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Reductive Mapping for Sequential Patterns of Humanoid Body Motion

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Abstract

Since a humanoid robot takes the morphology of human, users will intuitively expect that they can freely manipulate the humanoid extremities when try to control as pilots. However, it is not realized with simple devices because it is difficult to simultaneously issue multiple control inputs to the whole body. On the other hand, a small number of control inputs, such as a cam in a wind-up mechanical doll, can generate various motion patterns of extremities. In this sense, it is useful for motion pattern generation to get mapping functions bidirectionally between a large number of control inputs to a humanoid robot and a small number of control inputs that a user can intentionally operate. From a standpoint of multivariate analysis, by executing principal component analysis (PCA) in joint angle space, motion patterns are converted into low dimensional variables. The problem is to find such convenient variables not only for specific motion like walk but also multiple whole body motion patterns. This paper presents the results that 1 dimensional inputs can generate an approximate walking pattern and 3 dimensional inputs does 9 types of motion patterns with hierarchical nonlinear PCA (NLPCA).

1. Introduction

The production of specific movement like biped walk has become realized on a humanoid robot. However, it is still difficult for a user as a pilot to manipulate the extremities of the humanoid robot freely. In order to generate motion patterns of a humanoid robot, though we must handle at least the same number of control variables as degrees of freedom of joint angles, it is difficult to issue such a large number of control inputs to the whole body at a time.

Motion capture system can afford many simultaneous inputs to a humanoid robot[1]; on the other hand, instead of using such large scale measurement facilities, generating voluntary movement of its extremities with a small number of control inputs, e.g. given by a joystick, can be alternative techniques. As for the alternative case, robotics has embraced the method that the user directs the types of behavioral patterns, such as walk or raise-its-hands, for the goodness of intuitive operability. This method, however, is not enough flexible for users to manipulate the humanoid extremities freely. In the sense of flexible motion pattern generation with essential control variables, dynamical approaches that manipulate ZMP like [2] and kinematical approaches based on synergetics like [3] have been investigated. These approaches consider attidude and movement of humanoid extremities as constraints to satisfy, and are different from the methodology how to generate voluntary movement of humanoid extremities with fewer inputs.

For the purpose of generation of voluntary movement of humanoid extremities, our research focus on a dimensionality reduction algorithm that forms low dimensional variables out of multivariate inputs of joint angles. Since a wind-up mechanical doll makes the most use of geometric constraints on its linkage, the movements of joints are entrained to the workings of one cam. By looking at the correlation among joint angles, if the structure of the cam that produces the correlation are to be estimated from data, various motions of extremities can be generated by controlling reduced valuables, such as rotating the cam, rather than inputting original number of joints. From a viewpoint of multivariate analysis, principal component analysis (PCA) is useful in order to estimate the data structure which has significant correlation and convert the data into representative variables in lower dimension. Therefore, by applying PCA to the joint angle space where each joint angle forms a basis, the low dimensional control variables can be obtained that provide multivariate inputs to the whole body of humanoid robot. Then a nontrivial problem is to find such variables for not only single motion pattern but also multiple motion patterns. At this time, conventional PCA is not enough for dimensionality reduction because the data will have nonlinear correlation.

We have developed hierarchically arranged auto-associating neural networks. The auto-associating feed forward neural network performs Principal Components Analysis with Non-Linear bases, so called NLPCA[4]. This paper describes the hierarchical NLPCA neural networks that realize dimensionality reduction and reproduction of multiple whole body motion patterns. We describe that NLPCA suit better than PCA for the purpose. The result is shown that phase relationship among original motion patterns are well reserved in reduced space with nonlinear bases so that relation among motion patterns can quantitatively be evaluated.

The engineering application is to develop a joystick controller for voluntary movement. It might be possible to generate untrained motion patterns by the generalization power of neural networks. This application may also contribute the neurophysiologic study as a base to consider what kind of variables human manipulate while taking or learning voluntary movement.

2. Dimensionality Reduction Method for Humanoid Motion Pattern

2.1. Motion Pattern Representation and Functions of NLPCA

The arbitrary posture of a humanoid robot that has N joints can be represented as N-dimensional vector $\boldsymbol{x}$ in the joint angle space $\mathcal{J} \subset R^N$. The whole body motion pattern is expressed as consecutive orbit $\mathcal{O}_\mathcal{J} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \cdots\}$ in $\mathcal{J}$ if the pattern is regarded as a set of momentary snapshots of posture. This $\mathcal{O}_\mathcal{J}$ lies on some hyper curved surface $\mathcal{S}$ from a geometrical constraint of the humanoid robot. If $\mathcal{S}$ is modeled by the M nonlinear bases which form space $\mathcal{R} \subset R^M$, then $\mathcal{O}_\mathcal{J}$ are to be represented as $\mathcal{O}_\mathcal{R} \in \mathcal{R}$. While the number of the nonlinear bases M is generally fewer than the N joints, the dimensions of $\mathcal{O}_\mathcal{R}$ decrease. If this lower dimensional space $\mathcal{R}$ preserves the topology of $\mathcal{J}$, then $\mathcal{O}_\mathcal{R}$ will still be consecutive orbit.

The NLPCA neural network illustrated in Fig. 1, whose input and output layers have the same number of units, learns to approximate a function g which realizes identity mapping for

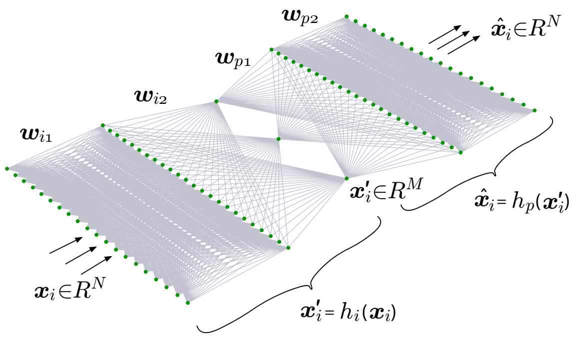

Figure 1: The left/right side layer denotes input/output layer of NLPCA neural network. The first half layers take role of injection and the latter half ones do projection.

given data set:

$$\hat{\boldsymbol{x}}_i = \hat{g}(\boldsymbol{x}_i) \quad (1)$$

where $\boldsymbol{x}_i$ denotes i-th vector of $O_\mathcal{J}$, and $\hat{g}$ denotes the approximate function of g. The squared error $e_i = \|\hat{\boldsymbol{x}}_i - \boldsymbol{x}_i\|^2$ is minimized by descent steepest method with the weight parameters $\boldsymbol{w}$ which connect units among layers. Here, $\|\cdot\|$ means the norm. By passing through the middle hidden layer, called feature layer, which has fewer number of units M than the number of input or output units N, data $\boldsymbol{x}_i \in R^N$ is injected into $\boldsymbol{x}'_i \in R^M$ and then re-projected on $\hat{\boldsymbol{x}}_i \in R^N$. That is, if we denote $\hat{g} = h_i \circ h_p$, the neural network has a good property of finding h_i that injects $\mathcal{O}_\mathcal{J}$ onto $\mathcal{S}$ and h_p that re-projects $\mathcal{O}_\mathcal{R}$ onto surrounding $\mathcal{O}_\mathcal{J}$ by just evaluating the magnitude of e_i:

$$\boldsymbol{x}' = h_i(\boldsymbol{x}) \equiv f(\boldsymbol{w}_{i2} f(\boldsymbol{w}_{i1}\boldsymbol{x})) \quad (2)$$

$$\hat{\boldsymbol{x}} = h_p(\boldsymbol{x}') \equiv f(\boldsymbol{w}_{p2} f(\boldsymbol{w}_{p1}\boldsymbol{x}')) \quad (3)$$

where $\boldsymbol{w}_{i1}, \boldsymbol{w}_{i2}, \boldsymbol{w}_{p1}$ and $\boldsymbol{w}_{p2}$ are weight matrices between two layers, and described from input layer to output layer in order. For notational clarity, f of $\boldsymbol{a}' = f(\boldsymbol{a})$ denotes a vector function: each element of $\boldsymbol{a}' \in R^K$ is a sigmoidal output of the corresponding element of the same dimensional vector $\boldsymbol{a} \in R^K$. Equations above are in the case of 5 layers network as shown in Fig. 1.

From sigmoidal continuity of f, if some two $\boldsymbol{x}_i$ are close each other, NLPCA neural network will maintain the topological relationship between corresponding two $\boldsymbol{x}'_i$. Hence consecutive orbit $\mathcal{O}_\mathcal{J}$ tends to inject into consecutive orbit $\mathcal{O}_\mathcal{R}$.

Our NLPCA neural network is sensitive to the range $(0, 1)$ for each activation value from the characteristics of sigmoid function f. For the nonlinear optimization to work well, appropriate scaling factor in input and output layer is required. There are many statistical solutions for normalization, e.g. subtracting the mean and dividing by variance of data. In this paper, we just used interior division between maximum and minimum of data for experimental result: in the input layer of neural network, any activation value is scaled within $(0,1)$ as linearly interior dividing point, and then the activation value of output layer scale back to original data range.

2.2. The Property of NLPCA and Comparison of Reduction Power between NLPCA and PCA

The property of NLPCA neural network is analogous to PCA: PCA firstly arranges one linear basis as the first principal axis to minimize information loss, that is equal to maximizes the variance, in data space, and then reduces the residual error with the second or more principal axes. The main difference is that NLPCA adopt nonlinear bases for the principal axes.

When a NLPCA neural network learns with one unit in the feature layer (that is $M = 1$), the activation value in the feature layer takes a role of first principal component. At this time, such a nonlinear basis as the principal axis is selected:

1. the direction that enlarge the variance
2. the magnitude that normalize the distribution within the range $(0,1)$ in $\mathcal{R}$

Here we asume $M = k$, and let the reduced vector with Eq. (2) for $\boldsymbol{x}_i$ be $\boldsymbol{x}_i'^k = ({x_i}_1', {x_i}_2', \cdots, {x_i}_k')$ and let the regenerated data with Eq. (3) for $\boldsymbol{x}_i'^k$ be $\hat{\boldsymbol{x}}_i^k$. Then the mean squred residual error of the identity mapping E_k is

$$E_k = \frac{1}{n}\sum_i^n \|\hat{\boldsymbol{x}}_i^k - \boldsymbol{x}_i\|^2 \qquad (4)$$

where n is the number of samples. Given an additional unit in the feature layer, NLPCA neural network learns to absorb the residual error of the first principal component E_1 by adjusting only the weights connected to the additional unit. When the learning converged, the activation value of the second unit ${x_i}_2'$ takes a role of the second principal component of $\boldsymbol{x}_i$. By adding units in the feature layer repeatedly, the k-th principal component ${x_i}_k'$ can be obtained.

Here we describe that NLPCA suit for low dimensional representation of whole body motion patterns better than PCA. We first prepared a motion pattern walk $\mathcal{O}_{\mathcal{J}}^{wk1}$ that has physical consistency on HOAP-1[1]. $\mathcal{O}_{\mathcal{J}}^{wk1}$ is a 20×1080 matrix sampled by every 5 msec: starts from standing position, takes 3 steps forward (left - right - left), and then returns to the initial standing position. The external appearance is shown in the top of Fig. 8. We tested the performance between NLPCA neural network and PCA for this data. PCA is computationally done by singular value decomposition. The left of Fig. 2 shows computed singular values for the matrix $\mathcal{O}_{\mathcal{J}}^{wk1}$. Observe that the exact rank of this matrix is given by the drop of the curve. In this case, the rank is 9. That means the first 9×1080 matrix gives the almost perfect approximation of $\mathcal{O}_{\mathcal{J}}^{wk1}$.

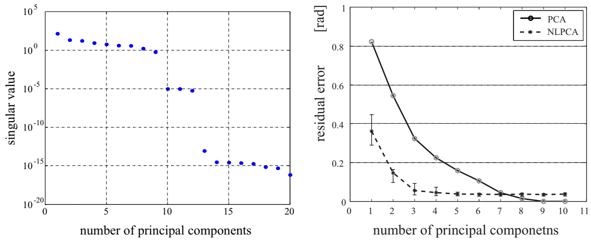

Figure 2: The left is the semilog plot of singular value of motion pattern walk. The right shows the norm of residual error to compare reproduction power between PCA and NLPCA. The vertical error bar on NLPCA shows the dispersion of ten trials and the asterisks are their average.

The right of Fig. 2 shows the comparison of the power of dimensionality reduction between PCA and NLPCA. By examining the mean of the residual error $\|\hat{\boldsymbol{x}}_i^k - \boldsymbol{x}_i\|$ shown in the ordinate of the figure, it is shown that NLPCA gives more precise approximation of identity mapping than PCA: the first 7 principal components with PCA are equivalent to 3 ones with NLPCA. The reason why the convergence of NLPCA levels off from 3D is that the lowest residue depends on learning rate η for iterative learning. This η cannot be too high because it never converges, nor can it be too low because it gets into local minima easily. The architecture of used NLPCA neural network consisted of almost the same one as Fig. 1: a single network with 20 units in input/output layer and 24 units in hidden layer, and only the number of units in the feature layer varies from 1 to 10. η was set to 0.03. A general error back propagation algorithm[5] is used for a descent steepest method.

[1] Humanoid Robot by Fujitsu Corporation that has 4DOF for each arm and 6DOF for each leg, that is totary 20 DOF. See URL below:
http://www.automation.fujitsu.com/products/products07.html

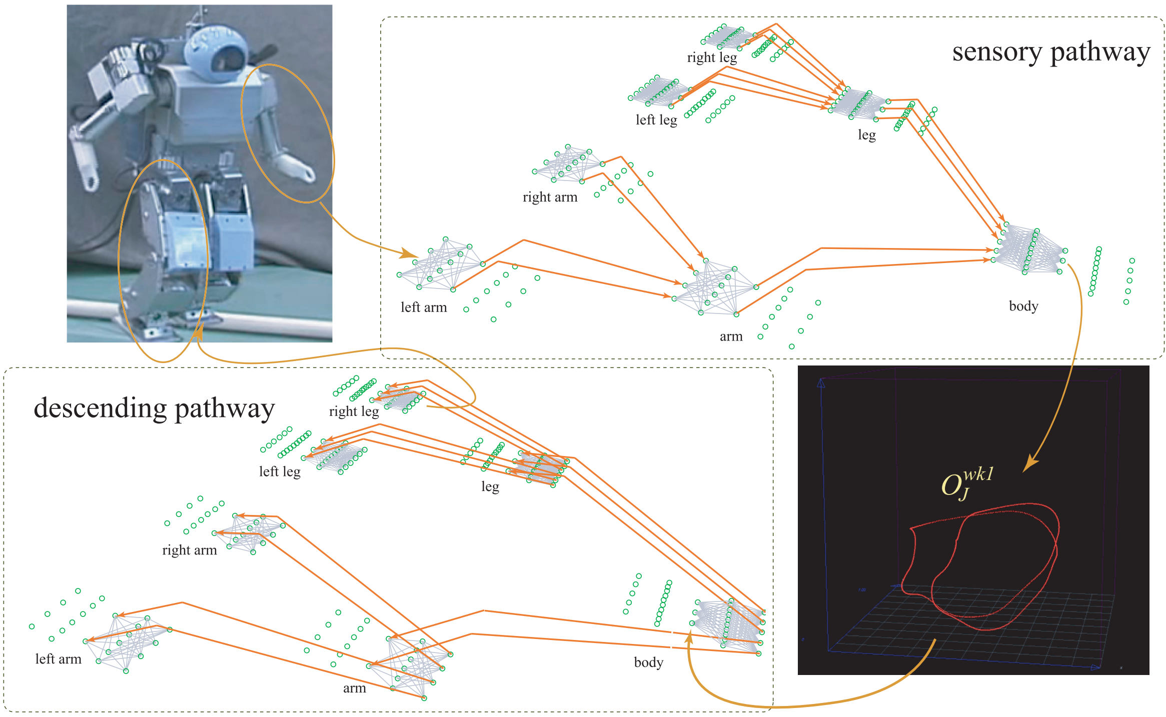

Figure 3: A design of hierarchical NLPCA neural networks. Two pathways are separately illustrated based on the difference of the functional aspects. The arc implies the flow of the signal transfer.

2.3. Hierarchical NLPCA Neural Networks

In order to suppress the bias and improve the convergency when two or more motion patterns are learned, we arrange several NLPCA neural networks hierarchically by each level as shown in Fig. 3. This hierarchical NLPCA neural networks works as a system for bidirectional conversion between low dimensional variables and multivariate variables. We briefly describe the algorithm of signal transfer below.

Firstly, independent four NLPCA neural networks are assigned to each of the arms and legs, and then each network is trained to learn the identity mapping. Here, let these networks which directly transfer sensorimotor signals are the bottom level and the others are superior level. Secondly, after each joint angle $\boldsymbol{x}_i$ is reduced to $\boldsymbol{x}'$ by Eq. (2), the activation value of the feature layer $\boldsymbol{x}'$ is referred to as an input $\boldsymbol{x}_i$ of superior neural network, and the superior neural network also learns the identity mapping for the reference input. Lastly, by repeating a similar procedure, reduced variables are obtained in the feature layer of superior neural network if learning converged. In this way, the former half of each NLPCA neural network is assigned to sensory pathway. Symmetrically, the latter half is used as descending pathway by following algorithm.

In the top level, the data $\boldsymbol{x}'_i$ which is directly pushed into the feature layer reproduce $\hat{\boldsymbol{x}}_i$ in the output layer by Eq. (3). This $\hat{\boldsymbol{x}}_i$ is projected into feature layer of inferior neural networks as $\boldsymbol{x}'_i$. This procedure is repeated until $\hat{\boldsymbol{x}}_i$ in $\mathcal{J}$ be finally obtained in the output layer of the bottom level NLPCA neural networks.

2.4. The Biological Plausibility

As for human nervous system, voluntary movement of the extremities is controlled by many descending and sensory pathway. Descending pathway is composed of motor neuron that transfers motor command towards motor endplate for motion execution. Sensory pathway transfers the consequence of motion execution back to motor neuron or superior central nerve. Therefore, to execute intentional behavior, activity in descending and sensory pathway must interact with well each other[6]. The fact has become clear that some spinal interneurons form groups depend on the projection-pathway, and those spinal interneurons receive input from both pathways and give activation relevant to motor command[7]. We do not intend to propose an imprudent hypothesis that our NLPCA method provides the model of spinal interneuron, but intend to bring evidence that hierarchical architecture has some reasonable biological functions as:

1. There exist a small number of group neurons that connects central nerves with functionally related muscles.

2. The spinal cord cannot be viewed as a simple relay of supraspinal motor commands to the periphery: the organization of spinal motor system will place strong constraints on the production of movement by supraspinal systems.

3. The efficiency of synaptic transmission of sensory pathway and descending pathway are turned cooperatively.

The feature point of our model is that some learning modules are prepared for the extremities and form sensory and descending pathway as a total system. And though both pathways are independent in each module, the synaptic weights are tuned in a couple while learning. Each module mutually exchange multivariate data and reduced data of motor command: raw data are converted into statistically significant information when transferred to superior modules, and the descending path is simultaneously maintained to reproduce fertile raw data. This is interesting because, even if the conversion from low dimensional data to high dimensional data does not have a unique solution, our model gives some useful, if not optimal, solution at any rate. This function mirrors certain aspect how humans learn their voluntary movement in the sense of procedural memory.

3. Internal Representation of Multiple Motion Patterns

3.1. Learning a Unique Motion Pattern "Walk"

We now apply hierarchical NLPCA neural networks to dimensionality reduction of motion patterns. The question is whether this can find some convenient low-dimensional representation of the data. We first prepared the hierarchical NLPCA neural networks which are almost the same structure as Fig. 3 except that only one unit is used in the feature layer at the top level of hierarchical NLPCA. The input (and also training target) is $\mathcal{O}_{\mathcal{J}}^{wk1}$ used in section 2.2. The top diagram of Fig. 4 shows one dimensional internal representation $\mathcal{O}_{\mathcal{R}}^{wk1}$ correspond to $\mathcal{O}_{\mathcal{J}}^{wk1}$. The ordinate denotes $\boldsymbol{x}'_i$ against the step i of the abscissa.

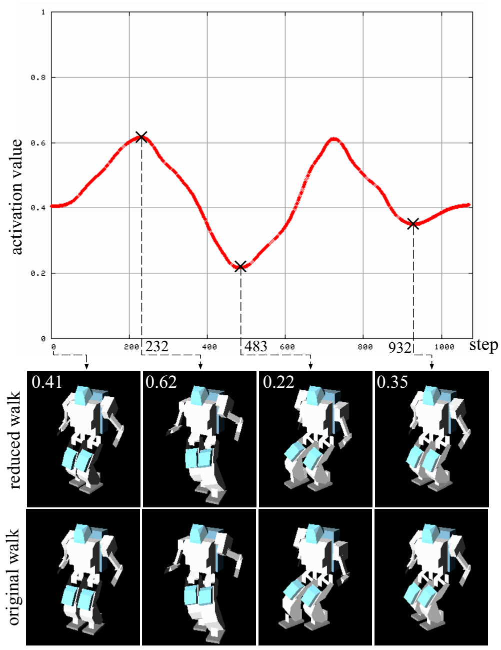

Figure 4: Internal representation of walk (top) and its external appearance (middle) compared to its original attitude (bottom).

The middle picture of Fig. 4 shows the humanoid attitude generated from $\boldsymbol{x}'_0 = 0.41$, $\boldsymbol{x}'_{235} = 0.62$, $\boldsymbol{x}'_{483} = 0.22$, $\boldsymbol{x}'_{945} = 0.35$, and the bottom one shows the corresponding original attitudes. Since kicking motion of supporting leg and swinging back motion of the same lifted leg are close in $\mathcal{J}$, the similar posture is injected into the same point in excessively reduced space $\mathcal{R}$. Therefore the switching phase of the supporting leg almost synchronizes with turning value of the orbit in $\mathcal{R}$. If the motion pattern "walk" is interpreted as a periodic motion with symmetric property, consequentially the hierarchical NLPCA neural networks extracted $\mathcal{R}$ that reflects its phase. This experimental result describes that appearance of periodic motion pattern can be generated by fluctuation of only one control variable with an appropriate nonlinear basis. Moreover, we found that such a basis can be acquired through a simple learning algorithm.

3.2. Learning Multiple Motion Patterns of Walk

We examined how the internal representation changes in the low dimensional space as motion patterns to be learned increase. In addition to the result of Fig. 4, that is just one walk pattern is learned, other 4 types of walk patterns are prepared; walk with bend forward $\mathcal{O}_{\mathcal{R}}^{wk2}$, walk with bend backward $\mathcal{O}_{\mathcal{R}}^{wk3}$, walk with short $\mathcal{O}_{\mathcal{R}}^{wk4}$ and stride $\mathcal{O}_{\mathcal{R}}^{wk5}$(Fig. 5). These motion patterns are created by converting human posture with the motion capturing system into the joint angle based on the kinematics of the humanoid robot HOAP-1[1]. The hierarchical NLPCA neural networks learn one set of data composed of $\mathcal{O}_{\mathcal{J}}^{p}(p = wk1, wk2, ..., wk5)$.

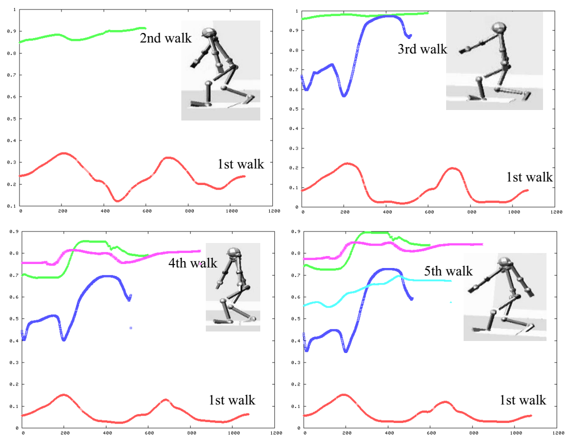

Figure 5: The state of varying internal representation with increment of captured walk patterns.

In case that the second walk pattern $\mathcal{O}_{\mathcal{J}}^{wk2}$ is additionaly learnd, those two reduced orbits distributed away from each other (the top-left of Fig. 5). This means that between-class variance of $\mathcal{O}_{\mathcal{J}}^{wk1}$ and $\mathcal{O}_{\mathcal{J}}^{wk2}$ is large in the scale of whole data set and the relationship is reflected on the first principal axis. The top-right of Fig. 5 also gives an expected result for $\mathcal{O}_{\mathcal{J}}^{wk3}$. In the bottom of the same figure, we see that $\mathcal{O}_{\mathcal{J}}^{wk4}$ traces near $\mathcal{O}_{\mathcal{J}}^{wk2}$ and $\mathcal{O}_{\mathcal{J}}^{wk5}$ does near $\mathcal{O}_{\mathcal{J}}^{wk3}$; these patterns resemble each other also in external appearance. Hence hierarchical NLPCA neural networks has a characteristics that provide a quantitative evaluation of the similarity among motion patterns. On the other hand, we also notice transition that the distribution of $\mathcal{O}_{\mathcal{J}}^{wk1}$ is shifted from area $(0.2, 0.6)$ to $(0.0, 0.2)$ with addition of walk patterns. This result indicates that the variety of multiple motion patterns leads localization for respective patterns.

3.3. Learning Various Types of Humanoid Motion Patterns

From the examination above, if the hierarchical NLPCA neural networks are trained more with various motion patterns, NLPCA will localize every pattern in its reduced space, and will find the topological relationship that similar patterns come near and different ones distribute away each other. So in addition to the result of Fig. 5, we train the neural networks to learn swing $\mathcal{O}_{\mathcal{J}}^{sw}$, throw $\mathcal{O}_{\mathcal{J}}^{th}$, kick $\mathcal{O}_{\mathcal{J}}^{kc}$ and squat $\mathcal{O}_{\mathcal{J}}^{sq}$ (Fig. 6). The right column part of the figure shows the humanoid attitudes that correspond to each $\boldsymbol{x}'$ whose value is described by top-left number in the picture.

The remarkable point is that all walk patterns by motion capture are injected into a specific area $(0.4, 0.6)$ and occupy this area. This means, since excessive reduction exclude the redundancy of the variety of original walk patterns, any posture looks like walk is injected into this area. The bottom of Fig. 6 shows the humanoid postures in this area. We confirm that $\boldsymbol{x}'_i = 0.4, 0.5, 0.6$ represent right-step-forward, neutral and left-step-forward in order, so that a rough walk pattern by motion capture can be produced by tracing sine curve in $(0.4, 0.6)$. In fact, observation of the posture to and fro reminds us of walking behavior.

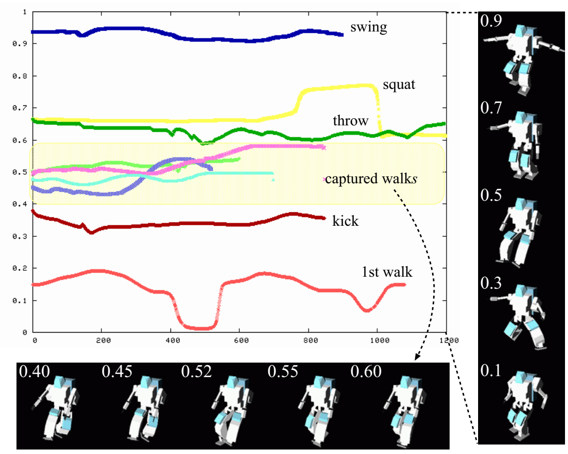

Figure 6: Internal representation of each motion pattern and corresponding attitude of humanoid robot.

The result above is interesting because different types of motion patterns never cross each other in their internal representation, even though such decay can easily be estimated that some of motion representations might pass all over the space $\mathcal{R}$. This result cannot be achieved by PCA because most of motion representations crossed over each other.

We noticed that walk pattern $\mathcal{O}_{\mathcal{R}}^{wk1}$ is injected apart from the other walk patterns. The external appearance of the regenarated motion from $\mathcal{O}_{\mathcal{R}}^{wk1}$ is shown in the middle of Fig. 8. The walk patterns by motion capture $\mathcal{O}_{\mathcal{J}}^{p}(p = wk1, wk2, ..., wk5)$ are generated just considering kinematical consistency, whereas $\mathcal{O}_{\mathcal{J}}^{wk1}$ is created considering physical consistency for biped locomotion in real emvironment. A twist around hip is important for balancing control to cancel the adverse yaw; this movement has a great effect on movements of other connected links. This split beetween $\mathcal{O}_{\mathcal{R}}^{wk1}$ and $\mathcal{O}_{\mathcal{R}}^{p}$ might reflect the difference between $\mathcal{O}_{\mathcal{J}}^{wk1}$ with the twist and $\mathcal{O}_{\mathcal{J}}^{p}$ without one. Though the roundhouse-high-kick $\mathcal{O}_{\mathcal{R}}^{kc}$ that has the kinematical twist (see the attitude of $\boldsymbol{x}' = 0.3$) had come nearer than $\mathcal{O}_{\mathcal{R}}^{wk1}$ against $\mathcal{O}_{\mathcal{R}}^{wk1}$, the experimental result seemed reasonable in that sense.

3.4. Motion Reproduction by the Learned Internal Representations

As illustrated in the middle of Fig. 8, the hierarchical NLPCA neural networks can not approximate the identity mapping well since the neural networks must represent various types of motion pattern. In this section, we attempt to improve the accuracy of reproduction of motion patterns while maintaining the structure of the first principal component described in previous section. Here, we assume that the original variety of motion pattern is to be regenerated by adding a kind of perturbation terms to the first principal component.

In order to absorb the residual error E_1 that is caused by excessive estimation of the underlying dimensionality, when the neural network with one unit in feature layer in the top level NLPCA neural network converges, then we add a second unit and train the neural networks again by following the procedure introduced in Section 2.2. Note that adding units means adding control variables for motion pattern generation.

The left of Fig. 7 shows internal representations of all motion patterns used in previous section with an additional unit. For comparison, we also prepared another hierarchical NLPCA neural networks that has the same structure except the number of unit in the feature layer is fixed two from the beginning, and train the neural networks to learn;

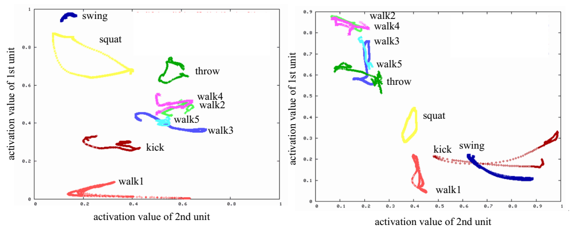

Figure 7: Comparison of internal representation between unit-increment learning(left) and learning with constant number of units from the beginning(right).

the right of the figure shows the internal rerpesentations with the hierarchical NLPCA. In the left of the figure the first unit's value of the ordinate can be interpreted as the first principal component that represents approxiamte external appearance of humanoid robot, and the second one of the abscissa can be interpreted as the perturbation, whereas the interpretation is unclear in the right of the figure. The intuitive structure of the formar unit-incremental learning approach has some advantages over the latter unit-fixed one from a robot control standpoint.

Additively another unit is trained in the same way after learning with 2 units had converged. The top of Fig. 8 illustrates external appearance of original $\mathcal{O}_{\mathcal{J}}^{wk1}$, the middle one does the motion pattern regenerated by the 1 dimensional $\mathcal{O}_{\mathcal{R}}^{wk1}$ as described in previous section and the bottom one does regenerated motion from the 3 dimensional $\mathcal{O}_{\mathcal{R}}^{wk1}$. Though the hierarchical NLPCA must produce 9 motion patterns with 3 dimensional internal representations, the identity mapping of motion patterns is rather precise.

4. Conclusion

This paper presented the hierarchical NLPCA neural networks that performs bidirectional mapping between multivariate control inputs and low dimensional internal representation of humanoid motion patterns. On a 20 DOF humanoid robot, we showed the results that 1 dimensional inputs can generate approximate walking pattern and 3 dimensional inputs do 9 types of motion patterns.

There are some researches about what kind of principle makes choice or combination of DOF in human for walk[8]; it is unclear what kind of quantitative representation produce various types of motions. Our approach takes motion patterns as the set of state points in joint angle space. In that sense, dimensionality reduction of motion patterns

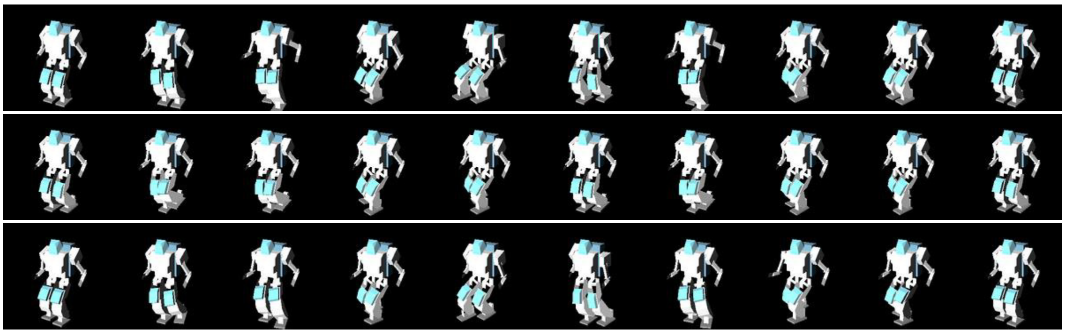

Figure 8: Comparison of external appearances; original walk $\mathcal{O}_{\mathcal{J}}^{wk1}$ (top) and the regenarated motion from the internal representation $\mathcal{O}_{\mathcal{R}}^{wk1}$ of 1D (middle) and 3D (bottom).

on humanoid robot is a problem of finding low dimensional manifold in the high dimensional space. We used NLPCA to overcome the nonlinearity of the manifold.

We think the attraction of a humanoid robot is in the variety of motor function of the extremities. It is said that human acquires the low dimensional control input from a large number of somatosensory information by exploiting synergy[9]. Moving the extremities and acquiring the manipulable input, then human can take motions such as lying down. Of course, human must solve the problem of dynamic stability like biped locomotion; however, it must be solved on the same principle that manipulate their extremities. Currently, the main stream of humanoid robot control is to stabilize the strongly nonlinear system of the rigid body. Therefore most of practical approaches considers lower extremities as just supporting sticks and upper extremities and head as constraints of motion. It is true that robotics must argue the dynamic stability whatever configuration the robot is; however, since a humanoid robot takes the morphology of human, we believe that the argument about motion pattern generation of the extremities with fewer input is also important as well as the dynamic problem.

Acknowledgements

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