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An Efficient Model for Learning Systems of High-Dimensional Input within Local Scenarios

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Abstract. We present an efficient solution for applying fuzzy control in systems with high-dimensional vision input. Instead of using selected input variables, statistical indices are extracted to feed the fuzzy controller. A sequence of training images within a local scenario is projected into a low-dimensional eigenspace. A B-spline controller is trained for mapping the inputs in the reduced eigenspace to the desired system output. Implementation with vision-based robot navigation validates the concept.

Keywords: fuzzy control, B-splines, dimension reduction, supervised learning, navigation.

1 Introduction

It is well-known that general fuzzy rule descriptions of systems with a large number of input variables suffer from the problem of the "curse of dimensionality". In many real applications, it is difficult to identify the correct influential factors and reduce their number to the minimum. A general solution to build fuzzy models is not only interesting from a theoretical point of view, but also practically meaningful since the application of fuzzy control could then be extended to a wider range of complex intelligent control problems.

In the recent literature on neuro-fuzzy modelling and machine learning, some standard benchmark problems with "middle"-dimensional input spaces, like "Box-Jenkins Gas Furnace Problem", "Mile-Per-Gallon", etc., are frequently discussed and simulation results are presented. In our industry consulting and research work on sensor-based robot control, we are faced with some high-dimensional problems concerning a large number of input variables whose importance and inter-dependence are not clearly known.

2 State of the Art

Two main methods examining the multivariate problem are "input selection" and "hierarchy".

Input Selection One implemented approach is "input selection", [3] and [1], which is in principle an experimental method to find the most important input variables among a large number of them. With this approach, all the combinatorial possibilities of the low-dimensional fuzzy model are considered and approximately tested. The selected inputs which enable the best result are viewed as the most influential ones to build an exact neuro-fuzzy model. There are two obvious problems with such a procedure of projection from a high dimension to a low one. First, all the other less influential inputs are discarded, which means an information loss for the controller. Secondly, the combinatorial number of lower-dimensional fuzzy controllers for a system with thousands or even millions of inputs is still too large to enumerate and to evaluate.

Hierarchy The solution with hierarchical structure assumes that the input information can be classified into groups, [8,4]. Within each group the inputs determine an intermediate variable, they can be decoupled from inputs of other groups. To realise such a grouping, there exists no general automatic approach but heuristics based on fusion of physical sensors.

If a fuzzy controller is only observed at each moment in time, the only input information to the controller comes from the whole set or a selected subset of the input variables. In our paper, this kind of information is called the horizontal index. Both "input selection" and hierarchical structure consider only the horizontal indices. They presume that inputs are independent and give no priority or importance of the selected input variables.

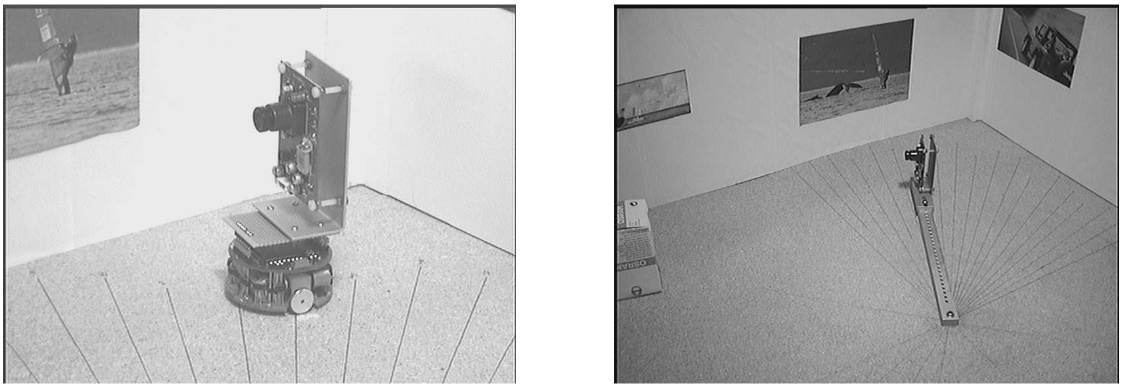
3 Concept of Dimension Reduction

3.1 Vision-Based Robot Navigation

As a typical problem with high-dimensional input, we investigate vision-guided robot navigation and control (Fig. 1).

In Fig. 2 (a) - (f), the same situation as in Fig. 1 is shown from camera perspective. The classical approaches of robot vision face two big problems: a). The image processing procedures, such as segmentation, feature extraction and classification are not robust in real environments; b). These processing algorithms are computationally expensive, thus the real-time requirement cannot be fulfilled in most cases.

It is a long-term research goal to find a general model which transforms raw image data directly to action values. For instance, an image has 512×512 pixels, each pixel is

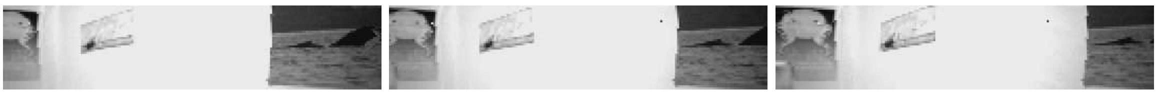


(a) The mobile robot mounted with a camera

(b) A setup for orientation learning

Figure 1: Experimental setup and the navigation environment.

(a) 45.0 Degrees (b) 47.5 Degrees (c) 50.0 Degrees



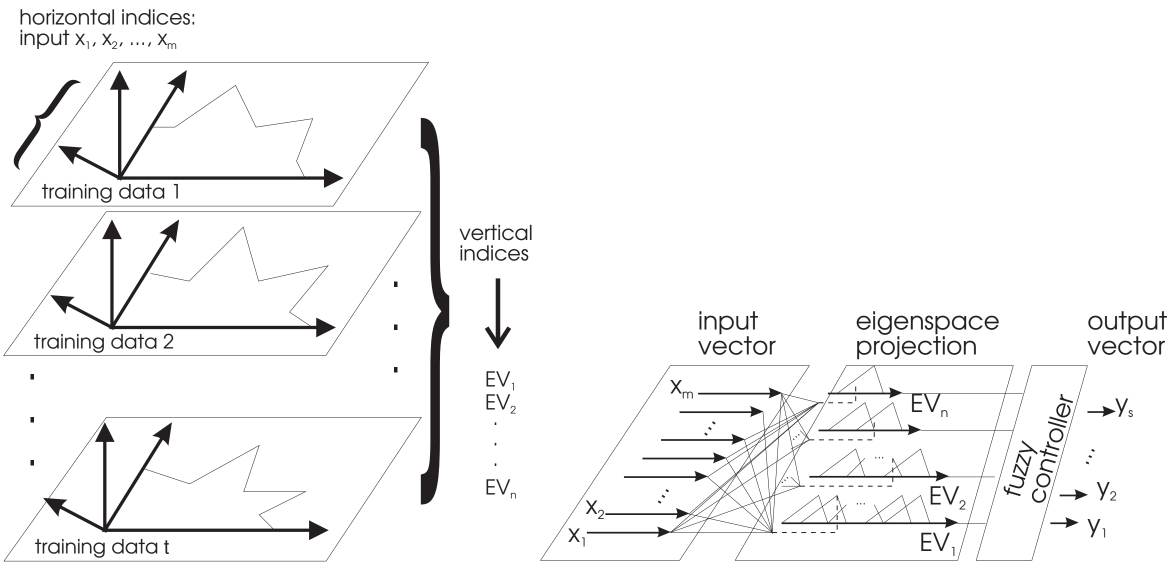
(d) 52.5 Degrees (e) 55.0 Degrees (f) 57.5 Degrees

Figure 2: Sample image sequence from 45.0 to 57.5 Degrees (the whole image sequence is taken from 0 to 90 degrees).

measured by brightness level. If no extra image processing is performed, then a control system with about a quarter of million input variables needs to be modelled. The outputs of the system are the position/orientation or the motion values of a robot.

3.2 Vertical versus Horizontal Indices

If the input vectors are considered as a pile of training data originating from a continuously varying scenarios, instead of being viewed only as a separate input vector, "vertical" indices can be extracted by statistical analysis. These vertical indices describe data distribution, variances, and most interesting for control – the eigenvectors, see Fig. 3(a).
For an input space $X_1 \times X_2 \times \cdots \times X_m$, if all the variables x_1 to x_m could vary in all their universes in the observed sampling procedure, the input data would scatter in the whole input space. Nevertheless, in a high-dimensional input space, if the observed process runs continuously, the input vector varies gradually. Under an appropriately separated



(a) Vertical information

(b) The structure of a fuzzy controller

Figure 3: Constructing fuzzy controllers by using statistical indices.

observation, i.e. within a local scenario of the robot environment, the input vectors possess a large grade of similarity in most cases. That means in the high-dimensional input space, the observed input data are correlated to a large degree.

3.3 Projection in Eigenspace

A well-known technique for dealing with multivariate problems in statistics is *Principal Component Analysis* (PCA). Until now, it is mainly applied in data compression and pattern recognition, [6]. In our opinion, this technique is also suitable for reducing the dimension of the input space of a general control problem.

An eigenvector, noted as EV_i, is computed as $[a_{1,i}, a_{2,i}, \cdots, a_{m,i}]^T$. The eigenvectors form an orthogonal basis for representing the original individual sensor images. Assume that the eigenvectors $EV_1, EV_2, \cdots$ are sorted according to the eigenvalues in a descending order. An eigenspace with a reduced dimension n can be formed with the first n eigenvectors. EV_i accounts for the ith dimension in the eigenspace. The projection of an input vector $[x_1, x_2, \cdots, x_m]$ onto eigenvector EV_i, called the ith principal component, is $a_{1,i}x_1 + a_{2,i}x_2 + \cdots + a_{m,i}x_m$. All projections of the sample data sequence form a manifold in the eigenspace.

Depending on how "local" the measuring data are and therefore how similar the observed sensor images look like, a small number of eigenvectors can provide a good summary of the all the input variables. It can be possible that two or three eigenvectors supply the most information indices of the original input space. In a very high-dimensional case, an efficient dimension reduction can be achieved by projecting the original input space into the eigenspace.

The eigenvectors of a covariance matrix can be efficiently computed by the perceptron approach [7]. This approach has three advantages over Jacobian method [2] if the number of the eigenvectors are pre-selected. First, the Jacobian method calculates all eigenvectors of the covariance or explicit covariance matrix of the input data; the perceptron method only calculates the first n eigenvectors, thus saves computation time. Second, Jacobian requires the construction of the covariance matrix of the input data. With large input data sets this is often critical regarding the amount of memory needed. Thirdly, the found eigenvectors with the perceptron method are already in descending order.

The image projection sequence can be shown as a parametrised manifold in low-dimensional subspace. In the example of Fig. 2, the computed eigenvectors are shown in Fig. 4.

(a) The first eigenvector (b) The Second eigenvector (c) The third eigenvector

Figure 4: First three eigenvectors of sample image sequence.

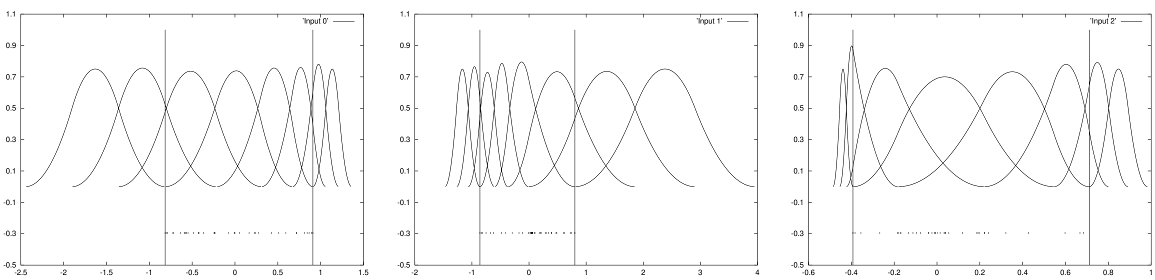
In the online application, the input data are first projected in the reduced eigenspace, then mapped to output based on the B-spline fuzzy control model, Fig. 3(b). The details about the B-spline fuzzy controller are explained in [10]. There are mainly two reasons to use a B-spline fuzzy controller: a). The global minimum is guaranteed; b). Simple supervised learning using gradient descent is easy to implement and enables rapid learning.

4 Experimental Results

We successfully applied the above approach in the “Box-Jenkins Gas Furnace problem” by simulation and showed that it provides much smaller Mean Squared Error than other models with input selection, [9]. The following experiment illustrates the application in a real robot vision system in a physical world.

To simulate an indoor environment, several pictures are attached to the walls of a white box. The input images are obtained from a low-cost black/white camera and processed by a standard PC frame-grabber. The camera is mounted to a relocatable alloy bar (see Fig. 1(b)). All images are transformed into 180×40 pixel subimages (see Fig. 2), i.e. a 7200 element input vector I. This vector is energy normalised, so that $|I| = 1$. The energy normalising makes the interpolation process insensitive to small illumination changes.

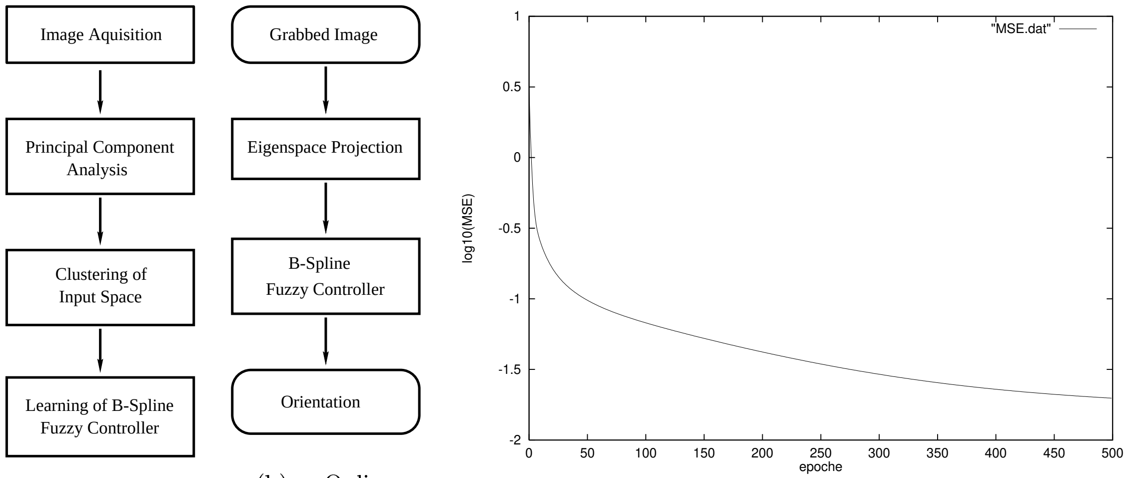
The first three eigenvectors of the whole image sequence are calculated by PCA in less than two minutes on a Pentium 100. In that way the 7200 dimensional input space is reduced to a three dimensional subspace.
Several techniques [5] have been used to search for the closest distance to the manifold and to interpolate a position or orientation of an object. If more eigenvectors are used, the search can be time expensive.



(a) Input 1 (b) Input 2 (c) Input 3

Figure 5: Input variables (eigenvectors) modelled with B-spline basis functions.

In this setup a B-spline fuzzy controller is used for classification/data interpolation. Third-order B-Spline basis functions are used as membership functions. If a large number of basis functions are used, an equidistant distribution provides excellent performance in reducing the Mean Square Error (MSE) of the training data but poor performance in interpolation of new data. If basis functions should be applied as less as possible, e.g. to keep the rule base as small as possible, a clustering method can be applied. Clustering is done by distance relationship. The clustering results are shown in Fig. 5. The vertical lines represent the minimum and maximum of the input data. The input projection in the reduced eigenspace is also shown (the dotted line in the lower half). Four clusters are selected four each input. Each cluster is modelled by a B-spline basis function with its peak point at the centre of weight of each cluster. For maintaining the partition of unity one virtual function is added to each end of the input interval.
The B-spline fuzzy controller is trained via gradient descent supervised learning [11]. The learning result, i.e. the MSE, is illustrated in Fig. 6(c). The maximum deviation is less than 4 degrees in online testing. At most positions the accuracy is around 1 degree. In the face of the simple, low-cost equipment relating to laboratory standards the results are more than encouraging.
The frame rate of the grabber is the only time limiting factor. Projection into eigenspace and interpolation can be done in “real-time”. The distinct steps in offline learning and online interpolation are presented in Fig. 6 (a) and (b).



(a) Learning phase

(b) Online orientation interpolation

(c) Logarithmic MSE curve of training data

Figure 6: Offline learning, online interpolation and the MSE curve.

5 Discussion and Future Work

We showed that by combining PCA with an adaptive fuzzy controller, complex image data can be efficiently applied for navigation purposes. A B-spline fuzzy controller is a suitable model thanks to its fast convergence and good interpolation capability. Within local scenarios, high-dimensional vision data can be compressed to a very compact format with the least loss of their information contents. A fuzzy/neuro controller can thus be trained for a robot to recognise "where I am". If more controllers of this type are "softly" switched between cascaded local scenarios, this approach can be extended to solve the general navigation problem of indoor environments consisting of more complex objects.

An important argument of using an adaptive fuzzy controller instead of other neural networks lies on the interpretability of the learned rule base. To visualise the learned rule base, fuzzy c-means can be used to cluster the input space. Each rule of the system can be modelled by using one controller for each cluster. The output is calculated by weighted summation of the controller outputs. So rules like "**IF** similarity(Image, EV1) is high **AND** similarity(Image, EV2) is low **AND** similarity(Image, EV3) is medium **THEN** Output is low" can be found.

We are currently investigating the problem with more degree of freedom in training images in a general indoor environment, such as radius change, illumination change, etc. The results were encouraging but the learning-error was usually larger than in one-dimensional application since the images of our learning environment were too ambiguous. To cope with the ambiguity problem we will use an omnidirectional view so that translation and rotation can easily be distinguished.

In the final test, the omnidirectional vision system will be mounted on the Khepera mini robot as our standard system shown in Fig. 1(a). The robot is used as a mobile autonomous platform for indoor navigation. Several other techniques have to be added for making this approach more robust to changes in environment, e.g. the addition/removal of objects and to do the navigation without a priori geometric models of the environment.

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