Predictive Coding for Dynamic Vision: Development of Functional Hierarchy in a Multiple Spatio-Temporal Scales RNN Model

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Abstract

The current paper presents a novel recurrent neural network model, the predictive multiple spatio-temporal scales RNN (P-MSTRNN), which can generate as well as recognize dynamic visual patterns in the predictive coding framework. The model is characterized by multiple spatio-temporal scales imposed on neural unit dynamics through which an adequate spatio-temporal hierarchy develops via learning from exemplars. The model was evaluated by conducting an experiment of learning a set of whole body human movement patterns which was generated by following a hierarchically defined movement syntax. The analysis of the trained model clarifies what types of spatio-temporal hierarchy develop in dynamic neural activity as well as how robust generation and recognition of movement patterns can be achieved by using the error minimization principle.

1 Introduction

Predictive coding is a plausible model of how brain predictions of possible lower level perception are caused by current higher-level intention (in the top-down pathway), as well as how the intention corresponding to the current perception can be inferred by prediction error (in the bottom-up pathway) [1, 2, 3]. Within this predictive coding framework, it has largely been assumed that perceptual patterns are encoded as corresponding (abstractly represented) intention states in higher cognition, and that the necessary functional hierarchy develops across multiple cortical regions [1, 3, 4]. The current study examines how a spatio-temporal hierarchy adequate for robust generation and recognition of compositional dynamic visual patterns can be developed, proposing a novel deterministic predictive coding type deep recurrent neural network model that can deal with dynamic visual images at the pixel level when the neural activity of the whole network is differently "tuned" to spatial and temporal scale properties in multiple levels simultaneously.

The proposed model is the predictive multiple spatiotemporal scales RNN (P-MSTRNN). It is compose of an RNN using different timescales at different levels (MTRNN) [4], and of deep convolutional generative adversarial networks (DCGAN) [5] in order to take advantage of their multiple spatial-scale property. The P-MSTRNN differs from prior predictive coding models for dynamic vision processing, because here spatial processing and temporal processing are performed simultaneously. (c.f. [6, 7]). The video dataset used in training and testing consisted in multiple cyclic human movement patterns performed by multiple subjects. A set of simulation experiments examined the spatio-temporal hierarchy as it develops during learning, and reveals that robust recognition of test patterns depends on learning spatial-temporal interdependencies in exemplar patterns exhibiting high degrees of variance.
2 Model

The newly proposed model, the predictive multiple spatio-temporal scales RNN (P-MSTRNN) is a hierarchical neural network model that utilizes spatio-temporal features for generating and recognizing dynamic visual images. The P-MSTRNN model is based on the multiple spatio-temporal scales RNN (MSTRNN) [8]. The original MSTRNN is a classification model for dynamic visual images without prediction mechanism. The P-MSTRNN differs from the MSTRNN because it learns, generates and recognizes patterns using the principle of prediction error minimization in the predictive coding framework.

2.1 Architecture

The P-MSTRNN consists of series of context layers and one input/output layer in the bottom as shown in Figure 1. Each context layer predicts its own neural state at each next time step by receiving the top-down signal from the next higher layer. The neural state of each context layer represents its top-down intention. The first context layer predicts next step visual inputs by receiving both the current visual input and the top-down signal from the 2nd layer. In the upward direction, the prediction error signal back-propagates inversely in the same pathway for the purpose of updating the connectivity weights as well as the intention at each context layer in the learning and recognition processes.

The model originates from the convolutional neural network (CNN) [9]. However, unlike the CNN, every context layer in the P-MSTRNN model is composed of two different types of units which function differently from the units composing CNN context layers.

The first type is the feature unit and the other is the context unit. Both feature unit and context unit are based on the leaky integrator neural units which decay to the value of the previous time step, thereby enabling both types of units to reflect a temporal hierarchy not possible in a CNN [10]. The set of feature units in the same layer forms a feature map (FM) and context units form context map (CM). FMs mainly contribute to spatial processing by receiving synaptic inputs from neighboring feature units. The CMs, on the other hand, contribute mainly to development of adequate dynamic information processing by taking advantage of their adjustable recurrent connectivity. The timescale which determine decay rate is differently set in all layers. The layers in the lower level have smaller time constants and the higher level layers have larger time constants. Therefore, the neural activity in the lower context layer is constrained to be faster while the one in the higher layers is constrained to be slower.

The forward dynamics of FMs in the first layer are shown in Equation (1) and (2).

\[
\hat{f}_{lp}^t = \left(1 - \frac{1}{\tau_l}\right)\hat{f}_{lp}^{t-1} + \frac{1}{\tau_l}\left(\sum_{q=1}^{Q_{l+1}} f_{l+1}^{t-1} * k_{lpqf}^q + \sum_{n=1}^{N_l} c_{l-1}^{ln} * k_{lpn}^r + I * k_{lpf}^f + b_{lp}\right) \\
\]

\[
f_{lp}^t = 1.7159 \tanh\left(\frac{2}{3}\hat{f}_{lp}^t\right) \\
\]

where \(\hat{f}_{lp}^t\) is the \(p^{th}\) FM’s internal state in the \(l^{th}\) layer at time step \(t\), \(\hat{f}_{lp}^{t-1}\) is the internal state of \(p^{th}\) FM in the \(l^{th}\) layer at \(t-1\) time steps, \(\tau_l\) is the timescale in the \(l^{th}\) layer and \(Q_{l+1}\) is the number of FMs in the \(l+1^{th}\) layer. The operation \(*\) is the convolution operator, \(k_{lpqf}^q\) is the kernel connecting the \(q^{th}\) FM in the \(l+1^{th}\) layer at \(t-1\) time steps and \(p^{th}\) FM in the \(l^{th}\) layer at time step \(t\). \(N_l\) is
the total number of CM in the \( l \)th layer and \( c_{lm}^{t-1} \) is the activation of the \( n \)th CM in the \( l \)th layer at time step \( t-1 \). \( k_{ij}^{lp} \) is the kernel connecting the \( n \)th CM in \( l \)th layer at the previous time step \( t-1 \) and the \( p \)th FM in the \( l \)th layer at the current time step \( t \). \( I \) is the input data frame from outside of the network and \( b_{rf}^p \) is the bias of \( p \)th FM in the \( l \)th layer. The first term of Equation (1) represents the decayed internal states of FMs from the previous time step \( t-1 \) with the decay rate \( (1 - \frac{1}{\tau}) \). The second term is the input to the current FM from the activation value of FMs in the \( l \)th layer at time step \( t-1 \). The third term represents the input from the CMs in the same layer at the previous time step \( t-1 \). The fourth term indicates the data frame fed to the current FM. After the internal state of the current FM is computed, an activation value is obtained using the hyperbolic tangent function in Equation (2)). When the layer which the current \( p \)th FM belongs to is other than the first layer, the term from the input data frame \( I \) no longer exists. Also, highest layer internal dynamics do not include the second term in Equation 1 due to the absence of any higher layer to provide values.

Equation (3) and (4) detail the forward dynamics of CMs.

\[
\hat{c}_{lm}^t = \left( 1 - \frac{1}{\tau} \right) c_{lm}^{t-1} + \frac{1}{\tau} \left( \sum_{n=1}^{N_l} c_{ln}^{t} \circ W_{cc}^{l,nn} + \sum_{q=1}^{Q_{l+1}} f_{t-1}^{(l+1)q} \circ W_{fc}^{l,mq} \right.
\]

\[
+ \sum_{r=1}^{R_l} f_{t-1}^{(l-1)r} \ast k_{lmr}^{fc} + b_{lm} \right) \tag{3}
\]

\[
c_{lm}^t = 1.7159 \tanh \left( \frac{2}{3} \hat{c}_{lm}^t \right) \tag{4}
\]

where \( c_{lm}^{t} \) is the internal state of the \( m \)th CM in the \( l \)th layer at time step \( t \) and \( c_{lm}^{t-1} \) is the activation value of the \( n \)th CM in the \( l \)th layer at time step \( t-1 \). \( W_{cc}^{l,nn} \) is the recurrent weight connecting the \( m \)th CM in time step \( t \) with the previous \( n \)th CM in time step \( t-1 \). \( W_{fc}^{l,mq} \) is the weight connecting the current \( m \)th CM with the \( q \)th FM in the \( l + 1 \)th layer at time step \( t-1 \). \( k_{lmr}^{fc} \) is kernel connecting the \( r \)th FM in \( l \)th layer at time step \( t-1 \) to current CM. \( \circ \) is the element-wise multiplication operator. The first term of Equation (3) is the leaky integrator input from the internal state of the CM from the previous time step \( t-1 \). The second term is the recurrent input to the current CM from the previous time step’s CM activation value. \( W_{cc}^{l,nn} \) is same size as CMs in the same layer. Accordingly, the activation values of the previous CM are multiplied with \( W_{cc} \) in an element-wise manner. In the CMs, this second term represents the recurrency and reinforces the temporal processes of the network.

The third term represents the input from the activation value of FMs in the \( l + 1 \)th layer. The fourth term is from the lower layer FMs. This term utilizes the bottom-up pathway allowing input data frames from outside of the network to be processed through all the layers of the network. For the internal state calculation of the CMs, if the layer is the highest layer, then there is no input from the upper \( l+1 \) layer and the third term in Equation (3) is unused. Likewise, if the layer is the lowest layer, then input from the lower layer does not exist and the fourth term in Equation (3) is unused. After the internal state is calculated, an activation value is obtained using the hyperbolic tangent function in Equation (4).

When calculating the convolution, there exist some cases in which the input map size is smaller than that of the output map. In these cases, zero-padding is used for the input maps. As for the element-wise multiplication, the map and weight sizes are always the same.

In the output layer, the output is calculated as,

\[
\hat{O}_t = \sum_{q=1}^{Q_1} (f_{t}^{1,q} \ast k_{fo}^{q} + b_o) \tag{5}
\]

\[
O_t = 1.7159 \tanh \left( \frac{2}{3} \hat{O}_t \right) \tag{6}
\]

where \( O_t \) is the internal state of the output layer, \( Q_1 \) is the number of FMs in the \( 1 \)st layer, \( k_{fo}^{q} \) is the kernel connecting the \( q \)th FM in the \( 1 \)st layer with the output map. \( b_o \) is the bias for the output map.
The internal state of the output is calculated from the FMs in the first layer by convolution, and the activation value of the output layer is obtained by applying the hyperbolic tangent function.

### 2.2 Learning, generation and recognition

The open loop generation method is used for training the network. When the network is utilized in the open loop generation manner, the network receives the current input frame from outside of the network and generates a (single or multiple) step prediction as an output frame. After the prediction for the current input is obtained, the difference between the output frame and the prediction target frame at time step \( t \) is calculated, resulting in the error for all time steps. This process is shown in the Equation below.

\[
E = \frac{1}{T} \sum_{t=1}^{T} E_t
\]

\[
E_t = \frac{1}{XY} \sum_{i}^{X} \sum_{j}^{Y} (O_{ij}^* - O_{ij})^2
\]

where \( E_t \) is the average error per pixel at time step \( t \) and \( E \) is the average error per pixel for total time steps \( T \). \( O_{ij}^* \) is the target pixel value in the \((i,j)\) position of the frame and \( O_{ij} \) is the output pixel in the \((i,j)\) position of the frame. The error calculated through this process is then used to optimize the parameters. A conventional back-propagation through time (BPTT) method is used for training the network. The weights, kernels, biases and initial states of the context layers are optimized using gradient descent.

Along with open loop generation, closed loop generation is also used for training the network. The closed loop generation method is a scheme in which next step output prediction is computed by using a copy of the output prediction from the previous step as the current input. In the closed loop method, error is also calculated in comparison with target signals. During training, error from open loop generation is used to optimize network parameters. As the training proceeds, both open loop error and closed loop error decrease. Closed loop error is always higher than that of open loop because closed loop prediction generates integration error over time steps without correction from factors outside of the network. Therefore, network training terminates when the closed loop error reaches a predefined lower bound threshold. At this point, the network guaranteed to successfully perform both open loop generation and closed loop generation.

In order for the network to learn to generate multiple data sequences, it must infer optimal initial states of all context units at all layers for each sequence, as well as optimal connectivity weights minimizing the sum of prediction errors for the whole network and all sequences. Inferred initial states for each training sequence represent the intention to generate that sequence.

The trained network is used for both generation and recognition of the learned sequence patterns. An intended pattern is generated by setting the initial states of all context units to corresponding values. On the other hand, a test sequence pattern can be recognized by inferring optimal internal states of all context units at the onset of immediately prior time steps by way of which the test sequence pattern can be reconstructed through closed-loop generation with minimal error in the temporal window. For this purpose, error BPTT is performed only within the immediate temporal window of \( w \) steps. The test input sequence pattern can be recognized in an on-line manner in terms of imitative synchronization with the input pattern by means of the error regression of the internal states of the context units while the temporal window shifts forward as time step proceeds.

### 3 Experiment

Experimental datasets consist of whole body human movement patterns generated according to a hierarchically defined movement syntax. Sub-primitives (arms and legs) are defined first. Each whole body movement primitive is composed of these sub-primitives, with sub-primitives being shared by all movements. Experiment 1 analyzed the self-organization of the spatio-temporal hierarchy as the model learned one subject’s 6 primitive movements. After training these primitives, the network
Experiment 2 examined the recognition capability of the trained model, specifically how robustness of recognition depends on variance in training exemplar patterns, and tested this by changing the number of subjects preparing training patterns.

3.1 Experiment 1

The dataset for this experiment consists of 6 whole body movement patterns performed by one subject. Each whole body movement pattern is hierarchically generated by combining predefined sub-primitives using legs and arms. Figure 2 describes the sub-primitives. There are three types of arm sub-primitives. Sub-primitive 1 (A1) is laterally extending arms. Sub-primitive 2 (A2) is vertically extending arms. Sub-primitive 3 (A3) is drawing a big circle with arms. In action space, these arm sub-primitives are represented as A1R (arm sub primitive 1, right), A1L (arm sub primitive 1, left), A2R, A2L, A3R and A3L. Leg sub-primitives appear in the second row of Figure 2. There are three types of leg sub-primitives. The first leg sub-primitive (L1) is raising the right and left leg alternatively. The second leg sub-primitive (L2) is standing still, moving neither leg. The third leg sub-primitive (L3) is bending both legs. All are shown in Figure 2. There are a total of 6 whole body action primitives. Their syntax is presented in Table 1. where the term "co-phase" involves two arm actions performed at once, and the "anti-phase" involves arm actions performed alternatively. As can be seen in the table, every sub-primitive (arm and leg) is utilized two times during every whole-body movement. For training data, each the whole body primitive is repeated for 6 cycles. The concatenated data for additional learning consisted of P1 and P5 alternated three times (P1-P5-P1-P5-P1-P5) with each primitive repeated for three cycles.

Table 2 specifies the network used for this experiment. The zeroth layer is the input/output layer and the rest of the layers are context layers. All of the weights and the kernel sizes are defined according to the maps with which the weights or kernels connect. To train the network, one-step prediction is used for experiment 1 and the learning rate was set at 0.001.

In experiment 1, training proceeded in two stages. The network was first trained with 6 basic primitives. When closed loop error decreased to the predefined level, the first training stage was terminated. Figure 3 shows an example of reconstructed images from closed loop output generation. In the second stage of training, the trained network from stage 1 learned additional concatenations of the 6 primitives. Same as stage 1, stage 2 was terminated when the closed loop error decreased to a
Table 2: Specifications of the network used-

| layer | feature map | context map |
|-------|-------------|-------------|
|       | size | number | kernel | size | time | constant | size | number | weight | size |
| 0     | 36.36 | 1      | 5.5    | -    | 0    | -        | 0    | -      | -      | 0    |
| 1     | 32.32 | 10     | 7.7    | 2    | 26.26| 10       | 26.26|        |        |      |
| 2     | 26.26 | 10     | 7.7    | 4    | 20.20| 10       | 20.20|        |        |      |
| 3     | 20.20 | 20     | 9.9    | 8    | 12.12| 10       | 12.12|        |        |      |
| 4     | 12.12 | 40     | 11.11  | 16   | 2.2  | 25       | 2.2  |        |        |      |
| 5     | 2.2   | 10     | 2.2    | 32   | 1.1  | 10       | 1.1  |        |        |      |
| 6     | 1.1   | 10     | 1.1    | 64   | 1.1  | 5        |      |        |        |      |

certain level. Figure 4 represents the transition of closed loop reconstruction of additional data from P1 to P5, and shows that the closed loop generation of additional concatenated data was successful (See video1 and 2 in the supplementary material). The neural activities of this network for the 6 basic primitives and additional data is presented in Figure 5.

![Figure 5](https://sites.google.com/site/academicpapersubmissions/nips2016)

Figure 5: Neural activations of different layers. Different colors represent different whole body primitives (Red-P1, Blue-P2, Cyan-P3, Yellow-P4, Green-P5, Magenta-P6). Dimensionality reduction was performed by PCA. The x-axis is the first principal component, and the y-axis is the second principal component. (A)-neural activity of CM in first layer. (B)–neural activity of FM in the third layer.

In Figure 5.A, the left plot shows neural activities of the CMs in the first layer corresponding to the 6 primitives and the right plot shows their neural activities corresponding to additional concatenated data. In Figure 5.B, the left plot shows neural activities in the third layer corresponding to the 6 basic primitives and the right plots are of additional data from third layer FMs. 6 cyclic patterns develop in Figure 5.A (left) while convergence toward 6 fixed points (starting from near the center) is observed in Figure 5.B (left). In Figure 5.A (right), concatenated data activations of P1 and P5 appear in similar position and in similar shape as the basic primitive shapes of P1 and P5 activations (left). In Figure 5.B (right), activity converges to a cyclic pattern rather than to a fixed point. It was found that this cyclic neural activity in the 3rd layer induces the cyclic neural activity corresponding to the cyclic switching between P1 and P5 in the 1st layer, as shown in Figure 5 (A) right. The model developed a temporal hierarchy via learning, enabling additional learning through the composition of primitives.

To uncover the spatial hierarchy developed in the model, we conducted another analysis with the same trained network. FMs were divided into four quadrants and neural activities recorded separately. Figure 6 shows one example of the resulting plots from the FM in the second layer. Figure 6.A presents the second quadrant of the map, with the upper left part of the map corresponding to left arm activation. Figure 6.A (left) plots data from P1 as a red trajectory and the right plot represent P6 data in red (right). Looking at table 1, P1 and P6 share the same left arm sub-primitive (A1L), with corresponding neural activations plotted in the same positions and in the same shapes. A similar analysis also applies to P2 and P5. In the same figure, P2 is presented in blue in the left plot and P5 is drawn in blue in the right plot. According to the syntax comprising primitives, P2 and P5 share the same left arm movement (A2L). And, for P3 and P4 trajectories drawn in (green), the same phenomena is observed. In the case of Figure 6.B, data is obtained from the third quadrant, which corresponds to left leg activation. P1 (red in the left plot of figure 6.B) and P3 (red in right plot of figure 6.B) share leg sub-primitives, L1. The pair, P2 and P4 pair (blue), and the pair P5 and P6 pair
Figure 6: Neural activations of different quadrants in the same map. Different colors represent the different sub-primitives. The plot data was obtained from the FM in the second layer and PCA was performed. (A)-second quadrant of the FM (Left plot: Red-P1, Blue-P2, Green-P3. Right plot: Red-P6, Blue-P5, Green-P4). (B)-third quadrant of the FM (Left plot: Red-P1, Blue-P2, Green-P5. Right plot: Red-P3, Blue-P4, Green-P6).

(green) also share leg sub-primitives. It is clearly shown that these pairs exhibit similar shapes of activation trajectories in similar positions of the phase plots. This analysis suggests that when whole body primitives share sub-primitives, neural activation in the same quadrants are the same, implying that the P-MSTRNN developed a spatial hierarchy combining sub-primitive limb-specific movement patterns.

3.2 Experiment 2

In experiment 2, the network structure and specifications are the same as those in experiment 1. However for experiment 2, the learning rate was 0.1, the window size was 20 and initial state inferencing was performed 100 times every step. The dataset used in this experiment consists of three types of whole body movement (P1, P4 and P5) as performed by five different subjects. The dataset exhibits roughly 15% variance in performance speed amongst subjects who also differed in shape and height. In order to see how such variances in exemplar training affect the network’s recognition ability, we compared two cases. First, a network was trained with a five subject dataset. Then, a second network was trained with only one subject’s data. For testing, three subjects not included in training data performed a sequence of three basic primitives containing all of the possible transitions from one primitive to another (P1-P4-P5-P1-P5-P4-P1). After training, imitative synchronization by error regression was conducted (see video3 in the supplementary material). Figure 7 shows a representative snapshot during a transition from P1 to P5 in the five subjects training case.

The transition between primitives occurs at around 660 time steps in Figure 7. Error rises sharply leading up to the transition, inducing modulation of context activity through error regression, resulting in the correct output pattern and transition. After the transition, error falls to near zero. As illustrated in the second column of figure 7, neural activations in the first layer show rapid changes compared to the those of the fourth layer. This is due to the fact that time constants increase as layer level increases. The first layer has smallest time constant, so shows relatively fast activation changes.

Figure 7: Results of imitative synchronization. The first column shows output, target and MSE. The second column shows the neural activities of FM in layer 1 and FM in layer 4. The activations are the result of PCA.

The average MSE per pixel in the two conditions (multi-subject train / single-subject train) according to the three test subjects were (0.0685 / 0.0941), (0.1019 / 0.1378) and (0.0813 / 0.0992). For all three

[https://sites.google.com/site/academicpapersubmissions/nips2016]
different test subjects, the network trained under the multi-subject training condition showed better results in imitative synchronization than did the network trained under the single-subject training condition. This suggests that increased variance in training results in more robust recognition ability. This result is analogous to that of [11] which used lower dimensional data compared to the present study.

Under the five subject condition, for identical movement primitives, each of the five subject’s individual movement patterns differed slightly from those of others, and this variance was well preserved in the closed-loop output generation of dynamic images. Figure 8 shows the corresponding analysis of neural activity in different layers in the network. (A) shows neural activations of CMs in the first layer and (B) shows those of CMs in the fourth layer. In the lower layer (Figure 8.A), the same primitives form clusters. At the same time, variations of neural activation patterns corresponding with the different subjects in the same cluster are well preserved (note the different shapes and the positions of the trajectories). As in the analysis of experiment 1, higher layer intentions represented in terms of different fixed points in (B) determine the corresponding cyclic activation patterns in the lower level shown in (A) by means of parameter bifurcation. In training with multiple subjects as shown in Figure 8 (B), three clusters emerge (one for each primitive), and fixed points vary within these clusters (reflecting subject variations). This implies that the higher level influences the lower level through the differentiation of fixed points within clusters of more or less robustly established primitives.

Figure 8: Neural activities of different layers. Different colors indicate different subjects. Three primitives with five subjects are plotted in both A and B. (A)-neural activations of CM of the first layer. (B)-neural activations of FM of the fourth layer. Dimensionality reduction is performed by PCA.

4 Conclusion

The current paper introduced a novel dynamic neural network model for generating and recognizing dynamic visual image patterns at the pixel level within a predictive coding framework. Our simulation experiments showed that the network model characterized by its multiple spatio-temporal scales property can learn to generate dynamic visual images representing human movement patterns through the development of an internal spatio-temporal hierarchy. The model can also recognize robustly test movement patterns performed by unfamiliar subjects through imitative synchronization by inferring intention states through the error regression scheme applied to context units. Future studies should focus on scaling the model in terms of number of pixels, as well as in terms of number and complexity of movement patterns.

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