Extracting and Interpreting Unknown Factors with Classifier for Foot Strike Types in Running

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Background

- If automatic coaching systems are actualized, many people can improve their skills more efficiently and effectively than now.

Related Work

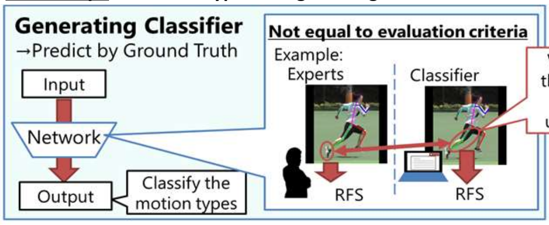
- Most of related works use machine learning, and predict evaluations based on experts' criteria, which could be biased.

For example: Deep learning systems learns diving players' scores given by judges and estimates unknown diving players' scores [Parmar et al., 2019]
→But, these systems are not helpful to extract new knowledge for the experts.

Our Goal

- To extract and interpret unknown factors, which experts do not know and/or did not experience.
- More specifically, from networks that classify motion types, we aim at obtaining unknown factors.

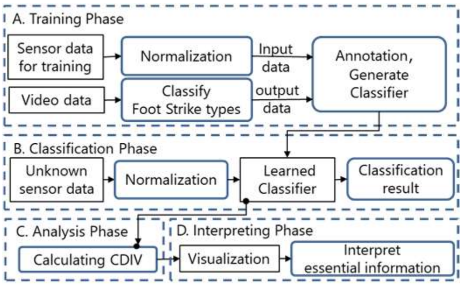
Case study: Foot strike type during running motion



Overview of the Proposed Method

Our proposed method has 4 phases.

A) Generate the classifier for classifying Rare foot strike (RFS) or Non-RFS type from train data.
B) Predict the foot strike type for test data.
C) Analyzing CDIV for two strike types from learned model.
D) Interpreting CDIV and obtaining unknown factors.



RFS: the heel contacts the ground first.

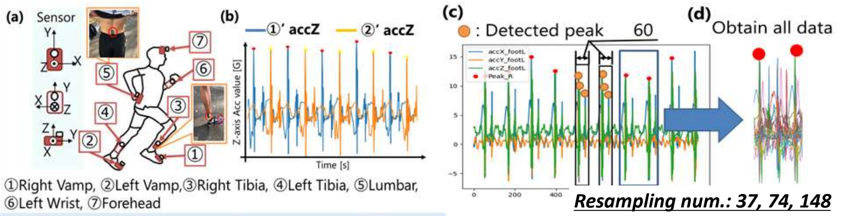
Non-RFS: the heel and ball of the foot contact the ground simultaneously or the ball contacts the before the heel.

CDIV: the degree of influence of the input for the output in Deep learning.

The Proposed Method and Experiments

1. Training Phase and Classification Phase

- Using 7 accelerometers for measuring running motions.
- When obtaining running gate cycle (RGC), we calculate the peak of LV or RV in z-axis values, which are the impact of contacting the ground.
- After calculating the peaks, we get the RGC to train with machine learning.
- As the normalization, we resample from each sensor data in the RGC, and all the accelerometer values are divided by 20G which is the measurement limitation.



Resampling num.: 37, 74, 148

2. Analysis Phase and Interpreting Phase

- We use the VGG-16 whose 2D-CNN is changed to a 1D-CNN.
- After training the classifier, we calculate which parts of the input influence on the prediction of each foot strike in running motion.
- We calculate the values of the heatmap from the input influence.

Input Influence:

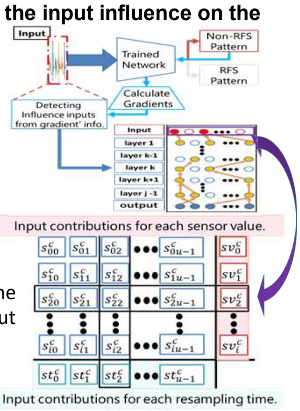
$$\alpha_{ij}^{c}=\begin{cases} ReLU\left(\frac{1}{N}\sum_{n=0}^{N-1}\frac{1}{K-1}\sum_{k=1}^{K-1}\omega_{kj}^{n}g_{ni}^{c}\right) & if\ i=0, \\ ReLU\left(\frac{1}{N}\sum_{n=0}^{N-1}\frac{1}{K-1}\sum_{k=0}^{K-2}\omega_{kj}^{n}g_{ni}^{c}\right) & if\ i=K-1, \\ ReLU\left(\frac{1}{N}\sum_{n=0}^{N-1}\frac{1}{K}\sum_{k=0}^{K-1}\omega_{kj}^{n}g_{ni}^{c}\right) & otherwise. \end{cases}$$

The value of heatmap:

$$s_{ij}^{c}=\frac{\alpha_{ij}^{c}}{\alpha_{max}^{c}}$$

$g^{c}\in R^{u\times N}$: the gradient value of the conv layer in front of the input layer(conv1)

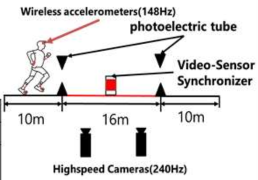
$\omega_{kj}^{n}\in R^{K\times d}$: the weight of the n-th channel, K is the kernel size in conv1



3. Experiments

- Collected running motions from 20 healthy subjects(all male, aged 19-26years) within ±5% of 10 km/h, 12 km/h and 15km/h.
- 3 subjects' data were used as training data for each type
- When training classifier, experiment conditions are below.

	About RGC of Left Leg				About RGC of Right Leg			
	Training Data		Test Data		Training Data		Test Data	
	Non-RFS	RFS	Non-RFS	RFS	Non-RFS	RFS	Non-RFS	RFS
Number of Data	257	203	695	350	247	206	712	355
Avg. RGC [Hz]	109.4	117.3	106.8	109.9	108.7	118.1	107.0	110.2



RFS type num.: 8
Non-RFS type num.: 12

Experimental Results & Discussion

- RGC of Right leg is higher accuracy than left one using all sensor data, especially the classifiers extracted the feature which includes a tibia information.
- From CDIV value, the sensor information about tibia is important to classify two foot strike types, and the result is similar to sports science knowledge.
- About unknown factors, classifier can be extracted about contacting the ground and swinging legs which is related to running skills.

- Evaluation of Test Data with Weight in Epoch No. 50 in all sensor data

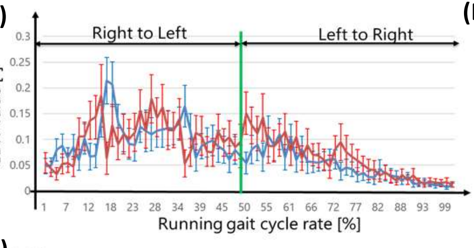
	Left leg gait cycle			Right leg gait cycle		
Resampling num	37	74	148	37	**74**	148
Acc.	0.889	0.899	0.823	0.916	**0.915**	0.894
Precision	0.957	0.926	0.946	0.966	**0.924**	0.842
Recall	0.768	0.802	0.666	0.815	**0.837**	0.840
F1 score	0.852	0.859	0.782	0.884	**0.878**	0.841

- Evaluation of Test Data with Weight in Epoch No. 50 in two sensor data (resampling num: 74)

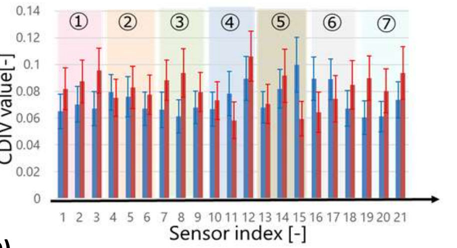
	Right leg gait cycle						
	RV	**RV-LV**	**RV-RT**	RV-LT	RV-LB	RV-LW	RV-FH
Acc.	0.701	**0.905**	**0.914**	0.881	0.831	0.705	0.873
Precision	0.865	**0.896**	**0.870**	0.946	0.842	0.887	0.896
Recall	0.531	**0.832**	**0.870**	0.757	0.707	0.534	0.764
F1 score	0.658	**0.863**	**0.870**	0.841	0.769	0.667	0.825

	Left leg gait cycle			
	LV	LV-RV	**LV-RT**	LV-LT
Acc.	0.813	0.808	**0.905**	0.839
Precision	0.777	0.814	**0.823**	0.863
Recall	0.699	0.677	**0.886**	0.716
F1 score	0.736	0.739	**0.853**	0.782

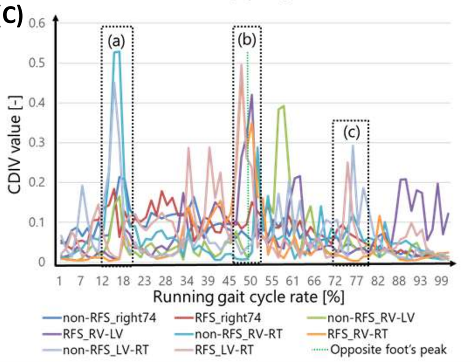
(A)



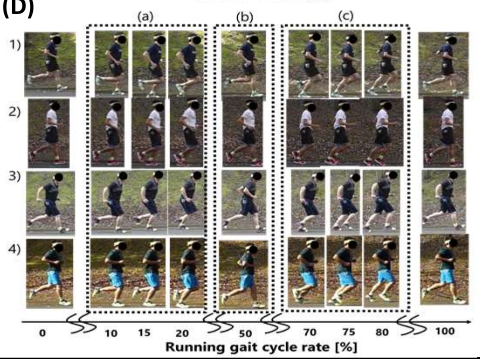
(B)



(C)



(D)



Conclusion

- We calculate two CDIVs: the contribution value for each resampling time and the contribution value for each sensor value.
- Our proposed method could extract and interpret the unknown factors that contain similar knowledge to the prior knowledge of experts, as well as new knowledge that are not included in conventional knowledge.