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# Hierarchical Deep Temporal Models for Group Activity Recognition

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## PROBLEM

Perform group activity recognition in two different contexts: Surveillance and Volleyball videos.

## CHALLENGES

1. Definition of group activity is **context dependent**. In surveillance video, it is based on what the majority of the people are doing, while in volleyball video, it is defined by what a few key players are doing.
2. It is a high level description of a video – Group activity is function of each individual activity.

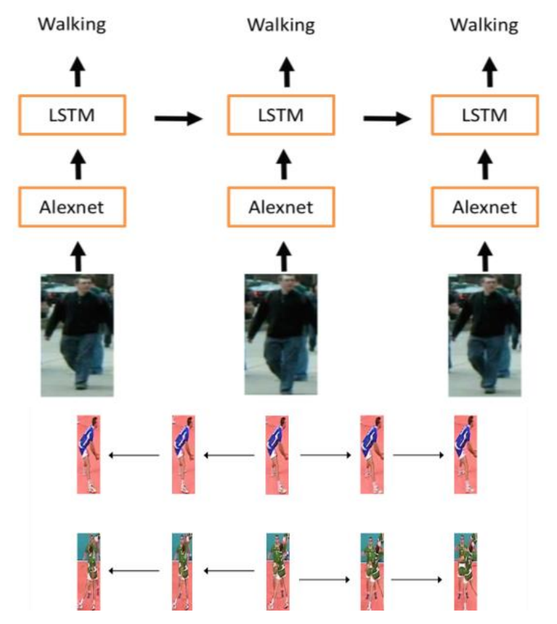
Group Activity = Majority's Activity
Group Activity = Key Player's Activity
Waiting
Group Activity – Right spike

## CONTRIBUTION

A novel deep temporal architecture that models group activities in a principled structured spatio-temporal framework based on modeling individual activities.

## STEP 1: BUILD PERSON REPRESENTATIONS

- **Target**: Build a spatio-temporal representation for every person's activity.
- Track a manually annotated bounding box for each person for a fixed temporal window around the target frame.
- Extract deep visual representation for each tracked person using Alexnet's fc7 features,
- Feed fc7 to a person LSTM to model the temporal dimension.
- Extract spatio-temporal features per person from its LSTM

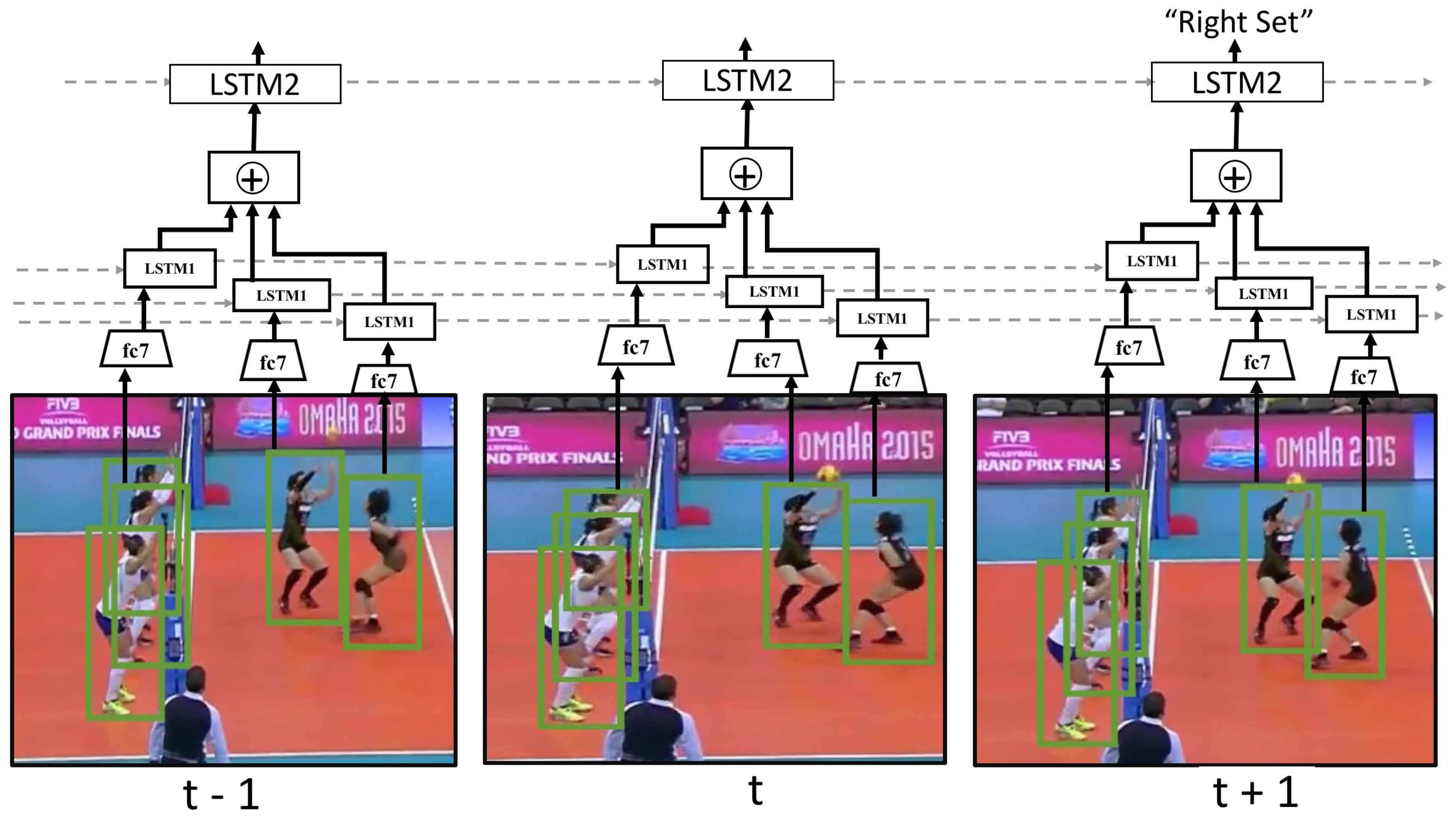


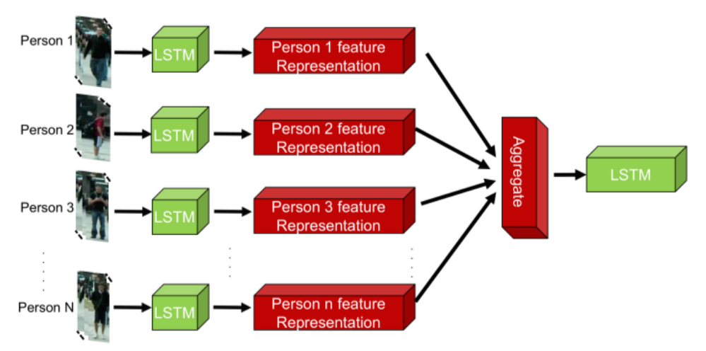
## STEP 2: BUILD GROUP ACTIVITY REPRESENTATION

- **Target**: Build a spatio-temporal representation for the group activity of a given frame
- Aggregate all individual person representations for every temporal step.
- For aggregation, standard pooling operators (e.g. max/avg pooling) are experimented
- Feed aggregated representation to a group level LSTM
- Extract spatio-temporal representation for the group activity from the top-level LSTM
- Learn a softmax classifier on top of the group activity representation.

## OVERALL MODELS

### Non-spatial Model




Person 1
Person 2
Person 3
Person N
LSTM
LSTM
LSTM
LSTM
Person 1 feature Representation
Person 2 feature Representation
Person 3 feature Representation
Person n feature Representation
Aggregate
LSTM

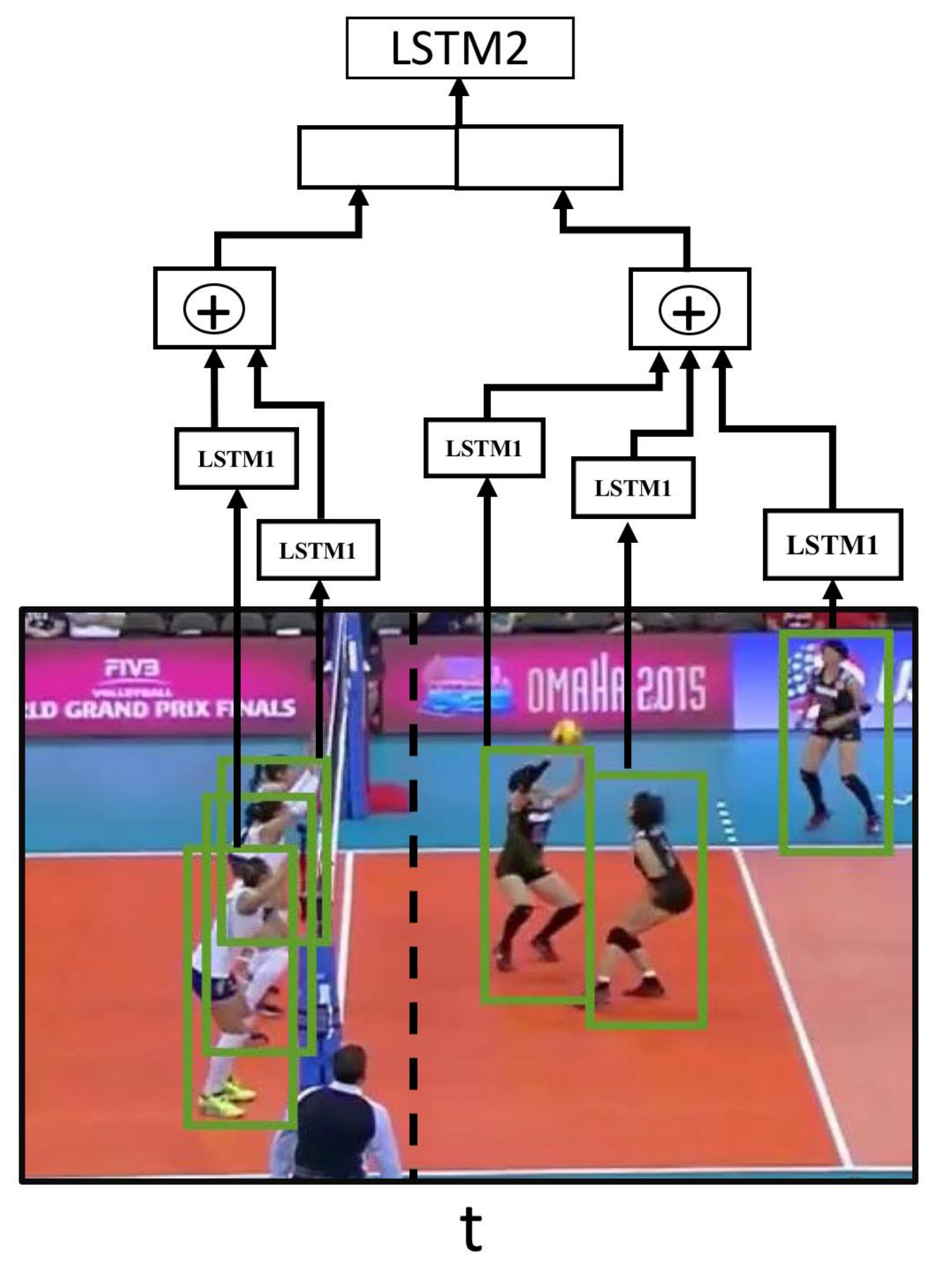
### PERSON LEVEL LSTMs

$$
\begin{aligned}
i_t &= \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i) \\
f_t &= \sigma(W_{xf}x_t + W_{hf}h_{t-1} + b_f) \\
o_t &= \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \\
g_t &= \phi(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \\
c_t &= f_t \odot c_{t-1} + i_t \odot g_t \\
h_t &= o_t \odot \phi(c_t)
\end{aligned}
$$

### Frame LEVEL LSTMs

$$
\begin{aligned}
P_{tk} &= x_{tk} \oplus h_{tk} \\
Z_t &= P_{t1} \diamond P_{t2} \ldots \diamond P_{tk}
\end{aligned}
$$

### Spatial Model



Frame LSTM

Concatenation

Team Pooling

Person LSTM

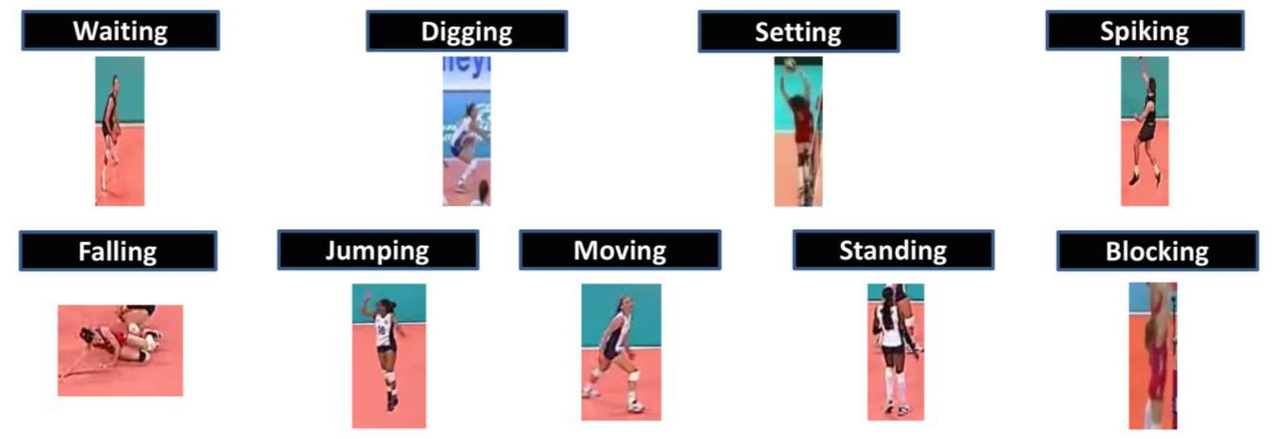
### Frame LEVEL LSTMs

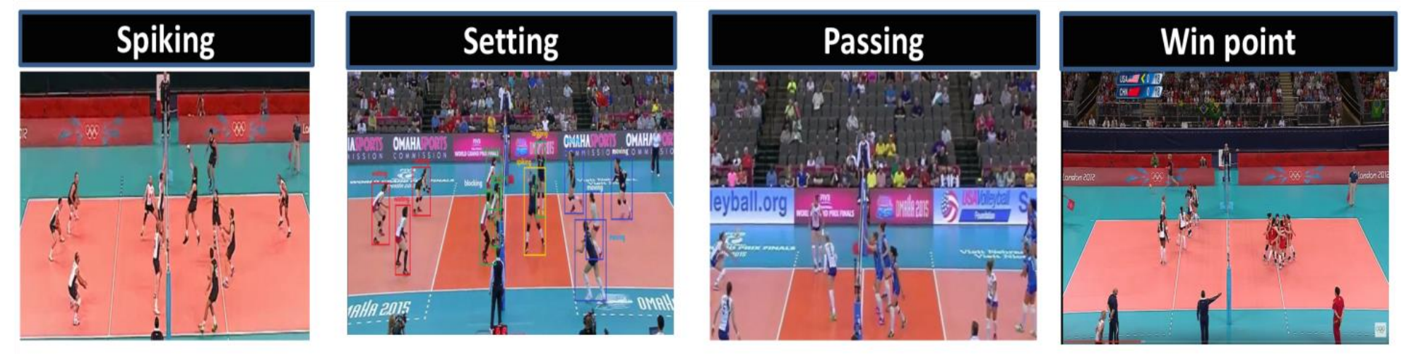
$$
\begin{aligned}
P_{tk} &= x_{tk} \oplus h_{tk} \\
S_m &= (m-1) * k/d + 1 \\
E_m &= m * k/d \\
G_{tm} &= P_{tSm} \diamond P_{t(Sm+1)} \ldots \diamond P_{tEm} \\
Z_t &= G_{t1} \oplus G_{t2} \ldots \oplus G_{td}
\end{aligned}
$$

- **Problem**: Pooling all players' representation in one representation reduces the model capabilities
- **Proposal**: players are split to several sub-groups and recognize the team activity based on the concatenation of each sub-group's representation.

## NEW VOLLEYBALL DATASET

- 4830 annotated frames from 55 publicly available YouTube videos.
- 9 person level labels, and 8 group activity labels.





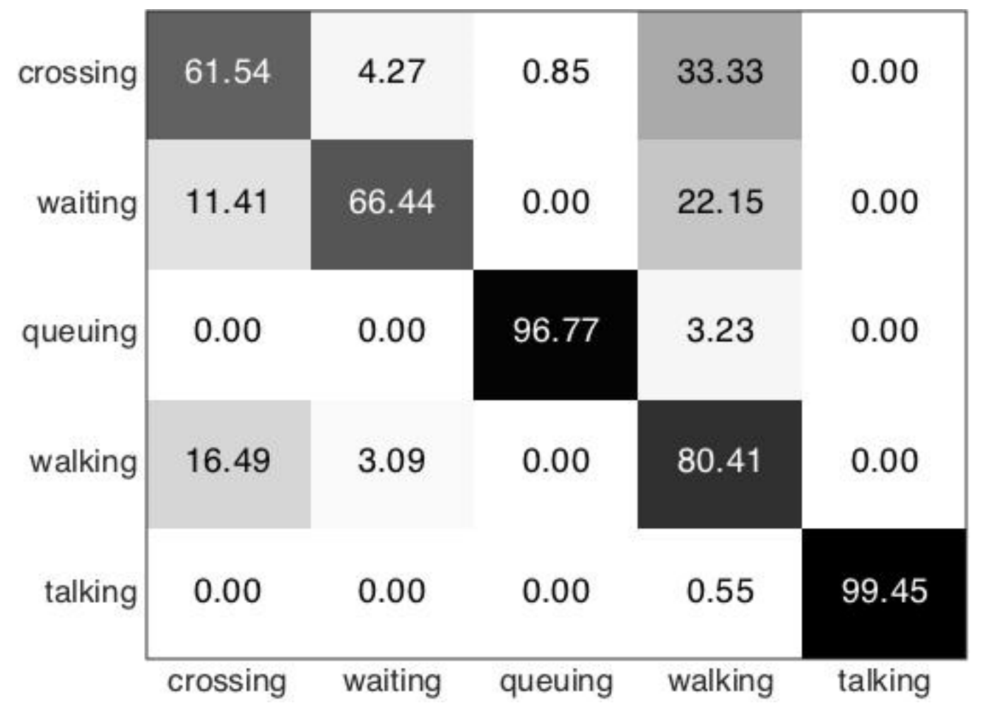
Left/right team variants

## EXPERIMENTS

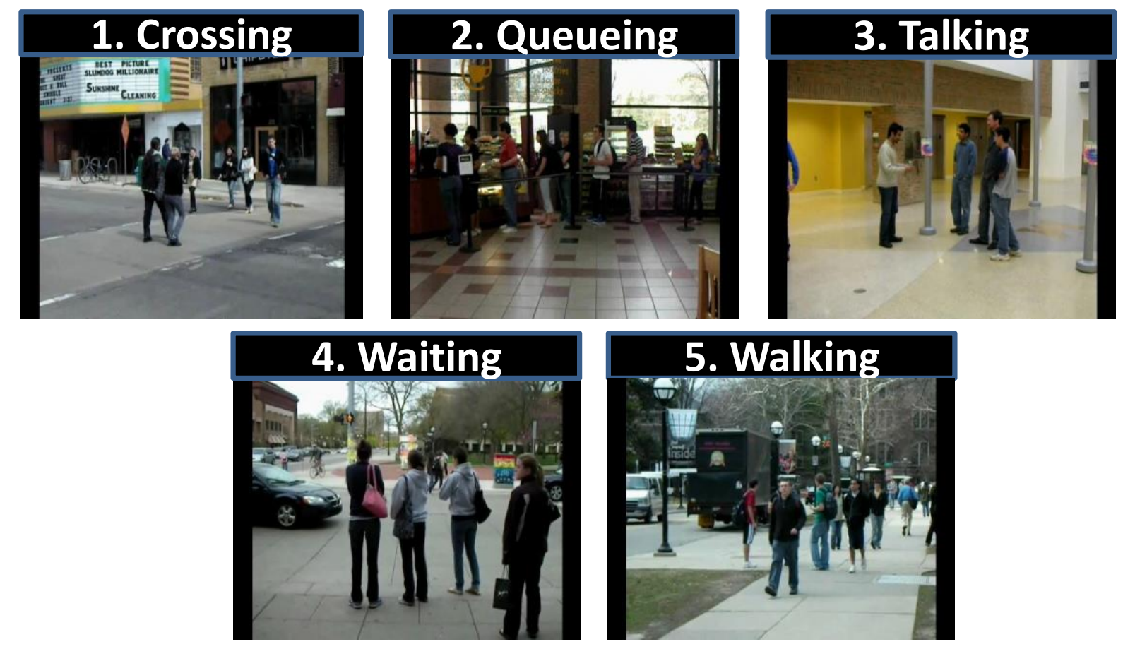
### Collective Activity Dataset

- Same label set for people and group activities
- 1925 video clips for training, 638 clips for testing

| Method | Accuracy |
|---|---|
| B1-Image Classification | 63.0 |
| B2-Person Classification | 61.8 |
| B3-Fine-tuned Person Classification | 66.3 |
| B4-Temporal Model with Image Features | 64.2 |
| B5-Temporal Model with Person Features | 64.0 |
| B6-Two-stage Model without LSTM 1 | 70.1 |
| B7-Two-stage Model without LSTM 2 | 76.8 |
| **Two-stage Hierarchical Model** | **81.5** |

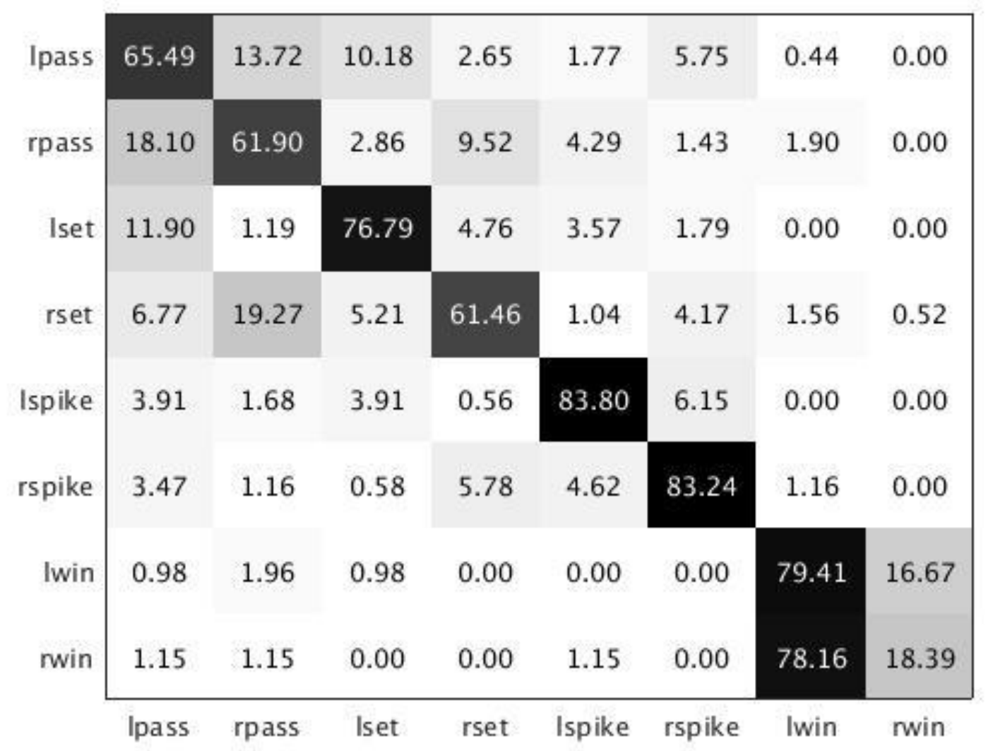


| | crossing | waiting | queuing | walking | talking |
|---|---|---|---|---|---|
| crossing | 61.54 | 4.27 | 0.85 | 33.33 | 0.00 |
| waiting | 11.41 | 66.44 | 0.00 | 22.15 | 0.00 |
| queuing | 0.00 | 0.00 | 96.77 | 3.23 | 0.00 |
| walking | 16.49 | 3.09 | 0.00 | 80.41 | 0.00 |
| talking | 0.00 | 0.00 | 0.00 | 0.55 | 99.45 |

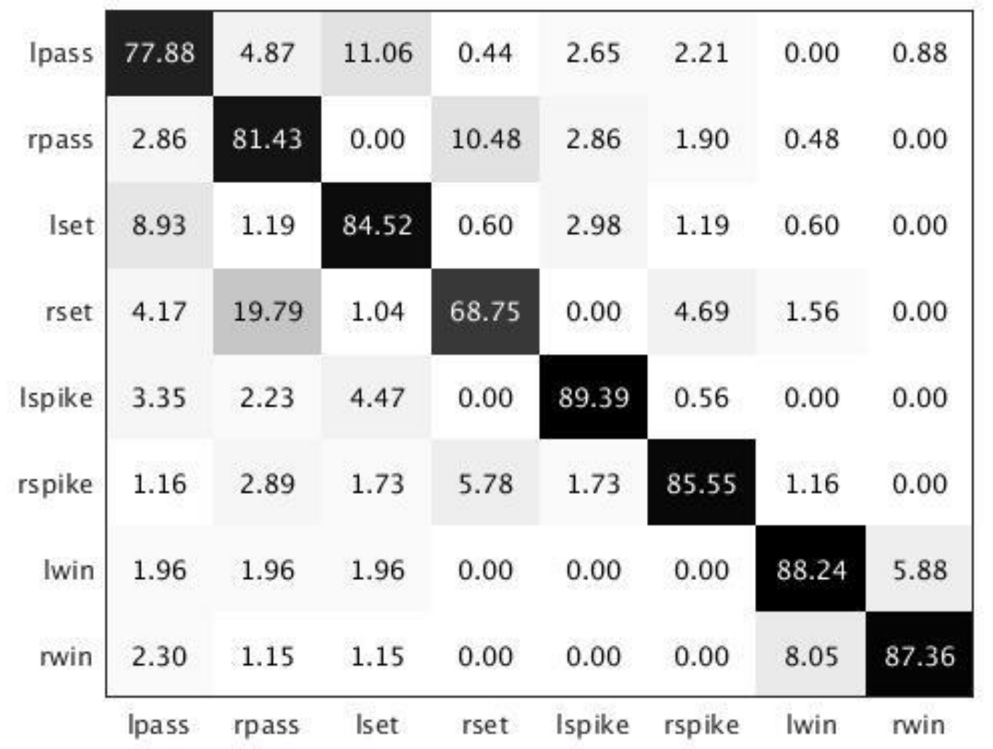


### Volleyball Dataset

| Method | Accuracy |
|---|---|
| B1-Image Classification | 66.7 |
| B2-Person Classification | 64.6 |
| B3-Fine-tuned Person Classification | 68.1 |
| B4-Temporal Model with Image Features | 63.1 |
| B5-Temporal Model with Person Features | 67.6 |
| B6-Two-stage Model without LSTM 1 | 74.7 |
| B7-Two-stage Model without LSTM 2 | 80.2 |
| **Our Two-stage Hierarchical Model** | **81.9** |
| IDTF (Improved Dense Trajectories) | 73.4 |
| IDTF - 1 group-box trajectories | 71.7 |
| IDTF - 2 groups-box trajectories | 78.7 |



| | lpass | rpass | lset | rset | lspike | rspike | lwin | rwin |
|---|---|---|---|---|---|---|---|---|
| lpass | 65.49 | 13.72 | 10.18 | 2.65 | 1.77 | 5.75 | 0.44 | 0.00 |
| rpass | 18.10 | 61.90 | 2.86 | 9.52 | 4.29 | 1.43 | 1.90 | 0.00 |
| lset | 11.90 | 1.19 | 76.79 | 4.76 | 3.57 | 1.79 | 0.00 | 0.00 |
| rset | 6.77 | 19.27 | 5.21 | 61.46 | 1.04 | 4.17 | 1.56 | 0.52 |
| lspike | 3.91 | 1.68 | 3.91 | 0.56 | 83.80 | 6.15 | 0.00 | 0.00 |
| rspike | 3.47 | 1.16 | 0.58 | 5.78 | 4.62 | 83.24 | 1.16 | 0.00 |
| lwin | 0.98 | 1.96 | 0.98 | 0.00 | 0.00 | 0.00 | 79.41 | 16.67 |
| rwin | 1.15 | 1.15 | 0.00 | 0.00 | 1.15 | 0.00 | 78.16 | 18.39 |



| | lpass | rpass | lset | rset | lspike | rspike | lwin | rwin |
|---|---|---|---|---|---|---|---|---|
| lpass | 77.88 | 4.87 | 11.06 | 0.44 | 2.65 | 2.21 | 0.00 | 0.88 |
| rpass | 2.86 | 81.43 | 0.00 | 10.48 | 2.86 | 1.90 | 0.48 | 0.00 |
| lset | 8.93 | 1.19 | 84.52 | 0.60 | 2.98 | 1.19 | 0.60 | 0.00 |
| rset | 4.17 | 19.79 | 1.04 | 68.75 | 0.00 | 4.69 | 1.56 | 0.00 |
| lspike | 3.35 | 2.23 | 4.47 | 0.00 | 89.39 | 0.56 | 0.00 | 0.00 |
| rspike | 1.16 | 2.89 | 1.73 | 5.78 | 1.73 | 85.55 | 1.16 | 0.00 |
| lwin | 1.96 | 1.96 | 1.96 | 0.00 | 0.00 | 0.00 | 88.24 | 5.88 |
| rwin | 2.30 | 1.15 | 1.15 | 0.00 | 0.00 | 0.00 | 8.05 | 87.36 |

## SUMMARY

- A two stage hierarchical model for group activity recognition
- LSTMs as a highly effective temporal model and temporal feature source
- Decent people-relation modeling with simple pooling
- **Code & Dataset**: https://github.com/mostafa-saad/deep-activity-rec

## ACKNOWLEDGMENT

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