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Auditory memory for random time patterns in cochlear implant users

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Keywords: cochlear implant, temporal pattern, learning, memory

Abstract

Learning new sounds is essential for normal hearing listeners and cochlear implant users alike, with the additional challenge for implant users that spectral resolution is severely degraded. Here, the rapid learning of stochastic temporal sequences was evaluated for cochlear implant users using electric pulse trains and for normal hearing listeners using matched acoustic pulse trains. Rapid perceptual learning was observed for both groups, with similar characteristics. Implant users were also able to learn ultra-fast electric temporal sequences unavailable to acoustic hearing. This suggests that cochlear implant users retain the plasticity mechanisms needed for rapid perceptual learning of complex temporal sequences.

I. Introduction

To navigate realistic sound scenes, listeners must combine the acoustic cues reaching their ears with auditory knowledge arising from past experience: Am I hearing the voice of a familiar person? Which phonemes are being uttered? Is the timbre of my friend's voice relaxed or anxious? Over the last ten years, it has been shown that adult normal-hearing (NH) listeners can display a remarkable form of implicit rapid perceptual learning (Agus, Thorpe, & Pressnitzer, 2010), which would presumably be useful to accumulate knowledge about familiar sounds. Here, we used a similar paradigm to probe rapid perceptual learning in adult listeners using a cochlear implant (CI). To make a fair comparison, we used a variant of the paradigm relying purely on temporal cues (Kang, Agus, & Pressnitzer, 2017; Kang, Lancelin, & Pressnitzer, 2018), because such cues can be represented peripherally at least as well for CI listeners as for NH listeners. The aim was two-fold: first, to ascertain whether or not rapid memory processes are available to post-lingually deafened CI listeners; second, to use direct electrical stimulation of the cochlea to better characterize the range of temporal cues amenable to auditory perceptual learning.

The original version of the rapid memory task used samples of noise to probe perceptual learning (Agus et al., 2010; Agus & Pressnitzer, 2013; Viswanathan, Rémy, Bacon-Macé, & Thorpe, 2016). Briefly, listeners were presented with short trials (e.g., 1s) containing either novel noises, or, unbeknownst to them, re-occurring noise samples that had been presented previously during an experimental block. An ancillary task was designed to measure unsupervised learning. Each trial could be either a full-duration sample of white noise, or a half-duration sample of noise seamlessly repeated to make up a full-duration trial. Overall, performance on this withintrial repetition detection task improved over the course of an experimental block for re-occurring

noise samples, which was evidence of rapid, robust, and unsupervised learning of complex sounds in NH adult listeners. Interestingly, brain imaging studies using MEG (Luo, Tian, Song, Zhou, & Poeppel, 2013), fMRI (Kumar et al., 2014) or EEG (Andrillon, Kouider, Agus, & Pressnitzer, 2015) implicated not only memory-related regions such as the hippocampus but also sensory regions in the learning process, more specifically secondary auditory cortex.

Rapid perceptual learning of novel sounds is arguably an even more acute need for CI users than for NH listeners. Post-lingually implanted adults have to transition from acoustic hearing to electric hearing, which must involve a thorough re-learning of the mapping between auditory cues and sound meaning. Prelingually implanted children may have to learn "impossible" cues that are transmitted by the implant but not available in acoustic hearing, such as fast electrical pulses in nominally low-frequency regions of the cochlea. Previous studies have shown the importance of perceptual training for CI users to improve the outcome of implantation, in particular for speech perception (Schumann, Serman, Gefeller, & Hoppe, 2014) or music perception (Fu & Galvin, 2007). On an even more basic level, the frequency-to-place mismatch arising from the uncertainty and limitations of electrode insertion can also be compensated by training if it is not too severe (Rosen, Faulkner, & Wilkinson, 1999; Schumann et al., 2014; Svirsky, Talavage, Sinha, Neuburger, & Azadpour, 2015). The type of learning mechanism evidenced in Agus et al. (2010), if it were present in CI listeners, would be an ideal candidate to explain at least in part such clinically-relevant training effects.

On a neural level, the available evidence makes it unclear as to whether impaired or intact rapid perceptual learning should be expected for CI users. Secondary auditory cortical areas, such as those implicated in rapid perceptual learning, have been shown to undergo plastic processes during the sound-deprivation period that accompanies deafness (Ponton, Moore, &

Eggermont, 1999), which could impair their contribution to learning after implantation. For CI users, implantation has been shown to trigger a cascade of neural plasticity processes, from sensory to language or even visuo-motor areas (Giraud, Truy, & Frackowiak, 2001; see Glennon, Svirsky, & Froemke, 2020 for a recent review). It is unclear whether such wide-reaching changes are enabled by intact perceptual learning abilities, or rather compensate for reduced underlying perceptual learning abilities.

An additional issue for CI users is the type of early auditory representations that are available to subsequent learning processes. It is well-known that listening through an implant severely reduces the accuracy of spectral information (e.g., Henry & Turner, 2003). However, temporal information seems largely preserved, at least up to moderate rates of about 300 Hz (McKay, McDermott, & Carlyon, 2000; Shannon, 1985; Zeng, 2002). In fact, there is evidence that the performance of CI listeners in several temporal processing tasks such as gap detection or musical rhythm perception is similar to that of NH listeners (Gfeller & Lansing, 1991; Kong, Cruz, Jones, & Zeng, 2004; Penner, 1977; Phillips-Silver et al., 2015; Shannon, 1989). Thus, it is likely that perceptual learning of novel sounds for CI users will require at least in part the learning of purely temporal cues.

The available neural data also motivate the study of temporal cues for perceptual learning. The encoding of cortical responses to temporal cues has been found to be similar for electric and acoustic hearing in human intracranial recordings (Nourski et al., 2013). Furthermore, training was shown to be able to improve the accuracy of the neural temporal cues in auditory cortex in animal models, for acoustic hearing (Schnupp, Hall, Kokelaar, & Ahmed, 2006) or, importantly, electric hearing (Vollmer & Beitel, 2011).

Lastly, a methodological consideration was a further reason to focus on time in the

present study. For a fair comparison of the learning processes between CI and NH listeners, any differences in the early representation of acoustic cues should be controlled for. It is easy to devise sounds with temporal cues that are similarly represented in CI users than NH listeners, basically by providing cues below the 300 Hz upper limit. So, for all these reasons, the following experiments aimed to study the perceptual learning of temporal cues.

Most of the previous studies probing rapid perceptual learning (e.g. Agus et al., 2010, 2013; Andrillon et al., 2015) used Gaussian noise as the stochastic stimulus to be learnt. Noise obviously contains both spectral and temporal cues, from which the spectral cues would be differently represented in CI and NH listeners and possibly favor NH listeners if performance was compared across populations, as argued above. We therefore used a variant of the paradigm where sequences of random time intervals served as the stochastic stimuli to be learnt. Kang et al. (2017) introduced this variant, using acoustic click trains with random inter-click intervals. They showed that rapid perceptual learning was observed for temporal cues in NH listeners, over a broad range of temporal intervals (from milliseconds to hundreds of milliseconds). The technique was also been extended to other sensory modalities, by using light flashes or tactile impulses to carry time intervals, with again an observation of perceptual learning (Kang et al., 2018).

Here, we probe yet another modality, electric hearing, using direct stimulation of the auditory nerve of CI users through the research interface of the implant. We used electrical pulses transmitted quasi-simultaneously to four electrodes of the CI, covering the useful frequency range of the device for each participant. A comparison group of NH listeners was also tested, using high-pass acoustic click trains with the same temporal characteristics as those presented to the CI group. Two average click rates, 10 Hz (Slow) and 40 Hz (Fast), were tested

in both groups. The average rates were chosen to ensure that the early representation of the acoustic cues would be accurate for both CI and NH participants. An additional pulse rate, 300 Hz (Ultra-Fast), was used for the CI group only, a situation testing temporal cues that would be impossible to experience acoustically because such ultra-fast click rates would induce accompanying spectral cues in NH listeners, due to cochlear filtering. Overall, the results showed preserved rapid perceptual learning abilities for CI users, and even the possibility for them to learn ultra-fast sequences.

II. Experiment

A. Participants

A total of ten CI users of Med-EL devices took part in the experiment (age range: 37 - 77, M = 55, SD = 15.6, 5 male, c.f. Table 1 for details). CI listeners were recruited in the Marseille area from a pool of CI users regularly tested in the laboratory. The CI branch of the experiment consisted of two different test sessions. Nine and eight participants, out of ten participants overall, participated in Test session 1 and Test session 2, respectively, seven of them participating to both test sessions. The experiment with CI listeners was approved by a local research ethics committee (Eudract 2012-A00438-35).

Table 1. Details of each CI subject.

Subject ID	Age	Duration of CI usage (y)	Etiology of deafness	Duration of profound bilateral deafness (y)	Electrode array	Type of implant	Sessions participated
M004	77	9	Unknown	10	standard long	sonata ti100	1 and 2
M005	39	5	Congenital hereditary	20	standard long	concerto	1
M010	38	9	Congenital	16	standard long	sonata ti100	1 and 2
M012	69	7	Unknown	2	standard long	pulsar 100	1
M013	75	4	Unknown	1	standard long	sonata ti100	1 and 2
M014	61	3	Auto-immune disease	1	flex 28	concerto	1 and 2
M015	51	3	Unknown	15	flex 28	concerto	1 and 2
M016	45	3	Congenital hereditary	20	flex 28	concerto	1 and 2
M017	70	2	Unknown	3	flex 28	concerto	1 and 2
M018	73	1	Otosclerosis	6	flex 28	synchrony	1 and 2

Nine NH listeners were recruited in the Parisian area for the control group. There was no attempt to match the CI and NH group in age or any other factor such as gender or education. The age range for the NH group was between 18 - 35 (M = 22.5, SD = 0.7, 2 male). Audiometry was performed for all NH listeners at 125, 250, 500, 1000, 2000, 4000, and 8000 Hz. All participants had audiometric thresholds better or equal to 20 dB HL. The experiment with NH listeners was approved by a local ethical committee (CERES, IRB: 20154000001072).

All participants from both groups provided written consent and were compensated for their participation by a small monetary payment (NH and CI listeners) and travel reimbursement (CI listeners).

B. Stimuli

Stimuli consisted of sequences of electrical (CI) or acoustical (NH) pulses separated by random inter-pulse-intervals (IPIs). The IPIs were drawn from a Poisson distribution with a refractory period. Three rate conditions were used with mean pulse rates of 10 (Slow), 40 (Fast), and 300 Hz (Ultra-Fast). The total stimulus duration was either 2 s for Slow and Fast rates conditions or 3 s for the Ultra-Fast rate condition. The refractory periods were 10 ms for the

Slow and Fast conditions, and 0.3 ms for the Ultra-Fast condition. They were introduced to prevent spectral cues due to cochlear filtering with the acoustic presentation used for NH listeners, but applied to both the CI and NH groups for fair comparison.

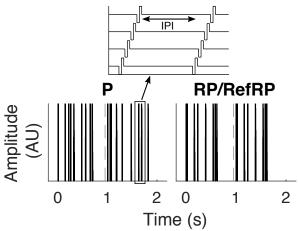


Figure 1. Illustration of the stimuli. An example of a repeated pulse train (RP or RefRP, right) and a fully random pulse train (P, left) for the Slow (10 Hz) rate condition. Inter-pulse intervals were drawn from a Poisson distribution with a 10 ms refractory period. Dashed lines indicate the midpoint of the click trains. For CI users, such stimuli were presented with direct stimulation of the implant, as illustrated in the inset. Each nominal pulse consisted of symmetric biphasic electric pulses with duration 45 μ s, presented almost simultaneously to 4 equally spaced electrodes (100 μ s delay between pulses, inter-pulse interval exactly applied within each electrode). For NH participants, the pulse sequences were presented as high-pass acoustic click trains accompanied by low-pass masking noise (see Kang et al., 2017).

For the CI group, electrical stimulation was achieved through the research interface of the implant. Each pulse consisted of four monopolar cathodic-first symmetric biphasic pulses transmitted quasi-simultaneously to four different electrodes (Figure 1). Each pulse had a phase duration of 45 µs and the delay between the offset of one pulse and the onset of the following pulse (presented on another electrode) was 100 µs to avoid direct electrical field summation (de Balthasar et al., 2003). The four electrodes were stimulated from apex to base and were regularly spaced across the electrode array to cover a large range of the neural population excited by the CI. Electrodes 1, 4, 7, and 10 were chosen for seven participants. For the remaining three

participants, some of these electrodes were switched off, so stimulation was as follows: electrodes 1, 4, 7, and 9 (M013 Ultra-Fast rate only, M014); 1, 4, 6, and 8 (M012); 2, 4, 7, and 10 (M004). Loudness was adjusted individually using the procedure described in section 2.4.

For the NH group, pulses were acoustic clicks with similar temporal characteristics to the Slow and Fast rate conditions used for the CI group. Each click had a nominal duration of 50 μ s. The random click trains, generated with the same Poisson distributions as for the CI group, were then high-pass filtered using an 8^{th} order Butterworth filter with a 1 kHz filter cut-off, to minimize spectral cues arising from cochlear filtering (Kang et al., 2017). The sound level was kept at an overall level of 65 dB SPL A-weighted, for both rate conditions.

C. Task

The task was identical for the CI and NH groups. Participants were told to report within-trial repeats, that is, to report pulse trains for which the first half was heard as identical to the second half (Kang et al., 2017).

Even though there were only two possible responses, there were in fact three different stimulus types. For the first stimulus type, the pulse trains had fully random IPIs for the whole duration of a trial, so 2 s in the Slow and Fast rate conditions (pulse train, P; Fig. 1 left). For the second stimulus type, a random sequence of IPIs with a 1-second duration was generated and immediately repeated, identically, to create a repeated pulse train (RP; Fig. 1 right) lasting also 2 s. For the third stimulus type, the generation procedure was identical to RPs. The only difference is that, without warning the participants about this possibility, the exact same sequence of IPIs was presented in several trials over the course of an experimental block, so that participants may have a chance to learn that particular sequence. This condition is termed reference repeated pulse trains (RefRP; Fig 1 right).

The Ultra-Fast condition had the same three types of stimuli, but with an overall stimulus duration of 3 s and three repeats of a 1 s sequence for the RP and RefRP conditions, in an attempt to make the within-trial repetition detection task easier.

Each test block comprised 80 trials, consisting of 40 Ps, 20 RPs, and 20 RefRPs. The different types of stimuli were presented in a pseudo-random order during an experimental block, with the only constraint that no two successive trials should contain RefRPs. Listeners were asked to report repetitions after each trial. There was no feedback during the main experiment.

D. Apparatus and Procedure

The Slow and Fast rate conditions were tested in a single session for the CI group and NH group. The Ultra-Fast rate condition was tested in a second session for the CI group only. We first describe the procedure for the Slow and Fast conditions for CI participants, all other conditions being derived from these.

CI participants were tested in a quiet room. The psychophysical procedures were programmed in Matlab and used the Research Interface Box (RIB2, University of Innsbruck) and a National Instruments card (PCI-6533, National Instruments, Austin, TX) connected to a PC to directly stimulate the implant.

The most comfortable loudness level (MCL) was measured individually on each of the 4 electrodes, at a constant rate of 40 Hz. Current level was progressively increased, starting at a subthreshold level. Participants were asked to indicate the loudness of each sound using a 10-point loudness chart with MCL corresponding to a level labelled "6". Once the MCLs for individual electrodes were collected, the 4-electrode stimulus was constructed by keeping fixed the relative level difference (in dB) across electrodes. Then, the MCL of the 4-electrode stimulus was measured once again, starting at subthreshold level and progressively increasing current

level. We finally checked that the multi-electrode pulse train at the rate of 10 Hz with the same current levels as for 40 Hz was still clearly audible, which was the case for all subjects. The same current levels were, therefore, used in both the Slow and Fast conditions.

After the MCL adjustment, a training session was provided. The training session consisted in detecting repetitions for trials that contained more within-trial repeats than in the main experiment, to make the repetition-detection task easier. Four blocks were run in increasing level of predicted difficulty: 10, 4, 3, and 2 repetitions of a 1s pulse train (Kang et al., 2017). Only P and RP stimulus types were included in these training blocks, in equal proportion. Note that no RefRP was included in the training. Each training block contained a total of 40 trials, except for the easiest 10 repetitions block which only contained 10 trials. Visual feedback on the correctness of the response was provided after each trial.

Finally, the main experiment was performed. Four blocks for each of the Slow and Fast rate conditions were run. Two blocks were presented after the full training session for each rate condition, in a randomised order across participants. Another two blocks for each condition were run after an additional training block (with 2 repetitions), in reverse rate condition order for each participant. The experiment lasted between 2.5h and 3h, which included ample time for breaks.

For the Ultra-Fast condition in the CI group, the same loudness adjustment procedure was used, but only for 300 Hz pulse trains. The training was similar but only included 3 blocks with 10, 4, and 3 repetitions of 1 s pulse train sequences. The main experiment lasted for about 2h.

For the NH group, the procedure was identical except that no loudness adjustment was needed; the same level was used for all participants and conditions. Training and testing procedures were the same as for the CI group in the Slow and Fast rate conditions. NH listeners were tested in a double-shielded booth (Industrial Acoustics). The experimental procedure was

coded in Matlab. Sounds were presented over an RME Fireface soundcard and Beyerdynamics DT 770 Pro headphones, at a sample rate of 44.1 kHz and a 16-bit resolution. The experiment for NH listeners lasted about 2h.

E. Statistical analyses

Performance in the within-trial repetition detection task was analysed in terms of the sensitivity index d' from signal detection theory (Macmillan & Creelman, 2004). "Yes" responses for the RP and RefRP stimulus types were considered as hits, while "yes" responses for the P stimulus type were considered as false alarms.

For the Slow and Fast rate conditions, which were run during a same session in counterbalanced order, a repeated-measures analysis of variance (ANOVA) was applied to the d' values. Stimulus type (RP and RefRP) and rate condition (10 Hz and 40 Hz) were within subject factors, while participants were random factors, for each group (CI and NH) separately. Mauchly's test for sphericity confirmed that the data meet the assumptions required for ANOVA. F-values and p-values meeting a level of p < 0.05 were treated as statistically significant. Generalised eta squared (η^2_g) was also computed to estimate effect sizes (Lakens, 2013). Mixed-design ANOVA combining both CI and NH groups was additionally run for group comparisons.

Post-hoc paired *t*-tests were also conducted, correcting for multiple comparisons using the Holm-Bonferroni method.

A paired *t*-test was conducted to compare the RP and RefRP *d'* values for the Ultra-Fast rate condition performed by CI listeners only.

The time-course of performance was analysed by considering the evolution of hit rates for each presentation of RefRP and RP, over subjects and test blocks, per rate conditions for NH and CI listeners. The values were fitted by the least-squares method, either with a flat line

corresponding to the average performance (1 parameter) or exponential functions (3 parameters). The best model was selected by taking into account the number of parameter of each model (Motulsky & Christopoulos, 2004).

III. Results

A. Average performance

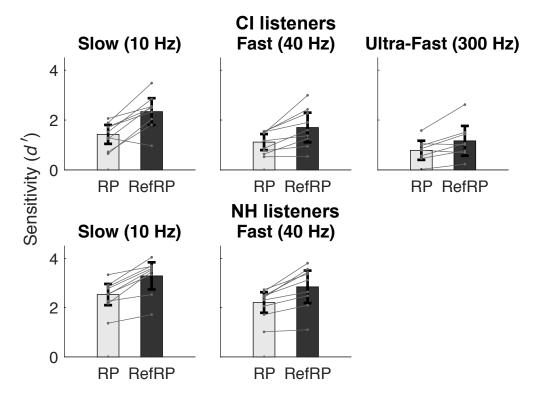


Figure 2. Average results for all experiments. Performance (d') is plotted for the different stimulus types (RP, light grey, and RefRP, black), in panels corresponding to the different rate conditions (Slow, Fast, or Ultra-Fast) and to the CI group (top) or NH group (bottom). Individual data points are indicated as dots, paired between the RP and RefRP for each participant with connecting lines. Black error bars represent 95% confidence intervals.

The results of the main experiment are shown in Figure 2. Qualitatively, the NH group shows higher performance (d' values) overall than the CI group. However, the critical comparison for perceptual learning consists of comparing the RP *versus* RefRP performance in

each condition, as the RP performance may be viewed as a baseline. Here, the results were similar between the CI and NH groups. In particular, in all cases, RefRP performance was higher than RP performance, suggesting that the task was performed more accurately for re-occurring sounds that may have provided an opportunity for learning.

The statistical analyses confirmed these observations. We first focus on the Slow and Fast rate conditions that were performed by both groups. For the CI group, the repeated measures ANOVA confirmed an effect of stimulus type (RP vs RefRP, F(1,8) = 27.50, p < 0.001, $\eta^2_g = 0.30$). Performance also differed across rate conditions (Slow vs Fast, F(1,8) = 11.63, p < 0.01, $\eta^2_g = 0.14$). No interaction between stimulus type and condition was found (F(1,8) = 2.41, p > 0.05, $\eta^2_g = 0.02$). Further post-hoc t-tests showed significant differences between RP and RefRP stimulus types for each rate condition (10 Hz: t(8) = -4.59, p < 0.01, 40 Hz: t(8) = -3.80, p < 0.01). For the NH group, a separate ANOVA also showed an effect of stimulus type (F(1,8) = 31.13, p < 0.001, $\eta^2_g = 0.18$) and an effect of rate condition (F(1,8) = 20.56, p < 0.01, $\eta^2_g = 0.15$) with no interaction between stimulus type and conditions (F(1,8) = 0.06, p > 0.05, $\eta^2_g = 0.0007$). Post-hoc paired t-tests further confirmed the effect of stimulus type for each rate condition (10 Hz: t(8) = -6.16, p < 0.001, 40 Hz: t(8) = -5.08, p < 0.001). Thus, for both groups and conditions, there was a performance advantage for RefRP over RP.

Finally, we ran a mixed-design ANOVA combining both groups. A significant effect of group on performance was observed (F(1,16) = 25.73, p < 0.001, $\eta_g^2 = 0.49$), confirming the observed difference in baseline. However, importantly, no interaction was observed between group and stimulus type or rate condition (F(1,16) = 0.60, p > 0.05, $\eta_g^2 = 0.003$; F(1,16) = 0.17, p > 0.05, $\eta_g^2 = 0.001$). This indicates that, even if the RP performance was better in NH listeners compared to CI listeners, there were similar benefits of increased exposure to RefRP in both

participants' groups.

For the Ultra-Fast rate condition, which was only run by CI listeners, a simple paired t- test showed that RefRP produced higher performance than RP (300 Hz: t(7) = -2.9, p < 0.05).

B. Time course

An advantage of RefRPs over RPs is consistent with perceptual learning caused by the reoccurring presentation of the same RefRP sequence throughout an experimental block (RP
sequences were different on each trial even within a block). However, a further test of the
presence of perceptual learning rests on the time course of performance: learning should
manifest itself by changes in performance over the course of the experimental block, as exposure
to the RefRP increases. Otherwise, it is in theory conceivable that a difference in average
performance could be due to a chance selection of particularly easy RefRPs compared to the
average difficulty of RPs (Agus et al., 2010). Note that performance changes associated to
learning could manifest themselves as increases in performance for RefRPs, obviously, but also
as decreases in performance for RP. Such decreases are predicted by criterion effects, because an
easier task for RefRPs as learning occurs induces a lesser propensity to report the comparably
more difficult RP trials (Agus et al., 2010).

The time course analysis was restricted to blocks for which putative learning had occurred, which we term "good blocks" (Agus et al., 2010; Kang et al., 2017). Good blocks were identified by computing the average hit rates for the RefRPs over the last 10 trials of a block. For the CI group, the average hit rates during the last 10 trials for RefRPs were not normally distributed, as shown by a one-sample Kolmogorov-Smirnov test (Slow: D(36) = 0.62, p < 0.001; Fast: D(36) = 0.60, p < 0.001; Ultra-Fast: D(40) = 0.57, p < 0.001). This deviation from normality suggests that the performance distribution is not homogeneous, consistent with the presence of good and bad

block. As in previous studies (Agus et al., 2010; Kang et al., 2017), we set a selection criterion of hit rate above 80% to identify good blocks. This led to 83%, 75%, and 55% good blocks in the Slow, Fast, and Ultra-Fast conditions, respectively. For the NH group, the one-sample Kolmogorov-Smirnov test also showed that average hit rate for RefRPs over the last 10 trials were also not normally distributed (Slow: D(36) = 0.76, p < 0.001; Fast: D(36) = 0.76, p < 0.001). The same selection criterion as for the CI group identified 92% and 97% good blocks in the Slow and Fast conditions, respectively.

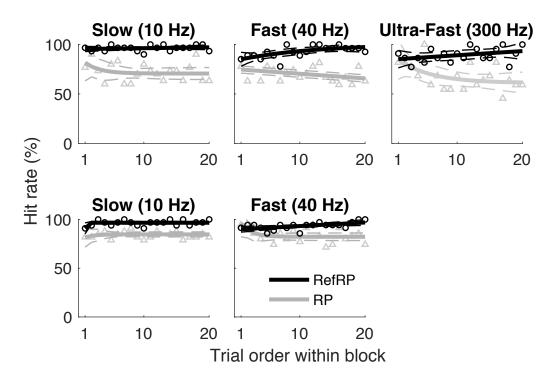


Figure 3. Time course of performance. The group-average hit rate is plotted as a function of presentation order within a block, for (grey triangles) and RefRP (black circles) stimulus types. The analysis is restricted to "good blocks" for which learning was hypothesized (see text). Panels as in Figure 2. Dashed lines indicate 95% confidence intervals.

Figure 3 shows the time course of performance (hit rate) for RP and RefRP stimulus types. We fitted exponential lines to the data and tested for significance of the changes by comparing

the fitted exponential model to a flat-line model, taking into account the different number of parameters for each model (Kang et al., 2017).

The results showed qualitative increases in RefRP performance in all cases except for the Slow condition, in both groups of participants. Given the high level of performance in these conditions, ceiling effects cannot be ruled out. The fitted exponential models also suggested decreases in performances in many conditions. However, the outcomes of the statistical comparisons were less clear-cut. For the Fast rate conditions, both the CI group and the NH group showed a significant advantage of the exponential model (CI: F(2,17) = 5.95, p < 0.05; NH: F(2,17) = 3.96, p < 0.05). No other test passed the significance criterion, either for RefRP in the Slow rate condition, of for RPs in all conditions. Note that for the Ultra-Fast condition, the exponential model advantage for RefRP approached our significance criterion (F(2,17) = 3.11, p = 0.071).

VI. Discussion

The present study tested for rapid perceptual learning of temporal patterns in CI listeners, comparing their performance to NH listeners. Stimuli were stochastic sequences of electric pulses for the CI group and high-pass filtered click trains for the NH group, but otherwise shared the same temporal characteristics. The pattern of data was remarkably similar in both groups, apart from a baseline difference. This suggests that rapid perceptual learning of temporal sequences is equivalent in CI and NH listeners. Furthermore, an Ultra-Fast sequence of electric pulses, containing fast temporal cues unavailable to the non-implanted auditory system, also appeared to be learnable.

A. Age and baseline performance

It is unclear what may have caused the baseline difference between CI and NH listeners, but age may be a candidate. We did not make any attempt to match the mean age or age range of the CI and NH groups, for practical reasons. The experiment was also generally longer for CI users, because of the loudness matching procedure. In any case, the baseline difference concerned both stimulus types, and did not interact statistically with the learning effect. If anything, our results then probably underestimate the ability to perform the sequence repetition-detection and learning tasks with a CI in younger CI users.

B. Effect of rate

Overall performance was generally better for Slow rates than Fast rates or Ultra-Fast rates for CI users. This is consistent with previous studies reporting a decrease in performance with increasing rate in various temporal tasks with CI listeners, such as rate discrimination or temporal jitter detection (Gaudrain, Deeks, & Carlyon, 2017; Macherey, Deeks, & Carlyon, 2011; Vandali & van Hoesel, 2012). Thus, it is likely that our observation of a decrease in overall performance with rate can be accounted for by mechanisms independent of the learning process. Consistent with this, the performance gain associated with learning (the RefRP advantage over RP) did not statistically interact with the performance change with rate.

C. Time course of learning

There is one caveat about the interpretation of the RefRP advantage over RP as perceptual learning in the present dataset. For CI listeners, two out of three rate conditions failed to show a significant increase in RefRP performance over time, which is a stringent criterion to ascertain rapid perceptual learning (Agus et al., 2010; Kang et al., 2017). So, in the most conservative perspective, we can only claim to have fully demonstrated perceptual learning occurs with a CI and electrical stimulation in Fast rate condition (40 Hz average rate). This in itself would be

enough to unequivocally confirm that temporal cues alone can support rapid perceptual learning (Kang et al., 2017), as our broadband electric stimulation procedure did not involve spectral cues.

However, several aspects of the data suggest that this caveat is most likely due to methodological issues, and that learning was in fact present for all tested conditions. First, and much to our surprise, baseline performance was high even for the CI group. This could have led to ceiling effects obscuring the changes in performance over time. Second, it is noticeable that we also failed to find evidence for changes in performance over time for the NH group, even though previous studies showed precisely such an effect for near-identical stimuli (Kang et al., 2017). Third, even though the model comparison statistics did not reach our significance criterion in many cases, all trends observed but one (so 9 out of 10 model fits) went in the expected direction: an increase in performance for RefRP and a decrease for RP. Finally, it would seem extremely unlikely that a statistical quirk produced easier RefRPs by chance for the 19 participants and 5 conditions. Rather, we would suggest that increasing the number of participants in follow-up studies could be useful to further characterise the time course of learning in CI listeners.

D. Ultra-Fast rates

Another intriguing aspect of the results is the advantage of RefRP over RP observed for the Ultra-Fast rates, combined with a strong trend for an increase in performance over time. Given the caveats discussed above, we would argue that CI listeners were able to learn the Ultra-Fast sequences. Such sequences contained purely temporal cues unavailable to the unaided human auditory system: very fast timing cues in low-frequency tonotopic channels, unaccompanied by any corresponding spectral cues. The largest difference between the Ultra-Fast electric temporal

cues and the expected temporal cues resulting from acoustic hearing would occur for the most apical electrode stimulated. Although electrode insertion data were not available for our subjects, several papers have provided such data for subjects implanted with the same electrode arrays (reviewed in Landsberger, Svrakic, Roland, & Svirsky, 2015). The mean insertion angles of the most apical electrode (electrode 1) are 557 and 471 degrees for the Standard long and Flex28 electrodes, respectively (c.f. Table 1). Assuming a cochlear length of 35 mm and using the frequency-place map of Stakhovskaya, Sridhar, Bonham, and Leake (2007), the mean characteristic frequency of the most apical electrode should, on average, be equal to 331 Hz and 500 Hz, depending on the electrode array. In normal hearing, a 300-Hz click train presented in this frequency region would necessarily produce spectrally-resolved components as the mechanical ringing of cochlear filters would overlap between successive clicks. Moreover, 300 Hz was only the average click rate of this condition, with the fastest possible cues corresponding to the refractory period of 0.3 ms, so 3.3 kHz.

Does this mean that CI participants learnt cues not normally available to acoustic hearing? This would seem to be consistent with the generality of rapid perceptual learning, which has been demonstrated over a range of stimuli (Agus et al., 2010; Kang et al., 2017; Kumar et al., 2014) and sensory modalities (Kang et al., 2018). Moreover, computational interpretations of the phenomenon have put forward generic neural plasticity mechanisms such as spike-dependent plasticity (Masquelier, Guyonneau, & Thorpe, 2008), which are not known to be tied to the specific temporal range of imposed by cochlear filtering. So, if the Ultra-Fast cues could be represented in the cortical regions implicated in auditory learning by imaging studies, then it is plausible that they could have been learnt.

Alternatively, it is also possible that CI users ignored the low-frequency electrodes and

exclusively relied on higher-frequency electrodes to learn the ultra-fast temporal cues. Still considering the electrode insertion values from the literature (Landsberger et al., 2015), the characteristic frequency of electrode 10 (i.e., the most basal electrode used here) is expected to be higher than 9 kHz for both electrode arrays. In a normal-hearing auditory system, such frequency channels could indeed encode at least some of the short IPIs present in the Ultra-Fast rate sequences. Such an alternative interpretation would be hard to completely rule out, for practical reasons. Stimulating only low frequency electrodes would only partially control for the issue, because of possible current leaks to neighbouring sites. Even if those leaks were avoided, it remains that our stimuli only have an average rate of 300 Hz, so some IPIs would be longer than the mean and could be used for learning. Increasing the stimulus average rate would put IPIs in a range where peripheral temporal coding is impaired with a CI.

In summary, the data show that CI users can learn temporal sequences containing timing cues unavailable to acoustic hearing. Whether this learning was achieved by ignoring such cues, or by actually benefiting from them in the learning process, remains an open issue.

E. Clinical considerations

Behavioural training and its underlying neural plasticity mechanisms are increasingly recognized as crucial to improving the outcome of implantation (for a recent review, Glennon et al., 2020). Our results are encouraging in this respect. For our limited sample of CI users, we observed fully preserved perceptual learning abilities compared to NH listeners.

In our laboratory setting, we took care to ensure that the peripheral representation fed to learning mechanisms would be equivalent in the two cases. But, given that the learning effect was equivalent across baseline task difficulty, this may not be a crucial constraint to observe in a real-life rehabilitation scenario. Also, as the Ultra-Fast condition further suggests, CI users may

even be able to adjust their learning to any kind of available cues, even cues that they may not have been exposed to pre-implantation.

Another aspect of our paradigm is that learning was fully unsupervised. In previous studies with NH listeners, we also showed that learning could occur with diverted attention (Andrillon et al., 2015) or during some sleep phases (Andrillon, Pressnitzer, Léger, & Kouider, 2017), strongly suggesting an implicit form of learning. Intriguingly, in an animal model of electric hearing, neural plasticity for the coding of temporal cues was observed with passive exposure subcortically and to a lesser extent cortically (Vollmer et al., 2017). If passive exposure could be shown to positively affect patients in a clinical setting, this could open up complementary rehabilitation strategies in addition to the preferred but resource-extensive active sessions with a clinician.

V. Conclusions

CI users and NH listeners performed a similar task designed to probe the rapid perceptual learning of temporal sequences (Kang et al., 2017). Both groups showed highly similar patterns of results, strongly suggesting preserved learning abilities for CI users. Being able to map or remap the cues provided by electric hearing to the acoustic world is clearly an essential part of the rehabilitation process for CI recipients. Our results suggest that, at least for an unsupervised and likely implicit learning task, their perceptual learning abilities are intact and suggest that they could be leveraged in broader rehabilitation strategies.

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