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Support Vector Machine Analysis to Detect Deviation in a Health Condition Monitoring System

[1, *] Yasutaka UCHIDA, [2] Tomoko FUNAYAMA and [1] Yoshiaki KOGURE
[1] Dept. of Life Science, Teikyo Univ. of Science, 2-2-1 Senjyusakuragi, Adachi-ku, Tokyo, 120-0045, Japan
[2] Dept. of Occupational therapy, Teikyo Univ. of Science, 2525 Yatsusawa, Uenohara-shi, 409-0193, Yamanashi, Japan
[1] Tel.: +81-3-6910-1010, fax: +81-3-3800
E-mail: uchida@ntu.ac.jp

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Abstract: In this study, support vector machine (SVM) learning was applied to a proposed monitoring system that captures changes in a person's health conditions using flexible force-sensing resistors and optimizing parameters. The system consists of eight flexible force-sensing resistors, a data acquisition device and a personal computer. Feature quantities were defined using the time difference between the output signal from sensor 1 which specifies the initiation of the measurement and that from other sensors. The measurement conditions were the normal range of motion, simulated limited shoulder and knee joint. The measurement data were divided into 30 sets for learning data and 15 sets for test data. The SVM module was used for analysis. Comparing the difference between the linear function kernel and radial basis function kernel, there was no major difference based on learning data. However, an 83 % accuracy rate was observed using the radial basis function kernel. For test data, the highest accuracy was obtained when t2 and t7 were used as the feature quantities.

Keywords: SVM, Machine learning, Classification, Health condition monitoring system, LabVIEW, Force-sensing resistors.

1. Introduction

Japan is purported to have the highest proportion of elderly citizens in the world, and its society is experiencing super-aging. According to 2019 estimates, 28.1 % of the Japanese population is aged 65 or above. This proportion is estimated to reach 40 % by 2060 [1]. There are many elderly people who live alone. The development of proper systems for self-management of health is necessary to aid those who live alone, not only the elderly but also frail people such as patients [2-3]. The important task is to notice signs of poor health as early as possible and be able to obtain medical treatment. Therefore, it is necessary to introduce a system that monitors their health conditions daily and issues a warning when it deviates from the normal range.

Various kinds of health and welfare equipment, that rely on Internet of Things (IoT) technology have been developed and distributed in the market. These include monitoring sensors, leaving-the-bed sensors, simple motion analyzing devices, and wearable devices that measure biological parameters [4- 6]. However, they are not being used effectively in the health and welfare field. It is necessary to correlate the performance of the equipment with on-site needs and privacy issues. Although there are many publications on the application of deep learning for health care monitoring, the field is still developing [7-8]. We have already proposed a physical condition monitoring system that uses force-sensing resistors is proposed [9-12]. In this paper, we have reported optimization on 3-class classification using support vector machine (SVM).

This research was conducted with the approval of the Teikyo University of Science's Ethics Committee.

2. Experiment

2.1. Survey Method

The test subject was a man in his 60s. There were three measurement conditions: normal range of motion, simulated limited right knee, and right shoulder. In the classification result, the normal range of motion is represented by black circles, the simulated limited right knee is represented by green circles, limited right shoulder is represented by red circles.

2.2. Health Condition Monitoring System and Data

The developed system consists of eight flexible force-sensing resistors (FSR®408) connected to a LabVIEW Data Acquisition (DAQ) NI-6210 device that is connected to a personal computer (PC) through a USB cable, as shown in Fig. 1. The voltage data were saved on the PC in a CSV file format. The first sensor was placed on the pillow and its output signal used the movement detection point as a reference. Three sensors were placed about 0.1 m apart at the edge of bed, and the remaining four sensors were placed about 0.2 m apart on the floor besides the bed [9]. A folding type bed was used in the experiment. The bed had a height of 0.4 m which is lower than a typical home bed. The second and subsequent sensors were located below the mat for protection. Thus, a very small output voltage was observed even when any weight was not added.

Fig. 2 shows details of the detecting circuit used in this experiment. The resistance value of the flexible force sensor changes in the range of 100 to 10 MΩ or more. Each flexible force-sensor was connected to a 1 kΩ resistor in series. The voltage drop across the 1kΩ resistor was used as the input voltage for the DAQ device. The sampling time was 10 ms, i.e., the output from each of the eight sensors was taken every 10 ms.

Fig. 3 shows the voltage output obtained from the DAQ. Each signal from the flexible force-sensors was smoothened by averaging adjacent data.

The quantification of feature quantities for SVM analysis was defined by the time difference. The reference time was the fall time of sensor s1 on the pillow. The difference between the reference time and the rise time of other sensors' (s2-s7) signals was defined as the response time, such as t2, t3, ...t7. For waveforms in which the rise time of the signal could not be detected, the final 10 seconds were used as the rise time of the sensor.

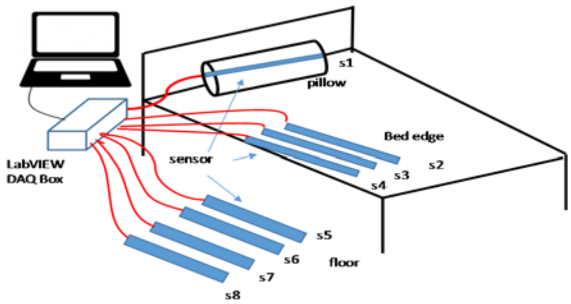


Fig. 1. Health Condition Monitoring System.

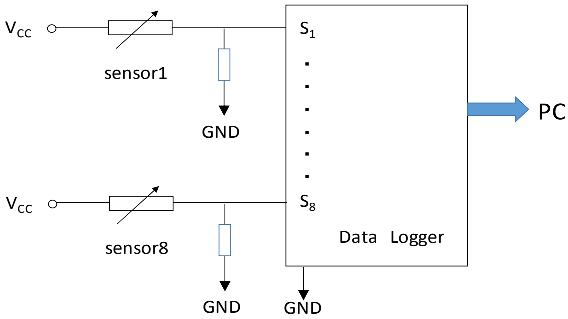


Fig. 2. Details of the detecting circuit.

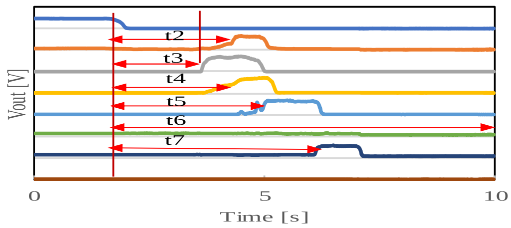


Fig. 3. Voltage output obtained by DAQ.

2.3. Analysis Method

The library for machine learning used scikit-learn, and the classification module used the SVM module. The measurement data were divided into two parts: 10 sets of data corresponding to 3 different conditions for learning data and 6 sets of data corresponding to 3 different conditions for test data. Five arbitrary sets were chosen from them to calculate the average value of accuracy rate.

The rise time of each sensor reflected the difference between the measurement conditions. A 2-D map of the rise time was used for comparison. Among the 2-D combinations, three combinations that are considered possible to classify were selected as feature quantities. Classification data used for the analysis were a combination of 2 kinds of 4 feature quantities with a high possibility of a high accuracy rate, because of comparing the selection of feature quantities of machine learning.

3. Results and Discussion

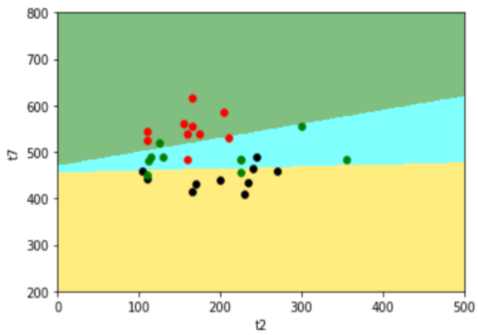
Fig. 4 (a), (b), (c) and (d) show the classification results using the pair t2 and t7 in the learning data. The kernels used in classification are linear kernel and radial basis function kernel using (C = 1.0, γ = 1E-6), (C = 1.0, γ = 1E-5) and (C = 10, γ = 1E-5). The unit value of t2 and t7 is 10 ms. For radial basis function, as the γ value increases, the boundary line changes from a straight line to a curve line and more accurate classification is achieved. The accuracy rate of classification obtained by linear and radial basis function kernel using (C = 1.0, γ = 1E-6), (C = 1.0, γ = 1E-5) and (C = 10.0, γ = 1E-5) applied to learning data are 80, 70, 80 and 80 %, respectively. After performing SVM learning using learning data, the 6 set of data for test were applied to the learning result to obtain an accuracy rate. The accuracy rates in the linear kernel and radial basis function kernel using (C = 1.0, γ = 1E-5), and (C = 10.0, γ = 1E-5) are 91.1, 86.7, 96.3 and 88.9 %, respectively.

The accuracy rate of radial function kernel was lower than that of linear function kernel. This result can be improved by optimizing C and γ parameters.

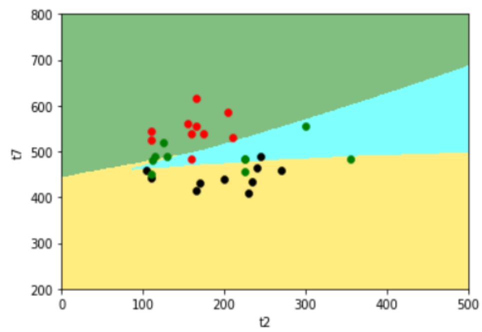
Fig. 5 (a), (b), (c) and (d) show classification results using the pair of t3 and t7 in the learning data and the kernel used for classifications which were linear kernel and radial basis function kernel using (C = 1.0, γ = 1E-6), (C = 1.0, γ = 1E-5) and (C = 1.0, γ = 0.5), respectively. The unit value of t3 and t7 is 10 ms. For radial basis function, as the γ value increased, the boundary line changed from a straight line to curve line for more accurate classification.

The accuracy rate of classification obtained by linear and radial basis function kernel using (C = 1.0, γ = 1E-5) from learning data were 76.7 % and 56.6 %, respectively. After performing SVM learning using learning data, 6 sets of data for test were applied to the learning result to obtain an accuracy rate. The accuracy rates in the linear and radial basis function kernel (C = 1.0, γ = 1E-6) and (C = 10.0, γ = 1E-5) were 94.4, 84.4 and 100 %, respectively. For (C=10.0, γ =1E-5), the classification was over-fitting. The accuracy rate of classification obtained from radial function kernel was lower than that obtained from the linear function kernel. This result can be improved by optimizing parameters of C and γ.

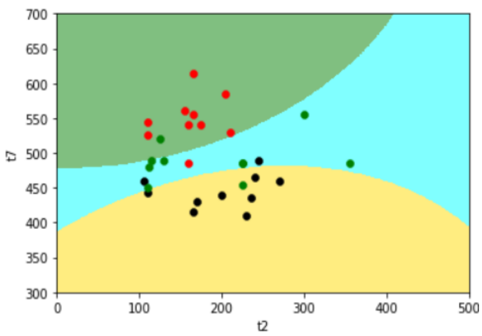
Fig. 6 (a), (b), (c) and (d) shows classification results using the pair of t4 and t7 in the learning data. The kernel used in classifications were linear and radial basis function (C = 1.0, γ = 1E-6), (C = 1.0, γ = 1E-5) and (C = 50, γ = 1E-6), respectively. The unit value of t4 and t7 is 10 ms. The accuracy rates obtained using learning data, linear kernel, (C = 1.0, γ = 1E-6) and (C = 50.0, γ = 1E-6) are 83.3, 60.0, and 83.3 %, respectively. After performing SVM learning using data for learning, 15 test data are applied to the learning result to obtain an accuracy rate. The accuracy rates in the linear and radial basis function kernels (C=1.0 γ =1E-6) and (C=50.0, γ =1E-6) are 88.3, 60.0 and 83.3 %, respectively.



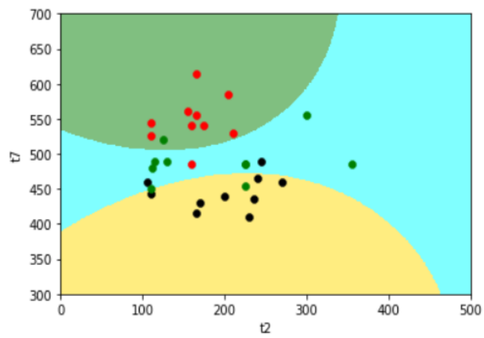
(a) Linear kernel



(b) Radial basis function kernel.
(C = 1.0, γ = 1 E-6)

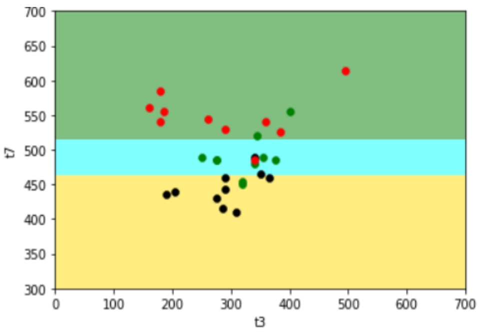


(c) Radial basis function kernel.
(C = 1.0, γ = 1E-5)

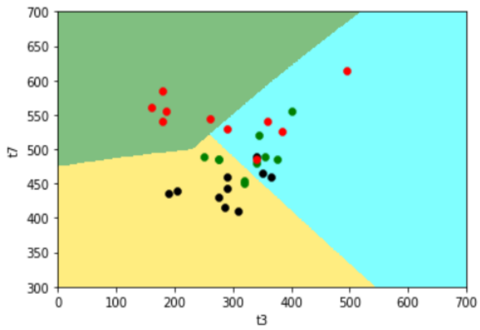


(d) Radial basis function kernel.
(C = 10, γ = 1E-5)

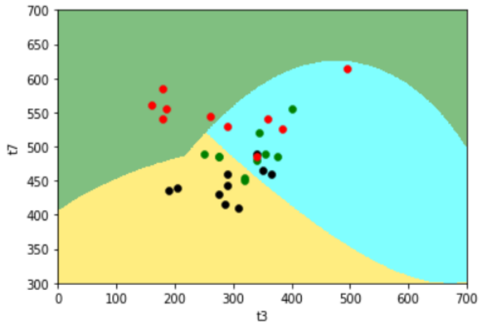
Fig. 4. Classification results for t2-t7.



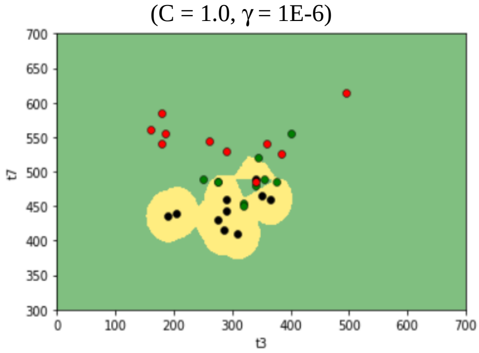
(a) Linear kernel



(b) Radial basis function kernel.
(C = 1.0, γ = 1E-6)

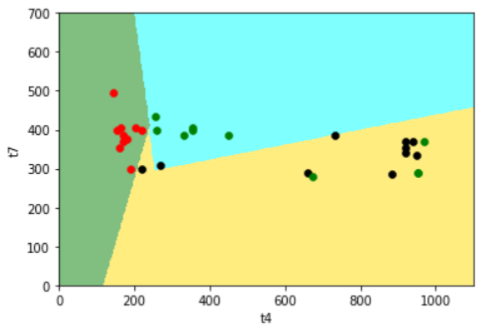


(c) Radial basis function kernel.
(C = 1.0, γ = 1E-5)

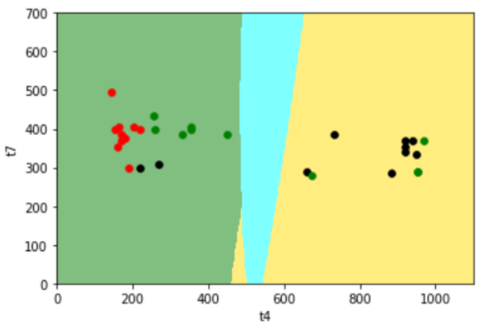


(d) Radial basis function kernel.
(C = 1.0, γ = 0.5)

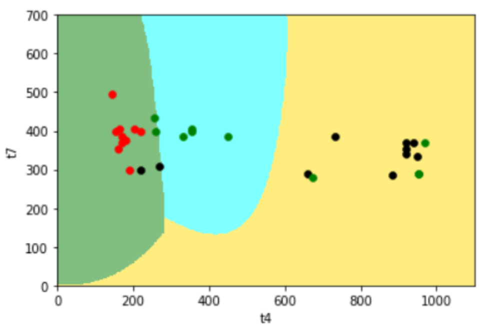
Fig. 5. Classification results for t3-t7.



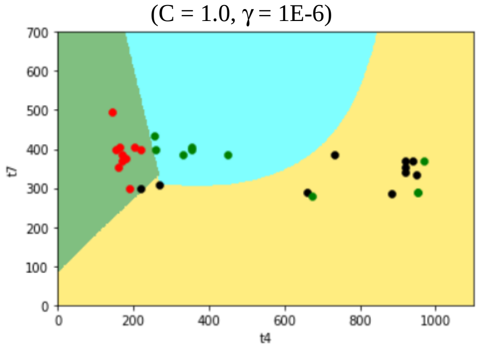
(a) Linear kernel.



(b) Radial basis function kernel.
(C = 1.0, γ = 1E-6)



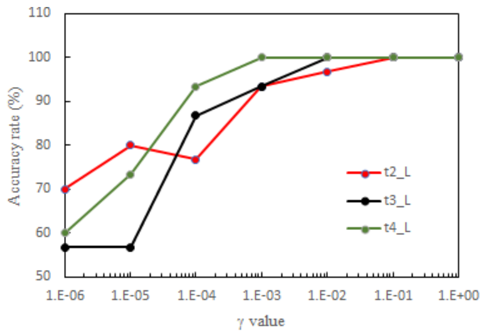
(c) Radial basis function kernel.
(C = 1.0, γ = 1E-5)



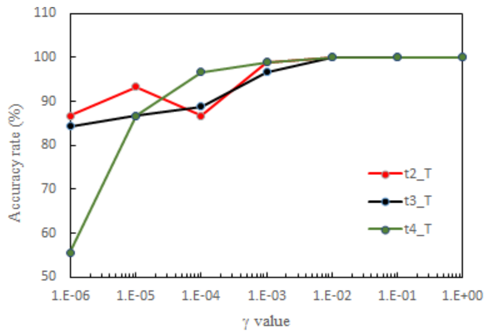
(d) Radial basis function kernel.
(C = 50.0, γ = 1E-6)

Fig. 6. Classification results for t4-t7.

Fig. 7 (a) and (b) shows γ value dependence of accuracy rate applied to learning and test data, respectively when the C is 1.0. For learning data, the accuracy rates is over 96 % in the region over γ value >1E-3. A similar accuracy rate of approximately 100 % is observed when test data are used with γ value of 1E-3 and above. However, in the region of lower γ value, the accuracy rate depends on the γ value.



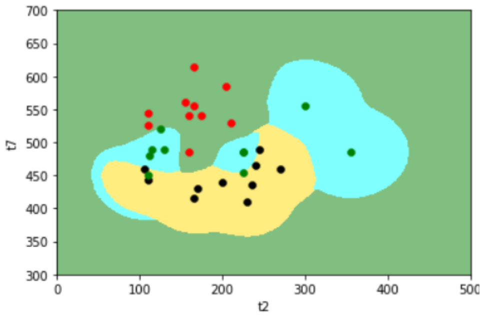
(a) Learning data



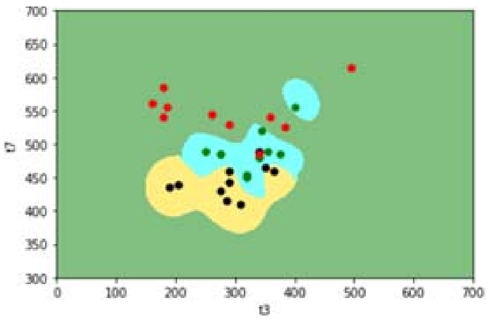
(b) Test data

Fig. 7. The γ value dependence of accuracy rate for learning and test data.

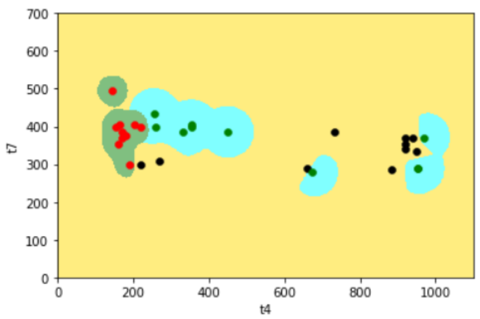
The classification results that obtained higher accuracy rate are shown in Fig. 8 (a), (b) and (c) correspond to t2-t7, t3-t7 and t4-t7, respectively. In these three cases which C = 1.0 and γ value 1E-3, the classification results are surrounded by complicated curves and divided into fine areas. In the region where the γ value is larger than 1E-3, the classification areas were surrounded by a smaller radius.



(a) t2-t7 results



(b) t3-t7 results



(c) t4-t7 results

Fig. 8. The classification results of t2-t7, t3-t7 and t4-t7 when C = 1.0 and γ = 1E-3.

4. Conclusions

Optimization of SVM classification was performed using linear and radial basis functions on the health condition monitoring system data. The classification accuracy rate strongly depended on the C and γ value. The classification results using large C and/or γ value indicate over-fitting. Owing to the use of learning data, the accuracy rate from the classification system using the pair of t4 and t7 as feature quantities was highest at 83.3 %. In the case of test data, the highest accuracy rate was when t2 and t7 were used as feature quantities.

Acknowledgements

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