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Identification and estimation of 3D yoga poses utilizing color-coded joint angular distance maps

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Abstract

This study presents a novel approach for generating joint angular displacement maps (JADMs) by computing the distance and angle between pairs of joints. The resulting JAD matrix is color-coded to represent the JADMs. The JADMs are then inputted into a lightweight deep network, which achieves an average recognition accuracy of 84% over joint distance maps (JADs).

1.Introduction

When trained with softmax scores, CNNs produce impressive results with images. Previous research reveal some uncertainty when taking color images coded from 3D skeleton data as input to convolutional neural networks (CNNs). To create color texture images for CNNs, for instance, the work in [1] employs joint distance mappings (JDMs) between skeletal joints. Similarly, [2] demonstrates how LSTM networks and CNNs may be used to classify photos from the NTU RGB-D database using reference joint distance maps. When applied to Kinect skeletal or 3D mocap data, the encodings produced highly accurate recognition results. The authors prove that training on several views of data using a multi-channel CNN architecture improves recognition accuracy to a respectable level.

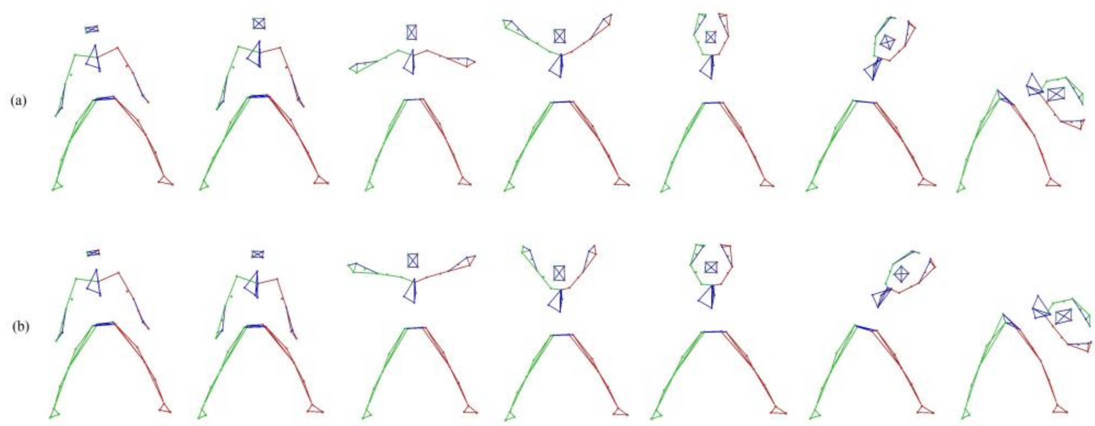

Fig. 1: Showing yoga pose variations in (a) Yoga learner with 6 months experience and (b) with 3 months of experience.

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Finding the right asana among all the possible permutations based on the static and dynamic joint motions that make up a whole asana is a difficult problem for yoga practitioners. Another difficulty arises while attempting to recognize asanas with incomplete poses because the yoga practitioner is unable to achieve a full expression of the asana. It is also being investigated how long a human subject should remain motionless in a pose before moving on to the next asana in a performance. The length of time that a subject can maintain this static stance depends on how well they can maintain their balance. Because of this, the difficulty shifts to one of machine learning's "frame length" varieties. Last but not least, a complete solution to pose estimation during complicated human motions like yoga is evaluated using machine learning algorithms fed 2D coded color texture photos of 3D data.

2.Methodology and result analysis

This portion of the chapter provides a high-level summary of the deep learning architecture used for action recognition. The convolutional neural network (CNN) is the foundation of the deep network built in this section. CNNs have been widely recognized as an effective method for the categorization of images, videos, and other data formats for the better part of a decade. The effort began with the creation of JADMs, followed by the building of a deep network to comprehend the JADMs' patterned architecture (as depicted in the picture.2

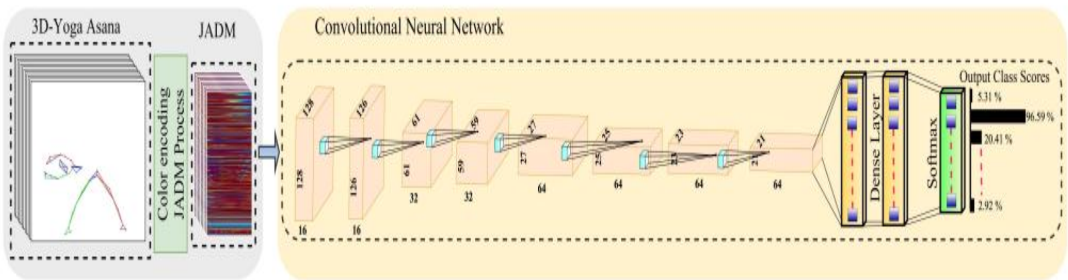

Fig. 2: Proposed CNN architecture for the Yoga Pose estimation using JAD Maps.

Figure.3, depicts the 39 body joints used to model the human body in the 3D yoga action skeleton database. To create the 3D skeleton, 39 markers were used, including 7 for each hand, 2 for the shoulders, 3 for the chest, 4 for the hips, 6 for each leg, and 4 for the head. Joints are consistently labeled in a linear progression from head to toe across the whole dataset.

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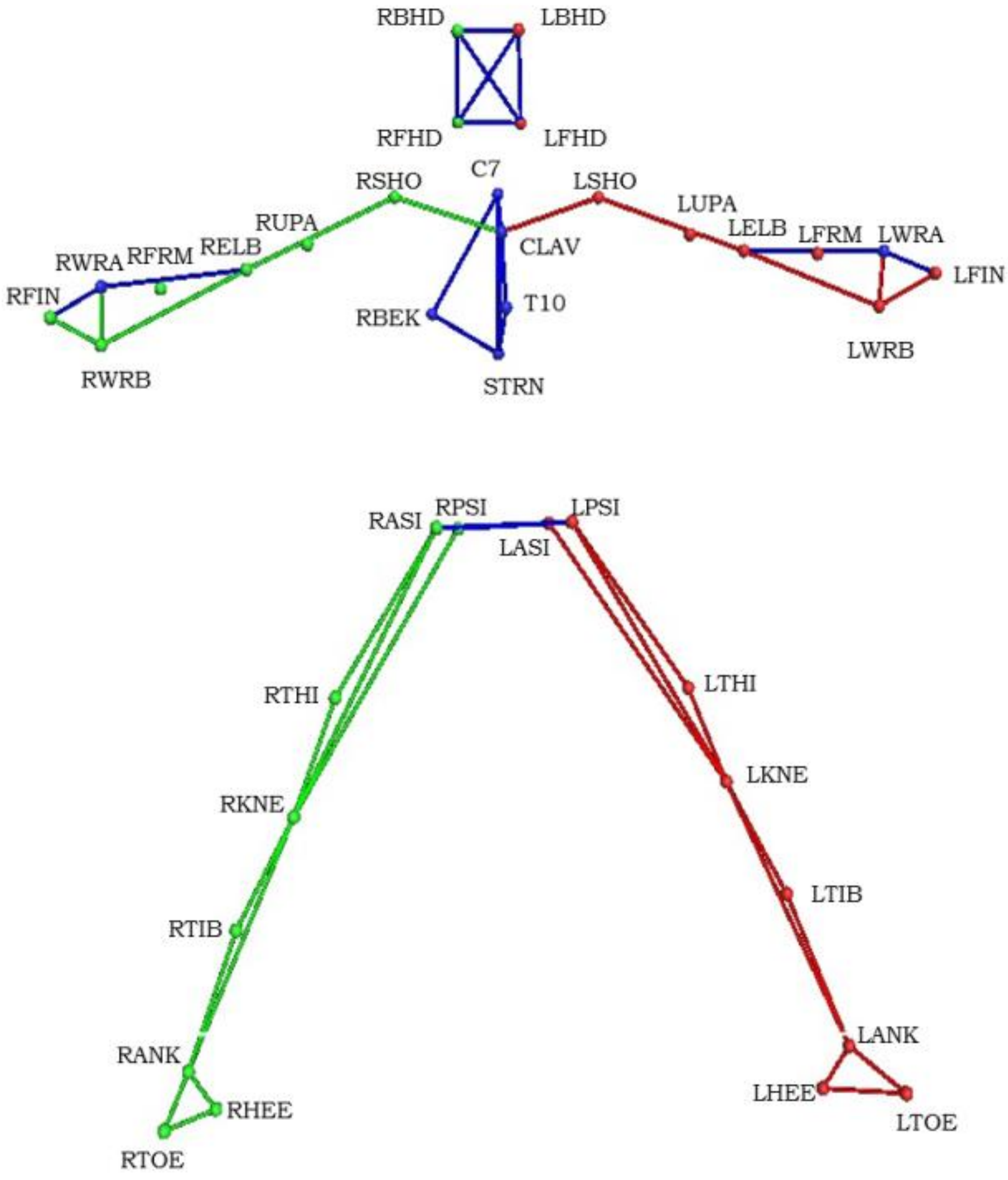

Fig. 3: Joints with class labels for Yoga action recognition

Ten yoga postures (asanas) involving JADMs and JDMs are depicted in the figure.4 confusion matrix. By combining angle data with distance maps, the confusion matrices highlight the impact of this combination.8

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Thadasanam	0.94	0.05	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Triyak Thadasanam	0.05	0.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Kati-Chakrasanam	0.00	0.00	0.95	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.00	0.03	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Vrukshasanam	0.00	0.00	0.00	0.99	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Santhulasanam	0.00	0.01	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Natarajasanam	0.00	0.00	0.00	0.00	0.00	0.97	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Trikonasanam	0.00	0.00	0.01	0.00	0.00	0.00	0.82	0.21	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Viloma-Trikonasanam	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.87	0.00	0.00	0.24	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Parivrutha-Trikonasanam	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.97	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.00
Veerabadrasanam Step I	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.93	0.02	0.00	0.00	0.02	0.00	0.04	0.00	0.00	0.00	0.00
Veerabadrasanam Step II	0.00	0.00	0.00	0.01	0.00	0.02	0.19	0.00	0.00	0.00	0.81	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Utkatasanam	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Padahastasanam	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Surya Namskaram	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.01	0.00	0.00	0.00	0.96	0.02	0.00	0.00	0.00	0.00	0.00
Pachimothasanam	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.91	0.00	0.00	0.09	0.00	0.00
Marjariasanam	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
Vyaghrasanam	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.96	0.00	0.00	0.00
Adho Mukha Svanasana	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.05	0.00	0.00	0.91	0.00	0.00
Kursiasana (Chair Pose)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.95	0.00
Vajrasana	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.03	0.97

Fig. 4: Confusion matrix for 20 class yoga poses tested with the proposed JADM's trained for 98 epochs on the proposed CNN architecture.

3.Conclusions

This chapter kicks off a series proposing new frameworks for human action recognition, with the goal of building a light CNN model on novel JADMs. We begin this section with HAI-1, a single-stream convolutional neural network trained to distinguish between different 3D skeletal-based HA classifications. In the past, we've developed models using a four-stream CNN architecture and a joint distance method (JDM) for each of the four directions (x, y, z, and xyz). In contrast, HAI-1 is a single-stream Convolutional Neural Network (CNN) model that uses newly-built Joint Angular Displacement Maps (JADMs) to represent spatio-temporal information in 3D mocap films in contrast to existing Joint distance maps, the JADM

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