Stage Conscious Attention Network (SCAN): A Demonstration-Conditioned Policy for Few-Shot Imitation

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Abstract

In few-shot imitation learning (FSIL), using behavioral cloning (BC) to solve unseen tasks with few expert demonstrations becomes a popular research direction. The following capabilities are essential in robotics applications: (1) Behavior in compound tasks that contain multiple stages. (2) Retrieving knowledge from few length-variant and misalignment demonstrations. (3) Learning from a different expert. No previous work can achieve these abilities at the same time. In this work, we conduct FSIL problem under the union of above settings and introduce a novel stage conscious attention network (SCAN) to retrieve knowledge from few demonstrations simultaneously. SCAN uses an attention module to identify each stage in length-variant demonstrations. Moreover, it is designed under demonstration-conditioned policy that learns the relationship between experts and agents. Experiment results show that SCAN can learn from different experts without fine-tuning and outperform baselines in complicated compound tasks with explainable visualization.

Introduction

Humans can learn to perform unseen compound tasks from different experts with few nonidentical demonstrations. The number of researches on few-shot imitation learning (FSIL) increases rapidly to verify whether the machine also has this ability. The above challenging settings of FSIL problem are illustrated in Figure 1, and most of existing works only solve them partially. To overcome the complexity of environment and concomitant complicated training process, behavioral cloning (BC) is leveraged to mimics the experts. Previous works (Finn et al. 2017; Duan et al. 2017; Yu et al. 2018, 2019; Dasari and Gupta 2020; Bonardi, James, and Davison 2020) only support one demonstration at once, which limits the capability of models. We argue that retrieving knowledge from few demonstrations simultaneously can break through the limitations and lead to better performance when conducting FSIL under these challenging settings.

Meta-learning based methods (Finn et al. 2017; Yu et al. 2018, 2019) learn a meta-policy \( \pi(a | s) \) that takes state \( s \) from current playout \( p \) and outputs an action \( a \) via BC. Before testing, the meta-trained policy uses expert demonstra-

Figure 1: Schema of few-shot imitation learning (FSIL).
In our FSIL problem, models need to solve the task in novel environment that is unseen during training. Few demonstrations are given to let models imitate. There are three challenges in our FSIL setting, (1) We conduct FSIL on compound tasks which contain multiple stages. (2) Demonstrations are length-variant. Each stage may locate at different timestamps. (3) Models need to learn the behavior from a different type of expert. None of previous works can solve these challenges concurrently. Moreover, learning from length-variant sequences is non-trivial, making our FSIL a challenging yet practical problem.

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However, it is difficult to encode length-variant demonstrations. Hence, most DC works \cite{Duan2017, Shao2020, Dasari2020} only contains one demonstration in $D$ and claim themselves one-shot imitation methods.

To handle demonstrations with variant lengths, some DC works apply task-embed techniques. The authors \cite{James2018, Bonardi2020} concatenate the first and last frames of each demonstration and average their features to generate task-embedding (alias sentence in their paper). Nevertheless, this method does not consider the importance of temporal transitions that are essential for policy learning and cannot provide efficient information in the case of long demonstrations given. Therefore, \cite{Dance2021} introduces a transformer-based network that considers both temporal and cross-demonstration information using attention mechanisms. They generate a task embedding by averaging the attention output of few demonstrations at each timestamp. The premise of this method is that frames at the same timestamp of each demonstration have similar knowledge. However, due to different initial states, the operating time of each stage could easily vary and result in temporal misalignment. Therefore, the model might be confused by the frame mixed with two distinct stages and degrade the performance.

We aim to design an attention mechanism that can identify important frames at different timestamp. Meanwhile, the attention mechanism should detect stages in compound tasks. A compound task containing multiple stages often appears in robotics problems. When solving compound tasks in FSIL problem, the policy needs to learn both perception and path planning. This makes solving compound tasks challenging. \cite{Yu2019} leverages an additional phase predictor to split the compound tasks, and then the policy only needs to adapt to each stage. The disadvantage is that the number of stages needs to be known in advance.

In this work, we propose a novel stage conscious attention network (SCAN). SCAN takes both demonstrations and playouts as input to learn the mapping due to the characteristic of DC method. Furthermore, SCAN applies novel stage conscious attention to let each playout frame has its attention score to each frame in the demonstrations. The frame features of demonstrations are weighted by attention scores to produce the same shape contexts. We then average them to generate the informative task-embedding. With stage conscious attention, SCAN can retrieves knowledge from few demonstrations simultaneously. Experimental results show that SCAN has a significant performance improvement compared to baselines with explainable visualizations. The overall contributions are summarized as follows:

- Our work is the first DC method that solves FSIL problem under the settings of compound task, length-variant demonstrations, and learning from a different expert.
- The novel stage conscious attention detects important frames of misalignment stages and is robust to length-variant demonstrations.
- Extensive experiment results express proposed SCAN is powerful, and explainable visualization also proves the effectiveness of novel stage conscious attention.

### Related Work

#### Few-shot Learning

Few-shot learning (FSL) has become popular since collecting a huge amount of labeled data is difficult in most research problems. The objective of FSL is to infer the unlabeled data (query set) by leveraging few labeled data (support set). FSL is first studied on image classification. There are many influential and well-known metric-learning-based FSL methods, such as Matching network \cite{Vinyals2016}, Prototypical network \cite{Snell2017}, and Relation Network \cite{Sung2018}. They try to learn the relationship between support and query sets rather than inferring the unlabeled data directly. Moreover, optimization-based method \cite{Finn2016}, object detection \cite{Karlnsky2021}, and imitation learning \cite{Silver2020}. Our work aims to develop a method that can learn unseen compound tasks with few-shot length-variant demonstrations from a different expert.

#### Few-shot Imitation Using RL/IRL

Reinforcement learning (RL) methods assume the reward function of environments is known. But, it is difficult to design reward functions that give precise feedback to policies in real-world problems. Therefore, inverse RL (IRL) \cite{Ng1999} infers a reward function from few expert demonstrations. Then, IRL policy can be trained by interacting with the environment under the inferred reward function. In addition, modern IRL methods \cite{Ho2016, Reddy2020} are usually GAN-like \cite{Goodfellow2014}. They assign a high reward to the states from demonstrations but a low reward to the states from collected agent samples. Since these methods only use rewards of states to train their model, they can handle the demonstrations without actions, which differs from BC. However, both RL and IRL methods need to interact with the target environment to train the policy. In other words, the learned reward function (IRL) or the well-trained policy (RL) do not be applicable to novel environments. In our FSIL problem, policies can only use demonstrations to fine-tune but cannot interact with the novel environment before performance evaluation. Thus, most RL and IRL methods are not available in our work.

A recent work \cite{Dance2021}, named demonstration-conditioned RL (DCRL), overcomes the limitation. DCRL requires interactions with environments in training. But, it solves FSIL tasks without fine-tuning in testing. Because DCRL is a DC policy method, it needs expert demonstrations from training environments to achieve fine-tuning-free. They store the tuples of (playout history, rewards, demonstrations) into the replay buffer to train the policy. The policy is a transformer-based architecture that its encoder generates task embeddings using cross-demonstration attention and the decoder predicts the actions. Moreover, the concept of "demonstration conditioned" echoes our motivations. But, designing all reward functions in training environments is quite time-consuming. Thus, we only compare SCAN with BC-based methods.
Compound Task. A compound task consists of multistage subtasks. The main challenge of compound tasks is that there is no signal (label) in demonstrations to identify each subtask when testing. Nevertheless, the policies for distinct subtasks are pretty different. Hence, it becomes impractical to use a single policy to solve compound tasks.

An intuitive solution is to link the relationship between subtask and primitive. The term primitive, which comes from the robotics field [Flash and Hochner, 2005; Manschitz et al., 2015], represents single elementary movements and is widely used in compound task problems. To be specific, each subtask may correspond to a single robot motion (primitive), such as pushing and grasping. Therefore, previous RL [Zeng et al., 2018; Marzari et al., 2021] and IL works [Yu et al., 2019; Lee et al., 2019; Lee and Seo, 2020] assume these primitives are known before testing since the end effector (gripper) are only capable for these primitives. Then, they develop a hierarchical structure that trains policies for each primitive separately and use a high-level control network to decide which policy should be executed with each subtask when testing. Nevertheless, the policies for distinct subtasks are pretty different. Hence, it becomes impractical to use a single policy to solve compound tasks.

Few-Shot Imitation Learning (FSIL)

To emphasize, we treat FSIL problem as imitation learning under FSL setting. In previous works, a policy is (trained or) tested over several tasks that are essentially the same but with different objects in the environments. Thus, we use the base environments $E^b$ and novel environments $E^n$ in problem statement. Notations are listed in Table 1.

### Problem Statement

A few-shot imitation learning (FSIL) problem is given by a base environment set $E^b$ and a novel environment set $E^n$, where $E^b \cap E^n = \emptyset$. Each environment $e^n$ in $E^b$ or $E^n$ contains a set of expert demonstrations (support set) $D^s$ and a set of agent playouts (query set) $P^q$. In addition, samples in $D^s$ or $P^q$ are in the same environment $e^n$ with distinct initial/end states. Moreover, the expert could be humans or other robot arms compared to the agent in playouts.

A policy $\pi$ with parameter $\theta$ is meta-trained in $e^n$ from base environments $E^b$ and meta-tested in $e^n$ from novel environments $E^n$. The policy $\pi$ needs to generate an action $a$ when receiving a current state $s$ from the playout $p^q \in P^q$. Then, the success rates of playout executions in all $e^n$ are used as performance evaluation. Thus, the playout samples in $e^n$ only contain the initial state $s_0$, and the following states are provided according to the action taken by the policy. At last, the objective of FSIL problem is to maximize the performance expectation of the policy where the expectation is taken over $e^n \in E^n$. Furthermore, the policy can only fine-tune its parameters using the demonstrations $D^s$ in $e^n$ (if needed), which means no interaction with novel environments are allowed before performance evaluation.

### Methodology

We introduce the stage conscious attention networks (SCAN) in details. SCAN needs following inputs: $K$ expert demonstrations (without actions) $F^D = \{F^d_i \mid i \in [0, K]\}$ and playout states that contains frames $F^p$, end-effector (EE) cropped frames $F^{crp}$, and EE vector $\tilde{V}^p$ (position and open amount). These inputs are widely used in FSIL works. Moreover, we apply inverse kinematics to compute joint parameters of the agent. Therefore, SCAN only needs to compute two outputs for each playout state: target positions $(x, y, z$ in continuous space) and the probabilities for EE open/closing.

SCAN is composed of three main components, including visual heads, stage conscious attention, and an ActorNet. We describe these components in following paragraphs, and the overall architecture of SCAN is shown in Figure 2.

### Visual Head

The objective of visual head is to retrieve meaningful embeddings of RGB-D frames either from $F^D$ or $F^p$. We leverage two resnet18 to extract RGB images and depth images separately, inspired by Shao et al. (2020). Moreover, since SCAN does not have object detection components, we insert a modified self-attention module at the head and tail of resnet18. The self-attention module is originally proposed in Zhang et al. (2019), we make the output dimension of the query-layer and key-layer the same as input dimensions and add the channel-wise softmax layer behind them. Detailed architecture is shown in supplementary.

Then, given a 4D frame inputs (sequence length $l^p$ for $F^p$ or $l^d$ for $F^d$), channel $C$, height $H$, width $W$), the visual head splits it into RGB and depth images and use the corresponding resnet18 to generate feature embeddings (FEs). These two FEs are concatenated and passed over a dense layer to obtain the output with shape $(l^p$ or $l^d$, 128). As shown in Figure 2, a shared-weights $V_{visual_{rgb}}$ extracts $emb^p$ from $F^p$ and each $emb^d_i$ from $F^d_i$. Another

| notation | meaning               |
|----------|-----------------------|
| $f, f^{crp}$ | frame, crop frame   |
| $\tilde{v}$ | vector               |
| $s := (f, f^{crp}, \tilde{v})$ | state               |
| $a$ | action                |
| $F := [f_0, f_1, ..., f_t]$ | sequence of frames  |
| $F^{crp} := [f_0^{crp}, f_1^{crp}, ..., f_t^{crp}]$ | sequence of crop frames  |
| $\tilde{V} := [\tilde{v}_0, \tilde{v}_1, ..., \tilde{v}_t]$ | sequence of vector   |
| $S := [s_0, s_1, ..., s_t]$ | sequence of state    |
| $A^* := \{a_0, a_1, ..., a_t\}$ | sequence of action   |
| $P^* := (S, A^*)$ | demonstration          |
| $D^*$, $D^n$ | set of $p^*, d^*$  |
| $e^*$ | environment            |
| $E^*$ | set of $e^*$          |
| $n \in \{b, n\}$ | base, novel             |

Table 1: Defined notations
Stage Conscious Attention (SCA). We assume that each frame in each demonstration $d^i$ (support sample) has a different importance to each frame in current playout $d^j$. The inverse dynamic model aims to help the agent perform more precise actions. The overall picture of ActorNet is shown in Figure 3. In ActorNet, there are two components, action head and inverse dynamics model. The action head concatenates four inputs ($emb^p$, $emb^{crp}$, EE vector $\vec{v}$, and $emb^{ask}$) and add 1D positional encoding $PE_{1D}$ to provide auxiliary time information. Then the action head predicts target positions and probability of open/close for each state in current playout (history), we denote the output as $out_{act}$.

$$in_{act} = PE_{1D}([emb^p; emb^{crp}; \vec{v}; emb^{ask}])$$

The $out_{act}$ is a vector of pairs $[\vec{\mu}_t, g_t]$ for the time $t$ state in the playout history. The $\vec{\mu}_t = [\mu_x, \mu_y, \mu_z]$ is a vector which contains means of three univariate Gaussian distributions that generate positions at time $t$. We use an additional learnable vector $\sigma$ for the standard deviation of the distributions. Besides, the $g_t$ is the probability of open/close control.

Afterwards, the inverse dynamic model concatenates time $t$ $emb^p$, $emb^{crp}$ and time $t + 1$ $emb^p$, $emb^{crp}$ as input $in_{inv}$, and use the similar architecture of action head to predict actions $out_{inv}$ for each state in playout history (except for the latest frame). The inverse dynamic model aims to help the action head know how actions cause frame changes.

$$in_{inv} = [[emb^p_t, emb^{crp}_t], [emb^p_{t+1}, emb^{crp}_{t+1}]]$$

To train SCAN, we use negative-log-likelihood (NLL) as loss functions. $L^{inv}$ calculates the NLL loss for the output.
Figure 3: Architecture of ActorNet. In ActorNet, an action head concatenates four input embeddings and adds a 1D positional encoding. Following by the several dense layers, the action head computes positions and probabilities of open/closed-gripper. The inverse dynamics model helps the action head know the precise actions that cause changes between frames.

Figure 4: Environments of PP and PPP task. PP and PPP task are compound tasks that contain two and three stages, respectively. Objects are unseen during training.

\( L_{\text{pos}}^{s} = -\frac{1}{K} \sum_{i=1}^{K} \sum_{j \in \{x, y, z\}} \frac{1}{2} \ln(2\pi) + \ln(\sigma_j) + \frac{(y_j - \mu_j)^2}{2\sigma_j^2} \)

We use the following loss for open/close control. The \( g_{\text{label}} \in \{0, 1\} \) is true probability of open the gripper. And, \( s \) indicates action head act or inverse dynamics model inv.

\( L_{\text{pos}}^{s} = -\frac{1}{K} \sum_{i=1}^{K} g_{\text{label}}^{i} \ln g + (1 - g_{\text{label}}^{i}) \ln(1 - g) \)

The total loss is the weighted sum of all losses, and \( \lambda_{\text{pos}} \), \( \lambda_{\text{g}} \) are the hyper-parameters.

\( L_{\text{total}} = \lambda_{\text{pos}} (L_{\text{pos}}^{s} + L_{\text{inv}}^{s}) + \lambda_{\text{g}} (L_{\text{act}}^{g} + L_{\text{inv}}^{g}) \)

Experiments

The goal of our experiments is to verify following assumptions: (1) the novel stage conscious attention has the ability to locate each primitive (stage) in length-variant demonstrations and highlight important frames for each play-out frame. (2) SCAN can learn a relationship mapping between different types of experts and agent. (3) Based on above assumptions, SCAN can retrieve knowledge from few demonstrations simultaneously and get a boosted performance rather than separately handling each demonstration.

Experiment Settings. We have two main experiments. (1) we evaluate all methods on two compound tasks, pick & place (PP) and pick & place & push (PPP), as shown in Figure 4. In PP task (2 stages), the agent needs to pick the cube and place it in the target bowl. Another bowl serves as the disruptor. Next, in PPP task (3 stages), the agent needs to push the sky-blue cup off the table after placing the cube. Note that the target bowl might be the front one or rear one. This means the directions of the trajectory are quite different, which makes our experiment challenging. Moreover, we follow the evaluation protocol in FSL problem. There are 56 novel environments composed of unseen objects. For each environment, we let methods play 20 times with different initial scenes and calculate the success rate. The average of successful rate and standard deviation in all novel environments are provided in Table 2. This experiment aims to evaluate whether SCAN can locate important frames and achieve dominating performance. (2) We design a extremely length-biased case to observe the robustness of methods when encountering sub-optimal demonstrations (still complete the task but with trivial moves) that have not been processed. To be clear, all methods are trained with optimal demonstrations. Then, we give few sub-optimal demonstrations in testing to analyze the relation between attention mechanism and performance changes, as shown in Figure 7 and 8. For all experiments, we build environments in CoppeliaSim and use the pyrep [James, Freese, and Davison 2019] toolkit to communicate with environments. We use Panda arm as the agent, and experts may be Panda arm or UR5.

Compared Baselines. Baselines are introduced below. All methods use our visual head and ActorNet for fair comparisons. Only the parts that handle few demonstrations are implemented. (1) BC: a conventional BC model takes states as input, no task-embedding generated. (2) meta-BC: a conventional BC is trained via MAML [Finn, Abbeel, and Levine 2017] in same expert setting and trained via DAML [Yu et al. 2018] in different expert setting. (3) TaskEmb: a DC method [James, Bloesch, and Davison 2018] averages concatenated embeddings of first and last frames as task-embeddings. (4) TANet: our implemented DC method that averages the output of cross-demonstration attention (at each timestamp) and apply the global attention to get the task-embeddings. The key idea of TANet is similar to the method in [Dance, Perez, and Cachet 2021], however, it is hard to build a transformer-based model with our visual head and ActorNet. Therefore, we design the TANet to evaluate the effectiveness of cross-demonstration attention.

Performance Comparison

We analyze the performance results of experiment 1 in Table 2. The success rate and standard deviation is the average of 56 novel environments. We have several observations from the results. (1) Except for TaskEmb, methods achieve better performance in 5-shot setting rather than 1-shot setting.
TaskEmb only uses frame features when generating task-embedding, and there is no other conversion process. Therefore, it is susceptible to frame features from novel environments. Without fine-tuning, TaskEmb performance of 1-shot and 5-shot is not much different. (2) The performance of DC methods has been dramatically improved after fine-tuning. But SCAN has slightly worse performance in PP task under the 1-shot setting. We infer that using only one demonstration to fine-tune may let models overfit. Therefore, the generalization of models is reduced. (3) SCAN has the best adaptability in most cases, regardless of whether the expert is the same as the agent. We claim that the proposed SCA learns the mapping from demonstration to playout. And, the learned mapping can provide enough information for SCAN to behave in a novel environment even without fine-tuning.

Furthermore, we also observe an interesting phenomenon. TANet has trouble in PP task, even with fine-tuning. Because the time misalignment between demonstrations in PP tasks is serious, averaging information at each timestamp like TANet causes the task to be incomprehensible. Our SCAN identifies the location of critical frames in demonstrations. Therefore, SCAN can learn and behave smoothly in PP task. However, TANet outperforms SCAN in the PPP task under the same expert setting. We infer two possible reasons regarding this phenomenon: (1) Although demonstrations of PPP task have longer lengths and more steps, their time misalignment are not severe. (2) Bowls are at the front of the agent, and many bowls have similar colors to the agent in novel environments, which interferes with SCAN that needs to pay attention to each frame.

### Effectiveness of Stage Conscious Attention (SCA)

#### Attention Result in Compound Tasks.

To verify whether SCA can detect crucial frames and generate informative task-embedding, Figure 5 and Figure 6 visualize attention maps and contexts generated by SCA in the compound tasks of experiment 1. To emphasize, all visualizations are under the setting of 5-shot and different experts. In Figure 6, attention scores of the stage where the agent is in progress focus on the same stage in demonstrations, whether the compound task has 2 or 3 stages. Notably, SCA locate critical frames in novel environments without fine-tuning. Furthermore, we do not use any hard restriction or loss function to guide SCA. It learns the ability proactively. On the other hand, Figure 6 illustrates t-SNE (van der Maaten and Hinton 2008) results of contexts and task-embeddings in the playout of Figure 5. The contexts come from different demonstration are tagged with distinct marker. In addition, we highlight stage locations in t-SNE results. At the beginning, generated contexts and task-embeddings are diverse since the initial states of demonstrations are various. Specially, contexts aggregate

### Table 2: Success Rate on Compound Tasks.

The average of success rate and standard deviation in all novel environments are provided. The type column represents whether the expert and the agent are the same or not. In the same expert setting, model can fine-tune when expert actions are provided. From the table, we have three main findings. (1) the 5-shot performance usually outperforms the 1-shot performance. (2) fine-tuning is helpful in most cases, but it might let model overfit on the demonstration in one-shot setting. (3) SCAN has the best adaptation ability and performance except for the case of same expert in PPP task.

| Type       | Models       | Fine-tune | PP task 1-shot | 5-shot | PPP task 1-shot | 5-shot |
|------------|--------------|-----------|---------------|--------|---------------|--------|
| same       | BC           | ✓         | 12.86% ± 12.74% | 28.84% ± 09.82% | 05.54% ± 09.76% | 28.57% ± 12.67% |
|            | meta-BC      | ✓         | 35.09% ± 34.99% | 43.11% ± 34.50% | 17.77% ± 18.47% | 18.39% ± 19.66% |
|            | TaskEmb 2018 | ✓         | 54.20% ± 25.74% | 83.39% ± 13.47% | 47.23% ± 18.85% | 58.39% ± 18.49% |
|            | TANet (ours) | ✓         | 28.75% ± 14.24% | 40.75% ± 12.37% | 46.43% ± 21.69% | 48.13% ± 18.79% |
|            | SCAN (ours)  | ✓         | 53.93% ± 20.54% | 64.82% ± 15.84% | 52.05% ± 21.04% | 68.57% ± 14.16% |
| differ     | meta-BC      | ✓         | 67.05% ± 21.31% | 75.45% ± 17.66% | 46.34% ± 13.18% | 47.86% ± 13.69% |
|            | TaskEmb 2018 | ✓         | 64.64% ± 21.50% | 85.00% ± 10.69% | 55.80% ± 20.24% | 58.48% ± 22.56% |
|            | TANet (ours) | ✓         | 06.52% ± 09.95% | 05.80% ± 08.17% | 00.00% ± 00.00% | 00.00% ± 00.00% |
|            | SCAN (ours)  | ✓         | 18.04% ± 09.81% | 18.66% ± 09.61% | 12.32% ± 14.70% | 12.23% ± 15.12% |
|            | meta-BC      | ✓         | 42.50% ± 14.82% | 47.95% ± 14.63% | 24.02% ± 26.30% | 25.54% ± 27.20% |
|            | TaskEmb 2018 | ✓         | 60.89% ± 14.70% | 65.27% ± 13.74% | 31.52% ± 10.60% | 32.41% ± 11.38% |

Figure 5: Attention maps of SCAN on compound tasks. Each row and column represent the frame from the playout and the demonstration. Besides, a lighter cell has a higher score, and we mark each primitive with the same color. The attention results show that SCAN can focus on corresponding frames (beginning of same stage) in the demonstration when executing each stage (in both tasks).
when each stage is over. The rest of contexts are generated during moving, such as moving to target cubes or bowls. It is impressive that contexts have these cluster attributes.

Robustness to Sub-optimal Demonstrations. Figure 7 and Figure 8 demonstrate the result of experiment 2. We choose one from 56 novel environments as the target environment and generate the sub-optimal demonstrations. Experts still completed the task in sub-optimal demonstrations but with trivial movements. In other words, the demonstration set is extremely length-biased, which all methods have never encountered during training. Then, we run all methods 20 times for the performance evaluation. Attention maps of SCAN and TANet baseline in this experiment are shown in Figure 7. It is the comparison with zero or three sub-optimal demonstrations in the demonstration set. Both methods work well when there are no sub-optimal demonstrations (bottom). However, TANet cannot handle the case that there are three sub-optimal demonstrations (top). Because the time misalignment is severe in the case, TANet is hard to retrieve knowledge by averaging at each timestamp of demonstrations, which can be reflected in success rates of Figure 8.

In Figure 8, TANet performs poorly when the number of sub-optimal demonstrations increases. Our SCAN is also affected by sub-optimal demonstrations, but it did not cause such a big reduction in performance. Moreover, TaskEmb only focuses on first and last frames of demonstrations, and thus, sub-optimal demonstrations would not affect its performance. However, first and last frames cannot provide efficient information when solving compound tasks. TaskEmb has a lower performance compared to other methods.

Conclusion

In this work, we conduct the FSIL problem under three challenging settings, including compound tasks, few length-variant demonstrations and learning from a different expert. Meanwhile, we found that most of works can only handle one demonstration at once or need external loss to learn from different experts. Hence, we propose a novel SCAN method that can retrieve knowledge from few demonstrations simultaneously and behave in novel environments without fine-tuning. Our stage conscious attention locates critical frames for each playout frame to alleviate the demonstration misalignment problem. Explainable visualization and outstanding performance illustrates the effectiveness of SCAN.
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Stage Conscious Attention Network (SCAN) :
A Demonstration-Conditioned Policy for Few-Shot Imitation
Supplementary Material

The supplementary material contains following contents:
- Summary of previous few-shot imitation methods
- Comparison between the conventional policy and the demonstration-conditioned policy.
- Details of proposed SCAN, including the architecture of visual head and implementation details.
- The progress how we build environments and collect demonstrations.
- Experiment on the importance of designed components.
- Verification and visualization of stage conscious attention (SCA) in different cases.

Few-shot Imitation Learning Methods
To provide a whole picture of FSIL methods, we list all classes of FSIL methods in Figure 1. Moreover, we summarize them according to their architecture and problem setting in Table 1. As illustrated in Table 1, we are the first work that conduct FSIL problem on all challenge settings. In following paragraphs, we introduce the demonstration-conditioned policy and compare it with conventional methods.

Demonstration-Conditioned Policy
The demonstration-conditioned (DC) policy \( \pi_{\theta}(a|s, D^*) \) needs both current observation \( s \) and demonstrations \( D^* \) as inputs to generate actions. We compare the conventional policy and demonstration-conditioned policy in Figure 2. When using conventional policy, demonstrations are served as batch data. The conventional policy fine-tunes its parameters with demonstrations and then discards them. They would not access the demonstrations when generating actions for current playout \( p^n \). This design has several limitations. (1) The demonstrations must contain expert actions for the supervised fine-tuning. (2) The policy might be misled if the expert in demonstrations is different from the agent.

By contrast, demonstration-conditioned policy treats demonstrations as the support set and learns the relationship between demonstrations and playouts during training. In addition, due to the characteristic of FSIL problem, the DC policy is equivalent to the metric-learning-based method in FSL. They both learn the relationship rather than infer-

Algorithm 1: Meta-train DC policy with \( K \)-shot demo

Require: base environments \( E^b \)
1: \( i = 1, \theta = \text{RandomInit()} \)
2: while \( i < \text{MaxEpoch} \) do
3: for each \( e^b \) in \( E^b \) do
4: \( j = 1, \mathcal{D}^b = \{ \} \)
5: while \( j \leq K \) do
6: Sample a video-only demo \( d^b := \{ F \}^b \) from \( e^b \)
7: \( \mathcal{D}^b = \mathcal{D}^b \cup \{ d^b \} \)
8: \( j = j + 1 \)
9: end while
10: Sample a playout \( p^b := (S, \hat{A})^b \) from \( e^b \)
11: \( \hat{A} = \pi_{\theta}(S, \mathcal{D}^b) \)
12: \( \theta = \theta - \nabla_\theta \mathcal{L}_{BC}(\theta, \hat{A}, \hat{A}) \)
13: end for
14: \( i = i + 1 \)
15: end while
16: return \( \theta \)

Figure 1: Previous FSIL works are categorized into meta-learning and demonstration-conditioned based. Meta-learning methods seek a meta-parameter set that can easily adapt to novel tasks. Besides, demonstration-conditioned methods generate actions by using both current states and demonstrations as input. Then, we classify methods into one-shot or few-shot based on how they use demonstrations to update their parameters. Only works that process few demonstrations simultaneously belong to few-shot class. Thus, meta-learning methods can only be in one-shot class.
Table 1: Problem setting of existing FSIL works. Our FSIL problem is under three challenging settings, including compound tasks (≥ 3 stages) (C), learn from few length-variant and misalignment demonstrations concurrently (F), and learn the behavior from a different type of demonstrator (D). We summarize existing FSIL methods according to algorithm architectures and problem settings. Duan et al. (2017) is the first FSIL work. They focus on the stacking task which contains multiple times of pick and place stages. Then, Finn et al. (2017) introduces the meta imitation learning (MIL). Afterwards, Yu et al. (2018) proposes the domain adaption meta-learning (DAML) which allows MIL algorithm imitates from different types of experts. Besides, James, Bloesch, and Davison (2018) is the first work based on the concept of task-embedding in FSIL problem. And them (2020) further extends it to imitate from a human demonstrator. Yu et al. (2019) applies DAML on compound tasks. Both Dasari and Gupta (2020) and Cachet, Perez, and Kim (2020) propose transformer-based methods to solve FSIL problem. At last, Dance, Perez, and Cachet (2021) extends their method to support few demonstrations.

Stage Conscious Attention Network (SCAN)

In this section, we describe the details of SCAN not mentioned in the main paper. First, we introduce the modified self-attention module and architecture of visual head. Then, the implementation details such as used optimizer, learning rate adjustment, and fine-tuning progress are provided.

Details of Visual Head

Self-Attention Module. Some works (Shao et al. 2020) have to use the object detection model to segment objects in visual inputs before generating actions. However, such a model is hard to train all its components from scratch. Inspired by (Wang et al. 2017), we assume that adding attention modules in feature extractor to extract more informative features may be an alternative method. Therefore, as shown in the top and mid of Figure 3, we introduce an attention version of ResNet18 (He et al. 2016), denoted as SA-ResNet18. To be specific, we insert a modified self-attention
Algorithm 2: Meta-test DC policy with K-shot demo

Require: novel environments $E^n$
Require: trained parameters $\theta$
Require: number of playout $N^{ply}$

1: for each $e^n$ in $E^n$ do
2: \hspace{1em} $j = 1$, $D^n = \{\}$
3: \hspace{1em} while $j \leq K$ do
4: \hspace{2em} Sample a video-only demo $d^n := \{F\}^n$ from $e^n$
5: \hspace{2em} $D^n = D^n \cup \{d^n\}$
6: \hspace{2em} $j = j + 1$
7: \hspace{1em} end while
8: \hspace{1em} $k = 0$, $cnt = 0$
9: \hspace{1em} for $k \leq N^{ply}$ do
10: \hspace{2em} $e^n = \text{RandomReset}()$
11: \hspace{2em} $s_0 = \text{initial state}$ from $e^n$
12: \hspace{2em} $t = 0$, $S = [s_0]$
13: \hspace{2em} $\text{done} = \text{False}$
14: \hspace{2em} while not $\text{done}$ do
15: \hspace{3em} $A = \pi_\theta(S, D^n)$
16: \hspace{3em} $s_{t+1}, \text{done} = e^n(s_t, A_t)$
17: \hspace{3em} $S = S, \text{append}(s_{t+1})$
18: \hspace{3em} $t = t + 1$
19: \hspace{2em} end while
20: \hspace{2em} if success then
21: \hspace{3em} $\text{cnt} = \text{cnt} + 1$
22: \hspace{2em} end if
23: \hspace{2em} $k = k + 1$
24: \hspace{2em} end for
25: \hspace{1em} success rate $sr = \text{cnt}/N^{ply}$
26: end for
27: calculate average of $sr$ and $\sigma$ over all $e^n$ in $E^n$

module at the head and tail of the ResNet18. Besides, the self-attention module is originally proposed in (Zhang et al. 2019). We change the output dimension of $1 \times 1$ convolution layer (query-layer and key-layer) from 1 to the input dimension, and then a channel-wise softmax layer is followed.

The motivation for this modification is that the input dimension of the self-attention module might be huge, such as 256 or 512. Using a $1 \times 1$ convolution layer to reduce such high-dimensional features to one dimension may cause loss of information. Hence, we let the output of these layer has the same dimension as the input and use the channel-wise softmax to decide the importance of each dimension in the output. The modified self-attention module can provide more meaningful knowledge since it retrieves and reserve the knowledge from input features effectively.

Architecture of Visual Head. As mentioned in Figure 3, visual head uses two SA-ResNet18 to extract RGB and depth images separately. This design is motivated by (Shao et al. 2020), and the intuition is that self-attention modules in SA-ResNet18 may focus on distinct areas of RGB and depth images. Then, we concatenate the output features and feed them into a fully connected layer followed by a dropout function with a dropout rate of 0.5. Since we deal with few-shot demonstrations, the dropout layer can avoid the following network components from overfitting on these data, which is beneficial to learn a more general model.

Implementation Details

In this section, we provide implementation details not stated in the main paper. Hyper-parameters for Visual head, ActorNet and training/testing are listed in Table 2 - 4. The dimension of output embeddings from visual head is 128. All activation functions are LeakyReLU except for the last hidden layer of ActorNet. We use Tanh function to limit the position outputs to a specified range and apply Softmax function to generate the probabilities of open/close control.

All methods are trained with ten epochs. There are 110 base environments in an epoch. For each base environment, five demonstrations and five playouts are sampled for training the models. No interactions with environments are allowed during training. Besides, model parameters are optimized by an Adam optimizer with the learning rate $2 \times 10^{-4}$.
| Hyper-parameter                  | Value        |
|---------------------------------|--------------|
| Dimension of output embedding   | 128          |
| Activation function             | LeakyReLU    |
| Dropout rate                    | 0.5          |

Table 2: Hyper-parameters for Visual head

| Hyper-parameter                  | Value        |
|---------------------------------|--------------|
| Dimension of output embedding   | 128          |
| Activation for hidden layer     | LeakyReLU    |
| Activation for position layer   | Tanh         |
| Activation for open/close layer | Softmax      |
| Max length of PositionalEncoding| 100          |

Table 3: Hyper-parameters for ActorNet

| Hyper-parameter                  | Value        |
|---------------------------------|--------------|
| Number of epochs for training   | 10           |
| Number of demonstrations for training | 5          |
| Number of playouts for training | 5            |
| Number of trails for testing    | 20           |
| Max time step for each trail in testing | 100         |

Table 4: Hyper-parameters used for training/testing

If fine-tuning is applied, the learning rate for fine-tuning is $2 \times 10^{-5}$. The final value of hyper-parameters is determined after several manual adjustments. We implement methods in PyTorch and conduct all experiments on a Ubuntu system that contains an Intel i9-9900KF CPU, 64GB RAM, and an NVIDIA RTX3090 24GB GPU. The approximate training time is two to three hours, and the testing time is three to five hours, depending on the performance of methods.

Environment Details

Composition of Base and Novel Environments

As stated in main paper, we build environments in CoppeliaSim, a robotic simulated software. About target objects that the agent need to pick, we use the cube object provided in CoppeliaSim and set its color into different colors during training and testing. Next, we download free 3D models of bowls from the internet. As shown in Figure 4, we collect eleven bowls for training (base environments) and eight bowls for testing (novel environments). Each bowl is paired with other bowls to form an environment. Thus, we have 110 base environments and 56 novel environments for each task.

Figure 4: Bowls used in environments. Each bowl is paired with other bowls to form an environment. (a) We have $11 \times 10 = 110$ base environments. And (b) we build $8 \times 7 = 56$ novel environments. Note that bowls in base and novel environments are disjoint. When solving a task (e.g. PP task), we train methods in base environments and evaluate their performance in novel environments.

Settings of Compound Tasks

We have two compound tasks in experiment 1. The operation space for both tasks is a table of 60 cm by 75 cm. Figure 5 illustrates the placement area of objects and the movement direction of the agent. All objects are set to dynamic mode, which means the objects may change positions or even leave the operating space due to collisions. Moreover, our compound tasks are challenging since the movement direction varies in different novel environments, and we do not apply fine-tuning to let the model adapt to the trajectory. Besides, the agent has 20 trails in each novel environment. Both positions of the cube and bowls are not fixed in each trial. In some previous works (e.g., Dasari and Gupta), only one of the positions may changes. Since our task has many challenging settings, we only have one cube on the table for the agent to pick. We would let the agent detect which object to be grasped from multiple objects in future research.

Figure 5: Configuration of compound tasks. The red area indicates the range in which the corresponding objects may be initially placed. The operating space of the agent is a table of 60 cm by 75 cm, which means the agent needs to move a long distance to complete the task. Moreover, the target bowl (in different environments) may be Bowl 1 or Bowl 2 when placing. The directions to areas of these two bowls are quite distinct, which makes our tasks challenging.

Details of Demonstration Collection

We assume that positions of objects and the status of robotic arms are known during demonstration collection. The rule-based methods are applied to demonstrate how to solve the task. There are two robotic arms in our dataset, UR5 and Panda. For each environment, we collect 40 demonstrations of UR5 arm and 40 demonstrations of Panda arm. Each demonstration contains frames, cropped frames, end-effector vectors, and actions. With these demonstrations, user can easily switch the roles of expert and agent. The size of demonstration files in PP tasks is 500 GB and the size of demonstrations in PPP tasks is 700 GB. The duration for collecting all demonstrations is about one day.
Visualization of contexts and attention in a successful case. The agent takes 35 steps to complete the task. We demonstrate playout frames of each time step in Playout (left up). In the Contexts (left bottom), the t-SNE result of contexts is generated at each time step. As previously stated, they are diverse at the beginning and converge at the end of each stage. This indicates that our stage conscious attention locate critical frames for playout frames at each time step, which can also be observed in attention results (right). In the attention results, the highest attention score of each playout frame is the frame at the same stage in the demonstrations. With the help of stage conscious attention, our method can retrieve knowledge from few misalignment demonstrations simultaneously and generate informative task-embeddings.

| Method | inv | self-attn | success rate        |
|--------|-----|-----------|---------------------|
| SCAN   | ✓   | ✓         | 12.41% ± 13.98%     |
| ✓ ✓    |     |           | 31.96% ± 17.87%     |
| ✔ ✓    |     |           | 65.27% ± 13.74%     |

Table 5: Importance of designed components. The inv represents the inverse dynamics model, and the self-attn indicates the self-attention module in visual head. The goal of the inverse model is to let the model know how the action affects the changes of frames. Moreover, the self-attention module aims to assist visual head to extract informative features. When any component is removed, the performance of SCAN is significantly reduced.

Ablation Study

To investigate the impact of components on the model, we conduct the ablation study on PP task under the setting of different expert and 5-shot and provide results in Table 5. When removing these components (inverse dynamics model and self-attention model), SCAN cannot locate the specific position of objects in novel environments, which causes a dramatically performance drop. Without the self-attention module, extracted features are not representative enough. Thus, the inverse dynamics module cannot learns the relationship between actions and the change of frames. There is a similar situation when the inverse dynamics module is removed, which proves that these components are beneficial.

Cases Studies of Context and Attention

We are curious about how stage conscious attention (SCA) works in different situations. Therefore, Figure 6 and Figure 7 visualize three different cases when SCAN solves the PP task under the setting of different expert and 5-shot.

From Figure 6, SCAN successfully solve the PP task. Attention maps indicate the SCA can locate corresponding frames in each stage. Moreover, the self-attention module aims to assist visual head to extract informative features. When any component is removed, the performance of SCAN is significantly reduced.

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Figure 7: **Visualization of contexts and attention in two different failure cases.** The max steps in a trial are 100. In (a), SCAN cannot pick the cube. We can find that SCAN has been focusing on the pick stage in demonstrations until the end, which means it knows that it has not completed the goal of this stage. Contexts are a mess in the case, and no aggregation occurs. Moreover, SCAN successfully picked the cube but did not put it in the target bowl in (b). And thus, attention scores focus on the place stage in demonstrations until the end. From the contexts, we can find an aggregation when the pick stage is completed, but there is no aggregation in the contexts generated afterward.