Collaboration between parallel connected neural networks - A possible criterion for distinguishing artificial neural networks from natural organs

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We find experimentally that when artificial neural networks are connected in parallel and trained together, they display the following properties. (i) When the parallel-connected neural network (PNN) is optimized, each sub-network in the connection is not optimized. (ii) The contribution of an inferior sub-network to the whole PNN can be on par with that of the superior sub-network. (iii) The PNN can output the correct result even when all sub-networks give incorrect results. These properties are unlikely for natural biological sense organs. Therefore, they could serve as a simple yet effective criterion for measuring the bionic level of neural networks. With this criterion, we further show that when serving as the activation function, the ReLU function can make an artificial neural network more bionic than the sigmoid and Tanh functions do.

When we see Michael Jackson on TV, it seems impossible that our left eye takes him as John, our right eye treats him as Paul, while our brain recognizes him as Michael correctly. Similarly, we know that there is smoke when we see the smoke and smell the smoke. It is less likely that our eyes see cola while our nose smells vinegar and then our brain concludes that it is smoke. From our own life experience, when two sense organs (e.g., eyes) share the same input (e.g., the image on the screen) and output (e.g., the brain) without direct connection in the middle, each of them would give the same judgement when the final output is correct.

But what if two artificial neural networks are connected in parallel and trained together? That is, they share the same input and output layers, while their hidden layers are separated from each other. Surely, we all know that even the state-of-the-art artificial neural networks do not replicate biological neural networks faithfully, but little is known about what exactly is the difference, especially in a quantitative way [1, 2]. In this work, by using the classification of Modified National Institute of Standards and Technology (MNIST) data set as an example, we find some properties that clearly distinguish the parallel-connected artificial neural networks (PNNs) apart from natural sense organs. Moreover, different types of PNNs will show these divergence to a different level. This finding could serve as a criterion for measuring the bionic level of an artificial neural network.

Results

Parallel connections of neural networks

Fig.1 shows the most basic structure of a conventional neural network, where each neuron connects with every neuron in the neighboring layers. In the following we will call it a fully-connected neural network (FNN), and use the notation \([n_0, n_1, ..., n_m]\) to denote an \(m\)-layer (without counting the input layer) FNN, where \(n_0, n_i (i = 1, ..., m - 1)\) and \(n_m\) are the numbers of neurons in the input layer, the \(i\)th hidden layer and the output layer, respectively.

In this work, however, we are interested in PNNs, which contain two or more FNNs (called sub-networks) being connected in parallel by sharing the same input and output layers, while there is no connection between the neurons in the hidden layers of different sub-networks, as illustrated in Fig.2. Let \([n_0, n_1, ..., n_{m_1}] + [n'_0, n'_1, ..., n'_{m_2}]\) denote a PNN consisting of two sub-networks \([n_0, n_1, ..., n_{m_1}]\) and \([n'_0, n'_1, ..., n'_{m_2}]\) (surely there should be \(n_0 = n'_0\) and \(n_{m_1} = n'_{m_2}\)).

PNN should not be confused with the technique where two or more sub-networks run in parallel and then the final result is obtained via majority voting. In this technique, the sub-networks are trained and optimized separately. But in a PNN, they are connected via the output layer and trained together, so that they will interact with each other and the optimization result will be different (as we shall show below). PNN also differs from the pooling technique used in, e.g., AlexNet [3] because: (i) A network with pooling can be viewed as a special case of an FNN where some of the weight parameters are set to 0, while this is not the case of a PNN consisting of sub-networks with different numbers of layers. (ii) When the pooling technique is applied to the first hidden layer,
some neurons in this layer connect with only a portion of the neurons in the input layer. But for every sub-network in a PNN, each neuron in the first hidden layer connects with all neurons in the input layer.

Note that the parallel connection of several 2-layer FNNs is actually still a single (but larger) FNN. For example, the [4, 5, 3] FNN showed in Fig.1 can also be viewed as a [4, 3, 3] + [4, 2, 3] PNN. Therefore, here we study only the PNNs which contain at least one m-layer FNN with m ≥ 3.

Experiments

The MNIST data set [4] is a widely-used resource for machine learning research [3]. It contains 70000 greyscale 28 × 28 pixel images of handwritten digits 0–9. Here we also use neural networks as classifiers to recognize the digits in these images, and study the classification accuracies of the FNNs within the PNNs. For this purpose, the numbers of neurons in the input and output layers of each of our PNNs and FNNs are taken to be 28^2 = 784 and 10, respectively, corresponding to the 784 input pixels and the 10 possible output digits 0–9.

We conducted the following experiments (see Methods section for the details of the computer programs), each of which displays a type of divergence from the properties of natural sense organs.

(1) Evolution of the classification accuracies.

(1.1) The [784, 48, 35, 10] + [784, 50, 10] PNN. We choose these values because the total number of learnable parameters (biases and weights) of the [784, 48, 35, 10] FNN is (48 + 35 + 10) + (784 × 48 + 48 × 35 + 35 × 10) = 39755, while that of the [784, 50, 10] FNN is (50+10) + (784×50+50×10) = 39760. From past experience, two FNNs with similar numbers of parameters will generally have similar performance when working alone. Thus, it will be interesting to see how they perform when being parallel-connected.

The activation function of every neuron is chosen as the sigmoid function (except in experiment (4) below)

\[ f(z) = \frac{1}{1 + e^{-z}}, \]

with

\[ z = w \cdot x + b \]

denoting the weighted input to the neuron, where w is the weight matrix, b is the bias vector, and x is the output from the previous layer.

Let us refer the [784, 48, 35, 10] FNN and the [784, 50, 10] FNN as Network 1 and Network 2, respectively. We first trained them separately for 60 epochs (i.e., epochs 0–59), then connected them in parallel and trained together for another 40 epochs (i.e., epochs 60–99). In the following, we call this procedure training method A. The classification accuracies of each sub-network and the whole PNN in each epoch is shown in Fig.3.

Note that there are two ways to calculate the classification accuracy of a single sub-network within a PNN. Before being connected with the other sub-network, each sub-network has its own output layer. For Network i (i = 1, 2), the weighted input to an output neuron (i.e., the neuron in the output layer) has the form

\[ z_i = w_i \cdot x_i + b_i. \]

At this time, there is no doubt that the classification accuracy of Network i is calculated by taking \( z_i \) into the sigmoid function to obtain the activation value of the neuron, then picking out the output neuron having the maximal activation value, and comparing its label with the actual handwritten digit corresponding to this input.

But when the two sub-networks are connected, they share the same output layer. The total weighted input to an output neuron becomes

\[ z = (w_1 \cdot x_1 + w_2 \cdot x_2) + b \]

where \( b = b_1 + b_2 \). If we want to calculate the current classification accuracy of Network i in the PNN, it is natural to set \( w_{i'} = 0 \) to bypass the contribution of Network \( i' (i' \neq i) \). But should we also set \( b_0 = 0 \) and use \( b_i \) alone to calculate \( z \)? That is, should we still use Eq. (3), or use

\[ z = w_i \cdot x_i + b \]

instead?

On one hand, for a fair comparison with the case when Network i was trained separately, it seems that we should still use \( z = w_i \cdot x_i + b_i \) to calculate the activation value and get the classification accuracy. Let \( \alpha_i \) denote the accuracy achieved this way.
FIG. 3: The classification accuracy of the [784, 48, 35, 10] + [784, 50, 10] PNN during 100 epochs of training. The two sub-networks are trained separately in epochs 0′−59, then connected in parallel and trained together in epochs 60′−99. The activation function of each neuron is chosen as the sigmoid function. \( \alpha \) sub-networks are trained separately in epochs 0′−59, then connected in parallel and trained together in epochs 60′−99. The \( \alpha \) function.

\[ \alpha \text{ denotes the classification accuracy of the whole PNN. } \alpha_1 (\alpha_2) \text{ is the accuracy of Network 1 (Network 2) calculated from Eq. (3), and } \alpha'_1 (\alpha'_2) \text{ is the accuracy of Network 1 (Network 2) calculated from Eq. (4).} \]

On the other hand, however, after the connection is made, the PNN is trained and optimized with \( b = b_1 + b_2 \) being treated as an entirety that serves as the bias value inherent in the output neuron. Therefore, using \( z = w_i \cdot x_i + b \) to calculate the classification accuracy of Network \( i \) appears to be a better description of its contribution within the PNN when Network \( 'i' (i' \neq i) \) is bypassed. Let \( \alpha'_i \) denote the accuracy thus achieved.

To avoid the dilemma, in Fig.3 we show both \( \alpha_1, \alpha_2 \) and \( \alpha'_1, \alpha'_2 \). Fortunately, though their exact values are different, we shall see that they display the same qualitative results. In epochs 0′−59 where both Networks 1 and 2 are trained separately, Fig.3 shows that \( \alpha_1 \) and \( \alpha_2 \) grow rapidly in the first few epochs, then tend to saturate. There is always \( \alpha_1 \simeq \alpha_2 \). More rigorously, we find that their optimized values are

\[ \max(\alpha_1) = 97.63\% \]  

at epoch 50 and

\[ \max(\alpha_2) = 97.49\% \]  

at epoch 56, respectively. This agrees with our guess that two FNNs with similar numbers of parameters generally have similar performance. (Note that \( \alpha'_1, \alpha'_2 \) and the classification accuracy \( \alpha_{\text{para}} \) of the whole PNN have no actual meanings at this stage since the two sub-networks have not been connected yet. Still we plot them in all figures for reference.)

But an interesting change emerges when Networks 1 and 2 are connected at epoch 60. From Fig.3 we can see that the performance of Network 1 (either measured by \( \alpha_1 \) or \( \alpha'_1 \)) remains much the same, but \( \alpha_2 \) and \( \alpha'_2 \) drop dramatically when the connected PNN is trained as a whole, showing that Network 2 alone gives less and less correct classification results in the PNN. At epoch 99 we have \( \alpha_2 = 78.55\% \) and \( \alpha'_2 = 60.35\% \), both are significantly lower than the maximal accuracy \( \max(\alpha_2) \) that Network 2 could reach alone. In fact, detailed data (see Data availability section) shows that \( \alpha_1 \) and \( \alpha'_1 \) drop too, though not by much. Even so, the whole PNN outperforms each single FNN with its classification accuracy \( \alpha_{\text{para}} \) surpassing both \( \max(\alpha_1) \) and \( \max(\alpha_2) \). At epoch 86 it is optimized with

\[ \max(\alpha_{\text{para}}) = 98.05\%, \]  

where we have

\[ \alpha_1 = 97.51\%, \]  
\[ \alpha'_1 = 96.98\%, \]  
\[ \alpha_2 = 90.14\%, \]  
\[ \alpha'_2 = 71.39\%. \]

These results indicate that in a PNN, the sub-networks work in a different way than they do alone. It is distinct from the majority voting scheme where each sub-network does its best to find the correct results to make the combination of sub-networks do even better. On the contrary, it seems that once connected, the PNN can automatically divide the labor of the sub-networks, so that at least some (if not all) of the sub-networks (e.g., Network 2 in the current case) turn to capture other features of the input, instead of letting every sub-network to reach directly for the solutions of the classification task alone (we will elaborate this point further in (3) below). Consequently, when the whole PNN is optimized, the sub-networks tend to work on a status that appears to be unoptimized on their own.

(1.2) Now let us train the [784, 48, 35, 10] + [784, 50, 10] PNN for 100 epochs with the two sub-networks connected in parallel from the very start. We call this procedure training method B thereafter. The result is shown in Fig.4.

We can see that the property found in experiment (1.1) becomes more significant. While the classification accuracy \( \alpha_{\text{para}} \) of the whole PNN remains high, both \( \alpha'_1 (\simeq \alpha_1) \) and \( \alpha'_2 (\simeq \alpha_2) \) are much lower than either

FIG. 4: The classification accuracy of the [784, 48, 35, 10] + [784, 50, 10] PNN during 100 epochs of training. The two sub-networks are connected and trained together in all the 100 epochs. The notations are the same as those of Fig.3.
\(\alpha_{\text{para}}\) or the maximums that they could reach alone (i.e., \(\max(\alpha_1) = 97.63\%\) and \(\max(\alpha_2) = 97.49\%\) as found in (1.1)). When \(\alpha_{\text{para}}\) peaks at epoch 87 with
\[
\max(\alpha_{\text{para}}) = 97.77\% ,
\]
there are
\[
\alpha_1 = 10.18\% , \quad \alpha_1' = 10.06\% , \quad \alpha_2 = 81.08\% , \quad \alpha_2' = 82.27\% .
\]
(11)
Thus, it shows that the trend of dividing the labor within the PNN turns out to be more obvious when the sub-networks are connected earlier and longer.

Another significant observation is that we have \(\alpha_1' < \alpha_2'\) now, in contrast to \(\alpha_1' > \alpha_2'\) found in (1.1). It means that the \([784, 48, 35, 10]\) sub-network is not necessarily superior to the \([784, 50, 10]\) one, nor vice versa. The division of labor is determined more by the way how the biases and weights of the sub-networks are initialized, rather than the structure (e.g., the number of layers) of the sub-networks.

(1.3) The \([784, 48, 35, 10] + [784, 48, 35, 10]\) PNN. The above \([784, 48, 35, 10] + [784, 50, 10]\) PNN is the combination of two different types of FNNs. We may take them loosely as an eye and a nose. Now let us study the combination of two eyes.

Again, we first trained them using training method A. The classification accuracies are shown in Fig.5. The trend in (1.1) also appears here, but less significant (note that the y-coordinate in Fig.5 starts from 90\%, while it is 50\% in Fig.3). More precisely, when being trained separately, the two sub-networks are optimized at epoch 56 simultaneously, where they reach
\[
\max(\alpha_1) = 97.81\% ,
\]
and
\[
\max(\alpha_2) = 97.63\% ,
\]
respectively. But when they are connected at epoch 60, \(\alpha_1, \alpha_1', \alpha_2, \) and \(\alpha_2'\) all start to drop. When the whole PNN is found optimized at epoch 90, there are
\[
\max(\alpha_{\text{para}}) = 98.17\% , \quad \alpha_1 = 96.22\% , \quad \alpha_1' = 94.95\% , \quad \alpha_2 = 96.53\% , \quad \alpha_2' = 96.17\% .
\]
(14)
At epoch 99 when the training ends, we have
\[
\alpha_{\text{para}} = 98.13\% , \quad \alpha_1 = 94.35\% , \quad \alpha_1' = 93.70\% , \quad \alpha_2 = 96.31\% , \quad \alpha_2' = 95.40\% .
\]
(15)
At first glance this result looks “normal” and more like the real combination of two eyes than the previous two experiments, since \(\alpha_1\) and \(\alpha_2\) do not stray away from their optimized values too much after being connected. But wait! In the current case the two sub-networks are trained separately for 60 epochs first. For natural sense organs this will be very unusual instead. (When was the last time that you saw a human infant growing with two eyes being trained separately?) Therefore, to compare with the behavior of natural sense organs, the following experiment should be more suitable.

(1.4) Like (1.2), we also trained the \([784, 48, 35, 10] + [784, 48, 35, 10]\) PNN using training method B. The result is shown in Fig.6.

We can see that the dropping of \(\alpha_1, \alpha_1', \alpha_2, \) and \(\alpha_2'\) becomes obvious again (comparing with the maximal values that they could reach alone in the first 60 epochs of (1.1) and (1.3)). When the PNN is optimized at epoch 57 with
\[
\max(\alpha_{\text{para}}) = 98.16\% ,
\]
(16)
there are
\[ \alpha_1 = 65.82\%, \]
\[ \alpha'_1 = 69.77\%, \]
\[ \alpha_2 = 68.32\%, \]
\[ \alpha'_2 = 55.22\%. \] (17)

In brief, all the above experiments display a property different from natural sense organs. That is, as mentioned at the end of (1.1), when two artificial neural networks are connected in parallel and trained together as a PNN, each of them tends to work on an unoptimized status when the whole PNN is optimized. On the contrary, despite that there are still many unknown mysteries about life, at least we can be sure that barely anyone has experienced instant deterioration of the eye sight and the sense of smell though our eyes and nose are connected to the same brain and fed with the same input.

(2) Weight distribution.

Here we study a \([784, 48, 35, 10] + [784, 24, 18, 10]\) PNN using training method B. In this PNN, both sub-networks have two hidden layers. But the numbers of neurons and parameters of Network 2 are approximately 50% of those of Network 1, so it is expected to be less powerful if working alone. Now let us study whether it also plays less contribution in the PNN.

The classification accuracies are shown in Fig.7. Like Fig.4 and Fig.6, \(\alpha_{\text{para}}\) remains high while \(\alpha_1, \alpha'_1, \alpha_2, \) and \(\alpha'_2\) are much lower. At epoch 89 the PNN is optimized with

\[ \max(\alpha_{\text{para}}) = 98.02\%, \] (18)

where
\[ \alpha_1 = 76.08\%, \]
\[ \alpha'_1 = 75.17\%, \]
\[ \alpha_2 = 38.33\%, \]
\[ \alpha'_2 = 43.98\%. \] (19)

It is not surprising to find \(\alpha_1 \gg \alpha_2\) and \(\alpha'_1 \gg \alpha'_2\).

But a smaller \(\alpha_i (\alpha'_i)\) does not always mean that Network \(i\) contributes less in the PNN (although sometimes it does). A better measure is the weights at the output layer. If the weights corresponding to one of the sub-network is much smaller than these of the other, then it means that the output neurons actually ignore the inputs from the first sub-network, so that the PNN leans mainly on the latter to produce the classification output.

When the current PNN is optimized at epoch 89, we extract the weights at the output layer (more rigorously, the weights of the outputs of the neurons in the last hidden layer which are used for calculating the weighted inputs to the output neurons). The data is shown in Fig.8. Intriguingly, we can see that the weights of Networks 1 and 2 are on the same level, even though \(\alpha_1 (\alpha'_1)\) is almost twice as much as \(\alpha_2 (\alpha'_2)\).

This experiment reveals that in a PNN, the contribution of an inferior sub-network could be comparable with that of the other sub-network. This is yet another property that differs from natural sense organs. For example, the two eyes of many people (me included) have visual acuity differences. Most of the time I find myself mainly relying on the better eye only, while the worse one contributes little for my vision. But the current experiment shows that this is not always the case for artificial neural networks.

(3) Disagreed results.

The result in (2) shows that a sub-network could still play an important role in the whole PNN even if its own
classification accuracy $\alpha'$ is low. Then what is this sub-network busy working on? To answer this question, recall that at the end of (1.1), we said that in a PNN, the sub-networks are turned to capture other features of the input. Now we elaborate this point with more data analysis.

For each handwritten digit image among the MNIST data set being input to the PNN as an evaluation data, let $y$ denote the actual digit that it stands for. $r_1$, $r_2$ and $r_p$ denote the classification results of Network 1, Network 2 and the whole PNN, respectively, where $r_1$ and $r_2$ are calculated from Eq. (4). (We also tried calculating using Eq. 3. The qualitative results below remain the same despite that the exact values will vary.) All the results that the PNN classifies correctly can be categorized as four types:

- **Type I:** $r_p = y$ and $r_1 = y$ and $r_2 = y$.
- **Type II:** $r_p = y$ and $r_1 \neq y$ and $r_2 = y$.
- **Type III:** $r_p = y$ and $r_1 = y$ and $r_2 \neq y$.
- **Type IV:** $r_p = y$ and $r_1 \neq y$ and $r_2 \neq y$.

The first five rows (without counting the header) of Table I list the number of each type of the results of the PNNs studied in (1) and (2), whose biases and weights take the values when $\alpha_{para}$ is optimized. For example, the first row is corresponding to the $[784, 48, 35, 10] + [784, 50, 10]$ PNN when its $\alpha_{para}$ is optimized at epoch 86 in experiment (1.1).

What really catches our eyes is that all PNNs have a non-trivial amount of type IV results, i.e., the results $r_1$, $r_2$ of both sub-networks disagree with the actual digit $y$, still the whole PNN gives the correct result $r_p$. This result once again reveals that the sub-networks collaborate in a different way from our natural sense organs. Try close your right eye and read the following text with your left eye. Now open your right eye and close your left eye and read it again. Surely your both eyes recognize the same text correctly every time. While we still do not know exactly what happens in our brain during this process, it is unlikely that our left eye sees X, right eye thinks it as Y, while our brain comes up with Z and it is correct! But the existence of type IV results reveals that artificial neural networks can indeed work this way.

Let us look at the type IV results even closer. Table II shows a portion of the 92 type IV results mentioned in the first row of Table I (the full list is also available, see Data availability section). We can see that $r_p$ is not a single-valued function of $r_1$ and $r_2$. For example, when $r_1 = 2$ and $r_2 = 5$, $r_p$ can either be 1, 7 or 8, which cannot be deduced from $r_1$ and $r_2$ uniquely. Thus, when serving as a part of the PNN for the classification task, it is clear that the actual task of each sub-network is not to provide its own classification result $r_1$ alone. Instead, it is to provide other information of the handwritten digit image via the distribution of its weighted input to all output neurons. Then the whole PNN gathers all these different informations from every sub-network and draws its final conclusion.

This is similar to the networks with pooling, where certain parts of the network take charge of capturing certain features of the input. But as we mentioned, in these networks each neuron in the pooling layer connects with a portion of the neurons in the previous layer only. Now our result shows that the division of labor also takes place even when every sub-network connects with all input neu-

### TABLE I: The numbers of different types of correct results of each PNN. The total number of the evaluation data is 10000. The activation function of each neuron is chosen as the sigmoid function. Field name explanation:

- **Training method**: The two sub-networks are connected from the very start and trained for 100 epochs.
- **Type I**: The number of results when both sub-networks make the right classification.
- **Type II**: The number of results when only Network 1 is wrong.
- **Type III**: The number of results when only Network 2 is wrong.
- **Type IV**: The number of results when both sub-networks are wrong but the whole PNN is right.

| PNN                  | Training method | Number of results | Total | Type I | Type II | Type III | Type IV |
|----------------------|-----------------|-------------------|-------|--------|---------|----------|---------|
| [784, 48, 35, 10]    | A               | 9805              | 7044  | 59     | 2610    | 92       |
| [784, 48, 35, 10]    | B               | 9777              | 118   | 8055   | 864     | 740      |
| + [784, 50, 10]      |                 |                   |       |        |         |          |
| [784, 48, 35, 10]    | A               | 9817              | 9244  | 340    | 211     | 22       |
| + [784, 48, 35, 10]  |                 |                   |       |        |         |          |
| [784, 48, 35, 10]    | B               | 9816              | 3138  | 2341   | 3812    | 525      |
| + [784, 48, 35, 10]  |                 |                   |       |        |         |          |
| [784, 48, 35, 10]    | B               | 9802              | 3222  | 1141   | 4262    | 1177     |
| + [784, 24, 18, 10]  |                 |                   |       |        |         |          |
| [784, 45, 79, 10]    | B               | 9776              | 0     | 8369   | 963     | 444      |
| + [784, 50, 10]      |                 |                   |       |        |         |          |

### TABLE II: Some of the type IV results of the [784, 48, 35, 10] + [784, 50, 10] PNN optimized in experiment (1.1). $r_1$, $r_2$ and $r_p$ denote the classification results of Network 1, Network 2 and the whole PNN, respectively.

| $r_1$ | $r_2$ | $r_p$ |
|-------|-------|-------|
| 0     | 0     | 2     |
| 0     | 2     | 2     |
| 2     | 2     | 0     |
| 2     | 2     | 2     |
| 2     | 2     | 2     |
| 2     | 2     | 2     |
| 3     | 3     | 3     |
| 3     | 3     | 3     |
| 3     | 3     | 3     |
| 3     | 3     | 3     |

Data availability
rons.

We would like to mention another interesting observation that we found when studying the [784, 45, 79, 10] + [784, 50, 10] PNN. We optimized this PNN with the training method B and obtained $\max(\alpha_{\text{para}}) = 97.76\%$ at epoch 91. The last row of Table I shows the numbers of different types of correct results at this stage. Surprisingly, the number of type I results turns out to be 0. That is, the two sub-networks never reach the correct classification result simultaneously, while the whole PNN still comes up with a very high classification accuracy. This seems to be another divergence from the property of natural sense organs. We repeated the training of this PNN three times and the absence of type I results occurs twice (see Data availability section for full data), therefore it does not seem to be a rare case.

(4) Using other activation functions.

The above experiments are all performed with the sigmoid function serving as the activation function. Now we try these PNNs by replacing it with the rectified linear unit (ReLU) function

$$f(z) = \max(0, z) \quad (20)$$

or the Tanh function

$$f(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}. \quad (21)$$

Like experiment (1.4), with each form of the activation functions, we trained the [784, 48, 35, 10] + [784, 48, 35, 10] PNN using training method B for 9 trials. The number of type IV results ($n_{IV}$) and $\max(\alpha_{\text{para}})$ of each trial are listed in Table III.

From the average of $n_{IV}$, we can see that although the PNN with ReLU function still shows divergence from the connection of natural organs, it is the closest among the three, since it has the lowest average $\bar{n}_{IV} = 457$. The PNN with sigmoid function ($\bar{n}_{IV} = 644$) could have been close, if not for the crazy high value $n_{IV} = 2086$ in Trial 4 (the average of the other 8 trials will drop down to 464). With the Tanh function, the result $\bar{n}_{IV} = 841$ is undoubtedly the highest. Even if we discard the highest value $n_{IV} = 1911$ in Trial 7, the average of the rest trials is still 707.

**Discussion**

In summary, when two sub-networks connect and form an PNN, our first three experiments show that there are three properties which distinguish artificial neural networks from the parallel connection of natural biological sense organs. Namely, experiment (1) shows that when the classification accuracy $\alpha_{\text{para}}$ of the PNN is optimized, the classification accuracies $\alpha_i$ and $\alpha'_i$ of each sub-network will be lower than the maximal values that could be obtained when being trained and optimized alone. Even if the sub-networks are trained and optimized separately beforehand, $\alpha_i$ and $\alpha'_i$ will drop once they are connected. But for natural organs such as two eyes, connecting to the same brain should not make the eye sight of each of them deteriorated. Training two eyes separately does not seem to be a common practice either. Also, experiment (2) shows that the contribution of an inferior sub-network to the whole PNN is on par with that of a superior sub-network. This is in contrast to two real eyes with visual acuity differences, where the better eye generally does most of the job. Moreover, experiment (3) shows that the PNN can output the correct result when both sub-networks give incorrect and disagreed results, i.e., the type IV results, which is also impossible for natural organs like we said in the introduction.

As an amusing thought, assume that someday we could build a robot with these artificial neural networks serving as sense organs. If these artificial organs are connected to the cyberbrain ever since the robot is “born”, then weird things happen as they “grow”. Like our experiments (1.2), (1.4) and (3), as they are trained together, they will eventually turn into fuzzy eyes, mishearing ears and malfunctioning nose, still the cyberbrain becomes more and more clever! While this may somehow like a wise old man, it does not appear to be the meaning of “bionics” that people agree with. On the other hand, experiments (1.3) suggested that the final result will look closer to natural organs if the artificial ones are trained and optimized separately before putting them together. Therefore, in the future if we want a robot that could act like human, then all parts have to be trained separately before being assembled. We could not expect them to be put together at “birth” and then grow and learn as an entirety like a human baby.

Back to the topic, these three experiments lead us to the idea that the three divergences from natural sense organs, especially the number (or ratio) of type IV results, can be used as a criterion for measuring the bionic

| Trial | sigmoid $n_{IV}$ ($\%$) | $\alpha$ (%) | ReLU $n_{IV}$ ($\%$) | $\alpha$ (%) | Tanh $n_{IV}$ ($\%$) | $\alpha$ (%) |
|-------|-----------------|-------------|-----------------|-------------|-----------------|-------------|
| 1     | 525             | 98.16       | 338             | 97.84       | 1056            | 97.72       |
| 2     | 684             | 98.04       | 1028            | 97.90       | 504             | 97.65       |
| 3     | 384             | 98.21       | 112             | 97.80       | 695             | 97.68       |
| 4     | 2086            | 98.16       | 950             | 97.91       | 629             | 97.75       |
| 5     | 256             | 98.08       | 224             | 97.84       | 504             | 97.90       |
| 6     | 284             | 98.13       | 393             | 97.65       | 364             | 97.86       |
| 7     | 234             | 98.18       | 638             | 97.81       | 1911            | 97.58       |
| 8     | 1056            | 98.19       | 175             | 97.83       | 515             | 97.91       |
| 9     | 286             | 98.18       | 259             | 97.92       | 1392            | 97.72       |
| Average | 644             | 98.15       | 457             | 97.83       | 841             | 97.75       |
level of an artificial neural network. The more serious
divergences we observe, the less likely it is for such a
network to mimic the actual internal mechanism of real
living creatures.

Experiment (4) further proves that this criterion can
indeed manifest the differences among neural networks
when other parameters fail. As shown in Table III, when
the activation function of an artificial neural network is
chosen as the sigmoid, ReLU, or Tanh functions, respec-
tively, there is no significant differences on their classifi-
cation accuracies. But when we look at their numbers of
type IV results, the ReLU function shows the potential
to make the neural network more bionic according to our
criterion.

This may somewhat deepen our understanding on the
ReLU (rectified linear unit) function. As pointed out in
chapter 3 of Ref. [6], “some recent work on image recog-
nition has found considerable benefit in using rectified
linear units through much of the network. However, ..., we
do not yet have a really deep understanding of when,
exactly, rectified linear units are preferable, nor why.”
Also in chapter 6, “a few people tried rectified linear
units, often on the basis of hunches or heuristic argu-
ments. ... In an ideal world we’d have a theory telling us
which activation function to pick for which application.
But at present we’re a long way from such a world. ...
Today, we still have to rely on poorly understood rules
of thumb and experience.” But now we find that even if
there is no obvious difference between ReLU and other
functions on the classification accuracy or other proper-
ties, still we can test their bionic level using our criterion.
And the observation that ReLU has benefit in tasks like
image recognition may indicate that it is a better approx-
imation of the input-output dependence of a real living
neuron than other functions do.

If this is indeed the case, then it can further lead to a
method for learning the input-output dependence of nat-
ural neurons, which is difficult to measure directly with
biological experiments. That is, we can try proposing
another form of the activation function, then build artifi-
cial networks upon it and test their bionic level with our
criterion. If they appear to be more bionic than the net-
works using ReLU function, then we know that the curve
of this activation function describes the input-output de-
pendence of natural neurons even better.

Note that our criterion does not indicate that one neu-
ral network is superior or inferior to another. It merely
tells which one is more bionic.

Finally, the activation function is only one of the char-
acters that can affect the bionic level of an artificial neu-
ral network. Other characters (e.g., the number of layers,
the usage of pooling, etc.) may also show their impact
if we study the number of type IV results. These works
could be considered for future researches.

Methods

Our PNNs were trained using the Python programs ac-
company with this paper (see Code availability section).
The programs are based on the program network2.py
supplied with Ref. [6], where the training methods in-
clude L2 regularization, the usage of the cross-entropy
cost function, randomly shuffling the training data, and
the weights input to a neuron are initialized as Gaussian
random variables with mean 0 and standard deviation
1 divided by the square root of the number of connec-
tions input to the neuron, as elaborated in chapter 3 of
Ref. [6]. Note that our purpose is to study the behav-iors of parallel-connected networks, instead of trying to
find the highest possible classification accuracy. Thus, to
keep things simple, we did not use other advanced train-
ing techniques, e.g., dropout, artificial expansion of the
training date, softmax, local receptive fields and pooling,
etc.

Due to the randomness in the initialization of the bi-
ases and weights and the shuffling of the training data,
the exact values of the classification accuracies in differ-
ent runs of the programs will vary. To avoid our results
being too extreme, the training of each PNN studied in
the Experiments section was repeated 3 times (9 times
for experiments (1.4) and (4)). Then we picked the one
whose max(αpara) takes the middle value of all runs, and
labelled it as Trial 1. The other runs were labelled as
Trials 2–3 (2–9). We used the data in Trial 1 to pot the
figures in the Experiments section. The data in Trials
2–3 (2–9) are not shown. But we also provide them with
the paper for reference (see Data availability section).

Data availability

The raw experimental data of this study are publicly
available at https://github.com/gphehub/pnn2204.

Code availability

The software codes for generating the ex-
perimetal data are publicly available at
https://github.com/gphehub/pnn2204.

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G.P.H. researched and wrote this paper solely.

Competing interests
The author declares no competing interests.