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TSA-Net: Tube Self-Attention Network for Action Quality Assessment

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https://github.com/Shunli-Wang/TSA-Net

Introduction

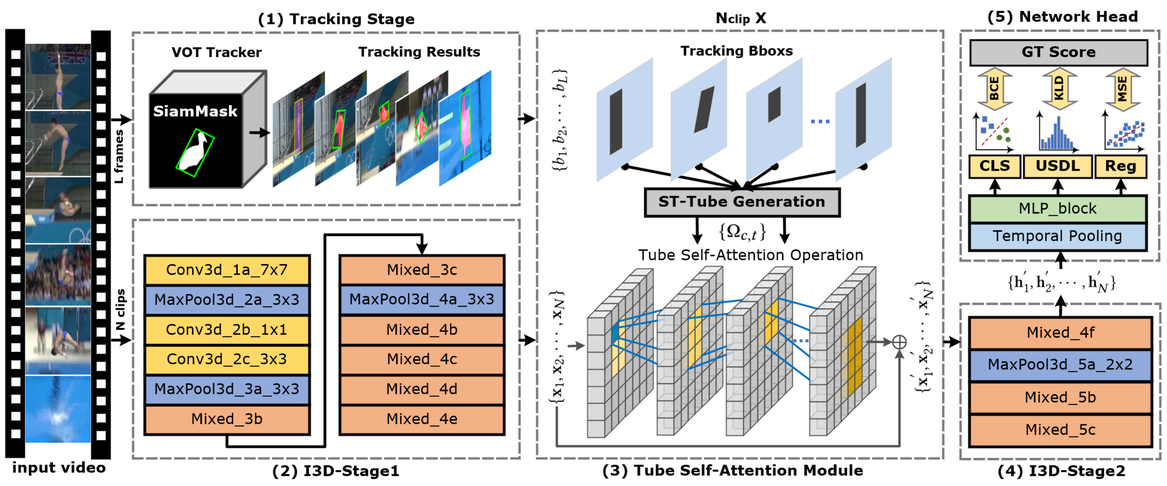
Models in HAR require distinguishing subtle differences between different actions.

Models in AQA require evaluating a specific action's advantages and disadvantages.

Human Action Recognition (HAR) → **Huge GAP** ← **Action Quality Assessment (AQA)**

- Most existing methods in AQA usually directly migrating the model from HAR tasks, which ignores the intrinsic differences within the feature map such as foreground and background information.
- To address this issue, we propose a Tube Self-Attention Network (TSA-Net) for action quality assessment tasks with the following merits:
  - ✔ High Computational Efficiency
  - ✔ High Flexibility
  - ✔ State-of-the-art Performance
- A dataset named FR-FS is proposed to explore the basic action assessment in the figure skating scene.

Framework



Overview of the proposed TSA-Net for AQA

- **1.Tracking**. VOT tracker is adopted to generate tracking results $\mathbf{B}$.
- **2.Feature Extraction-s1**. The input video is divided into N clips and the feature extraction is performed by I3D-Stage1 to generate $\mathbf{X}$.
- **3.Feature Aggregation**. ST-Tube is generated given $\mathbf{B}$ and $\mathbf{X}$, and then the TSA mechanism is used to complete the feature aggregation, results in $\mathbf{X}'$.
- **4.Feature Extraction-s2**. Aggregated feature $\mathbf{X}'$ is passed to I3D-Stage2 to generate $\mathbf{H}'$.
- **5.Network Head**. The final scores are generated by *MLP_Block*.

Experiments

- **Quantitative analysis on AQA-7 and MTL-AQA**

Comparison with SOTAs on AQA-7

Method	Diving	Gym Vault	Skiing	Snowboard	Sync. 3m	Sync. 10m	Avg. Corr.
Pose+DCT [27]	0.5300	-	-	-	-	-	-
ST-GCN [41]	0.3286	0.577	0.1681	0.1234	0.6600	0.6483	0.4433
C3D-LSTM [23]	0.6047	0.5636	0.4593	0.5029	0.7912	0.6927	0.6165
C3D-SVR [23]	0.7902	0.6824	0.5209	0.4006	0.5937	0.9120	0.6937
JRG [22]	0.7630	0.7358	0.6006	0.5405	0.9013	0.9254	0.7849
USDL [33]	0.8099	0.757	0.6538	**0.7109**	0.9166	0.8878	0.8102
NL-Net	0.8296	0.7938	**0.6698**	0.6856	0.9459	0.9294	0.8418
TSA-Net (Ours)	**0.8379**	**0.8004**	0.6657	0.6962	**0.9493**	**0.9334**	**0.8476**

Computational cost analysis on AQA-7

Method	NL-Net	TSA-Net	Comp. Dec.	Corr. Imp.
Diving	2.2G	0.864G	-60.72%	↑0.0083
Gym Vault	2.2G	0.849G	-61.43%	↑0.0066
Skiing	2.2G	0.283G	-87.13%	↓0.0041
Snowboard	2.2G	0.265G	-87.97%	↑0.0106
Sync. 3m	2.2G	0.952G	-56.74%	↑0.0034
Sync. 10m	2.2G	0.919G	-58.24%	↑0.0040
Average	2.2G	0.689G	-68.70%	↑0.0058

Results on MTL-AQA

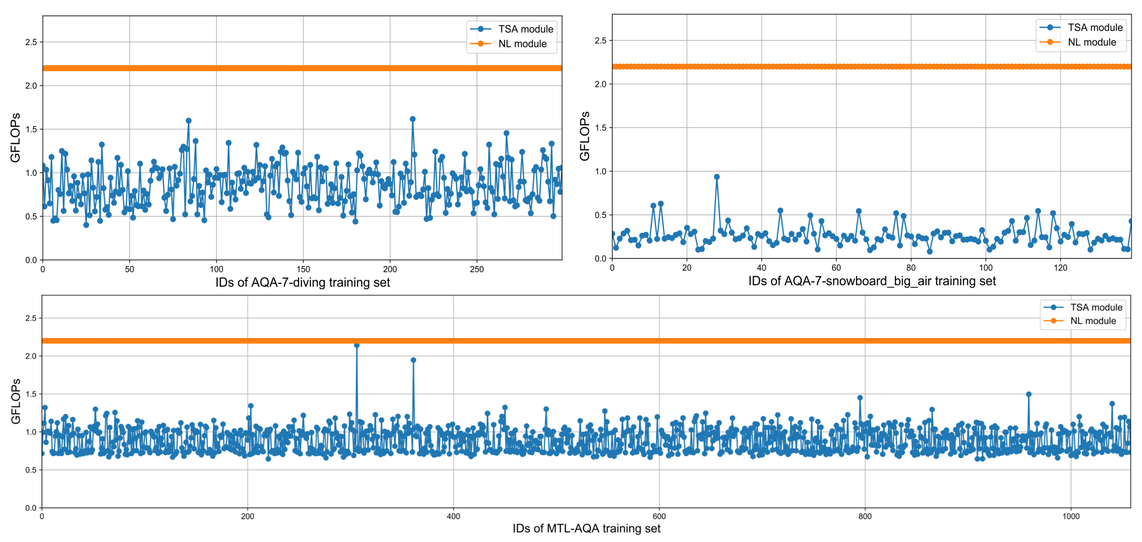
Method	Avg. Corr.
Pose+DCT [27]	0.2682
C3D-SVR [23]	0.7716
C3D-LSTM [23]	0.8489
C3D-AVG-STL [25]	0.8960
C3D-AVG-MTL [25]	0.9044
MUSDL [33]	0.9273
NL-Net	**0.9422**
TSA-Net	0.9393

TSA-Net achieves SOTA performance on AQA-7 and MTL-AQA datasets.

- **Visualization on AQA-7 and MTL-AQA**

Single object tracking strategy can handle these difficult situations perfectly:
★*Camera rotation* ★*Small target* ★*Synchronized diving* ★*Target loss*

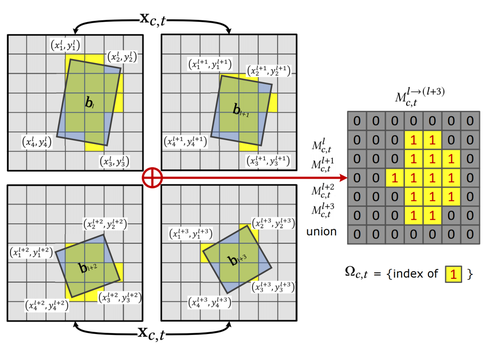
- **Computational cost comparison: TSA module *vs* Non-local**



TSA-Net can obtain better performance while reducing the computational cost.

TSA Module

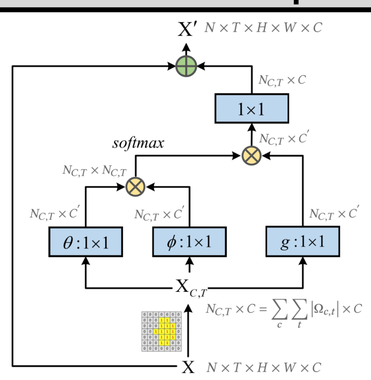
Step 1: Spatio-temporal Tube Gen.



Mask Generation

$$M_{c,t}^{l}(i,j)=\begin{cases}1, S(b_l,(i,j)) \geqslant \tau \\ 0, S(b_l,(i,j)) < \tau\end{cases}$$

Step 2: Tube Self-attention Operation



TSA mechanism

$$\mathbf{y}_p=\frac{1}{C(\mathbf{x})}\sum_{\forall c}\sum_{\forall t}\sum_{\forall (i,j)\in\Omega_{c,t}} f\left(\mathbf{x}_p,\mathbf{x}_{c,t}(i,j)\right)g(\mathbf{x}_{c,t}(i,j))$$

Computational Complexity Reduction $O\left((N\times T\times H\times W)\times(N\times T\times H\times W)\right) \Rightarrow O\left(\left(\sum_c\sum_t|\Omega_{c,t}|\right)\times\left(\sum_c\sum_t|\Omega_{c,t}|\right)\right)$

Conclusion

- In this paper, we present TSA-Net for AQA tasks, which is able to capture rich spatiotemporal contextual information in human motion.
- Experiments on AQA-7, MTL-AQA, and proposed FR-FS demonstrate that TSA-Net can capture long-range information and achieve high performance with less computational cost.
- An adaptive mechanism of ST-Tube will be explored to avoid the sensitivity of the TSA-Net to the size issue in future.

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