Qingchao Jiang

List of Publications by Year
in descending order

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70 papers	2,980 citations	172207 29 h-index	168136 53 g-index
70 all docs	70 docs citations	70 times ranked	1468 citing authors

#	Article	IF	Citations
1	Data-Driven Soft Sensing for Batch Processes Using Neural Network-Based Deep Quality-Relevant Representation Learning. IEEE Transactions on Artificial Intelligence, 2023, 4, 602-611.	3.4	6
2	Data-Driven Communication Efficient Distributed Monitoring for Multiunit Industrial Plant-Wide Processes. IEEE Transactions on Automation Science and Engineering, 2022, 19, 1913-1923.	3.4	9
3	Distributed Robust Process Monitoring Based on Optimized Denoising Autoencoder With Reinforcement Learning. IEEE Transactions on Instrumentation and Measurement, 2022, 71, 1-11.	2.4	8
4	Dynamic nonlinear process monitoring based on dynamic correlation variable selection and kernel principal component regression. Journal of the Franklin Institute, 2022, 359, 4513-4539.	1.9	5
5	Localâ€“Global Modeling and Distributed Computing Framework for Nonlinear Plant-Wide Process Monitoring With Industrial Big Data. IEEE Transactions on Neural Networks and Learning Systems, 2021, 32, 3355-3365.	7.2	64
6	Distributed-ensemble stacked autoencoder model for non-linear process monitoring. Information Sciences, 2021, 542, 302-316.	4.0	39
7	Neural network aided approximation and parameter inference of non-Markovian models of gene expression. Nature Communications, 2021, 12, 2618.	5.8	71
8	Variational Bayesian probabilistic modeling framework for data-driven distributed process monitoring. Control Engineering Practice, 2021, 110, 104778.	3.2	16
9	Imbalanced Classification Based on Minority Clustering Synthetic Minority Oversampling Technique With Wind Turbine Fault Detection Application. IEEE Transactions on Industrial Informatics, 2021, 17, 5867-5875.	7.2	79
10	Data-Driven Batch-End Quality Modeling and Monitoring Based on Optimized Sparse Partial Least Squares. IEEE Transactions on Industrial Electronics, 2020, 67, 4098-4107.	5.2	84
11	Deep relevant representation learning for soft sensing. Information Sciences, 2020, 514, 263-274.	4.0	35
12	Data-driven individualâ€“joint learning framework for nonlinear process monitoring. Control Engineering Practice, 2020, 95, 104235.	3.2	20
13	Data-Driven Two-Dimensional Deep Correlated Representation Learning for Nonlinear Batch Process Monitoring. IEEE Transactions on Industrial Informatics, 2020, 16, 2839-2848.	7.2	46
14	Multimodal process monitoring based on transition-constrained Gaussian mixture model. Chinese Journal of Chemical Engineering, 2020, 28, 3070-3078.	1.7	6
15	Recursive correlated representation learning for adaptive monitoring of slowly varying processes. ISA Transactions, 2020, 107, 360-369.	3.1	3
16	Neighborhood Stable Correlation Analysis for Robust Monitoring of Multiunit Chemical Processes. Industrial & Engineering Chemistry Research, 2020, 59, 16695-16707.	1.8	11
17	Fault Diagnostic Method Based on Deep Learning and Multimodel Feature Fusion for Complex Industrial Processes. Industrial & Engineering Chemistry Research, 2020, 59, 18061-18069.	1.8	14
18	Quality-relevant dynamic process monitoring based on dynamic total slow feature regression model. Measurement Science and Technology, 2020, 31, 075102.	1.4	9

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19	<scp>Dataâ€driven</scp> nonlinear chemical process fault diagnosis based on hierarchical representation learning. Canadian Journal of Chemical Engineering, 2020, 98, 2150-2165.	0.9	6
20	Data-Driven Model Predictive Monitoring for Dynamic Processes. IFAC-PapersOnLine, 2020, 53, 98-103.	0.5	0
21	Multiobjective Two-Dimensional CCA-Based Monitoring for Successive Batch Processes With Industrial Injection Molding Application. IEEE Transactions on Industrial Electronics, 2019, 66, 3825-3834.	5.2	41
22	Review and Perspectives of Data-Driven Distributed Monitoring for Industrial Plant-Wide Processes. Industrial & Engineering Chemistry Research, 2019, 58, 12899-12912.	1.8	220
23	Quality-Driven Kernel Projection to Latent Structure Model for Nonlinear Process Monitoring. IEEE Access, 2019, 7, 74450-74458.	2.6	12
24	Qualityâ€relevant dynamic process monitoring based on mutual information multiblock slow feature analysis. Journal of Chemometrics, 2019, 33, e3110.	0.7	21
25	Justâ€inâ€time learningâ€"multiple subspace support vector data description used for nonâ€Gaussian dynamic batch process monitoring. Journal of Chemometrics, 2019, 33, e3134.	0.7	14
26	Multimode Process Monitoring Using Variational Bayesian Inference and Canonical Correlation Analysis. IEEE Transactions on Automation Science and Engineering, 2019, 16, 1814-1824.	3.4	56
27	Deep Discriminative Representation Learning for Nonlinear Process Fault Detection. IEEE Transactions on Automation Science and Engineering, 2019, , 1-10.	3.4	12
28	Learning Deep Correlated Representations for Nonlinear Process Monitoring. IEEE Transactions on Industrial Informatics, 2019, 15, 6200-6209.	7.2	52
29	Neighborhood Variational Bayesian Multivariate Analysis for Distributed Process Monitoring With Missing Data. IEEE Transactions on Control Systems Technology, 2019, 27, 2330-2339.	3.2	19
30	Multivariate Statistical Monitoring of Key Operation Units of Batch Processes Based on Time-Slice CCA. IEEE Transactions on Control Systems Technology, 2019, 27, 1368-1375.	3.2	51
31	Joint-Individual Monitoring of Parallel-Running Batch Processes Based on MCCA. IEEE Access, 2018, 6, 13005-13014.	2.6	8
32	Optimal Variable Transmission for Distributed Local Fault Detection Incorporating RA and Evolutionary Optimization. IEEE Access, 2018, 6, 3201-3211.	2.6	12
33	Dynamic CCA-Based Distributed Monitoring for Multiunit Non-Gaussian Processes. IFAC-PapersOnLine, 2018, 51, 347-352.	0.5	6
34	Locally Weighted Canonical Correlation Analysis for Nonlinear Process Monitoring. Industrial & Engineering Chemistry Research, 2018, 57, 13783-13792.	1.8	26
35	Parallel PCAâ€"KPCA for nonlinear process monitoring. Control Engineering Practice, 2018, 80, 17-25.	3.2	163
36	Joint-individual monitoring of large-scale chemical processes with multiple interconnected operation units incorporating multiset CCA. Chemometrics and Intelligent Laboratory Systems, 2017, 166, 14-22.	1.8	13

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37	Data-Driven Distributed Local Fault Detection for Large-Scale Processes Based on the GA-Regularized Canonical Correlation Analysis. IEEE Transactions on Industrial Electronics, 2017, 64, 8148-8157.	5.2	92
38	Batch process monitoring based on self-adaptive subspace support vector data description. Chemometrics and Intelligent Laboratory Systems, 2017, 170, 25-31.	1.8	25
39	FRDPC subspace construction integrated with Bayesian inference for efficient monitoring of dynamic chemical processes. , 2017, , .		0
40	Data-Driven Optimized Distributed Dynamic PCA for Efficient Monitoring of Large-Scale Dynamic Processes. IEEE Access, 2017, 5, 18325-18333.	2.6	24
41	Output-related feature representation for soft sensing based on supervised locality preserving projections. , 2017, , .		2
42	Efficient Monitoring of Nonlinear Chemical Processes based on Fault-Relevant Kernel Principal Component Subspace Construction and Bayesian Inference. Journal of Chemical Engineering of Japan, 2017, 50, 648-656.	0.3	3
43	PCA-ICA Integrated with Bayesian Method for Non-Gaussian Fault Diagnosis. Industrial & Engineering Chemistry Research, 2016, 55, 4979-4986.	1.8	42
44	Performance-driven optimal design of distributed monitoring for large-scale nonlinear processes. Chemometrics and Intelligent Laboratory Systems, 2016, 155, 151-159.	1.8	26
45	Batch process monitoring based on multiple-phase online sorting principal component analysis. ISA Transactions, 2016, 64, 342-352.	3.1	25
46	Distributed monitoring for large-scale processes based on multivariate statistical analysis and Bayesian method. Journal of Process Control, 2016, 46, 75-83.	1.7	103
47	Bayesian Fault Diagnosis With Asynchronous Measurements and Its Application in Networked Distributed Monitoring. IEEE Transactions on Industrial Electronics, 2016, 63, 6316-6324.	5.2	45
48	Independent component analysis model utilizing de-mixing information for improved non-Gaussian process monitoring. Computers and Industrial Engineering, 2016, 94, 188-200.	3.4	21
49	GMM and optimal principal components-based Bayesian method for multimode fault diagnosis. Computers and Chemical Engineering, 2016, 84, 338-349.	2.0	77
50	Performance-Driven Distributed PCA Process Monitoring Based on Fault-Relevant Variable Selection and Bayesian Inference. IEEE Transactions on Industrial Electronics, 2016, 63, 377-386.	5.2	292
51	Nonlinear plant-wide process monitoring using MI-spectral clustering and Bayesian inference-based multiblock KPCA. Journal of Process Control, 2015, 32, 38-50.	1.7	85
52	Generalized Dice's coefficientâ€based multiâ€block principal component analysis with Bayesian inference for plantâ€wide process monitoring. Journal of Chemometrics, 2015, 29, 165-178.	0.7	28
53	Multiblock Independent Component Analysis Integrated with Hellinger Distance and Bayesian Inference for Non-Gaussian Plant-Wide Process Monitoring. Industrial & Engineering Chemistry Research, 2015, 54, 2497-2508.	1.8	36
54	Loading-Based Principal Component Selection for PCA Integrated with Support Vector Data Description. Industrial & Engineering Chemistry Research, 2015, 54, 1615-1627.	1.8	8

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55	Joint Probability Density and Double-Weighted Independent Component Analysis for Multimode Non-Gaussian Process Monitoring. Industrial & Engineering Chemistry Research, 2014, 53, 20168-20176.	1.8	8
56	Justâ€inâ€time reorganized PCA integrated with SVDD for chemical process monitoring. AICHE Journal, 2014, 60, 949-965.	1.8	94
57	Improved fault detection in nonlinear chemical processes using WKPCA-SVDD. Korean Journal of Chemical Engineering, 2014, 31, 1935-1942.	1.2	7
58	Independent component analysis-based non-Gaussian process monitoring with preselecting optimal components and support vector data description. International Journal of Production Research, 2014, 52, 3273-3286.	4.9	25
59	Plant-wide process monitoring based on mutual informationâ€“multiblock principal component analysis. ISA Transactions, 2014, 53, 1516-1527.	3.1	107
60	Fault detection and identification using a Kullback-Leibler divergence based multi-block principal component analysis and bayesian inference. Korean Journal of Chemical Engineering, 2014, 31, 930-943.	1.2	74
61	Probabilistic Weighted NPE-SVDD for chemical process monitoring. Control Engineering Practice, 2014, 28, 74-89.	3.2	29
62	Monitoring multi-mode plant-wide processes by using mutual information-based multi-block PCA, joint probability, and Bayesian inference. Chemometrics and Intelligent Laboratory Systems, 2014, 136, 121-137.	1.8	91
63	A Multi-SOM with Canonical Variate Analysis for Chemical Process Monitoring and Fault Diagnosis. Journal of Chemical Engineering of Japan, 2014, 47, 40-51.	0.3	13
64	Fault Detection in Non-Gaussian Processes Based on Mutual Information Weighted Independent Component Analysis. Journal of Chemical Engineering of Japan, 2014, 47, 60-68.	0.3	3
65	Fault detection in nonlinear chemical processes based on kernel entropy component analysis and angular structure. Korean Journal of Chemical Engineering, 2013, 30, 1181-1186.	1.2	16
66	Weighted kernel principal component analysis based on probability density estimation and moving window and its application in nonlinear chemical process monitoring. Chemometrics and Intelligent Laboratory Systems, 2013, 127, 121-131.	1.8	51
67	Fault Detection and Diagnosis in Chemical Processes Using Sensitive Principal Component Analysis. Industrial & Engineering Chemistry Research, 2013, 52, 1635-1644.	1.8	193
68	Double-Weighted Independent Component Analysis for Non-Gaussian Chemical Process Monitoring. Industrial & Engineering Chemistry Research, 2013, 52, 14396-14405.	1.8	20
69	Chemical processes monitoring based on weighted principal component analysis and its application. Chemometrics and Intelligent Laboratory Systems, 2012, 119, 11-20.	1.8	47
70	Multivariate Statistical Process Monitoring Using Modified Factor Analysis and Its Application. Journal of Chemical Engineering of Japan, 2012, 45, 829-839.	0.3	11