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Using Self-organizing Maps for Intelligent Camera-based User Interface

Objective

- Problem:
 - Human-Machine Interface
 - Growing fast
 - High importance in all technological systems
 - Most of the solutions based on complex methods
 - Require high-resource devices
 - Not viable for embedded systems
- Solution:
 - Low-cost
 - Camera-based gesture interface

Outline

- **Introduction**
- Motivation
- Implementation Details
- Evaluation
- Conclusions and future work

Introduction

- Human-machine Interface
 - Transparent
 - The user does not have to adapt to special conventions or rules;
 - The environment should be the one to adapt to the natural way of user interaction.
 - Hand gestures: the most natural and comfortable way
 - Most of the solutions consume significant resources
 - Embedded systems (camera) exhibit limited resources



Introduction

- Camera-based gesture interface
 - Model gestures capturing their temporal properties
 - Significantly reduces storage requirements
 - Appropriate for implementation in embedded systems
 - Self-organizing maps for gesture classification



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Motivation

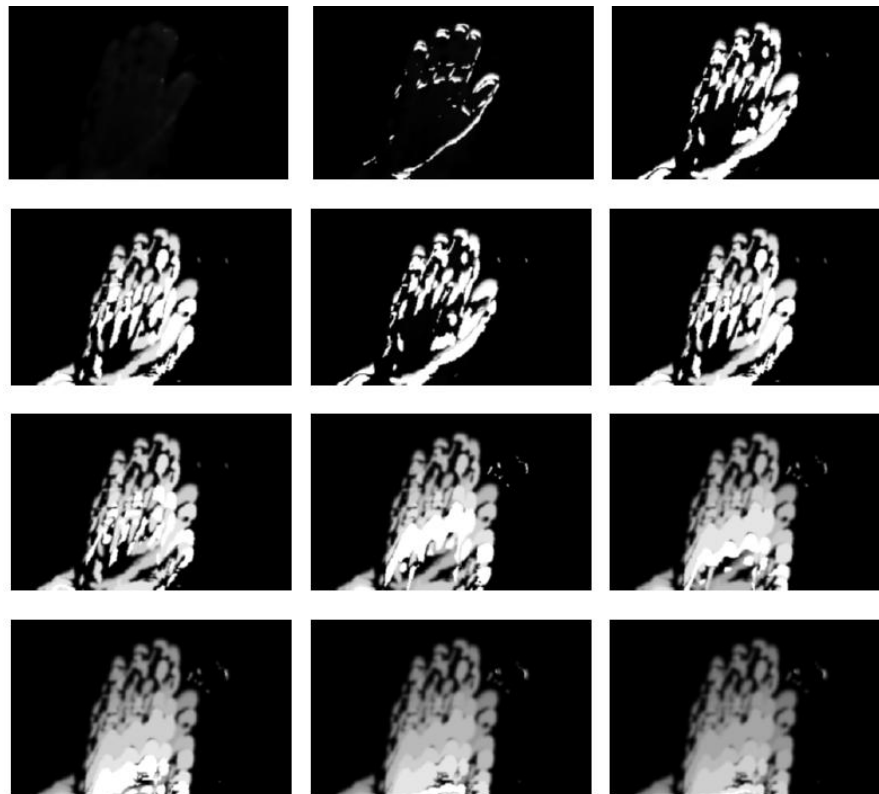
- Common SOM solutions
 - Two stages: the first stage captures the temporal properties → two learning algorithms
 - Standard characterization: trajectory of the hand, resultant direction of the movement, velocity of the movement...
 - Additional computational overhead

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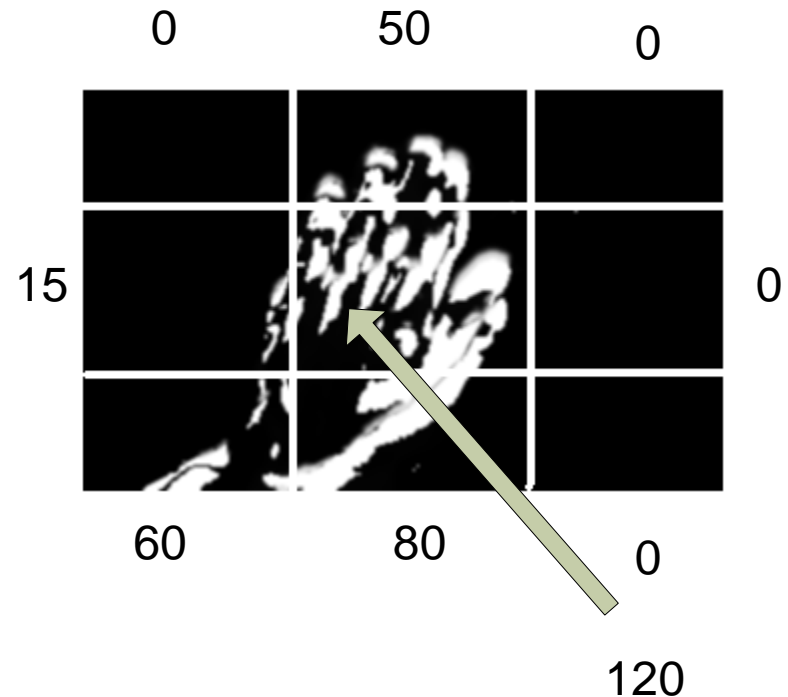
Implementation Details – Gesture Characterization

- Gesture: set of frames of variable size



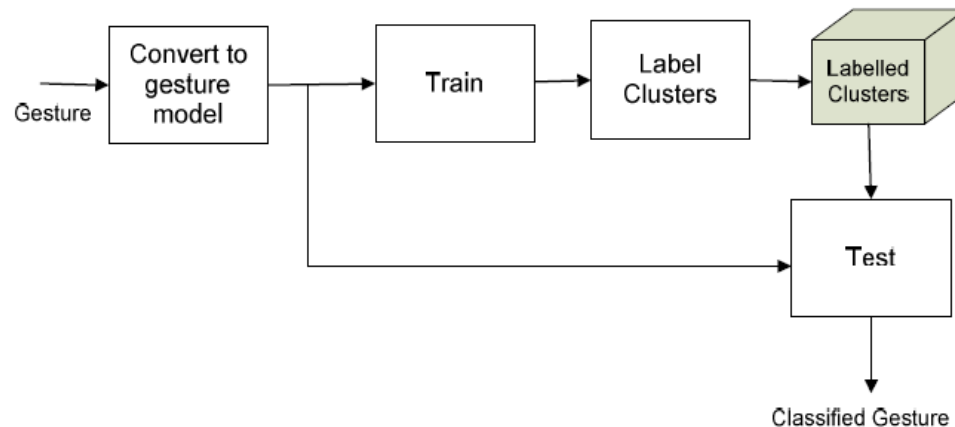
Implementation Details - Gesture Characterization

- Divide each frame into $n \times n$ parts
 - Assign to each part a value that corresponds to its luminosity (0 – 255)
 - Characterize temporal evolution of each part
 - E.g. 0 0 20 40 50 60 70 50 10, sliding window size 3
- | | |
|----------|------|
| 0 0 20 | 0.16 |
| 0 20 40 | 0.16 |
| 20 40 50 | 0.16 |
| 40 50 60 | 0.16 |
| 50 60 70 | 0.16 |
| 70 50 10 | 0.16 |
- Number of features not fixed → distance between sequences
 - Distance between two gestures the sum of absolute distances of the parts



Implementation Details - SOM

- Specific part: node update
 - If the node does not contain a feature from a certain input, we add it to the node with the value 0
 - Discard all the features that have at least 100 times smaller value of the maximal feature value of the node
- Label the nodes with the label of the gesture from the set of labeled gestures that is closest to the node according to the distance function



Advantages

- **Simplicity**
 - Gestures distinguished by clustering → no need to label all the gestures
 - The characterization significantly reduces the memory needed to store a gesture
 - 507kB reduced to 625B (5x5 division of the frame)
- Enables implementation on devices with limited resources

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Training and Testing Dataset

- Five types of gesture:
 - left-right
 - right-left
 - up-down
 - down-up
 - random gestures labeled as unknown
- 12 persons – 760 gestures
 - 1.08GB of storage space → after characterization 3.11MB

Results

- Testing with both 3x3 and 5x5 frame partitions
- Gestures left-right and right-left → confused with each other

Gesture	Detection Rate (%)
Unknown	88
Down-up	100
Up-down	92
Left-right	13
Right-left	13
Overall	80

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Conclutions and Future Work

- Low-cost algorithm for gesture classification
- Characterization of gestures that captures temporal properties of gesture
- Detection rate of up to 100% for certain gestures and overall detection of 80% at most
- Future work:
 - Add one more stage of SOM clustering in order to detect the users.

