



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

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Background

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- **Actualization of automatic coaching systems**
 - many people can improve their skills more efficiently and effectively than now
 - can avoid injuries.
- **Related works**

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 [1].



But, not helpful to extract **new knowledge** for the experts

[1] P. Parmar and B. T. Morris, "What and How Well You Performed? A Multitask Learning Approach to Action Quality Assessment," CVPR, 2019, pp.304-313.

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Goal

○ **Extract and Interpret **Unknown factors** (experts do not know and/or did not experience) from Classifier**

Generating Classifier
→ Predict by Ground Truth

Input → Network → Output

Classify the motion types

Not equal to evaluation criteria

Example: Experts | Classifier

RFS | RFS

When analyzing the difference, we could obtain unknown factors

○ **Case study : Foot strike type during running motion**

- ① Evaluation criteria as ground truth is clear.
 - RFS type: the heel contacts the ground first.
 - Non-RFS type: other case of contacting the ground to RFS
- ② Interpreting unknown factors in terms of many sport science knowledges about the foot strike.

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Overview of Proposed Method

A. Training Phase

Sensor data for training → Normalization → Input data

Video data → Classify Foot Strike types → output data

Input data + output data → Annotation, Generate Classifier

B. Classification Phase

Unknown sensor data → Normalization → Learned Classifier → Classification result

C. Analysis Phase

Classification result → Calculating CDIV

D. Interpreting Phase

Calculating CDIV → Visualization → Interpret **Unknown Factors**

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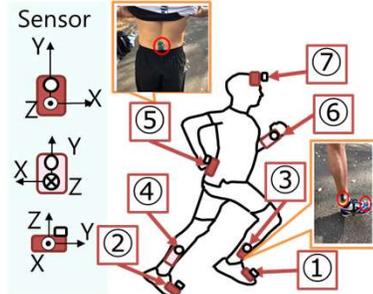


Training Phase & Classification Phase

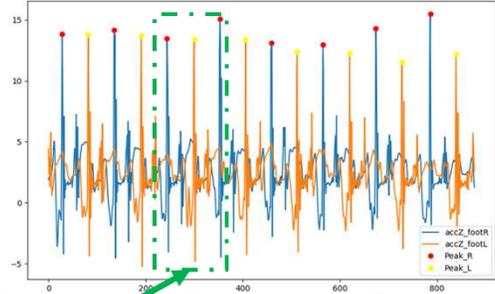
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- 7 accelerometers for measuring running motions.
- Foot strike type for runners is evaluated by videos

(a) Positions of Sensor



(b) Detecting the peak of Vamp



① Right Vamp, ② Left Vamp, ③ Right Tibia, ④ Left Tibia, ⑤ Lumbar, ⑥ Left Wrist, ⑦ Forehead

To normalize the peak to peak, we do resampling: 37, 74 and 148

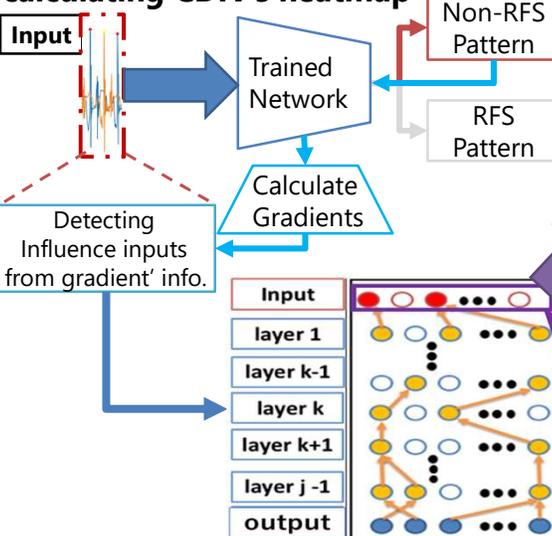
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Analysis Phase & Interpretation Phase

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○ Detecting influence of input by calculating CDIV's heatmap



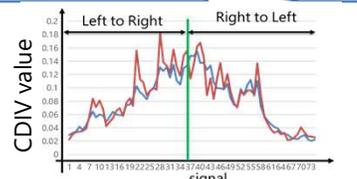
CDIV : the degree of influence of the input on the output in DL

s_{ij}^c : the value of heatmap for calculating CDIV

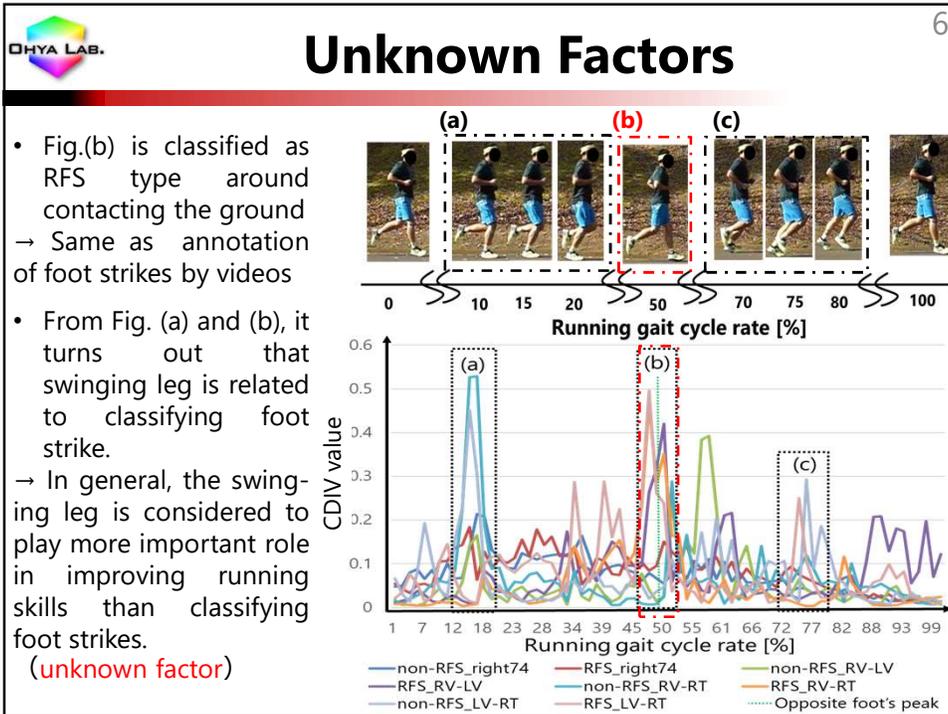
Input contributions for each sensor value.

s_{00}^c	s_{01}^c	s_{02}^c	...	s_{0u-1}^c	sv_0^c
s_{10}^c	s_{11}^c	s_{12}^c	...	s_{1u-1}^c	sv_1^c
s_{20}^c	s_{21}^c	s_{22}^c	...	s_{2u-1}^c	sv_2^c
...
s_{i0}^c	s_{i1}^c	s_{i2}^c	...	s_{iu-1}^c	sv_i^c
st_0^c	st_1^c	st_2^c	...	st_{u-1}^c	

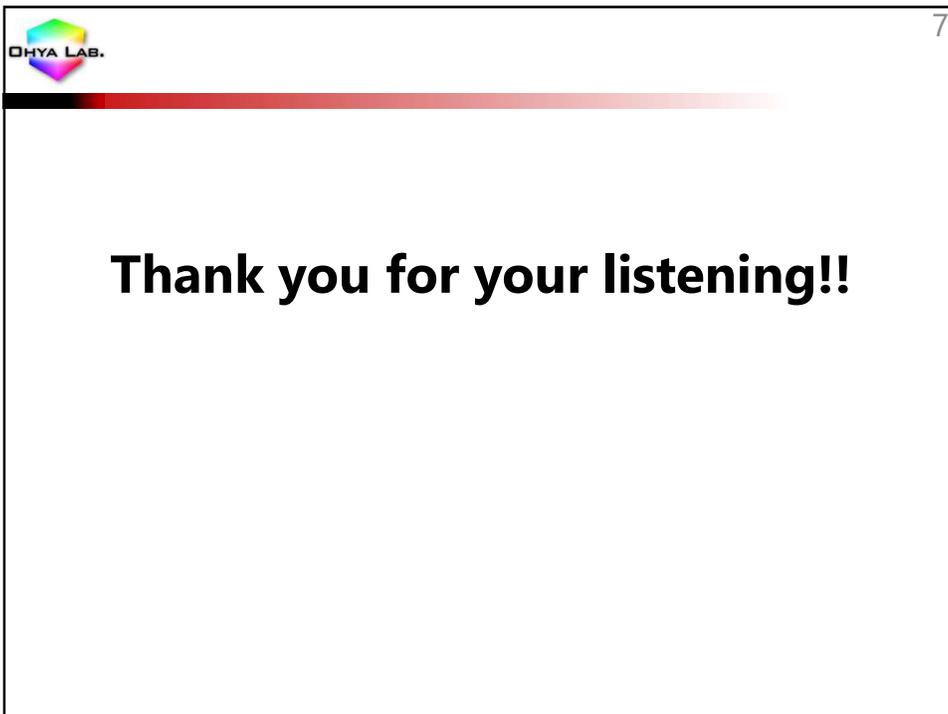
Input contributions for each resampling time.



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