High-Order Statistics for Skeleton-Based Hand Gesture Recognition

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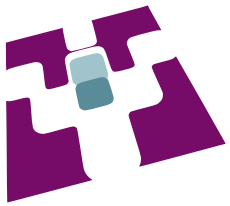


Neural Networks on the SPD Riemanian Manifold

Operate on matrices

Pros

- Richer and more aggregated data

Cons

- More complex data structure
- Less operators are available
- Local information may be hidden.

SPD Operators

- $GaussAvg(\{P_1, \ldots, P_n\})$: From Data to SPD.

$$GaussAvg(\{P_1, \ldots, P_n\}) = \begin{bmatrix} \Sigma + \mu\mu^T & \mu^T \\ \mu^T & 1 \end{bmatrix}$$

where Σ is the covariance matrix and μ the mean.

- $ReEig(X) \approx ReLu$

$$ReEig(X) = U \max(\epsilon I, \Lambda) U^T \text{ where } X = U\Lambda U^T$$

- $LogEig(X)$: Preprocessing to the new operator.

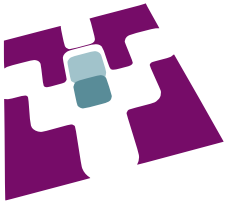
$$logEig(X) = U \log(\Lambda) U^T \text{ where } X = U\Lambda U^T$$

- $VecMat(X)$: From SPD to vectors

$$VecMat(X) = [X_{1,1}, \sqrt{2}X_{1,2}, \ldots, \sqrt{2}X_{1,n}, X_{2,2}, \sqrt{2}X_{2,3} \ldots \sqrt{2}X_{2,n}, X_{3,3} \ldots$$

- $vl(X)$

$$vl(X) = VecMat(logEig(ReEig(X)))$$



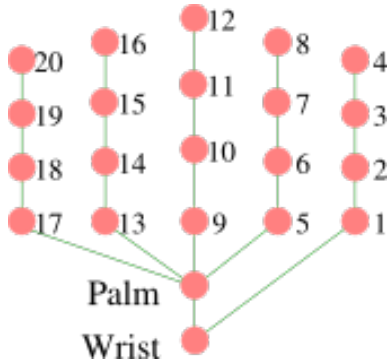
SPD operators: a last one

- $SPDAgg(X_1, \ldots, X_n)$: Attention network

$$SPDAgg(X_1, \ldots, X_n) = \sum_{i=1}^{n} W_i X_i W_i^T$$

Backpropagation of W_i should insure that $SPDAgg(x_1, \ldots, X_n)$ is SPD.

Inputs

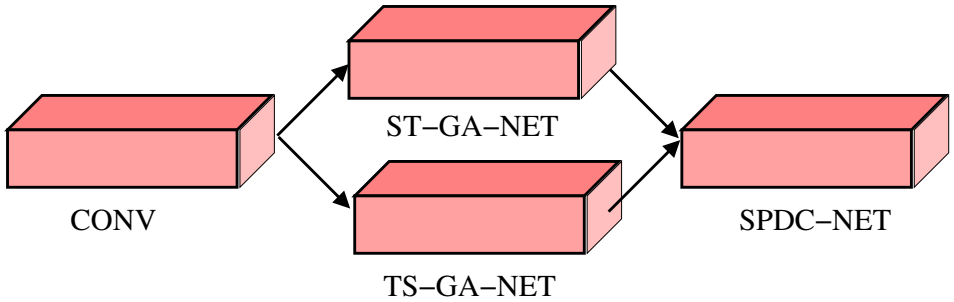


(a) Initial Graph

20	16	12	8	4
19	15	11	7	3
18	14	10	6	2
17	13	9	5	1

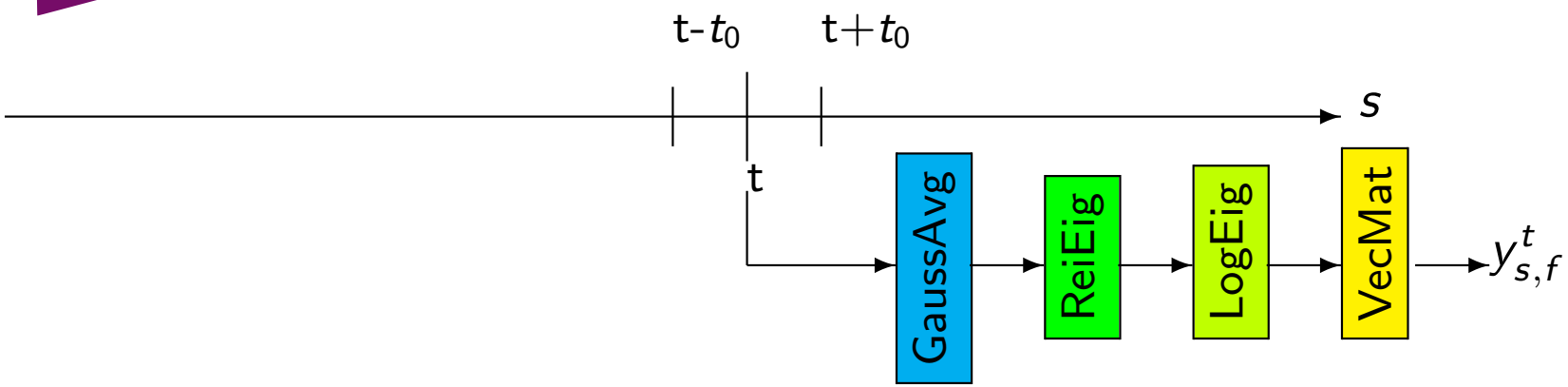
(b) Image encoding of joints. Each joint as a dim equal to 3.

Our convolutional network



- Conv: A classical 2D Image convolution.
- ST a spatio-temporal network
- TS a temporal-spatial network
- SPDC : a fusion step.

ST network

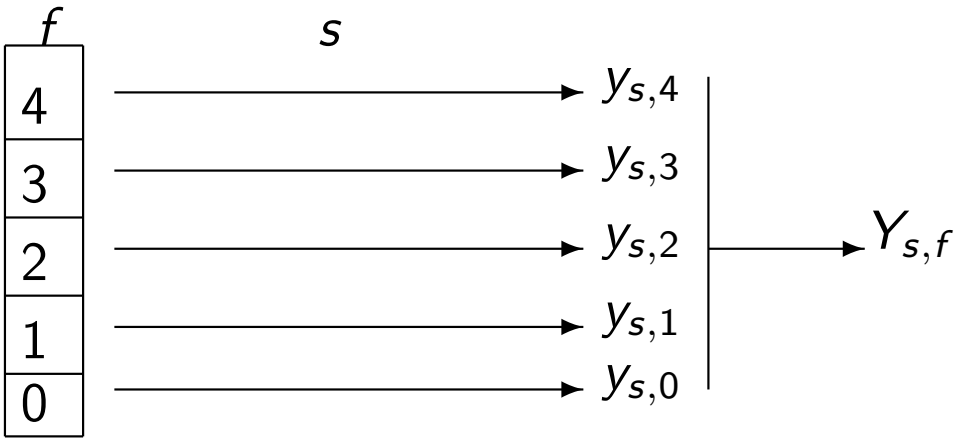


1. For a sequence s, each finger f, each time step t we compute

$$Y^t_{s,f} = GaussAvg(\{p_{s,j,i} \text{ with } j \in J_f, i \in [t - t_0, t + t_0]\}),$$

   J_f set of joints of finger f.
2. we compute $y^t_{s,f} = vl(Y^t_{s,f}) = VecMat(LogEig(ReEig(Y^t_{s,f})))$
3. We compute $Y_{s,f} = GaussAvg(\{y^t_{s,f}, t \in s\})$

TS Network



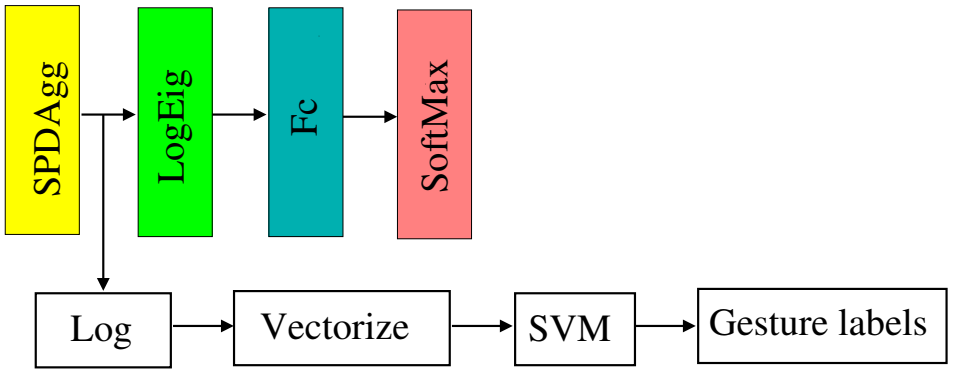
1. For each joint j let:

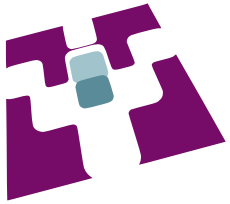
$$Y_{s,j} = GaussAvg(\{p^t_{s,j}, t \in s\})$$

2. Let $y_{s,j} = vl(Y_{s,j})$
3. compute for each finger f $Y_{s,f} = GaussAvg(\{y_{s,j}, j \in J_f\})$

SPDC Network

- for ST the sequence s is subdivided into 6 sub-sequences hence providing $5 \times 6 = 30$ SPD matrices.
- For TS s is subdivided into 20 subsequences of equal length providing $5 \times 20 = 100$ SPD matrices.
- we apply SPDAgg to merge all these matrices into a single one.



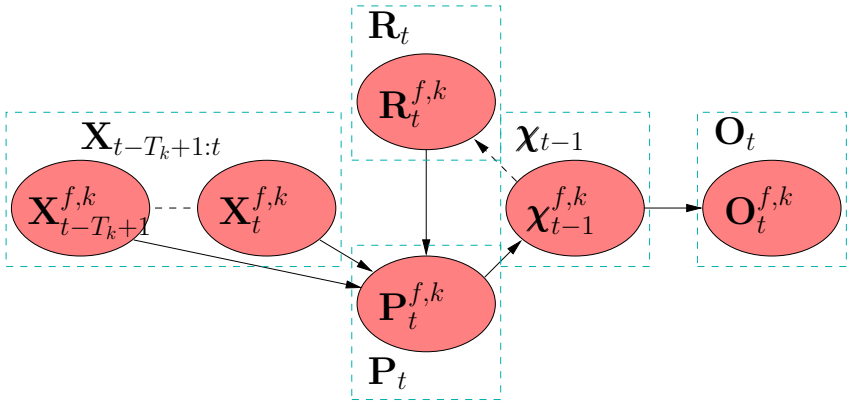


A recurrent Network

- Main Aim: Better take into account the time dimension.

Recurent version

Statistical Recurrent Unit (SRU):



$$\mathrm{P}_t^{f,k} = \mathrm{ReEig}\left(\frac{(w_p^k)^2}{(w_p^k)^2 + (w_x^k)^2} \mathrm{R}_t^{f,k} + \frac{(w_x^k)^2}{(w_p^k)^2 + (w_x^k)^2} h^k(\mathrm{X}_t^f) \right) \quad (1)$$

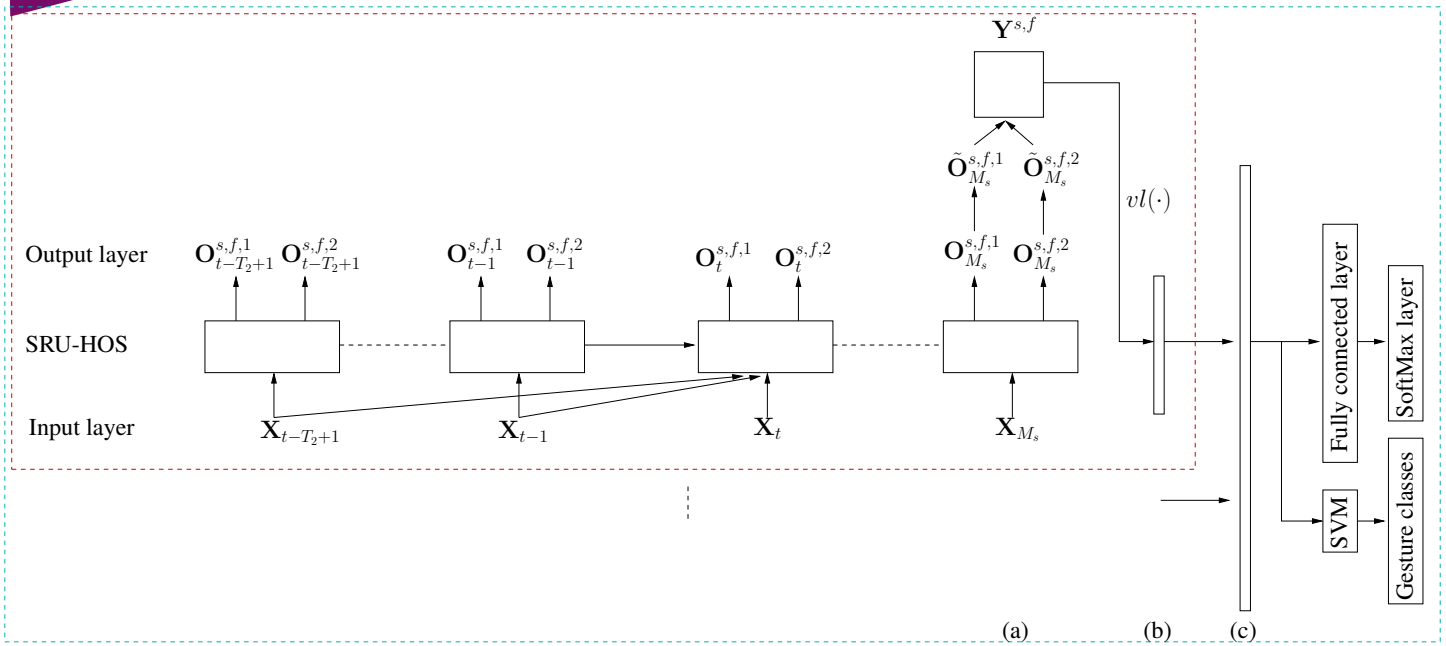
Finger f, time t, statistics of order k.

$$h^1(\mathrm{X}_t^f) = \begin{bmatrix} \boldsymbol{\Sigma}_t^{f,1} + \boldsymbol{\mu}_t^{f,1}(\boldsymbol{\mu}_t^{f,1})^T & \boldsymbol{\mu}_t^{f,1} \\ (\boldsymbol{\mu}_t^{f,1})^T & 1 \end{bmatrix} \quad \text{over the interval } [t - t_1, t].$$

$$h^2(X_t^f) = \mathit{GaussAvg}(\mathit{vl}(h^1(\mathrm{X}_t^f)) \quad \text{over the interval } [t - t_2, t].$$

$$\forall (f,k) \in \{1,\ldots,5\} \times \{1,2\}\ O^{f,k} = \mathit{SRU\_HOS}_k(X^f)$$

Our recurrent network

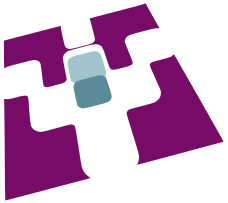


For all $(s, f) \in \{1, \ldots, 6\} \times \{1, \ldots, 5\}$:

$$\mathsf{Y}^{s,f} = \begin{bmatrix} \tilde{\mathsf{O}}^{s,f,2}_{M_s} + \mathsf{vl}(\tilde{\mathsf{O}}^{s,f,1}_{M_s})\mathsf{vl}(\tilde{\mathsf{O}}^{s,f,1}_{M_s})^T & \mathsf{vl}(\tilde{\mathsf{O}}^{s,f,1}_{M_s}) \\ \mathsf{vl}(\tilde{\mathsf{O}}^{s,f,1}_{M_s})^T & 1 \end{bmatrix},$$

Global representation:

$$[\mathsf{vl}(\mathsf{Y}^{1,1})^T, \ldots, \mathsf{vl}(\mathsf{Y}^{6,5})^T]^T$$



Experiments : Ablation study

- Recognition accuracy (%) of sub-networks ST-GA-NET and TS-GA-NET.

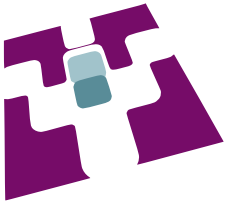
Network	FPHA	DHG (14 gestures)	DHG (28 gestures)
ST-HGR-NET	91.83	93.21	89.29
TS-HGR-NET	90.96	93.33	88.21
ST-TS-HGR-NET	**93.22**	**94.29**	**89.40**

- Relevance of $h^1()$ and $h^2()$ statistics

Statistics	DHG (14 gestures)	DHG (28 gestures)	FPHA
only $h^1(.)$	85.00	76.43	77.04
only $h^2(.)$	89.29	86.07	93.57
Full	**94.4**	**89.52**	**94.61**

- # of parameters

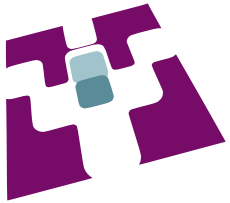
Model	Number of parameters
ST-TS-HGR-NET	672,243
SRU-HOS-NET	**18,894**



Experiments: Comparison with state of the art

- Performance of our method and state-of-the-art methods on DHG dataset.

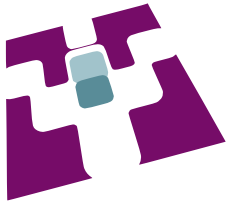
Method	**Year**	**Color**	**Depth**	**Pose**	**RNN/LSTM**	**Accuracy (%)**	
						14 gestures	**28 gestures**
HON4D [Oreifej and Liu, 2013]	2013	✗	✓	✗	✗	78.53	74.03
Devanne et al. [Devanne et al., 2015]	2015	✗	✗	✓	✗	79.61	62.00
Huang et al. [Huang and Gool, 2017]	2017	✗	✗	✓	✗	75.24	69.64
De Smedt et al. [Smedt et al., 2016]	2016	✗	✗	✓	✗	88.24	81.90
Devineau et al. [Devineau et al., 2018]	2018	✗	✗	✓	✗	91.28	84.35
SRU [Oliva et al., 2017]	2018	✗	✗	✓	✓	82.02	76.31
SRU-SPD [Chakraborty et al., 2018]	2018	✗	✗	✓	✓	86.31	80.83
ST-TS-HGR-NET [Nguyen et al., 2019]	2019	✗	✗	✓	✗	94.29	89.40
SRU-HOS-NET		✗	✗	✓	✓	**94.40**	**89.52**



Experiments: Comparison with state of the art

FPHA dataset.

Method	Year	Color	Depth	Pose	RNN/LSTM	Accuracy (%)
HON4D [Oreifej and Liu, 2013]	2013	✗	✓	✗	✗	70.61
Novel View [Rahmani and Mian, 2016]	2016	✗	✓	✗	✗	69.21
1-layer LSTM [Zhu et al., 2016]	2016	✗	✗	✓	✓	78.73
2-layer LSTM [Zhu et al., 2016]	2016	✗	✗	✓	✓	80.14
Moving Pose [Zanfir et al., 2013]	2013	✗	✗	✓	✗	56.34
Lie Group [Vemulapalli et al., 2014]	2014	✗	✗	✓	✗	82.69
HBRNN [Du et al., 2015]	2015	✗	✗	✓	✓	77.40
Gram Matrix [Zhang et al., 2016]	2016	✗	✗	✓	✗	85.39
TF [Garcia-Hernando and Kim, 2017]	2017	✗	✗	✓	✗	80.69
JOULE-color [Hu et al., 2015]	2015	✓	✗	✗	✗	66.78
JOULE-depth [Hu et al., 2015]	2015	✗	✓	✗	✗	60.17
JOULE-pose [Hu et al., 2015]	2015	✗	✗	✓	✗	74.60
JOULE-all [Hu et al., 2015]	2015	✓	✓	✓	✗	78.78
Huang et al. [Huang and Gool, 2017]	2017	✗	✗	✓	✗	84.35
Huang et al. [Huang et al., 2018]	2018	✗	✗	✓	✗	77.57
SRU [Oliva et al., 2017]	2018	✗	✗	✓	✓	72.17
SRU-SPD [Chakraborty et al., 2018]	2018	✗	✗	✓	✓	78.96
ST-TS-HGR-NET [Nguyen et al., 2019]	2019	✗	✗	✓	✗	93.22
SRU-HOS-NET		✗	✗	✓	✓	**94.61**



Conclusion

- Neural Network on SPD manifold provide promising results.
- How to generalize it to arbitrary graphs ?
  - We need SPD matrices (not a big deal but to study anyway),
  - We need meaningfull subgraphs to capture local information (much harder).

Questions ?

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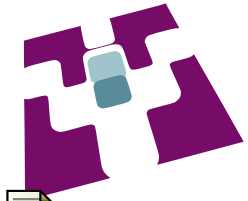

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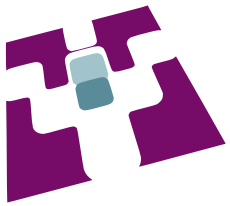

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