Can Neural Networks Recognize Parts?

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We have demonstrated neural networks can recognize parts by visual images. Input signals are gray scale photographs of objects consisting of some parts and output signals are their shapes. By training neural networks by a few set of images, without any supervision they become to be able to recognize the boundary between parts.

KEYWORDS: Neural network, visual intelligence, recognition of parts

1. Introduction

Visual intelligence (VI)\textsuperscript{1} plays very important roles in the visual cognition. In retina system, we can accept only two dimensional projections of three dimensional objects. Without any other informations, we have to recognize three dimensional object from it. Of course, there are infinitely many interpretations of this two dimensional image received, but usually we reconstruct unique three dimensional world. And it is often the proper interpretation (otherwise, we would be extinct).

VI provides us the set of rules of interpretation to have these proper reconstructions of three dimensional space. There are many tasks to be solved by VI, for example, reconstruction of roughness from gray scale image,\textsuperscript{2} recognition of depth from line drawings,\textsuperscript{3} and decision of motion from sequential still images.\textsuperscript{4}

One of such tasks is to recognize parts.\textsuperscript{5} When we view a pair of iron dumbbells, we recognize it as two spheres connected by a rod. Although there are some theories\textsuperscript{5} to explain how we can divide a pair of iron dumbbells into three parts, there are no theories about how we can learn rules suggested by these theories. In this paper, we demonstrate that even a set of simple neural networks can become to be able to recognize parts without any supervision if many enough number of combinations of parts are presented, even if there are no informations about what each part is. It seems to be very easier process than imagined.

In §2, we have defined the objects from which we generate visual images. Section 3 describes how to train neural networks so that it recognizes three dimensional shapes and parts from...
the visual images. Discussions and Conclusions are in §4 and §5, respectively.

2. Objects used

In order to make neural networks learn what the parts are, we have to present grey scaled images of three dimensional objects. However, if the objects are too complicated, training neural networks to learn them is simply time consuming. It is a waste of time. We need some simple images which are two dimensional projection of a set of three dimensional objects and are easily recognized as a set of parts by human beings. As such examples, we employ the images shown in Figs. 1. If someone asks “What does Fig. 1(a) look like?”, the answer may be “Five hemispheres on a plate with a round hollow”. These “hemispheres” and “a hollow” are the parts. It is very easy for us to recognize these parts. But how did we become to be able to do this?

3. Training neural networks

In order to check how easy it is to learn what the parts are, we try to train neural networks to recognize them. The neural networks used are standard three layered perceptrons,

\[
\mu_j = \sum_{i=1}^{L} a_{ij} x_i + a_{0j},
\]

\[
y_j = f(\mu_j),
\]

\[
\nu_k = \sum_{j=1}^{M} b_{jk} y_j + b_{0k},
\]

\[
z_k = f(\nu_k),
\]

where

\[
f(\mu) = \frac{1}{1 - \exp(-\mu)},
\]

and \(x_i, y_j\) and \(z_k\) are values of the input neurons, the neurons in the hidden layer and the output neurons respectively. \(a_{ij}\)s and \(b_{jk}\)s are connection coefficients which are trained by usual back propagation procedure.

In order to decide values of input \(x_i\)s, we have subdivided a image into \(20 \times 30\) lattices
(Fig. 2). $x_i (i = 1, \ldots, 600)$ takes 1(0) if center pixel is white (black). In total, $2^6 = 64$ images can be considered because each of the six parts has two possibilities that it can take.

### 3.1 Recognition of a hollow or a hemisphere

First, we would like to check whether neural networks can recognize both a hollow and a hemisphere successfully. Thus, we define six $z_k, (k = 1, \ldots, 6)$ as follows, while suffix $k$ corresponds to one of six parts; if the $k$th part is a hemisphere (a round hollow), $z_k$ takes 1(0).

We have employed 600 neurons in the hidden layer. Although one may think that it is too large for this simple task, it is not the case because later we use this for learning the three dimensional shapes.

In Fig. 3, we have shown the dependence of the average number of patterns $\bar{S}$ recognized correctly by trained neural networks upon a number $n$ of images used for training. Of course, $z_k$s take non integer values between 0 and 1, but we regard $z_k = 1(0)$ when $z_k > (<) 0.5$. Averages are taken over ten independent training for each $n$. As can be seen easily, if $n$ is
Fig. 3. Averaged number of correctly recognized patterns out of total 64 images as a function of number of trained images. (a hollow or a sphere recognition)

Fig. 4. Output $h_i$s for three dimensional shape recognition.

larger than one third of total number of images, neural networks correctly recognize hollows and hemispheres for all images. Thus, neural networks can recognize a hollow and a hemisphere correctly.

3.2 Recognition of 3D shapes

Next we try to make neural networks recognize three dimensional shapes. This time, outputs $z_k$s are the coarse grained height $h_k$ of a hollow or a hemisphere (Fig. 4). We have subdivided surface of three dimensional shapes into $15 \times 10 = 150$ lattices. $h_k$ takes value
Fig. 5. Output $h_i$s by trained neural networks. Input is an unknown (not used for training) image.

between 1 and 0. The surface of flat plate is regarded to have height 0.5, and the bottom of hollows has 0 and the top of hemisphere has 1.0.

In Fig. 5, we have shown the ability of trained neural networks. This neural networks are trained using 24 out of total 64 images. Then a image not used for training is presented. As can be seen easily, the neural networks can easily recognize the 3D shape even if unknown image is presented.

In Fig. 6, we have shown the dependence of the average number of patterns $\bar{S}$ recognized correctly by trained neural networks upon a number $n$ of images used for training. It is possible for neural networks to learn 3D shapes if $n$ is larger than 15. Thus, neural networks correctly recognize 3D shapes.

3.3 Recognition of parts

Until now, we did not provide any information about what the parts are. However, neural networks have learned it as shown below. In order to see whether the neural networks recognize parts, we have shown three hollows/spheres on a flat plane to the neural networks. If they can recognize what the parts are, they can reproduce 3D shapes. As shown in Fig. 7, neural networks can recognize each hollow/hemisphere as a part. Even if there is only one
Fig. 6. Averaged number of correctly recognized patterns out of total 64 images as a function of number of trained images. (3D shapes recognition)

Fig. 7. Recognition of parts

hollow/hemisphere on a plate, they can reproduce three dimensional shapes correctly. This means that without any supervisions, neural networks can recognize each hollow/hemisphere as a part.

4. Discussion

How do neural networks relate the regions of a grey scale image to the regions on a flat plate? We did not provide such a information at all. However, once neural networks recognize correspondence between parts in images (input information) and parts in 3D shapes (output information), it is essentially to find relations between 6 bit input and 6 bits output (In bit interpretation for example, a hemisphere corresponds to 1 and a hollow corresponds to 0.).
Fig. 8. (a) Averaged number of correctly recognized patterns out of total 64 images as a function of number of trained images (For 6 input/output neurons). (b) The same as (a) for 3D shape recognition with 50 neurons in hidden layers

Thus, it is a very easy task for neural networks.

In order to check the easiness, we use 6 neurons at input and output layers and 30 neurons at hidden layers. \( x_i \) and \( z_k \) take 0 or 1 and neural networks are trained such that \( x_i = z_k \) when \( i = k \). As shown in Fig. 8(a), it is possible for neural networks to do this. Thus, at maximum, neural networks need only 30 neurons in hidden layer. Thus, if neural networks recognize parts, the numbers of neurons can be as small as 600.

Actually, as shown in Fig. 8(b), neural networks can have the same ability as Fig. 6 even if the number of neurons is only 50. This is almost the number of neurons in the hidden layer of neural networks whose ability is shown in Fig. 8(a). Thus we can conclude that neural networks recognize parts well and can drastically reduce the number of neurons in hidden layers. This is how to learn what the parts are. If the simple network can recognize it so easily, our neuron can do the same without difficulty. This may be the reason why we became to be able to recognize the image as a set of parts. It can reduce the number of neurons in hidden layers drastically as expected. Without recognition of parts, it is impossible to reduce the number of neurons in the hidden layer.

5. Conclusion

In conclusion, we have shown that neural networks can divide the image into parts automatically during training process. It turns out to reduce number of used neurons in hidden layer, i.e., memories drastically. This may be the reason why we became to be able to recognize the image as a set of parts.
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