# Modelling Objects Using Kernel Principal Component Analysis

Rajkumari Bidyalakshmi Devi[1], Romesh Laishram[2], Yumnam Jayanta Singh[1]

[1]Department of Computer Science & Engineering and I.T,
Schools of Technology of Assam Don Bosco University
*Airport Road, Azara, Guwahati - 781017, Assam. INDIA.*
*bidrk09mit[at]gmail.com, jayanta[at]dbuniversity.ac.in*

[2]Manipur Institute of Technology, Manipur University,
*Takyelpat, Imphal West 795003. Manipur. INDIA.*
*romeshlaishram[at]gmail.com*

***Abstract:*** ***Object detection is a technologically challenging and practically useful field of computer vision.The success of object detection relies on modelling of an object class. Statistical shape modelling is one of the popular method. Object modelling starts with asset of examples shapes (the training set), and learn from this the pattern of variability of the shape of the class of objects for which the training set can be considered a representative sample. Modelling can considered as the process of modelling the distribution of the training points in shape space. In this paper we present Kernel principal component analysis (KPCA) based active shape models (ASM) for learning the intra –class deformation modes of an object. KPCA is the non-linear dimensionality reduction method. The comparison on performance and space of KPCA and principal component analysis (PCA) are shown***

***Keywords:*** ***Object model, KPCA, PCA, ASM.***

**Cite as: R.B Devi, R. Laishram, Y. J. Singh, "Modelling Objects Using Kernel Principal Component Analysis" ADBU J.Engg.Tech.,2(1)(2015) 0021102(5pp)**

## 1. Introduction

In many computer vision problems obtaining meaningful information from a raw image is of utmost importance for successful interpretation. Automated methods that promise fast and objective image interpretation have therefore stirred up much interest and have become a significant area of research activity. The problem of learning objects class models, a precursor to object detection, from cluttered images has received a lot of attention. The accuracy of object detection heavily relies on object class modeling. It usually involves modeling the distribution of data in high dimensional spaces. This study focus on statistical shape modeling [1, 2], where the intra class variability in a class of shapes may be learnt by modeling the distribution of shape vectors over a training set. This study follows some of the literature from the previous work proposed in [3]. The shape(s) model in novel images are forced to vary only in ways seen during process of training [4, 5]. The deformation modes, accounting for most of the total variability over the training set are analyzed using PCA [6].
The traditional PCA only allows linear dimensionality reduction. Still, traditional PCA will not be useful if the object has more complex structures which cannot be simplified in a linear sub-space. Luckily, kernel PCA allows to generalize traditional PCA to nonlinear dimensionality reduction [7, 8].

Through this study we are proposing a method to use KPCA for learning the intra class variability of an object class. The study observed that more complex structures can be modeled by incorporating KPCA and the number of eigen vectors required in representing the data is less. KPCA is a technique used for non-linear feature extraction. It is very much related to methods applied in Support Vector Machines (SVM). It has proved that this process is useful for various applications, such as de-noising [9]. It is consider as a pre-processing step in regression problems. KPCA has also been used to the construction of non-linear statistical shape models of faces [10].

The remainder of the paper is outline as follows. Section 2 describes the overall flow of the problem. Section 3 describes working principles of KPCA. Section 4 presents the simulation result and section V concludes the paper.

## 2. Related Works

In the recent year object detection has been based on certain shape description. Several earlier work for shape descriptor are based on silhouettes. Yet silhouettes are limited because they ignore internal contour and are difficult to extract from cluttered images as noted by Belongie and Malik [12]. Therefore more recent works represent shapes as loose collections of 2D points or other 2D features proposed the shape context which captures for each point the spatial distribution of all other points relative to it on the shape. This semi local representation allows to establish point to point correspondences between shapes even under non-rigid

deformations. Ferrari et al. [11, 13] present a scale invariant local shape features formed by short chains of connected contour segments. This work is capable of cleanly encoding pure fragments of an object boundary. The study offers an attractive compromise between information content and repeatability. It also encompass a wide variety of local shape structures. The generic features can be directly used to model any object. The feature of the particular object class can be adapted. The study of Shotton et al. and Opelt et al. [14] studied the learning of class-specific boundary fragments and their spatial arrangement as a star configuration. The study of Ferrari and Dalal and Triggs[13][15] achieve this functionality by encoding spatial organization by tilting object windows, and learning which feature combinations discriminate objects from background.
Recently, some study have tried to develop semi supervised algorithms not requiring segmented training examples .The key idea is to find combinations of features repeatedly recurring over many training images. Berg et al. [16] suggests to build the model from pairs of training images and remaining parts matching across several image pairs. A limitation common to these approaches is the lack of modeling of intra-class shape deformation assuming that a single shape can explain all the training set images. Moreover, as pointed out in study, locus is not suited for localizing objects in widely cluttered test set images. In same way the models are learned by study of Leordeanu et al [17]. The study sparse collections of features, rather than explicit shapes formed by continuous connected curves.

A related framework is adopted by Belongie and Malik [12], where matching is supported by shape contexts. Depending on the model structure, optimization scheme can be based on integer Quadratic Programming and spectral matching or graph cuts [17]. In the study of Cootes the shape model in novel images is constrained to vary only in ways those are seen during process of training. The deformation modes, accounting for most of the total variability over the training set are analyzed using PCA.

Kernel principal component analysis (KPCA) is a technique for non-linear feature extraction, closely related to methods applied in Support Vector Machines. In the various applications, such as de-noising [9] KPCA is used as a pre-processing step in regression problems. In study of Romdhani et. al. [10], the KPCA has been applied for the construction of non-linear statistical shape models of faces.

## 3. Object Modelling Process

The overall process of object modeling is briefly described in this section. This study follows some of the literature from the previous work proposed in [3]. The brief steps of the study are given.

### 3.1 Finding the shape model for an object

In order to find the model of an object, follow the steps:

a. First determine the model parts from set of objects
b. Assemble for an initial shape
c. Do refinement of the initial shape by iteratively matching it back onto the training set images.
d. Learn the shape deformation

The algorithm of the step3.1.1 consists of three steps:

a. First extract the local feature. For this purposed we have to align the windows. Let *a* be the geometric mean of the aspect ratios of the training window W. Each window is transformed to a canonical zero centered rectangle of height 1 and width a. This will removes translation and scale differences.
b. Next is to vote for parts that is each feature votes for possible location and scales of the target objects.
c. Local maxima. Of the voting space are considered as object position hypothesis.

### 3.1 Assemble an initial shape

a. Compute occurrences: A pairs of Adjacent Segments (PAS) is occurrence of model parts if they have the similar locations, shape and scale.
b. Compute connectedness: Two model parts have high connectedness if their occurrences frequently share a segment. Two parts sharing both segments have higher connectedness.
c. Assign the parts to occurrences: Suppose A(M)=P be a function handing over for a PAS, P to each model part of M.

Find the mapping A that maximize

$$\sum_{M} conf\,(M \rightarrow A(M) + \alpha \qquad \text{-----(1)}$$

$$\sum_{M,N} conn(M,N).l(A(M),A(N)) - \beta k \qquad \text{---(2)}$$

Where *l*(a,b) = 1 if occurrences a,b come from the same images, 0 otherwise; K is the number of images contributing occurrences to A;α,β are predefined weights. The first term prefers high confidence occurrences. The second term favors assigning connected parts to connect to occurrences. The last term served for selecting occurrences from images.

### 3.2 Refine an initial shape

This step refined the initial model shape. The key idea is match it back onto the training image window W, by applying a deformable algorithm. This algorithm consists of three steps:

a. Sampling process: Let's take sample of 100 equally spaced points from the initial sets of model shape, giving the point set S.
b. Back matching: Match S back to each training window w ϵ W by doing alignment and shape matching

c. Averaging: First align the back matched shapes and then update S, by setting it to possible a mean shape.

### 3.3 Deformation Model

In this stage a learning mechanism is performed to obtain a compact model of the intra class variations using the statistical shape analysis. Deformation means the geometric transformation from the shape of an instance of the object class to another instance. The target is to consider each model shape as a point in 2p-D space and model their distribution with the PCA.

This study employed KPCA for modeling the distribution.

The summary of the learning the shape model is summarized in the flow diagram shown in figure1. An example for the implementation of the different stages of object modeling is depicted in figure 2.

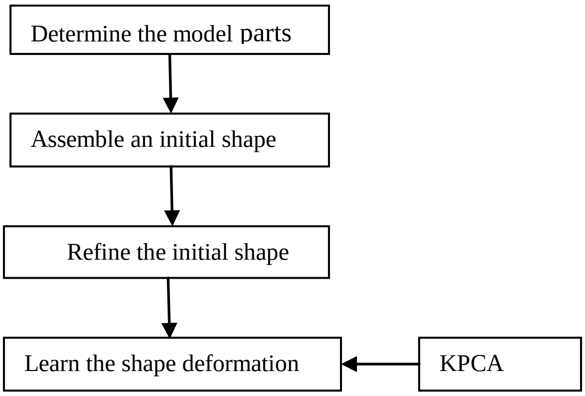



Figure1. Summary of object modeling algorithm

Figure2. Example of stages of the learning model

## 4. Kernel Principal Component Analysis

Kernel Principal Component Analysis can extract features in non-linear ways. Linear Principal Component Analysis is then performed in the feature space. This is express in terms of dot products in the feature space. Thus, the non-linear mapping need not be explicitly constructed. It can be particular by defining the form of the dot products. It uses terms of a Mercer Kernel function K. This study concentrate on the case of a Gaussian kernel function.

Suppose we have a nonlinear transformation $\phi(x)$ from the original D-dimensional feature space to an M- dimensional feature space, where usually $M \leq D$. In such way each data point $x_n$ is projected to a point $\phi(x_n)$. First assume that the projected new features have zero mean i.e.

$$\sum_n \phi(x_n) = 0 \qquad \text{--(3)}$$

And the covariance matrix N X N is given by

$$C = \frac{1}{N}\sum_{n=1}^{N} \phi(x_n)\phi(x_n)^T \qquad \text{--(4)}$$

$$Cv_i = \lambda_i v_i \qquad \text{-- (5)}$$

Where $i = 1,2,\ldots,M$.

From (4) and (5) We have

$$C = \frac{1}{N}\sum_{n=1}^{N} \phi(x_n)\{\phi(x_n)^T v_i\} = \lambda_i v_i \qquad \text{-- (6)}$$

This can be written as

$$v_i = \sum_{n=1}^{N} a_{in}\phi(x_n) \qquad \text{-- (7)}$$

Using (7) in (6), we have

$$\frac{1}{N}\sum_{n=1}^{N} \phi(x_n)\phi(x_n)^T \sum_{n=1}^{N} a_{in}\phi(x_n) = \lambda_i \sum_{n=1}^{N} a_{in}\phi(x_n) \qquad \text{-- (8)}$$

By defining a kernel function

$$k(x_n, x_m) = \phi(x_n)^T \phi(x_m), \qquad \text{--(9)}$$

and multiplying both sides of equation (8) by $\phi(x_l)^T$, we have

$$\frac{1}{N}\sum_{n=1}^{N} k(x_l, x_n) \sum_{m=1}^{N} a_{im} k(x_n, x_m) = \lambda_i \sum_{n=1}^{N} a_{in} k(x_l, x_n) \qquad \text{-(10)}$$

Or in matrix notation

$$K^2 a_i = \lambda_i N K a_i \qquad \text{--(11)}$$

Where $K_{n,m} = k(x_n, x_m)$ --(12)

And $a_i$ is the N-dimensional column vector of $a_{ni}$. $a_i$ can be solved by

$$Ka_i = \lambda_i N a_i \qquad \text{--(13)}$$

The resulting kernel principal components can be calculated by using

$$y_i(x) = \phi(x)^T v_i = \sum_{n=1}^{N} a_{in} k(x, x_n) \qquad \text{--(14)}$$

If the projected dataset $\{\phi(x_n)\}$ does not have zero mean, we can use the Gram matrix $\tilde{K}$ to substitute the kernel matrix **K**. The Gram matrix is given by

$$\tilde{K} = K - l_N K - K l_N + l_N K L_N \qquad \text{-- (15)}$$

where $l_N$ is the N X N matrix with all elements equal to 1/N.

Two commonly used kernels are:
Polynomial kernel $k(x,y)=(x^T y)^d$ and the Gaussian kernel

$$k(x,y)=\frac{\exp(-\|x-y\|^2}{2\sigma^2}$$ with parameter σ.

The standard steps of kernel PCA dimensionality reduction can be summarized as:

a. Construct the Kernel matrix named as K from the training data set $\{x_n\}$ using (12)
b. Compute Gram matrix $\widetilde{K}$ using (15)
c. Use (11) to solve for the vectors $a_i$
d. Compute the kernel principal components $y_i(x)$ using formula given in (14).

## 5. Simulation Output

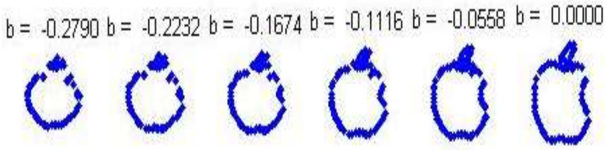
In this section the simulation results of our study on the object modeling problem. The experiments are performed on ETHZ shape classes [11]. In ASMs, the shape of an object is described with point distribution models, and traditional PCA is used to extract the principal deformation patterns from the shape vectors $\{x_i\}$. If we use kernel PCA instead of traditional PCA here, it is promising that we will be able to discover more hidden deformation patterns. Also fewer number of eigen vectors are sufficient as compared to PCA.

The intuitive understanding of the Gaussian kernel PCA makes use of the distance between different training data points. This is similar to k-nearest neighbor or clustering methods. With a well selected σ, Gaussian kernel PCA will have a proper capture range to enhance the connection between the data points that are close to each other in the feature space. Then by applying eigenvector analysis, the eigenvectors will describe the direction in a high-dimensional space in which the different clusters of data are dotted to the greatest extent. The performance of KPCA lies in the proper value of the kernel parameter. For Gaussian kernel PCA, the most important parameter is the σ in the Gaussian kernel. It is used to enhance the capture range of the kernel function. Suppose the σ is too small, all kernel values will be close to zero, and the kernel PCA will fail to extract any information of the structure of the data. In this work we have chosen σ= 20 and this value works well for our purpose.

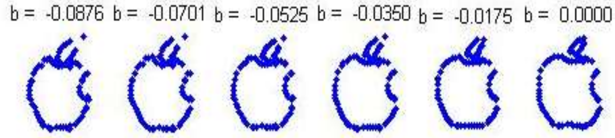
The experiments are performed for modeling of three different objects of ETHZ shape classes [11], namely apple, bottle and swan. The study considers six numbers of input images. The KPCA based ASM modeling generates the possible model of object immediately after single instance of modeling. In other words the first sets of principal component in the kernel feature space is enough to capture the variability in all the objects. However in PCA based ASM modeling more than nine or more principal components are required to model an object. PCA also gives different numbers of principal components for different objects. The effect of varying the first kernel PCA feature for the three objects are also seen. For comparative analysis only we are showing the first component of the PCA vector.

Result of study applying PCA to 'Apple' is shown in figure 3 with nine types of principle components and KPCA is shown as figure 4 with single principle components.

First generated Principle component(PCA)




Second generated Principle component(PCA)




……………………………………………………………………
It goes in similar manner
……………………………………………………………………

Ninth generated Principle component(PCA)

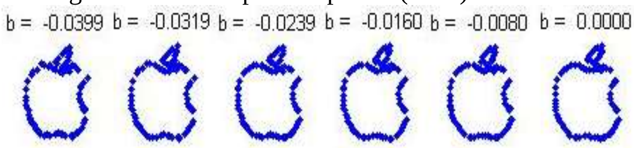



Figure3. Nos of Components required for PCA

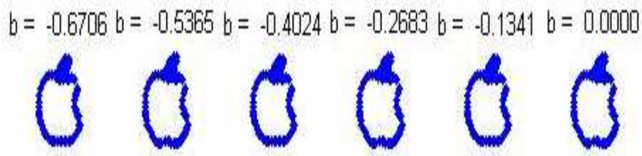



Figure4. Nos of Components required for KPCA

Figure5. The desired model of the object (Final model for PCA and KPCA)

## 6. Conclusion

In this paper, we discussed KPCA based non-linear ASM for deformation modeling and the algorithm has been tested on four different objects. The paper is an improvement of the previous work proposed in similar ways by incorporating KPCA for non-linear deformation modeling. This modification promises extraction of more complicated structures compared to traditional PCA-ASM. KPCA have significant faster performance over PCA. The space requirement is very less for KPCA as compare to PCA.

## References


[1] T. F. Cootes and C. J. Taylor. Statistical models of appearance for computer vision.online document, Postscript: www.isbe.man.ac.uk/˜bim/Models/app model.ps.gz.

[2] R.Davies, C.Twining, C.Taylor, "Statistical models of shape:optimization and evaluation", Springer, First Edition, ISBN: 978-1-84800-137-4 ,2008, DOI: 10.1007/978-1-84800-138-1.

[3] Vittorio Ferrari- Federic Jurie,Cordelia Schmid,2009,"From Image to shape models for object Detection" .,Int J Comput Vis (2010) 87: 284–303DOI 10.1007/s11263-009-0270-9

[4] Cootes, T. F. Taylor, C. J. Cooper D. H. Graham J.,Active shape models, their training and application. Computer Vision and Image understanding, 61(1):38, 1995.

[5] T. F. Cootes, A. Hill, and C. J. Taylor., " The use of Active Shape Models for locating structure in medical images", *Image and Vision Computing*, 12(6):355–366, 1994.

[6] I. T. Joliffe. "Principal Component Analysis", Springer Series in Statistics. Springer-Verlag, New York, 1986.

[7] Schlkopf, Bernhard, Smola, Alexander, and Mller,Klaus-Robert. "Nonlinear component analysis as a kernel eigenvalue problem", 1996.

[8] Scholkopf, Bernhard, Smola, Alexander, and Mller, Klaus-Robert. "Kernel principal component analysis", In Advances in Kernel Methods-Support Vector Learning, pp. 327{352. MIT Press, 1999.

[9] S. Mika, B. Sch¨olkopf, A. Smola, K.-R. M¨uller, M. Scholz, and G. R¨atsch. Kernel PCA and de-noising in feature spaces. In M. S. Kearns, S. A. Solla, and D. A. Cohn, editors, Advances in Neural Information Processing Systems, volume 11, pages 536– 542. MIT Press, Cambridge, MA, 1999.

[10] S. Romdhani, S. Gong, and A. Psarrou. A multi-view nonlinear active shape model using kernel PCA. In T. Pridmore and D. Elliman, editors, *Proceedings of the 10th* British Machine Vision Conference (BMVC99), pages 483–492.BMVA Press, 1999.

[11] V Ferrari, T Tuytelaars, L Van Gool, "Object detection by contour segment networks." Computer Vision–ECCV 2006. Springer Berlin Heidelberg, 2006. 14-28.

[12] S. Belongie, J. Malik, J. Puzicha, "Shape Matching and Object Recognition Using Shape Contexts", PAMI, 24:4, 2002.

[13] V.Ferrari, L. Fevrier, F. Jurie, C. Schmid, Groups of adjacent contour segments for object detection. Pattern Analysis and Machine Intelligence, 30, 36–51, 2008.

[14] V Ferrari, L Fevrier, F Jurie, 'Pattern Analysis and Machine Intelligence', IEEE Transactions on 30.1, 36-51, 2008

[15] J. Shotton, A. Blake, R. Cipolla, *Contour-based learning for object detection*, ICCV, 2005

[16] N. Dalal, , B. Triggs, Histograms of oriented gradients for human detection, CVPR, 2005

[17] A. Berg, T. Berg, T., & J. Malik. Shape matching and object recognition using low distortion correspondence, CVPR, 2005

[18] M. Leordeanu, M. Hebert, R. Sukthankar, Beyond local appearance: Category recognition from pairwise interactions of simple features, CVPR, 2005


**Author Profile**

Rajkumari Bidyalakshmi Devi is working as a project fellow at Department of Computer Science, Manipur University, Manipur, India. She received her Master of Technology Degree in Computer Science & Engg. from Assam Don Bosco University and B.E (Computer Science & Engg.) from Manipur University. She has published one paper in international journal. Her research area is image processing, Evolutionary Computation.

**Romesh Laishram, M.E.,** is presently working as Assistant professor in the department of Electronics & Communication Engineering, Manipur Institute of Technology, Imphal-India. He has published more than 15 research papers in refereed journals and conferences. He has also publish one book on "WiMAX: Call Admission Control". He is also a member of the editorial board in International Journal of Recent Advances in Engineering & Technology(IJRAET). His research area includes signal processing, image processing, Communication systems, VLSI design.

**Y. Jayanta Singh** is working as Associate Prof. and Head of department of Computer Science & Engineering and IT, School of Technology of Assam Don Bosco University, India. He has received Ph.D from Dr. B.A. Marathwada University, Maharashtra(2004). He has worked with several universities-Swinburne University of Technology (AUS), Misurata University with joint program from Nottingham Trent University, Skyline College University (Dubai) for with joint program from American National University. He has worked with Software developments firms-Keane Inc (Canada and India center), TechMahindra etc. His areas of research interest are Distributed Database, Cloud Computing, BigData, Digital Signal processing etc. He has published several papers in International and National Journal and Conferences. He is presently executing AICTE sponsored Research Project and consultancy works.