

Does Ventriloquism Aftereffect Transfer across Sound Frequencies? *A Theoretical Analysis via a Neural Network Model*

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Keywords: Visual-auditory Integration, Ventriloquism, Hebbian Plasticity, Aftereffect Generalization.

Abstract: When an auditory stimulus and a visual stimulus are simultaneously presented in spatial disparity, the sound is perceived shifted toward the visual stimulus (ventriloquism effect). After adaptation to a ventriloquism situation, enduring sound shifts are observed in the absence of the visual stimulus (ventriloquism aftereffect). Experimental studies report discordant results as to aftereffect generalization across sound frequencies, varying from aftereffect staying confined to the sound frequency used during the adaptation, to aftereffect transferring across some octaves of frequency. Here, we present a model of visual-auditory interactions, able to simulate the ventriloquism effect and to reproduce – via Hebbian plasticity rules – the ventriloquism aftereffect. The model is suitable to investigate aftereffect generalization as the simulated auditory neurons code both for spatial and spectral properties of the auditory stimuli. The model provides a plausible hypothesis to interpret the discordant results in the literature, showing that different sound intensities may produce different extents of aftereffect generalization. Model mechanisms and hypotheses are discussed in relation to the neurophysiological and psychophysical literature.

1 INTRODUCTION

In daily life, we are typically exposed to events that impact multiple senses simultaneously. Sensory information of various natures is continuously integrated in our brain to generate an unambiguous and robust percept (Ernst and Bulthoff, 2004). How multisensory integration is accomplished has become a central topic in cognitive neuroscience, but the neural bases still remain largely unclear.

A substantial part of research on multisensory integration has focused on visual-auditory interaction. A fascinating phenomenon occurs in case of visual-auditory spatial discrepancy: presenting a visual stimulus and an auditory stimulus synchronous but in spatial disparity induces a translocation of the sound perception towards the visual stimulus (i.e., visual bias of sound localization) (Welch and Warren, 1980; Bertelson and Radeau, 1981; Recanzone, 2009). This phenomenon is known as *ventriloquism*, as it can explain the impression of a speaking puppet created by the illusionist.

Although the effect in speech perception probably involves also cognitive factors, several studies have shown that visual bias of sound location occurs also with simple and meaningless stimuli, such as flashes and beeps (Bertelson and Radeau, 1981; Bertelson, 1998; Slutsky and Recanzone, 2001). Hence, it can be ascribed - at least partly - to an automatic attraction of the sound toward the visual stimulus. The general explanation for the ventriloquism effect is that the brain combines sensory information according to their reliability, attributing a higher weight to vision which has better spatial resolution than audition.

An interesting feature of the ventriloquism effect is that it can be long-lasting. That is, a period of exposure to a ventriloquism situation (adaptation phase) induces the so-called *ventriloquism aftereffect*: after the exposure, an auditory stimulus presented unimodally is perceived shifted in the direction of the preceding visual stimulus (Recanzone, 1998). It has been proposed that aftereffect reflects a form of rapid cortical plasticity whereby representation of acoustical space is altered

by the disparate visual experience.

The ventriloquism aftereffect has attracted the interest of several researchers (Recanzone, 1998; Lewald, 2002; Frissen et al., 2003; Woods et al., 2004; Frissen et al., 2005). These studies examined whether the aftereffect is specific to the spectral characteristics of the auditory stimuli used in the adaptation phase or instead it generalizes along the frequency dimension. To this aim, a pure tone stimulus at a specific frequency was used during the adaptation phase (together with a spatially disparate visual stimulus), and the magnitude of the aftereffect was measured using tones at the same frequency as the adaptation phase and at different frequencies. Unfortunately, these studies have provided rather diverging results. Specifically, in a first study (Recanzone, 1998) human subjects were exposed to either 750 Hz or 3 kHz tones synchronized with a spatially disparate flash. Strong aftereffect occurred only with tones at the same frequency as in the adaptation phase, and no aftereffect was observed with tones at the other frequency. Similar results were obtained by two subsequent studies on humans (Lewald, 2002) and on monkeys (Woods and Recanzone, 2004) showing no or little transfer of aftereffect between 1 kHz and 4 kHz stimuli. Hence, the aforementioned studies indicated that the aftereffect does not generalize over frequencies that are two octaves apart. Contrary to these results, other two studies reported generalization of aftereffect not only across two-octave frequency range (750 Hz and 3 kHz) (Frissen et al., 2003) but even across four-octave frequency range (400 Hz and 6.4 kHz) (Frissen et al., 2005). A possible reason for such differences is that higher sound intensities were used in studies reporting

generalization, compared to no generalization studies, but this factor has not been investigated and a clear explanation of the observed discrepancy is still lacking. A better comprehension of aftereffect generalization across frequencies can have important implications as it may provide information on which mechanisms and neuronal structures - and in particular which auditory cortical areas - are involved in ventriloquism. Indeed, frequency response properties of single neurons in auditory cortical areas may be put in relation with the extent of aftereffect generalization across frequencies.

Neural network models are particularly suitable to formulate hypotheses on the neural circuitry and learning mechanisms underlying multisensory integration and its perceptual phenomena. In the last decades, we investigated different aspects of organization and plasticity of multisensory integration via neurocomputational models (Magosso et al., 2008; Ursino et al., 2009; Magosso, 2010; Magosso et al., 2010a; Magosso et al., 2010b; Magosso et al., 2010c; Cuppini et al., 2011; Cuppini et al., 2012). In particular, in one recent work (Magosso et al., 2012) we have proposed a model of visual-auditory integration able to explain ventriloquism effect and to reproduce - by implementing Hebbian rules - the ventriloquism aftereffect. However, that model considered only the spatial features of the stimuli whereas the spectral characteristics of the auditory stimuli were completely neglected. Hence, it was not suitable to investigate the generalization of aftereffect across the frequencies, nor to assess which neural mechanisms may explain the observed differences.

Aim of this work was to develop an advanced version of our previous model in order to: i) mimic

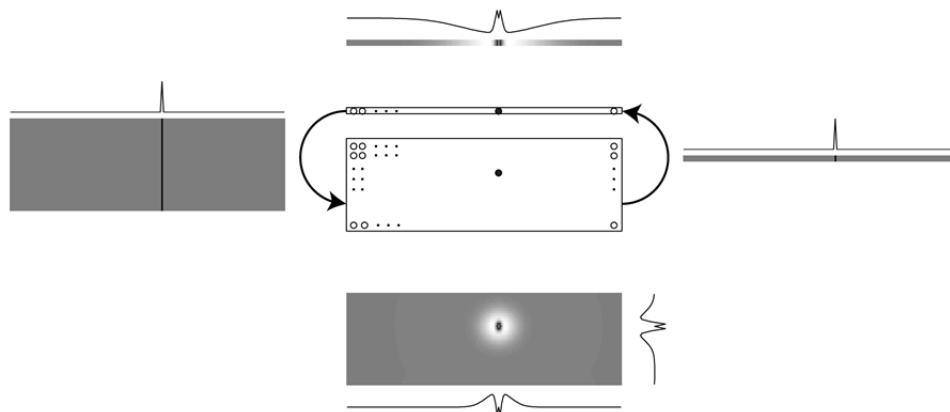


Figure 1: Network architecture. The two central rectangles represent the visual (array) and auditory (matrix) neurons. The other panels represent the basal connections that depart from the neurons marked with the two black bullets: the lateral panels represent inter-layer connections, while the top and bottom panels represent intra-layer connections. The darker the colour, the more positive the connection.

auditory neurons coding for both spatial and spectral properties of the stimulus; ii) reproduce ventriloquism effect and aftereffect in these new conditions; iii) investigate the generalization of aftereffect across sound frequencies; iv) provide a plausible interpretation of different extents of aftereffect generalization.

2 METHOD

The model is an extension of our previous one (Magosso et al., 2012), which included two *one-dimensional* (1D) layers of visual and auditory neurons, communicating via reciprocal synapses. Each neuron in both layers coded for a particular azimuth of the external stimulus.

In order to account for the spectral features of the auditory stimuli, the 1D layer of auditory neurons has been replaced by a *two-dimensional* (2D) matrix (figure 1), where each neuron codes for a particular azimuth-frequency pair of the external auditory stimulus. The synapses have been changed accordingly. In the new version of the model, the visual layer has been maintained unchanged.

2.1 Model Description

The model consists of a 1D visual layer and of a 2D auditory layer. The 1D visual layer contains N_p^v (= 180) visual neurons. They code for the azimuth of the external visual stimulus and are spatiotopically aligned (proximal neurons code for proximal positions). The 2D auditory layer contains $N_p^a \times N_f^a$ (= 180 x 40) auditory neurons. They code for a particular azimuth and a particular frequency of the external auditory stimulus, and are spatiotopically and tonotopically aligned (proximal neurons code for proximal positions and proximal frequencies). Azimuths are linearly spaced by 1° , so the neurons cover 180° along the spatial dimension; frequencies are logarithmically spaced so the auditory neurons cover approximately an eight-octave range along the spectral dimension (one octave every five neurons). Neurons within each layer communicate via lateral intra-layer synapses, and neurons in the two layers are reciprocally connected via inter-layer synapses. Hence, the net input $u(t)$ to a neuron is the sum of 3 contributions: an external input $e(t)$; a lateral input $l(t)$ (from other neurons in the same layer); a cross-modal input $c(t)$ (from neurons in the other layer). The activity $y(t)$ of each neuron is computed by passing the net input $u(t)$ through a first order dynamics and a steady-state sigmoidal relationship,

with the saturation level set at 1 (i.e., the activity of each neuron is normalized to the maximum). In the following, each of the three inputs is described. In order to avoid border effects, the layers have a circular structure, not shown here for brevity.

i) *The External Input $e(t)$* – The auditory external input is reproduced as a 2D Gaussian function since it mimics an auditory stimulus localized in space and in frequency (tone) filtered by the receptive fields (RFs) of the auditory neurons in the 2D space-frequency map

$$e_{ij}^a(t) = E_0^a \cdot \exp\left(-\frac{(i - i_p^a)^2}{(\sigma_p^a)^2} - \frac{(j - j_f^a)^2}{(\sigma_f^a)^2}\right) \quad (1)$$

E_0^a is the stimulus intensity (arbitrary units), i and j are the generic indices for auditory neurons along the spatial and spectral dimensions respectively, i_p^a and j_f^a are the indices at which the stimulus is centered; finally σ_p^a and σ_f^a define the width of the auditory RFs along the two dimensions.

The visual external input is mimicked as a 1D Gaussian function, representing a spatially localized visual stimulus (e.g. a flash) filtered by the RFs of the visual neurons in the 1D space map

$$e_i^v(t) = E_0^v \cdot \exp\left(-\frac{(i - i_p^v)^2}{(\sigma_p^v)^2}\right) \quad (2)$$

E_0^v is the stimulus intensity (arbitrary units), i is the generic index for visual neurons, i_p^v is the index at which the stimulus is centered and σ_p^v is related to the width of the visual RFs along the azimuth. To simulate the higher spatial resolution of the visual system, σ_p^v is assumed smaller than σ_p^a (Magosso et al., 2012).

ii) *The Lateral Input $l(t)$* – This input originates from the lateral connections within each layer. For the auditory neurons, we have

$$l_{ij}^a(t) = \sum_h \sum_k L_{ij,hk}^a \cdot y_{hk}^a(t) \quad (3)$$

where $L_{ij,hk}^a$ is the synaptic strength from the pre-synaptic auditory neuron at index hk to the post-synaptic auditory neuron at index ij , and $y_{hk}^a(t)$ represents the activity of the pre-synaptic neuron. Lateral auditory synapses are arranged according to a 2D Mexican hat, obtained as the difference of excitatory and inhibitory contributions each mimicked as a 2D Gaussian function:

$$L_{ij,hk}^a = L_{ex,ij,hk}^a - L_{in,ij,hk}^a \quad (4)$$

$$L_{ex,ij,hk}^a = L_{ex0}^a \cdot \exp\left(-\frac{(i-h)^2}{(\sigma_{ex,p}^a)^2} - \frac{(j-k)^2}{(\sigma_{ex,f}^a)^2}\right) \quad (5)$$

$$L_{in,ij,hk}^a = L_{in0}^a \cdot \exp\left(-\frac{(i-h)^2}{(\sigma_{in,p}^a)^2} - \frac{(j-k)^2}{(\sigma_{in,f}^a)^2}\right) \quad (6)$$

In order to obtain a Mexican hat, excitation is stronger but narrower than inhibition ($L_{ex0}^a > L_{in0}^a$; $\sigma_{ex,p}^a < \sigma_{in,p}^a$; $\sigma_{ex,f}^a < \sigma_{in,f}^a$).

For visual neurons, similar equations hold but in 1D dimension (equations in (Magosso et al., 2012)); that is lateral visual synapses are arranged according to 1D Mexican hat (figure 1). Autoexcitation and autoinhibition are avoided in each layer.

iii) *The cross-modal input $c(t)$* – This input originates from the inter-layer synapses. We assume that a visual neuron at position i sends an excitatory synapse (W_{av}) to all auditory neurons that code for the same azimuth (i.e. all auditory neurons along the i^{th} column of the matrix) and receives an excitatory synapse (W_{va}) from any of them. Hence, the cross-modal inputs are computed as

$$c_{ij}^a(t) = W_{av} \cdot y_i^v(t) \quad (7)$$

$$c_i^v(t) = \sum_j W_{va} \cdot y_{ij}^a(t) \quad (8)$$

Parameters for the 2D auditory input, 2D lateral auditory synapses and inter-layer synapses have been assigned: i) to maintain a confined activation in the auditory area preventing excessive spreading of excitation; ii) to avoid that a unimodal stimulus induces a phantom activation in the other non-stimulated layer. All other parameters have been taken from the previous paper (Magosso et al., 2012).

2.2 Model Hebbian Rules

According to the previous paper (Magosso et al., 2012), ventriloquism aftereffect may be explained assuming that - during exposure to a ventriloquism situation - lateral synapses within each layer can change according to Hebbian learning rules (adaptation phase).

In the present work, we adopted the same rules as in the previous paper (Magosso et al., 2012).

Specifically, in each layer, lateral excitatory and inhibitory synapses are subject to a potentiation Hebbian rule with a threshold for post-synaptic activity: excitatory synapses increase (up to a maximum saturation level), whereas inhibitory synapses decrease (at most down to zero) in case of correlated pre- and post-synaptic activity, provided that post-synaptic activity overcomes a given threshold (assumed equal to 0.5). The maximum saturation value for each excitatory synapsis has been assumed equal to the maximum strength in basal conditions (L_{ex0}^a for the excitatory auditory synapses). Furthermore, a normalization rule is adopted: the sum of excitatory synapses and the sum of inhibitory synapses entering a given neuron must remain constant. Hence, if some of the entering excitatory synapses increase, others decrease; if some of the entering inhibitory synapses decrease, others increase. All the equations of the Hebbian synaptic rules, having 1D formulation, can be found in our previous paper (Magosso et al., 2012). Equations with 2D formulation, holding for the 2D lateral auditory synapses, can be easily obtained.

Values for the learning rate were assigned so that synapses gradually reach a new steady-state pattern within 1000 updating steps. Simulation of an adaptation phase consisted in exposing the network to a spatially discrepant visual-auditory stimulation, and maintaining the stimuli for 1000 steps during which the lateral synapses are trained.

2.3 Evaluation of Model Performances

In psychophysical literature, ventriloquism effect and aftereffect are assessed by measuring the discrepancy between the perceived sound location and the actual sound location (perceptual shift). Hence, to evaluate model performances in response to a stimulation, we need to compute a quantity representing the perceived stimulus location from the activity $y(t)$ of all neurons within a layer. Here, we used the barycenter metric (Magosso et al., 2012): the perceived location is taken as the average position (barycenter) of the layer population activity. Hence, the perceived location of an auditory stimulus is computed as follows

$$z^a(t) = \frac{\sum_i \sum_j (y_{ij}^a(t) \cdot i)}{\sum_i \sum_j y_{ij}^a(t)} \quad (9)$$

To assess network behaviour before adaptation (basal conditions) and after adaptation, we stimulated the network starting from the resting condition (zero activity of all neurons). Stimuli were maintained throughout the overall simulation until

the network reached a new-steady state condition, at which the perceived stimulus location was computed.

3 RESULTS

We first verified the ability of the modified model to reproduce the ventriloquism effect in basal conditions; then adaptation phases were simulated and ventriloquism aftereffect and its generalization across sound frequencies were investigated.

Figure 2 shows the response of the network to a unimodal (visual or auditory) stimulation. In left panels (a and c), a visual stimulus (with intensity $E_0^v = 15$) is applied at 100° . Activation of visual neurons assumes high values very close to the position of the stimulus application, and declines rapidly to zero as moving away from it. In right panels (b and d), an auditory stimulus (with intensity $E_0^a = 20$) is applied at position 80° and at frequency 1.1 kHz. Activation in the auditory layer assumes lower values and has a wider extension, involving a larger number of neurons (both along the position and frequency dimensions). In both cases, unimodal stimulation does not produce any phantom activity in the other layer, which remains silent.

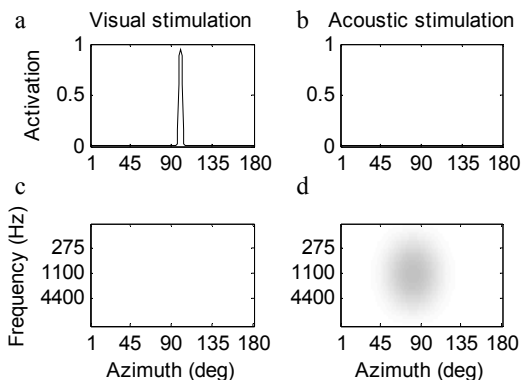


Figure 2: Activation for unimodal stimuli. Upper panels show plots of the visual activations; lower panels show maps of the acoustic activations (white = 0, black = 1).

Figure 3 shows the ventriloquism effect. A visual stimulus at position 100° (intensity $E_0^v = 15$) and an auditory stimulus at 80° and 1.1 kHz (intensity $E_0^a = 20$) are simultaneously presented to the network and the activation of the auditory layer is displayed at different snapshots during the simulation. Since auditory stimulation induces a large activation, involving also neurons at position 100° , a positive feedback occurs between visual and auditory neurons at that position thanks to the inter-layer

synapses (panel a). Hence, auditory neurons around 100° become rapidly very active (panel b); moreover, they reinforce reciprocally via lateral excitation and compete with more distant neurons via lateral inhibition (panel c and d). At steady state (last panel), the auditory activation is biased toward the position of the visual stimulus, resulting in a perceptual shift - perceived location minus actual location - of 4° . On the contrary, the perception of the visual stimulus exhibits a negligible shift (less than 0.1°). These values are within the range of real data (Bertelson and Radeau, 1981).

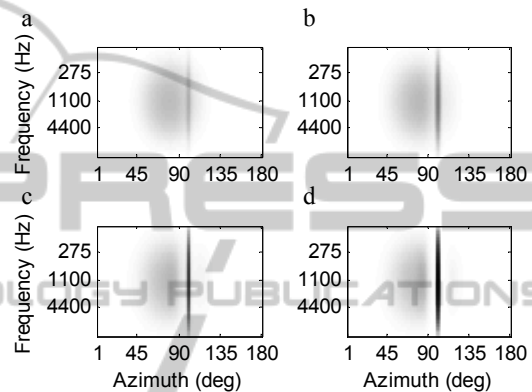


Figure 3: Acoustic activation at different simulation steps (20, 40, 70, 200) during bimodal stimulation (white = 0, black = 1).

Then, adaptation phases were simulated. In the first adaptation phase, the same stimuli as those used in figure 3 were delivered (visual stimulus: $E_0^v = 15$ at 100° ; auditory stimulus: $E_0^a = 20$, at 80° and 1.1 kHz). Hence, 1.1 kHz represents the adaptation frequency and 80° represents the adaptation position.

Results of synapses training are shown in figure 4. The figure displays the synapses - before and after adaptation - entering two auditory neurons that code for position 100° (the position of the visual stimulus) and for the adaptation frequency (1.1 kHz) (panels a and b) and the two-octave higher frequency (4.4 kHz) (panels c and d). Synapses targeting these two neurons exhibit similar changes that can be summarized as follows: i) stronger synapses are received from a wide area of neurons left of 90° spreading across frequencies and positions; ii) strongly reinforced synapses are received from a strip of neurons around 100° , covering almost all frequencies. These modifications are due to the pattern of auditory activation during adaptation (figure 3).

To assess the resulting aftereffect, the network was tested unimodally by applying an auditory stimulus at 80° (adaptation position), with intensity

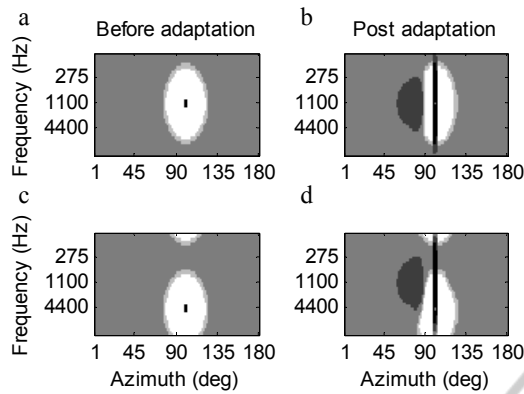


Figure 4: Synapses pre and post adaptation targeting neuron at 100°, 1.1 kHz (upper panels), and neuron at 100°, 4.4 kHz (lower panels). The colormap is discretized to enhance the quality of the panels. Brighter colours denote negative (inhibitory) synapses, darker colours denote positive (excitatory) synapses.

$E_0^a = 20$, at each of the two frequencies 1.1 kHz and 4.4 kHz (figure 5, panel a and b).

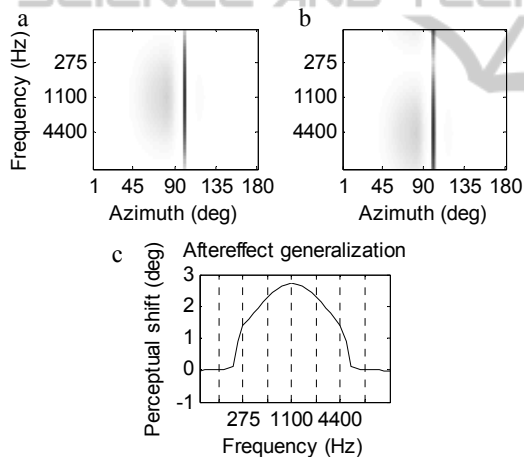


Figure 5: Aftereffect. Upper panels show the auditory activation, after training, in response to unimodal acoustic stimulation at the adaptation frequency and two octaves above. The lower panel shows the perceptual shift at all the frequencies analysed (one octave per grid line).

In both cases, after adaptation, the auditory stimulus induces an elongated area of high activation around position 100° that spans across the frequency dimension (that is, a large number of neurons coding for positions close to 100° are strongly activated), in agreement with synaptic modifications. Such activation results in a perceptual shift (perceived location minus actual location) equal to 2.71° for the testing stimulus applied at 1.1 kHz and 1.38° for the testing stimulus applied at 4.4 kHz. Finally, figure 5 panel c displays the values of the aftereffect

(perceptual shift) obtained by varying the testing stimulus over the whole range of frequencies. We can observe that in this case, the model exhibits a generalization of aftereffect across more than two-octave distance, in agreement with some experimental data (Frissen et al., 2003; Frissen et al., 2005).

As mentioned in the introduction, studies reporting generalization tend to use sounds at higher intensities than those showing no generalization. Therefore we investigated the effects of stimulating the network (both during the adaptation phase and the testing phase) with an auditory stimulus at different intensities, ranging from 17 to 23. Except for the auditory stimulus intensity, stimulus configurations during adaptation were the same as in figure 3. After each adaptation phase, the perceptual shift in sound localization (sound applied in 80°) was tested across the whole spectral range, and was displayed as a function of the test frequency.

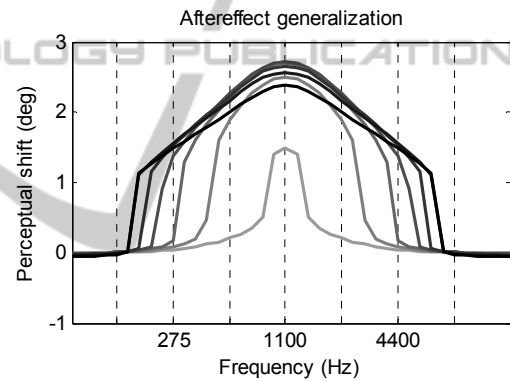


Figure 6: Influence of the acoustic stimulus intensity on the aftereffect generalization across frequencies (one octave per grid line). Different lines represent the shifts obtained for intensities ranging from 17 (brightest line) to 23 (darkest line).

Results for each sound intensity are reported in figure 6. The model predicts that the pattern of aftereffect generalization is largely influenced by the intensity of auditory stimulus. At low sound intensity ($E_0^a = 17$), a mild aftereffect (1.5°) occurs only at the adaptation frequency. As intensity is increased ($E_0^a = 18$), a stronger aftereffect occurs at the adaptation frequency and aftereffect generalizes approximately across one-octave range. Generalization enlarges at intensity E_0^a as high as 19; anyway, at two-octave distance (4.4 kHz) aftereffect is declined to zero. These two latter conditions (intensity $E_0^a = 18$ and 19) reproduce results of the two studies (Recanzone, 1998; Lewald, 2002) reporting no transfer of aftereffect across sounds that

differed by two octaves. As intensity of the auditory stimulus further increases ($E_0^a > 19$), aftereffect transfers to a larger range of frequencies showing a substantial value at two-octave distance – as in the studies by Frissen et al. (Frissen et al., 2003; Frissen et al., 2005) – and even generalizing across almost three octaves (intensity $E_0^a > 21$).

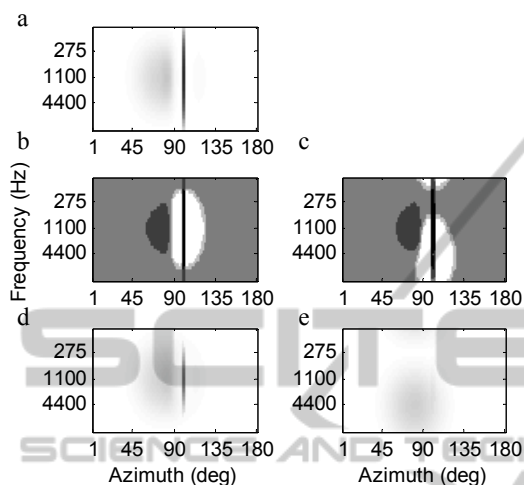


Figure 7: Reduction of aftereffect generalization for a small acoustic intensity ($E_0^a = 17$). Panel a show the response to bimodal stimulation before adaptation. Panels b and c show the synapses toward the neurons at 100° , 1.1 kHz and 100° , 4.4 kHz (two octaves above), after the adaptation (colormaps are discretized as in figure 4). Panels d and e show the activation of acoustic neurons in response to unimodal acoustic stimuli at 1.1 kHz and 4.4 kHz (position 80°), after adaptation. For panels a, d and e white = 0 and black = 1.

To better comprehend these differences, figure 7 displays some results in the exemplary case of stimulus intensity as low as 17. In particular, panel a shows the activation of the auditory area in the ventriloquism situation in basal synapses condition (i.e. before adaptation). The lower stimulus intensity induces a lower activation in the auditory layer, especially around actual sound position (compare with figure 3 panel d). This produces some differences in synapses training (panel b and c). Patterns of trained synapses are similar to those displayed in figure 4; however, the overall excitation from the area of neurons at left of 90° (i.e., around the adaptation position) is smaller, spreading less across sound positions and frequencies. The reduced synaptic reinforcement from neurons far from the adaptation frequency - joined with the low intensity of the testing stimulus - explains why the aftereffect remains confined to the adaptation frequency (figure 7, panel d and e). In particular, a mild aftereffect

(1.5°) occurs only with the testing stimulus at the adaptation frequency (panel d), while aftereffect is completely absent for the testing stimulus at two-octave distance (panel e).

4 CONCLUSIONS

In this work, we present a model of ventriloquism effect and aftereffect which is a modification of a model we previously developed (Magosso et al., 2012). The important extension concerns the inclusion of the spectral properties of auditory neurons, coding not only for the azimuth of the auditory stimulus (as in the previous paper) but also for its frequency. This extension has important implications since it allows the investigation of some important aspects of ventriloquism aftereffect that were neglected by the previous model.

Specifically, we explore generalization of aftereffect across sound frequencies, in order to provide a coherent interpretation of the discrepant results presented in the literature; indeed experimental results vary from aftereffect being limited to the adaptation frequency (Recanzone, 1998; Lewald, 2002) to aftereffect generalizing across two or even more octaves (Frissen et al., 2003; Frissen et al., 2005).

Results obtained by model simulations indicate that the intensity of the auditory stimulus used during the adaptation and testing phase may play a role in producing different extents of aftereffect generalization. In particular, at small sound intensities aftereffect remains confined close to the adaptation frequency, whereas at higher sound intensities it transfers across almost three octaves (figure 6). The model ascribes these differences to different amounts of activation in the auditory layer. In particular: i) Small sound intensities induce weaker and narrower activation in the auditory layer compared to high sound intensities. ii) During adaptation with small sound intensities, auditory neurons at the sound position (80°), far from the adaptation frequency, are not or little active (figure 7, panel a). Therefore, their synapses targeting other auditory neurons at the visual stimulus position (100°) do not reinforce sufficiently (figure 7, panel c). Conversely, during adaptation with high sound intensity, neurons at the sound position (80°), even far from the adaptation frequency, are active (figure 3, panel d) and their synapses targeting neurons at 100° reinforce (figure 4, panel d). iii) When a testing stimulus of low intensity is applied far from the adaptation frequency, it is not able to excite neurons

at 100° and no aftereffect is observed (figure 7, panel e); this is a consequence of the insufficient reinforcement of the synapses and of the low applied stimulation. Vice-versa, a testing stimulus of high intensity far from the adaptation frequency, produces a strong activation of neurons at position 100° (figure 5 panel b), thanks to the reinforced synapses further advantaged by the high applied stimulation.

Of course, pattern of synaptic modifications strongly depend on the adopted Hebbian rules. We adopted post-gating rules with local constraint (individual saturation) and global constraint (normalization). These rules are biologically plausible and were already proven to be suitable to reproduce ventriloquism aftereffect and a number of its properties (Magosso et al., 2012).

The model presented in this work include some fundamental components of self-organizing maps (Kohonen, 1982; Haykin, 1994; Kohonen, 1995). Indeed, it encompasses a competition process (mediated via long-range inhibition) and a cooperation process (mediated via short-range excitation) within each unimodal layer. Furthermore, it includes an unsupervised training phase, during which the network learns without any “teacher” throughout the repeated presentation of stimuli patterns, and extracts the main statistical properties of the external inputs. In this work, competition, cooperation, and adaptation drive the network to organize itself so that it maintains a spatial alignment across the two different sensory representations (visual and auditory): specifically, the auditory space map shifts to align with the displaced visual space map. In other words, the network - via adaptation to visual-auditory disparity - learns to re-assign the auditory input to a different category with respect to the pre-adaptation condition: in this case, the input category is the input spatial position which is signaled by the barycenter of auditory activation. According to the model, category re-assignment may occur even when the auditory input presented to the network after adaptation exhibits “altered” features with respect to the input used during the adaptation phase, specifically, different spectral features. Self-organizing maps are ubiquitous in the cortex especially in perceptual and motor areas (at different levels of visual processing, in the auditory cortex, in the somatosensory cortex, in the primary motor cortex) (Rolls and Treves, 1998), and also at linguistic and semantic levels (Kohonen and Hari, 1999). Several neurocomputational models has investigated how the principles of self-organization may explain the ability of pattern recognition,

category formation and plastic adaptation observed in biological neural systems (Fukushima, 1980; Miyake and Fukushima, 1984; Ritter, 1990; Kohonen and Hari, 1999; Xerri, 2012).

Results obtained by the model have several important correspondences with *in vivo*-data that may support model structure and hypotheses. First of all, studies on humans reporting aftereffect generalization (Frissen et al., 2003; Frissen et al., 2005) used sound intensities (70 dB and 66 dB) higher than those used in studies reporting no generalization (45 dB and 60 dB) (Recanzone, 1998; Lewald, 2002). The values of the aftereffect predicted by the model are in line with those found *in-vivo* when a similar visual-auditory spatial discrepancy (20°) was used in the adaptation phase (Lewald, 2002; Frissen et al., 2005). Finally, when aftereffect generalization was observed *in-vivo*, aftereffect amount showed a decreasing pattern with increasing difference between the testing and adaptation frequency (Frissen et al., 2005), in line with the pattern predicted by the model (figure 6).

Furthermore, the model behavior is in agreement with the properties of neurons in some auditory cortical areas (such as primary auditory area and caudomedial field). These neurons show a frequency tuning function (i.e., the preferential range of sound frequencies at which they respond) that enlarges as the sound intensity increases (Recanzone, 2000; Recanzone et al., 2000), thus exhibiting sharp tuning functions (compatible with no aftereffect generalization) at low sound intensity and broad tuning function (compatible with generalization) at high sound intensity. The model suggests that these auditory cortical areas could be the functional sites at which visual recalibration of auditory localization takes place.

Future developments and variations of the presented model are required to further deepen the comprehension of the neural basis of ventriloquism aftereffect and of its properties. In particular, additional analyses are required in order: i) To better investigate the response properties of model auditory neurons at light of the properties of real neurons. Indeed, as highlighted above, real auditory neurons exhibit spatial and tuning functions that modify with stimulus intensity (Rajan et al., 1990; Recanzone, 2000; Recanzone et al., 2000; Woods et al., 2006). Emergence of similar properties in the simulated neurons and their relationships with network parameters should be investigated. ii) To relate, in a more straightforward manner, stimulus intensities in the model with real sound levels used in psychophysical studies. At present, indeed, a direct

correspondence between model stimulus intensity and real stimulus intensity is lacking. iii) To simulate adaptation at different spatial positions with a fixed visual-auditory disparity. In the present work, the adaptation phase consisted in presenting a visual and an auditory stimulus in fixed spatial positions. In future, the network could be trained by presenting two cross-modal stimuli with assigned spatial difference but variable locations (as in experimental studies). iv) To mimic aftereffect generalization on even wider range of frequencies (i.e., four-octave range as reported by (Frissen et al 2005)). This would require to augment the number of neurons in the auditory layer. v) To explore the involvement of other potential factors (e.g. attentive factors) in producing different aftereffect generalizations. Focusing selective attention to either modality (visual or auditory) during the adaptation phase might impact the overall size of the aftereffects (Frissen et al., 2003). Selective attention in the model could be simulated via facilitatory/inhibitory effects on neuron activation and/or via increase/decrease of synaptic learning rate.

ACKNOWLEDGEMENTS

This work has been supported by the 2007-2013 Emilia-Romagna Regional Operational Programme of the European Regional Development Fund.

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