Problem (ICM)
Classify Human Activities

One important aspect of human behavior understanding is the recognition and monitoring of daily activities. A wearable activity recognition system can improve the quality of life in many critical areas, such as ambulatory monitoring, home-based rehabilitation, and fall detection. Inertial sensor based activity recognition systems are used in monitoring and observation of the elderly remotely by personal alarm systems[1], detection and classification of falls[2], medical diagnosis and treatment[3], monitoring children remotely at home or in school, rehabilitation and physical therapy , biomechanics research, ergonomics, sports science, ballet and dance, animation, film making, TV, live entertainment, virtual reality, and computer games[4]. We try to use miniature inertial sensors and magnetometers positioned on different parts of the body to classify human activities, the following data were obtained.

Each of the 19 activities is performed by eight subjects (4 female, 4 male, between the ages 20 and 30) for 5 minutes. Total signal duration is 5 minutes for each activity of each subject. The subjects are asked to perform the activities in their own style and were not restricted on how the activities should be performed. For this reason, there are inter-subject variations in the speeds and amplitudes of some activities.

Sensor units are calibrated to acquire data at 25 Hz sampling frequency. The 5-min signals are divided into 5-sec segments so that 480(= 60 × 8) signal segments are obtained for each activity.

The 19 activities are:

1. Sitting (A1);
2. Standing (A2);
3. Lying on back (A3);
4. Lying on right side (A4);
5. Ascending stairs (A5);
6. Descending stairs (A6);
7. Standing in an elevator still (A7);
8. Moving around in an elevator (A8);
9. Walking in a parking lot (A9);
10. Walking on a treadmill with a speed of 4 km/h in flat position and 15 deg inclined positions (A10);
11. Walking on a treadmill with a speed of 4 km/h in 15 deg inclined positions (A11);
12. Running on a treadmill with a speed of 8 km/h (A12);
13. Exercising on a stepper (A13);
14. Exercising on a cross trainer (A14);
15. Cycling on an exercise bike in horizontal position (A15);
16. Cycling on an exercise bike in vertical position (A16);
17. Rowing (A17);
18. Jumping (A18);

19. Playing basketball (A19)

Your team are asked to develop a reasonable mathematical model to solve the following problems.

1. Please design a set of features and an efficient algorithm in order to classify the 19 types of human actions from the data of these body-worn sensors.
2. Because of the high cost of the data, we need to make the model have a good generalization ability with a limited data set. We need to study and evaluate this problem specifically. Please design a feasible method to evaluate the generalization ability of your model.
3. Please study and overcome the overfitting problem so that your classification algorithm can be widely used on the problem of people's action classification.

The complete data can be downloaded through the following link:
https://caiyun.139.com/w/i/0F5CJUOrpy8oq

Appendix: File structure

- 19 activities (a)
- 8 subjects (p)
- 60 segments (s)
- 5 units on torso (T), right arm (RA), left arm (LA), right leg (RL), left leg (LL)
- 9 sensors on each unit (x, y, z accelerometers, x, y, z gyroscopes, x, y, z magnetometers)

Folders a01, a02, ..., a19 contain data recorded from the 19 activities.

For each activity, the subfolders p1, p2, ..., p8 contain data from each of the 8 subjects.

In each subfolder, there are 60 text files s01, s02, ..., s60, one for each segment.

In each text file, there are 5 units × 9 sensors = 45 columns and 5 sec × 25 Hz = 125 rows.

Each column contains the 125 samples of data acquired from one of the sensors of one of the units over a period of 5 sec.

Each row contains data acquired from all of the 45 sensor axes at a particular sampling instant separated by commas.

Columns 1-45 correspond to:

- T_xacc, T_yacc, T_zacc, T_xgyro, ..., T_ymag, T_zmag,
- RA_xacc, RA_yacc, RA_zacc, RA_xgyro, ..., RA_ymag, RA_zmag,
- LA_xacc, LA_yacc, LA_zacc, LA_xgyro, ..., LA_ymag, LA_zmag,
- RL_xacc, RL_yacc, RL_zacc, RL_xgyro, ..., RL_ymag, RL_zmag,
- LL_xacc, LL_yacc, LL_zacc, LL_xgyro, ..., LL_ymag, LL_zmag.

Therefore,

• columns 1-9 correspond to the sensors in unit 1 (T),
• columns 10-18 correspond to the sensors in unit 2 (RA),
• columns 19-27 correspond to the sensors in unit 3 (LA),
• columns 28-36 correspond to the sensors in unit 4 (RL),
• columns 37-45 correspond to the sensors in unit 5 (LL)

References

[1] Mathie M.J., Celler B.G., Lovell N.H., Coster A.C.F. Classification of basic daily movements using a triaxial accelerometer. Med. Biol. Eng. Comput. 42(5), 679-687, 2004

[2] Kangas M., Konttila A., Lindgren P., Winblad I., J¨ams¨a T. Comparison of low-complexity fall detection algorithms for body attached accelerometers. Gait Posture 28(2), 285-291, 2008

[3] Wu W.H., Bui A.A.T., Batalin M.A., Liu D., Kaiser W.J. Incremental diag nosis method for intelligent wearable sensor system. IEEE T. Inf. Technol. B. 11(5), 553-562, 2007

[4] Shiratori T., Hodgins J.K. Accelerometer-based user interfaces for the con trol of a physically simulated character. ACM T. Graphic. 27(5), 200