Advances in Intelligent Systems and Computing 250

Srikanta Patnaik
Xiaolong Li *Editors*

Proceedings of International Conference on Soft Computing Techniques and Engineering Application

ICSCTEA 2013, September 25–27, 2013, Kunming, China

Springer

Advances in Intelligent Systems and Computing

Volume 250

Series editor

Janusz Kacprzyk, Warsaw, Poland

For further volumes:
http://www.springer.com/series/11156

About this Series

The series "Advances in Intelligent Systems and Computing" contains publications on theory, applications, and design methods of Intelligent Systems and Intelligent Computing. Virtually all disciplines such as engineering, natural sciences, computer and information science, ICT, economics, business, e-commerce, environment, healthcare, life science are covered. The list of topics spans all the areas of modern intelligent systems and computing.

The publications within "Advances in Intelligent Systems and Computing" are primarily textbooks and proceedings of important conferences, symposia and congresses. They cover significant recent developments in the field, both of a foundational and applicable character. An important characteristic feature of the series is the short publication time and world-wide distribution. This permits a rapid and broad dissemination of research results.

Srikanta Patnaik · Xiaolong Li
Editors

Proceedings of International Conference on Soft Computing Techniques and Engineering Application

ICSCTEA 2013, September 25–27, 2013, Kunming, China

Springer

Editors
Srikanta Patnaik
Department of Computer Science and Engineering
SOA University
Bhubaneswar, Orissa
India

Xiaolong Li
Electronics and Computer Engineering Technology
Indiana State University
Indiana, IN
USA

ISSN 2194-5357 ISSN 2194-5365 (electronic)
ISBN 978-81-322-1694-0 ISBN 978-81-322-1695-7 (eBook)
DOI 10.1007/978-81-322-1695-7
Springer New Delhi Heidelberg New York Dordrecht London

Library of Congress Control Number: 2013956601

Printed on acid-free paper

Springer is part of Springer Science+Business Media (www.springer.com)

Preface

On behalf of the Programme Committee, we welcome you to *International Conference on Soft Computing Techniques and Engineering Application (SCTEA 2013)* held during September 25–27, 2013 in Kunming China. The main objective of SCTEA 2013 is to provide a platform for researchers, engineers, and academicians from all over the world to present their research results and recent developments in soft computing techniques and engineering application. This conference provides opportunities for them to exchange new ideas and application experiences face to face, to establish business or research relations, and to find global partners for future collaboration.

During the last decade, soft computing techniques have been recognized as one and most attractive alternatives to the standard, well-established "hard computing" paradigms. Traditional computing methods are often too cumbersome for the present day multiobjective problems, which requires a precisely stated analytical model and often consumes large computational time. Soft computing techniques, on the other hand, emphasize gains in understanding system behavior in exchange for unnecessary precision have proved to be important practical tools for many contemporary problems. There are various soft computing techniques available and popular for the engineering and other applications. They are artificial neural networks (NN), genetic algorithms (GA), fuzzy logic models (FLM), and particle swarm techniques. NNs and FLMs are universal approximators of any multivariate function because they can be used for modeling highly nonlinear, unknown, or partially known complex systems, plants, or processes. GA and particle swarm optimization techniques have emerged as potential and robust optimization tools in recent years.

The International Conference on Soft Computing Techniques and Engineering Application (SCTEA 2013) covers all areas of soft computing and its applications to engineering domain. We have received 232 numbers of papers through "Call for Paper," out of which 67 numbers of papers were accepted for publication in the conference proceedings through double blind review process. The broad areas, which are covered in this Conference, are: theoretical computer science, computer systems organization, soft computing, computing methodologies, computer applications, and software engineering application.

We are sure this proceeding will contribute to the knowledge of soft computing and particularly its application to various engineering domains. We are sure the participants will share their innovations in this conference.

Srikanta Patnaik
Xiaolong Li

Organizing Committee

General Chairs

Prof. Srikanta Patnaik, Computer Science and Engineering in SOA University, India

General Co-Chair

Dr. Xiaolong Li, Indiana State University, USA

Technical Program Committee

Prof. Ilona Weinreich, Koblenz University of Applied Sciences, Germany
Prof. Flaminia L. Luccio, Università Ca' Foscari Venezia, Italy
Dr. Rajarshi Gupta, University of Calcutta, India
Prof. Yi-Hsing Chang, Southern Taiwan University of Science and Technology, Taiwan
Prof. Min-Shiang Hwang, Asia University, Taiwan
Prof. Chien-Lung Hsu Chang-Gung University, Taiwan
Prof. Chien-Jen Wang, National University of Tainan, Taiwan
Prof. W. David Pan, University of Alabama in Huntsville, USA
Prof. Sotirios G. Ziavras, New Jersey Institute of Technology, USA
Dr. Afolabi Babajide Samuel, The Computer Professionals Registration Council of Nigeria, Nigeria
Prof. Mauricio Papa, The University of Tulsa, USA
Prof. Tianshi Lu, Wichita State University, USA
Prof. Rita Moura Fortes, Mackenzie Presbyterian University, Brazil

Dr. Cettina Santagati, University of Catania, Italy
Prof. Michael McAleer, Erasmus University Rotterdam, Netherland
Prof. Bo Yang, Shanghai Jiao Tong University, China
Dr. Vimal S. Joshi, Gujarat University, India
Dr. Michael Joseph, St. Joseph's College of Engineering and Technology, India
Prof. Roberto Caldelli, Universita' degli Studi Firenze, Italy
Dr. Akshi Kumar, Delhi Technological University, India
Prof. Chi-Lun Liu, Kainan University, Taiwan
Dr. Isabel Barbancho, Universidad de Malaga, Spain
Dr. Sunil R. Das FIEEE, University of Ottawa, Canada
Dr. Valentin Todorov, United Nations Industrial Development Organization, Austria
Dr. Qi Wang, University of the West of Scotland, United Kingdom
Dr. Izzat Al-Smadi, Yarmouk University, Jordan
Dr. Muhammad Rais, King Saud University, Saudi Arabia
Dr. Michael Joseph, Mother Teresa College of Engineering and Technology, India
Dr. Shunan Wu, Dalian University of Technology, China
Dr. Shan Chu, Stony Brook University, USA
Dr. B. K. Tripathy, VIT University, India
Dr. Carlo Trigona, University of Catania, Italy
Dr. R. Shashi Kumar, Bangalore University, India
Dr. Ki Young Kim, Samsung Advanced Institute of Technology, Korea

Contents

Research on Hierarchical Clustering Algorithm Based on Cluster Outline

Hai-Dong Meng, Jing-Pei Ren and Yu-Chen Song

Abstract The traditional hierarchical methods always fail to take both the features of connectivity and proximity of clusters into consideration at the same time. This paper presents a hierarchical clustering algorithm based on cluster outline, which effectively addresses clusters of arbitrary shapes and sizes, and is relatively resistant to noise and easily detects outliers. The definition of the boundary point and cluster outline is firstly given, and the standard and approach of measuring similarity between clusters is then taken with the feature of connectivity and proximity of clusters. The experiments on the Iris and image data sets confirm the feasibility and validity of the algorithm.

Keywords Connectivity · Proximity · Cluster outline · Hierarchical clustering

1 Introduction

Hierarchical algorithm in cluster analysis as a main method in data mining, no matter what the field of research and application is, has been developed largely and promoted greatly. In recent years, there are various hierarchical clustering algorithm put forward, which are partitioned into two categories in terms of the similarity standard: one for connectivity-based similarity and the other for proximity-based similarity. The first one is free to find clusters of arbitrary shapes, but

H.-D. Meng (✉) · J.-P. Ren · Y.-C. Song
Inner Mongolia University of Science and Technology, Baotou 014010, China
e-mail: haidongm@imust.edu.cn

J.-P. Ren
e-mail: fm190135@126.com

Y.-C. Song
e-mail: songyuchen@imust.edu.cn

S. Patnaik and X. Li (eds.), *Proceedings of International Conference on Soft Computing Techniques and Engineering Application*, Advances in Intelligent Systems and Computing 250, DOI: 10.1007/978-81-322-1695-7_1, © Springer India 2014

lack of the consideration for density of certain cluster; the second is only limited in discovering spherical-shaped clusters, but the best consideration for density is given in clustering. At present, there are some representative hierarchical clustering algorithms such as BIRCH, CURE, ROCK, and Chameleon algorithm, and all of them have both of merits and inadequacies. The BIRCH [1] algorithm cannot effectively discover non-spherical-shaped clusters because of the method of dealing with borders of clusters with the radius or diameter of clusters, and it is not feasible in addressing the high-dimensional data sets because the exact number of clusters and diameters can be hardly obtained. The CURE [2] algorithm can handle various shaped clusters, but the efficiency of the algorithm is low, and it is subjective to choosing the number of typical points, regardless of consideration for the connectivity between clusters. In 1999, Sudipno Guha put forward the ROCK [3] algorithm that adopts a approach about the global information based on the number of public linking points to measure the correlation of data points, this means the feature of connectivity is considered, but the proximity is ignored. In 1999, Karypis proposes the Chameleon [4] hierarchical clustering algorithm based on the dynamic modeling technology, though the Chameleon algorithm takes both connectivity and proximity into consideration, but there are still some shortcomings as follows: (1) The value of K in the K-nearest figure must be given before the experiment; (2) there is difficulty in the Min-Bisection. (3) the threshold of similarity must be given before the experiment [5], and in the literature [6], the probability of the limitation of dealing with high-dimensional data sets is pointed out in the Chameleon algorithm; In the stage of partition, an object may be assigned to a cluster, which doesn't actually belong to the cluster.

Considering the above clustering methods, the hierarchical clustering algorithm based on cluster outline is proposed in this paper, which reduces the influences of the existence of outliers, considers reasonably both the connectivity and proximity between clusters with an automatic choice of cluster centers, and optimizes the clustering result effectively.

2 Definition and Solution

2.1 The Definition of Boundary Point and Cluster Outline

Cluster boundary points are defined as follows: In a cluster with n-dimensional data set, all data objects are regarded as spatial points distributed in n-dimensional data space. If a spatial point is discussed and considered in certain scope (such as the similarity-measuring standards based on distance and density), and a spatial point does not belong to all of 2^n quadrants in n-dimensional data space at the same time, the point can be defined as a boundary point (as Figs. 1 and 2 shown in two-dimensional data space). The outline of a cluster consists of all boundary points belonging to the cluster (as Figs. 3 and 4 shown in two-dimensional data space).

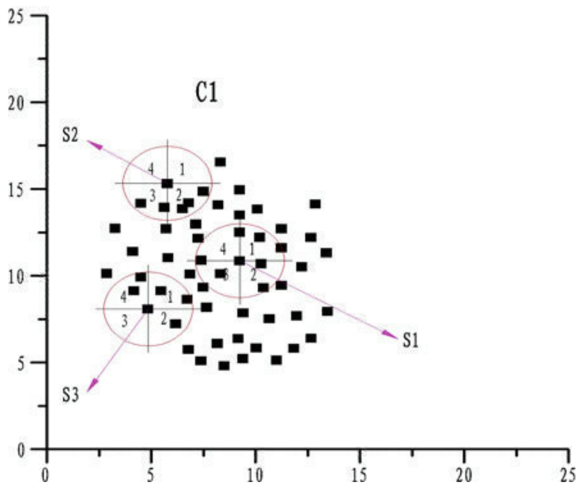

Fig. 1 Boundary points of cluster C_1

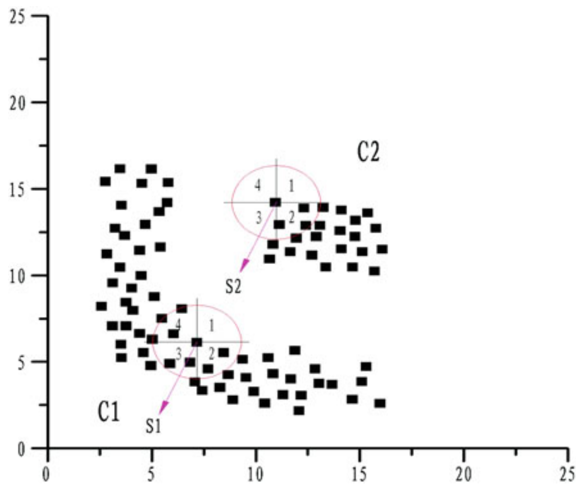

Fig. 2 Boundary points of cluster C_2

In Fig. 1, the point S_1 of the cluster C_1 is not an boundary point, because in its scope based on distance or density, there are always one or more points that can be found in any of its own quadrants of 1, 2, 3, and 4; the scope of the point S_2 does not touch any point in its own quadrants of 1 and 4, so the point S_2 is an boundary point; the third quadrant of the S_3 can cover no point, so the S_3 is an boundary point.

In Fig. 2, the points S_1 and S_2, respectively, from C_1 and C_2 are boundary points with the same as shown in Fig. 1.

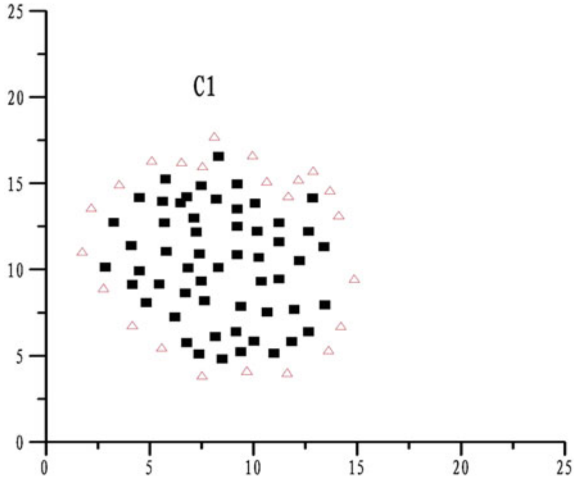

Fig. 3 Cluster outline C_1

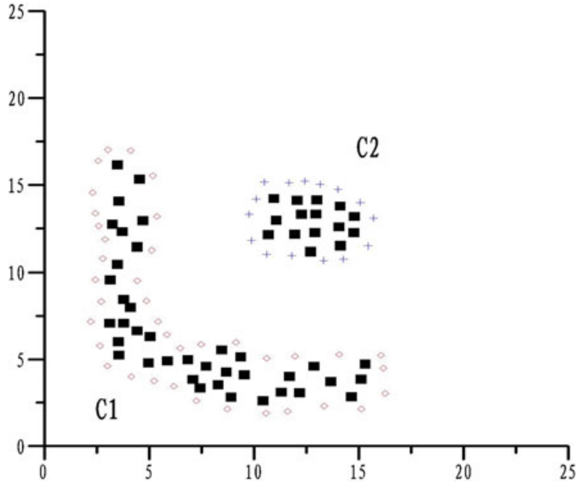

Fig. 4 Outlines of clusters C_1 and C_2

Cluster outline is defined as follows: All boundary points consist of the cluster outline; that is also the cluster outline is a collection of all boundary points.

In Fig. 3, the cluster outline C_1 consists of all red triangle symbols.

In Fig. 4, the cluster outline C_1 consists of all red diamond symbols, and C_2 all blue cross symbols.

2.2 The Solution of Cluster Outline

The solution of finding cluster outline aims at searching for all boundary points of cluster. Boundary points are the space within the cluster of a relative positional relationship of the points, so the cluster constructs the relative position of the point and point matrix. A complete solution of cluster outline includes three steps.

(1) Construction of the relative matrix P

Suppose a cluster C, $C = \{S_1, S_2, S_3, \ldots S_n\}$, and the cluster C is discussed and considered in two-dimensional data space consisting of the x axis and the y axis. The symbol D_0 represents the threshold of distance or density. The expression $D(S_i, S_j)$ represents the relative distance or density between the points S_i and S_j. The relative distance or density between the points S_i and S_j is defined as follows:

$$D(S_i, S_j) \leq D_0 \tag{1}$$

If the formula $D(S_i, S_j) \leq D_0$ is true, and the expression $S_{jX} > S_{iX}$ & $S_{jY} > S_{iY}$ is true, this means that S_j is in the first quadrant of S_i and $P_r = 1$. So we can get the following expressions:

$$\begin{aligned} S_{jX} > S_{iX} \;\&\; S_{jY} > S_{iY} \Rightarrow P_r = 1 \\ S_{jX} > S_{iX} \;\&\; S_{jY} < S_{iY} \Rightarrow P_r = 2 \\ S_{jX} < S_{iX} \;\&\; S_{jY} < S_{iY} \Rightarrow P_r = 3 \\ S_{jX} < S_{iX} \;\&\; S_{jY} > S_{iY} \Rightarrow P_r = 4 \end{aligned} \tag{2}$$

Note: for the point S_i, the value of X is the value of S_{iX}, and the value of Y is the value of S_{iY}.

The relative matrix P is constructed as follows:

$$P = \begin{matrix} \\ S_1 \\ S_2 \\ S_i \\ S_n \end{matrix} \begin{matrix} \begin{matrix} S_1 & S_2 & S_i & S_n \end{matrix} \\ \begin{pmatrix} 0 & P_r & P_r & P_r \\ P_r & 0 & P_r & P_r \\ P_r & P_r & 0 & P_r \\ P_r & P_r & P_r & 0 \end{pmatrix} \end{matrix} \quad \left(i < n;\ \text{if}\ D(S_i, S_j) > D_0,\ \text{then}\ P_r = 0\right) \tag{3}$$

(2) Search for boundary point

To figure out whether the point S_i is an boundary point or not, we can check the i column of S_i to find all different values of P_r. If the set composed of all values of P_r in the i column of S_i is not $\{1, 2, 3, 4\}$, the point S_i is an boundary point.

(3) Search for cluster outline

The cluster outline is a definite set of all boundary points belonging to cluster in the step (2).

3 The Design of Hierarchical Clustering Algorithm Based on Cluster Outline

3.1 The Clustering Between Clusters

(1) Standard of connectivity

Suppose that the outline of the cluster C_1 is P_{r1} and C_2 is P_{r2}. The symbol N shows the number of all shared boundary points between clusters. The calculation of N is as follows:

$$N_1 = \text{count}(P_{r1} \cap P_{r2}) \tag{4}$$

$$N_2 = \text{count}(P_{r1} \cap C_2) \tag{5}$$

$$N_3 = \text{count}(P_{r2} \cap C_1) \tag{6}$$

$$N_4 = N_2 + N_3 - N_1 \tag{7}$$

Note: N_1 represents the number of the same points of P_{r1} and P_{r2}; N_2 represents the number of the same points of P_{r1} and C_2; N_3 represents the number of the same points of P_{r2} and C_1. Figure 5 shows the connectivity of the cluster outlines.

In Fig. 5, the clusters C_1 and C_2 share with the points of the same shape and color. The number of all boundary points of C_1 and C_2 is 17, which contains 10 yellow diamonds, 4 dark red stars, and 3 light red sunshine-shaped points. That also means the connectivity of the outline of the clusters C_1 and C_2 is 17.

(2) Standard of proximity

Suppose that the number of clusters is N with its corresponding outline of each cluster: $S_1, S_{2,}\ldots, S_n, S_i = \{B_{i1}, B_{i2}, \ldots, B_{ij}\}$, where S_i represents the outline of the cluster i and B_{ij} represents the boundary point j of the cluster i, then the average distance as the measurement of proximity of clusters is defined. The following formula shows the average distance between the cluster outlines:

$$\overline{D}(S_i, S_j) = \frac{1}{n_{S_i} n_{S_j}} \sum_{B_i \in S_i} \sum_{B_j \in S_j} \text{dist}\left\|B_i - B_j\right\|. \tag{8}$$

3.2 The Clustering Between Clusters and Outliers

Considering a ratio r, the symbol n_r represents the number of all boundary points of one cluster, and the symbol n represents all points of the cluster. The ratio r can be set up as follows:

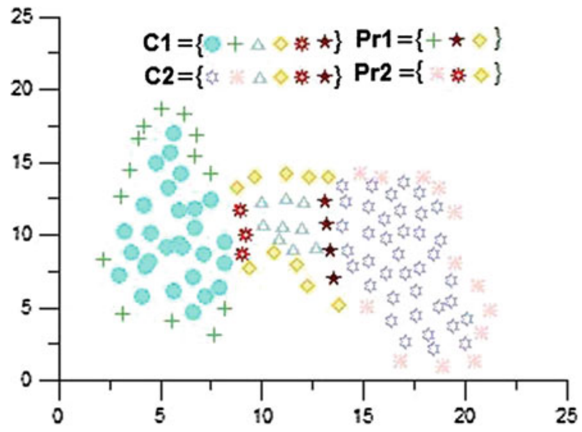

Fig. 5 Connectivity of the outlines of clusters C_1 and C_2

$$r = \frac{n_r}{n}(0 < r \leq 1) \tag{9}$$

The smaller the value of r, the denser the cluster, and vice versa.

When an outlier is assigned to a cluster to form a new cluster, the ratio of the new cluster is r' . If r' is less than or equal to r (the ratio of the original cluster), the outlier belongs to the new cluster. If the condition just mentioned is not true, we should keep the original situation not to be changed. The snake-shaped and linear clusters can be easily detected in this way to some degree.

3.3 The Process of the Algorithm

For a data set D_0, the hierarchical clustering algorithm based on cluster outline is as follows:

1. Input the value of threshold of distance or density$(d_{\min} < r_0 < d_{\max})$, the number of data points: n, and the number of clusters: K.
2. Construct distance or density matrix d_{matrix}.
3. Take a data point X from the data set D_0, search out all points based on the threshold of distance of X in d_{matrix}, and combine X and all the points into a cluster in the condition of the number of all data points more than n, or else set these points as temporary outliers.
4. Construct the relative matrix P and form outlines of all clusters with step 3.
5. Calculate the number of the shared boundary points between clusters (the connectivity matrix), begin to cluster from the biggest number, and readjust the cluster outline until there is K clusters or the number of the shared boundary points is up to n.
6. Repeat the step 4 for the new outline.

Fig. 6 Original image (500×375)

7. If the number of clusters is still more than K, then the proximity matrix can be calculated and the min distance can be combined into a cluster. Renew the cluster outlines until there are K clusters.
8. Handle the outliers according to equation (9).

4 The Experimental Analysis

Experiment 1: In order to facilitate the realization of the data sets and visualization of the experiment results, the experiment takes an image data as an experimental object, which consists of 500 pixels of width and 375 pixels of height. Each data point is represented by all RGB color values of the pixel. The following figures show the result of the experiment by contrast between the original image in Fig. 6 and the processed image in Fig. 7.

In Fig. 7, there are 10 clusters and an outlier data set. The experiment shows the advantage effectiveness in clustering with this algorithm.

Experiment 2: In order to validate further the feasibility and effectiveness of the hierarchical clustering algorithm based on cluster outline, the experiment 2 is given with the Iris data set from the UCI. The Iris data set is a kind of biometric data set of three various flowers, which includes 150 records divided into three clusters, each cluster has 50 records, and each record consists of four attributes.

The results of the clustering in the Iris data set are shown in Fig. 8 by contrast between the clustering algorithm based on the cluster outline, the CURE algorithm, and the various algorithms provided by SPSS statistical analysis software.

As shown in Fig. 8, the algorithm accuracy of the cluster outline and the centroid clustering in Iris data set obtained is more than 90 % (there are 14 records in error). They show a relatively good clustering effect.

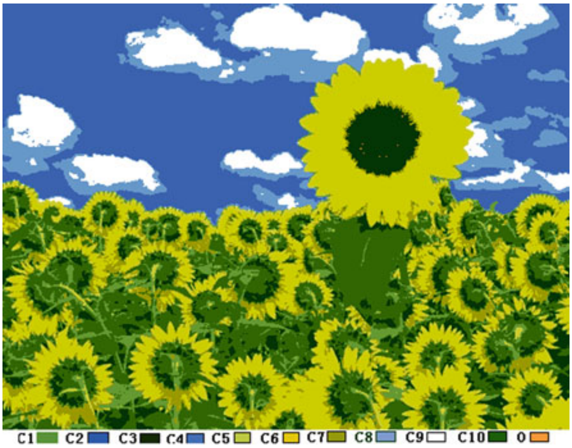

Fig. 7 Simulated image of experimental result

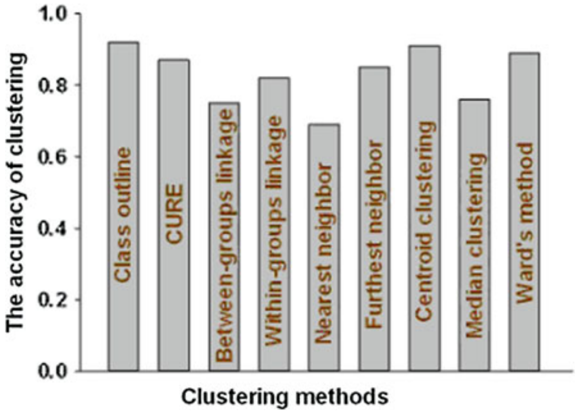

Fig. 8 Accuracy comparison between clustering algorithms

The values of threshold of the initial distance and number of points can be hardly determined in clustering. In order to address this, the initial value of threshold can be small, and then, the processed points are compared with the rest of the outliers; if the rest of the outliers are more than 10 % of the number of the total data points, the value of threshold of the outliers should be set bigger to cluster again. It can guarantee that the number of new clusters combining the subclusters in terms of connectivity is more than K, and then, subclusters are combined again in terms of proximity; if the value of threshold of the number of the initial data points is given too small, the number of clusters can be less than K, and it can also give rise to the worst situation that there is only one cluster including all data points.

There is almost no change in the time complexity of the cluster-outline-based algorithm, in contrast to other traditional clustering algorithms, and in the worst situation, the time complexity is $O(n^2)$, where the time is mainly consumed in dealing with distance matrixes and relative matrixes. However, the points of outline are processed instead of all points of whole clusters, so the space complexity is relatively low, especially for densely based clusters.

5 Conclusions

The feasibility and effectiveness of the hierarchical clustering algorithm based on cluster outline are proven in the experiments. Because of the standard of measuring the similarity between clusters based on both connectivity and proximity, the clusters with arbitrary shape, noise, or outliers can be easily discovered and detected. And the cluster outline is chosen to replace the whole cluster, so the task of dealing with huge data points can be avoided in the algorithm.

The concept of cluster outline has much practical utility in application, which can also be applied to other traditional clustering methods, such as discovering shapes of clusters by the visualization of cluster outline; measuring density of clusters by the proportion between the number of boundary points and all points of one cluster; and detecting noise or outliers.

Acknowledgments The research is founded in part by The Natural Science Foundation of Inner Mongolia under Grant No. 2012MS0611, Chunhui Project of Ministry of Education under Grant No. Z2009-1-01041, and Higher School Science Research Project of Inner Mongolia under Grant No. NJZZ11140.

References

1. Zhang, T., Ramakrishnan, R., Livny, M.: BIRCH: An efficient data clustering method for very large databases. Technical Report, Computer Sciences Department, University of Wisconsin–Madison (1995)
2. Guha, S., Rastogi, R., Shim, K.: Cure: An efficient clustering algorithm for large database. In: Proceedings of the 1996 ACM SIGMOD International Conference on Management of Data, pp. 73–84, Seattle, Washington (1998)
3. Guha, S., Rastogi, R., Shim, K.: ROCK: A robust clustering algorithm for categorical attributes. In: Proceedings of the 15th ICDE, pp. 512–521, Sydney (1999)
4. Karypis, G., Han, E.-H., Kumar, V.: Chameleon: hierarchical clustering using dynamic modeling. Computer **32**(8), 68–75 (1999)
5. Long, Zhen-Zhen, Zhang, C., Liu, F.-Y., Zhang, Z.-W.: An improved chameleon algorithm. Comput. Eng. **20**(35), 189–191 (2009)
6. Ma, X.-Y., Tang, Y.: Research on hierarchical clustering algorithm. Comput. Sci. **34**(7), 34–36 (2008)

Exploration of Fault Diagnosis Technology for Air Compressor Based on Internet of Things

Zheng Yue-zhai and Chen Xiao-ying

Abstract With the development of network and communication technology, this article puts forward to new methods and ideas on the fault diagnosis technology of air compressor based on Internet of Things, ensure the safe, stable, and reliable running of air compressors, and carry out some beneficial exploration for remote diagnosis technology of mechanical equipment.

Keywords Internet of Things · Air compressor · Fault diagnosis technology · Remote monitoring

1 Introduction

Compressed air is the second largest power after the electric power energy, air compressor (hereinafter referred to as the compressor) is the main part of manufacturing the compressed air, and it is the original motivation (typically a motor) that convert the mechanical energy into a air pressure energy. Air compressors are widely used in industrial production, and most of the work environments are harsh [1]. When a machine fails, it cannot be diagnosed and be treated immediately, this must cause the increase of the loss. So the establishment of remote intelligent control for monitoring the response of the system has become a pressing problem of air compressor technology for the early prediction of failure.

In this paper, the use of Internet of Things technology carries out a useful exploration of the air compressor fault diagnosis technology.

Z. Yue-zhai (✉) · C. Xiao-ying
Quzhou College, Quzhou, Zhejiang 324000, People's Republic of China
e-mail: zyz8602@126.com

C. Xiao-ying
e-mail: chxy1@163.com

S. Patnaik and X. Li (eds.), *Proceedings of International Conference on Soft Computing Techniques and Engineering Application*, Advances in Intelligent Systems and Computing 250, DOI: 10.1007/978-81-322-1695-7_2, © Springer India 2014

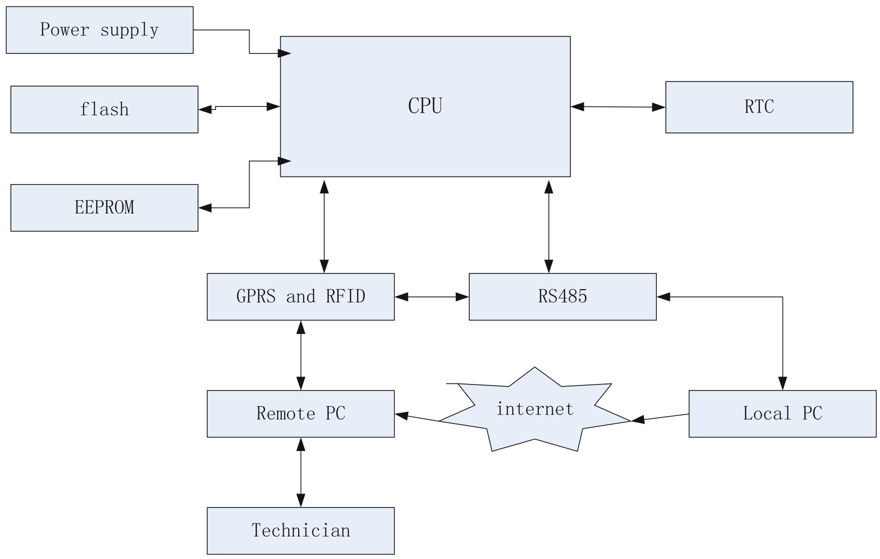

Fig. 1 Basic structural diagram of the system

2 The Remote Diagnosis System Designment of the Air Compressor Using Internet of Things

With the attention of the state to the Internet of Things technology, the Internet of Things technology has been more widely used in China. The application of the Internet of Things technology in air compressor for remote monitoring and diagnosis function conforms to the needs of society, and it will show considerable application prospects for the future development.

Basic structural diagram of the system, see Fig. 1

This system includes CPU with external GPRS system, flash memory, RS485 communication port; by the RS485 port, the real-time state of the compressor is transferred to a host computer and realizes the remote communication of the screw air compressor. The operator can start and stop the screw air compressor through the computer. The GPRS module and radio frequency identification (RFID) of the screw air compressor control system can fix the position of the air compressor, get to know where the parameters come, and ensure to control the machine correctly. The flash memory is used to store the historical running state, and when a mistake happens, the parameters can be drawn to help diagnose the problem and solve it. In addition, the acquisition of parameters can be transferred to the server through the Internet, there are many data from the working compressor in the server, and there is an expert diagnostic system according to the experience, the server can deal with collected data and make the plan of the equipment maintenance [2].

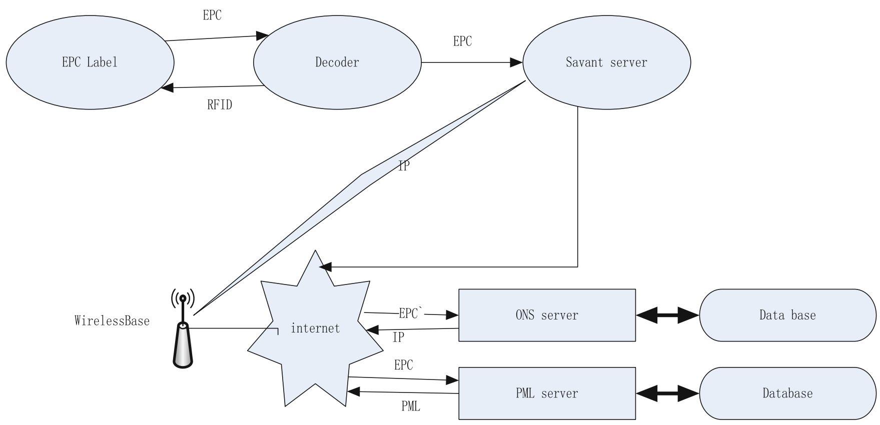

Fig. 2 Technical principle logic diagram

3 Field Information Collection with the Internet of Things Technology

In this paper, the technology of the Internet of Things is mainly used to locate the compressor, as well as its relevant technical indicators, operation parameters, etc.

Internet of Things is a kind of network that according to the agreed protocol, through the RFID, infrared sensors, global positioning system, laser scanners, and other information sensing devices, connects any objects with the Internet, and exchanges information and communication, and realizes the object's intelligent identification, location, tracking and monitoring and management. With the Use of the Internet of Things technology, people can implement intelligent and accurate regulation and operation of the devices in the network [3].

Internet of Things' key technology includes five segments: electronic product code (EPC), the information identification system (ID system), the EPC middleware (implementation information filtering and sampling), discovery service (information discovery service), the EPC information service (EPCIS). Its technical principle logic diagram is shown in Fig. 2:

There is a quite good coverage of wireless communication network in China, and it is a good infrastructure of the Internet of Things. The M2M business support platform launched by China mobile can provide the M2M business users of the data acquisition, transmission, processing, and business management, and other functions.

4 To Realize Remote Monitoring Using Communication Technology

This article adopts the type of site monitoring and remote monitoring, and through the GPRS network or the Internet, information is transmitted to the specified server, carries on the analysis processing, and achieves remote monitoring of equipment through the communication interface link.

Remote monitoring refers to the use of a computer to monitor and control of the remote industrial production process control system via a wired or wireless network system. A remote monitoring system is a computer hardware and software system that can achieve remote monitoring.

There are two types of remote monitoring system, one is no on-site monitoring system, but collects the data directly to a remote computer for processing, this remote monitoring has no difference with the general site monitoring except there is a long distance to transmit; the other is site monitoring and remote monitoring coexist. Generally, the remote monitoring adopts fieldbus technology connecting distributed sensors of monitoring equipment and develops the discrete cell to integrate unit, and at last, Intranet is built.

Remote monitoring function to achieve

1. Acquisition and process function: detect sample and pretreat all kinds of analog or digital signals, and output them in a certain form, such as printing form, display, or database server to help technician to analysis and know the situation of the compressor.
2. Supervision function: analyze, summarize, finish, and compute the detected real-time data, inputted parameters by the operators and so on, store them for the real-time data and historical data.
3. Management function: with the help of the existent valid data, images and reports related with the working condition, analysis, fault diagnosis, risk predict the working state, alarm with noise, light and electrical form.
4. Control function: Based on the detected processing information and predetermined control strategy, control output is formed and works on the compressor directly.

Because the remote monitoring system can realize real-time data collection of the site operation data and rapid concentration, the base for remote fault diagnosis technology is formed. The remote monitoring system connects with the enterprise Intranet; this makes it possible for manager to grasp the working states, and it works with the management strategy system, a much more advanced applying system will be built. It provides the possibilities of no-one on-duty at the site and achieves more profit ultimately.