Deep Episodic Memory: Encoding, Recalling, and Predicting Episodic Experiences for Robot Action Execution

Jonas Rothfuss*, Fabio Ferreira*, Eren Erdal Aksoy, You Zhou, and Tamim Asfour

Abstract—We present a novel deep neural network architecture for representing robot experiences in an episodic-like memory which facilitates encoding, recalling, and predicting action experiences. Our proposed unsupervised deep episodic memory model 1) encodes observed actions in a latent vector space and, based on this latent encoding, 2) infers action categories, 3) reconstructs original frames, and 4) predicts future frames. We evaluate the proposed model on two different large-scale action datasets. Results show that conceptually similar actions are mapped into the same region of the latent vector space. Based on this contribution, we introduce an action matching and retrieval mechanism and evaluate its performance and generalization capability on a real humanoid robot in an action execution scenario.

I. INTRODUCTION

Humans are ingenious: We have unique abilities to predict the consequences of observed actions, remember the most relevant experiences from the past, and transfer knowledge from previous observations to adapt to novel situations. The episodic memory which encodes contextual, spatial and temporal experiences during development plays a vital role to introduce such cognitive abilities in humans.

When it comes to cognitive robotics, the main challenge is the lack of a compact and generalizable scheme for encoding, storing, retrieving, and predicting spatio-temporal patterns of visual observations. Such a scheme would allow robots to create memory units to encapsulate gained information from past experiences which can then be recalled to adapt ongoing and future behavior. In this paper, we investigate how to endow a humanoid robot with similar cognitive abilities in a single coherent framework.

We introduce a novel deep neural network architecture for encoding, storing, and recalling past action experiences in an episodic memory-like manner. The proposed deep network encodes observed action episodes in a lower-dimensional latent space. Such a formulation in the latent space allows robots to store visual experiences, classify them based on their conceptual similarities and retrieve the most similar episodes to the query scene or action. The same network further leads to predict and generate the next possible frames of the currently observed action.

To the best of our knowledge, this is the first study introducing that cognitive abilities such as action representing, storing, memorizing, and predicting can be seamlessly achieved in a single coherent framework. This gives a great chance to artificial agents to autonomously infer the most probable behavior to adapt to the current scene. Take the example of the humanoid robot ARMAR-III standing in front of a table with box (see Fig. 1). What is the most suitable action and how can it be performed?

We hypothesise that a latent subsymbolic encoding that our network generates from visual observations are rich and descriptive enough to be compared with those collected from previously experienced episodes. In this way, ARMAR-III can trace all previous observations and select the most similar episode (e.g. “pushing the box” or “grasping the box”) in the latent space. The robot can further generate the same behavior (i.e. pushing or grasping) by directly transferring any relevant action information, e.g. motion profile.

Contribution: The contribution of this work is manifold: (1) We implement a new deep network to encode action frames in a low-dimensional latent vector space. (2) Such a vector representation is used to reconstruct the action frames in an auto-encoder manner. (3) We show that the same latent vectors can also be employed to predict the upcoming future action frames. (4) We benchmark the proposed network on two different well-known action datasets. (5) We propose a mechanism for matching and retrieving visual episodes and finally evaluate its performance on a real humanoid robot ARMAR-III in an action execution scenario.

II. RELATED WORK

In this section we discuss related work from two relevant perspectives. First, we describe the role of episodic memories in cognitive architectures. Second, we discuss contributions in the field of deep learning, emphasizing approaches towards action understanding.
A. Episodic Memory in Cognitive Architectures

In contrast to working memory where the information is temporarily stored for a finite length of time, the long-term memory holds the innate knowledge that enables operation of the system and facilitates learning. The episodic memory, considered as a part of the long-term memory, persists instances of past experiences which can be retrieved to further augment planning and inference [1]. Hereby, the persisted experiences can be represented in manifold ways.

Reinforcement learning based architectures such as CLARION [2] and BECCA [3] implement replay memories and use them to bias future behavior. A different approach is to persist instances of the working memory that were involved in solving a specific problem and subsequently retrieve previous solutions from the episodic memory. Thereby, planning can be enhanced and even facilitate one-shot learning capabilities [4]–[7]. Predominantly, instances stored in the episodic memory are symbolic high-level representations [7], [8]. However, some cognitive architectures also store perceptual instances in their episodic memory [6], [9].

When restricted to a specific context, symbolic representations and pre-specified perceptual instances stored in an episodic memory can indeed be a powerful approach for enhancing the reasoning capabilities of a cognitive system, as shown in Soar [4]. However, most of the described approaches are customized to a specific problem domain and rely on pre-defined, problem specific representations [6], [8]. In complex real world scenarios transferring and generalizing knowledge persisted in the episodic memory is very limited when pre-defined symbolic representations are used. Accounting for nuances and fuzziness may require interpolation between concepts, demanding more flexibility than traditional declarative memory concepts. Our proposed episodic memory, on the other hand, derives subsymbolic representation of actions in a data driven manner and, hence, requires no pre-defined information.

An approach towards an episodic-like memory of video scenes, based on subsymbolic representations, uses Fisher Vectors of convolutional neural network (CNN) percepts to generate encodings of temporal video segments [10]. Scenes originating from the same abstract category (e.g. restaurant), are shown to have the most similar Fisher Vectors, indicating that the subsymbolic representations allow for categorical inference from visual input. Although the approach is not limited to a specific context, it is not possible to reconstruct perceptual information from the Fisher Vector representations. In our work, we go one step further and reconstruct the upcoming future frames.

B. Action Understanding with Deep Neural Nets

Many deep neural network based approaches to understand human action videos combine CNNs and recurrent neural networks (RNNs) [11]–[13]. CNNs capture spatial information in each video frame and aggregate it into a higher-level representation which is then fed through a Long Short-Term Memory (LSTM) that captures temporal information throughout a sequence of frames. Instead of stacking an LSTM on top of a CNN, Shi et al. [14] combine the ideas of spatial weight sharing through convolution and temporal weight sharing through recurrence into a new model called convolutional LSTMs (convLSTM).

Overall, there are two main approaches with regard to deep learning based action understanding: 1) Supervised learning on activity recognition corpora [15]–[17] and 2) Unsupervised video frame prediction [18]–[21]. Latest models for activity recognition involve spatial and temporal attention mechanisms [22], [23], temporal pooling [24] and long-range temporal structure modelling [25].

Aside from human action recognition, the lack of comprehensively labelled video datasets makes supervised training challenging. Another approach towards learning to understand videos is the future frame prediction. Given a sequence of video frames, a deep neural network is trained to predict the next frame(s) in a video. To successfully predict future video frames, the network is forced to generate latent representations of the inherent structure and dynamics of videos.

Srivastava et al. [13] present a composite model consisting of three LSTM networks, conceptually combining an autoencoder with future frame prediction. The first LSTM serves as an encoding network which creates a representation vector of a given video frame sequence. Taking this representation vector as input, one decoder network attempts to reconstruct the frames that were given as input while another decoder predicts future frames. They show that the composite architecture outperforms both a pure autoencoder and future frame prediction model. However, since input and output space are VGG-16 features [26] instead of raw video frames, their model is not able to recover the raw video frames from the latent representation. Our approach is inspired by the composite encoder-decoder architecture but overcomes the described drawback by being able to encode raw frames in an end-to-end fashion and also reconstruct the raw frame sequence from the latent representation.

Subsequent work aims to predict the pixel changes between the current and the next frame [19]–[21] instead of regressing directly into the RGB-pixel space. While such models are shown to be useful for semantic segmentation [20] or planning robot motion [27], they do not create a representation of an episode that can be later reconstructed.

III. Method

A. The Neural Network Model

In this section, we describe our neural network model and the methods applied for comparing and matching visual experiences in the latent space. The network architecture is illustrated in Fig. 2.

We were inspired by the composite encoder-decoder architecture proposed in [13]. Our proposed model conceptually combines an autoencoder with future frame prediction and consists of one encoder and two decoders (see Fig. 2). In this model, a visual experience is represented as a sequence of consecutive video frames $X = X_r \| X_p = x_1, \ldots, x_k \| x_{k+1}, \ldots, x_n$, wherein $X_r$ is the first part of the
frame sequence until frame $x_k$ and $X_p$ represents the remaining $n - k$ frames.

The encoder network $E$ processes the sequence $X_r = x_1, ..., x_k$ and projects it into a latent vector space, yielding a representation of the given frame sequence as a single latent vector $V$ as:

$$ V = E(X_r) . $$

Subsequently, the vector $V$, indicated in red in Fig. 2, is forwarded to both decoders independently which receive the latent vector representation as input and construct a sequence of video frames in return. The first decoder, i.e. the reconstruction-decoder $D_r$, attempts to recover the frames $X_r = x_1, ..., x_k$ that were initially provided to the encoder. Therefore, $D_r$ is trained to output a frame sequence $Y_r = y_1, ..., y_k$ that matches $X_r$, such that

$$ D_r(V) = Y_r = y_1, ..., y_k . $$

The second decoder, the so-called prediction-decoder $D_p$, attempts to predict the future frames $Y_p = y_{k+1}, ..., y_n$ as,

$$ D_p(V) = Y_p = y_{k+1}, ..., y_n . $$

During training, $X_p$ is employed as ground truth for assessing how good the predictions $Y_p$ are and for also computing the error. It is important to note that for determining the reconstruction and prediction error during training, both image sequences $X_r$ and $X_p$ are used. However, during test time, only $X_r$ is fed into the encoder network.

The core idea of the proposed network structure rests upon the latent space vector $V$ being the only linkage between $E$ and both $D_r$ and $D_p$. The two decoder networks solely rely on $V$ as their only source of information to reconstruct a given scene and predict future frames. To obtain robust reconstructions and future frame predictions, the encoder is forced to compress the entire video frame sequence $X_r$ into a comparably low-dimensional latent representation $V$ and, at the same time, to preserve as much relevant information as possible. $E$ and $D_r$ together constitute an autoencoder architecture, requiring that relevant information is preserved throughout the network. However, this only involves remembering the frame sequence $X_r$ but not necessarily requires to capture abstract concepts such as temporal dynamics of objects or actors. By adding the frame predictor which has to extrapolate motions into the future, the encoder must capture higher-level concepts like the scene dynamics in $X_r$ and embed abstract concepts such as trajectories in $V$ so that $D_p$ can properly infer possible future frames.

The input and output frames $x_i$ and $y_i$ used in this work have a resolution of 128 × 128 pixels and 3 color channels together with an additional optical flow channel. Since the main task of the network is to capture spatio-temporal concepts, we make use of convolutional LSTM cells [14]. The encoder network $E$ is comprised of a stack of convolution LSTM and normal convolution layers (henceforth referred to as $convLSTM$ and $conv$ layers) in alternating order (see Fig. 2). While the conv layers are operated with a stride of 2 in order to reduce the spatial size of the feature maps, the convLSTM layers preserve the spatial size and forward information to the next time step through their hidden state and cell state. After the alternating series of conv and convLSTM layers in the encoder, we add a fully connected layer, followed by a fully connected LSTM layer $fc LSTM$ to the stack.

Fig. 2: Structure of the proposed composite encoder-decoder network. It represents the shape of an unrolled network over multiple time steps. The encoder $E$ receives multiple video frames as input and maps them into a latent vector space. The resulting vector representation $V$ (highlighted in red) is forwarded to the two decoder networks. The first decoder ($D_r$) is trained to reconstruct the video frames that were provided to the encoder while the second decoder ($D_p$) attempts to predict the future frames. The dashed box on the left depicts the layers of the encoder network. The label inside each layer denotes the kernel size of the convolutional layer or the number of hidden units of the fully connected (fc) layer, respectively.
With \( fc \) LSTM being the top layer of \( E \) and as LSTM cell connected over time, its cell state \( c_i \) and hidden state \( h_i \) represent the video frame sequence until the current time step \( t \). Once the entire frame sequence \( X_t = x_1, \ldots, x_k \) is processed by the encoder, the hidden state \( h_k \) and cell state \( c_k \) of \( fc \) LSTM at time step \( k \) are extracted and concatenated, yielding the latent vector \( V = h_k \| c_k \).

Both decoders have the inverted structure of the encoder, meaning that transposed convolution layers are used to increase the spatial size of the feature maps throughout the decoding layers until the full video frame resolution of \( 128 \times 128 \) is recovered.

To compute the error \( L \) during the network training, we use a linear combination of image reconstruction loss (\( L_{mse} \)) and gradient difference loss (\( L_{gd} \)) functions as follows

\[
L = (1 - \eta) L_{mse} + \eta L_{gd},
\]

where we set \( \eta = 0.4 \) to trade off between the two loss functions

\[
L_{mse} = \frac{1}{n} \sum_{i=1}^{n} \| y_i - x_i \|_2^2,
\]

\[
L_{gd} = \frac{1}{n} \sum_{i=1}^{n} \sum_{u,v} \| x_{u,v} - x_{u-1,v} \| - \| y_{u,v} - y_{u-1,v} \|_2^2 + \| x_{u,v-1} - x_{u,v} \| - \| y_{u,v-1} - y_{u,v} \|_2^2.
\]

The loss is computed over all ground truth frames \( x_i \) in \( X = X_t \| X_p \) and the output frames \( y_i \) in \( Y = Y_t \| Y_p \) which are produced by \( D_r \) and \( D_p \). The reconstruction loss \( L_{mse} \) compares the generated images \( y_i \) and ground truth images \( x_i \) in a pixel wise manner. When solely trained with \( L_{mse} \) loss, neural network models that regress on images are prone to linear blurring and unstable to small image deformations [11]. In contrast, the \( L_{gd} \) loss compares the horizontal and vertical image gradients of \( x_i \) and \( y_i \), thereby penalizing blurriness and enforcing sharper edges [18].

The described neural network is trained with mini-batch gradient decent using the adaptive learning rate method ADAM [28] in conjunction with an exponentially decaying learning rate schedule. After each network layer except the last encoder and decoder layer (since these are the output layers), we use layer normalization [29] and dropout with a dropout rate between 10\% and 20\%. In order to force the encoder to use the entire latent vector space and produce distinct representations \( V \), we add Gaussian noise \( N(0, \sigma) \) with \( \sigma = 0.1 \) to the latent vector \( V \) during the training, before forwarding \( V \) to the decoder networks. In all of our experiments, the vector \( V \) has a dimension of 2000.

The source code and experimental data are publicly available on the supplementary webpage.¹

## B. Matching Visual Experiences in the Latent Space

One of the central contributions of our work is to compare visual experiences based on their conceptual similarities encoded in the latent space. Given a new visual experience, we can retrieve the most similar episodes from the episodic memory that holds the hidden representations \( V_i \) of episodes experienced in the past. We use the cosine similarity

\[
\cos(V, V') = \frac{V \cdot V'}{|V||V'|}
\]

to measure the similarity of latent vectors. To find best matches in the latent space, we compute the cosine similarity \( \cos(V_q, V_i) \) between the query representation \( V_q \) and each of the \( V_i \) in the memory. Finally, the \( n \) memory instances corresponding to the \( V_i \) with the highest cosine similarity are retrieved from the memory.

## IV. Experimental Evaluation

We evaluate the hypothesis that the encoder-decoder network creates latent representations that embed the inherent dynamics and concepts of a provided visual episode. For this purpose, we train the neural network in an unsupervised fashion on two video corpora, analyze the similarity structure within the latent space and evaluate the network’s capabilities as feature extractor on two activity classification datasets. We assess the model’s abilities to reconstruct the past episode from the latent representation and predict future frames by qualitatively and quantitatively examining the generated frames. Finally, we introduce a matching and retrieval mechanism in the latent space and test its robustness in multiple settings including a robotic application.

### A. Datasets

For the evaluation of our methods we use the large-scale labeled video datasets ActivityNet [16] and 20BN-something-something [30]. We favored these two datasets over other popular datasets like UCF-101 [15] and HMDB-51 [17] since our emphasis is reasoning, planning and executing of robotic tasks in indoor household environment rather than understanding outdoor activities. The ActivityNet dataset [16], a benchmarking corpus for human activity understanding, consists of 10,024 training and 4926 validation video snippets collected from YouTube. It is organized in 93 higher level categories that comprise 203 different activity classes involving activities such as household work, sports and personal care.

While ActivityNet targets higher-level concepts like “vacuuming the floor” and “shovelling snow” that embed semantic meaning, the 20BN-something-something dataset [30] focuses on detailed physical properties of actions and scenes. It contains 174 classes such as “Pushing something from left to right” and “Putting something into something”. The core challenge of this novel dataset is that the type of involved objects as well as the background setting of a given scene only play a neglectable role. Rather than recognizing familiar items and scene backgrounds, the neural network needs to understand the physical composition and motion within the video clips. The dataset consists of 86,017 training and 11,522 validation videos in total.

¹h2t-projects.webarchivKIT.de/projects/episodicmemory
B. Training

Three different models are trained as summarized in Table I. The naming of the trained models is based on the trained dataset (i.e. actNet/20BN) and whether optical flow was employed as an additional channel to RGB. We train all models with \( n = 10 \) frames per video (selected equally spaced). The first \( k = 5 \) frames are fed into the encoder \( E \) to be reconstructed by \( D_e \) while the last five frames are employed as ground truth for the future frame predictor \( D_p \).

C. Conceptual Similarity and Proximity in the Latent Space

To investigate our hypothesis that conceptually similar videos are mapped into the same region of the latent space, we compute the pairwise cosine similarities (see section III-B) of latent vectors. To measure the conceptual similarity, we use the class labels provided in the datasets as the proxy value and assume that videos belonging to the same class are conceptually similar. We generate the latent representation for each video in the validation split of both ActivityNet and 20BN and subsequently compute all pairwise cosine similarities between the latent vectors.

In Fig. 3, the results are visualized as similarity matrices where each row and column of a matrix corresponds to a class label and each entry represents the mean pairwise cosine similarity between the latent vectors belonging to the respective classes. The class labels are arranged horizontally and vertically in the same order, ensuring that the diagonal elements of the matrix depict intra-class similarities and off-diagonals represent inter-class similarities. Due to lack of space, full similarity matrices with class labels are only provided on our supplementary website. Fig. 3 shows that in each matrix the intra-class similarity (diagonal elements) is considerably higher than the inter-class similarity. This is a clear indication that conceptual similarity of videos is reflected by the proximity of their vector representations in the latent space. Consequently, our proposed model captures high-level action concepts within two different datasets, although the model is trained in an unsupervised fashion and thus has never seen any class labels.

Since the latent representation must embed all information for the decoders necessary to reconstruct and predict frames, it may also encode many details (e.g. colors and shapes) in the background that are irrelevant for describing actions. To compile the information embedded in the latent representation to a subset that is more relevant for optimally separating the different classes within the latent space, we apply principal component analysis (PCA) on the mean latent vectors of each class. We assume that less important features are identically distributed in all the classes and thus share approximately the same mean value when averaged over the class. Hence, transforming the latent space towards the principal components computed on the covariance matrix of the mean vectors emphasizes relevant features and neutralizes less important features. Fig. 3(b) and 3(d) show that transforming the latent representations with PCA leads to a better distribution of latent vectors, pushing conceptually similar representations closer together while keeping representations of different classes farther apart.

D. Activity Classification

We argue that the proposed neural network model is also a strong feature extractor for video frame sequences, promoting categorical inference. In particular, we hypothesize that considering the latent representations as features, simple machine learning classifiers can be trained to distinguish between actions. To evaluate the hypothesis, we train various machine learning classifiers with the latent representations and measure the classification performance on both datasets. Therefore, the following settings are explored:

1) Different features for the classifiers: a) raw latent representations \( V \) (with 2000 dimensions) returned by the encoder and b) principal components of \( V \) as described in section IV-C.

2) Different machine learning classifiers: a) linear SVM, b) SVM with RBF kernel, c) Logistic Regression and d) K-nearest neighbor classifier (KNN).

We emphasize that the unsupervised training of our model and the supervised training of the machine learning classifiers are decoupled, meaning that both training steps are performed on different data. Since the model is trained on the training set of ActivityNet or 20BN, we only utilize the respective validation set for both training and testing the classifiers. For this purpose, the validation sets are randomly

| Dataset   | Model Name  | Optical Flow | Top1 Accuracy | Top5 Accuracy |
|-----------|-------------|--------------|---------------|---------------|
| ActivityNet | actNet      | ✓            | 61.22%        | -             |
|            | 20bn        |              | 20.30%        | 42.47%        |
| 20BN       | 20bn_optical_flow | ✓  | 24.19%        | 48.11%        |
split into a training (70%) and test subsets (30%). For parameter tuning and selection of the best classifier we use random permutation cross-validation with 10-folds on the training subset. The final accuracies are computed with the respective test split. The entire process of classifier training and determining the test accuracy is repeated 10 times with random train-test splits. Table I depicts the final classification accuracy of the best performing classifier for each trained model, averaged over the 10 train-test runs.

For ActivityNet, state-of-the-art action recognition models record an error rate of less than 20%. In the 2016 ActivityNet challenge the best accuracy, achieved among the models without audio features by [31], is 81.07%. Although our approach, with an accuracy of 61.22% on ActivityNet, is not able to compete in terms of accuracy, it is important to emphasize that our model is not purely designed for any action recognition task but rather for encoding and reconstructing visual episodes in a fully unsupervised manner. Therefore, observing a lower classification accuracy is not a drawback of our model. Activity classification is rather an additional feature that our network can naturally provide. Considering that we only use the validation set and simple classification algorithms for this task, far less labelled data is required compared to state-of-the-art action recognition models. Applying simple machine learning classifiers on top of the latent representations allows efficient adaptations to domain-specific areas in which activity classification is required but only little data is available to train a deep learning classifier end-to-end.

In case of 20BN, the cross-validation yields logistic regression as best performing classifier, achieving an accuracy of 24.19% when optical flow is added as fourth input channel. Therefore, observing a lower classification accuracy is not a drawback of our model. Activity classification is rather an additional feature that our network can naturally provide. Considering that we only use the validation set and simple classification algorithms for this task, far less labelled data is required compared to state-of-the-art action recognition models. Applying simple machine learning classifiers on top of the latent representations allows efficient adaptations to domain-specific areas in which activity classification is required but only little data is available to train a deep learning classifier end-to-end.

E. Frame Reconstruction and Future Frame Prediction

By reconstructing video frames and predicting upcoming frames the network resembles episodic memory-like capabilities. Fig. 4 shows sample matching results from both ActivityNet and 20BN for a qualitative assessment. The expected decline in prediction quality is very much due to the increase in the uncertainty about the future over successive time steps.

F. Matching Visual Episodes in the Latent Space

To investigate the proposed matching and retrieval of visual episodes introduced in section III-B we use the validation set of 20BN (11,522 videos) and split it in two parts. The first part (80%) forms the memory while the remaining 20% of the videos are employed as queries. Fig 6 (a) shows sample matching results from the 20BN dataset. The matching seems to be conceptually consistent, predominantly yielding visual episodes with the same action type and setting. However, we also observe that the background color biases the matching results, meaning that videos with dark backgrounds are more likely to be matched together. To mitigate this issue, we use a method that normalizes the background color of the videos before performing the matching.

Fig. 5: Peak-Signal-to-Noise-Ratio (PSNR) for each of the 5 reconstructed and predicted frames generated by 20bn_optical_flow (shown in blue), 20bn (shown in green), and ActivityNet (shown in orange) averaged over the entire validation dataset.

\[ \text{PSNR} = 10 \log_{10} \left( \frac{M_{XX}}{M_{YY}} \right) \]

where \( M_{XX} \) is the mean of the original frames and \( M_{YY} \) is the mean of the generated frames.
The proposed matching and retrieval mechanism was evaluated on different visual episodes of object manipulations. The figure depicts three exemplary query episodes and the corresponding 3 closest matches in the latent space. The latent representations are generated by the 20bn_optical_flow model. While (a) shows a query on the 20BN dataset, (b) and (c) comprise human demonstrations for the ARMAR-III robot (see section IV-G).

The background tends to be matched to videos in memory of the same kind. The same applies to bright videos respectively.

G. Case Study: Robot Action Prediction and Execution

Results in Fig. 6 (a) indicate that given a query action, our proposed network gives us a high chance to remember similar scenarios from a large video corpora, which is how an episodic memory functions. In this section, we investigate how our network can be applied to robot manipulation tasks.

For this purpose, we record 120 visual episodes in which a human subject is demonstrating to our humanoid robot ARMAR-III [32] how to perform 10 different manipulation actions such as “pushing two objects closer to each other” and “putting something behind something” (see Fig. 6 (b-c)). The reason of introducing this new dataset is twofold: First, we attempt to evaluate the scalability of our approach to new datasets that have much less training data. Second, for the purpose of action execution we require the depth cue which is missing in the ActivityNet and 20BN datasets. We store 100 of our new visual episodes to form the memory, whereas the remaining 20 episodes are introduced as queries to test the matching and retrieval mechanism with ARMAR-III. The visual episodes are fed through the encoder of the trained model 20bn_optical_flow, thereby receiving its respective latent representations. The cosine similarity in the latent space is then computed based on the first 50 principal components of the latent representations (see section III-B).

Fig. 6 (b-c) illustrate two exemplary query episodes and the corresponding 3 closest matches in the latent space from our recordings. For the great majority of the queries, the retrieved episodes are conceptually similar, indicating that the proposed episodic-like memory mechanism reliably matches visual episodes. Note that our proposed method may also return mismatches as in the case of Match 3 in Fig 6 (b).

So far, the matching and retrieval mechanism is evaluated on manipulation action videos where spatio-temporal cues are implicitly embedded. Going one step further, we investigate whether static scene frames can trigger recalling of past visual episodes. This gives a high chance to robots to autonomously predict and even execute an action that can possibly be performed in the observed scene. We conduct a pilot study to explore the use of our proposed method.

Fig. 7 illustrates a scenario where the robot ARMAR-III is observing a scene with a sponge on the table. Acquired images of this static scene are directly sent to our matching and retrieval mechanism which returns the matched episode where a subject is demonstrating “pushing a green cup”. Next, we apply a real-time object detector [33] to detect and track all objects in the recalled episode. This process yields the extracted pushing trajectory that the subject is following. The tracked motion information is then represented by dynamic movement primitives [34] to be further processed by the robot in order to execute the same pushing motion on the perceived sponge. Fig. 7 depicts sample frames from the best matched episode and detected objects together with the computed motion profile and snapshots from the robot execution of the recalled pushing action. See the supplementary movie showing the entire robot execution.

This experiment clearly supports our hypothesis that the proposed network model can help robots autonomously trace previous observations and select the one that matches best to the currently observed scene even without necessarily requiring any temporal cue. Hence, the robot can transfer relevant knowledge, e.g. the motion profile, from previous experiences to further apply the remembered action to novel objects in the scene. These findings play a vital role in cognitive robotics to infer possible actions, reason about the
action consequences, and even generate actions by transferring knowledge from the past experiences.

V. CONCLUSION

We proposed a deep neural network acting as an episodic memory. Given a set of training data, the proposed network first generates subsymbolic latent space action representation. Such a latent encoding can be used to distinguish actions, regenerate image frames, and predict future frames based on the spatio-temporal features extracted by the deep architecture. We conducted various experiments showing that the proposed framework can help robots gain multiple cognitive abilities such as action encoding, storing, inference, memorizing, and predicting in a single coherent framework.

Our approach is inspired by the composite encoder-decoder architecture proposed by [13]. However, their approach is solely based on fully-connected LSTMs and thus only able to process low-resolution \((32 \times 32)\) image patches or high-level representations of a pre-trained CNN. In contrast, our multi-layered convolutional LSTM architecture leverages both spatial and temporal weight sharing which makes it possible to process frame sequences with significantly higher resolution \((128 \times 128)\). Beyond benchmarking the latent representations as features for activity recognition, we show that conceptual similarity of videos is reflected by the proximity of their vector representation in the latent space. This property facilitates the use of simple machine learning classifiers (e.g. logistic regression or linear SVM) on top of the latent representations. Since these classifiers require considerably less training data than neural network-based classifiers, activity and scene understanding problems in robotics, for which no comprehensive dataset is available, could be efficiently overcome in this way.

The proposed matching and retrieval mechanism in the latent space resembles episodic memory-like capabilities such as the recollection of previously experienced virtual episodes. Retrieved episodes that are conceptually dissimilar (as in the case of Match 3 in Fig [1]) can mostly be ascribed to an unfavourable selection of frames due to the equally spaced frame extraction and thus leading to a poor capture of the dynamic content. It is noteworthy that due hardware constraints, this rather constitutes a technological than a model limitation.

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