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**TEMPORAL - SPATIAL RECOGNIZER FOR MULTI-LABEL
DATA**



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Universiti Utara Malaysia

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Abstrak

Pengecaman corak merupakan satu tugas perlombongan data yang penting dengan aplikasi praktikal dalam pelbagai bidang seperti perubatan dan pengagihan spesis. Aplikasi tersebut melibatkan pertindihan data yang terkandung di dalam set data berbilang label. Oleh itu, terdapat keperluan bagi algoritma pengecaman yang boleh memisahkan pertindihan data untuk mengenal pasti corak yang betul. Kaedah pengecaman corak sedia ada adalah sensitif terhadap gangguan dan data yang bertindih kerana ia tidak dapat mengenali corak apabila terdapat perubahan pada lokasi data. Kaedah tersebut juga tidak melibatkan maklumat temporal dalam proses pengecaman dan ini membawa kepada kualiti kelompok data yang rendah. Dalam kajian ini, satu kaedah penambahbaikan pengecaman corak berdasarkan Daya Ingatan Temporal Hierarki (HTM) dicadangkan. Algoritma imHTM (HTM yang ditambahbaik) mengandungi penambahbaikan dalam dua komponennya; pengekstrakan fitur dan pengelompokan data. Penambahbaikan yang pertama dikenali sebagai algoritma τ S-Layer Neocognitron yang menyelesaikan masalah perubahan lokasi data dalam fasa pengekstrakan fitur. Dalam pada itu, komponen kedua iaitu pengugusan data mempunyai 2 dua penambahbaikan, τ FCM dan cFCM (τ FCM dengan metrik had-Chebyshev), membolehkan pertindihan data yang terdapat dalam corak dipisahkan dengan tepat ke dalam kelompok data yang berkaitan dengan menggunakan pengelompokan temporal. Eksperimen ke atas lima set data telah dijalankan bagi membandingkan prestasi algoritma yang dicadangkan (imHTM) dengan kaedah pengecaman corak berasaskan statistik, templat dan struktur. Keputusan menunjukkan peratusan pengecaman yang berjaya adalah sebanyak 99% berbanding dengan kaedah pengecaman yang lain. Ini menunjukkan bahawa HTM yang ditambahbaik dapat membuat pengecaman corak yang optimum terutamanya bagi corak yang terdapat di dalam set data berbilang label.

Kata kunci: Model Temporal hierarki Daya Ingatan, Neocognitron, Pengecaman Corak, Data berbilang label, Perlombongan Data

Abstract

Pattern recognition is an important artificial intelligence task with practical applications in many fields such as medical and species distribution. Such application involves overlapping data points which are demonstrated in the multi-label dataset. Hence, there is a need for a recognition algorithm that can separate the overlapping data points in order to recognize the correct pattern. Existing recognition methods suffer from sensitivity to noise and overlapping points as they could not recognize a pattern when there is a shift in the position of the data points. Furthermore, the methods do not implicate temporal information in the process of recognition, which leads to low quality of data clustering. In this study, an improved pattern recognition method based on Hierarchical Temporal Memory (HTM) is proposed to solve the overlapping in data points of multi-label dataset. The imHTM (Improved HTM) method includes improvement in two of its components; feature extraction and data clustering. The first improvement is realized as τ S-Layer Neocognitron algorithm which solves the shift in position problem in feature extraction phase. On the other hand, the data clustering step, has two improvements, τ FCM and cFCM (τ FCM with limit-Chebyshev distance metric) that allows the overlapped data points which occur in patterns to be separated correctly into the relevant clusters by temporal clustering. Experiments on five datasets were conducted to compare the proposed method (imHTM) against statistical, template and structural pattern recognition methods. The results showed that the percentage of success in recognition accuracy is 99% as compared with the template matching method (Featured-Based Approach, Area-Based Approach), statistical method (Principal Component Analysis, Linear Discriminant Analysis, Support Vector Machines and Neural Network) and structural method (original HTM). The findings indicate that the improved HTM can give an optimum pattern recognition accuracy, especially the ones in multi-label dataset.

Keywords: Hierarchical Temporal Memory Model, Neocognitron, Pattern Recognition, Multi-label data, Data mining.

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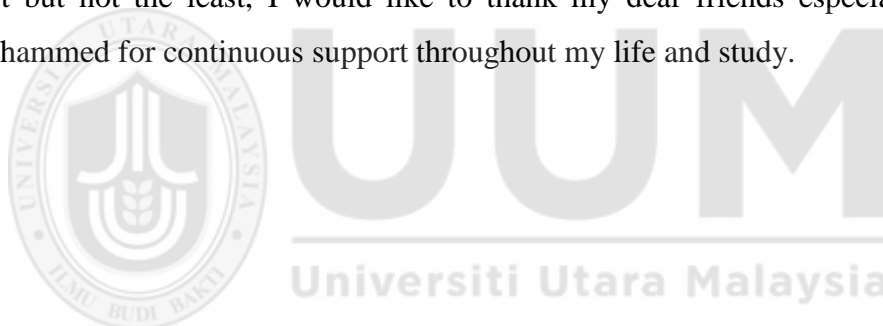


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Glossary of Terms

HTM	Hierarchical Temporal Memory
FCM	Fuzzy c-means clustering
PR	Pattern Recognition
RNN	Recurrent Neural Network
MPF	Memory Prediction Theory
MLT	Medical Laboratory Technician
MLD	Multi- label data
MLL	Multi- label learning
NCBI	National Center for Biotechnology and Information
ASR	Automatic speech recognition
ASIFT	Affine scale invariant feature transform
MRI	Magnetic resonance imaging
OSAD	Optimized Sum of Absolute Difference
SSD	Sum of Square Difference
NCC	Normalized Cross Correlation
SSTN	Sum Square T-distribution Normalized
SAD	Sum of Absolute Difference
PTM	Polyhedral template matching
PCA	Principal Component Analysis
DMSC	Discriminative multi-scale sparse coding
SVM	Support Vector Machines
LDA	Linear Discriminant Analysis
NN	Group Method of Data Handling
PNN	Probabilistic Neural Networks

PFCM	Possiblistic fuzzy c-means
CLA	Cortical Learning Algorithm
T S-layer	Time S-layer Neocognitron algorithm
T FCM	Temporal Fuzzy C-Means
imHTM	Improved Hierarchical Temporal Memory
HMM	Hidden Markov Model
c FCM	Chebyshev Fuzzy C-Means



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CHAPTER ONE

INTRODUCTION

1.1 Background

Pattern recognition (PR) is an operation of detecting patterns in data sets and using this data to characterize new data (Sao, Hegadi, & Karmakar, et al.,2014). It is defined as a classification of input data via extraction important features from a lot of noisy data (Paul, Magdon-Ismail, & Drineas, et al.,2016). The identification or interpretation of the pattern in an image can be described effectively with the help of Pattern Recognition (PR) (Kaur & Kaur, et al.,2013). PR is a form of machine learning, which is a field in artificial intelligence (Wu & Toet, et al.,2014). Machine learning in turn is divided into two main groups: supervised and unsupervised learning (Shwartz & Ben-David, et al.,2014). In supervised learning, the computer system is trained by using a classis that are previously defined, and then using this classes to classify unknown objects depending on the patterns that were detected in training (Bova et al., 2016). In an unsupervised learning, the classes are not defined beforehand, and the computer system clusters the data using a group of general rules (Serb, Bill, Ali Khiat, Legenstein, & Prodromakis, et al.,2016). Unsupervised is equivalent to classification known as clustering, which groups the input patterns into clusters depending on the measures of similarity (the distance between input patterns). Other approaches to PR involve semi-supervised learning, which try to find new similarity relationships using previously defined classes to determine new groups (Shwartz & Ben-David, et al.,2014). On the other hand, reinforcement learning is an approach that improve the decisions iteratively, depending on the feedback technique and assigning a reward criterion (Duan, Chen, Houthoof, Schulman, & Abbeel, et al.,2016).

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REFERENCES

- Abdel-Azim, G. (2016). New Hierarchical Clustering Algorithm for Protein Sequences Based on Hellinger Distance. *Applied Mathematics & Information Sciences*, 10(4), 1541-1549.
- Abdulfattah, G. M., & Ahmad, M. N. (2013). Face Localization Based Template Matching Approach Using New Similarity Measurements. *Journal of Theoretical and Applied Information Technology*, 57(3).
- Adhikari, S. K., Sing, J. K., Basu, D. K., & Nasipuri, M. (2015, 4-7 Jan. 2015). A spatial fuzzy C-means algorithm with application to MRI image segmentation. Paper presented at the 2015 *Eighth International Conference on Advances in Pattern Recognition (ICAPR)*.
- Adjouadi, M., Zong, N., & Ayala, M. (2005). Multidimensional Pattern Recognition and Classification of White Blood Cells Using Support Vector Machines. *Part. Part. Syst. Charact.*, 22, 107-118.
- Ahmad, S., & Hawkins, J. (2015). Properties of Sparse Distributed Representations and their Application to Hierarchical Temporal Memory. *arXiv:1503.07469*.
- Ahmed, M., & Aradhya, V. N. M. (2016). A Study of Sub-Pattern Approach in 2D Shape Recognition Using the PCA and Ridgelet PCA. *Int. J. Rough Sets Data Anal.*, 3(2), 10-31. Retrieved from doi: 10.4018/ijrsda.2016040102
- Ali, J., Ahma, A., George, L. E., Der, C. S., & Aziz, S. (2013). Red Blood Cell Recognition using Geometrical Features. *International Journal of Computer Science (IJCSI) Issues*, 10(1), 5.
- Amza, C. G., & Cicic, D. T. (2015). Industrial Image Processing Using Fuzzy-logic. *Procedia Engineering*, 100, 492-498. Retrieved from <http://dx.doi.org/10.1016/j.proeng.2015.01.404>
- Arel, I., Rose, D. C., & Karnowski, T. P. (2010). Deep Machine Learning - A New Frontier in Artificial Intelligence Research [Research Frontier]. *Computational Intelligence Magazine, IEEE*, 5(4), 13-18. Retrieved from doi: 10.1109/MCI.2010.938364
- Arimond, A. (2010). A Distributed System for Pattern Recognition and Machine Learning. (Diploma). Retrieved from TU Kaiserslautern, TU Kaiserslautern.
- Asgar, F., & Salehi, A. (2015). The biologically inspired Hierarchical Temporal Memory Model for Farsi Handwritten Digit and Letter Recognition. *International Journal of Computer Applications*, 129(16).
- Aytug Onan, Bulut, H., & Korukoglu, S. (2016). An improved ant algorithm with LDA-based representation for text document clustering. *Journal of Information Science*.
- Azad, R., Azad, B., & Brojeeni, H. R. S. (2014). Real-Time and Efficient Method for Accuracy Enhancement of Edge Based License Plate Recognition System Paper presented at the *International Conference on computer, Information Technology and Digital Media*
- Abdel-Azim, G. (2016). New Hierarchical Clustering Algorithm for Protein Sequences Based on Hellinger Distance. *Applied Mathematics & Information Sciences*, 10(4), 1541-1549.
- Abdulfattah, G. M., & Ahmad, M. N. (2013). Face Localization Based Template Matching Approach Using New Similarity Measurements. *Journal of Theoretical and Applied Information Technology*, 57(3).
- Adhikari, Sing, Basu, & Nasipuri. (2015, 4-7 Jan. 2015). A spatial fuzzy C-means algorithm with application to MRI image segmentation. Paper presented at the

- 2015 *Eighth International Conference on Advances in Pattern Recognition (ICAPR)*.
- Adjouadi, M., Zong, N., & Ayala, M. (2005). Multidimensional Pattern Recognition and Classification of White Blood Cells Using Support Vector Machines. *Part. Part. Syst. Charact.*, 22, 107-118.
- Ahmad, S., & Hawkins, J. (2015). Properties of Sparse Distributed Representations and their Application to Hierarchical Temporal Memory. *arXiv:1503.07469*.
- Ahmed, M., & Aradhya, M. (2016). A Study of Sub-Pattern Approach in 2D Shape Recognition Using the PCA and Ridgelet PCA. *Int. J. Rough Sets Data Anal.*, 3(2), 10-31. Retrieved from doi:10.4018/ijrsda.2016040102
- Aksoy, S. (2012). Structural and Syntactic Pattern Recognition. Retrieved from doi:10.3422/jnw.2012.06.014.
- Alqaisy, M. A., Yassen, M. T., Khalifa, F. S., & Salim, A. J. (2016, 9-10 May 2016). A dual-band bandpass filter using single unit cell of complementary split ring resonator with third harmonic reduction. Paper presented at the 2016 *Al-Sadeq International Conference on Multidisciplinary in IT and Communication Science and Applications (AIC-MITCSA)*.
- Amza, C. G., & Cicic, D. T. (2015). Industrial Image Processing Using Fuzzy-logic. *Procedia Engineering*, 100, 492-498. Retrieved from doi:<http://dx.doi.org/10.1016/j.proeng.2015.01.404>
- Arel, I., Rose, D. C., & Karnowski, T. P. (2010). Deep Machine Learning - A New Frontier in Artificial Intelligence Research *Computational Intelligence Magazine, IEEE*, 5(4), 13-18. Retrieved from doi:10.1109/MCI.2010.938364
- Arimond, A. (2010). A Distributed System for Pattern Recognition and Machine Learning. (Diploma), TU Kaiserslautern, TU Kaiserslautern.
- Asgar, F., & Salehi, A. (2015). The biologically inspired Hierarchical Temporal Memory Model for Farsi Handwritten Digit and Letter Recognition. *International Journal of Computer Applications*, 129(16).
- Assis, L. d. S., Soares, A. d. S., Coelho, C. J., & Van Baalen, J. (2016). An Evolutionary Algorithm for Autonomous Robot Navigation. *Procedia Computer Science*, 80, 2261-2265. Retrieved from doi:<http://dx.doi.org/10.1016/j.procs.2016.05.404>
- Aytug Onan, Bulut, H., & Korukoglu, S. (2016). An improved ant algorithm with LDA-based representation for text document clustering. *Journal of Information Science*. Retrieved from doi: 10.3211/22133/j.ins.7002441
- Azad, R., Azad, B., & Brojeeni, H. R. S. (2014). Real-Time and Efficient Method for Accuracy Enhancement of Edge Based License Plate Recognition System Paper presented at the *International Conference on computer, Information Technology and Digital Media*
- Badyalina, B., Shabri, A., & Samsudin, R. (2014). Streamflow Estimation at Ungauged Site Using Wavelet Group Method of Data Handling in *Int. Journal of Math. Analysis*, 8(11), 513 - 524
- Bal, A., & Saha, R. (2016). An Improved Method for Handwritten Document Analysis Using Segmentation, Baseline Recognition and Writing Pressure Detection. *Procedia Computer Science*, 93, 403-415. Retrieved from doi:<http://dx.doi.org/10.1016/j.procs.2016.07.227>
- Bezdek, J. C. (1981). *Pattern Recognition With Fuzzy Objective Function Algorithms: Kluwer Academic Publishers*.

- Bin Wang, Hiroki Yamamoto, Wu, J., & Ejima, Y. (2015). Neuroscience and Biomedical Engineering. *Bentham Science*, 1(2), 102-110. Retrieved from doi: 10.2174/2213385202666140207002441
- Bishop, C. M. (1995). Neural Networks for Pattern Recognition. Retrieved from doi:10.4566/j.ins.1995.03.045
- Bommes, M., Fazekas, A., Volkenhoff, T., & Oeser, M. (2016). Video Based Intelligent Transportation Systems – State of the Art and Future Development. *Transportation Research Procedia*, 14, 4495-4504. Retrieved from <http://dx.doi.org/10.1016/j.trpro.2016.05.372>
- Bova, N., & G, V. (2016). Deformable models direct supervised guidance. *Neurocomput.*, 177(C), 317-333. Retrieved from doi:10.1016/j.neucom.2015.11.023
- Boyat, A. K., & Joshi, B. K. (2015). A review Paper: Noise MOodels in Digital Image Prossesing. *Signal & Image Processing : An International Journal (SIPIJ)*, 6(2).
- Bradbury, J., Merity, S., & Socher, C. X. R. (2017). *QusiI-Recurrent Neural Networks*. Paper presented at *the International Conference on Learning Robotics (ICLR) 2017, Palo Alto, California*.
- Byrne, F. (2015a). Encoding Reality: Prediction-Assisted Cortical Learning Algorithm in Hierarchical Temporal Memory. *arXiv:1509.08255v1*.
- Byrne, F. (2015b). Encoding Reality: Prediction-Assisted Cortical Learning Algorithm in Hierarchical Temporal Memory. *Neural and Evolutionary Computing*, 2.
- Cabral, R. S., De la Torre, F., Costeira, J. P., & Bernardino, A. (2011). Matrix Completion for Multi-label Image Classification. Papper presented to the 6th *International Conference on Classification Techniques (ICCT)*, 201(1).
- Cai, W., Chen, S., & Zhang, D. (2010). Fast and Robust Fuzzy C-Means Clustering Algorithms Incorporating Local Information for Image Segmentation. *Pattern Recognition Letters 0031-3203*, 40(3), 825-838
- Chakraborty, S., & Parekh, R. (2015). An Improved Template Matching Algorithm for Car License Plate Recognition. *International Journal of Computer Applications* 118(25).
- Chattopadhyay, S., Pratihari, D. K., & Sarkar, S. C. D. (2011). A comparative Study of Fuzzy C-means Algorithm and Entropy-Based Fuzzy Clustering Algorithms. *Journal of Computing and Informatics*, 30, 701-720.
- Chen. (2017). Medical Image Segmentation Using Independent Component Analysis-Based Kernelized Fuzzy -Means Clustering. *Mathematical Problems in Engineering*, 201721 pages. Retrieved from doi:10.1155/2017/5892039
- Chen, G., Bui, T. D., & Krzyżak, A. (2016). Sparse support vector machine for pattern recognition. *Concurrency and Computation: Practice and Experience*, 28(7), 2261-2273. doi:10.1002/cpe.3492
- Chen, Y.-T. (2017). Medical Image Segmentation Using Independent Component Analysis-Based Kernelized Fuzzy -Means Clustering. *Mathematical Problems in Engineering*, 201721 pages. Retrieved from doi:10.1155/2017/5892039
- Coutinho, K., & Inoue, T. (2016). Deconstructing and constructing innate immune functions using molecular sensors and actuators. *SPIE 9871*. Retrieved from doi: 10.1117/12.2225185
- Das, & De. (2016, 23-25 Sept. 2016). Multilevel color image segmentation using modified genetic algorithm (MfGA) inspired fuzzy c-means clustering. Paper

- presented at the 2016 *Second International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN)*.
- Das, Pal, Ballester, & Blumenstein. (2014, 9-12 Dec. 2014). *A new efficient and adaptive sclera recognition system*. Paper presented at the *Computational Intelligence in Biometrics and Identity Management (CIBIM), 2014 IEEE Symposium on*.
- Das, S. (2013). Pattern Recognition using the Fuzzy c-means Technique. *International Journal of Energy, Information and Communications*, 4(1), 14.
- Deepa, & Revathy. (2012). Validation of Document Clustering based on Purity and Entropy measures. *International Journal of Advanced Research in Computer and Communication Engineering*, 1(3), 6.
- Diao, J., & Kang, H. (2014, 13-15 July 2014). An Integrated Hierarchical Temporal Memory Network for Real-Time Continuous Multi-interval Prediction of Data Streams. Paper presented at the *2014 Sixth International Symposium on Parallel Architectures, Algorithms and Programming*.
- Diplaris, S., Tsoumakas, G., Mitkas, P. A., & Vlahavas, I. (2005). Protein Classification with Multiple Algorithms. In P. Bozani & E. N. Houstis (Eds.), *Advances in Informatics: 10th Panhellenic Conference on Informatics, PCI 2005, Volos, Greece, November 11-13, 2005. Proceedings* (pp. 448-456). Berlin, Heidelberg: Springer Berlin Heidelberg.
- Dobrescu, R., Ichim, L., & Crişan, D. (2013). Diagnosis of Breast Cancer from Mammograms by Using Fractal Measures. *International Journal of Medical Imaging*, 1(2), 32-38. Retrieved from doi:10.11648/j.ijmi.20130102.14
- Dornaika, F., Traboulsi, Y. E., & Assoum, A. (2016a). Inductive and flexible feature extraction for semi-supervised pattern categorization. *Pattern Recogn.*, 60, 275-285.
- Dornaika, F., Traboulsi, Y. E., & Assoum, A. (2016b). Inductive and flexible feature extraction for semi-supervised pattern categorization. *Pattern Recognition*, 60, 275-285. Retrieved from doi:<http://dx.doi.org/10.1016/j.patcog.2016.04.024>
- Doulaty, M., Rose, R., & Siohan, O. (2016). Automatic Optimization of Data Perturbation Distributions for Multi-Style Training in Speech Recognition. Paper presented at the *International Conference on Sequence Learning Techniques 2016*.
- Duan, Chen, X., Houthoof, R., Schulman, J., & Abbeel, P. (2016). Benchmarking Deep Reinforcement Learning for Continuous Control. Paper presented at the *International conference on Memory learning ICML 2016*.
- Duan, Yao, M., Wang, J., Bai, T., & Yue, J. (2016). Integrative intrinsic time-scale decomposition and hierarchical temporal memory approach to gearbox diagnosis under variable operating conditions. *Advances in Mechanical Engineering*, 1(1).
- Duygulu, P., Barnard, K., Freitas, J. F. G. d., & Forsyth, D. A. (2002). Object Recognition as Machine Translation: Learning a Lexicon for a Fixed Image Vocabulary. Paper presented at the *ECCV '02 Proceedings of the 7th European Conference on Computer Vision-Part IV, London, UK*
- Eyupoglu. (2016, 2-3 Feb. 2016). Implementation of color face recognition using PCA and k-NN classifier. Paper presented at the *2016 IEEE NW Russia Young Researchers in Electrical and Electronic Engineering Conference (EIconRusNW)*.
- Fan, & Lin, C. J. (2007). A study on threshold selection for multi-label classification, 1-23. Retrieved from doi:10.1232/j.ins.2007.23.05.

- Fan, Sharad, Sengupta, & Roy. (2016). Hierarchical Temporal Memory Based on Spin-Neurons and Resistive Memory for Energy-Efficient Brain-Inspired Computing. *IEEE Trans Neural Netw Learn Syst*, 27(9). Retrieved from doi:10.1109/TNNLS.2015.2462731
- Fathima, N. (2013). Classification of Blood Types by Microscope Color Images. *International Journal of Machine Learning and Computing*, 3(4), 4.
- Flores, A., Linguraru, M. G., & Okada, K. (2010). *Boosted-LDA for Biomedical Data Analysis*. Retrieved from doi:10.1223/j.ins.2010.02.06
- Fouda. (2015). A Robust Template Matching Algorithm Based on Reducing Dimensions. *Journal of Signal and Information Processing*, 6, 109-122.
- Fukushima. (2013a). Artificial Vision by Multi-Layered Neural Networks: Neocognitron and its Advances. *Neural Networks*, 37, 103-119. Retrieved from doi: 10.1016/j.neunet.2013.09.016
- Fukushima. (2013b). Training Multi-Layered Neural Network Neocognitron. *elsevier*, 40, 18-31.
- Fukushima. (2016, 24-29 July 2016). Margined Winner-Take-All: New learning rule for pattern recognition. Paper presented at the 2016 *International Joint Conference on Neural Networks (IJCNN)*.
- Fukushima, & Shouno. (2015, 12-17 July 2015). Deep convolutional network neocognitron: Improved Interpolating-Vector. Paper presented at the 2015 *International Joint Conference on Neural Networks (IJCNN)*.
- Gabrielsson, J., Meibohm, B., & Weiner, D. (2016). Pattern Recognition in Pharmacokinetic Data Analysis. *AAPS Journal*. Retrieved from doi:10.1208/s12248-015-9817-6
- Garg, V. (2014). Inductive Group Method of Data Handling Neural Network Approach to Model Basin Sediment Yield *Journal of Hydrologic Engineering*, 20(6).
- George. (2008). How the Brain Might Work A Hierarchical and Temporal Model for Learning and Recognition. (PhD), Stanford.
- George, & Hawkins. (2005a, 31 July-4 Aug. 2005). A hierarchical Bayesian Model of Invariant Pattern Recognition in the Visual Cortex. Paper presented at the *Neural Networks, 2005. IJCNN '05. Proceedings. 2005 IEEE International Joint Conference on Neural Network*
- George, & Hawkins. (2005b). Invariant Pattern Recognition using Bayesian Inference on Hierarchical Sequences. *International Conference on Neural Networks, 2005. IJCNN '05. Proceedings. 2005 IEEE International Joint Conference*
- George, & Hawkins. (2012). USA Patent No.: I. Numenta.
- Gorokhovatskyi. (2016, 23-27 Aug. 2016). Neocognitron as a tool for optical marks recognition. Paper presented at the 2016 *IEEE First International Conference on Data Stream Mining & Processing (DSMP)*.
- Gottschlich, C. (2016). Convolution Comparison Pattern: An Efficient Local Image Descriptor for Fingerprint Liveness Detection. *PLOS ONE*.
- Grabusts, P. (2011). The Choice of Metrics for Clustering Algorithms. Paper presented at the *International Scientific and Practical Conference., Izdevniecība.,*
- Guarneros, M. J., Ochoa, J. A. C., & Trinidad, J. F. M. (2015). Prototype Selection for Graph Embedding Using Instance Selection. Paper presented at the *7th Mexican Conference on Computer Science , maxico.*
- Guichard., D. (2015). *Calculus Early Transcendentals*. USA: Creative Commons.,
- H, T. A., & Sachin, D. (2015). Dimensionality Reduction and Classification through PCA and LDA. *International Journal of Computer Applications* 122(17).

- Han, Kamber, & Pei. (2011). *Data Mining: Concepts and Techniques, 3rd Edition* Elsevier (Ed.)
- Hawkins, & George. (2006). Hierarchical Temporal Memory--Concepts, Theory, and Terminology. *Whitepaper, Numenta Inc, May*. doi:citeulike-article-id:7020873
- He, Z., Liu, L., Zhou, S., & Shen, Y. (2016). Learning group-based sparse and low-rank representation for hyperspectral image classification. *Pattern Recogn.*, 60, 1041-1056.
- Heinbockel, J. H. (2012). *Introduction to Calculus Volume I* (Vol. 1): Old Dominion University.
- Horvath, L., & Khoshnevisan, D. (2010). Weight Functions and Pathwise Local Central Limit Theorems. *Stochastic Processes and Their Applications*, 59(12), 105-123. Retrieved from doi:10.1016/0304-4149(95)00021-X
- Hou, S.-w., Feng, S., & Wang, H. (2016). Intelligent Process Abnormal Patterns Recognition and Diagnosis Based on Fuzzy Logic. *Computational Intelligence and Neuroscience*, 2016, 8. Retrieved from doi:10.1155/2016/8289508
<http://www.dti.unimi.it/fscotti/all>.
- Huan, X., Caramanis, & Sanghavi. (2012). Robust PCA via Outlier Pursuit. *Information Theory, IEEE Transactions*, 58(5), 3047-3064. Retrieved from doi:10.1109/TIT.2011.2173156
- Jaros, George, Hawkins, & Astier. (2014). Sequence learning in a hierarchical temporal memory based system: Google Patents.
- Jasmin Léveillé, Isao Hayashi, & Fukushima, K. (2014). A Probabilistic WKL Rule for Incremental Feature Learning and Pattern Recognition. *Journal of Advanced Computational Intelligence and Intelligent Informatics*, 18(4), 672-681.
- Jiang, Trundle, & Ren. (2010). Medical image analysis with artificial neural networks. *Computerized Medical Imaging and Graphics*, 34, 617-631.
- Jose, Nair, .Biju, Mathew, & Prashanth. (2016, 18-19 March 2016). Hidden Markov Model: Application towards genomic analysis. Paper presented at the 2016 *International Conference on Circuit, Power and Computing Technologies (ICCPCT)*.
- Ju, F., Sun, Y., Gao, J., Liu, S., Hu, Y., & Yin, B. (2016). Mixture of Bilateral-Projection Two-Dimensional Probabilistic Principal Component Analysis. Paper presented at the *IEEE Conference on Computer Vision and Pattern Recognition*.
- Jun, W., & Shi-Tong, W. (2010). Double Indices FCM Algorithm Based on Hybrid Distance Metric Learning. *Journal of Software*, 21(8), 1878-1888.
- Jurie, F., & Dhome, M. (2002). Real Time Robust Template Matching, 10. Retrieved from doi:10.3554/j.ins.2010.02.04
- Juvela1. (2016). Template matching method for the analysis of interstellar cloud structure. *Worldwide astronomical and astrophysical research*, 593, 12. Retrieved from doi:10.6554/ jaci.2016.02.05
- Kafrawy, P. E., Mausad, A., & Esmail, H. (2015a). Experimental Comparison of Methods for Multi-Label Classification in Different Application Domains. *International Journal of Computer Applications*, 114(19), 0975 – 8887.
- Kafrawy, P. E., Mausad, A., & Esmail, H. (2015b). Experimental Comparison of Methods for Multi-label Classification in different Application Domains. *IJCA Journal*, 114(19). Retrieved from doi:10.5120/20083-1666

- Kahkashan Kouser1, & Sunita. (2013). A comparative study of K Means Algorithm by Different Distance Measures. *International Journal of Innovative Research in Computer and Communication Engineering*, 1(9).
- Kalmar, A., & Vida, R. (2013). Extracting High Level Context Information using Hierarchical Temporal Memory *Asian Journal Of Computer Science And Information Technology*, 3(7), 27-34.
- Kannan, Ramathilagam, & Pandiyarajan. (2011). Modified bias field fuzzy C-means for effective segmentation of brain MRI *Transactions on computational science VIII* (pp. 127-145). Marina L. Gavrilova: Springer-Verlag.
- Karczmarek, P., Kiersztyn, A., Pedrycz, W., & Dolecki, M. (2017). An application of chain code-based local descriptor and its extension to face recognition. *Pattern Recognition*, 65, 26-34. Retrieved from <http://dx.doi.org/10.1016/j.patcog.2016.12.008>
- Kaur, N., & Kaur, U. (2013). Survey of Pattern Recognition Methods. *International Journal of Advanced Research in Computer Science and Software Engineering*, 3(2), 317-319.
- Khandelwal, C. S., Maheshewari, R., & Shinde, U. B. (2016). Review Paper on Applications of Principal Component Analysis in Multimodal Biometrics System. *Procedia Computer Science*, 92, 481-486. Retrieved from <http://dx.doi.org/10.1016/j.procs.2016.07.371>
- Kim, D. Y., & Jeon, M. (2014). Data fusion of radar and image measurements for multi-object tracking via Kalman filtering. *Information Sciences*, 278, 641-652. Retrieved from: <http://dx.doi.org/10.1016/j.ins.2014.03.080>
- Klimt, B., & Yang, Y. (2004). The Enron Corpus: A New Dataset for Email Classification Research. *springer*, 217-226.
- Kondo. (2011, 11-15 April 2011). Revised GMDH-type neural network using artificial intelligence and its application to medical image diagnosis. Paper presented at *the Hybrid Intelligent Models And Applications (HIMA), 2011 IEEE Workshop*
- Kostavelis, I., & Gasteratos, A. (2012). On the optimization of Hierarchical Temporal Memory. *Pattern Recognition Letters*, 33(5), 670-676.
- Kour, A. (2017). Face Recognition using Template Matching. *International Journal of Computer Applications*, 115(8). Retrieved from doi:10.5120/20170-2329
- Kouser1, K., & Sunita. (2013). A comparative study of K Means Algorithm by Different Distance Measures. *International Journal of Innovative Research in Computer and Communication Engineering*, 1(9), 2443-2447.
- Kravanja, J., Žganec, M., Žganec-Gros, J., Dobrišek, S., & Štruc, V. (2016). Robust Depth Image Acquisition Using Modulated Pattern Projection and Probabilistic Graphical Models. *Sensors*, 16(10).
- Kumar, R. (2011). *Pattern Classification*. Retrieved from Dept.of Computer Science & Engg. S.J.C.E,Mysore:
- Kunihiko, F. (2016). Artificial Vision by Deep CNN Neocognitron. *Intrntional Journal of Cognitive Neural Network (IJCNN)*, 977-984.
- Lai, D., & Garibaldi, J. (2013). Investigating Distance Metrics in Semi-supervised Fuzzy c-Means for Breast Cancer Classification. In L. Peterson, F. Masulli, & G. Russo (Eds.), *Computational Intelligence Methods for Bioinformatics and Biostatistics* (Vol. 7845, pp. 147-157): Springer Berlin Heidelberg.
- Larsen, P. M., Schmidt, S., & Schiøtz, J. (2016). Robust Structural Identification via Polyhedral Template Matching. *Modelling and Simulation in Materials Science and Engineering*, 24.

- Léveillé, J., Hayashi, I., & Fukushima, K. (2014). A Probabilistic WKL Rule for Incremental Feature Learning and Pattern Recognition. *JACIII*, 18(4), 672-681. Retrieved from doi:10.20965/jaciii.2014.p0672
- Li, & Khashanah, M. (2015, 7-10 Dec. 2015). The Predictive Power of Volatility Pattern Recognition in Stock Market. Paper presented at *the 2015 IEEE Symposium Series on Computational Intelligence*.
- Lipton, Z. C., & Berkowitz, J. (2015). A Critical Review of Recurrent Neural Networks for Sequence Learning. *arXiv:1506.00019v4 2015*.
- Liu, Lu, Feng, & Zhou. (2017). Learning Deep Sharable and Structural Detectors for Face Alignment. *IEEE Transactions on Image Processing*, PP(99), 1-1. Retrieved from doi:10.1109/TIP.2017.2657118
- Lopez-Perez, J. J., Ayala-Ramirez, V., & Hernandez-Belmonte, U. H. (2016). Dynamic Object Detection and Representation for Mobile Robot Application. In J. F. Martínez-Trinidad, J. A. Carrasco-Ochoa, V. Ayala Ramirez, J. A. Olvera-López, & X. Jiang (Eds.), *8th Mexican Conference on Pattern Recognition, MCPR 2016, Guanajuato, Mexico, June 22-25, 2016. Proceedings* (pp. 84-93). Cham: Springer International Publishing.
- Lou, X., Li, J., & Liu, H. (2012). Improved Fuzzy C-means Clustering Algorithm Based on Cluster Density. *Journal of Computational Information Systems*, 8(2), 727-737.
- Maciej Wielgosza, b., & Pietron´, M. (2016). Noisy video classification with Spatial Pooler of Hierarchical Temporal Memory. Retrieved from doi:10.1201/j.ins.2016.01.05.
- Mahalakshmi, Muthaiah, & Swaminathan. (2012). Review Article: An Overview of Template Matching Technique in Image Processing. *Research Journal of Applied Sciences, Engineering and Technology*, 4(24), 5.
- Maltoni, D. (2011). Pattern Recognition by Hierarchical Temporal Memory, 45. Retrieved from doi:10.1311/j.ins.2011.22.34.
- Maltoni, D., & Lomonaco, V. (2016). Semi-Supervised Tuning from Temporal Cohorence. Paper presented at the *International Conference on Learning Robotics ICLR 2016*.
- Manivannan, S., Li, W., Akbar, S., Wang, R., Zhang, J., & McKenna, S. J. (2016). An automated pattern recognition system for classifying indirect immunofluorescence images of HEp-2 cells and specimens. *Pattern Recognition*, 51, 12-26. Retrieved from <http://dx.doi.org/10.1016/j.patcog.2015.09.015>
- Mariyama, T., Fukushima, K., & Matsumoto, W. (2016). Automatic Design of Neural Network Structures Using AiS. In A. Hirose, S. Ozawa, K. Doya, K. Ikeda, M. Lee, & D. Liu (Eds.), *23rd International Conference on Neural Information Processing, (ICONIP) 2016, Kyoto, Japan, October 16–21, 2016, Proceedings, Part II* (pp. 280-287). Cham: Springer International Publishing.
- Marqu´es, I. (2010). *Face Recognition Algorithms*. (phd), euskal herriko, euskal herriko.
- Mehdizadeh, E., Golabzaei, A., & Chen, K. (2016). Electrical fuzzy C-means: A new heuristic fuzzy clustering algorithm. *Cogent Engineering*, 3(1), 1208397. Retrieved from doi:10.1080/23311916.2016.1208397
- Meyer, & Fingscheidt. (2016, 20-25 March 2016). Soft linear discriminant analysis (SLDA) for pattern recognition with ambiguous reference labels: Application to social signal processing. Paper presented at the *2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*.

- Min, Z., & Wenming, C. (2015). Recognition of Mixture Control Chart Pattern Using Multiclass Support Vector Machine and Genetic Algorithm Based on Statistical and Shape Features. *Mathematical Problems in Engineering*, 2015, 10. Retrieved from doi:10.1155/2015/382395
- Mnatzaganian, J., Fokoué, E., & Kudithipudi, D. (2016). A Mathematical Formalization of Hierarchical Temporal Memory's Spatial Pooler. (MS), Computer Engineering (KGCOE).
- Mokeyev, & Mokeyev. (2015). Pattern recognition by means of linear discriminant analysis and the principal components analysis. *Pattern Recognition and Image Analysis*, 25(4), 685-691. Retrieved from doi:10.1134/s1054661815040185
- Mullner, D. (2011). Modern Hierarchical, Agglomerative Clustering Algorithms. *Modern Hierarchical, Agglomerative Clustering Algorithms*. arXiv:1109.2378v1.
- Murali. (2015). Principal Component Analysis based Feature Vector Extraction. *Indian Journal of Science and Technology*, 8(35). Retrieved from doi:10.17485/ijst/2015/v8i35/77760
- Mussarat Yasmin, Sharif, M., & Mohsin, S. (2013). Neural Networks in Medical Imaging Applications: A Survey. *World Applied Sciences Journal*, 22(1), 12. Retrieved from doi:10.5829/idosi.wasj.2013.22.01.72188
- Mygdalis, V., Iosifidis, A., Tefas, A., & Pitas, I. (2016). Graph Embedded One-Class Classifiers for media data classification. *Pattern Recogn.*, 60, 585-595.
- Nai, W., Liu, Y., Rempel, D., & Wang, Y. (2017). Fast hand posture classification using depth features extracted from random line segments. *Pattern Recognition*, 65, 1-10. Retrieved from <http://dx.doi.org/10.1016/j.patcog.2016.11.022>
- Nasierding, & Kouzani. (2012). Comparative evaluation of multi-label classification methods. Paper presented at the 2012 9th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD).
- Ng, M., Li, M. J., Huang, J. Z., & He, Z. (2007). On the Impact of Dissimilarity Measure in k-Modes Clustering Algorithm. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 29(3), 503-507.
- Numenta, I. (2009). Numenta Node Algorithms Guide – NuPIC 1.7. Retrieved from doi:10.1134/s1054661815040185
- Olah, C., & Carter, S. (2016). Attention and Augmented Recurrent Neural Networks. *Distill*.
- Osegi, N. (2016). An Improved Intelligent Agent for Mining Real-Time Databases Using Modified Cortical Learning Algorithms *arXiv:1503.07469*.
- Otahal, M., Najman, M., & Stepankova, O. (2016). Design of Neuromorphic Cognitive Module based on Hierarchical Temporal Memory and Demonstrated on Anomaly Detection. *Procedia Computer Science*, 88, 232-238. Retrieved from <http://dx.doi.org/10.1016/j.procs.2016.07.430>
- Pablo, Menichini, Larese, M. G., & Riquelme, B. D. (2015). Automatic analysis of microscopic images of red blood cell aggregates. *SPIE*, 9531. Retrieved from doi: 10.1117/12.2181110
- Park, H., Ahn, T., Kim, K., Lee, S., Kook, S.-y., Lee, D., . . . Park, Y. (2015). Three-dimensional refractive index tomograms and deformability of individual human red blood cells from cord blood of newborn infants and maternal blood. *Journal of Biomedical Optics*, 20(11).

- Paul, S., Magdon-Ismael, M., & Drineas, P. (2016). Feature selection for linear SVM with provable guarantees. Original Research Article. *Pattern Recognition*, 60, 205-214.
- Pechenizkiy, M. (2005). The Impact of Feature Extraction on the Performance of a Classifier: kNN, Naïve Bayes and C4.5. In B. Kégl & G. Lapalme (Eds.), *Advances in Artificial Intelligence* (Vol. 3501, pp. 268-279): Springer Berlin Heidelberg.
- Pelillo, M., Elezi, I., & Fiorucci, M. (2016). Revealing structure in large graphs: Szemerédi's regularity lemma and its use in pattern recognition. *Pattern Recognition Letters*. Retrieved from <http://dx.doi.org/10.1016/j.patrec.2016.09.007>
- Peng, L., & Liu, Y. (2018). Feature Selection and Overlapping Clustering-Based Multilabel Classification Model. *Mathematical Problems in Engineering*, 2018, 12. Retrieved from doi:10.1155/2018/2814897
- Peter Mahler, L., Søren, S., & Jakob, S. (2016). Robust structural identification via polyhedral template matching. *Modelling and Simulation in Materials Science and Engineering*, 24(5), 055007.
- Poletaev, Pervunin, K. S., & Tokarev, M. P. (2017). Artificial Neural Network for Bubbles Pattern Recognition on the Images. *Journal of Physics*. Retrieved from doi:10.1088/1742-6596
- Pouliakis, A., Karakitsou, E., Margari, N., Bountris, P., Haritou, M., Panayiotides, J., . . . Karakitsos, P. (2016). Artificial Neural Networks as Decision Support Tools in Cytopathology: Past, Present, and Future. *Biomedical Engineering and Computational Biology*, 7, 1-18. Retrieved from doi:10.4137/BECB.S31601
- Rammal, A., Perrin, E., Vrabie, V., Bertrand, I., & Chabbert, B. (2017). Classification of lignocellulosic biomass by weighted-covariance factor fuzzy C-means clustering of mid-infrared and near-infrared spectra. *Journal of Chemometrics*, e2865-n/a. doi:10.1002/cem.2865
- Read, J., Martino, L., & Hollmén, J. (2017). Multi-label methods for prediction with sequential data. *Pattern Recognition*, 63, 45-55. Retrieved from <http://dx.doi.org/10.1016/j.patcog.2016.09.015>
- Reddy, K. S. P., & Raju, D. K. N. (2016). Design and Implementation of an Algorithm for Face Recognition by using Principal Component Analysis (PCA) in MATLAB. *International Journal of Advanced Research in Computer Science and Software Engineering*, 6(10).
- Rehman, H. U., Azam, N., Yao, J., & Benso, A. (2017). A three-way approach for protein function classification. *PLoS ONE*, 12(2).
- Romanuke, V. V. (2016). Optimal Pixel-to-Shift Standard Deviation Ratio for Training 2-Layer Perceptron on Shifted 60×80 Images with Pixel Distortion in Classifying Shifting-Distorted Objects. *Applied Computer Systems*, 19(1), 61–70. Retrieved from <https://doi.org/10.1515/acss-2016-0008>,
- Rowland, M. M., Coe, P. K., Stussy, R. J., Ager, A. A., Cimon, N. J., Johnson, B. K., & Wisdom, M. J. (1998). *The Starkey Habitat Database for Ungulate Research: Construction, Documentation, and Use*. Pacific Northwest, Research Station, USA.
- Rozado, D. (2011). Analysis and Extension of Hierarchical Temporal Memory for Multivariable Time Series. (PhD), Universidad Autonoma de Madrid

- Ryu, S., Kim, S., Choi, J., Yu, H., & Lee, G. G. (2017). Neural sentence embedding using only in-domain sentences for out-of-domain sentence detection in dialog systems. *Pattern Recognition Letters*, 88, 26-32. Retrieved from <http://dx.doi.org/10.1016/j.patrec.2017.01.008>
- Sao, P., Hegadi, R., & Karmakar, S. (2014). A Literature Review on Approaches of ECG Pattern Recognition *International Journal of Information Science and Intelligent System*, 3(2), 79-90.
- Sechidis, K., Tsoumakas, G., & Vlahavas, I. (2011). On the Stratification of Multi-label Data. In D. Gunopulos, T. Hofmann, D. Malerba, & M. Vazirgiannis (Eds.), *European Conference on Machine Learning and Knowledge Discovery in Databases, ECML PKDD 2011, Athens, Greece, September 5-9, 2011, Proceedings, Part III* (pp. 145-158). Berlin, Heidelberg: Springer Berlin Heidelberg.
- Serb, A., Bill, J., Ali Khat, R. B., Legenstein, R., & Prodromakis, T. (2016). Unsupervised learning in Probabilistic Neural Networks with Multi-state Metal-oxide Memristive Synapses. *Nature Communications*, 7(1261), 1-9.
- Shahrour. (2014). Virtual DMA Municipal Water Supply Pipeline Leak Detection and Classification Using Advance Pattern Recognizer Multi-Class SVM. *Journal of Pattern Recognition Research*, 9(1).
- Shwartz, S. S., & Ben-David, S. (2014). Understanding Machine Learning: From Theory to Algorithms. Retrieved from doi:10.2344/j.ins.2014.44.55.
- Singh, S. P., & Nair, K. (2013). Intelligent Controller for Reduction of Total Harmonics In Single Phase Inverters *American Journal of Applied Sciences*, 10(11), 1378-1385. Retrieved from doi:10.3844
- Singla, S., & Khera, B. S. (2016). A Comparative Study of K-Means, Fuzzy C-Means and Possibilistic Fuzzy C-Means Algorithm on Noisy Grayscale Images. Paper presented at the *International Conference on Advances in Emerging Technology*.
- Skrynnik, A., Petrov, A., & Panov, A. (2016). Hierarchical Temporal Memory Implementation with Explicit States Extraction. In Samsonovich, A. V. Klimov, V. V. Rybina, & G. V (Eds.), *Biologically Inspired Cognitive Architectures (BICA)* (pp. 219-225): Springer International Publishing.
- Soliman, A., Khalifa, F., Elnakib, A., El-Ghar, M. A., Dunlap, N., Wang, B., . . . El-Baz, A. (2017). Accurate Lungs Segmentation on CT Chest Images by Adaptive Appearance-Guided Shape Modeling. *IEEE Transactions on Medical Imaging*, 36(1), 263-276. Retrieved from doi:10.1109/TMI.2016.2606370
- Soltani, R., & Jiang, H. (2017). Higher Order Recurrent Neural Networks. Paper presented at the *International Conference on Learning Robotics (ICLR) 2017, Toronto*
- Song, J. P., Zhu, Z., Scully, P., & Price, C. (2013). Selecting Features for Anomaly Intrusion Detection : A novel Method using Fuzzy C-Means and Dcision Tree Classification. Paper presented at the *5th International Symposium, CSS 2013, Zhangjiajie, China*.
- Streich. (2010). Multi-label Classification and Clustering for Acoustics and Computer Security: *American Journal of Applied Sciences*, 12(11), 1378-1385. Retrieved from doi:10.1244/j.ins.2010.02.44.
- Sutskever, I., & Hinton, G. (2009). Temporal Kernel Recurrent Neural Networks, 15. Retrieved from doi:10.1522/j.ins.2009.02.45

- Tabacchi, Asensio, Pavón, Recuero, Mir, & Artal. (2013). A statistical pattern recognition approach for the classification of cooking stages. The boiling water case. *Applied Acoustics*, 74(8), 1022-1032.
- Taha, A. A., & Hanbury, A. (2015). Metrics for evaluating 3D medical image segmentation: analysis, selection, and tool. *BMC Medical Imaging*. Retrieved from doi:10.1186/s12880-015-0068-x
- Tan, L., McGarry, M. D. J., Houten, E. E. W. V., Ji, M., Solamen, L., Weaver, J. B., & Paulsen, K. D. (2017). Gradient-Based Optimization for Poroelastic and Viscoelastic MR Elastography. *IEEE Transactions on Medical Imaging*, 36(1), 236-250. Retrieved from doi:10.1109/TMI.2016.2604568
- Thornton, J., Main, L., & Srbic, a. A. (2012). Fixed Frame Temporal Pooling. Retrieved from doi:10.1233/s14880-010-0023-x
- Tokuda, K., & Zen, H. (2016). Directly Modeling Voiced and Unvoiced Components in Speech Waveforms by Neural Networks. Paper presented at the *IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*.
- Tsoumakas, & Katakis. (2015). Multi-Label Classification: An Overview. *International Journal of Data Warehousing and Mining*, 3(3), 1-13.
- Tu, Z., Xie, W., Cao, J., van Gemeren, C., Poppe, R., & Veltkamp, R. C. (2017). Variational method for joint optical flow estimation and edge-aware image restoration. *Pattern Recognition*, 65, 11-25. Retrieved from <http://dx.doi.org/10.1016/j.patcog.2016.10.027>
- Uga, M., Dan, I., Sano, T., Dan, H., & Watanabe, E. (2014). Optimizing the general linear model for functional near-infrared spectroscopy: an adaptive hemodynamic response function approach. *Neurophotonics*, 1(1).
- Wielgosz, M., & Pietron, M. (2016). OpenCL-accelerated object classification in video streams using Spatial Pooler of Hierarchical Temporal Memory. Retrieved from doi:10.1255/j.ins.2016.44.28.
- William, R. (2012). Hierarchical Temporal Memory Cortical Learning Algorithm for Pattern Recognition: *ProQuest*, UMI Dissertation Publishing (October 17, 2012).
- Wong. (2017). Parametric methods for comparing the performance of two classification algorithms evaluated by k-fold cross validation on multiple data sets. *Pattern Recognition*, 65, 97-107. Retrieved from <http://dx.doi.org/10.1016/j.patcog.2016.12.018>
- Wong, Summers, R. M., Kebebew, E., & Yao, J. (2017). Pancreatic Tumor Growth Prediction With Elastic-Growth Decomposition, Image-Derived Motion, and FDM-FEM Coupling. *IEEE Transactions on Medical Imaging*, 36(1), 111-123. Retrieved from doi:10.1109/TMI.2016.2597313
- Wu, & Deng, W. (2015). Adaptive Quotient Image with 3D Generic Elastic Models for Pose and Illumination Invariant Face Recognition. In J. Yang, J. Yang, Z. Sun, S. Shan, W. Zheng, & J. Feng (Eds.), *10th Chinese Conference on Biometric Recognition, (CCBR), Tianjin, China, November 13-15, 2015, Proceedings* (pp. 3-10). Cham: Springer International Publishing.
- Wu, & Toet, A. (2014). Speed-Up Template Matching Through Integral Image Based Weak Classifiers *ournal of Pattern Recognition Research*, 9(1), 12.
- Xia, X., Chen, Z., Luan, F., & Song, X. (2017). Signature alignment based on GMM for on-line signature verification. *Pattern Recognition*, 65, 188-196. Retrieved from <http://dx.doi.org/10.1016/j.patcog.2016.12.019>

- Xie, L., Yang, K., Peng, J., Gao, X., & Tan, Y. (2016). Application of Object Recognition in Locomotive Components Monitoring. Paper presented at the *19th World Conference on Non-Destructive Testing 2016*.
- Xu, R., & Wunsch, D. (2005). Survey of Clustering Algorithms. *IEEE Transactions On Neural Networks*, 16(3), 645-678.
- Yu, Y.-F., Dai, D.-Q., Ren, C.-X., & Huang, K.-K. (2017). Discriminative Multi-Scale Sparse Coding for Single-Sample Face Recognition with Occlusion. *Pattern Recognition*. Retrieved from <http://dx.doi.org/10.1016/j.patcog.2017.01.021>
- Zambrano, J. G., Guzmán-Ramírez, E., & Pogrebnyak, O. (2013). Search Algorithm for Image Recognition Based on Learning Algorithm for Multivariate Data Analysis: Intech publishing. Retrieved from doi: 10.5772/52179
- Zanaty, E. A. (2013). An Adaptive Fuzzy C-Means Algorithm for Improving MRI Segmentation. *Open Journal of Medical Imaging*, 3(4), 125-135. Retrieved from doi: 10.4236/ojmi.2013.34020.
- Zhang, An, L., Xu, J., Zhang, B., Zheng, W. J., Hu, M., . . . Yue, F. (2018). Enhancing Hi-C data resolution with deep convolutional neural network HiCPlus. *Nature Communications*, 9(1), 750. Retrieved from doi:10.1038/s41467-018-03113-2
- Zhang, Liu, F., Liu, J., Luo, J., Xie, Y., Bai, J., & Xing, L. (2017). Cone Beam X-ray Luminescence Computed Tomography Based on Bayesian Method. *IEEE Transactions on Medical Imaging*, 36(1), 225-235. Retrieved from doi:10.1109/TMI.2016.2603843
- Zhang, & Shen, L. (2014). An Improved Fuzzy C-Means Clustering Algorithm Based on Shadowed Sets and PSO. *Computational Intelligence and Neuroscience*, 7, 368-388. Retrieved from doi:10.1155/2014/368628
- Zhang, Z., Zhao, M., & Chow, T. W. S. (2013). Binary- and Multi-class Group Sparse Canonical Correlation Analysis for Feature Extraction and Classification. *IEEE Transaction on Knowledge and Datsa Engineering*, 25(10), 2192-2205.
- Zhou. (2000). Digital Image Processing and Interpretation. Retrieved from doi:10.1186/s12880-015-0068-x
- Zhou, Xie, L., Shen, W., Fishman, E., & Yuille, A. (2016). Pancreas Segmentation in Abdominal CT Scan: A Coarse-to-Fine Approach. *arXiv:1612.08230v*, 2016.
- Zhu, L., & Ma, L. (2016). Class centroid alignment based domain adaptation for classification of remote sensing images. *Pattern Recognition Letters*, 83, Part 2, 124-132. Retrieved from <http://dx.doi.org/10.1016/j.patrec.2015.12.015>
- Zipfel. (2014). Plant pattern-recognition receptors. *Trends Immunol*, 35(7). Retrieved from doi:10.1016/j.it.2014.05.004
- Zytoon, A. A. (2014). Standardized Uptake Value Variations of Normal Glandular Breast Tissue at Dual Time Point FDG-PET/CT Imaging. *International Journal of Medical Imaging*, 1(3), 56-65. Retrieved from doi:10.11648/j