Trajectory estimation and step detection

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Purpose

Propose a new pipeline for indoor navigation with Inertial Measurement Unit (IMU) sensors.

Motivation

- Indoor trajectory estimation
- Measure activity level

Method

- Combine step detection and trajectory estimation
- Use instant velocities
- Use attention mechanism for instant velocities

Problem statement

Find the superposition of functions F_{tr}, which transforms sensors data to trajectory estimation and F_{st} - to step labels.

Data

1. $\mathcal{A} \in \mathbb{R}^{3\times T}$ - accelerometer readings
2. $\mathcal{W} \in \mathbb{R}^{3\times T}$ - gyroscope readings
3. $\mathcal{S} \in \{0,1\}^2$ - steps labels

Minimization of loss function

$$\arg\min_{F_{\text{tr}},F_{\text{st}}} \mathcal{L}\left(\left(F_{\text{tr}}\left(\mathcal{A},\mathcal{W}\right),\mathcal{T}\right),\left(F_{\text{st}}\left(\mathcal{A},\mathcal{W}\right),\mathcal{S}\right)\right) \tag{1}$$

Combined loss function:

Loss function

$$\mathcal{L}(\hat{\mathbf{y}}_t,\mathbf{y}_t) = \|\hat{\mathbf{v}}_x - \mathbf{v}_t\|_2^2 - w(s_r \log p_r + s_l \log p_l), y_t = \left(v_x^t, v_y^t, s_r^t, s_l^t\right)$$

1. s_r^t, s_l^t - steps labels for right and left legs at timestamp t.
2. v_x^t, v_y^t - velocities on timestamp t.
3. p_r^t, p_l^t - predicted probability of step.

RMSE

Absolute trajectory error (**RMSE**) defined as the root mean square error between predicted and ground truth trajectories:

$$\mathcal{L}_{\text{tr}}(\hat{\mathcal{T}}, \mathcal{T}) = \left(\frac{1}{N}\sum_{i=1}^{N}\left((\hat{t_{x}}_i - t_{x\,i})^2 + (\hat{t_{y}}_i - t_{y_i})^2\right)\right)^{1/2} \tag{2}$$

MIE

Mean integral distance (**MIE**) between predicted and ground truth trajectories:

$$\mathcal{D}_{\text{tr}}(\hat{\mathcal{T}}, \mathcal{T}) = \frac{\sum_{i=1}^{N}\left((\hat{t_{x}}_i - t_{x\,i})^2 + (\hat{t_{y}}_i - t_{y_i})^2\right)^{1/2}\left((t_{x\,i} - t_{x\,i-1})^2 + (t_{y_i} - t_{y_{i-1}})^2\right)^{1/2}}{\sum_{i=1}^{N}\left((t_{x\,i} - t_{x\,i-1})^2 + (t_{y_i} - t_{y_{i-1}})^2\right)^{1/2}} \tag{3}$$

GAP

Distance between the first and the last points (**GAP**):

$$\mathcal{G}_{\text{tr}}\left(\hat{\mathcal{T}}\right) = \left(\left(\hat{t_{x\,1}} - \hat{t_{x\,N}}\right)^2 + \left(\hat{t_{y\,1}} - \hat{t_{y\,N}}\right)^2\right)^{1/2} \tag{4}$$

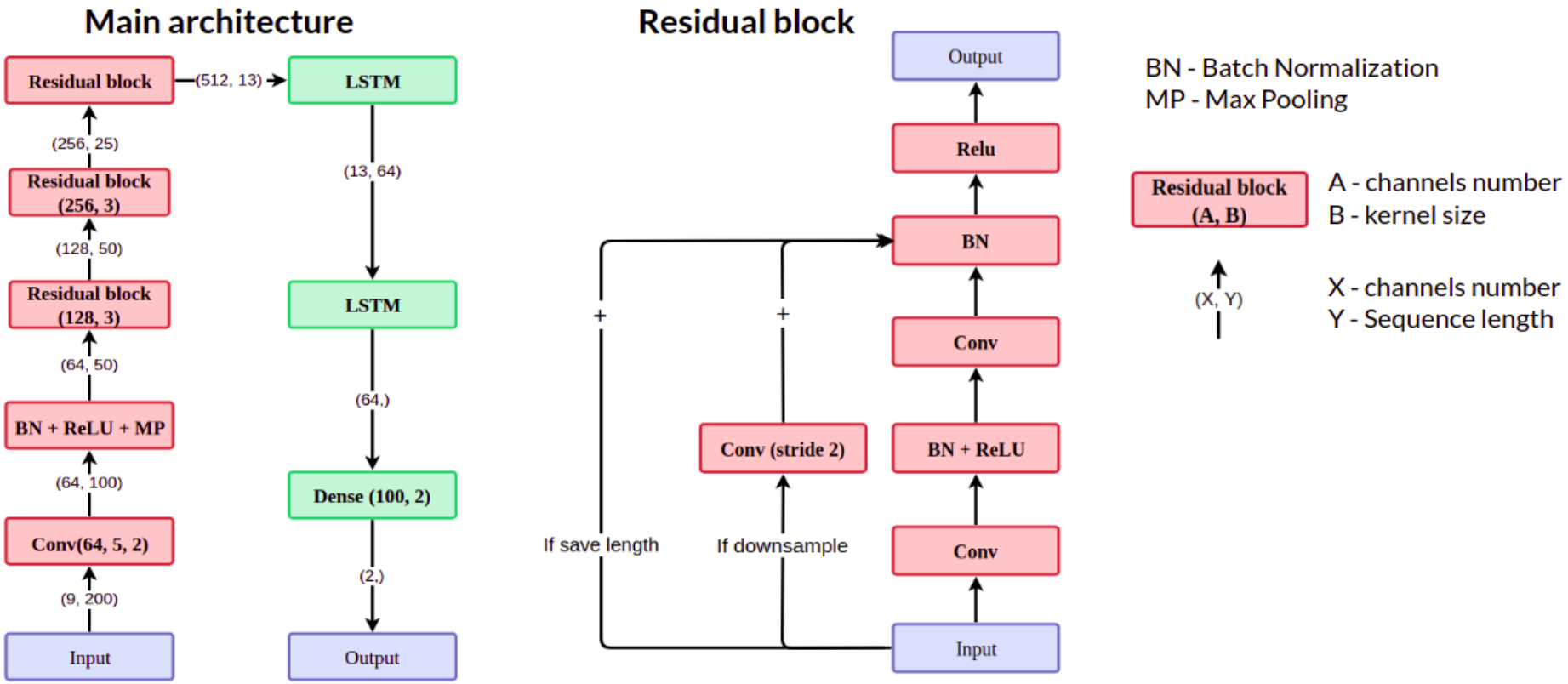
RTE

Relative trajectory error defined as the average RMSE over a fixed time interval — w, if the sequence is shorter than w we compute the positional error and scale it proportionally:

$$\mathcal{R}_{\text{tr}}(w, \hat{\mathcal{T}}, \mathcal{T}) \approx \frac{1}{\lfloor N/w \rfloor} \sum_{i=1}^{\lfloor N/w \rfloor} \left(\frac{1}{w} \sum_{i=1}^{w} \left(\left(\hat{t_{x\,kw+i}} - t_{x\,kw+i}\right)^2 + \left(\hat{t_{y\,kw+i}} - t_{y\,kw+i}\right)^2\right)\right)^{1/2} \tag{5}$$

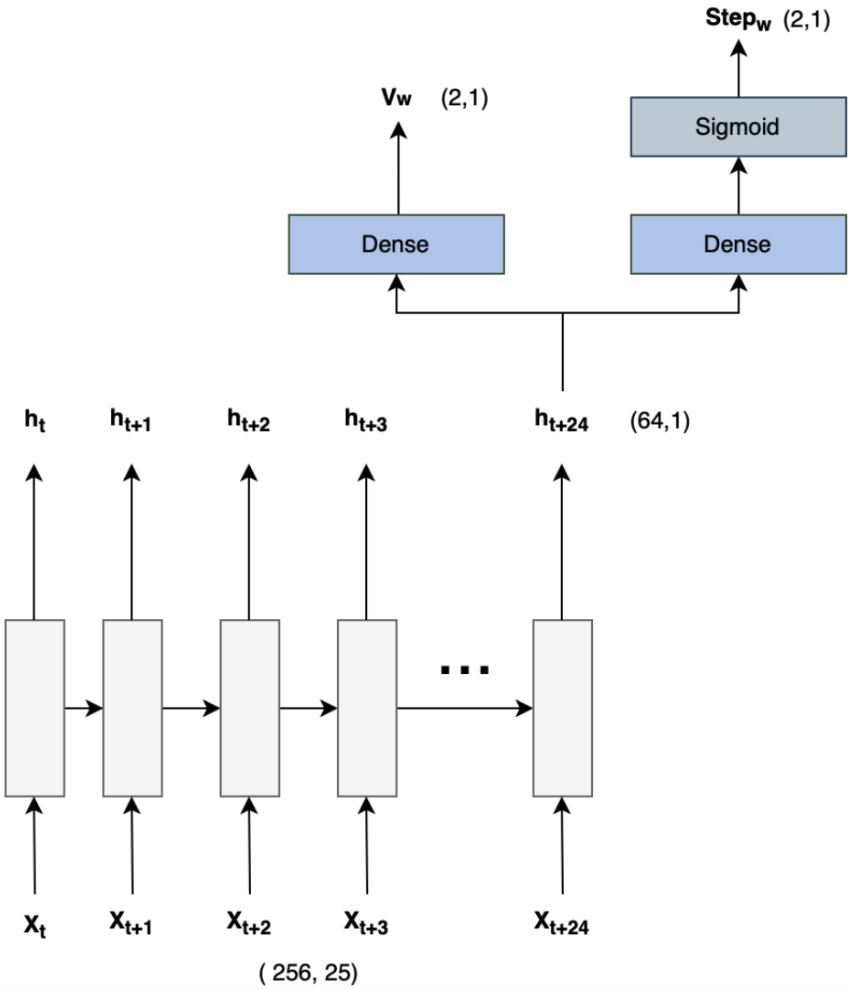
Baseline model

ResNet-18 without the last layer stacked with two LSTM layers



Baseline model

ResNetLSTM with step detection



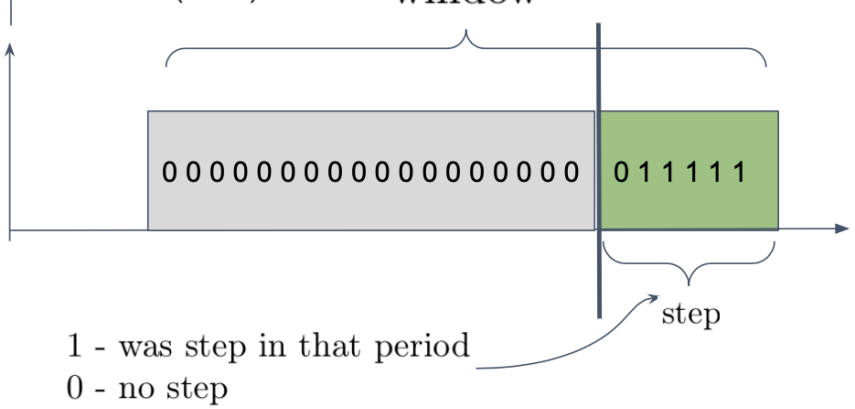
$$\mathcal{L}_w(\mathbf{y}_{true}, \mathbf{y}_{predict}) =$$

$$MSE(\mathbf{v}_{true}, \mathbf{v}_{predict}) + BCE(\mathbf{s}_{true}, \mathbf{s}_{predict}) =$$

$$\|\mathbf{v}_{true} - \mathbf{v}_{predict}\|_2^2 - w(p_{right}(\log s_{right}) + p_{left}(\log s_{left}))$$

$$y = \begin{pmatrix} v_x \\ v_y \\ s_r \\ s_l \end{pmatrix}$$

$w-$ weight for step loss.



1 - was step in that period
0 - no step

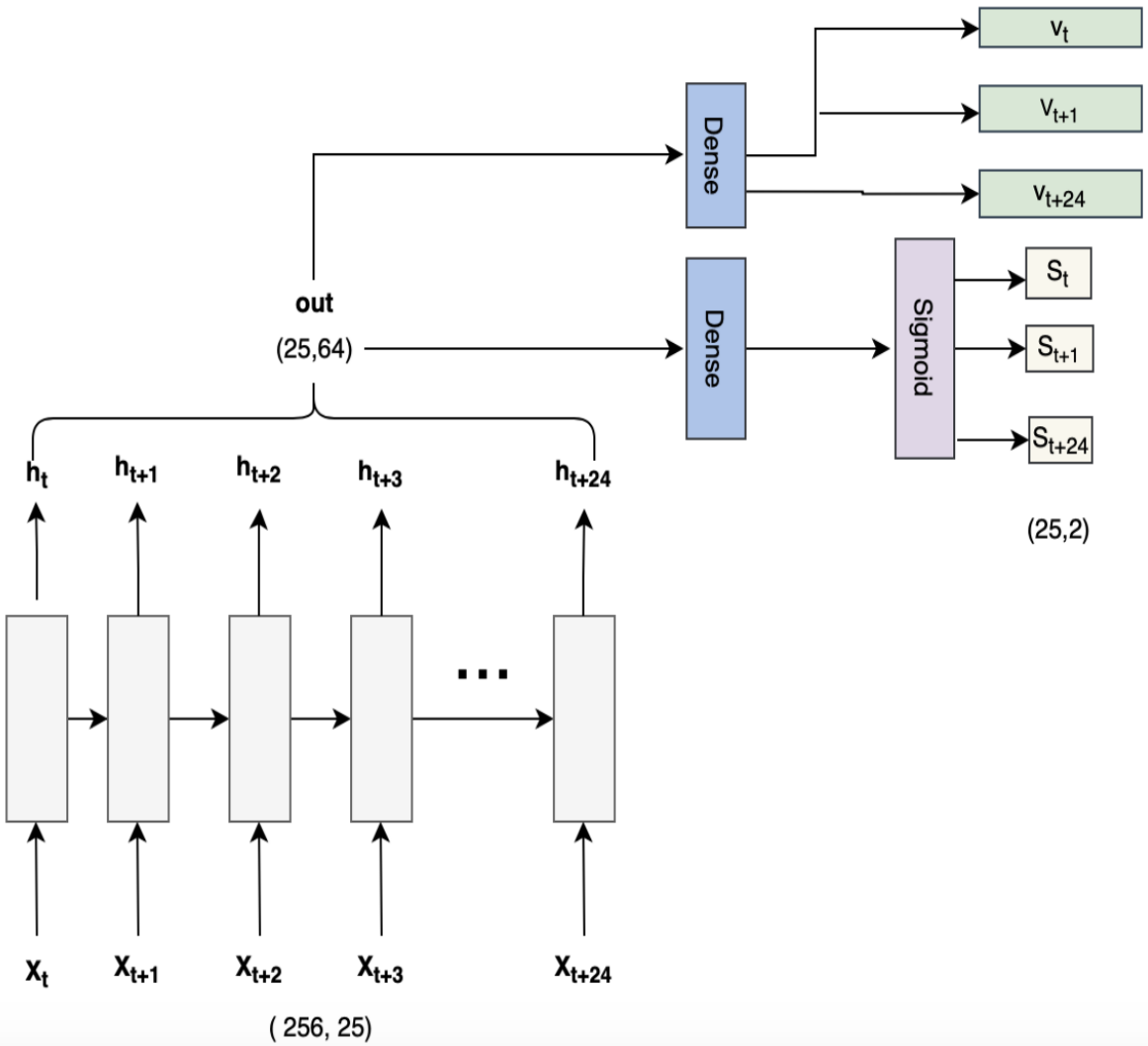
Results ResNetLSTM with step detection

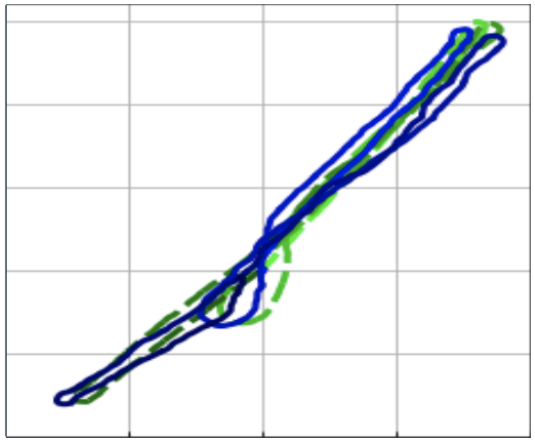
Model	**GAP** $\mathcal{G}_{\mathbf{tr}}$	**MIE** $\mathcal{D}_{\mathbf{tr}}$	**RMSE** $\mathcal{L}_{\mathbf{tr}}$	**RTE** $\mathcal{R}_{\mathbf{tr},\, w=10}$	$\mathcal{R}_{\mathbf{tr},\, w=30}$	$\mathcal{R}_{\mathbf{tr},\, w=60}$
RL	**11.69**	6.57	8.03	6.56	6.83	7.26
RL_step_bce_0.01	13.52	**5.72**	**7.56**	**5.96**	**6.26**	**6.75**
RL_step_bce_0.1	14.13	6.17	8.10	6.38	6.70	7.18
RL_step_mse_0.01	13.08	6.27	8.01	6.42	6.23	7.15

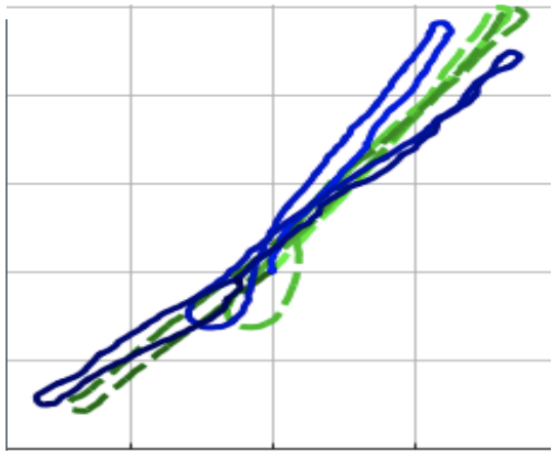
Model	**PRECISION**		**RECALL**		**F1**	
	Right	*Left*	*Right*	*Left*	*Right*	*Left*
RL_step_bce_0.01	0.60	0.63	0.55	0.60	0.60	0.60
RL_step_bce_0.1	0.67	0.68	0.65	0.64	0.66	0.65
RL_step_mse_0.01	0.65	0.67	0.64	0.63	0.64	0.64

ResNetLSTM and step detection results

Instant velocities







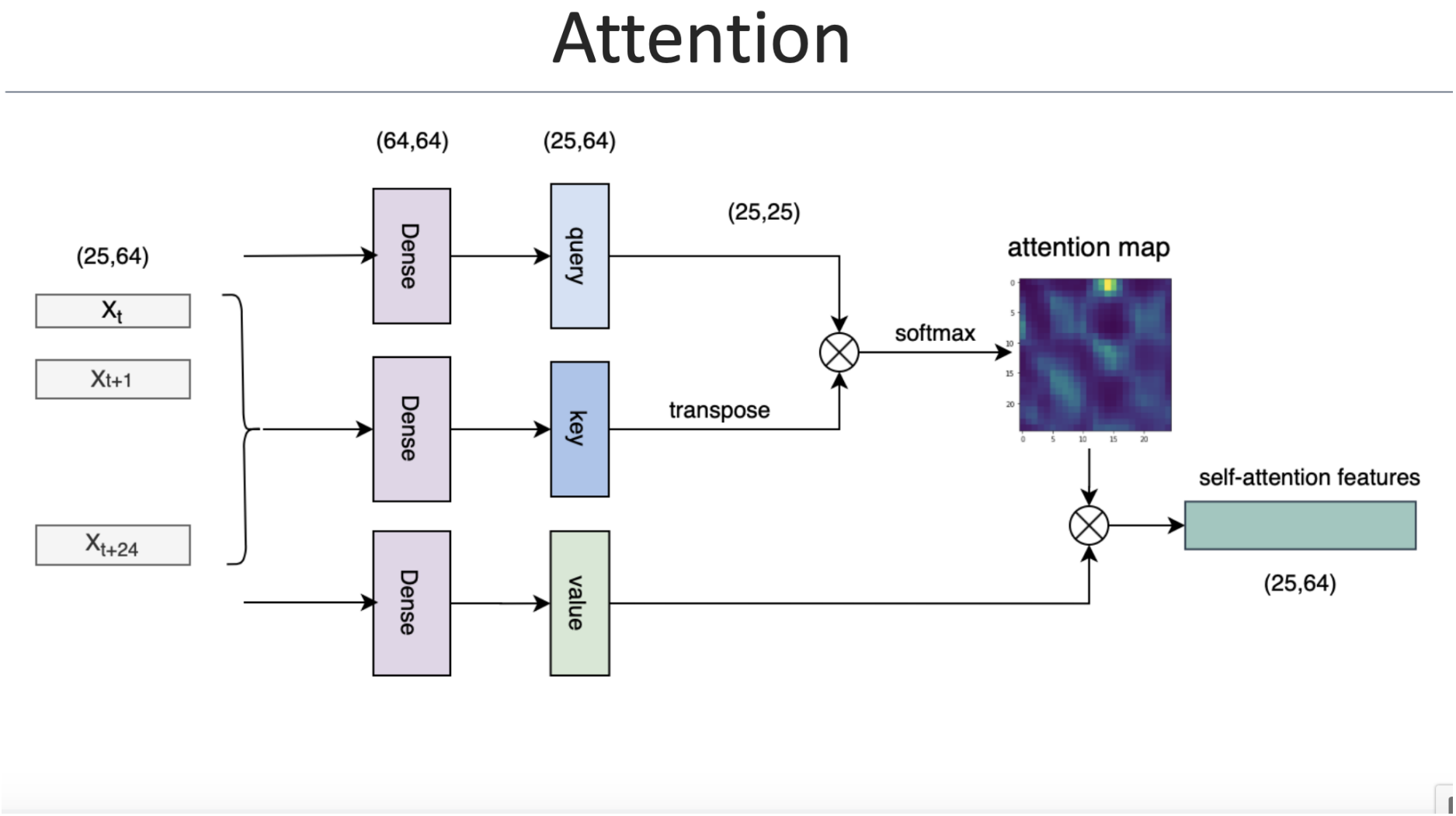
Architecture and comparison

Results ResNetLSTM with instant velocities

Model	**GAP** $\mathcal{G}_{\mathbf{tr}}$	**MIE** $\mathcal{D}_{\mathbf{tr}}$	**RMSE** $\mathcal{L}_{\mathbf{tr}}$	**RTE** $\mathcal{R}_{\mathbf{tr},\, w=10}$	$\mathcal{R}_{\mathbf{tr},\, w=30}$	$\mathcal{R}_{\mathbf{tr},\, w=60}$
RLI_step_bce_0.1	13.95	6.73	8.38	6.89	7.21	7.67
RLI_step_mse_0.005	12.85	5.98	7.79	6.18	6.47	6.91
RLI_step_mse_0.01	12.97	6.21	7.99	6.36	6.66	7.09

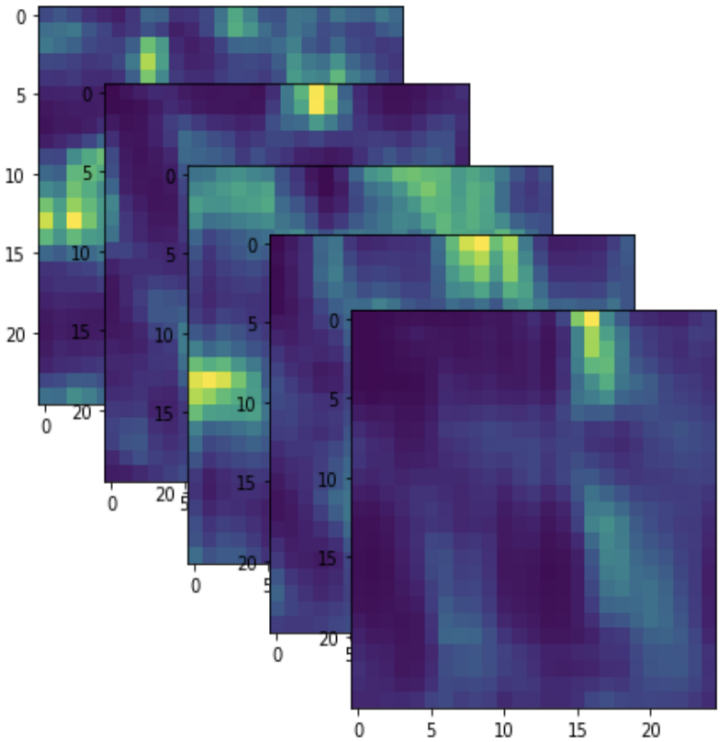
Model	**PRECISION**	**RECALL**	**F1**	**AVERAGE RELATIVE ERROR**
RLI_step_bce_0.1	**0.89**	**0.81**	**0.84**	**0.20**
RLI_step_mse_0.005	0.80	0.68	0.74	0.27
RLI_step_mse_0.01	0.81	0.73	0.77	0.25

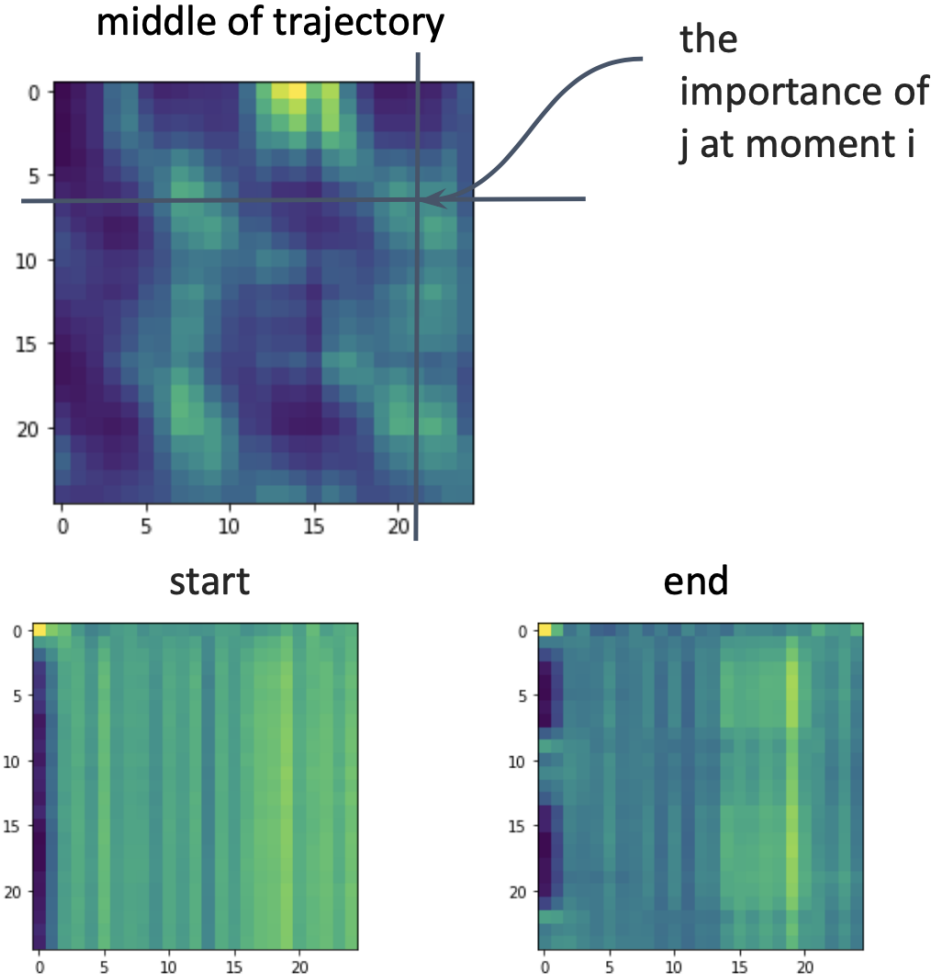
ResNetLSTM Instant velocity and step detection results



Attention layer

Attention maps





Results attention

Model	GAP	MIE	RMSE	RTE		
	$\mathcal{G}_{\mathbf{tr}}$	$\mathcal{D}_{\mathbf{tr}}$	$\mathcal{L}_{\mathbf{tr}}$	$\mathcal{R}_{\mathbf{tr},\, w=10}$	$\mathcal{R}_{\mathbf{tr},\, w=30}$	$\mathcal{R}_{\mathbf{tr},\, w=60}$
RLIA_step_bce_0.1	13.97	6.09	8.07	6.34	6.64	7.14
RLIA_step_mse_0.01	13.46	5.85	7.75	6.10	6.40	6.88

Model	PRECISION	RECALL	F1	AVERAGE RELATIVE ERROR
RLIA_step_bce_0.01	0.87	0.77	0.81	0.21
RLIA_step_mse_0.01	0.82	0.74	0.78	0.24

ResNetLSTM with self-attention and step detection results

Conclusion and future work

1. The quality of the proposed models is much better than quality of baseline approach.
2. The average relative error for step detection is less then 0.27.
3. Attention gives good quality and can be test on other datasets.