Singh, J., & Faubert, J. (2002). Aging and bilateral symmetry detection. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences, 57*(3), P241-P245.

Hohle, R. H. (1965). Inferred components of reaction times as functions of foreperiod duration. *Journal of experimental psychology*, *69*(4), 382.

Lacouture, Y., & Cousineau, D. (2008). How to use MATLAB to fit the ex-Gaussian and other probability functions to a distribution of response times. *Tutorials in Quantitative Methods for Psychology*, *4*(1), 35-45.

Lemus-Zúñiga, L. G., Navarro-Pardo, E., Moret-Tatay, C., & Pocinho, R. (2015). Serious games for elderly continuous monitoring. *Data Mining in Clinical Medicine*, 259-267.

Leth-Steensen, C., Elbaz, Z. K., & Douglas, V. I. (2000). Mean response times, variability, and skew in the responding of ADHD children: a response time distributional approach. *Acta psychologica*, *104*(2), 167-190.

Lima, S. D., Hale, S., & Myerson, J. (1991). How general is general slowing? Evidence from the lexical domain. *Psychology and aging*, *6*(3), 416.

Luce, R. D. (1986). *Response times* (No. 8). Oxford University Press.

Luna, B., Garver, K. E., Urban, T. A., Lazar, N. A., & Sweeney, J. A. (2004). Maturation of cognitive processes from late childhood to adulthood. *Child development*, *75*(5), 1357-1372.

Madden, D. J., Gottlob, L. R., Denny, L. L., Turkington, T. G., Provenzale, J. M., Hawk, T. C., & Coleman, R. E. (1999). Aging and recognition memory:

Changes in regional cerebral blood flow associated with components of reaction time distributions. *Journal of Cognitive Neuroscience*, *11*(5), 511-520.

Marquardt, D. W. (1963). An algorithm for least-squares estimation of nonlinear parameters. *Journal of the society for Industrial and Applied Mathematics*, *11*(2), 431-441.

Matzke, D., & Wagenmakers, E. J. (2009). Psychological interpretation of the ex-Gaussian and shifted Wald parameters: A diffusion model analysis. *Psychonomic bulletin & review*, *16*(5), 798-817.

McAuley, T., Yap, M., Christ, S. E., & White, D. A. (2006). Revisiting inhibitory control across the life span: Insights from the ex-Gaussian distribution. *Developmental neuropsychology*, *29*(3), 447-458.

McCabe, D. P., Roediger III, H. L., McDaniel, M. A., Balota, D. A., & Hambrick, D. Z. (2010). The relationship between working memory capacity and executive functioning: evidence for a common executive attention construct. *Neuropsychology*, *24*(2), 222.

Myerson, J., Hale, S., Wagstaff, D., Poon, L. W., & Smith, G. A. (1990). The information-loss model: a mathematical theory of age-related cognitive slowing. *Psychological review*, *97*(4), 475.

Myerson, J., Robertson, S., & Hale, S. (2007). Aging and intraindividual variability in performance: Analyses of response time distributions. *Journal of the experimental analysis of behavior*, *88*(3), 319-337.

Moreno-Cid, A., Moret-Tatay, C., Irigaray, T. Q., Argimon, I. I., Murphy, M., Szczerbinski, M., ... & Fernández, P. (2015). The Role of Age and Emotional Valence in Word Recognition: An Ex-Gaussian Analysis. *Studia Psychologica*, *57*(2), 83.

Moret-Tatay, C., Leth-Steensen, C., Irigaray, T. Q., Argimon, I., Gamermann, D., Abad-Tortosa, D., ... & de Córdoba Castellá, P. F. (2016). The Effect of Corrective Feedback on Performance in Basic Cognitive Tasks: An Analysis of RT Components. *Psychologica Belgica*, *56*(4).

Moret-Tatay, C., Moreno-Cid, A., Argimon, I. I. D. L., Quarti Irigaray, T., Szczerbinski, M., Murphy, M., ... & Fernández de Córdoba Castellá, P. (2014). The effects of age and emotional valence on recognition memory: An ex-Gaussian components analysis. *Scandinavian journal of psychology*, *55*(5), 420-426.

Moret-Tatay, C., Navarro-Pardo, E., Fernández-Muñoz, J. J., Vázquez-Martínez, A., Vázquez-Molina, J., & Civera-Mollá, C. (2015). The role of feedback on learning: Evidence through ex-Gaussian components. *Procedia-Social and Behavioral Sciences*, *191*, 2578-2581.

Navarro-Pardo, E., Navarro-Prados, A. B., Gamermann, D., & Moret-Tatay, C. (2013). Differences between young and old university students on a lexical decision task: evidence through an ex-Gaussian approach. *The Journal of general psychology*, *140*(4), 251-268.

Moret-Tatay, C., & Perea, M. (2011). Do serifs provide an advantage in the recognition of written words? *Journal of Cognitive Psychology*, *23*(5), 619-624.

Moret-Tatay, C., & Perea, M. (2011). Is the go/no-go lexical decision task preferable to the yes/no task with developing readers? *Journal of experimental child psychology*, *110*(1), 125-132.

Nguyen-Tri, D., Overbury, O., & Faubert, J. (2003). The role of lenticular senescence in age-related color vision changes. *Investigative ophthalmology & visual science*, *44*(8), 3698-3704.

Owsley, C. (2011). Aging and vision. *Vision research*, *51*(13), 1610-1622.

Perea, M., Moret-Tatay, C., & Carreiras, M. (2011). Facilitation versus inhibition in the masked priming same–different matching task. *The Quarterly Journal of Experimental Psychology*, *64*(10), 2065-2079.

Perea, M., Moret-Tatay, C., & Gómez, P. (2011). The effects of interletter spacing in visual-word recognition. *Acta Psychologica*, *137*(3), 345-351.

Perea, M., Moret-Tatay, C., & Panadero, V. (2011). Suppression of mirror generalization for reversible letters: Evidence from masked priming. *Journal of Memory and Language*, *65*(3), 237-246.

Posner, M. I., & Boies, S. J. (1971). Components of attention. *Psychological review, 78*(5), 391.

Ratcliff, R., Thapar, A., Gomez, P., & McKoon, G. (2004). A diffusion model analysis of the effects of aging in the lexical-decision task. *Psychology and aging*, *19*(2), 278.

Ratcliff, R., Thapar, A., & McKoon, G. (2001). The effects of aging on reaction time in a signal detection task. *Psychology and aging*, *16*(2), 323.

Ratcliff, R., Thapar, A., & McKoon, G. (2006). Aging and individual differences in rapid two-choice decisions. *Psychonomic Bulletin & Review*, *13*(4), 626-635.

Ratcliff, R., Thapar, A., & McKoon, G. (2010). Individual differences, aging, and IQ in two-choice tasks. *Cognitive psychology*, *60*(3), 127-157.

Ratcliff, R., & Murdock, B. B. (1976). Retrieval processes in recognition memory. *Psychological Review*, *83*(3), 190.

Salthouse, T. A. (1996). The processing-speed theory of adult age differences in cognition. *Psychological review*, *103*(3), 403.

Schaie, K. W., & Willis, S. L. (Eds.). (2010). *Handbook of the Psychology of Aging*. Academic Press.

Schmiedek, F., Oberauer, K., Wilhelm, O., Süß, H. M., & Wittmann, W. W. (2007). Individual differences in components of reaction time distributions and their relations to working memory and intelligence. *Journal of Experimental Psychology: General*, *136*(3), 414.

Sekuler, B., Patrick J. Bennett, Mortimer Mamelak, A. (2000). Effects of aging on the useful field of view. *Experimental aging research*, *26*(2), 103-120.

Shahidi, M., & Yang, Y. (2004). Measurements of ocular aberrations and light scatter in healthy subjects. *Optometry & Vision Science*, *81*(11), 853-857.

Smith, G. A., Poon, L. W., Hale, S., & Myerson, J. (1988). A regular relationship between old and young adults' latencies on their best, average and worst trials. *Australian Journal of Psychology*, *40*(2), 195-210.

Spieler, D. H., Balota, D. A., & Faust, M. E. (1996). Stroop performance in healthy younger and older adults and in individuals with dementia of the Alzheimer's type. *Journal of Experimental Psychology: Human Perception and Performance*, *22*(2), 461.

Sternberg, S., & Backus, B. T. (2015). Sequential processes and the shapes of reaction time distributions. *Psychological review*, *122*(4), 830.

Thorpe, S., Fize, D., & Marlot, C. (1996). Speed of processing in the human visual system. *Nature*, *381*(6582), 520-522.

West, R. L. (1996). An application of prefrontal cortex function theory to cognitive aging. *Psychological bulletin*, *120*(2), 272.

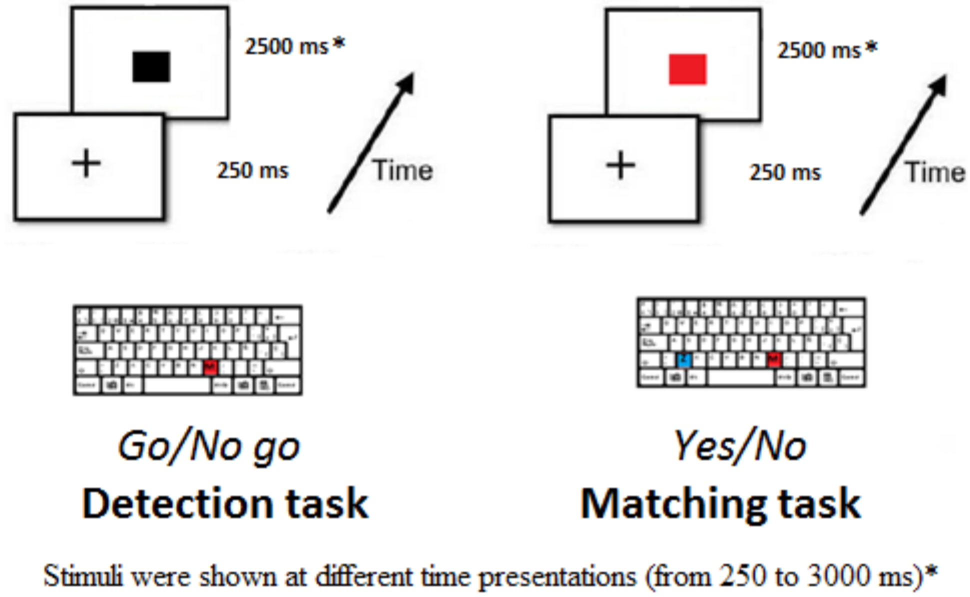

Figure I. Task displays and trial structure for the detection and matching task.

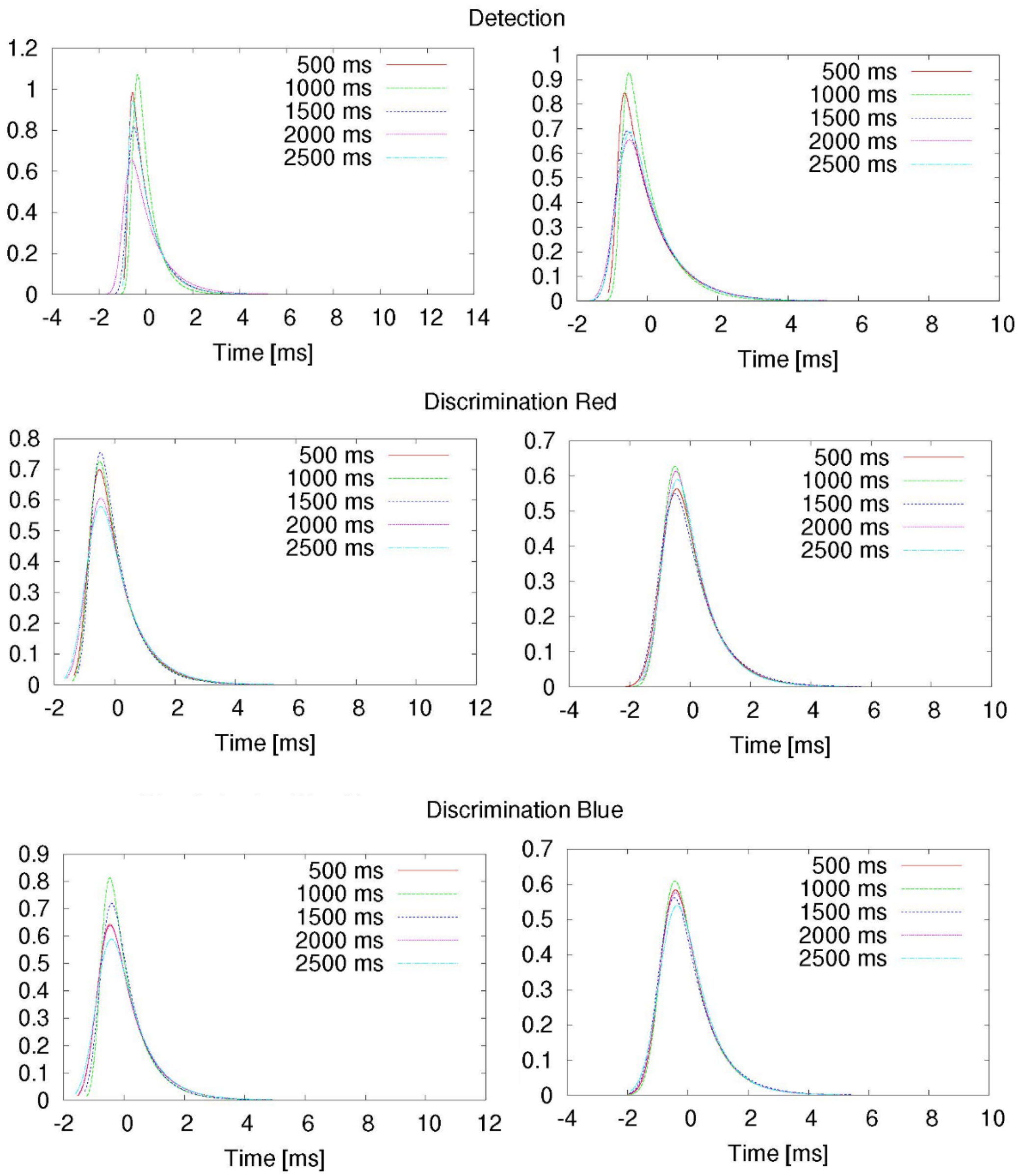

Figure II: Z-punctuation of the participants after a trimming in terms of presentation times and group of age. On the left side: young participants. On the right side: older participants.

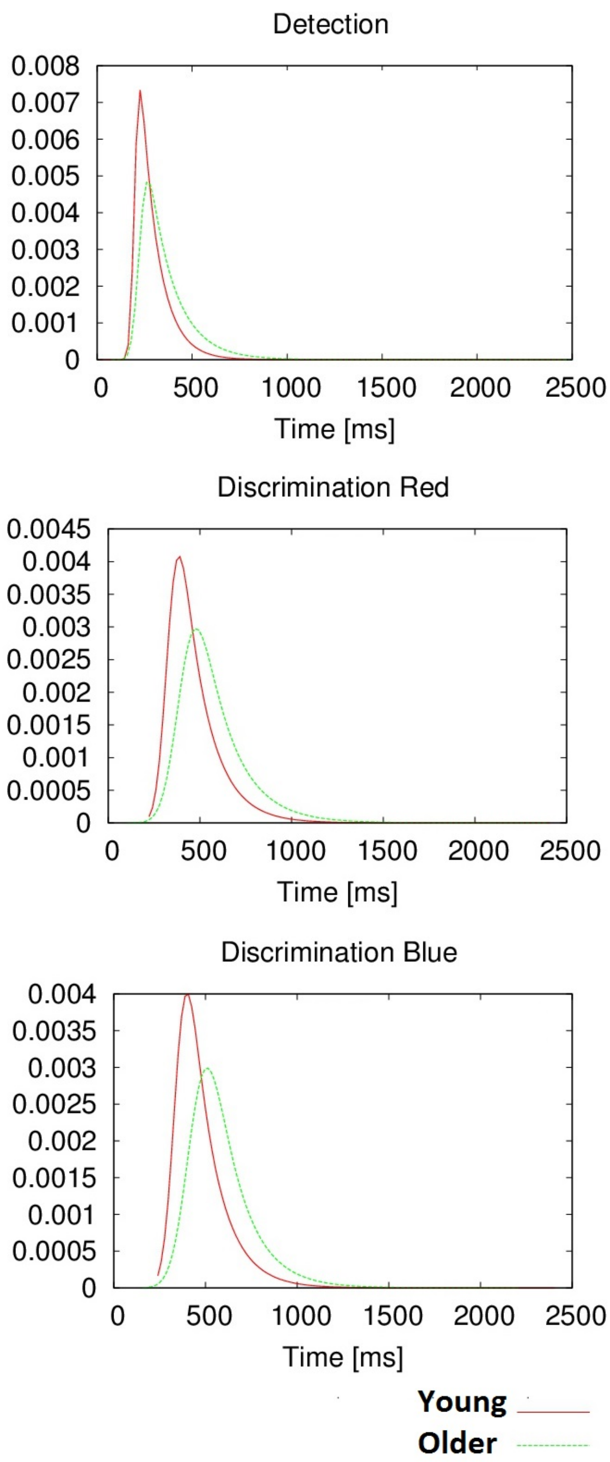

Figure III: The ex-Gaussian fit for the matching task task under varying the Presentation times. Red: young participants. Green: older participants.

Table 1: Differences between signal detection and discrimination averages (ms) and standard deviation (SD), under varying presentation times, for older and young participants.

Presentation times & Group		Detection				Discrimination (Red)				Discrimination (Blue)			
		Mean	SD	Hits	Triming	Mean	SD	Hits	Triming	Mean	SD	Hits	Triming
500	Older	404.17	116.90	99%	0.79%	576.06	117.02	97%	0.39%	580.99	121.32	98%	0.66%
	young	337.31	61.74	99%	0.26%	471.89	90.33	98%	0.53%	471.81	89.61	97%	0.26%
	Total	370.74	98.62	99%	1.05%	523.97	116.19	97.5%	0.92%	526.40	119.21	97.5%	0.92%
1000	Older	396.41	105.84	99%	1.05%	563.75	113.17	97%	0.53%	552.72	104.93	97%	0.79%
	young	333.24	58.92	99%	0.78%	465.15	91.26	97%	0.79%	459.18	85.08	98%	0.92%
	Total	364.82	90.70	99%	1.84%	514.45	113.40	97%	1.32%	505.95	105.8	97.5%	1.71%
1500	Older	361.11	73.10	99%	0.13%	553.09	100.04	97%	0.26%	555.46	99.39	97%	0.26%
	young	322.37	46.19	99%	0.13%	450.31	73.30	97%	0.53%	451.94	77.36	97%	0.26%
	Total	341.74	63.70	99%	0.26%	501.70	101.22	97%	0.79%	503.70	102.57	97%	0.53%
2000	Older	345.91	57.70	99%	0.13%	561.35	90.43	97%	0.66%	559.42	94.62	97%	0.92%
	young	312.74	32.10	99%	0.26%	451.51	70.97	97%	0%	452.01	69.5	96%	0.26%
	Total	329.33	49.22	99%	0.39%	5.064.334	97.79	97%	0.66%	505.72	98.53	96.5%	1.18%
2500	Older	351.97	66.22	99%	0.26%	561.61	83.98	97%	0.66%	572.60	79.44	96%	0.79%
	young	314.03	34.99	100%	0.26%	464.60	73.62	96%	0.13%	4.659.240	69.68	97%	0.39%
	Total	333.00	55.88	99.5%	0.53%	513.11	92.32	96.5%	0.79%	519.26	91.55	96.5%	1.18%

Table 2: μ, σ and τ parameters for older and young participants, with their uncertainty (error) and p-value

Task\Parameters	***μ***	***p***	***σ***	***p***	***τ***	***p***
Detection						
Older	223.99 ± 1.75	0.000000	31.17 ± 1.76	0.000386	133.31 ± 3.34	0.000000
Younger	198.16 ± 1.66		20.17 ± 2.55		90.98 ± 3.07	
Discrimination						
Red square stimuli						
Older	397.31 ± 6.64	0.000000	72.93 ± 8.36	0.003900	171.38 ± 7.20	0.000020
Younger	328.04 ± 2.54		48.28 ± 1.75		136.55 ± 3.82	
Red square stimuli						
Older	427.92 ± 4.26	0.000000	79.85 ± 5.82	0.000002	156.59 ± 5.30	0.001042
Younger	340.65 ± 2.71		51.47 ± 1.57		134.19 ± 4.29	

Table 3: μ, σ and τ parameters with their uncertainty (error) and *p*-value under vrying presentation times for older and young participan

		μ			σ			τ		
	Presentation times (ms)	Older	Young	*p*	Older	Young	*p*	Older	Young	*p*
Detection	500	215.72±4.39	196.88±4.25	0.002079	27.48±3.07	14.92±3.46	0.006678	175.47±8.67	106.26±7.18	0.000000
	1000	220.10±3.92	202.92±3.60	0.001254	31.04±5.30	28.23±5.49	0.712761	163.79±9.48	103.88±8.51	0.000003
	1500	226.10±3.72	197.93±2.97	0.000000	32.16±3.95	21.14±2.03	0.013300	118.05±6.17	86.05±5.39	0.000094
	2000	232.44±3.50	200.90±3.60	0.000000	31.94±3.21	22.55±5.55	0.143289	95.70±5.47	71.48±4.65	0.000756
	2500	232.72±3.93	193.06±3.55	0.000000	34.22±4.11	13.86±2.95	0.000059	105.77±6.66	85.61±6.00	0.024623
Discrimination (Red)	500	396.79±11.54	331.94±5.88	0.000001	77.70±15.91	46.60±4.20	0.058778	177.86±13.26	144.87±9.36	0.042174
	1000	386.29±9.52	322.09±5.79	0.000000	67.68±9.65	46.41±3.84	0.040599	186.80±12.67	147.37±9.63	0.013261
	1500	388.73±10.59	321.95±5.41	0.000000	71.05±9.47	43.55±3.33	0.006196	168.12±11.54	136.31±9.26	0.031726
	2000	397.33±8.69	331.40±5.09	0.000000	69.46±7.56	49.81±4.81	0.028444	172.30±11.27	120.32±7.31	0.000110
	2500	417.63±8.78	338.04±6.02	0.000000	73.37±7.63	55.13±6.12	0.062291	152.40±11.29	127.33±8.22	0.072730
Discrimination (Blue)	500	451.93±8.09	346.38±5.65	0.000000	71.71±10.41	52.58±3.93	0.085794	150.64±10.44	136.24±8.56	0.286384
	1000	412.51±10.35	332.24±6.00	0.000000	73.63±16.39	44.83±4.35	0.089490	178.79±11.36	158.35±10.94	0.195134
	1500	408.33±10.26	340.47±5.51	0.000000	73.03±12.70	52.11±3.64	0.113577	160.95±12.25	132.97±9.76	0.074166
	2000	420.49±9.6	338.64±5.81	0.000000	77.82±13.29	50.20±4.31	0.048134	160.51±12.30	125.49±8.85	0.020891
	2500	439.66±10.16	346.68±5.48	0.000000	82.31±13.43	54.87±5.57	0.059153	140.79±11.97	117.56±7.53	0.100572