Taking patterns for chunks: is there any evidence of chunk learning in continuous serial reaction-time tasks?

Luis Jiménez

Abstract When exposed to a regular sequence, people learn to exploit its predictable structure. There have been two major ways of thinking about learning under these conditions: either as the acquisition of general statistical information about the transition probabilities displayed by the sequence or as a process of memorizing and using separate chunks that can later become progressively composed with extended practice. Even though chunk learning has been adopted by some theories of skill acquisition as their main building block, the evidence for chunk formation is scarce in some areas, and is especially so in the continuous serial reaction-time (SRT) task, which has become a major research tool in the study of implicit learning. This article presents a reappraisal, replication and extension of an experiment that stands so far as one of the few alleged demonstrations of chunk learning in the SRT task (Koch and Ho 2000). It shows that the effects which were taken as evidence for chunk learning can indeed be obtained before any systematic training and thus surely reflect a preexistent tendency rather than a learned outcome. Further analyses of the effects after extended practice confirm that this tendency remains essentially unchanged over continuous training unlike what could be expected from a chunk-based account of sequence learning.

Introduction

One of the main issues concerning the mechanisms of implicit sequence learning is whether they could be described as the continuous accrual of statistical information about the underlying sequence, or as a discrete process of memorizing and using sequence fragments. Learning of separate chunks has been surprisingly difficult to substantiate empirically in the serial reaction-time (SRT) task, at least by using the standard procedure with homogeneous intervals between responses and stimuli. Actually, there is only one article that has reported clear evidence for chunking processes in a continuous SRT task (Koch and Hoffmann 2000), and this evidence was obtained selectively when the sequence was structured to follow a highly salient pattern. The goal of this study is to explore an alternative interpretation of these results, which might account for these effects as the result of some preexistent response tendencies specific to the arranged patterns. A conceptual replication of the most relevant condition from Koch and Hoffmann’s study does show that the effects that were taken as evidence for chunk learning can indeed be observed from the outset of training, and thus could be considered as reflecting overall response tendencies rather than an outcome of sequence learning. Further analyses conducted over long periods of practice show that this pattern remains essentially unchanged over training, unlike what could be expected from a chunk-based account of sequence learning.

Statistical versus chunk learning

Perruchet and Pacton (2006) have recently highlighted the potential interest of the comparison between statistical and chunk learning models for many research fields, ranging
from language acquisition to motor skill learning. The authors identified statistical learning (SL) with the type of learning implemented in connectionist networks such as the SRN (Christiansen et al. 1998; Cleeremans 1993) and described chunk learning (CL) as grounded on the existence of perceptual and attentional limitations that would restrict learning processes from spreading continuously over a large sequence. According to this limited-capacity perspective that is most explicitly stated in PARSER (Perruchet and Vinter 1998, 2002; Perruchet 2005), when participants focus their attention on learning about a particular fragment of a series they will learn specifically about this fragment, but they will also tend to learn comparatively less about the following transition between this chunk and its immediate successor. Models of chunk learning, such as PARSER and Competitive Chunking (Servan-Schreiber and Anderson 1990), describe the initial outcome of learning as fragmentary, but they also allow learners to gradually build up a more general representation of the sequence with extended practice. Indeed, the developed chunks are assumed to be processed just like primitive units once they reach a given strength criterion, and so they are allowed to enter into successive cycles of chunking that may eventually yield a unitary representation of larger parts of the sequence.

The recursive nature of this chunking process thus enable CL to end up producing representational outcomes very similar to those yielded by SL, but they do so by means of different learning mechanisms. Whereas SL assumes that responding to each trial is enough for the system to encode the relevant dimension, update the transition probabilities in accordance to the observed trial, and prepare for the next trial as predicted by the current context, CL tends to assume that all these computations cannot be accomplished at the same time. Thus, over the course of learning, these two models predict a different learning trajectory. SL is compatible with a continuous acquisition process that would be shaped exclusively by statistical constraints, whereas CL is affected by attentional constraints, and thus will tend to encode sequences into disjunctive chunks, at least early in training, before the recursive process can give place to the concatenation of these chunks into longer structures (cf. Perruchet and Gallego 1997).

Chunk learning in the SRT task

The search for empirical evidence of chunk learning has produced some positive results in paradigms in which the stimuli are presented simultaneously, such as in artificial-grammar learning (Servan-Schreiber and Anderson 1990). In sequence learning paradigms, some effects of chunk learning have arisen when fragmentary encoding is forced by the inclusion of pauses between chunks as it occurs in the discrete sequence production tasks (Verwey and Eikelmboom 2003; Verwey et al. 2002), or when different amounts of repetition of each fragment are provided by training on a trial-and-error basis (Sakai et al. 2003). Some related evidence has also been found when the sequence concerns the series of responses performed while the series of trials to be performed, rather than the series of responses produced to a single task (Koch et al. 2006; Schneider, in press). However, the evidence for chunk learning is surprisingly scarce in the SRT task, which has become the most popular paradigm in the study of implicit learning. In this task, participants are told to respond to a series of successive trials by pressing as fast and accurately as possible on a set of corresponding keys. The series of trials follows a regular sequence, and participants learn to exploit this sequence as it is shown by the production of faster reaction times (RT) in response to the regular trials, even though they are not told about the existence of a sequence, nor are they asked to learn about this predictable structure (Nissen and Bullemer 1987).

In the SRT task, it has become a standard to arrange a fixed response-to-stimuli interval (RSI) and to use homogeneous statistical structures such as the second-order conditional (SOC) structures (see Reed and Johnson 1994) in which all the responses are equally likely, and all transitions are equally predictable by relying on their relevant contexts. With this type of structures, the principles of SL would predict that participants will learn homogeneously about all parts of the sequence, and therefore any systematic departure from this flat learning pattern could be taken as evidence of chunk learning.

In practice, however, this straightforward prediction is difficult to test because, even if participants learn by encoding disjunctive fragments of the sequence, each of them could be making a different partition of the structure, and so the learning measures averaged over learners might convey the wrong impression that they are all acquiring consistent information about the whole sequence (cf. Perruchet and Gallego 1997). A simple way to circumvent this problem is to force all participants to break the sequence in precisely the same fragments, either by introducing pauses at some points in the sequence (Stadler 1993, 1995; Frensch et al. 1994) or by arranging relational patterns that make certain fragments to become more salient than other parts (Koch and Hoffmann 2000). The observation that participants represent disjunctive fragments when these fragments are temporally separated over training is not particularly illuminating for the debate about the “default” process of learning that takes place when the learners respond to a continuous sequence. On the contrary, if presenting participants with a relational, but yet continuous, sequence does produce any evidence of chunk learning, this at least could
be taken as showing that chunk learning occurs when the fragments are salient enough to capture learners’ attention in predictable ways.

The Koch and Hoffmann’s (2000) study

The most relevant results concerning this prediction were presented by Koch and Hoffmann (2000) in their Experiment 1. Specifically, in the condition D + K + from that experiment, 10 participants responded to a series of digits (1–6) by pressing one of six different keys depending on the digit identity. In this condition, there was a compatible mapping between the identity of the digit and the required response so that the six response keys were assigned from left to right to the digits 1–6. Over two practice blocks, participants got used to the task by responding to a control sequence of 24 items, which was repeated eight times over each block. Over the next three training blocks, participants were presented with a repeated series of 24 trials that followed this relational structure: 123214566541232343456654123234345 45456. As it can be observed, this sequence is structured in ascending and descending triplets of successive digits and keystrokes, and there is also a series of relational patterns that governs the succession between triplets, either as an inversion of the previous one or as a transposition of that previous run by one step. This structure is more easily appreciated by separating the triplets in the following way: 123 321 456 654 123 234 345 456. The training sequence was presented eight times over each of these three training blocks (3–5), and it was repeated again over block 7. Block 6 was designed as a control block that arranged eight repetitions of the control sequence. The measure of sequence learning was taken as the difference between participants’ responses to blocks 5 and 6.

According to this measure, participants learned to exploit this relational structure very efficiently as they responded 279 ms faster to the training structure than to the control block. Such a difference is unusually large for an SRT task, especially considering that (1) the sequence was 24 items long, (2) the participants had practiced it for only three training blocks and (3) they had been trained with the control sequence over the two initial practice blocks. Thus, over the block 6, when the control structure is reintroduced, the amount of practice given with each of these two structures is almost comparable, but the fact that participants’ responses were much slower to that of the control sequence did strongly indicate that responding was being driven by the relational patterns implemented over the training sequence.

In addition to showing such a strong learning effect, the authors presented two main sources of evidence for chunk learning. First, a representation of the average responding over block 5 displayed separately for each of the 24 items of the sequence did clearly indicate that responses were structured in triplets, so that RT was slower for the first item of each triplet, and got faster over its second and third items. Second, a summary of this effect was computed by averaging responses given to the first, second and third items over the eight triplets. This measure showed a significant advantage for the second and third positions, as compared to the first position of the triplets.

The alternative account

The results of Experiment 1 from Koch and Hoffmann (2000) appeared to bring about the clear conclusion that the use of relational patterns resulted in a strong effect of chunk learning. In the authors’ own words, these findings “... clearly support the notion that sequence learning in SRT tasks [...] can be conceptualized as a chunking process” (p. 33). In fact, the authors only discussed a minor caveat against this conclusion, concerned with the fact that the typical pattern did not arise in a few triplets that included a hand-switch within a chunk. However, a radically different picture may arise by considering the specific transitions that give place to slow RT at the beginning of each chunk. By looking at these specific transitions (see Fig. 1), one can see that half of the transitions between triplets corresponded precisely to hand-switches and that all the remaining transitions produced either immediate repetitions of the previous trial (at the beginning of the second and fourth triplets) or repetitions of the n-2 trial (i.e., reversals, at the beginning of the sixth and eighth triplet). Moreover, the seventh triplet started with a trial that implemented simultaneously a hand-switch and a reversal movement. Vaquero et al. (2006) have recently reported that reversals tend to produce slower responses in SRT tasks, regardless of any learning effect. Thus, if hand-switches produce slow responses, and if both immediate repetitions and reversals could also be expected to slow down performance, then it becomes possible that all these alleged effects of chunk learning could boil down to response patterns unrelated to learning. To test this possibility, I designed a conceptual replication and extension of the condition D + K + from Koch and Hoffmann’s (2000) Experiment 1. The main goals of this experiment were to assess whether: (1) the pattern of results that was taken as evidence for chunk learning could be observed from the outset of training before learning has had time to develop, and (2) providing further practice with the structure could allow for these chunk-learning effects to develop. According to the predictions of chunk learning models such as PARSER (e.g., Perruchet and Vinter 1998) or Competitive Chunking (Servan-Schreiber and Anderson 1990), we could expect to obtain an initially steeper learning curve for intra-chunk dependencies as compared to that observed for
the transitions between chunks, which might be followed later by a decline of such a difference when an extensive training could start producing the integration of former chunks into larger hierarchical structures.

**Method**

Participants performed an SRT task that required them to respond as fast and accurately as possible to the identity of a digit between 1 and 6, presented in black at the center of a cyan computer screen, by pressing a key that was consistently mapped to each digit. Digits 1–6 were assigned respectively to the keys “c”, “v”, “b”, “n”, “m”, and “,” on a Spanish “QWERTY” keyboard. The six digits kept written in white over the bottom row of the screen, approximately in front of the response keys, as a reminder of the mapping required between digits and response keys. Participants were told to hold the ring, middle, and index fingers from their left hand on the first three keys, and the index, middle and ring fingers from their right hand on the following three keys so as to make responding more efficient. Instructions were complemented with a first practice block of 18 random and unrecorded trials and were then followed by 19 experimental blocks, each composed of 192 trials.

**Design**

A relational structure identical to that used by Koch and Hoffmann (2000) was used to generate the digits over blocks 2–18. Thus, on each of these training blocks, participants responded to eight repetitions of the sequence: 123 321 456 654 123 234 345 456. Blocks 1 and 19 were arranged as test blocks, composed also by eight series of 24 trials. Instead of using a completely different structure for this test block and in order to have an initial block in which the response tendencies could be properly tested before learning took place, these blocks were designed to contain some exemplars of the training structure, together with other structures that could be useful for comparison purposes. Specifically, test blocks 1 and 19 contained eight series of 24 trials distributed in the following way. The first and the eighth series implemented an instance of the training sequence. The second and the seventh series involved the same triplets arranged over the training sequence, but with their order switched between successive pairs, thus producing the following series: 321 123 654 456 234 123 456 345. The four central series were intended to break the training triplets in a systematic way. Specifically, this was achieved over the third and sixth series by replacing the first item of each triplet with the digit corresponding to the same relative location from the other hand (so that the triplet 123 became 423, and so on). Over the fourth and fifth series, finally, the illegal triplets were made by replacing the third digit of each triplet in the same way so that the triplet 123 became 126, and so on.

**Participants**

Twelve students of the University of Santiago participated in the experiment in exchange for a fee of 5€. To further motivate them to cope with the speed and accuracy requirements of the task, they were told that 10% of the participants...
who yielded the best scores would receive an additional incentive of 3€.

**Procedure**

The experiment was designed using INQUISIT 1.33 (Millisecond Software, 2003). Upon arriving at the laboratory, participants were given written instructions about the nature of the SRT task. They were urged to optimize responding by keeping the response fingers on the keys and were informed that they would hear a brief tone upon the production of an error. Regardless of whether they responded accurately or produced an error, the next item appeared 250 ms after the last response. Between blocks, they were allowed to rest for a few moments, and received information about the average RT and the percentage of correct responses yielded over the last block. They were specifically reminded to keep this rate above 92%, and were instructed to take note of their scores on a response sheet in order to keep track of their own performance. When they were ready to proceed with the next block, they did so by pressing the space bar.

**Results**

Over the whole experiment, participants performed at a high level of accuracy. The percentage of correct responses amounted to 97.5% of the trials. The patterns of results obtained with RT and accuracy measures were generally consistent, and thus I will restrict this report to the RT data. For the rest of this section, I will focus successively on: (1) the effects of sequence learning on performance over successive training blocks; (2) the purported effects of chunk learning as analyzed by Koch and Hoffmann (2000); and (3) the response tendencies that can be identified before the start of the training blocks, which provide an alternative account for the triplet effect.

**Sequence learning**

Figure 2 represents the average RT for correct responses over successive blocks, including both test (1 and 19) and training blocks (2–18). An Analysis of Variance (ANOVA) with block (19) as a repeated-measure variable indicated that the effect of Block was significant, $F(18, 198) = 83.70; \text{MSE} = 2,032.8; P < 0.0001$. The analysis conducted specifically with the average RT to the 17 training blocks also showed a significant improvement with training $F(16, 176) = 64.65; \text{MSE} = 1,584.3; P < 0.0001$. The comparison between participants’ performance over blocks 18 and 19, which could be taken as the main measure of sequence learning, further confirmed the production of a strong learning effect, $F(1, 11) = 218.41; \text{MSE} = 2,559.9; P < 0.0001$. The average RT by the end of training was of 236 ms, but it rebounded to the initial levels of performance over the final test block, reaching an average RT of 541 ms.

**Purported chunk learning effects**

To get results comparable to those taken by Koch and Hoffmann (2000), I analyzed RT over block 4, which roughly corresponded to the same level of training with the structure that was provided in Koch and Hoffmann’s study by their block 5. As shown in Fig. 3 (panel a), performance over the 24 items of the series showed a pattern similar to that found in the original study, producing an increase in RT at the beginning of each triplet. A summary of this position effect was taken by Koch and Hoffmann by computing the mean RT separately for the keystrokes corresponding to the first, second and third positions over the eight triplets. Figure 3 (panel b) shows the results of such an aggregated analysis, not only for block 4, but also separately for all the training blocks. As it can be observed, the effect of position was clearly observed on block 4, $F(2, 22) = 25.97; \text{MSE} = 1,540.6; P < 0.0001$, but the same effect was already present over the first training block (i.e., block 2; $F(2, 22) = 39.63; \text{MSE} = 875.6, P < 0.0001$), and it did not appear to grow progressively with training over the next few blocks. An ANOVA computed on these scores with block (17) and position (3) as between-participants factors showed significant effects of Block, $F(16, 176) = 64.85, \text{MSE} = 4,758.6,$

The expected effects of Block, $F(8, 88) = 43.01$, MSE = 4,097.8, $P < 0.0001$; and position, $F(2, 22) = 50.97$, MSE = 6,584.8, $P < 0.0001$; but not a hint of a block x Position interaction, $F < 1$.

Response tendencies

The lack of interaction between Block and Position over the first half of training does clearly indicate that the differences between responding to elements internal to a chunk and to transitions between chunks were not gradually acquired, but they were rather present from the beginning of training, and they did not increase with practice. One may argue that, perhaps, the fragmentation effects could occur early in training, so that by the end of the first block participants would have already discovered the advantage of encoding the series as a collection of triplets. To test this possibility, I conducted a detailed analysis of the first block, separating the eight repetitions of the series and exploring whether it could be possible to detect an early increase in the effect of position within these initial series. As mentioned before, the effect of position was already significant in this first block, but there was no indication that this effect was developed over these initial repetitions of the sequence, since there was no significant interaction between position and series ($F < 1$).

Faced with these null results, it becomes important to analyze the existence of any preexistent response tendency that could account for the observation of these position effects from the very first block of training. To test this hypothesis, I analyzed these tendencies on the initial test block before the training phase. As mentioned above, this block contained two instances of the training series as well as two exemplars of a different series that included the same triplets in a scrambled order. It also included four more series that broke these triplets in systematic ways, by changing either the first or the third digit of each triplet. As a whole, then, three quarters of these trials were arranged to break either the chunk structure or the structure arranged between successive chunks. It is fair to assume, therefore, that chunk learning could not have arisen at this point, and that any systematic effect detected on this analysis should be better construed as depending on preexistent response tendencies.

Average RT were computed separately over this first test block for those trials corresponding to hand-switches, immediate repetitions and reversals in order to find out whether responding these patterns produced slower RT as compared to appropriate baseline trials. As there were a few cases over the training blocks implementing simultaneously a reversal and a hand-switch (namely, in the fragment 3434), I computed separately the average for reversals responded with the same hand and for reversals that

![Fig. 3](image-url)
involved a hand-switch. As a comparison term, I computed the baseline RT for those non-repeating and non-reversal transitions that required responding with the same hand. Figure 4 represents the average RT for each of these types of trials. As it can be observed, hand-switches took about 135 ms longer than the baseline, $F(1, 11) = 74.06; \text{MSE} = 1,474.3$, $P < 0.0001$, whereas same-hand reversals required an average of 93 ms more than other same-hand transitions, $F(1, 11) = 13.51; \text{MSE} = 3,870.9$, $P < 0.005$. When reversals also implied a hand-switch, they also produced RT slower than the baseline, $F(1, 11) = 22.66; \text{MSE} = 5,555.2$, $P < 0.001$, but they did not result in a further delay with respect to other hand-switches, $F < 1$. Surprisingly, immediate repetitions did not result in slower RT, but they actually produced responses faster (55 ms) than the baseline, $F(1, 11) = 14.47; \text{MSE} = 1,254.5$, $P < 0.005$.

As a whole, the response tendencies observed before training are strong enough to account for the early appearance of the position effect observed in this study. As it can be confirmed from a cursory inspection of Fig. 1, the first position of the triplets contained four hand-switches, three reversals and two immediate repetitions, whereas most of the transitions corresponding to the second and third positions were made with the same hand. It should not be surprising, therefore, that responding to the first position of the triplets would take more time, in general, than responding to their second or third elements.

The only evidence obtained in this study that could be taken as showing that participants learn to respond more slowly to the first elements of the triplets has to do with the change produced over training in the responses given to immediate repetitions. Within the initial test block, participants were shown to respond faster to repetitions than to other baseline trials, but this initial trend got progressively inverted over the next few blocks, and it reached a significant difference against repetitions over the block 8, $F(1, 11) = 5.01; \text{MSE} = 3,494.6$, $P < 0.05$. This specific change could indicate that participants were chunking the sequence at these particular joints and thus using the repetitions as markers of the limits between successive chunks. However, an alternative account of this effect might also be built on the fact that the sequence arranged in this study was not statistically homogeneous and thus that a form of statistical learning could also account for the appearance of differences in learning between parts of the sequence.

An inspection of the sequence does make clear that not all its transitions are equally predictable. In fact, the conditional probabilities of appearance of those trials containing immediate repetitions are especially low, and thus this could account for the relatively lower improvement observed in those specific trials. For instance, the probability of appearance of digit 3 immediately after another 3 is only of .20, and it only grows to .33 by considering its probability of appearance in the context of the two previous events (“23”). Similar figures hold for the repetition of digit 6. In contrast, the averaged conditional probability of appearance of any other same-hand transition in its relevant context amounts to .56 considering contexts of length 1, and goes up to .81 by considering contexts of length 2. Plainly, then, it is perfectly reasonable to assume that a form of statistical learning could account for the lower improvement observed in performance in response to immediate repetitions, without assuming that learners are using those repetitions as markers of the limits between successive chunks.

To further explore the idea that statistical learning could be compatible with the obtained results, I conducted a linear regression analysis on each training block, predicting the average RT obtained by all participants on each item of the sequence by relying on the distributions of conditional probabilities of orders 0, 1 and 2. The results of these analyses were significant through all the training blocks and showed that the transition probabilities could account for almost a third of the relevant variance in average RT over the first training block, $R = 0.62$; Adjusted $R^2 = 0.29$; $F(3, 20) = 4.19$, $P < 0.05$. This multiple correlation tended to grow with training, and it reached a maximum of predictive value by block 8, when they accounted for more than a half of the variance, $R = 0.76$; Adjusted $R^2 = 0.53$; $F(3, 20) = 9.54$, $P < 0.001$. Figure 5 shows the evolution of the slopes $\beta$ for each predictor with training. As it can be observed, the conditional probabilities of orders 1 and 2 were negatively correlated with RT, thus showing that more predictable successors tended to produce faster RT, and with practice second order transitional probabilities tended
were analyzed in epochs of V

Evolution with training of the slopes (β) of the regression functions which predict RT to each of the 24 elements of the sequence, based on the distributions of conditional probabilities of order zero, one and two. CP(0), β for the conditional probabilities of order 0, or unconditional digit frequency. CP(1), β for the conditional probabilities of each digit in the context defined by the previous digit. CP(2), β for the conditional probabilities of each digit in the context defined by two previous digits.

Fig. 5 - Evolution with training of the slopes (β of the regression functions) which predict RT to each of the 24 elements of the sequence, based on the distributions of conditional probabilities of order zero, one and two. CP(0), β for the conditional probabilities of order 0, or unconditional digit frequency. CP(1), β for the conditional probabilities of each digit in the context defined by the previous digit. CP(2), β for the conditional probabilities of each digit in the context defined by two previous digits.

to outscore the first-order distribution. Surprisingly, however, there was a positive relation between conditional probabilities of order 0 (i.e., item frequency) and RT. This positive relation tended to decrease with practice, but it was significant over the first two-thirds of training, indicating that participants tended to respond faster precisely to those trials that occurred less frequently. This could be interpreted as a consequence of the specific trials that happened to occur less frequently in that particular series (digits 1 and 6, requiring extreme responses), or perhaps as a tendency not to expect that the digits would reappear very often, and then responding slowly when they recur more frequently. In any case, regardless of the interpretation of this particular trend, what these regression analyses more generally indicate is that the evolution of RT with training is generally compatible with the predictions of a statistical learning process.

Discussion

This study was inspired by previous work reported by Koch and Hoffmann (2000) on the role of relational patterns and chunking processes in the acquisition of sequence learning. The conclusions raised by this extension of the original study converge with their conclusions concerning the relevance of relational patterns, but they stand in sharp contrast with their interpretation of the effects produced by these patterns as evidence of chunk learning.

The analysis conducted on the effects of these relational patterns over the first test block indicated that the relational patterns that had been designed as tools to force chunk learning produced other effects on performance that were independent from learning. Hand-switches and reversals produced significantly slower RT than did other transitions and they tended to occur at the beginning of the runs that were intended to force the segmentation of the sequence into triplets. Thus, the observation of slower RT at the beginning of a triplet could not be unequivocally taken as evidence of chunk learning. Moreover, the observed stability of this position effect, which arose on the very first block of training and was extended without changes over a long period of practice, is consistent with an interpretation of the effect as a result of these preexistent response tendencies, rather than as an evidence of chunk learning.

Despite possible differences in their detailed assumptions, the core of any chunk learning model (e.g., Perruchet and Vinter 1998; Servan-Schreiber and Anderson 1990) relies on the assumption that the representation of a chunk tends to improve performance differentially for those parts of the task that are represented within a chunk and for those that correspond to transitions between chunks. Thus, regardless of whether participants were able to learn to anticipate next chunk while responding to the current one (Verwey and Eikelboom 2003) or whether some composition process could arise later in practice to soften the difference between internal and external transitions, the difference between them should arise at some point in training for the chunk hypothesis to be grounded in empirical data. The analyses conducted in this study have shown that no such a difference arose in this experiment, neither early in practice, where these trends were analyzed in epochs of 24 trials to look for fine-grained differences, nor later on, where an extensive period of practice was provided. Some might argue that floor effects may have prevented the advantage of chunk internal events to arise in these conditions. Indeed, this could be a good point if participants reached a floor level of performance very early in training, but Fig. 3 (panel b) appears to show that performance over both the transition and internal trials kept improving with practice over a long training period, and thus that there was room enough for a relative difference between them to arise early in training.

In sum, the results obtained in this experiment do not sustain the claim that participants’ performance in this particular task is being affected by chunk learning, and they rather suggest that sequence learning affected performance in a continuous way throughout the whole sequence. At this point, however, it might be advisable to state more precisely what this conclusion may or may not imply.
Specifically, this does not amount to claim that chunk learning effects could not be expressed in other discontinuous settings in which sequence learning has been investigated, such as in the discrete sequence production task (Verwey and Eikelboom 2003; Verwey et al. 2002) or in the task sequence learning domain (Koch et al. 2006; Schneider, in press). It does not even imply that participants in the present SRT task have not noticed the existence of the relational patterns or that they have not learned anything about these specific patterns. Indeed, in their Experiment 2, Koch and Hoffmann (2000) did show that learning was far lower when participants responded to a sequence that was statistically analogous to that employed in their Experiment 1, but that differed in that the triplets were not made of continuous runs. Thus, it appears that including a relational pattern does produce an improvement in sequence learning that is arguably due to the fact that these relational patterns make the existence of a sequence far more salient, and thus improve sequence learning in general.

Although Koch and Hoffmann (2000) did not report on any direct measures of sequence learning, and measures of awareness are not included in the present experiment, informal comments made by some participants suggest that they were largely aware of the existence of these patterns. The large effect of learning can also be considered as a clue indicating that learning was explicit. However, in this context, it is particularly remarkable that the explicit acquisition of information about some specifically salient patterns were not selectively expressed in performance as a local improvement in response to these particular fragments of the sequence. This appears to indicate that, in these SRT tasks, explicit knowledge of fragments cannot be immediately translated into an effect of performance. One may argue that participants may have learned explicitly and simultaneously about the whole structure and therefore that the effect of learning could be immediately translated into an overall effect of performance over the whole sequence. However, this account does not seem very plausible, given the well known limits of human working memory. An alternative account for these results could be built by assuming that learning of some disjunctive chunks may have occurred explicitly, as participants noticed the relational patterns, but that this explicit knowledge could not be immediately translated into a local advantage for responding to those fragments because participants’ resources were already occupied in coping with the response demands made by each specific trial. If that were the case, chunk learning could still be reinforced from the continuous repetition of such salient patterns, but this learning would turn out to produce diffuse influences, rather than local effects in performance, by modulating participants’ reliance on any other source of sequence information. A similar effect of indirect modulation of the implicit effects derived from the learners’ explicit beliefs has been reported by Jiménez et al. (2006) who found that decreasing the validity of a sequence in intentional learners resulted in slower RT not only for the control trials, but also for those trials that were generated according to the sequence. In a similar vein, it is likely that noticing the existence of some repeated chunks could increase participants’ reliance on their implicit knowledge, thus producing a general advantage in performance that should not be restricted to the explicit chunks. This hypothesis about the modulating role of explicit chunk learning has the advantage of reconciling the observation of a relatively fast learning rate with the absence of the local effects that should be attributed to chunk learning without the need to assume that the whole sequence of 24 items has been learned explicitly and almost instantaneously. At the same time, this modulation hypothesis could contribute to change the research focus from one centered on solving the dilemma between chunk and statistical learning to another one more focused on the analysis of the potential interactions that may arise between them. As scientists, we have been trained to look for crisp dilemmas and to avoid the unparsimonious calls for complex interactions. However, cognitive science appears to be full of examples indicating that nature does not always select the clean designer’s view, but that it flows perfectly fine through interactions.

Acknowledgements This research has been supported by the Spanish Ministerio de Educación y Ciencia with grants BSO2003-05055, SEJ2005 25754-E and SEJ2006 27564-E. The author wishes to thank Gustavo Vázquez for his assistance in data collection, and Peter Frensch, Iring Koch, Pierre Perruchet and an anonymous reviewer for their thoughtful suggestions on an earlier version of the manuscript.

References


