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# A NEURAL NETWORK FOR CONTROLLING THE CONFIGURATION OF FRAME STRUCTURE WITH ELASTIC MEMBERS

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## Abstract

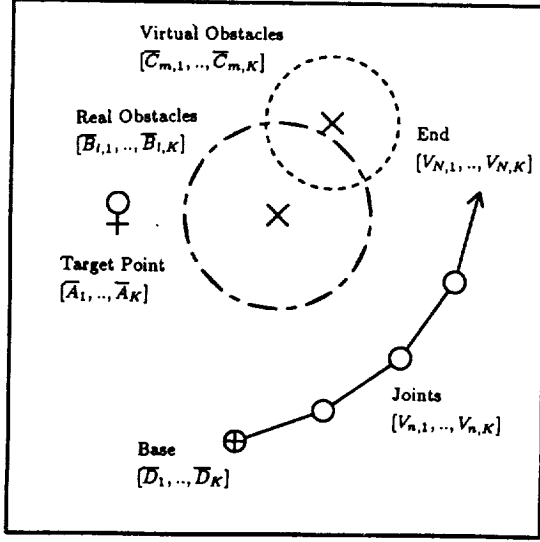
A neural network for controlling the configuration of frame structure with elastic members is proposed. In the present network, the structure is modeled not by using the relative angles of the members but by using the distances between the joint locations alone. The relationship between the environment and the joints is also defined by their mutual distances. The analog neural network attains the reaching motion of the manipulator as a minimization problem of the energy constructed by the distances between the joints, the target, the obstacles, etc. The network can generate not only the final but also the transient configurations and the trajectory. This framework with flexibility and parallelism is very suitable for controlling the Space Telerobotic systems with many degrees of freedom.

## 1. Introduction

In the field of Space Telerobotics, the frame structures with elastic members are paid attention as new types of robot manipulators, space cranes, etc[1]. They can be transformed to various configurations with ease. And also they can be easily disassembled / assembled and folded / unfolded. However, in general, it is very difficult to control such structure with excessive degrees of freedom. On the other hand, the applicability of neural networks to Robotics attracts a lot of researchers who produce interesting results. The possibility of parallel computation and/or the learning capability with generalization are especially emphasized as excellent characteristics of neural networks. Recently this field is expected to be in harmony with Space Telerobotics.

Tsutsumi et al. proposed a new method for controlling the configuration of the robot manipulator based on the Hopfield's neural network model[2]. According to this framework, the structure of the manipulator is modeled not by using the polar coordinate but by using the distances between the joint locations alone. The relationship between the environment and the joints is also defined by their mutual distances. The constraints, for instance, 'to keep the link lengths constant', 'to keep the safe distances between the farther joints', 'to avoid the obstacles', and 'to reach the target point', can be defined as energy terms based on the distances. By virtue of this formulation, the problem for the control resolves itself into how to find out the parameters so as to minimize the total energy. The neural network derived from the energy can control not only the ordinary manipulator with rigid links but also the elastic arm by weighting the energy terms adequately. And the processing speed does not depend on the number of degrees of freedom when the parallel analog hardware is employed.

In Sect.2, we describe the mathematical framework of the proposed method. In Sect.3, we apply it to 3-dimensional frame structure with elastic members and show the simulation results. The problems for the obstacles etc. and the future courses are discussed in the last section.



[Fig.1] The structure of the manipulator in the workspace with real and virtual obstacles.

## 2. Formulation and Neural Network

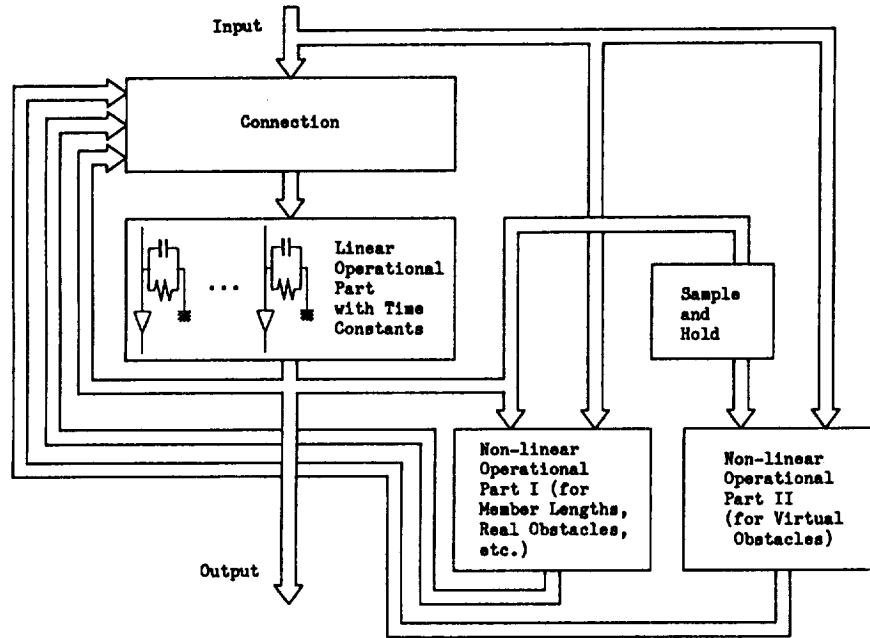
We consider an ideal robot manipulator as shown in Fig.1. The positions of the base, the movable joints, and the end are respectively given by  $\bar{D}_k$ ,  $V_{n,k}$  ( $n = 1, 2, \dots, N-1$ ), and  $V_{N,k}$  ( $k = 1, 2, \dots, K$ ). The target point is  $\bar{A}_k$  ( $k = 1, 2, \dots, K$ ).  $L$  real and  $M$  virtual obstacles are assumed to be located on the position  $\bar{B}_{l,k}$ ,  $\bar{C}_{m,k}$  ( $l = 1, 2, \dots, L$ ,  $m = 1, 2, \dots, M$ ,  $k = 1, 2, \dots, K$ ). The joints and the end have sensors which can get the information about the following distances:

$$\begin{aligned}
 S_{n,1} &= [\sum_{k=1}^K (V_{n,k} - \bar{D}_k)^2]^{1/2} & (n = 1, 2, \dots, N) \\
 S_{n,n'} &= [\sum_{k=1}^K (V_{n,k} - V_{n'-1,k})^2]^{1/2} & (n = 2, 3, \dots, N, n' = 2, 3, \dots, n, n \geq n') \\
 P_n &= [\sum_{k=1}^K (V_{n,k} - \bar{A}_k)^2]^{1/2} & (n = 1, 2, \dots, N) \\
 Q_{n,l} &= [\sum_{k=1}^K (V_{n,k} - \bar{B}_{l,k})^2]^{1/2} & (n = 1, 2, \dots, N, l = 1, 2, \dots, L) \\
 R_{n,m} &= [\sum_{k=1}^K (V_{n,k} - \bar{C}_{m,k})^2]^{1/2} & (n = 1, 2, \dots, N, m = 1, 2, \dots, M)
 \end{aligned} \tag{1}$$

If one can find out the set of  $V_{n,k}$  so that  $P_N \Rightarrow 0$  conserving the following constrains,

$$\begin{aligned}
 S_{n,n} &= \bar{S}_{n,n} & (n = 1, 2, \dots, N) \\
 S_{n,n'} &\geq \bar{S}_{n,n'} & (n = 2, 3, \dots, N, n' = 1, 2, \dots, n-1) \\
 P_n &\geq \bar{P}_n & (n = 1, 2, \dots, N-1) \\
 Q_{n,l} &\geq \bar{Q}_{n,l} & (n = 1, 2, \dots, N, l = 1, 2, \dots, L) \\
 R_{n,m} &\geq \bar{R}_{n,m} & (n = 1, 2, \dots, N, m = 1, 2, \dots, M)
 \end{aligned} \tag{2}$$

then the behaviour of the solution corresponds to the action of the robot manipulator. Here  $\bar{S}_{n,n}$  represent the desirable link lengths.  $\bar{S}_{n,n'}$  ( $n > n'$ ),  $\bar{P}_n$ ,  $\bar{Q}_{n,l}$ , and  $\bar{R}_{n,m}$  are radii of the keep-off



[Fig.2] Block diagram of the analog neural network employed here.

regions characterized by the cone-type potential. Based on the constraints given by Eq.(2), we define the following energies:

$$\begin{aligned}
 ES_{n,n} &= (1/2) * (S_{n,n} - \bar{S}_{n,n})^2 & (n = 1, 2, \dots, N) \\
 ES_{n,n'} &= (1/2) * F(S_{n,n'} - \bar{S}_{n,n'}) & (n = 2, 3, \dots, N, n' = 1, 2, \dots, n-1) \\
 EP_n &= (1/2) * F(P_n - \bar{P}_n) & (n = 1, 2, \dots, N-1) \\
 EP_N &= (1/2) * P_N^2 \\
 EQ_{n,l} &= (1/2) * F(Q_{n,l} - \bar{Q}_{n,l}) & (n = 1, 2, \dots, N, l = 1, 2, \dots, L) \\
 ER_{n,m} &= (1/2) * F(R_{n,m} - \bar{R}_{n,m}) & (n = 1, 2, \dots, N, m = 1, 2, \dots, M) \\
 EG_{n,k} &= (1/r_{n,k}) * \int_0^{V_{n,k}} g^{-1}(V) dV & (n = 1, 2, \dots, N, k = 1, 2, \dots, K)
 \end{aligned} \tag{3}$$

$$\text{where } g(x) = x \quad \text{and} \quad F(z) = \begin{cases} 0 & \text{if } z \geq 0 \\ z^2 & \text{otherwise} \end{cases}$$

Adding up these energy terms to get the total energy given by Eq.(4),

$$E = \sum_{n=1}^N \sum_{n'=1}^N ES_{n,n'} + \sum_{n=1}^N EP_n + \sum_{n=1}^N \sum_{l=1}^L EQ_{n,l} + \sum_{n=1}^N \sum_{m=1}^M ER_{n,m} + \sum_{n=1}^N \sum_{k=1}^K EG_{n,k} \quad (4)$$

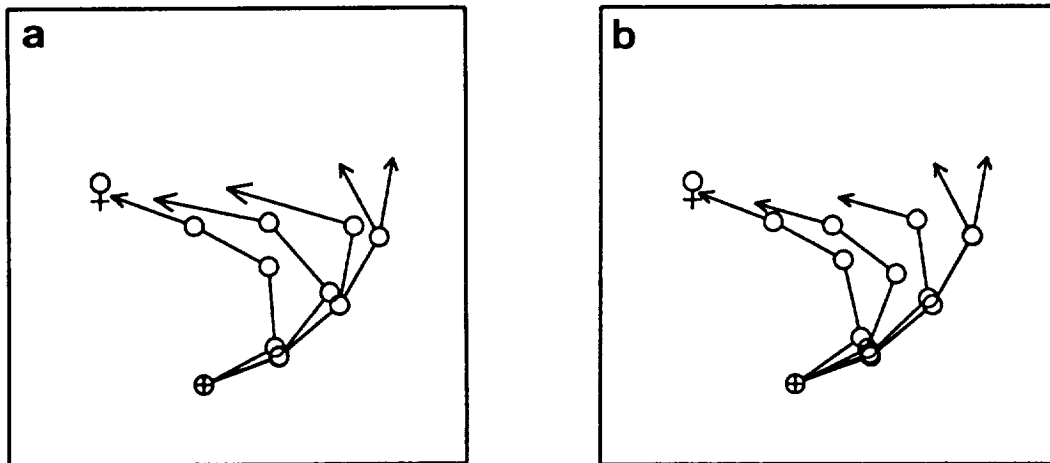
differentiating it with respect to time, and then employing the capacitances  $c_{n,k}$ , we can obtain the network equations as follows:

$$\begin{aligned} -c_{1,k} \frac{d}{dt} U_{1,k} &= (V_{1,k} - \bar{D}_k) * (1 - \frac{\bar{S}_{1,1}}{S_{1,1}}) - (V_{2,k} - V_{1,k}) * (1 - \frac{\bar{S}_{2,2}}{S_{2,2}}) \\ &+ \sum_{n'=2}^N (V_{n',k} - V_{1,k}) * f(1 - \frac{\bar{S}_{n',1}}{S_{n',1}}) \\ &+ (V_{1,k} - \bar{A}_k) * f(1 - \frac{\bar{P}_1}{P_1}) \\ &+ \sum_{l=1}^L (V_{1,k} - \bar{B}_{l,k}) * f(1 - \frac{\bar{Q}_{1,l}}{Q_{1,l}}) + \sum_{m=1}^M (V_{1,k} - \bar{C}_{m,k}) * f(1 - \frac{\bar{R}_{1,m}}{R_{1,m}}) + \frac{1}{r_{1,k}} U_{1,k} \\ \\ -c_{n,k} \frac{d}{dt} U_{n,k} &= (V_{n,k} - V_{n-1,k}) * (1 - \frac{\bar{S}_{n,n}}{S_{n,n}}) - (V_{n+1,k} - V_{n,k}) * (1 - \frac{\bar{S}_{n+1,n+1}}{S_{n+1,n+1}}) \\ &+ \sum_{n'=1}^{n-1} (V_{n,k} - V_{n',k}) * f(1 - \frac{\bar{S}_{n,n'}}{S_{n,n'}}) + \sum_{n'=n+1}^N (V_{n',k} - V_{n,k}) * f(1 - \frac{\bar{S}_{n',n}}{S_{n',n}}) \\ &+ (V_{n,k} - \bar{A}_k) * f(1 - \frac{\bar{P}_n}{P_n}) \\ &+ \sum_{l=1}^L (V_{n,k} - \bar{B}_{l,k}) * f(1 - \frac{\bar{Q}_{n,l}}{Q_{n,l}}) + \sum_{m=1}^M (V_{n,k} - \bar{C}_{m,k}) * f(1 - \frac{\bar{R}_{n,m}}{R_{n,m}}) + \frac{1}{r_{n,k}} U_{n,k} \\ &\quad (n = 2, 3, \dots, N-1) \\ \\ -c_{N,k} \frac{d}{dt} U_{N,k} &= (V_{N,k} - V_{N-1,k}) * (1 - \frac{\bar{S}_{N,N}}{S_{N,N}}) \\ &+ \sum_{n'=1}^{N-1} (V_{N,k} - V_{n',k}) * f(1 - \frac{\bar{S}_{N,n'}}{S_{N,n'}}) \\ &+ (V_{N,k} - \bar{A}_k) \\ &+ \sum_{l=1}^L (V_{N,k} - \bar{B}_{l,k}) * f(1 - \frac{\bar{Q}_{N,l}}{Q_{N,l}}) + \sum_{m=1}^M (V_{N,k} - \bar{C}_{m,k}) * f(1 - \frac{\bar{R}_{N,m}}{R_{N,m}}) + \frac{1}{r_{N,k}} U_{N,k} \end{aligned} \quad (5)$$

$$\text{where } U_{n,k} = V_{n,k} \quad \text{and} \quad f(z) = \begin{cases} 0 & \text{if } z \geq 0 \\ z & \text{otherwise} \end{cases}$$

Figure 2 shows the block diagram of the analog neural network represented by Eq.(5). The network has a direct feedback loop and indirect ones via non-linear operational parts. According to the same procedure as Hopfield proved, it is assured that the network output converges to a certain set of values[3].

Figure 3a shows an example of the network behaviour. The end of the manipulator can reach the target point retaining a natural posture. The links are of the same lengths in the final stage. However they lengthen in the transient state. This is because the energy for link lengths is relatively



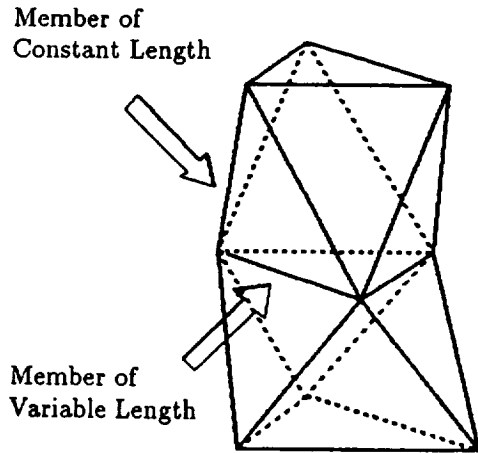
[Fig.3ab] Examples of simulation. (a) Case in which the energy terms are summed up without any weighting. (b) Case in which the adequately weighted energy terms are employed.

set smaller than the others. Figure 3b shows the case in which the energy term for link lengths is weighted severely. The link lengths in the trangent state are kept constant. Varieties of actions are caused by adjusting the balance of the energy terms alone. This means that not only rigid but also elastic types of robot manipulators can be easily represented.

### 3. Application to 3-Dimensional Frame Structure with Elastic Members

Tsutsumi et al. enhanced the proposed framework so as to control the configuration of the 2-dimensional truss effectively[4]. The simulation studies show that the motions for 'Rotation' and 'Stretching/Translation' are well-controlled, but 'Shrinking/ Translation' can not be attained. That is, the behaviour of the truss structure under this control method is very similar to that of spiral spring. This is because quadratic energy function is employed for the distances between the joints. Therefore the truss with curved configuration has less total energy than that with homogeneously shrunked members. In order to improve 'Shrinking/Translation', preliminarily shrunked 'Natural Position' was considered. Then introducing a 'Virtual Target Point' and stretching the truss to it, the control was assumed to start from this stretched position every time. It was named 'Initial Position'. The introduction of both short 'Natural Position' and tall 'Initial Position' gets rid of the practical shrinking motion from all modes of the behaviour and makes varieties of configurations possible.

In the present study, we further apply this framework to the variable geometry truss (VG-truss) which is a type of 3-dimensional frame structures with elastic members. Figure 4 shows the component of VG-truss conceived by Miura et al[5]. Here the lengths of the vertical members are assumed to be constant. The configuration of the truss can be changed by stretching or shrinking the horizontal members. We can formulate this structure according to the same procedure as described in Sect.2. That is, we first define the distances between the joints and those between the joints and the environment. Then we construct the energy terms based on the constraints necessary for desirable



[Fig.4] The structure of the 3-dimensional variable geometry truss.

behaviour. Differentiating the sum of the energy terms with respect to time, we can obtain the analog neural network whose block diagram is represented by Fig.2.

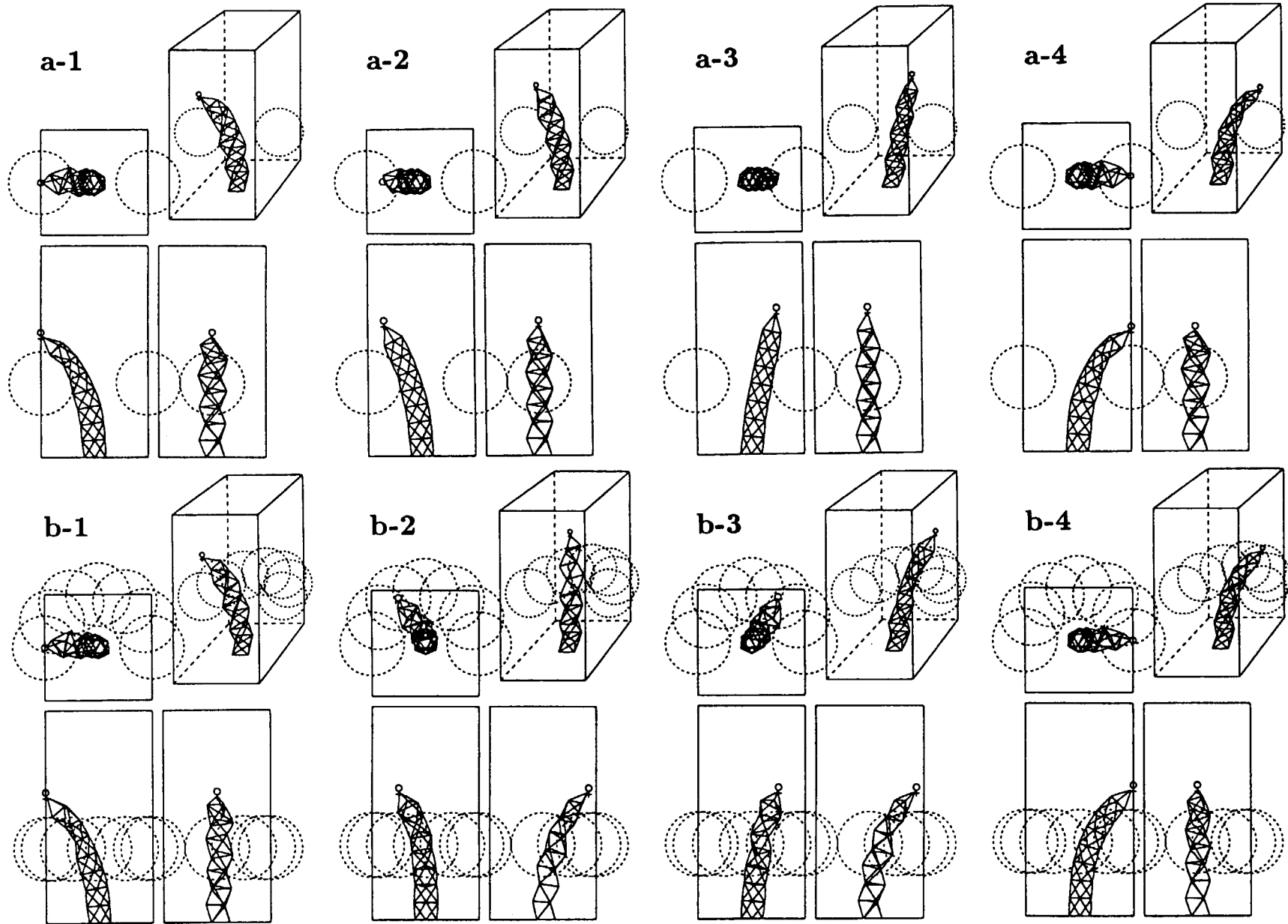
It is effective for 'Rotation / Stretching / Shrinking' motions to employ the above-mentioned concepts named 'Natural Position', 'Virtual Target Point', and 'Initial Position'. When the target point is placed at the side of the truss, the truss starts to curve and its end reaches the target point keeping the overall length of 'Natural Position'. Figure 5a shows an example of 'Rotation' using this nature. Here we introduce virtual obstacles to improve the configurations. It is further effective to divide the action into some parts by shifting the location of 'Virtual Target Point' in turn. Figure 5b shows another example of 'Rotation'. Multiple virtual obstacles are introduced to keep the curved configuration.

Figure 6a shows the case in which the target point is placed above the truss. The end reaches to the target point. In this case, the variable members near the end tend to expand and contract more, since the energy terms are summed up without any weighting. Therefore the transient configurations are irregular as shown in the figure. The behaviour of the structure is improved sharply by employing the sum of the adequately weighted energy terms. Figure 6b shows the example. Here we change the weighting factors a few times on the way for obtaining the more desirable transient configurations.

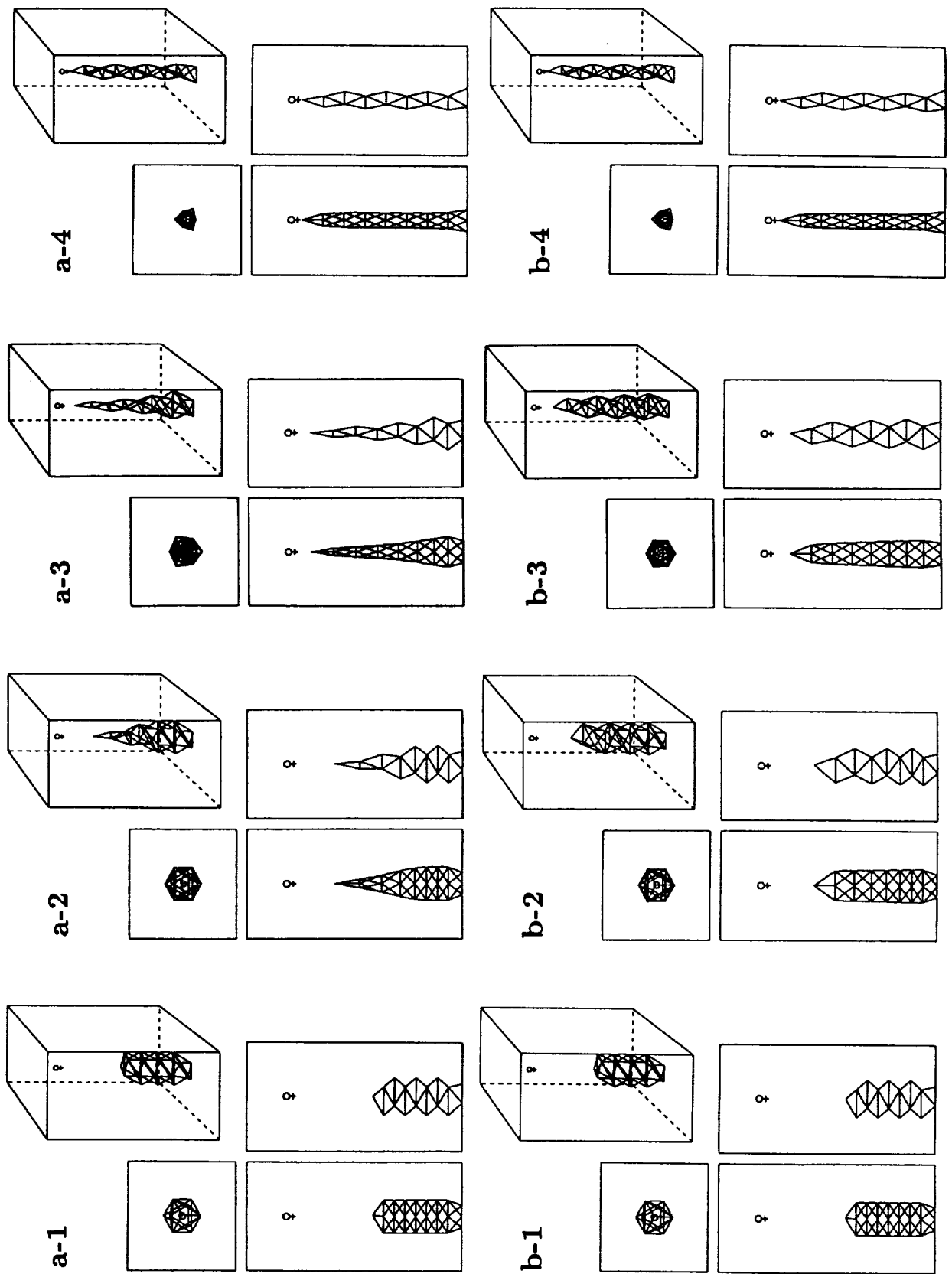
Figure 7a shows a simulation result when the target point is placed inside the truss. As already mentioned, the frame structure under this control method is poor at shrinking its member lengths homogeneously. Therefore the short 'Natural Position' is introduced here. The end can reach the target point shrinking its configuration, but the end of the truss sinks into the inside in the transient state. This is because the constraints for the distances between the farther joints are not taken into account here. It is clear that the truss can shrink its configuration successfully if such constraints are considered. Another method for better 'Shrinking/Translation' is to remove the target point temporarily. Since short 'Natural Position' is employed, the truss shrinks its overall length and it moves to 'Natural Position' unaffectedly. Figure 7b demonstrates the example.

#### 4. Discussion

As already mentioned, the frame structure under this control method behaves just like a spiral spring. In order to solve some problems caused by this nature, we introduced the concepts named

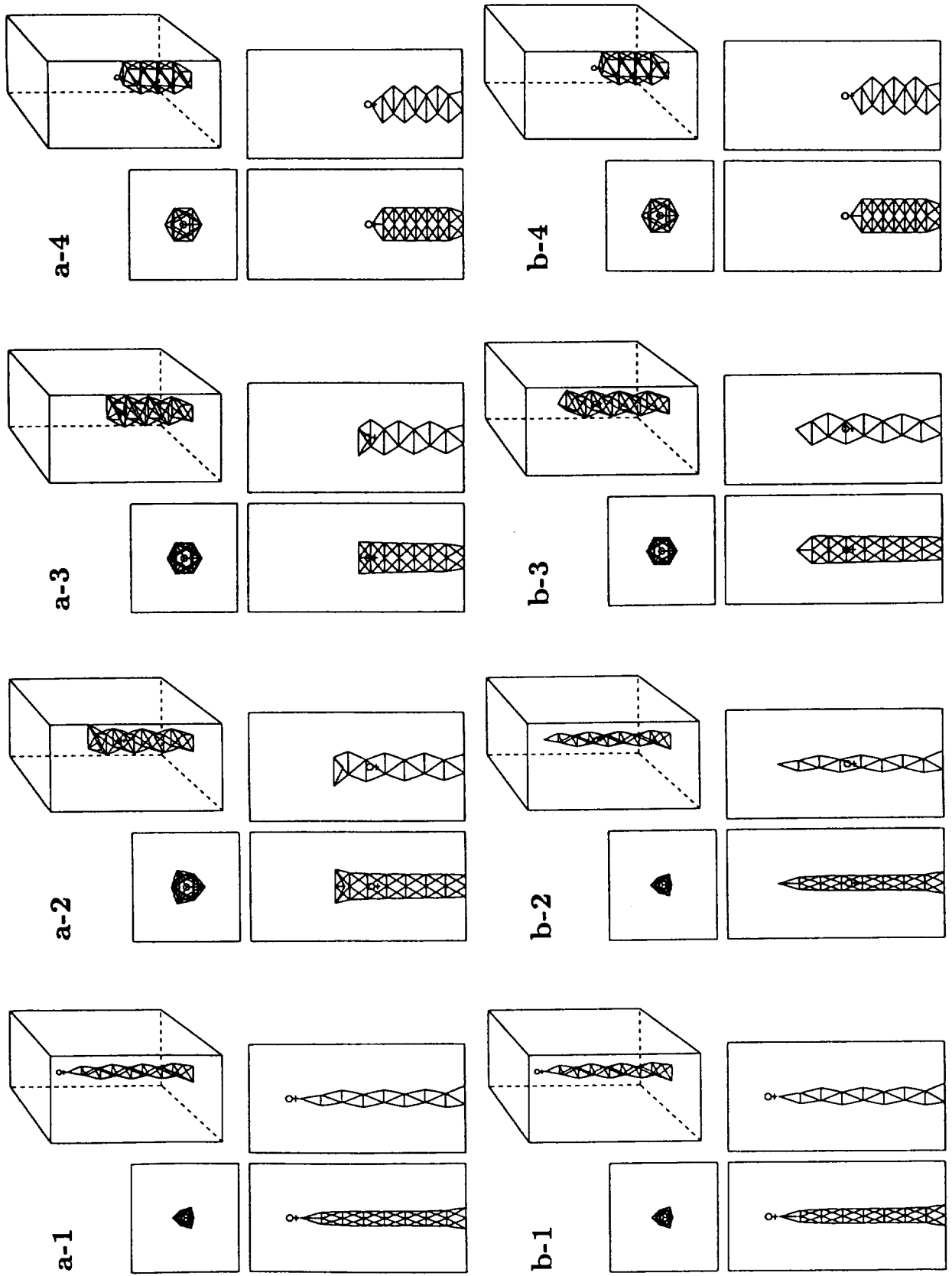


[Fig.5ab] Rotation. (a) Case I. (b) Case II.



[Fig. 6ab] Stretching/Translation. (a) Case I. (b) Case II.





[Fig.7ab] Shrinking/Translation. (a) Case I. (b) Case II.

'Natural Position', 'Virtual Target Point', 'Initial Position', and 'Virtual Obstacles'. Simulation studies demonstrate that the neural network can successfully realize the basic motions of frame structure with elastic members including 'Translation' and 'Rotation'. Although we did not exemplify 'Revolution' for want of space, it can be easily realized by using 'Virtual Target Point'. As shown in Fig.8, it is sometimes necessary for better configurations to manually change the weighting factors on the way. This is because the constraints for overall structure were not considered. We should take into account the higher-level constraints for more desirable configurations.

One of the severe problems to be solved is for the deadlock state caused by the obstacles in the workspace. Tsutsumi et al. proposed a learning strategy in which virtual obstacles are put on the deadlocked location of the end. It is very compatible with the network. However it is not a type of algorithm by which the synaptic connections are modified little by little repeating trial and error. It appears to be reasonable to divide the network into two parts, namely the one for the structure itself and the other for the environment. In this case, it will be effective to employ the mapping network with learning capability such as Backpropagation Network in order to acquire and utilize the information about the environment.

There remain a lot of future courses to be solved. However neural networks have high potentialities and they will be indispensable to Space Telerobotics. At the same time, the complicated problems in Space Telerobotics will give us good hints for modelling the neural networks.

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### References

- [1] Y.Seguchi, M.Tanaka, Y.Sasabe, H.Tsuji, and K.Okamura, "Evolution of Mast-type Truss to Robot Arm", Preprints of Japan-U.S.A. Symposium on Flexible Automation, pp.251-259, 1986
- [2] K.Tsutsumi and H.Matsumoto, "Neural Computation and Learning Strategy for Manipulator Position Control", Proc. of IEEE First Annual International Conference on Neural Networks (ICNN-87), Vol.IV, pp.525-534, 1987
- [3] D.W.Tank and J.J.Hopfield, "Simple 'Neural' Optimization Networks: A A/D Converter, Signal Decision Circuit, and Linear Programming Circuit", IEEE Trans. of CAS, Vol.33, No.5, pp.533-541, 1986
- [4] K.Tsutsumi, K.Katayama, and H.Matsumoto, "Neural Computation for Controlling the Configuration of 2-Dimensional Truss Structure", Proc. of IEEE ICNN-88, Vol.II, pp.575-586, 1988
- [5] K.Miura, H.Furuya, and K.Suzuki, "Variable Geometry Truss and its Application to Deployable Truss and Space Crane Arm", Acta Astronautica, Vol.12, No.7/8, pp.599-607, 1985

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