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模式识别中的二型模糊图模型

Type-2 Fuzzy Graphical Models for Pattern Recognition

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内 容 简 介

本书着重讨论了如何融合二型模糊集合理论与概率图模型来解决现实世界中的模式识别问题，例如语音识别、手写体汉字识别、主题建模和人体动作识别等应用。本书覆盖了二型模糊集合理论和概率图模型理论的最新进展，同时也详尽地介绍了融合两大理论的框架。本书不但适用于模糊逻辑和模式识别领域的研究生、研究学者和工业实践者，同时也可以作为没有上述研究背景的研究学者的宝贵参考读物。

本书作者曾嘉博士是苏州大学计算机科学与技术学院教授，刘志强博士是香港城市大学创意媒体学院教授。

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This book is dedicated to my family: Tian-Yi Zeng and Xiao-Qin Cao

Preface

This state-of-the-art book describes important advances in type-2 fuzzy systems that have been made in the past decade for real-world pattern recognition problems, such as speech recognition, handwriting recognition, and topic modeling. The success of type-2 fuzzy sets has been largely attributed to their three-dimensional membership functions to handle both randomness and fuzziness uncertainties in real-world problems. In pattern recognition, both features and models have uncertainties, such as nonstationary babble noise in speech signals, large variations of handwritten Chinese character shapes, uncertain meaning of words in topic modeling, and uncertain parameters of models because of insufficient and noisy training data. All these uncertainties motivate us to integrate type-2 fuzzy sets with probabilistic graphical models to achieve better overall performance in terms of robustness, generalization ability, or recognition accuracy. For example, we integrate type-2 fuzzy sets with graphical models such as Gaussian mixture models, hidden Markov models, Markov random fields, and latent Dirichlet allocation-based topic models for pattern recognition. The type-2 fuzzy Gaussian mixture models can describe uncertain densities of observations. The type-2 fuzzy hidden Markov models incorporate the first-order Markov chain into the type-2 fuzzy Gaussian mixture models, which is suitable for modeling uncertain speech signals under babble noise. The type-2 fuzzy Markov random fields combine type-2 fuzzy sets with Markov random fields, which is able to handle large variations in structural patterns such as handwritten Chinese characters. The type-2 fuzzy topic models focus on uncertain mixed membership of words to different topical clusters, which is effective to partition the observed (visual) words into semantically meaningful topical themes. In conclusion, these real-world pattern recognition applications demonstrate the effectiveness of type-2 fuzzy graphical models for handling uncertainties.

Suzhou, May 2013 — Jia Zeng
Hong Kong — Zhi-Qiang Liu

Acronyms

ABP	Active belief propagation
BP	Belief propagation
GLM	Generalized linear model
GMM	Gaussian mixture model
HMM	Hidden Markov model
LDA	Latent Dirichlet allocation
L-LDA	Labeled latent Dirichlet allocation
MF	Membership functions
MRF	Markov random field
PDF	Probabilistic density function
RBP	Residual belief propagation
T2 FGMM	Type-2 fuzzy Gaussian mixture model
T2 FHMM	Type-2 fuzzy hidden Markov model
T2 FMRF	Type-2 fuzzy Markov random field
T2 FS	Type-2 fuzzy sets

Contents

Chapter 1
Introduction

Abstract This chapter overviews the whole book. First, we introduce some fundamental concepts in pattern recognition. Pattern recognition can be viewed as a labeling process that bridges human (machine) perceptions to linguistic labels. Second, we motivate the use of probabilistic graphical models and type-2 fuzzy sets to handle two important uncertainties, namely randomness and fuzziness, existing universally in the labeling problem. Finally, we summarize our contributions, and provide the structure of this book.

1.1 Pattern Recognition

The term pattern recognition encompasses a wide range of information processing problems of great practical significance, from speech recognition to the classification of handwritten characters [1]. By patterns, we understand any relations, regularities, or structure inherent in some source of data [7]. Pattern recognition takes in raw data and makes decisions based on the "category" of the pattern [3], which deals with the automatic detection of patterns in data, and plays a crucial role in many modern artificial intelligence and computer science problems.

As shown in Fig. 1.1, the pattern recognition system includes five basic components: (1) sensing, (2) segmentation, (3) feature extraction, (4) classification, and (5) post-processing, where the components (1)–(3) simulate the human perception leading to the *feature space*, and the components (4)–(5) assign the linguistic labels to features for classification. From Fig. 1.1, we may view pattern recognition as a labeling process that uses *linguistic labels* (classes) to interpret the machine perception. Mathematically, the pattern recognition system reflects a functional relationship between the input and the output decision. This function is sometimes referred to as the *decision function*. Usually, we will choose a particular set or class of candidate functions known as *hypotheses* before we begin trying to determine the correct function. The ability of a hypothesis to correctly classify data not in the training set is known as its *generalization*. The process of determining the correct function (often

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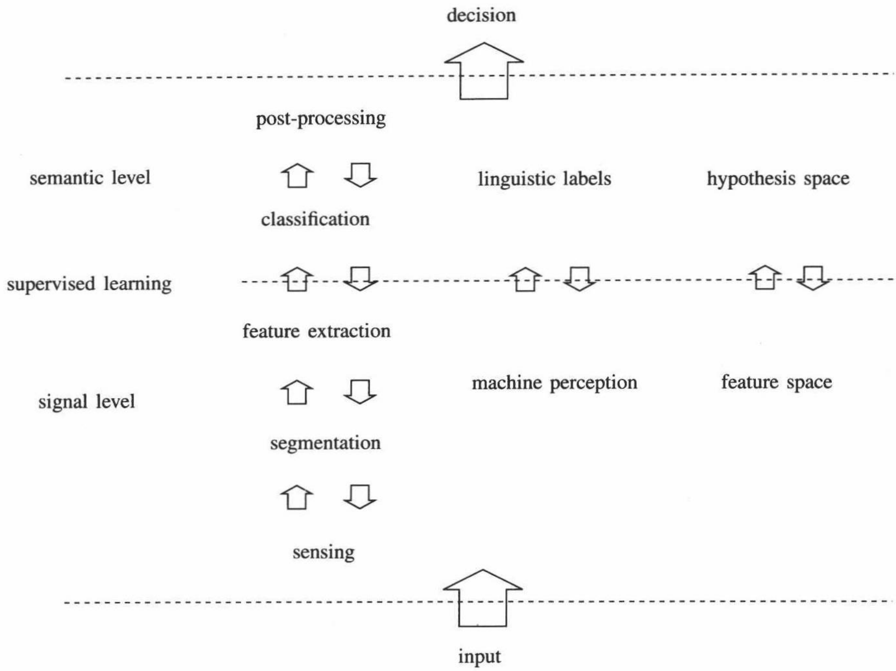

Fig. 1.1 The structure of the pattern recognition system

a number of adjustable parameters) on the basis of examples of input/output functionality is called *learning* or *training*. When the examples are input/output pairs, it is called *supervised learning*. The examples for training are generally referred to as the *training data*. The *learning algorithm* takes the training data as input, and selects a hypothesis from the *hypothesis space*. So the learning algorithm connects the feature space and the hypothesis space. Figure 1.1 shows two layers, signal level and semantic level, of the pattern recognition system. They correspond to machine perception and linguistic labels as well as feature space and hypothesis space.

Based on the above, pattern recognition involves three central problems:

1. How to extract features so that the feature space can be partitioned efficiently;
2. How to choose the set of hypotheses so that the hypothesis space contains the correct representation of the decision function;
3. How to design the learning algorithm to automatically determine the decision function from the feature space and hypothesis space.

To solve above problems, we have to incorporate knowledge about the problem domain called *prior knowledge*. The choice of the distinguishing features is to achieve a "good" *pattern representation*, and depends on the characteristics of the problem domain. The representation may naturally reveal the structural relationships among the components, and express the true underlying model of the patterns. We favor a small number of features, which may lead to both simpler decision regions and learning algorithm for classifiers [3]. The second problem is associated with the choice of functions that can best describe the variations of features within class. In this book, we assume a parametric form of the decision function so that the hypothesis space has a specific functional form with undetermined parameters. Hence prior knowledge about distinguishing features and the functional form of hypothesis plays a major role in successful pattern recognition systems. Therefore, the learning algorithm in the context of this book determines the parameters of the decision function based on the training data. The learning process adapts the hypothesis to fit the training data. In the meanwhile, we hope that the hypothesis is not only consistent with the training data, but also generalizes well to the unknown test data.

This book mainly focuses on handling uncertainties in pattern recognition. Specifically, we combine two techniques, probabilistic graphical models [4] and type-2 fuzzy sets [5], to handle some sources of uncertainties, and hope to improve the performance of pattern recognition systems.

1.2 Uncertainties

Inevitably, pattern recognition has to deal with uncertainties. In statistical pattern recognition, we focus on the statistical properties of patterns in terms of *randomness*, which is generally expressed in probability density functions (PDFs). The features are often called *observations*. The success of statistical pattern recognition has been largely due to its ability to recover the model that generated the patterns. It assumes the models which give rise to the data do not themselves evolve with time, i.e., the sources of data are stationary. Hence the probability densities with parameters estimated from a large amount of training data are enough to represent the random uncertainty of patterns. Note that the sufficient training data play key roles to characterize randomness in both practical and theoretical aspects.

Graphical models [2, 4, 6] use Markov properties as special hypotheses that can statistically represent the structural relationships in observations. They define the most important structural information by the neighborhood system, and encode such information in terms of randomness in the PDFs. To achieve the lowest probability of classification error, the Bayesian decision theory [3] provides the optimal decision boundary as shown in Fig. 1.2a, b. Two graphical models, namely hidden Markov models (HMMs) and Markov random fields (MRFs), have been widely explored as hypotheses for modeling sequential and two-dimensional patterns, respectively. The difference between HMMs and MRFs lies in their neighborhood systems. For example, HMMs are suitable acoustic models for phonemes, because HMMs reflect phonemes piece-wise stationary properties. On the other hand, MRFs are good at describing the stroke relationships of handwritten characters. The main advantages of using graphical models are twofold: Markov properties are able to model patterns statistical-structurally in terms of randomness. Besides, graphical models have efficient leaning and decoding algorithms with a tractable computational complexity.

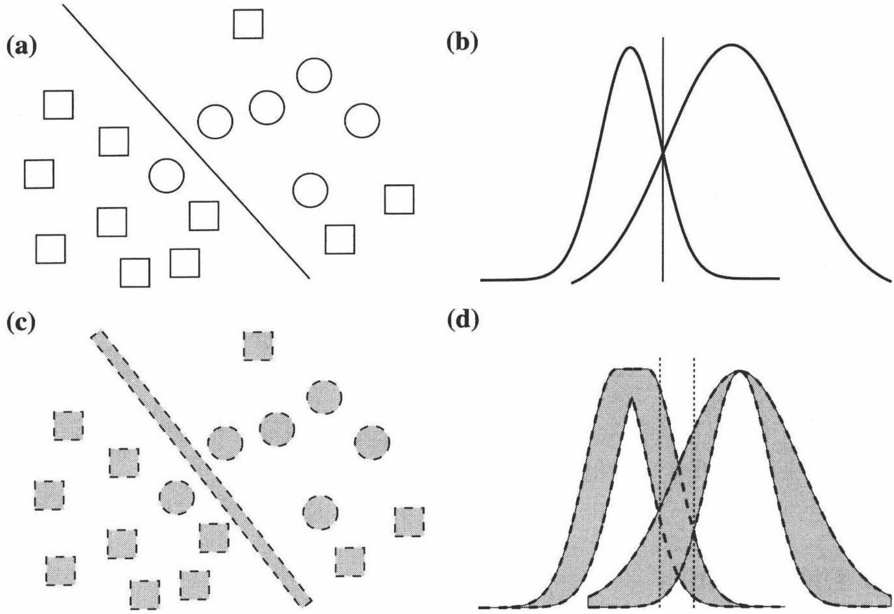

Fig. 1.2 The uncertainties exist in both the feature and hypothesis spaces. In **a** and **b**, the hypothesis space describes the randomness in the feature space, and the decision boundary is a *solid line* for two pattern classes, namely *circles* and *squares*. In **c** and **d**, after incorporating fuzziness, the fuzzy (*the shaded region*) hypothesis space describes both randomness and fuzziness in the fuzzy feature space, and the decision boundary becomes fuzzy denoted by the *shaded line*

However, in practice, we often encounter uncertainties that cannot be characterized by randomness as follows.

1. Uncertain Feature Space: Features (training and test data) may be corrupted by noise. Measurement noise is non-stationary, and the mathematical description of the non-stationarity is unknown (e.g., as in a time-varying signal-to-noise ratio (SNR)) (Fig. 1.2c);
2. Uncertain Hypothesis Space: Insufficient or noisy training data may result in uncertain parameters of the hypothesis, so that the decision boundary is also uncertain (Fig. 1.2d);
3. Non-stationarity: Features have statistical attributes that are non-stationary, and the mathematical descriptions of the non-stationarity are unknown.

All of these uncertainties can be considered as *fuzziness* resulting from incomplete prior knowledge, i.e., fuzzy features (we do not know if the training data are clean, stationary, and sufficient), fuzzy hypothesis (we do not know if the parameters imply the correct mapping), and fuzzy attributes (we do not know the attributes exactly).

Type-2 fuzzy sets is a good choice to describe the *bounded uncertainty* in both the feature and hypothesis spaces. Type-2 fuzzy sets have grades of membership

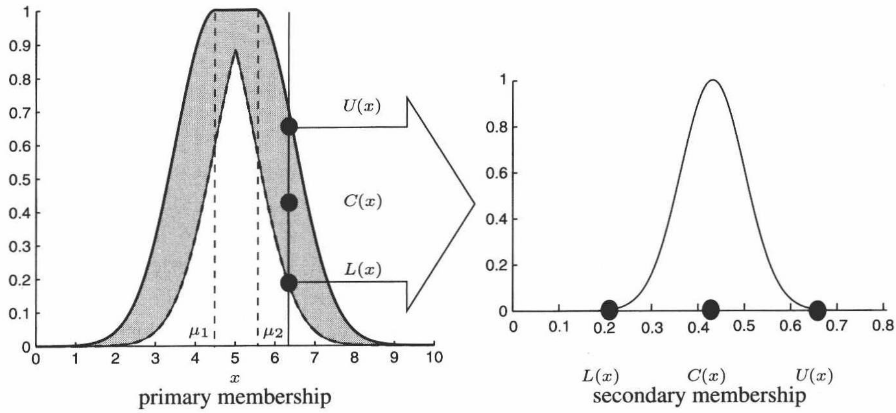

Fig. 1.3 A type-2 membership grade can be any subset in [0, 1]—the primary membership and corresponding to each primary membership, there is a secondary membership (which can also be in [0, 1]) that defines the possibilities for the primary membership. The *left* shows the uncertainty of the primary membership. The *right* shows the corresponding secondary membership of one of the bounded vertical-slice primary memberships $[L(x), U(x)]$ given the input x

that are themselves fuzzy. A type-2 membership grade can be any subset in [0, 1]—the primary membership and corresponding to each primary membership, there is a secondary membership (which can be in [0, 1]) that defines the possibilities for the primary membership [5]. Figure 1.3 shows an example of the type-2 fuzzy set. The primary membership is uncertain denoted by the bounded shaded region on the left, where its uncertainty is measured by the secondary membership on the right. Note that at each input x, the uncertainty of primary membership is reflected by the bounded interval $[L(x), U(x)]$. Hence, type-2 fuzzy sets provide a natural framework to simultaneously handle more uncertainties thanks to their three-dimensional membership functions. Using primary memberships, we may handle the randomness. On the other hand, we can handle the fuzziness of primary memberships by secondary memberships. Both randomness and fuzziness can propagate in the system through type-2 fuzzy set operations. By incorporating type-2 fuzzy sets, we can describe the fuzzy feature and hypothesis in terms of bounded uncertainty. We have two major advantages of using type-2 fuzzy sets: they can characterize patterns in terms of both randomness and fuzziness; meanwhile, type-2 fuzzy sets retain a controlled degree (bounded) of uncertainty based on prior knowledge.

In conclusion, on the one hand, we motivate the use of graphical models to represent structural patterns statistically. On the other hand, we incorporate type-2 fuzzy sets to handle both randomness and fuzziness within a unified framework.

1.3 Book Overview

In this book, we have made several contributions in the following four aspects:

1. We propose pattern recognition as the labeling problem, and use graphical models to describe the probabilistic interdependence of the labels. Four graphical models have been studied in deep, namely Gaussian mixture models (GMMs), hidden Markov models (HMMs), Markov random fields (MRFs), and latent Dirichlet allocation (LDA), where GMMs can detect probabilistic densities, HMMs are suitable to model one-dimensional sequential observations, MRFs are good at two-dimensional labeling problems, and LDA is used for probabilistic topic modeling tasks. By employing the Bayesian decision theory, we formulate the learning and decoding algorithms to obtain the best labeling configuration. We regard graphical models as a statistical-structural pattern recognition paradigm, because they statistically describe the structural information of labels and observations.
2. We investigate the mechanism of type-2 fuzzy sets for handling uncertainties. The three-dimensional membership function enables type-2 fuzzy sets to handle more uncertainties within a unified framework. Two important properties, secondary membership function and foot print of uncertainty, determine the capability of type-2 fuzzy sets for modeling bounded uncertainty. Also we review the recent advances of type-2 fuzzy sets for pattern recognition.
3. The major contribution of this book is that we integrate graphical models with type-2 fuzzy sets referred to as the type-2 fuzzy graphical models to handle both random and fuzzy uncertainties within a unified framework. We have developed the learning and decoding algorithms of the type-2 fuzzy graphical models based on type-2 fuzzy set operations. We show that the type-2 fuzzy graphical models can be viewed as embedded with many classical graphical models, so that the expressive power of type-2 fuzzy graphical models have been greatly enhanced.
4. We extensively explore many pattern recognition applications, such as density estimation, speech recognition, handwritten Chinese character recognition, and topic modeling of visual words for human action recognition. The experimental results are encouraging, which confirm the validity of the proposed type-2 fuzzy graphical models.

The first chapter is an introduction to the principal concepts of pattern recognition, and motivates the use of graphical models and type-2 fuzzy sets to handle uncertainties in pattern recognition. Chapter 2 deals with the labeling problem by using graphical models to model the probabilistic interdependency of labels. Type-2 fuzzy sets and fuzzy logic systems are introduced in Chap. 3. We handle random and fuzzy uncertainties within a unified type-2 fuzzy graphical model framework, and extends the graphical models' learning and decoding algorithms using type-2 fuzzy sets operations. Chapter 4 integrates type-2 fuzzy sets with Gaussian mixture models to estimate densities from noisy and insufficient data. Chapter 5 shows how to use type-2 fuzzy hidden Markov models to handle babble noise in speech recognition. Chapter 6 introduces how to use type-2 fuzzy Markov random fields to differentiate