Consideration of Human Motion's Individual Differences-based Feature Space Evaluation Function for Anomaly Detection

○Masaya Mori¹, Yuto Omae², Takuma Akiduki³, Hirotaka Takahashi¹

1 : Nagaoka University of Technology

2: National Institute of Technology, Tokyo College

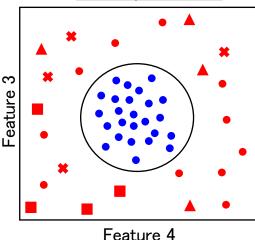
3: Toyohashi University of Technology

Introduction

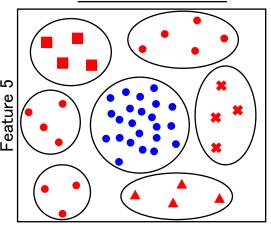
- Recently, various human activity recognitions from the data of inertial sensors by using machine learning are investigated[1][2].
- Two methods are mainly used for recognition.

Classification of machine learning

(a) Better feature space as anomaly detection



(b) Better feature space as class classification



Feature 6

• : Normal, **★** : Anomaly 1, **▲** : Anomaly 2, **■** : Anomaly 3, • : Anomaly N

Anomaly detection (a):

Anomaly detection judges the normal data and anomaly data.

Class classification (b):

Class classification regards anomaly data as an individual class (for example, anomaly 1, anomaly 2, anomaly 3, etc.). And judges not only the normal or anomaly class but also all classes.

- We need the feature space that the normal and anomaly data are separated like this.
- Problem occur when we consider various human activity recognition.
 - ⇒ It is the individual difference of human activity.

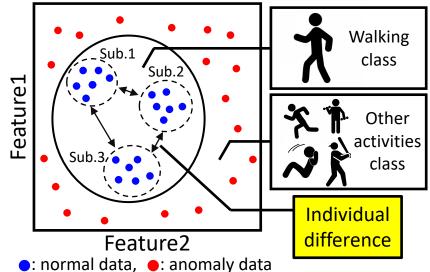
[1] A. M. Khan, Y. K. Lee, S. Y. Lee, T. S. Kim, A Triaxial Accelerometer-Based Physical-Activity Recognition via Augmented-Signal Features and a Hierarchical Recognizer, IEEE Transactions on Information Technology in Biomedicine, vol.14, pp.1166-1172, 2010.

Purpose

What are the individual differences?

For example, we want to classify the walking or other activities.

- 1. We plot the training data in the feature space.
- 2. The data of human activities are different by subjects.
- 3. Because, the height, body weight, leg length and so on are different.
- 4. Therefore, the training data for each of subjects are away such as the arrow of figure.
- These are the individual differences.



If we don't consider the individual difference, it is a possibility that it is incorrectly classified.

- ⇒ Evaluation function of the feature space considering the individual difference is necessary.
- Evaluation Function considered the individual difference for class classification is already proposed[3].
- Evaluation functions for anomaly detection are not considered the individual difference[4][5].
 - ⇒Therefore, we propose the evaluation function for anomaly detection.

[3] Y. Omae, H. Takahashi, Feature Selection Algorithm Considered Trial and Individual Differences for Machine Learning of Human Activity Recognition, Journal of Advanced Computational Intelligence and Intelligent Informatics, vol.21, no.5, pp.813-824, 2017.

The proposed CHI-FS evaluation function

We evaluate the feature space $\langle x_n, x_m \rangle$ in subject i.

Overlap function: Overlapped degree between normal data and anomaly data.

 $\text{M nor } \cdots \text{ Normal class}$ ano \cdots Anomaly class $i \cdots \text{ Subject } i$

$$D^{i}(x_{n}, x_{m}) = P_{c=\text{nor}}^{i}(x_{n}, x_{m}) \times P_{c=\text{ano}}^{i}(x_{n}, x_{m})$$



The blue region is low with the occurrence probability of data.

⇒ Values close to 0.

The yellow region is high with the occurrence probability of data.

 \Rightarrow Values close to 1.









We assume that normal data concentrate on one region.

⇒ We use the

multivariate normal distribution.





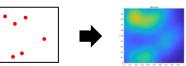


We calculate the probability density function of the normal data.

We assume that anomaly data scatter around normal data.

⇒ We use the

multivariate kernel distribution.



We calculate the probability density function of the anomaly data.

Error risk

$$I^{i}(x_{n}, x_{m}) = \int_{0}^{1} \int_{0}^{1} D^{i}(x_{n}, x_{m}) dx_{n} dx_{m}$$

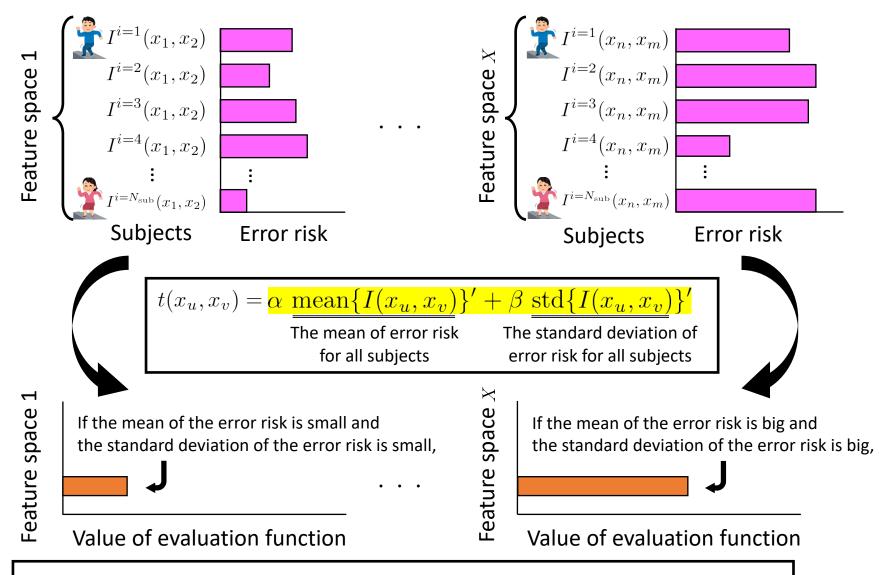
The error risk has a higher value if the coordinates of normal and anomaly with the higher probabilities of their occurrence overlap.

 \Rightarrow The feature space whose error risk is smaller is the important feature space for subject i.

The proposed CHI-FS evaluation function

Step

Step



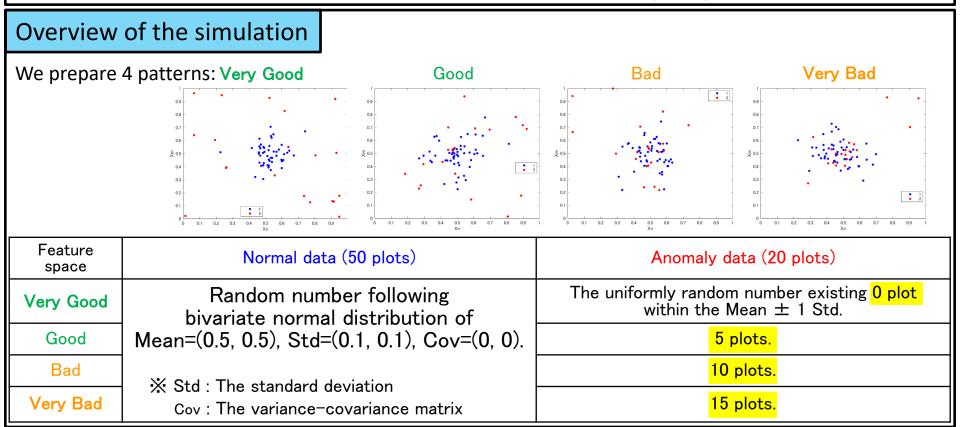
We consider the feature space as the best if the value of evaluation function is the smallest $(x^{\text{opt1}}, x^{\text{opt2}}) = \arg\min[t(x_u, x_v)]$.

Purpose of the simulation

We confirm an effectiveness of the proposed CHI-FS evaluation function by using simulation data.

The existing evaluation function: The between-class and within-class variance [6]

Minimum Reference Set (MRS) [7]



			Subjects								
Case	Subject 1	Subject 2	Subject 3	Subject	4	Subject 5					
01	Very Good	Very Good	Very Good	Very Go	od	Very Good					
02	Good	Good	Good	Good		Good					
03	Bad	Bad	Rad	Bad		Bad					
04	Very Bad	Very Bad	Very Dad	Very Ba	ad	Very Bad					
05	Very Good	Very Good	Very Good	Good		Good					
06	Very Good	Very Good	Very Good	Bad		Bad					
07	Vary Good	Vary Good	Vary Good	Very Ba	ad	Very Bad					
08	Very Bad	Very Bad	Very Bad	Very G	od	Very Good					
09	Very Bad	Very Bad	Very Bad	Good	_	Good					
10	Very Bad	Very Bad	Very Bad	Bad	It	means th	at the distribution of normal				
11	Good	Good	Good	Bad	/	/ anomaly data in the feature space of case 01 for subject 2 was 'Very Good'					
12	Bad	Bad	Bad	Good							
13	Very Good	Good	Bad	Very B	Cá						
14	Very Good	Good	Bad	Very Ba	ad	Bad					

0		The				
Case	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	expected ranking
01	Very Good	Very Good	Very Good	Very Good	od Very Good 1	
02	Good	Good	Good	Good	Good	3
03	Bad	Bad	Bad	Bad	Bad	12
04	Very Bad	14				
05	Very Good	Very Good	Very Good	Good	Good	2
06	Very Good	Very Good	Very Good	Bad	Bad	4
07	Vary Good	Vary Good	Vary Good	Very Bad	Very Bad	7
08	Very Bad	Very Bad	Very Bad	Very Good	Very Good	10
09	Very Bad	Very Bad	Very Bad	Good	Good	11
10	Very Bad	Very Bad	Very Bad	Bad	Bad	13
11	Good	Good	Good	Bad	Bad	5
12	Bad	Bad	Bad	Good	Good	8
13	Very Good	Good	Bad	Very Bad	Good	6
14	Very Good	Good	Bad	Very Bad	Bad	9

- 1. Case1 that all subjects are 'Very Good' is the first effective feature space.
- 2. Case5 that three subjects are 'Very Good' and two subjects are 'Good' is the second.
- 3. Case2 that all subjects are 'Good' is the third.
- 4. Case6 that three subjects are 'Very Good' and two subjects are 'Bad' is the fourth.
- 5. Case11 that three subjects are 'Good' and two subjects are 'Bad' is the fifth.

Cons			Subjects	The	The proposed CHI-FS	The between- class and	MRS		
Case	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	expected ranking	evaluation function	within-class variance	MIKO
01	Very Good	1	1	3	1				
02	Good	Good	Good	Good	Good	3	3	11	6
03	Bad	Bad	Bad	Bad	Bad	12	7	8	14
04	Very Bad	14	12	12	7				
05	Very Good	Very Good	Very Good	Good	Good	2	2	9	2
06	Very Good	Very Good	Very Good	Bad	Bad	4	4	2	4
07	Vary Good	Vary Good	Vary Good	Very Bad	Very Bad	7	10	10	5
08	Very Bad	Very Bad	Very Bad	Very Good	Very Good	10	11	14	13
09	Very Bad	Very Bad	Very Bad	Good	Good	11	14	1	11
10	Very Bad	Very Bad	Very Bad	Bad	Bad	13	13	7	9
11	Good	Good	Good	Bad	Bad	5	5	13	3
12	Bad	Bad	Bad	Good	Good	8	6	6	10
13	Very Good	Good	Bad	Very Bad	Good	6	9	5	8
14	Very Good	Good	Bad	Very Bad	Bad	9	8	4	12

The existing evaluation function:

- We could not obtain the expected result at the between-class and within-class variance.
 - → This evaluation function is not suited for anomaly detection problem.
- In the case of MRS, the first and second rank was same in the expected result, the third rank or later could not be same in the expected result.
 - → MRS may not be considered the individual difference.

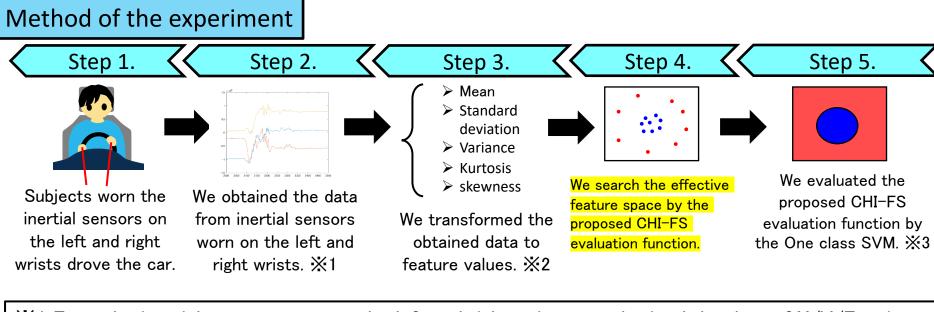
Case			Subjects	The	The proposed CHI-FS	The between- class and	MDC		
Oase	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	expected ranking	evaluation function	within-class variance	MRS
01	Very Good	1	1	3	1				
02	Good	Good	Good	Good	Good	3	3	11	6
03	Bad	Bad	Bad	Bad	Bad	12	7	8	14
04	Very Bad	14	12	12	7				
05	Very Good	Very Good	Very Good	Good	Good	2	2	9	2
06	Very Good	Very Good	Very Good	Bad	Bad	4	4	2	4
07	Vary Good	Vary Good	Vary Good	Very Bad	Very Bad	7	10	10	5
08	Very Bad	Very Bad	Very Bad	Very Good	Very Good	10	11	14	13
09	Very Bad	Very Bad	Very Bad	Good	Good	11	14	1	11
10	Very Bad	Very Bad	Very Bad	Bad	Bad	13	13	7	9
11	Good	Good	Good	Bad	Bad	5	5	13	3
12	Bad	Bad	Bad	Good	Good	8	6	6	10
13	Very Good	Good	Bad	Very Bad	Good	6	9	5	8
14	Very Good	Good	Bad	Very Bad	Bad	9	8	4	12

The proposed CHI-FS evaluation function:

- We obtained the expected result from the first to the fifth rank.
 - → These results suggest there is a possibility that we can search for the effective feature space considering the human motion's individual differences for anomaly detection by using the proposed CHI-FS evaluation function.

Purpose of the experiment

We perform the auto detection of the aimless driving including the drowsy driving by using the data of inertial sensors worn on the left and right wrists.



- *1 From the inertial sensors worn on the left and right wrists, we obtained the data of X/Y/Z-axis acceleration, its composited acceleration and X/Y/Z-axis angular velocity.
- X2 We prepared the 70 feature values, and constructed the 2415 feature spaces.
- 3 We draw the decision surface by One class SVM, calculate the F-measure of the feature space of each subject by the data of the inertial sensors during car driving. F-measure is evaluation measure of prediction result.

		F-measure	e(Individual	subject)		CHI-FS	Mean of					
Classification	Sub 1	Sub 2	Sub 3	Sub 4	Sub 5	Index	F-measure					
Evaluation	.846	.076	.381	.528	.485	.0056	.463					
value of the	.488	.572	.694	.167	.439	.0060	.472					
top 3 ranks	.241	.515	It means	It means that the F -measure for the subject 2 in								
•	.000	.047		the feature space having the second rank								
Evaluation value ~0.10	.000	.503	evaluation value is .572.									
Value 0.10	.417	.016	.414	.076	.043	.1006	.193					
	.000	.000	.006	.211	.310	.2000	.105					
value I † s	nows the	feature	.2002	.040								
		alue are	.2031	.267								
Evaluation	.204	.000	.000	.140	.064	.6251	.099					
value of the	.283	.031	.003	.088	.279	.7340	.137					
lowest ranks	.000	.000	.000	.123	.104	.9316	.045					

		F-measure		CHI-FS	Mean of		
Classification	Sub 1	Sub 2	Sub 3	Sub 4	Sub 5	Index	$F ext{-}measure$
Evaluation	.846	.076	.381	.528	.485	.0056	.463
value of the	.488	.572	.694	.167	.439	.0060	.472
top 3 ranks	.241	.515	.527	.264	.496	.0061	.409
	.000	.047	.267	.288	.549	.1001	.230
Evaluation value ~0.10	.000	.503	.117	.604	.446	.1002	.334
value 0.10	.417	.016	.414	.076	.043	.1006	.193
	.000	.000	.006	.211	.310	.2000	.105
Evaluation value ~ 0.20	.000	.000	.008	.168	.022	.2002	.040
Value 0.20	.491	.016	.057	.494	.280	.2031	.267
Evaluation value of the lowest ranks	.284	.000	.000	.146	.064	.6251	.099
	.283	.031	.003	.088	.279	.7340	.137
	.000	.000	.000	.123	.104	.9316	.045

Evaluation value of the top 3 ranks

- We confirmed that the effective feature space is selected the higher rank.
- In the case of the evaluation value .0060, the F-measure of subjects other than Sub 4 are over .400.
- The mean of F-measure is over .400.
- XF-measure : Evaluation measure of prediction result.
 - F-measure is bad the closer 0. F-measure is good the closer 1.

Classification		$F ext{-}measure$		CHI-FS	Mean of		
	Sub 1	Sub 2	Sub 3	Sub 4	Sub 5	Index	$F ext{-measure}$
Evaluation	.846	.076	.381	.528	.485	.0056	.463
value of the	.488	.572	.694	.167	.439	.0060	.472
top 3 ranks	.241	.515	.527	.264	.496	.0061	.409
e 1 .:	.000	.047	.267	.288	.549	.1001	.230
Evaluation value ~0.10	.000	.503	.117	.604	.446	.1002	.334
value 0.10	.417	.016	.414	.076	.043	.1006	.193
	.000	.000	.006	.211	.310	.2000	.105
Evaluation value ~ 0.20	.000	.000	.008	.168	.022	.2002	.040
Value 0.20	.491	.016	.057	.494	.280	.2031	.267
Evaluation	.284	.000	.000	.146	.064	.6251	.099
value of the	.283	.031	.003	.088	.279	.7340	.137
lowest ranks	.000	.000	.000	.123	.104	.9316	.045

Evaluation value of the other ranks

- As the evaluation value increased, the F-measure of the subjects is low overall.
- Evaluation value \sim 0.20 and the lowest ranks are also the case that F-measure of all subjects is less than .400.
- The mean of F-measure is less than .400.
- X F-measure : Evaluation measure of prediction result.

F-measure is bad the closer 0. F-measure is good the closer 1.

Conclusion

Contents of this research:

We proposed the Consideration of Human motion's Individual differences-based Feature Space(CHI-FS) evaluation function for anomaly detection.

The confirmation experiment of effectiveness:

- Demonstrate that the proposed CHI-FS evaluation function was superior to existing evaluation function by "Evaluation by using the simulation data".
- We confirmed the effectiveness of the proposed CHI-FS evaluation function by "Evaluation by using the data of the inertial sensors during car driving".
 - (> The anomaly detection of the aimless driving including the drowsy driving by inertial sensors worn on the left and right wrists.)
- These results also suggest there is a possibility that we can search for the effective feature space considering the human motion's individual differences for anomaly detection by using the proposed CHI-FS evaluation function.

Future works:

Applying the CHI-FS evaluation function to various cases.