One Shot Learning Gesture Recognition with Kinect Sensor

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June 12, 2012

The University Of Sheffield.

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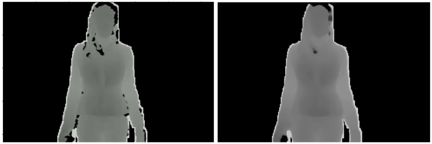

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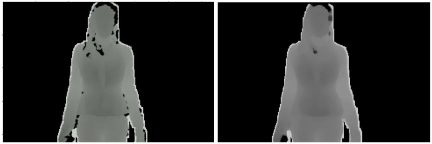

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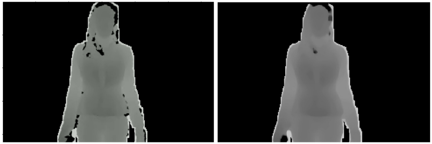

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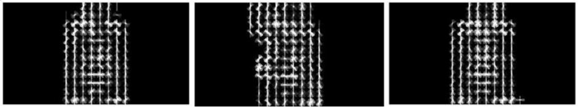

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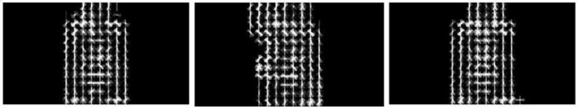

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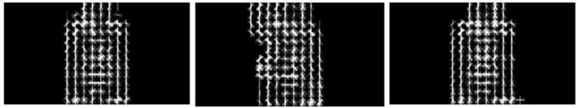

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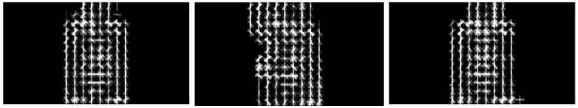

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where threshold is defined as:

$$Threshold = \sqrt{\sum_{t}^{nFrames} \sigma_t / (h \times w \times nFrames)} \tag{2}$$

where σ_t is the second moment (variance) of a single frame I_t; $h, w, nFrames$ are the height, width and frame number of that video sequence.

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$$\widetilde{I}(t;\tau) = \begin{cases} \tau & \text{if } \ B_t = 1, \\ \widetilde{I}(t+1;\tau) - 1 & \text{otherwise.} \end{cases} \tag{5}$$

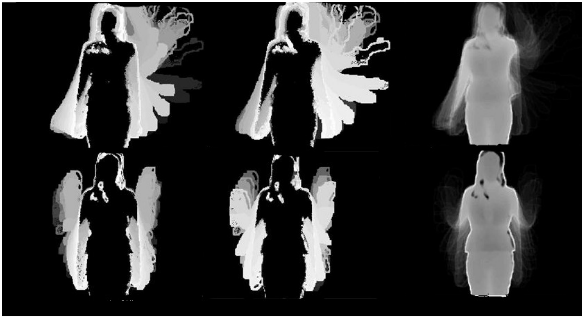
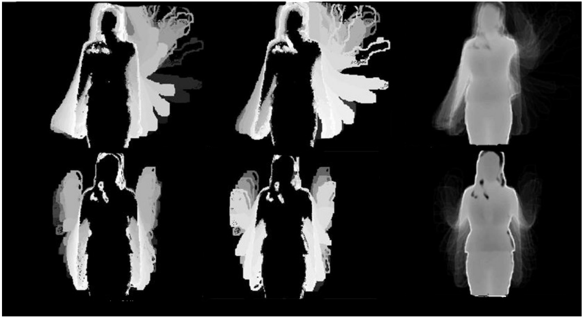


Figure: Illustration of the *MHI*, *INV* and *GEI* in two tokens (top row and bottom row). The projection images show that *MHI* emphasizes recent motion, ending frames whilst *INV* the beginning frames. *GEI* encodes the average gait information and is supplementary in repetitive actions where both *MHI* and *INV* are poor at representing.



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Methods	*GEI*	*MHI*	*INV*	*Extended-MHI*
$\mathfrak{LD}$	0.2761	0.3010	0.3022	**0.2600**

Table: Performance comparison of three elements in *Extended-MHI*

Multiview Spectral Embedding

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3. 4% improvement in $\mathfrak{LD}$

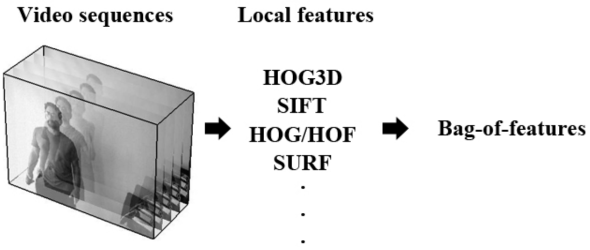
low-dimensional embedding

$$\underbrace{argmin}_{Y,\alpha} \sum_{i=1}^{m} \alpha_i^r tr(YL^i Y^T) \tag{6}$$

$$\text{s.t.} \sum_{i}^{m} i = 1 \tag{7}$$

Local approach

- Local features+Bag-of-Words



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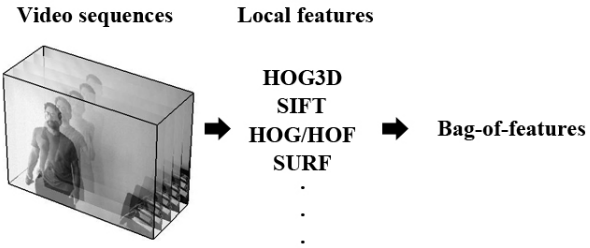


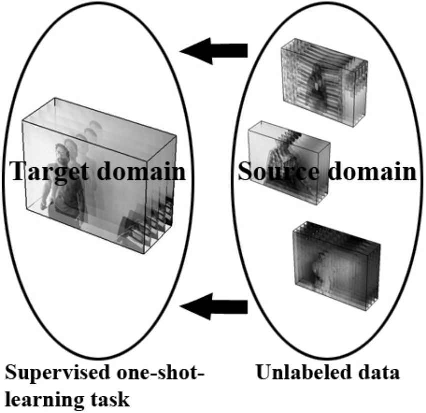
- Fail!!!

Local approach

- Why the local approach not working?
  - The local patterns used for training the codebook are not sufficient.
  - The Bag-of-Words histogram representation is not discriminative.

Transfer learning approach

- To incorporate more information into the supervised one-shot-learning task



Transfer learning approach

- Different from those action categories running or kicking, the given gesture categories are uniquely designed so that it is difficult to find related data that contains similar gestures as the given ones.
- One possible approach is to utilise the unlabelled data from the developmentvalidation batches to generate a more informative codebook or generate a higher level representation of the input.

END