

Fingerspelling recognition with two-steps cascade process of spotting and classification

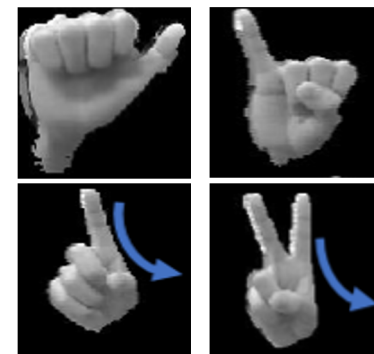
Masanori Muroi¹, Naoya Sogi¹, Nobuko Kato² and Kazuhiro Fukui¹

¹ Graduate School of Systems and Information Engineering,
University of Tsukuba, Japan

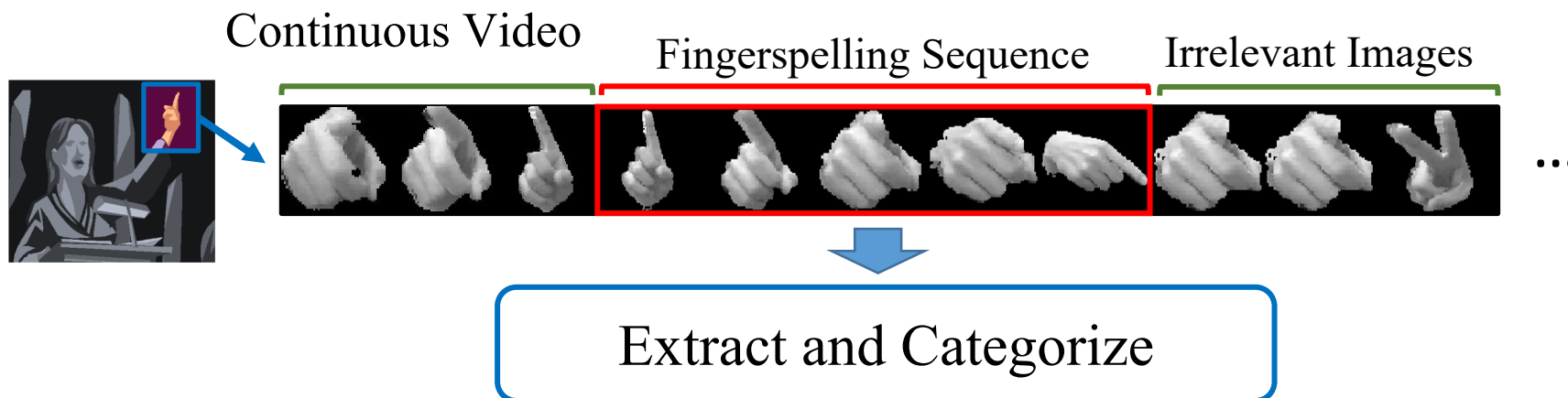
² Faculty of Industrial Technology,
Tsukuba University of Technology, Japan

Motivation

- Fingerspelling is a tool to express a certain letter by a hand shape.
- Used in conjunction with sign language

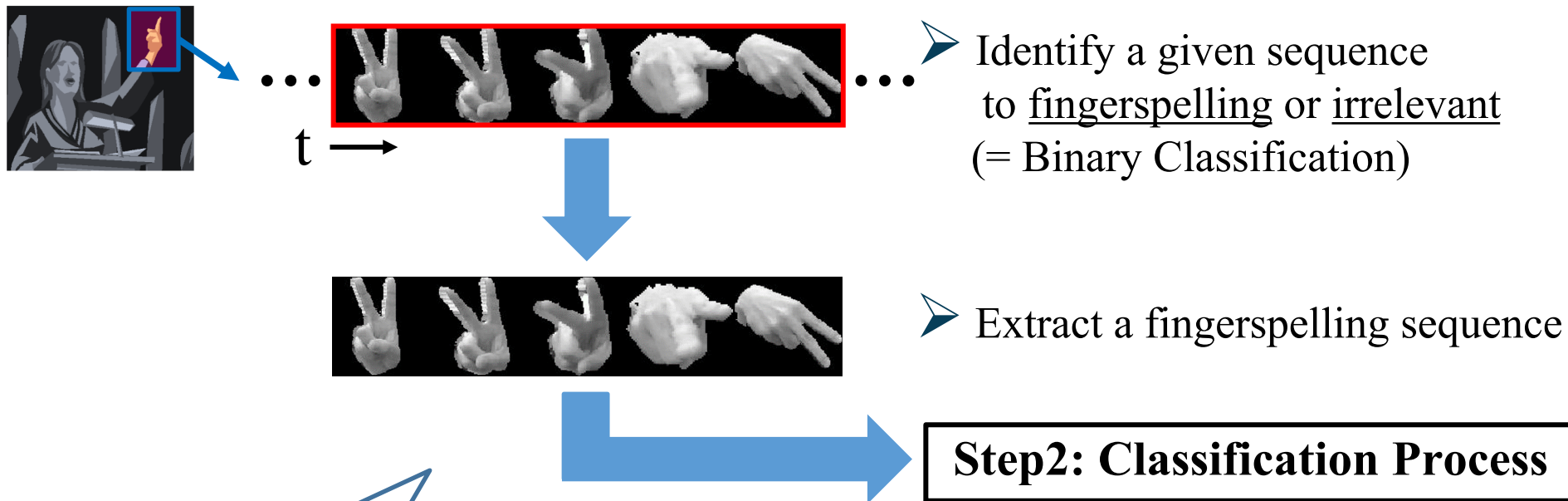


- **Main goal: Extract and categorize fingerspelling sequences in a continuous video.**



Basic Idea

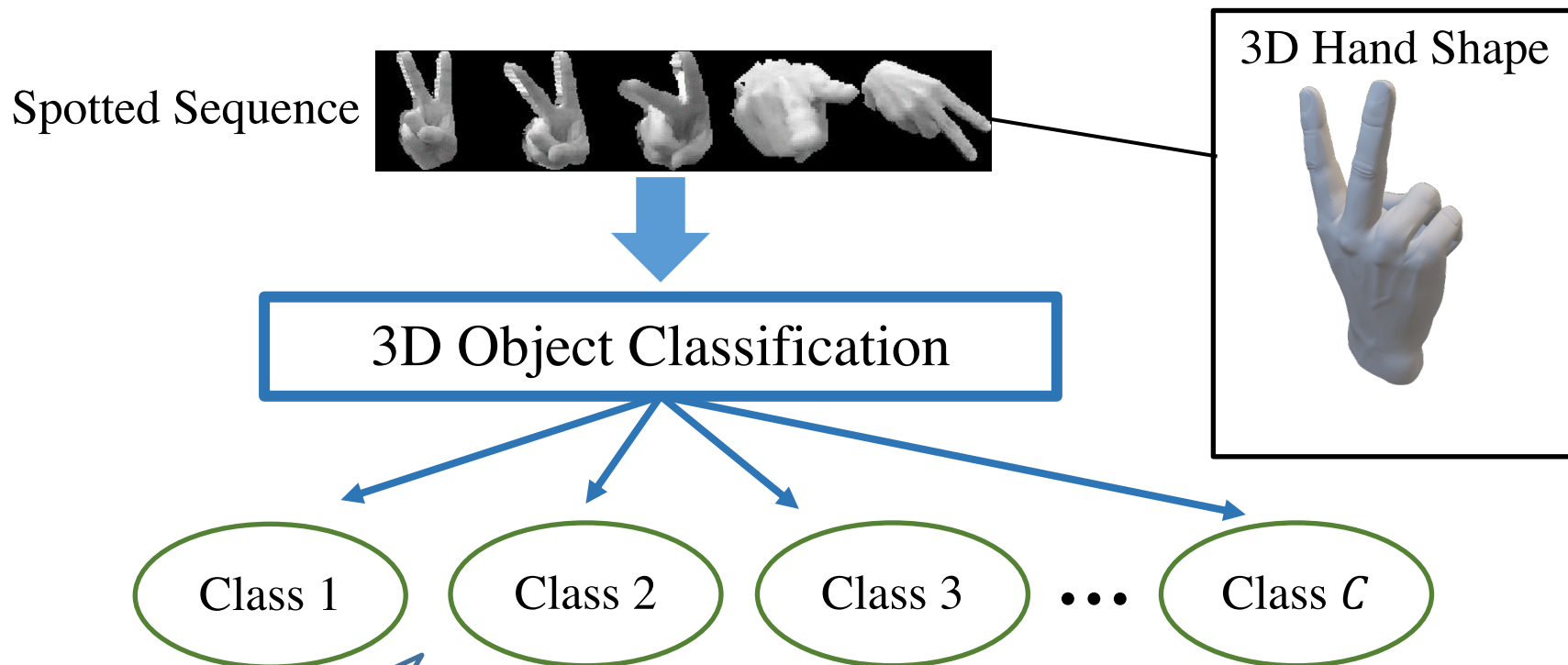
- Divide a whole process into two-steps: **Spotting** and **Classification**
- **Step 1. Spotting:** Segment and extract a fingerspelling sequence



We should consider temporal dynamic information.

Basic Idea

- **Step 2. Classification:** Classify the spotted fingerspelling sequence



We should consider **3D hand shape information**.

Solution to realize the Basic Idea

- Propose a fingerspelling recognition framework based on the two types of methods:

Spotting: **Temporal Regularized CCA (TRCCA)**[2]

- The smoothness on the temporal domain

Classification: **Orthogonal Mutual Subspace Method (OMSM)**[3]

with **CNN features**[4]

- The subspace representation of multiple images

[2] S. Tanaka, A. Okazaki, N. Kato, H. Hino and K. Fukui, Spotting ngerspelled words from sign language video by temporally regularized canonical component analysis, *2016 IEEE International Conference on Identity, Security and Behavior Analysis*, 2016, pp. 1-7.

[3] K. Fukui and O. Yamaguchi, The kernel orthogonal mutual Subspace method and its application to 3D object recognition, in *Asian Conference on Computer Vision*, 2007, pp. 467-476.

[4] N. Sogi, T. Nakayama, and K. Fukui, A method based on convex cone model for image-set classification with cnn features, in *2018 International Joint Conference on Neural Networks*, 2018, pp. 1-8.

Solution to realize the Basic Idea

- Propose a fingerspelling recognition framework based on the two types of methods:

Spotting: **Temporal Regularized CCA (TRCCA)**[2]

- The smoothness on the temporal domain

Classification: **Orthogonal Mutual Subspace Method (OMSM)**[3]

with **CNN features**[4]

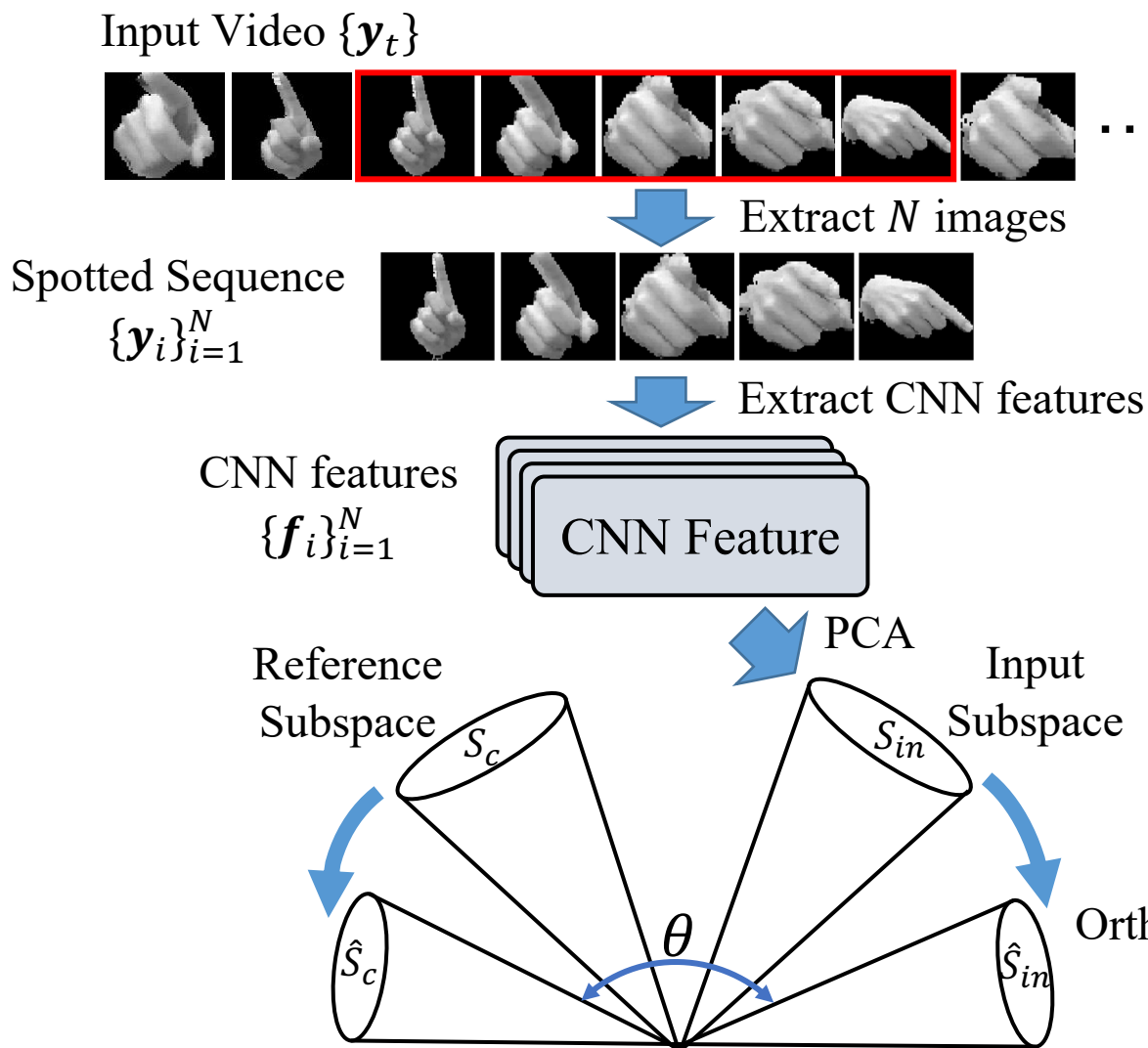
- The subspace representation of multiple images

[2] S. Tanaka, A. Okazaki, N. Kato, H. Hino and K. Fukui, Spotting ngerspelled words from sign language video by temporally regularized canonical component analysis, *2016 IEEE International Conference on Identity, Security and Behavior Analysis*, 2016, pp. 1-7.

[3] K. Fukui and O. Yamaguchi, The kernel orthogonal mutual Subspace method and its application to 3D object recognition, *in Asian Conference on Computer Vision*, 2007, pp. 467-476.

[4] N. Sogi, T. Nakayama, and K. Fukui, A method based on convex cone model for image-set classification with cnn features, *in 2018 International Joint Conference on Neural Networks*, 2018, pp. 1-8.

Proposed Framework for Fingerspelling Recognition



Step 1:

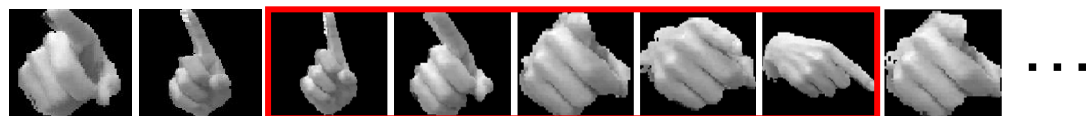
- Extract N fingerspelling images from an input video using TRCCA

Step 2:

- Extract CNN features from each frame of the spotted sequence
- The set of CNN features is classified by applying OMSM

Proposed Framework for Fingerspelling Recognition

Input Video $\{y_t\}$



■ Step 1:

- Extract N fingerspelling images from an input video using TRCCA

Extract N images

Spotted Sequence $\{y_i\}_{i=1}^N$



Extract CNN features

■ Step 2:

- Extract CNN features from each frame of the spotted sequence
- The set of CNN features is classified by applying OMSM

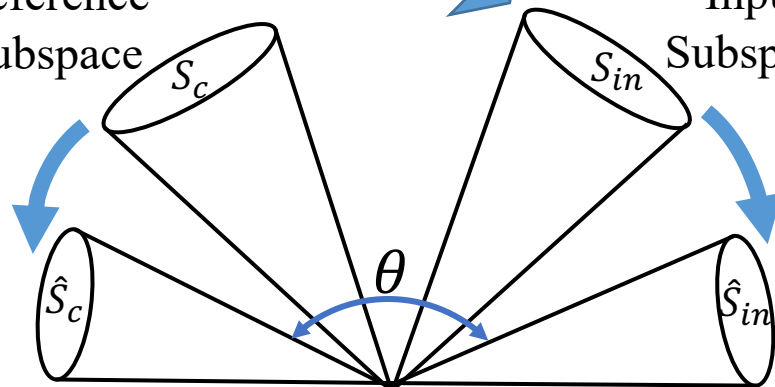
CNN features $\{f_i\}_{i=1}^N$



PCA

Reference Subspace S_c

Input Subspace S_{in}



Orthogonalize

Classification accuracy and recognition time

- Accuracies and recognition times of different frameworks.

Framework	Accuracy	Recognition Time
TRCCA [1]	64.1%	39.7 ms
CNN feat- OMSM	68.9%	52.7 ms
KOTRCCA [1]	79.0%	169.0 ms
TRCCA-CNN(softmax)	80.7%	56.9 ms
TRCCA-KOMSM[2]	86.9%	187.3 ms
TRCCA-CNN feat-OMSM(Proposed)	88.2%	91.2 ms