การสกัดโครงร่างของวัตถุที่มีลักษณะโครงสร้างสองมิติ โดยใช้การผสมกันของโครงข่ายประสาทเทียมชนิดจัดกลุ่มเองและการแปลงแบบคาร์ฮูเนน-เลิฟบนพื้นฐานของการแบ่งเป็นสองกลุ่มแบบเวียนบังเกิด

นายบัญชา อานนท์กิจพานิช

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EXTRACTING THE STRUCTURE OF 2-D STRUCTURAL OBJECTS USING COMBINATION OF SELF-ORGANIZING MAPS AND KARHUNEN-LOEVE TRANSFORM BASED ON RECURSIVE BIFURCATION

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บัญชา อานนท์กิจพานิช : การสกัดโครงร่างของวัตถุที่มีลักษณะโครงสร้างสองมิติโดยใช้การผสมกันของโครงข่ายประสาทเทียมชนิดจัดกลุ่มเองและการแปลงแบบคาร์ฮูเนน-เลิฟบนพื้นฐานของการแบ่งเป็นสองกลุ่มแบบเวียนบังเกิด. (EXTRACTING THE STRUCTURE OF 2-D STRUCTURAL OBJECTS USING COMBINATION OF SELF-ORGANIZING MAPS AND KARHUNEN-LOEVE TRANSFORM BASED ON RECURSIVE BIFURCATION) อ. ที่ปรึกษา : ศาสตราจารย์ ดร. ชิดชนก เหลือสินทรัพย์, 28 หน้า. ISBN 974-17-3415-8.

การระบุคุณลักษณะ, โครงสร้าง และสมบัติเฉพาะของกลุ่มข้อมูลที่ให้มา ถือเป็นขั้นตอนสำคัญก่อนกระบวนการจำแนกกลุ่ม, การรู้จำ, และกระบวนการแปลความหมายเพื่อความเข้าใจ ลักษณะที่สกัดออกมาได้จากกลุ่มข้อมูลนั้น ต้องคงรูปร่างของกลุ่มข้อมูลเดิมไว้ และสมบัติเฉพาะที่ไม่เกี่ยวข้องควรถูกแยกออกหลังจากกระบวนการสกัดนี้ การศึกษานี้เกี่ยวข้องกับการสกัดโครงร่างจริงทางเรขาคณิตของแต่ละชิ้นส่วนจากกลุ่มของวัตถุเชิงโครงสร้างสองมิติ วิธีการของเราตั้งอยู่บนพื้นฐานของโครงข่ายประสาทเทียมชนิดจัดกลุ่มเองและการแปลงแบบคาร์ฮูเนน-เลิฟ จำนวนของกลุ่มข้อมูลซึ่งไม่จำเป็นต้องกำหนดล่วงหน้าเช่นเดียวกับวิธีการอื่นๆ

ภาควิชา **คณิตศาสตร์** ลายมือชื่อนิสิต.....................................

สาขาวิชา **วิทยาการคณนา** ลายมือชื่ออาจารย์ที่ปรึกษา......................

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BANCHAR ARNONKIJPANICH : EXTRACTING THE STRUCTURE OF 2-D STRUCTURAL OBJECTS USING COMBINATION OF SELF-ORGANIZING MAPS AND KARHUNEN-LOEVE TRANSFORM BASED ON RECURSIVE BIFURCATION. THESIS ADVISOR : PROFESSOR CHIDCHANOK LURSINSAP, Ph.D., 28 pp. ISBN 974-17-3415-8.

Identifying the characteristics, structures, and features of a given set of data is the most essential step prior to the classification, recognition, and data interpretation process. Extracting the identified features must preserve data composition configuration. Any irrelevant features will be excluded after the extraction process. This study concerns the extraction of the actual 2-dimensional geometrical element frame from a set of 2-dimensional structural objects. Our approach is based on Self-Organizing Mapping and Karhunen-Loeve transformation that does not require predetermined number of clusters in advance as oppose to other approaches.

Department	**Mathematics**	Student's signature……………………....
Field of study	**Computational Science**	Advisor's signature……………………..
Academic year	**2003**	

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CHAPTER 1

INTRODUCTION

1.1 Problems Identification and Objectives of Work

Identifying the actual geometrical frame of a 2-D structural object by Multispace Karhunen-Loeve transform (MKL) [7] cannot be easily achieved because MKL supports only simple shapes. In addition, a number of eigenvectors must be specified prior to the MKL transformation. This prior specifying process is not feasible and impractical to automatically undertake when a given object is complicated. In this study, we propose a new adaptive technique to overcome these disadvantages by locally and recursively bifurcating the unsupervised clustering self-organizing mapping (SOM) and Karhunen-Loeve transformation. The number of eigenvectors can thus be determined during the geometrical frame identification process.

1.2 Scope of Work

The following conditions are considered in this study:

1. The real input data for testing are noiseless images of well-defined structural objects. No dense objects are considered.

2. The synthetic input data for testing will be generated by some mathematic functions.

The rest of this thesis is organized as follows. Chapter 2 reviews the literature. Background knowledge such as SOM, KL, and MKL is briefly summarized in Chapter 3. Chapter 4 describes the detail of the proposed geometrical frame identification procedures. Chapter 5 shows our experimental results for both real and synthetic data sets. Chapter 6 concludes the work and suggests some relevant future work.

CHAPTER 2

LITERATURE REVIEW

Identifying the characteristic, structure, and features of a given set of data is the most essential step prior to classification, recognition, and understanding process. The identified features must preserve the nature of the data and the irrelevant features should be excluded after the extraction process.

Several interesting techniques have been proposed. Rahul Singh, Vladimir Cherkassky, and Nikolaos Papanikolopoulos [1] presented a method for obtaining a skeletal description of planar sparse shapes by computing the principal curves of the given data points considered as the extracted structure of data points. Their method employed a minimum spanning tree to set the topology of the data points. A piecewise approximation of the principal curve is used to link each node of the topology. Thus, the connected curves represent the skeleton of given data points. The method is an evolutionary computation of skeleton topology which is adaptive during the iteration.

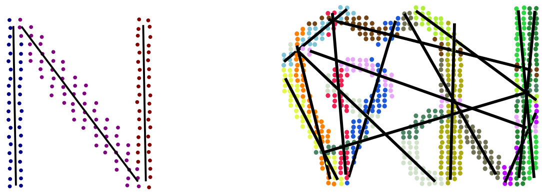
Derek C. Stanford and Adrian E. Raftery [2] proposed an automatic process of detecting the curvilinear features in spatial point patterns with or without background noise using principal curves based clustering with parametric modeling of noise and nonparametric modeling of a feature shape. The number of features and the amount of smoothing are simultaneously determined by approximate Bayes factors.

The application of principal curves for feature extraction was also studied by Kegl and Krzyzak [3]. Their algorithm presented an automatic method to find piecewise linear skeletons of the data points. This method is based on the previous work of Kegl, Krzyzak, Linder, and Zeger [4] which are piecewise linear curves. Their method consists of two main steps: finding skeleton topology of the dark pixel (or called the character) and improving it.

Majid Altuwaijri and Magdy Bayoumi [5] proposed an skeletonization algorithm for Arabic characters to be used in Arabic character recognition system. They employed the ART2 network which is a self-organizing neural network for the clustering of dark pixels of a character image. The skeleton is generated by plotting the center of each cluster and linking adjacent clusters by straight lines.

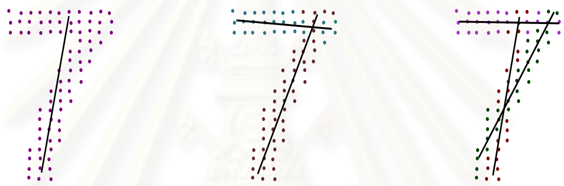
Hichem Frigui and Raghu Krishnapuram [6] proposed Robust Competitive Agglomeration (RCA) algorithm which combines the advantages of two major of traditional clustering algorithms: hierarchical and partitional clustering techniques. The advantage of hierarchical clustering is the number of clusters needs not be specified a priori. On the other hand, this clustering considered the data points in local processing. Thus, the information about the global knowledge such as the shape or size of the cluster was lost. The outcome of this restriction is a problem of separating overlapping clusters. A cluster can be partitioned by using either crisp or fuzzy clustering. The number of clusters must be specified prior to the clustering process. This approach is sensitive to noise and outliers.

The Multispace Karhunen-Loeve transform (MKL) proposed by Cappelli, Maio, and Maltoni [7] can extract frames of a given 2-dimensional object. The technique is sensitive to the shape of an object which is unsuitable to apply to a complex



(a) (b)

Figure 2.1: Two examples of frame identification using MKL. The lines represent the frame of each object. (a) Character N which has a simple structure. (b) A Thai character which has a complex structure.



(a) (b) (c)

Figure 2.2: The results of identifying the frame of character seven by MKL with different pre-specified numbers of lines.

structural object. Figure 2.1(b) shows the result of MKL when it is used to extract the frame of a Thai character. The extracted frame, denoted by lines, does not conform with the natural structure of the character. In addition, the number of lines must be specified prior to the extraction. A technique proposed by Perez and Vidal can be used to identify the frame of a structural object [8]. However, the technique is constrained by the pre-specified number of lines as those in MKL. Figure 2.2 illustrates the different results of identifying the frame of character seven with different numbers of lines.

CHAPTER 3

BACKGROUND KNOWLEDGE

An object consists of a set of vectors in a two dimensional space. To partition this set of vector into clusters, the proposed technique employs SOM as a means for defining the geometrical frame. The geometrical frame of each cluster is further broken down by Karhunen-Loeve transformation. The number of clusters is not pre-specified but is adaptively determined during the partitioning process. The basic concepts of self-organizing mapping and Karhunen-Loeve transformation are summarized in this chapter. As such we will review the concepts of MKL and compare our proposed approach with the MKL.

3.1 Self-Organizing Maps (SOM)

The SOM learning process is based on the concept of representing a set of data vectors by a neuron whose location among the data vectors is captured by its synaptic weight vector. Let $\mathbf{X}_k$ be a currently selected data vector and $\mathbf{W}_i$ the weight vector of neuron i. Neuron $i*$ is called a winner neuron with respect to $\mathbf{X}_k$ if its weight vector $\mathbf{W}_{i*}$ satisfies the following condition

$$\|\mathbf{W}_{i*} - \mathbf{X}_k\| = min_i \|\mathbf{W}_i - \mathbf{X}_k\|, \forall i, i = 1, \ldots, n \tag{3.1}$$

where n is the number of neuron. The winner neuron $\mathbf{W}_{i*}$ is updated with respect to data vector $\mathbf{X}_k$ by this simple learning rule

$$\mathbf{W}_{i*}^{(new)} = \mathbf{W}_{i*}^{(old)} + \eta(\mathbf{X}_k - \mathbf{W}_{i*}^{(old)}) \tag{3.2}$$

where η is a learning rate.

3.2 Karhunen-Loeve transform (KL)

Karhunen-Loeve transformation is a popular technique for projecting a large amount of data, which are derived from the patterns of interest, onto lower dimensional subspaces. The KL transformation is a powerful instrument for pattern representation and compression. The KL yields the orthogonal basis functions as the eigenvectors of the covariance matrix.

Let the set of input vector be $\mathbf{x}_i, i = 1, 2, \ldots, P$ of N dimensions. The covariance matrix of the input data is

$$A = \frac{1}{P}\sum_{i=1}^{P} (\mathbf{x}_i - \mathbf{c})(\mathbf{x}_i - \mathbf{c})^T \tag{3.3}$$

$$\mathbf{c} = \frac{1}{P}\sum_{i=1}^{P} \mathbf{x}_i \tag{3.4}$$

where $\mathbf{c}$ is the average vector. The matrix A can be written as the multiplication of three matrices by means of single value decomposition [9] as follow:

$$A = U * S * U^T \tag{3.5}$$

where S is a diagonal matrix, with nonnegative diagonal elements in decreasing order, U is a unitary matrix, and U^T is the transpose of U. We obtain the eigenvectors and eigenvalues from the eigenvector $\mathbf{e}_j$ which is a column vector in U, and the eigenvalue λ_j which is a scalar in the diagonal of S, respectively. Next, define a transformation matrix Ψ whose columns contain the eigenvector $\mathbf{e}_j$ corresponding to the m largest eigenvalue $\lambda_j, j = 1, 2, \ldots, m$. The reconstruction is given by $\tilde{\mathbf{x}} = \Psi\mathbf{a}$ where $\mathbf{a}$ is vector projection obtained from $\mathbf{a} = \Psi^T\mathbf{x}$.

This KL transformation is optimal [10]. The optimality is based on minimizing the mean squared error between the original vector and its reconstruction corresponding to

$$\sum_{j=m+1}^{N} \lambda_j = MSE(\mathbf{x}_i - \tilde{\mathbf{x}}_i), \quad i = 1, 2, \ldots, P \tag{3.6}$$

The *percentage mean-square reconstruction error* ζ is calculated by dividing equation 3.6 by the sum of all the A's eigenvalues:

$$\zeta = \frac{\sum_{j=m+1}^{N} \lambda_j}{\sum_{j=1}^{N} \lambda_j} \tag{3.7}$$

3.3 Multispace Karhunen-Loeve transform (MKL)

A multispace generalization of the KL transform (which is called MKL) partitions a given pattern set into several subsets called subspaces. Each subspace represents a subset of patterns that has similar characteristics, thus allowing more selective features to be extracted. This method consists of two main steps:

1. Partition the given data into a set of initial subspaces. In fact, choosing an unsuitable set of subspaces or applying inappropriate space-management techniques could cause a severe performance degradation. This is because any inappropriate partitioning may scatter the data into too many clusters and the information on the natural structure of the data will be lost. Figure

3.1(a) and (b) demonstrate the initial partitions and the result of partitioning the spiral data by Iterative Removing method, respectively. While figure 3.1(c) and (d) are the initial and partitioning result of Self-Organizing Maps.

2. Improve the shape of each subspace by iterative optimizing method [7] based on the *percentage mean-square average reconstruction error* ξ on the given data. The *percentage mean-square reconstruction error* ζ related to the KL spaces S_i is defined as follows:

$$\xi = \frac{\sum_{i=1}^{Q}(P_i \cdot \zeta(S_i))}{P} \tag{3.8}$$

where P is the number of given input vectors, P_i is a vector of subspace S_i, and Q is the number of subspaces.

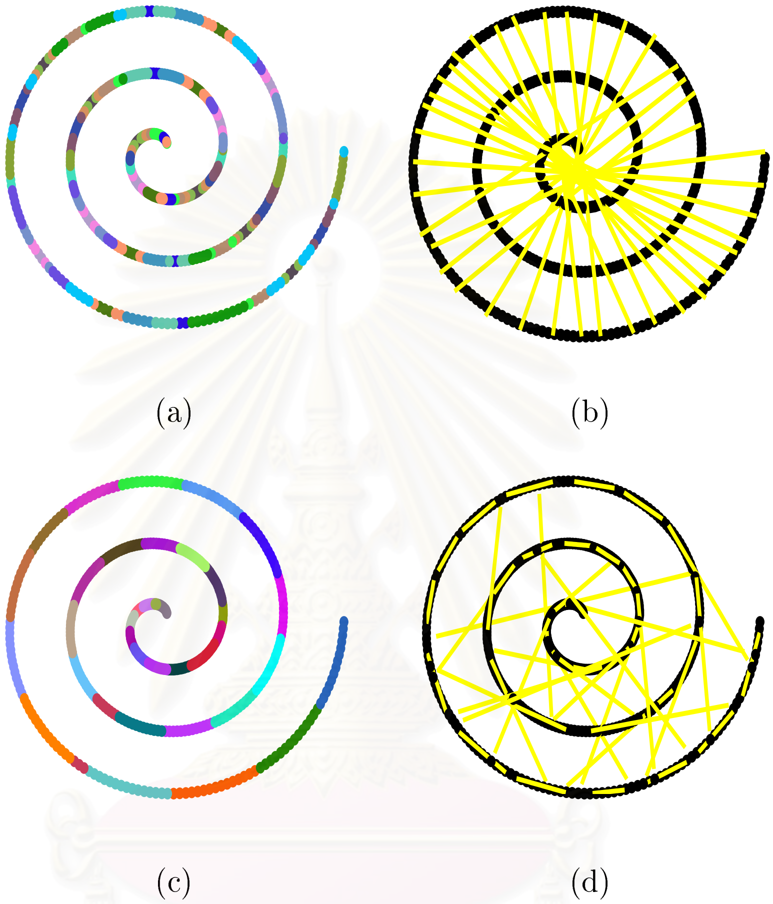


Figure 3.1: Examples of identifying the frames with different of the space-management techniques. Each color represents one cluster. The extracted frames are represented in yellow lines. (a) and (b) are initial partition and final partition resulted by Iterative Removing Method, respectively. (c) and (d) are initial and final partitioning resulted by Self-Organizing Maps, respectively.

CHAPTER 4

Geometrical Frame Identification

The proposed algorithm concerns only structural objects. The definition of a structural object will be given in the next section. There are two main steps required to identify the geometrical frame of a structural object. The first step is to prepare the input data and the second step is to identify the frame.

(a) (b)

Figure 4.1: Some examples of structural and non-structural objects. (a) A structural object. (b) A non-structural object, dense object.

4.1 Structural Objects

Definition 1 A structural object is an object that can be bifurcated into a set of sub-objects. Each sub-object must have the following properties.

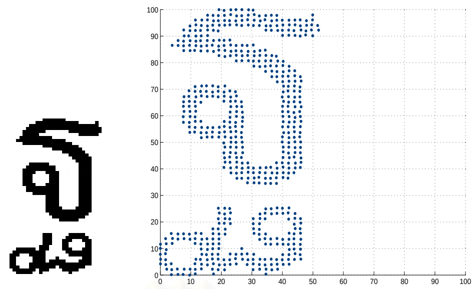
1. The direction of each sub-object can be represented by an eigenvector with maximum eigenvalue obtained from the covariance matrix of all data in the sub-object.

2. All data of the sub-object must gather along a line of the same dimension passing through these data. The standard deviation of the distance between each data and the line is less than or equal to the average distance among all pairs of data in the sub-object.

Some examples of structural and non-structural objects are shown in Figure 4.1. The object in Figure 4.1(a) is a structural object and it is bifurcatable into several structural sub-objects. But the object in Figure 4.1(b) is not a structural object since the object cannot be bifurcated into a set of sub-objects using the constraints.

4.2 Preparation Input data for the Geometrical Frame Identification

An object consists of a set of data points in a 2-dimensional space. The input data are obtained in two ways, real data and syntetic data. In case of real data, we use an image of object whose one pixel corresponds to one point in the cartesian coordinates. In case of syntetic data, the data are generated by using some mathematics functions. Both types of data must be normalized without deforming their original shapes for fitting the size of any input data within the specified 2-dimensional area, regardless of its actual size. Figure 4.2 shows the prepared data prior to the GFI computation. The image is a Thai character.



(a) (b)

Figure 4.2: An example of given input image and its normalized result. (a) The given image. (b) The normalized image in cartesian coordinates.

4.3 GFI computation

The identifying process starts with bifurcating a given object into two independent clusters, $\{cluster_i | i \in \{1, 2\}\}$, using self-organizing mapping (SOM). This process is to bifurcate the object into sub-objects and to find the local eigenvector of each sub-object. Each data point must belong to only one cluster. Then, Karhunen-Loeve transformation is employed to identify the eigenvector with maximum eigenvalue of each cluster. This eigenvector identifies the possible principal direction of the cluster. Then, a line drawn along this principal direction is used as the first candidate frame line of the cluster. Although, this approach sounds reasonable, it is infeasible in the real situation. The principal direction only states the direction of the frame. It does not specify the proper location of the frame line among the data points. In addition, the determination of accepting the shape of the bifurcated cluster cannot be performed by this frame line. To resolve this shape problem, four additional frame lines, namely $frame_{SCD_1}$, $frame_{SCD_2}$, $frame_{APD_1}$, and $frame_{APD_2}$, are introduced to define the boundaries or the out-

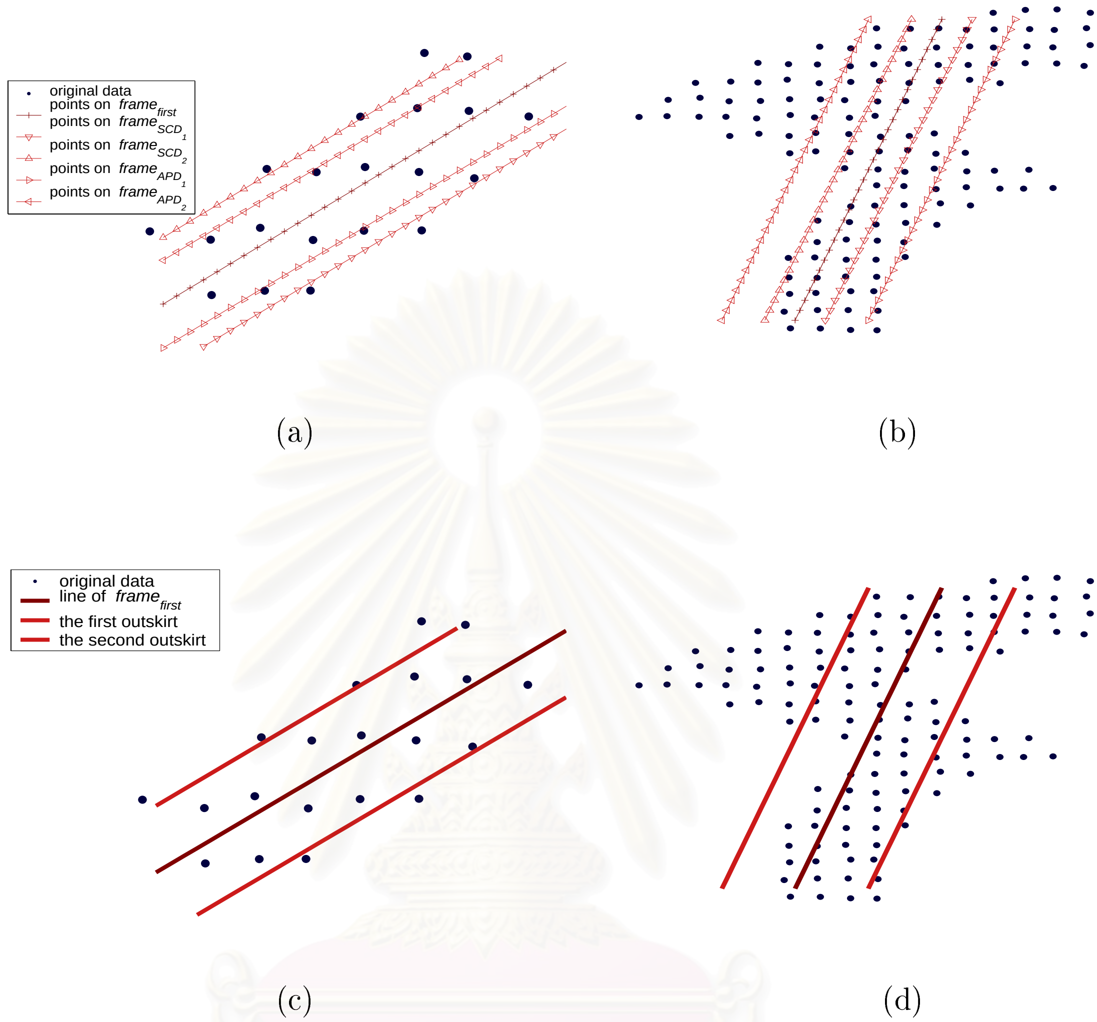


Figure 4.3: Two examples of acceptable and non-acceptable shapes. (a) An acceptable shape defined by $frame_{SCD_1}$, $frame_{SCD_2}$, $frame_{APD_1}$, and $frame_{APD_2}$. (b) A non-acceptable shape defined by $frame_{SCD_1}$, $frame_{SCD_2}$, $frame_{APD_1}$, and $frame_{APD_2}$. (c) and (d) $frame_{first}$ and *outskirts* of a cluster of (a) and (b) respectively.

skirts of the cluster. If the cluster is not acceptable then the cluster must be further bifurcated. Figure 4.3 illustrates two examples of an acceptable shape and a non-acceptable shape. The acceptable shape is illustrated in Figure 4.3(a). In Figure 4.3(b), the shape is non-acceptable and the cluster must be further bifurcated. The four additional frames are obtained from the principal frame line by moving the principal frame line upward, downward, leftward, and rightward with some statistical distances of the data points. The algorithms for computing these statistical distances are as follows.

Algorithm CLUSTER_AVG_SCATTER_DIST ($cluster_a$)

1. **begin**
2. **for** each $\mathbf{x}_i$ in $cluster_a$ **do**
3. let d_i be the distance between $\mathbf{x}_i$ and its nearest data point.
4. compute average distance of all d_i

   $avg_s = \frac{1}{|cluster_a|} \sum_{j=1}^{|cluster_a|} d_j.$
5. compute standard deviation of all d_i

   $std_s = \sqrt{\frac{1}{|cluster_a|-1} \sum_{j=1}^{|cluster_a|} (d_j - avg_s)^2}.$
6. **end**

The values of avg_s and std_s are used for defining $frame_{SCD_1}$ and $frame_{SCD_2}$ as the boundaries of a cluster. The boundaries can be considered in terms of the width of the cluster which is defined by

$$ScatterBound = avg_s + n * std_s \tag{4.1}$$

where a constant n is pre-determined to control the width of a cluster. Obviously, different values of n will produce different boundaries.

Algorithm AVG_PROJECTION_DIST ($cluster_a$)

1. **begin**
2. **for** each $\mathbf{x}_i$ in $cluster_a$ **do**
3. let d_i be the distance between $\mathbf{x}_i$ and its first principal frame.
4. compute average distance

   $avg_p = \frac{1}{|cluster_a|} \sum_{j=1}^{|cluster_a|} d_j$.
5. **end**

The value of avg_p is used for defining $frame_{APD_1}$ and $frame_{APD_2}$ which are parts of the boundaries of a cluster. These frames $frame_{SCD_1}$, $frame_{SCD_2}$, $frame_{APD_1}$, and $frame_{APD_2}$ are computed to find *outskirts* of $cluster_a$ by these rules. If avg_s is greater than avg_p then $frame_{SCD_1}$ and $frame_{SCD_2}$ are used as the outskirts otherwise $frame_{APD_1}$ and $frame_{APD_2}$ are used instead. The algorithm for identifying the geometrical frame of a given object is explained in the following.

Algorithm GEOMETRICALFRAMEIDENTIFICATION

1. **begin**
2. let a set $AcceptedClus = \phi$.
3. bifurcate the given data into $\{cluster_i | i \in \{1,2\}\}$

   using self-organizing mapping.
4. **for each** $cluster_i, i = \{1,2\}$ **do**
5. **begin**
6. the Karhunen-Loeve transformation is employed to identify the

eigenvector with maximum eigenvalue of $cluster_i$. A line drawn in the direction of this eigenvector is considered as the first principal frame or called the candidate frame $frame_{first}$ of $cluster_i$

7. compute avg_s and std_s of $cluster_i$.

8. compute avg_p of $cluster_i$.

9. move the first principal frame by avg_s and avg_p up and down or left and right and get $frame_{SCD_j}$ and $frame_{APD_j}$, for $j = \{1, 2\}$.

10. compute $outskirts$ of $cluster_i$

11. set $ScatterBound \leftarrow avg_s + n * std_s$.

12. **if** average distance of each point on $frame_{first}$ and $outskirts$ to its pair nearest point in $cluster_i < ScatterBound$

13. **then**

14. accept this $frame_{first}$ and $cluster_i$
    $AcceptedClus = AcceptedClus \cup \{cluster_i\}$.

15. **else**

16. recursively bifurcate $cluster_i$ by calling step 3.

17. **endif**

18. **end**

19. try to merge two adjacent clusters in $AcceptedClus$ and identify a new frame using steps 6 to 14.

20. **end**

The geometrical frame lines obtained by the GeometricalFrameIdentification algorithm may not conform with the natural geometrical frame of the given object due to too many clusters. To correct the geometrical frame, a merging procedure must be introduced in step 19. Figure 4.4 shows an example of merging four cluster and re-identify the frames. Notice that the number of clusters are gradually and adaptively determined during the identification process. There is no need to pre-specified the number of clusters as in the other techniques.

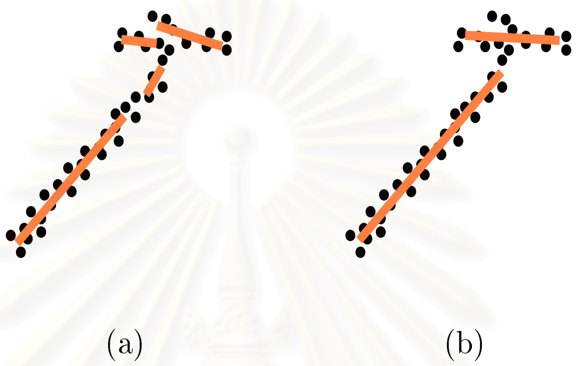


Figure 4.4: An example of merging some clusters and obtaining a new frame better the previous frame. (a) before merge. (b) after merge.

Figure 4.5 shows the process of GeometricalFrameIdentification when it is applied to a Thai character. The given original data in Figure 4.5(a) is bifurcated into two sub-objects shown in Figure 4.5 (b) and (c). Both figures are non-acceptable shapes. Thus, they are recursively bifurcated into sub-objects is illustrated in Figures 4.5 (d) and (e), respectively. On the other hand, if any sub-objects are acceptable shapes then the new obtained clusters must be checked adjacency for merging two adjacent clusters and identifying a new frame, if possible. This process is recursively performed until all generated frames are acceptable.

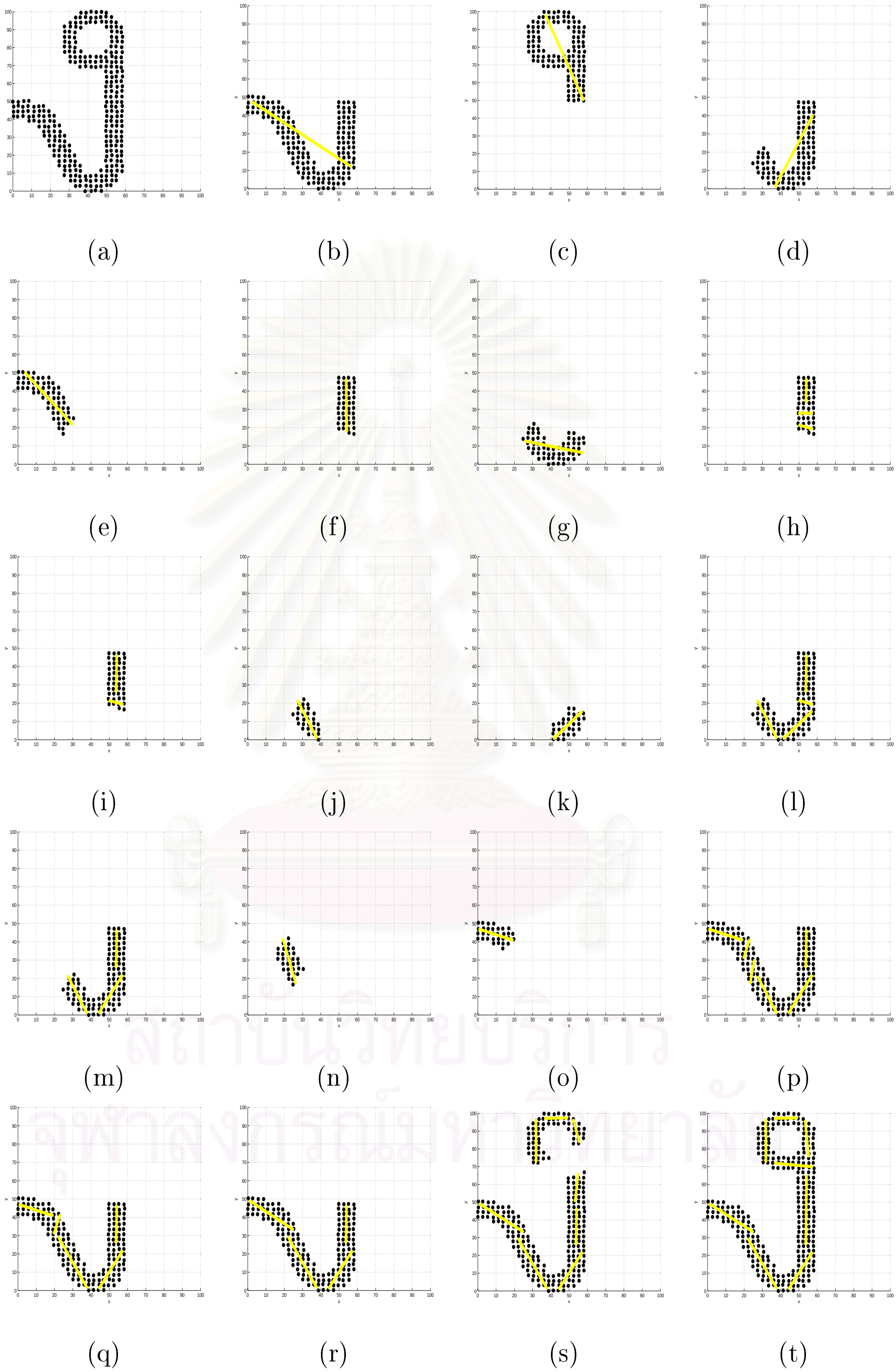


Figure 4.5: A step-by-step of the process of GEOMETRICALFRAMEIDENTIFICATION when it is applied to a Thai character.

CHAPTER 5

EXPERIMENTAL RESULTS

The performance of GFI is compared with the previous MKL method on both the syntetic and real data sets in several fields of applications such as piecewise linear approximation, feature extraction, and clustering. One important parameter controlling the geometrical frame of an object is n which is defined in equation 4.1. If n is large then the geometrical frame will be deformed from its natural frame and the detail of the frame is reduced. But if n is small then the geometrical frame will approach its natural frame. Figure 5.1 shows an example of a sine curve and its different geometrical frames generated from different values of n's.

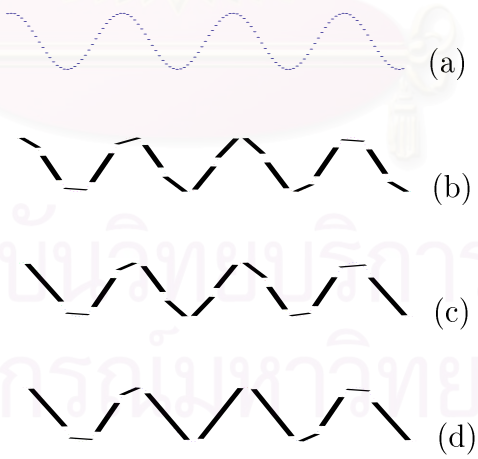
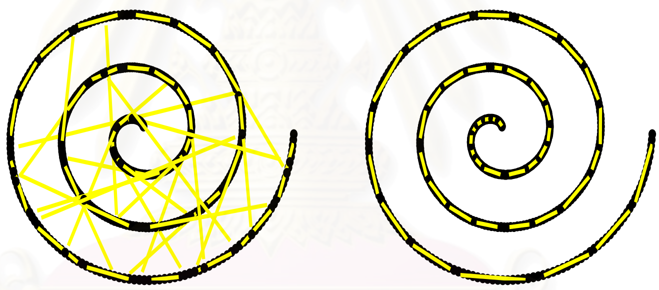


Figure 5.1: An example of a sine curve identified by using different values of n. (a) A given sine curve. (b) When $n = 0$. (c) When $n = 1$. (d) When $n = 2$.

5.1 Piecewise Linear Approximation

The representation of curves is an important issue in several fields such as contour analysis, pattern classification, signal processing, and pattern recognition in general. We attempt to define and locate the set of points that give the most appropriate description of the curve by finding a set of r straight lines $(y = a_1 + b_1x)$, $(y = a_2 + b_2x)$, $\ldots$, $(y = a_r + b_rx)$ that optimally fit an ordered set of N points (x_1, y_1), (x_2, y_2), $\ldots$, (x_N, y_N). By the method of [8] and MKL, a number of straight lines must be specified prior to obtaining the piecewise linear approximation. This is not feasible and impractical to automatically determine when a given object is complicated as in the case of a spiral shown in Figure 5.2.



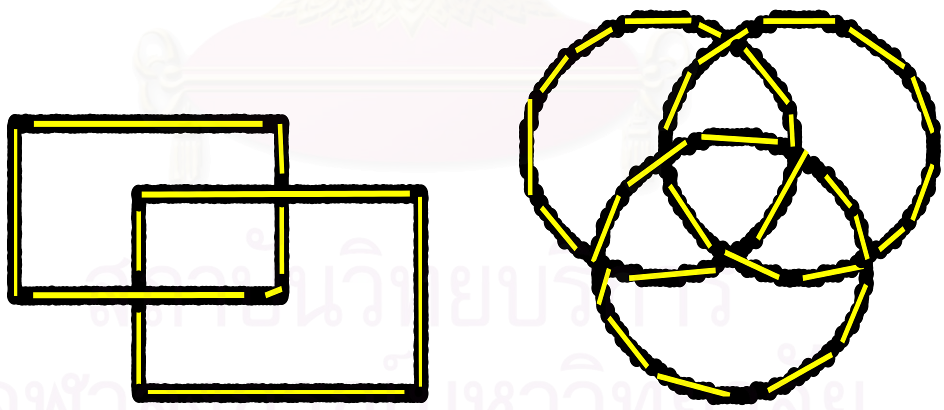
(a) (b)

Figure 5.2: The piecewise linear approximation for spiral function. (a) MKL result. (b) Our result.

Figure 5.2(a) which is the result of MKL cannot extract the natural frames of a spiral because this algorithm globally considers the data. This implies that several portions of data scattered at different locations may be assigned to the same cluster. Our technique takes a different approach by considering only the local features of the data.

5.2 Feature Extraction

The feature extraction is a pre-processing of many applications such as image processing, speech recognition, pattern classification and recognition. The goal of feature extraction in image processing is to enhance and improve an input image before other processing step. The identified frames of an object can be used to represent the features of the object. Figure 5.3 demonstrates the feature extraction of overlapped objects. In addition, two different types of data are tested. The first type consists of five complex structured Thai characters illustrated in Figure 5.4. The geometrical frames of these five characters are identified by MKL and our techniques. The comparison results are summarized in Figure 5.4. The second type is a set of isolated English characters bounded by a frame, e.g. a license plate of a car. Figure 5.5 shows the result of frame identification by MKL and our technique.



(a) (b)

Figure 5.3: The feature extraction of overlapped objects, (a) and (b) Our results.

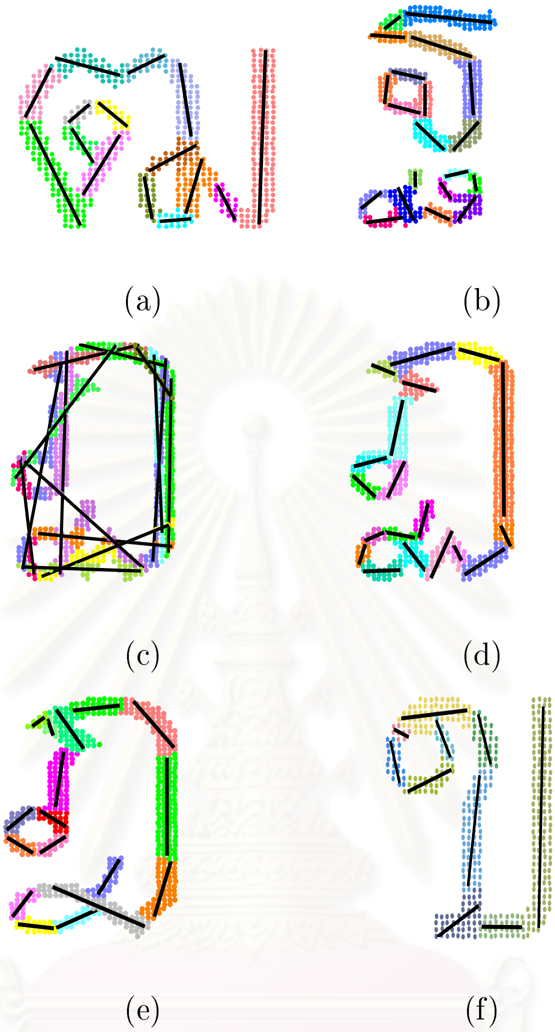
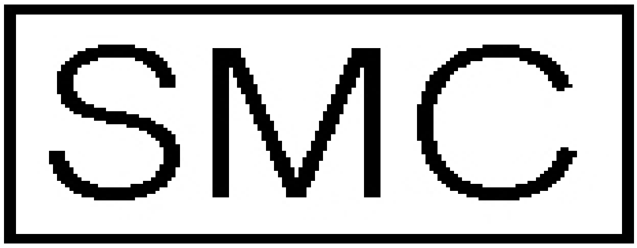
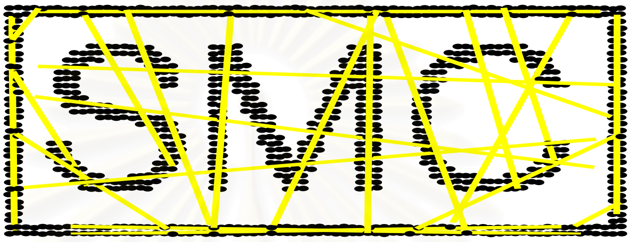


Figure 5.4: The feature extraction of Thai characters. (a) and (b) Our results. (c) MKL result. (d),(e), and (f) Our results.



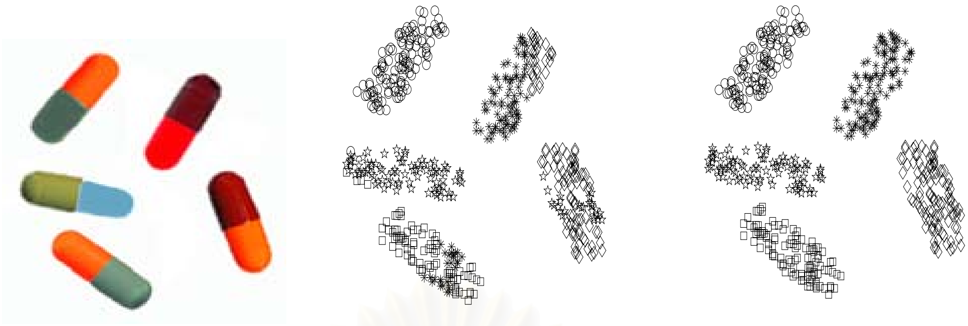
(a)



(b)

(c)

Figure 5.5: The feature extraction of a sign board. (a) Given object. (b) MKL result. (c) Our result.



(a) (b) (c)

Figure 5.6: Comparison of clustering of capsules image data between MKL and GFI. (a) Given data. (b) Clustering by MKL. (c) Clustering by our technqiue.

5.3 Clustering

Cluster analysis is one of the popular tools for exploring the underlying structure of a given data set and is being applied in wide varieties of engineering and scientific disciplines such as medicine, psychology, biology, sociology, pattern recognition, and image processing. The general clustering problem has major two issues:

1. determination of the number of groups in the clustering.

2. the shape of each group after the clustering.

The first issue can be managed by using the GFI because the number of eigenvectors is automatically determined during the GFI process. For the second issue, the structure revealed by MKL is based on the global covariance of the data set and only the global structure is defined to share the data points among these clusters. Thus, the outcome of the technique may not preserve the natural geometrical frame of all the relevant clusters. Figure 5.6 shows the clustering result of the given capsule image data. Our technqiue produces the correct clustering.

CHAPTER 6

CONCLUSION

This work presents a new method for identifying geometrical frame of 2-D structural objects using combination of SOM and KL which is based on the recursive bifurcation technique. The characteristic of our algorithm is local and adaptive, the algorithm rests primarily on the eigenvector established according to a predefined bound. This bound, in turn, can scatter to cover the object, whereby forming a cover frame. This provides greater flexibility to control the detail of the generated frame. In addition, the SOM learning process depends on the order of selecting an input during the training. Different selecting orders will lead the neurons to different locations which obviously generate the different results. The algorithm can be applied to many applications such as piecewise linear approximation, feature extraction, clustering, and image pre-processing. It is, however, sensitive to noise and unevenly scattered data. In addition, the appearance of an obtained frame does not look natural as the principal curve does. Thus, further development should concern the improvement of the appearance which can be acheived by applying the spline interpolation to each bifurcated sub-object, and the robustness with respect to noise and the sparseness of data.

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