Engineering Advances, 2022, 2(2), 194-197
https://www.hillpublisher.com/journals/ea/
ISSN Online: 2768-7961

Human Skeleton Coordinate Pose Recognition

Aodi Ding

Faculty of Applied Mathematics and Computer Sciences, Belarusian State University, Minsk, Belarus.

How to cite this paper: Aodi Ding. (2022) Human Skeleton Coordinate Pose Recognition. *Engineering Advances*, 2(2), 194-197.
DOI: 10.26855/ea.2022.12.010

Received: November 20, 2022
Accepted: December 18, 2022
Published: December 30, 2022

***Corresponding author:** Aodi Ding, Faculty of Applied Mathematics and Computer Sciences, Belarusian State University, Minsk, Belarus.
Email: Aodiding541@gmail.com

Abstract

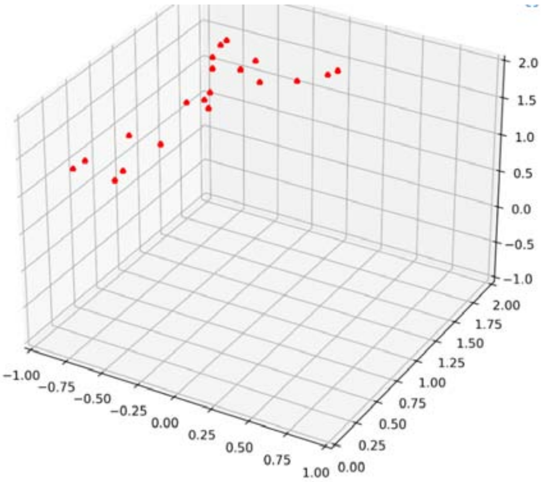
The action of a character is composed of a 3D matrix of 20 three-dimensional coordinate points. The 20 points are the coordinates of the bones of the character's body. I divided the 1,000 data into four types of character actions. Now I use the Naive Bayes model and the linear Gaussian model to analyze the human skeleton coordinates, and judge which model is more suitable for human skeletal action prediction through the accuracy of the test set and the results of the confusion matrix. Of course, We can also use the character Actions are divided into more categories. We can capture specific actions to determine the behavioral state of the characters, and identify actions that endanger others. In the security field, this behavioral state of characters can help identify dangerous rioters so that we can take precautions in advance.

Keywords

Linear Gaussian, Naive Bayes

1. Introduction

In this experiment, the character action data set is used. Each datum has 20 three-dimensional coordinates of bones. In order to make the relationship between each coordinate, I used numerical numbers. Now I show the physical relationship represented by 20 points in the data, each variable has a three-dimensional coordinate, and a total of 60 variables show the skeleton model of a person. We connect 20 bone coordinates through the relationship of line segments, which is a model composed of human actions [1]. Now I have divided the data into four categories: "hands up", "right arm on the side", "squat down" and "right arm in front". I have divided more than 2000 data into four types. If there are hundreds of actions and postures in the real security and defense situation, but for the sake of faster data calculation, the four types of data are enough to allow us to complete all the experimental purposes [2]. Now I use coordinate graphics to show the basic data model of the character.



(1) 20 point human skeleton

Figure 1 is the graphical representation of the first data of 2000 data, which is composed of 20 points. We can see the figure of a person. In order to show the relationship between each point and show the action of the person more clearly, I used a straight line to connect the corresponding bone endpoints. We can clearly see the relationship between each bone, which now constitutes a clear figure action pattern. In our dataset, data types from the histogram, According to the column chart, we have about 2000 data, and about 500 action types of each character. Therefore, I can use Bayesian and linear Gaussian methods to build models respectively based on these data.

2. Research Methodology/Theoretical Basis

2.1 Naive Baye Method

In the Naive Bayes model each of the 60 variables that define the body position are considered independent given the class. The training process for this model will consist in estimating by MLE the values for the mean and variance for each variable and class [3].

$$P(C=k \mid \text{ instance }) \propto P(C=k) \prod j=120 p\left(x_i, y_i, z_i \mid x_{p(i)}, y_{p(i)}, z p(i), C=k\right) \tag{1}$$

EM algorithm

First, input the obtained data set. The algorithm has the initial probability of each instance, which belongs to each class we want to cluster the instances, and the optional skeleton structure when loading comes from all data sets. The algorithm will assume that all variables are independent in a given class (naive Bayesian model) [4]. The output of the EM algorithm is to obtain the model and the probability distribution of each instance.

Establish a naive Bayesian model, and first use the test data set to measure the results. Each test data set consists of four probability results, corresponding to the probability of action A, B, C, D, respectively. I find out the maximum value of each data and make the maximum value of each data into a line graph. We can clearly see the probability of the test set in naive Bayes. Each probability is more than 90%, which shows that it is feasible to recognize human motion prediction with naive Bayes.

2.2 Linear Gauss principle

In the second model, we will use the linear Gaussian model and the Gaussian distribution of maximum likelihood estimation. One vector y contains the observations of the variable of interest, and one matrix X contains the observations of the parent variable of Y. The two elements should have the same number of observations (i.e. rows). The output is a list containing estimated beta values and Gaussian standard deviations. The input of the function model is an example of the data set and model. The function calculates the logarithmic probability, receives a logarithmic probability vector and outputs a vector of the same size. Its value is between [0,1] and adds up to 1.Same as the Bayesian model, but we calculate the mean based on beta and parent variables according to the following formula:

$$p\left(x_i \mid x_{p(i)}, y_{p(i)}, z_{p(i)}, C\right) \qquad = \operatorname{Normal}\left(\beta_{01}+\beta_{11} x_{p(i)}+\beta_{21} y_{p(i)}+\beta_{31} z_{p(i)} ; \sigma^2\right) \tag{1}$$

$$p\left(y_i \mid x_{p(i)}, y_{p(i)}, z_{p(i)}, C\right) \qquad = \operatorname{Normal}\left(\beta_{02}+\beta_{12} x_{p(i)}+\beta_{22} y_{p(i)}+\beta_{32} z_{p(i)} ; \sigma^2\right) \tag{2}$$

$$p\left(z_i \mid x_{p(i)}, y_{p(i)}, z z_{p(i)}, C\right) \qquad = \operatorname{Normal}\left(\beta_{03}+\beta_{13} x_{p(i)}+\beta_{23} y_{p(i)}+\beta_{33} z_{p(i)} ; \sigma^2\right) \tag{3}$$

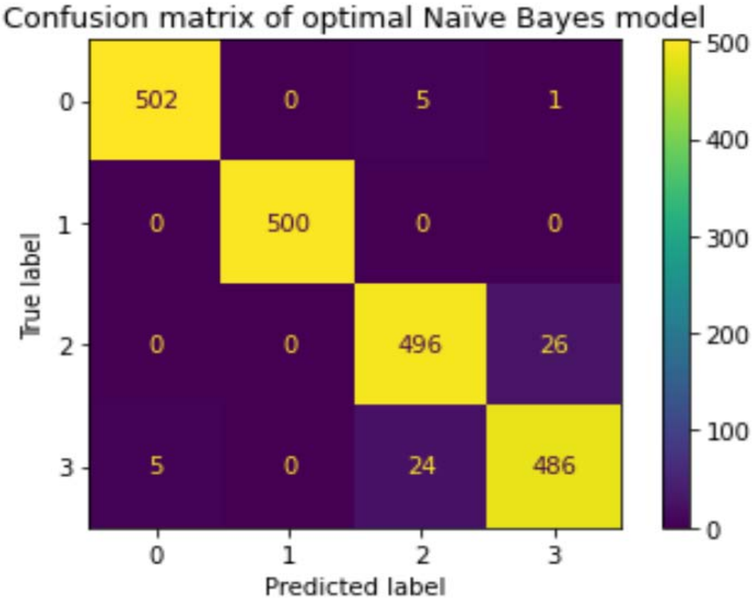
3. Results and discussion

3.1 Cross validation to select the optimal model parameters

This evaluation validates our model and allows us to continue evaluating them performance. The confusion matrix highlights the differences [5]. All instances of class 2 are correctly classified. However, 3 instances of class 1 are predicted to belong to class 3, and 25 instances are predicted to belong to class 8. In addition, 48 instances of class 3 are predicted to belong to class 8, and 21 instances of class 8 are predicted to belong to class 3. The cross-validation function is described above. For this test, the provided datasets were used sequentially as training and validation sets. Then extract the best model and use the validation dataset as a testset. Compare to beta and sigma stored in model_lg. Their differences are compared with 1e-10. With this, we know that our model is at least as good as 1e-10. The models provided are similar. Since the dataset was shuffled, the function did not output the same model when cross-validating twice, resulting in different accuracies on the validation set.

3.1.1 Bayesian model

The Bayesian model data set is best training model is selected by cross validation, and its accuracy is calculated. The plain Bayesian classification model does is to classify the dataset into labels with the largest posterior probability among n labels based on the prior probability based on the minimum error rate Bayesian decision principle. Finally, we can see the training results through the confusion matrix.

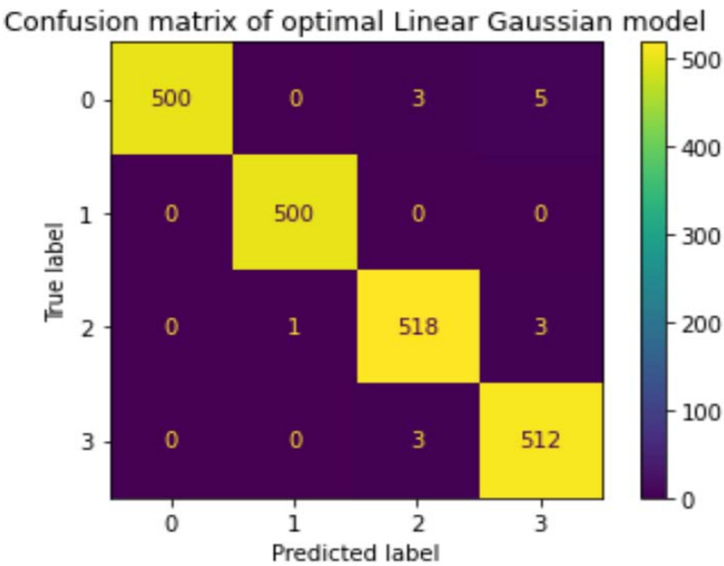


(2) Bayesian confusion matrix

Bayesian model cross-validation is helpful to extract better models than the previous models learned from the entire data set, using the optimal parameter detection results can be easily found from the confusion matrix, from the overall color distribution can be seen that the overall effect is very good, but in more than two thousand data, the judgment error 61 times, it is obvious that from here we also need to improve the accuracy of the model again, in order to make the action prediction model more accurate.

3.1.2 Gaussian model

The confusion matrix can be used to observe the performance of the model on each category, and the accuracy and recall of the model corresponding to each category can be calculated. Through the confusion matrix, we can observe which categories are not easy to distinguish directly, and visualize the model classification.



(3) Gaussian confusion matrix

As shown below, the second model classifies all the instances in the entire dataset, and by comparison, we can easily see that the second trained model produces better accuracy. I must also point out that none of these naïve Yes models can beat any linear Gaussian model [6]. From the confusion matrix species of more than 2000 data, in the linear Gaussian model species only 15 data prediction error, such a performance has been very good, the Bayesian model accuracy rate is only 97%, but linear Gaussian model accuracy rate reached 99.26%, with a high accuracy prediction as the basis, the prediction action is safer.

4. Conclusion

Through the comparison of the two models, the linear Gaussian model is more suitable for the human skeleton coordinate posture recognition in this experiment, and the accuracy rate has reached nearly 97%. This accuracy rate is enough to complete the prediction of human movements, which will help us in many application scenarios in the field of human security and camera recognition. When the coordinate data of human movements are read through infrared devices or graphic recognition sensors, we can more accurately judge whether a person's action posture is a safe action or a dangerous action through model classification and recognition. In our laboratory, we have proved that the linear Gaussian model has better accuracy than the naive Bayesian model. The linear Gaussian function considers the parent variable. This information is essential to produce better results and make better predictions. However, Na ï ve Bayes is a simpler model. If the relationship between variables is unknown, it can be used safely. Cross validation is a good tool for extracting better models. Finally, we got a linear Gauss action recognition model with an accuracy rate of 99.26%, which can effectively complete the campus early warning security model. Of course, this is only a corner of the action recognition field. In other fields, I believe that with such a high accuracy rate of action recognition model as the basis, it will certainly have excellent performance in other fields.

References

[1] D. Berry. Statistics—A Bayesian Perspective. Duxbury Press, 1996.

[2] P. Domingos, M. Pazzani. On the optimality of the simple Bayesian classfier under zero -one loss. Machine Learning, 29 (2) (1997) 103-130.

[3] N. A. Zaidi, J. Cerquides, M. J. Carman, G. I. Webb. Alleviating naive Bayes attribute independence assumption by attribute weighting. Journal of Machine Learning Research, 14 (2013) 1947-198.

[4] S. Villa, M. Rossetti. Learning continuous time Bayesian network classi fiers using MapReduce. Journal of Statistical Software, 62 (3) (2014), 1-2.

[5] C. Andrieu, N. de Freitas, A. Doucet, and M.I. Jordan. An introduction to MCMC for machine learning. Machine Learning, 50(1-2):5-43, 2003.

[6] Z. Ghahramani and G. Hinton. The EM algorithm for mixtures of factor analyzers. Technical Report CRG-TR-96-1, Department of Computer Science, University of Toronto, 1996. Available.