Maximum Likelihood Integration of Rapid Flashes and Beeps

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This manuscript contains 20 pages including one figure and two tables

Theme: Sensory Systems
Topic: Visual Psychophysics and Behavior
Keywords: Signal Detection Theory; Fuzzy Logical Model of Perception; Audiovisual Integration; Maximum Likelihood Integration; Intermodal Attention; Information Reliability Hypothesis

Acknowledgements

The authors wish to thank Dr. Aki Vehtari, Rolf P. Würtz and Bram Bolder for useful comments on an earlier version of this manuscript.

Abstract

Maximum likelihood models of multisensory integration are theoretically attractive because the goals and assumptions of sensory information processing are explicitly stated in such optimal models. When subjects perceive stimuli categorically, as opposed to on a continuous scale, maximum likelihood integration (MLI) can occur before or after categorization—early or late. We introduce early MLI and apply it to the audiovisual perception of rapid beeps and flashes. We compare it to late MLI and show that early integration is a better fitting and more parsimonious model. We also show that early MLI is better able to account for the effects of information reliability, modality appropriateness and intermodal attention which affect multisensory perception.

Introduction

Maximum likelihood models of multisensory integration are theoretically attractive because the goals and assumptions of sensory information processing are explicitly stated in such optimal models. We call this application of the maximum likelihood principle for maximum likelihood integration (MLI). Recently, MLI has been studied for *continuous perception,* where stimulus attributes, such as spatial location, are perceived on a continuum [2,5-7]. When applied to this type of stimuli, MLI operates on continuous probability distributions such as the normal distribution. For *categorical perception*, where stimulus attributes, such the number of events, are perceived in categories, MLI has been studied for decades mostly under the name of the Fuzzy Logical Model of Perception (FLMP) [12]. When applied to this type of stimuli, MLI operates on discrete probability distributions such as the multinomial distribution. Such models can be called *late* MLI because they assume that multisensory integration occurs *after* categorization. But, if categorization is based on an early, continuous internal representation, then MLI could operate on this representation prior to categorization. This kind of models can be called *early* MLI.

Here, we shall compare an early and late MLI by applying both models to the counting of rapid flashes and beeps. Shams et al. found that a single rapid flash of light was perceived as two flashes when accompanied by two rapid tone beeps indicating that audition affects vision when counting the number of rapid events [16,17]. In a previous report [4], we replicated and extended the findings of Shams et al. Since these data will be used for model testing in the current report, we shall briefly summarize them in the following. We used an expanded factorial experimental design with visual stimuli of 1-3 flashes, auditory stimuli of 1-3 beeps and all 9 audiovisual combinations. For audiovisual stimuli, our experiments had two attentional conditions. In the *count-flashes* condition, the participants were instructed to count the flashes and ignore the beeps as in Shams et al.'s original experiment. In the *count-beeps* condition, the instructions were to count the beeps while ignoring the flashes. Each stimulus type in each condition was presented twenty times in pseudorandom order and the participants responded in categories 1, 2 or 3. These response counts form the empirical basis for the model testing in this study.

Both conditions were included in two experiments. In Experiment 1, the sound level was 80 db(A) which is a clearly audible sound level close to that used by Shams et al. In Experiment 2, the sound level was 10 dB(A) which was close to the participants' auditory threshold.

In Experiment 1 we were able to replicate Shams et al.'s finding in the count-flashes condition—i.e. we also found a strong fission illusion. However, contrary to Shams et al., we also found a strong fusion illusion—i.e. 2 flashes were often perceived as 1 when accompanied by 1 beep. In the count-beeps condition we found no influence from the number of flashes on the perceived number of beeps. In the count-flashes condition of Experiment 2, both fission and fusion illusions persisted indicating that the effect is very robust to variations in stimulus signal-to-noise ratio (SNR). The effects were, however, weaker than in Experiment 1. In the count-beeps condition of Experiment 2, we found visually induced auditory fission and fusion illusions.

We discussed our results in terms of four hypotheses on what determines the relative influence from each modality on the multisensory percept. Three of these apply to multisensory integration in general and any quantitative model of multisensory integration should therefore be able to account for them.

The *information reliability hypothesis* states that the modality receiving the more reliable information (e.g. through a high SNR) will have a greater effect on perception [15]. Two findings agree with this. First, the number of beeps had a stronger influence on the number of perceived flashes in Experiment 1, where auditory information reliability was higher, than in Experiment 2. Second, the number of flashes had a weaker influence on the number of perceived beeps in Experiment 1 than in Experiment 2.

The *modality appropriateness hypothesis* states that the modality more appropriate (i.e. sensitive) for the discrimination has a greater effect on perception [21]. In fact, modality appropriateness may be seen as a contribution to information reliability so that the more appropriate modality provides more reliable information given the same stimulus SNR.

For a temporal discrimination task such as counting rapid events, audition, with its superior temporal resolution, should be more appropriate. In concordance, to find visual influence on audition it was necessary to lower the auditory SNR to near subjects' auditory threshold while auditory influence on vision persisted at that point.

The *directed attention hypothesis* states that shifting attention between sensory modalities affects perception [20]. This effect was clearest in Experiment 1 where counting beeps was not influenced by the number of flashes but counting flashes was strongly influenced by the number of beeps. The effect was also present in Experiment 2. The clear difference between the count-flashes and count-beeps conditions indicates that flashes and beeps are not always integrated to a unitary percept. Subjects are able to focus attention on either flashes or beeps and this significantly affects the number of events they count. This poses a problem for all maximum likelihood based theories of integration. Since the stimuli are identical and the maximum likelihood rule is mandatory and univalent, an explanation is needed for the difference in the audiovisual percepts. The solution lies in a change of the processing of the unimodal stimuli or in a change in prior assumptions. One way that attention could affect unimodal perception is, according to the gain theory of attention [10,19], to increase the gain of a stimulus with respect to the unattended stimulus or background noise. This should be equivalent to increased reliability and attending a stimulus would have the effect of increasing the reliability of the stimulus. Thus to model the difference between the count-flashes and count-beep conditions, we only need to model the change in stimulus reliability resulting from shifting attention between vision and audition.

In the following, we shall describe two models of categorical multisensory integration. The first is early MLI which consist of MLI of a continuous internal representation and a model of classification based on signal-detection theory [9]. The second is late MLI which consists of MLI of categorical percepts. This model is also known as the FLMP. Both models assume that audition and vision provide independent information. This assumption has been used also in previous studies [2,6,10,11,16].

Early MLI

Early MLI describes integration based on a continuous internal representation prior to categorization. Maximum likelihood as the principle governing multisensory integration has recently been studied for stimuli falling on a continuum [2,6,7]. In these studies, it has been assumed that the stimulus, *S*, causes an internal representation, *x*, in the brain. In the process, perceptual Gaussian noise is added so that the probability of an internal representation value given a stimulus is given by

(1) $$P(x \mid S) = \sqrt{\frac{r}{2\pi}} \exp\left(-\frac{r(x-\mu)^2}{2}\right)$$

where μ and r denote mean and reliability of the internal representation, respectively. The reliability, r, relates to the standard deviation, σ, of the Gaussian distribution as

(2) $$r = \frac{1}{\sigma^2}$$

For audiovisual stimulation, we assume that an auditory stimulus, S_{A}, and a visual stimulus, S_{V}, are independently distributed with internal representation means μ_A and μ_V respectively, and reliabilities r_A and r_V, respectively. Then the maximum likelihood integrated internal representation, x_{AV}, is also Gaussian distributed with mean

(3) $$\mu_{\mathrm{AV}} = w\mu_{\mathrm{A}} + (1-w)\,\mu_{\mathrm{V}}$$

where the weight, *w*, is

(4) $$w = \frac{r_A}{r_A + r_V}$$

and the reliability

(5) $$r_{AV} = r_A + r_V$$

It is reasonable to equate the reliability in this model with that of the information reliability hypothesis. Then, this model contains the information reliability hypothesis in the form of Eqs. 3-4. When a modality is more reliable it is weighted higher.

Since our stimuli were designed so that, in each experiment, the events within each modality had the same duration and SNR we assume that they had the same information reliability and therefore we do not allow it to depend on the number of flashes or beeps. As we have outlined above, since the effects of modality appropriateness and directed attention can be quantified in terms of their effects on information reliability, early MLI is able to account for those effects. In accordance with the modality appropriateness hypothesis we allow the information reliability to depend on the sensory modality. In accordance with the directed attention hypothesis we allow the information reliability to vary with attended modality as described by the gain theory of attention [10,19]. This means that the reliabilities should actually have two subscripts where the first subscript designates the modality of the stimulus and the second subscript the attended modality, so that $r_{AV,V}$ designates the reliability for the audiovisual count-flashes condition which, based on Equation 5, is given by $r_{AV,V} = r_{A,V} + r_{V,V}$. The reliability, $r_{A,V}$, is a fictive quantity which can be interpreted as the auditory reliability when vision is attended. Similarly, the reliability for the audiovisual count-beeps condition is given by $r_{AV,A} = r_{A,A} + r_{V,A}$. The reliabilities of unimodal stimuli, $r_{A,V}, r_{V,V}, r_{A,A}, r_{V,A}$, are free parameters. Directed attention affects also the weight, w, according to Equation 4, so that the weight for the count-flashes condition is $w_{count-flashes} = \dfrac{r_{A,V}}{r_{A,V} + r_{V,V}}$ and the weight for the count-beeps condition is $w_{count-beeps} = \dfrac{r_{A,A}}{r_{A,A} + r_{V,A}}$.

The mean of the internal representation, μ, depends both on the number of flashes or beeps and on the modality. For the current data set there is an internal representation mean for each of the three unimodal stimuli in both the auditory and the visual modality. These are free parameters. They are combined using Equation 3 to give an internal representation mean for each of the 9 audiovisual stimuli in both the count-flashes and count-beeps conditions.

In the above model, the stimulus could be categorical as well as continuous. In order to test the model for categorical responses, a model of categorization is needed. A category, C, is defined by an interval, $[x_{\min}^{C}, x_{\max}^{C}]$ of internal representation values. One endpoint may be replaced with plus or minus infinity if appropriate. When an internal representation value falls inside the interval, the stimulus is estimated to belong to the category; when it falls outside the interval, the stimulus is estimated not to belong to the category. The probability of a stimulus being classified as belonging to category C is then

(6)
$$\begin{aligned} &P(C \mid S) = \\ &P\left(x_{\min}^{C} < x < x_{\max}^{C} \mid S\right) = \\ &\int_{x_{\min}^{C}}^{x_{\max}^{C}} \sqrt{\frac{r}{2\pi}} \exp\left(-\frac{r(x-\mu)^2}{2}\right) dx = \\ &\Phi\left(\frac{\mu - x_{\min}^{C}}{\sigma}\right) - \Phi\left(\frac{\mu - x_{\max}^{C}}{\sigma}\right) \end{aligned}$$

where Φ is the standard normal probability function. For the current experiments the categories were 1, 2 and 3 and the corresponding response probabilities are:

(7)
$$\begin{aligned} &P(C = 1 \mid S) = 1 - \Phi\left(\frac{\mu - x_{12}}{\sigma}\right) \\ &P(C = 2 \mid S) = \Phi\left(\frac{\mu - x_{12}}{\sigma}\right) - \Phi\left(\frac{\mu - x_{23}}{\sigma}\right) \\ &P(C = 3 \mid S) = \Phi\left(\frac{\mu - x_{23}}{\sigma}\right) \end{aligned}$$

where x_{12} is the boundary between category 1 and 2; and x_{23} is the boundary between category 2 and 3. The category boundaries x_{12} and x_{23} are free parameters.

To summarize, the free parameters of the model are the information reliability for each modality and each attentional state (4 in total), the means of the internal representations for each unimodal stimulus (6 in total) and the category boundaries (2 in total). The model thus has 12 free parameters. If only either the count-flashes or count-beeps condition is modeled, then the number of free parameters is reduced by one to 11, because there is one attentional condition less.

Many of the free parameters only have sensible values within a certain interval. The means of the internal representations should not be far from what is expected from stimulus values. Using unrestricted optimization, the internal representation could take nonsensical values like very large and/or negative values. We restricted the means of the internal representations to lie in the interval [0; 4]. In the strictest sense, this implies that the normal distributions of Equations 6-7 should be truncated but since, in practice, their means never came within one standard deviation of interval limits, the effect of truncation would have been small. The category endpoints should lie between the internal representation values of the categories so that the category boundary between category 1 and 2 should lie between values x=1 and x=2.

Late MLI

Late MLI is based on response probabilities and does not address stimulus processing prior to classification. The integrated percept is the normalized product of the unimodal response probabilities:

(8) $$P(C_i \mid S_A, S_V) = \frac{P(C_i \mid S_V)P(C_i \mid S_A)}{\sum_{j=1}^{N_{cat}} P(C_j \mid S_V)P(C_j \mid S_A)}$$

where N_{cat} is the number of response categories. This model is known as the FLMP in audiovisual speech research [12] and as the baseline category logit in the literature on Generalized Linear Models [1].

When modeling only one attentional condition, the free parameters of late MLI are simply the unimodal response probabilities. In our experiment, there were 3 response categories of which only 2 were independent because the total number of stimulus presentations was constant. Therefore, 2 free parameters are required for each of the 6 unimodal stimuli so that late MLI has 12 free parameters when modeling only one attentional condition.

Since late MLI does not specify the categorization process, it leaves no room for modeling the effect of information reliability, modality appropriateness or directed attention. Therefore, the only way to account for the results of both attentional conditions is to model them separately which doubles the number of free parameters to 24.

Results

The models were fitted to the data with an iterative optimization algorithm by maximizing the multinomial likelihood, L, of the response counts

(9) $$\mathrm{L} = N!\prod_{p}\prod_{s}\prod_{c=1}^{3}\frac{P\left(C_{p,s,c} \mid S_{p,s}\right)^{n_{p,s,c}}}{n_{p,s,c}!}$$

where N is the number of times each stimulus was presented (N=20) and n is the response counts. The index p runs over all participants; index, s, runs over all auditory, visual and audiovisual stimuli, and the index, r, runs over the three response categories.

We first fitted both models to the count-flashes and count-beeps conditions separately. The error measure is the negative log likelihood, displayed in Table 1. The higher the negative log likelihood, the less likely the data given the model, and the worse the fit. For Experiment 1, the error measure was lower for early MLI in both conditions. For

Experiment 2, the error measure was higher for early MLI in both conditions. Summing across experiments and conditions, the error measure was lower for early MLI indicating that it fitted the data at least as well as late MLI overall. Furthermore, early MLI had 1 free parameter less for each subject, attentional condition and experiment so that it in all had 38 free parameters less than late MLI.

Table 1 here

For late MLI, separate modeling of each attentional condition is the only option, whereas early MLI offers the advantage of modeling the amount of auditory and visual influence through the weights, *w*. We fitted the early MLI model using this option in order to compare that to late MLI. The error measures are displayed in Table 2. They were lower for early MLI in both Experiments 1 and 2 indicating that it fitted the data at least as well as late MLI overall. This is remarkable since early MLI now had 228 free parameters less than late MLI. However, late MLI was fitted to the unimodal data points twice—once in the count-flashes condition and once again in the count-beeps condition—and the number of degrees of freedom was increased accordingly. Early MLI was only fitted to unimodal data points once. This results in the data set having the same number of degrees of freedom for the two models despite early MLI having fewer free parameters than late MLI.

Table 2 here

We have described how early MLI quantifies the relative influence of each modality through the weight, *w*, which summarizes the effects of information reliability, modality appropriateness and directed attention. We therefore analyze the distributions of weights across subjects which are displayed in Figure 1.

Figure 1 here

In the count-beeps condition of Experiment 1 where we found no influence from vision, the auditory weights were near the maximum of 1 (mean 0.97). In the count-beeps condition of Experiment 2 where we found influence from both audition and vision, the auditory weights are distributed around a mean of 0.62. Similarly, in the count-flashes condition in Experiment 1 we found influence from both modalities, and also here the weights were widely distributed, with a mean of 0.52. In the count-flashes condition of Experiment 2, the auditory weights were smaller (mean 0.34) which is in agreement with our finding that the auditorily induced visual illusions decreased in number compared with Experiment 1.

Discussion

We have constructed an early MLI model of multisensory integration of categorical percepts, tested it on audiovisual integration of rapid flashes and beeps and compared it to a late MLI model. We base our evaluation on three principles: goodness-of-fit, model flexibility and model interpretability.

The error measure was lower overall for early MLI both when the count-flashes and count-beeps conditions were modeled separately and when they were modeled together. The error measure is, in itself, not a good measure of model adequacy without knowing its distribution. Both early and late MLI belong to the class of generalized linear models for which the deviance or root mean square error is used as error measure because it is asymptotically chi-squared distributed and thus provides *p*-values as an indicator of model adequacy. However, for sparse data, such as ours, the error measure is not chi-squared distributed [1] and we have therefore not attempted to obtain *p*-values. Our conclusion is therefore only that early MLI fitted the data at least as well as late MLI overall.

The number of free parameters was lower for early MLI than for late MLI regardless of whether it was fitted to the count-flashes and count-beeps blocks separately or whether the difference between the blocks was modeled through a change in information reliability. In the former case, early MLI employed 38 fewer free parameters than late MLI and in the latter case it employed 228 fewer free parameters. We base our main conclusion on this: Early MLI is preferable since it provides a more parsimonious explanation for the underlying mechanism of audiovisual integration—especially so when the effect of attentional condition is parameterized as a change in information reliability. The fact that only late MLI was fitted to unimodal responses twice in the latter case does not alter our conclusions for two reasons. First, two fits are uninformative and useless. Second, even though the double fit virtually increases the number of data points, the data still have no more degrees of freedom for late MLI than for early MLI.

The double fitting of late MLI to the unimodal parameters can be interpreted as an attempt at capturing the effect of directed attention under the assumption that the effect on unimodal perception is small even if it propagates to a large effect on bimodal perception. This assumption is unfounded but the literature on modeling categorical integration has consistently made it [12]. At first, it might seem appropriate to model audiovisual responses from auditory and visual responses but this neglects that auditory responses were given when audition was attended and visual responses were given when vision was attended. The paradox only clearly manifests itself when audiovisual responses are given when either audition or vision is attended and a clear effect is seen.

Another model evaluation criterion is interpretability which is a more loosely defined model selection criterion. Decades of multisensory research have indicated that information reliability, modality appropriateness and directed attention affect the relative influence of the sensory modalities on multimodal perception. These effects were also clearly demonstrated using conventional hypothesis testing in our previous report [4]. Early MLI captures both the magnitude and the direction of these effects in the weighting factor, w, which reflects the relative influence of audition and vision. In comparison, late MLI can detect a change but cannot account for its cause, magnitude or direction. Therefore, we conclude that early MLI is more interpretable than late MLI.

Both early and late MLI claim to be optimal under the assumption that audition and vision provide independent information..The crucial difference between them is in their assumptions on perceptual noise. Whereas perceptual noise is pivotal to early MLI, late

MLI has no explicit assumptions on perceptual noise. Implicitly, however, late MLI actually assumes noiseless perception—i.e. it assumes that the unimodal response probabilities are known with infinite precision. This is the basis of a very severe criticism of late MLI: If a very small unimodal response probability doubles in magnitude, it may also double the bimodal response probability which might not be small so that a very small change in unimodal perception might propagate to a large change in bimodal perception [3,14]. This hyper-flexibility enables the model to account for a broad class of data. Hyper-flexibility is indicative of too many free parameters and as we have seen here, an early model can describe the data better with fewer free parameters. Furthermore, assuming significant perceptual noise, as has been done by e.g. the classical signal detection theory, has been successful in describing several perceptual phenomena. Therefore, the noisy early MLI is in better agreement with our general knowledge on the perceptual system than is late MLI .

Shams and co-workers conducted an event-related potentials (ERP) study of the illusory flash occurring when one flash is accompanied by two beeps [18]. They found that the illusory flash elicited an ERP similar to that of an actual flash. The onset of this ERP was approximately 170 ms after the onset of the actual flash indicating activity in what is traditionally thought of as modality specific visual cortex. Other ERP studies, using different types of stimuli, have also concluded that crossmodal interactions occur at short latencies in cortical areas considered to be modality-specific [8,11,13]. These neurophysiological findings support the notion of early rather than late audiovisual integration.

In conclusion, we find that for the audiovisual integration of rapid flashes and beeps, early MLI accounts for the experimental results with fewer free parameters than late MLI. Early MLI also offers an immediate and direct interpretation of the free parameters and can account for the effects of information reliability, modality appropriateness and directed attention.

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Tables

Table 1

		Early MLI		Late MLI			
		error	params. /subject	error	params. /subject	#subjects	Δparams.
Exp. 1 80 dB	Count-flashes	437	11	455	12	10	10
	Count-beeps	196	11	220	12	10	10
Exp. 2 10 dB	Count-flashes	411	11	389	12	9	9
	Count-beeps	444	11	437	12	9	9
	Sum	1488	44	1501	48		38

Table 1 – The error measure (negative log likelihood) summed across all subjects and the number of free parameters, params., for early and late MLI fitted to count-flashes and count-beeps conditions separately. The total number of additional free parameters in late MLI compared to early MLI is displayed in the rightmost column.

Table 2

		Early MLI		Late MLI			
		error	params. /subject	error	params. /subject	#subjects	Δparams.
Exp. 1 80 dB	Both together	568	12	675	24	10	120
Exp. 2 10 dB	Both together	724	12	826	24	9	108
	Sum	1292	12	1501	24		228

Table 2 – The error measure (negative log likelihood) summed across all subjects and the number of free parameters for the early and late MLI fitted to count-flashes and count-beeps conditions together. The total number of additional free parameters in late MLI compared to early MLI is displayed in the rightmost column.

Figure

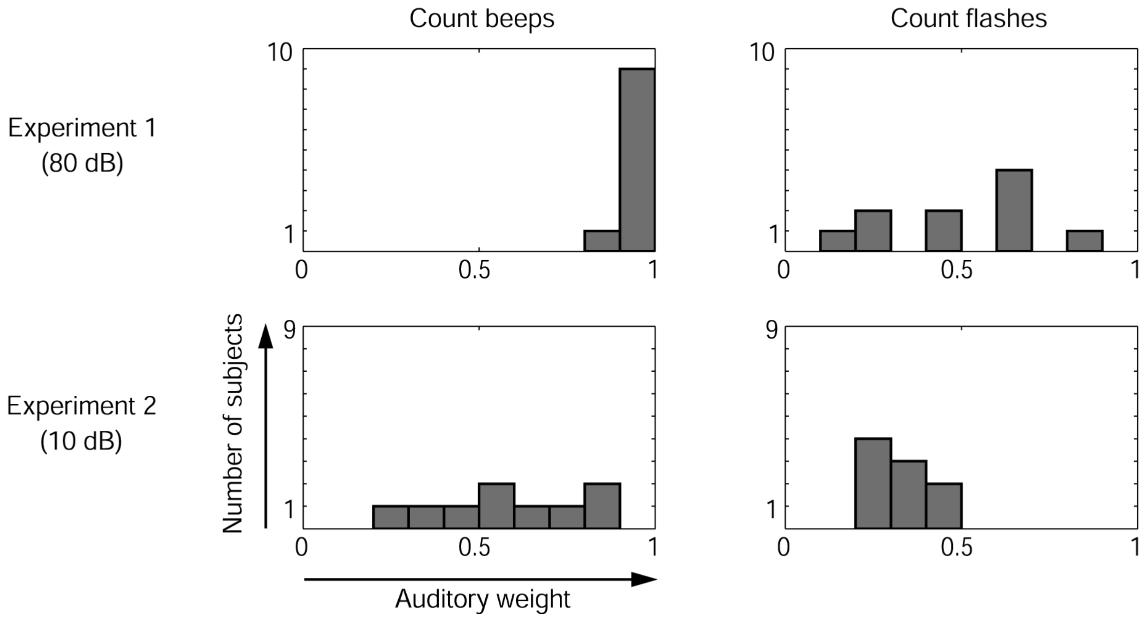

Figure 1 – Histograms of the auditory weights of early MLI for each experiment and attentional condition.