INTERACTIONS BETWEEN HEMISPHERES WHEN DISAMBIGUATING AMBIGUOUS HOMOGRAPH WORDS DURING SILENT READING

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Abstract: A model of certain aspects of the cortex related to reading is developed corresponding to ongoing exploration of psychophysical and computational experiments on how the two hemispheres work in humans. The connectivity arrangements between modelled areas of orthography, phonology and semantics are according to the theories of Eviatar and Peleg, in particular with distinctions between the connectivity in the right and left hemisphere. The two hemispheres are connected and interact both in training and testing in a reasonably "natural" way. We found that the RH (right hemisphere) serves to maintain alternative meanings under this arrangement longer than the LH for homophones. This corresponds to the usual theories (about homographs) while, surprisingly, the LH maintains alternative meanings longer then the RH for heterophones. This allows the two hemispheres, working together to resolve ambiguities regardless of when the disambiguating information arrives. Human experiments carried out subsequent to these results bear this surprising result out.

1 INTRODUCTION[1]

Neuropsychological studies have shown that both cerebral hemispheres process written words, but they do it in somewhat different ways (e.g., Iacoboni & Zaidel, 1996, Grindrod & Baum, 2003).

Previous simulation work has examined the activation of meanings of ambiguous words with polarized meanings (where one meaning is much more frequent (dominant) in the language) and has shown that transfer of information from a 'right hemisphere' (RH) network to a 'left hemisphere' (LH) network, when context biasing to the nondominant meaning is presented after the initial presentation of the word, is the most efficient mechanism for "recovery" from erroneous activation of the dominant meaning. That is, there are systematic cases where the LH purported architecture could not recover by itself; nor could the RH perform at high levels of performance (Peleg et al., 2007, 2010). Other simulation work (Weems & Regggia, 2004) suggests that different connections can produce different results.

This paper examines different possible connections between networks representing the two hemispheres and how these differences affect the results of processing homophones. (Monaghan & Pollmann, 2003) shows that when stimuli have to be matched in a complex task (such as whether two letters have the same name), performance is better when stimuli are presented across the hemispheres of the brain. Furthermore, they argue that for simpler tasks (such as whether two letters have the same shape), better performance is achieved when stimuli are presented unilaterally. They show that this bilateral distribution advantage effect emerged spontaneously in a neural network model learning to solve simple and complex tasks with separate input layers and separate, but interconnected, resources in a hidden layer. They also show that relating computational models to behavioral and imaging data helps to understand hemispheric processing and generating testable hypotheses.

This paper presents the computational advantage of having two networks that can exchange information: LH fully connected (Orthography,

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Phonology and Semantics) and RH lack of connection between Orthography and Phonology.

2 BACKGROUND

Behavioral studies have shown that the LH is more influenced by the phonological aspect of written words whereas lexical processing in the RH is more sensitive to visual form. A large amount of psycholinguistic literature indicates that readers utilize both frequency and context to resolve lexical ambiguity (e.g., Titone, 1998 , Peleg et al., 2004). Although hemispheric specialization for LH in language processing is assumed, it is also assumed that the RH plays a significant role in language function, especially when ambiguous words are presented in context (e.g. Burgess & Simpson, 1988).

Behavioral studies examining the disambiguation of homophones (e.g., “bank”) suggest that all meanings of an ambiguous word are initially activated in both hemispheres, but at different speeds. While the LH quickly activates both meanings and then selects one alternative (the contextually compatible meaning when prior contextual information is biased, or the salient, more frequent meaning when embedded in non-constraining contexts), the RH activates the nondominant meaning more slowly, and maintains both alternate meanings (including less salient, subordinate and contextually inappropriate meanings).

Previous studies also suggests that exchange of information between the LH and the RH networks will produce better performance and can help the LH recover the subordinate meaning, when it is appropriate to the context (This task the LH could not perform in isolation.)

2.1 Research Goals

The main goal is to investigate how different types of information (phonological, lexical and contextual) are utilized during silent reading in the two connected networks simulating the left and right hemispheres. Specifically the results are crucial for answers regarding inter-hemispheric relation during the disambiguation process of homophones.

We achieved this goal by building a neural network that can process word information (phonological, lexical and contextual) and resolve the meaning of ambiguous words in Hebrew. The network is based on (Peleg et al., 2007 & 2010) LH and RH networks architecture while adding connections between regions (Orthography, Phonology and Semantics) in various ways.

The connected networks after training, demonstrate the effects of context and frequency on the resolution of homophones. The computer model consists of "weakly coupled" neural networks that can deal with ambiguity of a written or a spoken word in Hebrew. The main idea is to investigate some questions regarding the "weakly coupled" connection properties such as when, how and where information is transferred and determines the degree of transferred information while shedding light on the division of labor between hemispheres. The "weakly coupled" networks should support the same properties when disconnected and additional or improved properties when connected.

Furthermore, we measure the time it take for the connected networks to resolve the meaning and the paths the networks use to do so. Then we compare the results to existing psycholinguistics theories of how humans process the language. One of the reasons to build computational models is the ability to change parameters, aspects and connection properties of the models in ways that are not possible with human subjects. This provides us with an insight into the mechanisms of reading and understanding the meaning of words.

3 PREVIOUS WORK

3.1 Kawamoto’s network

Kawamoto (Kawamoto, 1993) designed his neural network model in such a way that the entire word, including its orthographic, phonological and semantic features occurs as an “attractor” in the recurrent network.

According to his model, the more frequent a certain meaning of the word in a certain context is, the stronger the attractor it will be, and the completion of other features (semantic and phonological) would usually fall into this attractor.

Another factor examined was the time lapse between accessing the dominant meaning and the time lapse of accessing the secondary (subordinate) meaning (Kawamoto, 1993).

3.2 Hazan’s Network

Peleg, Eviatar, Hazan & Manevitz in (Peleg et al., 2007 and (Peleg et al., 2010) designed a two-hemisphere model based on Kawamoto’s model (see

Figure 1). The model includes two separate networks. One network incorporates Kawamoto's version, and successfully simulates the time course of lexical disambiguation in the LH. In the other network based on the behavior of the disconnected RH of split brain patients (Zaidel & Peters, 1981), a change was made in Kawamoto's architecture, removing the direct connections between orthographic and phonological units. (Peleg et al, 2010)

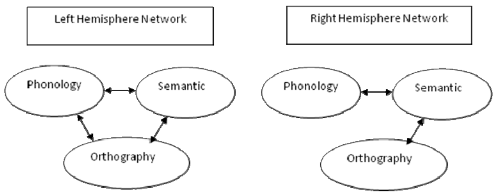

Figure 1: Hazan's network architecture.

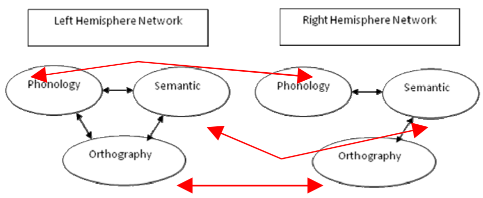

Figure 2: Illustration of network that include CC connections between Corresponding regions of LH & RH.

3.3 Weems & Reggia Network

Weems & Reggia tested hemispheric specialization and independence for word recognition while comparing three computational models: Callosal Relay (strong right to left, minimal left to right connectivity, output from LH), Direct Access (minimal connectivity between hemispheres, separate outputs) and Cooperative (strong connection, single output) and showed advantage for the Cooperative model together with a slight performance dropdown (Weems & Reggia, 2004).

4 COMPUTATIONAL SIMULATION

The simulation is based on (Peleg et al., 2007) LH and RH network which includes the implementation as described by (Kawamoto, 1993) with some changes in the encoding. The simulation includes the "Corpus Callosum" (CC) that was implemented as a connection from LH units to RH units in a various ways including "One to One [2]", "One to Many [3]", within regions and between regions [4] (See Figure 2).

3.4 The Learning Stage

The network was trained with a simple error correction algorithm (Kawamoto, 1993) taking into consideration a learning constant and the magnitude of the error determining a bipolar activity of a single unit. This activity is determined by the input from the environment, the units connected to it (within the hemisphere and from the CC) and a decay in its current level of activity. The learning process was achieved by altering the weights between the units of the network to minimize the error between the activation level and the network input.

$$\Delta W_{ij} = \eta(t_i - i_i) * t_j \text{ , where } i_i = \sum_j W_{ij} t_j$$

n – Learning constant.

t_i , t_j – target activation levels of unit i and j.

i_i – net value of unit i.

In a learning trial an entry was selected randomly from the lexicon. Dominant and subordinate meanings were selected with a ratio of 5 to 3 roughly based on linguistic considerations. The learning phase was divided to the following steps:

A. Initialization of units with random values.
B. Random order of sets of words.
C. The network was trained with 48 words.
D. The network was tested if more training is needed. If so another 48 words were chosen to continue the training. The testing had to fulfill these conditions:

- Presenting the orthographic part of word leads the network to select the dominant meaning.
- Presenting the orthographic part of word with a clue to the subordinate meaning leads the network to select the subordinate meaning.

The learning was stopped when the conditions were fulfilled for each group of words (homophones, hetrophones and normal words) separately or when the training set ended.

In a learning trial an entry was selected randomly from the lexicon. Dominant and subordinate meanings were selected with a ratio of 5 to 3 roughly based on linguistic considerations. We performed different experiments that include different learning stages. First, the learning stage

[2] One to One: each neuron from LH/RH is connected to the corresponding neuron in the other hemisphere.

[3] One to Many: each neuron from LH/RH is connected to a group of neurons in the corresponding area of the other hemisphere.

[4] Regions: Orthography, Phonology and Semantics.

was done while the LH and RH are disconnected. We connected them only while testing the model. Second, the learning stage was done when the LH and RH are connected via the CC. This was performed in two manners: free learning (no restriction on the CC weights) and restricted learning. In the restricted learning the weights on the CC did change but were limited to 0.1 - 0.3.

3.5 Testing the Model

After the networks were trained they were tested by presenting just the orthographic part of the entry as the input (to simulate neutral context) or by presenting part of the semantic (subordinate meaning) sub-vector after presenting the orthography (to simulate contextual bias). In each simulation the input sets the initial activation of the units.

Each unit was influenced from the following sources:

A. External stimuli (orthophonic part of word or clues).
B. Previous values from the last iteration multipled by the decay rate.
C. Sum of the inner connected units output multipled by the weights.
D. Sum of the inter-hemispheric connected units output (Simulates the CC).

The activity of unit a at time t+1 is:

$$a(t+1) = LIMIT\left[\delta a(t) + \left[\sum_j w_{ij}(t)\, a_j(t)\right] + s_i(t)\right]$$

where:

$$LIMIT = \begin{cases} 1 & x > 1 \\ -1 & x < -1 \\ x & otherwise \end{cases}$$

δ – the decay variable.

The decay variable was set dynamically starting from 0.6 , increasing while network is progressed and ending at value of 1 when the run is completed.

In order to assess lexical access, the number of iterations through the network requiered for all the units in the spelling, pronunciation or meaning fields to become saturated, was measured. A response was considered an error if the pattern of activity did not correspond with the input; non convergent if all the units did not saturate after 50 iterations.

Testing was done after training the connected LH and RH or after setting fixed weights on the CC. In the latter case in different experiments the weights were fixed uniformly at values that varied between 0.05 to 0.50 or one value was chosen for the weights from LH to RH and a different one for RH to LH.

In order to test the maintenance of alternative meanings, tests were run where no semantic clues were given for various numbers of iterations (and thus the networks started to converge towards the dominant choice), and then clues for the subordinate meaning were given. The differences in recovery of the RH and LH in the different cases were measured.

3.6 Results and Analysis

In each simulation, 12 identical networks were used to simulate 12 subjects in an experiment by varying their training randomly. During the testing phase the network received various inputs. First the orthography of a word and then the inputs including clues from the word meaning. The level was set to +0.25 if the corresponding input feature was positive, -0.25 if it was negative and 0 otherwise.

Result of each trial was recorded including the number of iterations needed for coverage and the total number of errors. The data was separated for:

- Group of words (homophones , hetrophones and normal words).
- Type of clues (to subordinate or to dominate).
- Number of clues.
- CC weights or weight limitation.
- Mean and standard deviations were calculated.

In this work the focus was on the different type of connections in the different ambiguity task (hetrophonic vs. homophonic).

3.7 Results

Previous results of (Peleg et al., 2007 & 2010) indicated that without transfer of data between LH and RH the LH cannot recover to the subordinate meaning after receiving semantic clues and thus selects the dominant meaning. The RH was able to perform this recovery and select the subordinate meaning (See Figure 3). This phenomenon was called the "Change of heart".

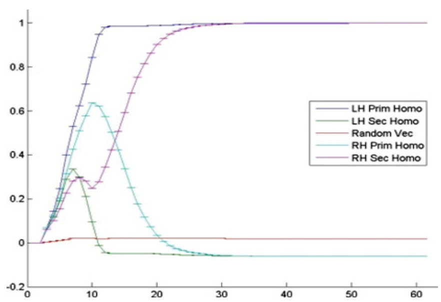

Figure 3: Network performance without CC. Only RH can perform the "Change of heart" for homophones.

Our initial results indicated that when setting the weights of CC from RH to LH to 0.25 in a "One to One" connection the transfer of data from RH to LH can help the LH perform the "Change of heart" and select the subordinate meaning (See Figure 4).

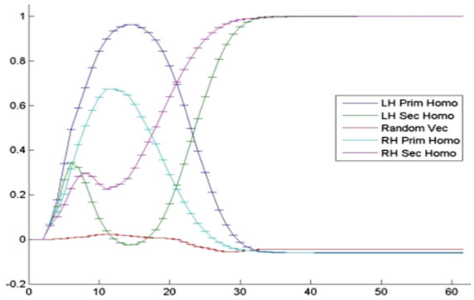

Figure 4: Network performance with CC. RH & LH can perform the "Change of heart" for homophones.

3.7.1 Homophones

Table 1 shows the results of average convergence time[5] for LH and RH when presenting a homophonic word without clues, the recovery status (in general) when presenting a word with clues[6] to the subordinate meaning and the sum of errors and non-convergences.

Table 1: RH & LH convergence time (in iterations) Homophones with no context (* Errors and Non-conv are out of 96 in each hemisphere).

Network architecture	LH	RH	Errors* LH/RH		Non-conv* LH/RH	
Without CC	40.32 (3.42)	41.54 (4.19)	29	0	37	0
With CC: Weights fixed at 0.25 (RH to LH)	39.18 (3.24)	41.06 (2.93)	11	0	14	0
With CC: Weights fixed at 0.25 (LH phonology to RH phonology, RH semantics to LH semantics).	39.77 (4.21)	40.69 (4.48)	23	12	19	7
With CC: Weights fixed at 0.25 RH to LH and 0.10 LH to RH.	39.84 (5.33)	40.14 (4.77)	21	9	17	11
With CC: Weights fixed at 0.25 (All, Both ways)	40.36 (6.03)	40.79 (5.64)	31	24	33	19

Connected learning yield the following results:

A. Free learning of CC weights caused the LH and RH to lose their special properties. LH became slower while selecting the dominant meaning and the RH lost its ability to perform the "Change of heart" when presented with clues to the subordinate meaning (See Figure 5).

B. Restricted learning was able us to cause the LH and RH to not lose their special properties. Both RH and LH performed the "Change of heart" but LH recovery is partial (See Figure 6).

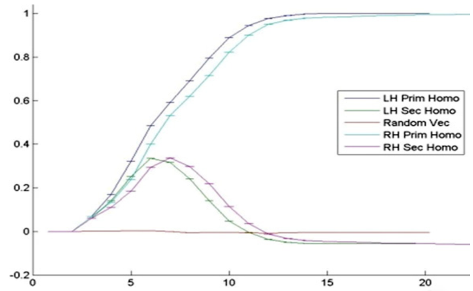

Figure 5: Network performance with CC (Free learning). RH & LH cannot perform the "Change of heart" for homophones.

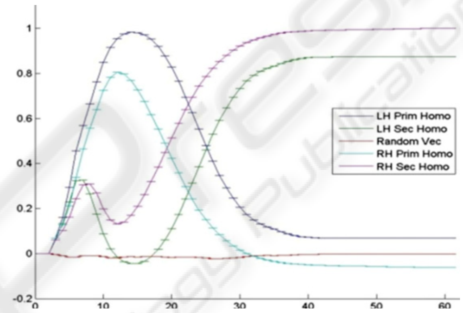

Figure 6: Network performance with CC (CC weights are fixed at 0.25). RH & LH can perform the "Change of heart". Note LH recovery is partial.

Table 2: Network performance in resolving hetrophone (various architectures) [*Errors and Non-conv are out of 96 in each hemisphere]. Case 2 in this table above seems to be the optimum for resolving hetrophone ambiguity.

Network architecture	LH	RH	Errors* LH/RH		Non-conv* LH/RH	
Without CC	30.39 (4.88)	28.07 (5.14)	0	11	0	5
With CC: Weights fixed at 0.25 (LH to RH)	30.14 (5.11)	27.51 (5.37)	0	7	0	3
With CC: Weights fixed at 0.25 (RH phonology to LH phonology, LH semantics to RH semantics).	29.77 (6.52)	29.23 (5.93)	7	13	5	9
With CC: Weights fixed at 0.25 LH to RH and 0.10 RH to LH.	29.63 (7.13)	28.36 (7.20)	9	16	4	2
With CC: Weights fixed at 0.25 (All, Both ways)	29.32 (9.31)	29.95 (8.67)	19	18	12	15

3.7.2 Hetrophones

Table 2 shows the results of average convergence time[7] for LH and RH when presenting a hetrophonic word without clues, the recovery status (in general) when presenting the word with clues[8] to the

[5] Standard deviation in parentheses.

[6] Using different number of clues changed the results but in a uniform way when comparing the results of different architectures. The result presented is for 4 clues out of 8.

[7] Standard deviation in parentheses.

[8] Using different number of clues changed the results but in a uniform way when comparing the results of different architectures. The result presented is for 4 clues out of 8.

subordinate meaning and the sum of errors and non-convergences.

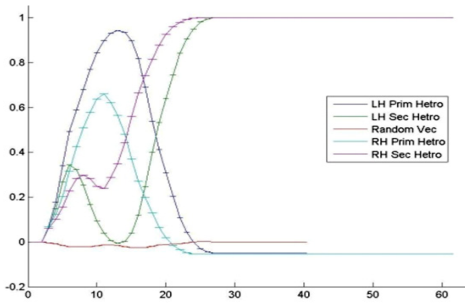

Figure 7: Network performance when weights on CC are fixed at 0.25 (LH to RH). Both LH and RH can perform the "change of heart" for heterophones.

Figure 7 and 8 shows the time course of convergence corresponding to case 2 in the table above. Trails where performed for various CC weights between 0.1 to 0.3 (with 0.05 intervals), one way or both way, same regions or between regions.

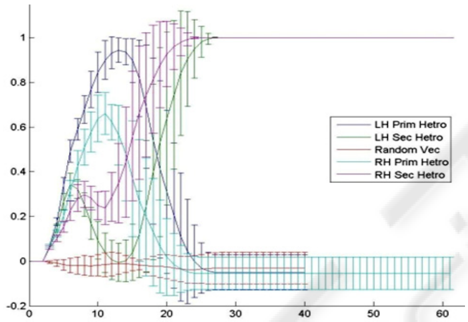

Figure 8: The same diagram as the previous figure but presented here with standard deviation.

4 DISCUSSION

4.1 Homophones vs. Hetrophones

Previous work (Peleg et al., 2007 & 2010) showed that in the homophone case running the LH without data transfer from RH has substantially worse performance, both in number of iterations to convergence and in the ability to perform the "Change of heart" when presented with clues to the subordinate meaning.

(Peleg et al., 2010) demonstrated the above by transferring the data between the hemispheres artificially. After some iterations the data from the RH was copied to the LH and was clamped for further iterations. Transfer of data from RH to LH in homophones yieled better performance for the LH even in cases when the RH has failed to perform the recovery.

This work shows that:

1. Connecting the LH and RH in a more natural way draws the same conclusions in homophones (See Table 1 - Row 2 and Figure 3).
2. Data transfer in homophones is more beneficial when done from RH to LH (See Table 1 - Row 2 compared to Table 1 Row 3-5).
3. Data transfer in hetrophones can be more beneficial when done from LH to RH (See Table 2 - Row 2 compared to Table 1 Row 3-5). Note that results are less conclusive.
4. Connection between the hemispheres via the CC is "weakly coupled" as compared to the inner hemisphere connections (See Table 1 and Table 2 Rows 2-5)[9].

Word processing is different in LH and RH when comparing different tasks such as homophone and hetrophone disambiguate resolution. In homophones the RH has less error and non-convergence cases then LH but in the cost of convergence time. Whereas in hetrophone the LH has less error and non-convergence cases then RH but again in the cost of convergence time[10]. The convergence time drawback in performance is an advantage when trying to perform the "change of heart" from dominate to subordinate meaning because then the subordinate meaning is still available in the “slower” hemisphere. This ability to perform the "change of heart" more efficiently helps when transferring data between hemispheres. The diffrence in convergence time is due to the networks architectures.

4.2 Connected Learning vs. Separate Learning

Results of connected learning also point out some interesting facts. In general connected learning has better performance in convergence time then with separate learning.

Further, it is shown that free learning of the CC weights causes the network to lose the "weakly coupled" proportions and therefore the LH and RH lose their special properties (convergence time and

[9] Weights on the CC must be more than 0.05 in order to make a difference and less than 0.30 to prevent non convergence. Note that, in contrast, inner hemispheric weights vary from -1 to 1, and forms a relative strong intra-hemispheric connection between the hemispheric regions orthography , phonology and semantics.

[10] Note that in hetrophones the different time course of the LH is not so significant than in homophones and therefore the results are not as conclusive as in homophones.

"Change of heart"). Furthermore, learning with bounded weights on the CC produces the desired properties only if the CC bounded weights are less in proportion to the interior hemispheric natural boundary of weights (1 to -1), thus forming a "weakly coupling" between the hemispheric networks.

Results of LH and RH after connected learning are slightly different then in separate learning. In performance variables such as convergence time there is a slight advantage to connected learning but in errors measurements connected learning shows worse results (in comparison to the results demonstrated in separate learning).

As mentioned above the LH and RH has a different time course and that each hemisphere has a different time course in homophones and heterophones. In separate learning it is shown that the different between homophone and hetrophones in the RH are not significant but are significant in the LH. Further, separate learning shown than the RH has a longer time course both in homophones and in hetrophones. The different time course is maintained in connected learning but it is noted that the significant difference between homophones and hetrophones is more prominent and that in the connected learning the time course of RH is longer only in homophones while in hetrophones the LH has a longer time course.

In connected learning we can see that there is an advantage to transfer data from RH to LH in homophones and help the LH recover where in hetrophone the transfer of data from LH to RH has no significant effect. Note that in hetrophones transfer of data from RH to LH has a negative effect on the LH ability to recover.

4.3 Consequences for Human Experiments

Recently, behavioral studies have been performed by Peleg and Eviatar (Peleg & Eviatar, 2007 & 2010) designed to test certain intra-hemispheric connectivity assumptions that they put forward. These studies combined divided visual field (DVF) techniques with a semantic priming paradigm.

The behavioral studies were conducted in Hebrew and combined a divided visual field (DVF) technique with a semantic priming paradigm. Subjects were asked to focus on the center of the screen and to silently read sentences that were presented centrally in two stages. First, the sentential context was presented for 1500 ms and then the final ambiguous prime was presented for 150 ms. After the prime disappeared from the screen a target word was presented to the left visual field (LVF) or the right visual field (RVF) for the subject to make a lexical decision. Targets were either related to the dominant or the subordinate meaning or unrelated. Magnitude of priming was calculated by subtracting reaction time (RT) for related targets from RT to unrelated targets. The most interesting results were observed in the subordinate-biasing context condition (“The fisherman sat on the bank”): At 250 SOA both meanings (money and river) were still activated in both hemispheres (Peleg & Eviatar, 2009). However, 750 ms later (1000 SOA), a different pattern of results was seen in the two visual fields. For homophones (e.g., “bank”), previous results were replicated: the LH selected the contextually appropriate meaning, whereas both meanings were still activated in the RH These studies, although limited to reaction time did succeed in implying different patterns of activation of both meanings in the two hemispheres. Our simulations correspond to their intra-hemispheric connectivity assumptions and produce results that fit well with those human experiments and thereby further support the theoretical underpinnings of Peleg and Eviatar (Peleg & Eviatar, 2009). Here the interpretation of the similarity of activation to dominant and subordinate meanings at iterations is taken as parallel to maintenance of the corresponding meanings in the hemispheres.

Our work suggests a refinement of these experiments to check as well the connectivity strength between hemispheres. One possible method to do this, would be to use Dynamic Causal Modeling (Friston et al., 2003) to test the effective connectivity between hemispheres during fMRI studies. Such an experiment is currently being prepared.

Our prediction as indicated above is that the RH is functionally connected to the LH and vice versa but in an asymmetric manner, with (1) the RH being more strongly connected to LH than vice versa and (2) the inter-hemispheric connections are relatively weak compared to the intra-hemispheric connections. In addition, our experiments indicate that the major learning changes should be intra-hemispheric.

5 SUMMARY

We implemented a model of both the RH and LH, with architectural differences between the hemispheres as proposed by the theories of Peleg and Eviatar (Peleg & Eviatar, 2009). The hemispheres are linked together in a natural fashion, both during learning and functioning. The results of the simulations show that the connections between the hemispheres allow additional functionality for the LH as observed in humans ("change of heart"); and the hemispheres also perform at comparative speeds that also qualitatively match human DVF experiments.

Further, our work predicts connectivity strength between the two hemispheres in architectural regions; and thus suggests new human experiments.

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