MUTUAL GENERATIVE TRANSFORMER LEARNING FOR CROSS-VIEW GEO-LOCALIZATION

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ABSTRACT
Cross-view geo-localization (CVGL), which aims to estimate the geographical location of the ground-level camera by matching against enormous geo-tagged aerial (e.g., satellite) images, remains extremely challenging due to the drastic appearance differences across views. Existing methods mainly employ Siamese-like CNNs to extract global descriptors without examining the mutual benefits between the two modes. In this paper, we present a novel approach using cross-modal knowledge generative tactics in combination with transformer, namely mutual generative transformer learning (MGTL), for CVGL. Specifically, MGTL develops two separate generative modules—one for aerial-like knowledge generation from ground-level semantic information and vice versa—and fully exploits their mutual benefits through the attention mechanism. Experiments on challenging public benchmarks, CVACT and CVUSA, demonstrate the effectiveness of the proposed method compared to the existing state-of-the-art models. Code will be available.

Index Terms— Cross-view geo-localization, Generative Learning, Transformer

1. INTRODUCTION
Geo-localization provides the geographical location of a street view image which is of paramount importance for autonomous driving [1, 2], robot navigation [3], and routing [4] in a GPS-denied environment. Recent years have seen significant research interest in CVGL as satellite GPS-tagged images are readily available, yet challenging [5] due to the drastic differences in viewpoint and appearance between ground-level optical imagery and aerial-level satellite pattern.

As shown in Figure 1, the existing deep models usually design a two-branch network [6, 7], i.e., Siamese-like model, for learning the higher-order representations from each modality, respectively, and then perform feature similarity estimation to order the most similar matches. However, these models are still incapable of fully resolving the intrinsic visual differences between multi-modal. The Vision Transformer [8, 9] is evaluated as a way to drill down into more representational feature encoding in order to alleviate the shortage. Generative Adversarial Network (GAN) [10] brings satellite images closer to ground-level views. Although their remarkable achievements indicate the benefits of establishing inter-modal relationships in CVGL, the mutual benefit of inter-modal is still poorly explored.

To overcome the shortage, we present a novel Mutual Generative Transformer Learning (MGTL), as shown in Figure 1, to exploit the mutual benefits inter-modal for CVGL. Specifically, we carefully design two symmetrical generative sub-modules, i.e., Ground-to-Satellite (G2S) and Satellite-to-Ground (S2G), in a Siamese-like framework to produce the cross-modal knowledge, e.g., S2G takes the aerial information and skillfully simulates the ground-aware knowledge, the produced knowledge is further used to enhance the aerial pattern representation under a Transformer-based framework and vice versa. The experiment results on various benchmarks demonstrate the superiority of our proposed model.

The contributions of the proposed MGTL can be summarized

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Decoder

tails.

like knowledge from ground-level information and S2G com-

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a ground-view image

Siamese-like deep model contains two cross-modal knowl-

dge from ground-level information and S2G com-

 defeats the contrariwise operation. Please refer to § 2 for de-

tails.

as follows:

• A novel cross-modal knowledge guided learning ap-

proach for CVGL. To the best of our knowledge, this

is the first tempt to build the mutual interaction be-

tween modalities, i.e., ground-level image and aerial-

level pattern, in the specified task.

• Cross-attentive Transformer to exploit the benefits

of generative cross-modal knowledge. Unlike exist-

ing Transformer-based CVGL models only can perform

self-attentive reasoning in the respective modality, our

proposed MGTL performs cross-supported information
to enhance the high-order representation.

• State-of-the-art localization accuracy on widely-

used benchmarks. Our MGTL outperforms existing
deep models on various datasets, i.e., CVUSA [11] and
CVACT [12].

2. OUR APPROACH

2.1. Problem Formulation

Let the CVGL model be indicated as the function \( F_{\Theta} \) pa-

terized by weights \( \Theta \), which takes an image pair consists

a ground-view image \( I_G \) and a satellite-view image \( I_S \) as in-

put and produces their corresponding representations \( F_G \) and
\( F_S \). Our goal is to learn \( \Theta \) from the labeled training triplet
\( \{ I_G, I_{SP}^{i}, I_{SN}^{i} \}_{i=1}^{M} \), where \( I_G \) is the ground-view image, \( I_{SP}^{i} \) and \( I_{SN}^{i} \) are the positive and nega-
tive samples relative to \( I_G \), respectively.

2.2. Mutual Generative Transformer Learning

Our proposed MGTL mainly contains three components:
Modality Independent Feature Extractor (MIFE), Cross-

Modality Interaction (CMI), and Generative Knowledge
Supported Transformer (GKST). Please refer to Figure 2 for
the overview.

Modality Independent Feature Extractor (MIFE) \( f_{\text{MIFE}} \).
\( f_{\text{MIFE}} \) takes an image pair \( < I_G, I_S > \) as input and produces
two modality-specific semantic representations \( < F^*_G, F^*_S > \).

Formally, given an image pair \( I_G \in \mathbb{R}^{H_1 \times W_1 \times 3} \) and \( I_S \in \mathbb{R}^{H_2 \times W_2 \times 3} \), a multi-branch backbone (i.e., a Siamese-like
VGG-based FCN network with parameters \( \Theta_{\text{MIFE}} \)) is per-
formed to simultaneously extract features for each modality:

\[
F^*_G = f_{\text{MIFE}}(I_G; \Theta_{\text{MIFE}}), F^*_S = f_{\text{MIFE}}(I_S; \Theta_{\text{MIFE}}),
\]

where the \( F^*_G \in \mathbb{R}^{c \times h \times w} \) and \( F^*_S \in \mathbb{R}^{c \times h \times w} \) are \( c \) channels
and \( h \times w \) spatial resolution high-order semantic representa-
tions for ground-view and satellite-view, respectively.

Cross-modal Interaction (CMI) \( f_{\text{CMI}} \). With the pur-
pose of mining the mutual knowledge between multi-modal,
CMI takes the information from one modality and produces
another-modality-aware knowledge. To alleviate the limita-
tion of feature location on learning receptive field, we first
re-encode the features \( F^*_G \) and \( F^*_S \) with position informa-
tion:

\[
\hat{F}_G = F^*_G + \text{PE}_G, \hat{F}_S = F^*_S + \text{PE}_S,
\]

where \( \text{PE}_G \) and \( \text{PE}_S \) are the positional encoding of feature
maps \( F^*_G \) and \( F^*_S \), respectively. The position-aware repre-
sentations are further normalized as: \( \hat{F}_G = \text{LN}(\hat{F}_G) \) and
\( \hat{F}_S = \text{LN}(\hat{F}_S) \) to maintain representational capacity. Inspired
by VAE [13], we design two generative sub-modules \( f_{\text{G2S}} \) and \( f_{\text{S2G}} \) with the encoder-decoder structure, i.e., shown as
Figure 3, to form the cross-modal interaction module \( f_{\text{CMI}} \)
and produce the cross-modal-aware knowledge:

\[
L_S = f_{\text{G2S}}(\hat{F}_G), L_G = f_{\text{S2G}}(\hat{F}_S),
\]

Generative Knowledge Supported Transformer (GKST) \( f_{\text{GKST}}\). Up till the present moment, we have acquired the

Fig. 2. Overview of the proposed MGTL. MGTL is a
Siamese-like deep model contains two cross-modal knowl-
edge generative sub-modules, i.e., G2S produces satellite-
like knowledge from ground-level information and S2G com-
pletes the contrariwise operation. Please refer to § 2 for de-
tails.

Fig. 3. Illustration of the generative G2S and S2G sub-
modules.

\( F_S \).
intra-modal representation $\hat{F}_G(\hat{F}_S)$ and the generative cross-modal knowledge $L_S(L_G)$. To learn the final representation $F_G$ and $F_S$, we design a generative knowledge supported transformer (GKST) to fully use all information. Formally, the GKST $f_{\text{kst}}$ takes $\hat{F}_G \in \mathbb{R}^{c \times h \times w}(F_S \in \mathbb{R}^{c \times h \times w})$ and $L_S \in \mathbb{R}^{c \times h \times w}(L_G \in \mathbb{R}^{c \times h \times w})$ as input and produces the final high-order representations $F_G(F_S)$. Taking the ground-view as an illustration, we feed the intra-modal representation and cross-modal knowledge into a multi-head cross-attention layer to learn the representative features:

$$Q'_l = \hat{F}_G W'_l, K'_l = L_S W'_l, V'_l = L_S W'_l,$$

where $W'_l, W'_K$ and $W'_V$ are learnable parameters. The updated representations $F_G$ can be achieved by follows:

$$F'_G = \text{MH}(Q', K', V') + \hat{F}_G.$$

We can easily obtain the final satellite-view feature maps $F_S$ in a similar way.

**Recurrent Learning Process.** To fully mine the benefits of the cross-modal knowledge, we can further formulate the learning process recurrently as follows:

$$\hat{F}_G = f_{\text{fatt}}(L_S^{-1}, \hat{F}_G^{l-1}), L_S^{l-1} = f_{\text{fatt}}(\hat{F}_G^{l-1}),$$

$$F_S = f_{\text{fatt}}(L_G^{l-1}, F_S^{l-1}), L_G^{l-1} = f_{\text{fatt}}(F_S^{l-1}),$$

where $\hat{F}_G^{l-1} = \text{LN}(\hat{F}_G^{l-1}), F_S^{l-1} = \text{LN}(F_S^{l-1})$. Note that, at the beginning ($l=1$), $F_G^0$ and $F_S^0$ are produced by Eq. 2, and the final representations $F_G$ and $F_S$ are produced by the last layer.

### 2.3. Implementation Details

**Modality Independent Feature Extractor.** Following [6], we employ two independent VGG-16 [20] pre-trained on ImageNet [21] as the backbone and perform the polar-transform on $I_S$ to make the modality closer to $I_G$. We average the feature maps produced by the backbone along height followed by a FCN layer to prepare a more compact feature $F_G$ and $F_S$ with the resolution $384 \times 1 \times 20$.

**Cross-modal Interaction.** The encoder and decoder are both implemented by two fully-connected layers with the GELU activation layer inside.

**Loss Function.** Following [6], we employ a margin triplet loss for final representation learning:

$$\text{Loss}_{\text{triplet}} = \log(1 + e^\gamma(d_{\text{pos}} - d_{\text{neg}})),$$

where $d_{\text{pos}}$ and $d_{\text{neg}}$ indicate the Euclidean distance between the positive and the negative pairs, respectively. The cross-modal knowledge generation module is supervised by:

$$\text{Loss}_{\text{gen}} = \sum_{l=0}^{L-1} (\text{Loss}^{l}_{S2G} + \text{Loss}^{l}_{G2S}),$$

where $\text{Loss}^{l}_{S2G}$ and $\text{Loss}^{l}_{G2S}$ are implemented via MSE [22] loss: $\text{Loss}^{l}_{S2G} = L_{\text{MSE}}(L_G, F_G^l)$ and $\text{Loss}^{l}_{G2S} = L_{\text{MSE}}(L_S^l, F_S^l)$, and $L$ is the recurrent steps. Finally, the overall learning loss is computed as:

$$\text{Loss} = \text{Loss}_{\text{triplet}} + \lambda \text{Loss}_{\text{gen}},$$

where $\lambda$ is the balancing factor.

### 3. EXPERIMENTS

#### 3.1. Experimental Setting

**Dataset:** Following [5, 6, 9], we evaluate the performance on two widely-used challenging benchmarks *i.e.*, CVUSA [11] and CVACT [12]. Both datasets contain 44416 ground-aerial image pairs and split them into 35532 image pairs for training and 8884 pairs for testing.

| Model          | CVUSA r@1 | CVUSA r@5 | CVUSA r@10 | CVUSA r@1% | CVACT, val r@1 | CVACT, val r@5 | CVACT, val r@10 | CVACT, val r@1% |
|---------------|-----------|-----------|------------|----------|---------------|---------------|----------------|----------------|
| 2015 Workman, et al. [14] | - | - | - | 34.30 | - | - | - | - |
| 2016 Vo, et al. [15] | - | - | - | 63.70 | - | - | - | - |
| 2017 Zhai, et al. [16] | - | - | - | 43.20 | - | - | - | - |
| 2018 CVM-Net [17] | 22.47 | 49.98 | 63.18 | 93.62 | 20.15 | 45.00 | 56.87 | 87.57 |
| 2019 Liu, et al. [12] | 40.79 | 66.82 | 76.36 | 96.12 | 46.96 | 68.28 | 75.48 | 92.04 |
| 2019 Regmi, et al. [18] | 48.75 | - | 81.27 | 95.98 | - | - | - | - |
| 2019 SAFA [6] | 89.84 | 96.93 | 98.14 | 99.64 | 81.03 | 92.80 | 94.84 | 98.17 |
| 2020 CVFT [7] | 61.43 | 84.69 | 90.49 | 99.02 | 61.05 | 81.33 | 86.52 | 95.93 |
| 2020 DSM [19] | 91.96 | 97.50 | 98.54 | 99.67 | 82.49 | 92.44 | 93.99 | 97.32 |
| 2021 Toker, et al. [10] | 92.56 | 97.55 | 98.33 | 99.57 | 83.28 | 93.57 | 95.42 | 98.22 |
| 2021 L2LTR [9] | 94.05 | 98.27 | 98.99 | 99.67 | 84.89 | 94.59 | 95.96 | 98.37 |

**Table 1. Quantitative results** on the CVUSA [11] and CVACT [12] dataset. Results are cited directly, the best results are highlighted.
Table 2. Ablation study of the proposed approach. 'w/' and 'w/o' means the posed MGTL is or is not equipped with CMI, respectively.

| Model   | Backbone | Param.↓ |
|---------|----------|---------|
| L2LTR [9] | ResNet50 | 195.9M  |
| MGTL    | VGG16    | 72.29M  |

Table 3. Complexity comparison between L2LTR [9] and the proposed MGTL.

| Scene | CMI (L=1) | CMI (L=3) | CMI (L=5) | Naïve (L=6) |
|-------|-----------|-----------|-----------|-------------|
| r@1   | 86.44     | 89.08     | 94.11     | 93.81       |
| r@5   | 96.20     | 96.89     | 98.30     | 98.28       |
| r@10  | 97.74     | 98.17     | 99.03     | 99.02       |
| r@1%  | 98.64     | 99.30     | 99.74     | 99.71       |

Table 4. Detailed ablation study of different parameter settings. 'L' is the recurrent learning steps.

3.2. Main Results

Baselines: All recently published CVGL models are compared. We totally select 11 STOAs, which are trained under their recommended setting, for omni-directional comparison.

Performance on CVUSA and CVACT: The comparison results with 11 STOAs on CVUSA [11] and CVACT [12] are shown in Table 1. It shows that our MGTL achieves better performance than all baselines across all metrics on CVUSA and most metrics on CVACT_val. Our model receives 94.11% and 85.35% top-1 (r@1) retrieval accuracy on CVUSA and CVACT_val, respectively.

3.3. Ablation Study

Effect of Recurrent Learning: Table 4 reports the localization performance under different recurrent learning iterations. Accuracy improved with the increase of learning steps proves that recurrent learning can help to produce a strong representation with the generative cross-modal knowledge. However, when further raising the learning steps (L=9), the gains are not noticeable and even go down. As increasing of the learning steps, the quantity and quality of the new generative knowledge would gradually become more difficult.

Effectiveness of CMI: We carefully study the impact in different settings. When we remove CMI, i.e., 'w/o' in Table 2, and keep the workflow in the Siamese-like network independent, we can observe that the performance degrades significantly. Besides, if we use the local-receptive CNNs to produce the generative knowledge, i.e., 'Naïve' in Table 4, the localization accuracy degradation still be observed.

Complexity Analysis of MGTL: Table 2 reports the complexity of our model with different configurations. The fully-equipped model costs 4.43 GLOPs and 79.27M memory. We also compare the complexity with the recent baseline, as shown in Table 3. L2LTR [9] slightly exceeds our MGTL only in the r@5 metric, but it tolerates almost thrice the complexity of our model.

4. CONCLUSION

In this paper, we propose a novel multi-modal learning network, i.e., MGTL, to tackle the cross-view geo-localization problem. We build and inject the generative cross-modal knowledge into a Transformer-based framework to support intra-modal high-order information mining. Sufficient experiments demonstrate that our model can fully benefit from cross-modal and set the new record on several widely-used challenging benchmarks. Our findings suggest that the novel perspective can benefit other multi-modal computer vision problems, such as joint perception of Lidar and vision.
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