

Sergey Subbotin

Editor

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Edited by

Sergey Subbotin *

* National University "Zaporizhzhia Polytechnic", Faculty of Computer Science and Technologies,
69063, Zaporizhzhia, Ukraine

Table of Contents

- Cover and Preface
- Organization, Committees and Reviewers

Session 1: Information Technologies for Decision Making, Optimization and Control

- Algorithmic support for the detection characteristics improving of the monitoring object
Elena Chernetsova, Anatoly Shishkin 1-11
- Decision support during the vessel control at the time of negative manifestation of human factor 12-26
Pavlo Nosov, Serhii Zinchenko, Ihor Popovych, Michail Safonov, Ihor Palamarchuk, Valeriia Blakh
- Optimization calculation of vortex type granulation devices: application of software products and computer modeling 27-41
Artem Artyukhov, Jan Krmela
- Complex technical system condition diagnostics and prediction computerization 42-56
Nickolay Rudnichenko, Vladimir Vychuzhanin, Andrii Polyvianchuk, Vasyl Mateichyk
- Smart crossover mechanism for parallel neuroevolution method of medical diagnostic models synthesis 57-69
Serhii Leoshchenko, Sergey Subbotin, Andrii Oliinyk, Viktor Lytvyn, Matviy Ilyashenko
- Monitoring system for the tests of the Mg implants 70-78
Galyna Tabunshchik, Vadym Shalomeev, Peter Arras
- The monitoring system based on a multi-agent approach for moving objects positioning in wireless networks 79-90
Oleksii Tohoiev, Ivan Burlachenko, Iryna Zhuravska, Volodymyr Savinov
- Parametric synthesis of a dynamic object control system with nonlinear characteristics
Oleg Nikonov, Igor Kyrychenko, Vladyslav Shuliakov, Fastovec Valentyna 91-101
- Intelligence analysis method of automation control system archive database for controlling hot blast stove block 102-117
Oleksiy Koyfman, Oleksandr Simkin, Kseniia Serdiuk
- Situational management of urban engineering networks with intelligent support for dispatching decisions 118-131
Aleksandr Stenin, Iryna Drozdovych, Mariya Soldatova
- Application of genetic algorithm in problems of approximation of complex multidimensional dependencies and identification of parameters of theoretical models
Dmitry Glukhov, Tatsiana Hlukhava, Aliaksandr Lukyanau 132-143
- Linear quadratic gaussian control for robotic excavator 144-155
Alexander Gurko, Igor Kyrychenko, Aleksandr Yaryzhko, Oleksandr Kononykhin
- Packing equal spheres by means of the block coordinate descent method 156-168
Georgiy Yaskov, Andrey Chugay
- Bi-soft open sphere topology model of configuration space for reactive joint motion planning of unmanned vehicles 169-183
Volodymyr Sherstiuk, Maryna Zharikova, Ruslan Levkivskyi
- Genetic algorithms as an optimization approach for managing electric vehicles charging in the smart grid 184-198
Sergiy Korotunov, Galyna Tabunshchik, Vyacheslav Okhmak

Session 2: Information Systems and Data Processing

- Implementation of web system optimization method 199-210
Galina Kirichek, Stepan Skrupsky, Mariia Tiahunova, Artur Timenko

- Decentralized electronic voting system based on blockchain technology developing principals 211-223
Kateryna Isirova, Anastasiia Kiian, Mariia Rodinko, Alexandr Kuznetsov
- Linguistic analysis method of ukrainian commercial textual content for data mining 224-244
Oleg Bisikalo, Victoria Vysotska
- Application of the universal meta-formalism to substantiate and research intelligence properties 245-265
Alexander Sosnitsky, Anatoly Shevchenko
- Designing complex intelligent systems on the basis of ontological models 266-277
Kostyantyn Tkachenko, Olga Tkachenko, Oleksandr Tkachenko
- Structuring of a transaction database using the rough set theory 278-287
Igor Kovalenko, Alyona Shved, Kateryna Antipova, Yevhen Davydenko

Session 3: Advanced Info-Communicational Technologies

- Multi-layer model and training method for information-extreme malware traffic detector 288-299
Alona Moskalenko, Viacheslav Moskalenko, Artur Shaiekhov, Mykola Zaretskyi
- Analysis and experimental realization of the logistic map using Arduino Pro Mini 300-310
Volodymyr Rusyn, Sergey Subbotin, Aceng Sambas
- A method of hidden faults opposition for FPGA-based components of safety-related systems 311-322
Oleksandr Drozd, Vitaliy Romankevich, Alexei Romankevich, Mykola Kuznietsov, Myroslav Drozd
- Docker container based PaaS cloud computing comprehensive benchmarks using LAPACK 323-337
Dmitry Zaitsev, Piotr Luszczek
- A model of semantic web service in a distributed computer system 338-351
Nataliia Kulykovska, Stepan Skrupsky, Tetiana Diachuk
- Autonomous distributed systems and their simulation 352-363
Valeriy Kolesnikov
- Promoting training of multi agent systems 364-378
Petro Kravets, Vasyl Lytvyn, Victoria Vysotska, Yevhen Burov
- Information-measuring technologies in the metrological support of heat flux measurements 379-393
Vitalii Babak, Svitlana Kovtun, Oleg Dekusha
- Inter-domain routing method under normalized quality of service based on hierarchical coordination 394-408
Oleksandr Lemeshko, Maryna Yevdokymenko, Zhengbing Hu, Oleksandra Yeremenko
- Experimental research of optimizing the Apache Spark tuning: RDD vs data frames 409-425
Sergii Minukhin, Maksym Novikov, Natalia Brynza, Dmytro Sitnikov
- Models of information processing optimization for technical interoperability in a network of distributed situational centers 426-435
Oleksii Kovalenko, Vitalii Vishnevsky, Vladimir Kosolapov

Session 4: Information Technologies for Computer Modeling

- Method of monitoring of young athletes' physical state indicators based on wearable devices usage 436-449
Anzhelika Parkhomenko, Anastasiia Volynska, Yaroslav Zalyubovskiy, Andriy Parkhomenko, Marina Kalinina
- Computer modeling of microstructures with probabilistic cellular automata method using different nucleation rate functions 450-461
Oleksii Vodka
- Assessing the possibility of a country's economic growth using static bayesian network models 462-473
Mariia Voronenko, Dmytro Nikytenko, Jan Krejci, Nataliia Savina, Volodymyr Lytvynenko
- Computer modeling of multi-mass electromechanical systems 474-488
Olena Nazarova

- Decision support system for microclimate control at large industrial enterprises 489-498
Natalia Pankratova, Petro Bidyuk, Igor Golinko
- Enterprise architecture modeling support based on data extraction from business process models 499-513
Dmytro Orlovskyy, Andrii Kopp
- Software for simulation of bio-like systems and processes using movable cellular automata 514-525
Vladimir Zhikharevich, Kateryna Hazdiuk, Sergey Ostapov
- An integrated approach to improve effectiveness of industrial multi-factor statistical investigations 526-535
Victoria Miroshnichenko, Alexander Simkin
- Information technology in the modeling of dry gas seal for centrifugal compressors 536-546
Lyudmyla Rozova, Gennadii Martynenko
- Simulation modeling of external perturbations affecting wheeled vehicles of special purpose 547-556
Oleg Nikonov, Igor Kyrychenko, Vladyslav Shuliakov
- Parallel simulation of rock deformation processes 557-568
Yevhen Tiurin, Antonina Andriieva
- Irregular layout problem for additive production 569-579
Andrey Chugay, Aleksandr Pankratov, Tetyana Romanova

Session 5: Computing in Applications

- The data errors control in the modular number system based on the nullification procedure 580-593
Victor Krasnobayev, Alexandr Kuznetsov, Alina Yanko, Kateryna Kuznetsova
- The analysis of the methods of data diagnostic in a residue number system 594-609
Victor Krasnobayev, Alexandr Kuznetsov, Alina Yanko, Tetiana Kuznetsova
- Extrapolation to calculate the probability of a double spending attack 610-620
Nikolay Poluyanenko, Alexandr Kuznetsov, Elizaveta Lazareva, Andrey Marakushyn
- On parallel algebraic multilevel preconditioner with approximate inversion by basis matrix method 621-632
Vsevolod Bohaienko
- Managing multifractal properties of the binary sequence generated with the Markov chains 633-645
Roman Odarchenko, Oleksii Smirnov, Hanna Driieva, Oleksandr Driiev, Volodymyr Simakhin, Serhiy Bondar
- Hiding data in cover images using a pseudo-random sequences 646-660
Alexandr Kuznetsov, Alexey Smirnov, Ludmila Gorbacheva, Vitalina Babenko
- Cryptosystem based on a key function of a real variable 661-674
Viktor Avramenko, Volodymyr Demianenko
- Autocorrelation criterion for quality assessment of random number sequences 675-689
Emil Faure, Iryna Myronets, Artem Lavdanskyy
- Analysis of algorithms for constructing dense sequencing of digraphs vertices 690-703
Valentina Turchyna, Kostiantyn Karavaiev
- Algorithm for fixing singular defects of polygon meshes based on half-edge data structure 704-717
Danylo Sovhelia, Natalya Sokolova

Session 6: Intelligent Information Technologies

- The quality indicators of decision tree and forest based models 718-743
Sergey Subbotin
- Online credibilistic fuzzy clustering of data using membership functions of special type 744-753
Alina Shafronenko, Yevgeniy Bodyanskiy, Iryna Klymova, Olexii Holovin
- Intelligent data analysis in hr process management 754-768
Mykola Ivanov, Nataliia Maksyshko, Sergey Ivanov, Nataliia Terentieva

- Bagging-based instance selection for instance-based classification 769-783
Dmytro Kavrin, Sergey Subbotin
- Optical-electronic system of automatic detection and high-precision tracking of aerial objects in real-time 784-803
Ihor Shostko, Andrew Teviashev, Yuliia Kulia, Anton Koliadin
- Neural model of conveyor type transport system 804-818
Oleh Pihnastyi, Valery Khodusov
- Multicomponent analyzer of volatile compounds characterization based on artificial neural networks 819-831
Taras Chaikivskiy, Bogdan Sus, Oleksandr Bauzha, Sergiy Zagorodnyuk
- Adaptive fuzzy clustering approach based on evolutionary cat swarm optimization 832-842
Alina Shafironenko, Yevgeniy Bodyanskiy
- A constrained method of constructing the logic classification trees on the basis of elementary attribute selection 843-857
Igor Povkhan
- Using the elman neural network as an identity map in defect detection task 858-871
Volodymyr Khandetskyi, Nadiia Karpenko
- Decision support system for the machine learning methods selection in big data mining 872-885
Nikolay Rudnichenko, Vladimir Vychuzhanin, Igor Petrov, Denis Shibaev
- Neural network forecasting of earth globe seismic activity level 886-899
Vadym Tiutiunyk, Leonid Chernogor, Olha Tiutiunyk, Tural Agazade
- Information technology of hot-metal ladle car handwritten numbers recognition from photo image 900-912
Anastasiia Serhiienko, Yevhen Chychkarov, Iryna Syrmamiikh
- Information-extreme machine learning on-board recognition system of ground objects with the adaptation of the input mathematical description 913-925
Dovbysh Anatolii, Naumenko Igor, Myronenko Mykyta, Savchenko Taras
- Development of a network attack detection system based on hybrid neuro-fuzzy algorithms 926-938
Olexander Belej, Liubov Halkiv
- Cattle breed identification and live weight evaluation on the basis of machine learning and computer vision 939-954
Oleg Rudenko, Yuriy Megel, Oleksandr Bezsonov, Antonina Rybalka
- Physiological signals analysis, recognition and classification using machine learning algorithms 955-965
Iurii Krak, Anatolii Pashko, Oleg Khorozov, Oleg Stelia
- Intelligent forecasting in multi-criteria decision-making 966-979
Vladyslav Borysenko, Galyna Kondratenko, Ievgen Sidenko, Yuriy Kondratenko
- Machine learning classification of multifractional Brownian motion realizations 980-989
Ljudmyla Kirichenko, Vitalii Bulakh, Tamara Radivilova
- An informetric view on relations between global brands and research activity 990-1000
Serhiy Shtovba, Olena Shtovba
- Decision tree based targeting model of customer interaction with business page 1001-1012
Hrystyna Lipyana, Anatolii Sachenko, Taras Lendyuk, Serhiy Nadvynychny, Sergii Grodskiy

Session 7: Information Technologies for Data Mining, Signal and Image Processing

- Image classification based on the kohonen network and the data space modification 1013-1026
Volodymyr Gorokhovatskyi, Iryna Tvoroshenko
- Image structural classification technologies based on statistical analysis of descriptions in the form of bit descriptor set 1027-1039
Volodymyr Gorokhovatskyi, Svitlana Gadetska, Natalia Stiahlyk
- Analysis of voice signal phase data informativity of authentication system user 1040-1053
Mykola Pastushenko, Yana Krasnozheniuk, Oleksandr Lemeshko
- Speech vocal clustering methods 1054-1066
Eugene Fedorov, Tetyana Utkina, Kostiantyn Rudakov, Andriy Lukashenko,

Ihor Zubko, Maryna Chychuzhko, Valentyna Lukashenko

- [Online video summarization with the Kohonen SOM in real time](#) 1067-1078
Oleksii Gorokhovatskyi, Oleh Teslenko, Volodymyr Zatkhei
- [Application of the fuzzy clustering technique for processing and analysis of medical images](#) 1079-1093
Alexander Stepanenko, Andrii Oliinyk, Ievgen Fedorchenko
- [Bit speed control method in compression of predicted frames in video sequence](#) 1094-1106
Vladimir Barannik, Valeriy Barannik, Oleg Kulitsa, Anna Hahanova
- [Robust object detection in images corrupted by impulse noise](#) 1107-1116
Rykhard Bohush, Sergey Ablameyko, Yahor Adamovskiy

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Speech Vocal Clustering Methods

Eugene Fedorov¹[0000-0003-3841-7373], Tetyana Utkina¹[0000-0002-6614-4133],
Kostiantyn Rudakov¹[0000-0003-0000-6077], Andriy Lukashenko²[0000-0002-6016-1899],
Ihor Zubko¹[0000-0002-3318-3347], Maryna Chychuzhko¹[0000-0001-5329-7897],
Valentyna Lukashenko¹[0000-0002-6749-9040]

¹ Cherkasy State Technological University, Cherkasy, Shevchenko blvd., 460, 18006, Ukraine
{t.utkina, ckc, k.rudakov, i.zubko, m.chychuzhko}@chdtu.edu.ua,
fedorovee75@ukr.net

² E. O. Paton Electric Welding Institute, Kyiv, Bozhenko str., 11, 03680, Ukraine
ineks-kiev@ukr.net

Abstract. The problem of increasing the clustering efficiency of vocal speech sounds is considered. Centroid and medoid clustering methods that use normalized distances which increases the efficiency of clustering, are proposed. Characteristics and quality criteria based on them are suggested for these methods. These methods have been investigated on TIMIT database and are intended for intelligent biometric identification systems.

Keywords: vocal speech sound, centroid, medoid, clustering, inter-cluster distance, intra-cluster distance, compression ratio.

1 Introduction

Automated biometric identification of a person means decision-making based on acoustic and visual information, which improves the quality of recognition of the person under investigation. Unlike the traditional approach [1], computer biometric identification speeds up and increases the likelihood of recognition, which is especially critical in conditions of limited time.

A special class of biometric identification of a person is formed by methods based on acoustic information [2].

To increase the efficiency of analysis, storage and transmission of a speech signal, knowledge of the structure of vocal speech sound is required, for which the following clustering methods are used.

Traditional methods (without the use of artificial neural networks and metaheuristics) [3-6] search for a solution faster than metaheuristic methods, some methods do not require setting of the number of clusters, but perform only a directed search for a solution and some methods require setting of the number of clusters or additional parameters.

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Neural network methods [7-10] perform a search for a solution faster than metaheuristic methods, but perform only a directed search for a solution and require exact setting of the number of clusters.

Metaheuristic methods [11-14] perform a random search for a solution, but the search for a solution is longer than that of other methods, and require exact setting of the number of clusters.

Thus, only some traditional methods do not require an exact setting of the number of clusters, but instead require setting of additional parameters.

The aim of the work is to increase the clustering efficiency of vocal speech sounds by providing an adaptive number of clusters, a minimum number of set parameters and parallel information processing.

To achieve this goal, it is necessary to solve the following tasks:

1. to develop a centroid clustering method;
2. to create medoid clustering methods;
3. to determine the characteristics and quality criterion of the clustering method;
4. to conduct a numerical study of the proposed clustering methods.

2 Problem statement

The problem of increasing the clustering efficiency of vocal speech sound comes down to the problem of finding such vector of parameters Θ^* that satisfies the criterion $F = SSWB + \frac{1}{C} \rightarrow \min_{\Theta}$, where $SSWB$ is the ratio of the sums of average intra-cluster and inter-cluster distances, C is the compression ratio of speech sound.

3 Literature review

Traditional clustering methods include:

1. Partition-based (partitioning-based) or center-based methods

In this case, a cluster is a set of objects, each of which is closer to the center of this cluster than to the center of any other cluster. The center of the cluster is usually a centroid (average value of the coordinates of all objects in the cluster) or a medoid (an object of the cluster, the average difference of which from other objects in the cluster is minimal). These methods consider intersecting areas with a high density of objects as different clusters, for example, K-means [15], PAM (k-medoids) [16], FCM [17], ISODATA [18] methods. The advantage of these methods consists in a quick search for a solution; some of them do not require setting of the number of clusters and have poor sensitivity to noise or random emissions. The disadvantage of these methods consists in the presence of only a directed search for a solution; a problem with clusters of different shapes, sizes and densities; some of them require setting of the number of clusters and are sensitive to noise or random emissions or require setting of additional parameters.

2. Model mixture or distribution-based or model-based methods

In this case, a cluster is described by the probability density function. These methods should be used when clusters are of different sizes, and the set of objects of all clusters can be described by a mixture of distribution densities, for example, EM method [19]. The advantage of these methods consists in a quick search for a solution; determination of the shape and size of each cluster by the corresponding distribution density. The disadvantage of these methods consists in the presence of only a directed search for a solution; requirement for precise setting of the number of clusters; sensitivity to noise or random emissions; the difficulty of choosing the appropriate distribution density.

3. Density-based methods

In this case, a cluster is an area with a high density of objects, which is separated by areas with a low density of objects from areas with a high density of objects. These methods consider intersecting areas with a high density of objects as a single cluster. These methods should be used when noise and random emissions are present, clusters have different shapes and sizes, and the number of clusters is unknown. Methods that define clusters (for example, DBSCAN method [20]) and those that provide visualization of clusters (for example, OPTICS method [21]) are distinguished. The advantage of these methods consists in the absence of a requirement to set the number of clusters; the presence of various shapes and sizes of a cluster; poor sensitivity to noise or random emissions. The disadvantage of these methods consists in the presence of only a directed search for a solution; a problem with clusters of heterogeneous density; slow search for a solution.

4. Hierarchical methods

These methods provide visualization of a cluster tree called a dendrogram. On a dendrogram, pairs of clusters that are joined (in the case of agglomerative methods) or obtained as a result of separation (in the case of divisive methods) are connected by a U-shaped arc, the height of which corresponds to the distance between clusters. By the method of constructing a dendrogram, these methods are divided into agglomerative or bottom up ones – each object is considered as a singleton cluster, after which a stepwise combination of pairs of the closest clusters is performed (for example, centroid communication, Ward, single communication, full communication, group average methods [22, 23]) and divisive or top down ones – all objects are considered as one cluster, and at each step one of the constructed clusters is divided into a couple of clusters (for example, DIANA, DISMEA methods [22, 23]). The advantage of these methods consists in the absence of a requirement to set the number of clusters; visibility; some of them don't strongly tend to clusters of a certain shape and size and have poor sensitivity to noise or random emissions. The disadvantage of these methods consists in the presence of only a directed search for a solution; slow search for a solution; some of them strongly tend to clusters of a certain shape and size, are sensitive to noise or random emissions, tend to discard clusters of high power.

Usually, the methods listed above either require setting of the number of clusters or have a slow search for a solution or require setting of additional parameters, which leads to a decrease in the clustering efficiency.

Therefore, the urgent task is to increase the clustering efficiency of vocal speech sounds by providing an adaptive number of clusters, a minimum number of set parameters and parallel information processing.

4 Method clustering of vocal speech sound

4.1 Centroid clustering of vocal speech sound based on minimum distance method

Centroid clustering of vocal speech sound based on the author's minimum distance method includes the following steps:

1. Set a lot of samples of vocal speech sound $S = \{s_i(n)\}$, $i \in \overline{1, I}, n \in \overline{1, N}$, which are in a single amplitude-time window, where I is the number of samples, N is the length of the sample. Set the number of quantization levels of a speech signal L (for an 8-bit sound sample $L = 256$). Set normalized threshold ε , $0 < \varepsilon < 1$. Set the number of clusters $K = 0$.
2. Calculate normalized squared distance between each pair of sound samples

$$D_{ij} = \frac{\|s_i - s_j\|^2}{NL^2}, \quad i \in \overline{1, I}, \quad j \in \overline{1, I}.$$

3. Calculate the distance between each sound sample and a lot of sound samples

$$d_i = \sum_{j=1}^I D_{ij}, \quad i \in \overline{1, I}.$$

4. Determine the number of sound sample with a minimum distance

$$i^* = \arg \min_i d_i, \quad i \in \overline{1, I}.$$

5. Set a sound sample with a minimum distance as the new cluster center, i.e. $m_{K+1} = s_{i^*}$, set the number of sound samples in the new cluster per unit, i.e. $a_{K+1} = 1$, increase the number of clusters, i.e. $K = K + 1$.
6. Set the sound sample number $i = 1$.
7. If $i^* = i$, then go to step 13.
8. Calculate normalized squared distance between the i^{th} sound sample and cluster centers

$$D_k = \frac{\|s_i - m_k\|^2}{NL^2}, \quad k \in \overline{1, K}.$$

9. Calculate the smallest normalized squared distance between the i^{th} sound sample and cluster centers

$$d^* = \min_k D_k, k \in \overline{1, K}.$$

10. Determine the number of the cluster with a minimum distance

$$k^* = \arg \min_k D_k, k \in \overline{1, K}.$$

11. If $d^* \leq \varepsilon$, then calculate the new center of the k^{th} cluster, i.e. $m_{k^*} = \frac{a_{k^*} m_{k^*} + s_i}{a_{k^*} + 1}$,

increase the number of sound samples in the k^{th} cluster, i.e. $a_{k^*} = a_{k^*} + 1$.

12. If $d^* > \varepsilon$, then set the i^{th} sample as the new cluster center, i.e. $m_{K+1} = s_i$, set the number of sound samples in the new cluster per unit $a_{K+1} = 1$, increase the number of clusters, i.e. $K = K + 1$.

13. If $i < I$, then go to the new sample, i.e. $i = i + 1$, go to step 7.

The method results in an adaptive set of centroids.

4.2 Medoid clustering of vocal speech sound based on minimax distance method

Medoid clustering of vocal speech sound based on minimax distance method, unlike the traditional version, preliminarily determines the number of a sound sample with a minimum distance for a non-random choice of the first cluster center and includes the following steps:

1. Set a lot of samples of vocal speech sound $S = \{s_i(n)\}$, $i \in \overline{1, I}, n \in \overline{1, N}$, which are in a single amplitude-time window, where I is the number of samples, N is the length of the sample. Set the number of clusters $c = 0$.
2. Calculate the squared distance between each pair of sound samples

$$D_{ij} = \|s_i - s_j\|^2, i \in \overline{1, I}, j \in \overline{1, I}.$$

3. Calculate the distance between each sound sample and a lot of sound samples

$$d_i = \sum_{j=1}^I D_{ij}, i \in \overline{1, I}.$$

4. Determine the number of sound sample with a minimum distance

$$i^* = \arg \min_i d_i, i \in \overline{1, I}.$$

6

5. Set a sound sample with a minimum distance as the new cluster center, i.e. $\phi_{c+1}(n) = s_{i^*}(n)$, $n \in \overline{1, N}$, increase the number of clusters, i.e. $c = c + 1$.

6. Calculate the squared distance between each sound sample and each cluster center

$$D_{ik} = \|s_i - \phi_k\|^2, \quad i \in \overline{1, I}, \quad k \in \overline{1, c}.$$

7. Calculate a minimax squared distance between sound samples and cluster centers

$$d^* = \max_i \min_k D_{ik}, \quad i \in \overline{1, I}, \quad k \in \overline{1, c}.$$

8. Determine the number of sound sample with a minimax squared distance

$$i^* = \arg \max_i \min_k D_{ik}, \quad i \in \overline{1, I}, \quad k \in \overline{1, c}.$$

9. If $c = 1$, then set a sound sample with a minimax squared distance as the new cluster center, i.e. $\phi_{c+1}(n) = s_{i^*}(n)$, $n \in \overline{1, N}$, increase the number of clusters, i.e. $c = c + 1$, go to step 6.

10. Calculate the average squared distance between cluster centers

$$\varepsilon = \frac{2}{c^2 - c} \sum_{i=1}^c \sum_{j=i}^c \|\phi_i - \phi_j\|^2.$$

11. Verification of the termination condition.

If $d^* > \frac{\varepsilon}{2}$, then set a sound sample with a minimax squared distance as the new cluster center, i.e. $\phi_{c+1}(n) = s_{i^*}(n)$, $n \in \overline{1, N}$, increase the number of clusters, i.e. $c = c + 1$, go to step 6.

12. Calculate the distance between each sound sample and each cluster center

$$D_{ik} = \|s_i - \phi_k\|, \quad i \in \overline{1, I}, \quad k \in \overline{1, c}.$$

13. Determine for each sound sample the cluster center closest to it

$$u_i = \arg \min_k D_{ik}, \quad i \in \overline{1, I}, \quad k \in \overline{1, c}.$$

The method results in an adaptive set of medoids.

4.3 Medoid clustering of vocal speech sound based on subtractive clustering method

Medoid clustering of vocal speech sound based on subtractive clustering method, unlike the traditional version, uses the normalization of squared distances for calculat-

ing the potentials of sound samples to specify normalized standard deviations and includes the following steps:

1. Set a lot of samples of vocal speech sound $S = \{s_i(n)\}$, $i \in \overline{1, I}, n \in \overline{1, N}$, which are in a single amplitude-time window, where I is the number of samples, N is the length of the sample. Set the number of quantization levels of a speech signal L (for an 8-bit sound sample $L = 256$). Set the threshold to stop the method δ , $0 < \delta < 1$. Set standard deviations σ_a and σ_b , $\sigma_b > \sigma_a$, $0 < \sigma_a < 1$, $0 < \sigma_b < 1$. Set the number of clusters $c = 0$.
2. Calculate the potential of each sound sample

$$P(i) = \sum_{j=1}^I e^{-\frac{4\|s_i - s_j\|^2}{\sigma_a^2 N L^2}}, \quad i \in \overline{1, I}.$$

3. Determine the number of sound sample with a maximum potential

$$i^* = \arg \max_i P(i), \quad i \in \overline{1, I}.$$

4. Set the potential $P(i^*)$ as the new cluster potential, i.e. $\bar{P}(c+1) = P(i^*)$.
5. Calculate the new potential of each sound sample

$$P(i) = P(i) - \bar{P}(c+1) e^{-\frac{4\|s_i - \phi_{c+1}\|^2}{\sigma_b^2 N L^2}}, \quad i \in \overline{1, I}.$$

6. Verification of the termination condition.

If $\frac{\bar{P}(c+1)}{\bar{P}(1)} \geq \delta$, then set a sound sample with the highest potential as the new cluster center, i.e. $\phi_{c+1}(n) = s_{i^*}(n)$, $n \in \overline{1, N}$, increase the number of clusters, i.e. $c = c + 1$, go to step 3.

7. Calculate the distance between each sound sample and each cluster center

$$D_{ik} = \|s_i - \phi_k\|, \quad i \in \overline{1, I}, \quad k \in \overline{1, c}.$$

8. Determine for each normalized sound sample the cluster center closest to it

$$u_i = \arg \min_k D_{ik}, \quad i \in \overline{1, I}, \quad k \in \overline{1, c}.$$

The method results in an adaptive set of medoids.

4.4 Medoid clustering of vocal speech sound based on minimum average distance method

Medoid clustering of vocal speech sound based on the author's method of minimum average distance includes the following steps:

1. Set a lot of samples of vocal speech sound $S = \{s_i(n)\}$, $i \in \overline{1, I}, n \in \overline{1, N}$, which are in a single amplitude-time window, where I is the number of samples, N is the length of the sample. Set the number of quantization levels of a speech signal L (for an 8-bit sound sample $L = 256$). Set the radius of the neighborhood of sound samples ε , $0 < \varepsilon < 1$. Set the number of clusters $c = 0$. Set a lot of samples of speech sound that haven't fallen into existing clusters, $\tilde{S} = \{s_i(n)\}$.
2. Calculate normalized squared distance between each pair of sound samples

$$D_{ij} = \frac{\|s_i - s_j\|^2}{NL^2}, \quad i \in \overline{1, I}, \quad j \in \overline{1, I}.$$

3. Calculate the distance between each sound sample and a lot of sound samples

$$d_i = \sum_{j=1}^I D_{ij}, \quad i \in \overline{1, I}.$$

4. Determine the neighborhood of each sound sample

$$U_{i,\varepsilon} = \{j \mid D_{ij} < \varepsilon, j \in \overline{1, I}\}, \quad i \in \overline{1, I}.$$

5. Determine the neighborhood of the sound sample with a minimum average distance

$$i^* = \arg \min_{i \in \tilde{S}} \frac{d_i}{|\tilde{S}|},$$

$$U^* = U_{i^*,\varepsilon}.$$

6. Calculate the new distance between each sound sample and a lot of sound samples that haven't fallen into existing clusters

$$d_i = \begin{cases} 0, & i \in U^* \\ d_i - \sum_k D_{ik}, & i \notin U^*, k \in U_{i,\varepsilon} \cap U^*, i \in \tilde{S}. \end{cases}$$

7. Determine the new neighborhood for each sound sample that hasn't fallen into existing clusters.

$$U_{i,\varepsilon} = \begin{cases} \emptyset, & i \in U^* \\ U_{i,\varepsilon} \setminus U^*, & i \notin U^*, i \in \tilde{S}. \end{cases}$$

8. Set a sound sample with a minimum average distance as the new cluster center, i.e.

$$\phi_{c+1}(n) = s_{i^*}(n), \quad n \in \overline{1, N}, \quad \text{increase the number of clusters, i.e. } c = c + 1.$$

9. Verification of the termination condition.

If $\tilde{S} \setminus U^* \neq \emptyset$, then $\tilde{S} = \tilde{S} \setminus U^*$, go to step 5.

10. Calculate the distance between each sound sample and each cluster center (code-book vector)

$$D_{ik} = \|s_i - \phi_k\|, \quad i \in \overline{1, I}, \quad k \in \overline{1, c}.$$

11. Determine for each sound sample the cluster center closest to it

$$u_i = \arg \min_k D_{ik}, \quad i \in \overline{1, I}, \quad k \in \overline{1, c}.$$

The method results in an adaptive set of medoids.

5 Determination of characteristics and quality criterion for clustering methods of vocal speech sound

To evaluate clustering methods, the following characteristics are used in the work:

1. The sum of average intra-cluster distances:

— in the case of centroid clustering methods

$$SSW = \sum_{k=1}^K \left(\frac{\sum_{i=1}^I \chi_{A_k}(s_i) \|s_i - m_k\|^2}{\sum_{i=1}^I \chi_{A_k}(s_i)} \right),$$

— in the case of medoid clustering methods

$$SSW = \sum_{k=1}^c \left(\frac{\sum_{i=1}^I \chi_{A_k}(s_i) \|s_i - \phi_k\|^2}{\sum_{i=1}^I \chi_{A_k}(s_i)} \right),$$

$$\chi_{A_k}(s_i) = \begin{cases} 1, & s_i \in A_k \\ 0, & s_i \notin A_k \end{cases},$$

where A_k is a cluster.

2. The sum of inter-cluster distances:

– in the case of centroid clustering methods

$$SSB = \sum_{k=1}^K \|m_k - m\|^2,$$

$$m = \frac{\sum_{i=1}^I s_i}{I}$$

– in the case of medoid clustering methods

$$SSB = \sum_{k=1}^c \|\phi_k - \phi_1\|^2.$$

3. The ratio of the sums of average intra-cluster and inter-cluster distances

$$SSWB = \frac{SSW}{SSB}.$$

In addition, to assess the quality of clustering methods, the following characteristics – compression ratio for speech sound – is proposed in the work:

$$C = \frac{I}{c},$$

where I is the number of samples of vocal speech sound, c – the number of clusters.

The following criterion for the quality of clustering, which means choosing such a value Θ that minimizes the sum of the inverse of compression ratio and the ratio of the sums of average intra-cluster and inter-cluster distances, is formulated in the paper:

$$F = SSWB + \frac{1}{C} \rightarrow \min_{\Theta}. \quad (1)$$

For centroid clustering of vocal speech sound based on minimum distance method $\Theta = \varepsilon$. For medoid clustering of vocal speech sound based on subtractive clustering method $\Theta = (\sigma_a, \sigma_b, \delta)$. For medoid clustering of vocal speech sound based on minimum average distance method $\Theta = \varepsilon$.

6 Experiments and results

Numerical experiments were carried out using notebook Intel Core i5 8th Gen, MATLAB package, CUDA technology of parallel information processing on the Ge-

Force 920M graphics card with the number of threads in the block $N^s = 1024$. In this case, the most time-consuming (computational complexity $O(I^2)$, where I is the number of samples of vocal speech sound) step 2 of all four proposed clustering methods was parallelized. This made it possible to speed up the search for a solution.

For speech signals containing vocal sounds, the sampling frequency $f_d = 8$ kHz and the number of quantization levels $L = 256$ were set. The length of the sample of vocal speech sound $N = 256$.

For modified method of subtractive clustering, the following fixed parameter values $\delta = 0.01$, $\sigma_b = 1.25\sigma_a$ were set.

The results of a numerical study of the proposed clustering methods for vocal sounds of people from TIMIT database are presented in Table 1.

The result presented in Table 1 shows that the author's method of minimum average distance provides the smallest F value, calculated according to (1). The compression ratio is approximately 7.5, i.e. the number of stored samples is reduced by about 7.5 times.

Based on the experiments, the following conclusions can be drawn.

The author's method of minimum distance should be used only when centroids are required, and not medoids, since it has the largest F and the lowest compression ratio.

Table 1. Results of a numerical study of vector quantization methods

Characteristics of clustering methods	Author's method of minimum distance	Modified minimax distance method	Modified subtractive clustering method	Author's method of minimum average distance
Compression ratio	4.5429	10.7500	7.5834	7.5834
F	0.3157	0.2712	0.2420	0.2400
Number of parameters	1	0	3	1

The modified method of minimax distance performs a coarser adjustment of the number of clusters than the modified method of subtractive clustering and the author's method of minimum average distance, because it does not use parameters. On the other hand, an operator does not need to set any parameters, the values of which are established empirically.

The modified method of subtractive clustering performs finer adjustment of the number of clusters than the modified method of minimax distance, because it uses parameters. It requires more complex setting than the author's method of minimum average distance, because it uses three parameters, the values of which are established empirically.

The author's method of minimum average distance performs finer adjustment of the number of clusters than the modified method of minimax distance, because it uses

parameters. It requires simpler adjustment than the modified method of subtractive clustering, because it uses only one parameter, the value of which is established empirically.

7 Conclusions

The article considers the problem of increasing the clustering efficiency of vocal speech sounds. The following clustering methods are proposed – the author’s method of minimum distance, the author’s method of minimum average distance, the modified method of minimax distance (unlike the traditional version, it preliminarily determines the number of a sound sample with a minimum distance for non-random choice of the first cluster center), the modified method of subtractive clustering (unlike the traditional version, it uses squared distances normalization to set normal standard deviations in calculating the potentials of sound samples). Characteristics and quality criteria based on them are proposed for these methods. The proposed methods allow to increase the clustering efficiency of vocal speech sounds by providing an adaptive number of clusters, a minimum number of specified parameters and parallel information processing. The proposed methods are intended for software implementation on GPU using CUDA technology, which speeds up the process of finding a solution. Software that implements the proposed methods has been developed and researched on TIMIT database. The conducted experiments have confirmed the operability of the developed software and allow to recommend it for use in practice when solving problems of biometric identification of a person. Prospects for further research are to test the proposed methods on a wider set of test databases.

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