

# Human Action Recognition: Pose-based Attention draws focus to Hands

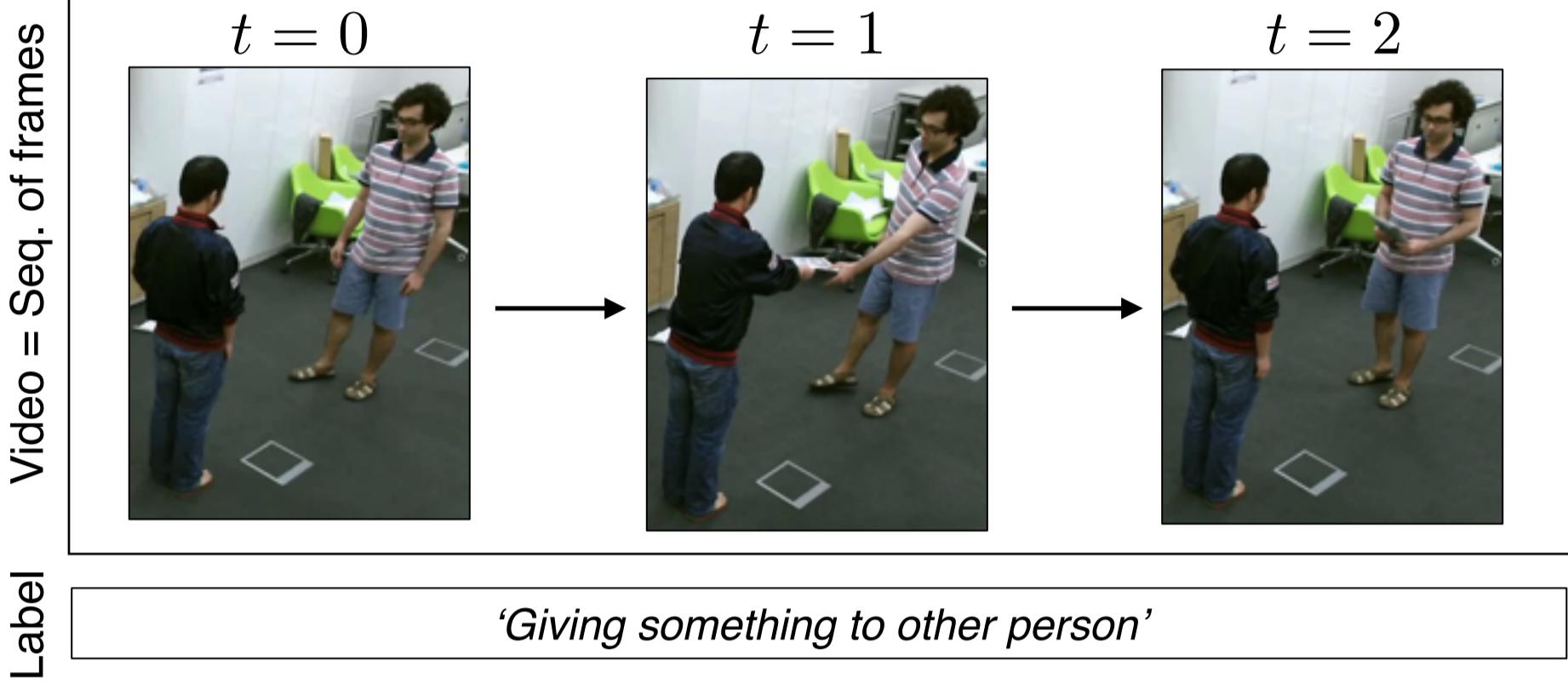
**PROBLEM DEFINITION & MOTIVATIONS**

**Overview**

- Video Understanding
- Human Action Recognition
- Video captured by Microsoft Kinect3D (3D human pose - RGB - Depth)

**Main challenges**

- High dimensional data
- Spatio-Temporal information
- Noise in the human pose



Video = Seq. of frames

Label: 'Giving something to other person'

**Problem statement:**  
How can an attention mechanism select the most discriminative parts of the video?

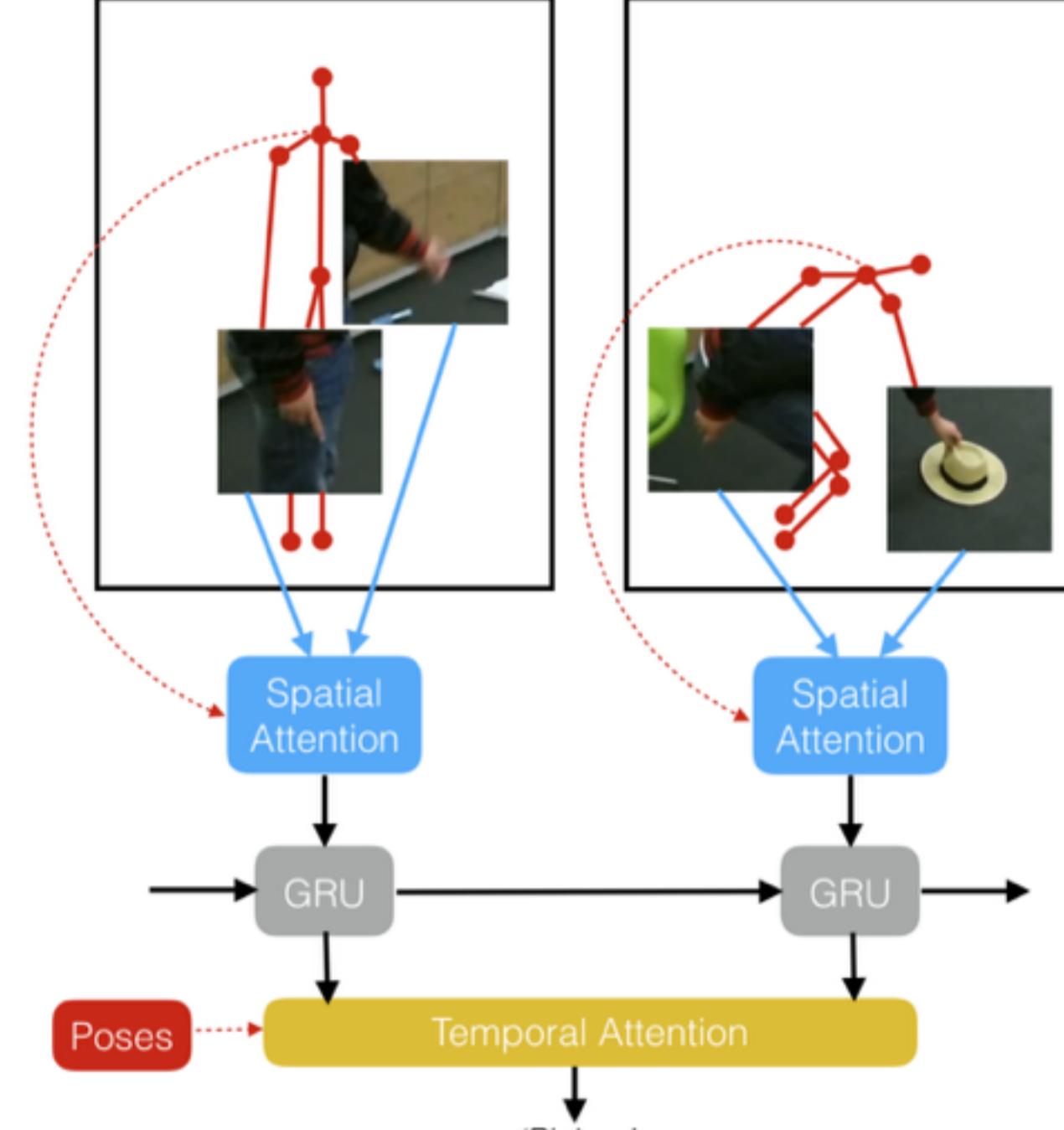
**MAIN IDEA**

- Two modalities
  - ✓ 3D skeleton coordinates
  - ✓ RGB frames
- Two stream model

**RGB**

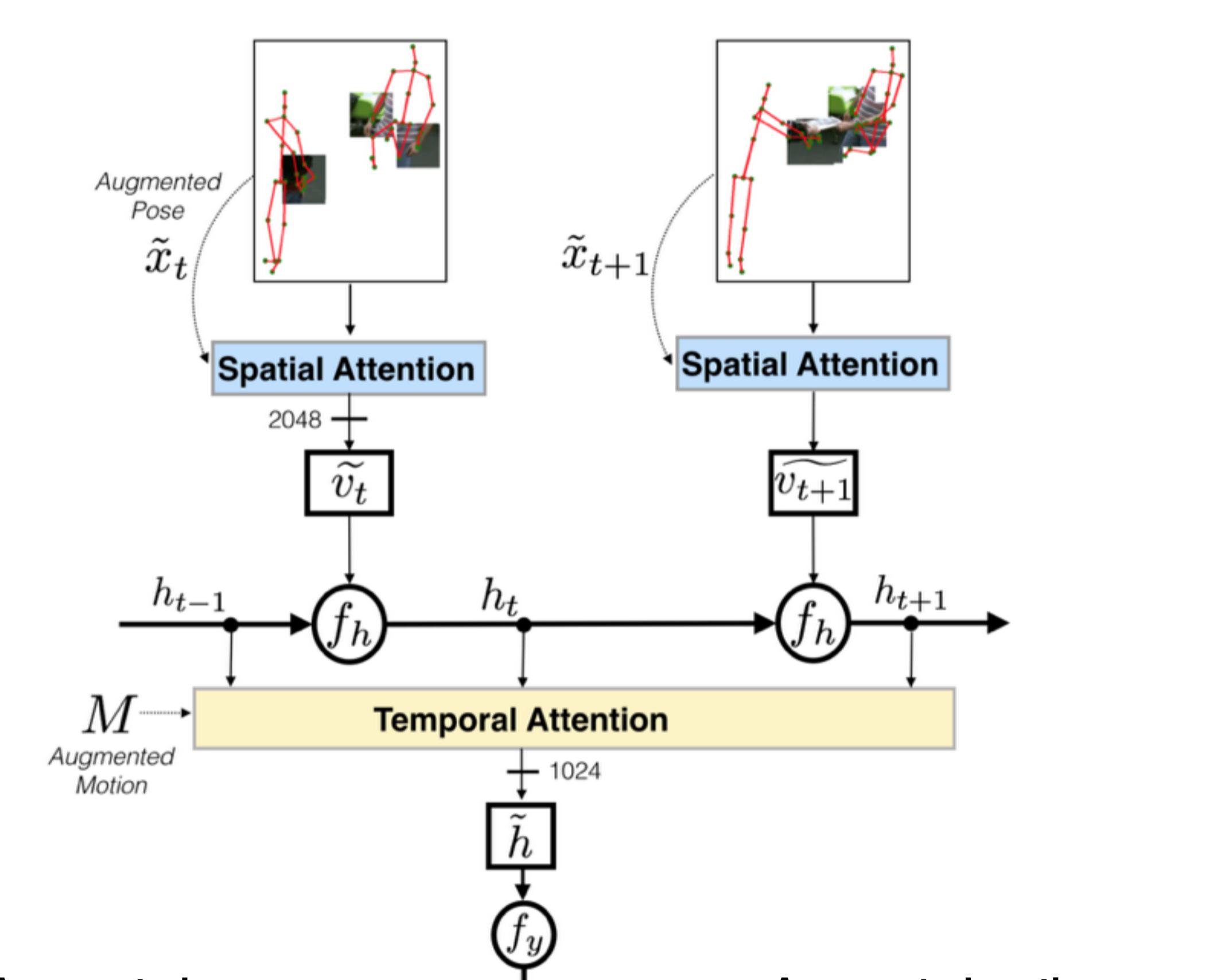
- Spatial attention mechanism over RGB hands crops
- Spatial attention adjusted at each timestep
  - Conditioned on augmented pose
- Temporal Attention on hidden states
  - Conditioned on augmented motion

**Pose**  
Standard Deep-GRU



**PROPOSED APPROACH**

**STA-HANDS**



**Augmented pose**

$$\tilde{x}_t = \begin{bmatrix} x_t \\ \dot{x}_t \\ \ddot{x}_t \end{bmatrix}.$$

**Augmented motion**

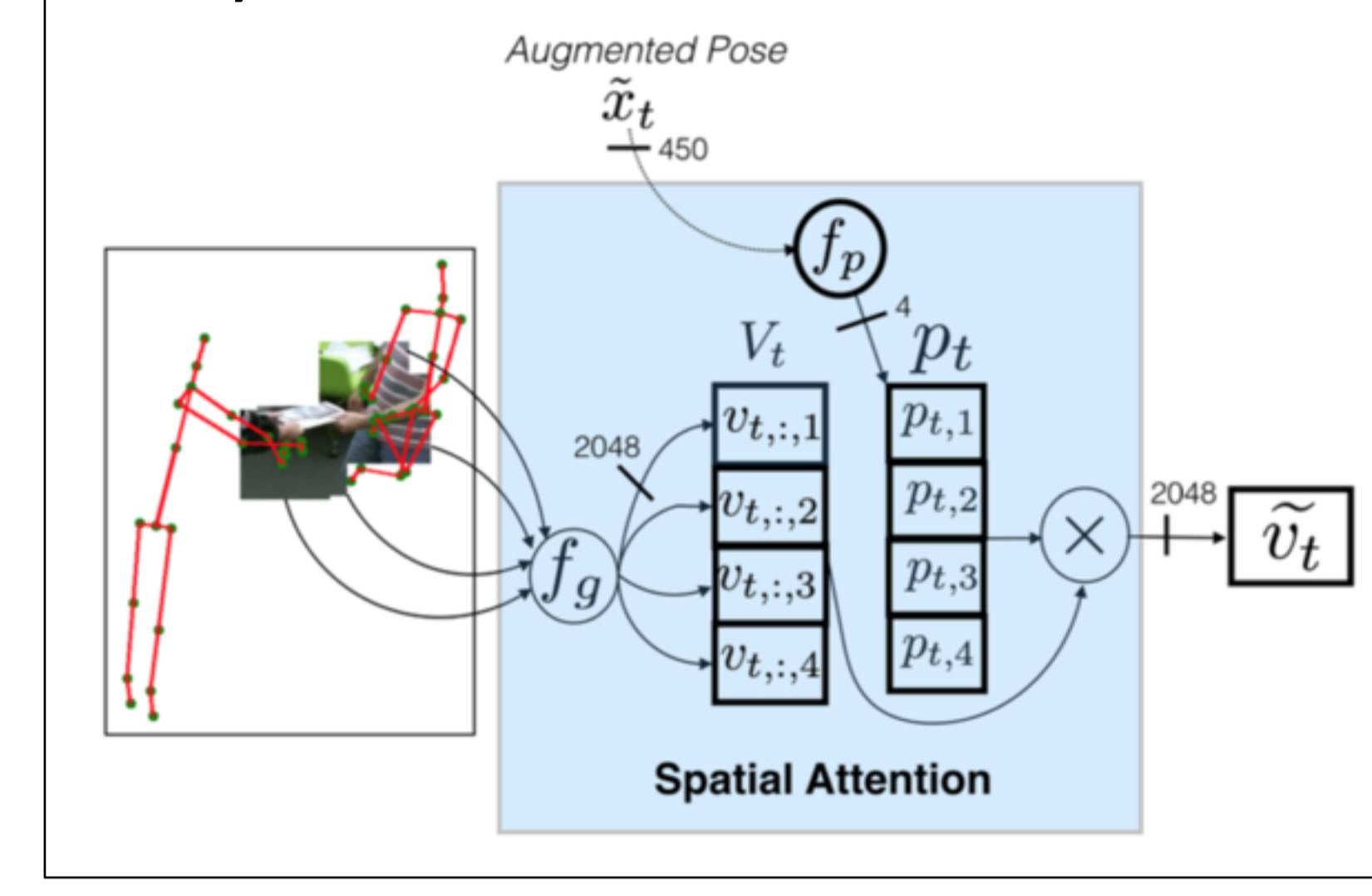
$$\tilde{m}_t = \left[ \sum_{j \in J} |\dot{x}_{t,j}| \right].$$

**M** = { $\tilde{m}_t$ }<sub>t=1...T</sub>

**ATTENTION ON HANDS**

**SA-Hands: Spatial Attention around Hands crops**

- Inception features from RGB crops around hands
- Attention weights computed given
  - ✓ augmented pose
- Fully differentiable

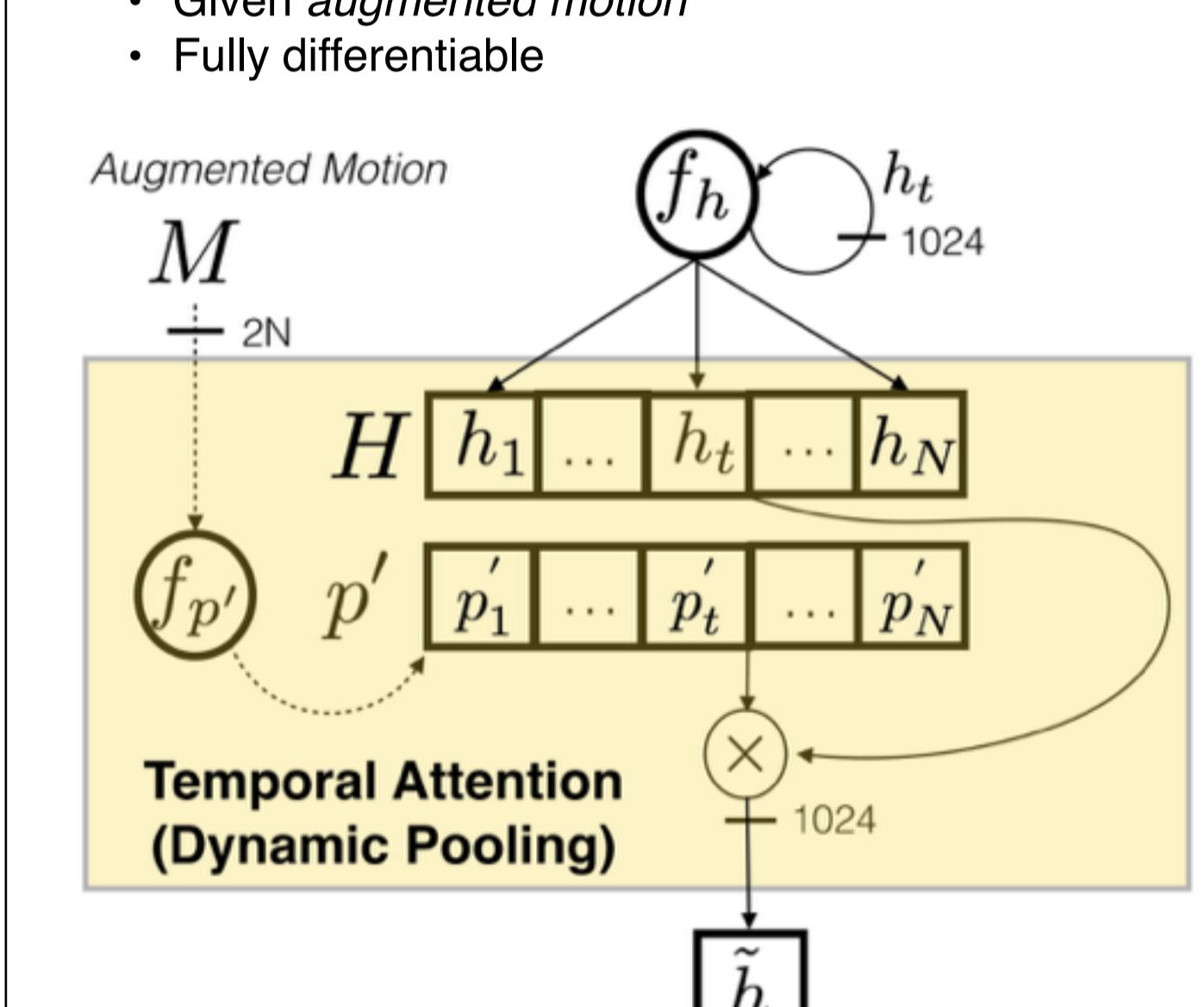


**Glossary:**

- $f_g$  : Inception feature vector
- $p_t$  : Spatial Attention weights for each hand
- $\tilde{v}_t$  : Output of the Spatial Attention framework - Input of the LSTM
- $f_h$  : GRU
- $\tilde{x}_t$  : Augmented Pose

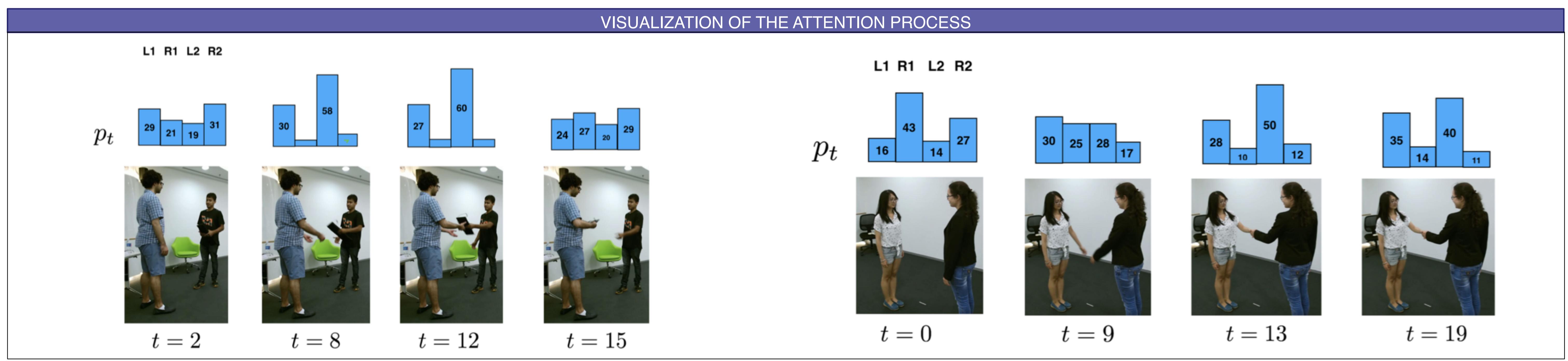
**Temporal Attention on LSTM features**

- Can be seen as a dynamic pooling
- Weighted average of hidden states
- Given augmented motion
- Fully differentiable



**Glossary:**

- $h_t$  : hidden state at timestep t
- $p'_t$  : Temporal Attention weights
- $\tilde{h}$  : Final features vector
- $f_y$  : Classifier
- $M$  : Augmented Motion



**EXPERIMENTAL RESULTS**

Methods	Pose	RGB	CS	CV	Avg
Lie Group [35]	X	-	50.1	52.8	51.5
Skeleton Quads [9]	X	-	38.6	41.4	40.0
Dynamic Skeletons [13]	X	-	60.2	65.2	62.7
HBRNN [8]	X	-	59.1	64.0	61.6
Deep LSTM [30]	X	-	60.7	67.3	64.0
Part-aware LSTM [30]	X	-	62.9	70.3	66.6
ST-LSTM + TrustG. [24]	X	-	69.2	77.7	73.5
STA-LSTM [33]	X	-	73.2	81.2	77.2
GCA-LSTM [25]	X	-	74.4	82.8	78.6
JTM [36]	X	-	76.3	81.1	78.7
MTLN [17]	X	-	79.6	84.8	82.2
DSSCA - SSLM [31]	X X	74.9	-	-	
Deep GRU [A]	X	-	<b>68.0</b>	<b>74.2</b>	<b>71.1</b>
STA-Hands [B]	o X	<b>73.5</b>	<b>80.2</b>	<b>76.9</b>	
A+B	X X	<b>82.5</b>	<b>88.6</b>	<b>85.6</b>	

Table 1: Results on the NTU RGB+D dataset with Cross-Subject (CS) and Cross-View (CV) settings (accuracies in %, o means that pose is only used for the attention mechanism).

**Comparison**

- State of the art on NTU RGB+D (NTU) (~57'000 videos - 60 classes)
- First to combine 3D skeleton data and RGB frames on NTU

**Ablation Study**

- Attention Conditioning: pose features > hidden state
- Attention mechanism has a high impact on RGB only stream
  - ✓ Spatial Attention : + 3.5 points
  - ✓ Temporal Attention : + 3.2 points
  - ✓ Spatio-Temporal Attention : + 5.4 points
- Still a significant impact on the two stream model
  - ✓ Spatial Attention : + 1.6 points
  - ✓ Temporal Attention : + 1.4 points
  - ✓ Spatio-Temporal Attention : + 2.8 points

Table 2: Effects of the conditioning on the spatial attention and the temporal attention (RGB stream only, accuracies in %).

RGB stream methods	Spatial Attention	Temporal Attention	CS	CV	Avg	
	Hidden state	Augmented Pose	Augmented Pose			
Sum	-	-	-	68.3	74.6	71.5
Concat	-	-	-	68.9	75.2	72.0
SA-Hands	X	-	-	69.8	76.2	73.0
ST-Hands	-	X	-	<b>71.0</b>	<b>78.9</b>	<b>75.0</b>
STA-Hands	-	X	X	70.5	76.6	73.6
STA-Hands	X	-	X	72.2	77.8	75.0
STA-Hands	-	X	X	<b>73.5</b>	<b>80.2</b>	<b>76.9</b>
STA-Hands	X	X	X	72.8	78.3	75.6

Table 3: Effects of conditioning the spatio-temporal attention on different latent variables in the RGB stream for the two-stream model (accuracies in % on NTU). The pose stream is always the same: (Deep GRU) for every row.