A Neural-Network to get Correlated Information among Multiple Inputs

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Abstract

Humans can obtain useful information from sensor inputs and motion signals. The author takes a stand on the importance of the information which commonly exists among multiple inputs, which is called correlated information here, especially among sensor and motion signals. First, a method to get correlated information is proposed. In this method we enter multiple inputs to plural neural-networks respectively and make each output of each network communicate with that of the other network. Basic experiments were examined and it was confirmed that the correlated information can be extracted.

1. INTRODUCTION

Machines have become intelligent using sensor and motion signals. Especially in the last few years, it has become to be focused to not only improvement of precision but higher-level recognition by using multiple sensor signals, i.e. sensor integration[1]. In the brain, there is the association area which is said to associate motion and sensory signals, such as vision, auditory and somato-sensory, with each other.

Let us think how the integration is realized in living creatures. It is thought to be done taking a form of extracting the correlated information when human makes various concepts and learns spatial recognition and so on. For example, the abstract concept *piano* is formed by visual information, the shape of piano and the word "piano", and auditory information, the sound of piano and the pronunciation "piano" and other information about piano. In the other hand the R. Held and A. Hein's experiment[2] shows us that it is important for getting the spatial recognition ability not only to use vision but also to move intentionally. We can think the reason of this fact is that spatial recognition ability can be obtained by learning of the correlation between visual sensor signals and somato-sensory signals or motion isignals. We can get these abilities by an efficient unsupervised learning method in which only inputs are needed. And these abilities are needed for real *machine intelligence* which means that a machine starting from scratch has to be getting some knowledge through its experiences and become intelligent gradually.

Some methods to realize sensor-integration using neural-network were proposed already[3][4]. But in these methods, extraction of correlated information among multiple inputs is not done. Then in this paper, the author defines extraction of correlated information among multiple inputs first. Next, a method to realize the learning of this extraction by neural-network is proposed. A method to make extracted plural dimensions of correlated information orthogonal to each other is also proposed here. At last, basic experiments to examine these methods are described.

2. DEFINITION AND METHOD OF EXTRACTING CORRELATED INFORMATION

2.1 Importance and Definition

As mentioned above, some models to realize sensor-integration using neural-network has been proposed[3][4]. These methods use the architecture which was proposed by Hinton and Rumelhart et. al.[5]. This architecture uses layered network with fewer hidden units, as shown in Fig.1, and we can get compressed information as outputs of hidden units which represent correlation between inputs and supervisors for output units which is the same or similar signals as input. So if the supervisors are prepared automatically, we can realize unsupervised learning. But in this architecture, the information to calculate supervisors remain as much as possible in the internal representation. So, extraction

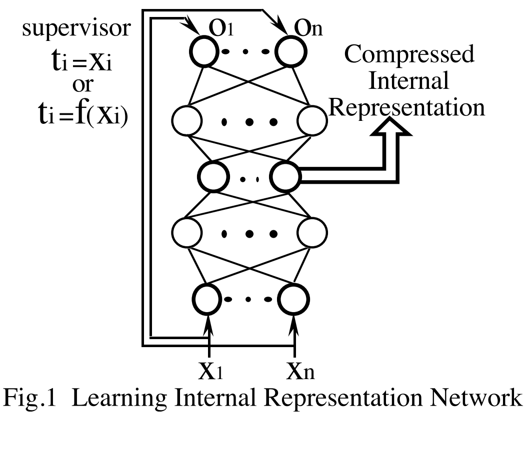

Fig.1 Learning Internal Representation Network

of the correlated information is not done and the efficient compression cannot be done.

In this paper the idea of extracting the correlated information among multiple inputs as defined below is introduced. Assuming that given two kinds of information vectors which change according to time are $\boldsymbol{x}(t)=[x_1(t),x_2(t),...,x_m(t)]$ and $\boldsymbol{y}(t)=[y_1(t),y_2(t),...,y_n(t)]$ respectively, and the extracting correlated information is defined to extract the vector $\boldsymbol{r}(t)=[r_1(t),r_2(t),...,r_l(t)]$ which is defined as

$$\mathbf{r}(t) = \boldsymbol{f}(\boldsymbol{x}(t)) = \boldsymbol{g}(\boldsymbol{y}(t)). \qquad (1)$$

$\boldsymbol{f}, \boldsymbol{g}$: vector functions which have same dimension as $\boldsymbol{r}$

This means to find out pairs of functions $f_i(\boldsymbol{x}(t))$, $g_i(\boldsymbol{y}(t))$ and the number of the pairs which are independent of each other and in which the values of $f_i(\boldsymbol{x}(t))$ and $g_i(\boldsymbol{y}(t))$ are always equal. By the progress of this learning, the higher level of information can be imaged even if only one kind of information is given, and this method has a probability of a general abstracting method.

2.2 The Method of Extracting for One Output

Here it is proposed to use the basic architecture shown in Fig.2 to extract the correlated information. The multiple inputs are entered to each layered network and then exchange the outputs of one network as the supervisors of the other network. Both networks are trained by error-back-propagation method. If the error becomes a value around 0 by learning, the outputs of both networks must be equals and must be the function of the network input. For this simple reason, the output become the correlated information among multiple inputs as shown in eq.(1).

In order to extract the correlated information, we must avoid the trivial solution

$$f(\boldsymbol{x}(t)) = g(\boldsymbol{y}(t)) = const.. \qquad (2)$$

To avoid a state like this and to use an appropriate value range, the Value Range Expanding Operation is proposed. In this operation, for every cycles, which includes learning of some number of patterns, for example 100 patterns, the input pattern which gave the maximum output value in the last cycle is re-entered to the network and the network learned by the given supervisor 0.9. And the input pattern which gave the minimum output value is also re-entered and learned by the supervisor 0.1.

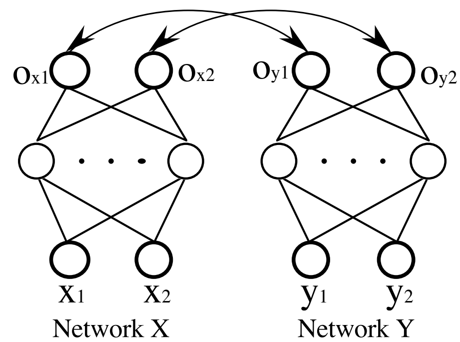

Fig2 A network structure to get correlated informations among multiple inputs

Here let us look at the cortex structure including the association area. It is layered structured and made of cells which expand perpendicularly like cone cells, and cells which expand horizontally like horizontal cells[6]. Making an analogy between this structure, and that proposed in this paper, the author thinks that the perpendicularly expanding cells correspond to the layered network and the horizontally expanding cells correspond to the organization to exchange network outputs.

2.3 The Orthogonality Method of the Correlated Informations

In many cases, the correlated information vector is higher than two dimensions. For example, if we try to extract the three dimensional spatial position, we need at least three types of signals. In this case, we prepare plural output neurons in each network making a one-to-one correspondence between networks, exchange output value with each other according to this correspondence as shown in Fig.2, and make these networks learn as the outputs of them become same values as the correspondent output values. Here the method in which one output of one network is given to the correspondent output of the other network as the supervisor and make these networks learn with back_propagation method is employed. But as plural output values become either almost same value or the opposite value which is symmetric at 0.5 (when one value is near 0, the other is near 1 if the activation function is symmetric at 0.5) after learning, we can't extract information of two dimensions. To solve this problem and to extract plural informations effectively, each output neuron affects to each other to have a different value during learning. It is called Orthogonality Method here. Concretely, the degree of independence $I_j(n)$ of the jth output to the other outputs at the nth input pattern is defined as follows.

$$I_j(n) = \frac{\{\sum_i o_{ij}(n) - mid_j\}^2}{\sum_{k \neq j}\{\sum_i o_{ok}(n) - mid_k\}^2 + \alpha} \tag{3}$$

$o_{ik}(n)$: the output of the kth output neuron in the ith network at the nth input pattern
mid_k : the average between the maximum and minimum value of $\sum_i o_{ik}(n)$ in the last cycle
α : small constant value. 0.001 is proper from experiences.

Using this value, the Value Range Expanding Operationthe is done as follows. Input patterns which gave the maximum I value when $\{\sum_i o_{ij}(n)\text{-}mid_j\}$ is positive, are re-entered to the network and the network is learned by the supervisor of 0.9, and the input patterns which gave the maximum I value when $\{\sum_i o_{ij}(n)\text{-}mid_j\}$ is negative, are re-entered to the network and the network is learned by the supervisor of 0.1.

But after this learning the maximum output value in one cycle is sometimes larger than the output value when the independence value I is maximum. This shows that orthogonality between plural outputs is not enough. Then the input pattern which gave the maximum output value in one cycle, re-enter to the network and the network is learned by the supervisor which is same as the output value when the independence value I is maximum. And about the minimum output value, the network is learned like the maximum. So the output value when the independence value I is maximum becomes close to the maximum output value, and we can realize to make plural correlated informations orthogonal to each other.

3. BASIC EXPERIMENTS

3.1 One Output

First the basic function of this architecture at the case of only one correlated information is examined. Let the correlated information r be

$$r = x_1 + x_2 = 3y_1y_2. \tag{4}$$

and (x_1,x_2) and (y_1,y_2) are given to the two networks respectively and make them learned on condition that x_1, x_2, y_1 are chosen using random number independently and y_2 is decided by entering x_1, x_2 and y_1 to the eq.(4). Figure 3 shows the fluctuations of the sum of maximum and minimum value in each cycle. Figure 4 shows the fluctuation of the sum of errors without those at the Value Range Expanding Operation. The error means how close these two outputs are. Looking at both figures, we can recognize roughly that at first the output values are random and the error is large, but then both output values become to be near 0.5 and the error become to be 0. We can also recognize that the more time passed the larger is the difference between maximum and minimum value gradually by the Value Range Expanding Operation. Figure 5 shows the output values of both networks corresponding to the correlated information r. This figure shows us that the output value is decided from only the correlated value r, and it can be said that we can extract the correlated information from multiple inputs, $\boldsymbol{x}$ and $\boldsymbol{y}$.

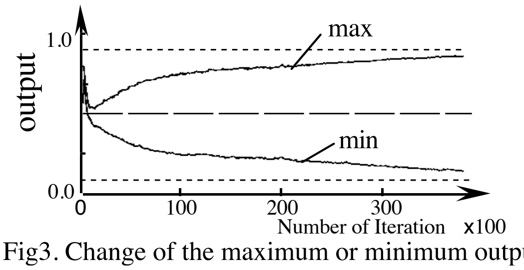

Fig3. Change of the maximum or minimum output

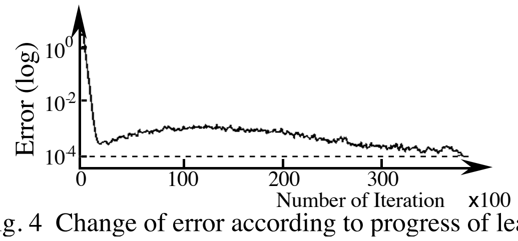

Fig. 4 Change of error according to progress of learning

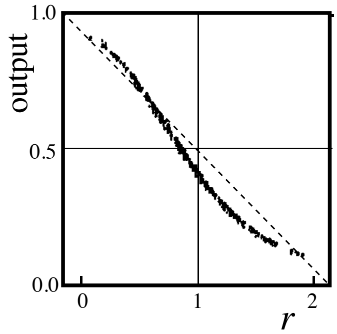

Fig.5 Output of each network corresponding to related information r

3.2 Two Outputs

Here the Orthogonality Method is tried to be examined. Following relations are set up.

$$x_1 = (r_1 + r_2) / 2.0$$
$$x_2 = (r_1 - r_2 + 1.0) / 2.0$$
$$y_1 = r_1 r_2$$
$$y_2 = \{(r_1+1.0) / (r_2+1.0) - 0.5\} / 1.5 \qquad (5)$$

x_i : Input of Network No.1
y_i : Input of Network No.2
r_i : Correlated Information (Randomly chosen)

After learning we can get two outputs as shown in Fig.6 (a) (b) respectively. It shows us two outputs corresponding to r_1, r_2. The angle between the big arrow in Fig.6 (a) and that of Fig.6 (b) is about 90°, exactly 88°, so it can be said that two outputs are made orthogonal to each other.

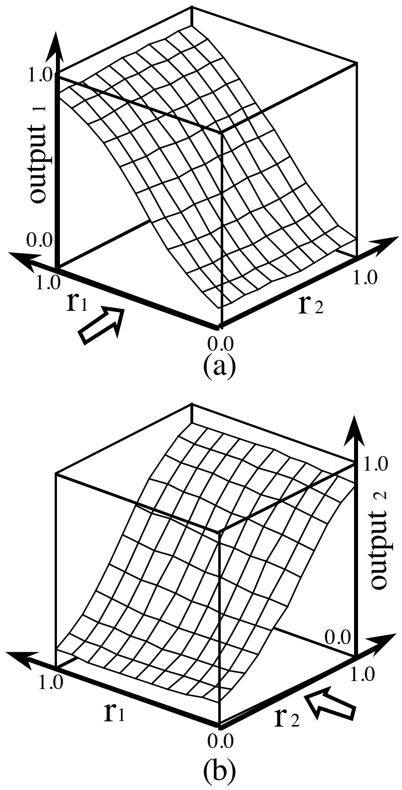

Fig.6 Two outputs corresponding to two correlated informations r_1 r_2

4 CONCLUSION

It has been proposed that it is important to extract the correlated information from multiple inputs, especially sensor inputs as one of the sensor-integration methods. Value Range Expanding Operation proposed in this paper was confirmed to be useful to get the correlated information effectively, and it was confirmed that the extracted information was orthogonal to each other after learning by the proposed Orthogonality Method if extracted information has two dimensions.

The author thinks that the architecture proposed in this paper is a model of the association area in the cortex. But as the Value Range Expanding Operation or the Orthogonality Method are too artificial that it needs much help from human, the author thinks the model should be improved to be more self-organizing.

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