Generalized Visual-Tactile Transformer Network for Slip Detection

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Abstract: Slip detection plays a vital role in robotic dexterous grasping and manipulation, and it has long been a challenging problem in the robotic community. Different from traditional tactile perception-based methods, we propose a Generalized Visual-Tactile Transformer (GVT-Transformer) network to detect slip based on visual and tactile spatiotemporal sequences. The main novelty of GVT-Transformer is its ability to address unaligned vision and tactile data in various formats captured by various tactile sensors. Furthermore, we train and test our proposed network on a public and our visual-tactile grasping datasets. The experimental results show that our method is more suitable for sliding detection tasks than previous visual-tactile learning methods and more versatile.

Keywords: Information and sensor fusion, Perception and sensing, Intelligent robotics, Deep neural networks, Visual-tactile fusion perception.

1. INTRODUCTION

With the rapid development of representation learning methods (see Sünderhauf et al. (2018)) and robot learning methods (see Kroemer et al. (2019)), the perception and decision-making ability of the robots have been improved rapidly, and it has been possible to solve Rubik’s cube with one hand (see OpenAI et al. (2019)), play Jenga (see Fazeli et al. (2019)) and perform other complex manipulation tasks (see Sanchez et al. (2018)). However, there are still some fundamental but challenging issues in robotic grasping and manipulating tasks. For grasping, it is necessary to manage the force distribution between the object and gripper before lifting and during grasping to ensure grasping stability (see Stachowsky et al. (2016)). Manipulation additionally deals with the contact dynamics between objects and the gripper during executing desired motions or undergoing changes form the external environment (see Wu et al. (2019)). For these issues, the primary issue is how to adjust actions to respond to changing contacts. Detecting slip and incipient slip can assist robots to automatically adjust the grasping force to provide a solution to this problem (see Su et al. (2015)). It is not surprising that many studies have developed various tactile sensors and corresponding learning methods to address this issue in the past decades (see Yousef et al. (2011), Van Wyk and Falco (2018)). Some recent review papers about slip detection and robotic tactile perception can be found in Francomano et al. (2013) and Luo et al. (2017).

Humans can naturally estimate the grasping force required to lift an unknown object and grasp it and can adjust the force accordingly. In this process, humans mainly rely on the sensory-sensitive tactile afferents (FA-I, SA-I, FA-II, and SA-II) with a reasonable distribution and excellent neural processing system (see Yousef et al. (2011)). Furthermore, vision also plays a critical role in this determination process, especially when the performance of current tactile sensors is far less than that of humans.

Recently, robotic visual-tactile perception has successfully been used for a variety of tasks, such as surface classification (see Gao et al. (2016)), object recognition (see Liu et al. (2017)), contact-rich tasks (see Lee et al. (2019)), etc. These studies strongly suggest that visual-tactile perception has better performance than visual-only or tactile-only perception. Unfortunately, most of the existing studies fuse the visual and tactile data by Early Fusion (EF) methods that have been shown to the lack of ability to capture modal-specific and cross-modal features in other multimodal sequence learning tasks (see Li et al. (2018), Zadeh et al. (2018)). Additionally, the existing methods are designed for tasks with specific tactile data format (e.g., image, matrices, vector, etc.) and aligned sequences, which leads to significant limitations on these platform generalization performance.
To tackle these issues, we propose a Generalized Visual-Tactile Transformer network (GVT-Transformer) to learn features from aligned or unaligned visual-tactile sequences for slip detection. Our primary contributions are:

- A representation learning method from which appropriate visual-tactile features can be learned for a slip detection task.
- We demonstrate that the proposed method is more suitable for sliding detection tasks than the traditional early-fusion method.
- We show that the generalization of our proposed model for tactile sensors with different data formats and whether the sequences from the two modalities are aligned.

2. RELATED WORK

2.1 Slip Detection

Slip detection has always been one of the hot research fields in robot manipulation community. Yousef et al. (2011) presents a robotic grasp controller that allows a parallel jaw gripper to gently pick up and set down unknown objects once a grasp location has been selected. The controller selects an appropriate initial grasping force, detects whether an object is slipping from the grasp, increases the grasp force as needed, and determines when to release an object to set it down. Later, Stachowsky et al. (2016) proposes a slip detection and correction strategy for precision robot grasping by a common matrix tactile sensor. More recently, Dong et al. (2017) detect slip using a GelSight sensor by directly measuring the relative displacement between the marker and texture for textured objects. Zhang et al. (2018) and Zapata-Impata et al. (2019) both adopt CNN with ConvLSTM networks to learn spatiotemporal tactile features for slip detection, and the tactile signal is captured by BioTac and FingerVision sensors, respectively. Unfortunately, tactile-only perception may not achieve the desired detection performance due to the limitation of sensing capability.

Adding visual perception is an intuitive solution. Li et al. (2018) proposes a visual-tactile learning method based on a deep neural network to detect slip, which shows the importance of visual-tactile fusion perception in slip detection tasks. A compact and multimodal representation of the sensory inputs was learned by self-supervision (see Calandra et al. (2018)), which can be used to improve the sample efficiency of policy learning. However, these methods concatenate features from visual and tactile modalities directly, which is called early-fusion and have been shown the lack of the ability to capture modal-specific and cross-modal features (see Zadeh et al. (2018)). Additionally, most of the above methods are explicitly designed for tactile sensors with different data formats and sample rates, which leads to significant limitations in platform generalization performance.

2.2 Transformer Network

Vaswani et al. (2017) introduces the transformer network for neural machine translation tasks firstly in 2017. It consists of an encoder and a decoder constructed with the self-attention mechanism (see Parikh et al. (2016)), and shows powerful temporal information capture capabilities from the source domain to the target domain. In addition, transformer networks have also been successfully applied to many other tasks (see Strubell et al. (2019)). More recently, Tsai et al. (2019) proposes a Multimodal Transformer to model multimodal human language time-series without explicitly aligning the data.

We absorb strong inspirations from the multimodal transformer to extend to a visual-tactile setting. Visual-tactile learning is different from conventional multimodal learning in that it is more focused on the capture of cross-modal and cross-temporal interaction features. It pays more attention to the ability to extract the fusion features of two modalities simultaneously, which is not implemented in Tsai et al. (2019).

3. TASK FORMULATION

We define the slip detection task as a binary classification problem, as shown in Fig. 1. Given the visual $X_V$ and tactile $X_T$ sequences, the slip detector model $\mathbb{F}_{sp}$ output the detection result $y$ (slip or not). This task is formulated as

$$
y = \mathbb{F}_{sp}(X_V, X_T)
$$

$$
X_V = \{x_0^v, x_1^v, ..., x_{T_V}^v\}
$$

$$
X_T = \{x_0^t, x_1^t, ..., x_{T_T}^t\}
$$

where $y = 0$ or 1, which $y = 0$ denotes a slip occurs at the current moment. $x_0^v$ and $x_0^t$ represent the first element in the visual and tactile sequences, respectively. $T_V$ and $T_T$ indicate the length of two sequences. Note that $T_V$ and $T_T$ are usually not equal due to the different sample rates of visual and tactile sensors, which means the model $\mathbb{F}_{sp}$ may need to address unaligned sequences from the two modalities.

4. PROPOSED METHOD

The overall architecture of GVT-Transformer is shown in Fig. 2. Firstly, the feature extraction modules and temporal convolution layers are used to extract visual and tactile features. Next, the modal-specific and cross-modal features are extracted by modal-specific and cross-modal transformers, respectively. Then, the modal-specific and cross-modal features of each modal are concatenated and fed into a fusion transformer layer. Finally, the final tactile and visual features are concatenated and sent into a classification layer to obtain an output. The detailed description of each component in GVT-Transformer is shown in this section.
Cross-modal Transformer (T     V)
Cross-modal Transformer (V     T)
Visual-specific Transformer

Finally, the output of CMAT→V is obtained by

\[ X_{cross}^{[0]}_{T→V} = \text{Corr}_{T→V} \times V_T \] (7)

Note that the modal-specific transformers do not change the shape of the input feature maps.

4.4 Cross-modal Transformers

Similar to Tsai et al. (2019), we also build cross-modal transformers to extract cross-modal features in visual-tactile learning. Also, the biggest difference between the module constructed in this paper and Tsai et al. (2019) is that the number of input feature channels of different modalities is not necessarily consistent, which ensures that our proposed model can address different tactile data. The detailed architecture of the Cross-Modal Attention module (CMA_{T→V}) is shown in Fig. 3(b), which is the core module of the proposed cross-modal transformer (T' → V').

Given the features \( X_{V→V} \in \mathbb{R}^{N \times d_V^V}, X_{T→V} \in \mathbb{R}^{N \times d_V^T}, \) and \( X_{T→T} \in \mathbb{R}^{N \times d_T^T}, \) CMA_{T→V} first obtains three features by

\[ \begin{align*}
Q_V &= X_{V→V}W_Q, \quad W_Q \in \mathbb{R}^{d_V^V \times d_K} \\
K_{T→V} &= X_{T→V}W_K, \quad W_K \in \mathbb{R}^{d_V^T \times d_K} \\
V_T &= X_{T→T}W_V, \quad W_V \in \mathbb{R}^{d_T^T \times d_V^T}
\end{align*} \] (5)

where \( Q_V \in \mathbb{R}^{N \times d_K}, K_{T→V} \in \mathbb{R}^{N \times d_K}, \) and \( V_T \in \mathbb{R}^{N \times d_V^T}, d_k \) is a scaled dimension of \( Q_V \) and \( K_{T→V} \), which is set as \( \sqrt{d_V^V} \) in this paper. Next, the correlation matrix of all positions of the two modal sequences can be calculated by

\[ \text{Corr}_{T→V} = \text{SoftMax} \left( \frac{Q_VK_{T→V}^T}{\sqrt{d_k}} \right) \] (6)

where \( \text{Corr} \in \mathbb{R}^{N \times N}. \) Finally, the output of \( \text{CMA}_{T→V} \) is obtained by

\[ X_{T→V}^{cross[0]} = \text{Corr}_{T→V} \times V_T \] (7)
where $X_{T\rightarrow V}^{cross}[0] \in \mathbb{R}^{d_T^v \times d_T^v}$. The superscripts [0] represents the cross-modal features obtained by inputs passing through the cross-modal attention module for the first time. In the next layers, $X_{V\rightarrow V}$ will be replaced by the output of the previous layer as the new input, while $X_{T\rightarrow V}$ and $X_{T\rightarrow T}$ will not.

$$X_{T\rightarrow V}^{cross}[i] = CMA_{T\rightarrow V}(X_{T\rightarrow V}^{cross}[i-1], X_{T\rightarrow V}, X_{T\rightarrow T})$$ \hspace{1cm} (8)

where $i > 0$ is the index of transformer layers.

In this way, the cross-modal transformer ($T \rightarrow V$) uses the CMA$_{T\rightarrow V}$ instead of self-attention module in model-specific transformers to complete the cross-modal features ($T \rightarrow V$) extraction. The different key parts of cross-modal and modal-specific transformer are shown in Fig. 4.

### 4.5 Fusion Transformers and the Classification Module

After the modal-specific and cross-modal features extraction, we concatenate these features and sent them into visual and tactile fusion transformers to extract the final feature of each modal. The architecture of these fusion transformers are the same as the model-specific transformer, as shown in Fig. 3(a).

Finally, the extracted final visual ($X_V^R \in \mathbb{R}^{d_V^r \times d_V^r}$) and tactile ($X_T^R \in \mathbb{R}^{d_T^r \times d_T^r}$) features are concatenated and fed into the fully connected (FC) layers for classification, and the final classification result $y$ is obtained by

$$y = FC((X_V^R \oplus X_T^R))$$ \hspace{1cm} (9)

where $y = 0 \text{ or } 1$.

## 5. EXPERIMENTS AND ANALYSIS

In this section, we perform comparative experiments on two visual-tactile slip detection datasets to verify the performance of the proposed GVT-Transformer model. Our goal is to answer the following two questions:

1. Is our proposed model more suitable for slip detection tasks than the Early Fusion (EF) method?
2. Can the proposed model accommodate unaligned visual and tactile sequence data and different tactile sensors?

5.1 Visual-Tactile Grasping Datasets Introduction

**D0:** Li et al. (2018) build a visual-tactile grasping dataset for slip detection tasks, in which the training data is acquired by a GelSight tactile sensor (see Yuan et al. (2017)), and a camera mounted on the gripper, respectively. Note that the train-test partition of D0 is not completely consistent with the original paper.

**D1:** We collect visual and tactile sequence data by two XELA tactile sensors (see Tomo et al. (2015)) and a camera mounted on a gripper, as shown in Fig. 6. An example of collected visual-tactile sequences is shown in Fig. 5. In total, we perform 5,000 grasps on 17 dairy objects, and the number of grasping routines is nearly 10 times as D0 did. For more detailed information of D1, please refer to our detailed dataset.

Note that the visual-tactile sequences of D0 are aligned, while D1 is not.

5.2 Experiments on D0

**Implementation details:** We use Inception-V3 as the backbone CNN to extract features, and the sequence length is set to 8 according to Li et al. (2018). The detailed parameters of GVT-Transformer on dataset D0 is shown in Table 1. We use Xavier initialization, cross-entropy loss function, Adam optimizer with a learning rate of 5e-5, and a batch size of 64 to train the models on an Nvidia GeForce Titan X GPU platform with PyTorch 1.3.0 package.

**Results:** The precision, recall, and F1 score of the two models on D0 are shown in Table 2. The detection performance of the proposed method is not inferior and even better than EF in an aligned situation, which answers our first question.

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1. https://drive.google.com/drive/folders/1IcYp4oIjFWUlw-X8Ei27JSBiaeiV32Ts?usp=sharing
### Table 1. Details network parameters of GVT-Transformer on D0

| Layers Operations FeatureMap | T/V CNN Inception v3(avg-pool) | 8 × 2048 |
|------------------------------|-------------------------------|----------|
| T/V-CF outdim(64),kernel(2),padding(0) | 7 × 64 |
| T/V-S TF layers(3),head(4) | 7 × 64 |
| T/V-C TF layers(3),head(4) | 7 × 64 |
| T/V-B TF layers(5),head(4) | 7 × 128 |
| Classification FC(256,64),FC(64,2) | 2 |

5.3 Experiments on D1

**Implementation details:** We set the initial network parameters of GVT-Transformer shown in Table 3, and the detailed parameter optimization process can be found in the supplementary material. Note that the training strategy here is the same as experiments on D0 except for batch size (512) and learning rate (1e-6).

**Table 3. Initial parameters of proposed model**

| Layers Operations FeatureMap | T/V CNN Inception v3(avg-pool) | 5 × 2048 |
|------------------------------|-------------------------------|----------|
| T Signal No operations pad(0) | 11 × 92 |
| T/V-S TF layers(5),head(8) | 10 × 32/4 × 64 |
| T/V-C TF layers(5),head(8) | 10 × 64/4 × 32 |
| T/V-F TF layers(5),head(8) | 10 × 96/4 × 96 |
| Classification FC(192,64),FC(64,2) | 2 |

**Ablation study:** To further study the influence of the individual components in GVT-Transformer, we perform a comprehensive ablation analysis on dataset D1. The results are shown in Table 4.

**Table 4. An ablation study of GVT-Transformer on D0**

| Parameters | Precision (%) Recall (%) F1 score (%) |
|------------|--------------------------------------|
| Tactile-only | 96.83 | 90.66 | 93.20 |
| No modal-spec | 85.58 | 89.69 | 87.48 |
| No cross-modal | 83.39 | 69.99 | 74.74 |
| GVT-Transformer | 97.43 | 90.12 | 93.37 |
| Adapted EF | 90.83 | 90.89 | 92.50 |

5.4 Experiments on robots

A slip detection experiment based on GVT-Transformer is performed on our robot to verify its effectiveness in practice. A Nestlé bottle with a half bottle of water is selected as a grasping object. We first set the initial grasping force of 15N, which is sufficient to hold and hold the bottle stably. During the lifting process, we suddenly set the grasping width to 71 mm so that a slip will occur without causing the water bottle to fall. In this grasping routine, the three-dimensional force readings of two XELA tactile sensors and the slip detection labels changes are shown in Fig. 7. Obviously, the label changes immediately following the command and the grasping video can be found in https://youtu.be/oGkhw09yGwM.

6. CONCLUSION

A transformer network-based slip detection method named GVT-Transformer is proposed to solve the unaligned visual-tactile sequence learning problem in this paper. Specifically, modal-specific and cross-modal transformers of GVT-Transformer are presented to capture modal-specific and cross-modal features, respectively. Furthermore, The experimental results show that our proposed method not only outperforms traditional early fusion methods in detection performance but also more suitable for unaligned situation. A sliding detection experiment carried out on a real robot also confirm the proposed method.

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2 https://drive.google.com/file/d/1XoWQMfuC8ZM6jIpeF1q4Yz26gQ4QCR/view?usp=sharing
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