indongwang / activityrecognition



Must-read papers about deep learning for activity recognition

Here we provide a list of Must-read papers about deep learning for activity recognition. The references are based on this survey: Deep Learning for Sensor-based Activity Recognition: A Survey

[Ordered by their citations]

331 lines (162 sloc)

1. Feature learning for activity recognition in ubiquitous computing[C]

Plötz T, Hammerla N Y, Olivier P

11.6 KB

IJCAI Proceedings-International Joint Conference on Artificial Intelligence. 2011, 22(1): 1729.

2. Can deep learning revolutionize mobile sensing?[C]

Lane N D, Georgiev P

Proceedings of the 16th International Workshop on Mobile Computing Systems and Applications. ACM, 2015: 117-122.

3. Deep Convolutional and LSTM Recurrent Neural Networks for Multimodal Wearable Activity Recognition[J]

Ordóñez F J, Roggen D

Sensors, 2016, 16(1): 115.

4. Time series classification using multi-channels deep convolutional neural networks[C]

Zheng Y, Liu Q, Chen E, et al

International Conference on Web-Age Information Management. Springer International Publishing, 2014: 298-310.

5. Convolutional neural networks for human activity recognition using mobile sensors[C]

Zeng M, Nguyen L T, Yu B, et al

Mobile Computing, Applications and Services (MobiCASE), 2014 6th International Conference on. IEEE, 2014: 197-205.

6. Deep convolutional neural networks on multichannel time series for human activity recognition[C]

Yang J B, Nguyen M N, San P P, et al

Proceedings of the 24th International Joint Conference on Artificial Intelligence (IJCAI), Buenos Aires, Argentina. 2015: 25-31.

7. DeepEar: robust smartphone audio sensing in unconstrained acoustic environments using deep learning[C]

Lane N D, Georgiev P, Qendro L

Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing. ACM, 2015: 283-294.

8. PD disease state assessment in naturalistic environments using deep learning[C]

Hammerla N Y, Fisher J, Andras P, et al

Twenty-Ninth AAAI Conference on Artificial Intelligence. 2015.

9. Deep, Convolutional, and Recurrent Models for Human Activity Recognition using Wearables[J]

Hammerla N Y, Halloran S, Ploetz T IJCAI, 2016.

10. Human activity recognition with smartphone sensors using deep learning neural networks[J]

Ronao C A, Cho S B

Expert Systems with Applications, 2016, 59: 235-244.

11. Human Activity Recognition using Wearable Sensors by Deep Convolutional Neural Networks[C]

Jiang W, Yin Z

Proceedings of the 23rd ACM international conference on Multimedia. ACM, 2015: 1307-1310.

12. Deep activity recognition models with triaxial accelerometers[C]

Alsheikh M A, Selim A, Niyato D, et al

Workshops at the Thirtieth AAAI Conference on Artificial Intelligence. 2016.

13. A Deep Learning Approach to Human Activity Recognition Based on Single Accelerometer[C]

Chen Y, Xue Y

Systems, Man, and Cybernetics (SMC), 2015 IEEE International Conference on. IEEE, 2015: 1488-1492.

14. From smart to deep: Robust activity recognition on smartwatches using deep learning[C]

Bhattacharya S, Lane N D

2016 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops). IEEE, 2016: 1-6.

15. Deep Convolutional Neural Networks for Human Activity Recognition with Smartphone Sensors[C]

Ronao C A, Cho S B

International Conference on Neural Information Processing. Springer International Publishing, 2015: 46-53.

16. Hand Gesture Recognition Using micro-Doppler Signatures with Convolutional Neural Network[J]

Kim Y, Toomajian B

IEEE Access, 2016. [0]

17. Multi-modal Convolutional Neural Networks for Activity Recognition[C]

Ha S, Yun J M, Choi S

Systems, Man, and Cybernetics (SMC), 2015 IEEE International Conference on. IEEE, 2015: 3017-3022.

18. Deep learning for human activity recognition: A resource efficient implementation on low-power devices[C]

Ravi D, Wong C, Lo B, et al

Wearable and Implantable Body Sensor Networks (BSN), 2016 IEEE 13th International Conference on. IEEE, 2016: 71-76.

19. Recognizing human activity in smart home using deep learning algorithm[C]

Fang H, Hu C

Control Conference (CCC), 2014 33rd Chinese. IEEE, 2014: 4716-4720.

20. Deepsense: A unified deep learning framework for time-series mobile sensing data processing[C]

Yao S, Hu S, Zhao Y, et al

Proceedings of the 26th International Conference on World Wide Web. International World Wide Web Conferences Steering Committee, 2017: 351-360.

21. A deep learning approach to on-node sensor data analytics for mobile or wearable devices[J]

Ravì D, Wong C, Lo B, et al

IEEE journal of biomedical and health informatics, 2017, 21(1): 56-64.

22. Evaluation of deep convolutional neural network architectures for human activity recognition with smartphone sensors[C]

Ronaoo C A, Cho S B

Proc. of the KIISE Korea Computer Congress. 2015: 858-860.

23. Deep Neural Network for RFID Based Activity Recognition[C]

Li X, Zhang Y, Li M, et al

Wireless of the Students, by the Students, and for the Students (S3) Workshop with MobiCom. 2016.

24. A-Wristocracy: Deep learning on wrist-worn sensing for recognition of user complex activities[C]

Vepakomma P, De D, Das S K, et al

2015 IEEE 12th International Conference on Wearable and Implantable Body Sensor Networks (BSN). IEEE, 2015: 1-6.

25. Recognizing Human Activities from Raw Accelerometer Data Using Deep Neural Networks[C]

Zhang L, Wu X, Luo D

2015 IEEE 14th International Conference on Machine Learning and Applications (ICMLA). IEEE, 2015: 865-870.

26. Exploiting multi-channels deep convolutional neural networks for multivariate time series classification[J]

Zheng Y, Liu Q, Chen E, et al

Frontiers of Computer Science, 2016, 10(1): 96-112.

27. Comparing Deep and Classical Machine Learning Methods for Human Activity Recognition using Wrist Accelerometer[C]

Gjoreski H, Bizjak J, Gjoreski M, et al

IJCAI-16 Workshop on Deep Learning for Artificial Intelligence

28. Deep Learning for RFID-Based Activity Recognition[C]

Li X, Zhang Y, Marsic I, et al

Proceedings of the 14th ACM Conference on Embedded Network Sensor Systems CD-ROM. ACM, 2016: 164-175.

29. Lasagna: towards deep hierarchical understanding and searching over mobile sensing data[C]

Liu C, Zhang L, Liu Z, et al

Proceedings of the 22nd Annual International Conference on Mobile Computing and Networking. ACM, 2016: 334-347.

30. Daily activity recognition based on DNN using environmental sound and acceleration signals[C]

Hayashi T, Nishida M, Kitaoka N, et al

Signal Processing Conference (EUSIPCO), 2015 23rd European. IEEE, 2015: 2306-2310.

31. Human activity recognition with HMM-DNN model[C]

Zhang L, Wu X, Luo D

Cognitive Informatics & Cognitive Computing (ICCI* CC), 2015 IEEE 14th International Conference on. IEEE, 2015: 192-197.

32. Sensor-based gait parameter extraction with deep convolutional neural networks[J]

Hannink J, Kautz T, Pasluosta C F, et al

IEEE journal of biomedical and health informatics, 2017, 21(1): 85-93.

33. Human activity recognition from accelerometer data using Convolutional Neural Network[C]

Lee S M, Yoon S M, Cho H

Big Data and Smart Computing (BigComp), 2017 IEEE International Conference on. IEEE, 2017: 131-134.

34. Human activity recognition with inertial sensors using a deep learning approach[C]

Zebin T, Scully P J, Ozanyan K B

SENSORS, 2016 IEEE. IEEE, 2016: 1-3.

35. Ensembles of Deep LSTM Learners for Activity Recognition using Wearables[J]

Guan Y, Ploetz T

arXiv preprint arXiv:1703.09370, 2017.

36. Deep Recurrent Neural Network for Mobile Human Activity Recognition with High Throughput[J]

Inoue M, Inoue S, Nishida T

arXiv preprint arXiv:1611.03607, 2016.

37. Towards multimodal deep learning for activity recognition on mobile devices[C]

Radu V, Lane N D, Bhattacharya S, et al

Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct. ACM, 2016: 185-188.

38. Human Activity Recognition in a Smart Home Environment with Stacked Denoising Autoencoders[C]

Wang A, Chen G, Shang C, et al

International Conference on Web-Age Information Management. Springer International Publishing, 2016: 29-40.

39. A Deep Learning Framework using Passive WiFi Sensing for Respiration Monitoring[J]

Khan U M, Kabir Z, Hassan S A, et al

arXiv preprint arXiv:1704.05708, 2017.

40. Human Activity Classification With Transmission and Reflection Coefficients of On-Body Antennas Through Deep Convolutional Neural Networks[J]

Kim Y, Li Y

IEEE Transactions on Antennas and Propagation, 2017, 65(5): 2764-2768.

41. Unsupervised deep representation learning to remove motion artifacts in free-mode body sensor networks[C]

Mohammed S, Tashev I

Wearable and Implantable Body Sensor Networks (BSN), 2017 IEEE 14th International Conference on. IEEE, 2017: 183-188.

42. Deep Convolution Neural Networks and Learning ECG Features for Screening Paroxysmal Atrial Fibrillatio Patients[J]

Pourbabaee B, Roshtkhari M J, Khorasani K

IEEE Transactions on Systems, Man, and Cybernetics: Systems, 2017.

43. Transforming Sensor Data to the Image Domain for Deep Learning-an Application to Footstep Detection[J]

Singh M S, Pondenkandath V, Zhou B, et al

arXiv preprint arXiv:1701.01077, 2017.

44. Device-free Wireless Localization and Activity Recognition: A Deep Learning Approach[J]

Wang J, Zhang X, Gao Q, et al

IEEE Transactions on Vehicular Technology, 2016.

45. Convolutional neural networks for human activity recognition using multiple accelerometer and gyroscope sensors[C]

Ha S, Choi S

Neural Networks (IJCNN), 2016 International Joint Conference on. IEEE, 2016: 381-388.

46. An Effective Deep Autoencoder Approach for Online Smartphone-Based Human Activity Recognition[J]

Almaslukh B, AlMuhtadi J, Artoli A

International Journal of Computer Science and Network Security (IJCSNS), 2017, 17(4): 160.

47. LSTM Networks for Mobile Human Activity Recognition[J]

Chen Y, Zhong K, Zhang J, et al

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48. Binarized-BLSTM-RNN based Human Activity Recognition[C]

Edel M, Köppe E

Indoor Positioning and Indoor Navigation (IPIN), 2016 International Conference on. IEEE, 2016: 1-7.

49. Impact of Physical Activity on Sleep: A Deep Learning Based Exploration[J]

Sathyanarayana A, Joty S, Fernandez-Luque L, et al

arXiv preprint arXiv:1607.07034, 2016. [0]

50. PCA Based Optimal ANN Classifiers for Human Activity Recognition Using Mobile Sensors Data[C]

Walse K H, Dharaskar R V, Thakare V M

Proceedings of First International Conference on Information and Communication Technology for Intelligent Systems: Volume 1. Springer International Publishing, 2016: 429-436.

51. Real-Time Activity Recognition on Smartphones Using Deep Neural Networks[C]

Zhang L, Wu X, Luo D

Ubiquitous Intelligence and Computing and 2015 IEEE 12th Intl Conf on Autonomic and Trusted Computing and 2015 IEEE 15th Intl Conf on Scalable Computing and Communications and Its Associated Workshops (UIC-ATC-ScalCom), 2015 IEEE 12th Intl Conf on. IEEE, 2015: 1236-1242. 【0】

52. Unsupervised feature learning for human activity recognition using smartphone sensors[M]

Li Y, Shi D, Ding B, et al

Mining Intelligence and Knowledge Exploration. Springer International Publishing, 2014: 99-107.

53. Deep convolutional feature transfer across mobile activity recognition domains, sensor modalities and locations[C]

Morales F J O, Roggen D

Proceedings of the 2016 ACM International Symposium on Wearable Computers. ACM, 2016: 92-99.