Hierarchical effects of task-engagement on amplitude modulation encoding in auditory cortex

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Running title: Task-engagement and neural discrimination in A1 and ML

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Abstract:

We recorded from middle lateral belt (ML) and primary (A1) auditory cortical neurons while animals discriminated amplitude modulated (AM) sounds, and also while they sat passively. Engagement in AM discrimination improved ML and A1 neurons’ ability to discriminate AM using both firing rate and phase-locking; however, task engagement affected neural AM discrimination differently in the two fields. The results suggest that these two areas utilize different AM coding schemes: a ‘single-mode’ in A1 relies on increased activity for AM relative to unmodulated sounds, and a ‘dual-polar mode’ in ML which uses both increases and decreases in neural activity to encode modulation. In the dual-polar ML code, non-synchronized responses might play a special role. The results are consistent with findings in the primary and secondary somatosensory cortices during discrimination of vibrotactile modulation frequency, implicating a common scheme in the hierarchical processing of temporal information among different modalities. The time course of activity differences between behaving and passive conditions was also distinct in A1 and ML and may have implications for auditory attention. At modulation depths \( \geq 16\% \) (approximately behavioral threshold), A1 neurons’ improvement in distinguishing AM from unmodulated noise is relatively constant or improves slightly with increasing modulation depth. In ML, improvement during engagement is most pronounced near threshold and disappears at highly suprathreshold depths. This ML effect is evident later in the stimulus, and mainly in non-synchronized responses. This suggests that attention-related increases in activity are stronger or longer-lasting for more difficult stimuli in ML.

Key Words: auditory cortex, attention, sound processing, neural coding
Introduction:

Amplitude modulation (AM) --a change in amplitude envelope over time -- is an important information-bearing parameter in speech recognition (Rosen 1992; Shannon et al. 1995; Smith et al. 2002; Steinschneider et al. 1999; Van Tasell et al. 1987) and in segregating sound sources in complex listening environments (Bregman et al. 1990; Fishman et al. 2012; Grimault et al. 2002; Micheyl et al. 2013). Accordingly how auditory cortex (AC) processes AM and other temporal modulations has been studied extensively (Bendor and Wang 2007; 2010; Bieser and Müller-Preuss 1996; Eggermont 1991; Eggermont 1994; Kajikawa et al. 2008; Liang et al. 2002; Lu et al. 2001; Lu and Wang 2000; Malone et al. 2007; Schreiner and Urbas 1988). Since most AC research was performed in primary auditory cortex (A1), we have yet to form a precise understanding of how temporal sound properties are processed throughout the auditory cortical network.

Macaque AC has been proposed to have three processing stages: 1) a primary stage with three core fields, 2) a secondary stage with seven belt fields, and 3) at least two parabelt fields (Kaas and Hackett 2000; 1999). This classification is based on the anatomical connections between the thalamus, core, belt, and parabelt areas (de la Mothe et al. 2006a; b; Hackett et al. 1998; Morel et al. 1993; Morel and Kaas 1992; Rauschecker et al. 1997; Romanski et al. 1999b), as well as on physiological properties such as first-spike latencies (Lakatos et al. 2005; Recanzone et al. 2000a), the level of spectral integration, and response preference to pure tones and more complex sounds (Imig et al. 1977; Kosaki et al. 1997; Kusmierek and Rauschecker 2009; Lakatos et al. 2005; Petkov et al. 2006; Rauschecker and Tian 2004; Rauschecker et al. 1995; Recanzone et al. 2000a; Wessinger et al. 2001).

In addition to the three-stage hierarchical processing model, AC has been proposed to contain two parallel pathways: anterior AC for sound recognition/categorization, constituting the auditory “what” pathway, and posterior AC for auditory spatial tasks, constituting the auditory “where” pathway (Kaas and Hackett 2000; 1999; Kusmierek et al. 2012; Rauschecker and Tian 2000; Recanzone et al. 2000b; Romanski et al. 1999a; Romanski et al. 1999b; Russ et al. 2008; Tian et al. 2001). Tian et al. (2001) have
recorded single-unit responses to monkey calls presented at different spatial positions in the anterior-lateral (AL), middle-lateral (ML), and caudal-lateral (CL) belt cortices, and shown that AL neurons are more selective for monkey calls than ML or CL, CL neurons have a greater spatial selectivity than AL or ML, and ML neurons show intermediate selectivity to both space and monkey calls. One interpretation of these results is that ML may be the branching point of auditory “what vs. where pathways”. ML is located immediately lateral to A1, and is heavily interconnected with A1 (Morel et al. 1993). Thus, sound representations in ML may reflect a transformation one level higher than in A1.

Several studies have demonstrated that neural discrimination ability can improve when animals are actively discriminating sounds versus sitting passively (Fritz et al. 2003; Knudsen and Gentner 2013; Lee and Middlebrooks 2011). Recently, our laboratory has shown that A1 neurons’ ability to discriminate AM improves with task engagement compared to a passive listening condition (Niwa et al. 2012a). Here, we examine how this behaviorally-modulated improvement in neural AM discriminability evolves at the next processing stage in the auditory cortical hierarchy.

Materials and Methods:

Subjects:
Two female (W and V) and one male (X) adult rhesus macaque (Macaca mulatta) monkeys were used in this study. ML recording was done in the right hemisphere of monkeys W and X. A1 recording was done in the right hemisphere of all three monkeys. Some analyses from these A1 recordings have been previously presented (Niwa et al. 2012a). We only present new and more detailed analysis of the A1 data (which help to reveal the differences between A1 and ML) in the current paper. All procedures conformed to the U.S. Public Health Service (PHS) policy on experimental animal care and were approved by the UC Davis animal care and use committee.

Stimuli:
Stimuli were 800-ms sinusoidally amplitude-modulated (AM) broadband noise bursts. Modulation frequencies were 2.5, 5, 10, 15, 20, 30, 60, 120, 250, 500, and 1000Hz. Depth sensitivity functions were
collected at one fixed modulation frequency with modulation depths of 0% (unmodulated), 6%, 16%,
28%, 40%, 60%, 80%, and 100%. The unmodulated noise served as a comparison to determine how well
neurons could determine whether or not a sound was modulated. For all these stimuli the noise carrier
was ‘frozen’; the noise was created using the same random number sequence producing a stimulus
waveform that was identical on all trials, save for the modulation envelope.

Sound generation has been described previously (O'Connor et al. 2010). The sound signals were
constructed using Matlab (MathWorks), digital-to-analog converted (Cambridge Electronic Design,
Model 1401), passed through programmable (TDT Systems PA5) and passive attenuators (Leader LAT-
45), amplified (Radio Shack MPA-200), and delivered to a speaker. We used two different sound booths
(IAC: 2.9 x 3.2 x 2.0 m and 1.2 x 0.9 x 2.0 m) equipped with different speakers positioned at ear level.
One booth had a Radio Shack PA-110 speaker 1.5 m in front of the subject, while the other had a Radio
Shack Optimus Pro-7AV positioned 0.8 m in front of the subject. Sounds were generated at a sampling
rate of 100 kHz, and had cosine-ramped onsets and offsets with 5.0-ms rise and fall time. Sound intensity
was calibrated with a sound-level meter (Bruel&Kjaer model 2231) to 63 dB sound pressure level at the
approximated midpoint of the animals’ two pinnae.

Behavioral task:

The monkeys were trained to discriminate AM-noise from unmodulated noise. This also can be
regarded as AM detection because subjects detect whether a sound was amplitude modulated. Task-
specifics were as follows. First, monkeys began a trial by pressing and holding down a lever for at least
500 ms. Then, two 800-ms sounds were presented sequentially with a 400-ms inter-sound interval (ISI).
Within a trial, the first (standard) sound was always unmodulated noise, and the second sound (test
stimulus) was either another unmodulated noise (non-target) or an AM noise (target). Note that herein we
reserve the word stimulus for test sound (not the standard). During each recording session, the modulation
frequency of target stimuli was set at the best modulation frequency (BMF) of the multiple-unit (MU)
response from the same electrode (see Physiological recording section below). Target modulation depths
were 6, 16, 28, 40, 60, 80, and 100%, presented with equal probability. Subjects were trained to release the lever in response to AM targets. They were required to wait for stimulus offset to respond, and to respond within an 800-ms response window following the target stimulus offset. When the test stimulus was an unmodulated non-target (12.5% of the trials), subjects were required to continue depressing the lever for the entire response window. Subjects were given liquid rewards for all correct responses: hits (a lever release for target trials) and correct rejections (withholding lever release for non-target trials). We notified subjects of incorrect responses -- misses (not releasing the lever on target trials) and false alarms (releasing the lever on non-target trials) -- by turning off an incandescent light placed in front of them.

Subjects were also given a time-out period of 15-60 sec following false-alarms. This enabled us to keep the false alarm rates at the relatively low level of ~10% as reported in Niwa et al 2012b. Behavioral thresholds were reported in Niwa et al 2012a.

Unit recording:

The neural recording procedures were described previously (Niwa et al. 2012a; b; 2013), so we will briefly recap them here. To allow AC access, a 2.7 cm diameter CILUX chamber (Crist Instruments) was implanted over the portion of parietal cortex immediately above AC. The chamber held a plastic grid with 27-gauge holes, covering a 15 x 15 mm area at 1 mm intervals. Each recording day, a stainless steel, trans-dural guide tube was inserted through a grid hole. A tungsten microelectrode (1-4MΩ, FHC; 0.5-1MΩ, Alpha-Omega) was put through the guide tube, and lowered through parietal cortex into ML or A1 by a hydraulic microdrive (FHC). During this macaques were head-restrained by a titanium post.

Electrophysiological signals were amplified (AM Systems model 1800), filtered (0.3 – 10 kHz; AM Systems model 1800 and Krohn-Hite model 3382), and sent to an A/D converter (CED Model 1401, 50 kHz sampling rate). Action potentials were assigned to individual neurons on- and off-line using SPIKE2’s (CED) waveform-matching algorithm.

At each recording site, we first determined the best modulation frequency (BMF) of MU activity by presenting unmodulated noise and 100% depth, 800-ms AM-noise at all modulation frequencies.
ROC areas (ROCa), based on both firing rate and vector strength (VS, a measure of phase-locking), were calculated at each modulation frequency (see Neurometric analysis section for details). BMF_{VS} was defined as the modulation frequency with the greatest VS-based ROCa, while BMF_{SC} was the frequency with the firing-rate-based ROCa most deviant from 0.5. The further the ROCa from 0.5, the larger the difference between responses to AM and unmodulated noise. This means the BMF was the modulation frequency at which the unit could best distinguish AM from an unmodulated sound. When BMF_{VS} and BMF_{SC} were different, we chose either BMF_{VS} or BMF_{SC} as the modulation frequency for the subsequent ‘AM sensitivity’ experiment. This selection was alternated from day to day to avoid a bias towards one of the BMF measures.

After BMF determination, the AM sensitivity of single-units (SUs) and MUs was assessed by collecting response vs. modulation depth functions at the BMF during two behavioral conditions: (1) while animals performed the task (behaving condition), and (2) while they were presented with the same stimuli and received randomly timed liquid rewards for sitting quietly (passive condition). The sequence of behaving and passive experiments was alternated daily to eliminate order effects. For recording, the monkeys sat in an acoustically transparent primate chair, with their head restrained to the chair, in a double-walled, sound-attenuated, foam-lined booth.

Data analysis:

Neurometric analysis:

Receiver operating characteristic (ROC) analysis (Green and Swets 1974) was used to quantify how well a neuron distinguishes AM from unmodulated noise. A detailed description of this analysis was presented in (Niwa et al. 2012a), so we briefly describe that analysis here. Neural ROC area (ROCa), in our analysis, represents the neural discriminability of AM-noise from unmodulated noise; the probability an ideal observer can detect a signal (the modulation) based solely on neural responses. An ROCa of 1 (or 0) means the neural response is 100% accurate in predicting whether the sound was modulated; values of 0.5 mean the neural response can only predict at chance level whether the sound was modulated. An
ROCa of 1 means the neural response to AM is always greater than the response to unmodulated noise; an
ROCa of 0 means the neural response to AM is always less than the unmodulated noise response. To
calculate neural ROCa, first we quantify a unit’s response to AM (for example, with firing rate) for each
trial to create a probability distribution of the neural measure from all repeated trials. In the same way,
we also create a probability distribution for the unit’s response to unmodulated sound using the same
measure. From these two probability distributions, we determine the proportion of trials (P_{AM}) where the
neural response to AM exceeds a criterion level, and the proportion of trials (P_{unMod}) in which neural
response to the unmodulated noise carrier exceeds the same criterion value. One hundred pairs of P_{AM} and
P_{unMod} are determined using 100 criteria values that were selected from the full range of both distributions.
P_{AM}, the proportion of AM trials where the neural response exceeds the criterion is directly comparable to
hit rate for behavior. P_{unMod}, the proportion of responses to the unmodulated noise carrier that exceeds the
criterion, is directly comparable to the false alarm rate. The plot of all P_{AM} and P_{unMod} pairs forms the
neural ROC, and the area under this is called the neural ROCa.

All analyses were also performed with the discriminability index, d’, which also measures how
well a neuron discriminates AM from unmodulated noise. d’ is the number of standard deviations
separating the means of the AM and unmodulated noise response distributions. An advantage of d’ is that
it is unbounded (ROC area is bounded by 0 and 1), so larger differences always results in a larger d’. This
allows d’ to distinguish between well-separated distributions for which ROCa has a ceiling (or floor)
effect. The disadvantage of d’ is that its relationship to behavioral performance is less straightforward
than ROCa. As was seen previously in A1 (Niwa et al 2012a) differences between behaving and passive
conditions were almost always more pronounced with d’, because many neurons show ceiling or floor
effects at ROCa of 1 or 0.

**Phase-Projected Vector Strength (VSpp)**

Vector strength, VS, measures the degree of a neuron’s phase-locking, and is defined as
where $n$ is the total number of spikes, and $\theta_i$ is the phase of each spike in radians,

$$
\theta_i = 2\pi \left( \frac{t_i \text{ modulo } p}{p} \right)
$$

where $t_i$ is the time of the spike relative to the stimulus onset, and $p$ is the stimulus modulation period (Mardia and Jupp 2000).

VS has problems measuring phase locking when the number of spikes ($n$) is small. When spikes are randomly distributed in time VS should be 0, but when working with a small number of spikes VS tends to give values spuriously higher than 0. For example, if a cell fires one spike on a trial, VS would be 1. If a cell fires two spikes randomly, a high VS would also likely result, because the probability that two random spikes fire 180 degree out of phase with each other (relative to the stimulus modulation period) is low. So for spikes occurring randomly in time, VS will tend towards non-zero values for small numbers of spikes, and will get closer to 0 as the number of spikes increases. For determining ROCa, we need to calculate VS on a trial-by-trial basis. Because some single-units fire only a few spikes in a single trial, bias of VS in low spike-count trials can become a problem.

Phase-projected vector strength (VS$_{pp}$, Yin et al. 2011) circumvents this. In determining VS$_{pp}$, first, VS is calculated for each trial. Then, the mean phase angle of each trial is compared with the mean phase angle of all trials (global response), and the standard VS values are penalized if they are not in agreement. VS$_{pp}$ is calculated on a trial-by-trial basis as follows:

$$
VS_{pp} = VS_t \cos(\phi_t - \phi_c)
$$

where $VS_t$ is the standard vector strength per trial, calculated as in Eq. 1, $\phi_t$ is the mean phase angle of the trial, and $\phi_c$ is the mean phase angle of global response (calculated from the unit’s response to 100% AM collapsed across all repeated trials). Whereas VS ranges from 1 to 0, VS$_{pp}$ may range from 1 (all spikes in phase with the mean phase of the global response) to −1 (all spikes 180 degrees out of phase with the
global mean phase) with 0 corresponding to random phase with regard to the global mean phase. Except
for the cases of low spike counts, the two VS measures were in good agreement (Yin et al. 2011).

Identification of cortical areas

ML was identified based on physiological responses to tones and band-pass noise as was done
previously (Niwa et al. 2013). First, pure-tone frequency tuning was assessed at (or near) each recording
site by varying tone frequency and intensity. An initial estimate of the best frequency (BF) of the site was
used to determine the range for the automated procedure where frequencies typically spanned three-
octaves (usually in 1/5 octave steps) centered on the initial BF estimate, and intensities typically spanned
80 dB with a 10 dB steps between 10-90 dB SPL. Tones (100 ms) were presented in a random order, and
repeated at least twice for each frequency-intensity combination. From a two-dimensional response
matrix, the neuron's frequency tuning curve was obtained using the contour line (Matlab's "contourc"
function) at the mean spontaneous rate plus two standard deviations. The BF and threshold were
determined from this frequency tuning curve. A tonotopic map was created for each animal from the BF.
We determined the location of A1 based on a systematic BF increase from anterior to posterior, and
approximately constant BF along the medial-lateral axis. The border of A1 and ML was determined
based on the lack of response robustness to tones, slower tone response latency, and wider width of
frequency tuning for ML locations (Kosaki et al. 1997; Merzenich and Brugge 1973; Morel et al. 1993;
Rauschecker et al. 1997; Recanzone et al. 2000a). Putative ML was identified as a narrow strip of 2-3
mm width located lateral to the physiologically determined A1/ML border.

When time permitted, we also recorded unit responses to 100-ms band-pass noise (BP noise)
having various center frequencies, filter widths (1/3, 1/2, 1, and 2 octaves), and intensities. Intensities
typically were the same as for frequency tuning. BP noises were presented in random order and repeated
one to three times for each combination of center-frequency, filter-width, and intensity depending on the
available time. Firing rate was calculated using the 0-100 or 0-150 ms window after stimulus onset
depending on the response profiles at each recording site. A two-dimensional response matrix (intensity
x frequency) was obtained for each filter-width size. The frequency tuning curve was estimated in the same way as above for each filter-width size, and the BF and the preferred filter width size were determined. The anterior-posterior border of ML (the borders with AL and CL) was estimated using a systematic change in BF using band-pass noise tuning.

Results:

We recorded spiking activity from 57 multiple-units (MUs) and 97 single-units (SUs) in ML of monkeys W and X while they discriminated AM (behaving condition) and while they were passively presented the same AM stimulus set (passive condition). These results were compared to 57 MUs and 142 SUs recorded from A1 of monkeys V, W, and X.

Effect of engagement on ML neurons’ rate-based AM discriminability depends on the time period of stimulus presentation.

Animals’ engagement in AM discrimination affects ML neurons’ AM discriminability differently during the first (0-400-ms) and second (400-800-ms) halves of the test stimulus. This is exemplified by three ML neurons whose responses are depicted in Figures 1-3. The neuron in Fig. 1 shows improvement in firing-rate based AM discriminability due to task engagement during the first half of the test stimulus, but deterioration during the second half. The neuron in Figure 2 shows a change in its firing-rate response characteristics to modulation depth from monotonically increasing during the first half to non-monotonic during the second. The neuron in Figure 3 shows a change in its firing-rate response characteristics to modulation depth, from monotonically increasing during the first stimulus half to monotonically decreasing during the second half.

For the ML SU in Fig. 1, in the passive condition, the firing rate increases with depth during both first and second halves of the stimuli (Fig. 1C-D, solid squares). In the behaving condition, the dependence of firing rate on modulation depth appears different than in the passive condition. During the first half, the firing rate roughly increases monotonically with depth (Fig.1C, open circles) as in the passive condition. During the second half, firing rate decreases with increasing depth in the behaving condition.
condition (open circles in Fig.1D). The decrease during behavior is largely due to increased activity 500 to 650 ms after stimulus onset for 0-40% depth in the behaving condition (Fig.1B), which lessens at higher depths. This pattern of activity between 500-650 ms is not seen in the passive condition (Fig. 1A).

During the first half of the stimulus the neuron can better discriminate AM in the behaving than the passive condition. When the SU’s firing rate during 0-400 ms in the behaving and passive conditions is compared, the rate response to both unmodulated noise and low modulation depth AM (0-16%) is slightly greater in the behaving than passive condition (open circles vs. solid squares in Fig.1C). However, at higher modulation depths (particularly at 28-40%) firing rate increases much more in the behaving condition (Fig. 1C). As a result, in this 400 ms window, this SU exhibits greater response differences between AM and unmodulated noise in the behaving than passive condition (Fig.1C). This suggests that engagement in the AM task improves neural AM discrimination at modulation depths >16% (which is approximately behavioral threshold) during this portion (the first 400 ms) of the stimulus, which is supported by neurometric analysis (Fig. 1E).

In contrast to the first half of the stimulus, this SU better discriminates AM from unmodulated noise in the passive condition during the second half of the stimulus (Fig. 1 F). From 400-800 ms after stimulus onset, the response to unmodulated noise was still higher in the behaving than the passive condition, but the response to 60-100% AM was quite similar in both behaving and passive conditions (Fig.1D). The result is that, during behavior, the firing rate response to 60-100% AM is slightly less than the firing rate response to unmodulated noise during the second half of the stimulus (the last three open circles, at 60-100%, are slightly less than first open circle, at 0%, on Fig.1D). This leads to poorer neural discrimination ability (points closer to ROCa = 0.5) during the second half in the behaving than the passive condition. The neurometric functions appear to show that the neuron weakly discriminates AM with increased firing rate relative to the unmodulated noise response at low depths, and with decreased activity relative to the unmodulated noise response at higher depths. This is seen in Fig. 1F as ROC areas > 0.5 for 6-40% and < 0.5 for 60-100%. However, these points are all relatively close to ROCa = 0.5.
Figure 2 shows an example neuron that discriminates AM with increased firing rate relative to the unmodulated noise response at low depths, and with decreased activity relative to the unmodulated noise response at higher depths. In this example a permutation test showed that ROCa was significantly above 0.5 in the behaving condition during the 2nd half at 16% depth, and significantly below 0.5 at 60 and 80% depths. In the passive condition, this SU and the SU in Fig. 3 monotonically increase firing rate with modulation depth during early and late portions of the stimulus period (C-D, solid squares). Again, in the behaving condition, these SUs monotonically increase firing rate with depth only during the first half of the stimulus (C, open circles), and not in the second half (D, open circles). Also during the first 400 ms, AM discrimination is better in the behaving condition (Figs. 2E, 3E), but comparisons of neural discriminability during the 400-800 ms period after stimulus onset are more complicated. The SU in Fig. 3 decreases firing rate relatively monotonically with depth (Fig.3F white circles). For all 3 example neurons, firing rate during the 400-800-ms period is greater in the behaving (than passive) condition for 0-40% AM, and smaller in the behaving condition for 60-100% AM (Figs. 1D, 2D, 3D).

**ML population summary: Behavioral state affects rate-based AM discriminability differently for neurons with increasing and decreasing rate-vs.-depth functions**

For the entire ML population, the dependence of performance on task-engagement is strikingly different during the stimulus’s first and second half. During engagement, neuronal AM sound discrimination improves during the first half and worsens during the second half of the stimulus (Fig. 4A-D). During the first half, firing-rate-based ROCa is significantly greater in the behaving than passive condition for MUs (Fig. 4A) and SUs (Fig. 4B). On the other hand, during the second half, ML ROCas are significantly worse in the behaving condition (Fig. 4C-D). Note that Fig. 4 A-D has a smaller scale than the rest of Fig. 4 to better display ML differences between behaving and passive conditions. Fig. 4 A-D appears to show that task engagement significantly improves rate-based AM discriminability during the first half of the stimulus, but significantly impairs it during the second half. This differs from A1 where (1) ROCa monotonically increases with modulation depth for behaving and passive conditions, (2) population ROCa increased for all depths (although not significantly at all depths) in the behaving
compared to the passive condition for both halves (albeit smaller improvements were seen for the second half in the behaving compared to the passive condition, Fig. 4 I-L).

However, when we consider the potential contribution of neurons that encode modulation by decreasing firing for modulated sounds, a different picture emerges. The further ROCa is from 0.5, the better a unit is at discriminating a modulated from an unmodulated sound. An ROCa of 1 means perfect ability to discriminate AM from an unmodulated sound with increased firing rate for AM; an ROCa of 0 means perfect ability to discriminate AM from an unmodulated sound with decreased firing rate for AM. Therefore reflecting ROCa around 0.5 (Fig. 4 E-H, M-P) for each neuron reveals how well they discriminate AM from an unmodulated noise adjusting for neurons that encode AM with decreased activity. It should be noted that this mathematically is similar to taking the absolute value, so all ROCas will increase, just like the mean of a series of positive and negative numbers will always be smaller than the mean of their absolute values. What is important in (Fig. 4 E-H, M-P) is how differences between active and passive change with reflection and how shapes of functions change. When we reflect ROCa in ML, we see significant improvement during the first, and now also during the second half (Fig. 4 G-H) of the stimulus. Also the function monotonically increases for reflected ROCa as opposed to the nonmonotonic functions for ROCa (Fig. 4 C-D). For A1, reflecting ROCa (compared to not reflecting) resulted in smaller or no improvements in the passive compared to the behaving condition (Compare Fig. 4 I to 4M, 4J to 4N, 4K to 4O, and 4L to 4P). We will further probe this by analyzing population mean ROCas separately for increasing and decreasing cells, which will allow a clearer picture to emerge.

Separately analyzing cells whose firing rate either increases or decreases as a function of modulation depth is important to understand possible neural codes for AM. In ML, some neurons increase firing rate with increasing modulation depth, while others decrease firing rate with depth, but most A1 neurons increase firing rate with modulation depth and few decrease (Niwa et al. 2013). The brain could use the ML information for AM discrimination by separately decoding increasing and decreasing functions as two complementary populations of neurons (or subtracting them). Improved AM discriminability for neurons with increasing rate-depth functions would result in increased ROCa (from
0.5), while for neurons with decreasing rate-depth functions improved AM discrimination would yield
decreased values below 0.5. If both populations show AM discrimination improvement, the net effect on
ROCa of the summed activity across the entire population of neurons would be reduced because the
increase in ROCa from cells with increasing functions would cancel the decrease in ROCa by cells with
decreasing functions. Therefore, population summaries will be presented separately for increasing and
decreasing rate functions as well as for the entire ML population; i.e., combining ‘increasing’ and
‘decreasing’ cells (where an increasing cell refers to a neuron with an increasing rate-depth function).

Before showing the population summary for ‘increasing’ and ‘decreasing’ functions, we need to
discuss how these two groups are defined. As shown by the three SU examples (Figs. 1-3), the slope of
neurometric curves for one neuron can change signs between the first and second stimulus halves, and
between behaving and passive conditions. Since a neuron’s response depends both on the time during the
stimulus and task conditions, we needed a way to estimate their composite response to modulation depth.
To do this, we first created a neurometric firing-rate-based ROCs-depth function during the entire
stimulus separately for behaving and passive conditions. We then averaged the two functions, and
calculated the slope with linear regression (Fig. 5, top). We defined a response as ‘increasing’ if it had a
positive slope, and ‘decreasing’ if it had a negative slope. It is important to note that increases in ROCa
from 0.5 correspond to increases in firing rate and decreases in ROCa from 0.5 are decreases in firing
rate. All ROCa-depth curves start at 0.5 for 0% depth by definition, so an increasing ROCa-depth curve
also would result in an increasing firing rate versus depth curve (and vice-versa for decreasing). The SU
examples from Figs. 1-3 are shown in red and all had positive slopes (Fig. 5B red bars; Figs. 1, 2 and 3
neuron’s slopes = 0.0023, 0.0041, and 0.0015 respectively). The distribution of the slopes is shown for
MUs (Fig.5A) and for SUs (Fig.5B) in ML, where 72% of the MU and 63% of the SU recordings had
increasing functions. For comparison, the distribution of slopes is also shown for MU (Fig.5C) and SU
(Fig.5D) recordings in A1, where 81% of MU and 78% of SU recordings had positive slopes. The slope
magnitudes in ML were significantly lower than in A1 (p = 0.0013; rank sum test), and the proportion of
increasing SU functions in ML was significantly lower than in A1 (p = 0.0067; chi-squared).
For the population of ‘increasing’ units in ML, AM discriminability is significantly better in the behaving than the passive condition during the first half (0-400 ms) of the stimulus. During this period, MUs firing-rate-based ROCa is significantly greater in the behaving than passive condition for 16-100% AM (Fig.6A). SUs were also more sensitive in the behaving condition, although fewer depths reached significance (Fig.6B). To test the overall effect of task engagement, ROCa data were combined across depths in each condition, and a single Wilcoxon signed-rank test was performed. For MUs and SUs, we found a significant increase in across-depth, rate-based ROCa in the behaving compared to the passive condition (Fig. 6 A-B, number in lower right corner of each plot), indicating that task-engagement significantly improves neuronal AM discriminability in the first half of the stimulus for ‘increasing’ cells.

On the other hand, during the second half of the test stimulus, there was no significant change in ROCa between the behaving and passive conditions at any individual depth, nor collapsed over depths for MUs and SUs with increasing rate-depth functions, except for a small difference at 16% (p = 0.0179) for SUs (Fig. 6D). Although no statistically significant difference in ROCa was found between the behaving and passive conditions at high modulation depths (60-100%) during the second half, the population mean ROCa in the behaving condition at these depths appear lower than the ROCa in the passive condition (Fig.6 C-D). The lack of a significant difference might be due to the large unit-to-unit variability in the change in ROCa between the two conditions. Fig.6 E,G (MUs) and F, H (SUs) show pair-wise comparisons of ROCa between the behaving and passive conditions for all ‘increasing’ MUs and SUs at 60, 80, and 100% depths. Each point on these plots represents a unit, whose ROCa in the behaving condition is given on the y-axis and the passive ROCa on the x-axis. Points falling on the diagonal line indicate no change in ROCa between the two conditions. Points above the diagonal line indicate increased ROCa in the behaving compared to the passive condition, and those below indicate a decrease during behavior. During the second half of the stimulus, points are spread widely across the diagonal line (Fig. 6G and H), showing unit-to-unit variability in how ROCa changes between the two conditions. However, some neurons’ ROCas lie far below the diagonal line, falling into the bottom right quadrant of the plots. These units are largely responsible for pulling down the population-mean ROCa for the
behaving condition. Units lying in this quadrant fire less to AM than to unmodulated noise in the
behaving condition (ROCa < 0.5), but fire more to AM than to noise in the passive condition (ROCa >
0.5); they flip the sign of their response to AM from ‘positive’ (excitatory) in the passive condition to
‘negative’ (suppressive) in the behaving condition during the second half of the stimulus. It is important
to remember that classifying a unit’s response as increasing or decreasing is based on averaging ROCa for
behaving and passive conditions over the entire 800 ms stimulus, which explains why units that decrease
during the final 400 ms in the behaving condition can be classified as increasing. The examples shown in
Fig.1-3 are representative of SUs that decrease their activity during the second half of the test stimulus
only in the behaving condition (see Fig.1-3). Interestingly, when the same scatter plots are made for the
first half of the stimulus (Fig.6 E-F), few points fall into the fourth quadrant, suggesting that the reversal
of response sign occurs only later during the test stimulus. This effect may occur because AM at the
highest modulation depths can be discriminated very easily, and the decision to respond may be made
during the stimulus. Also, the fact that the animals are not permitted to respond until after stimulus offset,
requiring them to suppress early behavioral responses to AM at higher depths, may cause sustained
inhibition of firing to these AM stimuli as the test stimulus continues in time.

For the population of ML units with decreasing rate-depth functions, AM discriminability is
significantly better in the behaving than passive condition during the second half of the stimulus (Fig. 7C-
D); during the first half the effect is weaker for MUs (Fig. 7A) and non-existent for SUs (Fig. 7B).
Remember that for ‘decreasing’ units, lower ROCa (toward 0) means better AM discriminability. During
the first half, MU firing-rate based ROCa is significantly lower in the behaving than passive condition,
but the effect is relatively small and limited to near-threshold depths (Fig. 7A). During the second half of
the stimulus, MU rate-based ROCa is significantly lower (better) in the behaving than passive condition
at most depths above behavioral threshold (Fig. 7C). For SUs, engagement in the task significantly
improves AM discriminability only during the second half of the test stimulus (Fig. 7D).

Together, these results demonstrate that rate-based AM discriminability for ML cells with
increasing rate-depth functions improves under conditions of active engagement early during the
stimulus, but the improvement disappears later (Fig. 6). On the other hand, the improvement in rate-based AM discriminability for ML cells with decreasing functions is more pronounced later during the stimulus (Fig. 7).

Comparison of the change in rate-based AM discrimination over time between A1 and ML

We conducted ROC analyses using several time-windows for A1 and ML, and found that (1) the AM discriminability of cells with increasing rate-depth functions in the behaving condition is more strongly dependent on the time-course of stimulus presentation in ML than in A1, and (2) engagement in the AM task affects the AM discriminability of cells with decreasing functions differently in A1 and ML.

For this analysis, rate-based ROC areas were calculated using 400 ms time-windows beginning at 0, 100, 200, 300, and 400 ms after stimulus onset to determine the change in AM discriminability over time.

For ML ‘increasing’ units, the discriminability of 100-60% AM stimuli in the behaving condition declines as the time-window slides from the start to the end of stimulus presentation for both MUs (left three panels in Fig.8A) and SUs (left three panels in Fig.8B). Note that the ML population-mean AM discriminability in the behaving condition over time actually becomes worse than the passive, as indicated by the crossing of the two plots (60%-100% depth). In contrast to ML, A1’s rate-based AM discriminability at higher depths in the behaving condition always stays at or above the level seen in the passive condition (Fig.8C for MUs and D for SUs). The decline in AM discriminability over time in ML in the behaving condition is absent for 6-40% AM stimuli (right 4 panels in Fig.8A and B). Instead, AM discriminability in the behaving condition appears constant or improves slightly over the time-course of stimulus presentation.

For ML ‘decreasing’ units, the population mean ROCa in the behaving condition declines steeply toward 0 as the time-window slides from the start to the end of stimulus for both MUs (Fig.8E) and SUs (Fig.8F). The decline of ML ROCa in the passive condition is not as steep as in the behaving condition. The result is an increase in the difference in ROC area between these two conditions over time; the improvement in AM discriminability due to engagement in the task is greater later during the stimulus at all depths, for both MUs and SUs (recall that lower ROCa means better discriminability for ‘decreasing’
units). For A1 ‘decreasing’ units, the population mean ROCa at 60-100% depth in the behaving condition also declines toward 0 as the time-window slides from the start to the end of stimulus (Fig. 8G-H), while a decline is not clearly seen for the passive condition. The key difference between A1 and ML is that for decreasing functions in A1, ROCa at 60-100% depths in the behaving condition starts much worse (closer to 0.5) than the passive condition early during the test stimulus, and goes toward the passive level over time. Thus, in A1 AM discriminability during the early stimulus period is worse in the behaving than the passive condition, and improves toward the passive level over time. In ML decreasing functions at higher depths, ROCa for behaving and passive conditions is similar early in the stimulus and over time the behaving condition gains an advantage.

The aggregate results of Fig. 8 suggest that, in ML, decreasing cells improve their AM discriminability throughout the test stimulus, although the improvement is larger later. One interpretation is that in ML, both increasing and decreasing cells are suitable and relevant for encoding AM depth. Rate response to unmodulated noise increases later during the stimulus causing ROC areas to decrease over time.

Our analysis revealed that in ML, ROCas in the behaving condition appear to decrease over time at a faster pace than in the passive condition. This is true for higher modulation depths, and for units with both increasing and decreasing rate-depth functions. The ROCa quantifies the overlap between firing rate distributions in response to AM and unmodulated noise, but it does not explicitly tell us what caused the decline in ROCa. Two possible sources that can cause ROCa to decline are 1) decreased firing rate in response to AM and/or 2) increased firing rate in rate response to unmodulated noise. The results presented below indicate that the increase in the response to unmodulated noise over time is a major contributor to the decline in ROCa in the behaving condition.

The population-average firing rate (relative to spontaneous rate) in the behaving and passive conditions was analyzed using the same time windows as in Fig. 8, and shown separately for cells with increasing (Fig. 9 A-D) and decreasing (Fig. 9 E-H) rate-depth functions. For ML ‘increasing’ units, the population-mean firing rate in the behaving condition shows a decrease over time in response to
60~100% AM for MUs (left three panels in Fig. 9A, open circles), while the rate decrease in the passive is lesser than in the behaving condition. Thus, this difference can contribute to the faster decline in ROCas (steeper slope in curves of Fig. 8) for the behaving condition compared to passive (Fig. 8A). For SUs, the change in population-mean firing rate in response to AM at higher modulation depth is similar between behaving and passive conditions (left three panels in Fig. 9B for SUs), and it seems unlikely that the firing rate change to these AM stimuli is the sole cause of the faster decline (steeper slope) in ROCas in the behaving condition. In response to unmodulated noise (0%), the population-average firing rate drops after the 0-400 ms time window, which includes the onset response, then increases over time in both behaving and passive conditions (the right-most panels in Fig. 9A and B). However, the slope of the increase is steeper in the behaving than passive condition for both MUs and SUs. This differential rate of increase for firing rate over time for unmodulated noise in behaving and passive conditions (Fig. 9A-B, 0%) likely contributes to the steep decline in population-average ROCa in the behaving condition for ML cells with increasing functions at higher (60-100%) modulation depths (Fig. 8 A, B).

For ML cells with decreasing functions, the population-average firing rate for unmodulated sound (0%) also increases steeply over time in the behaving condition, while the rate increase is less obvious in the passive condition (the right most panels in Fig. 9E for MUs and F for SUs). This steep increase in response to unmodulated noise over time (Fig. 9) likely contributes to the steep decline of population-average ROC areas in the behaving condition for ‘decreasing’ ML units (Fig. 8 E-F).

In A1, we also observe a similar firing rate increase over time in response to unmodulated noise in the behaving condition for both ‘increasing’ and ‘decreasing’ units (the right-most panels in Fig.9 C, D, G, and H). Thus, this property -- increased responses to unmodulated noise late in the behaving condition -- seems general because it is common to both A1 and ML. Note that we also observe a similar increase in firing rate at lower modulation depths (6-28%), suggesting that the increased activity over time may be related to difficulty detecting AM in these stimuli (also refer to Figures 1-3).

Which area discriminates AM better based on firing rate: ML or A1?

In addition to the difference in time-dependence of AM discriminability, A1 and ML show a
significant difference in the overall level of AM discriminability. For ‘increasing’ units, rate-based ROCa in A1 is significantly greater than that in ML for both MUs and SUs, during both first and second half of the test stimulus, and in both behaving and passive conditions. In Fig. 10, this can be seen as the increasing functions for all time periods (blue lines) having values significantly greater than 0 (filled symbols are significant) at all suprathreshold depths for all four conditions. In contrast, ML only shows an advantage in discrimination for decreasing units during the second half in the behaving condition, (Solid red line, square symbols), while no significant difference between A1 and ML was found for decreasing units during the first half in the behaving condition. In the passive condition, ROCa for 28% AM for ‘decreasing’ MUs and 60% AM for ‘decreasing’ SUs was significantly better in A1 than in ML during the first half of the test stimulus (red dashed line with filled circles), while a significant difference was not found during the second half (red dashed line with squares). Note that in Fig. 10 the scale is twice as large for MUs reflecting that ROCa differences between A1 and ML were roughly twice as large for MUs than SUs. The aggregate results show that engagement in the AM task worsens the AM discriminability of ‘decreasing’ neurons in A1, but improves that of ML decreasing neurons especially during the later portion of the stimulus, making AM discriminability in ML better than A1 during the later time period. This also implicates the importance of a ‘decreasing’ rate code in ML, but not in A1.

**VSpp-based AM discriminability in ML improves due to animals’ engagement in the AM discrimination task.**

We examined whether AM discrimination based on phase-locking improves when animals engage in the AM discrimination task. Phase-projected vector strength (VSpp) was used as a measure of phase-locking (see Method for details). Fig.11 shows an example SU in ML with improved VSpp-based AM discrimination due to task-engagement. The SU robustly phase-locks to 20Hz AM at higher modulation depths (Fig.11A-B). VSpp was calculated for each trial in the time-window with onset response excluded (time window = 80-800 ms). Trial-averaged VSpp increased in the behaving condition compared to the passive condition at all depths except 28% and 0% (Fig.11C). VSpp-based ROCa increased in the behaving compared to the passive condition at all modulation depths (Fig.11D), indicating that the AM
discrimination based on phase-locking improved for this SU when the animal engaged in the AM task.

In ML, the population-average VSpp-based ROCa significantly improves in the behaving condition compared to passive at 100%, 80%, and collapsed-depths for MUs (Fig.11E) and at 60% and collapsed-depths for SUs (Fig.11F). These results indicate that AM discriminability, based on phase-locking, significantly improves due to engagement in the AM task. Unlike rate-based ROCa, we did not find a decline in VSpp-based ROCa in the behaving condition during the stimulus (Fig.11 G-J). However, the improvement in VSpp-based AM discrimination due to engagement appears to be greater earlier during the stimulus.

Similar to rate-based AM discrimination, A1 and ML show a significant difference in the overall level of AM discrimination based on phase-locking. When VSpp-based ROCas from the behaving condition are compared, A1 had significantly greater values than ML at 100, 80, 60, 40, 28, and 16% for MUs, and at 100, 80, 60, and 6% for SUs. These results show that neurons in A1 are significantly better at detecting the presence of AM using phase-locking than those in ML, regardless of the behavioral conditions.

**Synchronizing vs. non-synchronizing responses**

A proposed model of hierarchical processing of temporal modulation involves a transformation from a temporal to a rate-code (e.g., from a phase-locking to an average firing rate code). This model is supported by findings that the maximum modulation frequency to which neurons phase-lock decreases and non-synchronizing responses become more prominent with auditory system ascension. Therefore, neural responses that encode AM exclusively by changing firing rate without synchronizing to the stimulus envelope (non-synchronized response) are proposed to reflect coding at a more highly processed stage and to have a special role in AM perception (Bartlett and Wang 2007; Bendor and Wang 2007; Liang et al. 2002; Lu et al. 2001). Note that for both synchronized and non-synchronized responses, some have ‘increasing’ rate-depth functions while others have ‘decreasing’ ones. In the previous sections, we have shown that neural responses with ‘increasing’ and ‘decreasing’ rate-depth functions show different
task-engagement effects. Therefore, we subdivided neural response by type (synchronizing vs. non-
synchronizing) and the sign of the rate-depth function slope (increasing vs. decreasing), and examined the
effect of task engagement on neuronal AM discrimination (Fig. 12: each row has a ROCa scale for
optimum comparison of behaving and passive conditions).

For increasing ML synchronizing responses, AM discrimination significantly improved with task
engagement during the first half of the stimulus, while no significant improvement was found during the
second half (dark green plots in Fig. 12 E-H, compare with Fig. 6 A-D for similarity). In contrast, for ML
non-synchronizing responses with ‘increasing’ functions, improvements in the rate-based AM
discriminability due to task engagement persisted later in the stimulus for AM, but this was true only at
near-threshold depths (dark blue plots in Figs. 12 A-D). To quantify near- versus supra-threshold effects,
we collapsed the three nearest threshold depths (6-16, and 28%), and the most-supra-threshold depths (60,
80 and 100%). We then compared active and passive ROCa for ML increasing non-synchronized units.
For both SUs and MUs, there was a significant difference between behaving and passive near-threshold
(Wilcoxon paired tests, p =2.8 x 10^-4 SU; p = 3.1 X 10^-3 MU), but not supra-threshold (p=.16 SU, p=.34
MU). A possible interpretation relates to attention. It could be that attention is engaged longer for the
more difficult to discriminate, near-threshold, sounds.

For A1 responses with ‘increasing’ functions, the improvement for non-synchronizing responses is
more pronounced with d’ measures, because their AM discrimination ability is extremely good, and many
units encounter a ceiling effect when measured with ROC areas (bounded by 1). However, regardless of
the measures used, A1 improvement (Fig. 12M-T darker colors) of rate-based AM discrimination does
not show as clear or interesting 1st and 2nd half differences as in ML.

For both A1 and ML non-synchronizing responses show much better AM sensitivity compared to
synchronizing responses regardless of behavioral state.

For responses with ‘decreasing’ functions, task engagement generally improves rate-based AM
discriminability for ML units, but degrades it for A1. For ML synchronizing responses with ‘decreasing’
functions, task engagement significantly improves AM discriminability during the second half of the
stimulus, but less so during the first (light green plots in Figs. 12 E-H). For ML non-synchronizing responses with ‘decreasing’ functions, task engagement significantly improves AM discriminability during the first and second half of the stimulus, and the improvement is larger during the later period (light blue plots in Figs. 12 A-D). In fact, in the behaving condition during the 2nd half of the stimulus, the mean discrimination ability (distance from ROCa = 0.5) for decreasing ML units is better than that for increasing units. For A1 responses with ‘decreasing’ functions, regardless of response type (synchronizing or non-synchronizing), task engagement worsens rate-based AM discrimination especially during the first half of the stimulus, and the degradation diminishes or disappears in the second half (light blue plots in panels M-P and light green plots in panels Q-T in Fig. 12).

Additionally, we examined whether VSpp-based AM discriminability improves due to task engagement for synchronizing responses. Note that in the previous section, the entire ML population was analyzed (Fig. 11), but here we focus only on units with significant synchronizing responses. We found that VSpp-based ROCa significantly improved for ML synchronizing responses during the first and the second halves of the stimulus (Figs. 12 I-L). Once again, the effect size and number of significant conditions for VSpp-based ROCa were larger with d’ because many units have an ROCa near 1. For this measure the only of the 8 conditions shown in Fig. 12 I-J and U-V not to reach significance was for A1 SUs in the 2nd half of the stimulus; all 7 remaining conditions did. Although task engagement has slightly different effects on rate-based and VSpp-based discrimination, their absolute discriminability levels are roughly comparable; i.e., the population average, rate-based ROCa is comparable to VSpp-based ones for synchronizing responses (compare dark green plots in Fig. 12, E-H with red plots in I-L). This suggests that synchronizing responses can encode AM equally well using phase-locking and average firing rate.

Discussion

Differences between A1 and ML were found by investigating how behavioral engagement in AM discrimination affects neurons’ ability to discriminate the same sounds. While little is known about attention- and state-related effects in higher auditory areas, these differences appear related to three key
issues. First, they may relate to how attention modulates neural responses. The differing response time
courses and neural response type differences between ML and A1 may relate to the degree to which this
study taps into more selective forms of attention, and possibly the time course of attention including
disengagement after a decision is made. Second, the results have implications regarding neural coding. In
particular, these results elucidate possible decoding differences, such as simply pooling activity from A1
as opposed to ML, where both increases and decreases in activity must be accounted for by higher areas.
Third, the results imply a special role for non-synchronized responses. Before addressing these issues
contrasting A1 and ML, we must relate the results to what is already known in A1, because little is known
of attention and engagement effects beyond A1.

**Comparing neural activity during passive listening and active behavior in A1**

Our results show that engagement in the AM task improves A1 and ML neurons’ ability to
discriminate AM based on both firing-rate and phase-locking. When compared to a passive condition,
auditory task engagement can (1) change stimulus-evoked and spontaneous firing rates of AC cells
(Benson and Hienz 1978; Hocherman et al. 1976; Miller et al. 1972; Otazu et al. 2009; Pfingst et al.
1977), (2) create facilitative frequency tuning of A1 neurons in tone detection (Fritz et al. 2003; Miller et
al. 1972), (3) sharpen spatial tuning of A1 neurons in sound localization (Benson et al. 1981; Lee and
Middlebrooks 2011), (4) sharpen frequency tuning (David et al. 2012), and (5) increase neural selectivity
for complex sounds (Knudsen and Gentner 2013). Furthermore, Otazu et al. (2009) have shown that the
sound-evoked and spontaneous firing rate of A1 neurons is modulated by engagement in either an
auditory or olfactory task, demonstrating that A1 neurons’ firing rate can be modulated by attending to
non-auditory attributes. It is largely unknown what components in task engagement cause the myriad of
observed changes in neural response properties. There are multiple, possible contributing sources to the
changes observed in our study, including general-attention and feature-selective attention.

In A1 attention might activate a multiplicative response increase. Jaramillo and Zador (2011) have
shown that temporal expectation improves A1 neurons’ frequency discrimination ability by increasing
responses at the target frequency and decreasing responses at surrounding frequencies. They conclude
that this is consistent with a multiplicative effect. The A1 data we present here and previously (Niwa et al. 2012a) are also consistent with a multiplicative effect since the engagement effects appear larger for stimuli that evoke higher firing rates. Such multiplicative effects are often thought to be indicative of attention. Our ML data show something different, suggesting feature-selective attention. We believe this because some of the ML effects are most pronounced near threshold and occur for time windows at which stimulus-specific attention is more likely engaged.

Recently, larger neural discrimination improvements have been found for a feature that is selectively attended in contrast to simply attending to sound. Spatial tuning of A1 neurons improved when animals performed a sound periodicity detection task, suggesting a general attention effect, rather than a spatial feature-attention effect. However, engagement in a sound localization task improved spatial tuning more than performing the periodicity detection task (Lee and Middlebrooks 2011). This suggests that attention’s effects were feature-specific.

These results suggest that both general and feature-selective attention influence A1 responses, and are consistent with our A1 results.

**Relationship to plasticity in AC**

Our results show rapid changes in neural discrimination when an animal switches between behaving and passive conditions. In addition to immediate attention effects, long-term training could lead to plastic changes which are often highly interrelated with plasticity (Polley et al 2006; Fritz et al. 2007) that can improve AC neurons discrimination ability (e.g., Jeanne et al. 2011; Thompson et al. 2013). In our animals, plastic changes due to training might be dormant in the passive condition, and only activated when the animal engages in the task. This would allow for the cortical circuit in the passive condition to be in a state open to the analysis of many possible signals, but during task-performance the circuit is optimized for AM detection.

**Comparisons between A1 and ML**

1. **Phase-locking**
An interesting finding in this and an earlier study (Niwa et al. 2012a) is that phase locking -- the precision with which a neuron follows temporal modulation -- improves with active engagement. Here, we also find that, while in the passive condition ML does not phase lock as well as A1, ML improves more than A1 with behavioral engagement. This is consistent with A1’s ability to improve temporal precision of firing due to training (Fritz et al. 2005; Kilgard and Merzenich 1998; Kilgard et al. 2001; Schnupp et al. 2006). Furthermore, (Jakkamsetti et al. 2012) have shown that a higher AC area (rat PAF) normally time locks worse than A1, but that environmental enrichment improves temporal locking in PAF more than in A1. Finally, in our study phase-locking improves with engagement and becomes as sensitive to AM as firing rate. When combined, all the evidence suggests that learning and attention can improve phase-locking to sound, such improvements are more pronounced in higher cortical areas, and that phase-locking could play a meaningful role in sound processing.

2. Possible implications about attention

ML ‘increasing’ cells’ AM discriminability during behavior worsens later in the stimulus (Figs. 1-4, 8), but no such effect was seen in A1. A1 ‘increasing’ cells’ AM discrimination during behavior remains above the passive level throughout the stimulus. The late decline in ML’s AM discrimination for increasing units appears greater at higher modulation depths (Fig. 6C,D, Fig. 8 A,B). Raw firing rate to AM and unmodulated noise (Fig.9 A and B) indicates that the late ROCa decline in ML is due to the combination of firing rate decreases to AM and increases to unmodulated noise in the behaving compared to the passive condition. At modulation depths far above the animals’ behavioral thresholds, listening to the entire test stimulus is not likely required before making a decision. The observed decrease in AM discriminability may be due to a decrease in attention to high-depth AM later during the stimulus, combined with increased attention to unmodulated noise (particularly later in the stimulus), where animals may be attending more in an attempt to detect AM in the unmodulated stimuli.

Other evidence supporting a different type of attention effect in ML derives from partitioning our analyses by increasing and decreasing units. Non-synchronized increasing units show the most improvement during behavior later in the stimulus near behavioral threshold (Fig. 12B,D, and Fig. 6 C,D
show a small effect averaged for all units). This suggests engagement improves performance in the second half only for the most difficult to discriminate sounds that require the most and longest attention, reflecting its time course. In A1 this effect was not observed.

3. Overall AM discrimination ability of units

AM discriminability of units with increasing depth-sensitivity functions appears better in A1 than ML. A1 neurons better discriminate AM with phase-locking than ML neurons in both behaving and passive conditions. A1 neurons also better discriminate AM using a rate code with increasing rate-depth functions in both conditions. The exception to A1’s better performance is for rate coding using decreasing rate-depth functions. AM discrimination by ‘decreasing’ cells was significantly better in ML than in A1, although this occurs only during the second half of the test stimulus in the behaving condition. The result suggests that ‘decreasing’ ML cells may be important for AM detection.

4. AM Coding Schemes

Our results suggest that to decode the population of A1 neurons’ activity, aggregate activity increases correspond to more strongly modulated AM. In contrast, in ML the output code is likely the difference in activity between neurons that increase and decrease rate with modulation depth. AM discriminability of ‘decreasing’ cells in A1 significantly worsens with task engagement (Figs.8, 12), while discriminability of ML ‘decreasing’ cells improves with task engagement (Figs. 7, 8, 12). This is another piece of evidence supporting the importance of the rate code carried by ‘decreasing’ ML cells. It also suggests that, in A1, increases in activity represent modulation, since task engagement actually reduces the performance of ‘decreasing’ cells in this region by increasing the response to AM during behavior. Therefore, the ‘reduction’ of AM discriminability in A1 ‘decreasing’ cells is not necessarily bad for AM coding. If one assumes that the brain interprets an increase in A1’s aggregate pooled activity (by indiscriminately pooling the activity of all A1 neurons) as evidence of an AM signal, then the reduction of ‘decreasing’ cells’ discriminability can actually render a benefit to the AM discriminability of an A1 population and ultimately to the animal’s behavioral performance. The difference in behavioral modulation of ‘decreasing’ cells’ AM discriminability in ML and A1 suggests that different coding
schemes are used in these areas; a ‘single-mode’ in A1, using only increasing rate, and a ‘dual-polar mode’ in ML, using both increasing and decreasing rate.

The heightened importance of decreasing rate-depth functions in ML is particularly interesting. The emergence of decreasing functions in ML, and the fact that their ability to discriminate AM improves with attention, and that they are very sensitive (Figs 12) may be beneficial for AM coding in ML. While it is well established that positively correlated noise in the activity of similarly tuned neurons limits their coding capacity (Shadlen et al. 1996; Zohary et al. 1994), it has been shown that positively correlated noise among neurons with increasing and decreasing functions can improve their coding efficiency (Romo et al. 2003). Thus, the apparent loss of AM discriminability in ML can be at least partially compensated for by the emergence of decreasing functions if the noise in the activity of cells with increasing and decreasing functions is positively correlated.

**Comparison to a recent study looking at attention and non-primary AC**

Recently Dong et al 2013 compared neural responses in multiple cortical areas while cats discriminated click trains to responses in a passive condition. While some of their results are similar to ours, one apparent discrepancy is that they report increases and decreases in driven responses in lower AC (dorsal tonotopic AC), but only increases in higher ventral non-tonotopic AC. Major differences in methods, species and analysis prevent direct comparison. Their dorsal ‘lower’ cortical area probably includes both A1 and ML in monkeys, and their ventral area is probably much higher than any belt area (perhaps similar to temporal pole or insular cortex in monkeys). So the hierarchical areas between the two studies are not comparable. Their task is relatively easy from a sensory perspective (discriminating 15 Hz from 50 Hz which is highly suprathreshold), and is unlikely to place high demands on feature-selective attention, whereas our animals are performing around threshold level. For us, particularly in A1, decreases refer to the slope of firing rate versus modulation depth functions. For them decreases refer to decreases in activity to both stimuli, not on changes in the neurometric (response versus frequency) function. Much of the complexity we see occurs between 400 and 800 ms after stimulus onset, while their
stimuli are only 320 ms. Finally, comparison are made difficult by numerous other differences in experimental design: performance level, neuronal inclusion criteria (they only include neurons that fire at least 2 standard deviations above spontaneous level to one of the two stimuli), and species. This highlights that experimental differences can have large impacts on physiological results, particularly attention-related effects that depend critically on the difficulty of discriminating or detecting stimuli.

**Is there a special role for non-synchronized responses?**

AM encoding is hypothesized to transform from temporal- to rate-based representations as information is processed from lower to higher auditory areas (Lu and Wang 2004; Nelson and Carney 2004). This is supported by the decrease in the upper limit of modulation frequency to which neurons phase-lock and by the increase in prominence of rate-based AM coding when ascending from lower to higher areas (Blackburn and Sachs 1989; Creutzfeldt et al. 1980; de Ribaupierre et al. 1980; Frisina et al. 1990; Langner and Schreiner 1988; Lu and Wang 2004; Nelson and Carney 2007; Preuss and Muller-Preuss 1990; Rees and Moller 1983; Rouiller et al. 1981), and the emergence of non-synchronized firing-rate encoding of temporal modulation in higher areas (Bendor and Wang 2007; Lu and Wang 2004).

Several lines of evidence support a special contribution for non-synchronized responses in temporal discrimination. In A1, non-synchronized (increasing) responses are more sensitive to AM than synchronized responses (Figs 12), and the non-synchronized responses increase sensitivity with engagement. Non-synchronized increasing ML responses, although slightly less sensitive than those in A1, yield similar early-stimulus results. During the second half of the stimulus, ML non-synchronized increasing responses show depth dependent improvement in the behaving condition (Fig 12 B,D) consistent with a more pronounced or longer-lasting attention effect near-threshold.

ML non-synchronized decreasing responses also show large improvements during behavior and are more AM-sensitive than synchronizing responses, particularly later in the stimulus (Fig. 12 A-D). Lastly, during the entire stimulus, both increasing and decreasing non-synchronized ML responses improve during behavior (Fig. 12 A-D), whereas for synchronized responses improvements only occur in the first
half for increasing and only during the second half for decreasing functions (Fig. 12 E-H). Together this
suggests that increasing (A1 and ML) and decreasing (ML) non-synchronized responses have properties
that make them particularly well-suited for AM processing. This is further supported by recent studies in
behaving cats showing non-synchronized responses’ discrimination ability more closely match the
animal’s behavioral performance than synchronized responses (Dong et al. 2011) and non-synchronized
rate responses are modulated by attention but synchronizing ones were not, (Dong et al. 2013).

Comparison of ML activity in our task to somatosensory cortical activity during
flutter frequency discrimination tasks

Our study shares similarities with results from the primary and secondary somatosensory cortices
(S1 and S2). Romo et al. conducted extensive studies examining the neural codes underlying perception,
memory, and decision making during vibrotactile discrimination, where monkeys were trained to report
whether the frequency of a first flutter stimulus is greater than the flutter frequency of a second stimulus
(Hernandez et al. 2010; Hernandez et al. 2000; 2002; Luna et al. 2005; Romo et al. 2002; Romo et al.
2003; 1998; Salinas et al. 2000). First, S2 neurons’ flutter frequency coding capacity was significantly
lower than S1 neurons’ (Salinas et al. 2000); similarly we find ML neurons generally have lower AM
discriminability than A1 cells. Second, transformation of encoding schemes appears to occur from a
single-mode of ‘increasing’ rate response in S1 to a dual-mode of ‘increasing’ and ‘decreasing’ responses
in S2 (Hernandez et al. 2002; Salinas et al. 2000). Salinas et al. (2000) showed that 92% of S1 neurons
encoded an increase in flutter frequency with monotonically increasing firing rate, and only 8 % used
decreasing rate. In S2, 58% had increasing rate versus flutter-frequency functions, and 42% decreasing.
Our results also suggest that the primary sensory area, A1, employs a ‘single-mode’ encoding with mainly
increasing rate-depth functions, while the secondary area, ML, employs a ‘dual-polar-mode’ with both
increasing and decreasing rate-depth functions. Although ours and Romo group’s studies use different
behavioral tasks in different sensory modalities, there is a general principle: a meaningful temporal
feature (flutter frequency or modulation depth) in primary sensory cortex is encoded primarily by one
type of response: an increase in activity. But in the secondary area two types of responses – activity
increases or decreases – encode the feature. The similarities in our results suggest a common scheme in
hierarchical processing of temporal information shared in sensory cortices of different modalities.

Hierarchical processing of temporal information in AC

Electrophysiological studies have examined single-unit responses to AM and other types of
temporal modulation across different auditory areas (Bendor and Wang 2007; 2010; Bieser and Müller-
2008; Liang et al. 2002; Lu et al. 2001; Lu and Wang 2000; Malone et al. 2007; Nelson and Carney 2004;
Schreiner and Urbas 1988; Scott et al. 2010; Wojtczak et al. 2011). Although we have yet to form a
precise understanding of how temporal sound properties are processed in parallel and/or hierarchical AC
networks, an interesting trend is evident; a temporal resolution gradient may be present along the
posteromedial-to-anterolateral axis on primates’ superior temporal gyrus (STG). For example, in awake,
non-behaving squirrel monkey, a gradient of neurons’ ability to phase-lock to AM was shown across
cortical areas, where A1 had the best temporal resolution (Bieser and Müller-Preuss 1996). The areas
anterior and lateral to A1 had lower phase-locking-based BMFs, thus lower temporal resolution. (Scott et
al. 2010) also showed that in awake, non-behaving macaques, areas anterior and lateral to A1 (areas R
and lateral belt cortices) have lower phase-locking BMFs compared to A1, and to an area posteromedial
to A1 (CM). This gradient was also shown in human epileptic patients, showing degradation of temporal
resolution along the posteromedial to anterolateral direction over the HG (Brugge et al. 2009), implicating
a flow of temporal processing in the AC hierarchy in the posteromedial-to-anterolateral direction
(Gueguin et al. 2007).

Other temporal response properties besides the resolving power for AM frequency exhibit
gradients in posterior-to-anterior and/or medial-to-lateral directions over the STG. Neurons’ preferred
FM frequency decreases in a posterior to anterior direction in the lateral belt (Tian and Rauschecker
In addition, there may be a posterior-to-anterior and/or medial-to-lateral gradient of response latency (Kajikawa et al. 2005; Kajikawa et al. 2008; Kusmierek and Rauschecker 2009; Lakatos et al. 2005; Recanzone et al. 2000a; Scott et al. 2010). Our result showing lower AM discriminability based on phase-locking in ML compared to A1 may be consistent with the idea that temporal response deteriorates in a medial to lateral direction.

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**Figure Captions:**

**Figure 1.** An example of the activity of an ML single-unit (SU) showing improvement in firing-rate based AM discriminability due to task engagement during the first half of the test stimulus, but deterioration during the second half. **A** and **B**, raster plots of a single-unit (SU) response to 30 Hz AM as modulation depth is varied from 0% (bottom) to 100% (top) in the passive (**A**) and behaving (**B**) conditions. **C-D**, average firing rate during the first (**C**) and second (**D**) halves of the stimulus is plotted as a function of modulation depth for passive (solid square) and behaving (open circle) conditions. **E** and **F**, ROC area based on firing rate during the first (**E**) and second (**F**) halves of the stimulus is plotted as a function of modulation depth for passive (solid square) and behaving (open circle) conditions. Neural ROC area yields the probability that an ideal observer would detect modulation based solely on the neural responses. ROC area of 0.5 corresponds to chance performance. The farther ROC area is from 0.5 the better the neuron is at discriminating AM from an unmodulated sound. An ROC area of 1 or 0 = perfect
AM detection, where 1 indicates higher firing rates for modulated sounds than to the unmodulated sound, and 0 indicates lower firing rate to modulated sounds.

**Figure 2.** An example of an ML SU that shows a change in its firing-rate response characteristics to modulation depth from monotonically increasing during the first half to non-monotonic during the second. Data is presented in the same format as Fig.1.

**Figure 3.** An example of an ML SU that shows a change in its firing-rate response characteristics to modulation depth from monotonically increasing during the first stimulus half to monotonically decreasing during the second half. Data is presented in the same format as Fig.1.

**Figure 4.** Population ROCa-depth functions for first and second halves of the test stimulus in ML and A1.

A and B, ML population-mean ROC areas based on firing rate during the first half of the stimulus are plotted as a function of modulation depth for the passive (solid square) and behaving (open circle) conditions, for all recorded MUs (A) and SUs (B) in ML. C and D, population-mean, rate-based ROC areas for the second 400 ms of the stimulus are shown for MUs (C) and SUs (D). (E-H) plots are the same is in A-D except ROCa is reflected around 0.5. This means the y-axis is the absolute value of the difference in ROCa from 0.5. So, for example an ROCa of 0.4 $\rightarrow$ reflected ROCa of 0.6, and an ROCa of 0.1 $\rightarrow$ reflected ROCa of 0.9, etc. (I-L) is the same as A-D except for A1. (M-P) is the same as E-H except for A1. In all panels, p values denote Wilcoxon signed-rank test comparing collapsed-depth ROC areas between behaving and passive conditions. Asterisks (*) denote individual modulation depths where a Wilcoxon signed-rank test yielded a value of p < 0.05.

**Figure 5.** Top, demonstration of how the neurometric slope was calculated. A-D, Distributions of the slopes of neurometric (ROC area vs. modulation depth) functions by linear regression for MUs in ML (A), SUs in ML (B), MUs in A1 (C), and SUs in A1 (D). The slopes of the three examples of Figs. 1-3 are shown in red (Fig. neuron’s 1 slope = 0.0023, Fig. 2’s slope = 0.0041, Fig. 3’s slope = 0.0015).

**Figure 6.** Summary of AM discrimination ability for the population of ML cells with increasing rate-modulation-depth functions. A-D, data is presented in the same format as in Fig.4 A-D. Asterisk (*) denotes individual modulation depths where a Wilcoxon signed-rank test yielded a value of p <0.05. The
plots of firing-rate based ROC areas during the first half of the stimulus for 60% (left), 80% (middle), and 100% (right) AM, for MUs (E) and SUs (F). Each unit’s ROC area in the passive condition is plotted on x-axis and that for behaving condition on y-axis. G and H, the same as E and F, but for ROC areas during the second half of the stimulus. Diagonal line is where ROC area is equal for both conditions and the quadrants are marked at ROC area = 0.5.

**Figure 7.** Summary of AM discriminability for the population of ML cells with decreasing rate-vs-modulation-depth functions. A-D, data is presented in the same format as in Fig.6 A-D.

**Figure 8.** ROC areas (based on firing-rate) are calculated in 400-ms time windows starting at various times (0, 100, 200, 300, and 400 ms) after stimulus onset. A-D, population-mean, rate-based ROC area of ‘increasing’ cells is plotted as a function of start time of the windows at each modulation depth (from 100% on the left most panel to 6% on the right) for the passive (solid square) and behaving (open circle) conditions, for MUs in ML (A), SUs in ML (B), MUs in A1 (C), and SUs in A1 (D). E-H, population-mean, rate-based ROC area of ‘decreasing’ cells is plotted as a function of start time of the time windows at each modulation depth (from 100% on the left most panel to 6% on the right) for the passive (solid square) and behaving (open circle) conditions, for MUs in ML (E), SUs in ML (F), MUs in A1 (G), and SUs in A1 (H).

**Figure 9.** Firing-rate relative to spontaneous rate is calculated in 400-ms time windows starting at various times (0, 100, 200, 300, and 400 ms) after stimulus onset. Layout is the same as Figure 8 except firing rate rather than ROC area is shown. The firing rate in response to unmodulated noise (0%) is included here, and changes in this contribute to changes in the neurons ability to detect of AM.

**Figure 10:** Plot showing the advantage of A1 neurons ability to discriminate AM when compared to ML. For increasing units this is calculated by subtracting ML mean ROC area from A1 ROC area (A1-ML). Therefore higher values mean A1 neurons can better discriminate AM than ML neurons. For decreasing
units this is calculated by subtracting A1 mean ROC area from ML ROC area (ML-A1). This is required because for decreasing units lower ROC areas correspond to better discrimination ability.

This was done for both MUs (A) and SUs (B) in 8 conditions noted in the legend. The conditions were created by splitting 3 categories (increasing vs. decreasing, behaving vs. passive, and 1\textsuperscript{st} vs. 2\textsuperscript{nd} half) in to the eight combinations of them. Filled symbols represent points with significant differences between A1 and ML by a 2-sample t-test (P < 0.05); open symbols values were not significantly different between A1 and ML.

**Figure 11.** Improved neural discrimination in the behaving compared to the passive condition using vector strength in. (A-D) Example of ML SU that improved phase-locking in the behaving condition. Raster plots of SU response to 15Hz AM in the passive (A) and behaving (B) conditions. C, phase-projected vector strength (VSpp) is plotted as a function of modulation depth for the passive (solid square) and behaving (open circle) conditions. D ROC area (D) based on VSpp is plotted as a function of modulation depth. Note in (D) that the behaving point (white circle) is covering the ability to see the passive point (black square) at 0% depth (both behaving and passive are 0.5 for ROC area by definition).

E-F, ML population-mean ROC areas based on phase projected vector strength (VSpp) during the entire stimulus duration (80-800 ms, the onset response is excluded) are plotted as a function of modulation depths for the passive (solid square) and behaving (open circle) conditions, for all recorded MUs (E) and SUs (F). G and H, population-mean ROC areas based on VSpp during the first half of the stimulus (80-400 ms, the onset response is excluded) are plotted as a function of modulation depths for the passive (solid square) and behaving (open circle) conditions, for all recorded MUs (G) and SUs (H). I and J, population-mean ROC areas based on VSpp during the second half of the stimulus (400 – 800 ms) are plotted as a function of modulation depths for the passive (solid square) and behaving (open circle) conditions, for all recorded MUs (I) and SUs (J). In all panels, p values are denoted showing Wilcoxon signed-rank test comparing collapsed-depth ROC areas between behaving and passive conditions.
Asterisk (*) denotes individual modulation depths where a Wilcoxon signed-rank test yielded a value of $p < 0.05$.

**Figure 12.** Effect of task engagement on AM discriminability is shown separately for synchronized/non-synchronized and ‘increasing’/‘decreasing’ responses. **A** and **B**, ML population-mean rate-based ROC areas for non-synchronized responses are plotted for ‘increasing’ (dark blue lines) and ‘decreasing’ (light blue lines) responses, during the first half (0-400 ms, **A**) and the second half (400-800 ms, **B**) for MUs. Solid squares are the passive and open circles are the behaving conditions. Asterisks (*) denotes depths at which the differences between active and passive were significant ($p < 0.05$). P values at the top of each subplot denote whether differences between active and passive were significant for increasing units collapsed across all depths and at the bottom of each subplot are for decreasing units collapsed across all depths. **E** and **F**, population-mean rate-based ROC areas for synchronized responses are plotted for ‘increasing’ (dark green lines) and ‘decreasing’ (light green lines) responses, during the first half (0-400 ms, **E**) and the second half (400-800 ms, **F**) for MUs in ML. Asterisks (*) and p values are formatted the same as in **A-D**. **I** and **J**, population-mean VSpp-based ROC areas for synchronized responses during the first half (80-400 ms, **I**) and the second half (400-800 ms, **J**) for MUs in ML (**K-L** for SUs). **C**, **D**, **G**, **H**, **K**, and **L**, the same as **A, B, E, F, I, and J**, but for SUs in ML. **M-X**, the same as **A-L**, but for A1 units. In all panels, p values are denoted showing Wilcoxon signed-rank test comparing collapsed-depth ROC areas between behaving and passive conditions. Asterisk (*) denotes individual modulation depths where a Wilcoxon signed-rank test yielded a value of $p < 0.05$. Layout of **A-H, M-T** are described above.
Figure 1

(A) Passive condition
(B) Behaving condition

(C) Firing rate (spikes/s) for the first half of the trial.
(D) Firing rate (spikes/s) for the second half of the trial.

(E) Rate-based ROCA for the first half of the trial.
(F) Rate-based ROCA for the second half of the trial.
Figure 2

(A) Passive condition

(B) Behaving condition

(C) Firing rate (spikes/s) vs. modulation depth (%)

(D) Firing rate (spikes/s) vs. modulation depth (%)

(E) Rate-based ROCA vs. modulation depth (%)

(F) Rate-based ROCA vs. modulation depth (%)
Figure 3

A Passive condition  B Behaving condition

C first half  D second half

C

E rate-based ROCA  F

E

F

Passive condition Behaving condition

Figure 3
**Figure 4**

A1

ML

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**Population mean ROCA**

**Modulation depth (%)**

---

*behavioring*  
*passive*
Figure 5
Figure 6

Increasing’ functions

First half  Second half

A MUs

population mean ROCA

0 50 100 0 50 100

Modulation depth (%)

0.5

p = 0.896

0.6

0.7

0.8

B SUs

population mean ROCA

0 50 100 0 50 100

Modulation depth (%)

0.5

p = 3.00 x 10^-13

0.6

0.7

0.8

C MUs

population mean ROCA

0 50 100 0 50 100

Modulation depth (%)

0.5

p = 2.17 x 10^-13

0.6

0.7

0.8

D SUs

population mean ROCA

0 50 100 0 50 100

Modulation depth (%)

0.5

p = 0.790

0.6

0.7

0.8

E MUs

ROC area in behaving condition

ROC area in passive condition

60% 80% 100%

F SUs

ROC area in behaving condition

ROC area in passive condition

60% 80% 100%

G MUs

ROC area in behaving condition

ROC area in passive condition

60% 80% 100%

H SUs

ROC area in behaving condition

ROC area in passive condition

60% 80% 100%

MUs

SUs
‘Decreasing’ functions

First half
A MUs

Second half
C MUs

B SUs

D SUs

population mean ROCA

Modulation depth (%)

0 50 100 0 50 100

p = 0.0190

p = 3.91 x 10^-12

p = 0.557

p = 1.74 x 10^-10

---

Figure 7
Fig 8: Population average rate-based ROC area

- **Increasing** rate-vs-depth functions
  - Panel A: MUs
  - Panel B: SUs
  - Panel C: MUs
  - Panel D: SUs
  - Panel E: MUs
  - Panel F: SUs
  - Panel G: MUs
  - Panel H: SUs

- **Decreasing** rate-vs-depth functions
  - Panel A: MUs
  - Panel B: SUs
  - Panel C: MUs
  - Panel D: SUs
  - Panel E: MUs
  - Panel F: SUs
  - Panel G: MUs
  - Panel H: SUs

Beginning of 400-msec time windows relative to stimulus onset (msec)

---

- **Behaving** (open circles)
- **Passive** (filled squares)

Fig 8
Figure 9

Beginning of 400-msec time windows relative to stimulus onset (msec)

- Decreasing' rate-vs-depth functions
- Increasing' rate-vs-depth functions

Legend:
- Behaving
- Passive
Figure 10

A MUs

B SUs

Modulation depth (%)

A1 discrimination advantage (ROC area)

2nd half, behaving, ‘decreasing’ response

‘Increasing’ responses

‘Decreasing’ responses
Figure 11
Figure 12