SUPPLEMENTARY MATERIAL

A1. Extended legend to Figure 1

Figure 1 shows **s**implified block diagrams describing the relationship between the lexical items and their semantic representation, at different proficiency stages during L2 learning. Continuous lines with terminal arrows denote excitatory synapses, while dashed lines with terminal balls denote inhibitory synapses. The line thickness is proportional to the synaptic strength. S represents a semantic store. L1 and L2 are two translation equivalent lexical items, in the native language (L1) and in the second language (L2) . I1 and I2 are inhibitory interneurons which realize a competition network. The upper panels (Fig. 1a) refer to the "basal model" at different proficiency levels. The bottom panels (Fig. 1b) refer to the "Extended Model". The latter also incorporate direct links (either excitatory or inhibitory) between lexical items.

A2. The basal Model description

The feature layer

In the following, each oscillator will be denoted with the subscripts *ij* or *hk*. In the present study we adopted an exemplary network with 4 areas ($F = 4$) and each area is made by N1xN2 ($N1 = N2 = 20$) oscillators (400 neural groups per area).

Each single oscillator consists of a feedback connection between an excitatory unit, x_{ij}, and an inhibitory unit, y_{ij} while the output of the layer is the activity of all excitatory units. This is described with the following system of differential equations:

$$\frac{d}{dt} x_{ij}(t) = -x_{ij}(t) + H\left(x_{ij}(t) - \beta \cdot y_{ij}(t) + E_{ij}(t) + V_{ij}^{L}(t) + I_{ij} - \varphi_x - z(t)\right) \quad (1)$$

$$\frac{d}{dt} y_{ij}(t) = -\gamma \cdot y_{ij}(t) + H\left(\alpha \cdot x_{ij}(t) - \varphi_y\right) + J_{ij}(t) \quad (2)$$

where H() represents a sigmoidal activation function defined as

$$H(\psi) = \frac{1}{1+e^{-\frac{\psi}{T}}} \tag{3}$$

Parameters α and β define the excitatory-inhibitory coupling within the same neural group; in particular, α significantly influences the amplitude of oscillations. Parameter γ is the reciprocal of a time constant and affects the oscillation frequency. The self-excitation of x_{ij} is set to 1, to establish a scale for the synaptic weights. Similarly, the time constant of x_{ij} is set to 1, and represents a scale for time *t*. φ_x and φ_y are offset terms for the sigmoidal functions in the excitatory and inhibitory units. I_{ij} represents the external stimulus for the oscillator in position *ij*, coming from the sensory-motor processing chain which extracts features. E_{ij} and J_{ij} represent coupling terms (respectively excitatory and inhibitory) from all other oscillators in the features network (see Eqs.4-7), while V_{ij}^{L} is the stimulus (excitatory) coming from the Lexical Layer (Eq. 8). *z(t)* represents the activity of a global inhibitor whose role is to ensure separation among the objects simultaneously present. In particular, the inhibitory signal prevents a subsequent object to pop up as long as a previous object is still active (see previous papers for its description, (Cuppini, Magosso, & Ursino, 2009; Ursino, Magosso, & Cuppini, 2009).

The coupling terms between units in Feature Areas, E_{ij} and J_{ij} in Eqs. (1) and (2) are computed as follows

$$E_{ij} = \sum_{h}\sum_{k} W_{ij,hk} \cdot x_{hk} + \sum_{h}\sum_{k} L_{ij,hk}^{EX} \cdot x_{hk} \tag{4}$$

$$J_{ij} = \sum_{h}\sum_{k} W_{ij,hk} \cdot x_{hk} + \sum_{h}\sum_{k} L_{ij,hk}^{IN} \cdot x_{hk} \tag{5}$$

where *ij* denotes the position of the postsynaptic (target) neuron, and *hk* the position of the presynaptic neuron, and the sums extend to all presynaptic units in the Feature Areas. The symbols $W_{ij,hk}$ represent inter-area synapses, subjects to Hebbian learning (see next paragraph), which favour synchronization. The symbols $L_{ij,hk}^{EX}$ and $L_{ij,hk}^{IN}$ represent lateral excitatory and inhibitory synapses among units in the same area. It is worth noting that all terms $L_{ij,hk}^{EX}$ and $L_{ij,hk}^{IN}$ with units *ij* and *hk* belonging to *different* areas are set to zero. Conversely, all terms $W_{ij,hk}$, linking units *ij* and *hk* in the *same* area, are set to zero.

The Mexican hat disposition for the intra-area connections has been realized by means of two Gaussian functions, with excitation stronger but narrower than inhibition. Hence,

$$L_{ij,hk}^{EX} = \begin{cases} L_0^{EX} \cdot e^{-\left[(i-h)^2+(j-k)^2\right]/\left(2\sigma_{ex}^2\right)} & \text{if } ij \text{ and } hk \text{ are in the same area} \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

$$L_{ij,hk}^{IN} = \begin{cases} L_0^{IN} \cdot e^{-\left[(i-h)^2+(j-k)^2\right]/\left(2\sigma_{in}^2\right)} & \text{if } ij \text{ and } hk \text{ are in the same area} \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

where L_0^{EX} and L_0^{IN} are constant parameters, which establish the strength of lateral (excitatory and inhibitory) synapses, and σ_{ex} and σ_{in} determine the extension of these synapses.

Finally, the term V_{ij}^{L} coming from the Lexical Layer is calculated as follows

$$V_{ij}^{L} = \sum_h \sum_k W_{ij,hk}^{L} \cdot x_{hk}^{L} \quad (8)$$

where x_{hk}^{L} represents the activity of the neuron *hk* in the Lexical Layer and the symbols $W_{ij,hk}^{L}$ are the synapses from the Lexical Layer to the feature layer (which are subject to Hebbian learning, see below).

The Lexical Layer

In the following each element of the Lexical Layer will be denoted with the subscripts *ij* or *hk* (*i, h* = 1, 2, …, M_1; *j, k* = *1,2,…,* M_2) and with the superscript *L*. In the present study we adopted $M_1 = M_2 = 40$. Each single element exhibits a sigmoidal relationship (with lower threshold and upper saturation) and a first order dynamics (with a given time constant). This is described via the following differential equation:

$$\tau^L \cdot \frac{d}{dt} x_{ij}^L(t) = -x_{ij}^L(t) + H^L\left(u_{ij}^L(t)\right) \tag{9}$$

τ^L is the time constant, which determines the speed of the answer to the stimulus, and $H^L\left(u^L(t)\right)$ is a sigmoidal function. The latter is described by the following equation:

$$H^L\left(u^L(t)\right) = \frac{1}{1 + e^{-\left(u^L(t) - \vartheta^L\right)p^L}}; \tag{10}$$

where ϑ^L defines the input value at which neuron activity is half the maximum (central point) and p^L sets the slope at the central point. Eq. 10 conventionally sets the maximal neuron activity at 1 (i.e., all neuron activities are normalized to the maximum).

The overall input, $u_{ij}^L(t)$, to a lexical neuron in the *ij*-position can be computed as follows:

$$u_{ij}^L(t) = I_{ij}^L(t) + V_{ij}^F - G^L \cdot \left(1 - z^L(t)\right) - C_{ij}^L; \tag{11}$$

$I_{ij}^L(t)$ is the input produced by an external linguistic stimulation. V_{ij}^F represents the intensity of the input due to synaptic connections from the feature network; this synaptic input is computed as follows:

$$V_{ij}^F = \sum_h \sum_k W_{ij,hk}^F \cdot x_{hk}; \tag{12}$$

where x_{hk} represents the activity of the neuron *hk* in the Feature Areas and $W_{ij,hk}^F$ the strength of synapses from the Feature Areas to the Lexical Layer. These synapses are subject to a Hebbian training during the learning of words in a language. The term $G^L \cdot \left(1 - z^L(t)\right)$ accounts for the inhibitory action by the decision network. In particular, $z^L(t)$ is a binary variable representing the output of the decision network (1 in case of correct detection, 0 in case of incorrect detection – see (Ursino et al., 2009)); hence, the strength of the inhibition shifts from the value G^L to 0 when the decision network shifts from the OFF to the ON state. It is worth noting that the external linguistic input $I_{ij}^{L}(t)$, when present, is set sufficiently high to overcome the inhibition received from the decision network. The term C_{ij}^{L} represents the inhibition that the neuron at position *ij* in the Lexical Layer receives from units in the "Competition Area". This competition is triggered only in case of multiple words representing the same object (as in bilingualism) and is computed as follows:

$$C_{ij}^{L} = \sum_{h} \sum_{k} W_{ij,hk}^{I} \cdot x_{hk}^{I} \; ; \qquad (13)$$

where x_{hk}^{I} is the output of the inhibitory interneuron at position *hk* in the Competition Area, and $W_{ij,hk}^{I}$ are the inhibitory synapses from a presynaptic inhibitory interneuron at position *hk* to the post-synaptic neuron at position *ij* in the Lexical Layer. These synapses are trained during the learning of a second language. All synapses $W_{ij,hk}^{I}$ with *ij* = *hk* are set to 0.

The Competition Area

This area is composed of M1xM2 units (that is, the same number as in the Lexical Layer); they receive synapses from the element in the Lexical Layer located at the same position (the "master") and may send inhibition to all other lexical units. Moreover, they also receive an external input (say I_{ij}^{BIAS} in Eq. (15)) coming from high-level top-down influences, which try to inhibit a non target word. This input is normally set to zero, but may assume a high value in problems like language selection or language switching (see Discussion).

Outputs are computed with equations similar to (9) and (10), with an analogous meaning of symbols, i.e.

$$\tau^{I} \cdot \frac{d}{dt} x_{ij}^{I}(t) = -x_{ij}^{I}(t) + H^{I}\left(u_{ij}^{I}(t)\right); \qquad (14)$$

with

$$u_{ij}^{I}(t)=x_{ij}^{L}(t)+I_{ij}^{BIAS}$$
$$H^{I}\left(u_{ij}^{I}(t)\right)=\frac{1}{1+e^{-\left(u_{ij}^{I}(t)-\vartheta^{I}\right)p^{I}}} \tag{15}$$

The connections from the lexical units to the units in the Competition Area are not subject to a Hebbian learning; conversely they are supposed to be assigned a priori.

A3. Synapse training in the basal model

Training has been subdivided in three different phases: i) learning of objects; ii) learning of words in a first language (L1 words); iii) learning of words in a second language (L2 words). The first phase is common to both models; it was described in details in previous papers (Cuppini et al., 2009) hence only a brief description is given here. The second and third training phases are described in greater details since they represent points of novelty of the present study, moreover they involve different sets of synapses in the two versions of the model. The three phases of learning are described first in the basal model, and then in the Extended Model by stressing the differences between the two versions.

Phase 1: Learning of objects

Learning of objects involves training of the synapses $W_{ij,hk}$ linking units belonging to different Feature Areas.

Recent experimental data suggest that synaptic potentiation occurs if the pre-synaptic inputs precede post-synaptic activity by 10 ms or less. (Markram, Lubke, Frotscher, & Sakmann, 1997). Hence, in our learning phase we assumed that the Hebbian rule depends on the present value of post-synaptic activity, $x_{ij}(t)$, and on the moving average of the pre-synaptic activity (say $m_{hk}(t)$) computed during the previous 10 ms. We define a moving average signal, reflecting the average activity during the previous 10 ms, as follows

$$m_{hk}(t) = \frac{\sum_{m=0}^{N_s-1} x_{hk}(t - mT_S)}{N_s} \quad (15)$$

where T_S is the sampling time (in milliseconds), and N_S is the number of samples contained within 10 ms (i.e., $Ns = 10/T_S$). The synapses linking two units (say ij and hk) are then modified as follows during the learning phase

$$\Delta W_{ij,hk}(t+T_S) = W_{ij,hk}(t) + \beta_{ij,hk} \cdot x_{ij}(t) \cdot m_{hk}(t) \quad (16)$$

where $\beta_{ij,hk}$ represents a learning factor.

In order to assign a value for the learning factor, $\beta_{ij,hk}$, in our model we assumed that inter-area synapses cannot overcome a maximum saturation value. This is realized assuming that the learning factor is progressively reduced to zero when the synapse approaches its maximum saturation. Furthermore, units belonging to the same area cannot be linked by a long-range synapse. We have

$$\beta_{ij,hk} = \begin{cases} \beta_0 \left(W_{\max} - W_{ij,hk} \right) & \text{if } ij \text{ and } hk \text{ belong to different areas} \\ 0 & \text{otherwise} \end{cases} \quad (17)$$

where W_{max} is the maximum value allowed for any synapse, and $\beta_0 W_{\max}$ is the maximum learning factor (i.e., the learning factor when the synapse is zero).

Eq. (17) implies that each inter-area synapse approximately increases according to a sigmoidal relationship, with upper saturation $W_{\max}$. The slope of this sigmoidal relationship (hence the increasing rate) is determined by parameter β_0.

Phase 2: Learning of first language L1

We trained synapses from the Feature Areas to Lexical Layer, $W_{ij,hk}^{F}$, and connections from lexical units to the features layer, $W_{ij,hk}^{L}$, simultaneously. These long-range synapses are initially set at zero, and then are increased with a Hebbian rule, using the correlation between the pre-synaptic and the post-synaptic activity, $x_{ij}(t)$ or $x_{ij}^{L}(t)$. The synapses linking two units (say *ij* and *hk*) are then modified as follows

$$W_{ij,kh}^{F}(t+T_S)=W_{ij,hk}^{F}(t)+\beta_{ij,hk}^{F}\cdot x_{ij}^{L}(t)\cdot x_{hk}(t) \tag{18}$$

$$W_{ij,kh}^{L}(t+T_S)=W_{ij,hk}^{L}(t)+\beta_{ij,hk}^{L}\cdot x_{ij}(t)\cdot x_{hk}^{L}(t) \tag{19}$$

where $\beta_{ij,hk}^{F}$ and $\beta_{ij,hk}^{L}$ represent learning factors.

Moreover, we assumed that inter-area synapses cannot overcome a maximum saturation value. This is realized assuming that learning factors are progressively reduced to zero when synapses approach saturation. We have

$$\beta_{ij,hk}^{F}=\beta_{0}^{F}\cdot\left(W_{\max}^{F}-W_{ij,hk}^{F}\right) \tag{20}$$

$$\beta_{ij,hk}^{L}=\beta_{0}^{L}\cdot\left(W_{\max}^{L}-W_{ij,hk}^{L}\right) \tag{21}$$

where $W_{\max}^{F}$ and $W_{\max}^{L}$ are maximum values allowed for any synapse, and $\beta_{0}^{F}W_{\max}^{F}$ and $\beta_{0}^{L}W_{\max}^{L}$ are maximum learning factors (i.e., learning factors when synapses are zero).

In this case too, each synapse increases according to a sigmoidal relationship, with the slope determined by β_0 and with upper saturation $W_{\max}$.

Phase 3: Learning of the second language L2

During learning of the second language, the L1 and the L2 words are simultaneously active, and both send an excitatory input - via already existing synapses - to their corresponding inter-neurons in the Competition Area, making them active. Thus, the inhibitory synapses from the interneurons in the Competition Area to the lexical units are reinforced by a Hebbian mechanism, depending on the present value of the pre-synaptic and the post-synaptic activity (respectively $x_{hk}^{I}(t)$ and $x_{ij}^{L}(t)$). The equation for synapse learning is

$$W_{ij,hk}^{I}(t+T_S)=W_{ij,hk}^{I}(t)+\beta_{ij,hk}^{I}\cdot x_{ij}^{L}(t)\cdot x_{hk}^{I}(t); \qquad \text{with ij} \neq \text{hk} \tag{22}$$

where β^I represent the learning rates. In this case too, we assumed that synapses cannot overcome a maximum saturation value. Hence,

$$\beta^I_{ij,hk} = \beta^I_0 \cdot \left(W^I_{\max} - W^I_{ij,hk}\right) \tag{23}$$

$W^I_{\max}$ is the maximum value allowed for any synapse and $\beta^I_0 W^I_{\max}$ is the maximum learning rate.

Furthermore, during this phase the synapses linking the Feature Areas and the L2 word (i.e., $W^F_{ij,hk}$ and $W^L_{ij,hk}$) are reinforced with the same Hebbian mechanism described by Eqs. 18-21.

At the end of the L2-training, an element in the Lexical Layer receives an inhibitory input mediated by the Competition Area only from the other word referring to the same object representation, and exhibits a bi-directional link with its semantics in the Feature Areas.

A4. The Extended Model - Differences with respect to the Basal Model

Differences in the Lexical Layer

The Extended Model differs from the basal model due to the presence of direct connections among units of the Lexical Layer. All other aspects and equations described in the "Supplementary Materials" with reference to the basal model hold for the Extended Model too.

In the Extended Model, the overall input, $u^L_{ij}(t)$, to a generic *ij* neuron in the Lexical Layer includes an additional term S^L_{ij} which accounts for the influences from other lexical units:

$$u^L_{ij}(t) = I^L_{ij}(t) + S^L_{ij}(t) + V^F_{ij} - G^L \cdot \left(1 - z^L(t)\right) - C^L_{ij} \tag{24}$$

where:

$$S^L_{ij} = \sum_h \sum_k L^L_{ij,hk} \cdot x^L_{hk} \tag{25}$$

$L^{L}_{ij,hk}$ is the strength of the synaptic connection linking the *hk* presynaptic neuron in the Lexical Layer with the postsynaptic *ij* neuron in the Lexical Layer. Such synapses may be inhibitory or excitatory and are trained during the learning of language L1 and L2 (see section below).

Differences in training the Lexical Layer

Connections within the Lexical Layer are initially set at zero; then during the learning of languages L1 and L2, which involves activation of units in the Lexical Layer, they are subjected to a Hebbian mechanism. In particular, we assumed that the weight of the connection between two lexical units changes whenever the pre-synaptic neuron is active (pre-synaptic gating); the sign of the change (positive or negative) depends on the activity (above or below a given threshold) of the post-synaptic neuron.

This learning rule is realized as follows:

$$L^{L}_{ij,kh}(t+T_S) = L^{L}_{ij,hk}(t) + \beta^{SL}_{ij,hk} \cdot x^{L}_{hk}(t) \cdot \frac{sign\left(x^{L}_{hk}(t)-\theta^{L}\right)+1}{2} \cdot x^{L}_{ij}(t) \cdot sign\left(x^{L}_{ij}(t)-\theta^{L}\right) \qquad (24)$$

where *hk* and *ij* denote the position of the pre-synaptic and post-synaptic neuron in the Lexical Layer. $\beta^{SL}_{ij,hk}$ is the learning factor. The term $\frac{sign\left(x^{L}_{hk}(t)-\theta^{L}\right)+1}{2}$ is used to verify that the presynaptic element is active (i.e., its activity is greater than a threshold θ^{L}, whose value is set just above the baseline activity of the units in this area), and in this case the synapse can change its strength. If the post-synaptic neuron is active $\left(x^{L}_{ij}(t) > \theta^{L}\right)$, the term $sign\left(x^{L}_{ij}(t)-\theta^{L}\right)$ is positive and the connection weight increases; if the postsynaptic element is silent $\left(x^{L}_{ij}(t) < \theta^{L}\right)$, the term $sign\left(x^{L}_{ij}(t)-\theta^{L}\right)$ becomes negative and the strength of the synapse decreases. Accordingly, the synapse linking two units in the Lexical Layer may be both excitatory or inhibitory.

Moreover, we assumed that the intra-layer synapses are limited within given bounds ($\left[-L^{L}_{\max}, +L^{L}_{\max}\right]$). This is obtained by using the following equation for the learning rate:

$$\beta_{ij,hk}^{SL} = \beta_0^{SL} \cdot \left(L_{\max}^{L} - \left| L_{ij,hk}^{L} \right| \right) \tag{25}$$

where $L_{\max}^{L}$ is the absolute value of the upper and lower limits, and $\left| L_{ij,hk}^{L} \right|$ denotes the absolute value of the current synaptic strength.

According to the previous description, in the Extended Model, the following direct synapses originate within the Lexical Layer during the training phases:

1) Learning of language L1 – During this phase only one element (corresponding to the L1 word) is active in the Lexical Layer. Hence inhibitory synapses sprout from the activated L1 word to all other silent units in the same area.
2) Learning of language L2 – During this phase the L2 word is given as input to the network together with its translation in the L1 language. Accordingly an excitatory synapse originates from L2 word targeting the simultaneously active L1 word, whereas the inhibitory synapse from L1 to L2 word (previously created) becomes weaker (it rises towards zero) and may even become positive. Of course in this phase, inhibitory synapses are formed from L2 word to all other silent units in the Lexical Layer.

A list of parameters used in the present work is provided in Table 1.

A5. Simulation of a patient with lesions (Extended Model)

We simulated naming tasks in the case of a high-proficiency bilingual (i.e., we used parameters values at the end of the training period), assuming the presence of a lesion either in the competitive mechanism, or in the semantic network. The effect of a lesion was simulated by reducing the strength of the synapses leaving some units. This hypothesis is plausible, since a single unit in the model represents a group of neurons coding for the same information, hence a reduction in the number of neurons is reflected in a reduction in the strength of the outward synaptic activity.

Some examples concerning an L1 naming task are shown in Fig. A1. In these simulations, the semantic representation of an object was given to the network together with a strong top-down input to favor the response of the L1 word. With normal synapses the L1 word clearly wins the competition. The simulation was then repeated by reducing the strength of synapses from the semantic network to the L1 word (10% and 20% synaptic reduction, left-hand panels) or reducing the strength of the competition from L1 to L2 (30% and 40% reduction, right-hand panels).

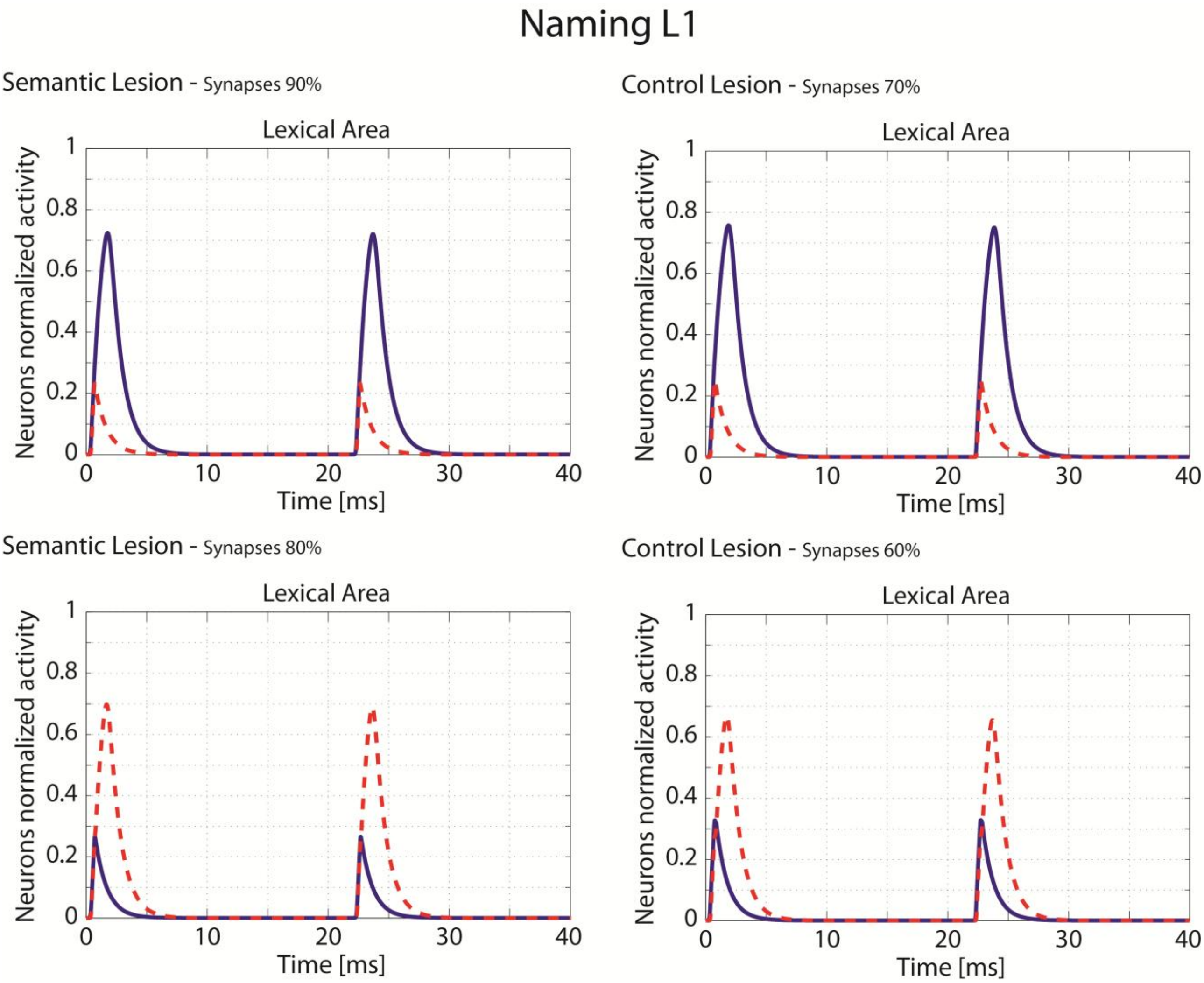

Figure A1 – Examples of the "Extended Model" behavior, with different simulated neural lesions. The figure shows the responses to a word production task (features are given as input) performed in the L1 language (i.e., the L2 word receives an external inhibition), obtained in case of a perfect bilingual condition (the network presented high proficiency both in L1 and in L2). Panels report the activities of L1 (solid line) and L2 (dashed line) words evoked in the Lexical Area. The simulated lesions were mimicked by weakening either the synapses from the Semantic Network ("Semantic Lesion") entering the L1 word, or the inhibitory connections from the Control Area ("Control Lesion") to the L2 word. In the left column, L1 and L2 activities are shown assuming that the semantic synaptic strengths are reduced to the 90% of the intact efficacy (upper left panel) or to 80% of the intact efficacy (bottom left panel). In the first condition the model is still able to correctly perform the L1 Naming task: the most activated word is in the L1 language. Conversely, in the second condition the L1 Naming task is no longer properly carried out: the higher activity in the Lexical Area corresponds to the L2 word. The right column reports the case of lesions to the connections coming from the "Competition Area", reduced to 70% of the intact value (upper panel) and to the 60% (lower panel). In the first case, the network still correctly performs the L1 Naming task; in the second case, the L1 Naming task fails: the L2 word emerges as the dominant element in the Lexical Area.

Results show that when the reduction is below a given threshold, L1 still wins the competition. Conversely, if the synapse is damaged above a given threshold, the L2 word is evoked instead of the L1 word, resulting in the interference of L2 on L1.

A similar behavior (but with the opposite interference of L1 on L2) would occur if the synapses targeting into L2 were damaged. Of course, in a real patient, neurons and their emerging synapses may be damaged in a random fashion (some in L1, some in L2), thus resulting in a more complex interference of the two languages. These simulations underline the future potentiality of the model for the study of clinical problems.

It is worth noting that the present model is more sensitive to a damage from the semantic to the lexical layer (-20%) than to a reduction of the competition strength (-40%). This result depends on a variety of factors, such as on the values reached by the competition strength at the end of the training phase (see Fig. 4), on the top-down input used to select a language, and on the number of features used to represent the object (just four in the present model). Hence it cannot be easily generalized to different situations. More complex behaviors may be analyzed in future works, training the network with several L1 and L2 words and using more complex paradigms for synapse damage (for instance, random lesions) and more sophisticate and realistic object representations.

Table 1. Parameters Values.

Feature Areas

α	0.3
β	2.5
γ	0.5
T	0.025
φ_x	0.7
φ_y	0.15

Lexical Layer

ϑ^L	10
p^L	0.5
τ^L	1
G^L	20

Competition Area

ϑ^I	0.3
p^I	20
τ^I	0.1

Lateral intra-area synapses in Feature Areas

L_0^{EX}	9	σ_{ex}	0.8
L_0^{IN}	3	σ_{in}	*3.5*

Object attributes

Obj1	[5,5; 5,35; 35,35; 35,5]

Lexical Units

Wr1_L1	[5,5]
Wr1_L2	[30,20]

Hebbian rule synapses Feature Areas - Lexical Layer

T_S	10 ms
β_0^L	0.01
W_{max}^L	2.5
β_0^F	0.01
W_{max}^F	2.5

Hebbian rule inter-area synapses in Feature Areas

T_S	10 ms
β_0	0.033
W_{max}	1

Hebbian rule intra-area synapses Lexical Layer

T_S	10 ms
β_0^{SL}	0.01
L_{max}^L	35
θ^L	0.1

Hebbian rule synapses Lexical Layer - Competition Area

T_S	10 ms
β_0^I	0.001
W_{max}^I	70

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