CTNN: Corticothalamic-inspired neural network

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Abstract

Sensory predictions by the brain in all modalities take place as a result of bottom-up and top-down connections both in the neocortex and between the neocortex and the thalamus. The bottom-up connections in the cortex are responsible for learning, pattern recognition, and object classification, and have been widely modelled using artificial neural networks (ANNs). Current neural network models (such as predictive coding models) have poor processing efficiency, and are limited to one input type, neither of which is bio-realistic. Here, we present a neural network architecture modelled on the corticothalamic connections and the behaviour of the thalamus: a corticothalamic neural network (CTNN). The CTNN presented in this paper consists of an auto-encoder connected to a difference engine, which is inspired by the behaviour of the thalamus. We demonstrate that the CTNN is input agnostic, multi-modal, robust during partial occlusion of one or more sensory inputs, and has significantly higher processing efficiency than other predictive coding models, proportional to the number of sequentially similar inputs in a sequence. This research helps us understand how the human brain is able to provide contextual awareness to an object in the field of perception, handle robustness in a case of partial sensory occlusion, and achieve a high degree of autonomous behaviour while completing complex tasks such as driving a car.

Glossary

ANN = artificial neural network
CTNN = corticothalamic neural network
LGN = lateral geniculate nucleus
MGB = medial geniculate body
MSE = mean square error
RTN = reticular nucleus
VB = ventrobasal complex

1 Introduction

The neocortex is a thin sheet of neural tissue enveloping most of the older parts of the mammalian brain, measuring only 2.5mm thick and functionally connected as an extensive hierarchy of cortical columns [1] [2]. The neocortex receives all of its sensory input from the thalamus, with the exception of olfaction. The thalamus acts as a relay station between visual, auditory and somatosensory sensory inputs and the neocortex, modulating the input based on previously processed information [3] [4] [5].

The connections between the thalamus and the neocortex are referred to as corticothalamic connections [6] and consist of both bottom-up (feed forward) and top-down (feedback) connections [7]. Corticothalamic connections play an important role in cognition [8], attention direction [9] [10] [11], awareness [12], emotional control [13], prediction [14], and salience detection [15]. In 2003 Alitto and Usrey [3] published a seminal paper describing the corticothalamic circuitry for the visual, auditory, and somatosensory systems (see Figure 1). In this paper there are two key observations we reference: (1) all three sensory systems (visual, auditory, and somatosensory) share a similar basic modular structure: a generalized processing unit which we call a “generalized computational unit” in this paper, and (2) while the thalamus receives input sensory systems, it also receives top-down (feedback) connections from the cortex by means of the reticular nucleus (RTN). The
thalamus is then responsible for comparing the incoming signal to the top-down prediction signal, and sending a moderated signal back to the cortex (see Figure 1). That is what we will model in this paper.

Which sensory signals make their way to the cortex? To answer this question we start with the neocortex. The neocortex maintains a picture of the current situational context in the form of a mental representation [16] [17]. The mental representation of the current context is maintained in the neocortex for roughly 100ms, which aligns with a wave of alpha-peak activation in the cortex [18]. The mental representation of the current situational context plays an important role in the neocortex, as it is continuously compared against the real-time incoming sensory data to assist in directing one’s attention [19] [18] [14] [20]. The differences between incoming sensory data and the current context as understood at higher levels in the cortex are calculated at the level of the thalamus and a moderated signal is sent up into the neocortex as an activity pattern [18] [3] [14]. The thalamus plays a key role in calculating the difference between incoming sensory data and the current context [21] [22] [23] [24] [25], and plays a central role in the model proposed in this paper.

Bio-inspired computational architectures have had a significant impact in the field of machine learning and artificial intelligence. In 1950s, the neural network [26] was first proposed as an adaptive architecture capable of learning, inspired by the bottom-up connections in the cortex. Since then the field has expanded significantly, and today multi-layered neural networks with one or more hidden layers can perform a broad range of complex tasks such as handwriting recognition [27], image classification [28] [29] and representative learning [30]. Computational processing of sensory input data is an ever expanding field of research, and there are a plethora of software modules addressing specific types of incoming sensory data [31], with a notable focus on auditory [32] and visual processing [33]. Corticothalamic connections in the human cortex, by contrast, are found in modular structures that seem to repeat themselves for visual, auditory and somatosensory sensory inputs [3]. If the cortex processes visual, auditory and somatosensory data using similar generalized computational units, then can we produce a single generalized computational model that will also process visual, auditory and somatosensory input data?

In this paper, using a cognitive architecture approach [34], we propose such a generalized computational model capable of simultaneously processing different inputs types. We model both bottom-up and top-down connections in the neocortex, and bottom-up and top-down connections between the thalamus and the cortex. A key point is that adding the thalamus as a lower level is not equivalent to just adding another layer to the cortex, as its logical structure is quite different than that of adjacent cortical layers [3]. In particular, it does not store data for future use by altering connection weights, as the cortex does. Instead, the thalamus contains relay cells influenced by feedback connections from the cortex [5] [9]. In the next section we take a closer look at corticothalamic connections.
1.1 Corticothalamic connections

The neocortex is functionally connected as a hierarchy of cortical columns [1] [2] with plastic connection weights between neurons that are adjusted through experience both via Hebb’s rule, and via neuromodulators spread from sub-cortical nuclei via the ascending systems [35] [36]. We do not model the latter feature here; that is a possible topic for future research.

Cortical columns can be divided into 6 distinct layers (I-VI) [1], which can be grouped into 3 named layers: the supragranular layer (I-III), granular layer (IV) and the infragranular layer (V-VI) [37] (see Figure 2). The connections between the layers in the cortex can be classified as either feedforward (bottom-up) or feedback (top-down) connections. These connections occur within cortical columns, and also between cortical columns (see Figure 2).

Figure 2: Supragranular layer (I-III), granular layer (IV) and the infragranular layer (V-VI) in the neocortex.

Sensory information first enters the thalamus (the LGN in the case of vision) before proceeding to the functional hierarchy of cortical regions responsible for processing that specific sensory signal (e.g. V1 and V2 in the case of vision) [21] [22] [23] [24] [25]. From the thalamus, information is sent to the granular layer in lower-level cortical columns [3] [19] [38]. Within a single cortical column, feedforward connections transmit information from the granular layer to the supragranular layer in the same cortical column [24] [19]. From the supragranular layer, feedforward connections send information to the granular layer in another cortical column, in a higher functional region [24] [19].

Feedback connections between cortical columns connect the infragranular layer in higher regions of the hierarchy of cortical columns to the supragranular layer in lower functional regions [24] [19]. Within a single cortical column, feedback occurs between the supragranular layer and the infragranular layer in the same cortical column. The lowest cortical columns in the functional hierarchy of cortical columns then connects back to the thalamus, specifically the reticular nucleus (RTN) [3].

Corticothalamic connections (Figure 1) are the connections between the thalamus and the cortical columns in the neocortex [6]. These connections consist of both feed forward (bottom-up) and feedback (top-down) connections [7]. Corticothalamic connections play an important role in cognition [8], attention direction [9] [10] [11], awareness [12] emotional control [13], prediction [14], and salience detection [15]. As stated by Briggs and Usrey [39], "the corticothalamic projection cannot be viewed in isolation, but must be considered as an integral part of a thalamic-cortical circuit which intimately interconnects the thalamus and cortex for sensory processing".

The central point we focus on is that there is no direct route from the eye or ear or somatosensory senses to the cortex: they all go through the thalamus, with essentially the same architecture in all three cases [3] (see Figure 1). That is where expectations of what should be observed are compared with incoming data - what is actually observed - and a moderated signal is sent up to the cortex as the only input from the actual data to the cortex for higher level processing. Thus the thalamus acts on the incoming data as a difference engine between expectations and what is detected. It is why this structure is not the same as just another cortical layer with both upward and downward connections between layers. This architecture is used both because it allows a very effective form of predictive coding, and it is very efficient in terms of reducing computational load on the cortical areas. In addition, this architecture also demonstrates robustness when affected by occlusions of one or more of the senses.
1.2 Aim of this paper

In this paper, using a cognitive architecture approach [34], we present a input agnostic, multi-modal neural network inspired by corticothalamic connections: a Corticothalamic Neural Network (CTNN). The CTNN combines both visual and auditory inputs at the input and encoding layer, and also has the ability to combine separate input types as a significant step in the binding problem. The CTNN is a bio-inspired neural network that incorporates top-down connections similar to the corticothalamic connections in the cortex.

The key point which our model focuses on is stated by Andy Clark [40] in discussing Radical Predictive Processing: “The core flow of information is top-down, not bottom-up, and the forward flow of sensory information is replaced by the forward flow of prediction error.” However, apart from the gustatory system, all sensory inputs reach the cortex only via the thalamus [3]; that is where the prediction error signal is generated.

In this paper we demonstrate the following:

1. A CTNN should have high processing efficiency, specifically when processing sequences of sequentially similar inputs (e.g. images). In this paper we model the CTNN after the cortex and the thalamus in the human brain, and demonstrate how the CTNN reduces computational processing at higher levels, in favour of processing at lower levels. By reducing processing at higher levels, the human brain is allowed to process other tasks (e.g. allowing the driver of the car to have a conversation while simultaneously driving): provide insight into how autonomous behaviour may arise.

2. A CTNN should be input type agnostic: It should be able to accept various input types including auditory, visual and somatosensory.

3. A CTNN should be multi-modal: It should be able to process multiple input types simultaneously, combining them to an emergent realization.

4. A CTNN should be able to demonstrate robustness when there is partial occlusion of one or more sensory inputs.

The CTNN presented in this paper has many significant implications and applications, as listed below:

1. Both the human cortex and computers have many sensory inputs, but limited capacity to focus conscious attention. Reducing computational processing at the higher cognitive level (in the cortex) frees up the cortex to focus computational attention to other important tasks (e.g. planning, movement, communication) under certain conditions. By doing so we simulate automated (unconscious) processing in the brain.

2. This research could have applications such as multi-modal biometrics and security.

3. This research could also have impact in the field of integrating heterogeneous sensors, as for example in the Internet of Things (IOT), as we present an input agnostic generalized computational model.

4. This research could also assist with challenges like establishing object permanence (e.g. when a person walks behind a car in a surveillance video), or filling in data when there is sensory occlusion.

The architecture presented here represents an implementation of the core of Andy Clark’s paper “Whatever next?” [2]. He states (Section 2.3)

“in the context of bidirectional hierarchical models of brain function, action-oriented predictive processing yields a new account of the complex interplay between top-down and bottom-up influences on perception and action, and perhaps ultimately of the relations between perception, action, and cognition. As noted by Hohwy [17], p.320) the generative model providing the “top-down” predictions is here doing much of the more traditionally “perceptual” work, with the bottom-up driving signals really providing a kind of ongoing feedback on their activity (by fitting, or failing to fit, the cascade of downward-flowing predictions)… Hierarchical predictive coding delivers, that is to say, a processing regime in which context-sensitivity is fundamental and pervasive.”

Thus what we present here is a key form of top-down causation in the brain [22]. What is new in this paper is focusing on the role of the thalamus in this process, in accordance with [3], thereby providing a computational model that clarifies how different the role of the thalamus is from just adding in another cortical layer.
1.3 Structure of the paper

In section 2 we consider the relation of our model to other models. In section 3 we describe the architecture of the Corticothalamic Neural Network. In section 4 we describe the simulations run, and the observations made, and then draw conclusions in Section 5.

2 Relation to existing models

In this section, we consider the relation of our model to other models. Section 2.1 discusses the relation to predictive coding models, Section 2.2 explains why this architecture gives high processing efficiency, and Section 2.3 explains how it is input agnostic and multi-modal.

2.1 Relation to predictive coding models

The current computational models that are similar to what we present here in some ways are predictive coding models. Predictive coding models are computational architectures which include both bottom-up and top-down connections, allowing for bio-realistic predictions of the current context to be fed back down to the sensory inputs by higher cognitive regions. There have been many distinctive predictive coding architectures developed over the last 20 years, including:

| Predictive coding models | Primary Author | Date |
|--------------------------|----------------|------|
| Retinal Predictive Coding [43] | Srinivasan | 1982 |
| Linear Predictive Coding [44] | O’Shaughnessy | 1988 |
| Cortical Predictive Coding [45] | Rao and Ballard | 1999 |
| Restricted Boltzmann machine (RBM) [46] | Hinton | 2006 |
| Free Energy Predictive Coding [47] | Friston | 2009 |
| BC-DIM Predictive Coding [48] | Spratling | 2009 |
| Predictive Sparse Decomposition [49] | Kavukcuoglu | 2010 |
| Stacked Denoising Auto-encoders [50] | Vincent | 2010 |
| Deep Predictive Coding Networks [51] | Chalasani | 2013 |
| PredNet [52] | Lotter | 2016 |
| Multilevel Predictor Estimator [53] | Kim | 2017 |
| Deep Predictive Coding [54] | Wen | 2018 |
| LPCNet [55] | Valin | 2019 |

Despite the extensive literature, there are key advantages of bio-inspired top-down connections that are not currently being realized in existing predictive coding models. These unrealized advantages include:

1. High processing efficiency, specifically when processing sequences of sequentially similar inputs (e.g. images).

2. Input Agnostic: Ability to accept various input types including auditory, visual and somatosensory.

3. Multi-modal: Ability to process multiple input types simultaneously, combining them to a emergent realization. This should allow for the model to demonstrate occlusion robustness, maintaining a high reconstruction accuracy even when a specific sense is partially occluded.

In the following sections, we discuss these advantages in more detail.

2.2 High processing efficiency

In the literature reviewed, computational efficiency is rarely measured and presented. In the one case where computational efficiency was commented on [54], the top-down connections at each layer in the neural network resulted in doubling the computational requirements of the predictive coding network, compared to a standard neural network with only bottom-up connections.

Biologically speaking, top-down connections allow for certain computations to be handled at lower levels of processing (i.e. the thalamus) freeing up the higher levels of processing (i.e. the cortex) [5]. This is not currently realized in existing predictive coding models, but is achieved here.
2.3 Input Agnostic / Multi-modal

Computational processing of sensory input data is an ever expanding field of research, and there are a plethora of software modules addressing specific types of incoming sensory data [31], with a notable focus on auditory [32] and visual processing [33]. Corticothalamic connections in the cortex, by contrast, are found in modular structures that seem to repeat themselves for visual, auditory and somatosensory sensory inputs [3]. If the cortex processes visual, auditory and somatosensory data using similar generalized computational units, then can we produce a single generalized computational model that will equally process visual, auditory and somatosensory input data?

Multi-modal deep neural networks have been shown to improve learning [56], and even fill in the missing information in both images [57] and speech data [58]. However, current predictive coding models do not demonstrate the ability to process different inputs types (input agnostic), nor do they demonstrate the ability to process multiple input types simultaneously (multi-modal). In the literature reviewed, each publication only demonstrated the use of one input type, either the processing of images (e.g. CIFAR 10, MNIST), audio (e.g. Birdsongs), or text (e.g. WMT17 QE task).

| Predictive coding models                                      | Input Type Used |
|--------------------------------------------------------------|-----------------|
| Retinal Predictive Coding [43]                               | Visual          |
| Linear Predictive Coding [44]                                | N/A (Theoretical) |
| Cortical Predictive Coding [45]                              | Visual          |
| Restricted Boltzmann machine (RBM) [46]                      | Visual          |
| Free Energy Predictive Coding [47]                           | Auditory        |
| BC-DIM Predictive Coding [48]                                | Visual          |
| Predictive Sparse Decomposition [49]                         | Visual          |
| Stacked Denoising Auto-encoders [50]                         | Visual          |
| Deep Predictive Coding Networks [51]                         | Visual          |
| PredNet [52]                                                 | Visual          |
| Multilevel Predictor Estimator [53]                          | Text            |
| Deep Predictive Coding [54]                                  | Visual          |
| LPCNet [55]                                                  | Auditory        |

3 Corticothalamic Neural Network

In this paper we implement a simplified architecture derived from that shown in Figure 1, keeping its essential feature in terms of the relation of the neocortex to the thalamus. Thus we present a generalized computational model that can extend to the visual, auditory and somatosensory systems.

We discuss in this section the computational model overall (Section 3.1), the difference engine (Section 3.3), which is our representation of the function of the thalamus, the reconstruction module (Section 3.2), and the dataset we used to explore the functionality of our model (Section 3.4).

3.1 Computational Model

To model the cortex’s ability to classify and reconstruct, we present an auto-encoder neural network with 3 encoding and 3 decoding layers. The encoding layers model the cortex’s ability to classify objects, while the decoding layers model the cortex’s ability to reconstruct an image (i.e. predict) from a classification class. The auto-encoder model represents the first cortical processing level of the neocortex, for each sense (e.g. region V1 in visual processing).

The input layer of the auto-encoder consisted of 1,568 nodes (visual 28x28 pixels + audio 28x28 pixels), the encoded layer consisted of 100 nodes, and the output layer of the auto-encoder matched the input layer size: 1,568 nodes (visual 28x28 pixels + audio 28x28 pixels). The output layer of the auto-encoder was connected in series to (1) a reconstruction engine, and then (2) to a difference engine, inspired by the behaviour of the thalamus (see Figure 3). The reconstruction engine models the reticular nucleus (RTN) in the thalamus, and the difference engine models the part of the thalamus responsible for processing the sensory input (e.g. LGN in the case of the visual sensory system).
3.2 Reconstruction Engine

The reconstruction module represents the reticular nucleus (RTN) in the thalamus. In our model, this module converts the 1D output of the decoder (1,568 nodes) into a 2D representation of the visual and audio reconstruction: visual 28x28 pixels + audio 28x28 pixels. This is done so that the output of the auto-encoder could easily be compared to the incoming sensory signal. The output of the reconstruction module is then fed to the difference engine, as an inhibitory signal.

3.3 Difference Engine

The difference engine takes the pixel-wise difference between the incoming signal (excitatory) and the reconstruction (inhibitory). What sets this difference engine apart from other computational models is that it has a built in threshold mechanism. Inspired by the biological behavior of the thalamus, the difference engine only sends a moderated signal to the auto-encoder if the difference between the incoming sensory signal and the reconstruction exceeds a given internal threshold (see Figure 3). The difference score \( D \) is calculated as the Mean Square Error (MSE) of the difference between the incoming sensory signal \( y \) and the reconstruction \( \tilde{y} \) (see Equation 1 and Equation 2). If the difference score is significant (i.e. it exceeds a given threshold) then the difference engine, modelled after the thalamus, sends the input signal \( y \) to the auto-encoder, modelled after the cortex. Thus the difference score \( D \) is defined by

\[
D = \frac{1}{n} \sum_{i=1}^{n} (y_n - \tilde{y}_n)^2
\]  

(1)

and the output \( O \) is defined by

\[
O = \begin{cases} 
  y & \text{if } D \geq TH \\
  0 & \text{if } D < TH
\end{cases}
\]  

(2)

where \( TH \) is the threshold.

The CTNN model we present does not make use of recurrent connections, and therefore we do not take into account any temporal components to a series of images during training and testing. This model could be further extended by addition of many more layers [59][60].

Figure 3: The computational architecture of an auto-encoder model inspired by the corticothalamic connections in the cortex. The reconstruction engine models the reticular nucleus (RTN) in the thalamus, and the difference engine models the part of the thalamus responsible for processing the sensory input (e.g. LGN in the case of the visual sensory system).
3.4 Dataset

In this paper, our aim is to demonstrate (a) performance on both auditory and visual input types simultaneously, as well as (b) performance over a sequence of similar images. There exist a wide range of audio and visual datasets, commonly used with auto-encoders, including:

| Dataset Name            | Audio Datasets                                                                                           |
|-------------------------|-----------------------------------------------------------------------------------------------------------|
| MNIST [61]              | 60,000 images of digits 0-9                                                                            |
| Spoken Digit Dataset [62]| 1,500 WAV files of spoken digits 0-9                                                                      |
| CUAVE [63]              | 36 speakers saying the digits 0-9, in Matlab format                                                       |
| AVLetters [64]          | 10 speakers saying the letters A to Z, three times each. Raw audio was not available for this dataset.    |
| AVLetters2 [56]         | 5 speakers saying the letters A to Z, seven times each. This is a new high definition version of the AVLetters dataset. |
| TIMIT [65]              | 630 speakers of eight major dialects of American English, each reading ten phonetically rich sentences.   |

However, Handwritten digits and spoken words were not similar enough to test for computational efficiency with sequences of similar elements of the dataset, so we chose datasets with high degrees of similarity between elements of the same class (see Figure 4).

Figure 4: Example of similar handwritten and typeset digits: Handwritten digits of the same class are less similar compared to a typeset dataset.

For the visual dataset, we use a Courier typeset dataset (digits 0-9) of 28x28 pixels per image [66]. For the audio dataset, we generated a dataset of tones, where each digit received a unique tone. Each tone was converted into a visual representation of 28x28 pixels, to match the representation of the visual image. The visual and audio representations were then combined into a single input of 1,568 pixels wide (see Figure 5).

Figure 5: Visual, audio, and combined visual and audio datasets.

In addition to the datasets, we dynamically create sequences of similar digits, such that the number of sequentially similar values can be controlled for testing purposes. We avoided sequentially duplicate images, and rather generated images of the same digit class (see Figure 6).

![Handwritten dataset:](image1) ![Typeset dataset:](image2)

![Visual data (Courier Typeset):](image3) ![Audio data (unique tones):](image4) ![Combined Audio and Video:](image5)

4 Results

In this section, we discuss training of the CTNN (Section 4.1), and the observations made relating to high processing efficiency (Section 4.2), input agnostic / multi-modal features (Section 4.3) and occlusion robustness (Section 4.4).
4.1 Neural network training

The auto-encoder was trained on the entire training set of 300 images (30 images x 10 digits) of Courier typeset 0-9. The compile loss function used was the Mean Squared Error (MSE), and training took place over 200 epochs. After 200 epochs, the loss (training data) dropped to 0.0036, and the loss (testing error) dropped to 0.0034, as shown in Figure 7.

4.2 Observation 1: High processing efficiency

It was observed that passing a sequence of images to the predictive coding model resulted in a significant difference for each new incoming input sequence. Mathematically, the mean squared error (MSE) exceeded 100 for each image in the sequence (see Figure 8).

We then created an input sequence with some sequentially similar inputs, to observe how similar images affected the processing efficiency. It was observed that passing a sequence of images containing sequential similar images to the predictive coding model resulted in a significantly lower difference for repeated images of the same digit class, compared to images from a different digit class. Mathematically, the mean squared error (MSE)
exceeded 100 for each images of different classes, while the MSE dropped below 20 for similar images in the same digit class (see Figure [9]).

In this model, we set the threshold to 100. Then only if the difference score (MSE) exceeded this threshold value, was the input image sent to the auto-encoder, for the reconstruction to be updated. If the difference score (MSE) fell below the threshold value, the auto-encoder was not sent any information, and the reconstruction remained the same.

From an efficiency perspective, the more times the auto-encoder is engaged the less computationally efficient the model is. For example, if the auto-encoder is required to process every incoming image, then the process requires the full attention of the auto-encoder at a high computational expense. However, if the auto-encoder is not required for a specific sequence, then we achieve higher overall computational efficiency, and the process behaves in a way that resembles ‘autonomous’ behaviour.

The number of sequentially similar values in a sequence was then varied, and the number of time the auto-encoder was passed an image was plotted against the percentage of sequentially similar values in the sequence (see Figure [10]).

Figure 9: Results from passing the predictive coding model an input sequence with some sequentially similar inputs. The first row shows the previous reconstruction, the second row contains the incoming input, the third row the new difference and MSE score, and the last row the new reconstruction (if a new one is generated).

Figure 10: Number of Neural Network calls for a varying number of sequentially similar images in a sequence. The results show that the computational efficiency of the predictive coding model is directly proportional to the number of similar images in the sequence.
The results from this experiment show that the computational efficiency of the CTNN is directly proportional to the number of similar images in the sequence. From these results we can conclude that thalamus-inspired architecture can reduce overall computational requirement in a predictive coding model proportional to the number of sequentially similar inputs in the dataset. In practice this means that when a sequence of inputs appear similar (e.g. driving down a straight road), the neural network would have reduced involvement, simulating ‘autonomous’ activity.

4.3 Observation 2: Input Agnostic / Multi-modal

In this paper we have presented a predictive coding model can accept both visual and auditory inputs (input agnostic), as well as a combined visual and auditory input (multi-modal). This could be extended to accept other input types (e.g. pressure, touch, temperature), depending on the pre-processing of the input signals.

4.4 Observation 3: Occlusion Robustness

It was anticipated that the CTNN model could demonstrate robustness with respect to input occlusions of one or more sense. To test this we presented the CTNN model with a visual and auditory input, where 50% of the visual input was occluded (see Figure 11). The visual occlusion test demonstrated that the predictive coding model was able to successfully reconstruct the missing visual data.

![Figure 11: Visual occlusion test: The input and reconstructions when 50% of the visual input is occluded.](image)

The same test was conducted by occluding 50% of the auditory data, and the test again demonstrated that the predictive coding model was able to successfully reconstruct the missing auditory data (see Figure 12).

![Figure 12: Auditory occlusion test: The input and reconstructions when 50% of the auditory input is occluded.](image)

To conduct a comprehensive test, the percentage occlusion of both the visual and auditory inputs were varied. It was expected that at low occlusion rates for a single input type (e.g. visual), the reconstruction would demonstrate a high level of robustness. The results were visualized as a heat map (see Figure 13). The results that the CTNN model is robust to occlusions to individual inputs (e.g. if you can see the number, but cannot hear the tone) up to a significantly high level: only if the visual and auditory sensory inputs were occluded past 70%, then the reconstruction accuracy dropped below 90%. This is a remarkable result, demonstrating how a multi-modal model can maintain accuracy well above the occlusion percentage.

5 Conclusion

In this paper we present an auto-encoder model as shown in Figure 3, inspired by the corticothalamic connections and the behaviour of the thalamus (Figure 1): the Corticothalamic Neural Network (CTNN). We have demonstrated the following significant features:

1. The CTNN demonstrates high processing efficiency, specifically when processing sequences of sequentially similar inputs (e.g. images), simulating how autonomous behaviour may arise. Specifically, we have demonstrated that thalamus-inspired architecture reduces overall computational requirement proportional
The CTNN is input type agnostic and multi-modal: It can accept as inputs various types including auditory, visual and somatosensory, can process multiple input types simultaneously, combining them to an emergent realization, as discussed in Section 4.3. This is a result of the architecture shown in Figure 1.

3. The CTNN demonstrated a high degree of robustness when there was partial occlusion of one or more sensory input. This is discussed in Section 4.4 and illustrated in Figures 11, 12, and 13.

The CTNN presented in this paper demonstrates how the human cortex may generate predictive mental representations, how corticothalamic connections can reduce the frequency of information sent from lower levels of processing to the higher level of processing in the cortex, and how corticothalamic connections may reduce processing at higher levels of processing in the cortex. The corticothalamic circuitry described by Allito and Usrey [3] is the result of millions of years of optimisation via Darwinian evolutionary processes; it must have major functional advantages over other possibilities. The CTNN presented in this paper is a first step towards implementing that design in much more complex ANNs.

In the following sections we discuss the research implications (Section 5.1), limitations on current work (Section 5.2), future work (Section 5.3), and supporting material (Section 5.4).

5.1 Research Implications

Corticothalamic circuitry is very complex [3] [8] [10] [11] [5] [4] and we have focused only on one element in that function; but it is indeed a key element. Future research may include the implementation of this model with various input types as discussed in this paper (e.g. auditory, somatosensory) and the way that stored experience in the neocortex enables meaningful downward predictive information based in past experience to influence sensory experience and ‘fill in’ missing data [67] [16].

We suggest that the prediction of the complete context (i.e. the decoded image) could in fact be generated from only a partial sensory picture. This may be limited to one sensory channel (for example, seeing a tree trunk may generate the context of an entire tree), or across more than one sensory channel (for example if you hear a dog bark, you may expect to see a dog run past). We are of course aware that Generative Neural Network models [68] [68] [69] have such a capability. The hypothesis will be that adding to such networks components representing the corticothalamic interactions, as discussed here, will add to that capability and produce an even more powerful Generative Neural Network.

The neural network representation of the neocortex in our model could of course be made much more complex, thereby providing a useful direction of extension of standard deep neural network models [70] thereby
benefiting from the power of deep learning networks [71]. As such there is no point in comparing in depth what is presented here with existing deep neural network models: rather an eventual Deep Corticothalamic Neural Network should be the subject of such investigation.

The computation model presented in this paper does not take into consideration recurrent networks, and therefore temporal data sets, which may be another area for future research. In addition, this research could be extended to linguistic or text recognition algorithms. In this paper we use an unlabelled dataset, but this can be extended to training the network on a labelled dataset. In this paper, the model generated its own set of ‘eigen-concepts’. They so happen to be quite similar to the numerical digits we have given names to in the English language, but they do not strictly match one-to-one. Training the model to recognize a set of ‘correct’ words to match an image against is considered future work.

Finally the project has the potential to gain extra power when it is extended to include the features of a Salience Affected Neural Network, as presented in [36]. This will include another key feature of the way the human brain works: namely emotion (affect) plays a key role in intellectual functioning [72] [73] [74] [75]. Thus this adds another dimension to the neural processes which nature has found important enough to hard-wire into our brains [13]. There must be major cognitive benefits for this selective process to have happened; it should therefore have the potential to give substantial extra power to AI projects. In effect it is addressing the issue of supervised versus unsupervised learning: the affective systems in the brain provide supervision of learning by being what Gerald Edelman calls a ‘value system’ [76] [77]. This has the remarkable feature of enabling one-time learning of individual instances of a class [36]. As emphasized by Mark Lee [72],

“Human learning takes place through interactions, not by the offline processing of vast quantities of data. This is the difference between biological brains and computer brains. A brain-centric approach to artificial intelligence ignores the fact that human learning requires a body to fully support the life of the brain and the role that this physical interaction plays. Modern robotics is showing how important this is and will be the real test-bed of artificial brains.”

The thalamus plays a key role in these interactions, which involve the relation between attention, affect, and sensory selection [75], [79], [13], [11] [80].

A Salience-Affected CTNN will be a good step in the right direction, because affective effects occur through interaction of the neocortex and the limbic system, which is a more primitive part of the brain related to salience effects [73] [13]. All memories have emotional tags attached to them, and this plays a key role in human mental life, enabling our predictions based on those memories to have a significant directional quality (“Is it good or bad?”) that is otherwise missing.

5.2 Limitations of the current work.

To the authors’ knowledge, this is the first work in the open literature where an architecture has been proposed inspired by the corticothalamic interaction. We have only shown some results from limited experiments. Many more experiments will be needed to show the strength and weaknesses in a variety of situations, for example involving face and voice recognition, and situations such as driving down a road.

Secondly, we have tried to keep our architecture use-agnostic. This is a limitation in the sense that as per “no free lunch theorems” the real strength of an algorithm is demonstrated by the right choice of the use. On the other hand an architecture that works for a variety of contexts is obviously a powerful mechanism. We have not extensively investigated this trade off.

5.3 Future work

There are many topics that arise as a result of this work, but specific topics may include:

1. Extending the input agnostic model presented here, to accept other heterogeneous sensors

2. Extending the model to a recurrent neural network, allowing it to process time-series sequences of images.

3. Seeing if this kind of architecture might assist in rectifying some of the problems of mis-classification currently occurring in Deep Learning models [81].

4. It may be that augmented reality [82] can be the ideal application for this work. For AR to work there needs to be a subsystem like the thalamus, otherwise the images will always be grainy and sluggish unless supported by massive computational power and data throughput.

1 To be distinguished from ‘one shot learning’, which applies to generalising from one class to another.
2 “A Frame of Mind” at https://medium.com/rsa-journal/a-frame-of-mind-26b130545c20
5.4 Supporting Material

The source code for the CTNN, as well as records of the tests conducted in this paper are publicly available online [83]. For additional information, please contact the corresponding author.

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