RELATING PERCEPTION AND PRODUCTION OF SIMPLE RHYTHMIC PATTERNS - EXPLANATION OF THE REGRESSION EFFECT -

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Abstract

The so-called regression effect is often observed in the rhythm perception and production domain: a sequence of durations is perceived as more contrasted then they are performed, while the same rhythms are produced as less contrasted. The current study offers a possible explanation to this effect by relating perception and production of simple rhythmic patterns using a Bayesian framework. Thirty-six pianists took part in three independent experiments involving perception (identification), production (synchronization) and familiarity judgments tasks of three-interval rhythmic patterns. Indeed, the regression effect was observed. Applying the results of the familiarity judgments as a prior probability of rhythmic categories, Bayes' rule was used to predict perception data from the obtained production data, and the difference between perception and production could be considerably reduced.

The so-called regression effect (Marks, 1974) has been demonstrated in many modalities such as loudness, duration, brightness, smell, and taste. It is also often observed in the rhythm perception and production: While perception means of rhythm categories, especially those of the categories having more contrasted durations, are often observed at the positions where the durations are even more contrasted (Sternberg, Knoll, & Zukofsky, 1982), production means tend to assimilate towards the equal durational ratio (Povel, 1981; Repp, Windsor, & Desain, 2002; Sadakata, Ohgushi, & Desain, 2004). Many attempts have been made to explain this effect. For example, Poulton (1989) postulates an internal mid-value reference, reasons from the subject's tendency to leave room for extreme stimuli that might arrive later, and elaborates this, using effects of the time sequence of trials. In the current study, we propose that the Bayesian approach to relate perception and production (Sadakata, Desain, & Honing, 2006) may be able to explain this effect, instead of the traditional way of comparing mean interval durations of perception and production.

Bayesian modelling is based on the notion of conditional probability, written as $p(c|t)$, which gives the probability of c occurring when t occurs. Here c stands for rhythm categories and t for performances. Bayes' rule relates the following probabilities, $p(c|t)$, $p(t|c)$, $p(c)$ and $p(t)$, as

$$p(c|t) = \frac{p(t|c) \times p(c)}{p(t)} \quad (1).$$

This could be interpreted that $p(c|t)$, the probability of a rhythm category being perceived as c when a performance t is presented, is predicted from $p(t|c)$, the probability of that performance being produced when given a rhythm category as instruction, multiplied the prior probability of that rhythm category $p(c)$, divided by $p(t)$, the probability of the performance arising in any category.

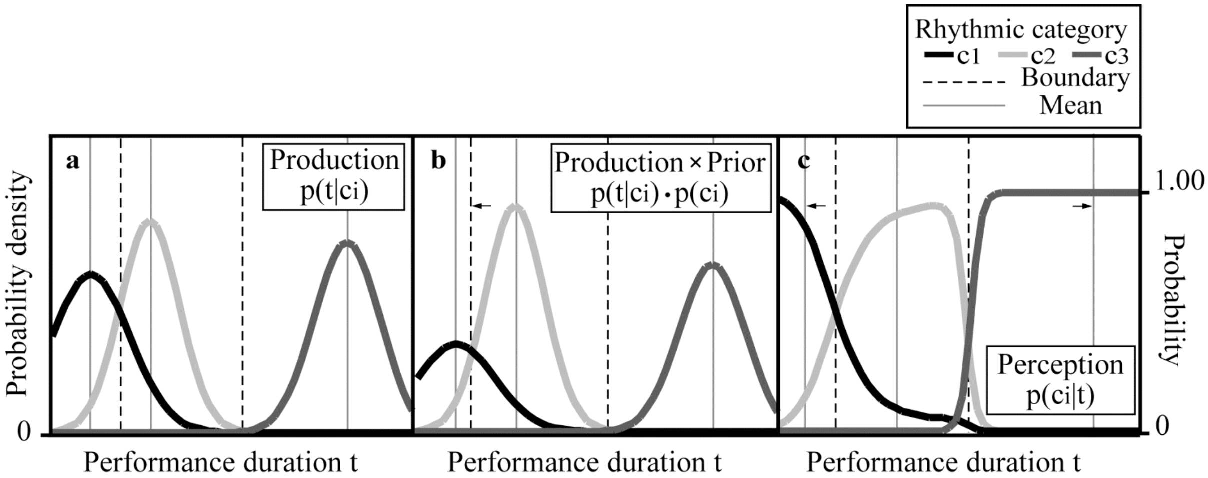

Fig.1 **a**: an example of production distributions of two-interval rhythms. **b**: an example of production distribution multiplied by priors. Arrow indicates a shift of categorical boundary between c_1 and c_2. **c**: an example of perception distribution. Two arrows indicate shift of category means of c_1 and c_3.

Fig.1 shows this process. The examples described are two-interval rhythms. The y-axes of Fig.1a and Fig.1b are probability density while that of Fig.1c is probability. Each production density curve $p(t|c_i)$ from Fig.1a is scaled by a prior probability $p(c_i)$ in the Fig.1b. Accordingly, the boundaries between categories shift (see arrow in Fig.1b). Then the curves are re-normalized by dividing by their sum, $p(t)$. This makes the curves sum to one for each value of t. Fig.1c presents these transformed curves.

Arrows in Fig.1c show that the perception means predicted from the production data shift towards extremes, in accordance with the regression effect. Thus, not only predicting the correct categorical boundaries, but interpreting the relation between rhythm perception and production according to the Bayesian framework also seems to offer an explanation for the nature of the regression effect. The key is a competition among rhythmic categories. In perception, the categories at the middle range are surrounded by other competing categories to be perceived. If given performance t is too far from the mean of c_2, another competing category, c_1 (or c_3), will have a high probability to be perceived too. Therefore, the possible shift of the mean of c_2 is limited. However, this competition is one-sided for categories at the outmost range, c_1 and c_3. Any performance in more contrasted (outward) range could be incorporated as a part of the outmost category. In other words, the positions of these outmost categories are not constrained towards an outward shift. On the other hand, in production, such competition among categories is not likely to be involved, as the category to be produced is already known.

This approach has been already shown to explain the regression-like effect on two-interval sequence (Sadakata et al., 2006). Fig.2 shows a great discrepancy between means of perception and production on a logarithmic scale as has reported in Sternberg et al. (1981). The same figure also presents that the production means shift in the direction of reducing the discrepancy when it is fed in the Bayes' formula (the priors of each category here are weighted according to the Farey tree, a complexity measure of durational ratios; Cvitanovic, Shraiman, & Soderberg, 1985).

In this study, we looked into the empirical data of three measurements involving perception (identification), production (synchronization) and familiarity judgments tasks of three-interval rhythmic patterns to further validate the hypothesis.

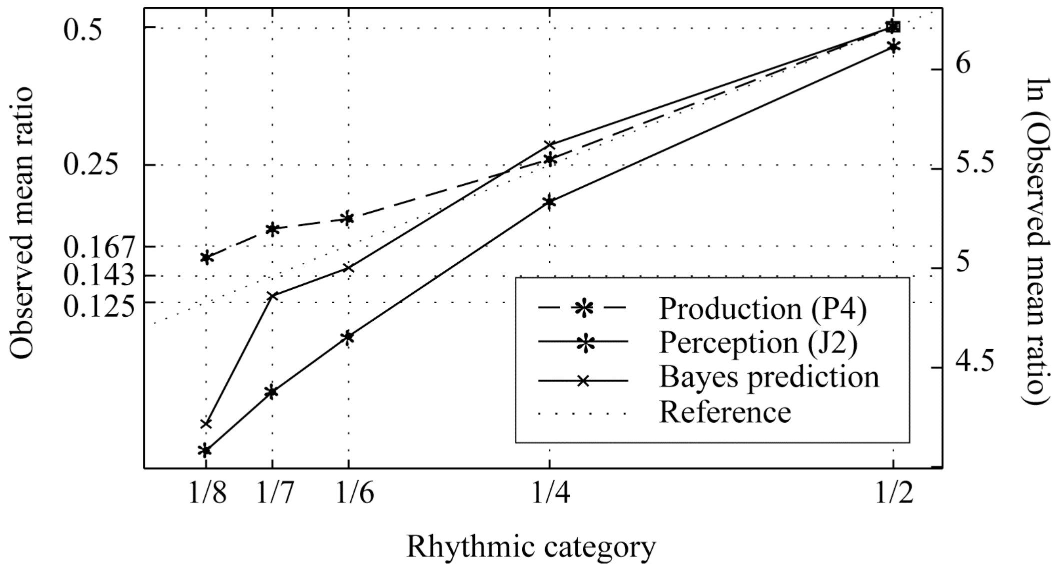

Fig.2 Observed means of production (P4) and perception (J2) data (ratio of the first interval relative to the total duration) in Sternberg et al. (1981), and the means of perception as predicted from P4 by Bayes' rule and Farey tree priors on a logarithmic scale.

Method

Three-interval patterns sampled from a performance space (Desain & Honing, 2003), consisting of four sound onsets (three-interval) were used. Their total interval duration was one second. The three axes in Fig. 3a represent the three inter-onset intervals. Any rendition of a three-interval rhythm, for which the total duration is one second, is expressed as a point on the grey triangle surface, presented as a "ternary plot" in Fig. 3b. The 66 dots in Fig. 3b indicate the rhythmic patterns that were presented as performance. The dots in Fig.3c represent the 38 rhythms used as 1) music notations to be associated with sound stimuli in perception experiment and 2) music notations to be produced and to be rated in production and judgment experiments.

Thirty-six pianists participated in all three experiments. Experiments were driven by the POCO system (Desain & Honing, 1992). The sound was presented through loudspeakers. The participants could adjust the loudness of the sound to a comfortable listening level. Participants were given the opportunity to practice each task three times before the experiment.

Perception

The participants had to associate the presented 66 performances (Fig. 3b) with one of 38 musical notations (Fig 3c). The performance patterns were embedded in a simultaneous metrical context that was a sequence of one-second intervals. We used the "high conga" sound on a General MIDI synthesizer to present the performance patterns and the "low conga" sound to present the one-second time intervals. Centroid (centre) of each category was calculated based on the timing of associated performances.

Production

The participants performed the presented musical notations on the MIDI keyboard (YAMAHA DX-7 using General MIDI piano sounds, a single finger on the middle C key) in time with the metronome sound and had to repeat the score six times. The 38 music notations (Fig. 3c) were used as stimuli to be performed. The musical notations were presented on the screen of a computer. Centroid of each category was calculated based on the timing of performances.

Familiarity Judgment

The same 38 rhythmic notations (Fig.3c) were used as stimuli to be judged. Pianists were asked how common these notations were in their daily practice using a five-point scale from “very common (1)” to “very rare (5)”. The results were normalized and averaged to weight the prior probabilities of each category.

Results and Discussion

Success of Bayesian prediction

A Bayesian approach was applied to relate the results of three measurements. The production data distributions served as input, $p(t|c)$. They were calculated using Parzen’s method (Parzen, 1962). Observation distributions were smoothed with a θ = 0.04.

First, we tested how well the Bayesian method predicted the perception centroids as compared to the production data. For this, Euclidean distance between ‘perception and production centroids’ and ‘perception and Bayesian prediction centroids’ were compared. More discrepancy between perception and production centroids is expected than that between perception and Bayesian prediction centroids. A statistical test revealed that the distance was significantly larger for production and perception centroids (average 0.046, std 0.02) than that between the Bayes predictions and perception centroids (average 0.034, std 0.02) [t-test (one-sided), t=2.49, df=74, p = .0074]. Thus, as in the two-interval data, the approach succeeded to significantly reduce the discrepancy between the perception and production data.

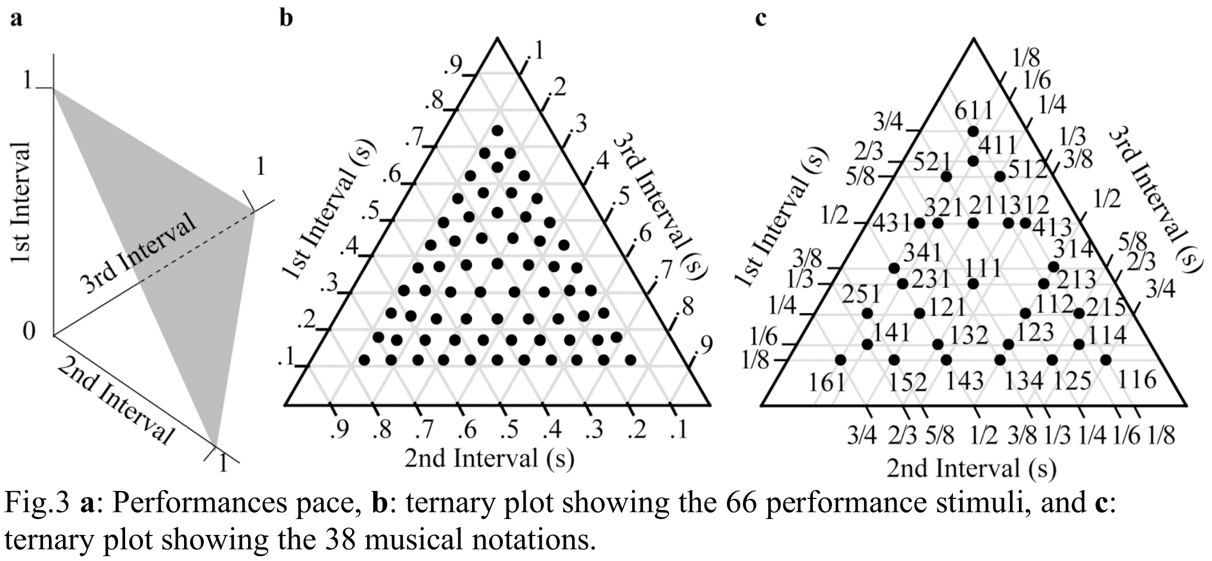

Fig.3 **a**: Performances pace, **b**: ternary plot showing the 66 performance stimuli, and **c**: ternary plot showing the 38 musical notations.

The regression effect

Fig. 4 shows the 38 centroids of perception and production for inward (Fig. 4a) and outmost (Fig. 4b) categories to see if there was indeed the regression-like effect occurred. In contrast to the inward categories that showed more inconsistent relation between perception and production, perception centroids of the outmost categories tended to be toward contrast (towards the outside of the plot) than that of production. Fig. 4c presents centroids of the same outmost categories plus that of Bayes prediction with familiarity priors. The plot reveals that the most of the predicted centroids shifted towards extremes. Thus, the position of the production centroids became more contrasted when they were fed in the Bayes formula to predict perception.

In line with the regression effect, the discrepancy between perception and production centroids tended to be more emphasized in the outmost area, where a more contrasted tendency among perception centroids was observed. We have further shown that these production centroids shifted to the right direction by applying the Bayesian formula. Therefore, this powerful framework may be a key to disclose the essence of the regression effect.

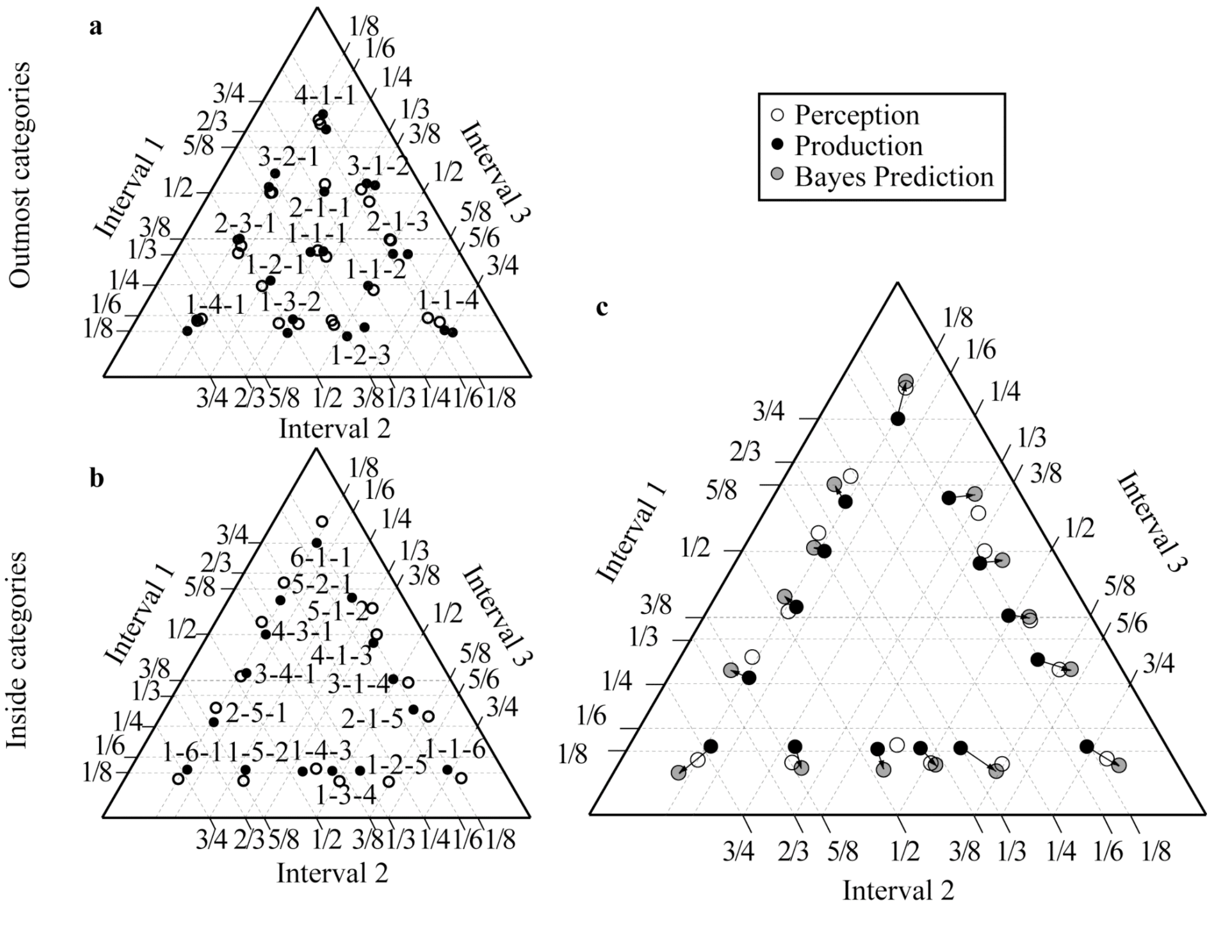

Fig.4 The centroids of perception and production for inside categories (**a**) and for outmost categories (**b**). **c**: the centroids of perception, production and the Bayes prediction.

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