Parallel Type Two-axial Actuator Controlled by a Multi-layered Neural Network

Masahiro Ohka, Yasuhiro Sawamoto*, Shiho Matsukawa**,*
*Tetsu Miyaoka***, Yasunaga Mitsuya*****
*Department of Complex Systems Science, Graduate School of Information Science, Nagoya University,
Furo-cho, Chikusa-ku, Nagoya, 464-8601
**Olympus Corporation,
2-3-1 Nishishinzyuku, Shinzyuku-ku, Tokyo 163-0914
*** Department Information System, Shizuoka Institute of Science and Technology,
Toyosawa 2200-2, Fukuroi, 437-8555
**** Mitsuya Nano-engineering Laboratory,
Urbane Motoyama 301, Hashimoto-cho 1-64, Chikusa-ku, Nagoya, 464-0035, Japan

Abstract:
We experimentally design a parallel typed two-axial micro actuator, which is utilized for the key part of the tactile display. The parallel typed two-axial actuator was composed of two bimorph piezoelectric elements and two small links connected by three joints. We formulated kinematics for the parallel typed two-axial actuator because the endpoint is controlled in the two-dimensional coordinate. Since relationship between applied voltage and displacement cause by the voltage shows a hysteresis loop in the bimorph piezoelectric element used as components of the two-axial actuator, we produce a control system for the two-axial actuator based on a multi-layered artificial neural network to compensate the hysteresis. The neural network is comprised of 4 neurons in the input layer, 10 neurons in the hidden layer and ones neuron in the output layer. The output neuron emits time derivative of voltage; two bits signal expressing increment or decrement condition is generated by two input neurons; one of the other two input neurons and the other calculate current values of voltage and displacement, respectively. The neural network is featured with a feedback loop including an integral element to reduce number of neurons. In the learning process, the network learns the hysteresis including a minor loop. In the verification test, the endpoint of the two-axial actuator traces the desired circular trajectory in the two-dimensional coordinate system.

1. INTRODUCTION

In order to enhance presentation reality of a tactile display[1]-[7], pressure distribution and shearing force should be presented simultaneously on the display pad, because there are pressure and shearing force accepting points (mechanoreceptive units) distributing on human palm and finger surfaces[8][9]. Thus, we are studying a two-axial micro-actuator[10][11] to develop a tactile display pad comprised of two-axial actuators. Since the size of each actuator used in the array should be miniaturized because of the need for high distribution density on the stimulus points of the display pad, we adopt a bimorph piezoelectric element as a basic part of the two-axial actuator. The parallel typed two-axial actuator was composed of two bimorph piezoelectric elements and two small links connected by three joints. We formulated kinematics for it due to two-dimensional control of its endpoint (movable end, hereafter) in the two-dimensional coordinate system.

The movable end of the two-axial actuator does not follow same route in increment and decrement of applied voltage because the present two-axial actuator utilizes piezoelectric elements possessing a hysteresis phenomenon. Although feedback control is effective to compensate the hysteresis phenomenon and to make the movable end follow the desired trajectory, additional sensors for measuring displacement of the movable end are required to realize the feedback control. However, the feedback control is not suitable for the present actuator because the actuator array requires huge number of actuators to apply it to the tactile display.

In the present study, a new control method for the piezoelectric actuator is established on the basis of a multi-layered artificial neural network [12]-[14] to achieve the sensor-less control of the actuator. Since the network scale becomes huger without a new idea to learn the hysteresis loop, we apply causality to formulate the modified neural network. In the causality which is a basic idea of the classical physics, a certain current time derivative of physical variable is determined by current physical variables if all physical variables can be measured at a certain instant.

On the basis of the causality, we assumed that the current time increment of the voltage is determined by the current voltage, the current displacement and flags indicating increment or decrement condition. The present network is comprised of 4 neurons in the input layer, 10 neurons in the hidden layer and one neuron in the output layer. The current values of voltage and displacement are input to the two of the 4 neurons in the input layer; two bits signal expressing increment or decrement condition calculated from time derivative of displacement are input to the other two neurons; the output neuron emits time derivative of voltage. After time integration operation is performed to the output, the integrated output is used as voltage value, which should be applied to the actuator.

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Simultaneously, the voltage is applied to the input neuron as feedback signal. Although in the other researcher's study the idea of using the neural network has been also used to control the piezoelectric actuator [15], it is noted that the integration operation is included in the abovementioned feedback loop to reduce the network scale.

After learning data are obtained from the hysteresis loop including a minor loop, the present neural network learns them using the algorithm of error back-propagation method. In the experiment, this method is applied to the two-axial actuator. The weight matrices of the right and left actuators are separately determined because there is a difference between a right and left piezoelectric elements. In the evaluation experiment, the movable end of the two-axial actuator is moved along a circular trajectory to examine difference between the desired trajectory and the movable end's trajectory.

2. TWO-AXIAL ACTUATOR

2.1 Kinematics of Parallel Type Two-axial Actuator

Figure 1 and 2 show mechanism and photograph of the two-axial actuator, respectively. It is composed of two piezoelectric elements, three joints and two small links to generate two-dimensional displacement as shown in Fig. 1. The displacement of movable end (the center joint C) is controlled by controlling the displacement of right and left bimorph type piezoelectric elements. First, to formulate kinematic equation of the two-axial actuator, nomenclatures used in the formulation are shown as follows:

a : length of the small link.
b : distance between joint A and B in reference configuration.
u_x : x-directional displacement of movable end C.
u_y : y-directional displacement of movable end C.
u_R : bending displacement of right piezoelectric element.
u_L : bending displacement of left piezoelectric element.
V_R : applied voltage of right piezoelectric element.
V_L : applied voltage of left piezoelectric element.
θ : establishment angle of piezoelectric element.
$\dot{x}$: the time derivative of the variable x .

Coordinates of points A' and B' are calculated from geometrical relationship shown in Fig 1 as follows. That is,

Point A': $\left(-\frac{1}{2}b + u_L \sin\theta,\ \sqrt{a^2 - \frac{b^2}{4}} - u_L \cos\theta \right)$

Point B': $\left(\frac{1}{2}b - u_R \sin\theta,\ \sqrt{a^2 - \frac{b^2}{4}} - u_R \cos\theta \right)$

where, $a > b/2$.

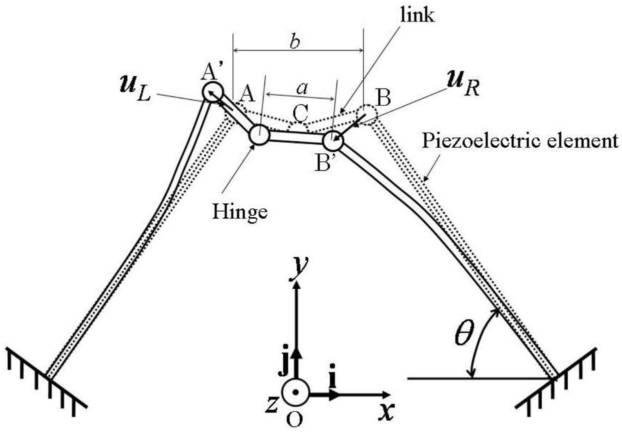

Fig. 1 Principle of the parallel typed two-axial actuator

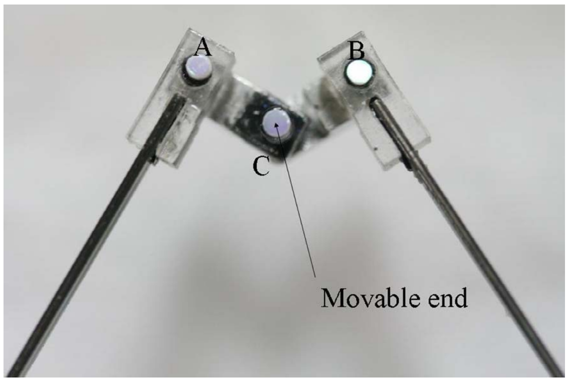

Fig. 2 Prototype of the parallel typed two-axial actuator

When the vector of movable end is expressed as $\mathbf{u} = u_x\mathbf{i} + u_y\mathbf{j}$, the following expressions are obtained from the condition of link length being constant.

$$\left(u_x + \frac{1}{2}b - u_L \sin\theta \right)^2 + \left(u_y - \sqrt{a^2 - \frac{b^2}{4}} + u_L \cos\theta \right)^2 = a^2 \quad \text{......} \quad (1)$$

$$\left(u_x - \frac{1}{2}b + u_R \sin\theta \right)^2 + \left(u_y - \sqrt{a^2 - \frac{b^2}{4}} + u_R \cos\theta \right)^2 = a^2 \quad \text{......} \quad (2)$$

The following equations are obtained from differentiating Eq.(1) and (2).

$$2\left(u_x + \frac{1}{2}b - u_L \sin\theta \right)\left(\dot{u}_x - \dot{u}_L \sin\theta \right) + 2\left(u_y - \sqrt{a^2 - \frac{b^2}{4}} + u_L \cos\theta \right)\left(\dot{u}_y + \dot{u}_L \cos\theta \right) = 0 \quad \text{...} (3)$$

$$2\left(u_x - \frac{1}{2}b + u_R \sin\theta \right)\left(\dot{u}_x + \dot{u}_R \sin\theta \right) + 2\left(u_y - \sqrt{a^2 - \frac{b^2}{4}} + u_R \cos\theta \right)\left(\dot{u}_y + \dot{u}_R \cos\theta \right) = 0 \quad \text{...} (4)$$

Simultaneous equation composed of Eq.(3) and (4) is written as following matrix expression:

$$\begin{pmatrix} \dot{u}_L \\ \dot{u}_R \end{pmatrix} = \begin{bmatrix} \dfrac{A_{11}}{A_{11}\sin\theta - A_{12}\cos\theta} & \dfrac{A_{12}}{A_{11}\sin\theta - A_{12}\cos\theta} \\ -\dfrac{A_{21}}{A_{21}\sin\theta + A_{22}\cos\theta} & -\dfrac{A_{22}}{A_{21}\sin\theta + A_{22}\cos\theta} \end{bmatrix} \begin{pmatrix} \dot{u}_x \\ \dot{u}_y \end{pmatrix} \tag{5}$$

$$A_{11} = u_x + \frac{1}{2}b - u_L \sin\theta \tag{6}$$

$$A_{12} = u_y - \sqrt{a^2 - \frac{b^2}{4}} + u_L \cos\theta \tag{7}$$

$$A_{21} = u_x - \frac{1}{2}b + u_R \sin\theta \tag{8}$$

$$A_{22} = u_y - \sqrt{a^2 - \frac{b^2}{4}} + u_R \cos\theta \tag{9}$$

2.2 Neural Network Including Feedback Loop

In the present research, we are attempting to achieve the sensor-less control of the actuator, which is established by a new control method of piezoelectric actuator using a neural network model. The present structure of network is featured with causality as a basic idea, in which time increment of physical variable is determined at a certain instant, if all current physical variables can be measured at the moment.

Generally, it is well known that in piezoelectric actuator slope of the voltage-displacement curve is different noticeably between increment and decrement sequences of applied voltage. If the above-mentioned causality is applied to control method of piezoelectric actuator, the time increment of voltage at a certain instant can be determined by current voltage, current displacement and information related to whether increment or decrement condition.

Figure 3 shows structure of the present neural network; it is comprised of 4 neurons in the input layer, 10 neurons in the hidden layer and one neuron in the output layer. The output neuron emits time derivative of voltage; two bits signal expressing increment or decrement condition is generated by two input neurons; one of the other two input neurons and the other show current values of voltage and displacement, respectively. After time integration the output time derivative of displacement is not only used for voltage that should be applied to piezoelectric element, but also fed to the neuron in the input layer through a feedback loop. The neural network is featured with the feedback loop including an integral unit to reduce number of neurons.

In the learning process, synaptic connection's weight $w_{ij}^{(s)}$ is adjusted by using the back propagation algorithm for neural networks after the feedback loop shown in Fig.3 is removed. Where, the suffix s shows layers and s = 0 and 1

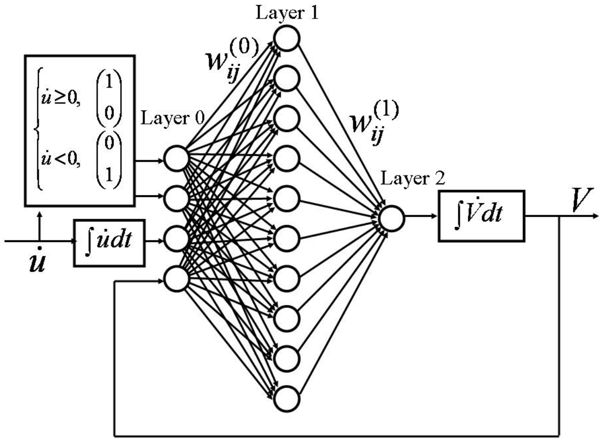

Fig.3 Neural network with a feedback loop

are input layer to the hidden layer and the hidden layer to the output layer, respectively. The suffix i and j denote the neurons number and depend on layer; if s = 0, then i = 0,1,2,3 and j = 0,1, …,9; if s = 1, then i= 0,1, …,9 and j = 0. Since the error back propagating method to adjust synaptic connection's weight is introduced at many other references [12]-[14], expressions related to it are abbreviated in the present paper.

Voltage history including increment and decrement process is applied to piezoelectric element to obtain data for network learning. In the network learning, we used data composed of about one hundred patterns of two bits expressing increment or decrement, applied voltage, displacement and displacement derivative *dV/du* of voltage. Therefore, the value of displacement derivative *dV/du* of voltage will be output from the output neuron. Since *du/dt* is given from the trajectory planning, the time derivative of voltage is calculated by multiplying *du/dt* by *dV/du*.

In addition, usual error back propagation is applicable to the present neural network with removing the feedback loop from the present network. This is different from the RTRL [15] of recurrent neural networks.

2.3 Control System

In the present two-axial actuator, the positional error will be caused by individual differences about not only the inclination of a linear portion in the hysteresis loop but also non-linearity and width of the loop. The influence of the individual difference is modified by individually putting in the characteristic of right and left actuators according to the neural network model.

Figure 4 shows block diagram of the control system designed on the basis of the above-mentioned idea. The neural network is incorporated into this control system to control right and left piezoelectric elements.

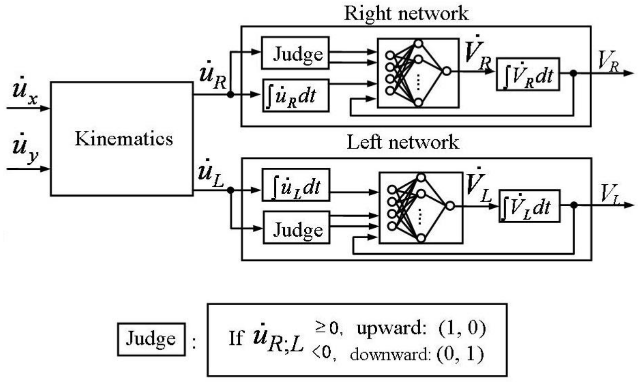

Fig. 4 Block diagram for controller equipped with neural networks

At first, $\dot{u}_x$ and $\dot{u}_y$ are decided from designed trajectory in two-dimensional area. The displacement rates of right and left type piezoelectric elements $\dot{u}_L$ and $\dot{u}_R$ are calculated by substituting $\dot{u}_x$ and $\dot{u}_y$ into the kinematic equation Eq. (5). Then, u_L and u_R is obtained by numerical integral of $\dot{u}_L$ and $\dot{u}_R$.

The 0th and the 1st neurons of right and left neural networks in the input layer accept binary number 1 or 0 judging increment or decrement condition. The condition of increment or decrement is simply decided according to sign of $\dot{u}_L$ and $\dot{u}_R$. If the sign is positive or negative, the judgment is increment or decrement. For example, if the input vector of the left piezoelectric element is $(1 \ \ 0 \ \ u_L \ \ V_L)^T$ or $(0 \ \ 1 \ \ u_L \ \ V_L)^T$, the condition is specified as increment or decrement.

Since the displacement derivative of the voltage is output from the output neuron of the neural network as previously mentioned, the time derivative of voltage is calculated by multiplying the time derivative of displacement by it. In addition, after integration the voltage is applied to the piezoelectric element, and is fed to the input layer through the feedback loop.

3. EXPERIMENTAL PROCEDURE

3.1 Prototype of the Two-Axial Actuator

The parallel typed two-axial actuator is comprised of two bimorph type piezoelectric elements, two small links and three joints as shown previously in Fig. 2. The piezoelectric element (length: 31mm, width: 2.0mm, thickness: 0.50mm) is disassembled from Braille cell SC9[5], which has been developed for the visually handicapped person by KGS Ltd. The small links of 5mm in length made of aluminum alloy are used in this actuator. Since the two links or the link and the piezoelectric element end are connected with a joint of the aluminum alloy, they are able to rotate mutually. The center of the three joints was

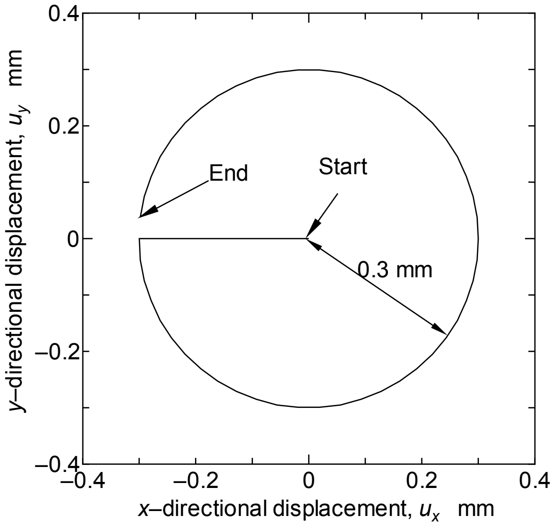

Fig. 5 Circular trajectory

functioned as the movable end.

3.2 Evaluation Apparatus

We used a microscope (OLYMPUS, inverted research microscope: IX71) for measures displacements of the three joints. The 1.25-power PlanApo×1.25 for objective lens and the 0.35-power U-TV0.35×C-2 for a camera adaptor were used. The movement trajectories of joint A, B and C were measured by image data processing of image retrieved by a CCD camera mounted in the microscope. For convenience of tracking joint centers, the circular reflector of aluminum were attached on joint A, B and C shown in Fig. 2. In the image data processing, centroid coordinates of these circular reflectors were obtained with noise reduction and circular regression. The above-mentioned operation was executed in each stepwise voltage variation to measure trajectories of the three joints. Multifunctional universal image analysis software (Library Ltd., cosmos 32 Ver4.6) was used for the image processing.

3.3 Experimental Procedure

After experiment A was performed for adjusting weight $w_{ij}^{(s)}$ of synaptic connection, experiment B was performed to verify the present control method as follows:

Experiment A: this experiment is performed to examine the relationship between applied voltage and displacements of right and left piezoelectric elements. In this experiment, 100V datum voltage was applied to right and left piezoelectric elements at first and it was made a starting point. In discussion in the subsequent sections, the voltage 100V will be expressed as 0V. In the beginning the voltage is sequentially increased to 50V at intervals of 10V, and then

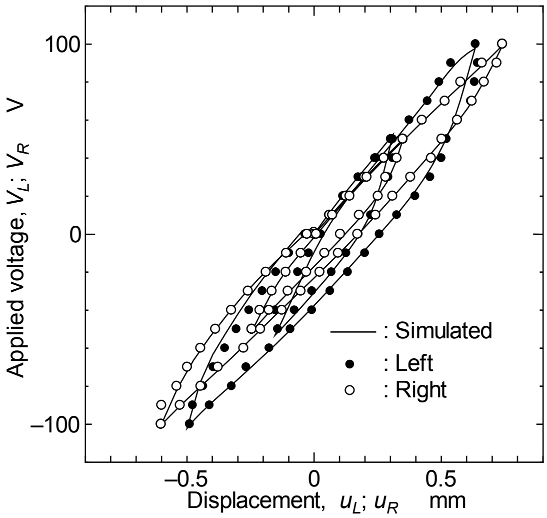

Fig.6 Learning results of left and right elements

the applied voltage is decreased to -50 V at intervals of 10V. Subsequently, it is decreased to -100V after increased to 100V at intervals of 10V. In addition, it is increased to the starting point 0V at intervals of 10V. Centroid displacements of joint A, B and C were measured at every stepwise variation.

Experiment B: After the weight of the synaptic connections of right and left neural network are adjusted based on hysteresis characteristic of the right left piezoelectric element obtained from experiment A, the experiment that along a circular trajectory in the two-dimensional surface of movable end C. Figure 5 shows the planned trajectory; the movable end is made to move along a circle of 0.3mm in the radius after along *x*-axis.

4. Experimental result and discussion

4.1 Learning Result

The hysteresis loops of the right and left piezoelectric elements obtained by experiment A are shown in Fig.6 by ● and ○, respectively. As shown in Fig.6, although displacement amplitudes and the inclinations coincide on right and left piezoelectric elements, precise hysteresis characteristics such as the loop width are considerably different. The solid line in Fig.6 is output result of the control system shown in Fig.4. The output result from the neural network almost coincides with the experimental result for not only a large loop of ±100 V but also a small inside loop of ±50 V. Therefore, the high accuracy learning result is obtained as abovementioned.

In addition, 100 thousands times of iteration was needed to obtain the learning result of Fig.6. The calculation was

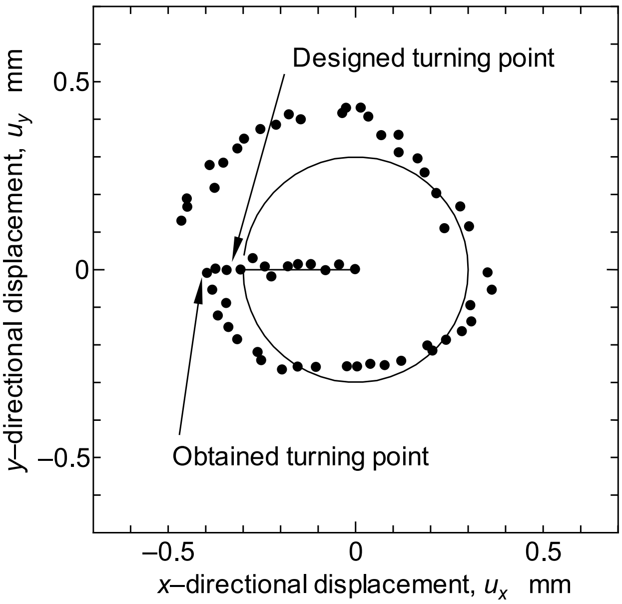

Fig. 7 Experimental result for tracing circular trajectory

executed on a notebook computer (Panasonic, CF-R4), and required about 15 minutes to complete the learning calculation.

4.2 Circular Trajectory

Next, experimental result is compared with output of the present system on circular trajectory to verify the present system; the comparison is shown in Fig.7. As shown in Fig.7, experimental result traced precisely the x-axis in the period of the first straight line tracing. However, after the turning point passes, it gradually parts from the desired trajectory. Especially, deviation between the desired circular trajectory and the experimental result becomes larger after passing the fourth quadrant.

When we investigated the voltage history around the turning point shown by the arrow in Fig. 7, the applied voltage is adjusted to make the movable end trace along the circular trajectory after the turning point as well in spite of the movable end keeping along the straight line after the turning point. The deviation between the designed turning point and obtained turning point is about 0.08mm. The abovementioned result seems to be caused by a play of the joint bearing of about tens μm. It will be improved to change the present bearing to a highly accurate bearing or an elasticity hinge in the future.

In addition, the loop data memorized to the system are limited within two loops large and small ones; it seems that there is a limit to follow not straight trajectories but two-dimensional trajectories such as a circular trajectory. It is necessary to increase number of minor loops of learning data.

5. CONCLUSION

The control method of two-axial actuator was presented to enhance positioning accuracy and to apply it to the tactile display. In order to realize sensor-less control of piezoelectric actuators possessing obvious hysteresis characteristic, we established a new neural network model including feedback loop based on causality that the time derivative of applied voltage was determined by increment or decrement condition, current voltage and displacement.

The two-axial micro actuator was composed of the right and left bimorph piezoelectric elements, two links and three joints. The control system was also developed with incorporating the neural network for compensation of the hysteresis characteristic.

The learning was terminated within reasonable calculation time; after the learning process, it was able to reproduce hysteresis characteristics including the minor loop in high accuracy. To confirm the present system, two-dimensional test was performed along circular trajectory. As a result, the movable end followed almost the trajectory but came apart from the trajectory with time spending.

In the future, it is necessary to enhance accuracy of in software with increasing number of learning data and accuracy joint bearings with exchanging the present hand-made one for precise one.

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